Feasibility of the "4 per 1000" Initiative Through the Adoption of Agroforestry in Colombia

Feasibility of the "4 per 1000" Initiative through the Adoption of Agroforestry in Colombia

Johan Arango-Quiroga

A Thesis in the Field of Sustainability

for the Degree of Master of Liberal Arts in Extension Studies

Harvard University

March 2019

Abstract

This research explores the feasibility of the 4 per 1000 initiative in Colombia through the adoption of agroforestry practices. Agroforestry (AF) has the potential to provide environmental benefits through the sequestration of carbon in agricultural land that has been managed in a conventional fashion. I followed a meta-analysis approach using a comprehensive dataset with 56 studies from different regions of the world. This dataset also included environmental, physical, and management information to explore potential correlations with changes in soil organic carbon (SOC). Although all the AF practices provide a significant SOC gain in croplands, some practices did not provide the SOC rate needed to meet the annual increase required by the 4 per 1000 initiative for the Colombian context. These practices include alley cropping, agrisilviculture, shelterbelts, windbreaks, and riparian buffers. Another objective of my research was to evaluate the connection between soil C sequestration and financial benefits. The recent development of a Colombian Voluntary Carbon Market and the creation of a Carbon Tax have the potential to scale-up AF projects across the country and generate a significant number of greenhouse gas offsets. I evaluated the market value using the net present value (NPV) approach. I further explore the role that different interest rates, soil C sequestrations (low vs. high scenario), C prices, and duration of the AF project have on the GHG offset market value.

Table of Contents

List of Tables ix

List of Figures xi

Definition of Terms xiv

Chapter I. Introduction 1

Research Significance and Objectives 2

Background 3

4 per 1000 Initiative 4

Why is Soil Organic Carbon (SOC) Important? 5

Loss of Carbon in Global Soils 7

Criticisms and limitations of the 4 per 1000 initiative 8

How do soils gain or lose C? A primer in soil carbon dynamics 9

The impact of environmental conditions, the physical properties of soils, and farm management on SOC content 11

Potential for Soil Carbon Sequestration 12

Carbon Farming - Best Management Practices for Soil Carbon Sequestration 13

Crop Residues and Straw Retention 13

Cover Crops and Green Manure 15

Organic Amendments 18

Fertilizer Management – A balanced approach 21

Agroforestry 25

Tillage 32

Alternatives practices to increase carbon content in global soils ..34

Greenhouse gas emissions and agriculture in Colombia 35

Climate change policies, laws, and C pricing in Colombia 36

Voluntary Carbon Markets (VCM)...38

Voluntary Carbon Markets in Colombia...40

Research Question, Hypothesis and Specific Aims 42

Specific Aims...43

Chapter II. Methods 45

Literature search and study selection 45

Dataset...47

Data analysis and potential explanatory variables 50

Establishing a SOC baseline for Colombian croplands 54

Potential C payments of AF systems 55

Chapter III. 58

Results 58

Responses of soil organic carbon in agroforestry systems in different land uses..58

Responses of soil organic carbon in agroforestry systems in different agroecological zones 61

Correlations - Linear meta-regressions of environmental, physical, and management variables..62

Multiple linear meta-regressions - The role of environmental, physical, and management variables..63

SOC content in Colombian croplands...67

Soil organic carbon rates in agroforestry systems 69

Net Present Value – Investing in greenhouse gas offsets in AF projects 69

Chapter IV..72

Discussion 72

Effect of AF on SOC sequestration – Land use 72

Effect of AF on SOC sequestration – Agroecological zones...................................73

The role of environmental, physical, and management predictors 74

Potential for soil C sequestration 76

Voluntary Carbon Markets in Colombia and NPV 78

Research Limitations 79

Questions for further sustainability research 80

Conclusions 83

References 85

Appendix 116

Appendix A. Random effects model to test the effect of the conversion of different land uses (forest, grassland, uncultivated land, conventional agriculture) to agroforestry systems 116

