CRANFIELD UNIVERSITY

Thomas Fungenzi

Evaluating Long Term Soil Organic Matter Dynamics of Cocoa Farms in Indonesia

School of Water, Energy, and Environment

PhD
Academic Year: 2018 - 2021

Supervisor: Dr Ruben Sakrabani
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ABSTRACT

In Sulawesi, Indonesia, cocoa (*Theobroma cacao* L.) yields are suboptimal. Most cocoa farms are agroforestry systems, thought to be efficient at storing large carbon stocks (C), protecting the soil from degradation, and recycling nutrients. Despite this, inappropriate management practices can lead to the progressive deterioration of soil fertility and constrain cocoa productivity. One critical component of soil fertility is soil organic matter (SOM). Although organic additions are available to producers, the SOM dynamics of cocoa farms are poorly understood, precluding the development of evidence-based practices for SOM and fertilizer management. Hence, this research was conducted to determine the relationship between organic matter additions, soil fertility, and cocoa production, using meta-analysis, field experimentation, a chronosequence study, and modelling.

The meta-analysis, which incorporated 37 references from 14 countries, showed that the mean C stock of 15 to 35-year old cocoa systems (including shade trees, and soil to 10 cm depth) was ~85 Mg ha^{-1}. For this age range, the mean C stocks for aboveground cocoa, shade trees, litter, and roots were approximately 9.8, 37.4, 1.0, and 11.4 Mg ha^{-1}, respectively. The mean soil C stock (0-10 cm) was ~24 Mg ha^{-1}. If taken from deeper soil layers, soil C stocks can be substantial and may exceed plant C. Large differences observed within the same age classes suggest that modified designs and practices can increase C storage for a particular pedoclimatic context.

The continuation of an already established field experiment (a randomized block experiment with 16 cocoa trees for each four repetitions, including applications of mineral fertiliser, compost and dolomite alone and in combinations) indicated that compost application (locally made of 60% cow manure, 15% empty oil palm bunches, 10% rice straw, 10% diverse leaves (banana, grass, *Gliricidia,* and maize), 5% cocoa pod husks, and a EM4 micro-organism mix; 10 kg $tree^{-1}$ $year^{-1}$) increased cocoa yields (over four years) to 1.8 Mg dry bean ha^{-1}, three times that of a control treatment with no additions. The four-year cumulated yield of the fertiliser-only treatment was 0.98 Mg dry bean ha^{-1}. The tree survival rate was low in the fertiliser-only blocks (on average 41% after 7 years). No additional yield effect was observed by adding fertiliser or dolomite to the compost treatment. Soil responses were variable. For example, measured 25% HCl extractable P declined across all treatments, and a loss of soil organic C (SOC) occurred across all treatments with composts. This suggests that the maintenance of SOM

through compost additions requires a systematic understanding of their losses and inputs.

A chronosequence study across 13 Sulawesian cocoa farms (0.5-31 years old) indicated significant SOM losses within cocoa plantations in the first 1-5 years after planting, as SOM mineralisation was greater than the rate of new SOM addition. Soil samples (0 - 100 cm) were collected in 20 cm increments to determine SOM, SOC, and N contents, clay-adjusted SOM, SOC, and N contents, and SOM, SOC and N stocks. The observed decline between 0.5 and 2 years in SOM (-46%) was also associated with declines in SOM per unit clay (-40%). These findings suggest that from the moment a plot is cleared in preparation for planting, the high temperatures and precipitation found in Sulawesi can result in rapid soil degradation through fast SOM mineralisation. Future research should focus on the first years after planting, and farm practices, such as strategic organic additions, should target this sensitive period.

The modelling study provides a framework to predict SOM variations on cocoa farms. The model combined the AMG soil model (Andriulo et al., 1999; Clivot et al., 2019; Saffih-Hdadi & Mary, 2008) with a cocoa growth curve from the chronosequence dataset. An annual SOM mineralisation rate of 0.125 (unitless) was calculated using the characteristics of a representative farm of the chronosequence dataset (averaging the local variables of each farm) and represent a relatively high rate compared to other world locations. Backward modelling was used by optimisation to simulate SOM dynamics in each of the 13 farms. The simulations indicated that SOM could deplete rapidly after planting, and the long-term trend can either be a decline or a build-up and even exceed planting levels. In general, farms with a high initial SOM content tended to lose SOM, whereas farms with a low initial SOM content tended to gain SOM in the long term (after 20-30 years of cultivation). The model was also applied to calculate the amounts of various organic inputs required to offset SOM losses fully. This model was programmed in R, and an RStudio Shiny app was developed to allow for user-friendly simulations. Future research should include further calibration of model parameters, improved modelling of pruning and shade trees in residue deposition, and making crop growth responsive to environmental parameters.

The above results highlight that Sulawesian cocoa farms are particularly at risk of SOM losses in the initial years after planting. This is a critical period during which organic additions could support cocoa productivity and provide other environmental benefits. Recommendations for SOM management and future

research are proposed to limit soil degradation and improve the C balance of cocoa farms.

Keywords:

Cocoa, soil organic matter, modelling, compost, Indonesia, Sulawesi

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LIST OF ABBREVIATIONS

AGB	Aboveground biomass
AMG	Andriulo-Mary-Guérif soil model
BD	Bulk density
BGB	Belowground biomass
BIO	Microbial biomass (RothC pool)
BS	Base saturation
C	Carbon
C/SOM	Carbon content of soil organic matter
CI	Confidence interval
C:N	Carbon to nitrogen ratio
CO_2	Carbon dioxide
CRUK	Cocoa Research United-Kingdom
d	Soil sampling depth
D30	Diameter at 30 cm height
D50	Diameter at 50 cm height
DBH	Diameter at breast height
D_{eff}	Root fraction in sampling depth (depth effect)
DPM	Decomposable plant material (RothC pool)
E	Root exudation coefficient
EOM	Exogenous organic matter
EOM_{freq}	Frequency of application of organic inputs
EOM_{k1}	Humification rate of organic inputs
$EOM_{position}$	First year of application after planting
EOM_{rate}	Rate of application of organic inputs
Exch.	Exchangeable
Extract.	Extractable
FP	Functional parameter
FR_F	Fine root fraction
FR_{TOR}	Annual fine root turnover rate
GHG	Greenhouse gas
GPS	Global positioning system
GR	Growth parameter (growth rate)
HSD	Honestly significant difference
HUM	Humified organic matter (RothC pool)
k_{1A}	Humification coefficient of aboveground residues
k_{1B}	Humification coefficient of belowground residues
k_2	SOM mineralisation rate
L_{max}	Growth parameter (upper asymptote)
LOI	Loss on ignition
LV	Local variable
MAPE	Mean absolute percentage error
MDB	Bulk density of the mineral fraction of the soil
MLR	Multiple linear regression

N	Nitrogen
NPK	Ratio of content percentages of three main nutrients in a fertiliser: nitrogen, phosphorus, and potassium
OMDB	Bulk density of the organic fraction of the soil
P	p-value (if not referring to phosphorus)
PSD	Particle size distribution
R^2	Coefficient of determination
RDR_A	Fraction of aboveground biomass deposited annually
RMSE	Root mean square error
RPM	Recalcitrant plant material (RothC pool)
RSR	Root-to-shoot ratio
S	Standard error of the estimate
SOC	Soil organic carbon
SOM	Soil organic matter
SOM_{split}	SOM split ratio
t	time (year after planting)
TH	Total height
UNFCCC	United Nations Framework Convention on Climate Change
USDA	United States Department of Agriculture
β	Cocoa root distribution parameter
δ	Growth parameter (shape parameter)

1. INTRODUCTION

1.1 Background

One of the greatest challenges facing humankind is to ensure a sufficient, safe, and sustainable supply of food while at the same time preserving ecosystem functions and associated goods and services. The management of soil, and particularly soil organic matter (SOM), has a fundamental role in supporting essential ecosystem services, such as food production and climate regulation (Baveye et al., 2016). Improving our understanding of how diverse land uses and soil management practices can accumulate or deplete SOM is therefore critical. From an agricultural standpoint, the decrease of SOM by mineralisation can be beneficial because it results in the release of soil nutrients available for the crop. However, from an environmental perspective, the mineralisation of SOM generates carbon dioxide, which is a major greenhouse gas (GHG). SOM depletion can also cause soil degradation by disrupting soil functioning (e.g., by reducing a soil's ability to maintain its structure and store water, by being associated with a reduction of the nutrient), reducing plant productivity, and facilitating erosion (Bot & Benites, 2005).

Long-term experiments have been developed worldwide to monitor changes in SOM under different treatments (Richter et al., 2007). However, despite their critical importance, this type of experiment requires a substantial investment of time and resources (Johnston & Poulton, 2018). Also, even though the knowledge obtained from those experiments is extremely useful, the whole information generation process is "slow" because results are obtained progressively (of the order of a decade). One way to anticipate the effect of different interventions on long-term SOM stock variations is through the complementary use of computer simulation models. From the simplest to the most complex ones, a plethora of soil models have been developed over the decades (Campbell & Paustian, 2015). Some consider SOM as a single pool of matter (i.e., mono-compartmental models such as Hénin-Dupuis, Hénin & Dupuis, 1945), while others categorize SOM into several pools according to their relative cycling rates or the nature of the organic matter (i.e., multi-compartmental models such as RothC, Coleman & Jenkinson, 1996). Some models focus on SOM, while others prefer an elemental approach to simulate the variations of soil carbon (C), sometimes in conjunction with other key elements including nitrogen (N). SOM model applications are diverse. SOM models have been used, for example, to compare specific agricultural or forestry systems and practices (Francaviglia et al., 2012), to assess the potential for soil

C-sequestration (Smith et al., 2020), or evaluate the response of SOM stocks to climate change (Wang et al., 2017). However, not all agricultural systems have received the same level of scrutiny regarding SOM dynamics (Manners & van Etten, 2018). To date, there is a paucity of research on cocoa (CocoaSoils, 2019).

Figure 1.1: Botanical illustration of cocoa (Theobroma cacao L.), showing a branch with leaves, pods, and an open pod with its beans (Bernecker, 1867)

Cocoa (*Theobroma cacao L.*; Figure 1.1) is an understorey tropical tree crop grown to produce beans that are used in the manufacture of chocolate, cocoa powder, and cocoa butter. The largest natural populations of the species exist in Central and South America, and the crop was introduced to South-East Asia in the 1600s and to West Africa in the 1800s (Carr & Lockwood, 2011). Cocoa is often cultivated by hand in agroforestry systems using shade trees (Figure 1.2) and other associated plant species like banana or timber trees, without using agricultural machinery (Voora et al., 2019). Cocoa cultivation systems are diverse, ranging over a gradient of density and diversity of associated plants (Notaro et al., 2020), from full-sun irrigated monocultures, to farms shaded with a single species like *Gliricidia sepium* (named "*madre de cacao*" in Spanish) and to multi-storied agroforestry systems such as the Brazilian *cabrucas*. However, endeavours to modernize cocoa plantations like other fruits crops are increasingly focusing on full-sun systems without shade trees. Nonetheless, it is thought that currently, large-scale plantations (>40 ha) only represent 5% of the world's cocoa production (Anga, 2016). This diversity of farm systems and designs is accompanied by significant differences in terms of ecosystem services delivery (Wainaina et al., 2021).

Like other tree crops, cocoa has a long lifecycle. It is commonly asserted that cocoa farms are productive for 20-30 years, but the production can be very variable and complicated by many factors other than tree age. It is believed that full-sun farms reach higher yields, faster than shaded systems, but their production phase could be shorter than shaded farms. Conversely, shaded farms may reach lower yields, but produce for a more extended period (van Vliet et al., 2015). Some cocoa farms can be very old, with trees older than 80 years old. However, farmers are advised to rehabilitate (i.e., restore the productive capacity of a potentially productive orchard) or restore (i.e., replant with new trees) their farm after several decades of cultivation (Somarriba et al., 2021).

Figure 1.2: Four cocoa farms of increasing age in Sulawesi (Indonesia)

The current global production area of cocoa is approximately 12.2 million ha (FAO, 2020), and despite an increase in the quantity produced, the average world cocoa yield per hectare has tended to stagnate (Figure 1.3, Figure 1.4, Figure 1.5). Even though cocoa represents only 0.7% of the global land-use footprint of crop production, it can cover a significant area in the main producing countries (Chatham House, 2017), including 16 Low Human Development Countries (Voora et al., 2019).

Cocoa is an essential source of income for 40-50 million smallholders (2-5 ha) and their households, who provide more than 70-90% of global cocoa production while living on less than $2 per day (Voora et al., 2019; WCF, 2009, 2012). Cocoa is perceived as the most important crop in Côte d'Ivoire (1st ranked global producer of cocoa beans; with 27% of the global land footprint of cocoa production) and Ghana (2nd ranked global producer; with 25% of the land footprint) (Bymolt et al., 2018; Chatham House, 2017).

Beyond its socioeconomic significance, cocoa also has strong links with environmental concerns such as climate change and deforestation. Cocoa is a drought sensitive crop (Carr & Lockwood, 2011) and climate change is affecting the distribution of areas suitable for its cultivation (Bunn et al., 2019; Schroth et al., 2016). In the past, the expansion of cocoa cultivation often resulted in deforestation (Ruf, 2001; Ruf et al., 2015), and even if today, cocoa industries are committed to prevent further deforestation (IDH, 2017), climate change and soil degradation will most likely lead farmers to expand cocoa into forested areas (Askew, 2020), or to decide to replace it by other crops.

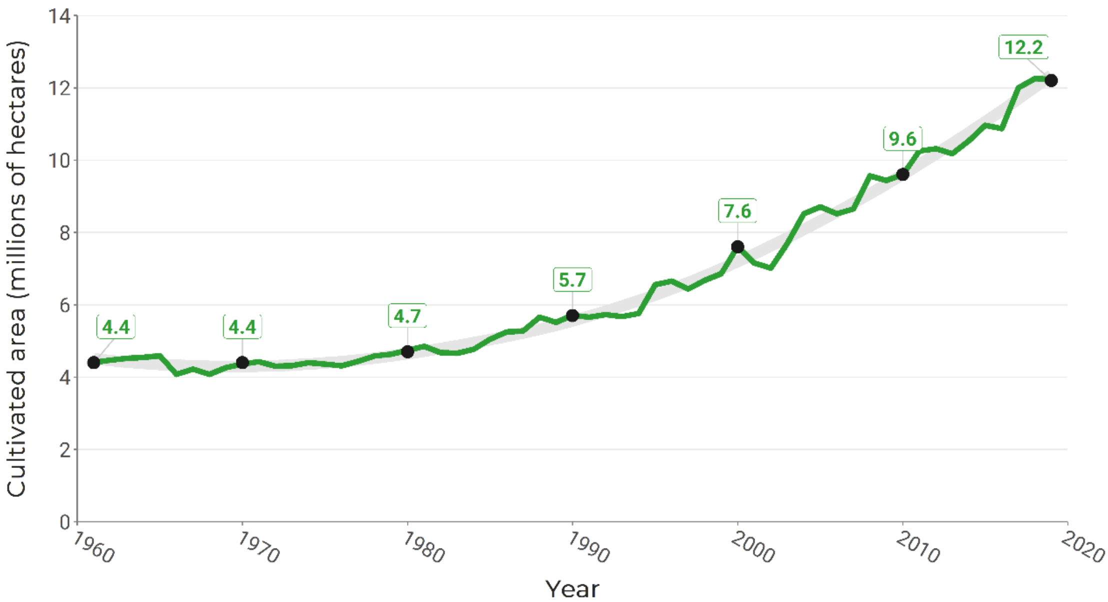


Figure 1.3: Global area cultivated with cocoa from 1961 to 2019 (FAO, 2020)

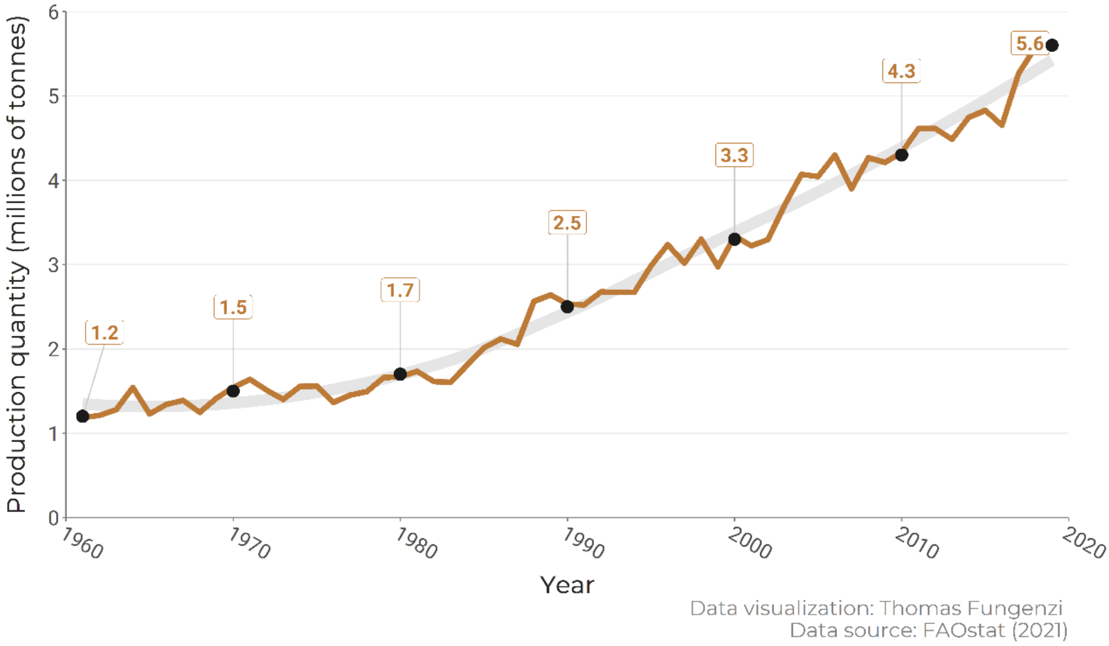


Figure 1.4: Global cocoa bean production from 1961 to 2019 (FAO, 2020)

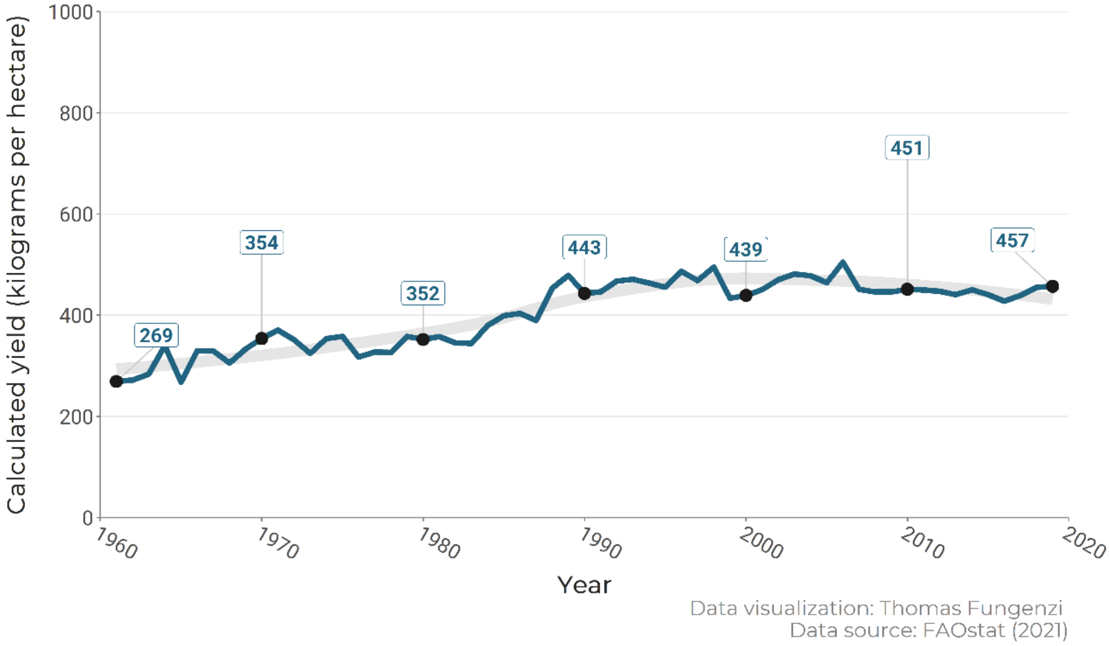


Figure 1.5: Estimated global cocoa bean yield from 1961 to 2019 (FAO, 2020)
Yields were estimated by dividing the world bean production by the cultivated area.

Increasing yields has been identified as one of the best approaches to improve the living standards of cocoa farmers and, at the same time, reducing the extent of shifting cultivation which can result in deforestation (van Vliet et al., 2021). Unfortunately, the cause for low cocoa yields is multifactorial. Low productivity results from a combination of factors such as the infestation of pests and diseases, a lack of water during droughts, insufficient fertilization, not having access to good planting material, and inadequate farm management, all of them due to a lack of resources and/or knowledge (Bastide, 2016, 2017; van Vliet et al., 2015). In many regions of the world, cocoa yields are *suboptimal*, *unstable*, and *heterogeneous* (Bastide, 2016, 2017; van Vliet et al., 2015):

- *Suboptimal*: Currently, mean cocoa yields are around 450 kg ha^{-1} yr^{-1}, but there is evidence from research stations and industrial plantations that yields can exceed 2,000 kg ha^{-1} yr^{-1}.
- *Unstable*: The yield varies greatly over the lifetime of a stand and often reaches a peak between 5 to 10 years before declining in the long term. The production phase can be short and decline rapidly. Yields can also vary greatly from one year to the next.
- *Heterogenous*: At the plot scale, some trees may produce very few pods while others are associated with most of the production.

Many of cocoa's agronomical challenges can be summarized by the fact that cocoa has only be recently domesticated using modern techniques as compared to other crops. For example, the harvest index (i.e., the dry mass of the economic component divided by the total biomass) of cocoa plants is relatively low (Bastide, personal communication). In other words, cocoa trees spend a lot of energy to produce vegetative biomass but very few harvested fruits. Pruning plays an important role in controlling the tree's shape to optimize productivity and clippings affect the flux of C and nutrients returning to the soil. Many aspects of cocoa cultivation, such as pollination, plant nutrition and pathology remain to be improved.

According to the Global Soil Partnership (2022): "Soil fertility is the ability of a soil to sustain plant growth by providing essential plant nutrients and favourable chemical, physical, and biological characteristics as a habitat for plant growth". In perennial plantations like cocoa, soil fertility decline can be manifested by a range of degradation processes such as soil acidification, SOM decline, soil structure deterioration, and plant nutrient exhaustion (Hartemink, 2003). One of the most significant ways to improve cocoa yields is to prevent soil degradation and enhance soil fertility (CocoaSoils, 2019; Kongor et al., 2019; Mulia et al., 2019; Quaye et al., 2021). Low soil fertility is a prevalent problem in cocoa-growing regions (Adeniyi et al., 2017; Kongor et al., 2019). Research has highlighted that inappropriate practices can lead to progressive land degradation (Hartemink, 2003, 2005), despite a relatively good soil conservation capacity of the cocoa agroforestry system compared to other crops (i.e., good level of nutrient recycling, ground cover provided by the canopy and the litter). The prolonged cultivation of cocoa can sometimes lead to high degradation levels if no restoration measures are implemented. In cocoa systems, one of the main causes of degradation is most certainly the depletion of non-replaced nutrients after harvest (Hartemink, 2005).

Soil organic matter (SOM) is often acknowledged as the key indicator of soil fertility (Jörg Gerke, 2022; Obalum et al., 2017; Tiessen et al., 1994). Improving and maintaining soil fertility can be achieved by managing SOM levels and dynamics correctly (Johnston et al., 2009b; Vanlauwe et al., 2010). The study of SOM reflects key aspects of soil functioning and is sensitive to soil and crop management. It has direct and indirect influences on plants (Oldfield et al., 2017). SOM is, for example, a reservoir of plant nutrients (Powlson et al., 2013), is often linked to water holding capacity (Lal, 2020), buffers pH (Jiang et al., 2018), contributes to cation exchange capacity (Solly et al., 2020), can stimulate plant growth (Canellas & Olivares, 2014), and acts as a reservoir of matter and energy for soil micro-organisms (Kallenbach et al., 2016). It is generally accepted that higher SOM contents are desirable, even though it remains difficult to identify upper and lower thresholds (Loveland & Webb, 2003; Oldfield et al., 2015, 2019). This obstacle is particularly due to the fact that SOM encompasses an extremely large diversity of molecules and constituents.

To address this low and declining fertility problem, the use of organic inputs – like composts, manures, and mulches – may be an appropriate solution accessible to resource-limited farmers. By applying organic inputs to the soil, it is possible to benefit from positive effects on soil's functions, such as the improvement of soil structure and nutrient availability. The addition of organic materials has been used in other cases to improve soil fertility (Diacono & Montemurro, 2010; Palm et al., 2001). However, at this stage, cocoa soil managers do not have access to an evidence-based approach for the rational use of organic inputs that could help determining the types, rates, frequency and timings of organic input applications. In agricultural systems in general, although manuring is an ancient practice, there is no readily available model to link organic additions to desired agricultural outcomes. This situation prevents any detailed and reliable recommendations for the intended use of organic additions (Oldfield et al., 2015).

Research on the relationships between cocoa and soil fertility has received little attention since the 80's (CocoaSoils, 2019; Manners & van Etten, 2018; Silva & Giller, 2020). SOM dynamics in cocoa systems has never been modelled in detail. Studies on this topic were limited to discrete measurements (e.g., Beer et al., 1990; Smiley & Kroschel, 2008) or simple regressions (e.g., Silatsa et al., 2017). The monitoring of SOM changes and the C-cycling has been covered for a wide diversity of cocoa systems including age, management levels, climates, and types of shade tree. Nevertheless, mathematical models of the in-situ C-cycling processes in place are missing. Research on these topics is scarce and has not been updated by considering the progress made since the 1980's in the wider agronomy and soil science landscape.

Despite a substantial lack of knowledge about cocoa soils compared to other crops (Manners & van Etten, 2018; Silva & Giller, 2020), that does not mean that nothing has been done. Several themes can be distinguished from the cocoa soil literature (note that some of these themes overlap):

1. The relationship between soil properties and cocoa productivity (e.g., Singh et al., 2019);
2. The evaluation of the effects of inputs (e.g., fertiliser, composts, liming agents, pesticides) on soil properties and cocoa growth and productivity (e.g., Mulia et al., 2019);
3. The evaluation and comparison of C-stocks or soil properties of a given system or across systems (e.g., shaded or not shaded) or regions (e.g., Blaser et al., 2018; Niether et al., 2020; Saputra et al., 2020);
4. The assessment of long-term physical, chemical and biological soil changes occurring during cultivation (e.g., Hartemink, 2005);
5. The relationships between cocoa farming practices and soil ecology (e.g., Tondoh et al., 2015).

Further information regarding these topics will be provided in the following chapters on this thesis.

At this stage, there is a lack of understanding of SOM dynamics in cocoa farms, which could be enhanced by developing and using improved models. Such a modelling tool could be used to anticipate SOM stock variations and estimate the inputs needed to maintain SOM at particular levels. Furthermore, the availability of a SOM model applicable to cocoa could also benefit other endeavours, such as ones related to climate change mitigation (Bunn et al., 2019), and to other similar perennial systems as well, such as coffee, palm oil, or rubber cultivation. Complementary to field experiments, modelling experiments must be undertaken to sustainably safeguard cocoa production and offer pertinent farm and soil management recommendations.

The experimental focus of this research project was Indonesia. Indonesia was the third-largest cocoa-producing country globally after Côte d'Ivoire (~1,400,000 t of cocoa beans) and Ghana (~860,000 t of cocoa beans), producing ~730,000 t of cocoa beans in 2014 and exporting approximately half of its production (Chatham House, 2017; FAO, 2020). In Indonesia, the harvested area rapidly increased from ~750,000 ha in 2000 to ~1,700,000 ha in 2014 (Chatham House, 2017; FAO, 2020), representing ~4% of the Indonesia's land footprint of crop production. The land used to harvest cocoa was multiplied by ten between 1990 and 2010, reaching a plateau of approximately 17,000 km^2 (FAOSTAT, 2020). However, Indonesia's production of cocoa beans has decreased since 2010-2015, apparently because of declining yields per hectare that started in the early 1990s (FAOSTAT, 2020). More recently, a report from the International Cocoa Organization (ICCO) highlighted than Indonesia's cocoa output was declining (Harsono, 2020), downgrading it to the sixth globally, overtaken by Ecuador (3^{rd}), Cameroon (4^{th}) and Nigeria (5^{th}). The challenge for Indonesian farmers seems to be insufficient access to seedlings and fertilizers (Harsono, 2020) as well as pest and disease attacks, ageing orchards which were not rehabilitated or restored, an overall suboptimal management of land resources leading to low productivity (Leksono et al., 2021), and the competition with palm oil being lucrative than cocoa. Despite the relative importance of Indonesia, research organizations have allocated few resources to address its needs. Historically, most of the academic literature has been concentrated in West Africa, and increasingly in America. In conjunction with the sponsors of this research project, Indonesia, and more particularly Sulawesi – where two thirds of Indonesia's cocoa production is located (Leksono et al., 2021) – was selected to study SOM dynamics in cocoa farms.

1.2 Research aims and objectives

The low cocoa yields and reduction in soil fertility on cocoa farms in Indonesia provided the initial rationale for this thesis. Improving soil fertility by adding organic matter was perceived as a way to reverse these trends.

The **strategic aim** of this thesis was to improve our understanding of SOM dynamics on cocoa farms. More specifically, this research sought to describe and explain the temporal variations of SOM and C stocks in cocoa farms using a combination of approaches, including literature reviews, field sampling, laboratory measurements, and modelling.

The **applied aim** of this project was to propose a SOM management strategy for cocoa cultivation in Indonesia.

Five objectives were defined to meet those goals:

1. Firstly, to assess the existing temporal dynamics, variability, and distribution of C storage in cocoa systems across the world by the critical analysis of available data.
2. Secondly, to compare the effects of soil inputs (fertilizer, compost, and dolomite) on key soil properties and cocoa growth and productivity, through experimentation.
3. Thirdly, to characterize SOM dynamics on a chronosequence of Indonesian cocoa farms.
4. Fourthly, to describe and predict SOM dynamics in cocoa farms by using a modelling approach, building upon the knowledge obtained from the other objectives, and simulate the effect of organic inputs on SOM stocks.
5. Finally, to propose a suite of SOM management recommendations for cocoa farms in Indonesia, based on a synthesis of the research.

1.3 Thesis structure

The thesis is composed of seven chapters. Chapter 1 introduces the thesis. Chapters 2 to 5 each correspond to a study formatted as a research article, following the same order as the research objectives (except objective 5). Chapter 6 summarizes and discusses the findings and addresses objective 5. Chapter 7 concludes the thesis and makes recommendations for future research. The structure of the thesis is illustrated in Figure 1.6.

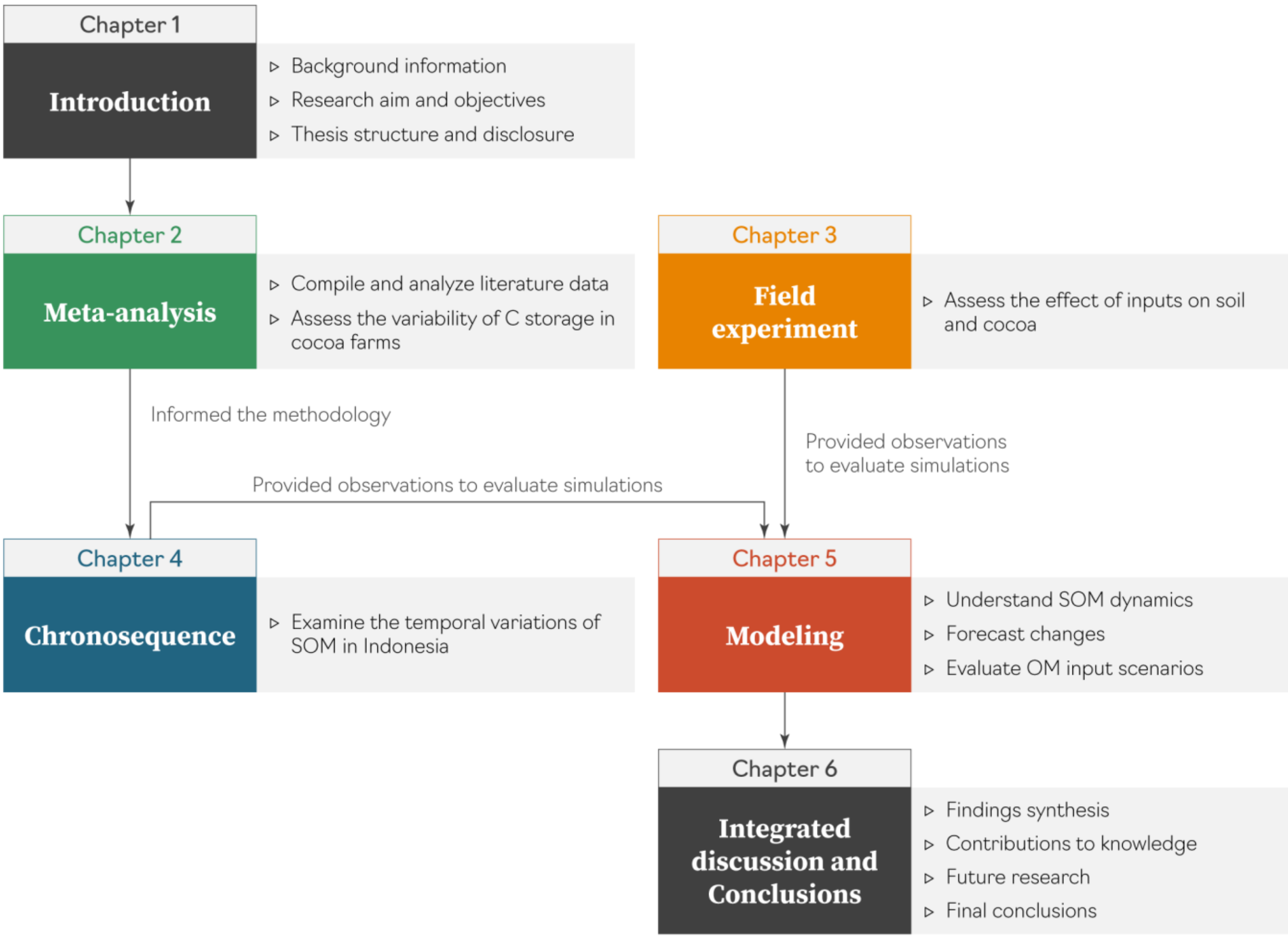


Figure 1.6: Visual representation of the thesis structure

Chapters structured by published, submitted and proposed research articles

The first objective was addressed by compiling and analysing data on biomass and C partitioning in different plant and soil reservoirs associated with cocoa farms from Africa, America, and Asia. A large dataset compiling 37 references was created, including soil and farm data contributions from Mondelez International Inc., Prof. Eduardo Somarriba (CATIE Turrialba), and Dr Ariani Wartenberg (Berkeley LUC LAB). The resulting study consisted of a meta-analysis summarizing the data on C stocks partitioning and temporal variability from the main producing countries. The methodologies and farm typologies of those studies were examined to inform the following chapters. This study showed a large variability in C stocks because of the broad diversity of cocoa cultivation systems and the disparity between C measurements in the reviewed studies, stressing the importance of harmonizing and standardizing C assessments in complex agroforestry systems.

The second objective was approached by conducting a field experiment involving combinations of different inputs, including compost, fertilizer, and dolomite. The experiment compared the effects of these treatments on key soil properties and cocoa productivity. This study continued an existing field experiment (Mulia et al., 2019) located in Bone-Bone (Sulawesi, Indonesia), which monitored cocoa and soil's response to the same treatments during the first four years after planting a cocoa farm on a moribund site. The initial experiment was prolonged by collecting and analysing data obtained from years four to seven with the same treatments applied. This study revealed the considerable effect of compost applications on cocoa productivity, significantly exceeding the effect of fertilizers while being insufficient to detect a significant change in C stocks despite large input rates (10 kg compost tree^{-1} year^{-1}).

The third objective consisted of forming a chronosequence of cocoa farms, which was accomplished by visiting 13 cocoa farms located in Sulawesi, distributed across three locations (Tarengge, Mambu, and Pussui), ranging from 0.5 to 31-years-old. Cocoa trees were measured to estimate their biomass thanks to an allometric relationship (Smiley & Kroschel, 2008) and formulate a growth curve. Soil samples were collected up to 1 m 100 cm by 20 cm increments to provide a thorough picture of SOM, C, and N distributions. Several approaches were applied to improve the comparability of soil data from distinct sites, such as the calculation of SOM stocks with bulk density and corrections for clay contents. This study provided preliminary evidence to support the hypothesis (detailed in

Chapter 4) that young plantations display a rapid decline in SOM, C, and N stocks. The long-term trend, however, suggested a rapid recovery instead of a slow build-up.

The fourth objective used information obtained from the other chapters to develop a model of SOM dynamics in cocoa farms. More specifically, an existing soil model called AMG (acronym of the initial developers names, Andriulo, Mary and Guérif: Andriulo et al., 1999; Clivot et al., 2019; Saffih-Hdadi & Mary, 2008) was modified to adapt it to the particular features of a cocoa farm and simulate a perennial instead of an annual arable crop. The model predicted variations of SOM stocks corresponding to the hypothesis of Chapter 4, and within the range of observed values obtained from the chronosequence. The model was used to simulate the effect of organic inputs on SOM stocks and calculate the input rates necessary to maintain SOM at planting levels, as an indication of the efforts required to prevent SOM decline. The model was straightforward and can be easily upgraded to address limitations posed by the initial modelling assumptions (development directions presented in Chapter 5).

1.4 Disclosure and dissemination from the Ph.D. thesis

Thomas Fungenzi produced each study under the academic supervision of Dr. Ruben Sakrabani and Prof Paul J. Burgess. All experimental work was organized and undertaken by Thomas Fungenzi at Cranfield University (UK), with occasional support from the University laboratory staff and a visiting student, Habibah Begum. Two field activities and sampling trips were performed in Sulawesi (Indonesia), with logistical and technical support from Mars Inc. and Barry Callebaut.

Several people contributed to several of the studies, and some were acknowledged as co-authors:

- Dr Ariani Wartenberg (UC Berkeley), Dr Nicholas Cryer (Mondelez International) and Prof. Eduardo Somarriba (CATIE) contributed to Chapter 2 by providing cocoa farm and soil data instrumental in forming a global dataset used during the meta-analysis and by reviewing and commenting on the draft before submission.
- Dr Smilja Lambert (Mars Wrigley) and Dr Peter McMahon (University of Sydney) contributed to Chapter 3 by providing the data necessary to run the analyses and reviewing and commenting on the draft before submission. Mars' Cocoa Development Centre in Tarengge was also active in helping with the acquisition of data from cocoa farms and the Bone-Bone field experiment.
- Samantha Forbes (Mars Wrigley) and Hamran Hamran (Mars CDC Tarengge) provided help to obtain complementary tree measurements used in Chapter 4.

When the thesis was submitted, one research article had been published in *Experimental Agriculture*, a peer-reviewed scientific journal (Chapter 3). One research article had been submitted to *Agriculture, Ecosystems & Environment* (Chapter 2) but was rejected until several improvements were made, including the acquisition of more data. The other two studies (Chapter 4 and 5) have not been submitted yet to a journal.

Paper accepted for publication

Fungenzi, T., Sakrabani, R., Burgess, P., Lambert, S., & McMahon, P. (2021). Medium-term effect of fertilizer, compost, and dolomite on cocoa soil and productivity in Sulawesi, Indonesia. *Experimental Agriculture, 57*(3), 185-202. doi:10.1017/S0014479721000132

Paper submitted but rejected with option to resubmit

Fungenzi, T., Sakrabani, R., Burgess, P., Somarriba, E. J., & Wartenberg, A. C. (NA). Global Meta-Analysis on Carbon Storage in Cocoa Plantations. *Submitted to Agriculture, Ecosystems & Environment*

Oral and Poster presentations

Apart from research articles, a poster summarizing the early work of the thesis was presented during the 2019 World Agroforestry Congress at Montpellier (20-25th May 2019). An oral presentation and a poster presentation were delivered during the Early Career Conference of the British Soil Science Society in 2019 at Sheffield (16-17th April 2022).

2. META-ANALYSIS OF CARBON STORAGE IN COCOA PLANTATIONS

Highlights

- Carbon stock data from 37 references, comprising 457 farm plots, was synthesised;
- Carbon stocks were evaluated in five reservoirs: aboveground cocoa, aboveground shade, belowground root, surface litter, and soil;
- Shade trees and soil were the largest reservoirs of C;
- Methodological inconsistencies between the studies make adequate comparisons difficult.

Summary

In this meta-analysis, one of the most widespread agroforestry systems, cocoa, was evaluated to estimate its carbon stocks dynamics over the course of its life cycle in agroforestry plantations. The compiled dataset gathered 37 references from 14 countries in Africa, Central & South America, and Southeast Asia. It covers a broad age range of cocoa plantations, from newly planted to 80-years-old plantations, with most of the observations made on cocoa plots younger than 35-years-old. Tree densities and management intensities ranged from full sun monocultures to densely shaded agroforests. Carbon (C) was allocated and assessed in five reservoirs: aboveground cocoa, aboveground shade, belowground root, surface litter, and soil. Classes of 5-year intervals were defined to study the effect of plot-age onto these different reservoirs. In the studies, plant C stocks were generally estimated from allometric equations, and soil C stocks were determined from soil samples. The mean aboveground C content of cocoa trees reached a plateau between 15 and 35 years, averaging 9.8 (±0.4; 95% CI) Mg of C ha^{-1}, corresponding to cocoa 'maturity' phase. Between 15 and 35 years, the mean shade tree aboveground C was 37.4 (±2.6; 95% CI) Mg ha^{-1}. The mean soil C stocks (0-10 cm) ranged from 23.6 (±4.1; 95% CI) Mg of C ha^{-1} at planting, to 23.9 (±1.2; 95% CI) Mg in the 15 to 35- years-old plots, and 30~34 Mg of C in the oldest recorded plots. Root C reached 10~12 Mg ha^{-1} between 5 and 10 years and then generally remained stable. Litter C appears to remain stable, between 1 and 2 Mg of C per ha. Cumulatively, it was found that cocoa systems, including soil to 10 cm depth, can reach more than 100 Mg C ha^{-1} for some of the oldest plots. At a typical age of cocoa rehabilitation or renovation at 20-30 years, the corresponding value was 40~50 Mg ha^{-1}. The analysis

emphasizes the importance of shade trees in C sequestration within cocoa systems.

Keywords: Cocoa, Soil organic matter dynamics, Carbon pools, Meta-analysis, *Theobroma cacao*.

2.1 Introduction

Agroforestry systems have been recognized by the UNFCCC (United Nations Framework Convention on Climate Change) as a potential measure to mitigate climate change by mitigating the rise of atmospheric CO_2 levels through the sequestration of significant amounts of C in vegetation and soil sinks (Albrecht & Kandji, 2003; Dupraz & Liagre, 2008; B. M. Kumar & Nair, 2011; Montagnini & Nair, 2004; Nair et al., 2009; Pandey, 2002; Rosenstock et al., 2019). One of the most widespread forms of tropical agroforestry comprises cocoa plants (*Theobroma cacao* L.) under shade trees, a system that forms a major source of income for millions of farmers along a belt covering parts of Africa, Central and South America, and South-East Asia. Various reviews have shown that agroforestry systems, such as shaded cocoa, can store more carbon (C) in their biomass and soil pools than annual and perennial monocultures (De Stefano & Jacobson, 2018; Feliciano et al., 2018; Nair et al., 2009; Shi et al., 2018). Soil C storage can be particularly useful because of its potentially long immobilization time and the large stock it can represent (i.e., approximately 80% of the terrestrial C is in the soil; (Lal et al., 2018; Lorenz & Lal, 2014; Paustian et al., 2019; C. E. Stewart et al., 2007). Beyond climate mitigation concerns, high levels of soil organic matter (SOM) can improve the levels of crop production, and are associated with, for example, a greater stock of nutrients, water-holding capacity, and improved pH buffering (Brady & Weil, 2017; Havlin et al., 2016; Johnston et al., 2009a; Oldfield et al., 2017; Woomer & Swift, 1994).

Carbon is stored in several reservoirs (also called interchangeably pools, or compartments) in a cocoa agroforestry system, including aboveground cocoa and shade tree biomass, roots, litter, and soil. According to the IPCC (2000), a carbon stock is “the absolute quantity of carbon held within a pool at a specified time”. The age of both the cocoa and shade trees, which can be several decades, is likely to be a major driver of changes in C stocks (Jagoret et al., 2011, 2017, 2018). Variations in C stocks between cocoa systems are expected for several reasons. For example, cocoa trees can be planted at a range of densities. There is also a range of shade species: some species like bananas are established during the first three years of cocoa establishment, some are intercropped and offer an additional revenue source, such as rubber, coconut, timber, and some are used to fix nitrogen (N) such as *Gliricidia* and *Leucaena* species. A leaf-litter layer at the soil surface is a typical feature of cocoa systems: cocoa trees are deciduous, and leaf fall is associated with drought stress. Beyond land preparation at planting, the level of soil management is minimal, although some farmers do apply fertilizers, composts, manures, or processed pod husks. The level of mechanization is typically low, with most field operations completed by hand (Wood & Lass, 2008).

Despite the importance of cocoa cultivation (FAO, 2003; Fountain & Huetz-Adams, 2018), the role of C storage (by agroforestry and soil systems) on climate change (Albrecht & Kandji, 2003; Montagnini & Nair, 2004; Paustian et al., 1997), and the widespread view that soil C is the keystone indicator of soil fertility (Brady & Weil, 2017; Doran et al., 1996; FAO, 2005; Ontl & Sculte, 2012; Rice, 2005), to the authors knowledge there has been no global review on C sequestration in cocoa systems. Research on these systems seems to have occurred only at the local level (e.g., Mohammed et al., 2016; Smiley & Kroschel, 2008) or at a world-region scale (e.g., Somarriba et al., 2013 in five countries of Central America). Hence this paper aims to synthesize data on C storage in cocoa systems. The main objectives of this study were (1) to characterize the typology of the cocoa plantations in the dataset, (2) to assess the temporal dynamic and variability of C stocks in cocoa systems, and (3) to examine correlations between potential C stocks predictors.

2.2 Methodology

2.2.1 Search procedure, eligibility criteria, and data compilation

The data search followed a non-systematic approach in order to include as many references as possible instead of restricting the findings to only one search engine or limited set of keywords. The available literature was initially identified using several search engines: Google Scholar, ScienceDirect, Scopus, Scielo, Web of Science, and ResearchGate. The main keywords were “soil”, “organic”, “matter”, “stocks”, “sequestration”, “cocoa”, “cacao”, “Theobroma”, and “carbon”. They were used using multiple combinations such as “soil organic matter cocoa” or “Theobroma soil carbon”. Cocoa industries, including Mars Inc., Mondelez International, and Barry Callebaut, as well as researchers and institutions involved in cocoa research were also contacted to obtain data. Among the results, only the ones reporting C stocks for at least one reservoir (or contents for soil C) and the age of the plots were utilised (age referring to years after planting). The references (see Table 2.1) were then examined for four main categories of information: (1) contextual data such as the study's authors and publication year, (2) climatic data such as rainfall and temperature at the study location, (3) crop and vegetation data such as the reported basal areas per hectare, and (4) soil data such as C contents and bulk densities. The complete list of variables is available in the appendix (see Table A - 2.1). The second stage involved a review of the references cited by those studies to see if some of them matched our criteria. As a result, 37 references were identified in total. The data reported was then integrated into the project datasheet. In some situations where the information was unclear, the authors were contacted to seek clarification or raw datasets. When only a chart without data labels was given (i.e., making it difficult to accurately determine a value), a graph digitizer was used (https://automeris.io/WebPlotDigitizer/) to extract the data. Both one-time studies and chronosequences were included in the collection. When several soil depths were studied, each was recorded. It was not possible to create sub-groups for specific environmental conditions (e.g., soil type or climate) due to the small number of studies for each potential sub-group. No additional criteria were applied to assess the validity of the findings in terms of sample size due to risk of bias because reported statistics such as standard deviations or confidence intervals (e.g., only 7% of soil C and SOM contents were not associated with a standard deviation, error of confidence interval).

In total, the 37 references yielded 250 observations for cocoa aboveground C stocks, 242 for aboveground shade C stocks, 236 for litter C stocks, 242 for root C stocks, and 381 for soil C stocks. The years of publication can be categorized into two periods. The first was around 1980-1990 and the second after 2000, with a fairly equal distribution of references for both periods (refer to Figure A - 2.1 and Table A - 2.2 in the appendix for more details). About half of the studies were chronosequences, with the majority being Type II chronosequences (Hartemink, 2005), i.e., different plots of different ages monitored simultaneously. The references covered four continents, spread over 14 countries (see Table 2.2). The greatest number of studies were based in Central America, with 234 cocoa plots, corresponding largely to the large spatial scale of Somarriba et al.'s (2013) study. However, the country with the largest concentration of cocoa plots (187) was Indonesia, mostly derived from the Mondelez International (2015) dataset. From Africa, only 25 individual cocoa plots were integrated into this study, despite the amount of cocoa research implemented there, because each study only included a few plots. A broad diversity of pedoclimatic contexts was covered by the dataset (see Table A - 2.3).

Table 2.1: List of references used for the meta-analysis

Code	Authors	Year	Journal
1	Adejuwon & Ekanade	1987	Catena
2	Adejuwon & Ekanade [†]	1988	Catena
3	Alpizar et al.	1986	Agroforestry Systems
4	Aranguren et al.	1982	Plant and Soil
5	Beer et al.	1990	Agroforestry Systems
6	Boyer	1973	Café Cacao Thé
7	Boyer cites several authors (1954-70)	1973	Café Cacao Thé
8	Dawoe et al.	2009 & 2010	Thesis & Plant and Soil (same data)
9	de Oliveira Leite & Valle [†]	1990	Agriculture, Ecosystems and Environment
10	Fassbender et al. [‡]	1988	Agroforestry Systems
11	Gama-Rodrigues et al.	2010	Environmental Management
12	Gockowski et al. [•]	2001	NA
13	Heuveldop et al.	1988	Agroforestry Systems
14	Isaac et al.	2005	Agroforestry Systems
15	Jordan [‡]	1983	Proceedings of a seminar held in CATIE, Turrialba, Costa Rica
16	Kummerow et al. [‡]	1982	NA
17	Leuschner et al.	2013	Agroforestry systems
18	Ling [†]	1986	NA
19	Mohammed et al.	2016	Carbon Balance and Management
20	Monroe et al.	2016	Agriculture, Ecosystems and Environment
21	Morales et al.	2017	Acta Agronomica
22	Norgrove & Hauser	2013	Tropical Ecology
23	Oke & Olatiilu	2011	Journal of Environmental Protection
24	Owusu-Sekyere et al.	2006	West Africa Journal of Applied Ecology
25	Rajab et al.	2016	Plos One
26	Saj et al.	2013	Agroforestry systems
27	Santhyami et al.	2018	Biodiversitas
28	Smiley & Kroschel	2008	Agroforestry Systems
29	Tondoh et al.	2015	Global Ecology and Conservation
30	UNESCO *	1978	SSSA Special Publication
31	Utomo et al.	2016	Journal of Cleaner Production
32	Vanhove et al.	2016	Agriculture, Ecosystems and Environment
33	Vitousek & Sanford °	1986	Annual Review of Ecology, Evolution, and Systematics
34	Wessel [†]	1985	NA
35	Somarriba et al.	2013	Agriculture, Ecosystems and Environment
36	Mondelez International	2015	Private report
37	Wartenberg et al.	2017	Agriculture, Ecosystems and Environment

† reviewed by Hartemink (2005)
‡ cited by Beer et al. (1990)
• cited by Dawoe (2009)
* cited by Greenland et al. (1992)
° cited by Isaac et al. (2005)

Table 2.2: Geographical distribution of the studies

Continent	Country	Number of plots
Africa	Cameroon	9
	Ghana	9
	Ivory Coast	3
	Nigeria	4
	Sub-total	***25***
	Proportion of the total	***5%***
Asia	Indonesia	187
	Malaysia	2
	Sub-total	***189***
	Proportion of the total	***41%***
N. & S. America	Mexico	1
	Brazil	8
	Costa Rica	39
	Venezuela	2
	Guatemala	71
	Honduras	33
	Nicaragua	49
	Panama	40
	Sub-total	***243***
	Proportion of the total	***53%***
	Total	**457**

2.2.2 Data conversions

a. Carbon stored in vegetation

Vegetation biomass and/or C stocks were mostly determined with allometric equations (see Table 2.3). Trees were measured using trunk diameters, for example, at 30 or 130 cm from the ground (i.e., respectively 'D30' and 'DBH', diameter at breast height). Total height (TH) or the length of stems and branches was additionally used in some allometric equations. The structures of the equations varied: some were power relationships (for instance, equation Equation 2.2), some were linear (as with equation Equation 2.4). Because of the diversity of shade species, various allometric equations were used by the source references to estimate their biomass. Some were generic for several species, and some were species-dependent. For each study, only one estimation of C stocks was given, corresponding to their selection of a unique or single set of allometric equations. In other words, they did not apply different equations to compare how the estimations of stocks would vary. Readers are invited to refer to each specific publication to review their respective methodologies in detail.

In addition to allometric estimates, Rajab et al. (2016) undertook an inventory of soil fine root biomass (< 2 mm) down to 3 m depth which was added to belowground biomass, as the Cairns equation they used does not include fine root biomass. Alpizar et al. (1986), Beer et al. (1990), Dawoe (2009), and Somarriba et al. (2013) did the same but at different depths (0-15-30-45 cm for Alpizar et al. and Beer et al.; 0-30 cm for Dawoe with roots ≤ 0.5 cm ; 0-20 cm for Somarriba et al.). Leuschner et al. (2013) assessed belowground biomass (both fine and coarse roots) directly in soil pits down to 3 m. Norgrove & Hauser (2013) applied a root:shoot ratio of 0.13 to derive the total biomass based on Zuidema et al. (2005) partitioning model.

Because it is difficult to distinguish between cocoa and shade tree roots, studies rarely distinguish between the two, and only report root C stocks. In this study, when cocoa and shade tree roots were both reported, the total root C stock was calculated by combining the two.

Table 2.3: Examples of allometric equations used in the references to estimate cocoa and shade trees biomass

Targeted stock	Equation number	Allometric equation	Variables	References
Aboveground cocoa biomass	Equation 2.1	$log\ AB = (-1.684 + 2.158\ log(D_{30}) + 0.892\ log\ (TH)$	D30: diameter at 30 cm (in cm). TH: total height of the cocoa tree (in m).	Somarriba et al. (2013)
	Equation 2.2	$AB = 0.202 \times D^{2.112}$	D: stem diameter at breast height at 50 cm height (in cm)	Smiley & Kroschel (2008) Leuschner et al. (2013)
	Equation 2.3	$AB = WD \times CSA \times (L + 2.32PB)$	WD: average wood density (0.34 Mg m^{-3}). CSA: mean cross-sectional surface area of the trunk (in m²). L: trunk length (in m) PB: number of primary branches.	Boyer (1973) Norgrove & Hauser (2013)
	Equation 2.4	$AB = -0.0376 + (0.133\ \mathrm{BA})$	BA: stem basal area at breast height (in cm²).	Beer et al. (1990) Rajab et al. (2016)
Aboveground cocoa and shade trees biomass	Equation 2.5	$AB = e^{-2.134 + 2.53\ ln(DBH)}$	DHB: diameter at breast height (in cm).	Brown, (1997) Dawoe (2009)
Shade tree biomass	Equation 2.6	$AB = e^{(-2.557+0.940\ln(\rho D^2 H))}$	ρ: wood specific gravity (in g cm^{-3}). D: stem diameter at breast height (in cm). H: total tree height (in m).	Leuschner et al. (2013) Chave et al. (2005)
Aboveground Gliricidia biomass	Equation 2.7	$AB = 0.1185 \times D^2$	D: stem diameter measured at breast height (in cm).	Foroughbakhch et al. (2006) Leuschner et al. (2013)
Belowground biomass	Equation 2.8	$BB = 0.142 \times D^{2.064}$	D: stem diameter.	Smiley & Kroschel (2008)
	Equation 2.9	$BB = e^{(-1.0587 + 0.8836\ \ln(AB))}$	AB: aboveground biomass, dry (kg per tree).	Cairns et al. (1997) Somarriba et al. (2013) Rajab et al. (2016)

Equation 2.2 was chosen in this study because it was developed on cocoa farms developed on Sulawesi (just like this study).

To convert plant biomass stocks to plant C stocks, Smiley & Kroschel, (2008) indicated that conversion factors vary from 0.4 to 0.5 (Brown, 1997; Snowdon et al., 2000). The values used or directly measured by the references studying plant C stocks are summarized in Table 2.4.

Table 2.4: Conversion factors used to convert biomass stocks to carbon stocks

Reference	Refer to	C content
Dawoe et al. (2010)	Average for cocoa litter	0.430
Isaac et al. (2005)	Average for cocoa canopy	0.451
	Average for upper story canopy	0.447
Leuschner et al. (2013)	Leaves	0.420
	Stem wood and branches	0.460
	Coarse roots	0.450
	Fine roots	0.440
Mohammed et al. (2016)	Cocoa biomass	0.420
	Litter	0.370
	Shade trees and stumps	0.42-0.456
Norgrove & Hauser (2013)	All trees and litter	0.450
Rajab et al. (2016)	Stem wood and branches	0.470
	Coarse roots	0.440
	Fine roots	0.420
	Litter	0.450
Saj et al. (2013)	Cocoa and other trees biomass	0.475
Santhyami et al. (2018)	Aboveground biomass	0.500
Smiley & Kroschel (2008)	Aboveground and belowground biomass	0.450
Somarriba et al. (2013)	Aboveground biomass	0.500
	Coarse root biomass	0.470
Tondoh et al. (2015)	Average for cocoa litter	0.363

b. Carbon stored in the soil

SOM or C was determined through the analysis of soil samples collected in the field. The majority of the references employed elemental analysers, while a few followed the Walkley-Black method (i.e., Dawoe, 2009; Morales et al., 2017; Norgrove & Hauser, 2013; Tondoh et al., 2015; Utomo et al., 2016).

c. Missing values

For most cases, the data shared in the references did not cover the entire set of variables of this meta-analysis. To address this and fill gaps in the dataset, it was necessary to estimate some of the results from the reviewed publications.

If the date of planting and the date of the measurement were given, the age of the plot was logically deduced.

To convert cocoa plant biomass to C, a coefficient of 0.48 was applied, corresponding to an estimate of an average C concentration in cocoa biomass (FAO, 2005; Ma et al., 2018; Thomas & Martin, 2012). Conversely, a ratio of 2.08 (i.e., 1/0.48) was used to estimated plant biomass from plant C.

To convert SOM to C (stocks or contents), a coefficient of 0.58 was chosen (Cambardella et al., 2001; Pribyl, 2010). Conversely, a ratio of 1.72 (i.e., 1/0.58) was applied to transform soil C values into SOM. When only C contents were given, topsoil C stocks were calculated by using the bulk density of the topsoil (0-10, 0-15, 0-20 cm, or deeper, depending on what was available), and a surface layer thickness of 10 cm (see Equation 2.10):

$$Stock = d \times 10000 \times Content \times BD$$ **Equation 2.10**

where C stocks per hectare ($Stock$) are in Mg ha^{-1}, sampled depth (d) is set to 0.1 m, 10000 is one hectare in m^2, the C content ($Content$) in g.100g^{-1}, and bulk density (BD) in g cm^{-3}.

As with soil C, the same depth-distribution problem occurs with root C. The heterogeneity of the sampling depths used in the studies reviewed, restricts optimal comparisons and the possibility to make a simple, direct summary of the results. To address this issue, the reported root C of the top sampled layer was used, which could be 10, 15, or 20 cm depth or more. As most of the root C values were obtained from allometric equations, depth heterogeneity did not have a major impact (93% of the observations came from Somarriba et al. 2013). The values reported in the results are totals of available values, including fine and coarse roots of cocoa and shade trees altogether.

In numerous cases, bulk density was not reported. If C stocks per hectare, C contents, and sampling depths were available, bulk density was recalculated by rearranging Equation 2.10. However, certain references provided neither C stocks nor C contents (but did mention depth). In this case, bulk density was estimated by using Equation 2.11 described by Adams (1973), in terms of the SOM content ($SOM\%$; in %), bulk density of the mineral fraction of the soil (MBD), and the bulk density of SOM ($OMBD$), in g cm^{-3} (method applied in other peer-reviewed studies such as Guo & Gifford (2002) and Post & Kwon (2000):

$$BD = 1 \; / \; [\; (SOM\% \; / \; OMBD) + (\; (1 - SOM\%) \; / \; MBD) \;] \qquad \textbf{Equation 2.11}$$

To find *MBD* and *OMBD*, the approach previously used by Mann (1986) and Shi et al. (2018) was adapted. Observed bulk densities and their corresponding SOM or SOC were derived from the dataset, and the predicted bulk density was calculated using Equation 2.11. Then, the Chi-square of the difference between observed and predicted bulk densities was determined. Excel's Solver add-in was applied to find optimal values for *OMBD* and *MBD,* minimizing the sum of Chi-square. Optimized values were 0.103 for *OMBD* and 1.683 for *MBD* (with a Chi-square of 5.382, a mean bias of -0.057%, and a root mean squared error of prediction of 13.77%. The relationships between SOM contents and observed and predicted bulk densities are displayed in the appendix (see Figure A - 2.2).

If rainfall, temperature, or altitude indications were missing, they were approximated by using the name of the location and extracting data from WorldClim Version 2 (for rainfall and temperatures; when the GPS location was given; Fick & Hijmans, 2017), from climate-data.org (for rainfall and temperatures; when GPS location was unknown, i.e., using the village name) and Google Earth (for altitudes).

2.2.3 Statistical analysis and data visualization

To meet the three objectives, the dataset was examined from several perspectives. The typology of the cocoa plantations (objective 1) was described in terms of pedoclimatic contexts, the age distribution of the plots, observed cocoa and shade tree densities, and shade species. The distribution and temporal variability of C across the main reservoir of the cocoa systems (objective 2; i.e., aboveground cocoa, aboveground shade tree, roots, litter, and soil) was examined by using boxplots, displaying a six-number summary: minimum, first quartile, median, third quartile, maximum and mean. Observations were distributed in age class intervals of 5 years (left-closed, right-opened). Because the ages ranged from 0 to more than 80 years-old , there were 17 classes (i.e., 16 from 0 to 80 and an additional one for farms aged 80 or older). Classes of 5 years were chosen as they provided a balance between being representative and practicality of use. Correlations between non-time variables (objective 3) evaluated the relationships between (1) basal areas[1] and cocoa aboveground C stocks, (2) roots and aboveground C stocks (i.e., root:shoot ratios), and (3) soil texture and soil C contents. The data was aggregated in a Microsoft Excel worksheet (v.1901 for Office 365). Data analysis and visualization were performed in Microsoft Excel v.1901 for Office 365 and R v.3.6.1 using the *ggplot2* package.

2.3 Results

2.3.1 Age distribution of the studied cocoa farms

Most cocoa plots were younger than 35 years old (Figure 2.1), an age beyond which cocoa productivity can decline. Although older plantations are often replaced, some very old cocoa farms (greater than 80 years) were present. In total, the dataset identified 475 individual cocoa plots, and only 4% did not have a reported age (see Table A - 2.4 in the appendix for exact values).

[1] Basal areas: defined as the cross-sectional area of the trunk or branches at breast height (m^2 ha^{-1}), or in some cases, at the trunk cross-sectional areas at 30 or 50 cm from the surface.

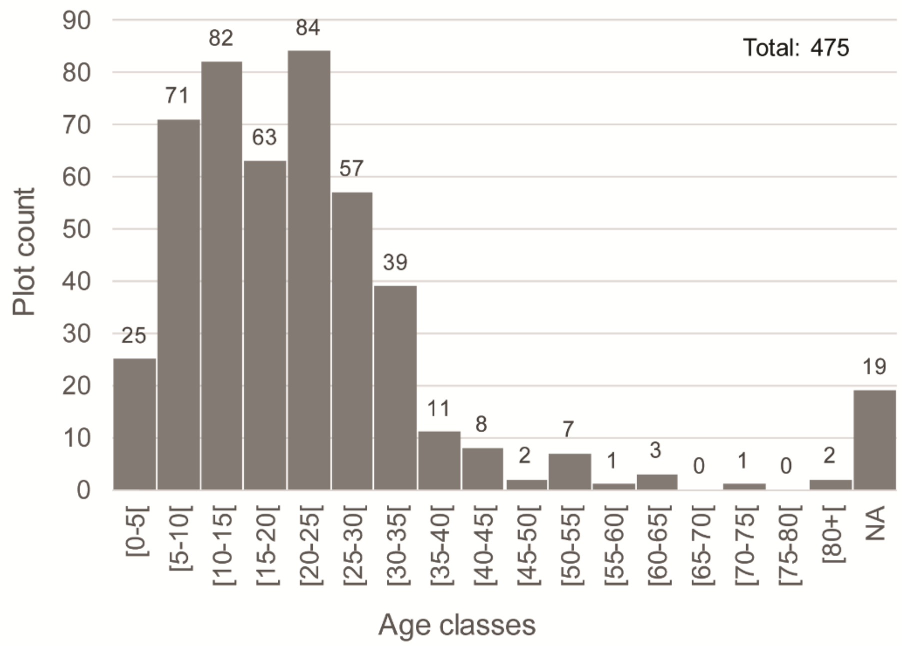


Figure 2.1: Distribution of the 5-year age classes of the cocoa farm plots

Note that age class intervals are left-closed and right-opened: including the left bound of the interval and excluding the right one (e.g., [5-10[does not include the 5-year-old plots).