Appendix B. Random effects model to test the effect of agroecological zones in conventional agricultural land converted to agroforestry systems. 124

Appendix C. Mean soil organic carbon in Colombian cropland for the topsoil ..130

Appendix D. Linear meta-regressions for climatic, physical, and management variables in conventional agricultural land converted to agroforestry systems (all 4 types of AF included)..131

Appendix E. Linear meta-regressions for climatic, physical, and management variables in conventional agricultural land converted to alley cropping 133

Appendix F. Linear meta-regressions for climatic, physical, and management variables in conventional agricultural land converted to agrisilviculture 135

Appendix G. Linear meta-regressions for climatic, physical, and management variables in conventional agricultural land converted to silvopasture 138

Appendix H. Linear meta-regressions for climatic, physical, and management variables in conventional agricultural land converted to shelterbelts, windbreaks, or riparian buffers 140

Appendix I. Soil organic carbon rates calculated under the random-effects model 142

Appendix J. Net Present Value calculations for AF projects with a high and low soil C sequestration rate with different interest rates and duration of projects....143

List of Tables

Table 1. Examples of Cover Crops 16

Table 2. Environmental and management practices that provide some explanation to SOC changes after introducing cover crops as green manure. 17

Table 3. A few examples of cover crops in Colombian agriculture 18

Table 4. Definition of different types of amendments 19

Table 5. Effect of incorporating organic amendments on SOC content – a few examples. 20

Table 6. Time needed to reach equilibrium in croplands under different fertilizer managements...24

Table 7. Types of agroforestry systems. 25

Table 8. Environmental and Socio-Economic Benefits of Agroforestry 26

Table 9. Number of reported SOC observations in different land uses (top row: forest, conventional agriculture, grassland, uncultivated) converted to agroforestry systems (left column: agrisilviculture, alley cropping, shelterbelt-windbreaks-riparian buffers, and silvopasture). 49

Table 10. Linear meta-regression of environmental, physical, and management variables. 64

Table 11. Multiple meta-regressions of environmental, physical, and management variables. 66

Table 12. Total soil organic carbon stock (Mg ha-1) in Colombian Croplands for the top 30 cm (103.6 Mg C ha^{-1}). Results were estimated based on the geospatial analysis of data obtained from SoilGrids250m (www.soilgrids.org) (Hengl, et al., 2017), FAO GLC-Share Land Cover database (Latham, 2014) and the Database of Global Administrative Areas (GADM) (GADM, 2005), using ESRI ArcGIS software (version10.3; www.esri.com) 68

Table 13. SOC rates (Mg C ha-1yr-1) computed with Random-Effects Model 70

List of Figures

Figure 1. The 4 per 1000 initiative.. 5

Figure 2. Left) Soil Organic Matter Aerobic and Anaerobic Degradation Right) A summarized illustration of a balanced soil carbon dynamic with carbon inputs from photosynthesis and carbon losses by respiration. 10

Figure 3. (a) Effects of climate zone on mean changes in SOC (g kg-1) in croplands subjected to different fertilizer management including the unbalanced application of chemical fertilizer (UCF), the balanced application of chemical fertilizers (CF), chemical fertilizers with straw application (CFS), and chemical fertilizers with manure application (CFM). (b) Effects of climate zone on SOC change rates (g kg-1yr-1) subjected to UCF, CF, CFS, and CFM. 24

Figure 4. Colombia's greenhouse gas emissions 35

Figure 5. a) National and regional carbon pricing worldwide. b) Colombia has a carbon tax implemented and is considering an emissions trading scheme................................. 38

Figure 6. Historical voluntary carbon offset issuances and retirement............................ 40

Figure 7. Flowchart illustrating the search strategy and article selection process for studies reporting soil C sequestration in agroforestry systems....................................... 46