2.3.2 Density of cocoa trees and shade species

The densities of cocoa trees per hectare were derived from the equivalent spacings. In total, 21% of the cocoa farms had spacing between 3 m x 3 m and 3 m x 4 m, corresponding to the often recommended density at planting of between ~800 and ~1100 cocoa seedlings per hectare (see Figure A - 2.3 and Table A - 2.5 for the detailed distributions). A quarter of the plots had a density of 400 to 625 cocoa trees per hectare, which approximately corresponds to a 4 m x 5 m spacing. About 18% of the plots had less than 400 cocoa trees per hectare, which can be considered very sparse.

In terms of shade-tree density, about one-fifth of the plantations had less than 100 shade trees per hectare (refer to Table A - 2.6 for the exact breakdown). Another fifth had between 100 to 200 shade trees per hectare, and a further fifth had between 200 and 400 trees per hectare. Higher densities accounted for about 10% of the plots. Approximately 30% of the plots included in our analysis did not report cocoa and shade tree densities. The shade species recorded on the cocoa farm are fully listed in the appendix (Table A - 2.7). For about half of the plots (53%), shade species were not reported. Only ten plots were listed as unshaded monocultures. References described systems with or without shade tree mixtures, mostly composed of *Gliricidia, Erythrina, Cordia, Cocos,* and *Hevea*.

2.3.3 Temporal C dynamics

a. Basal area

There was substantial variation in the reported basal area of the cocoa trees, which is the primary measure to estimate plant C stocks (Figure 2.2a and Table A - 2.8). For cocoa stands less than 35 years old, the mean basal area value was about 10 to 11.5 $m^2\ ha^{-1}$, although the dispersion was large (standard deviation = 5.75 $m^2\ ha^{-1}$).

b. Aboveground C

Estimates of cocoa aboveground C stocks varied widely (Figure 2.2b), but mean and median values tended to reach a plateau of ~10 Mg C ha^{-1} between 15 and 35 years, roughly corresponding to the period at which cocoa reaches 'maturity'.

Carbon stocks in shade tree aboveground C stocks were on average about four times that of cocoa trees (~40 Mg ha^{-1}, between 15 and 35 years). Even though this reservoir includes plots with different shade species, variability in aboveground shade tree C stocks was comparatively small compared to cocoa aboveground C stocks, with the first three quartiles of the data generally below 50 Mg ha^{-1} (Figure 2.2c). Almost all the aboveground shade tree C stocks estimates were below 100 Mg ha^{-1}, but some farms have reported higher C stocks. No clear relationship emerges between the age of the cocoa farm and the quantity of aboveground C stored in shade trees ($R^2 = 0.0094$, $P = 0.14$). Most of the observations were made on cocoa farms younger than 35-years old.

c. Litter C

Litter C stocks were the smallest of the considered compartments (Figure 2.2d), with a mean value of about 1.14 Mg ha^{-1} for the observations on farms younger than 35 years old. Up to the age of 35 years, the level of litter C stocks was relatively consistent. By contrast, larger litter C stocks were reported for farms older than 35 years old, but very few observations were available. In this dataset, 24 observations were available for the total annual litterfall deposition rate (including litter from cocoa and shade trees), including 18 where cocoa and shade leaves were segregated (Figure 2.3). Overall, total yearly litter deposition rates varied between ~3 and ~11 Mg $ha^{-1}\ yr^{-1}$, with some very high values reported for 30 years old farms, at ~20 Mg $ha^{-1}\ yr^{-1}$.

d. Root C

The majority of data documenting root C storage (93%) was from Somarriba et al. (2013). Overall, root C storage values varied less widely over time than aboveground C. While aboveground C increased in range over time, mean values of root C tended to reach a plateau of 10-12 Mg ha^{-1} between 5 to 10 years, with maximum values around 21-22 Mg ha^{-1} (see Figure 2.2e). Between 10 and 40 years, the stock of root C appeared stable.

e. Soil C

Estimated soil C stocks also exhibit a large variability (see Figure 2.2f). Most of the reported results ranged between ~10 to 40 Mg ha^{-1} and were sampled at 0-15 cm depth. The mean stock (0-10 cm) between 0 and 35 years old is 23.5 Mg ha^{-1} (23.9 between 15 and 35 years). Relatively speaking, younger stands tend to store less soil C than older ones. A slight increase of soil C stock seems to occur over time, but the effect is less pronounced than the change in aboveground biomass C. Performing a linear regression on soil C stocks and cocoa farm ages (younger than 35 years old, to exclude old farms for which few observations were available) resulted in a very weak but slightly positive correlation ($R^2 = 0.013$; p-value = 0.014):

Soil C stocks = 0.1244 × Cocoa farm age + 18.776 (figure not shown).

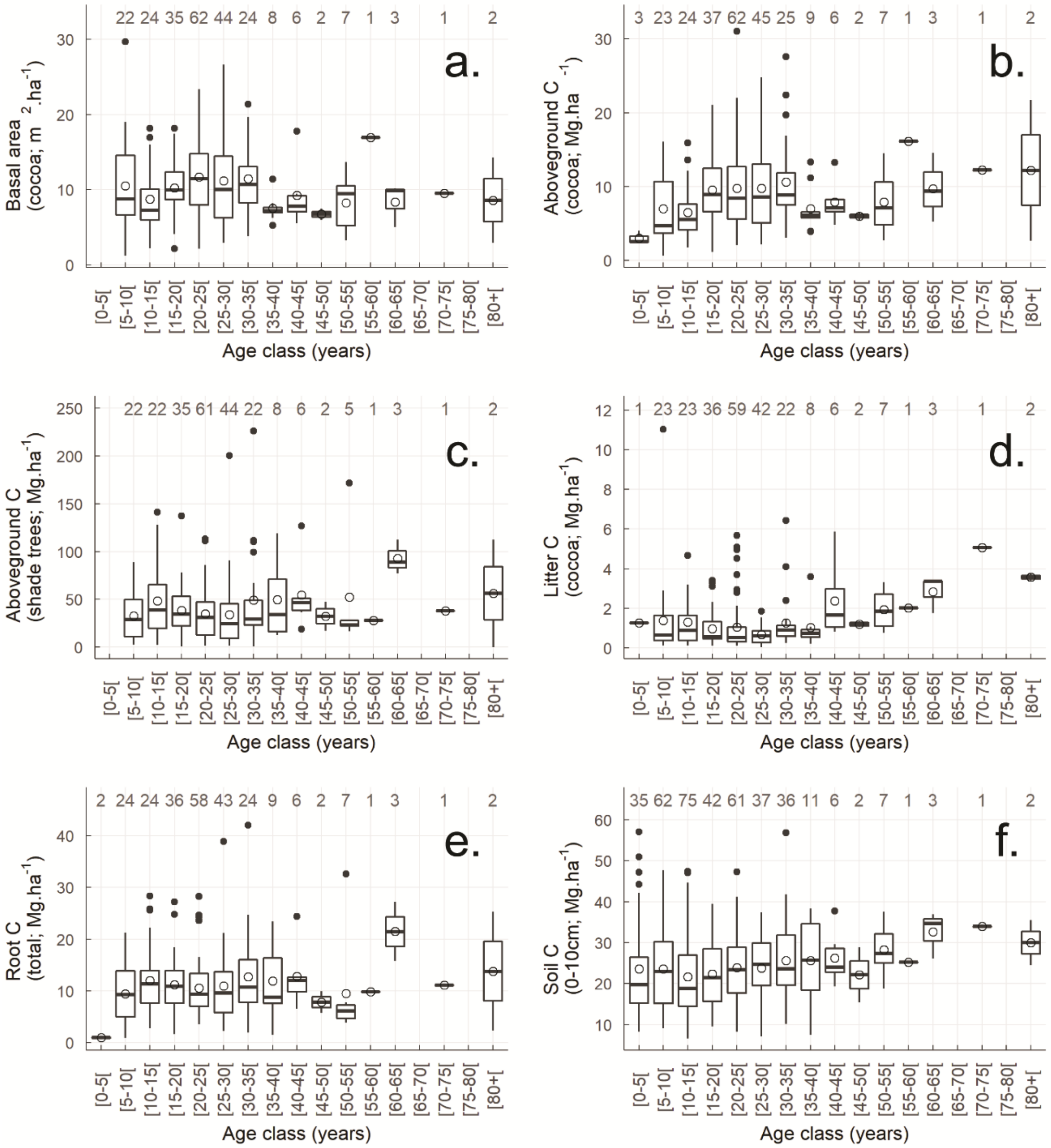


Figure 2.2: Boxplots of the C stocks according to the cocoa age class

a. cocoa basal areas;
b. cocoa aboveground C stocks;
c. shade aboveground C stocks;
d. litter C stocks;
e. root C stocks (include cocoa and shade trees indistinctively);
f. soil C stocks (estimated at 0-10 cm).

Open circles symbolize the mean, and dots are outliers. Age class intervals are left-closed and right-opened. The top rows of numbers are the counts of observations for each age class interval.

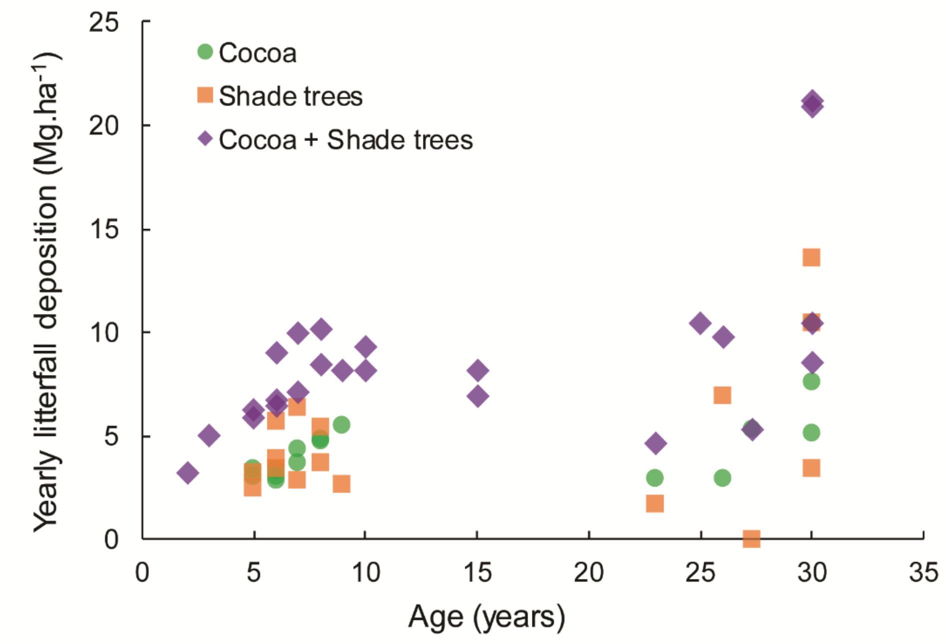


Figure 2.3: Yearly litterfall deposition rates (dry matter).

f. Cumulative C stocks

Cumulatively, C stocks of cocoa plantations (between 0 and 35 years old) including soil to a depth of 10 cm averaged 76.4 Mg ha^{-1} (Table 2.5). The corresponding value for ‘mature’ cocoa plantations between 15 and 35 years old was 85.4 Mg ha^{-1}. Overall, aboveground C stocks of shade trees accounted for the largest stock, followed by soil (0-10 cm), roots, aboveground cocoa, and lastly litter. Apart from litter, the mean value of all stocks seems to increase with the time from planting (see Figure 2.4 and Table 2.5). The number of observations, corresponding to each boxplot of Figure 2.2, and to each average of Table 2.5, is available in the appendix with additional summary statistics (Table A - 2.8). The exact dispersion of each observation is displayed in scatterplots in the appendix in Figure A - 2.4.

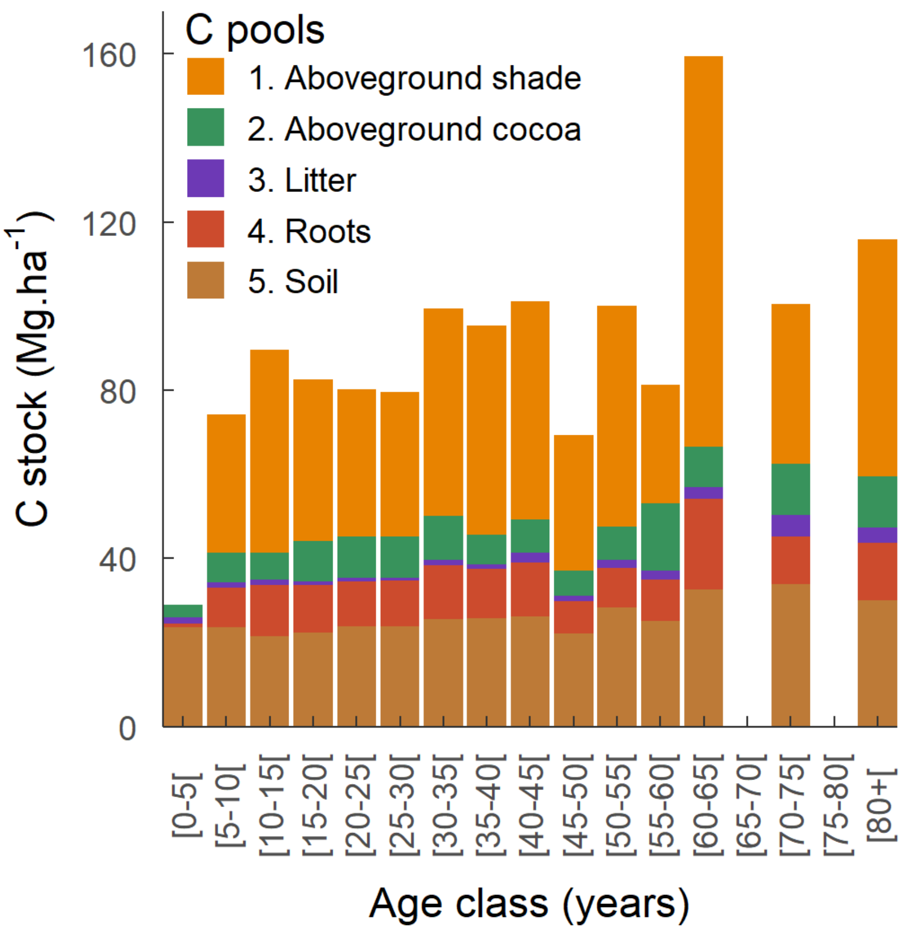


Figure 2.4: Average stocks of C cumulated for the different reservoirs of a cocoa plantation

Age class intervals are left-closed and right-opened. No observations for the aboveground shade trees at [0-5[years; no data for any of the reservoirs at [65-70[and [75-80[years intervals. Soil C stocks were estimated to a depth of 10 cm.

Table 2.5: Summary of C stocks and cumulative amounts

Age class (years)	Average cocoa basal area (m^2 ha^{-1})	Average C stock (Mg ha^{-1})								
		Aboveground			Litter	Roots	Biomass	Soil	Cumulated Total
		Cocoa	Shade trees	Sub-total			Sub-total*		
[0-5[	-	3.0	-	3.0	1.3	1.0	5.3	23.6	28.8
[5-10[	10.5	7.0	32.8	39.8	1.4	9.4	50.7	23.6	74.3
[10-15[	8.7	6.5	48.3	54.8	1.3	12.0	68.1	21.6	89.7
[15-20[	10.2	9.5	38.4	47.9	1	11.2	60.1	22.4	82.5
[20-25[	11.7	9.7	35.0	44.7	1	10.6	56.3	23.9	80.3
[25-30[	11.2	9.8	34.2	44.0	0.7	11.0	55.6	23.8	79.5
[30-35[	11.4	10.6	49.3	59.9	1.3	12.7	73.9	25.6	99.5
[35-40[	7.5	7.0	49.7	56.7	1	11.9	69.6	25.7	95.3
[40-45[	9.2	7.9	54.5	62.4	2.4	12.8	77.6	26.2	103.9
[45-50[	6.7	6.0	32.3	38.3	1.2	7.8	47.3	22.1	69.5
[50-55[	8.3	7.9	52.4	60.3	1.9	9.5	71.7	28.3	100.0
[55-60[	17	16.2	28.1	44.3	2	9.8	56.1	25.2	81.3
[60-65[	8.4	9.7	92.8	102.5	2.8	21.5	126.7	32.6	159.3
[65-70[	-	-	-	-	-	-	-	-	-
[70-75[	9.5	12.3	37.8	50.1	5.1	11.2	66.3	34.0	100.3
[75-80[	-	-	-	-	-	-	-	-	-
[80+[	8.6	12.2	56.3	68.5	3.6	13.8	85.9	30.0	115.9

Age class intervals are left-closed and right-opened.
* Plant sub-total include aboveground, roots and litter C stocks, but not soil.

2.3.4 Correlation between carbon stocks

A very strong positive linear correlation was found between cocoa basal areas and aboveground C stocks (R^2 = 0.93; p-value < 0.001). However, it can be noticed that the more the cocoa basal area increases, the larger the range of aboveground C stocks is (see Figure A - 2.5 in appendix). Three outliers were excluded, which reported stocks of C reaching between ~60 to 100 Mg ha^{-1} for cocoa only (reported in Santhyami et al., 2018).

In terms of the ratio of total root C stocks to cocoa and shade tree aboveground C stocks, the mean ratio was 0.22:1, with values ranging from 0.16:1 to 0.33:1.

Although it is generally expected to observe a positive correlation between clay and C contents,, in this study, the highest C contents were found in soils with the lowest clay contents (as depicted in Figure A - 2.6 in appendix). Conversely, the lowest C contents were found with soil with the highest clay content.

2.4 Discussion

This meta-analysis assessed the C stocks of cocoa systems and highlighted how diverse they could be. The time since planting seems to drive changes, but local differences (e.g., previous land use, planting densities, pruning practices, climate) most likely result in high variability between locations for all C stocks. On average, aboveground cocoa C attained a plateau around 10 Mg ha^{-1} of C after 15 years, when stands achieve maturity. Various shade levels and species were found, and on average aboveground shade C reached 39 Mg ha^{-1} of C between 15 and 35 years after planting. Mean soil C stocks increased from ~23 to 30~34 Mg ha^{-1} of C in the oldest recorded plots. Litter was the smallest of the C stocks, with limited variations between 1 and 2 Mg ha^{-1} of C. Root C attained on average ~11 Mg ha^{-1} of C between 5 and 10 years and then remained stable. More than 100 Mg ha^{-1} of C can be attained in the oldest plots when all stocks are cumulated, but recommended cropping durations of 20~30 years would lead to average cumulated C stocks of 40~50 Mg ha^{-1}.

2.4.1 Importance of aboveground C pools, especially from shade trees

A specific challenge of determining the C pools of cocoa systems is the large diversity of systems especially relating to shade management. The wide range of shade intensities and the possible arrangements of species adds complexity to the analysis, especially when only ~60% of the references reported this crucial information. Some of this is a result of measurements being taken on farmers' fields rather than within controlled experiments. An additional source of missing information is the possible additions of organic manure, compost, and the return of cocoa pod shells to the sites.

Cocoa basal areas and cocoa aboveground C stocks were strongly correlated, despite the differences between allometric equations, because most of the estimations were obtained from one study (Somarriba et al., 2013). A large disparity of measured cocoa basal areas was observed between and within the age classes. Of course, cocoa growth results in rapidly increasing basal areas, but other local factors are certainly needed to explain intra-class variabilities, such as the structure and density of the shade trees, climate (e.g., temperature, aridity), and management (e.g., the influence of practices such as pruning). From a production standpoint, relating these total cocoa basal areas to the density of cocoa and shade trees (i.e., to assess a mean tree basal area) could be useful in a future study, as Jagoret et al. (2017) already highlighted that basal area is a key performance indicator.

The aboveground C of shade trees was the largest stock across all age classes, and hence these results suggest that plant pools are effective targets to store C in cocoa systems. In shaded cocoa systems, shade trees and cocoa trees will compete with each other for light, water, and nutrients, with implications for C accumulation in each reservoir (Dupraz & Liagre, 2008). Therefore, complex aboveground and belowground interactions determine C acquisition dynamics in agroforests. To date, these interactions are not well understood, and optimal cocoa-shade canopy designs are yet to be developed (Somarriba et al., 2018). However, Blaser et al. (2018) report that 30% canopy cover by shade trees is typically a maximum in a commercial plantation, with higher levels of canopy cover resulting in more detrimental than positive trade-offs. Even though soil represents a large stock, the accumulation of vegetation biomass occurred in a shorter period. Because of the large volume that some shade species can attain, it should be noted that a minority of trees can hold a major part of the stock, equivalent to many cocoa trees.

2.4.2 Litter C

Litter C values were largely obtained from one-off observations in the field. They did not correspond to deposition over time, for example, over a year. Leaves are likely to form the primary inputs of C in this reservoir. Fontes (2006) estimated that the deposition of leaves could be as much as 7 Mg ha^{-1} yr^{-1}, and the values in Figure 2.3 suggest deposition rates of 3 to 11 Mg ha^{-1} yr^{-1}, which implies that the mean litter values of about 1 Mg ha^{-1} only represents a proportion of the yearly flux of leaves. Cocoa agroforestry systems can develop a thick layer of leaf litter (Gama-Rodrigues et al., 2011), and field observations made during this study indicate that cocoa roots can expand and derive nutrients and water from this layer. A thick leaf layer is usually considered a feature of good cocoa management as it increases soil cover and provides a reserve of nutrients. However, unlike many temperate soils where there is an organic matter gradient decreasing from the surface, field observations in Sulawesi (Indonesia) suggest that the C-rich layer may only extend a few centimetres (Kummerow et al., 1982). Two distinct layers could be seen: organic and mineral, instead of a gradient penetrating the soil. Under high temperatures and moisture, it can be argued that organic matter decomposes quickly *outside* the soil, with little contribution to structure formation at depth (Gama-Rodrigues et al., 2011). In other words, with no incorporation or bioturbation, only a small proportion of leaf C seems to be transferred to the soil.

Unlike the steady increase in aboveground plant C, the amount of litter C appeared relatively consistent with time after planting. By contrast, yearly litter deposition rates increased during the first decade of the cocoa stand (both cocoa and shade tree leaf litter). It could be hypothesized that although litter deposition rates increase during the establishment phase of cocoa trees, the leaf litter rapidly decomposes, and hence the amount of leaf litter remains relatively consistent. Once the cocoa stand attains maturity, the rates of deposition may possibly remain stable, as the trees are pruned to maintain a specific height for ease of harvest. Overall, an equilibrium is reached, with fast decomposition rates limiting the build-up of litter C over time.

2.4.3 Root C

More C was found in root (cocoa and shade trees combined) than in the aboveground C stocks of cocoa plants alone. It was not possible to separate the root mass of the cocoa and shade trees. The mean ratio of the root to the aboveground C in the cocoa and shade trees was 0.22:1. This is similar to a ratio of 0.20:1 for perennial crops reported by Borden et al. (2019) and Cardinael et al. (2018). The ratio between root biomass and aboveground biomass can also depend on shade tree management, with more biomass allocated belowground by cocoa when it is associated with other species (Borden et al., 2019).

2.4.4 Soil C

Soil was the second-largest C stock after aboveground shade tree C in terms of magnitude. However, it could probably come first if a thicker layer was considered. Deep stocks, below the traditionally studied rooting depths of 0 to 20~30 cm, are substantial, especially because they will remain stable for a long time (Borchard et al., 2019; Gross & Harrison, 2019). Across the dataset, there was no consistent trend in how soil C varied with time from planting. One reason for this is differences in previous land use (Blaser et al., 2018). For example, if cocoa is planted on previously forested land with C-rich soil, the net change between newly planted cocoa and old farms is likely to be negative. Conversely, a plot rehabilitated and previously cropped with annuals will likely see an increase of soil C stocks, because of the increased inputs of organic matter by cocoa and shade trees. Such differences could explain why soil C stocks declined in full-sun cocoa farms studied by Tondoh et al. (2015) whereas Jagoret et al. (2012) found increases after cocoa afforestation of savannahs. An additional factor is how the density of cocoa and shade trees vary with time. A declining density may reduce new carbon assimilation, but conversely, decomposing dead trees may also increase soil C inputs. Another unknown is the contribution of root exudates. Although their production rates are unclear, they could be supplying significant amounts of C directly to the soil (Kuzyakov & Domanski, 2000a; Pausch & Kuzyakov, 2018).

Another reason for the lack of a consistent time effect could be the diversity of soils under scrutiny. Looking for an eventual clustering of the results by soil texture, the correlation between soil C, clay, and sand contents was examined. Plotting the relationship showed a negative correlation with clay contents. Surprisingly, a positive relationship between soil C and sand contents was observed. These results suggest that at this scale of analysis, soil texture alone is not a good predictor of C stocks. Although texture affects the capacity of the soil to bind organic matter, it does not limit how much C can be present (Hassink, 1996; Hassink et al., 1997; Krull et al., 2001). In practice, soil C contents are the result of a balance, and large inputs, whether there are coming from the vegetation or the application of composts or manures, can override the maximum protection capacity of the soil mineral particles (i.e., physically protected in clay-promoted aggregates or adsorbed on active surfaces; Hassink, 1996; Hassink et al., 1997; Six et al., 2002). This C may not be stabilized but can still be present. Regardless of the explanation for this observation, contrary to conventional wisdom, this result is a clear indication that soil texture may not be an insurmountable obstacle when considering soil C sequestration since high stocks were observed in sand-rich soils, usually less favourable. It is necessary to investigate the sites where these unconventional observations were made to provide further explanation to this observation.

Low soil organic matter or C is sometimes highlighted as a sign of degradation in cocoa plantations (Adeniyi et al., 2017). Out of the 361 topsoils examined, only 18 (5%) had a C content lower than 1%. A large group of soils (40%) had a C content between 1 and 2%, while a further 40% had a C content between 2 and 4%. On the other hand, 15% of the farms had soil C contents higher than 4%, with the maximum value at 11%. Whether these values are constraining the sustainability of cocoa production still requires further research (Loveland & Webb, 2003). Soil C still remains a fuzzy indicator to quantify the complexity of soil fertility (Oldfield et al., 2019; Vonk et al., 2020).

2.4.5 Uncertainties due to methodological constraints

Although a global analysis was attempted, cocoa production in Africa is underrepresented even though Ghana and Ivory Coast are top global cocoa producers. Most of the data mainly relied on one reference for aboveground C stocks (Somarriba et al., 2013) and two references for soil C stocks (Mondelez International, 2015; Somarriba et al., 2013). The inclusion of datasets such as Borden et al. (2019), found after the analysis, may improve the geographical distribution of the results.

A strength of this meta-analysis was to include both plant and soil C reservoirs in the analysis. The examined data encompassed a wide diversity of the variables established by different methods. For instance, some references only looked at soil C, others only biomass. Some studies reported C stocks, and some reported stocks in terms of dry biomass. Some studies proposed belowground stocks in terms of fine roots only. Some made the distinction between coarse and fine roots. Some distinguished between cocoa and shade tree roots. Some studies did not and reported only total root C stocks. The methods for assessing vegetation C used different allometric equations. Some equations had a linear structure ($y = a + bx$), while others had an exponential form ($y = ax^b$). This study did not explore the sensitivity of vegetation C stocks to these differences. However, it should be noted again that most of these observations came from one study (Somarriba et al., 2013), which applied the same approach throughout. There were also differences in the soil depth examined and not all reported bulk densities, increasing the uncertainties when extrapolating from soil C contents to stocks. As reported by (Nair, 2011), research on C stocks is strengthened by including such measurements and following guidelines (Brown, 1997; Macdicken, 1997).

Almost all estimates of C stocks at this scale for any agricultural or agroforestry system include uncertainties. From the measurements of average basal areas, to the estimation of aboveground and belowground C stocks from allometric equations, then converted using a unique coefficient, and finally averaged by age classes, there is room for error build-up. That is why it is useful to present the variation in the data using different metrics such as means, medians, standard error and deviations, quartiles, as well as scatter plots. For example, a plant C to dry mass content of 50% was assumed, but it can vary from ~42 to ~50% (Ma et al., 2018). Similarly, the C content of SOM is traditionally set at 58% but could go down to 40% (Nelson & Sommers, 2018; Soil Survey Staff, 2004). The critical review of Pribyl (2010) suggests using a soil organic matter C content of 50%. In this study, only C stocks are shared, while the principal dataset also included biomass.

The soil C comparisons were based on a derived value for 0-10 cm. For example, it was assumed that if a SOC of 2.5% was reported for 0-20 cm, then the SOC at 0-10 cm was also 2.5%. The decline in soil organic C with depth has been termed as an *anisotropic* distribution (Peng, 2011). Hence the approach adopted here is probably underestimating the actual C concentration at 0-10 cm for soils sampled deeper than 10 cm. (i.e., the thicker the layer of soil sampled, the higher the underestimation). A correction could have been applied to compensate for this by assuming a single depth distribution of SOC for all soils, but the likely heterogeneity of the depth distribution of soil C between locations would have introduced another, albeit smaller, source of error.

2.4.6 To what extent do cocoa systems sequester C and mitigate greenhouse gas emissions?

This final section examines the results in the content of the climate change theme of this special issue. Focusing on sequestration first, this study demonstrates that cocoa systems can store high quantities of C over time. Using the age distribution of the cocoa farms of this database, it is possible to calculate a weighted average for the cumulated C stocks, attaining 81.8 Mg ha^{-1}, which is substantially greater than that achieved using annual crops such as maize and rice. According to FAOSTAT (FAO, 2019), cocoa was harvested on 11.8 million ha in 2017 (118 000 km^2). This is similar to the value of 10.3 million ha indicated by world production in 2018 of 4652 Mt (ICCO, 2019) and a supposed mean yield of 450 kg ha^{-1}. Assuming that approximately 11 million ha are occupied by cocoa cultivation and that those cocoa systems are similar to those reported here, the global amount of C stored worldwide in cocoa systems (including soil to a depth of 10 cm) is equivalent to a total of about 0.9 Gt of C (900 MtC), equivalent to 3.3 GtCO_2.

It is anticipated that GHG emissions from an established cocoa plantation are low. Cocoa cultivation is not demanding in fossil fuels because it is not mechanized, and there is only limited use of synthetic fertilizers (Wood & Lass, 2008) (Wood & Lass, 2008). In Colombia, a life cycle assessment of the C footprint of cocoa production, from cradle-to-farmgate, found that cocoa systems emitted around 8~9 kg of CO_2 per kg of cocoa bean produced (Ortiz-Rodríguez et al., 2016). In fact, they reported that the main contributor to GHG emissions was the anaerobic decomposition of cocoa pods left on the ground (85% of the total emissions). In contrast, estimations from CATIE found that cocoa plantations can be net sinks of C, with 34.8 kg of CO_2 captured per kg of cocoa produced (Feed the Future, 2017). In their study, emissions were estimated to be 4.98 $kgCO_2$ per kg of beans, while capture reached 39.8 $kgCO_2$ per kg of beans. The 'Climate-Smart Cocoa' project in Ghana, for its part, assessed the net GHG footprint of cocoa to be 20 $kgCO_2$ per kg of cocoa produced. A possible diminution to only 2 $kgCO_2$ per kg of bean produced is mentioned.

Deforestation is one of the major sources of global C emissions (i.e., 2.97 $GtCO_2.yr^{-1}$ in the tropics; Smith et al., 2014). Historically, the expansion of cocoa has been made at the expense of forests (Ruf et al., 2015). Converting high-C reservoirs like forests to cocoa resulted in a net loss of C. From a chronological standpoint, this initial land-use conversion can be identified as the first source of emissions. Preventing deforestation may therefore be an effective strategy to forestall emissions from cocoa. Unfortunately, climate change is expected to shift the location of the land suitable for cocoa, reducing suitable areas in some countries while increasing the suitability of others (Bunn et al., 2019; Ruf et al., 2015). During recent decades, the cocoa industry has been committed to preventing further deforestation by promoting the sustainable intensification model through several initiatives (e.g., REDD+, CocoaSoils, Climate Smart Cocoa, Cocoa Action, and the Cocoa & Forests initiative; Ingram et al., 2018). The world demand for cocoa is expected to continue increasing, suggesting that, higher yields will need to be derived from existing areas to prevent further deforestation (Wessel & Quist-Wessel, 2015). Further research is required to develop optimal cocoa systems capable of delivering on sustainability challenges: economically viable, C-negative, and locally-adapted to the near-future climate.

2.5 Conclusions

This study examined the temporal dynamics and variability of a range of C stocks in cocoa plantations. Large differences within the same age classes were observed for almost all C stocks, except litter. The differences in C stocks between plots of similar age reflect the potential importance of management in selecting the appropriate density of cocoa and shade trees to optimize C storage and the importance of different pedoclimatic contexts.

Shade trees stored the greatest amount of C because of the size they can attain compared to cocoa. Hence planting or conserving shade trees on cocoa plantations is critical for C management. In this study, soil C assessments were restricted to 0-10 cm; using a deeper depth increment would arithmetically increase the importance of soil C as a pool.

The challenge is to identify the canopy structure and arrangement that optimizes cocoa yields and the provision of other ecosystem services such as C sequestration. These results suggest that C storage potentials need to be determined according to the local context. More research is also required to develop the best adaptation strategies in a climate change context, primarily because of the long-term installation of cocoa orchards. Regarding the variation of C stocks, further work is needed to understand the underlying mechanisms driving trends and characterize how specific cases lead to different stocks of C. Also, because soil is one of the largest reservoirs of C with shade trees, further research is needed to evaluate the potential of different soils (i.e., types, depths). While no clear trend was revealed for soil C, modelling diverse farms, at contrasting locations, with various management types will certainly reveal what can be achieved by cocoa farms, both in the vegetation and the soil reservoirs of C. To the knowledge of the authors, no model has been applied to cocoa to study its C dynamics, even though modelling could address most of the aforementioned research topics. This study also creates a valuable database for future assessments of C stocks in cocoa agroecosystems.

3. MEDIUM-TERM EFFECT OF FERTILIZER, COMPOST, AND DOLOMITE ON COCOA SOIL AND PRODUCTIVITY IN SULAWESI, INDONESIA

Highlights:

- The productivity of each treatment was low (highest yield: 628 kg dry beans per ha)
- Over four years, the cumulated average cocoa bean productivity of composted treatments was 270-300% that of the control (including tree mortality rates);
- Fertilizers did not outperform compost and only provided a slight improvement compared to dolomite alone (respectively, 160 and 145% increased yield relative to the control; including tree mortality rates);
- Fertilized treatments could overtake the composted ones if the trends are sustained during the following years;
- Several soil nutrient contents and soil organic C significantly decreased over the four-year study despite additions.

Summary:

In Indonesia, management practices that reduce soil fertility could be limiting cocoa (*Theobroma cacao* L.) production. This research investigated the effects of fertilizers and organic amendments comprising different combinations of NPK + urea, dolomite, and manure-based compost on soil properties and cocoa productivity. An existing field experiment in South Sulawesi, Indonesia, was continued to assess these treatments' effects on cocoa trees from the age of 2.9 years to 7.4 years. The treatments were first applied in 2012, five months after planting and subsequently twice a year. Soil analyses were performed before planting (2011), after 3 years (2014), and finally after 7 years (2018). Productivity was assessed yearly between the age of 3.5 and 7.4 years old. The highest yields were obtained from the plots receiving compost, although the yield benefits diminished over time. Inorganic fertilizer alone doubled the yield compared to the control, while compost and compost + fertilizer yields tripled it. With dolomite alone, the yield cumulated over 4 years (between 3.5 and 7.4 years) was 41% higher than the control. The positive effect of compost on cocoa yields can potentially be attributed to (1) physical changes in soil structure increasing soil water availability, (2) the chemical improvement of nutrient availability, and (3) biologically, by promoting the activity of beneficial organisms. The application of dolomite increased soil pH, Ca, and Mg contents. Soil organic C greatly declined since 2014 in the composted treatments, even though 10 kg of compost was applied per tree per year, probably because of the compost's low C:N ratio. Future studies should assess different fertilizer formulations and combinations with organic inputs and explore the mechanisms by which compost promotes cocoa productivity.

Keywords: Compost, fertilization, soil fertility, cocoa productivity, Indonesia.

3.1 Introduction

Cocoa (*Theobroma cacao* L.) is a major cash crop for millions of farmers, particularly in developing countries. Indonesia is one the largest cocoa-producing countries, with about 50 to 75% of national output from Sulawesi. From 1990 to 2010, the land allocated for cocoa production in Indonesia increased 10-fold, reaching a plateau of approximately 17 000 km^2 in 2010 (FAOSTAT, 2020). However, the gross production of cocoa has decreased since 2010 because of declining yields per hectare that started in the early 1990s (FAOSTAT, 2020). Because of the limited availability of land, productivity per hectare will need to increase if Indonesia is to contribute to the increasing global demand for cocoa.

The decline of productivity of cocoa plantations has been related to inadequate management leading to problems such as lower soil fertility and increased levels of pests and disease (Asare et al., 2018). Due to a lack of resources to improve existing farms, low profits have often pushed farmers to move cultivation to forested areas (Ruf, 2001). To prevent deforestation, many public and private stakeholders in the cocoa industry seek to improve crop productivity on existing farms (Carodenuto, 2019; Weber, 2017). The revitalization of cocoa farms is being implemented through improved planting material, the integrated control of pests and diseases, optimal shade control, and long-term soil fertility management (Asare et al., 2018; Wood & Lass, 2008).

Soil fertility often deteriorates on cocoa farms (Adeniyi et al., 2017). Typically, cocoa trees planted on a freshly cleared forest initially benefit from high soil fertility due to high soil organic matter levels and well-developed soil structure. However, the subsequent removal of the harvested pods and beans can reduce soil nutrient levels (Boyer, 1973; Fassbender et al., 1988; Hartemink, 2005;

Thong & Ng, 1978; van Vliet et al., 2015), and soil fertility declines if they are not replenished with organic or mineral/inorganic fertilizers (Aikpokpodion, 2010; Hartemink, 2005). Soil degradation can also occur due to soil acidification after using prolonged use of acidifying fertilizers like urea, organic matter decay, the removal and leaching of basic cations (Goulding, 2016). This can lead to the increased availability of toxic elements such aluminium, iron and manganese (Lal et al., 1989).

To maintain soil fertility, farmers typically apply amendments and fertilizers to replenish nutrient stocks and correct soil acidity. Few peer-reviewed studies have evaluated the effects of these amendments on both cocoa productivity and soil properties. Where this is research has been undertaken, it often focuses on short-term effects on seedlings or young cocoa trees (Ahenkorah et al., 1987; van Vliet et al., 2015; Wessel, 1971). Verlière (1981) reported that only a few fertilizer experiments with cocoa had provided significant results, and there was a need to determine the interactions between shade management, cocoa nutritional needs, and productivity. Fewer fertilizer studies have been conducted in South-East Asia than in West Africa, and the work completed in Sulawesi is scarce (Mulia et al., 2019). In addition, there have been few studies examining the combined effects of fertilizers, organic inputs (e.g., compost or manure), and other amendments (e.g., lime dolomite).

To address this lack of information for Indonesia, Mulia et al. (2019) reported the responses for the first four years of a cocoa field trial established in 2011 which investigated various combinations of fertilizers and amendments (organic and inorganic). Because the treatments were continued after the first four years, this study aims to evaluate the effects of the treatments on soil properties, growth, and yield on more mature cocoa plants in order to develop fertilizer recommendations based on organic amendments.

3.2 Methodology

3.2.1 Experimental site

The experimental area has been described in detail by Mulia et al. (2019), but the main points are repeated here for clarity. The plot is located in Bone-Bone, South Sulawesi, Indonesia (2.605833°S, 120.612333°E). The principal activities carried out between 2011 and 2018 on the experiment are presented in Table A - 3.1, Table A - 3.2, and Table A - 3.3. Cocoa plants of clone PBC123, also known as

Sulawesi 1, were planted at a 3 by 3 m spacing (square grid) in December 2011, i.e., 1111 trees per hectare. Shade trees of *Gliricidia sepium* were planted at the same time as the cocoa trees, as well as existing coconuts. In January 2016, after the completion of Mulia's study, new cocoa trees were planted to replace the ones that died during the first phase of the experiment. However, after this replanting, productivity was not recorded on those trees. Monthly precipitation for the 2011-2018 period (Table A - 3.4 in supplementary material) was obtained from Mars's Cocoa Research Station, located in Tarengge, approximately 20 km from the site (South Sulawesi, Indonesia).

3.2.2 Treatments

Initially, the experiment followed a randomized block design repeated four times (Table 3.1), with 16 cocoa trees for each repetition (in a 4 trees by 4 trees square grid fashion without border). As described in Mulia et al. (2019), there was a control treatment with no fertilizers or amendments (Treatment A), and treatments comprising either the application of NPK fertilizer + urea (Treatment B), compost (Treatment C), and dolomite (Treatment D). Subsequently, four possible combinations of the three primary inputs were implemented with cumulated application rates (Treatments E to H). There were eight treatments in total, coded from A to H (one control + three with individual inputs + four with combinations of inputs). The treatments described in Table 3.1 were split into two applications applied at six-month intervals. The inorganic fertilizer applied to each tree was a mix of 374 g of Phonska (15% N, 15% P_2O_5, and 15% K_2O with traces of S) and 250 g urea. The compost was locally made of 60% cow manure, 15% empty oil palm bunches, 10% rice straw, 10% diverse leaves (banana, grass, *Gliricidia,* and maize), and 5% cocoa pod husks. A micro-organism mix (EM4) was also applied to the compost. The compost treatments comprised the application of 5 kg of compost to each tree twice a year (10 kg per year, distributed in six small pits located at 1 m from the trunk). The full chemical composition of the compost is described by Mulia et al. (2019). The dolomite amendment comprised 18-22% of MgO, but the content for other constituents such as carbonates or calcium oxide CaO was unknown, but typical contents are around 22% Ca, 13% Mg, 13% C, and 52% O in elemental terms (Mineralogical Society of America, 2003).

Table 3.1: Breakdown of the treatments applied between 2012 and 2018 (adapted from Mulia et al., 2019)

Rates in g tree^{-1} year^{-1}, equivalent to kg ha^{-1} year^{-1} (considering a density of 1000 cocoa trees per hectare)								
Treatment		**C**	**N**	**P**	**K**	**Ca**	**Mg**	**S**
A	**No amendment**	0	0	0	0	0	0	0
B	**Mineral fertilizer**	0	120.5	24.5	46.6	0	0	Trace
C	**Compost (10 kg)**	930	130	37	45	551	15	18
D	**Dolomite (5 kg)**	650	0	0	0	1100	650	0
E	**B + C**	930	250.5	61.5	91.6	551	15	18
F	**B + D**	650	120.5	24.5	46.6	1100	650	Trace
G	**C + D**	1580	130	37	45	1651	665	18
H	**B + C + D**	1580	250.5	61.5	91.6	1651	665	18

Soil amendments and fertilizers were applied twice per year per tree to provide total quantities as follows: 374 g NPK (“Phonska’) and 250 g urea (mineral fertilizer), 5 kg dolomite, and 10 kg compost. Combinations (Treatments E–H) were additive. The columns on the right show the total quantities of elements (g) provided per tree each year in each treatment. Phonska is a subsidized compound fertilizer made from three raw materials: urea, DAP (diammonium phosphate), rock phosphate, MOP (potassium chloride), and “other macronutrients” according to the manufacturer (https://www.pupukkaltim.com/en/distribution-product-product-knowledge). At the time of planting, mineral fertilizer, 100 g NPK (Phonska) and 150 g triple superphosphate (36%), was added to each tree in equal amounts to provide adequate and uniform nutrient conditions for the establishment of all plants in the first few months after planting out (Mulia et al., 2019).

3.2.3 Sampling and analyses

a. Soil

In each plot, one soil sample was collected, at the centre of the plot, 1 m from a cocoa trunk, at a depth of 0-20 cm, below the scraped surface litter, using an auger. The same day, samples were air-dried before being ground and sieved to < 2 mm. The core ring method was used to collect bulk density samples on each experimental unit, next to the soil sample, at 0-5 cm depth. These were later air-dried at 60°C for 48 hours before weighing. In total, 32 soil samples were collected for soil analyses and bulk density measurement, corresponding to eight treatments with four repetitions each. The samples were then split with one sample sent to Asian-Agri Laboratory in North Sumatra, Indonesia, and the second sample was sent to Cranfield University in the United Kingdom. The analytical methods corresponding to each soil property are listed in Table 3.2 (Asian-Agri analyses) and Table 3.3 (Cranfield University analyses). A difference must be noted between the term “extractable”, referring to Asian-Agri analyses (using HCl at 25% v/v as an extractant), and the term “total” which refers to Cranfield analyses (using microwave-assisted *aqua regia* digestion).

b. Growth of cocoa

Mulia et al. (2019) reported the height of each cocoa tree. In this study, the cocoa growth was determined from the circumference of the trunks (30 cm from the soil surface) because the trees had recently been pruned. These measurements were converted to mean basal areas per treatment (formula and results available in Table A - 3.5). Both the soil sampling and the trunk measuring occurred at the same time in December 2018. The number of dead cocoa trees was used to calculate average survival rates per treatment and is presented in the supplementary material (Table A - 3.6).

c. Productivity and bean quality

From January 2015 to December 2018, cocoa tree productivity was assessed by counting the total number of pods produced per tree over a year, and measuring the weight of pods and the annual yield of cocoa beans per plot, as described in Mulia et al. (2019). A pod index (*PI*, number of pods required to produce 1 kg of dry beans) for each treatment was derived from the pod counts and the mean pod weights (*PI* = 1000 ÷ average yield per pod in grams; Table A - 3.7). The number of healthy and infected pods was also recorded. The pods were categorized as being uninfested or infested following the method previously described in McMahon et al. (2015). A sample of the harvested beans was also collected in November 2017 to determine the waste fraction and the average weight of the fresh beans. Harvest quality results were obtained from the Mars Laboratory in Makassar (Sulawesi, Indonesia). The mean pod count per tree, yield per pod, pod index, and proportion of infected pods for each year and treatment is presented as supplementary material (Table A - 3.7). In Mulia's study, productivity data covered the second semester of 2014 and the first of 2015, whereas this study recorded the annual yields from January 2015 to December 2018.

d. Yield estimates

Basal areas, dry bean yields, and pod counts were averaged *per surviving tree* (≤ 16) and then extrapolated to 1000 trees to provide a *per hectare* value (as in Mulia et al., 2019). Additionally, the average yield *per planted tree* was also calculated, this time dividing the yield per plot by the number of initial trees, 16, and then multiplying by 1000 to derive the adjusted yield per hectare. Averaging per surviving tree minimizes treatment differences due to mortality rates. However, it can lead to the confounding effect in that those trees with lower competition (i.e., where the mortality is high) could show greater growth rates and higher yields on a *per tree* basis.

e. Statistical analysis

Means and standard deviations of the four replicates were calculated for each variable (growth, productivity, and the soil analyses) and each treatment. Statistical differences between the treatments (for basal areas, dry bean yields and soil analyses) were evaluated by submitting the individual observations to an ANOVA followed by a Tukey HSD test in R 3.6.0 using the package “agricolae” (at P = 0.05). If ANOVA assumptions were not met, the Kruskal-Wallis test was applied using the “kruskal” function (at P = 0.05), and multiple comparisons between the treatments were obtained by using Fischer’s least significant difference *posthoc* test (with a level of significance at 0.05). Because of the lack of dispersion data in 2014, the Welch one-sample t-test was used to estimate the statistical difference between the two soil sampling periods, 2014 and 2018. In this case, it was assumed that the 2014 result was equal to the true mean because we lacked dispersion data for 2014 (Table A - 3.8).

3.3 Results

3.3.1 Tree basal areas and survival rates

Tree basal areas and survival rates in December 2018, seven years after planting, are presented in Figure 3.1a. Compared to the control (Treatment A) and the mineral fertilizer only plots (Treatment B), it was found that significantly higher mean basal areas occurred where compost and dolomite together (Treatment G) and the full combination were applied (Treatment H). The observed basal areas (of surviving trees only) were relatively heterogeneous for all treatments, with coefficients of variation ranging from 25 to 41% (Table A - 3.5). Treatment B had the lowest survival rate (41%), followed by the control (67%) and dolomite Treatment D (72%). All the other treatments had a survival rate higher than 80%.

3.3.2 Yields and harvest quality

a. Dry bean yield

Dry bean yields for each treatment from 2015 to 2018 are shown in Figure 3.1b and detailed in Table A - 3.9. Productivity was very low in 2015, with a pattern similar to Mulia et al.'s (2019) results for 2014-2015 (low for A, B, D, F; high for C, E, G, H). In 2015, the treatments receiving no compost (Treatments A, B, D, and F) provided the lowest annual yields of only 110 kg ha^{-1} on average, much lower than the gloval average. In 2016, the mean yields increased, but the treatments without compost (A, B, D, F) again significantly produced less than the composted treatments (C, E, G, H). The following year, differences between treatments were less marked. Finally, in 2018, only the yield in the mineral fertilizer treatment (B) was greater than the yield in the control treatment (A); the other treatments' yields were similar (see Figure 3.1b). The coefficients of variation associated with a given year declined from 69% in 2015 to 27% in 2018 (Table A - 3.9). Over the four years, the compost-only Treatment (C), the fertilizer and compost Treatment (E), and the compost and dolomite Treatment (G) produced the highest cumulative yields (2600-2750 kg ha^{-1}; Table A - 3.9).

b. Pod count and yield per pod

The pattern for pod counts in 2015 and 2016 (Table A - 3.7) was similar to dry bean yields: treatments with compost (C, E, G, and H) had high pod counts (27-47), the treatments without compost (A, B, D, and F) had low counts (5-16). From 2017, the differences in pod counts between treatments reduced and seemed to converge in a similar way as did the dry bean yields.

The mean yield of dry beans per harvested pod was highly variable across treatments over between 2015 and 2018 (Table A - 3.7), ranging from a minimum of 10.8 g attained by Treatment D in 2015, to a maximum of 30.3 g (for pod-producing replicates for the mineral fertilizer Treatment B in 2017. The low yields obtained in 2015 were associated with the smallest mean yield per pod of 12.4 g across all the treatments. Mean yields of dry beans per pod increased to 23.2 g in 2016 and 26.8 g in 2017, before declining to 19.1 g in 2018.

c. Yield index

To partially account for the differences in competition caused by the replanting in 2016, a yield index was calculated for each treatment (Table A - 3.10). It was determined as the ratio of the yield of dry beans per hectare (kg) divided by the basal area (cm^2). On average, the mineral fertilizer Treatment B had the highest yield index of around 10 g cm^{-2}, while the value for the other treatments ranged from 3.8 to 5.6 g cm^{-2}.

d. Pod index

The dolomite Treatment D attained the highest pod index in 2015 (Table A - 3.7), reaching 96 pods kg^{-1}, equating to a very small mean pod size of 10.8 g. The lowest pod index of 33 pods kg^{-1} was attained by the mineral fertilizer Treatment (B) in 2017 when the mean pod weight reached 30.3 g. In 2016 and 2017, the pod indices were uniform across treatments with a mean value of 44 and 38 pods kg^{-1}. Even though yields were more uniform in 2018, pod indices differed, ranging from 43 pods kg^{-1} (Treatment B) to 70 pods kg^{-1} (Treatment G).

e. Proportion of infected pods, dry bean weight, and fraction of waste beans

The proportion of infected pods was high, ranging from 62% to 97% for individual treatments per year (Table A - 3.7), and there was no consistent treatment effect. The analysis of a production sample, collected in November 2017, revealed differences between average dry bean weights (Table A - 3.11). The smallest beans were obtained for Treatment B (1.25 g), which were lower than the control (1.30 g). The largest beans were found for Treatment D (1.59 g). Compared to the mineral fertilizer Treatment B, Treatments C to H produced beans that were, on average, 18% heavier, while those in the control were only 65% of the weight of those in the mineral fertilizer Treatment B. The fraction of waste beans ranged from 18% (Treatment E) to 8% (Treatment F), with the others between 10 and 14%.

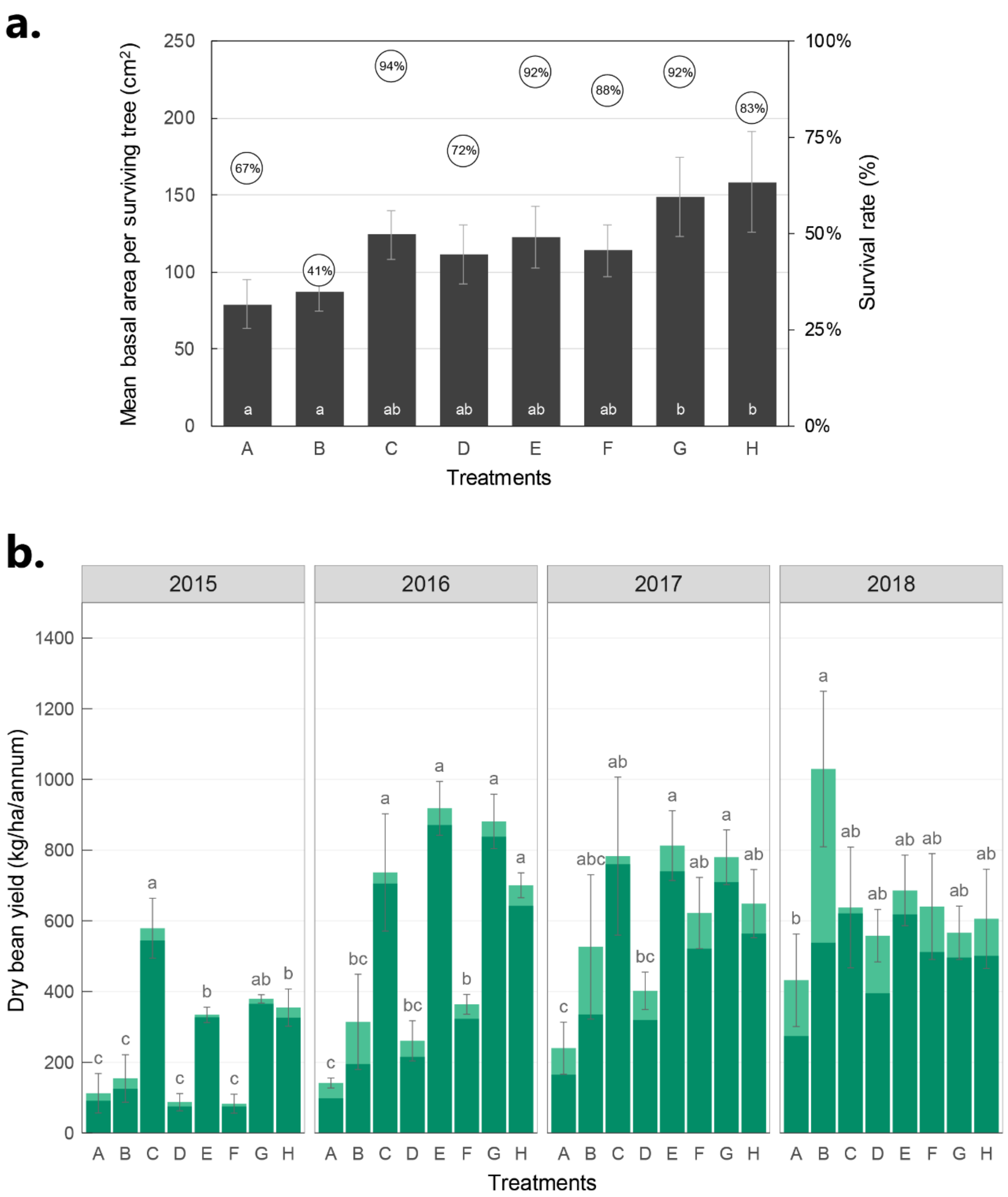


Figure 3.1: Effect of soil amendments on (a) mean basal area per cocoa tree and survival rates in December 2018 and (b) annual yield of dry beans in each year from 2015 to 2018

In December 2018, cocoa trees were 7.4 years old (89 months). For each variable, means correspond to an average of the four replicates. Error bars represent standard errors of the mean based on surviving trees (light bars). Upper case letters on the X-axis refers to each treatment, namely: A is control; B is mineral fertilizer; C is compost; D is dolomite; E is mineral fertilizer and compost; F is mineral fertilizer and dolomite; G is compost and dolomite; H is the full combination. Treatments with the same lower-case letter are not statistically significant ($P > 0.05$). For (b), the dark bars represent the harvest averaged for 16 initially planted trees, while the addition of light bars shows the average yield calculated per surviving tree (i.e., excluding dead trees, excluding mortality). From 2016, one replicate of Treatment B was excluded from the average calculation, as all trees were dead, leaving three replicates instead of four. Statistical significance was tested within each year, not pooled all together across all four years.

3.3.3 Soil properties

The results of the soil analyses are presented in Table 3.2 and Table 3.3, and the soil changes that occurred over the four years from 2015-2018 are shown in Figure 3.2 (arranged in terms of soil property) and Figure A - 3.1 (arranged in terms of the treatments). The mean annual rates of change for each element in kg ha^{-1} $year^{-1}$ are presented in Table A - 3.12.

a. Bulk density and pH

The mean surface bulk density of the soil was statistically similar for each treatment, with a mean value of 1.09 g cm^{-3}. For all treatments, soil pH values increased between 2014 and 2018 (Table 3.2). Treatments A, B, and C, which did not receive dolomite, were the most acidic in 2018 with pH values ranging from 5.21-5.36 (Table 3.2). The pH was about neutral (6.75-6.87) for Treatments D, F, and G, where dolomite was applied. The pH of E and H were intermediate (respectively 5.79 and 6.25).

b. Carbon (C)

Despite the addition of compost, the soil organic C contents across the treatments in 2018 were statistically similar, with a mean value of 1.25% (Table 3.2). The soil organic C content in Treatments C, G, and H significantly declined since 2014 (Figure 3.2). Subsequent analyses of the total C after dry combustion (following ISO 10694:1995, in Table 3.3) determined with an elemental analyzer at Cranfield University on sample duplicates also showed no statistical difference between treatments. However, the mean total soil carbon content of 1.65% was about 30% higher than the organic carbon values. Possible reasons for the higher reading could be the presence of inorganic forms of C (included in the Cranfield measurement) or a systematic difference between the Elementar and Walkley-Black methods (De Vos et al., 2007; Jha et al., 2014; Meersmans et al., 2009; Roper et al., 2019).

c. Nitrogen (N)

Despite the different treatments, there was no statistical difference between treatments in the level of soil N, determined within either the Kjeldahl method (Table 3.2) or the Elementar Analyzer (Table 3.3). The N values reported in 2018 of 0.123-0.153% were broadly similar to measurements made in 2014 and reported by Mulia et al. (2019). In 2018, the C:N ratios based on the measurements with the Asian-Agri’s dataset were approximately around 9:1. The C:N ratio determined using Cranfield University’s data also indicated similar results between treatments, but the higher C measurement resulted in a higher mean C:N ratio of 12:1.

d. Phosphorus (P)

In 2018, the extractable P content in the control Treatment A (18.4 ppm) was significantly lower than that (68.4 ppm) in Treatment E receiving mineral fertilizer and compost (Table 3.2). The other treatments were not statistically different. The total P contents also followed the same pattern, with the value (283 ppm) for Treatment A being statistically less than that (366 ppm) for Treatment E; the rest were statistically similar (Table 3.3). The extractable P contents measured in 2018 (18-68 ppm) were substantially lower than those measured in 2014 (227-471 ppm; Figure 3.2).

In 2018, the mean value for available P (Bray 1) for each treatment ranged from 1.9 to 12.6 ppm (Table 3.2). These values were significantly lower than those (10-40 ppm) in 2014 and those (13 ppm) in 2011 prior to planting. The fraction of available P relative to total P ranged from 5% (Treatment D) to 25% (Treatment C). The higher pH observed for Treatment D was not associated with a noticeable increase in P availability (lowest available P at 1.9 ppm), nor did the addition of compost affect P availability (higher for Treatments C and E, 10.3 ppm on average, but not G and H, 4.2 ppm on average).

e. Potassium (K)

There were no statistical differences for exchangeable (Ammonium acetate pH 7 extraction), extractable (25% HCl extraction), and total K (HCl/HNO_3 extraction) between the treatments in 2018 (Table 3.2). However, the measured exchangeable K significantly decreased in all treatments from 2014 to 2018 (Figure 3.2). In 2018, the mean value across all treatments was below adequate levels for cocoa (between 117 and 235 ppm, according to Nelson et al., 2011). By contrast, between 2014 and 2018, extractable K significantly increased with all the treatments, except in Treatment B, where it decreased (although not statistically significant), and in the control for which the change was negative but not significant (Figure 3.2).

f. Calcium (Ca)

In 2018, there were treatment differences in the level of extractable and total Ca (Table 3.2 and Table 3.3). Treatments D and F, which received dolomite, had higher concentrations than all other treatments. The lowest levels were found in the control (Treatment A) and the plots receiving only mineral fertilizer (Treatment

B). Extractable Ca increased significantly in the dolomite treatments, with a peak at 2 g kg^{-1} for Treatment F. The treatment effects on exchangeable and total Ca were similar to those for extractable Ca. The highest values occurred where dolomite was applied. Again, there was potentially an outlier in Treatment F, where a reading reached 5.7 g kg^{-1}, perhaps due to the presence of incompletely dissolved dolomite. After 2014, the Ca contents of all the treatments which did not receive dolomite decreased to low levels (below 250-500 ppm).

g. Magnesium (Mg)

In 2018, there was no treatment effect on the level of extractable Mg (Table 3.2), but the exchangeable (Table 3.2) and total Mg (Table 3.3) showed a similar treatment response to Ca. The highest contents corresponded to the treatments with dolomite application; the lowest values were observed for the control and mineral fertilizer only plots. There was again a peak for extractable and total Mg for Treatment F, possibly due to the presence of dolomite, while the other observations were closer to 900 ppm. The lowest values were found for Treatments A, B and E, slightly significantly exceeded by Treatment C . For exchangeable Mg, a pattern similar to Ca was found: highest where dolomite was applied, peaks for Treatments F and D and minimums for the control and the mineral fertilizer Treatments, A and B. As for Ca, one very high Mg measurement was found for one of the samples, suggesting the presence of high concentrations of dolomite. As with extractable Ca, the extractable Mg contents have only slightly significantly increased since 2014 in the plots without dolomite, while they largely increased where dolomite was applied Table 3.2.

h. Sodium (Na)

In 2018, no statistical differences were found between the treatments for exchangeable Na contents (Table 3.2). However, between 2014 and 2018, the Na contents decreased for all treatments (but statistically significant only for Treatments A, C, D, E, and H; Figure 3.2). Sodium adsorption ratios were all very low (<1), suggesting no salinity-related physico-chemical degradation risks on soil structure (USDA NRCS, 2017).

i. Aluminium (Al)

Distinctively, the lowest exchangeable Al contents were recorded in the treatment with the application of dolomite, which also decreased compared to 2014. Overall, total Al contents were statistically the same for all treatments, around 2% Table 3.3).

j. CEC & Base saturation

The treatments did not appear to influence the cation exchange capacity (CEC), which was low in all the treatments (between 5.89 in Treatment B and 8.11-8.36 in Treatment D and E; Table 3.2). The treatments showed distinct base saturations. Treatment F attained 125% of saturation, possibly due to very high Ca and Mg found in the samples, themselves most likely coming from the dolomite.

Table 3.2: Soil bulk density, pH, organic carbon and nitrogen content and extractable and exchangeable nutrient contents in December 2018, 6.5 years after treatments A–H were first applied

Treatment	○ Bulk density (g cm^{-3})	* pH (water)	† Org. C (%)	‡ N (%)	C/N	†† CEC (cmol kg^{-1})
A	1.12 a (0.01)	5.36 c (0.58)	1.26 a (0.17)	0.138 ab (0.01)	9.13	6.65 ab (1.04)
B	1.10 a (0.08)	5.30 c (0.38)	1.21 a (0.11)	0.123 b (0.03)	9.84	5.89 b (1.25)
C	1.12 a (0.03)	5.21 c (0.46)	1.22 a (0.10)	0.140 ab (0.02)	8.68	7.37 ab (0.83)
D	1.06 a (0.06)	6.83 a (0.17)	1.35 a (0.11)	0.138 ab (0.03)	9.80	8.36 a (0.58)
E	1.08 a (0.10)	5.79 bc (0.25)	1.40 a (0.18)	0.153 ab (0.02)	9.15	8.11 a (0.90)
F	1.09 a (0.06)	6.87 a (0.35)	1.17 a (0.33)	0.153 a (0.02)	7.69	6.94 ab (0.90)
G	1.10 a (0.06)	6.75 a (0.19)	1.24 a (0.22)	0.135 ab (0.02)	9.19	7.16 ab (0.20)
H	1.06 a (0.09)	6.25 ab (0.43)	1.17 a (0.19)	0.128 ab (0.04)	9.16	6.82 ab (0.61)
Average	1.09	6.04	1.25	0.138	9.08	7.16
Stat sign.	0.839	<0.001	0.641	0.511 (K-W)	na	0.010

Treatment	§ Extractable (ppm)				‡‡ Exch. Al (ppm)
	P	Ca	Mg	K	
A	18.4 b (1.4)	95.8 e (5.2)	334 e (18)	666a (57.6)	705 a (24.3)
B	33.8 ab (15.8)	95.9 e (10.4)	329 e (11.2)	641a (61.1)	743 a (59.4)
C	32.1 ab (19.7)	117 d (13.6)	383 d (24.7)	715a (76.1)	720 a (4.4)
D	38.4 ab (22.8)	947 a (64.0)	980 a (63.7)	704a (88.1)	20.9 c (1.4)
E	68.4 a (24.6)	167 c (32.3)	427 d (41)	745a (18.8)	678 a (99.5)
F	48.3 ab (16.6)	2010 a (2438.3)	1540 a (1280)	699a (53.1)	27.0 c (18.3)
G	33.4 ab (15.1)	630 b (118)	804 b (65.1)	678a (68.7)	30.4 bc (6.8)
H	37.2 ab (29.6)	386 bc (201)	620 c (71.9)	716a (75.5)	141 b (111)
Average	38.8	556	677	696	383
Stat sign.	0.076	<0.001 (K-W)	<0.001 (K-W)	0.457	<0.001 (K-W)

Soil treatments were applied twice per year, beginning in May 2012. Soil properties were determined in the soil laboratory of the Asian-Agri Laboratory in North Sumatra, Indonesia (samples collected in December 2018). Soil treatments are: A, control; B, mineral; C, compost; D, dolomite; E, mineral/compost; F; mineral/dolomite; G, compost/dolomite; H, all amendments. Means are calculated on four samples and given to three significant figures. Numbers in brackets are standard deviations. Treatments with the same letter are not statistically different (P > 0.05). K-W attached to a statistical significance refers to the p-value of Kruskal-Wallis test, used if ANOVA assumptions were not met. Methods: ♠After Fahmy (1977); ○Core ring method; ∗pH (water) determined by AIAT Soil Laboratories, Maros; †Walkley-Black method; ‡Kjeldahl method; §25% HCl extraction; ¶Bray-I method; ††Ammonium acetate (pH 7) extraction; ‡‡KCl (1 N) extraction. “na” stands for not applicable (calculated data). ¥ B.S. refers to Base Saturation.

(Table 3.2 continued)

Treatment	¶ Available P (ppm)	†† Exch. Bas. Cation (ppm)				Total (cmol kg^{-1})	¥ B.S. (%)
		Ca	Mg	K	Na		
A	3.66 bc (1.15)	85.2 d (29.7)	20.1 d (6.4)	39.1 a (9.03)	12.6 a (2.97)	0.45	6.77
B	4.83 ab (0.61)	81.2 d (23.7)	21.9 d (5.3)	37.1 a (7.14)	13.8 a (3.75)	0.45	7.60
C	8.12 a (2.69)	150 c (51.6)	40.1c (12.6)	37.1 a (3.48)	12.6 a (1.33)	0.69	9.36
D	1.90 c (0.20)	1840 a (219.8)	813 a (126.3)	34.2a (4.05)	13.8 a (1.88)	8.07	96.5
E	12.6 a (7.33)	247 c (91.6)	84.5 c (52.3)	40.1 a (2.58)	13.8 a (0.00)	1.13	13.9
F	9.53 b (12.34)	1860 a (708.6)	931 a (343.0)	41.1 a (7.14)	15.5 a (4.35)	8.66	125
G	3.95 b (1.13)	1190 b (187.0)	651 ab (121.8)	45.0 a (8.95)	15.5 a (2.20)	5.83	81.4
H	4.48 b (1.71)	884 b (255.3)	490 b (186.3)	39.1 a (2.20)	14.4 a (2.89)	4.39	64.3
Average	6.13	792	382	39.1	14.0	3.71	50.6
Stat sign.	0.006 (K-W)	<0.001 (K-W)	<0.001 (K-W)	0.757	0.713	na	na

Soil treatments were applied twice per year, beginning in May 2012. Soil properties were determined in the soil laboratory of the Asian-Agri Laboratory in North Sumatra, Indonesia (samples collected in December 2018). Soil treatments are: A, control; B, mineral; C, compost; D, dolomite; E, mineral/compost; F; mineral/dolomite; G, compost/dolomite; H, all amendments. Means are calculated on four samples and given to three significant figures. Numbers in brackets are standard deviations. Treatments with the same letter are not statistically different (P > 0.05). K-W attached to a statistical significance refers to the p-value of Kruskal-Wallis test, used if ANOVA assumptions were not met. Methods: ♠After Fahmy (1977); ○Core ring method; ∗pH (water) determined by AIAT Soil Laboratories, Maros; †Walkley-Black method; ‡Kjeldahl method; §25% HCl extraction; ¶Bray-I method; ††Ammonium acetate (pH 7) extraction; ‡‡KCl (1 N) extraction. “na” stands for not applicable (calculated data). ¥ B.S. refers to Base Saturation.

Table 3.3: Total contents of selected soil elements of the experiment in December 2018

Treatment	‡ Total (%)		♠ Total (ppm)
	C	N	P
A	1.64 a (0.152)	0.139 a (0.0101)	283 b (37.7)
B	1.52 a (0.143)	0.128 a (0.00465)	285 ab (23.2)
C	1.58 a (0.0837)	0.133 a (0.00767)	320 ab (35.2)
D	1.75 a (0.117)	0.140 a (0.011)	296 ab (27.5)
E	1.82 a (0.219)	0.147 a (0.016)	366 a (57.7)
F	1.70 a (0.161)	0.136 a (0.0118)	340 ab (37.3)
G	1.64 a (0.284)	0.134 a (0.020)	289 ab (20.2)
H	1.54 a (0.139)	0.130 a (0.00804)	296 ab (23.6)
Average	1.65	0.136	309
Stat. sign.	0.253	0.424	0.021

Treatment	♠ Total (ppm)			
	Ca	Mg	K	Na
A	98.4 e (27.3)	352 d (43.7)	667 a (70.0)	94.1 ab (26.8)
B	98.7 e (21.3)	398 cd (57.3)	800 a (212)	114 ab (23.6)
C	134 de (41.5)	460 c (65.6)	913 a (258)	136 a (23.1)
D	1120 a (94.9)	1020 a (80.9)	776 a (196)	127 ab (33.1)
E	177 d (81.9)	406 cd (74.1)	684 a (193)	94.5 b (16.4)
F	1850 ab (1890)	1500 ab (1280)	584 a (131)	85.4 b (2.19)
G	758 bc (128)	754 ab (164)	569 a (355)	102 b (78.2)
H	481 c (130)	635 b (88.1)	797 a (259)	120 ab (48.7)
Average	589	691	724	109
Stat. sign.	<0.001 (K-W)	<0.001 (K-W)	0.386	0.150 (K-W)

Soil treatments were applied twice per year, beginning in May 2012. These soil properties were determined at Cranfield University laboratory (samples collected in Indonesia in December 2018). Soil treatments are: A, control; B, mineral; C, compost; D, dolomite; E, mineral/compost; F; mineral/dolomite; G, compost/dolomite; H, all amendments. Means are calculated on four samples and given to three significant figures. Numbers in brackets are standard deviations. Treatments with the same letter are not statistically different ($P > 0.05$). K-W attached to a statistical significance refers to the p-value of Kruskal-Wallis test, used if ANOVA assumptions were not met. ‡ The total soil contents of these elements were determined after dry combustion (SOP based on ISO 10694:1995) while the total contents marked by ♠ were analysed by ICP-MS after using an HCl/HNO_3 extractant (SOP based on ISO 11047:1998).

(Table 3.3 continued)

Treatment	♠ Total (%)		♠ Total (ppm)			
	Al	Fe	Cu	Zn	Mn	B
A	1.98 a (0.223)	1.83 a (0.245)	2.38 a (0.660)	5.76 a (1.24)	55.3 ab (11.0)	1.92 ab (0.272)
B	2.08 a (0.286)	1.85 a (0.221)	2.42 a (0.409)	6.17 a (1.54)	67.0 ab (9.12)	1.99 ab (0.664)
C	2.11 a (0.185)	1.83 a (0.152)	2.66 a (0.96)	7.82 a (2.35)	81.2 a (11.2)	2.46 a (0.696)
D	2.17 a (0.347)	2.00 a (0.304)	2.39 a (0.792)	6.64 a (1.07)	63.1 ab (13.9)	2.19 ab (0.737)
E	2.01 a (0.170)	1.86 a (0.135)	3.33 a (0.661)	7.66 a (1.88)	57.9 ab (14.0)	1.28 bc (0.402)
F	1.75 a (0.133)	1.75 a (0.175)	2.70 a (0.750)	9.12 a (5.57)	49.3 ab (11.2)	0.889 c (0.530)
G	1.77 a (0.479)	1.73 a (0.130)	2.43 a (0.568)	6.42 a (1.33)	46.7 b (22.1)	1.35 bc (1.80)
H	1.99 a (0.451)	1.84 a (0.364)	3.29 a (0.221)	10.4 a (7.15)	63.2 ab (14.6)	1.68 abc (0.740)
Average	1.98	1.84	2.7	7.5	60.5	1.72
Stat. sign.	0.476	0.812	0.242	0.671 (K-W)	0.047	0.091 (K-W)

Soil treatments were applied twice per year, beginning in May 2012. These soil properties were determined at Cranfield University laboratory (samples collected in Indonesia in December 2018). Soil treatments are: A, control; B, mineral; C, compost; D, dolomite; E, mineral/compost; F; mineral/dolomite; G, compost/dolomite; H, all amendments. Means are calculated on four samples and given to three significant figures. Numbers in brackets are standard deviations. Treatments with the same letter are not statistically different ($P > 0.05$). K-W attached to a statistical significance refers to the p-value of Kruskal-Wallis test, used if ANOVA assumptions were not met. **‡** The total soil contents of these elements were determined after dry combustion (SOP based on ISO 10694:1995) while the total contents marked by ♠ were analysed by ICP-MS after using an HCl/HNO_3 extractant (SOP based on ISO 11047:1998).

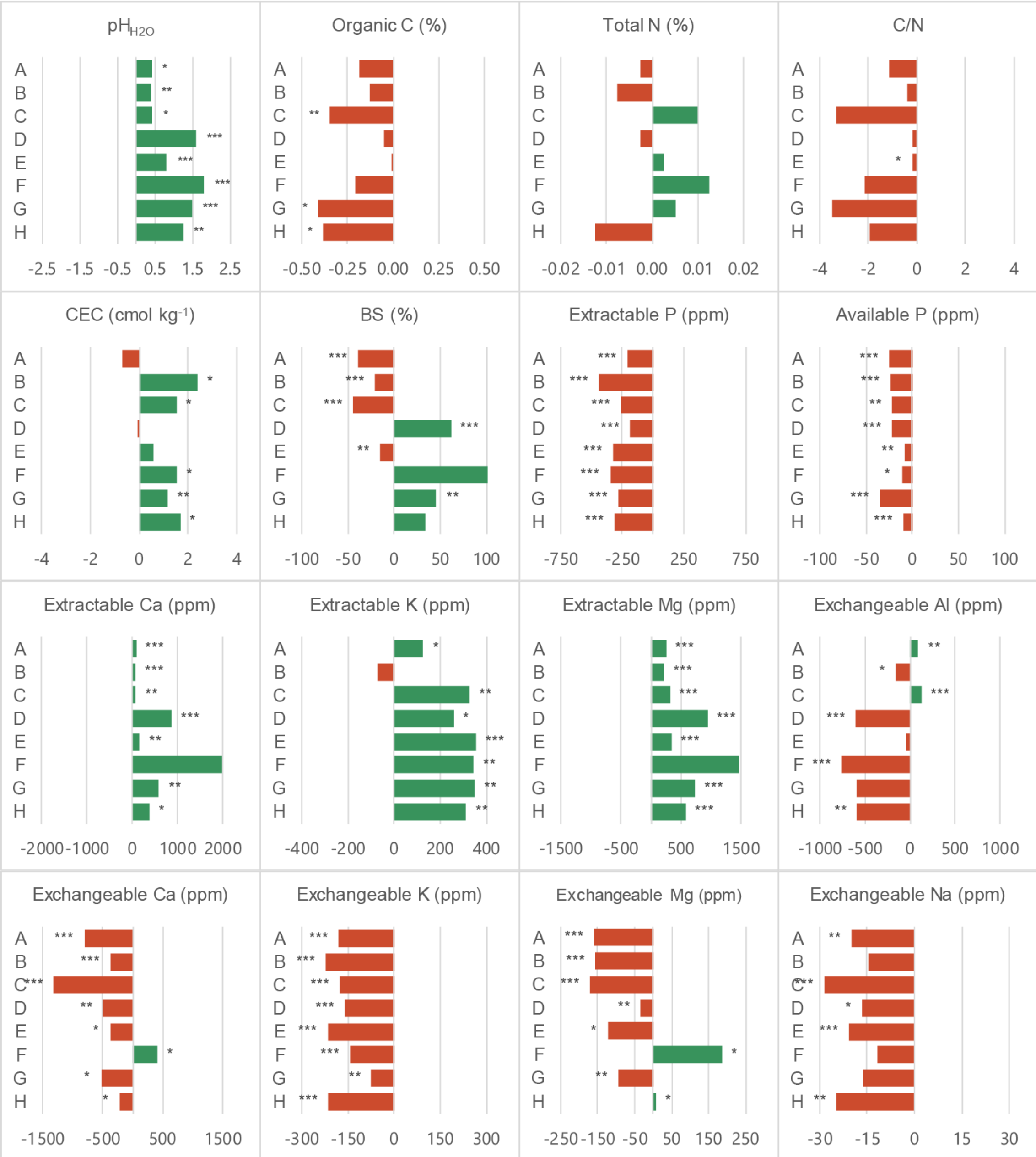


Figure 3.2: Summary of the differences observed in the soil properties between 2014 and 2018

Each difference was calculated by taking 2014 as the initial value and 2018 as the final one. Soil treatments are: A, control; B, mineral; C, compost; D, dolomite; E, mineral/compost; F; mineral/dolomite; G, compost/dolomite; H, all amendments. The colour red indicates an a decrease while the colour green indicates an increase relative to 2014. Stars rating correspond to the following rule, calculated after a Welch one-sample t-test: $P \leq 0.001$, ***; $P \leq 0.01$, **; $P \leq 0.05$, *. Bars with no stars indicate no statistical difference between the two years (p=0.05). Please refer to Table A - 3.8 in the supplementary material for the exact p-values). For extractable Ca and Mg, Treatment F had the largest effect, but the difference is not significant, only because the variability was very high. The mean annual rate of change for each element in kg ha^{-1} $year^{-1}$ is shown in Table A - 3.12.

3.4 Discussion

3.4.1 Modelling approach: balancing simplicity and complexity

To the authors knowledge, before this study, no process-based model had been proposed to predict the temporal variations of SOM stocks in cocoa plantations. For this study, knowledge of SOM dynamics in cocoa farms was solely based on field experiments using predominantly false-time chronosequences. To address this knowledge gap, the approach of this study was to develop, evaluate and apply a model describing SOM dynamics in cocoa farms.

Finding the right balance between simplicity and complexity during model development is a dilemma (Monteith, 1996; Paola & Leeder, 2011). This study made it possible to develop, evaluate, and apply a straightforward and flexible model by using the common-sense approach to problem-solving (Grant & Swannack, 2007) and the adaptation of AMG (Clivot et al., 2019). This model is more straightforward than other models like WaNuLCAS (Van Noordwijk & Lusiana, 1998) and requires a limited number of parameters to function. This model entails a dedicated plant component, allowing and simplifying the simulation of residue inputs increasing over the years, while other models like RothC (Coleman & Jenkinson, 1996) tend to repeat the same amount of inputs each year. This model makes the simulation of tree-like crops easy, as long as a growth curve can be determined for the site in question. Coded in the popular and accessible R programming language, this model can be easily modified to suite the particular needs of the modeler. In addition, a user-friendly interface was developed with the Shiny framework to allow non-programmers to quickly run simulations.

3.4.2 Recontextualization

The aim of extending the study by Mulia et al. (2019) was to determine if the yield responses of seven-year-old cocoa trees to different soil amendments were similar to those reported for three-year-old trees and if the differences in responses could be related to soil chemical properties. This information was then used to develop soil management recommendations.

The initial study (Mulia et al., 2019) highlighted the beneficial effects of compost in increasing cocoa trees' height, increasing flowering and yields, and pod quality.

There were no obvious treatment effects on leaf nutrient contents and pest and disease incidence. The initial study also highlighted that mineral fertilizer and dolomite application to the young cocoa trees were associated with high mortality rates. In terms of soil fertility, it was suggested that the high yields in the compost treatments were associated with increased nutrient availability and uptake. Mulia et al. (2019) also suggested that the mineral fertilizer application could have resulted in nutritional deficiencies in Ca and Mg due to nutrient imbalances with K. This discussion examines how an additional four years of measurements improves understanding of the medium-term effects of the different soil amendments.

3.4.3 Soil response to treatments

The effect of the treatments on soil properties is considered in terms of the effect of the compost, the mineral fertilizer, and the dolomite.

a. Effect of the compost

Despite the addition of almost 1 Mg of organic carbon (OC) per hectare per year from 2012 to 2018, compost inputs did not result in significantly higher soil surface bulk density (0-5 cm), CEC, and soil C contents than the control. Several factors could explain this.

First, although the mean value of SOC in the treatments ranged from 1.17% to 1.40%, these differences were not statistically different. A difference of 0.33% SOC over one hectare to a depth of 20 cm and assuming a bulk density of 1.09 g cm^{-3}, is equivalent to 7 Mg per hectare. Hence, the level of replication (four per treatment) described in this paper would be insufficient to identify a statistically significant difference from the addition of approximately 6 Mg of SOC per hectare over six years. Such analysis highlights the very high levels of replication needed to detect soil changes because of the innate spatial variability in soil properties (Upson et al., 2016).

A second factor relates to the mode of compost application. Compost was applied in six small pits, surrounding the cocoa trees (Table A - 3.2). However, even though soil was sampled at the same distance from the trunk, the location of the sampling was randomly positioned. Moreover, since only one sample was collected per treatment, it was easy to miss one of those little pits and therefore miss the localised effect of compost addition.

A third factor is that the compost had a low C:N ratio (7:1), suggesting that it was prone to rapid mineralisation instead of being turned into more ‘passive’ and recalcitrant forms of soil organic matter through humification (Brady & Weil, 2017; Nicolardot et al., 2001; Tian et al., 1992). By contrast, the use of more recalcitrant organic matter (e.g., higher C:N or lignin:N ratios) could be a more promising method to raise SOM levels (Talbot & Treseder, 2012).

Various authors have argued that a key benefit of compost addition is the increase in soil water holding capacity (Adugna, 2016; Blanco-Canqui & Lal, 2007; Nguyen, 2013; C. Smith, 2018; Zemánek, 2011). This is useful as cocoa yield is strongly affected by soil water regimes (Abdulai et al., 2020; Dada, 2018; Kotei, 2019). Compost may have improved soil water storage which may have resulted in different levels of drought stress between the composted and non-composted treatments.

b. Effect of dolomite

Between 2015 and 2018, the dolomite (without compost) plots received about 4950 kg Ca ha^{-1} and 2900 kg Mg ha^{-1}; the changes in measured soil contents were equivalent to 1820-4300 kg Ca ha^{-1} and 2006-3074 kg Mg ha^{-1}. Seven years after the experiment’s start, the pH in the top 20 cm of the four treatments receiving dolomite ranged 6.25-6.83, compared to 5.21-5.79 in the treatments receiving no dolomite. Although the addition of dolomite alone increased cumulative yields (2015-2018; excluding mortality rates; Table A - 3.9) relative to the control (+41%; presumably because of the higher pH increasing nutrient availability), the increase was less than that from the addition of compost alone (+196%) and the addition of mineral fertilizer alone (+119%; Figure 3.1b). The effect of dolomite on soil pH may also have contributed to alleviate Al toxicity (Figure 3.2).

c. Effect of mineral fertilizer

In the initial study (Mulia et al., 2019), mineral fertilizer alone did not have a beneficial effect on yield, but seven years after planting, in 2018, the mineral fertilizer Treatment B was the only treatment producing a statistically higher yield than the control plot (Table A - 3.9). However, if yields including mortality rates are considered (dark bars in Figure 3.1), this improved performance is no longer apparent. Mineral fertilizer addition to young tree crops can be problematic, and high rates can lead to toxicities and root scorching (Gauthier et al., 2014). This is less of a problem once a tree has established a robust root system. Also, regularly harvesting cocoa pods removes N, P, and K, and can create deficiencies for these nutrients. For example, a yield of approximately 1000 kg ha^{-1} associated with Treatment B would represent the removal of approximately 40 kg of N, 6 kg of P, and 62 kg of K per hectare (Singh, Sanderson, et al., 2019). Compared to the control plot, the mineral fertilizer treatment led to higher yields in 2016, 2017, and 2018. Despite this, there was no significant measurable difference in the selected soil properties between the control and the mineral fertilizer plot. This absence of build-up suggests that fertiliser input rates could be inferior than plant demand and/or that significant leaching could occur.

d. Calcium and Magnesium availability

Mulia et al. (2019) reported that the poor initial yields in the fertilizer treatment were due to the low availability of soil Ca and Mg. By contrast, in 2018, the soil analyses detected low Ca and Mg contents (both total and exchangeable) for the compost (alone) and the mineral fertilizer + compost treatments (C and E). Treatments C and E were amongst the most productive plots, while their soil Ca, and Mg contents were similar to the controls. These new result suggest that point measurements of soil Ca and Mg contents may not be good indicators of crop productivity because low soil Ca and Mg contents may also be a result of increased plant uptake. Presumably, by promoting the activity of beneficial micro-organisms (Bünemann et al., 2006), compost could enhance the availability of nutrients like Ca. This could have resulted in similar soil Ca and Mg availabilities between the composted and non-composted plots. The difference would simply be that plants absorbed more nutrients under the influence of compost, therefore resulting in similar levels to other treatments. Determining the tissue contents of these elements would be necessary to confirm this hypothesis.

e. Exchangeable Aluminium

Mulia et al. (2019) also associated low initial yields with high concentrations of exchangeable Al and low pH. The exchangeable Al contents at year 7 ranged from 21-30 ppm for Treatments D, F, and G, which received dolomite, and up to 705-743 ppm for Treatments A, B, and C, which did not. In both cases, the soil Al concentrations are substantially above the levels reported by Shamshuddin et al. (2004), who determined a critical limit at 10 µM for exchangeable Al^{3+} (0.27 ppm) and 15 µM for $Al^{3+} + AL(OH)^{2} + Al(OH)_{2}^{+}$ (40 ppm). The current results show that high productivity was obtained for the compost (Treatment C) and the compost + mineral fertilizer (Treatment E) plots, which featured high exchangeable Al contents (720 and 678 ppm; also reported for Treatment C by Mulia et al., 2019), comparable to the control and mineral fertilizer only treatments

(A and B; 705 and 743 ppm). On the other hand, low exchangeable Al concentrations for two low yield treatments, dolomite only and dolomite + mineral fertilizer (D and F; Table 3.3) were observed. These observations imply that Al toxicity, even though it may affect yields (Baligar & Fageria, 2005), may not be not a determining factor. The presence of SOM may still offset Al toxicity, but the soil analyses revealed no significant difference in soil C contents across all treatments. Nevertheless, with the same C contents, differences in the microbiological profiles and the type of organic compounds present could play a role in mitigating Al toxicity (Shamshuddin et al., 2004; Zhang et al., 2020).

3.4.4 Cocoa response to treatments

Seven years after field planting, the highest cumulative yields were still achieved from those treatments that had received compost (e.g., treatments C, E, G, and H). The most effective single treatment to improve cocoa productivity was compost (C). The treatment including compost alone (C) led to higher survival rates, basal areas, and cumulative dry bean yields than the control (A), mineral fertilizer (B), and dolomite (D) alone treatments (except in 2018 for dry bean yields). Of the combined treatments, the treatment without compost (F) resulted in lower yields than those with compost (E, G, and H).

From year four to seven, the yield benefits of compost tended to decline relative to the other treatments. In 2015, which was a particularly dry year (Table A - 3.4), the benefit from compost was however, particularly strong. However, by 2018 the cocoa yields had become similar within all the treatments receiving additions, although they remained greater than the control treatment yields. Hence as the cocoa trees became more established, the benefits of adding organic material declined, and the benefits of supplying specific nutrients such as N (removed during harvesting) became more important.

The results indicate that the basal area of seven-year-old cocoa plants was not a good predictor of yield since the largest cocoa trees were not the most productive (Figure 3.1). Verlière (1981) suggested that the positive relationship between basal area and yield is only significant for younger trees (Jones & Maliphant, 1958; Longworth & Freeman, 1963), and this was observed in the initial phase of this experiment (Mulia et al., 2019).

Despite the various soil measurements, no immediately obvious relationship was found between soil nutrient levels and yields. For example, although yields varied between treatments in 2018, soil N levels across the treatments were similar. By contrast, there was evidence of the yield benefits of SOM and an increase in soil pH. Nevertheless, it appeared that yield benefits from compost and/or dolomite addition had declined by years six and seven. The benefits of compost may have been particularly pronounced in 2015, because of the low rainfall in that year (Table A - 3.4). Another factor related to compost application could be the quantity of organic P provided by the compost (50% more than the fertilizer input). For example, a strong positive correlation (r = 0.85) between organic P and cocoa yields was reported for Southern Nigeria (Omotoso, 1971).

One difficulty limiting the results' interpretation is that soil characteristics were only measured at the beginning of year four and the end of year seven, whereas the yields were measured continuously. In addition, the lack of significant differences between treatments in many chemical soil properties also constrained the identification of relationships. One possible way of addressing this is to construct models describing the inputs and outputs of nutrients.

Over the first seven years, one of the lowest cumulative yields was achieved in the plots where only mineral fertilizer was applied. These results do not mean that mineral fertilizers should be avoided. Instead, one of the largest cumulated yields was obtained from the compost + fertilizer (Treatment E; three times higher than the control), and fertilizer alone led to double the yield of the control treatment. Furthermore, the rate at which productivity was increasing during the last three years for the fertilizer-only treatment (B) suggests that productivity could continue to rise substantially as the cocoa matures. Conversely, the average yield of the four composted treatments all declined during the last three years, while the non-composted increased but was still higher than the control (although not statistically). Another argument in favour of fertilizer is the high yield index reached for this treatment, surpassing the others.

As described before, it appears that the yield-response was different between the composted and non-composted treatments. In 2015 (dry year), the response to treatments was strong for the composted treatment and less for the non-composted ones. In the following years, the yields slowly declined for the composted treatment, while the non-composted treatments gradually increased. In 2018, productivity was equivalent for all, except for the control (lowest average yield) and the fertilizer treatment (highest average yield). It is hypothesized here that in the long run, fertilizer can be particularly helpful in maintaining productivity, while compost is useful in encouraging high yields during establishment and particularly during drought. Continuing the analysis for more years as the cocoa further matures could support or contradict these trends.

It is also important to note that no additional effects on yields when combining the treatments were observed. For example, the yields of the treatment combinations with compost were approximately at the same level as compost alone. In Treatment E, there was no benefit from using the fertilizer as compared to compost alone. Cumulative yields for the fertilizer + dolomite treatment was slightly lower than fertilizer alone (when excluding mortality rates), suggesting that the addition of dolomite reduced the benefits of fertilizer application. The full treatment combination did not give the highest yields. However, if the productivity including mortality rates (averaging per 16 trees) is considered, dolomite + fertilizer showed an improvement. The cumulated productivity of Treatment F (dolomite + fertilizer) was also 1.27 times higher than Treatment B (fertilizer alone). In addition, average survival rates were also increased by adding dolomite. The survival rate of Treatment F (88%) was more than double that of Treatment B (41%), and showed an improvement as compared to the control. Treatment A had a survival rate of 67%, which means that adding dolomite approximately halved the mortality rate of the control treatment (33% for A, 12% for F).

A secondary cause suggested by Mulia et al. (2019) for the response to the treatments was the young age of the cocoa trees. It is presumed that young cocoa trees are more sensitive to environmental factors than older trees. In this study, cocoa age seems to be an essential factor since yields increased over time but also became almost homogenous between treatment at year seven. The explanation behind the harmonization of yields by 2018 across the trial is uncertain. The positive effects of amendments may have been only useful in the first years of cocoa growth and development, but yield disparities between treatments had narrowed after seven years. One reason could be as simple as the design of the trial itself. A block size of 16 trees separated spaced by 3 m may not be enough. Belowground, root systems may now be accessing adjacent plots and therefore blending the responses. Expansion of the root zone, possibly resulting in access to soil nutrition sources in adjacent plots, may have been influential.

3.4.5 Developing fertilization and amendment recommendations

The mean annual rate of change of soil nutrients can provide insights into the quantity of each element that is either taken up or lost by leaching or volatilization (Table A - 3.12). This in turn can feed into appropriate cocoa fertilization rates.

There were major differences in the contents of certain soil nutrients between those reported for 2014 by Mulia et al. (2019) and those reported here for 2018 (Figure 3.2 and Figure A - 3.1). For example, available P and exchangeable K declined drastically in four years. This could result from substantial leaching associated with the low nutrient retention capacity of the soil and the local climate (the USDA soil type was sandy loam Mulia et al. (2019) and annual rainfall was 2723 mm; Table A - 3.4). However, total N concentrations were maintained over four years. Another explanatory factor for the decline in nutrients is the uptake by cocoa trees and the associated shade trees at a rate higher than the rate of inputs. Based on those averages, the stock of extractable K, Ca and Mg, declined, even in the control plot, suggesting that the supply of these nutrients may be insufficient for this plot. Considering SOC, the statistically significant changes that occurred over 4.5 years for Treatments C, G, and H correspond respectively to annual rates of change of 1671, 1986, and 1853 kg of C ha^{-1} yr^{-1}, while 930, 1580, and 1580 kg ha^{-1} of C were applied yearly via the amendments. About 896 kg of C ha^{-1} yr^{-1} were lost on average in the control plot, almost equivalent to the compost treatment inputs. However, for the composted treatments, the loss of soil C was 1.5 to 2 times higher. This could suggest that the application of compost with a low C:N ratio was associated with increased decomposition of the pre-existing soil organic matter (Kuzyakov, 2010), whereas the incorporation of more recalcitrant forms of organic inputs could have resulted in greater soil organic matter stability. The reported rate of change of extractable P was extremely large, and initially a technical error was assumed. The Asian-Agri laboratory manager double-checked the 2018 results, and the analysis of total P at Cranfield University was repeated three times. In theory, “extractable” (Asian-Agri) (Table 3.2) and “total” (“Cranfield) contents (Table 3.3) should be similar (i.e., “pseudo-total”), but on this occasion, the quantities varied widely. Unfortunately, the 2014 and 2018 soil samples were not stored by Asian-Agri, preventing additional analyses. Because Cranfield’s results were consistent, it is possible that there is a technical error in the values of extractable P reported from Asian-Agri in 2018. This issue raises the question of the consistency and comparability of chemical analyses between different laboratories, methods, and years. The soil analyses presented by Mulia et al. (2019) were produced by ICCRI (*Indonesian* Coffee and Cocoa Research Institute) and AIAT (Assessment Institute of Agricultural Technology), while ours came from Asian-Agri and Cranfield University laboratories.

The above analysis demonstrates the difficulty in developing appropriate fertilizer and amendment recommendations based on soil nutrient measurements alone.

However, soil measurements can provide insights within an experiment examining yield responses. Two other tools for developing fertilizer recommendations are analysis of plant tissue and nutrient budgets. A nutrient budget requires considering the flows in terms of inputs and the quantity of nutrients being removed either as harvested pods or stored in the cocoa and shade trees' accumulated biomass. Nitrogen can illustrate this issue since additional inputs may have increased yields but did not lead to a measurable change in 2018.

3.5 Conclusions

The effects of the treatments on soil properties were variable, with distinct changes for some variables (such as organic C, pH, and extractable nutrients like P, K, Ca and Mg) and little to no response for others (such as total N). Composted treatments resulted in the highest cocoa cumulative yields (on average, 2.8 times the control, excluding mortality rates, over 2015-2018). In contrast, the addition of mineral fertilizer, dolomite and fertilizer + dolomite without compost provided yields that were 1.7 times the control (excluding mortality rates). The composted treatments yielded significantly more pods than all other treatments. The relative benefits from compost (with a low C:N ratio) compared to fertilizer applications were greatest in the initial years of establishment, gradually declining as the cocoa matured. Furthermore, soil C contents were similar between treatments despite the inputs and were not adequate to raise soil C levels. This issue raises questions about the feasibility of improving soil carbon storage in cocoa systems. The effect of altering the C:N ratio of the compost could be an area for further study, as well as experimenting with other combinations of organic inputs. The results also demonstrate that developing a site-specific soil fertility management strategy cannot be based on soil nutrient analysis alone, but soil nutrient analysis can be useful when integrated with experimental yield results and the analysis of nutrient flows. While it seemed that adding compost was sufficient to support cocoa productivity, the applications may be unattainable to many farmers. For this reason, future research should evaluate other combinations of compost + fertilizer + dolomite, with lower compost application rates than this experiment, combined with other organic inputs, to determine which ones are the most cost-effective to meet cocoa farmers and the crops' needs.

4. DYNAMICS OF SOIL ORGANIC MATTER, CARBON, AND NITROGEN IN A CHRONOSEQUENCE OF COCOA FARMS IN SULAWESI, INDONESIA

Highlights

- SOM, C, and N declined rapidly after planting;
- SOM, C, and N recovered quickly in the medium-term and remained stable in the long term;
- Long-term stocks of SOM, C, and N were lower than the planting levels;
- Soil management practices should target the critical degradation period after planting with adequate organic inputs.

Summary

In cocoa plantations, the temporal variations of soil organic matter (SOM) contents are unclear, although changes can significantly affect soil functioning and cocoa productivity. A simple conceptual model to describe the temporal variations of SOM during the development of a cocoa plantation was proposed to address this issue. Using a space-for-time approach with three sets of cocoa farms located in Sulawesi (Indonesia) (one ranging from 0.5 to 15-years-old and including 7 farms, and two sets ranging from 2 to 31-years-old, each including 3 farms), the temporal variation of SOM, carbon (C), and nitrogen (N) contents was examined at five depths (0 to 1 m by 20 cm increments). To improve the comparisons between the farms, SOM, C, and N stocks (0-20 cm) were calculated to account for soil bulk density differences. Texture-adjusted SOM, C, and N contents were also calculated to further account for difference in soil texture and improve the comparability of the results. and used texture-adjusted contents by dividing SOM, C, and N contents by the clay content of each sample. In agreement with the conceptual model, it was found that SOM may deplete rapidly during the early years after planting. After reaching a minimum, the data indicates that SOM may also rapidly build-up, but may not return to pre-planting levels. Both soil bulk density- and texture-adjusted data support this hypothetical dynamic. This study suggests that in tropical perennial plantations (e.g., oil palm, rubber, and coffee) and settings like Indonesia (i.e., where high temperatures and precipitations greatly stimulate SOM mineralisation), the early years after planting should be considered as a critical but overlooked period of soil degradation.

Finally, potential approaches to prevent this degradation and develop conservation and regenerative measures to ensure sustainable soil use in similar tropical perennial plantations are discussed.

Keywords: cocoa, soil organic matter, carbon, nitrogen, dynamics.

4.1 Introduction

Cocoa (*Theobroma cacao L.*) is a major income source for 5-6 million farmers, especially smallholders (Voora et al., 2019), in West Africa, South-East Asia, and Central and South America. Cocoa orchards can be productive for a hundred years or more (Wood & Lass, 2008), but peak production typically occurs at around 25 years under both shaded and non-shaded conditions (van Vliet et al., 2015). Like many perennial crops, cocoa trees require a sustained level of management to achieve long-term productivity as poor management in one year can have effects in subsequent seasons. Poor decisions taken at establishment can affect yields at maturity that can be irreversible or difficult to rectify.

The long-term sustainability of perennial crops requires the maintenance of soil fertility (Syers, 1997), to prevent soil degradation (Hartemink, 2003, 2006), soil acidification (Arafat et al., 2019), and/or reduced yields and yield quality (Hartemink, 2005; Zhao et al., 2018). As fertilization practices are often inadequate to replenish lost nutrients (Lambert et al., 2020; Praseptiangga et al., 2020; Snoeck et al., 2016), authors have argued for an improved understanding of cocoa's nutritional needs and access by growers to soil testing (Dossa et al., 2018; Snoeck et al., 2016; Wessel & Quist-Wessel, 2015b). The current global average cocoa yield stands around 450 kg ha^{-1}, while research stations report annual yields above 2000 kg ha^{-1} (Andres et al., 2016; van Vliet et al., 2015). Hence, it can be argued that a better understanding of fundamental soil components, such as soil organic matter (SOM), carbon (C), and nitrogen (N), could help to reduce the gap between actual and potential cocoa yields. SOM can support cocoa productivity by stabilizing soil structure, increasing the ion exchange capacity, and enhancing water availability (Fageria, 2012; Johnston et al., 2009a; Lal, 2016; Seiter & Horwath, 2004). A large stock of SOM can also provide a reservoir of nutrients reducing the need for external inputs (Seiter & Horwath, 2004).

Many studies of the C dynamics of cocoa agroecosystems have compared the C stock in the above-ground plant biomass of shaded and full-sun cocoa systems, which can be relatively easy to measure either directly or using allometric models (see Chapter 2). By contrast, there are few studies describing changes in soil C storage in cocoa agroecosystems (see Chapter 2), and those that do typically only focus on topsoil measurements less than 20 cm deep, or only in one topsoil soil layer. There are few studies that have used a true chronosequence to quantify the effect of the time from cocoa establishment on soil C and at a specific location. One alternative method is to use a false-time series, also called a space-for-time chronosequence, where data is obtained from different locations of different age (Huggett, 1998; Lehmann & Joseph, 2015; Pickett, 1989; Walker et al., 2010). However even then, many studies have omitted measurements of the first months after establishment and are limited to sites less than 15 years old (Beer et al., 1990; Dawoe et al., 2010; Fassbender et al., 1988; Monroe et al., 2016; Smiley & Kroschel, 2008).

Dawoe et al. (2010), using a false-time series and including early measurements, reported a rapid decline in soil organic carbon (SOC) in the first two years after field planting, followed by higher contents at 15- and 30-years-old. Isaac et al. (2005) showed a similar decline in SOM during the first two years after planting cocoa on previous forest land, but the SOM continued to decline to year 15, followed by some recovery by year 25. In contrast, Beer et al. (1990) noted a tendency for SOM to increase over ten years while comparing two shade systems, but the gains were not statistically significant.

Based on the above analyses, this paper sought to address two research questions. The first was: what are the temporal dynamics of SOM, soil C, and N on cocoa farms in Indonesia? The second question was: what are the implications for soil management best practice?

4.2 Material & methods

4.2.1 Initial hypothesis

This study of the effect of time from cocoa planting on SOM and soil C and N levels was initially based on a hypothesis that the variations of C and N levels could be described in four phases (Figure 4.1).

- Phase 1: For the hypothesis, it was assumed that cocoa is planted on a freshly cleared plot where SOM may initially be high because of the build-up of SOM from previous vegetation cover with a high biomass (forest or old cocoa farm).

- Phase 2: However, it was then proposed that SOM levels would decline during cultivation as low levels of plant cover and canopy density during the early years of cocoa establishment result in low organic matter production and inputs. In addition, high levels of solar radiation reaching the ground can raise soil temperatures and accelerate SOM mineralisation.
- Phase 3: The third phase predicts that SOM eventually stops declining, reaches a minimum value, and starts to increase as organic matter inputs from the cocoa and shade trees exceed the losses from mineralisation.
- Phase 4: Lastly, the level of SOM may start to plateau as a new equilibrium is reached.

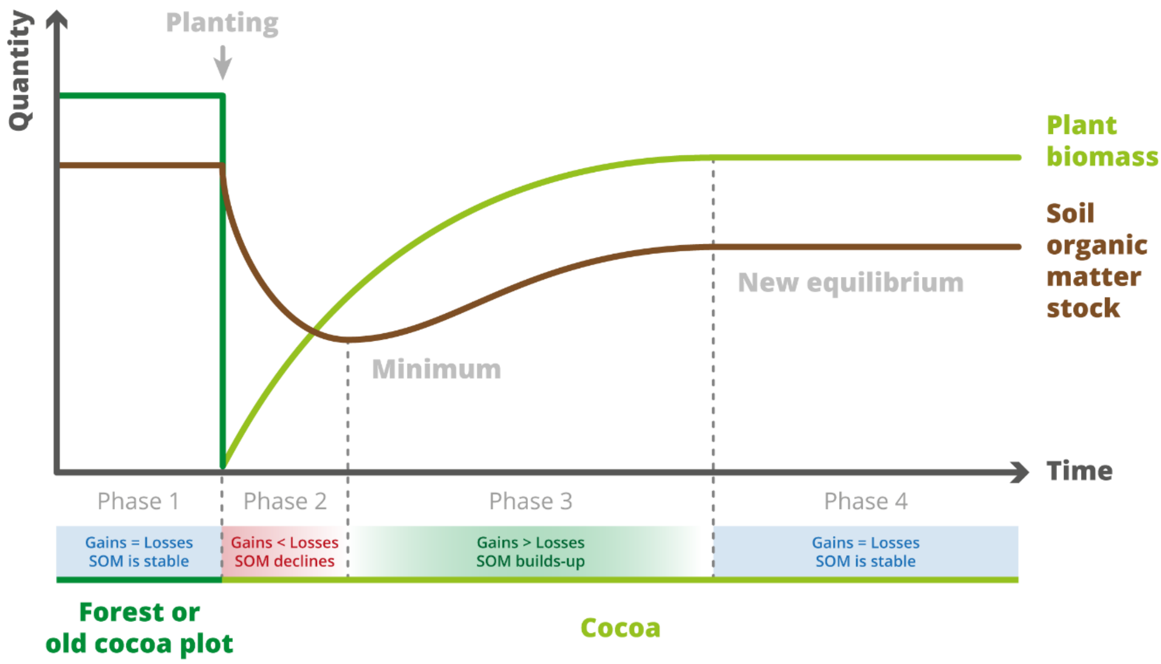


Figure 4.1: Hypothetical soil organic matter dynamic in cocoa farms

4.2.2 Site descriptions

To test the hypothesis described above, a false-time chronosequence was developed using seven plots located in Indonesia around Tarengge, East Luwu Regency, in South Sulawesi (Figure 4.2), and three plots at each of two sites, 5 km apart, in West Sulawesi. The sites in West Sulawesi, 200 km away from Tarengge, were near the villages of Mambu and Pussui.

The average elevation is 29 m in Tarengge, 20 m in Mambu, and 64 m in Pussui. The mean annual temperature is approximately 27°C at each site and remains fairly constant through the year (Figure 4.3). Mean annual rainfall across the three sites ranges from 2142 mm at Pussui to 2973 mm at Tarengge. During the dry season (approximately July to October), the driest months receive on average about 80-100 mm of rain. This climatic profile places Sulawesi in the Af category of the Köppen-Geiger classification (“tropical rainforest climate”).

The terms *plot age* and *cocoa age* were used interchangeably to refer to the time (in years) since the cocoa trees were planted. Each farm was coded with a letter. The seven plots located around Tarengge were 0.5-, 1-, 2-, 5-, 7-, 12-, and 15-years-old, and given the farm codes A to G (detailed in Table A - 4.1). The second set at Mambu was given farm codes H, I, J, and the three sites at Pussui were given farm codes K to M, with plots aged 2, 20, and 31-years-old. The previous land uses were either cocoa, rice, oil palm, vegetable, sweet potato, peanuts, or forest (recent history detailed in Table A - 4.2 for Tarengge’s farms and Table A - 4.3 for Pussui’s and Mambu’s farms).

Figure 4.2: Location of the farms at Tarengge (7), Mambu (3) and Pussui (3) used for the chronosequences (13 in total)

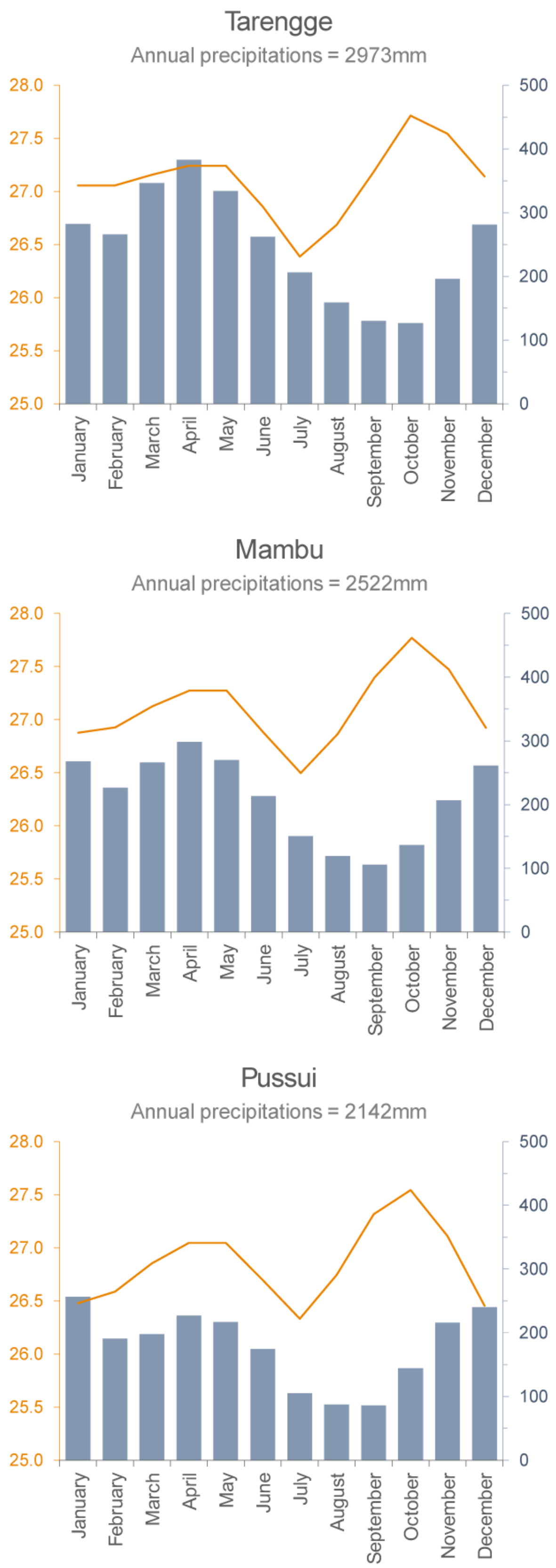


Figure 4.3: Climographs of the three chronosequences' locations

Left y-axis: average monthly temperature (°C). Right y-axis: monthly precipitations (mm). Source: WorldClim.

4.2.3 Field measurements and laboratory analyses

a. Farm information

During a field survey, the farmers were interviewed about the planting date (year, and if possible, month) and densities (number of cocoa trees per hectare). They were asked to report the shade tree species present and their approximate densities. Information was also collected about their fertilizer and organic input practices (timing, composition, and dose). Each plot's GPS location was recorded. According to the farmers, the approximate plot sizes ranged from 0.25 to 2 ha. In Pussui, soil samples were collected from a forest plot adjacent to farm K (the forest is coded N in Table A - 4.1) to serve as a comparison point, using the sampling and analytical methodology as the cocoa plots. The purpose was to compare the recently planted plot K to an adjacent forest and assess short-term changes that may have occurred two years after conversion. Plot K was the only site resulting from recent deforestation.

b. Assessment of cocoa growth

In order to estimate how cocoa's organic inputs would evolve over time, it was assumed that litterfall was proportional to the biomass of the trees (Dawoe et al., 2010), i.e., larger trees produced more litter and belowground inputs than small trees. To model how cocoa biomass (and therefore cocoa organic deposits) increased over time, trunk measurements, an allometric equation, and a non-linear regression model were combined. The trunk circumference of 16 trees per farm was measured at 30 cm from the ground surface and the results converted to biomass per hectare using an allometric relationship developed by Smiley & Kroschel (2008) in Sulawesi. Subsequently, it was found that a Weibull growth curve (Mahanta & Borah, 2014) was a good fit to model cocoa growth for the experimental farms. The methodology is presented as supplementary material (see appendices A.4). The performance of the fitter growth curve was evaluated by calculating the coefficient of determination (R^2), the absolute measure of the standard distance between predictions and measurements (S), and the mean absolute percent error (MAPE).

c. Soil sampling and analyses

Five soil samples were collected in each farmer plot, at five different depths from 0 to 100 cm in 20 cm increments, after removing any surface leaf litter. Plot sizes ranged from 0.25 to 2 ha. Each soil sample was extracted with a hand auger (Edelman type, suitable for clay and sand) 1 m away from a cocoa tree trunk.

Five soil rings were used on each plot to determine soil bulk density (BD) at a 0-5 cm depth. Each sample was air-dried at 60°C for 48 h. The BD was found by dividing the dry weight by the ring volume. The soil sampling pattern followed a quincunx pattern (⚄) at the plot scale, that is, one sample taken approximately at the centre of a representative area of the plot, surrounded by four other cores taken in adjacent rows, diagonally. Soil samples were then air-dried for two days before being packaged and sent to Cranfield University in the United Kingdom. They were then stored in a drying cupboard and later manually ground and sieved to < 2 mm before analysis. Particle size distribution (PSD) was determined by following sieving and sedimentation (ISO 11277;1998), using only three samples out of the five samples per plot and down to a depth of 60 cm. Results from the PSD analysis were converted into soil texture types according to the USDA classification system. SOM contents were calculated from the loss-on-ignition (LOI) method (British Standard BS EN 13039:2000) on three samples per plot at each depth (except 0-20 cm where all five samples were used). Soil total carbon (C), as well as total nitrogen (N), were analysed using the dry combustion method (ISO 10694:1995) on three samples per plot at each depth (except 0-0.20 m where five samples were used). Because the soils of the region tend to be strongly to very strongly acidic (Hengl et al., 2017), it was assumed that inorganic C (i.e., mainly carbonates) was absent and that the total C should be equal to soil organic C (SOC).

As the chronosequence involved comparing different sites with soils belonging to different textural classes, it was decided to use the concept of clay saturation by SOC to account for differences in soil textures (Dexter et al., 2008; Jensen et al., 2019; Johannes et al., 2017; Knadel et al., 2015; Prout et al., 2020). SOM-to-clay (SOM/clay), C-to-clay (C/clay), and N-to-clay (N/clay) ratios (element content in % divided by the clay content in %) were calculated. A high C/clay index was assumed to correspond to a higher complexation of SOM to clay particles and *vice versa*. High levels of N may also be related to high clay levels as up to 95% of soil N can be organic (Bingham & Cotrufo, 2016), and clays generally play a major role in stabilizing SOM (Sarkar et al., 2018).

Adjusted and non-adjusted for texture SOM, C, and N contents were plotted against the age of each farm for graphical analysis of potential trends. The correspondence between cocoa age and SOM, C, and N was assessed and compared against clay and clay + silt content using Kendall's rank correlation coefficient (τ, tau) to evaluate the influence of texture on SOM, C, and N.

To account for differences in soil BD (Rollett et al., 2020), SOM, C, and N contents of the 0-20 cm layer were converted to stocks per hectare by using the BD obtained in each farm with Equation 4.1:

$$Stock\ (Mg\ ha^{-1}) = Content\ (\%) \times Area\ (m^2) \times Depth\ (m) \times Bulk\ density\ (g\ cm^{-3}) \times 100 \quad \text{Equation 4.1}$$

Stock calculations were not extrapolated to soil layers deeper than 20 cm because the BD for deeper layers was not measured.

Loss-on-ignition (LOI) measurements are based on the loss in mass after placing soil samples in a furnace at 450°C. While it is inexpensive and straightforward, this method is criticized for underestimating SOM content (Hoogsteen et al., 2015; Jensen et al., 2018; Konen et al., 2002; Pribyl, 2010). The estimation of the content of SOM can be influenced and biased by factors other than SOM alone. For example, structural water loss from clay minerals and the decomposition of inorganic C (carbonates) at high temperatures could lead to overestimations of SOM contents (Hoogsteen et al., 2015). Dehydration and dihydroxylation of clays, oxides, and salts occur at different temperatures depending on their types (Pansu & Gautheyrou, 2006). Conversely, incomplete combustion (insufficient heat or duration) can lead to an underestimation of SOM contents.

A modified approach proposed by Jensen et al. (2018), which used the soil PSD (clay and eventually fine silt, depending on the results) to derive the SOM content from LOI measurements, was followed to address this issue. The method is based on successive multiple linear regression (MLR), evaluating the performance of different models in their ability to predict SOC contents. In this study, the process was changed to predict LOI instead of SOC. Clay, fine silt, and SOC contents were the independent variables. The analysis was conducted in R, using the *lm* function of the package *stats*. The relationship between the measured LOI and adjusted SOM contents was plotted to show the effect of the correction. The measured and adjusted contents were separately categorized on a clay content and soil depth basis to assess their potential influence.

To study the transformation of SOM over time, C:N ratios and the C content of SOM (C/SOM) were calculated. C:N ratios can provide an indication on the decomposition and mineralisation rates of SOM. A higher C content of SOM can indicate a higher fraction of compounds with high C content such as humic substances (J. Gerke, 2018; Piccolo et al., 2018; Pribyl, 2010), woody tissues (lignin and aliphatic compounds, Klingenfuß et al., 2014) and black carbons

(Tomczyk et al., 2020), often associated with slow decomposition rates. Also, while it is often assumed that SOM is 58% C ("van Bemmelen factor", Pribyl, 2010), there is no universal content that can reliably be used everywhere. As such, quantifying the C content of SOM can also help to characterize SOM in cocoa plots in Sulawesi and avoid future misleading conversions with inaccurate factors.

4.2.4 Statistical analyses

The raw results were subjected to an analysis of variance in R version 3.6.0 (R Core Team, 2019). Normality was tested with the Shapiro-Wilk test ('*shapiro.test*'), while homogeneity was tested with Levene's test ('*levene*' function). Levels of statistical significance were assessed through a Tukey HSD test, using the '*agricolae*' package (at $P < 0.05$; De Mendiburu, 2020). The Kruskal-Wallis test was applied if ANOVA assumptions were not fulfilled (using the '*kruskal.test*' and '*kruskal*' functions with $P < 0.05$). Means and standard errors were calculated for each plot, depth, and variable. Association between SOM, C and N and cocoa age, clay content and clay + fine silt contents (non-parametric data) were evaluated using Kendall's tau with the '*Kendall'* function using the package of the same name (McLeod, 2011). Correlations were assessed with the '*cor.test*' function of the '*ggpub*' package.

4.3 Results

4.3.1 Cocoa growth curve

Based on the cocoa tree trunk measurements and the allometric equation of Smiley & Kroschel (2008), the aboveground cocoa tree biomass increased rapidly when the trees were young (< 4 years), typically reaching a dry mass of 50 kg per tree within four years. Beyond four years, the growth rate was lower, typically taking another eight years to gain an additional 50 kg of biomass per tree, reaching 100 kg at 13 years old. The average girth continued to increase over the first 30 years after field planting.

Belowground biomass increased at a slower rate taking approximately eight years to reach 50 kg of root biomass. The mean ratio of aboveground biomass to belowground biomass (i.e., shoot-to-root ratio) was about 1.65. Variability in trunk size increased with age, certainly because the tree stand becomes more heterogeneous over time under various pressures (e.g., certain trees thrive more than other because they will not suffer from the same level of water stress, light competition, pests and disease attacks, etc.).

The fit to the non-linear models was good, with a coefficient of determination (R^2) of 0.998 for above and belowground biomass. The absolute measure of the standard distance between predictions and measurements (S) was 4.59 kg for aboveground biomass and 2.79 kg for belowground biomass. The mean absolute percent error (MAPE) was 25.8% for aboveground biomass and 27.1% for belowground biomass, indicating that, on average, the distance of the model from the measurement is around 26-27% of the actual value.

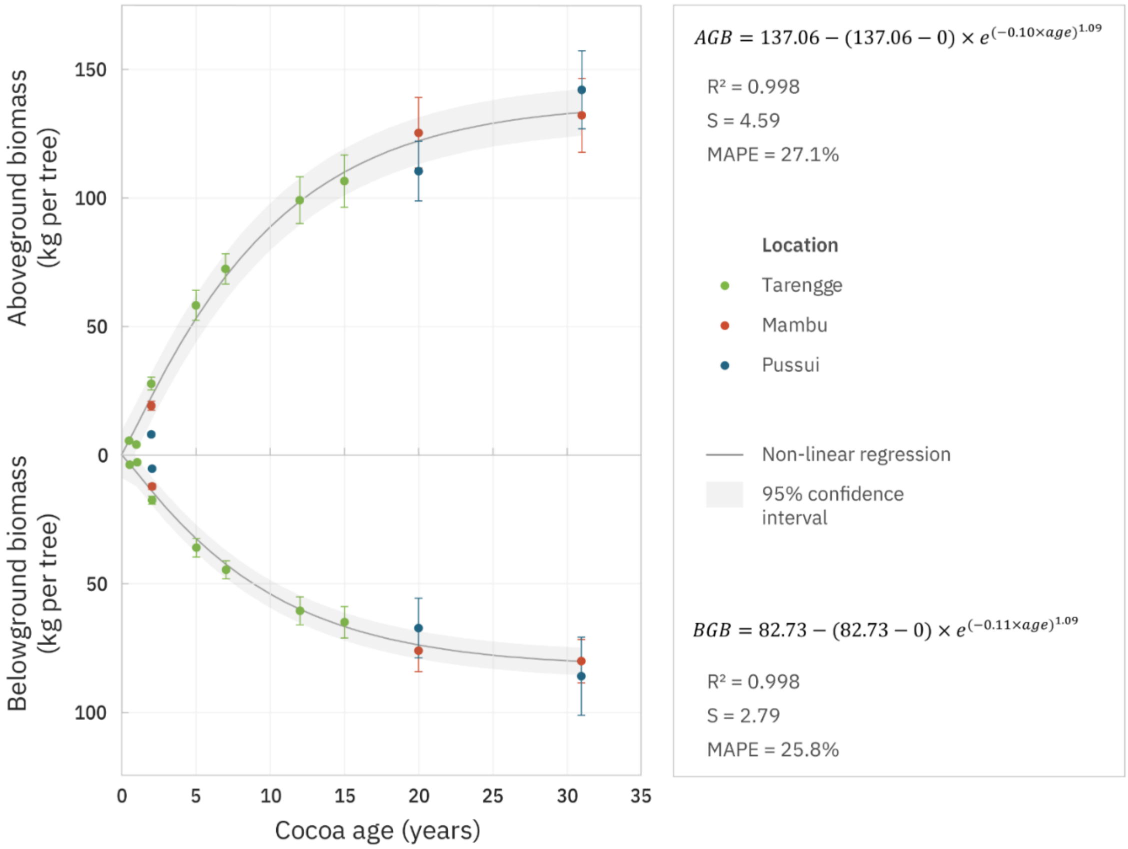


Figure 4.4: Accumulation of plant biomass by the cocoa trees

AGB stands for aboveground biomass. BGB stands for belowground biomass. The error bars represent ±1 standard error. The grey areas represent the 95% confidence interval around the fitted non-linear models. R^2 corresponds to the coefficient of determination, equal to the percentage of variation of the dependent variable explained by the model. S is the standard error of the estimate and is the average distance between the points and the fitted line. MAPE is the mean absolute percentage error.

4.3.2 Particle size distribution and bulk density

In Tarengge, all soils were loams, clay loams, or sandy clay loams, with clay contents ranging from 18.8 to 30.1% (Table 4.1). In Mambu (Table 4.2), texture classes were sandy loams, sandy clay loams, or silty clay loam with clay contents of 15.6 to 38.7%. In Pussui (Table 4.2), some soil had clay contents from 31.1 up to 48.8%, and texture classes were clay, silty clay, or clay loam. Visualization is available in the supplementary material (Figure A - 4.1).

In the cocoa plots, surface BDs (0 to 5 cm) ranged from 1.16 to 1.55 g cm^{-3}, and they were not correlated to farm age (Spearman's r P = 0.48; Table 4.3). The lowest BD was recorded in the forest plot in Pussui, 1.12 g cm^{-3}, adjacent to the 2-year-old farm K at 1.13 g cm^{-3}. The highest BD (1.55 g cm^{-3}) was found on the plot recently cultivated with rice (farm B). The average BD across all farms was 1.31 g cm^{-3}.

Table 4.1: Mean particle size distributions in the farms of Tarengge (South Sulawesi, Indonesia) at selected soil depths

Location	Farm code	Cocoa age (years)	Depth (cm)	Coarse Sand (%) 600-2000 µm	Medium Sand (%) 212-600 µm	Fine Sand (%) 50-212 µm	Coarse Silt (%) 20-50 µm	Fine Silt (%) 2-20 µm	Clay (%)	Texture class (USDA) <2 µm
Tarengge, South Sulawesi	A	0.5	0-20	3.1	9.4	31.1	12.6	19.2	24.6	Loam
			20-40	1.8	9.0	31.0	10.0	19.7	28.6	Clay loam
			40-60	2.6	10.2	27.7	11.4	18.1	30.1	Clay loam
	B	1	0-20	2.6	12.0	30.0	13.0	23.7	18.8	Loam
			20-40	2.1	11.7	30.0	10.5	25.9	19.8	Loam
			40-60	2.3	10.6	27.0	10.7	25.2	24.2	Loam
	C	2	0-20	6.5	15.3	36.6	10.8	12.1	18.8	Sandy clay loam
			20-40	7.5	16.4	35.3	8.8	11.3	20.6	Sandy clay loam
			40-60	10.2	14.8	33.9	8.8	10.7	21.7	Sandy clay loam
	D	5	0-20	4.2	15.3	34.7	11.5	13.0	21.4	Sandy clay loam
			20-40	3.8	15.0	34.0	8.6	13.5	25.2	Sandy clay loam
			40-60	4.3	13.6	31.8	9.0	14.5	26.8	Sandy clay loam
	E	7	0-20	6.8	17.3	24.7	10.4	17.7	23.0	Loam
			20-40	6.1	18.9	24.7	9.5	19.0	21.8	Loam
			40-60	9.6	17.1	22.6	7.6	19.7	23.4	Sandy clay loam
	F	12	0-20	1.6	6.9	30.3	15.7	26.0	19.6	Loam
			20-40	1.1	6.8	28.7	14.5	26.0	22.9	Loam
			40-60	1.5	6.6	28.2	11.3	27.2	25.2	Loam
	G	15	0-20	6.0	13.2	33.9	11.3	13.0	22.6	Sandy clay loam
			20-40	5.1	14.8	32.9	9.8	14.4	23.0	Sandy clay loam
			40-60	10.6	12.4	30.2	9.2	12.8	24.8	Sandy clay loam

n = 5 for soil depths 0-20 cm and n = 3 for soil depths 20-40 and 40-60 cm.

Table 4.2: Mean particle size distributions of the farms of Mambu and Pussui (West Sulawesi, Indonesia) at selected soil depths

Location	Farm code	Cocoa age (years)	Depth (cm)	Coarse Sand (%) 600-2000 µm	Medium Sand (%) 212-600 µm	Fine Sand (%) 50-212 µm	Coarse Silt (%) 20-50 µm	Fine Silt (%) 2-20 µm	Clay (%) <2 µm	Texture class (USDA)
Mambu, West Sulawesi	H	2	0-20	0.2	0.7	14.8	18.2	31.7	34.4	Silty clay loam
			20-40	0.1	0.8	16.0	15.1	29.5	38.7	Silty clay loam
			40-60	0.1	0.9	17.1	14.0	29.7	38.2	Silty clay loam
	I	20	0-20	0.1	2.8	58.5	11.2	11.5	15.9	Sandy loam
			20-40	0.0	3.9	60.7	9.2	10.7	15.6	Sandy loam
			40-60	0.4	3.8	52.4	9.9	12.6	20.9	Sandy clay loam
	J	31	0-20	0.0	0.9	51.7	13.4	14.2	19.8	Sandy loam
			20-40	0.0	1.1	62.1	9.6	10.5	16.6	Sandy loam
			40-60	0.0	1.1	61.2	11.2	10.8	15.7	Sandy loam
Pussui, West Sulawesi	K	2	0-20	0.4	1.4	17.3	10.4	26.6	43.9	Clay
			20-40	0.3	1.1	18.3	10.2	28.0	42.2	Clay
			40-60	0.5	1.4	16.9	10.0	31.2	40.1	Silty clay
	L	20	0-20	1.8	6.0	21.5	16.0	23.7	31.1	Clay loam
			20-40	1.0	4.6	19.4	15.2	24.5	35.2	Clay loam
			40-60	0.9	4.0	17.6	15.1	23.4	39.0	Clay loam
	M	31	0-20	4.1	12.6	10.8	8.0	31.1	33.4	Clay loam
			20-40	0.9	3.7	6.5	6.3	35.8	46.9	Silty clay
			40-60	0.7	2.8	5.4	7.0	35.3	48.8	Silty clay
	Forest	NA	0-20	0.5	2.2	22.4	14.2	25.2	35.6	Clay loam
			20-40	0.3	1.7	20.5	12.2	25.6	39.8	Clay loam
			40-60	0.3	1.7	20.1	12.6	23.5	41.8	Clay

n = 5 for soil depths 0-20 cm and n = 3 for soil depths 20-40 and 40-60 cm.

Table 4.3: Surface bulk density of the farms of the chronosequence

Location	Farm code	Age (years)	Mean (n=5) bulk density (0-5 cm; g cm^{-3})
Tarengge	A	0.5	1.16 (0.11) bc
	B	1	1.55 (0.06) a
	C	2	1.27 (0.02) abc
	D	5	1.41 (0.06) abc
	E	7	1.37 (0.03) abc
	F	12	1.43 (0.03) ab
	G	15	1.27 (0.11) abc
Mambu	H	2	1.23 (0.02) bc
	I	20	1.34 (0.03) abc
	J	31	1.36 (0.05) abc
Pussui	K	2	1.13 (0.07) bc
	L	20	1.33 (0.04) abc
	M	31	1.21 (0.09) bc
	Forest	-	1.12 (0.05) c
Average	(all farms)		1.31

Numbers in parenthesis represent ± 1 standard error. Mean bulk densities with the same letters are not statistically different (Tukey HSD, p-value < 0.001).