Figure 8. Caterpillar plots - Summary of the meta-analytic literature estimating changes in soil organic carbon after converting (a) forest, (b) conventional agriculture, (c) grassland, and (d) uncultivated land into agroforestry systems...................................... 59

Figure 9. Caterpillar plots - Summary of the meta-analytic literature estimating changes in soil organic carbon after converting conventional agriculture into different agroforestry systems.. 60

Figure 10. The response ratio (lnRR) for soil organic carbon in different land use covers converted to an agroforestry system.. 61

Figure 11. The response ratio (lnRR) for soil organic carbon in different agroecological zones.. 62

Figure 12. Response ratio (lnRR) plotted against quantitative environmental, physical, and management predictors. (a) MAP in all observations from all types of AF systems, (b) MAT in agrisilviculture, (c) soil depth and (d) time in silvopasture, and (e) MAT in Shelterbelts, Windbreaks, and Riparian Buffers. 65

Figure 13. SOC in Colombian Soils. Maps were created based on a geospatial analysis of data obtained from SoilGrids250m(www.soilgrids.org) (Hengl, et al., 2017) and the Database of Global Administrative Areas (GADM) (GADM, 2005), using ESRI ArcGIS software (version10.3; www.esri.com). 67

Figure 14. Colombian cropland. Maps were created based on the geospatial analysis of data obtained from FAO GLC-Share Land Cover database (Latham, 2014) and the Database of Global Administrative Areas (GADM) (GADM, 2005), using ESRI ArcGIS software (version10.3; www.esri.com). 67

Figure 15. SOC in Colombian Croplands. Maps were created based on the geospatial analysis of data obtained from SoilGrids250m (www.soilgrids.org) (Hengl, et al., 2017), FAO GLC-Share Land Cover database (Latham, 2014) and the Database of Global

Administrative Areas (GADM, 2005), using ESRI ArcGIS software (version10.3; www.esri.com). 68

Figure 16. Net present value for a 20 year-long agroforestry project with a high soil C sequestration rate (1.35 Mg C ha-1yr-1) with different carbon prices (COP $10000, $15000, $20000, $25000) and different interest rates (2%, 4%, and 6%). 71

Figure 17. Net present value for a 20 year-long agroforestry project with a low soil C sequestration rate (0.13 Mg C ha-1yr-1) with different carbon prices (COP $10000, $15000, $20000, $25000) and different interest rates (2%, 4%, and 6%). 71

Definition of Terms

Agrisilviculture: is an agroforestry system that combines the production of agricultural and forest crops.

Agroforestry (AF): the practice that integrates trees and/or shrubs with crops and/or livestock on the same land-management unit.

Alley cropping: is an agroforestry system that combines trees with crops in the alleyways.

Best management practices (BMP): refers to agricultural practices that maintain or improve soil quality and soil C rates.

Carbon stock: refers to the amount of carbon stored in a reservoir. In the context of forests and agriculture, it is the amount of carbon stored in the world's plants, soils, dead wood, and litter.

Carbon tax: is one of the two major market-based options to lower emissions where a fee is imposed on the burning of carbon-based fuels by setting a price per ton on carbon.

Colombian peso (COP): is the currency of Colombia. As of February 7, 2019, US $1 Dollar is equivalent to COP $3,102.70.

Conventional or industrial agriculture: refers to the form of modern farming that integrates industrialized production of crops with reliance on, but not limited to, monoculture systems and the use of machinery, synthetic fertilizers and pesticides, and genetic technology.

Greenhouse gas offset: is a reduction, avoidance, or sequestration of greenhouse gas emissions made to compensate for or to offset an emission made elsewhere.

Land-use change/land conversion: process by which human activities transform the landscape, and it is a main driver of changes in the levels of carbon stored in soils.

Silvopasture: is an agroforestry system that combines trees, forages, and livestock in a single operation.

Soil carbon sequestration: the removal of carbon dioxide from the atmosphere into the soil.