4.3.3 Relationship between SOM and LOI

Four models were examined to determine the best relationship between SOM and loss on ignition (LOI). The model with the lowest RMSE of 0.32 was Equation 4.2, where LOI is the loss on ignition (% or g/100g), β_0 is the y-intercept of the MLR, β_{clay} is the coefficient for the clay content factor, $Clay$ is the measured clay content (% or g/100g), β_{SOC} is the coefficient for the measured soil organic carbon content, and SOC is the measured soil carbon content (% or g/100g). The adjusted R^2 was 0.91.

$$LOI = \beta_0 + \beta_{clay} \times Clay + \beta_{SOC} \times SOC \qquad \text{Equation 4.2}$$

The values of β_0, β_{clay}, and β_{SOC} are provided in Table 4.4.

Table 4.4: Parameters of the multiple linear regression used to convert LOI to SOM contents

Coefficient	Estimate	Std. Error	t value	Pr(>|t|)	Significance
β_0	0.50	0.16	3.05	4.06E-03	**
β_{clay}	0.05	0.01	7.66	2.72E-09	***
β_{SOC}	1.70	0.15	11.44	4.98E-14	***

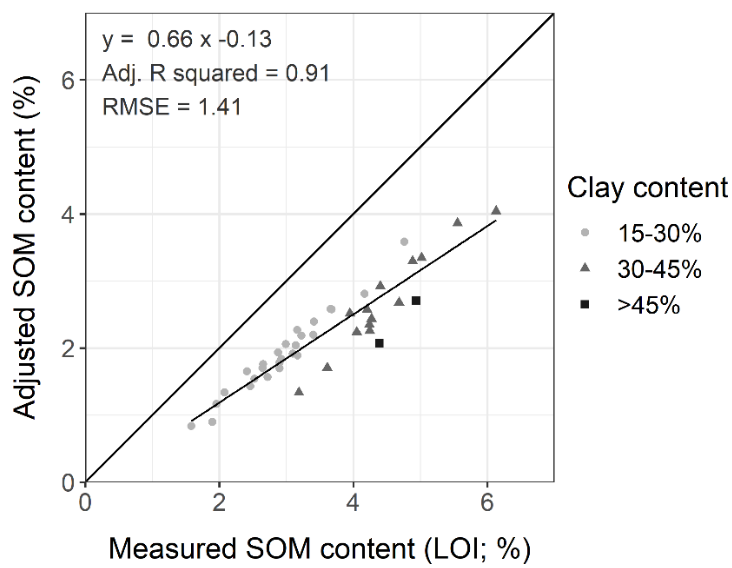
Lastly, an adjusted content of SOM was calculated using Equation 4.3. This calculation assumes that $\beta_{clay} \times Clay$ corresponds to the bias leading to the overestimation of SOM due to structural water losses (Jensen et al., 2018).

$$SOM = LOI - \beta_{clay} \times Clay \qquad \text{Equation 4.3}$$

The results suggest that each unit of clay is associated with 5% of structural water (β_{clay}), but more realistically may include the compounded effects of other losses occurring during LOI (i.e., not accounted for in the MLR, for loss of certain salts and free iron). The estimate of the SOC coefficient β_{SOC} was 1.70 and corresponded to the conversion factor from SOC to SOM. It was close to the traditional SOM/SOC value of 1.72 (58% C in SOM; (Pribyl, 2010)).

Observing Figure 4.5, the difference caused by the adjustment was substantial and can be noted since the adjusted SOM contents were approximately two-thirds of the measured SOM content. The mean difference (n = 42) between measured and adjusted SOM contents was 1.7 g/100g. The larger the measured SOM content, the larger the deviation of the adjusted SOM content. However, categorizing per sampling depth or clay content did not show a large effect, even though it seems that higher clay contents and depths led to slightly lower adjusted SOM contents. The intercept coefficient β_0 suggests that LOI systematically overestimated SOM contents by 0.5 g/100g, regardless of the clay or SOC content.

A



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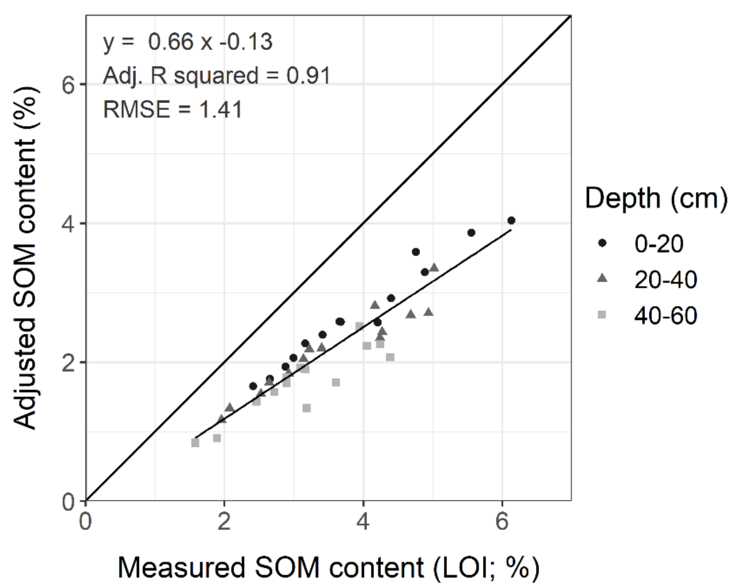

Figure 4.5: Comparison of the measured SOM content (using loss-on-ignition) and the adjusted SOM content

The adjusted SOM content is equal to the measured LOI, deducted from structural water loss, itself estimated to be proportional to clay content ($\boldsymbol{SOM} = \boldsymbol{LOI} - \mathbf{0.05} \times \boldsymbol{Clay}$). The top figure (A) presents the results categorized per clay content (A), while the bottom figure (B) categorizes the data per sampling depth. Adj. R squared is the adjusted R^2, and RMSE stands for root mean square error. Both correspond to the performance of the multiple linear regression used to calculate the adjustment factor (n = 42).

4.3.4 Soil organic matter, carbon, and nitrogen contents

a. Soil depth between 0 and 20 cm

The highest values of SOM (4.04%), C (1.97%), and N (2103 ppm) were all found at 0-20 cm at Pussui, in the 2-year-old cocoa plot, at levels similar to the adjacent forest (Figure 4.6 and Table A - 4.4).

At Tarengge, six months after planting, the mean SOM (0-20 cm) was 3.59% (Figure 4.6). The SOM value (0-20 cm) at the sites sampled one and two years after planting were lower at 2.27% and 1.76%, respectively. In the sites sampled more than two years after planting, the SOM levels increased to 2.06-2.58% (Figure 4.6 and Table A - 4.4). At Mambu and Pussui, the SOM values of the youngest sites (2-years-old) were respectively 2.57% and 4.04%. A similar pattern of an initial high value, a low value and then a high value for SOM was apparent at Mambu and Pussui: starting at 2-years-old with the highest SOM content, reaching the lowest content at 20-years-old, followed by a slight increase at 31-years-old.

One method to compensate for differences in clay contents between sites is to express the SOM contents per clay unit (Figure 4.7 and Table A - 4.5). The SOM/Clay values (0-20 cm) were more consistent than those for SOM alone. Across the Tarengge, Pussui, and Mambu sites, the SOM/Clay values started at a high value, declined to a minimum at about two years after planting before increasing and stabilizing at a higher value after 5 years (Figure 4.7). The highest SOM/Clay quotient was found in the youngest cocoa plot (Tarengge, 2-year-old: 0.15). Presenting the SOM values as a SOM value per clay unit resulted in similar values at Mambu and Pussui, suggesting that, for the 0-20 cm layer, the almost constant difference between Mambu and Pussui for SOM, C and N were related to the different soil clay contents (Table A - 4.5).

Across the surface soil layers (0-20 cm) investigated at the Tarenge sites, the highest value of C (1.62%) and N (1554 ppm) were found at the site planted within the previous six months (Table A - 4.5). From this high point, in a similar way to SOM, the C and N contents (0-20 cm) declined between 0.5 and 2 years, followed by higher values in subsequent years. However, there was substantial variation in values between 2 and 15 years, with the highest value obtained for the 7-year-old site. The trend in C and N at Pussui was similar to that for SOM (Figure 4.6). At Mambu, the trends for C and N were also broadly similar to that for SOM although, whereas the SOM content at the 31-year-old site tended to be greater than that at the 20-year site, the values of C and N were similar at the 20- and 31-year-old sites.

Adjusting the topsoil C and N contents (0-20 cm) for clay content (Figure 4.7) also allowed the convergence of Tarengge's, Pussui's, and Mambu's results. The decline in C and N from year 0 to year 2 remained apparent, and the value for texture adjusted C and N then varied before stabilizing at a lower value than that at the plots with the youngest cocoa bushes.

b. Soil depth below 20 cm

The lowest SOM, C, and N contents were not found in the deepest soil layers (80-100 cm) samples, but in the 40-60 cm, at Mambu in the 31-year-old cocoa farm (SOM: 0.84%; C: 0.23%; N: 329 ppm).

In Tarengge, the temporal variation of SOM in the deeper soil layers followed a similar trend as in the topsoil but attenuated, showing a narrower range as depth increases (Figure 4.6 and Table A - 4.4). Indeed, the decline and recovery observed at soil depths below 20 cm more less prominent than that of the 0-20 cm layer, especially for the initial post-planting decline.

In Mambu, the same decline of SOM content was observed up to 40 cm. No soil sample could be obtained below 40 cm in Mambu but found that SOM, C, and N declined across all sampled depths. In Mambu, while topsoil (0-20 cm) SOM/clay, C/clay, and N/clay seemed first to increase between 2 and 20 years and then decrease between 20 and 31-years-old, this was not always repeated at greater depths (Figure 4.7 and Table A - 4.5). For example, C/clay and N/clay declined at 40-60 cm, whereas SOM/clay decreased and then increased.

In Pussui, instead of having the same trend as topsoil SOM, the results could be summarized by saying that in almost all cases, it was observed that SOM, C, and N increase over time below 20 cm (only exception being SOM at 40-60 cm). Regarding SOM/clay ratios, Pussui farms followed approximately the same trend as Mambu, both at 20-40 and 40-60 cm. There was no general trend for SOM/clay, C/clay, and N/clay: the quotients generally increased between 2 and 20 years, but between 20 and 31 years, both increases and declines were found, similar to Mambu's results in most cases.

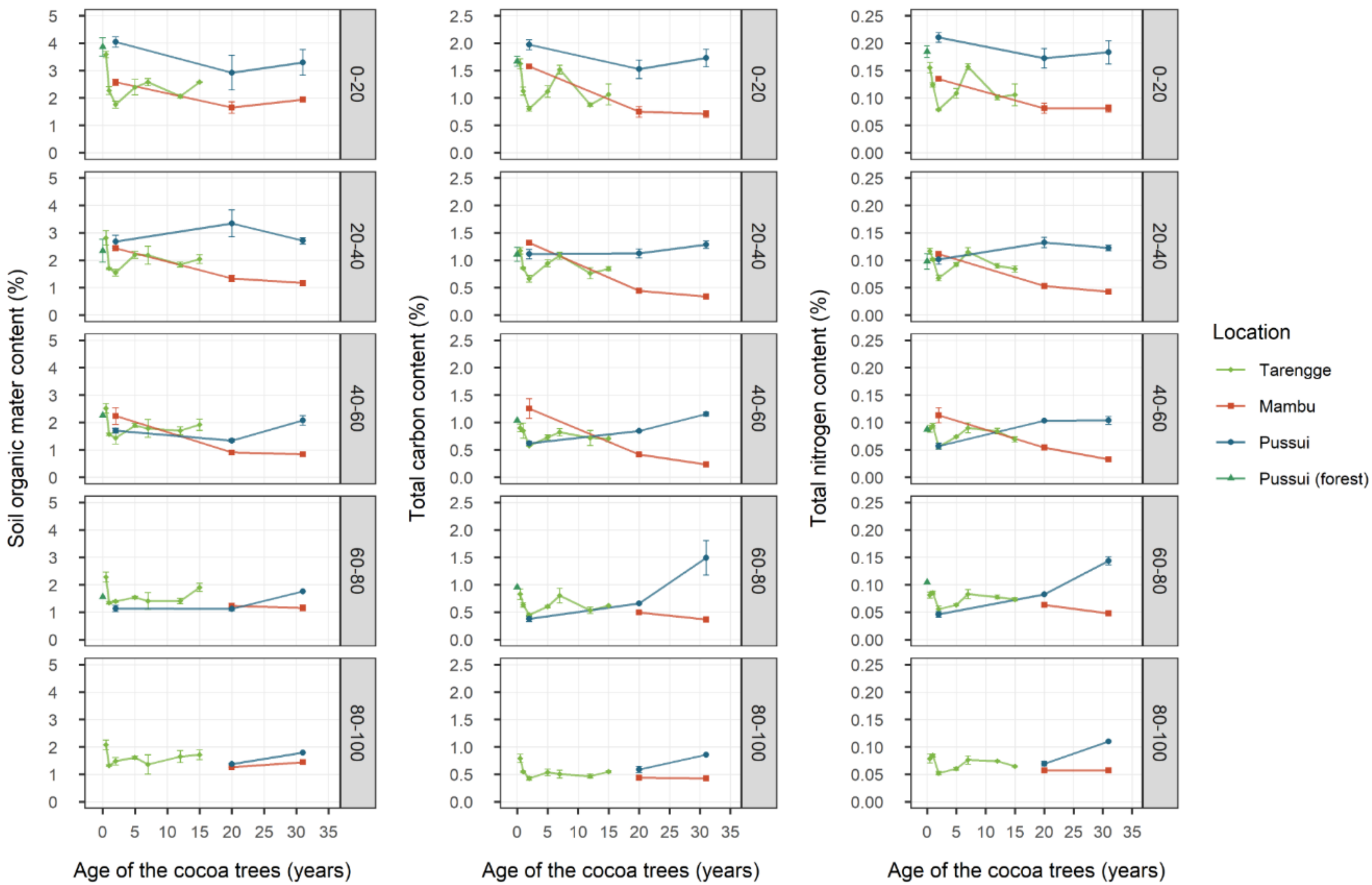

Figure 4.6: Temporal changes of soil organic matter (SOM), carbon (C), and nitrogen (N) contents in the 13 farms of the chronosequence (and a forest) at five depths (0-100 cm by 20 cm increments)

SOM contents were obtained from LOI and corrected for potential structural water loss linked to clays (Jensen et al., 2018). Carbon and nitrogen contents were determined through dry combustion. Error bars represent the ± 1 standard error. Five samples were obtained for the 0-20 cm layer, and three samples below 20 cm, except for the sites H at 40-60 cm, M at 60-80 cm, and L at 80-100 cm with only two samples; and N at 40-60 cm, N at 60-80 cm and M at 80-100 cm with only one sample, and no samples were obtained for H, K, and N at 80-100 cm (the soil was too compact to push down the auger by hand.

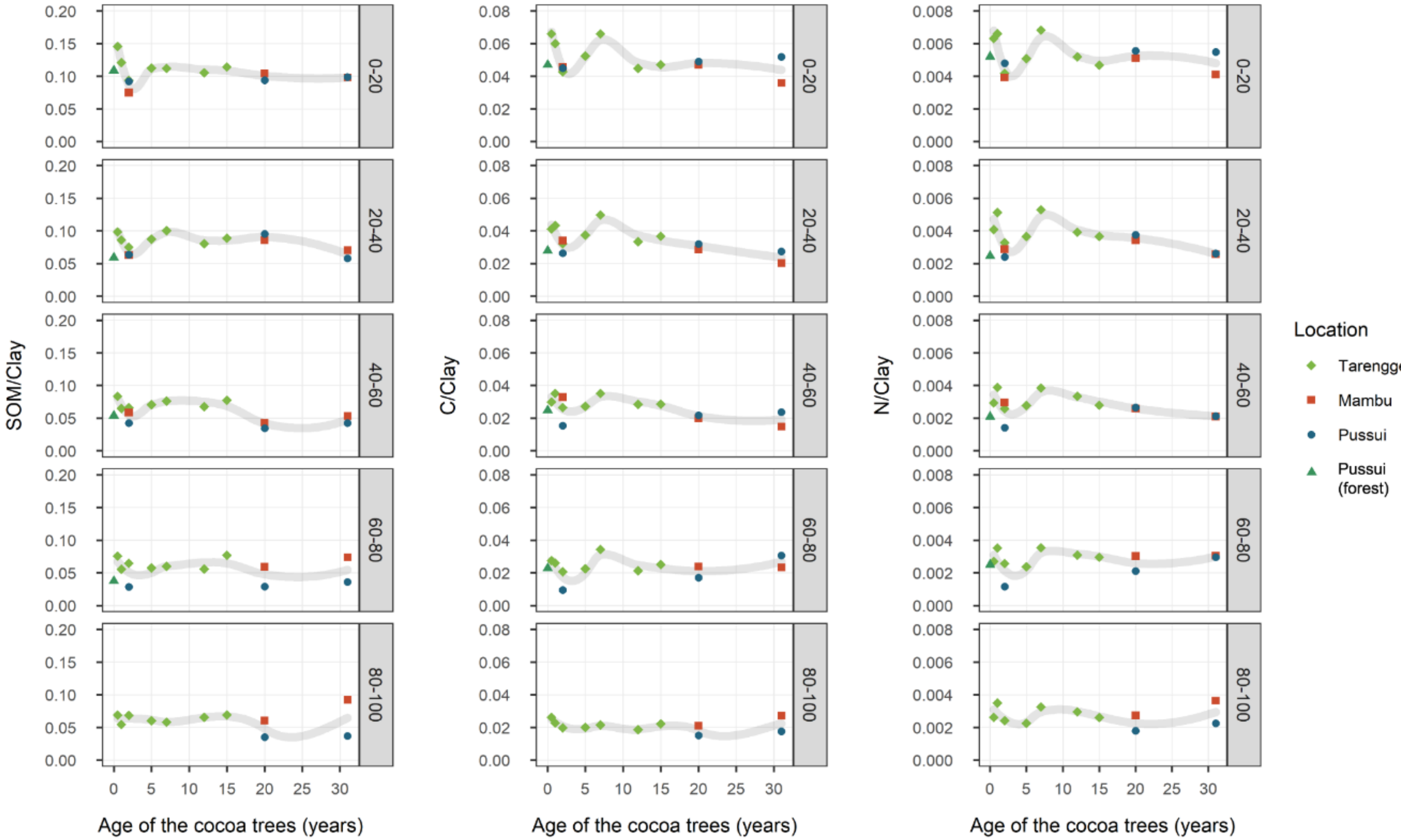

Figure 4.7: Temporal changes of soil organic matter, carbon, and nitrogen contents adjusted for clay content in the 13 farms of the chronosequence (and a forest) at five depths (0-100 cm by 20 cm increments)

Each index is calculated as the ratio of soil component (% C, N, or SOM) divided by soil clay content (%). SOM contents were obtained from LOI and corrected for potential structural water loss linked to clays (Jensen et al., 2018). Carbon and nitrogen contents were determined through dry combustion. I used the clay content of the 40-60 cm layer for the 60-80 and 80-100 cm sampling depth. The grey line represents a loess regression with span = 0.6, excluding the forest plot. Note that all C/clay ratios are below the 1/13 threshold (1/3 ≈ 0.077) proposed by Johannes et al. (2017), suggesting that a "*degraded*" structural quality could be expected for all cocoa soils (assuming that this concept applies to this pedoclimatic context).

4.3.5 Soil organic matter (SOM), carbon (C), and nitrogen (N) stocks (0-20 cm)

In Tarengge, the stock of SOM declined from 91 Mg ha^{-1} down to 50 Mg ha^{-1} between 0.5 and 2 years, following the same pattern as SOM contents, representing a loss of approximately 46% of the SOM stock in 1.5 years. After two years, the SOM stock increased, reaching 74 Mg ha^{-1} at 15 years. In Mambu and Pussui, the decline between 2 and 20 years was of a similar magnitude; respectively, 28 and 36 Mg ha^{-1} of SOM seem to be lost in 18 years (−41 and −34%). In Mambu, SOM stock increased from 41 to 53 Mg ha^{-1}, while in Pussui, the gain was negligible (only +3.4 Mg ha^{-1}, from 71 to 74 Mg ha^{-1}). The stock variations of C and N were very similar to each other and SOM, except for the 7-year-old farm in Tarengge. For this farm, the C and N stocks were much higher than the other years, comparable to the 0.5-year-old farm (approximately 40 Mg of C and 4 Mg of N per ha). Accounting for differences in soil BD by using stocks instead of contents produced convergent results between contents, clay-adjusted quotients, and SOM stocks, supporting the initial hypothesis (i.e., a trend not merely caused by differences in BD nor by differences in clay contents).

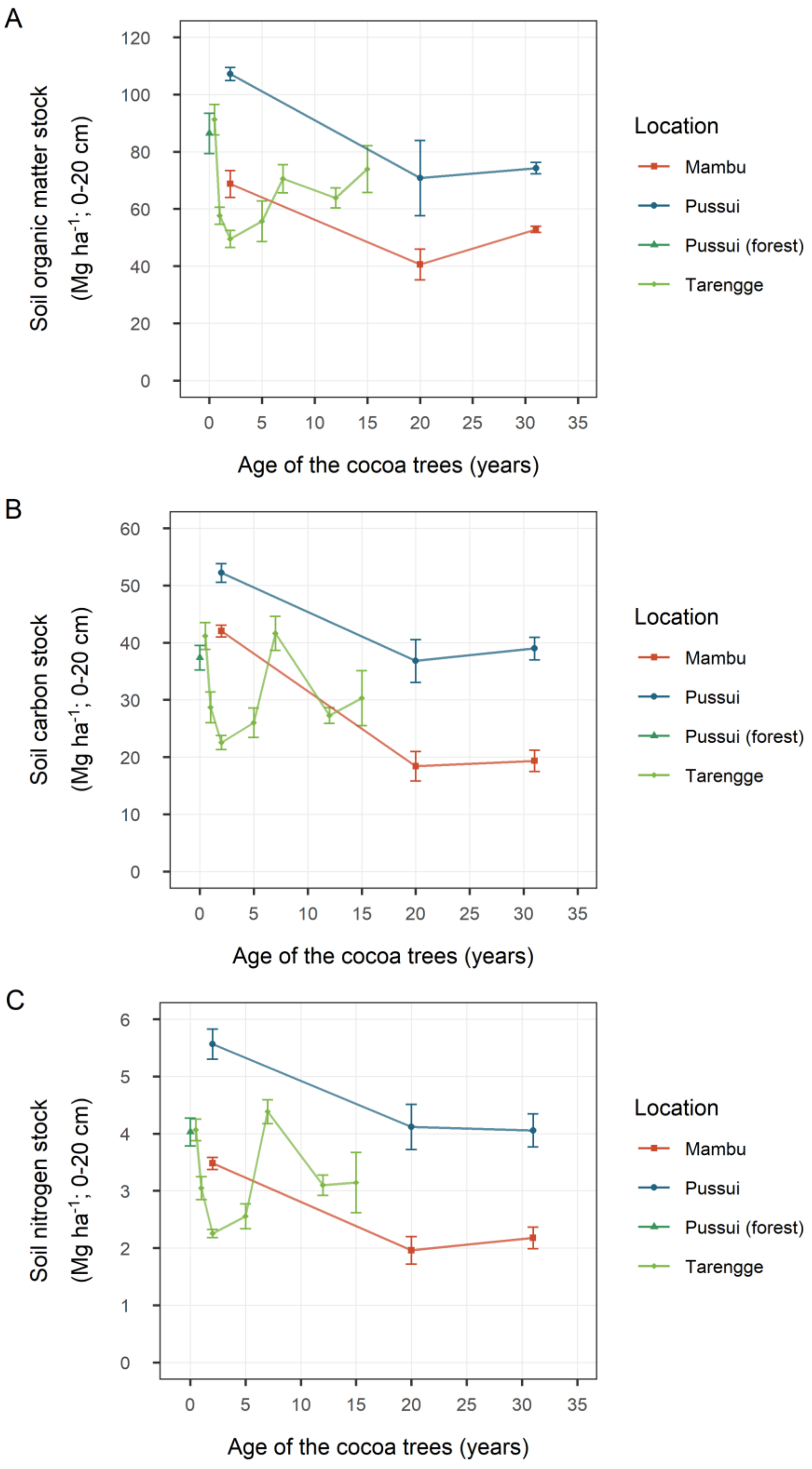

Figure 4.8: Temporal changes of soil organic matter (SOM), carbon (C) and nitrogen (N) stocks (Mg ha^{-1}) in the 13 farms of the chronosequence (and a forest) at the 0-20 cm depth

A: Soil organic matter (SOM); B: Soil carbon (C); C: soil nitrogen. SOM contents were obtained after loss-on-ignition and corrected for potential structural water loss linked to clays (Jensen et al., 2018). Carbon and nitrogen contents were determined through dry combustion. Error bars represent the standard error. Mean calculated with five samples per plot. Stocks were determined by using the 0-5 cm bulk density (core ring method).

4.3.6 C:N ratios and C/SOM fraction

The C:N ratios were low, between 6:1 to 12:1, and did not show a clear temporal trend. Even though the C:N ratio slightly decreased on average with depth, the difference was slight (from 9.6:1 at 0-20 cm down to 7.9:1 at 80-100 cm). The C contents of SOM (C/SOM) ranged from 17% to 42%. As with C:N ratios, no clear temporal trend was observed. Again, C/SOM seemed to decline with depth (from 33% at 0-20 cm down to 20% at 80-100 cm). Surprisingly, all these factors were well below the commonly used factor of 58%. The C and N peaks observed at year 7 in Tarengge (Figure 4.6, Figure 4.7, Figure 4.8) are not related to a higher clay content of a higher BD (Table 4.1, Table 4.3). Instead, the decorrelation for this farm between SOM on one side, and C and N on the other, is revealed by a higher C/SOM content at 0-20 cm (Figure 4.9): 61% while the rest of Tarengge's samples range from 39 to 50%.

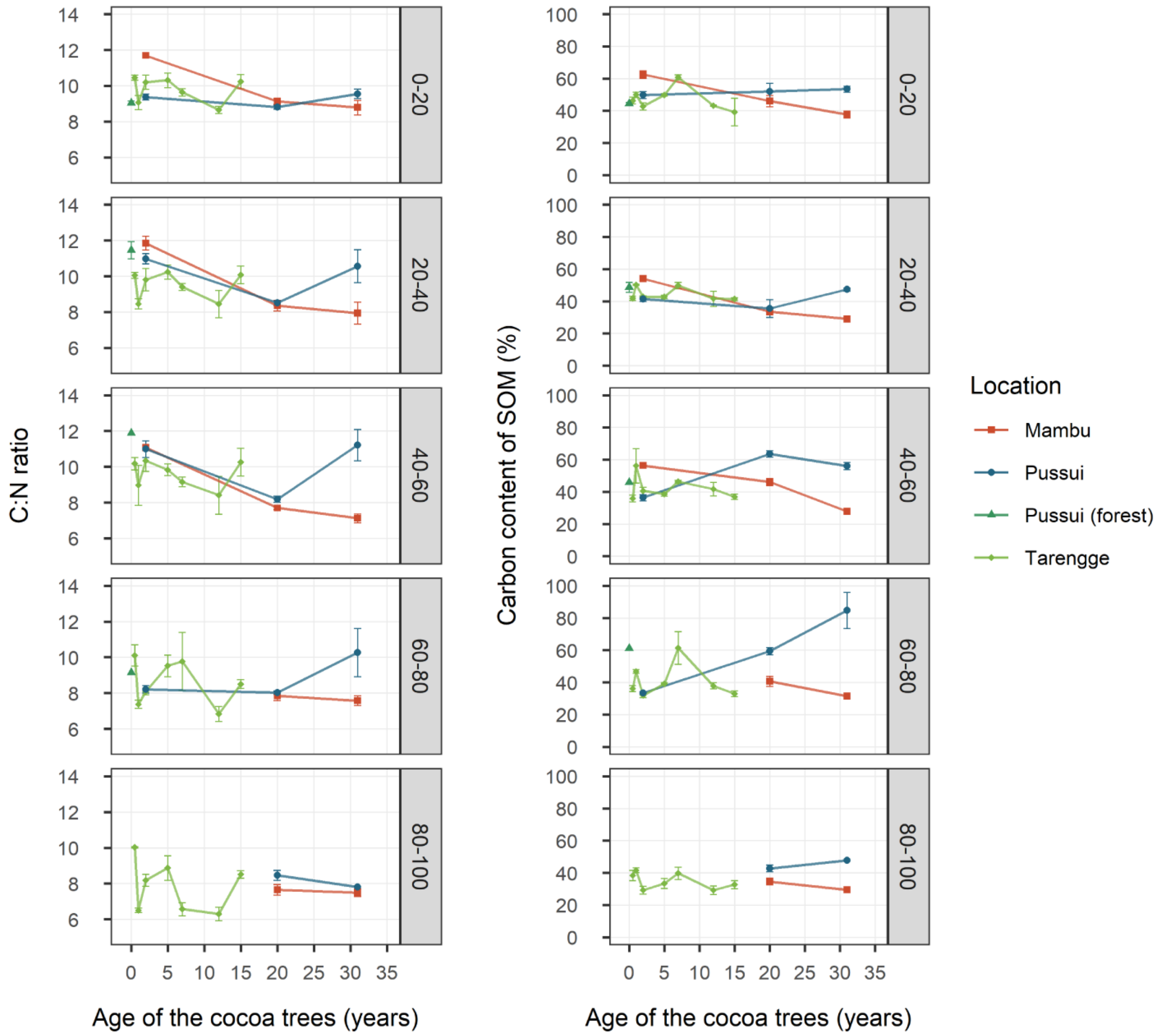

Figure 4.9: Changes of soil C:N ratios and carbon contents of soil organic matter

Carbon-to-nitrogen ratios (C:N) were determined as the division of C by N contents obtained after dry combustion. The C content of soil organic matter (SOM) was determined by dividing the C contents obtained after dry combustion by the percentage of SOM estimated after loss-on-ignition, corrected for potential structural water loss linked to clays (Jensen et al., 2018). Means calculated with five samples per plot for the 0-20 cm layer and three samples for the other sampling depths. Error bars denote ±1 standard error.

4.3.7 Correlations

The analysis of Kendall's tau correlation coefficients revealed that SOM, C, and N contents were not significantly correlated with farm age (Table 4.5). However, the temporal variations of SOM were predominantly negative, indicating a decline over time. On the contrary, SOM, C, and N contents were significantly and positively correlated with clay and fine silt + clay contents between 0 and 40 cm. Below 40 cm, the associations were not all significant but still all positive. Including fine silt seldomly lead to higher correlation coefficients (only for C at 40-60 cm, and N at 20-40 and 40-60 cm). The upper sampling layers were not associated with higher coefficients (i.e., no noticeable depth effect).

Table 4.5: Kendall's tau correlation coefficients

	Depth (cm)	Age	Clay	Fine silt + Clay
SOM	**0–20**	–0.07 (ns)	0.69 (**)	0.59 (**)
	20–40	–0.20 (ns)	0.74 (***)	0.62 (**)
	40–60	–0.30 (ns)	0.49 (*)	0.31 (ns)
	60–80	–0.11 (ns)	0.27 (ns)	0.03 (ns)
	80–100	0.02 (ns)	0.42 (ns)	0.20 (ns)
C	**0–20**	–0.28 (ns)	0.69 (**)	0.69 (**)
	20–40	–0.23 (ns)	0.69 (**)	0.67 (**)
	40–60	–0.25 (ns)	0.54 (*)	0.56 (**)
	60–80	–0.05 (ns)	0.36 (ns)	0.42 (ns)
	80–100	–0.09 (ns)	0.75 (**)	0.60 (*)
N	**0–20**	–0.12 (ns)	0.64 (**)	0.64 (**)
	20–40	–0.20 (ns)	0.56 (**)	0.64 (**)
	40–60	–0.12 (ns)	0.51 (*)	0.64 (**)
	60–80	0.02 (ns)	0.30 (ns)	0.48 (*)
	80–100	–0.15 (ns)	0.44 (ns)	0.66 (**)

Significance level in parenthesis: ns: $P > 0.05$; *: $P \leq 0.05$; **: $P \leq 0.01$; ***: $P \leq 0.001$. Calculated with the *Kendall* package in R. SOM stands for soil organic matter; C for soil carbon; and N for soil nitrogen. SOM contents were obtained after loss-on-ignition and corrected for potential structural water loss linked to clays (Jensen et al., 2018).

4.4 Discussion

4.4.1 Temporal dynamics of SOM, C, and N in a cocoa farm

Cocoa growth seems consistent across locations

The performance of the trunk growth pattern fitted to the observations of this study explained more than 99% of the variance of our observations (for aboveground and belowground estimations, R^2 = 0998) was high. This result suggests that despite differences between sites, cocoa growth could be relatively consistent and could be described accurately with a logarithmic-like model, like many other tree species (which in this case was replaced by a Weibull function to fix the mathematical problem posed by values between 0 and 1 resulting in negative values). Assuming that this pattern is not just the result of random chance or small sample size, the growth of the cocoa trees followed the trend described in this research's conceptual hypothesis.

The amount of aboveground and belowground biomass predicted by the growth curve was much higher than the results obtained in the meta-analysis (Figure 2.2). If assuming an approximate plant C content of 50%, the average aboveground cocoa biomass stock at 30 years was ~20 Mg ha^{-1}. In contrast, the 30-year aboveground biomass stock found in this study was ~130 kg tree^{-1}. Assuming a tree density of 1111 trees ha^{-1} (3 x 3 m spacing), ~130 kg tree^{-1} would lead to an estimate stock per hectare of ~144 Mg ha^{-1}, about seven times that of the average value found in the meta-analysis. Assuming a lower density of 625 trees ha^{-1} (4 x 4 m spacing) would lead this value to be ~81 kg ha^{-1}, still much higher than the range of values found in Chapter 2. The procedure implemented to estimate biomass using Smiley & Kroschel's (2008) allometric equation, fully detailed in Smiley (2006), was checked several times and no errors were found. This issue highlights then allometric equations used in the cocoa literature may pose a risk of misestimating cocoa biomass or C stocks when they are used in other locations without being validated first. Further work is required to compare allometric equations used in cocoa research and evaluate the limits of their validity domain.

It is highly likely that the SOM inputs generated by the cocoa trees are strongly correlated with the size – and age – of the cocoa trees. However, the experimental design adopted in this study did not capture data to describe cocoa's deposition of organic matter. Aboveground inputs through litterfall have nevertheless been studied (Dawoe et al., 2010) and seem to be closely linked, if not proportional to cocoa tree biomass. However, estimating cocoa's inputs to SOM is accompanied by several challenges. For example, the growth model adopted in this study used trunk size to estimate cocoa biomass, but this simple allometric relationship could be insufficient to describe both cocoa biomass and the litterfall rate accurately. Also, belowground inflows of organic matter through root turnover, rhizodeposition (and other inputs from other sources) are poorly quantified, even if they may represent a significant fraction of the total SOM inputs (Kuzyakov & Domanski, 2000b). Until light is thrown on these pathways, the simple approach adopted here shows that cocoa biomass and potential SOM inputs may be reduced to a simple logarithmic growth, with parameters easily determined on-site. However, this approach would only allow modelling of the temporal dynamics of SOM inputs retrospectively since old plantations would be necessary to measure trunks and draw growth parameters from them. In any case, retrospective modelling can still be useful to inform the temporal dynamics of cocoa trees and the soils on which they grow in order to anticipate dynamics in other settings.

The "rapid initial decline" phase supported by our results

The results show an abrupt decline in SOM contents in Tarengge between 0.5 and 2 years. However, it is difficult to determine if this observation is due to SOM content variability across and within sites (artifact due to natural randomness) or a real phenomenon. This observation was confirmed by SOM/Clay quotients and accounting for BD differences with SOM stocks. The rapid decline was further corroborated by C and N, which followed the same pattern. This suggests a 40% depletion of SOM/clay in 1.5 years (27% per year), representing a considerable loss in a short amount of time. In terms of SOM stocks, this drop would correspond to a loss of 42 Mg SOM ha^{-1} in 1.5 years (28 Mg SOM ha^{-1} in one year), going from 91 Mg SOM ha^{-1} down to 50 Mg SOM ha^{-1} (−46%). With such a rapid fall, which should be considered a brutal soil degradation event, it is legitimate to wonder: is it even possible? Is this phenomenon likely to occur or due to a misinterpretation of the data? Are there good reasons to believe in the likelihood of this process? Can other examples be found in the scientific literature reporting similar events?

Sulawesi: A particular case study

SOM decomposition rates are high in the tropics because of high temperatures and moisture levels throughout the year (Ross, 1993; Sanchez & Logan, 1992), with local differences (Greenland & Nye, 1959). For example, reported C loss rates can range from 1.8 to 12.8% per annum in cultivated lowland tropical forest zones (Greenland & Nye, 1959). However, it should be emphasized that loss rates are possibly higher with a cocoa system because, after a sudden shift of land use (vegetation clearing), litter inputs that could attenuate SOM losses are virtually reduced to zero, and a different microclimate influences the systems. The flux of new plant litter inputs and rhizodeposits anterior to vegetation clearing is almost entirely interrupted. New inputs will come only from the (much smaller) young, planted trees and the sporadic vegetation that was not eliminated by manual and chemical weeding. In this case, which combines an abrupt transition between drastically distinct systems, with almost bare land at planting and environmental conditions promoting SOM decomposition, one could expect SOM losses to occur rapidly.

Evidence from other studies

Smiley & Kroschel (2008) observed very different variations in soil organic C (SOC) stocks in two different locations of Central-Sulawesi (Indonesia). In Palolo, they sampled eight farms from age 2 to 15. Topsoil (0-15 cm) SOC stocks remained relatively stable over time, only showing a slight increase of approximately (+11 Mg C ha^{-1}) between the farm of age 2 (34 Mg C ha^{-1}) and 15 (45 Mg C ha^{-1}), which is still +33% of the 2-year-old farm. However, when considering a deeper soil profile (0-100 cm), it appears that they observed a decline between 2 and 4 years (i.e., -15% in 2 years from 137 Mg C ha^{-1} to 117 Mg C ha^{-1}), followed by a continuous increase until 15 years (reaching 160 Mg C ha^{-1}). In Napu, the age range was shorter, going from 1- to 8-years-old, and included six farms. The trend for the 0-100 cm sample was different from Palolo, showing instead a significant increase between 1 and 3 years (going from 119 up to 197 Mg C ha^{-1} in just two years), followed by an equivalent decrease (going from 197 Mg C ha^{-1} down 96 Mg C ha^{-1} at year 8). Similarly, topsoil stocks (0-15 cm) increased between 1 and 3 years, followed by a decline between 3 and 8 years. Isaac et al. (2005) studied C and N dynamics in a false-time chronosequence in Ghana in farms aged 2, 15, and 25-years-old, established in converted forests. They measured the highest SOC stocks (0-15 cm) at two years (22.6 Mg C ha^{-1}) and lower comparable levels at 15 and 25 years (respectively 17.6 and 18.2 Mg C ha^{-1}). They also report that 16% of the original SOC stock had been lost within the first two years after conversion. They stated that similar studies have established that significant declines occur during the first five years after conversion (Houghton et al., 1991; Juo & Kang, 1989; Van Noordwijk et al., 1997). Mohammed et al. (2016) assessed SOC stocks in eight shaded and eight unshaded cocoa farms in Ghana, ranging from 7- to 28-years-old. The results showed considerable variations between the different locations, ages, and shade management, making it difficult to extract a particular trend. Nijmeijer et al. (2019) also used a false-time chronosequence to evaluate the effect of the previous land use on the C dynamics of cocoa systems in Central Cameroon. Cocoa farms planted after savannah showed a steady increase in SOC stocks and may potentially attain similar levels of cocoa established after forests. There was no apparent trend for the cocoa plots planted after forests, which showed highly variable SOC contents. Dawoe et al. (2010) measured a 17.3% decline in SOM stocks between zero (forest) and three-year-old cocoa farms in Ghana, equivalent to an annual loss of 5.8%, three times lower than the decline observed in this study. Beer et al. (1990) did not measure a significant change over time, but as the results of this study suggest, a five-year gap between two measurements can mask a rapid decline followed by a rapid recovery.

Van Straaten et al. (2015) estimated that deforestation of lowland tropical forests for tree cash crops (i.e., cacao, rubber, and oil palm) could decrease SOM stocks by up to 50%, and the higher the initial stock of soil C, the higher the loss. Using their exponential decay function leads us to find a SOM stock reduction of 8.4% two years after deforestation and a 17.9% decline in five years. However, some caution should be taken as their timescale was *years after deforestation* (i.e., not years since planting), and the shortest gap between forest and cocoa was large, around 20 years (cocoa farms were not necessarily first-generation farms, they may be planted on older cocoa farms or other types of crops). In this study, only two farms (K and L) were planted on a cleared forest, and for the others, farmer records about forests being present within the last 31 years were not available. Also, it is worth mentioning that Van Straaten et al. (2015) did not find a positive trend for soil C stock recovery in the long run because they assumed that SOM stock changes would follow only an exponential decay function.

Short-term changes (i.e., less than five years) are rarely examined, perhaps because SOM changes are often assumed to be slow, assuming they will take at least five to ten years to detect. The literature search was extended to other systems than cocoa, such as forests converted to grass, rubber, or other crops to fill this information gap. While soil, climate, and land use vary, searching for extreme changes can inform us about possible SOM rates of change and provide valuable comparisons.

Zingore et al. (2005) provided empirical evidence supporting the “rapid initial decline” hypothesis in woodland soils cleared for arable cropping in Zimbabwe.

Using C^{13} data and assuming an exponential decline of SOC stocks, they report losses as high as 24% during the first two years after clearing.

Ledo et al. (2020) used a global dataset of paired observations to evaluate the effect of land-use change from annual to perennial crops (709 field studies). The authors also found a potential rapid decline in topsoil (0-30 cm) soil C stocks during the first five years, followed by a rapid recovery and build-up over time (5 to 10 years), to finally end up with a slight decrease between 10 and 20 years. However, their non-linear regression model was fitted on high-variability data. Nevertheless, they do mention that this pattern was repeatedly observed for single sites with multiple observations.

Models can also provide indirect information to further evaluate the research hypothesis of the present study. Using a modelling approach, Detwiler (1986) found that, five years after clearing, cultivation led tropical soils to lose 40% of their C content, whereas grasslands led to a decrease of 20%. Mishra et al. (2021) used RothC to simulate changes in SOM stocks in different perennial plantations in North-East India. According to their simulations, areca, cashew, and tea plantations may have respectively lost 29%, 28%, and 23% of their SOM stock in five years. A global modelling study used RothC to estimate average SOC decomposition rates for various world regions and land uses (Morais et al., 2019). Among other places, Indonesia showed some of the highest estimated mineralisation rates for several land uses, around 7% per year. However, potential mineralisation rates are theoretically higher than those of net changes. Using AMGv2's equation and the average parameters found in Tarengge would give an estimated SOM yearly mineralisation rate of 20%. Using RothC (assuming that 2.5 Mg of plant inputs per year and the pedoclimatic conditions of Tarengge) would suggest that potential monthly decomposition rates could be as high as 88% for the 'decomposable plant material' pool (DPM), 6% for the 'recalcitrant plant material' pool (RPM), 13% for the 'microbial biomass' pool BIO and 0.4% for the 'humified organic matter' pool (HUM).

Cocoa litter quality

After analysing both cocoa and forest litter, Dawoe et al. (2010) found higher contents of lignin and polyphenol in cocoa litter than in forest litter (respectively 14.1-14.6% and 2.71-3.39% in cocoa litter versus 11.2% and 1.8% in forest litter). Because of its "low quality" (Palm et al., 2001), cocoa litter might delay the replenishment of SOM after planting, thereby exposing the soil to a more extended period of losses as compared to residues with low lignin and polyphenol contents, more rapidly converted to SOM. While the labile fraction of cocoa residues might quickly contribute to increasing SOM stocks, a non-negligible fraction could take more time to be converted to SOM because of the inhibitive influence of cocoa leaves phenolic compounds (reflected by the accumulation of leaf litter). In the long-term, the recalcitrant nature of cocoa leaves may contribute to accumulating high levels of SOM but could leave young plantations (i.e., freshly cleared from their vegetation) more prone to SOM depletion in the short term.

Organic matter transfer from litter to soil

Nevertheless, decomposition rates are not enough to estimate litter's contribution to SOM. Zheng et al. (2021) pointed out that litter mass loss rates do not inform us about its conversion to different forms of SOM and the extent to which organic matter is transferred and stored in the soil. In other words, cocoa litter may be slow to decompose, but it is yet to be determined which fraction of the lost mass may transfer to soil. For example, this proportion can be encapsulated by the k_1 humification coefficient (Janssen, 1984) or the ISMO and ISB indices (Peltre, 2010), but these remain unknown for cocoa litter. A synthesis of stable isotope studies by Zheng et al. (2021) indicates that slowly decomposing litter may significantly increase soil C and N transfer than rapidly decomposing litter. Assuming this conclusion applies to cocoa, it be could hypothesised that cocoa litter may be better incorporated into the soil than "high-quality" litter despite its slow decomposition.

Distinction between litter stock decomposition and SOM decomposition

Litter decomposes, and during the process, a fraction is converted to SOM ("k_1") and qualified as the rate of humification of organic matter (Andriulo et al., 1999). Other sources of inputs include all the other organic matter forms generated in situ, such as rhizodeposits (root exudates and root turnover) and any dead organisms and its excreta entering the system. Traditionally, studies interested in C dynamics in agroforestry systems measure litterfall rates, but the underground organic matter pool is perhaps overlooked. Very little data about the potential contribution of roots to SOM (Villarino et al., 2021) is available. Very few studies have measured plant rhizodeposits, and even less have examined tree rhizodeposits in the tropics. The rate at which SOM can be effectively deposited in the soil in the tropics is poorly understood. What is the flow rate of rhizodeposits from cocoa trees? To better explain SOM and C dynamics in cocoa agroforestry systems, and to other tropical perennial systems in a broader sense, research must determine the magnitude of these contributions, their fluctuations over different time intervals (e.g., daily, seasonally, over a particular phase of the life cycle of a tree) and their biochemical composition. Until then, the ability to predict SOM dynamics in tropical perennial systems will remain biased and incomplete.

Soil organic matter after the initial decline: build-up or decline? Fast or slow?

In Tarengge, a recovery of SOM contents (0-20 cm) can be observed after an initial rapid decline. This rebound was also observed for soil C (0-20 cm), but the recovery was not maintained after seven years because lower C contents were detected for the farms older than 7-years-old. This observation does not support the idea that SOM slowly builds-up after the initial rapid decline. On the contrary, a rapid recovery was found for SOM/clay and C/clay, followed by a moderate decrease instead of a slow build-up.

In Mambu and Pussui, the hypothesis of a minimum followed by a higher plateau at maturity holds SOM contents and stocks (0-20 cm). The trends observed with texture-adjusted SOM could suggest that, in the long term, SOM could slowly decline or reach an new equilibrium. In Pussui, the texture-adjusted SOM contents were lower than for the forest sample but increased slowly over time.

Soil organic matter may potentially recover in the long-term

The final assumption, "*maturity levels lower than at planting*", is not fully supported by the results of this study. This claim is valid for Tarengge, but the oldest plot of the series is only 15-years-old. In Mambu and Pussui, this assumption was supported by the SOM contents data, but not with texture-adjusted SOM contents because final levels were similar to the initial ones. Nevertheless, the challenge posed by the interpretation of Mambu and Pussui is that the results may miss a significant decline occurring between planting and the second year. Consequently, it is unsure whether SOM levels at maturity are lower than the SOM levels at planting . Furthermore, the data utilised in this study only included two farms with cocoa planted on a former forest.

Using texture-adjusted indicators helps to compare different sites in false-time chronosequences

By analysing SOM, C, and N contents divided by soil's clay contents, this study has by adjusting SOM, C, and N contents in large part addressed a major limitation of false-time chronosequences: texture differences between sites. Using only SOM, C, and N contents without adjusting for soil texture would have led to totally different interpretations of the data and poses a risk of making false conclusions. For example, by noticing that the pair of 2-year-old farms of Mambu and Pussui had both relatively higher clay contents than their corresponding 20-year-old farms. Using SOM non-adjusted for texture would have complicated the interpretation of the results. SOM contents could have been assumed to decline between 2 and 20 years. Alternatively, this change could have been attributed to the effect of texture only, and therefore missing a possible change masked by this difference in clay content.

Despite the usefulness of these corrections (Johannes et al., 2017; Prout et al., 2020), texture-adjusted indices have been sparsely used in peer-reviewed literature. Their use may be limited to particular cases where the researcher wishes to compare element concentrations between sites with different textures. Nevertheless, it could be argued that these cases are frequent in soil science. By essence, comparing two soils with the same PSD is unlikely. While categorizing sites per texture may be helpful, the intervals associated with each texture class are relatively large. For instance, in USDA's soil textural classes, a "clay" soil could be 60% or 100% clay, but those two different PSDs, even though they belong to the same classes, could behave very differently regarding their ability to store SOM. Although texture classes are helpful to reduce soils' variability to distinct categories, they can form an unnecessary impediment and avoidable bias to soil evaluation. As a matter of fact, if soil texture is essential to explain SOM storage, new techniques based on the continuous distribution of soil particles (i.e., instead of discrete ranges like 0-2 µm for clays or 50-2000 µm for sand) would allow more accurate analyses. To this argument, it could also be added that soil texture classes are not standardized at the world level (see comparisons of PSD ranges in Pansu & Gautheyrou, 2006). As a result, researchers use the terms *clay*, *silt,* and *sand* to describe particles of different sizes depending on the country they come from, which is not optimal and could be improved by agreeing on a single textural scale at the world level (Martín et al., 2018).

Relationships between SOM, C, and N

Examining C:N ratios indicated that C:N ratios were all relatively low at all depths and cocoa farm ages. This indicator suggests that SOM could be susceptible to fast cycling since N may not be a limiting factor to decomposition. This information supports the argument that SOM losses can occur rapidly. It is commonly stated that substances with a C:N ratio below 20 (or 25) result in a net release of N, while substances above this limit lead to a net immobilization of soil N (Havlin et al., 1999). As an indication, cocoa litter was reported to have a C:N ratio of approximately 47:1 (Isaac et al., 2005).

When trying to characterize SOM using the C content of SOM (C/SOM), no conclusive results were obtained. The C contents of SOM were very low, and values around 58% or above would have been expected, denoting a possible increase in C-rich and compounds like humic substances, woody tissues, or black C. Instead, C/SOM fractions were well below the traditional van Bemmelen factor of 58% and below the average C content of plant tissues, approximately 45% (Ma et al., 2018). The lowest C/SOM values reported in this study were *circa* 20%, which joins some of the highest factors reported by Pribyl (2010).

Overall, the hypothetical dynamic is partially supported by the results

To summarize, the results partially validated the proposed hypothetical dynamic with some deviations. Namely, the proposed variations in SOM, C, and N were observed, but the changes may occur faster than foreseen. The initial decline of SOM may be more rapid than expected, occurring during the first three years after planting. Similarly, instead of a slow recovery corresponding to the growth of the cocoa trees, a rapid recovery was observed (i.e., taking two to three years instead of a decade, corresponding to cocoa trees of five to six years old). Later, a slow decline was observed instead of an equilibrium, perhaps due to inputs decreasing in the long term, related to tree mortality or a drop in vigour. Finally, the long-term level does appear to be lower than the initial levels. Overall, the trend resembles the initial hypothesis, but the main transition points are *right-skewed*, occurring earlier than expected.

4.4.2 Implications for soil management

A sensitive period for soil

In Sulawesi and under similar climates, soils may be extremely sensitive to SOM losses during the early years after vegetation clearance. This degradation period probably lasts until cocoa trees are large enough to protect the soil (e.g., cooling down the soil due canopy-induced shading) when the deposition of plant residues and rhizodeposits is sufficient to build up SOM. Such a rapid decline in SOM, C, and N stocks is a significant degradation event that should be considered and addressed by a better soil management plan.

Replanting cycles could lead to gradual soil degradation

The trend observed for SOM/Clay (0-20 cm) suggests that each cultivation cycle could pose a risk of gradually depleting SOM stocks. If the plot is cleared for replanting, it is logical to assume that new losses will occur. Because a slow decline was observed in the long-term, each replanting cycle could further deplete SOM stocks. In sum, cocoa cultivation could lead to a slow degradation process interrupted by alternating short, abrupt declines and recoveries occurring rapidly after every planting. If the long-term recovery does not reach pre-planting levels, this cycle could repeat itself, perhaps until only the most protected and recalcitrant forms of SOM remain.

Offsetting losses with organic matter inputs in the short term

Several approaches could be used to prevent this process. First, the initial decline could be counterbalanced by application of sufficient organic matter inputs at the beginning of each cycle. Using manures, composts, mulches, or a combination of different sorts of organic material could help reduce the impact of each planting cycle. Using the data mentioned before (Section 4.4.1), the need for SOM could be as large as approximately 28 Mg ha^{-1} yr^{-1} (i.e., corresponding to the loss of 28 Mg ha^{-1} yr^{-1}), which would mean even higher organic inputs when taking into account their SOM yield (i.e., the "k_1" humification coefficient; Janssen, 1984). To provide a rough example and establish a sense of scale, using a mature cattle manure with a k_1 of 50% (Van-Camp et al., 2004) would require approximately 60 Mg ha^{-1} yr^{-1} to offset the losses or 80 Mg ha^{-1} yr^{-1} of green waste compost with a k_1 of 35%. Assuming a typical planting density of 1111 trees ha^{-1}, these amounts would represent 73 and 56 kg per cocoa tree per annum. Unfortunately, such high rates may give a discouraging idea of the scale of the challenge facing the cocoa industry and maybe unattainable to smallholders. Nevertheless, this type of intervention could only be performed once when replanting, and spreading this investment over 20-30 years could probably make it much more feasible.

Offsetting losses through long-term SOM management

Another complementary approach could be to maintain or improve SOM stocks over time, using smaller but regular organic inputs. Residues with slow to intermediate decomposition rates should be periodically applied to increase SOM stocks. In tropical sandy soils, Puttaso et al. (2011) have shown that N-rich residues with low availability of energy-rich substrate like cellulose, and moderate amounts of lignins and polyphenols were best suited to accumulate SOM. In their study, cellulose-rich residues with low lignin and polyphenols contents like rice straw were detrimental to SOM accumulation. Other inputs like biochar have the potential to increase soil C stocks significantly. However, although biochar manufacturing was historically a low-tech process (e.g., pit or mound kilns), current approaches seem to ignore those methods to only focus on high-tech solutions, inaccessible to smallholders (Duku et al., 2011; Munkhbat et al., 2013; Pratt & Moran, 2010). These solutions and a range of other improved practices adapted to tropical soil are discussed by de Moura et al. (2016).

On the other hand, a recent study reported that increased litter inputs may not necessarily lead to higher soil C storage because they could instead stimulate the decomposition of minerally-associated organic C through a priming effect (Sayer et al., 2019), meaning that simply increasing inputs may not be the right strategy to restore SOM stocks in the long-term. As a matter of fact, research undertaken on a cocoa field experiment (Fungenzi et al., 2021; Mulia et al., 2019) in Sulawesi (Indonesia) showed that compost additions (10 Mg ha^{-1}) could lead to significant yield improvements while, at the same time, SOM declined.

Appropriate integration of shade trees and intercrops could enhance the accumulation of SOM with positive effects on soil fertility without compromising cocoa productivity (Wartenberg et al., 2020). However, increasing shade tree diversity alone may not be enough to mitigate soil degradation on cocoa plots planting after deforestation. Forest strips and regular fallows could be implemented to regenerate secondary forests to restore soil health in the long term (Wartenberg et al., 2017), assuming that smallholders could be compensated for the corresponding loss of income.

While assessing the SOM balance is a practical tool that could help pilot soil management in cocoa systems (Brock et al., 2013; Kwiatkowska-Malina, 2018), no publications using this approach were found.

Does soil organic matter 'actually matter' to cocoa? (Are SOM losses worth preventing?)

All things considered, a crucial question is to determine whether a decline in SOM is detrimental to cocoa production. To what extent is this loss of SOM a problem, if it is an issue at all? After all, cocoa trees could still perform well on soils with low SOM contents. To answer this question, further evaluating the effect of organic matter additions on cocoa productivity is recommended. In a field experiment conducted in Sulawesi (Fungenzi et al., 2021; Mulia et al., 2019), it was demonstrated that compost additions (10 Mg ha^{-1} yr^{-1}) could significantly increase cocoa dry bean yields (i.e., five times more than fertilizers). This result provides a proof of concept that cocoa soils could largely benefit from the application of suitable organic inputs.

Transposability of this dynamic: a particular combination of factors that could be found elsewhere

It should be emphasized that this phenomenon may exist in cocoa farms but could also occur with other perennial crops cultivated in the tropics like coffee, tea, rubber, and banana, provided that the combination of risk-factors is gathered: high air temperatures, high and frequent precipitations, and an abrupt transition between a vegetation-rich to almost bare soil. The results of this study and literature review both highlighted that the early years after planting might be when significant damage to soil occurs, and as such, management plans should address this phenomenon accordingly to enhance the sustainability of perennial tropical production agroecosystems.

4.4.3 Limitations of this study and opportunities for future research

False-time chronosequences and site comparability

The main limitation of this study resides in the comparability of different sites, which is a typical constraint of space-for-time chronosequences. Comparing different farms may introduce significant errors in the results, making comparisons invalid. Using SOM, C, and N stocks instead of soil contents is one way to address this issue, but including soil texture – as it was done with SOM/clay – can help to adjust for differences in soil texture between sites.

Sampling equivalent soil masses is another approach that should be considered (von Haden et al., 2020; Wendt & Hauser, 2013). Several other factors could significantly influence the results observed in this study. For example, farms differ in management, shade tree intensity, and the previous land uses. While the approach adopted in this study tried to cover a broad and detailed temporal range of farms, the research team did not have access to a database that could have helped to select comparable farms. Without minimal information about cocoa farms, it was challenging to find farms sharing the same characteristics, which could have helped limit errors and differences introduced by the false-time approach. This study relied only on the knowledge of experienced field assistants to find farms of appropriate age. Farmers' memory was the only source of information about their farm features and history. While the field assistants and the farmers were instrumental in performing this study, it be cannot stressed enough that the absence of a farm database restrains research's ability to produce precise results. The root cause is probably the vast diversity of existing cocoa agroforestry systems, making farm-to-farm comparisons difficult.

Repeating farm surveys at the beginning of a study to find comparable candidates is costly and takes much time. Nonetheless, to facilitate research on cocoa, developing a network of well-monitored cocoa farms would be recommended, with some basic but essential information about their key features (e.g., previous land use, shade tree species, and densities). In addition to long-term experiments on research stations, which are essential to monitor plantations and treatments throughly, the value of such a network of cocoa farms can be advocated. Cocoa industries are improving their data collection on cocoa farms for traceability reasons (e.g., “Katchilé” app of Barry Callebaut), and this approach opens the way to develop a database of cocoa farms which could be used for research purposes by also including agronomical data of specific cocoa farms. This progress would greatly facilitate future on-farm research. If comparing farms having different soils and management can lead to questionable results, one of the most effective solutions should be to monitoring true chronosequences andchanges in soil properties on the same farms from pre-planting onwards.

Monitoring short-term changes

Although rapid declines have been observed in the aforementioned studies, this phenomenon should be assessed by monitoring rapid SOM changes right after planting a cocoa farm, perhaps by sampling every 4-6 months for 3-5 years. If cocoa planting involves leaving the land cleared for a prolonged time before planting (several months), soil sampling should scrutinize possible changes occurring during this post-clearance and pre-planting period. Sampling before land preparation (e.g., forest clearing) could help monitor soil changes occurring during this transition period when the ecosystem is experiencing an abrupt shift. This particularity also emphasizes that real-time chronosequences are needed to monitor cocoa soil changes accurately.

4.5 Conclusions

The results of this study suggest that cocoa farms' initial stock of SOM could rapidly decline after planting due to a combination of different factors. The association of high temperatures and high annual precipitations throughout the year promotes the fast decomposition of SOM. Following planting, vegetation clearing reduces organic matter inputs and may lead to SOM outputs exceeding inputs, resulting in a net loss of SOM. However, as cocoa trees grow, their contribution to SOM seems to quickly attain a turning point where SOM gains overtake losses, driving SOM contents to increase and reach a new equilibrium. Nevertheless, this recovery may not reach pre-planting levels, and each replanting could lead to a further cycle of degradation. Furthermore, crops grown under similar climates (such as coffee, tea, banana, or rubber) may also be affected by this phenomenon, expanding the areas prone to rapid post-planting soil degradation. Using pedoclimatic data should be the next step to determine which zones may be at risk since temperature and rainfall are the main drivers of SOM mineralisation in the tropics. Future research should consider the first years after planting as a possible sensitive period, where significant soil degradation could occur. The results of this study should incite farmers and other stakeholders to reconsider their practices, and measures should be taken to prevent rapid post-planting soil degradation, especially because SOM losses may be difficult to compensate.

5. MODELLING SOIL ORGANIC DYNAMICS IN INDONESIAN COCOA FARMS

Highlights

- The AMG soil model was adapted to simulate SOM dynamics in perennial tree crops like cocoa
- SOM may decline rapidly after planting a cocoa farm
- SOM stocks may build up slowly on the long-term
- Long-term SOM stocks can be lower or higher than the levels at planting
- The early years after planting would require significant organic inputs to fully compensate for SOM losses

Summary

The fate of soil organic matter (SOM) has important consequences for soil fertility and climate change. Due to the long-term nature of SOM dynamics, modelling is a valuable approach to predicting SOM stocks' variations and anticipating the potential effects of soil management decisions. Nonetheless, not all land uses and agricultural systems have received the same level of scrutiny. In particular, knowledge of SOM dynamics in perennial tropical systems like cocoa remains limited. The objective of this study was to model SOM dynamics in a cocoa farm. It was hypothesized that the SOM stock would rapidly decline after planting before slowly building up over the long term. The AMG soil model (Clivot et al., 2019) was adapted to meet the requirements of cocoa and test this hypothesis because it represented a straightforward and versatile option. The model was evaluated by using data from 13 Sulawesian cocoa farms (Indonesia). The model was also used to estimate the quantities of organic inputs (such as rice straw, cattle manure, goat manure, rameal wood chips and biochar) required to offset SOM losses completely. The different simulations supported the hypothesis. Due to the fast decomposition of SOM (the local conditions suggested a SOM mineralisation coefficient of 0.125), the early years after planting were characterized by a significant decline of the SOM stock because plant inputs were insufficient to compensate for the losses. Significant degradation through SOM depletion may occur in tropical soils during the early years after clearing a biomass-rich system. This simple model was reasonably accurate as the results fitted with the range of observations obtained on the farm dataset (RMSE = 19.22 Mg SOM ha^{-1}; 0-20 cm) and can be easily adapted to simulate other tree-like crops but must be validated and calibrated with true rather than false-time chronosequences. Several opportunities for improving the model representativeness are presented.

Keywords: Modelling, soil organic matter, cocoa, Indonesia, *Theobroma cacao*.

5.1 Introduction

5.1.1 Background information

Soil organic matter conservation is at the nexus of critical societal issues such as sustainable agricultural production and climate change mitigation (Janzen, 2004). Soil organic matter (SOM) is one of the most important constituents of soils and plays a major role in the global carbon (C) cycle (Baveye et al., 2020) since SOM is composed of approximately 50% of C (Pribyl, 2010). SOM regulates critical soil functions and properties (Murphy, 2015), and its fate in soil depends on environmental conditions and land management practices (Brady & Weil, 2017; Söderström et al., 2014). Soils can store or emit C into the atmosphere (Navarro-Pedreño et al., 2021). Therefore, predicting the temporal variations of SOM stocks is crucial for making the best-informed decisions regarding farm management practices (Baveye et al., 2020; Blankinship et al., 2018). Land-use changes involving the conversion of “natural” to agricultural ecosystems can significantly deplete SOM stocks (as much as 60-75%, Lal, 2004), thereby emitting C into the atmosphere. The soil C debt of 12,000 years of human land use may have reached 133 Pg C (Sanderman et al., 2017, 2018). Conserving and even increasing SOM stocks is critical to sustain agricultural production and contribute to climate change mitigation (Minasny et al., 2017; Oldfield et al., 2015, 2019).

Many models have been developed to simulate the dynamics of SOM or C in soil for different crops or rotations under various pedoclimatic contexts (Campbell & Paustian, 2015). Nevertheless, several crops have been largely underrepresented. Cocoa (*Theobroma cacao L.*) has not received sufficient attention with regards to modelling SOM dynamics. Running searches on Web Of Knowledge with the search words “cocoa + model + soil + organic + matter” and “cocoa + model + soil + carbon” did not return any study using a predictive modelling approach[2]. The only article referring to modelling was Silatsa et al. (2017), but their method consisted of fitting a non-linear model to a false-time chronosequence, not developing or applying a predictive model. At the same time, the expansion of the land used for growing cocoa has been accelerating for the past 50 years, going from 4.4 million ha in 1970 to 12.2 in 2020 (FAO, 2020), often at the expense of natural forest ecosystems (Ruf, 2001; Ruf et al., 2015). Nevertheless, cocoa farming can be “climate-friendly” when more sustainable practices are implemented (Schroth, Jeusset, et al., 2016).

5.1.2 Problem statement

Despite the tremendous economic, environmental, and sociological importance of cocoa farming (Voora et al., 2019), mechanistic understanding of cocoa SOM dynamics remains superficial. Field studies have been conducted to assess plant and SOM or C (see references of Chapter 2), but to date , the lessons learned from these experiments have not been gathered to generate a mathematical model of SOM dynamics in cocoa fields. Ignorance of what happens to SOM limits stakeholders ability to manage cocoa soils optimally if not corrected. Predicting variation in SOM stocks offers an opportunity to improve the productivity and sustainability of cocoa farming. With a predictive model describing SOM dynamics, it will be easier to effectively manage the organic component of soil fertility in a well-informed manner. Cocoa soils could be preserved from SOM depletion, and it will be possible to compensate the environmental footprint of cocoa farming by increasing soil C-sequestration.