Soil degradation: refers to the decline in soil quality or health resulting in a diminished capacity to provide goods and services.

Soil erosion: a type of soil degredation characterized by the displacement of the upper layer of soil.

Soil organic carbon (SOC): is a measurable component of organic matter and it refers only to the carbon component of organic compounds.

Soil organic matter (SOM): is the fraction of the soil that consists of plant and animal tissue in various stages of decomposition, and is composed mainly of carbon, hydrogen and oxygen – with small amounts of other elements.

Riparian buffers: are the combination of trees, shrubs, and perennial plants grown adjacent to streams, lakes, or wetlands.

Windbreaks or shelterbelts: are agroforestry systems that consist of planted trees or shrubs intended to protect wind-sensitive crops.

Voluntary carbon market (VCM): enables businesses, governments, NGOs, and individuals to offset their emissions by purchasing offset that were created through a clean development mechanism or in the voluntary market.

Chapter I.

Introduction

Soils are the third largest of the five global carbon pools, but soil's ability to absorb and store carbon has declined due to land use and soil degradation (Lal, 2008; Paustian et al., 2016). Soil degradation has been partly driven by the adoption of conventional agricultural practices, especially the preparation of land by mechanical agitation (also known as tillage) and crop residue burning (Montgomery, 2007; Farooq et al., 2011). Despite the fact that carbon has been lost from soils since the establishment of agriculture (Lal, 2016), it has been reported that the adoption of best management practices (BMP) may lead to increased levels of soil carbon (Paustian, 2016). An extensive body of research has inspired the 4 per 1000 initiative that seeks to increase global soil carbon by 0.4 percent per year (Lal, 2016). Some of the practices that increase soil carbon sequestration include, but are not limited to, planting cover crops, incorporating organic amendments, retaining crop residues, adopting agroforestry (AF) (Lal, 2004; Friedrich et al., 2012; Marongwe et al., 2011).

The increasing release of greenhouse gases (GHG) into the atmosphere has prompted considerable interest in the role that natural sinks have in the uptake of carbon. Minasny et al. (2017) explored the question of whether the 4 per 1000 initiative was feasible in 20 regions/countries around the world, and provided insights into which BMP could lead to increases in the rate of carbon sequestration. However, for many countries, there are significant gaps in the research and literature related to answering this question.

Research Significance and Objectives

The adoption of this initiative on a global scale presents a particular challenge to countries that have large numbers of farmers and small-holders with limited access to resources. My research intends to evaluate the feasibility of the 4 per 1000 initiative for Colombia through the adoption of agroforestry (AF) systems. I also acknowledge the need to include a financial analysis to explore how carbon payments and the generation of greenhouse gas offsets could drive the adoption of AF. In alignment with the 4 per 1000 initiative, the conclusions drawn from this research could lead to the adoption of a practice that provides several co-benefits such as: mitigation of human-induced GHG, the adaptation of the global food and agricultural systems to climate change, improvement of the health of soils, and increasing agricultural productivity (Al-Kaisi & Yin, 2005; Lal, 2010). Additionally, my research intends to encourage policymakers to use the 4 per 1000 initiative as a framework for pursuing more targeted strategies to increase the content of soil carbon sequestration in Colombian soils through the adoption of feasible agricultural practices. My research might also encourage researchers in other nations to complete similar analyses for agroforestry, or different agricultural practices, for a particular national context, and to adjust policies and implementation strategies to achieve the goals set out by the 4 per 1000 initiative, which might also improve the sustainability of agriculture.

My Research Objectives are:

- To further understanding of the potential mitigation effects that can be achieved by increasing soil carbon sequestration through the adoption of AF in Colombia,

- To lead to more informed policy decisions to encourage AF as one BMP that increases the rates of carbon sequestration to meet the goal established by the 4 per 1000 initiative, and
- To identify an economic incentive to foster the adoption of BMPs that enhance soil conditions and carbon sequestration.