5.1.3 Research design

The objective of this study was to describe the SOM dynamics of a cocoa farm using a modelling approach. More specifically, this study sought to build, assess, and apply a model capable of predicting the temporal variations of SOM stocks in a cocoa farm . The intent was also to simulate the effect of various exogenous organic matter (EOM) input scenarios onto SOM stocks to prevent SOM depletion. Ultimately, it is anticipated that this model will be easily adjustable to simulate other similar perennial systems.

[2] The agroforestry model WaNuLCas (Van Noordwijk & Lusiana, 1998) offers the possibility to model cocoa farms and SOM dynamics, but no publications addressing cocoa were found.

It was hypothesized that the SOM dynamics of a Sulawesian cocoa farm would correspond to the hypothetical pattern presented in Chapter 4, that is, an initial rapid decline of the SOM stock after planting followed by a slow build-up in the long term. The “common-sense approach to problem-solving” described by Grant & Swannack (2007) was followed to develop the model. This approach is based on modelling theory and relies on system thinking. To evaluate the model, the results of a simulation obtained with baseline values from Sulawesian cocoa farms were compared to the false-time chronosequence presented in Chapter 4. The sensitivity of the model to different input parameters was analysed. Finally, the model was applied to each farm of the dataset to assess SOM dynamics and predicted how much SOM would be necessary to offset losses in the average farm.

5.2 Material & methods

5.2.1 Methodological approach

This study followed a three-stage approach, including a series of successive operations (Table 5.1). The first stage consisted of developing the model. The work began by providing an overview of the main components and characteristics of the conceptual model, translating those concepts to mathematical equations, and finally, by quantifying each parameter. The second phase focused on evaluating the performance and behaviour of the model through regression and sensitivity analysis. The third stage of this modelling experiment involved the application of the model to simulate different scenarios. A preliminary step of reverse modelling was carried out first to determine the initial condition of the modelled system. Several metrics were then used to assess the SOM dynamics of different restoration scenarios aiming to conserve SOM stocks during cocoa cultivation.

Table 5.1: Methodological stages and operations

Stage	Operations
1) Model development	1.1) Model presentation 1.2) Mathematical description 1.3) Parametrization
2) Model evaluation	2.1) Regression analysis 2.2) Sensitivity analysis
3) Model application	3.1) Reverse modelling 3.2) Metrics to assess SOM dynamics 3.3) Restoration scenarios

5.2.2 Model development

c. Model presentation

Main characteristics of the model

The stock of SOM results from a balance between inputs and outputs. Over time, it may reach a dynamic equilibrium if the system is stable (constant or regular inputs and outputs). Soil organic matter models differ in the number of compartments they allocate to SOM. Some consist of a single SOM compartment (Hénin & Dupuis, 1945; Yang & Janssen, 2000), while the more recent models are multi-compartmental (e.g., AMG, RothC, CENTURY; respectively Andriulo et al., 1999; Coleman & Jenkinson, 1996; Parton, 1996). In this study, it was decided to use the AMG model (version 2) for its simplicity (limited number of parameters) and adaptability (easily modified to simulate perennial tree crops). The model was adapted to fit the particularity of perennial systems because the original version of AMG was developed to simulate annual arable crops.

With AMG, two pools of SOM are delimited: an active and a passive pool. The active pool receives inputs and incurs losses while the passive pool is treated as inalterable, inactive in SOM transformations during the simulation (in this case, 35 years, 4 years longer than the false-time chronosequence of Chapter 4). The processes are simulated discretely, using annual time steps. It was supposed that SOM inputs come mainly from litterfall and rhizodeposition (root turnover and exudates; Shaw & Burns, 2007). Those input flows are assumed to be proportional to cocoa biomass and age. Outputs of SOM are estimated to come only from mineralisation. Loss by erosion or other forms of material transfer are assumed insignificant in comparison .

With this version, the model of cocoa SOM dynamics combines two sub-models. The first sub-model represents cocoa growth and development by simulating the accumulation and loss of tree biomass based on temporal and allometric relationships developed for Sulawesian cocoa farms (see Chapter 4). The lost biomass (litterfall and rhizodeposition) is transferred to the soil as residues. The second sub-model is based on the AMG model (named after its initial developers, Andriulo, Mary and Guérif: Andriulo et al., 1999; Clivot et al., 2019; Saffih-Hdadi & Mary, 2008). A stable SOM fraction is initialized at the start of the model and remains unchanged over time. A fraction of fresh residues is converted to active SOM. The transfer rates between fresh residues and active SOM depend on environmental factors and the type of plant residues (mainly leaves, branches, twigs, and fine roots). The final model can be classified according to its underlying hypotheses (J. Smith & Smith, 2007):

- Output: Quantitative (because the output, *SOM stock*, is a quantitative measure) and Deterministic (because the output is not subject to probabilities)
- Input: Dynamic with regards to soil processes, but Static with regards to cocoa growth
- Scope: Predictive/Explorative (because it is intended to be used in different settings)
- Application: Functional (because it describes changes, not to explain how changes happen)

<u>Conceptual model</u>

In Figure 5.1, the SOM model is mapped with a Forrester diagram (Grant & Swannack, 2007; Haefner, 2005). It is a visual representation used in system dynamics to illustrate the flow of measurable quantities and the variables that control them. Rectangles symbolize the state variable of the model. The driving, constant, and auxiliary variables are represented with circles and rhombuses.

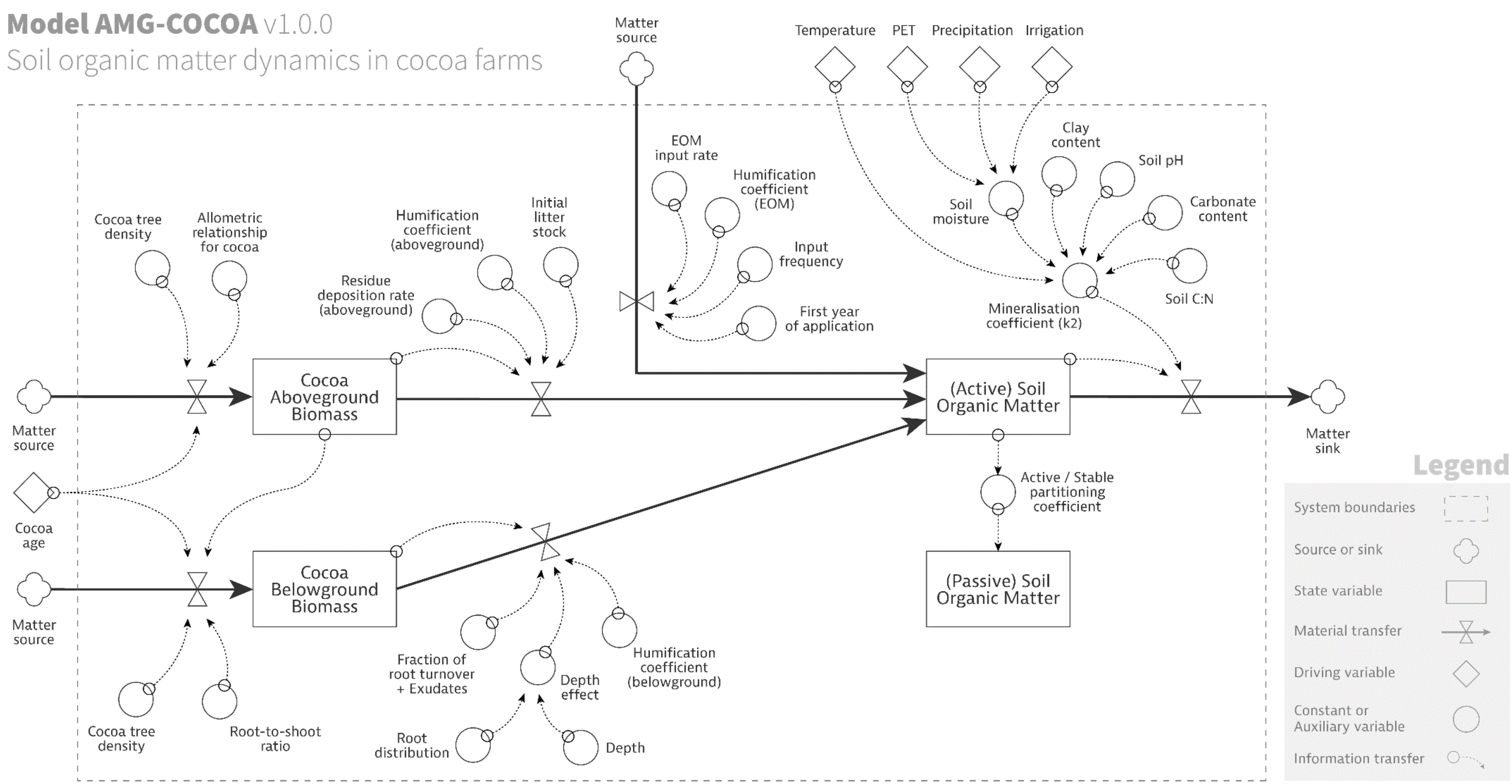

Figure 5.1: Forrester diagram representing the dynamics of soil organic matter (SOM) in cocoa farms

EOM stands for exogenous organic matter. PET stands for potential evapotranspiration.

Modelling choices and assumptions

The model makes several critical assumptions regarding the boundaries of the system of interest, as listed below. Most of them result in modelling limitations, which could be improved in future versions. Some of them are modelling choices, subjective decisions made during the model's development:

1. Cocoa growth is predicted by a static growth curve
2. Shade trees and other associated species are not considered
3. Constant cocoa tree density
4. Low resolution between the different types of residues (e.g., leaves and branches are bundled into one type)
5. Residue deposition rates are proportional to trunk diameter
6. Residues cannot last more than one year. No intermediate state between residues and SOM or loss
7. Material transfers of SOM (like erosion) out of the system are discounted
8. Use of the AMGv2 function to estimate SOM mineralisation rate

Validity domain

Given the limited size of the false-time chronosequence dataset, it was assumed the model to be only valid for Sulawesi or for cocoa farms cultivated under similar pedoclimatic conditions (see Table 5.3 for details about the local variables at each farm of the false-time chronosequence).

Time-wise, the model was assumed to provide acceptable predictions for 30-35 years since the growth curve was established for a 31-year false-time chronosequence. The evolution of cocoa growth or litterfall deposition rates beyond this term was ignored. Gathering more data from very old farms could help clarify what SOM dynamics beyond 35 years, but the usefulness of such an endeavour would be limited considering that old cocoa farms should have been rehabilitated by then.

Because the farm management approaches of the false-time chronosequence dataset differed (e.g., in terms of shade tree density and species used), a word of caution should be expressed regarding the applicability of the model to very different types of shade management. In addition, the current approach did not include shade trees as explicit contributors to SOM inputs. The model can be improved to consider a specific growth curve and plant deposition rates (aboveground and belowground), determined for each shade tree or associated species.

Expected behaviour

In cocoa farms established on freshly deforested lands or mature cocoa farms, SOM stocks are expected to decline first since fewer inputs come from the vegetation, while potential SOM mineralisation rates will remain relatively high (i.e., *outputs* > *inputs*). Over time an increase in the stock of SOM is expected because inputs will increase with the growth of the cocoa trees and could exceed outputs. The SOM stock may not return to pre-clearing levels in the long term if a sufficient long-term SOM management recovery plan does not compensate for the initial SOM losses. This hypothetical SOM trend was discussed in Chapter 4.

d. Mathematical description

Initialization

The initial stock ($SOM_{stock[t=0]}$; Mg ha^{-1}) is calculated by using the product of soil bulk density (BD; g cm^{-3}), sampling depth (d; cm) and initial SOM content ($SOM_{content[t=0]}$; %) with Equation **5.1** (multiplying by 100 to convert the result to Mg ha^{-1}). Then, the stock of passive SOM that will remain constant during the simulation is found by multiplying the initial stock of SOM with a split ratio (SOM_{split_ratio}; unitless) representing the estimated fraction of active SOM out of the total stock of SOM, as proposed in Clivot et al. (2019) with Equation 5.2. The total stock of SOM is simply the sum of active and passive SOM.

$$SOM_{stock[t=0]} = 100.BD.d.SOM_{content[t=0]} \quad \text{Equation 5.1}$$

$$SOM_{passive[t=0]} = (1 - SOM_{split\_ratio}).SOM_{stock[t=0]} \quad \text{Equation 5.2}$$

SOM balance equation

The model represents the variation of the stock of SOM per hectare ($SOM_{stock[t]}$; Mg ha^{-1}), resulting from the balance between yearly *inputs* and *outputs* (Equation 5.3). Soil organic matter inputs come from the aboveground and belowground pools of cocoa biomass and are added to the passive pool of SOM (respectively, $SOM\_in_{A[t]}$, $SOM\_in_{B[t]}$, $SOM_{passive}$). SOM outputs are applied to the active pool only and are equal to the SOM mineralisation coefficient k_2 (unitless) multiplied to the current stock of active SOM ($SOM_{active[t]}$). This balance is calculated each year to predict the stock of SOM of the following year (Equation **5.4**).

$$SOM_{stock[t+1]} = SOM_{stock[t]} + \left(inputs_{[t]} - outputs_{[t]}\right).\Delta t \quad \text{Equation 5.3}$$

$$SOM_{stock[t+1]} = SOM_{passive} + SOM_{active[t]} + SOM\_in_{A[t]} + SOM\_in_{B[t]} - SOM_{out[t]}$$ Equation 5.4

Cocoa growth, aboveground and belowground biomass

Cocoa tree growth is not well documented, as only a few studies have reported measurements (e.g., Asigbaase et al., 2021; Smiley, 2006; Smiley & Kroschel, 2008; see Chapter 2 for more information), with often limited timesteps. Thus, very few datasets are available to estimate or derive cocoa tree growth parameters. A three-step approach was followed to obtain a relationship linking age to the biomass present in the trees (see Chapter 4). First, the trunk diameters of cocoa trees in a 0.5 to 31-years long false-time chronosequence in Sulawesi were measured. Then, an allometric relationship (Smiley & Kroschel, 2008) was used to convert the trunk sizes into tree biomass stocks, above and belowground. Finally, a non-linear regression was performed on this dataset to obtain a pair of mathematical equations linking the age of the cocoa stand to its estimated biomass stocks (one equation for the aboveground biomass, one for the belowground biomass).

It should be noted that this relationship was developed in Sulawesi on thirteen slightly different farms (varying in terms of shade level, soil type, and other factors). One of the cocoa model's future major improvements is replacing it with a dynamic growth model responding to environmental conditions. It should be stressed that with this approach, the model does not take into account the effect of environmental factors: growth is purely time-correlated and should be parametrized with local measurements. Therefore, cocoa tree growth parameters should be estimated in other locations to apply the model in other areas.

The cocoa tree sub-model begins by calculating the aboveground and belowground biomass. The biomass in the two compartments depends on the planting density of the cocoa trees (D; tree ha^{-1}), age (t; years), and an allometric relationship linking age to biomass. A non-linear equation was used (Equation 5.5) to determine the relationships between cocoa tree age and aboveground biomass ($AGB_{[t]}$). Belowground biomass ($BGB_{[t]}$) is estimated by applying a cocoa root-to-shot ratio (*RSR*; unitless) to aboveground biomass (Equation 5.6).

$$AGB_{[t]} = D.\left(L_{max} - L_{max}.e^{(-GR.t)^{\delta}}\right)/1000$$ Equation 5.5

$$BGB_{[t]} = RSR.AGB_{[t]}$$ Equation 5.6

With the growth parameters:

- L_{max} : the maximum amount of biomass attainable by a cocoa tree (kg);
- GR : the growth rate of the cocoa trees (kg year^{-1});
- δ : shape parameter controlling the x-ordinate for the point of inflection of the growth curve (unitless).

<u>Aboveground and belowground inputs from plant biomass</u>

The method to calculate the inputs from the aboveground biomass reservoir differs from the belowground reservoir. In the following equations, subscript *A* refers to aboveground inputs and subscript *B* to belowground inputs.

Aboveground inputs

The approach described by AMG was simplified. For this model, fresh organic matter inputs are not explicitly individualized as a distinct reservoir because, at the end of each time step, annual organic matter inputs are directly converted into active SOM, and the remainder is leaving the system (i.e., the “non-humified” fraction is returned to the atmosphere). In other words, residue deposition and conversion to SOM are assumed to occur during the same year. This approach can also be modified in the future if it is judged that a significant pool of residues persists for more than one year.

Concerning residue deposition, the yearly amount of organic matter inputs is expected to increase with time and is relatively proportional to the total amount of cocoa biomass. Several studies have covered litterfall dynamic (e.g., Dawoe et al., 2010; Fassbender et al., 1988; Somarriba et al., 2013), but often with minimal time steps (e.g., 2, 5, 10 year-old cocoa, just like for cocoa growth measurements). To simplify, it was assumed here that yearly, a fixed percentage of the aboveground biomass is turned annually into residues (RDR_A; unitless). Following the logic of AMG, a fixed humification coefficient (k_{1A}; year^{-1}) was also used to estimate the fraction of aboveground inputs remaining as SOM after one year. The amount of SOM inputs coming from the aboveground reservoir of biomass ($SOM\_in_{A[t]}$; Mg ha^{-1}) is calculated by using Equation **5.7**.

$$SOM\_in_{A[t]} = k_{1A}.RDR_A.AGB_{[t]} \qquad \text{Equation 5.7}$$

Inputs due to pruning and exports due to harvest are not yet integrated into the model. As opposed to AMG, this model does not include a harvest removal coefficient. With AMG, this coefficient was introduced to study the effect of crop residue removal, as with straw removal for wheat or corn stalk removal. The harvest and removal of cocoa pods do not reduce cocoa biomass because the allometric equation predicts only the biomass of roots, branches, twigs, and leaves. There is, therefore, no reason to subtract harvest from tree biomass since pods are not accounted for.

Conversely, the return of cocoa pod husks can be simulated with the model and considered an EOM input. At this stage, the influence of pruning on residue deposition is ignored. A further improvement could include prunings, considering, for example, its frequency and intensity (percentage of biomass removed from the tree every n year).

Initial litter stock

With this model, none of the deposits of the current year will persist during the following year. This choice eliminates the existence of a litter reservoir since litter inputs are directly, either converted to SOM or lost atmospherically during the yearly timestep. However, it is possible to consider that a certain amount of litter ($Litter_{[t=0]}$; Mg ha^{-1}) is already present at planting. The SOM inputs from the initial litter stock are calculated during the first timestep by adding the litter stock to residues deposited the same year (Equation **5.8**).

$$SOM\_in_{A[t=1]} = k_{1A}.(RDR_A.AGB_{[t=1]} + Litter_{[t=0]}). \qquad \text{Equation 5.8}$$

Belowground inputs

Belowground contributions to SOM had to be adapted because, with the arable version of AMG, all the crop roots are left in the field as crop residue after harvest. With perennial crops like cocoa, roots remain in the ground, and therefore belowground inputs are not the result of a harvest but only of root turnover and the production of rhizodeposits. It was considered that belowground inputs come from two sources, the turnover of fine roots and the production of root exudates, as with the original AMG version.

Roots are often divided into categories according to their diameter. A common approach is to distinguish fine roots (≤ 2 mm) from coarse roots (> 2 mm), which may also be characterized by different productivity and turnover rates. The finer the roots, the more often they are renewed. Therefore, the fraction of belowground biomass occupied by fine and coarse roots was estimated (procedure explained in the following 5.2.2.e Parametrization section). An estimated annual turnover rate for fine roots was then used, assuming that coarse roots do not contribute to SOM inputs, corresponding to the fraction of fine roots annually converted to SOM. Inputs from fine roots are calculated as the product of belowground biomass (BGB; Mg ha^{-1}), the fine root fraction (FR_F; unitless), the annual turnover rate of fine roots (FR_{TOR}; unitless) as well as the humification coefficient specific to belowground biomass (k_{1B}; year^{-1}).

No references where found that quantified belowground inputs linked to cocoa root exudation and other belowground deposition processes unrelated to root turnover. The yearly production of root exudates is also estimated to be proportional to cocoa biomass. Values reported for other plants were used to estimate cocoa exudation (Jones et al., 2009; Kuzyakov & Domanski, 2000b; Kuzyakov & Schneckenberger, 2004; Pausch et al., 2013; Pausch & Kuzyakov, 2018). More specifically, a coefficient was used to estimate the relative contribution from root exudates associated with fine root biomass (E; year^{-1}). As with fine roots, SOM inputs coming from root exudation are calculated as the product of belowground biomass (BGB; Mg ha^{-1}), the fine root fraction (FR_F; unitless) and the annual exudation coefficient (E; year^{-1}), as well as the humification coefficient specific to belowground biomass (k_{1B}; year^{-1}).

Another factor addresses the fraction of cocoa root biomass found for the studied soil layer (adjustment used by Clivot et al., 2019, proposed by Gale & Grigal, 1987) and depends on the typical distribution of cocoa roots (D_{eff}; unitless) and the sampled depth (d; cm). This depth effect is calculated with Equation **5.9**.

$$D_{eff} = 1 - \beta^d \qquad \text{Equation 5.9}$$

Overall, belowground SOM inputs (SOM_in_B; Mg ha^{-1}) are calculated by using Equation **5.10**.

$$SOM\_in_{B[t]} = k_{1B}.FR_F.(E + FR_{TOR}).BGB_{[t]}.D_{eff} \qquad \text{Equation 5.10}$$

<u>Inputs of exogenous organic matter (EOM)</u>

The non-cocoa contribution to SOM from EOM (e.g., compost, manure, plant residues) follows the same logic as aboveground and belowground inputs. For each input, the contribution to SOM is equal to the product of the yearly application rate (on a dry mass basis; EOM_{rate} ; Mg ha^{-1} yr^{-1}) and the humification coefficient (EOM_{k1}; unitless) relative to the nature of the EOM input (SOM yield, one year after application), based on average reference values (e.g., 0.25 for fresh cattle manure, 0.40 for compost, 0.85-0.96 for peat; Clément & N'Dayegamiye, 2009). This coefficient can be determined through incubation experiments or estimated using the Van Soest biochemical fractionation method (Peltre, 2011). Each year, the inputs of SOM coming from EOM ($EOM\_in_{[t]}$) are calculated with Equation **5.11** and are added to the cocoa tree aboveground and belowground SOM inputs with Equation **5.12** (same as Equation **5.4** but includes EOM inputs).

$$EOM\_in_{[t]} = EOM_{rate} . EOM_{k1} \quad \text{Equation 5.11}$$

$$SOM_{stock[t+1]} = SOM_{passive} + SOM_{active[t]} + SOM\_in_{A[t]} + SOM\_in_{B[t]} + EOM\_in_{[t]} - SOM_{out[t]} \quad \text{Equation 5.12}$$

In the R program, the model also takes in the argument EOM_{freq} corresponding to the frequency of application of the EOM inputs every *n* year (e.g., "1" if EOM inputs are applied every year, "2" if they are applied every two years, and so on). It is also possible to delay the first application with another argument $EOM_{position}$ to indicate after how many years after planting the first application is made (e.g., "1" if the EOM is applied the first simulation years, "2" if inputs started only the second simulation year, and so on).

<u>SOM outputs by mineralisation</u>

The outputs of SOM are only controlled by the yearly rate of mineralisation of the active pool (referred to as k_2, as in the Hénin-Dupuis and AMG models). This rate is hardly measurable at a yearly scale or would require a considerable sampling effort because of the local heterogeneity of SOM contents. It usually takes several years or even decades to detect a significant change. Mineralisation rates are usually in the 0 to 7% range (a loss of 0-7% each year; (Morais et al., 2019)) but could be as high as 20 to 50% in the first years after deforestation in tropical climates (Dawoe et al., 2010; Mishra et al., 2021; Van Straaten et al., 2015). Several functions have been proposed to estimate k_2 from climate and soil data, although to the authors knowledge, none have as yet been applied to cocoa or calibrated in tropical regions (except Saffih-Hdadi & Mary, 2008, who used AMG with a long-term dataset from Thailand, but for cereal crops). It was decided to use version 2 of the AMG model, which includes six input variables to estimate k_2: soil moisture, temperature, pH, clay, carbonate content, and C:N ratio.

Yearly outputs of SOM (SOM_{out}) are determined by using the annual coefficient of mineralisation (k_2; unitless) applied to the current stock of active SOM (SOM_{act}; Mg ha^{-1}), with Equation **5.13**.

$$SOM_{out[t]} = k_2 . SOM_{act[t]} \quad \text{Equation 5.13}$$

SOM mineralisation rate

This annual mineralisation coefficient is estimated by applying rate modifying factors to a potential mineralisation rate (k_0). To each rate modifying factors correspond a function corresponding to the effect of temperature ($f(T)$), a proxy of soil moisture ($f(H)$, using annual precipitations P, potential evapotranspiration PET and irrigation water H as inputs), soil pH ($f(pH)$), soil C/N ratio ($f(C/N)$), and soil clay ($f(A)$) and carbonate contents ($f(CaCO_3)$). The pattern for each modifying function is illustrated in Figure A - 5.1 in appendix. For more information about the development of this equation and details about each function, refer to Clivot et al. (2019).

$$k_2 = k_0.f(T).f(H).f(A).f(CaCO3).f(pH).f(C/N) \quad \text{Equation 5.14}$$

With $k_0 = 0.290$ as the potential mineralisation rate per year.

e. Parametrization

Functional parameters

Functional parameters refer to model parameters that are independent of the local conditions of the cocoa farms. In theory, they remain the same for different cocoa farms, which will only differ in soil, climate, and management. Each functional parameter is listed in Table 5.2. The following sections will present the rationale behind each value.

Table 5.2: Summary of the default values used for each functional parameter

Functional parameter	Notation	Value	Unit	Source
Growth parameter (upper asymptote)	L_{max}	137.06	kg tree^{-1}	Chapter 4
Growth parameter (growth rate)	GR	0.1	kg tree^{-1} year^{-1}	Chapter 4
Growth parameter (shape parameter)	δ	1.09	unitless	Chapter 4
Root-to-shoot ratio	RSR	0.23	unitless	Borden et al. (2019)
Soil sampling depth	d	20	cm	Chapter 4
Root fraction in sampling depth (depth effect)	D_{eff}	0.8	unitless	Kummerow et al., (1982); Moser et al., (2010); Niether et al., (2019)
Cocoa root distribution parameter	β	0.923	unitless	Moser et al., (2010); Niether et al., (2019)
Fraction of aboveground biomass deposited annually	RDR_A	0.09	year^{-1}	Dawoe (2009); Dawoe et al. (2010)
Fine root fraction	FR_F	0.28	unitless	Rajab et al. (2016)
Annual fine root turnover rate	FR_{TOR}	0.985	year^{-1}	Muñoz & Beer (2001)
Root exudation coefficient	E	0.5	year^{-1}	Kuzyakov & Domanski, (2000); Kuzyakov & Schneckenberger (2004); Pausch et al. (2013)
SOM split ratio	SOM_{split}	0.4	unitless	Clivot et al. (2019)
Humification coefficient of aboveground residues	k_{1A}	0.21	year^{-1}	Dawoe (2009); Dawoe et al. (2010)
Humification coefficient of belowground residues	k_{1B}	0.39	year^{-1}	Clivot et al. (2019)
SOM mineralisation rate	k_2	(location dependent)	year^{-1}	Clivot et al. (2019)
Rate of application of organic inputs	EOM_{rate}	(scenario dependent)	Mg ha^{-1} year^{-1}	User choice
Humification rate of organic inputs	EOM_{k1}	(input dependent)	year^{-1}	Depends on the input
Frequency of application of organic inputs	EOM_{freq}	(scenario dependent)	year	User choice
First year of application after planting	$EOM_{position}$	(scenario dependent)	year	User choice

Relationship between cocoa age and biomass

Cocoa tree growth was modelled using a Weibull equation with the following parameters (see Chapter 4):

- The maximum amount of aboveground biomass that a cocoa tree can reach was set to 137.06 kg (upper asymptote parameter L_{max} of the Weibull growth model).
- The minimum amount of aboveground biomass of a cocoa tree was set to 0 kg (lower asymptote L_{min} parameter of the Weibull growth model).
- The growth rate of the aboveground biomass of a cocoa tree was set to 0.1 (parameter k of the Weibull growth model).
- The parameter controlling the curve inflection x-ordinate was set to 1.09 (parameter δ of the Weibull growth model).

Root-to-shoot ratio

Belowground biomass was calculated by multiplying the aboveground biomass with the average root-to-shoot ratio (RSR) found by Borden et al. (2019), equal to 0.23. The initial root-to-shoot ratio found in Chapter 3 was much higher (0.39). It was inferred after using the quotient of results obtained with the allometric equations proposed by Smiley & Kroschel (2008). As explained by Borden et al. (2019), an average ratio of 0.23 seemed more appropriate.

Sampling depth and distribution of cocoa roots

It was assumed that approximately 80% of the cocoa root mass was located in the top 0-20 cm of the soil profile (Moser et al., 2010; Niether et al., 2019). Using this estimation, it was possible to calculate the depth-distribution parameter for cocoa (see calculation with Equation **5.15** below).

$$D_{eff} = 1 - \beta^{d} \quad \text{Equation 5.15}$$

$$0.8 = 1 - \beta^{20}$$

$$\beta = 0.923$$

Aboveground residue deposition rate of cocoa trees

The annual deposition rate of aboveground residues RDR_A from cocoa trees is based on Dawoe et al. (2010), who used litter traps to assess monthly litterfall in Ghana. In their experiment, they measured the annual litterfall production of shaded cocoa tree stands. They also estimated cocoa tree biomass stocks with an allometric equation and the number of trees per hectare. Applying a linear regression between the tree biomass and annual litterfall ($R^2 = 0.98$) allows a strong relationship to be formulated between the two. However, cocoa and shade tree litterfalls were not discriminated against in their study, and the relative contribution of cocoa and shade trees to the annual production of litter could not be determined. It was decided to set this aboveground residue deposition rate to 0.06, meaning that 6% of the aboveground biomass is converted into surface litter every year. The reasoning and calculations are presented in appendix A.5. With this approach, inputs obtained from the aboveground biomass are not deducted from the stock. They are merely estimated from the aboveground biomass stock without resulting in a mass loss. It can be considered that this biomass deposition is uncaptured by the cocoa growth model at a yearly timescale (the allometric relationship does not capture the effect of litterfall and pruning). A future improvement of the model could be to make litterfall and pruning reduce aboveground biomass effectively, with an actual transfer of matter from the aboveground stock to the litter or SOM stock.

Fine root fraction, turnover, and exudation

Cocoa root biomass (fine and coarse roots), productivity, and turnover rates have been estimated by several authors (Borden et al., 2019; Kummerow et al., 1982; Moser et al., 2010; Muñoz & Beer, 2001; Niether et al., 2019; Rajab et al., 2016; Schneidewind et al., 2016). A short literature review presents their results in the appendix (appendix A.5). It was decided to divide the root system into two categories: fine roots (≤ 2 mm) and coarse roots (> 2 mm), determine the relative fraction of belowground biomass they represent (fixed percentage constant during the tree's lifetime) and their respective turnover rate.

Results obtained by Rajab et al. (2016) were used to estimate the fraction of fine roots FR_F at 0.28. They measured the fine roots biomass of cocoa and shade trees in three different types of cocoa farms (cocoa monoculture, cocoa-*Gliricidia*, cocoa-multispecies). Using a plot digitizer, the raw data was obtained from figure 2 and the average ratio of fine root biomass to belowground biomass calculated.

The fine-root annual turnover rates of shaded cocoa systems were evaluated by Muñoz & Beer (2001), who compared *Erythrina poeppigiana* or *Cordia alliodora* systems, and found values ranging from 0.90 to 1.07. They noted a strong seasonal effect, with higher turnover rates during the wet season (1.00 and 0.73 respectively) and lower during the dry season (0.07 and 0.17 respectively). It was decided to select an average fine root turnover rate FR_{TOR} of 0.985 ((0.90 + 1.07)/2).

The fraction of coarse roots would theoretically be $1 - FR_F = 1 - 0.28 = 0.72$. However, no turnover rate was found for coarse roots and it was therefore assumed that only fine roots would contribute to SOM inputs.

No references measuring the production of root exudates or rhizodeposition by cocoa trees were found. Research suggests that the net rhizodeposition-to-root ratios could be in the order of 0.25 to 0.5 (Kuzyakov & Domanski, 2000b; Kuzyakov & Schneckenberger, 2004; Pausch & Kuzyakov, 2018). With their definition, rhizodeposition does not entail root turnover, only the loss of production of organic compounds released in the soil. It was chosen to group all of these extra-root inputs into a single coefficient. In this model, the default root exudation coefficient was set to 0.5.

Humification coefficient of aboveground residues

The humification coefficient of aboveground residues k_{1a} was set to 0.21, using data from litterfall decomposition experiments from Ghana (Dawoe, 2009; Dawoe et al., 2010). In their study, Dawoe et al. found an average annual coefficient of decomposition k of 0.23 for cocoa litter. However, its meaning was not similar to the humification coefficient despite a similar notation (‘*k*’). Rearranging Olson’s equation (Olson, 1963), also used by Dawoe et al., it is possible to convert Olson’s *k* to AMG’s k_{1a}, the amount of remaining organic matter after one year (see Equation **5.16**).

$$k_{1a} = 1 - \frac{X}{X0} = 1 - e^{(-k.t)} \qquad \text{Equation 5.16}$$

$$k_{1a} = 1 - e^{-0.23 \times 1} = 1 - 0.79 = 0.21$$

With k_{1a} as the humification coefficient of cocoa litter (no unit), *X* as the amount of matter left after one year (Mg), *X0* as the initial amount of matter (Mg), *k* as Olson’s annual coefficient of decomposition (no units), and *t* the duration of the decomposition (one year). This value is relatively low compared to Olson’s estimations for tropical rainforests, which had a *k* of 4 (corresponding to a k_1 of 0.98), meaning that cocoa litter decomposes much slower than tropical rainforest litter.

Humification coefficient of belowground residues

The humification coefficient of belowground residues k_{1b} was set to 0.39. This value corresponds to the value used by Clivot et al. (2019).

Active and passive SOM split ratio

The fraction of active SOM over total SOM, SOM_{split} was fixed to 0.4, using the lower value of the range proposed by Clivot et al. (2019).

<u>Local variables</u>

Local variables refer to parameters specific to each cocoa farm. They include soil (e.g., soil pH and clay content), climate (e.g., annual rainfall and mean temperature), and management parameters (e.g., cocoa tree density per hectare). The local conditions of the baseline model were parametrized by using data collected from a false-time chronosequence of 13 cocoa farms located in Sulawesi (Chapter 4). Soil sampling depth was set at 20 cm. Each of the other local soil and climate variables was averaged from the dataset (excluding the forest plot of the series). Soil pH was not measured during this chronosequence study, but according to the SoilGrids database (Hengl et al., 2017), the sites' pH would be 4.95 and this value was used as a baseline for the simulation. On a previous study conducted in Bone-Bone (approximately 28 km from Tarengge and 180 km from the Mambu and Pussui farms), a soil pH of 4.7 was recorded, very close to the SoilGrids estimation. No soil carbonates data was available. Sulawesi does not seem to have Calcisols that could contain significant carbonate contents. Because the soils of Sulawesi are predominantly acidic and highly weathered (Suwardi, 2019), it was assumed the carbonate content to be null. Soil C:N ratio was set at 9.67 (average of the 13 farms). In terms of climate, the average annual precipitations was fixed to 2677 mm, the annual average air temperature at 27°C (average of the 13 farms, data obtained from WorldClim; Fick & Hijmans, 2017) and PET was 1728 mm (calculated with the Thronwaite equation and the SPEI R package; Beguería & Vicente-Serrano, n.d.). The cocoa farms were not irrigated (irrigation water = 0 mm). The planting density was fixed at 931 trees per hectare (average of 13 plots) and assumed no mortality over time.

Table 5.3: Summary of the local variables for each farm and the default values used for the model

Symbol	Location	Tarengge						
	Farm	**A**	**B**	**C**	**D**	**E**	**F**	**G**
	Age (years)	**0.5**	**1**	**2**	**5**	**7**	**12**	**15**
	Cocoa tree density (trees ha^{-1})	625	1100	800	625	625	1100	1100
	Mean annual temperature (°C)	27.1	27.1	27.1	27.1	27.2	27.1	27.1
	Mean annual cumulated rainfall (mm year^{-1})	2968	2978	2977	2968	2977	2978	2968
	Mean annual cumulated PET (mm year^{-1})	1741	1762	1754	1746	1764	1762	1746
	Water inputs from irrigation (mm year^{-1})	0	0	0	0	0	0	0
	Soil bulk density (g cm^{-3})	1.16	1.55	1.27	1.41	1.37	1.43	1.27
	Soil clay content (%)	24.6	18.8	18.8	21.4	23.0	19.6	22.6
	Soil carbonate content (%)	0	0	0	0	0	0	0
	Soil pH (unitless)	4.9	4.9	5.0	4.9	5.0	4.9	4.9
	Soil C/N (unitless)	10.5	9.1	10.2	10.3	9.7	8.6	10.1
	SOM content (%)	3.59	2.27	1.76	2.40	2.58	2.06	2.58
	Measured SOM stock (Mg ha^{-1}; 0-20 cm)	91.3	57.6	49.5	55.7	70.6	63.9	74.0
	SOM/clay (%/%)	0.146	0.121	0.094	0.112	0.112	0.105	0.114
	Initial litter stock (Mg ha^{-1})	NA	NA	NA	NA	NA	NA	NA

Symbol	Location	Mambu			Pussui			Average
	Farm	**H**	**I**	**J**	**K**	**L**	**M**	**(all farms)**
	Age (years)	**2**	**20**	**31**	**2**	**20**	**31**	**NA**
	Cocoa tree density (trees ha^{-1})	1100	1100	625	1100	1100	1100	931
	Mean annual temperature (°C)	27.1	27.1	27.1	26.4	26.7	26.7	27.0
	Mean annual cumulated rainfall (mm year^{-1})	2079	2066	2066	2083	2057	2057	2556
	Mean annual cumulated PET (mm year^{-1})	1756	1752	1752	1605	1662	1662	1728
	Water inputs from irrigation (mm year^{-1})	0	0	0	0	0	0	0
	Soil bulk density (g cm^{-3})	1.23	1.34	1.36	1.13	1.33	1.21	1.31
	Soil clay content (%)	34.3	15.9	19.8	43.9	31.1	33.4	25.2
	Soil carbonates (g kg^{-1})	0	0	0	0	0	0	0
	Soil pH (unitless)	5.1	4.9	4.9	5.0	5.0	5.0	4.95
	Soil C/N (unitless)	5.6	9.2	8.8	9.4	8.8	9.5	9.2
	SOM content (%)	2.57	1.66	1.94	4.04	2.92	3.30	2.59*
	Measured SOM stock (Mg ha^{-1}; 0-20 cm)	68.8	40.6	52.9	107.2	70.8	74.3	67.5
	SOM/clay (%/%)	0.075	0.104	0.098	0.092	0.094	0.099	0.110
	Initial litterstock (Mg ha^{-1})	NA	NA	NA	NA	NA	NA	1

Soil bulk density was obtained with core rings on the 0-5cm layer; Soil carbonates were assumed to be null because of the acid soil pH; SOM contents were obtained from loss-on-ignition and corrected for structural water loss using clay contents (see Chapter 3); NA stands for not applicable. * The initial SOM content and stock for the "average farm" was calculated using the average SOM/clay ratio of Farm A and B (the youngest two of the series).

5.2.3 Model evaluation

Model evaluation was performed through three analyses:

a. Regression analysis
b. Numerical sensitivity analysis
c. Graphical sensitivity analysis

a. Regression analysis

The first phase involved measuring performance by simulating with the default model values (using the average of all farms of the false-time chronosequence as inputs for the local variables, available in Table 5.3) and confronting the result to the observations. Overall, this first evaluation phase consisted of observing the model behaviour to see if the trend fits within the observed values and corresponds to the hypothesized dynamics presented in Chapter 3 (rapid decline followed by a slow recovery). To measure performance, the root mean square error (RMSE) was used. Because the local variable inputs correspond to an average “virtual” farm and since different conditions were observed in the 13 farms of the dataset, the simulation was expected to correspond to the hypothetical dynamics with an average result (*within the point cloud*).

b. Numerical sensitivity analysis

The following evaluation phase involved a numerical sensitivity analysis. Iteratively, a +10% change was applied to each functional parameter and a 35-year simulation run to assess the model’s output’s influence. An elasticity index was then calculated for each functional parameter by comparing the newly obtained final SOM stock to the final SOM obtained with the default parameters, using the approach followed by van der Werf et al. (2007). This elasticity index is calculated with Equation **5.17** and Equation **5.18**. The symbol FP stands for the functional parameter, $FP_{+10\%}$ refers to the functional parameter multiplied by 1.1, $SOM_{stock[t=35]FP}$ corresponds to the 35-year SOM stock with the standard parameter value, and $SOM_{stock[t=35]FP+10\%}$ refers to the 35-year SOM stock with the parameters with a +10% change.

$$Elasticity\ Index = \frac{\Delta Output/Output}{\Delta Parameter/Parameter}$$ Equation 5.17

$$Elasticity\ Index = \frac{(SOM_{stock[t=35]FP+10\%} - SOM_{stock[t=35]FP})/SOM_{stock[t=35]FP}}{(FP_{+10\%} - FP)/FP}$$ Equation 5.18

c. Graphical sensitivity analysis

Independent simulations were run with a range of values for each functional parameter and local variables during a final evaluation phase, reflecting potential ranges each could attain. A graph was produced for each parameter and variable to show how this range of potential values would influence the results. Thus, this sensitivity analysis was graphical (Grant & Swannack, 2007). Because the uncertainty for specific parameters can be great, running a range of possible values helps to increase understanding as to how strongly they could influence the output. For example, the split ratio between active and passive SOM is challenging to estimate and was only based on the proposition made by the developers of the original AMG model (Clivot et al., 2019). To observe the influence of different values, a set of four simulations were run with equidistant split ratios: 0.2, 0.4, 0.6, and 0.8. While a graphical analysis entails a certain level of subjectivity (i.e., when choosing the potential range of values for each parameter), it is necessary to observe the behavioural changes induced in the model's output. A graphical analysis completes the numerical analysis by revealing the trend before the final value (35-year SOM stock) is reached. Indeed, the elasticity index alone could mask significant variations occurring before the final value.

5.2.4 Model application

a. Reverse modelling

After completing the parametrization and evaluation of the model, a reverse modelling approach was used to simulate the trend occurring in each farm of the false-time chronosequence. The goal was to use the local conditions of each farm (and the default functional parameters values) and visualize the dynamics of SOM leading to the measured observations and the future trend. The main obstacle for this approach was that the initial stock of SOM present at planting was unknown. The solution was to use reverse modelling (also called backward modelling) to infer the initial SOM stock, given the current observed stock and the local variables of the plot as inputs.

In practice, the method was to iteratively run many simulations for a given farm using a range of possible initial SOM contents. A sequence of initial SOM contents starting from 0% to 10% in 0.01% increments was used as data input. From these simulations, the one that provided the closest match to the observed SOM stock was retained. It was thus possible to show what could have been the initial SOM content leading to the observations and continue the simulation up to 35 years to simulate the expected future trend.

b. Assessment of SOM dynamics

Information about the estimated initial and final SOM content, the minimum value reached between these start and end points (if any), and the corresponding farm age (equivalent to the moment where SOM inputs begin to exceed SOM output) were extracted. This age can be interpreted as the duration of a degradation phase during which SOM losses occur (Equation 5.19). SOM dynamics were evaluated using several metrics (see equations below in Table 5.4). For example, the initial trend in SOM change was assessed. Whether SOM stocks started to increase or decrease, the initial rate of change between the first two years of the simulation (Equation 5.25) was calculated. If SOM stocks started to decline, the average rate of change was calculated by calculating the slope between the initial stock and the attained minimum (Equation 5.27). The duration of this loss phase (Equation 5.19) and the amount of SOM lost in absolute and relative terms (quantity of SOM lost and percentage of the initial stock; Equation 5.21 and Equation 5.22) were reported. If SOM stocks showed an increase after a decline, the average recovery rate (calculated as the slope of the line between the minimum and the final years; Equation 5.26) was reported. The duration of this recovery phase, which is simply the difference between the total duration of the simulation and the duration of the degradation phase (Equation 5.20) was also recorded. Finally, the size of the gap between the initial SOM stock and the final one, which could be a positive or a negative change (Equation 5.23 and Equation 5.24), was also noted. As with the characterization of the SOM stock minimum, this gap was presented in absolute and relative terms (quantity and percentage; (Equation 5.21 and Equation 5.22).

Table 5.4: Criteria and corresponding formulas to evaluate SOM dynamics

Evaluation criteria	Calculation	Equation label
Duration of the degradation phase (year)	$Year_{SOM\ min}$	Equation 5.19
Duration of the build-up phase (year)	$Year_{final} - Year_{SOM\ min}$	Equation 5.20
Absolute loss at minimum ($Mg\ ha^{-1}$)	$SOM_{[t=0]} - SOM_{min}$	Equation 5.21
Relative loss at minimum (%)	$\frac{SOM_{[t=0]} - SOM_{min}}{SOM_{[t=0]}}$	Equation 5.22
Absolute final difference ($Mg\ ha^{-1}$)	$SOM_{final\ year} - SOM_{[t=0]}$	Equation 5.23
Relative final difference (%)	$\frac{SOM_{[t=0]} - SOM_{final\ year}}{SOM_{[t=0]}}$	Equation 5.24
Initial rate of change between year 0 and year 1 ($Mg\ ha^{-1}\ year^{-1}$)	$SOM_{[t=1]} - SOM_{[t=0]}$	Equation 5.25
Average gain rate during the build-up phase ($Mg\ ha^{-1}\ year^{-1}$)	$\frac{SOM_{final\ year} - SOM_{year\ min}}{Year_{final} - Year_{min}}$	Equation 5.26
Average loss rate during the degradation phase ($Mg\ ha^{-1}\ year^{-1}$)	$\frac{SOM_{min} - SOM_{[t=0]}}{Year_{min}}$	Equation 5.27

c. SOM maintenance scenarios with EOM inputs

The final modelling step consisted of simulating various SOM maintenance scenarios in order to determine which strategy would be necessary to limit the loss of SOM during cocoa cultivation (if losses occur). The approach was to offset yearly losses of the average farm (Table 5.3) by using a variable annual rate of input.

Using a single rate of inputs has the advantage of being simple but might not prevent some losses from occurring. Degradation may still occur during the early years after planting. Using a variable rate of inputs is a more complicated approach because the result is a series of input rates (35 input rates), but more powerful to prevent degradation by being responsive to year-to-year differences. Each approach would result in a net-zero loss of SOM after 35 years of cocoa cultivation but would have different practical implications regarding management and effects on soil properties and crop response.

Independent simulations were run for each type of EOM, and the parameters characterizing these SOM maintenance scenarios were: (1) the annual rate of input (Mg ha^{-1} yr^{-1} of dry matter), (2) the estimated coefficient of humification of each EOM, and (3) the type of approach followed (i.e., constant or variable rate of input). To limit the number of combinations, these scenarios were applied to only one 'model farm', namely the average farm presented in Table 5.3. To cover a sizeable range of humification coefficients, it was chosen to simulate five different EOMs, arranged in Table 5.5 by increasing k_1.

Table 5.5: List of EOMs and their approximate humification coefficient k_1.

EOM	Approximate k_1	Reference
Rice straw	0.10	Chabalier et al., 2006
Cattle manure	0.30	Chabalier et al., 2006
Goat manure	0.50	Montaigne et al., 2019
Rameal chipped wood	0.70	Montaigne et al., 2019
Biochar	1.00	Montaigne et al., 2019

Note that these values are approximative and may vary significantly for some EOMs. For example, values reported for cattle manure could range from 0.2 to 0.6 depending on the reference, which also made the distinction between straw-rich and straw-poor cattle manure.

5.3 Results

5.3.1 Model evaluation

a. Evaluation of the default run

The results of the simulation with default values for each parameter are presented in Figure 5.2. At 35 years, aboveground and belowground biomass are respectively around 125 and 29 Mg ha^{-1} (Figure 5.2A). Plant SOM inputs followed the same growth type as cocoa biomass: a logarithmic-like growth, quickly increasing at the beginning but slowing down as time goes on (Figure 5.2A & Figure 5.2B). The yearly outputs of SOM, beginning by being high (about 5 Mg ha^{-1} year^{-1}), rapidly decline to reach a minimum at approximately eight years (about 5 Mg ha^{-1} year^{-1}), to finally almost linearly increase up to levels comparable to the initial one (about 5.4 Mg ha^{-1} year^{-1}). As a reference, the annual SOM mineralisation coefficient (k_2) is estimated to be 0.125 for the model farm, meaning that each year, SOM losses can reach 12.5% of the SOM stock if they are not compensated for by inputs. Inputs become higher than outputs at eight years (Figure 5.2B). Mechanically, the stock of SOM follows the variations of inputs and outputs (Figure 5.2C). During the first eight years, outputs are higher than inputs, and therefore the SOM stock rapidly decreases from approximately 68 Mg ha^{-1} down to 51 Mg ha^{-1}. After eight years, the stock slowly increases since SOM inputs are higher than outputs. The final stock of SOM at 35 years is close to 70 Mg ha^{-1}, meaning that with this simulation, the long-term SOM dynamics led to slight SOM gains. Comparing observed and predicted SOM stocks shows that the simulation is relatively accurate (Figure 5.2D), but because the variation between the farm is significant (Figure 5.2C), so makes the error of the model (RMSE = 19.12 Mg ha^{-1}).

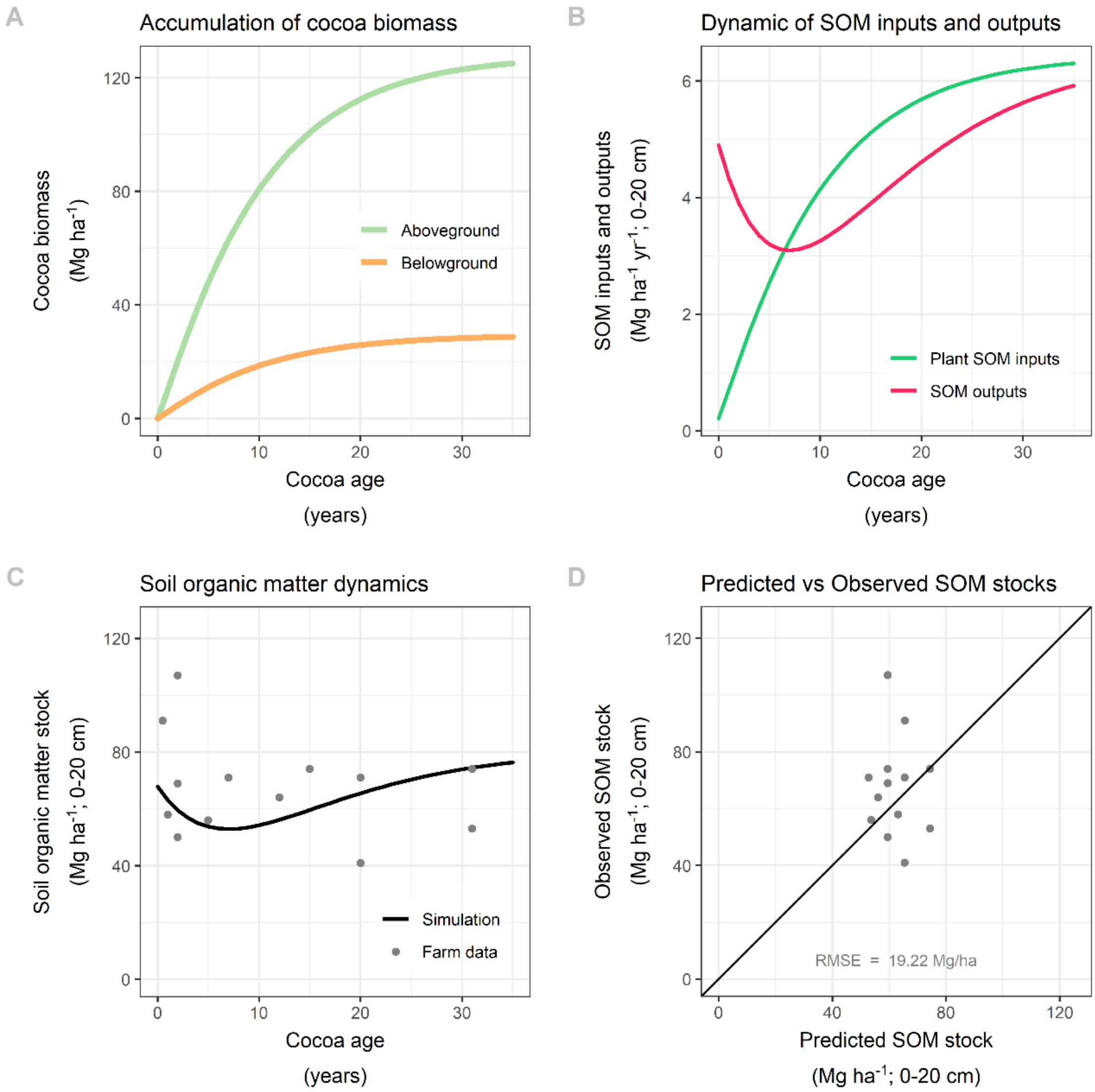

Figure 5.2: Results of the baseline simulation with default values

Note on the subplot D that the predicted SOM value for the 6-months-old Farm C was interpolated as the mean of the predicted stocks at year 0 and year 1 (predicted SOM stock = 65.52 Mg ha^{-1}) because the model only works at a yearly time step.

b. Elasticity indices

Raking the elasticity of each functional parameter showed that the cocoa root biomass distribution parameter had the most influence on the results after a 10% increase (Table 5.6). Mathematically, this parameter is raised to the exponent of soil sampling depth. A slight change will, therefore, be amplified to the power 20 in this case. A cocoa root distribution parameter of 1.0153 has no ground in reality because it would lead the fraction of roots present in the 0-20 cm layer to be negative (-35%). While all functional parameters are used in some way to multiply a variable to obtain a new value, the root distribution parameter is the only one raised to a power higher than 1. Thus, the other functional parameters are more comparable in terms of elasticity. Apart from sampling depth, the parameter that influenced the final result the most was the value of the upper asymptote used for the cocoa growth model. Increasing the potentially attainable cocoa tree biomass by 10% led to the largest change in final SOM stock (approximately +5 Mg ha^{-1} of SOM). The parameter with the least influence on the result was the root exudation coefficient (only approximately +0.5 Mg ha^{-1} of SOM). Apart from the cocoa root distribution parameter, each increase in the other functional parameters led to an enlargement of the final SOM stock.

Table 5.6: Data used to calculate elasticity indices for each functional parameter.

Parameter	Symbol	Baseline value (BV)	BV+10%	Final SOM stock using BV	Final SOM stock using BV+10%	Elasticity index	Rank (absolute value)
Cocoa root distribution parameter (unitless)[a]	β	0.923	1.0153	76.36	34.8	-5.44[a]	1
Growth parameter (upper asymptote; kg tree^{-1})	d	137.06	150.766	76.36	81.06	0.62	2
Soil sampling depth (cm)	d	20	22	76.36	80.2	0.5	3
Fraction of roots in the 0-20 cm layer (unitless)[b]	L_{max}	0.8	0.88	76.36	79.33	0.39[b]	4
Root-to-shoot ratio (unitless)	D_{eff}	0.23	0.253	76.36	79.24	0.38	5
Fine root fraction (unitless)	SOM_{split}	0.28	0.308	76.36	79.24	0.38	6
Humification coefficient of belowground residues (year^{-1})	RSR	0.39	0.429	76.36	79.24	0.38	7
SOM split ratio (unitless)	FR_F	0.4	0.44	76.36	79.05	0.35	8
Humification coefficient of aboveground residues (year^{-1})	k_{1B}	0.21	0.231	76.36	78.36	0.26	9
Annual fine root turnover rate (year^{-1})	k_{1A}	0.985	1.0835	76.36	78.27	0.25	10
Fraction of aboveground biomass deposited annually (year^{-1})	FR_{TOR}	0.09	0.099	76.36	78.19	0.24	11
Root exudation coefficient (year^{-1})	RDR_A	0.5	0.55	76.36	77.33	0.13	12
Growth parameter (growth rate; kg tree^{-1} year^{-1})	GR	0.1	0.11	76.36	77.13	0.1	13
Growth parameter (shape parameter; unitless)	δ	1.09	1.199	76.36	76.99	0.08	14

[a] Note that applying a 10% increase to the root distribution parameter β was not mathematically sound as it led to negative belowground biomass, hence the resulting extreme elasticity index. Instead, the effect of increasing the fraction of roots present in the 0-20 cm by 10% was calculated (88% instead of 80%), highlighted with [b].

Among the local variables, a 10% increase in cocoa tree planting density led to the largest increase in final SOM stock (+4.7 Mg ha^{-1}). The local variable with the strongest influence on the final result after a 10% increase was the soil pH from pH 4.95 to pH 5.445 (-14 Mg ha^{-1}). This could be attributed to its logarithmic nature and the way the modifying factor is set by AMG (**Error! Reference source not found.**). Apart from mean annual temperature and soil C/N, increasing all the other local variables by 10% led to augmenting the final SOM stock. Changes in local variables predominantly resulted in larger differences than functional parameters. A 10% increase in rainfall, PET and irrigation barely affected the result.

Table 5.7: Data used to calculate elasticity indices for each local variable

Parameter	Baseline value (BV)	BV+10%	Final SOM stock using BV	Final SOM stock using BV+10%	Elasticity index	Rank (absolute value)
Soil pH (unitless)	4.95	5.445	76.36	62.34	-1.84	1
Mean annual temperature (°C)	27	29.7	76.36	65.71	-1.39	2
Soil C/N (unitless)	9.2	10.12	76.36	71.53	-0.63	3
Cocoa tree density (trees ha^{-1})	931	1024.1	76.36	81.06	0.62	4
Soil clay content (%)	252	277.2	76.36	79.18	0.37	5
Soil bulk density (g cm^{-3})	1.31	1.441	76.36	79.12	0.36	6
Initial SOM content (%)	2.59	2.849	76.36	79.12	0.36	7
Soil carbonate content (%)	10	11	76.36	77.01	0.09	8
Initial litterstock (Mg ha^{-1})	1.00	1.1	76.36	76.53	0.02	9
Mean annual cumulated rainfall (mm year^{-1})	2556	2811.6	76.36	76.35	0	10
Mean annual cumulated PET (mm year^{-1})	1728	1900.8	76.36	76.39	0	11
Water inputs from irrigation (mm year^{-1})	100	110	76.36	76.37	0	12

Note: Because the default model assumed that carbonate content and irrigation inputs were null, the baseline values were respectively changed to 10% $CaCO_3$ and 100 mm of irrigation water inputs.

c. Graphical sensitivity analysis

Observing the 24 graphs corresponding to the 24 parameters of the model (12 functional parameters in Figure 5.3 and Figure 5.4 and 12 local variables in Figure 5.5 and Figure 5.6) indicates that some variables have a similar influence on the output. For example, the fraction of aboveground residues, the root-to-shoot ratio, the humification coefficients and the cocoa tree planting density all control how large plant SOM inputs can be. They show similar patterns, with an initial decline during the early years, whatever their value is, followed by an increase for which the slope can be flat or steep depending on their value. This behaviour suggests that a SOM stock decline may be inevitable during the early years because plant inputs will be too low to offset the losses. However, the long-term trend can be anything between a very slow and/or rapid accumulation. With the values used in this subjective analysis, no systematic decline is observed. For some parameters, the effect on SOM dynamics was more complex than varying the rate at which SOM build-up in the long term. For instance, changing the initial SOM content shows that the SOM stock can largely increase with a low starting SOM content (1%), whereas the SOM stock can largely decrease when starting with a high initial SOM content (5%). Comparing the humification rate of aboveground and belowground residues indicates that aboveground residues play a larger role in increasing SOM stock than roots because a larger mass is deposited every year. When examining the local variables, it can be noticed that some have a much larger effect on the SOM stock than others. For example, increasing PET leads to significant gains in SOM stocks, while large increases in rainfall have almost no effect.

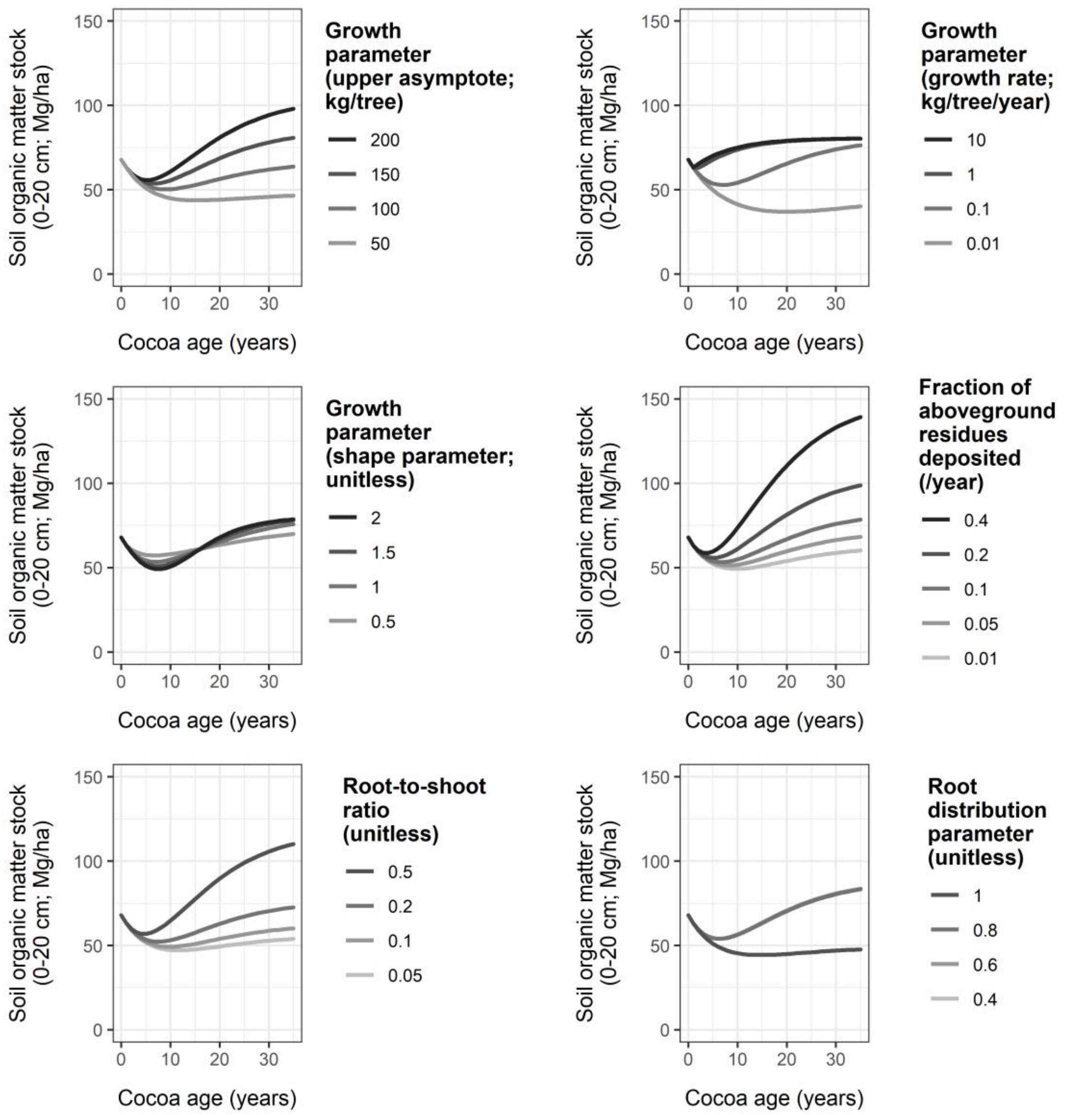

Figure 5.3: Graphical sensitivity analysis of the model parameters (functional parameters 1/2)

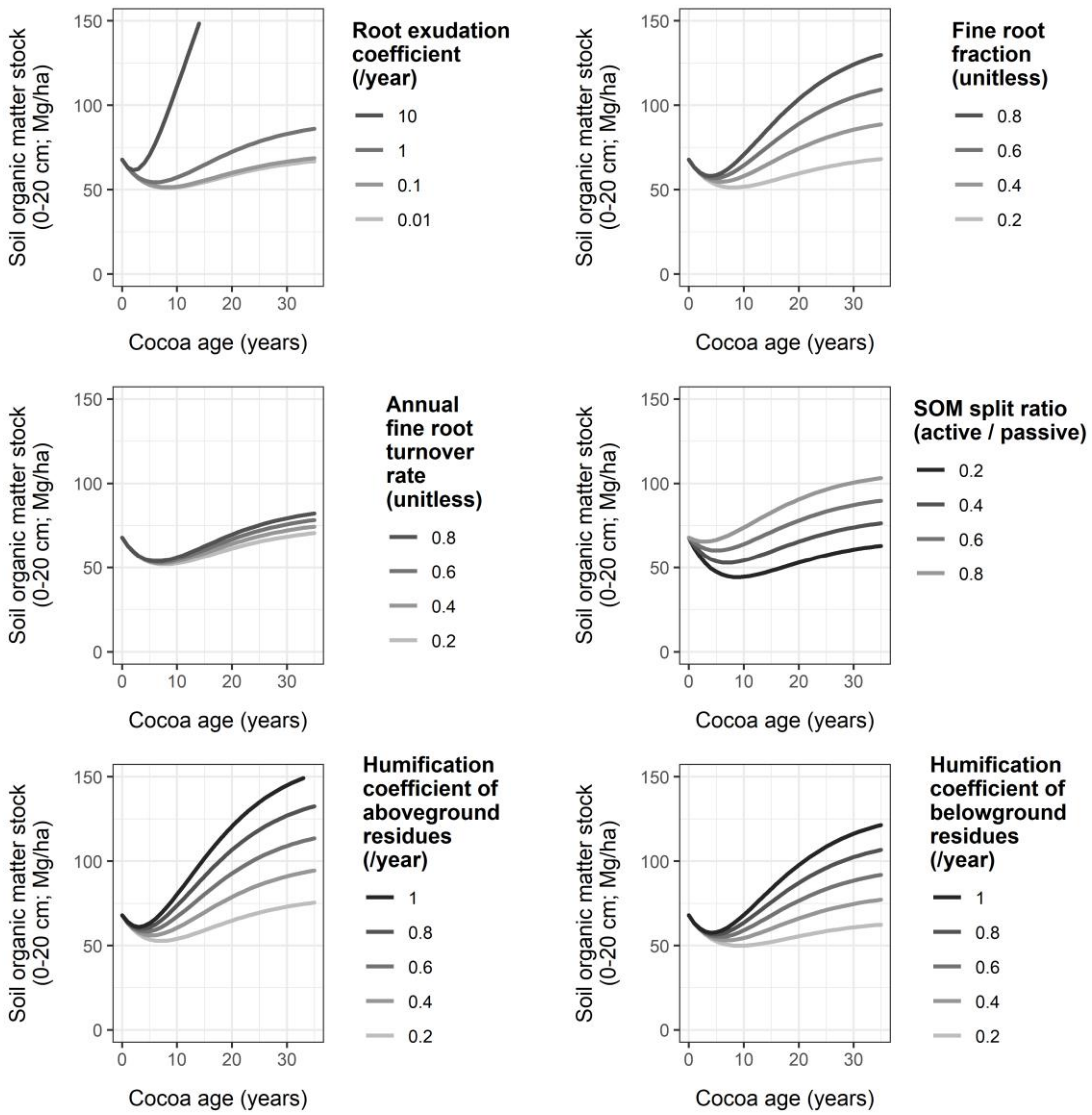

Figure 5.4: Graphical sensitivity analysis of the model parameters (functional parameters 2/2)

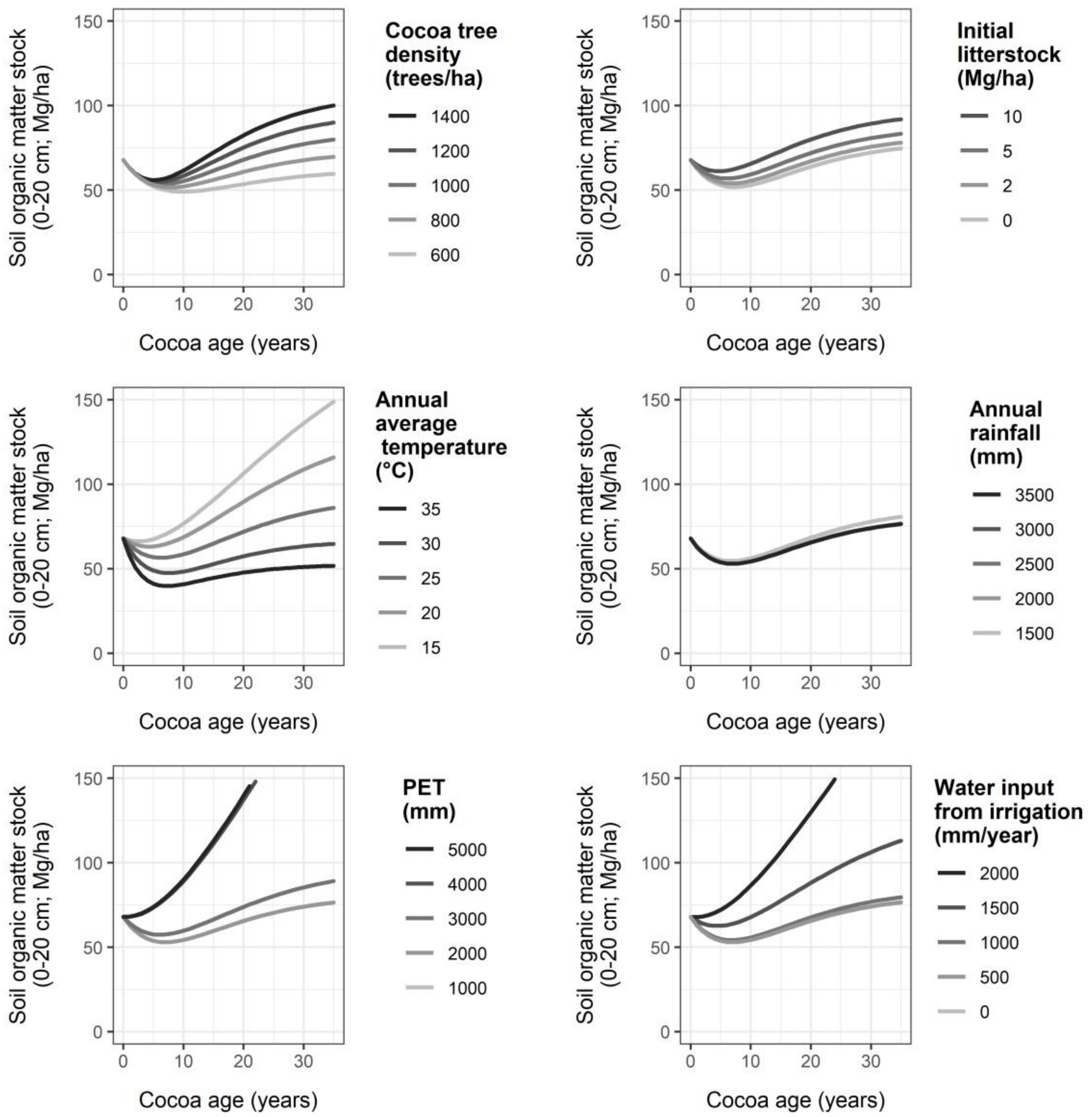

Figure 5.5: Graphical sensitivity analysis of the model parameters (local variables 1/2)

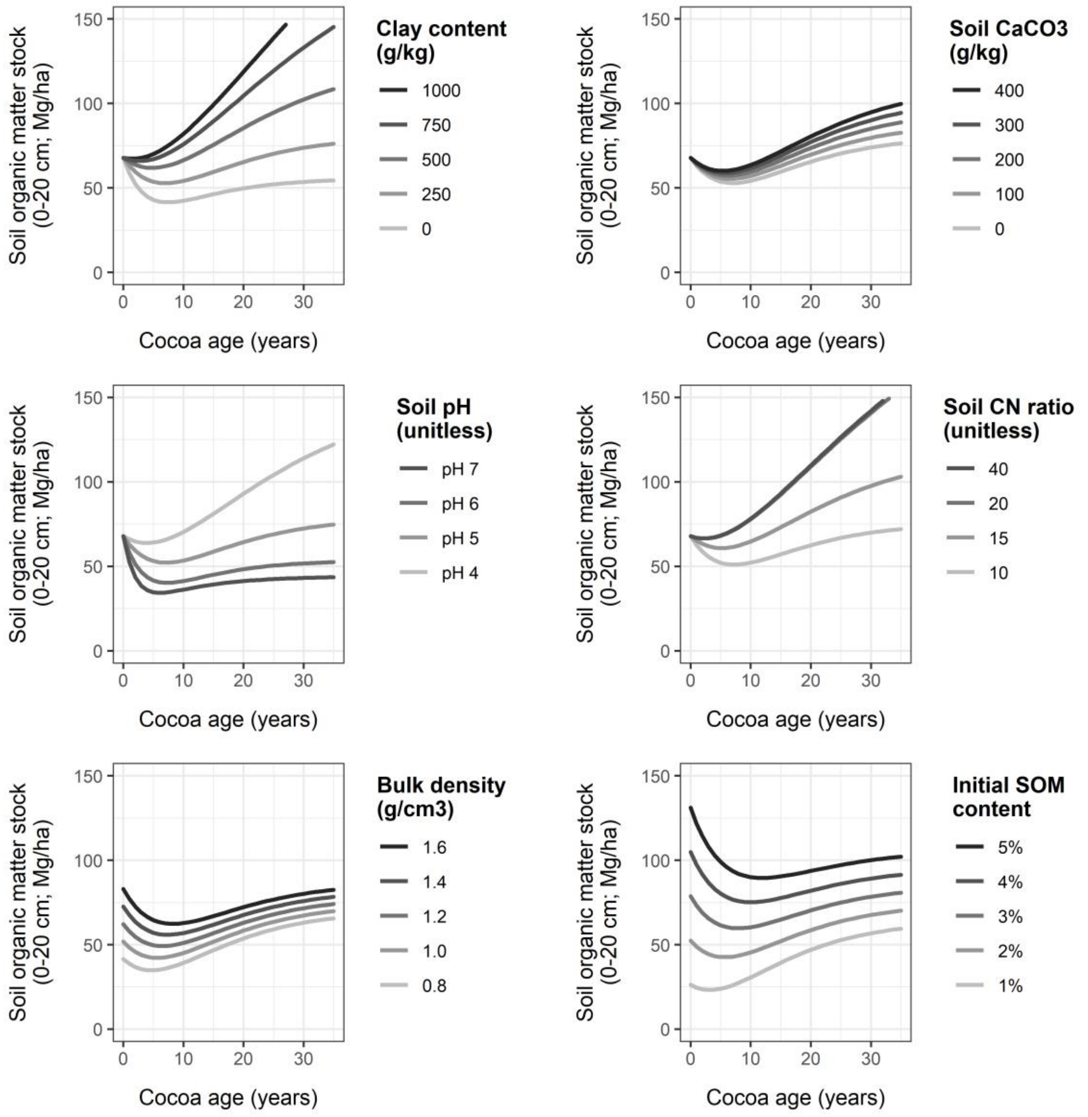

Figure 5.6: Graphical sensitivity analysis of the model parameters (local variables 2/2)

5.3.2 Model application

a. Simulation of each farm with reverse modelling and assessment of SOM dynamics

Reverse modelling SOM dynamics for each cocoa farm of the dataset indicate that all of them exhibit the same "rapid decline followed by a long-term build-up " pattern. A sample of four visualizations is available in Figure 5.7. No case where SOM dynamics would continually increase or decrease over time was observed. The lengths of the degradation phase (period of SOM loss) ranged from 2 to 14 years over the 35-year simulation. The decline between the initial and the minimum SOM stocks ranged from −7.9% and −38.8%, respectively attained after 2 and 14 years. In the long term, only 4 out of the 12 farms displayed final SOM stocks lower than the initial ones (farms C, D, E, and J). In relative terms, the difference between the initial and the final SOM stocks ranged from −33.4% to +378.3% (respectively farms E and I). The largest gains occurred in the farm with the lowest predicted initial SOM content. However, the opposite was not true. The largest loss (farm E) did not occur in the farm with the highest initial SOM content (farm K). The highest initial loss rate was −9.2 Mg ha^{-1} $year^{-1}$ (farm E). The average loss rates during the degradation phase ranged from −3.1 to −0.4 Mg ha^{-1} $year^{-1}$, whereas the average gain rates during the build-up phase ranged from +0.3 to +1.6 Mg ha^{-1} $year^{-1}$.

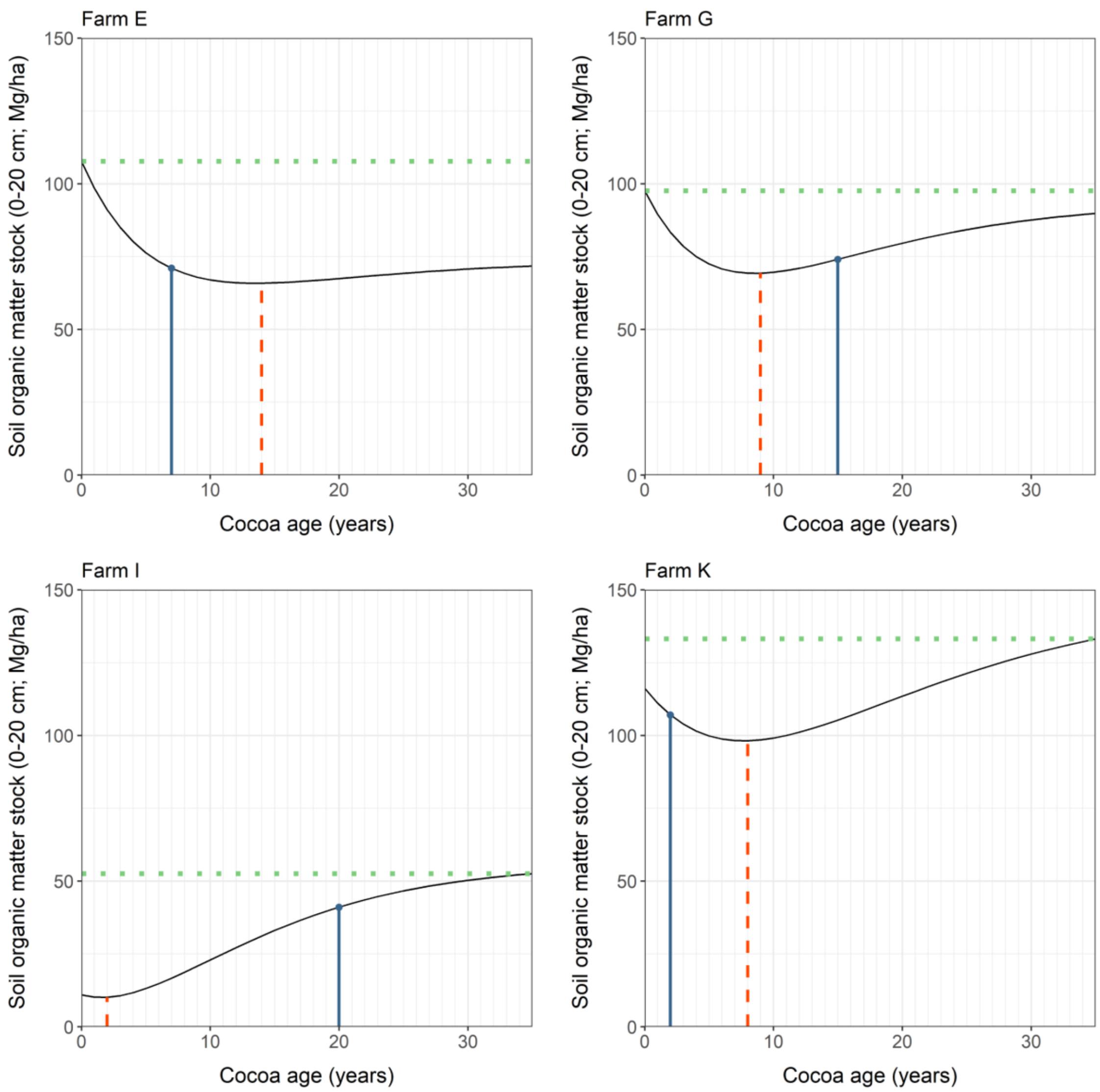

Figure 5.7: Example of SOM dynamics obtained by reverse modelling

The simulated farm was farm E, G, I and K. The black line represents the simulated SOM dynamics. The blue dot represents the SOM stock measurement obtained for the farm. The vertical blue line shows the age at which this observation obtained. The vertical orange dashed line represents the age when a minimum is reached. The horizontal green dotted line is aligned with the maximal SOM stock. For example, for farm I, the simulation suggests that the initial SOM stock was approximately 53 Mg ha^{-1} (0-20 cm). The minimum was reached at 2 years (approximately 10 Mg ha^{-1}).

Table 5.8: Characteristics of the SOM dynamics of each farm of the dataset

Location	**Tarengge**	**Tarengge**	**Tarengge**	**Tarengge**	**Tarengge**	**Tarengge**
Farm	**B**	**C**	**D**	**E**	**F**	**G**
Age	**1**	**2**	**5**	**7**	**12**	**15**
Bulk density ($g\ cm^{-3}$)	1.55	1.27	1.41	1.37	1.43	1.27
Observed SOM content (% ±SE)	2.27 ±0.29	1.76 ±0.24	2.4 ±0.56	2.58 ±0.26	2.06 ±0.14	2.58 ±0.04
Simulation						
Predicted initial SOM content (%)	2.03	2.38	2.77	3.93	2.67	3.84
Predicted minimum SOM content (%)	1.58	1.63	1.81	2.40	2.09	2.73
Predicted final SOM content (%)	2.49	2.19	2.11	2.62	3.09	3.53
Predicted initial SOM stock ($Mg\ ha^{-1}$)	62.9	60.5	78.1	107.7	76.4	97.5
Predicted minimum SOM stock ($Mg\ ha^{-1}$)	49.0	41.5	51.0	65.9	59.8	69.3
Predicted final SOM stock ($Mg\ ha^{-1}$)	77.3	55.5	59.4	71.8	88.2	89.8
Evaluation criteria						
Duration of the degradation phase (years)	6	8	11	14	7	9
Duration of the build-up phase (years)	29	27	24	21	28	26
Absolute loss at minimum ($Mg\ ha^{-1}$)	-13.9	-19.0	-27.1	-41.8	-16.6	-28.3
Relative loss at minimum (%)	-22.1%	-31.4%	-34.7%	-38.8%	-21.7%	-29.0%
Absolute final difference ($Mg\ ha^{-1}$)	+14.4	-4.9	-18.7	-35.9	+11.9	-7.8
Relative final difference (%)	+22.9%	-8.1%	-23.9%	-33.4%	+15.5%	-8.0%
Initial rate of change between year 0 and year 1 ($Mg\ ha^{-1}\ year^{-1}$)	-4.9	-5.9	-6.7	-9.1	-5.3	-7.9
Average loss rate during the degradation phase ($Mg\ ha^{-1}\ year^{-1}$)	-2.3	-2.4	-2.5	-3	-2.4	-3.1
Average gain rate during the build-up phase ($Mg\ ha^{-1}\ year^{-1}$)	+1.0	+0.5	+0.3	+0.3	+1.0	+0.8

(Table 5.8 **continued)**

Location	**Mambu**	**Mambu**	**Mambu**	**Pussui**	**Pussui**	**Pussui**
Farm	**H**	**I**	**J**	**K**	**L**	**M**
Age	**2**	**20**	**31**	**2**	**20**	**31**
Bulk density ($g\ cm^{-3}$)	1.23	1.34	1.36	1.13	1.33	1.21
Observed SOM content (% ±SE)	2.57 ±0.23	1.66 ±0.41	1.94 ±0.16	4.04 ±0.37	2.92 ±1.24	3.3 ±0.91
Simulation						
Predicted initial SOM content (%)	3.21	0.41	1.94	5.14	1.94	1.18
Predicted minimum SOM content (%)	2.48	0.38	1.47	4.34	1.70	1.08
Predicted final SOM content (%)	3.59	1.96	1.99	5.89	3.36	3.19
Predicted initial SOM stock ($Mg\ ha^{-1}$)	79.0	11.0	52.8	116.2	51.6	28.6
Predicted minimum SOM stock ($Mg\ ha^{-1}$)	61.1	10.2	43.9	98.2	45.1	26.1
Predicted final SOM stock ($Mg\ ha^{-1}$)	88.3	52.6	54.1	133.1	89.4	77.3
Evaluation criteria						
Duration of the degradation phase (years)	7	2	8	8	4	3
Duration of the build-up phase (years)	28	33	27	27	31	32
Absolute loss at minimum ($Mg\ ha^{-1}$)	-17.9	-0.8	-12.7	-18.0	-6.5	-2.5
Relative loss at minimum (%)	-22.7%	-7.9%	-24.0%	-15.5%	-12.5%	-8.7%
Absolute final difference ($Mg\ ha^{-1}$)	+9.8	+41.6	+1.4	+16.9	+37.8	+48.7
Relative final difference (%)	+11.8%	+378.3%	+2.6%	+14.6%	+73.2%	+170.6%
Initial rate of change between year 0 and year 1 ($Mg\ ha^{-1}\ year^{-1}$)	-5.6	-0.8	-3.7	-5	-2.8	-1.5
Average loss rate during the degradation phase ($Mg\ ha^{-1}\ year^{-1}$)	-2.6	-0.4	-1.6	-2.3	-1.6	-0.8
Average gain rate during the build-up phase ($Mg\ ha^{-1}\ year^{-1}$)	+1.0	+1.3	+0.5	+1.3	+1.4	+1.6

Note that farm A was not simulated because it was six months old. Since the model has a yearly time step, it cannot predict SOM dynamics for this age.

b. SOM maintenance scenarios with EOM inputs

The summary of the yearly rates of inputs needed to compensate for the SOM losses of the model farm of the dataset (Table 5.3) are presented in Table 5.9 and Figure 5.8, using five different types of EOMs. As expected, the input with the higher humification coefficient will require lower rates of inputs to prevent SOM decline. Using biochar (with a k_1 hypothetically equal to 1), approximately 29 Mg ha^{-1} would be required to offset the loss over the entire course of the 35 years of cultivation. Conversely, ten times more rice straw (with a k_1 hypothetically equal to 0.1), 286 Mg ha^{-1} would be necessary to achieve the same result. In all cases, no inputs would be required from 14 years onwards as this period corresponds to the time where plant SOM inputs exceed the annual SOM losses, independently of the EOM type (Figure 5.8).

Table 5.9: Predicted rate of inputs from 0 to 35 years to compensate SOM losses for five types of EOM

Year	Annual rate of inputs (Mg ha^{-1} year^{-1})				
	EOM_{k1} = 0.1	EOM_{k1} = 0.3	EOM_{k1} = 0.5	EOM_{k1} = 0.7	EOM_{k1}= 1
0	46.86	15.62	9.37	6.69	4.69
1	42.01	14.00	8.40	6.00	4.20
2	36.99	12.33	7.40	5.28	3.70
3	32.20	10.73	6.44	4.60	3.22
4	27.72	9.24	5.54	3.96	2.77
5	23.58	7.86	4.72	3.37	2.36
6	19.77	6.59	3.95	2.82	1.98
7	16.28	5.43	3.26	2.33	1.63
8	13.10	4.37	2.62	1.87	1.31
9	10.21	3.40	2.04	1.46	1.02
10	7.59	2.53	1.52	1.08	0.76
11	5.22	1.74	1.04	0.75	0.52
12	3.08	1.03	0.62	0.44	0.31
13	1.15	0.38	0.23	0.16	0.12
14	0.00	0.00	0.00	0.00	0.00
15	0.00	0.00	0.00	0.00	0.00
16	0.00	0.00	0.00	0.00	0.00
17	0.00	0.00	0.00	0.00	0.00
18	0.00	0.00	0.00	0.00	0.00
19	0.00	0.00	0.00	0.00	0.00
20	0.00	0.00	0.00	0.00	0.00
21	0.00	0.00	0.00	0.00	0.00
22	0.00	0.00	0.00	0.00	0.00
23	0.00	0.00	0.00	0.00	0.00
24	0.00	0.00	0.00	0.00	0.00
25	0.00	0.00	0.00	0.00	0.00
26	0.00	0.00	0.00	0.00	0.00
27	0.00	0.00	0.00	0.00	0.00
28	0.00	0.00	0.00	0.00	0.00
29	0.00	0.00	0.00	0.00	0.00
30	0.00	0.00	0.00	0.00	0.00
31	0.00	0.00	0.00	0.00	0.00
32	0.00	0.00	0.00	0.00	0.00
33	0.00	0.00	0.00	0.00	0.00
34	0.00	0.00	0.00	0.00	0.00
35	0.00	0.00	0.00	0.00	0.00
Total	**285.76**	**95.25**	**57.15**	**40.81**	**28.59**

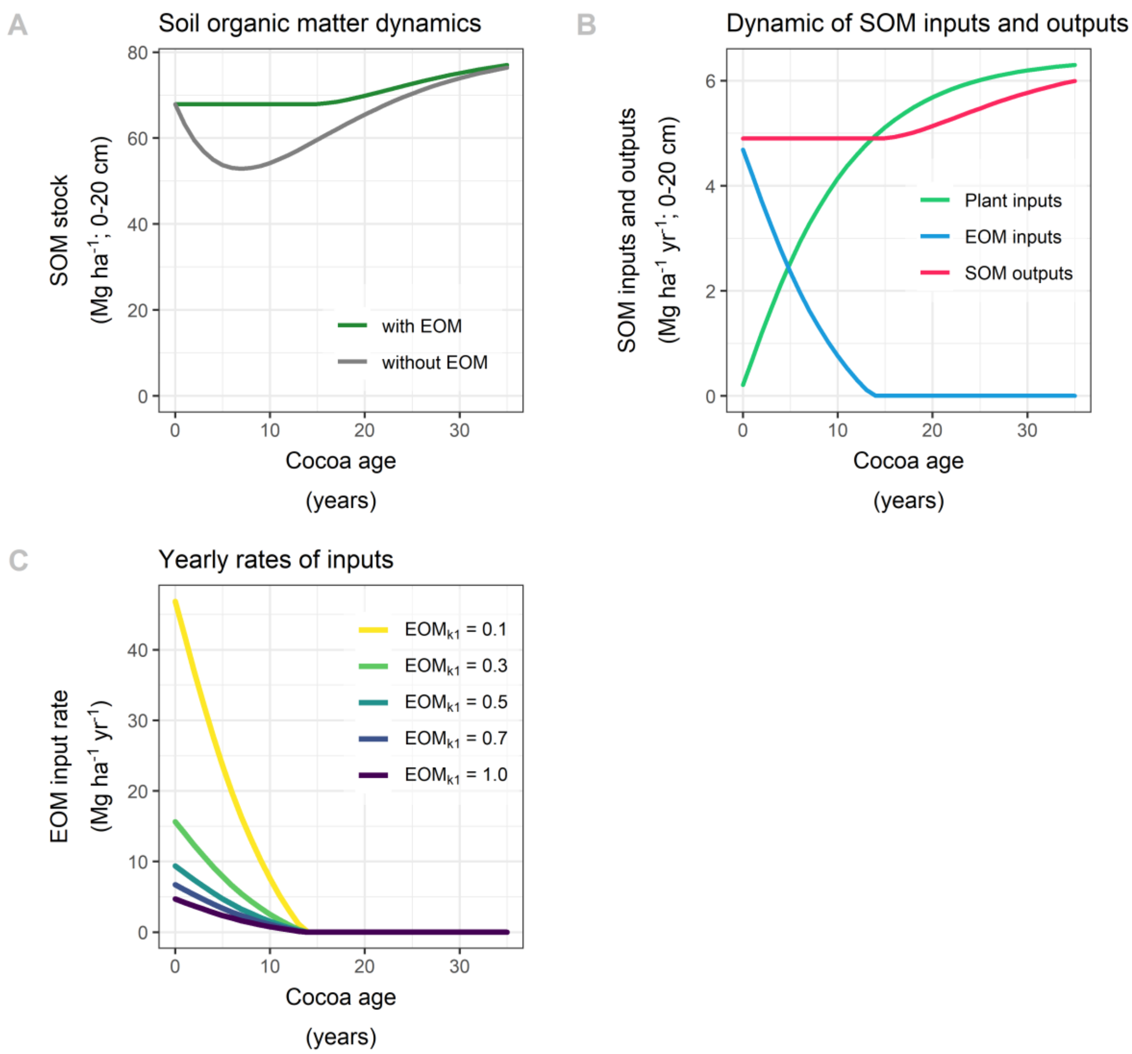

Figure 5.8: Modelled effects of cocoa age and exogenous organic matter (EOM) on A) soil organic matter (SOM) stocks, B) SOM inputs and outputs, and C) EOM yearly input rates

Note on subplot B: Whatever the EOM input is, the blue line indicates the amount of SOM necessary to balance SOM outputs (red line) with plant SOM inputs (green line). Dividing this rate of SOM input from EOM by the k_1 coefficient respective to the EOM of interest can provide the effective amount of EOM needed meet those inputs. For example, if 2 Mg ha^{-1} of SOM inputs are needed from an EOM (of k_1 = 0.2) to offset SOM losses, 10 Mg ha^{-1} of this EOM will be needed the preceding year (2 / 0.2 = 10).

5.4 Discussion

5.4.1 Summary of the main findings

Overall, the SOM trend obtained by running the model with default values matched the theoretical dynamic presented in Chapter 4. The results indicate that SOM stocks rapidly declined during a first phase (1 – 14 years) before slowly building up during a second phase (14 – 35 years). This dynamic was the case for the baseline simulation and the trends obtained with reverse modelling for each farm of the dataset. The baseline simulation was relatively accurate because the simulation with default values was within the range of observations obtained from the false-time chronosequence. The SOM stock rapidly declined during the first years after planting because SOM inputs coming from the cocoa trees were lower than SOM outputs. Eventually, a tipping point is reached when SOM inputs from the cocoa trees become larger than SOM outputs.

5.4.2 Approach: balancing simplicity and complexity

To knowledge, before this study, no process-based model had been proposed to predict the temporal variations of SOM stocks in cocoa plantations. knowledge of SOM dynamics in cocoa farms was solely based on field experiments using predominantly false-time chronosequences. To address this knowledge gap, the approach of this study was to develop, evaluate and apply a model describing SOM dynamics in cocoa farms.

Finding the right balance between simplicity and complexity during model development is a dilemma (Monteith, 1996; Paola & Leeder, 2011). This study made it possible to develop, evaluate, and apply a straightforward and flexible model by using the common-sense approach to problem-solving (Grant & Swannack, 2007) and the adaptation of AMG (Clivot et al., 2019). This model is more straightforward than other models like WaNuLCAS (Van Noordwijk & Lusiana, 1998) and requires a limited number of parameters to function. This model entails a dedicated plant component, allowing and simplifying the simulation of residue inputs increasing over the years, while other models like RothC (Coleman & Jenkinson, 1996) tend to repeat the same amount of inputs each year. This model makes the simulation of tree-like crops easy, as long as a growth curve can be determined for the site in question. Coded in the popular and accessible R programming language, this model can be easily modified to suite the particular needs of the modeler. In addition, a user-friendly interface was developed with the Shiny framework to allow non-programmers to quickly run simulations.

5.4.3 Interpretation of the results

Using the function defined by AMGv2 leads to an estimated annual SOM mineralisation coefficient k_2 of 0.125, meaning that for the average Sulawesian farm, if not replaced, 12.5% of the current active SOM stock can be lost yearly. For example, with a SOM stock for the model farm of 50 Mg ha^{-1}, corresponding to an active stock of 27 Mg ha^{-1}, approximately 3.4 Mg ha^{-1} would be consumed yearly. This rate is much higher than the values typically reported in the literature. For example, results obtained by Saffih-Hdadi & Mary (2008) ranged from 0.019 to 0.348, the latter corresponding to a long-term experiment in Thailand (i.e., the only tropical long-term experiment of their dataset). The other eight long-term experiments were located in Europe and resulted in an average coefficient of 0.051. Under a temperate climate, lower annual rainfalls and mean temperature and a winter season can significantly slow down SOM mineralisation compared to a humid tropical location like Sulawesi. As mentioned in Chapter 4, SOM loss rates can be relatively high in tropical settings.

When the cocoa tree SOM inputs exceed 12.5% of the current active SOM stock for a specified soil depth, a tipping point is reached, and SOM starts to build up since a monotonic growth describes the cocoa growth model for the 35 years of the simulation (i.e., inputs continuously increase over time), and that the amount of biomass produced and converted to SOM becomes at a certain point larger than SOM outputs.

As opposed to the hypothesis that long-term SOM stocks would be lower than the planting levels, the backward modelling approach suggested that diverse trends could occur, suggesting that cocoa cultivation may not lead to long-term soil degradation through SOM decline (i.e., if the baseline is the SOM stock before planting). The sensitivity analysis shows that by varying the local conditions, it is possible to obtain opposite outcomes. For instance, by increasing soil pH by 10%, a much lower SOM stock can be obtained at 35 years (-14 Mg ha^{-1}; Table 5.7). Conversely, increasing parameters inhibiting SOM losses can lead to significantly higher SOM stocks at 35 years. For example, the SOM stock rapidly increases if the fraction of aboveground biomass deposited as residues exceeds 0.4 (Figure 5.3 1/2). Another example is the initial SOM content (Figure 5.3 2/2): the long-term SOM stock will surpass the initial one if the initial content is low (1-2%), while the long-term SOM stock can be lower than the initial one if the initial SOM content is high (4-5%).

Except with some “extreme values” for variables like PET (4000 mm), water inputs (2000 mm), or clay content (1000 g/kg), the SOM stock in all cases invariably declines for an initial period after planting. The hypothetical SOM dynamic can explain this behaviour. When the cocoa trees are very young, their contribution to SOM inputs is insufficient to offset SOM losses, leading to a decline in SOM stock.

The long-term trend can vary, and a turning point was always reached when the biomass inputs surpassed the outputs. The results differ from the hypothetical trend because the long-term trend is not necessarily a slow build-up. As seen with the graphical sensitivity analysis, the SOM stock can rapidly bounce back in the long term, or conversely, increase slowly. No continuous decline was observed for any of the tested parameter values, although exponential decay models are used to model the transitions between land-uses (Van Straaten et al., 2015). However, given that each variable was tested independently, it is not excluded that a combination of factors promoting SOM losses can lead to a continuous decline of the SOM stock from the initial planting value. In Farm E, after reaching a minimum at year 14, the long-term SOM stock barely increased. It is possible to imagine a location with a combination of low clay content, high initial SOM content, and a higher annual average temperature could lead to SOM losses being higher than gains. With the same reasoning, it is also possible to imagine the SOM stock to almost continually build up when conditions inhibiting SOM loss are combined (i.e., low SOM mineralisation rate combined with high SOM inputs). A short SOM loss phase should be still expected at the very beginning because the inputs from the cocoa trees are minimal when the trees are young, but the analysis of the results indicate that a variety of situations are possible (long-term decline or build-up, higher or lower than initial levels).

5.4.4 Implication of the results

a. Model application: reverse modelling approach and assessment of SOM dynamics

Because of a lack of long-term experiments to fully validate the model's accuracy, it was chosen to rely on reverse modelling to simulate the SOM dynamic at each farm of the dataset (except farm A because it was only six months old). This choice was not meant to replace a model validation phase but was used to generate potentially helpful information until more data is available to fully validate the model. The trend simulated at each farm matched the hypothetical SOM dynamic (rapid decline followed by a slow build-up). A way to verify the accuracy of the predictions would be to go back to the same farm and verify if, after a few years, the new observations correspond to the predictions made by the model.

As discussed in Chapter 4, the difference between the initial and the long-term SOM stocks reported in the literature vary widely. Some studies observe a long-term build-up (Isaac et al., 2005), while others describe a long-term decline (Van Straaten et al., 2015). The analysis can be hindered by the fact that the SOM stock is often not determined at planting (as discussed in Chapter 4), but a few years later (i.e., 3-5 years, the period during which according to this study and literature can entail significant SOM losses). For the farms of the dataset, the long-term relative differences between initial and final stocks seem to fit within the range of values available in the literature (see references discussed in Chapter 4, section "Evidence from other studies"). The lowest predicted relative difference was -33%. The highest predicted relative difference was +378%, which can be interpreted as high, but this particular plot had the lowest observed SOM content (1.66% at 20 years; farm I; Table 5.3). This situation led the reverse modelling procedure to predict a very low initial SOM content of 0.41%. It could be assumed that it is not unlikely that on a SOM-depleted plot, the plantation of a cocoa farm could lead to significant restoration of SOM to higher levels (hence the +378%, leading to a moderate final SOM content of 1.96%).

b. Model application: SOM maintenance with EOM inputs

Estimating EOM inputs needed to offset SOM losses throughout the cocoa cultivation period (35 years) showed that if inputs with a low humification coefficient are used, substantial input rates are required to cancel SOM losses entirely. With a k_1 of 0.1, the first annual inputs would have to reach almost 50 Mg ha^{-1} (of dry matter). Conversely, lower input rates are necessary when using EOM with a high humification coefficient such as biochar. Overall, this quick estimation showed the challenge of preserving SOM stocks under a humid tropical climate. Consistently applying such input rates might be unfeasible, but the results indicate that the younger the plantation is, the more significant the SOM losses may be. Using large inputs of EOMs at planting and during the early years after planting, even if the rates are below the estimations, could still minimize the depletion of SOM to manageable levels until the cocoa trees reach an age after which SOM depletion is offset by organic matter inputs . Soil management programs should prioritize the early years after planting by applying as much as possible large amounts of EOMs.

5.4.5 Limitations and recommendations

a. Model assumptions and possible developments

1. Cocoa growth is predicted by a static growth curve

At this stage, the model simulates cocoa tree growth using a pre-determined growth curve. Selecting a perennial tree crop from a list and defining the site's pedoclimatic context would significantly ameliorate the model capabilities. At this stage, only the SOM annual mineralisation rate is sensitive to environmental factors. Nonetheless, cocoa tree growth and residue deposition dynamics can be adjusted manually to account for local differences. A significant update would be to create a dynamic cocoa growth model, which could also account for the effect of soil properties on crop growth. For instance, the build-up of SOM in the soil can potentially increase soil water holding capacity or nutrient retention and availability, and this improvement can support plant growth, generating more residues behind, and so on.

2. Shade trees and other associated species are not considered

While the model can be used for mono-specific perennial crops, it ignores the potential influence of shade trees or multi-specific plant covers. To be more representative of many agroforestry systems, the model should include a growth curve or a growth model for each associated species, with their dynamics and responsiveness to environmental parameters. One challenge will be to model how shade trees or other associated species interact (Wartenberg et al., 2017). How will associations influence their respective growths and residue deposition patterns, above and belowground? A core issue remains that, while information was already limited about cocoa residue deposition rates (aboveground and belowground), data may be even more scarce for shade tree species. It seems that there is a significant research gap about litterfall deposition for shade tree species and even more for rhizodeposition. Furthermore, determining how each species respond to different pedoclimatic contexts and management decisions adds another difficulty. Adding the possible interaction effects between species and a diverse agroforestry system can become challenging to model until more information is gathered.

3. Constant cocoa tree density

The base model did not include tree mortality. However, during the lifespan of a cocoa farm or any perennial crop, the loss of some trees is expected. As a result, the long-term crop SOM inputs are likely overestimated. At the plot scale, every dead tree would result in lowering residue deposition. It is possible to introduce a mortality factor to improve the representativeness of the model, in the form of a gradual loss of trees (i.e., reaching an estimated tree density at a certain age), or even punctual tree death events (e.g., as a result of drought or storm randomly timed). In a similar fashion, tree replanting and replacement could also be modelled.

4. Low resolution between the different types of residues

At this stage, this version bundles all plant parts into two simple compartments: aboveground and belowground biomass. As a result, there is also a lack of resolution when residues are formed. Partitioning plant residues into more accurate types could improve the quality of the model. Each plant part may have very different biochemical profiles, which play a significant role in the speed and pattern of their decomposition, the nature, and the yield of the produced SOM (i.e., different k_1 coefficients). Aboveground, litterfall collection indicates that cocoa litter mainly consists of leaves (Dawoe et al., 2010). However, it is essential to know if those proportions are valid for all ages and agroecosystem types. Considering the role of the associated species like shade trees will be crucial to account for the relative contribution of the different types of residues produced by each species.

5. Residue deposition rates are proportional to trunk diameter

The choice to use a single aboveground residue deposition rate was made to simplify the model, but only one reference was used to set this parameter's value (Dawoe et al., 2010). With this approach, litterfall is directly proportional to the aboveground biomass, but in reality, different conditions could increase or decrease the fraction of leaves lost by the tree. It is known that cocoa leaf life cycle are also influenced by climate (De Almeida & Valle, 2008). Event like droughts can trigger higher leaf losses shedding. This question also applies to other perennial species. Litterfall rates may not be reducible to a simple coefficient. At this stage, it is difficult to know if this approach tends to under or overestimate litterfall deposition. Seasonal variations of litterfall are not considered by this model yet, as the time step is annual. However, it is worth mentioning that litterfall is closely related to climate conditions, as cocoa trees shed leaves during periods of water stress. Therefore, environmental factors can still influence the amount of litter that is being created. However, it is not clear from the literature if litterfall is mainly caused by soil water deficit, or if other factors such as temperature and air humidity could also play a role (De Almeida & Valle, 2008). Another cocoa model, CASE2 (Zuidema et al., 2005), proposed an approach to estimate litterfall by using both the age of the cocoa leaves and soil water stress.

Overall, it appears that the trunk growth rate of cocoa decreases with age (see Chapter 4). However, the way trunk enlargement relates to the actual amount of biomass present in the tree and the total amount of litterfall produced is currently poorly understood. For example, it is unclear how well this relationship holds over the long term (e.g., when cocoa enters a senescence phase). As discussed previously (Chapter 4), it seems that allometric relationships used to predict cocoa tree biomass in Sulawesi may not be valid in other locations (Smiley, 2006).

Finally, the influence of pruning was not simulated in this version. Pruning is a source of litterfall but not captured by the typical litterfall experiments. Therefore, it can be assumed that this model underestimates the actual inputs of aboveground residues. This issue is complicated by the fact that allometric equations used to estimate cocoa biomass are developed on pruned trees. Pruning intensity and frequency can severely alter the aboveground biomass of a cocoa tree (Schneidewind, Niether, Armengot, et al., 2019). Measuring trunk diameter may not be sufficient to estimate aboveground cocoa biomass accurately. Before and after pruning, the same tree has the same trunk diameter, but different aboveground biomasses.

Consequently, the model could be improved by using more information about the relationship between pruning frequency and intensity and the quantity of biomass removed from a tree, adding to the model complexity but improving its representativeness. This flux could play a critical role as pruning most likely removed more branches than leaves than “natural” litterfall, and branches most certainly decompose more slowly than leaves. Once again, considering species other than cocoa adds to the difficulty of this update since residue deposition rates and pruning practices differ between species.

Similarly to aboveground biomass, belowground residue deposition is assumed to be proportional to belowground biomass. It was decided that belowground SOM inputs could come from two sources: fine root turnover and rhizo-exudation. In cocoa but also for other plants, limited information is available about these two fluxes. They were assumed to be directly proportional to belowground biomass, but it is not known if this relationship remains stable over time (Kuzyakov & Domanski, 2000b). For example, it could be hypothesized that fine root turnover or exudation slows down when the tree gets older. As with aboveground residue deposition, it could also be expected that those two fluxes respond to environmental changes.

Even though a root-to-shoot ratio of 0.23 was used, values can vary, as highlighted by Borden et al. (2019), who reported values ranging from 0.12 (minimum of cocoa trees in monoculture) to 0.38 (maximum of cocoa trees in mixture with *Terminalia ivorensis*). Their observation indicates that shade trees can influence cocoa root distribution. With such a range of possible shoot-to-root ratios, the model would benefit from integrating shade trees' effect on root biomass. Just like aboveground biomass, the root-to-shoot ratio could also vary with time, and specific management practices like pruning and fertilization may affect belowground biomass are unknown.

6. *Residues cannot last more than one year—no intermediate state between residues and SOM or loss.*

The residues deposited annually are, for one part, entirely converted into SOM (mass of inputs, m, times k_1) whereas the other part ($m - m.k_1$) is entirely decomposed (leaving the system as CO_2 and other losses), for the other part. While this assumption might hold for easily decomposable residues such as leaves, it might not be optimal to represent more resistant residues like branches. To account for a longer timeframe, an upgraded version of the model could include one or two “fresh residues” state variables (i.e., one for the aboveground pool and one the belowground pool). Then, using the insights provided by the ISMO index, it could be possible to calculate how much of each residue inputs is left after one year. This way, the stock left after one year can be added to the stock of the following year. This remainder can follow a similar degradation dynamic as the previous year and contribute to SOM additions with the new inputs from fresh residues. Otherwise, the model could for example be improved by integrating a function of exponential decay to continue the decomposition of fresh residues over several years.

7. Offsite material transfers of SOM are discounted

As explained in the model overview, other forms or SOM losses are assumed to be insignificant within this model. Generally speaking, cocoa farms do not seem to suffer from soil erosion, due primarily to the good canopy and ground cover (also provided by shade trees) drastically reduces the risks of generating erosive runoff. Nevertheless, integrating erosion could also be a future improvement, particularly when inappropriate land-clearing methods and insufficient soil cover which could provoke erosive events (Hartemink, 2005).

8. Use of AMGv2 to Sulawesi to estimate SOM mineralisation rate

The AMGv2 model was developed with data from long-term arable farm experiments in a temperate climate, mainly in France. Only one publication using AMG for a tropical location was found (Khon Kaen, Thailand; Saffih-Hdadi & Mary, 2008), which evaluated the effect of straw residue export on SOC in cereal systems (such as wheat, barley and maize) and compared the several models (DAISY, CENTURY, ROTHC, CN-SIM). The AMG model adequately simulated SOC dynamics in all sites (including Khon Kaen), better fitting the other models for seven out of nine experiments. Additional studies should be undertaken to assess the performance of AMG in tropical settings, to adjust the soil mineralisation rate (k_2) function if necessary (Equation 5.14). Conditions that were probably not faced during the calibration of k_2 have most likely not included soils with a very low pH (below 5), high annual average temperature, high annual rainfall, and high PET. Conversely, comparable values may likely be found at temperate and tropical sites for other local variables like clay contents, soil carbonates, and soil CN. It is worth mentioning that the experimental sites of the first publication about AMG (Andriulo et al., 1999) were in the rolling pampas of Argentina (humid subtropical climate), suggesting that AMG could apply to climates other than those found in Europe, where the model has been extensively used.

b. Limitations around reverse modelling

While the reverse modelling approach can be helpful to reconstruct the history of a plot and anticipate its future evolution, many uncaptured factors could invalidate such predictions. For instance, minimal information was available about the management practices of the plot or the plot condition at planting (and previous land use). The way a farmer may have managed shade trees by planting and removing species can influence the observed SOM content. Another example is the lack of information about organic amendment use. Recurrent inputs could lead to bias the current observation, overestimating what the SOM content would have been without them.

5.5 Conclusions

The AMG soil model was adapted during this study to develop a flexible and straightforward tool to predict SOM dynamics in perennial cocoa plantations. It appears that the hypothetical SOM dynamic (rapid decline followed by a slow build-up) was valid for the conditions found in the false-time chronosequence used. The results supported the hypothesis that SOM declines rapidly during the yearly cocoa farm, but this conclusion needs to be validated with real-time chronosequences . With the dataset for Sulawesi, the long-term trend was a slow build-up, as postulated by the hypothetical SOM dynamic. However, the results of this modelling experiment suggest that alternative outcomes are possible. The long-term SOM stock at 35 years can under a specific range of site conditions be lower or higher than the initial SOM stock. The results indicate that cocoa farming can both contribute to storing C in soils as well as emit C. Determining the local conditions at the farm scale can provide SOM maintenance approaches via EOM inputs to limit the emission of atmospheric C and preserve soil fertility by minimizing/reversing SOM losses. The results indicate that early years after planting are associated with high SOM losses and a critical phase for soil degradation. While more research should be undertaken to validate the model and improve the parameter calibration, this in initial period of SOM losses should be targeted with sufficient organic matter inputs to increase soil C stocks and work towards SOM maintenance and climate change mitigation. This research offered an approach to estimate the type and quantity of organic matter inputs required to offset SOM losses. Future research can improve the model’s representativeness and applicability to other locations and systems by addressing the model’s assumptions' limitations.

6. INTEGRATED DISCUSSION AND CONCLUSIONS

This chapter begins by restating the aims and objectives described in the Introduction of this thesis. Then, each objective is addressed by summarizing the main findings, interpreting them, discussing limitations, and proposing key recommendations and areas for future research. Finally, a conclusions summary specifies the contributions to knowledge and the key recommendations from this research thesis.

6.1 Research aims and objectives

The **strategic aim** of this thesis was to improve the understanding of SOM dynamics on cocoa farms. More specifically, the research sought to describe and explain the temporal variations of SOM and C stocks of cocoa farms using a combination of approaches, including literature reviews, field sampling, laboratory measurements, and modelling. The **applied aim** of this project was to propose a SOM management strategy for cocoa cultivation in Indonesia.

Five objectives were defined to meet those goals:

1. Firstly, to assess the existing temporal dynamics, variability, and distribution of C storage in cocoa systems by analysing available data.
2. Secondly, to compare the effects of soil inputs (fertilizer, compost, and dolomite) on soil properties and cocoa growth and productivity through experimentation.
3. Thirdly, to characterize SOM dynamics on a false-time chronosequence of Indonesian cocoa farms.
4. Fourthly, to describe and predict SOM dynamics in cocoa farms using a modelling approach and simulate the effect of organic inputs on SOM stocks.
5. Finally, to propose SOM management recommendations for cocoa farms in Indonesia, based on a synthesis of the research.

Each objective is considered in the following subsections.

6.2 Synthesis of the findings

6.2.1 Objective 1: Assessing the existing information on C storage in cocoa systems

The objective in Chapter 2 was to critically evaluate and interpret available data on SOM and C storage in cocoa systems. Before fully implementing the study, the intention was to focus on SOM. However, the variety of approaches used by the researchers and the diversity of cocoa systems meant that it was also necessary to consider soil and plant C stocks in addition to SOM.

The research synthesis and meta-analysis of 37 references described in Chapter 2 provided an overview of C storage in diverse cocoa farms from contrasting regions. Chapter 2 represents, to date, the largest combined dataset on C storage in cocoa systems. Most of the data covered cocoa farms younger than 35 years old (219 data points for aboveground cocoa C stocks, 359 for soil C), as only a few plots older than that were found (31 data points for aboveground cocoa C, 22 for soil C). Unfortunately, the dataset was geographically unbalanced because no large dataset was available for Africa, which represented only 5% of the farm plots, as opposed to America (53%) and Asia (41%), despite Africa being the largest global producing region. Although researchers and institutions in Africa were contacted, only limited additional data were provided, suggesting either a lack of large-scale studies in Africa or an inability or reluctance to make that data available.

During the process of aggregating the data, it was possible to identify the methods used by the researchers to determine plant and soil C stocks in cocoa farms. The research highlighted the allometric equation proposed by Smiley & Kroschel (2008), which was subsequently used in Chapters 3 and 4. The process of collating the farm ages also highlighted the importance of obtaining data for both younger (<10 years) and older farms (>20 years) in a chronosequence (Chapter 3).

Considerable variations exist between the aboveground C stocks of cocoa farms ranging from as low as 5 Mg ha^{-1} to as high as 20 Mg ha^{-1}. These disparities can be partly explained by differences in age (Beer et al., 1990a; Smiley, 2006), the variety of planting densities and shading intensities (Rajab et al., 2016), pruning techniques (Schneidewind, Niether, Sauer, et al., 2019), and other farm management practices and factors (Mohammed et al., 2015). Shade trees typically formed a larger store of C than cocoa trees, approximately 4-5 times as large on average across all farm ages. This large gap suggests that shade trees can strategically enhance C storage on cocoa farms. While aboveground cocoa C stocks rarely surpassed 20 Mg ha^{-1}, aboveground shade tree C stocks could reach 100 Mg ha^{-1}. Because of a lack of access to cocoa yield data, the effect of shade trees on cocoa productivity was not evaluated. Nonetheless, from a diversification perspective (Cerda et al., 2014; Vaast & Somarriba, 2014), those trees can represent another source of income for farmers (e.g., timber and fruits, carbon offsets and payments) and improve biodiversity.

Litter provided a mean C reservoir of 1 Mg ha^{-1}. There was no measurable increase of the average litter C stock over time from the examined dataset.

Because of differences in soil sampling depth, the calculation of soil C was standardized to a depth of 10 cm. The mean soil C stocks (0-10 cm) was 23 Mg ha^{1}, with values across the 250 sites ranging from 10 Mg ha^{-1} to approximately 40 Mg ha^{-1}. In Chapter 2, results demonstrated that soil C contents were negatively correlated to clay content and positively to sand content (all depths considered together). The reason for this was that soils with the highest sand contents also tended to display relatively high C contents. This observation contradicts general relationships that find higher C contents in clay soils rather than sandy soils (Brady & Weil, 2017). It could be worth examining these sites more closely and asking farmers about their practices to explain this observation.

The process of completing the meta-analysis highlighted the importance of studies describing as clearly as possible the previous land use, the history of farm management, baseline SOM or C levels before pre-planting land preparation or at planting, and any significant organic matter inputs. Chapter 2 identified that the studies reviewed used different approaches to describe the structure of the agroforestry system and the intensity of shading (e.g., tree densities, sizes, and canopy cover), particularly for locally heterogeneous, diverse, and “disorderly” agroforestry systems. The appropriateness of allometric equations used to estimate plant C stocks was rarely evaluated. Destructive studies were uncommon because they are laborious, and one can question the suitability of using an allometric equation without verifying its validity in another context. The studies used different shoot:root ratios to convert aboveground to belowground estimations. The provenance of litter and roots (cocoa or shade trees) was rarely assessed. Soil bulk density was frequently absent from soil measurements, which hinders the calculation of both SOM and C stocks. The studies reviewed in Chapter 2 adopted various analytical methods to assess soil C levels (e.g., Walkley-Black, loss-on-ignition, elemental analysis), making comparing SOM and

C values more difficult. The studies used varying soil sampling depths (e.g., 10, 15, 20, 30 cm), limiting the comparability of their results. An additional constraint when aggregating the data was that researchers used inconsistent size boundaries between fine and coarse roots (sometimes 2 mm, sometimes 5 mm).

Contributions to knowledge

This study:

- gathered, to the authors knowledge, the largest dataset on plant on soil C storage in cocoa farms, cocoa and shade tree densities, and shade tree species;
- presented the most comprehensive statistical description of C distribution across five reservoirs (aboveground cocoa, aboveground shade, belowground root, surface litter, and soil), dispersion, and temporal variation in cocoa farms;
- highlighted critical methodological differences in existing work (e.g., different soil depths, measurement of soil C or SOM, different root measurements, different allometric equation for tree C, different plant C carbon contents);
- provided an approximate global estimation of C storage in cocoa farms (0.9 Gt of C across 11 million ha, i.e.; a mean of 82 t C ha^{-1}).
- provides knowledge to inform future studies and projects interested in quantifying C storage and dynamics in cocoa farms, including in particular C inventories for C offsets studies, climate mitigation initiatives and other sustainable development projects.

6.2.2 Objective 2: Effects of soil inputs on soil properties and cocoa productivity

Chapter 3 evaluated the effects of different types of organic and mineral inputs on soil properties and cocoa growth and productivity to inform the development of better soil management recommendations.

This experimental study provided a continuation of a previous experiment (Mulia et al., 2019) located in Bone-Bone, Sulawesi, Indonesia, conducted by Mars Inc. and BPTP (Indonesia Assessment Institute for Agricultural Technology). The field experiment initially consisted of an unproductive site shaded by coconut. The soil displayed low N and SOC contents and a low base saturation. It was replanted with PBC123 cocoa seedlings and shade trees of *Gliricidia sepium*. The experiment design consisted of four randomized blocks of 16 cocoa trees for each replicate. A locally-made compost composed of 60% cow manure, 15% empty oil palm bunches, 10% rice straw, 10% diverse leaves (banana, grass, *Gliricidia,* and maize), 5% cocoa pod husks, and micro-organism mix (EM4) was used alone and in combination with mineral fertiliser or dolomite inputs (5 kg per tree per application). The inorganic fertilizer treatments included the application of Phonska (a rice NPK fertilizer used in Sulawesi by cocoa farmers) and urea (respectively 374 g and 250 g per tree per application). The third treatment consisted of dolomite applications (2.5 kg per tree per application). Each treatment was applied alone and in additive combinations. With the control, this raised the total number of treatments to eight. Each treatment was continuously applied at six-month intervals. Tree basal measurements and soils samples were collected in December 2018, when the cocoa trees were 7.4 years old. Yields, pod counts, mortality rates, and rates of infected pods were all assessed during the four previous years (2015, 2016, 2017, and 2018). The soil properties analysed in 2018 were compared to the previous measurements obtained in 2014.

Applying compost did not lead to significantly lower soil BD, or higher SOC, or cation exchange capacities (CEC) than observed in the control treatment. Possible reasons for this lack of significant response could be an insufficient number of samples, the localized application of compost in small pits which may not have been directly sampled, and a potentially high decomposition rate due to the compost's low C:N ratio. However, while no differences in soil properties were measured, the cocoa responses to compost applications were pronounced, with cocoa yields higher than in the control also obtained in treatments receiving fertilizer or dolomite . Combinations with compost did not lead to additional beneficial effects on yield, suggesting that compost addition alone was enough to alleviate the principal yield-limiting factors.

There were also treatment effects on the mortality of the cocoa plants, with higher mortality found in the mineral fertilizer treatment than the control. This result may have been caused by the mineral fertilizer “scorching” the roots of the young cocoa plants. Even so, the mean dry bean weight (1.25 g) in the mineral fertilizer treatment was lower than in the other treatments (except for the control). The largest mean dry bean weight was found in the dolomite treatment (1.59 g). The highest yield index (i.e., dry bean yield divided by the basal tree area) was found in the fertilizer-only treatment. As found in the preceding study (Mulia et al., 2019), combining inorganic fertilizer and compost did not lead to clear yield benefits as compared to compost alone. Still, fertilizers could have a role to play in correcting soil nutrient deficiencies and limiting long-term nutrient depletion. The current fertilizer formulation used by Sulawesian cocoa farmers is formulated for rice (for lack of a better alternative). Adequate fertilizer formulations should be available to cocoa farmers to not waste resources on unsuitable inputs (Mulia et al., 2019).

Unlike the situation with the compost, adding dolomite affected the measured soil properties. Soil pH, BS, C:N ratios, and cation concentrations (exchangeable Ca and Mg, and extractable Ca, Mg, and K) were significantly increased where dolomite was applied. However, these changes in soil properties did not feed through to higher yields than the control treatment, as the yield in the dolomite and the control treatment were statistically similar (p-values > 0.05).

Overall, compost application was an effective method for increasing cocoa yields, although the benefits tended to reduce over time. As the trees mature, the competition between trees for light, water, and nutrients will likely increase. Continuing the assessment for a few more years would help determine if this trend is maintained. In any case, this experiment provided evidence that organic inputs can play a strategic role in improving cocoa productivity in degraded cocoa plantations.

The compost application rate used in this experiment was 10 kg tree^{-1} year^{-1}. This application rate is probably unachievable by most cocoa farmers, but such applications could be possible if there were local initiatives to recover and recycle organic wastes (Fungenzi, 2015; Meidiana & Gamse, 2010). Poorly managed organic wastes currently are a pollution issue in Indonesia, and their use for enhancing cocoa growth is a currently untapped opportunity. Redirecting unused waste to produce organic compost could address an existing pollution problem and increase cocoa yields. For this reason, cocoa industries (and other agricultural businesses) should advocate for and support the development of the organic waste treatment sector in Indonesia.

Contributions to knowledge

This study:

- showed that the application of compost can significantly increase cocoa yields (2.8 times the control, excluding mortality rates; 2.9 times the control, including mortality rates; over 2015-2018), more than the current fertilization practices or applications with dolomite;
- revealed that adding mineral fertilizer and/or dolomite to compost applications did not produce compounded yield benefits;
- suggested that current soil management fertilization practices must be reviewed and improved: despite additions, cocoa yields were still low as compared to experimental potentials (van Vliet et al., 2015), and significant soil C and nutrient depletion occurred.
- provided critical insights about cocoa soil fertility management to inform cocoa agronomists, cocoa farm owners and other decision-makers working on cocoa nutrition.

6.2.3 Objective 3: Characterizing SOM temporal variations on Indonesian cocoa farms

Chapter 4 examined the temporal variation of SOM, C, and N in a false-time chronosequence of cocoa farms located in Sulawesi, Indonesia. This study determined the typical temporal variation in SOM found on Indonesian cocoa farms from planting to maturity. The assumption was that SOM would decline rapidly after planting because of the combination of low organic matter inputs occurring when the cocoa and shade trees are young and the high SOM mineralisation rates expected under a perpetually hot and wet climate. The objective was to determine if a particular trend was observed or not and if the trend matched with the hypothesized conceptual dynamics.

The study gathered data from 13 cocoa farms, ranging from 0.5 to 31 years old (plus one adjacent forest plot) to create a false-time chronosequence. Cocoa trees trunks were measured to estimate the relative dynamics of biomass growth and potential deposition of organic matter as litter and belowground inputs. Soil samples were collected from 0 to 100 cm in 20 cm increments. Soil BD was only measured in the surface layer (0-5 cm) as deeper BD measurements would have required significantly higher resources (a core extraction machine or digging 65 one-meter deep soil pits to extract intact cores manually).

Across the various sites, the growth of cocoa trees was described using the Weibull growth curve. The collated data demonstrated that the initial growth of the cocoa trees was relatively consistent (i.e., the trunk diameters were relatively similar) irrespective of local differences imposed by shade tree type and planting densities. By contrast, the variation in the growth rate of individual cocoa trees tended to increase as they matured, perhaps because inter-tree competition increases as the canopy closes and competition increases for light, water, and nutrients (Bastide, personal communication). Some trees become dominant, whereas others struggle to compete for resources.

Cocoa biomass estimations obtained in Chapter 4 were significantly higher than the results obtained in Chapter 2 (i.e., about twice as high if a density of 625 trees ha^{-1} was used, seven times higher than with a density of 1111 trees ha^{-1}). A comparison of the behaviour of the allometric equations (Table 2.3) using dummy values (unpublished) showed that same values can lead to significantly different estimations by each allometric equation. This finding suggests that these allometric equations should be compared and evaluated to delimit their validity domain, and perhaps determine if a single equation could be used in cocoa research to determine accurately biomass stocks accurately with a minimal number of a parameters such as trunk diameter and tree height. Work is also much needed to consider the relationships of cocoa biomass estimations with pruning.

A limitation to this study was that shade trees morphology were not measured. Farmers were only asked to record the name of species and the approximate density. Shade trees C stocks should be systematically measured to improve the quality of future studies on C storage in cocoa farms.

The collated data generally showed a rapid decline in SOM from land preparation and planting right after between 2-14 years after planting. The decline was substantial and equivalent to approximately -46% of the SOM stock (0-20 cm) in 2 years (-42 Mg SOM ha^{-1}). Even though this observation could be caused by the natural variability of SOM and C contents of the dataset used, the results adjusted for clay content and soil BD also showed the same pattern. However, real-time chronosequence should be studied to evaluate this trend. Even if adjusting for clay content and soil BD ameliorates site comparability, initial SOM stocks at planting were not known and represent a significant limitation the false-time chronosequence developed in this study.

An analysis of the literature showed that most experimental studies on cocoa do not record SOM or soil C changes within the first five years after planting. If considering longer-term changes, a -46% depletion of the SOM stock is not unreasonable, but there is a lack of research interested in short-term changes. In the study area, the level of precipitation is high (> 2500 mm per year), and the mean annual temperature is approximately 27°C. In such conditions, SOM mineralisation rates could be amongst the highest in the world, as also argued modelling estimations (see Chapter 4; Morais et al., 2019). The process of developing a new cocoa plantation from either an old cocoa plot or a forest with abundant standing biomass could lead to faster changes in SOM contents than observed, for example, in temperate arable crops.

The chronosequence showed a relatively rapid increase in SOM stocks after reaching a minimum point that occurred two years after planting. Although the humid tropical climate enables rapid declines in SOM, the same climate can also support high rates of cocoa and shade tree above and below ground biomass accumulation which can also rapidly restore SOM levels to their pre-planting levels. However, eventually, a point is reached when the SOM tends to stabilize at a new equilibrium rather than continue to increase. This observation suggests that SOM accumulation soon becomes balanced with increased rates of SOM breakdown, with tree mortality being also one way in which inputs may be reduced.

While Chapter 2 gathered data from external sources, Chapter 4 focused on using new primary data collection, which could fill some gaps identified during the meta-analysis. Namely, this study helped to collect data points for a wide age range, with more data points about young cocoa farms (e.g., 0.5, 1, 2, 5 years old), to examine more precisely the variations in SOM that could occur early on after planting. As compared to many other studies on this topic, this study provided a more detailed description of the dynamics of cocoa farms by measuring not only SOM or C, but both, and also N. Five depths were measured in each farm, down to 100 cm, which is rarely observed in other studies. Also, C and N elemental analysis was performed on soil samples, a more precise technique than the traditional wet chemistry approach (Chatterjee et al., 2009). Furthermore, this study attempted to use soil data transformation techniques to improve the quality of comparisons between different sites. Calculating stocks using soil BD measurements provided more accurate comparisons of C storage than gravimetric contents only (Rollett et al., 2020). SOM contents obtained using loss-on-ignition (LOI) were also corrected to take into account the clay contents and the “structural water” held by minerals released during the LOI analysis, which would have otherwise biased the results by overestimating SOM contents (Hoogsteen et al., 2015; Jensen et al., 2018; Konen et al., 2002; Pribyl, 2010). Using clay-adjusted ratios (SOM-to-clay, C-to-clay, N-to-clay) also allowed more valid comparisons than using SOM, C, and N contents only (Dexter et al., 2008; Jensen et al., 2019; Johannes et al., 2017; Knadel et al., 2015; Prout et al., 2020.

The cocoa trunk size data obtained from this experiment formed the basis for formulating a non-linear relationship relating cocoa age to aboveground and belowground cocoa biomass. This relationship was used in the modelling chapter (Chapter 5).

Contributions to knowledge

This study:

- proposed a schematic representation of SOM dynamics in cocoa farms;
- demonstrated that soil SOC dynamics in the first five years after planting are often underappreciated by soil studies but could be a critical soil degradation phase when rapid SOM losses occur;
- demonstrated that organic inputs should be applied during this 1-5 years SOM-depletion phase to improve cocoa farming sustainability in Sulawesi.

6.2.4 Objective 4: Modelling SOM dynamics of cocoa farms

The modelling study in Chapter 5 incorporates knowledge obtained during the three preceding studies (Chapters 2, 3, and 4) to deliver a tool (the model) that can be used to and inform SOM management in cocoa farms. A modelling approach was used to represent SOM dynamics in cocoa farms. By adapting the existing AMG soil model, a new model was generated to describe the variations of SOM stocks in Indonesian cocoa farms. This work filled a significant research gap in the cocoa literature, a *knowledge application gap* of soil models to predict SOM stock variations (Müller-Bloch & Kranz, 2015). Although soil carbon C models exist and have been applied to other crops, nothing (to my the authors knowledge) has at the time of writing, been published for cocoa. To some extent, this research gap could also be categorized as a *theoretical gap* (Miles, 2017), as developing this model offered a simple theoretical framework to understand SOM dynamics in cocoa (and other tree crops).