Background

The first part of this section introduces the 4 per 1000 initiative as a framework to inspire decision makers to focus on agricultural practices that have the potential to promote soil health. I also address the criticisms and limitations of this initiative raised by experts on this topic. I will then provide a brief overview of the importance of increasing global SOC levels from a social and environmental perspective. After that, I include a brief explanation of soil C dynamics and how human activities have contributed to losing soil C over time. I also incorporate a brief introduction of BMP that have the capacity to maintain and improve soil quality, and to increase global SOC levels. Among these BMP, a discussion of agroforestry is included—its definition and classification via regularly practiced types. Studies are presented that claim AF systems have the potential to increase soil C. I then discuss additional co-benefits that AF might provide beyond soil C sequestration.

In the second part of this background, I move away from dealing with questions related to the potential soil C sequestration rate and agroforestry in order to delve into the Colombian context. Here, I present the relevant information related to the domestic emissions of GHG – including the agricultural sector. I also introduce the latest developments in policy and legal frameworks relevant to my research. These include the Colombian Carbon tax, recent decisions made at the national level in Colombia to address the commitments made in the Paris Agreement, the Voluntary Carbon Market (VCM) and the generation of GHG offsets. I also provide a general background on VCM to give a broad picture of this evolving climate mitigation mechanism.

4 per 1000 Initiative

In December 2015, the French Minister of Agriculture, Stéphane Le Foll, launched the 4 per 1000 initiative at COP21. Signatories to this initiative commit to a voluntary action plan to implement farming practices that increase the content of carbon sequestered in world soils (Chambers et al., 2016; Lal, 2016). The value 4 per 1000 is the ratio of annual global anthropogenic emissions from fossil fuels versus the rough estimate of global soil carbon stock to 2 m of soil depth (Batjes, 1996) (Figure 1). The potential carbon uptake that could be obtained from embracing management programs and practices in alignment with this initiative would allow for the storage of an additional 1.2 gigatonnes of carbon (GtC) per year in global soils (Paustian et al., 2016). Minasny et al. (2017) estimated that compliance with this initiative would sequester a total of 161 tonnes of SOC per hectare. Considering that the global land area is 149 million km^2, adoption and compliance would yield an average C sequestration rate of 0.6 tonnes of C per hectare per year (161 tonnes SOC x 0.004 ≈ 0.6 tonnes of C). It is of note that the adoption of this initiative on a global scale presents a particular challenge to countries with numerous farmers and small-holders lacking sufficient resource access; these countries are required to engage in “careful planning” (Lal, 2016).

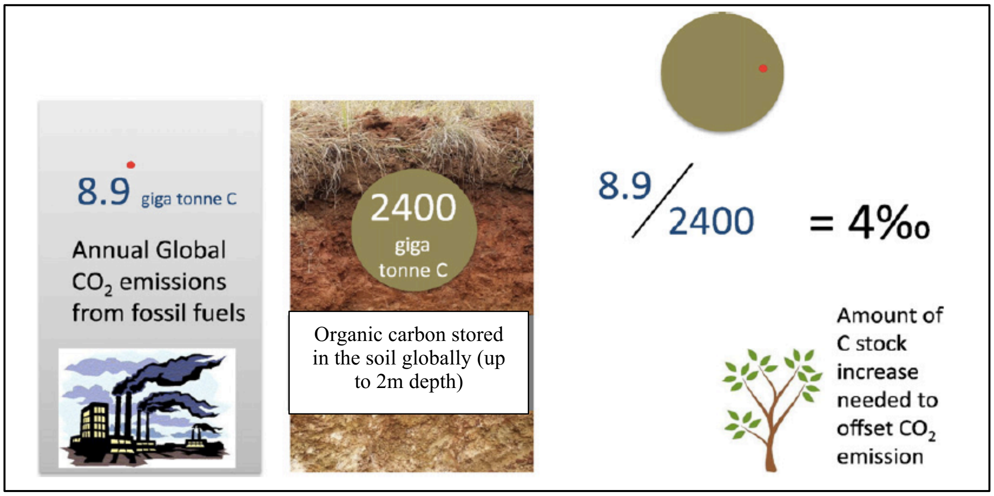


Figure 1. The 4 per 1000 initiative (Minasny et al., 2017).