The preliminary phase of completion of this objective involved a critical review of existing models. Several options were initially considered, including RothC (Coleman & Jenkinson, 1996), MOMOS-TAO (Kaboré et al., 2011; Pansu et al., 2009), CASE2 (Zuidema et al., 2005), and WaNuLCAS (Van Noordwijk & Lusiana, 1998). In the end, the preferred approach was to adapt a simple soil model: AMG (Clivot et al., 2019). RothC appeared as a good option, and some unpublished work was completed during this project to modify it and fit it to the it to the particularity of a perennial system (i.e., provide variable C inputs rates instead of a constant one). The Windows (Coleman & Jenkinson, 1996), R (SoilR package, Sierra et al., 2012), and Stella versions (Nichols, 2019) of RothC were obtained, but there was not enough time to use them during this thesis (each study took a lot time). Combining the MOMOS-TAO models was explored as it represented a promising and modern take on SOM dynamics. However, the authors lack of experience with VENSIM posed a challenge, and the developers of MOMOS and TAO were unable to provide training at the required time. The CASE2 model was also studied as a potential option, but because the only available version was scripted in FORTRAN (an obsolete programming language) and also because of the focus of the model on plant physiology without soil components, the CASE2 option was also put aside. The WaNuLCAS model was also examined as an agroforestry model including a plant and soil component, with variables already parametrized for cocoa. Unfortunately, technical issues prevented its use. WaNuLCAS runs on the Stella software platform, but the available version seemed to function with a discontinued version of the Stella. Stella developers offered to convert the “old” WaNuLCAS file to make it compatible with the latest versions of the Stella program, but running the model led to errors. Such experiences demonstrate that technical issues posed by the language or program used can be obstacles that hamper model adoption and development by other users (except for RothC, available in many versions). Developing the R version of AMG allowed it to be adapted to the research needs of this thesis. All the mathematical formulas were available and easy to code in R, which also offered the possibility to produce a user-friendly interface with the Shiny framework, to quickly run simulations and extract information. R is open-source, free, and one of the most popular data science languages, and future users of the cocoa AMG model developed here could have full control over the model script to easily modify and improve it, transparently.

The method used to develop an adapted version of AMG, suitable to cocoa farms, was based on the “common-sense approach to ecological modelling” proposed by Grant & Swannack (2007). The methodology consisted of three main steps: (1) model development, (2) model evaluation, and (3) model application. To develop the model, the AMG model needed to be modified. A major change consisted in modifying the plant inputs, which were previously crop residues left in the field after harvest (i.e., aboveground residues like straw and belowground residues like roots). Instead of an annual crop, the plant component was replaced with a perennial crop. This modification was achieved by proposing a simplified cocoa growth model based on trunk measurements at the sample farms and an allometric equation developed in Sulawesi (Smiley & Kroschel, 2008). A shoot-to-root ratio was used to estimate the dynamics of belowground biomass. Considering that tree roots also persist for a more extended period than arable crops, it was necessary to model how roots would contribute to SOM inputs by estimating root turnover instead of assuming that the entire root system would be deposited after harvest like with the arable version of AMG.

This plant component of the model is *retrospective* in the sense that the user must possess data about the growth dynamics of the simulated plot. The proposed cocoa growth model described how cocoa biomass could have developed on the 13 farms evaluated. However, to improve the applicability to other locations, it is necessary to have information about the biomass accumulation for the site of interest. A potential area for future research is making the model's plant component sensitive to climate and soil variables. This update would help reduce the need to rely on plant biomass measurements and estimations.

The application of the model indicated that, as it was hypothesized in Chapter 4, SOM mineralisation rates can be extremely high in Sulawesi (k_2 of 0.125). Another estimation from (Morais et al., 2019), using RothC, estimated SOM mineralisation rates to be approximately 0.07. For all 13 farms evaluated, the early years after planting were all followed by a decline in SOM because SOM inputs are lower than the outputs early on. The duration of the SOM loss phase depended on the local variables. The long-term trends could either be a continual decrease in SOM stocks, or a significant increase, even exceeding SOM levels at planting. Large gains and losses were simulated with the model farm of the dataset. In relative terms, they ranged from -33% to +378%. In absolute terms, they corresponded to -36 to +42 Mg ha^{-1}. The predicted final SOM stocks at 35 years ranged from 53 to 133 Mg ha^{-1} (0-20 cm).

The functional parameter that most influenced the final SOM stock at 35 years was the upper limit of cocoa aboveground biomass. This parameter directly controls the quantity of aboveground and belowground organic matter inputs. The effect of the other functional parameters was roughly equivalent because of their similar weighting in model equations. The local variables with the largest modelling effect on the final SOM stock were soil pH and the mean annual temperature. However, it should be noted that these evaluations were the results of applying the same relative change to each parameter, although their units differed. A subjective analysis of the graphical outputs suggested that plots with a high initial SOM content will lead to lower long-term SOM stocks. This is because the high starting SOM stocks can be beyond the replenishment of capacity of the young cocoa system resulting in rapid and potentially unrecoverable depletion. By contrast plots with a low initial SOM content often led to higher long-term SOM stocks (see Figure 5.6 2/2: initial SOM content). This trend is due to the fact that SOM losses are proportional to the SOM stock, and hence a low stock means that the initial C losses are lower and easier to replenish. Overall, the long-term trend is determined by the balance between the local rate of SOM mineralisation and the SOM input rate. Once again, the amount of biomass was a determining factor as it controls the amount of inputs deposited on and in the soil. Belowground deposits were also larger contributors than aboveground deposits (respectively 70.2 and 98.7 Mg ha^{-1} when cumulated over 35 years with the default run).

As indicated above, the initial SOM content at planting was an important determinant of future SOM stocks. This information is often unknown. In this study, the mean SOM content of all farms (2.59%) was used. An alternative approach would be to use a recent measurement of SOM content when simulating a plot about to be planted (e.g., grassland or arable field crop) or replanted (i.e., old cocoa farm). The alternative approach used to estimate initial SOM content was to calculate it through backward modelling. This computation was achieved by optimizing the model function with a range of initial SOM contents until the simulation matched with the measured SOM content obtained for the studied year. Using data from an adjacent plot comparable to the planting conditions would help assess the plausibility of this backward modelling estimation.

In the AMG model, some variables were assumed to remain constant. For example, soil BD is fixed, but in reality, it may vary with SOM contents, as shown in Chapter 1. Findings from the literature (Mann, 1986; Shi et al., 2018) and the results obtained in Chapter 1 showed that this relationship was not linear (Figure A - 2.2). The issue is similar for other soil properties like C:N ratios and pH, which should potentially vary over the development course of a cocoa orchard. Leaf litter could be expected to affect soil properties (Giweta, 2020).

The model development phase revealed that additional studies would be needed to calibrate and validate this model, primarily because no long-term experiments were available to realize those modelling steps. In particular, the influence of pruning on tree biomass should receive more attention to represent the flux of residues from the trees to the soil. The model used an estimated annual fraction of aboveground biomass lost from the trees, but this value was obtained from litterfall experiments excluding pruning deposition (Dawoe, 2009; Dawoe et al., 2010). As suggested in Chapter 5, pruning could be integrated into the model using a couple of coefficients like frequency and intensity. At this stage, the extent to which the model underestimates the organic matter inputs from the trees remains unknown. Pruning residues may represent more than twice the amount of litterfall inputs (assuming a plant C content of 48%, approximately 5-9 Mg organic matter ha^{-1} $year^{-1}$ Schneidewind et al., 2019) and therefore constitute a key point to improve the model.

Following litterfall and pruning, resulting in the deposition of organic residue on the soil surface, the next phase in the organic matter cycle is decomposition and transfer to SOM. Several studies have investigated this subject (see Zheng et al., 2021, which compilated data from 25 litter decomposition studies); however, their approaches focused more on nutrient release than on organic matter assimilation in the soil. The model developed in this study used a *humification* coefficient to consider that what remained after one year was equivalent to SOM. It is important to note that the name of this coefficient is derived from AMG, which itself is the descendant of the Hénin-Dupuis model (Andriulo et al., 1999; Hénin & Dupuis, 1945) and the view that SOM is formed during a chemical process of *humification*. Currently, the cocoa SOM model developed in this study uses the term humification to label the process through which organic inputs are converted, assimilated into SOM, and not the mere formation of humic substances. The scientific views on SOM formation are evolving, and the boundary separating SOM from what it is not is sometimes debated amongst soil scientists (Lehmann & Kleber, 2015). There is an increasing awareness that whilst separating C components into categories such as plant residues, belowground roots, and SOM can be helpful, a full C balance requires each of these components to be summed together (Rivas Casado et al., 2021). Very often, the division between what is plant residue and what is SOM can be fuzzy because SOM formation theoretically starts as soon as organic residues begin to decompose. If it is accepted that the *soil continuum model* of Lehmann & Kleber (2015), deciding that what is left of organic inputs after one year *becomes* SOM can be debated. One can see that the soil scientist and the modeler may have conflicting needs when deciding about the boundary between SOM and fresh residues. Having a distinct limit between SOM and non-SOM simplifies the activity of the modeler but is certainly too simplistic for the soil scientist. Notwithstanding this concern, a model is by definition a simplified representation of reality, so some tolerance should provided for the modeler’s efforts. A way to perhaps improve future soil models would be to integrate this gradual, continuous and contentious nature of SOM, instead of fixing a clear-cut limit between SOM and non-SOM.

One additional observation is that soil scientists perhaps make a recurrent misnomer. This issue results from a gap existing between what soil scientists mean by SOM and what they actually measure. Whereas the definition of SOM is rather broad and clear (i.e., *all organic materials found in soil that are part of or have been part of living organisms*; Chenu et al., 2015), soil scientists almost always measure SOM on 2 mm sieved soil samples. All other forms of decaying organic matter larger than this physical boundary are excluded from the analysis. One could argue that using this approach is helpful for practical reasons but concede that SOM analyses underestimate SOM stocks. For example, large leaf fragments, large root debris, and dead soil fauna which theoretically fit the SOM continuum concept, are filtered out from the typical laboratory analyses. Instead of talking about SOM, soil scientists only consider a limited subset of it. The effect of limiting SOM to anything < 2 mm remains to be evaluated. To which extent are soil analyses underestimating the actual amount of SOM?

Beyond those concerns for converting organic matter to SOM and the boundaries that separate them, future research should also investigate the relationships between litter traits, their decomposition patterns, and how they influence soil functioning (Bai et al., 2022; Sauvadet et al., 2020).

Additional studies are necessary to model the effect of litter traits on nutrient availability and other essential aspects of soil functioning like soil structure formation. To improve the capacity of soil models to anticipate changes in soil health after organic additions, other functions that are influenced by C and nutrient dynamics – like structure formation – should be considered (Kibblewhite et al., 2008). In a climate change context, the improvement of soil structure and the enhancement of soil water storage capacity deserve more attention.

Two of the most significant areas for model improvement consist of including shade trees instead of cocoa trees only and making the plant component sensitive to environmental factors. Likewise, modelling plant responses induced by soil changes would be a valuable research area to model feedbacks between the plant and soil components (Oldfield et al., 2017). Estimating changes in soil properties induced by changes in SOM contents using pedotransfer functions is an understudied topic in plant and soil modelling but has great potential. For example, estimating changes in water-holding capacity, CEC, and soil physical structure, as well as their subsequent effect on agronomic yield, represents a great opportunity (Lal, 2006) that is yet to be fully exploited. Having the capacity to predict the response of cocoa productivity to environmental factors and farming practices like organic matter additions would help compare different cultivation plans and their economic viability. Refining the model by considering seasonal variations and their effects on plant growth, litter transformation, and soil properties could be fruitful for future work. This change would require shifting the modelling time step to a daily or monthly one.

In the second step of Chapter 5, the plant and SOM dynamics model was applied to simulate the effect of organic inputs on SOM stocks. In addition, it was used to calculate the quantity of different organic matter inputs required to compensate for SOM losses over time. This model application can be used to provide insights for the development of a SOM management strategy in cocoa farms, with a focus on Sulawesi in Indonesia.

The model application phase indicated that the long-term dynamic of SOM stocks could vary from one farm to another. When crops are planted on SOM-depleted soils and with the right local conditions, SOM stocks could significantly increase. Conversely, when crops are planted on SOM-rich soils, with conditions favourable to SOM mineralisation, the long-term SOM dynamics could result in continuous losses. Approximately 30 Mg ha^{-1} of SOM would be required to compensate for the net losses occurring during the first 14 years out of 35 years of cultivation of the average farm of the baseline simulation. After 14 years, inputs from the cocoa trees were sufficient to offset the losses. To attain those SOM inputs, the exogenic organic matter (EOM) inputs need to be differentiated by the approximate humification coefficient of the considered EOM since the k_1 coefficient represents the estimated fraction of EOM inputs converted to SOM. For example, if cattle manure is considered as an EOM input (k_1 = 0.3) during 14 years (the SOM shortage period of the baseline simulation of Chapter 5), the total quantity applied per tree would be 30 ÷ 0.3 = 90 kg (dry matter). Considering biochar (k_1 = 1), the total quantity of inputs required to cancel the loss of SOM would be 30 ÷ 1 = 30 kg per tree. The higher the k_1 coefficient of the input, the lower becomes the application rate to offset SOM losses. Also, the simulation has shown that those EOM inputs become progressively smaller as organic matter inputs from cocoa trees increase, and eventually become zero (after 14 years for this baseline simulation). The highest rates of inputs would be needed at planting to compensate for the imbalance between high SOM output and low SOM inputs during the first 14 years. Such inputs would also benefit the growth of the young cocoa trees, and as was demonstrated Chapter 3, could potentially substitute for mineral fertilizers and amendments.

Contributions to knowledge

This study:

- modified the conceptual and mathematical structure of the AMG soil model to the particularities of a perennial tree crop system like cocoa;
- developed an R program and a Shiny application to allow other users to model SOM changes in perennial tree crops (tropical or not), with and without EOM input scenarios;
- produced a tool to estimate the amount of EOM needed to compensate SOM losses;
- found that the early years after planting can experience large SOM losses, but intensity and duration are site-dependent;
- identified key research areas required to improve and calibrate the model while advancing our understanding of organic matter fluxes in cocoa farms;

- provided a pivotal first step to simulate the forecast the dynamics of C in diversified cocoa farming scenarios (necessitating minor model additions) to address climate mitigation goals of the cocoa industry.

6.2.5 SOM management on cocoa farms: recommendations and future research

This section synthesizes the knowledge gained during this thesis and outlines key principles and workstreams to improve SOM management in Indonesia cocoa farms.

Importance of SOM

Applying an adequate SOM management strategy can provide production and environmental benefits (Lal, 2015, 2016). Maintaining good SOM levels on cocoa farms is valuable as it supports the growth, development, and yield of cocoa trees, and it can reduce the need for farmers to purchase and use external inputs (Fungenzi et al., 2021; Mulia et al., 2019; Oldfield et al., 2019). High, rather than low, SOM levels are also beneficial in reducing atmospheric CO_2 levels, and hence are positive in reducing climate change (Albrecht & Kandji, 2003; Bossio et al., 2020).

Challenge with Indonesia: fast SOM mineralisation

However, maintaining high SOM levels on young cocoa farms can be problematic in the unfavourable settings of Indonesia. High and frequent precipitation and high ambient temperatures favour SOM losses (Davidson & Janssens, 2006; Sierra et al., 2009). In this study, the modelled annual rate of SOM losses (k_2) could be as high as 0.125, meaning that each year, the SOM content of a farm that receives no inputs (i.e., bare soil, no vegetation, no organic inputs) would potentially decline by 12.5%. Estimations using RothC suggested an approximate yearly mineralisation rate of 7% (Morais et al., 2019). As a point of reference, this coefficient is generally around 0.5-5% in temperate arable fields (COMIFER, 2005).

Site-specific strategies

Characterizing the climate and soil of the site is essential to inform a suitable SOM management strategy. Cocoa farms can be highly diverse, and their context controls their potential to store or lose SOM. While it may not be necessary to gather data to address each model parameter to begin making recommendations, this research has shown that the variation of SOM stocks are highly dynamic in a location like Sulawesi. Under those circumstances, characterizing the pedoclimatic context of the farm is a prerequisite.

Soil monitoring

Determining the initial SOM stock present on the farm before or at planting is critical. Farms with high SOM stocks risk experiencing losses, which, to be compensated, can require significant organic inputs if the location presents features promoting SOM losses (e.g., low clay contents, high pH, low tree density, low residue deposition rates). On the other hand, planting cocoa at a SOM-depleted location can result in net SOM gains in the long term and could be a possible strategy to restore a degraded site.

SOM should be monitored as frequently as possible (every year or two years), especially during the early years after planting, to determine the trend followed by the farm and regularly adjust farm interventions such as OM inputs. Recent technological developments could help cocoa industries proceed to rapid soil assessment using proximal soil sensors instead of relying on traditional and laborious soil sampling and analysis methods (England & Rossel, 2018). Using adjustment procedures, such as the ones used in Chapter 4 (i.e., using stocks instead of contents, correcting LOI results for soil clay content, calculating SOM/clay ratios) and other techniques such as equivalent soil mass sampling (Wendt & Hauser, 2013), should be implemented to improve comparisons between different locations and age of stand.

Long-term cocoa experiments, and the soil data archives they can generate, seem to be notably lacking from the cocoa literature. Research on long-term soil changes typically preferred *space-for-time* approaches (as in Chapter 4) instead of *real-time-series*, probably because they demand fewer resources to be conducted (Huggett, 1998; Lehmann & Joseph, 2015; Pickett, 1989; Walker et al., 2010). However, the fundamental understanding of cocoa cultivation systems will remain limited without real-time chronosequences obtained from well-maintained and controlled research stations or farmer-maintained farms. For instance, long-term experiments are decisive to calibrate plant and soil models (Bayer et al., 2006). The value of such experiments increases with time and makes them crucial to ensure the sustainability of food production systems (Johnston & Poulton, 2018).

Farm data are a complementary source of information, but it seems that Sulawesian cocoa farmers keep very few records about their farms. During fieldwork, it was impossible to obtain historical cocoa bean production data. The absence or the reluctance to share such information limits our capacity to extract valuable insights from farm data.

Leverage high plant productivity to maximize SOM deposits

A farmer's goal should be to maximize the on-site production of plant biomass and its regular return to the soil in order to build up SOM and improve soil functioning. Although SOM mineralisation rates are high in Indonesia, its climate is favourable to developing abundant above and below ground cocoa and shade tree biomass capable of supplying large amounts of organic matter. Indonesia hosts some of the most C-rich ecosystems globally (Gibbs, 2006, 2008; Guillaume et al., 2018; Sullivan et al., 2017). Farm designs and practices will consequently be decisive to take advantage of this opportunity. However, note that even diversified agroforests may not lead to improving C stocks and soil properties to the same level as natural forest systems (Wartenberg et al., 2017). Keeping or planting shade trees is one method to increase residue deposition on the farm. The regular pruning of some of those trees can be a strategic driver to control the flux of organic matter and nutrients returned to the soil (Asigbaase et al., 2021b; Tangjang et al., 2015). Field experiments will be needed to determine the correct pruning frequencies and intensities, limit competition between shade and cocoa trees and optimize C capture by the vegetation. With this in mind, multi-story agroforestry is a sensible option to accumulate desired ecosystem services and reduce land degradation risks.

Application of exogenous organic matter (EOM)

Another crucial component of an effective SOM strategy for cocoa farms is to use EOMs to improve soil functioning and increase cocoa productivity. If feasible, local EOMs like crop residues, manures, and mulches should be considered, as they will necessitate lower transportation costs.

Organic inputs should be applied at planting, with compost in the planting holes and mulch applied to the soil surface. Localized compost applications, incorporated with soil or placed in pits, may be more effective than broadcasting it on the surface, concentrating the effect in hotspots and yielding benefits (i.e., threshold effect; Oldfield et al., 2020) instead of "diluting" the inputs, resulting in minimal effects. Locally-made biochar should be considered as an option to improve soil pH, CEC, and potentially build up long-term stocks of stable C (Salifu et al., 2020; Sasmita et al., 2017; Vignesh et al., 2012). In addition, recent research suggests that biochar can mitigate cadmium accumulation by cocoa trees (Ramtahal et al., 2019), which is a concern of the cocoa industry. Vermicompost has also been shown to be a promising soil amendment to improve cocoa growth (Chavez et al., 2016; Wayuono et al., 2019).

The development of supply chains capable of providing EOMs appears to be a critical aspect of a successful SOM strategy. In addition to the on-farm production of organic matter (e.g., litterfall, root turnover, tree pruning, hedges, cover crops), external sources of organic matter can diversify the nature of inputs used to maintain soil health. At the same time, those supply chains can also address other concerns, such as waste management and their associated environmental impacts (Ayilara et al., 2020; Dhokhikah & Trihadiningrum, 2012; Fungenzi, 2015; Meidiana & Gamse, 2010; Shukor et al., 2018). There is also an argument that mineral and synthetic fertilizer prices could become unaffordable to Indonesian farmers if world energy prices increase. Finding local sources is a strategic way to moderate the costs of organic matter and nutrient inputs. A systematic approach is required to identify solutions for those complementary issues.

If possible, the local annual SOM losses can be estimated by calculating the k_2 coefficient at the farm (calculated with the AMG version 2 formula) using mean annual temperature, potential evapotranspiration (PET), irrigation water inputs, annual precipitations, clay content, and soil $CaCO_3$ content, pH, and C:N ratios). This value can be used to predict how much SOM could be theoretically lost each year. An upper limit for EOM inputs could be estimated as (approximately) k_2 times the current SOM stock to maintain the current levels. SOM gains obtained from fresh EOM inputs can be estimated using their estimated k_1 and dry matter content (found in reference tables).

Avoid bare soil

Bare soil encourages high SOM losses since no vegetation is available to provide aboveground and belowground organic matter inputs. Some farmers completely clear out the vegetation before planting and leave the soil bare below the cocoa tree (Figure 6.1). Such practice is probably detrimental to soil health as it lead to significant SOM losses. This site shown in the photograph below(farm B) had the highest soil BD of the farm dataset (1.55 g cm^{-3}). Instead of keeping the farm free of vegetation other than cocoa and shade trees, shade-tolerant cover crops should be considered to improve the organic matter inputs. Using a legume could have the capacity to stimulate cocoa leaf litter decomposition. Besides a live cover, mulches should also be considered, especially prior to planting. Growing a large plant cover (e.g., through fallowing) can provide a significant cover and result in useful above- and below-ground SOM inputs. Soil structural improvement will also come from those interventions. However, it should be determined if benefits outweigh competition for water and nutrients.

Figure 6.1: Example of a one-year-old cocoa farm with soil left almost entirely bare and prone to soil degradation

Litter dynamics

Litter decomposition can improve soil quality and can contribute to restoring degraded soils (León & Osorio, 2014). However, the accumulation of cocoa leaf litter in certain farms shows that it is not always rapidly decomposed, incorporated in the soil, and does not provide nutrients for the trees. Several factors may be limiting litter decomposition, such as a lack of water or cofactors regulating the decomposition of cocoa leaves. Solutions stimulating litter decomposition should be investigated. Options like leaf shredding or gathering litter in pits could be tested. Spraying or mixing the cocoa leaf litter with N-rich materials or biostimulants could increase the litter decomposition rate.

In addition, the interactions litter plays with cocoa and shade trees, other than nutrient cycling, need to be elucidated (Veen et al., 2019).

Cocoa tree nutrition

Managing SOM and organic matter inputs effectively cannot be achieved independently from adequate soil fertility management (Gram et al., 2020). Fertilizer adoption in general low by cocoa farmers (Wartenberg et al., 2018), and further research is required to improve cocoa fertilizer recommendations (CocoaSoils, 2019). At this stage, recommendations are generally based on production targets, aiming to replace nutrients removed by harvest. However, other approaches can be useful and complementary, including measuring soil nutrient availability (Snoeck et al., 2016). If farmers have access to soil tests, soil analysis results can be compared to recommended sufficiency ranges. At the same time, there is a paucity of modern experiments determining cocoa (and shade tree) responses after fertilizer additions, which can be particularly useful in establishing recommended fertilizer application rates (van Vliet et al., 2015). Such experiments can also help quantify nutrient cycling and the rates at which litter can supply nutrients to the crop. More information on plant, litter, and soil response to fertilizer application would help determine the best soil input strategy and how fertilizer and organic inputs can complement each other.

Cocoa carbon balance and accounting

From an environmental standpoint, further work needs to be done to assess the C balance of cocoa farms. Indeed, cocoa businesses have committed to reducing their net contributions to GHG (Barry Callebaut, n.d.; Mars Inc., 2021; Mondelez International, 2020; Nestlé, 2021; Valrhona, n.d.). A standard evaluation method could be developed to account for those efforts and make valid comparisons between different systems in order to find optimal solutions. Considering that complex multi-story agroforests are likely the best approach to store large stocks of C, investigations are needed to assess their storage rates and capacities accurately. Monitoring changes with empirical data and modelling plant and soil C variations will be two essential and complementary approaches to achieve this goal.

Organic matter decomposition can emit potent GHG like methane and nitrous oxide (Brenzinger et al., 2018; L. G. Smith et al., 2019). There is a need to evaluate and limit the risk of emitting GHG resulting from litter decomposition and SOM mineralisation, as well as additional emissions produced by organic inputs used to offset initial SOM losses.

Bridging the gap between organic inputs, the soil, and plant responses

To develop effective soil management strategies using organic inputs, a major challenge lying at the core of soil health and fertility concepts remains to be solved. It remains common practice to describe, evaluate, and predict the effect of applying organic inputs on measurable soil properties without explicitly quantifying the link with crop response. With this approach, it is as if there was a black box between the intervention (e.g., applying compost) and soil response, and the crop response. For this reason, researchers are unable to link quantitative, predictive targets for SOM to agricultural outcomes. This problem is illustrated by the recurrent discussion about the quest for an optimal SOM level (Loveland & Webb, 2003; Oldfield et al., 2015, 2017, 2020). Is there a lower critical threshold below which plant functioning is negatively impacted? Similarly, is there an upper limit above which no plant benefits occur? For example, field experiments and models help to anticipate quantitative and qualitative SOM changes, but the next step is missing. How will the crop respond to such soil changes? Can models predict soil functional changes that have a direct and measurable effect on crop growth and development?

This problem is not new. It was, for example, expressed by Russell in 1977: "[…] a major problem facing the agricultural research community is to quantify the effects of [SOM] on the complex soil properties subsumed under the phrase soil fertility, so that it can help farmers develop systems which will minimize any harmful effects this lowering [of SOM] brings about".

Twenty years after, Janzen et al. (1997) posed the same comment: "Even when considering only one function (productivity), […] identifying optimum SOM values is exceedingly complex. If we add to this the need to consider other equally important soil functions (e.g., role as environmental buffer), then the objective of identifying optimum values becomes wholly unrealistic. More appropriate may be an effort to understand the demands placed on soil in specific ecosystems, and then to determine what changes in SOM content and composition would enhance the capacity of that soil to fulfil those functions."

Fast forward another eighteen years, and this problem is still on the agenda as Oldfield et al. (2015) explain, "SOM is generally considered *the* indicator of soil health […]. However, the numerical level that would be considered good, or what change in [SOM] levels constitutes a significant functional change, has not been established".

The approach in modelling SOM feedbacks, as developed in this thesis, can be helpful in advancing this area of research. A prerequisite for this approach is to have two good models, one capable of anticipating soil functional changes after applying a particular input and another able to predict crop responses following the variation of this soil functional change. A first approach would be to quantitively predict how various rates of addition of a particular organic matter input affect a critical soil functional property by using a dedicated soil model or a pedotransfer function. Meanwhile, a plant model could predict the response of a crop to changes in this same functional property. By coupling changes in SOM to changes in another critical property, inputs would result in predictable crop responses.

Until the gap between the soil and plant is filled by a functional understanding of key soil processes leading to plant responses, the effect of organic matter additions will remain relatively quantitatively unpredictable. Deepening our understanding of such mechanisms is fundamental to developing evidence-based organic inputs to improve soil health and achieve sustainable soil management in the long term.

6.3 Conclusions

This study was designed and undertaken to improve scientific understanding of SOM dynamics and its management on cocoa farms. Summarizing existing data on C storage on cocoa farms from various regions around the world has revealed that they can display significant temporal variations and spatial differences in SOM dynamics. The mean C stock of 15-35-years-old cocoa farms was ~85 Mg ha^{-1} (including shade trees, and soil to a 10 cm depth). The literature analysis and the field and modelling experiments conducted during this research indicated that SOM stocks can decline rapidly in settings like Sulawesi but could also recover rapidly. Using a false-time chronosequence, a decline of -40% in SOM per unit clay was observed between 0.5 and 2 years after planting. The long-term trends can translate either into net gains or net losses, depending on the combination of pedoclimatic context, farm design, and practices such as organic inputs. Comparing mineral and organic inputs revealed that compost can significantly increase cocoa yields, without additional benefits from adding fertilizer and/or dolomite. Including tree mortality rates, the dry bean yield of the composted treatments was ~270-300% that of the control, whereas the fertilizer with/without dolomite was ~170% that of the control. This research has also shown that shade trees can play a major role in storing C. The mean aboveground C stock of shade trees was four times the aboveground cocoa C stock (respectively ~40 and ~10 Mg ha^{-1}). The findings of this study have highlighted that, in locations like Sulawesi, the early years after planting can represent a critical but overlooked period at risk of soil degradation through SOM depletion because plant inputs are insufficient to compensate for the losses, leaving the soil with a net SOM-deficit.

The model developed during this study can be used to explore the long-term changes occurring in cocoa soils and assist in planning effective and sustainable cocoa farm management strategies. Notwithstanding its limitations, the model provides a useful contribution to understanding SOM dynamics in perennial tree crops like cocoa. Although long-term experiments were lacking to calibrate and validate the model, this model can serve as a valuable tool to evaluate EOM inputs scenarios. More research is needed to refine the structure and the parameters of this model in order to improve its applicability to other locations and its representativeness. Further experimentation into the effect of pruning cocoa trees and the role of shade trees into SOM dynamics is strongly recommended. Taken together, these findings suggest that practical solutions can be developed to maintain, restore and improve soil health on cocoa farms. Nevertheless, one of the ultimate unresolved challenges is for soil scientists and agronomists to link SOM changes to functional changes resulting in predictable plant responses and thus solve a puzzle that has been pending for a long time.

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APPENDICES

A.1. Appendices to Chapter 1

(empty: only used to make table and figure numbering more convenient)

A.2. Appendices to Chapter 2

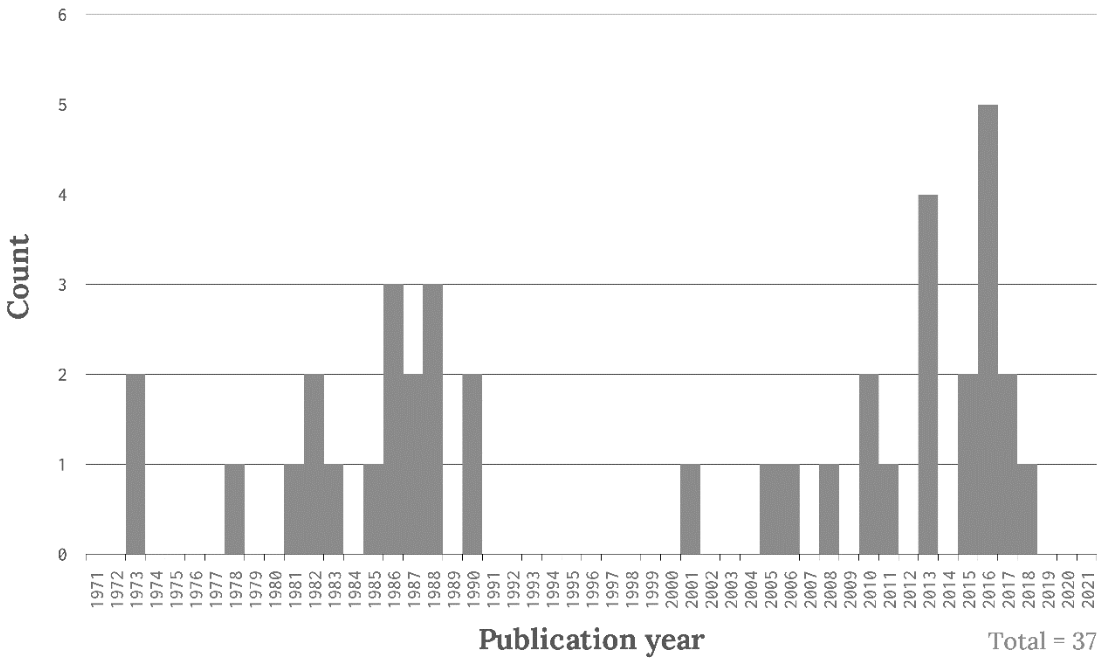

Figure A - 2.1: Chronological distribution of the studies of the meta-analysis

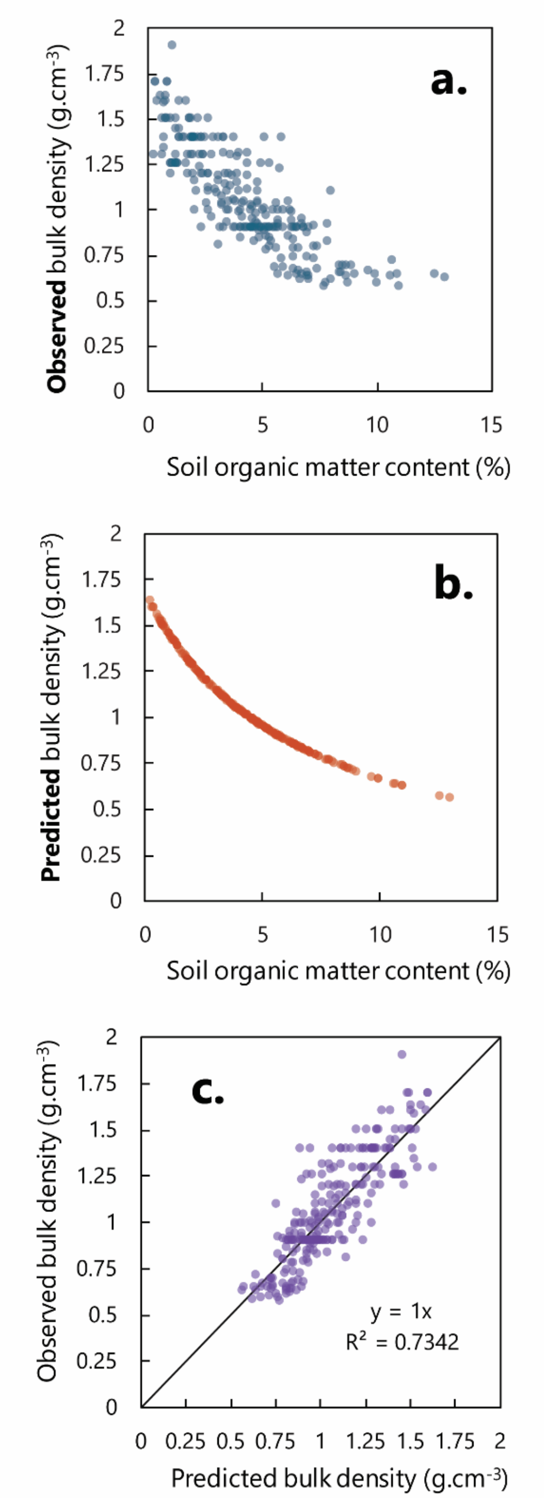

Figure A - 2.2: Relationships between soil organic matter and observed and predicted bulk densities

- **a.** Relationship between observed soil organic matter content and observed bulk density.
- **b.** Modelled relationship between predicted bulk densities and observed soil organic matter contents (the relationship is expressed in Equation 2.11, with constants equal to 0.103 for OMBD, and 1.683 for MBD).
- **c.** Observed vs. predicted bulk densities using Stewart et al. (1970) relationship, optimized to minimize the sum of chi² values. The line represents the 1:1 relationship.

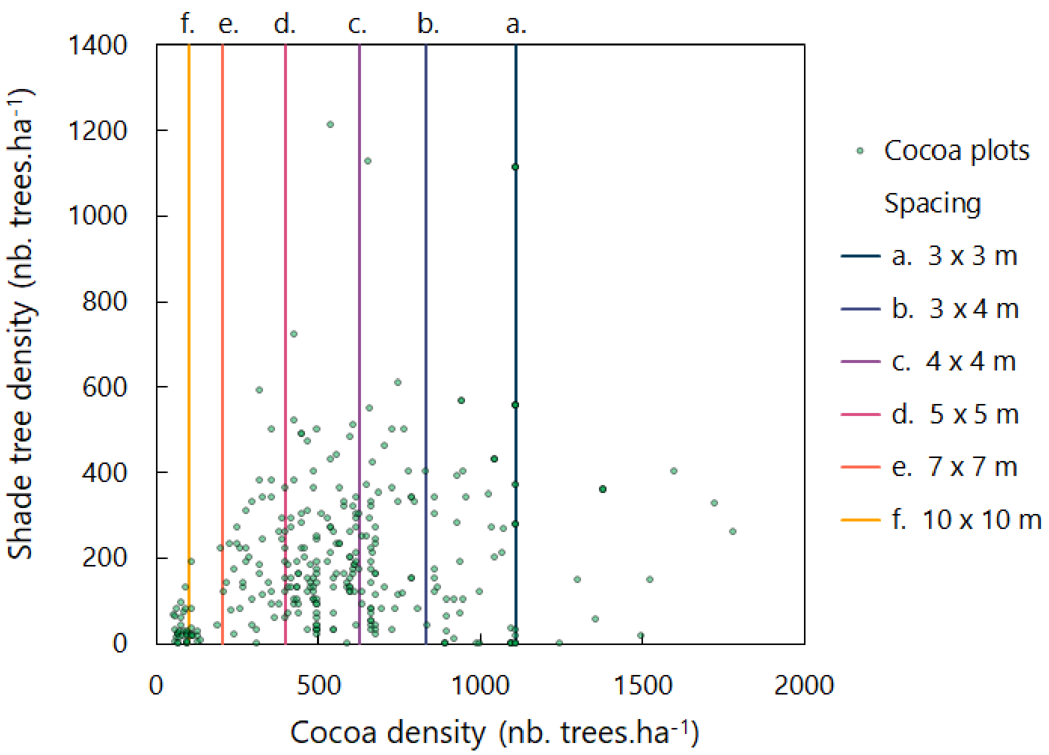

Figure A - 2.3: Distribution of the cocoa and shade trees densities for each plot

Vertical lines represent theoretical spacings for cocoa for comparison purposes. One outlier has been removed (coming from Isaac et al., 2005): a cocoa plot with a density of 3125 cocoa trees per hectares at age 2, probably a nursery).

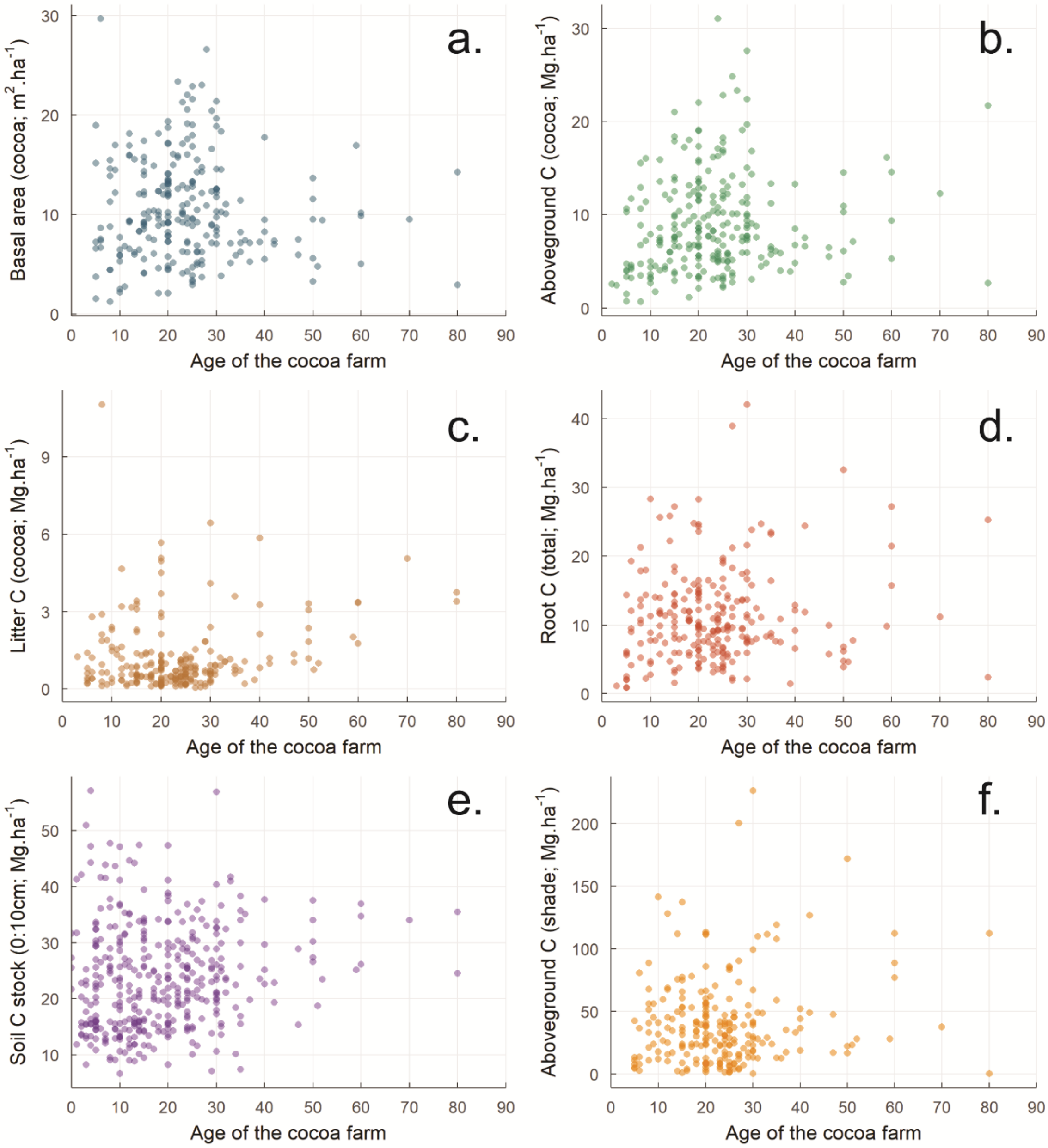

Figure A - 2.4: Scatterplots of the age distribution of the different C stocks

a. Cocoa basal areas (n = 241);
b. Cocoa aboveground C stocks (n = 250);
c. Shade aboveground C stocks (n = 242);
d. Litter C stocks (n = 236);
e. Total root C stocks (n = 242; includes indistinctively cocoa and other species);
f. Soil C stocks (n= 381).

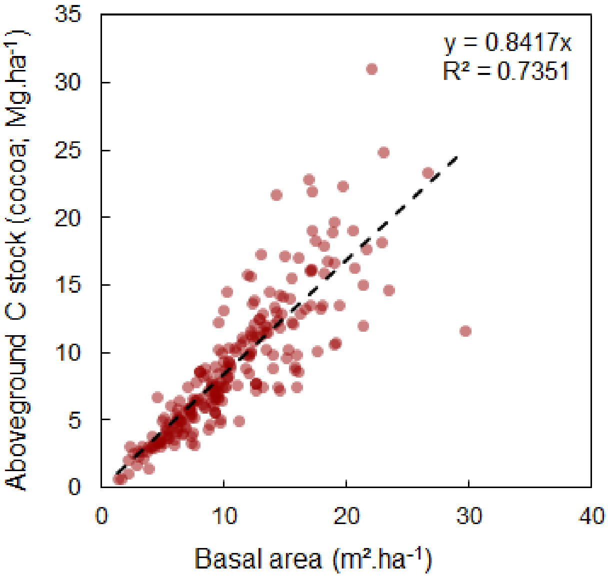

Figure A - 2.5: Relationship between cocoa basal areas and estimated aboveground C stocks (n = 242)

Three outliers were removed, with aboveground C stocks of 61.89, 99.23, and 103.42 Mg ha^{-1}, respectively corresponding to basal areas of 22.70, 34.42, and 29.15 m^2 ha^{-1}.

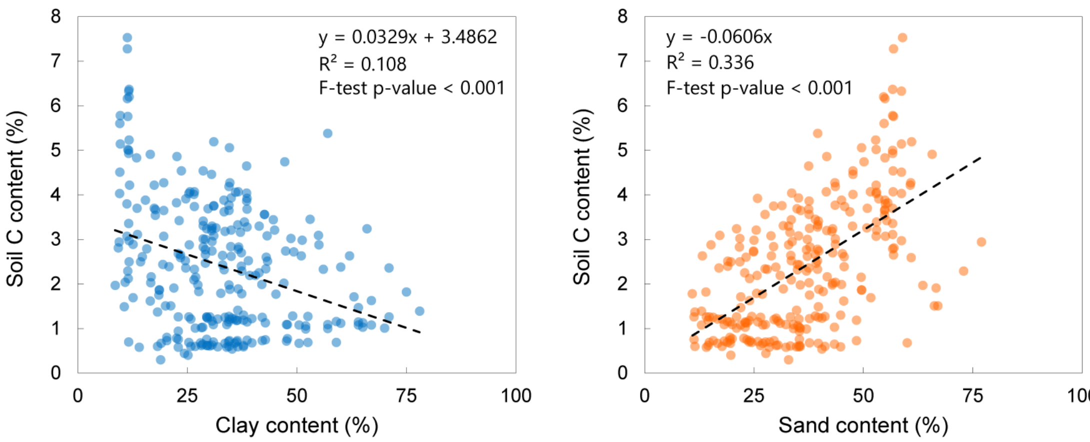

Figure A - 2.6: Relationships between clay (left-hand figure), sand (right-hand figure), and soil C contents (all depths; n = 267)

Table A - 2.1: Variables compiled in the dataset of meta-analysis and corresponding references

Variable	Unit	Range of results	List of references *	Nb. of studies
Authors	-	-	1:37	37
Journal	-	-	1:37	37
Publication year	year	1973-2018	1:37	37
Country, Region, District, Town	-	-	1:37 (country level)	37
Altitude	m	9-1153	3, 4, 5, 8, 11, 13, 17, 19:23, 25:28, 35:37	19
Annual rainfall	mm yr^{-1}	324-3936	1:6, 8, 9, 11, 13, 14, 17:23, 25:29, 31, 32, 35:37	31
Average temperature	Avg. C° yr^{-1}	18.5-29	2:5, 8, 9, 11, 13, 14, 17:21, 23, 25:39, 31, 32, 35:37	26
Shade trees species or type of comparative ecosystem	-	-	**NA:** 1, 2, 4, 6:8, 10:12, 14:17, 19:27, 29:36; **Hevea:** 20, 27, 31; **Coconut:** 17, 27, 31, 36; **Cordia:** 3, 5, 13; **Erythrina:** 3, 9, 11, 13, 20, 21; **Gliricidia:** 17, 18, 20, 21, 25, 28, 31, 36, 37	**NA**: 30 **Hevea**: 3 **Coconut**: 4 **Cordia**: 3 **Erythrina**: 6 **Gliricidia**: 9
Age of the plantation (or comparative ecosystem)	years	0-80	**NA**: 1, 6, 7, 9, 10, 15, 19, 24, 27, 30, 31, 33, 34 **Age available for all others**	**NA**: 13
Cocoa density	Nb. of trees ha^{-1}	55-3215	3:6, 11, 13, 14, 17, 18, 20, 22, 23, 25:28, 31, 32, 35, 37	21
Shade trees or other species densities	Nb. of trees ha^{-1}	0-1210	3:5, 8, 9, 11, 13, 14, 17, 18, 20, 22, 23, 25, 26, 27, 28, 35, 37	19
Mean diameter at breast height (DBH), or at 50 cm	cm	3.36-12.4	**DBH (cocoa)**: 8, 17, 22, 23 **D50 (cocoa)**: 28	**DBH (cocoa)**: 4 **D50 (cocoa)**: 1
Basal area per hectare	$m^2\ ha^{-1}$	1.23-34.42	**Cocoa**: 17, 23, 25, 27, 35	5
Yearly deposition of litterfall	Mg dry wt $ha^{-1}\ yr^{-1}$	3.2-21.2	**Cocoa and shade trees**: 4:10, 13:15, 17, 18, 24, 25, 30, 33, 34	17
Litter present at the time	Mg dry wt ha^{-1}	0.13-23.27	3, 5, 8, 22, 29, 35	6
C in litter present at the time	Mg C ha^{-1}	0.05-11.02	8, 17, 27, 35	4
Aboveground biomass	Mg dry wt ha^{-1}	1.32-62.08 (cocoa) 0-452.22 (shade)	**Cocoa and shade trees**: 3, 5, 8, 14, 17, 22, 23, 25, 35	9
Belowground biomass	Mg dry wt ha^{-1}	1.78-18.58	**Total**: 3, 5, 8, 17, 22, 25	6
Total biomass	Mg dry wt ha^{-1}	9.6-301.1	3, 5, 8, 14, 17 22, 23	7
Aboveground C	Mg C ha^{-1}	0.66-103.42 (cocoa) 0-226.11 (shade)	**Cocoa**: 3, 5, 8, 14, 17, 22, 23, 24, 27, 35 **Shade:** 17, 25, 35	**Cocoa:** 10 **Shade:** 3
Belowground C		0.85-42.02 (total)	**Total**: 3, 5, 8, 17, 22, 23, 25, 35	8
Total Biomass C		4.3-278.2	12, 14, 17, 25, 28, 35	6
Biomass C sequestration rate	Mg C $ha^{-1}\ yr^{-1}$	2.8-17.8	5, 14, 25, 35	4
Yield (cocoa beans)	kg dry wt $ha^{-1}\ yr^{-1}$	0-1920	3:6, 17, 18, 25, 35, 37	11

Table A - 2.2: (continued A. 1) Variables compiled in the dataset of meta-analysis and corresponding references

Variable	Unit	Range of results	List of references *	Nb. of studies
Soil Type	WRB, or other	-	1, 2, 3, 4, 8, 11, 14, 17:19, 21, 24, 25, 27, 32, 37	16
Depth of sampling	cm	0-250	1:5, 8, 11, 14, 17, 19:22, 24, 25, 28, 31, 32, 35:37	21
Bulk density	g cm^{-3}	0.42-1.9	**Given:** 1, 3, 5, 8, 11, 14, 19:22, 28, 31, 35, 37 **Calculated:** 5, 21, 28 **Estimated:** 1, 2, 4, 24, 25, 32, 36 **NA:** 3, 4, 6, 7, 9, 10, 12, 13, 15:18, 23, 26, 27, 30, 35	**Given**: 14 **Calculated**: 3 **Estimated**: 7 **NA**: 18
Sand, silt and clay contents	%	Sand: 9.3-77 Silt: 2.4-70.3 Clay: 8.5-78	1, 2, 8, 11, 20, 22, 35, 37	8
Texture	class	-	1:3, 5, 8, 11, 14, 19, 20, 22, 25, 27, 29, 35, 37	15
Soil organic matter contents (from the top sampled layer)	%	0.21-19.28	**Given:** 1:3, 5, 21, 31 **Calculated:** 3, 5 **Estimated:** 4, 8, 11, 14, 19:22, 24, 25, 28, 29, 32, 35:37 **NA:** 3, 4, 6, 7, 9, 10, 12, 13, 15:19, 23, 26, 27, 30, 33:35	**Given**: 6 **Calculated**: 2 **Estimated**: 16 **NA**: 19
Soil organic matter stocks (from topsoil values, converted to 0-10 cm)	Mg ha^{-1}	2.73-98.56	**Given:** 3, 5 **Calculated:** 1, 3, 21, 31 **Estimated:** 2, 4, 8, 11, 14, 17, 19:22, 24, 25, 28, 29, 32, 35:37 **NA:** 3, 4, 6, 7, 9, 10, 12, 13, 15:18, 23, 26, 27, 30, 33:35	**Given**: 2 **Calculated**: 4 **Estimated**: 18 **NA**: 19
Soil C contents (from the top sampled layer)	%	0.12-11.21	**Given**: 4, 8, 19, 21, 22, 24, 25, 28, 29, 31, 35:37 **Calculated**: 3, 8, 11, 14, 20, 32 **Estimated**: 1:3, 5 **NA**: 3, 4, 6, 7, 9, 10, 12, 13, 15:18, 23, 26, 27, 30, 33:35	**Given**: 13 **Calculated**: 6 **Estimated**: 4 **NA**: 19
Soil C stocks (from topsoil values, converted to 0-10 cm)	Mg ha^{-1}	1.56-57.09	**Given**: 8, 11, 14, 17, 20:22, 28, 37 **Calculated**: 3, 19, 21, 29, 31, 35 **Estimated**: 1:5, 24, 25, 32, 36 **NA**: 3, 4, 6, 7, 9, 10, 12, 13, 15:18, 23, 26, 27, 30, 33:35	**Given**: 9 **Calculated**: 6 **Estimated**: 9 **NA**: 19

Table A - 2.3: Summary of the pedoclimatic contexts of each study of the meta-analysis

Code	Country	Altitude	Rainfall	Avg. T°	Soil Type	Age
		m	mm yr^{-1}	C° yr^{-1}	WRB FAO, or other	years
1	Nigeria	-	1500	-	Red yellow latosols, alfisols, ferruginous tropical soils, alfisols, egbeda association, orthic luvisols	-
2			1300	28		13
3	Costa Rica	625	2648	22	Inceptisol	1, 5, 10
4	Venezuela	12	740	25	Entisol	30
5	Costa Rica	625	2648	22	-	0, 10
6	Cameroon	-	1700	-	-	30
7	-	-	-	-	-	-
8	Ghana	375	1575	29	Ferric lixisols / Leptosols-Regosols	3, 15, 30
9	Brazil	-	1862	23	-	-
10	-	-	-	-	-	-
11	Brazil	115	1500	26	Highly weathered reddish-yellow Ferralsols	30
12	Cameroon	-	-	-	-	15, 25, 40
13	Costa Rica	625	2648	22	-	6, 7, 8
14	Ghana	-	1054.5	26.1	Orchosol–oxysol	2, 15, 25
15	-	-	-	-	-	-
16	-	-	-	-	-	11
17	Indonesia	585-1050	2844-3534	20.8-24.4	Acrisols on silt- and clay-rich substrate, Cambisols on sand- and silt-rich substrate	6
18	Malaysia	-	1850	21	Oxisol, ultisol	9
19	Ghana	149.5	1175	28	Orchosol–oxysol	-
20	Brazil	100	1500	24	-	4, 20, 30, 35
21	Mexico	10	2275	26	Gleysols	3, 8, 16, 28
22	Cameroon	540	1533	-	-	35
23	Nigeria	600	1367	27	-	10
24	Ghana	-	-	-	Ferric acrisols, ferric lixisol	-
25	Indonesia	556	2165	25	Cambic umbrisol	20, 22, 23, 26, 28, 30
26	Cameroon	700	1600	25	-	4, 15, 31, 40
27	Indonesia	25-276.5	324-368	25.5-28.5	Lithosol, alluvial, podzolic & peat	-
28		622-1152.5	1638-2225	24-24.5	-	1:5, 8, 9, 12, 15
29	Ivory Coast	-	1626.7	26	-	5, 10, 20
30	-	-	-	-	-	-
31	Indonesia	-	1919	26.5	-	-
32	Malaysia	-	2300	26	Haplic ferralsols	22
33	-	-	-	-	-	-
34	Ghana	-	-	-	-	-
35	Costa Rica, Panama, Honduras, Guatemala, Nicaragua	17-774	1025-3936	18.5-27.7	-	5:80
36	Indonesia	9-726	1436-3761	22.8-27.4	-	2:34
37	Indonesia	35-143	2080	26.5	Orthic acrisols & dystric fluvisols	7:21

Table A - 2.4: Distribution of the cocoa farm ages

Age class (years)	Frequency	Proportion	
[0-5[	25	5.3%	20.2%
[5-10[	71	14.9%	
[10-15[	82	17.3%	30.5%
[15-20[	63	13.3%	
[20-25[	84	17.7%	29.7%
[25-30[	57	12.0%	
[30-35[	39	8.2%	10.5%
[35-40[	11	2.3%	
[40-45[	8	1.7%	5.1%
[45-50[	2	0.4%	
[50-55[	7	1.5%	
[55-60[	1	0.2%	
[60-65[	3	0.6%	
[65-70[	0	0.0%	
[70-75[	1	0.2%	
[75-80[	0	0.0%	
[80+[	2	0.4%	
Sub-total	456	100%	
NA	**19**	**4%**	
Total	475	**100%**	

Age class intervals are left-closed and right-opened. 'NA' refers to the plots for which age was not mentioned.

Table A - 2.5: Distributions of the densities of cocoa trees across all plots included in our meta-analysis

Spacing (m)	**Cocoa density** (Nb. Trees ha^{-1})	**Frequency**	**Proportion**
> 5x5	[0 - 400[	82	18%
5x5 to 4x4	[400 - 625[	116	25%
4x4 to 3x4	[625 - 833[	54	12%
3x4 to 3x3	[833 - 1111[	41	9%
3x3 to 2.5x3	[1111 - 1333[	21	5%
2.5x3 to 2.5x2.5	[1333 - 1600[	6	1%
2.5x2.5 to 2x2	[1600 - 2500[	3	1%
≤ 2x2	≤2500	1	0%
NA		135	29%
	Total	459	

NA refers to the plots for which density was not mentioned in the study. Density intervals are left-closed and right-opened.

Table A - 2.6: Distributions of the densities of shade trees across all plots included in our meta-analysis

Spacing (m)	**Shade density** (Nb. Trees ha^{-1})	**Frequency**	**Proportion**
> 10x10	[0 - 100[	98	21%
10x10 to 7x7	[100 - 204[	91	20%
7x7 to 5x5	[204 - 400[	87	19%
5x5 to 4x4	[400 - 625[	32	7%
4x4 to 3x4	[625 - 83[	1	~0%
3x4 to 3x3	[833 - 1111[	0	0%
3x3 to 2x3	[1111 - 1333[	6	1%
≤ 2 x3	≤1333	0	0%
NA		144	31%
	Total	459	

NA refers to the plots for which density was not mentioned in the study. Density intervals are left-closed and right-opened.

Table A - 2.7: Description given for the shade tree species or structure

Shade species or the compared ecosystem	Nb. of plots	Proportion	List of References
30 species incl. *Terminalia superba, Ceiba pentadra, Isolona hexaloba*	1	0.22%	22
Cabruca	2	0.43%	11, 20
Castilloa elastica, Erythrina sp., and *Artocarpus altilis*	1	0.22%	4
Cocos nucifera L.	1	0.22%	27
Cocos nucifera L. + *Gliricidia* + *Leucaena*	1	0.22%	31
Cordia	1	0.22%	3
Cordia / Erythrina	1	0.22%	3
Erythrina	2	0.43%	3, 11
Erythrina / Gliricidia / Cedrela / Colubrina	1	0.22%	21
Erythrina fusca	1	0.22%	9
Erythrina glauca	1	0.22%	20
Full sun	10	2.17%	24, 25, 27, 29, 31, 32
Gliricidia maculata	1	0.22%	18
Gliricidia sepium	17	3.69%	25, 28
Gliricidia sepium & *Cocos nucifera* L.	1	0.22%	17
Hevea braziliensis	3	0.65%	20, 27, 31
Hevea braziliensis & *Gliricidia sepium*	2	0.43%	20
Light shade	1	0.22%	6
Mixture	6	1.30%	4, 8, 19
Mixture, *Gliricidia sepium*	36	7.81%	37
Mixture, mostly *Cocos nucifera* L. and *Gliricidia sepium*	120	26.03%	36
Multi-strata	4	0.87%	25, 27
***NA* (not mentioned)**	245	53.15%	1, 2, 12, 14, 16, 26, 34, 35
Various, classified according to the density of the mixture	2	0.43%	23
Total	**461**		

Table A - 2.8: Summary statistics of the different C pools for each age class (table split across two pages)

Basal area of the cocoa trees in relation to their age.

Age class (years)	Average basal area (cocoa; m² ha^{-1})	Nb. Of Obs.	Std. Dev.	Std. Err.
[0-5[	-	-	-	-
[5-10[	10.5	22	6.6	1.4
[10-15[	8.7	24	4.7	1
[15-20[	10.2	35	3.8	0.6
[20-25[	11.7	62	4.9	0.6
[25-30[	11.2	44	6.1	0.9
[30-35[	11.4	24	4.6	0.9
[35-40[	7.5	8	1.8	0.6
[40-45[	9.2	6	4.4	1.8
[45-50[	6.7	2	1.1	0.8
[50-55[	8.3	7	3.8	1.4
[55-60[	17	1	-	-
[60-65[	8.4	3	2.9	1.7
[65-70[	-	-	-	-
[70-75[	9.5	1	-	-
[75-80[	-	-	-	-
[80+[	8.6	2	8	5.7
	total	**241**		

Aboveground C stocks of the cocoa farms in relation to their age (cocoa trees only).

Age class (years)	Average aboveground C stocks (cocoa; Mg ha^{-1})	Nb. Of Obs.	Std. Dev.	Std. Err.
[0-5[	3.0	3	0.9	0.5
[5-10[	7.0	23	4.6	1.0
[10-15[	6.5	24	3.6	0.7
[15-20[	9.5	37	4.8	0.8
[20-25[	9.7	62	5.4	0.7
[25-30[	9.8	45	6.0	0.9
[30-35[	10.6	25	5.9	1.2
[35-40[	7.0	9	3.2	1.1
[40-45[	7.9	6	2.9	1.2
[45-50[	6.0	2	0.7	0.5
[50-55[	7.9	7	4.3	1.6
[55-60[	16.2	1	-	-
[60-65[	9.7	3	4.7	2.7
[65-70[	-	-	-	-
[70-75[	12.3	1	-	-
[75-80[	-	-	-	-
[80+[	12.2	2	13.5	9.5
	total	**250**		

Aboveground C stocks of the cocoa farms in relation to their age (shade trees only).

Age class (years)	Average aboveground C stocks (shade; Mg ha^{-1})	Nb. Of Obs.	Std. Dev.	Std. Err.
[0-5[	-	-	-	-
[5-10[	32.8	22	25.8	5.5
[10-15[	48.3	22	37.9	8.1
[15-20[	38.4	35	27.5	4.6
[20-25[	34.5	62	26.4	3.4
[25-30[	34.2	44	35.7	5.4
[30-35[	45.2	24	49.7	10.2
[35-40[	49.7	8	42.3	15.0
[40-45[	54.5	6	37.3	15.2
[45-50[	32.3	2	21.6	15.3
[50-55[	37.4	7	60.3	22.8
[55-60[	28.1	1	-	-
[60-65[	92.8	3	18.0	10.4
[65-70[	-	-	-	-
[70-75[	37.8	1	-	-
[75-80[	-	-	-	-
[80+[	56.3	2	79.2	56.0
	total	**242**		

Litter C stocks of the cocoa farms in relation to their age.

Age class (years)	Average litter C stock (cocoa; Mg ha^{-1})	Nb. Of Obs.	Std. Dev.	Std. Err.
[0-5[	1.3	1	-	-
[5-10[	1.4	23	2.3	0.5
[10-15[	1.3	23	1.2	0.2
[15-20[	1.0	36	0.9	0.1
[20-25[	1.0	59	1.3	0.2
[25-30[	0.7	42	0.5	0.1
[30-35[	1.3	22	1.4	0.3
[35-40[	1.0	8	1.1	0.4
[40-45[	2.4	6	1.9	0.8
[45-50[	1.2	2	0.2	0.2
[50-55[	1.9	7	1.0	0.4
[55-60[	2.0	1	-	-
[60-65[	2.8	3	0.9	0.5
[65-70[	-	-	-	-
[70-75[	5.1	1	-	-
[75-80[	-	-	-	-
[80+[	3.6	2	0.2	0.2
	total	**236**		

Root C stocks of the cocoa farms in relation to their age.

Age class (years)	Average root C stock (total; Mg ha^{-1})	Nb. Of Obs.	Std. Dev.	Std. Err.
[0-5[	1.0	2	0.2	0.1
[5-10[	9.4	24	6.1	1.2
[10-15[	12.0	24	7.1	1.4
[15-20[	11.2	36	5.6	0.9
[20-25[	10.6	58	5.3	0.7
[25-30[	11.0	43	6.7	1.0
[30-35[	12.7	24	8.7	1.8
[35-40[	11.9	9	7.5	2.5
[40-45[	12.8	6	6.1	2.5
[45-50[	7.8	2	3.0	2.1
[50-55[	9.5	7	10.3	3.9
[55-60[	9.8	1	-	-
[60-65[	21.5	3	5.7	3.3
[65-70[	-	-	-	-
[70-75[	11.2	1	-	-
[75-80[	-	-	-	-
[80+[	13.8	2	16.2	11.5
	total	**242**		

Soil C stocks of the cocoa farms in relation to their age.

Age class (years)	Average soil C stock (total; Mg ha^{-1})	Nb. Of Obs.	Std. Dev.	Std. Err.
[0-5[	23.6	35	12.4	2.1
[5-10[	23.6	62	9.8	1.2
[10-15[	21.6	75	9.8	1.1
[15-20[	22.4	42	7.7	1.2
[20-25[	23.9	61	8.0	1.0
[25-30[	23.8	37	7.6	1.3
[30-35[	25.6	36	9.7	1.6
[35-40[	25.7	11	9.9	3.0
[40-45[	26.2	6	6.6	2.7
[45-50[	22.1	2	9.6	6.8
[50-55[	28.3	7	6.3	2.4
[55-60[	25.2	1	-	-
[60-65[	32.6	3	5.7	3.3
[65-70[	-	-	-	-
[70-75[	34.0	1	-	-
[75-80[	-	-	-	-
[80+[	30.0	2	7.7	5.5
	total	**381**		

A.3. Appendices to Chapter 3

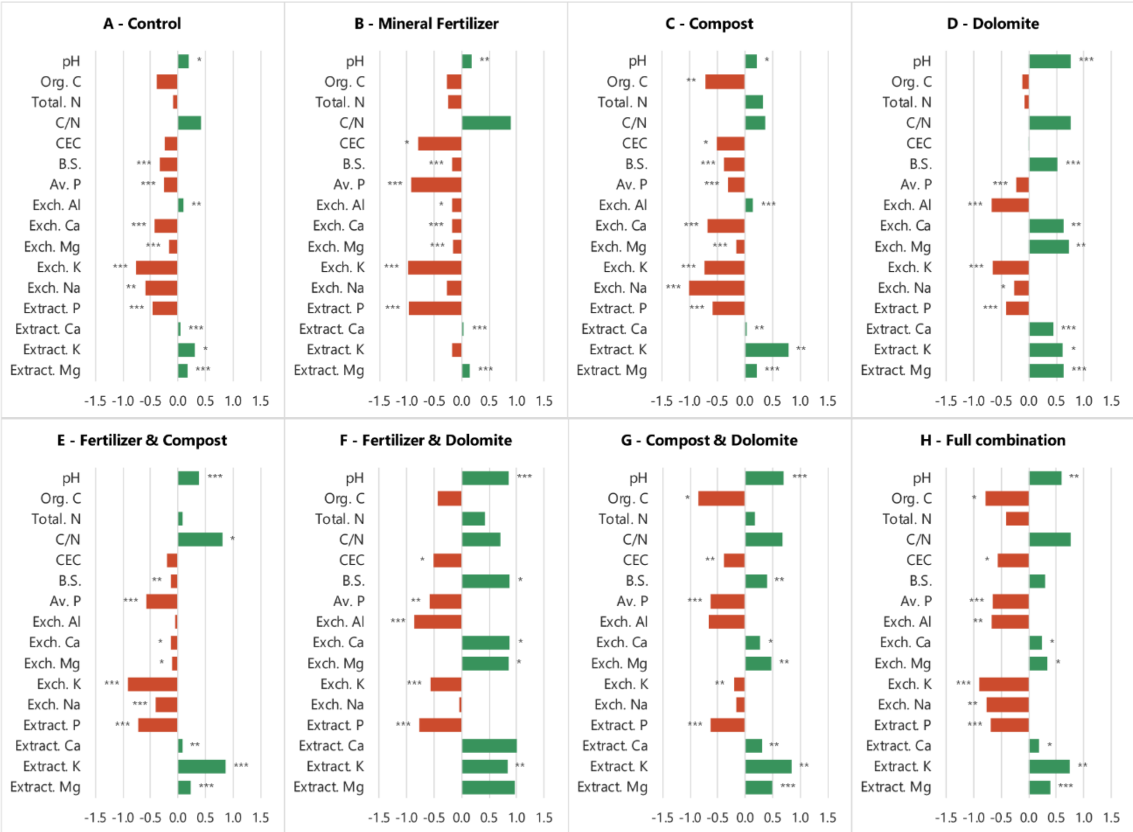

Figure A - 3.1. Summary of the effect of each treatment on soil properties

The length of the horizontal bars refers to the difference between 2014 and 2018. To combine variables with different units, the means for 2014 and *2018* were normalized, to replace them with a number between 0 and 1 ($x_{normalised} = (x_i - x_{min})/(x_{max} - x_{min})$). The values reported here correspond to the difference between those normalized values, ranging from -1 to 1. The closer to 1, the stronger the increase of the values between 2014 and 2018 ($x_{max(2018)} - x_{min(2014)} = 1 - 0 = 1$). Conversely, the closer to -1, the larger the decrease ($x_{min(2018)} - x_{min(2014)} = 0 - 1 = -1$). A value of 0 indicates no change because the difference between the two normalized values is null. Stars rating correspond to the following rule, calculated after a Welch one-sample t-test: $P \leq 0.001$, ***; $P \leq 0.01$, **; $P \leq 0.05$, *. Bars with no stars indicates no statistical difference between the two years (p=0.05). Please refer to Table A - 3.8 in the supplementary material for the exact p-values). For extractable Ca and Mg, F had the largest effect, but the difference is not significant because the variability was very high.

Table A - 3.1. Operational timeline of the experiment

Date	Operation	Details
2011	Baseline soil analysis	(Exact month not mentioned)
Dec-2011	Cocoa planting	With five-month-old-nursery-raised cocoa clones PBC123 Applying 100 g NPK (Phonska) + 150 g TSP (36%) per tree
May-2012	First treatment application	And later every year, twice a year
	Tree height measurement	-
Jan-2013	Tree height measurement	Each month until Jan-2014
Feb-2013	First leaf analysis	-
July-2013	CPB[a] and PPR[b] incidence	Fortnightly between July 2013 and December 2018
Aug-2013	First harvest	Annual yield, harvest twice a month between 2014 and 2015
June-2014	Soil and leaf analysis	-
Feb-2015	VSD[c] incidence	Each month between February 2015 and December 2018
Sep-2015	CPB and PPR incidence	-
Jan-2016	Replanting	New trees planted to replace the dead ones
2015 to 2018	Productivity, flowering and pest/disease incidence yearly recordings	
Dec-2018	Soil sampling and tree measurements	This study

[a] Cocoa Pod Borer; [b] Phytophthora Pod Rot; [c] Vascular-Streak Dieback

Table A - 3.2. Description of plot maintenance activities

Operation	Description	Details
Pests	CPB[a] treatment	Spraying (knapsack sprayer) / Prevathon (Chlorantraniliprole) @ 1 ml/L
	Helopeltis treatment	Spraying (knapsack sprayer) / Prevathon (Chlorantraniliprole) @ 1 ml/L
Diseases	PPR[b] treatment	Spraying (knapsack sprayer) / Score (Difenoconazole) @ 1.7 ml/L
	VSD[c] treatment	Spraying (knapsack sprayer) / Score (Difenoconazole) @ 1.7 ml/L
Pruning	Shape/production pruning	Manual - Scissors and Long Pruner
	Maintenance pruning	Manual - Scissors and Long Pruner (Water shoot/Chupon)
Soil inputs	Compost	Dig 6 holes 10-20 cm deep around the tree / 100 cm from the trunk / 5 kg per tree
Sanitation	Infected pod removal	Remove infected pods
	Branch removal	Tidy removal branches in the middle of cocoa trees row
Harvesting	Manual harvesting	Harvest ripe pods by plot / Evaluation
Weed control	Mechanical weeding	Mechanical - grass cutter machine

[a] Cocoa Pod Borer; [b] Phytophthora Pod Rot; [c] Vascular-Streak Dieback

Table A - 3.3. Calendar of plot maintenance activities

Operations	Description	January				February				March				April				May				June			
		1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
Pests	CPB[a] treatment																								
	Helopeltis treatment																								
Diseases	PPR[b] treatment																								
	VSD[c] treatment																								
Pruning	Shape/production pruning																								
	Maintenance pruning (Water Shoot/Chupon)																								
Soil inputs	Compost, fertilizer, and dolomite application																								
Sanitation	Infected pod removal	Every Harvest & Pruning																							
	Branch removal	Every Harvest & Pruning																							
Harvesting	Manual																								
Weed Control	Mechanical																								

[a] Cocoa Pod Borer; [b] Phytophthora Pod Rot; [c] Vascular-Streak Dieback

(Table A - 3.3 continued)

Operations	Description	January				February				March				April				May				June			
		1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
Pests	CPB[a] treatment																								
	Helopeltis treatment																								
Diseases	PPR[b] treatment																								
	VSD[c] treatment																								
Pruning	Shape/production pruning																								
	Maintenance pruning (Water Shoot/Chupon)																								
Soil inputs	Compost, fertilizer, and dolomite application																								
Sanitation	Infected pod removal	Every Harvest & Pruning																							
	Branch removal	Every Harvest & Pruning																							
Harvesting	Manual																								
Weed Control	Mechanical																								

[a] Cocoa Pod Borer; [b] Phytophthora Pod Rot; [c] Vascular-Streak Dieback

Table A - 3.4. Monthly precipitations

Year	Monthly precipitations (mm)					
	2014	**2015**	**2016**	**2017**	**2018**	**Average**
January	198	98	216	96	176	157
February	161	211	348	114	142	195
March	236	261	294	355	261	281
April	316	276	274	128	255	250
May	305	267	383	308	223	297
June	384	381	194	416	424	360
July	489	53	210	167	329	250
August	249	58	182	97	238	165
September	99	72	273	306	228	196
October	177	7	213	331	118	169
November	106	76	191	385	142	180
December	273	218	209	272	149	224
Total	**2992**	**1977**	**2987**	**2974**	**2684**	**2723**

This data was obtained from Mars's Cocoa Development Centre located in Tarengge (South Sulawesi, Indonesia); approximately 20km from the experiment.

Table A - 3.5. Basal areas and the formula used to convert trunk circumferences to areas

Treatment	Basal area (cm²)	Coefficient of variation
A	78.9a (31.7)	0.4
B	87.6a (25.2)	0.29
C	124.5ab (31.6)	0.25
D	111.6ab (38.7)	0.35
E	122.9ab (39.8)	0.32
F	114.2ab (33.8)	0.3
G	149.2b (51.7)	0.35
H	158.7b (65.4)	0.41

Numbers in brackets are standard deviations.

$$Area = \frac{Circumference^2}{4\pi}$$

Table A - 3.6. Survival rates per individual plot and treatment

Block	Treatment	Number of surviving trees	Survival rate (over 16 original trees)	Average survival rate per treatment
1	A	7	44%	67%
	B	12	75%	41%
	C	16	100%	94%
	D	6	38%	72%
	E	15	94%	92%
	F	12	75%	88%
	G	13	81%	92%
	H	13	81%	83%
2	A	15	94%	-
	B	2	13%	-
	C	16	100%	-
	D	12	75%	-
	E	15	94%	-
	F	13	81%	-
	G	15	94%	-
	H	12	75%	-
3	A	10	63%	-
	B	7	44%	-
	C	14	88%	-
	D	14	88%	-
	E	14	88%	-
	F	16	100%	-
	G	16	100%	-
	H	13	81%	-
4	A	11	69%	-
	B	5	31%	-
	C	14	88%	-
	D	14	88%	-
	E	15	94%	-
	F	15	94%	-
	G	15	94%	-
	H	15	94%	-

Table A - 3.7. Pod count, yield per pod, pod indices and proportion of infected pods per treatment and year

Average pod count per tree (and standard error)				
	2015	2016	2017	2018
A	8 (2)	5 (0.2)	9 (1.1)	22 (2.5)
B	10 (2.1)	12 (2.3)	17 (2.8)	44 (3.4)
C	47 (1.4)	32 (3.5)	27 (3.3)	34 (2.5)
D	8 (0.8)	11 (1.2)	15 (0.9)	32 (0.9)
E	27 (0.8)	39 (1.4)	30 (2.3)	33 (1.5)
F	6 (0.7)	16 (0.4)	21 (1.4)	27 (2.6)
G	33 (0.7)	42 (1.2)	33 (1.2)	39 (2.2)
H	29 (1.7)	35 (0.8)	27 (1.3)	35 (3.3)
Mean yield (g) per pod (and standard error)				
	2015	2016	2017	2018
A	13.7 (0.8)	25.9 (0.9)	25.4 (0.7)	18.7 (0.9)
B	14.7 (0.8)	25 (0.2)	30.3 (0.4)	23.6 (0.9)
C	12.3 (1.0)	23.2 (0.3)	28 (0.6)	17.9 (1.1)
D	10.8 (0.6)	23.7 (0.2)	26.9 (0.8)	17.3 (0.8)
E	12.3 (0.4)	23.5 (0.6)	27.3 (0.8)	20.5 (1.1)
F	12 (0.9)	23.5 (0.8)	28.8 (0.6)	23.5 (0.8)
G	11.6 (0.2)	21.1 (0.4)	23.6 (0.3)	14.5 (0.4)
H	12 (0.3)	20 (0.4)	24.1 (0.7)	16.9 (0.4)
Mean pod index (and standard error)				
	2015	2016	2017	2018
A	77 (5.1)	39 (1.5)	40 (1)	55 (2.8)
B	71 (4.1)	40 (0.4)	33 (0.5)	43 (1.8)
C	88 (6.9)	43 (0.6)	36 (0.8)	59 (3.8)
D	96 (5.2)	42 (0.4)	38 (1.2)	59 (3.1)
E	82 (2.6)	43 (1.3)	37 (1.0)	51 (2.9)
F	90 (6.8)	43 (1.4)	35 (0.8)	43 (1.6)
G	87 (1.8)	48 (0.8)	42 (0.6)	70 (1.9)
H	84 (2.4)	50 (1.0)	42 (1.2)	60 (1.7)
Mean proportion of infected pods (and standard error)				
	2015	2016	2017	2018
A	0.91 (0.01)	0.67 (0.03)	0.65 (0.04)	0.89 (0.01)
B	0.89 (0.03)	0.69 (0.01)	0.62 (0.02)	0.82 (0.01)
C	0.95 (0.01)	0.71 (0.02)	0.7 (0.01)	0.92 (0.01)
D	0.92 (0.01)	0.67 (0.02)	0.69 (0.03)	0.93 (0.01)
E	0.96 (0)	0.78 (0.01)	0.78 (0.03)	0.92 (0.01)
F	0.94 (0.01)	0.78 (0.02)	0.77 (0.03)	0.91 (0.01)
G	0.97 (0)	0.75 (0.01)	0.83 (0.02)	0.95 (0)
H	0.95 (0.01)	0.77 (0.01)	0.8 (0.01)	0.96 (0.01)

Table A - 3.8. Evaluation of the statistical significance of the differences between the two years of soil analyses, 2014 and 2018

Treatment	* pH (water)	† C (%)	‡ N (%)	C/N	†† CEC (cmol.kg^{-1})
A	*	0.111	0.718	0.274	0.261
B	**	0.101	0.638	0.935	*
C	*	**	0.423	0.050	*
D	***	0.423	0.886	0.837	0.918
E	***	0.959	0.809	*	0.275
F	***	0.301	0.342	0.227	*
G	***	*	0.604	0.138	**
H	**	*	0.579	0.769	*

Treatment	§ Extractable (ppm)				‡‡ Exch. Al (ppm)
	P	Ca	K	Mg	
A	***	***	*	***	**
B	***	***	0.098	***	*
C	***	**	**	***	***
D	***	***	*	***	***
E	***	**	***	***	0.384
F	***	0.201	**	0.107	***
G	***	**	**	***	0.089
H	***	*	**	***	**

Treatment	¶ Available P (ppm)	†† Exch. Bas. Cation (ppm)					B.S. (%)
		Ca	Mg	K	Na	Total	
A	***	***	***	***	**	***	***
B	***	***	***	***	0.092	***	***
C	**	***	***	***	***	***	***
D	***	**	**	***	*	**	***
E	**	*	*	***	***	**	**
F	*	*	*	***	0.809	*	*
G	***	*	**	**	0.080	**	**
H	***	*	*	***	**	0.082	0.062

The reported p-values were calculated after a Welch one-sample t-test (p-value = 0.05). Because there was only one measurement in 2014, coming from a composite of four sample, it was used as the ‘true mean’ in the tests, to which 2018 observation were compared to. Star rating correspond to the following rule: P ≤ 0.001, ***; P ≤ 0.01, **; P ≤ 0.05, *. The exact value was reported if P > 0.05. “na” stands for not applicable (calculated data). Methods: ♣After Fahmy (1977); °Core ring method; *pH determined by AIAT Soil Laboratories, Maros; †Dry ashing method; ‡Kjeldahl method; §25% HCl extraction; ¶Bray-I method; ††Ammonium acetate (pH 7) extraction; ‡‡KCl (1 N) extraction.

Table A - 3.9. Cocoa dry bean yields summary

	Average productivity (kg ha^{-1}) for surviving trees only (i.e., excluding mortality rates)								
Treatment	**2015**	**2016**	**2017**	**2018**	**Mean**	**σ**	**C.V.**	**Cumulated**	**% relative to the control***
A	112	141	240	432	231	144	0.62	925	100 %
B	154	314	526	1029	506	381	0.75	2024	219 %
C	579	737	783	638	684	93	0.14	2737	296 %
D	87	261	402	558	327	201	0.61	1308	141 %
E	334	918	813	686	688	254	0.37	2751	297%
F	83	364	622	640	427	262	0.61	1709	185%
G	379	881	780	566	652	224	0.34	2607	282 %
H	355	701	648	606	577	153	0.27	2310	250 %
Mean	261	540	602	644					
σ	179	303	203	173					
C.V.	0.69	0.56	0.34	0.27					

σ stands for standard deviation.

C.V. is the abbreviation for the coefficient of variation.

* % relative to the control calculated as:

$$Percentage\ relative\ to\ the\ control = \frac{Cumulated\ productivity\ treatment\ x}{Cumulated\ productivity\ treatment\ A} \times 100$$

(Table A - 3.9 continued)

Treatment	**Average productivity (kg ha^{-1})** for 16 initially planted trees (i.e., including mortality rates) 2015	2016	2017	2018	Mean	σ	C.V.	Cumulated	% relative to the control*
A	91	98	165	274	157	85	0.54	627	100 %
B	125	137	228	489	245	169	0.69	978	156 %
C	478	496	490	406	467	42	0.09	1870	298 %
D	73	194	281	363	228	124	0.55	910	145 %
E	279	628	544	446	474	150	0.32	1897	302 %
F	69	264	449	464	311	186	0.60	1246	199 %
G	318	612	556	398	471	136	0.29	1883	300 %
H	295	499	459	419	418	88	0.21	1672	266 %
Mean	216	366	396	407					
σ	149	216	150	67					
C.V.	0.69	0.59	0.38	0.16					

σ stands for standard deviation.

C.V. is the abbreviation for the coefficient of variation.

* % relative to the control calculated as:

$$Percentage\ relative\ to\ the\ control = \frac{Cumulated\ productivity\ treatment\ x}{Cumulated\ productivity\ treatment\ A} \times 100$$

Table A - 3.10. Yield index per treatment

Treatment	Yield Index
A	5.58ab (3.47)
B	10.29a (0.92)
C	4.93b (1.98)
D	5.21ab (2.01)
E	5.54ab (1.19)
F	5.5ab (2.08)
G	3.8b (0.73)
H	3.9b (2.01)

The yield index is calculated by dividing the dry bean yield by the basal area. Numbers in brackets are standard deviations.

Table A - 3.11. Harvest quality metrics (production sample collected in November 2017)

Treatment	Average dry bean weight (g)	Waste fraction (%)
A	1.30	11%
B	1.25	12%
C	1.44	14%
D	1.59	14%
E	1.46	18%
F	1.39	8%
G	1.51	10%
H	1.46	10%

Table A - 3.12. Initial and final stocks in soil elements as well as changes between the two soil sampling (sampling depth: 20 cm; bulk density of 1.09g cm^{-3})

Treatment	Org. C	N	Av. P	Exch. Al	Extractable				Exch. Bas. Cation			
					P	Ca	K	Mg	Ca	Mg	K	Na
Initial estimated stocks in kg ha^{-1} (June 2014)												
A	31 392	3 052	65	1 341	495	31	1 176	184	1 826	360	409	50
B	28 994	2 834	198	1 953	1 027	47	1 556	237	856	350	503	40
C	34 008	2 834	98	1 294	637	109	851	145	2 962	397	392	65
D	30 520	3 052	52	1 347	485	171	977	79	1 555	350	358	40
E	30 520	3 270	170	1 588	856	31	851	184	1 022	381	477	45
F	30 084	3 052	157	1 706	866	47	778	171	647	344	332	35
G	35 970	2 834	137	1 341	685	93	724	145	1 555	472	188	40
H	33 790	3 052	146	1 582	761	31	887	92	1 031	392	469	60
Final estimated stocks in kg ha^{-1} (December 2018)												
A	27 359	2 998	8	1 537	40	209	1 452	728	186	44	85	28
B	26 269	2 671	11	1 619	74	209	1 398	717	177	48	81	30
C	26 487	3 052	18	1 571	70	256	1 559	835	328	87	81	28
D	29 376	2 998	4	46	84	2 063	1 535	2 137	4 002	1 772	75	30
E	30 411	3 325	27	1 478	149	364	1 624	930	540	184	87	30
F	25 561	3 325	21	59	105	4 386	1 523	3 357	4 063	2 031	89	34
G	27 032	2 943	9	66	73	1 374	1 479	1 752	2 593	1 420	98	34
H	25 452	2 780	10	307	81	842	1 561	1 351	1 927	1 069	85	31
Mean annual rate of change in kg ha^{-1} yr^{-1}												
A	-896	-12	-5 ***	+43 **	-101 ***	+39 ***	+61 *	+121 ***	-365 ***	-70 ***	-72 ***	-5
B	-606	-36	-17 ***	-74 *	-212 ***	+36 ***	-35	+107 ***	-151 ***	-67 ***	-94 ***	-2
C	-1671 **	+48	-6 **	+61 ***	-126 ***	+33 **	+157 **	+153 ***	-585 ***	-69 ***	-69 ***	-8
D	-254	-12	-4 ***	-289 ***	-89 ***	+420 ***	+124 *	+457 ***	+544 **	+316 **	-63 ***	-2
E	-24	+12	-10 **	-25	-157 ***	+74 **	+172 ***	+166 ***	-107 *	-44 *	-87 ***	-3
F	-1005	+61	-11 *	-366 ***	-169 ***	+964	+166 **	+708	+759 *	+375 *	-54 ***	0
G	-1986 *	+24	-11 ***	-283	-136 ***	+285 **	+168 **	+357 ***	+231 *	+211 **	-20 ***	-1
H	-1853 *	-61	-12 ***	-283 **	-151 ***	+180 *	+150 **	+280 ***	+199 *	+150 *	-85 ***	-6

The stock for each element was found by using its content for a given year, assuming a surface bulk density of 1.09 g cm^{-3} (measured only in 2018), a depth of 20 cm, and a one-hectare area. The mean annual rate of change corresponds to the difference between the two stocks divided by 4.5 years, the time separating the two sampling years. Stars denotes a statistically significant difference over 4.5 years (see **Error! Reference source not found.**) with: P ≤ 0.001, ***; P ≤ 0.01, **; P ≤ 0.05, *. Strong changes that are not statistically significant (e.g., extractable Ca for treatment G) may be so because of the dispersion of the data.

A.4. Appendices to Chapter 4

Tables and Figures

(next page)

Table A - 4.1: Information on the sampled sites

Farm code	Location	GPS coordinates		Elevation	Date of planting	Cocoa age (years)	Approx. area (ha)	Spacing (m)	Density at planting (trees/ha)	Shade trees	
										Name	Density/ha
A	Tarengge	-2.5435921	120.7730789	39	Jun-2018	0.5	1	4x4	625	Coconut Banana Durian	100 100 10
B	Tarengge	-2.5610000	120.7886830	24	2017	1	~0.5-1	3x3	1100	Banana	200
C	Tarengge	-2.5508982	120.7815024	21	Oct-2016	2	1	3.5 x 3.5	800	Coconut Durian	8 in total
D	Tarengge	-2.5476821	120.7789080	32	2013	5	1.25	4x4	625	Coconut Gliricidia	unknown
E	Tarengge	-2.5594396	120.7979403	26	2011	7	1	4x4	625	Gliricidia Mangosteen	200 in total
F	Tarengge	-2.5605486	120.7892268	27	2006	12	0.25	3x3	1100	Gliricidia Mangosteen	16
G	Tarengge	-2.5470437	120.7791196	32	2003	15	2	3x3	1100	Coconut Durian Ambarella	unknown
H	Mambu (Luyo, Polewali)	-3.3837967	119.1471476	20	Oct-2016	2	0.25	3x3	1100	Coconut Banana Teak	25 50 10
I	Mambu (Luyo, Polewali)	-3.3765312	119.1501627	20	1998	20	0.6	3x3	1100	Coconut Gliricidia Banana	unknown
J	Mambu (Luyo, Polewali)	-3.3766798	119.1506868	19	1987	31	0.4	4x4	625	None	
K	Pussui (Polewali)	(confidential)	(confidential)	109	Nov-2016	2	0.7	3x3	1100	Langsat Teak	15 20
L	Pussui (Polewali)	-3.3643024	119.1021837	40	1998	20	0.4	3x3	1100	Langsat	30
M	Pussui (Polewali)	-3.3636655	119.1034222	43	1987	31	0.8	3x3	1100	Lamtoro (Leuceana) Coconut Langsat	200 (3 years old) 15 50

Table A - 4.2: Recent land-use history of the farm visited in Tarengge

	Location	Tarengge	Tarengge	Tarengge	Tarengge	Tarengge	Tarengge	Tarengge
	Farm	A	B	C	D	E	F	G
Year	Age	0.5	1	2	5	7	12	15
2018		Cocoa	Cocoa	Cocoa	Cocoa	Cocoa	Cocoa	Cocoa
2017		Cocoa	Cocoa	Cocoa	Cocoa	Cocoa	Cocoa	Cocoa
2016		Cocoa	Rice?	Cocoa	Cocoa	Cocoa	Cocoa	Cocoa
2015		Cocoa	-	Oil-palm	Cocoa	Cocoa	Cocoa	Cocoa
2014		Cocoa	-	Oil-palm	Cocoa	Cocoa	Cocoa	Cocoa
2013		Cocoa	-	Oil-palm	Cocoa	Cocoa	Cocoa	Cocoa
2012		Cocoa	-	Oil-palm	VS	Cocoa	Cocoa	Cocoa
2011		Cocoa	-	Cocoa	VS	Cocoa	Cocoa	Cocoa
2010		Cocoa	-	Cocoa	VS	G? ⟶ Cocoa?	Cocoa	Cocoa
2009		Cocoa	-	Cocoa	VS	-	Cocoa	Cocoa
2008		Cocoa	-	Cocoa	Rice?	-	Cocoa	Cocoa
2007		Cocoa	-	Cocoa	-	-	Cocoa	Cocoa
2006		Cocoa	-	Cocoa	-	-	Cocoa	Cocoa
2005		Cocoa	-	Cocoa	-	-	Rice?	Cocoa
2004		Cocoa	-	Rice	-	-	-	Cocoa
2003		VSP	-	Rice	-	-	-	Cocoa
2002		VSP	-	Rice	-	-	-	Rice
2001		VSP	-	Rice	-	-	-	Rice
2000		VSP	-	-	-	-	-	Rice
1999		VSP	-	-	-	-	-	Rice
1998		Rice	-	-	-	-	-	Rice
1997		-	-	-	-	-	-	Rice
1996		-	-	-	-	-	-	Rice
1995		-	-	-	-	-	-	Rice
1994		-	-	-	-	-	-	Rice
1993		-	-	-	-	-	-	Rice

Grey cells code for years cultivated with the same cocoa as the one visited in 2018. Light grey cell represents incomplete years (hence for A being 0.5 years old in 2018, as it was planted in June 2018). Dark grey cells represent complete years. V means vegetables, S means sweet-potato, P means peanuts, and G means grassland. A question mark indicates that the farmer was unsure about the land use. Hyphens indicate the absence of information about land use. For farm E, the farmer knew that another cocoa crop was cultivated on this field before he replanted in 2011, but he did know for how long. However, he thinks that even before, the land was a grassland.

Table A - 4.3: Recent land-use history of the farm visited in Mambu and Pussui

Year	Location	Mambu	Mambu	Mambu	Pussui	Pussui	Pussui
	Farm	H	I	J	K	L	M
	Age	2	20	31	2	20	31
2018		Cocoa	Cocoa	Cocoa	Cocoa	Cocoa	Cocoa
2017		Cocoa	Cocoa	Cocoa	Cocoa	Cocoa	Cocoa
2016		Cocoa	Cocoa	Cocoa	Cocoa	Cocoa	Cocoa
2015		Cocoa	Cocoa	Cocoa	Forest	Cocoa	Cocoa
2014		Cocoa	Cocoa	Cocoa	Forest	Cocoa	Cocoa
2013		Cocoa	Cocoa	Cocoa	Forest	Cocoa	Cocoa
2012		Cocoa	Cocoa	Cocoa	Forest	Cocoa	Cocoa
2011		Cocoa	Cocoa	Cocoa	Forest	Cocoa	Cocoa
2010		Cocoa	Cocoa	Cocoa	Forest	Cocoa	Cocoa
2009		Cocoa	Cocoa	Cocoa	Forest	Cocoa	Cocoa
2008		Cocoa	Cocoa	Cocoa	Forest	Cocoa	Cocoa
2007		Cocoa	Cocoa	Cocoa	Forest	Cocoa	Cocoa
2006		Cocoa	Cocoa	Cocoa	Forest	Cocoa	Cocoa
2005		Cocoa	Cocoa	Cocoa	Forest	Cocoa	Cocoa
2004		Cocoa	Cocoa	Cocoa	Forest	Cocoa	Cocoa
2003		Cocoa	Cocoa	Cocoa	Forest	Cocoa	Cocoa
2002		Cocoa	Cocoa	Cocoa	Forest	Cocoa	Cocoa
2001		Cocoa	Cocoa	Cocoa	Forest	Cocoa	Cocoa
2000		Cocoa	Cocoa	Cocoa	Forest	Cocoa	Cocoa
1999		Cocoa	Cocoa	Cocoa	Forest	Cocoa	Cocoa
1998		Cocoa	Cocoa	Cocoa	Forest	Cocoa	Cocoa
1997		Cocoa	-	Cocoa	Forest	Forest	Cocoa
1996		Cocoa	-	Cocoa	Forest	Forest	Cocoa
1995		Cocoa	-	Cocoa	Forest	Forest	Cocoa
1994		Cocoa	-	Cocoa	Forest	Forest	Cocoa
1993		Cocoa	-	Cocoa	Forest	Forest	Cocoa
1992		Cocoa	-	Cocoa	Forest	Forest	Cocoa
1991		Cocoa	-	Cocoa	Forest	Forest	Cocoa
1990		Cocoa	-	Cocoa	Forest	Forest	Cocoa
1989		Cocoa	-	Cocoa	Forest	Forest	Cocoa
1988		Cocoa	-	Cocoa	Forest	Forest	Cocoa
1987		Cocoa	-	Cocoa	Forest	Forest	Cocoa

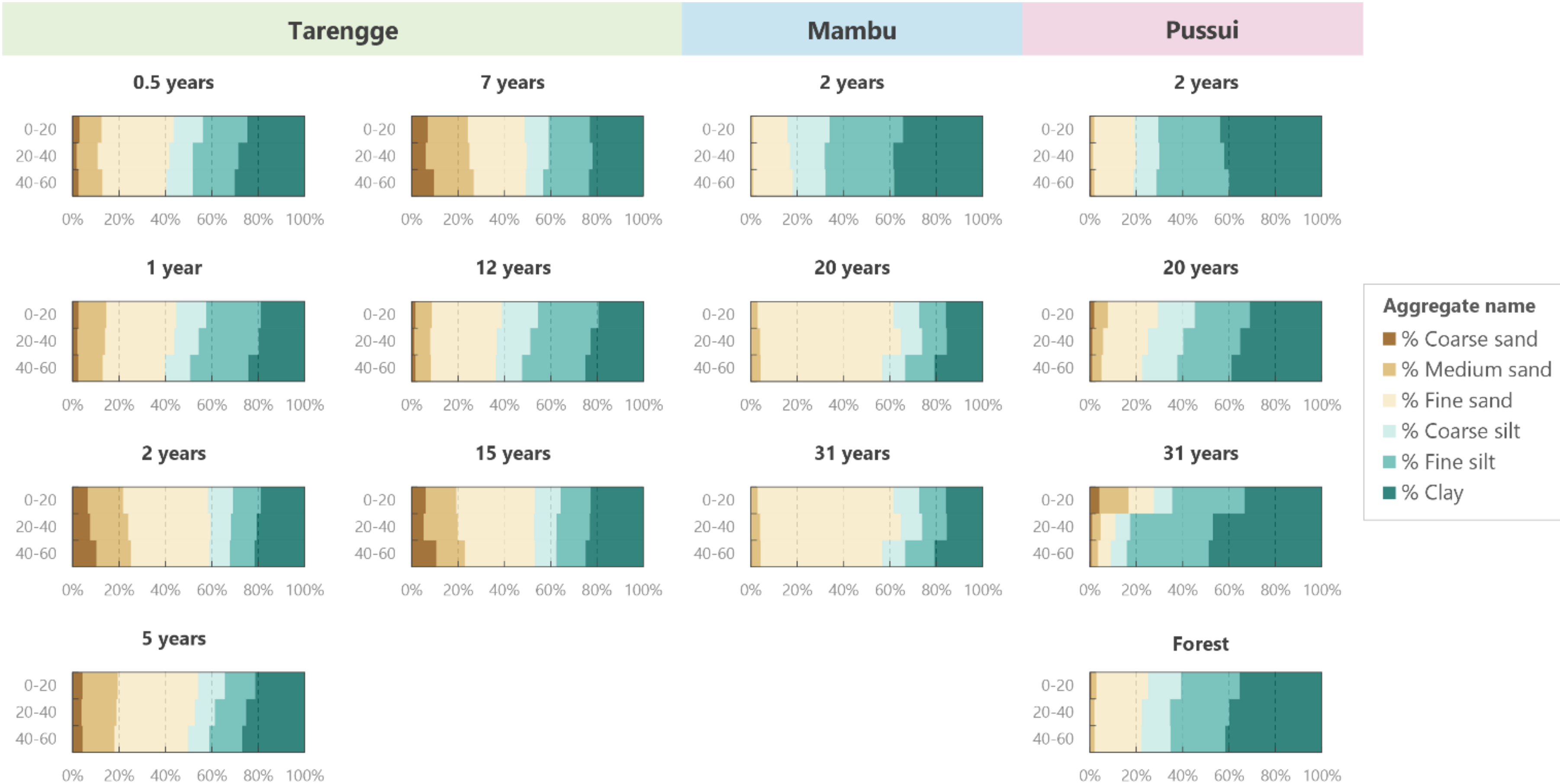

Figure A - 4.1: Visual representation of the particle size distribution of the farms of the chronosequence

Table A - 4.4: SOM, C, and N contents for each farm and depth

Location		Tarengge	Tarengge	Tarengge	Tarengge	Tarengge	Tarengge	Tarengge
Age (years)		0.5	1	2	5	7	12	15
Farm Code		A	B	C	D	E	F	G
	Depth							
SOM content * (%)	0-20	3.59 ±0.22	2.27 ±0.29	1.76 ±0.24	2.4 ±0.56	2.58 ±0.26	2.06 ±0.14	2.58 ±0.04
	20-40	2.81 ±0.52	1.7 ±0.06	1.54 ±0.24	2.2 ±0.25	2.19 ±0.64	1.84 ±0.17	2.04 ±0.32
	40-60	2.52 ±0.35	1.57 ±0.08	1.43 ±0.42	1.89 ±0.15	1.78 ±0.65	1.7 ±0.27	1.92 ±0.39
	60-80	2.28 ±0.35	1.34 ±0.1	1.4 ±0.07	1.54 ±0.1	1.4 ±0.61	1.41 ±0.2	1.9 ±0.29
	80-100	2.08 ±0.35	1.32 ±0.06	1.48 ±0.27	1.62 ±0.11	1.36 ±0.69	1.65 ±0.43	1.72 ±0.34
C content (%)	0-20	1.62 ±0.18	1.13 ±0.15	0.8 ±0.09	1.12 ±0.2	1.52 ±0.16	0.88 ±0.06	1.06 ±0.37
	20-40	1.17 ±0.12	0.86 ±0.03	0.66 ±0.12	0.94 ±0.13	1.08 ±0.12	0.76 ±0.2	0.85 ±0.07
	40-60	0.9 ±0.14	0.85 ±0.27	0.57 ±0	0.73 ±0.08	0.82 ±0.13	0.72 ±0.27	0.71 ±0.12
	60-80	0.83 ±0.19	0.63 ±0.07	0.45 ±0.06	0.6 ±0.05	0.8 ±0.26	0.53 ±0.11	0.62 ±0.01
	80-100	791 ±153	550 ±35	428 ±60	539 ±123	506 ±141	469 ±68	550 ±46
N content (ppm)	0-20	1554 ±182	1239 ±74	786 ±39	1084 ±171	1572 ±106	1016 ±86	1058 ±386
	20-40	1166 ±104	1014 ±39	675 ±100	920 ±63	1154 ±147	897 ±86	843 ±114
	40-60	885 ±125	941 ±80	558 ±63	741 ±37	902 ±176	842 ±100	692 ±92
	60-80	813 ±108	852 ±65	556 ±100	633 ±37	828 ±161	777 ±73	732 ±57
	80-100	788 ±155	846 ±59	523 ±59	603 ±51	762 ±145	744 ±25	646 ±25
Location		Mambu	Mambu	Mambu	Pussui	Pussui	Pussui	Pussui
Age (years)		2	20	31	2	20	31	NA
Farm Code		H	I	J	K	L	M	Forest
	Depth							
SOM content (%)	0-20	2.57 ±0.23	1.66 ±0.41	1.94 ±0.16	4.04 ±0.37	2.92 ±1.24	3.3 ±0.91	3.86 ±0.66
	20-40	2.43 ±0.15	1.34 ±0.22	1.17 ±0.2	2.68 ±0.46	3.35 ±0.96	2.71 ±0.23	2.35 ±0.82
	40-60	2.24 ±0.59	0.9 ±0.15	0.84 ±0.14	1.71 ±0.17	1.34 ±0.12	2.07 ±0.35	2.26 ±NA
	60-80	NA	1.23 ±0.18	1.16 ±0.2	1.13 ±0.22	1.12 ±0.14	1.76 ±0	1.56 ±NA
	80-100	NA	1.26 ±0.02	1.45 ±0.1	NA	1.38 ±0.05	1.8 ±NA	NA
C content (%)	0-20	1.57 ±0.05	0.75 ±0.19	0.71 ±0.12	1.97 ±0.18	1.52 ±0.33	1.73 ±0.31	1.67 ±0.17
	20-40	1.32 ±0.07	0.44 ±0.06	0.34 ±0.02	1.11 ±0.17	1.12 ±0.16	1.28 ±0.13	1.11 ±0.25
	40-60	1.26 ±0.35	0.42 ±0.05	0.23 ±0.03	0.62 ±0.08	0.85 ±0.03	1.15 ±0.08	1.04 ±NA
	60-80	NA	0.5 ±0.05	0.37 ±0.09	0.38 ±0.1	0.66 ±0.02	1.49 ±0.62	0.95 ±NA
	80-100	NA	437 ±66	427 ±24	NA	590 ±112	0.86 ±NA	NA
N content (ppm)	0-20	1347 ±59	812 ±182	809 ±129	2103 ±174	1724 ±349	1832 ±412	1846 ±206
	20-40	1112 ±74	531 ±55	427 ±41	1015 ±172	1323 ±188	1223 ±100	978 ±276
	40-60	1130 ±272	541 ±78	329 ±55	568 ±110	1032 ±18	1039 ±139	900 ±NA
	60-80	NA	631 ±29	479 ±94	461 ±102	823 ±31	1438 ±145	1000 ±NA
	80-100	NA	570 ±43	570 ±18	NA	695 ±78	1100 ±NA	NA

* SOM contents were obtained from LOI and corrected for potential structural water loss linked to clays (Jensen et al., 2018). Carbon and nitrogen contents were determined through dry combustion. Values after ± correspond to the confidence interval (1.96 times the standard error). NA stands for depths where it was not possible to obtain a sample (soil too compact). ±NA correspond to plots where only one core was obtained, therefore not associated with a standard error.

Table A - 4.5: SOM-to-clay, C-to-clay, and N-to-clay ratios for each farm and depth

Location		Tarengge	Tarengge	Tarengge	Tarengge	Tarengge	Tarengge	Tarengge
Age (years)		0.5	1	2	5	7	12	15
Farm Code		A	B	C	D	E	F	G
	Depth							
SOM-to-Clay ratio	0-20	0.15	0.12	0.09	0.11	0.11	0.11	0.11
	20-40	0.10	0.09	0.07	0.09	0.10	0.08	0.09
	40-60	0.08	0.06	0.07	0.07	0.08	0.07	0.08
	60-80	0.08	0.06	0.06	0.06	0.06	0.06	0.08
	80-100	0.07	0.05	0.07	0.06	0.06	0.07	0.07
C-to-Clay ratio (x 1 000)	0-20	66	60	43	52	66	45	47
	20-40	41	43	32	37	50	33	37
	40-60	30	35	26	27	35	29	29
	60-80	27	26	21	22	34	21	25
	80-100	26	23	20	20	22	19	22
N-to-Clay ratio (x 100 000)	0-20	631	660	418	508	683	519	468
	20-40	408	512	328	365	529	392	366
	40-60	294	389	258	277	385	334	280
	60-80	270	352	257	237	354	308	296
	80-100	261	350	242	225	325	295	261
Location		Mambu	Mambu	Mambu	Pussui	Pussui	Pussui	Pussui
Age (years)		2	20	31	2	20	31	NA
Farm Code		H	I	J	K	L	M	Forest
	Depth							
SOM-to-Clay ratio	0-20	0.07	0.10	0.10	0.09	0.09	0.10	0.11
	20-40	0.06	0.09	0.07	0.06	0.10	0.06	0.06
	40-60	0.06	0.04	0.05	0.04	0.03	0.04	0.05
	60-80	NA	0.06	0.07	0.03	0.03	0.04	0.04
	80-100	NA	0.06	0.09	NA	0.04	0.04	NA
C-to-Clay ratio (x 1 000)	0-20	46	47	36	45	49	52	47
	20-40	34	29	20	26	32	27	28
	40-60	33	20	15	15	22	24	25
	60-80	NA	24	23	9	17	31	23
	80-100	NA	21	27	NA	15	18	NA
N-to-Clay ratio (x 100 000)	0-20	392	511	409	479	555	549	519
	20-40	288	341	257	241	376	261	246
	40-60	296	259	210	142	265	213	208
	60-80	NA	302	305	115	211	295	249
	80-100	NA	273	363	NA	178	225	NA

Estimation of a cocoa growth curve for Sulawesi: methodology

Measurements and allometry

The average girth of cocoa trunks was assessed on 16 trees located approximately at the center of each cocoa plot. Circumference was measured at 30 cm from the soil surface, and then converted the circumferences to diameters (D30). The diameter at breast height was not measured because cocoa typically produces many branches below this height. If multiple stems were present at a 30 cm height, each one was measured, and the square root of the sum of squares of each diameter was calculated to consolidate the measurements into one value (see Stewart & Salazar, 1992). Finally, the 16 diameters were averaged. The average diameter was used to estimate the amount of phytomass stored in cocoa trees using the allometric equation developed by Smiley & Kroschel (2008) for cocoa in Sulawesi, both for the aboveground and the belowground components (Table A - 4.6).

Table A - 4.6: Allometric equations proposed by Smiley & Kroschel to estimate cocoa above and belowground biomass

Component (kg per tree)	Formula
Aboveground cocoa biomass (AGB)	$AGB = 0.202 \times D50^{2.112}$
Belowground cocoa biomass (BGB)	$BGB = 0.142 \times D50^{2.064}$

D50 represents the diameter at 50 cm from the ground. Because our data used diameter at 30 cm, we analysed the difference between D30 and D50 on 112 cocoa trees in Tarengge (16 trees in 7 farms). A statistical difference was found between D30 and D50 (t-test paired two samples for means: two-tail p-value < 0.001). However, if only one-stemmed cocoa trees are considered (53 out of the 112 of our analysis), no statistical difference was found (t-test paired two samples for means: two-tail p-value = 0.99).

Because Smiley (2006) did not consider forking trees when developing this allometric relationship, it was decided to apply a correction factor to our D30. After running a linear regression between D30 and D50 on the 112 trees, it was found that D50 was equal to 1.04 x D30 ($R^2 = 0.98$; p-value < 0.001). This conversion factor was used to convert D30s to D50s and estimate cocoa biomass.

Using age as a predictor of cocoa biomass

A non-linear model was then fitted to the results of each allometric relationship, using age as the independent variable and the allometrically-predicted biomass as the dependent one. A four-parameter non-linear model was chosen to minimize best the standard error of the regression (only three parameters in practice, since the lower asymptote β is here equal to zero):

$$B = L_{max} - (L_{max} - L_{min}) \times e^{(-k \times age)^{\delta}}$$

Where:

- B: allometrically-predicted biomass in kg per tree
- L_{max}: upper asymptote
- L_{min}: lower asymptote
- k: growth rate
- δ: parameter controlling the x-ordinate for the point of inflection
- age: age of the cocoa tree in years

The model's optimal parameters were found using Excel's Solver add-in by minimizing the sum of the differences between observed and predicted biomasses. If several plots of the same age were present, only the average biomass was retained for the model. For example, there were two plots of 31 years old, and only one mean biomass value was kept.

For aboveground biomass, the growth model was:

$$AGB = 137.06 - (137.06 - 0) \times e^{(-0.10 \times age)^{1.09}}$$

For the belowground biomass, a one-parameter non-linear relationship was selected:

$$BGB = 82.73 - (82.73 - 0) \times e^{(-0.11 \times age)^{1.09}}$$

Their performance was assessed by calculating the coefficient of determination ‘R^2’, the standard error of the estimate ‘S’, and the mean absolute percent error ‘MAPE’ presented in Table A - 4.1 for each allometric relationship.

Table A - 4.7: Parameters and evaluation of the cocoa growth model

		Aboveground biomass	Belowground biomass
Growth model parameters	**Upper asymptote**	137.06	82.73
	Lower asymptote	0	0
	Growth rate	0.1	0.11
	X-ordinate inflection parameter	1.09	1.09
Performance	**R^2**	0.998	0.998
	S	4.59	2.79
	MAPE	27.1%	25.8%

A.5. Appendices to Chapter 5

Aboveground residue deposition rate (*RDR_A*)

To estimate the annual fraction of aboveground biomass converted to aboveground deposits, cocoa litterfall studies were searched. More particularly, the interest was towards associations between annual litterfall rates to cocoa and shade trees aboveground biomass stock per hectare, to assess if the quotient litterfall / aboveground biomass showed a possible temporal trend over time.

To set a value to this parameter, data from Ghana was used (Dawoe, 2009; Dawoe et al., 2010). As seen on the table and graph below, annual litterfall rates are strongly correlated to the amount of aboveground present. Because the study did not make a distinction between cocoa and shade tree litter, the relative contribution of shade trees and cocoa trees is not known. The change in annual litterfall rate does not seem to be more strongly correlated to cocoa or shade tree biomass.

In the 3 years-old plantation, litterfall deposits were relatively large as compared to the total aboveground biomass (40%). For the older plantations, 15 and 30 years-old, litterfall only represented 6% of the total aboveground biomass. Comparatively, cocoa biomass began by representing 40% of the total aboveground biomass while is only represented approximately 30% of this stock in the 15 and 30 years-old plantations.

The chronosequence also comprised very different shade and cocoa densities. It was decided to select a residue deposition rate of 0.06, corresponding to what was observed for the 15 and 30 years-old plantations. However, this remain a gross estimate and simplification of the reality, since it may be greatly influence by the age, the shade tree species and the cocoa and shade tree densities and many other variables influencing tree growth and litterfall production.

Table A - 5.1: Cocoa aboveground biomass and litterfall deposition rates obtained by Dawoe, (2009) and Dawoe et al. (2010)

Age (years)	**3**	**15**	**30**
Cocoa density (trees ha^{-1})	1500	1100	900
Shade tree density (trees ha^{-1})	16	35	26
Cocoa mean DBH (cm)	3.36	10.50	12.40
Shade tree mean DBH (cm)	24.2	38.5	51.3
Annual litterfall production (Mg ha^{-1})	5	8.2	10.4
Standing litter (Mg ha^{-1})	3.6	5.8	5.9
Cocoa biomass (Mg ha^{-1}) [a]	5	43.8	57.5
Shade tree biomass (Mg ha^{-1}) [a]	7.65	91.2	127.7
Total aboveground biomass (Mg ha^{-1})	12.65	135	185.2
Cocoa biomass / Total biomass	0.40	0.32	0.31
Shade tree biomass / Total biomass	0.60	0.68	0.69
Annual litterfall production / Cocoa biomass	1.00	0.19	0.18
Annual litterfall production / Shade tree biomass	0.65	0.09	0.08
Annual litterfall production / Total biomass	0.40	0.06	0.06

[a] Cocoa and shade tree biomasses calculated by using Brown’s equation (see Table 2.3).

Belowground biomass, root turnover, and exudation rate

Short literature review:

Kummerow et al. (1982) reported that the non-woody fine roots (< 1 mm) were concentrated in the litter layer and to a 5 cm depth, with a large fraction found in the very top 0-1 cm (90% of the fine-root growth happened in the 0-10 cm layer). The strong conical taproots can grow downwards to 10-1.5m, depending on the soil conditions. Lateral roots are mainly horizontal and concentrated in the upper 30 cm, and they can be several meters long in cocoa farms aged six years and older. They studied the weekly dynamics of fine roots and found a relatively constant fine root concentration over time, about 40 g m^{-2} (400 kg ha^{-1}), during their six-month experiment in Bahia (Brazil). They also found that root growth activity did not appear to be correlated with seasonal variations. However, they found a negative between the decrease of fine root activity and the occurrence of flushing. Therefore, root growth activity is episodic but seems to be influenced by flushes more than seasonal changes. Shoot flushing occurred when fine root growth activity was the slowest. It is also mentioned that, since roots can extend past the cocoa tree canopy, it is unclear which tree the fine roots belong to.

Muñoz & Beer (2001) measured fine root biomass and productivity in cocoa plantations shaded by *Erythrina poeppigiana* or *Cordia alliodora* in Costa Rica. Fine root biomass was approximately 1 Mg ha^{-1} and varied little during the year (max values of the beginning of the rainy season of 1.85 Mg ha^{-1} under *C. alliodora* and 1.2 Mg ha^{-1} under *E. poeppigiana*). Great fine root productivity was 34-68 kg ha^{-1} 4 $week^{-1}$ for cocoa at the beginning of the rainy season, while it reached 205 and 120 kg ha^{-1} 4 $week^{-1}$ at the end of the rainy season (respectively under *C. alliodora* and *E. poeppigiana*. They estimated the annual fine root turnover to be 0.9 and 1.07, respectively (close to one in both systems).

Moser et al. (2010) found that 83% of fine root (≤ 2 mm) and 86% (> 2 mm) of coarse root biomass was found in the 0-40 cm soil layer. They recorded aboveground biomass and root biomass dynamics and productivity before and after a 13-month desiccation experiment to a depth of 3 m (20 increments, at three distances from a cocoa stem: 0-50, 50-100, >100 cm). They also analyzed litterfall (leaves and pods) during a year, sorting the results by species.

Nygren et al. (2013) used a combination of field sampling and modeling to study the root distribution of cocoa trees shaded by *Inga edulis* in 16 years-old cocoa farms in Costa Rica. The FracRoot model was used to simulate the coarse root architecture of the two tree species and estimate their respective root system lengths and masses. Fine roots (≤ 2 mm) were not part of the simulation, and their length, biomass, and necromass density were determined after core sampling down to 50 cm. A significant fraction of cocoa roots was located in the 0-2 cm layer. The authors proposed a function to describe the fine root biomass density distribution along with depth: $\rho_M = 2.0688 \times d_s^{-0.370}$ ($R^2 = 0.89$, $P \leq 0.0002$). The coarse root system mass had a linear relationship the squared stem basal diameter: $M_s = 0.03562 \times D_s^2$ ($R^2 = 0.80$). Simulated coarse root biomass ranged from 820 to 1556 kg ha^{-1}, whereas the measured cocoa fine root biomass was 3,550 kg ha^{-1} and the cocoa fine root necromass 313 kg ha^{-1}. The C/N ratio of cocoa roots ranged from 30.6 to 39.5.

Rajab et al. (2016) compared bean yield and carbon storage in three widespread cocoa cultivation systems of Central Sulawesi: non-shaded monoculture, cacao with *Gliricidia sepium* as dominant shade tree and cacao with dense and diverse shade cover. Soil and root samples were collected down to 60 cm (0-10, 10-20, 20-40, 40-60 cm). Pits were excavated to assess root biomass down to 300 cm. Roots were separated in fine (<2 mm diameter), large (2-5 mm) and coarse (>5 mm) categories. Litter traps were installed to assess litter production.

The total plant C stocks of multi-shade systems was five times higher than monoculture (from 11 to 57 Mg ha^{-1}). Cacao bean yield remain comparable across the systems (2.0-2.1 Mg ha^{-1} yr^{-1}). Leaf litter represented approximately 90% of all litter inputs in the monoculture and the *Gliricidia* systems, and about 80% in the multi-shade system. Total fine production did not differ between the systems, but fine root productivity tended to decrease with increasing shade levels. Cocoa fine roots production was larger than that of shade trees in both shaded and full-sun systems. Cocoa shoot:root ratio ranged from 3.7 to 5.3. All trees confounded, fine root biomass production ranged from 1.5 to 1.9 Mg ha^{-1} year^{-1} whereas coarse root biomass 0.2 to 1.1 Mg ha^{-1} year^{-1}.

Niether et al. (2019) evaluated the above and belowground production of biomass in a range of cocoa systems in Bolivia (conventional and organic crossed with monoculture and agroforestry, as well as successional agroforestry). They found approximately 80% of the total fine roots in the uppermost 25 cm of the soil, ranging from 74 to 87%. The mean annual fine root production of all the systems was comparable, except in conventional monoculture, which was much lower. They confirmed the observation of Kummerow et al. (1982), showing that coarse lateral roots can reach horizontally the trunk of a neighboring cocoa tree at a 4 m distance.

Borden et al. (2019) aimed to overcome the respective limitations of using allometric equations, destructive sampling, and ground penetrating radar geo-imagery to bridge the gap between those approaches and offer a better estimation of cocoa root mass and its variation. Their method was implemented on cocoa monocultures and shaded systems (with *Entandrophragma angolense* or *Terminalia Ivorensis*). Using destructive sampling, they estimated that a 15-year-old cocoa tree has an average root-to-shoot ratio of approximately 0.23 ± 0.02 but could range from 0.19 ± 0.02 to 0.28 ± 0.05 depending on the system. They found that cocoa allocated more biomass in their root system in shaded systems than in monocultures. They did find that coarse root biomass was significantly correlated to DBH. They found a ratio of 3.3 ± 0.2 (n = 3) between excavated lateral roots to taproot biomass. They emphasized that allometric equations can translate to misestimations of belowground biomass and that site- and species-specific allometric equations are preferable, when available, instead of using generalized equations, especially for belowground biomass.

Schneidewind et al. (2016) analysed litterfall, pruning residuals, and litter decomposition in a matrix of monoculture/agroforestry versus conventional/organic cocoa farms in Bolivia. The total annual litterfall per system ranged from approximately 1.23 to 2.23 Mg C ha^{-1} (approximately 2.26 to 4.46 Mg organic matter ha^{-1} if using a carbon content of 50%). The quantity of pruning residues ranged from 2.58 to 4.28 Mg C ha^{-1} (approximately 5.16 to 8.92 Mg organic matter ha^{-1} if using a carbon content of 50%). They report C/N ratio of cocoa leaves ranging from 20.2 to 24. After 290 days, the remaining litter mass was approximately 60% for all systems and management types.

SOM mineralisation rate: behaviour of each rate modifying factor

In Figure A - 5.1, the behaviour of each SOM mineralisation rate modifying factor was visually presented. Each was calculated with the equations provided by Clivot et al. (2019) and a range of possible values.

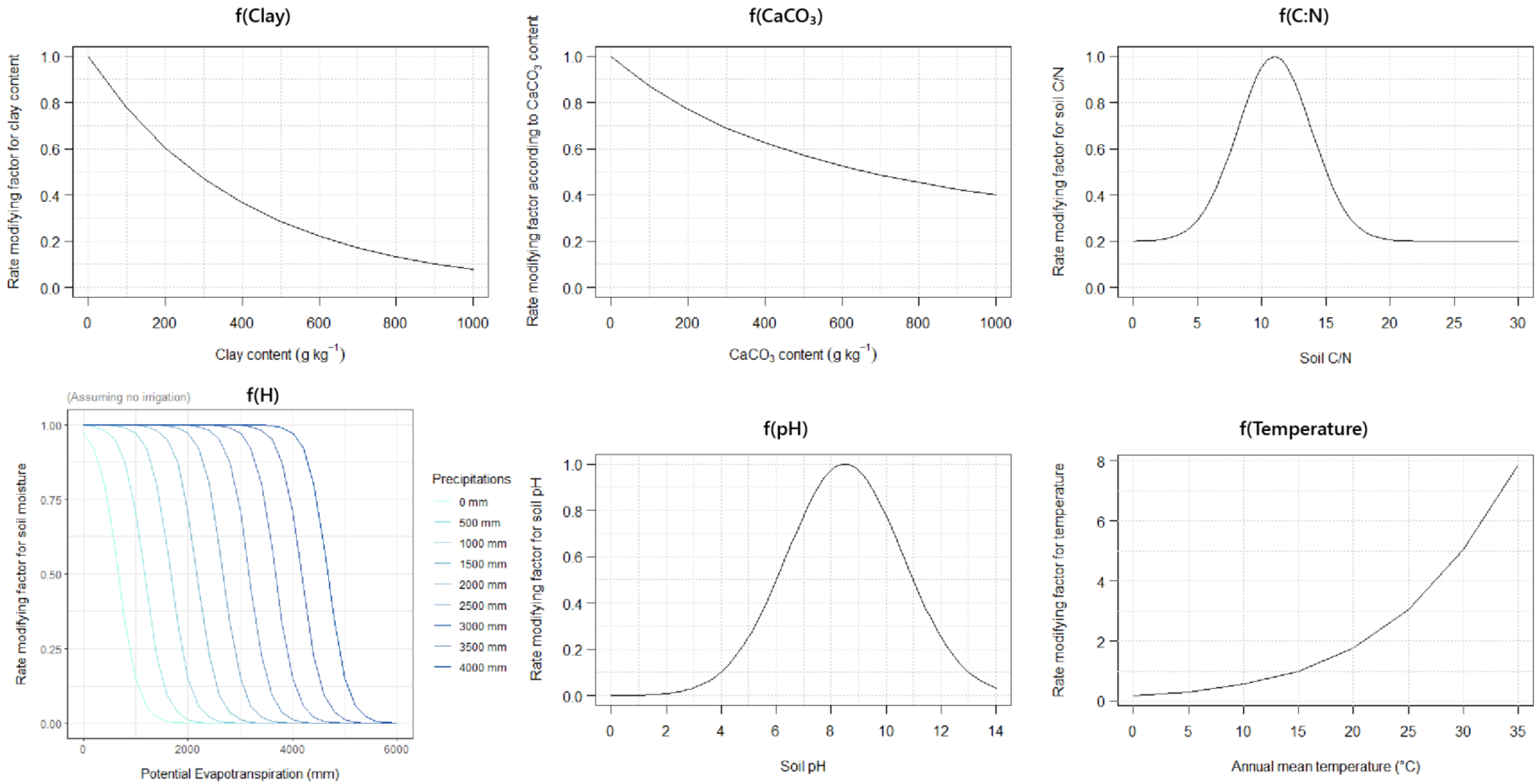

Figure A - 5.1: Behaviour of the rate modifying factors for soil organic matter mineralisation, as described in the AMG model (v2)

Calculation of each rate modifying factor

SOM mineralisation rate modifying factors: temperature

The effect of the temperature on SOM mineralisation is described by the function $f(T)$:

$$f(T) = \frac{a_T}{1 + b_T . \exp(-c_T . T)}$$

with $f(T) = 0$ if $T \leq 0$

and $b_T = (a_T - 1) . \exp(c_T . T_{ref})$

with $a_T = 25$, $c_T = 0.120$ K^{-1}, $T_{Ref} = 15°C$.

SOM mineralisation rate modifying factor: soil moisture proxy

The effect of the soil moisture on SOM mineralisation is described by the function $f(H)$:

$$f(H) = \frac{1}{1 + a_H . \exp\left(-b_H . \frac{P - PET - IW}{1000}\right)}$$

with $a_H = 3.0\ 10^{-2}$ and $b_H = 5.247$ m^{-1}

SOM mineralisation rate modifying factor: clay content

The effect of soil particle size distribution on SOM mineralisation is estimated by the function $f(A)$:

$$f(A) = \exp(-a_m . Clay)$$

with $a_m = 2.519\ 10^{-3}$ and $Clay$ standing for the soil clay content.

SOM mineralisation rate modifying factor: carbonate content

The effect of soil carbonate content on SOM mineralisation is described by the function $f(CaCO_3)$:

$$f(CaCO_3) = \frac{1}{1 + c_m . CaCO_3}$$

with $c_m = 1.50\ 10^{-3}$ (g kg^{-1}) and $CaCO_3$ standing for the soil calcium carbonate content.

SOM mineralisation rate modifying factor: soil pH

The effect of soil pH is described by $f(pH)$, and only the initial soil pH is accounted for in the model:

$$f(pH) = \exp\left(-a_{pH}.\left(pH - b_{pH}\right)^2\right)$$

with$-a_{pH} = 0.112$, $b_{pH} = 8.5$ and pH standing for the initial soil pH.

SOM mineralisation rate modifying factor: soil C/N ratio

In AMG, the C/N ratio influences SOM mineralisation. However, only the C/N of the start of the experiment is considered by the model's equations with the function $f(C/N)$:

$$f(C/N) = 0.8.\exp\left(-a_{C/N}.\left(C/N - b_{C/N}\right)^2\right) + 0.2$$

With $a_{C/N} = 0.06$ and $b_{C/N} = 11$

Results of the simulations of each individual farm of the dataset

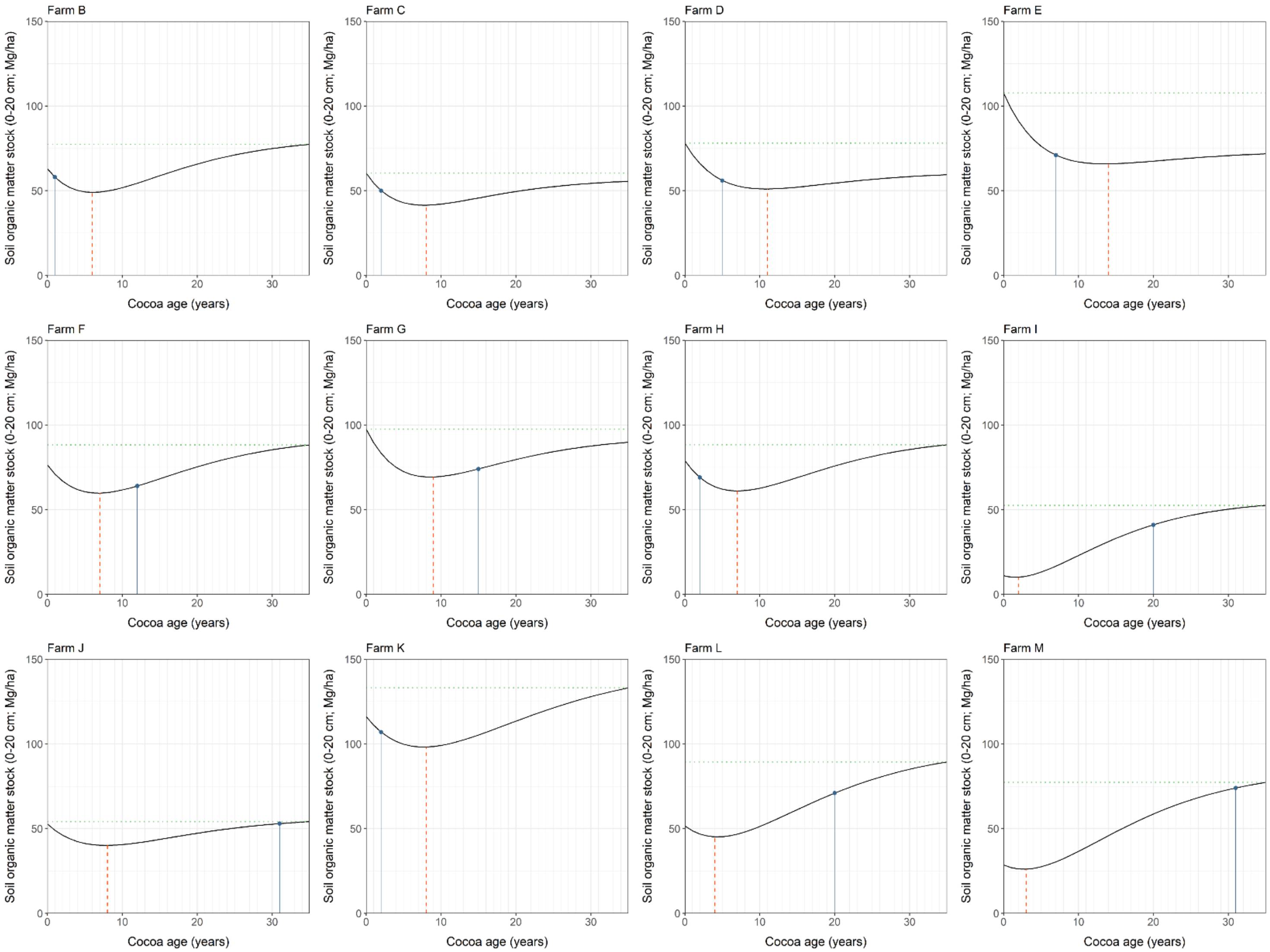

Figure A - 5.2: Simulation of SOM dynamics of the 13 farms of the dataset