Why is Soil Organic Carbon (SOC) Important?

Soil organic matter (SOM) contains large amounts of organic carbon and originates primarily from the decomposition of plant litter (Castellano, Mueller, Olk, Sawyer, & Six, 2015). A large portion of C derived from the decomposition process is emitted into the atmosphere in the form of carbon dioxide (CO_2). About 10-20% of that C forms soil organic matter (SOM), which is also composed of essential elements such as nitrogen (N), phosphorous (P), and sulfur (S) (Rice, Fabrizzi, & White, 2007). Rice et al. (2007) summarize the relationship between SOM supporting ecosystem services and essential soil functions. First, SOM plays a significant role in ecosystem services, such as improved drought tolerance, root growth, plant production, decreased fertilizer inputs, improved water quality, and decreased erosion. Second, SOM is a critical component in soil functions, such as water holding capacity, soil biodiversity, nutrient reserves, cation exchange capacity, bulk density, and soil structure.

SOM is a strong indicator of healthy and productive soils, making it a vital component of the terrestrial biosphere. Organic matter improves soil structure, which can enable increased productivity (Langdale, West, Bruce, Miller, & Thomas, 1992). Good soil structure leads to greater porosity and water infiltration, resulting in less soil erosion (Schertz et al., 1989; Benito & Diaz-Fierros, 1992). SOM also enhances aggregation, which makes soils less apt to crusting and compaction (Diaz-Zorita & Grosso, 2000). Additionally, SOM improves cation exchange, increases plant root growth, and supports important soil microorganisms and fauna (Brevick, 2010; Allison, 1973; Wardle et al., 2004). The implementation of practices that decrease SOM adversely affect soil sustainability. Decreased levels of SOM and SOC drive nutrient depletion; offsetting this loss requires applying higher amounts of fertilizer (Rice et al., 2007). A depletion of SOC and SOM levels also causes soils to become more susceptible to erosion, further disrupting the sustainability of farming systems.

The implementation of practices that increase soil carbon sequestration also drive social and economic benefits. Kimble et al. (2007) outlined a comprehensive list of both on-farm and off-site benefits. The on-farm advantages include, but are not limited to, lower production costs, labor cost savings, reduced energy costs, reduced use of machinery, reduced maintenance and machinery repair needs, and potential eligibility to receive payments for sequestering C through federal programs or carbon markets. Some of the off-site benefits include improved air quality from reduced soil erosion, reduced runoff, which is closely connected to improved water quality, flood mitigation, protection of wildlife, and increased sustenance recreation sources such as fishing. Though practices that increase SOC would lead to benefits that have been widely reported, other human activities have also unfavorably affected global soils' capability to store C.

Loss of Carbon in Global Soils

Soils' ability to uptake carbon is, and has been, affected by human interventions, like land use conversion and agricultural practices. Soils store 2,500 GtC (1,550 Gt of soil organic carbon and 950 Gt of soil inorganic carbon), but their ability to uptake carbon has been depleted by at least 320 Gt of SOC (Lal, 2004) since the spread of agriculture around 9,000 years ago (Ruddiman et al., 2015). Haider (1999) estimates that "[t]he loss of C due to soil degradation in the past 1,000 years represents 16-20 % of the present-day global soil C stock…to 1 [meter] depth" (240 to 300 Gt of SOC). Farooq et al. (2015) posit that since the beginning of the industrial era, circa 1850, the "conversion of forest to agricultural land has depleted the soil C pool by [about] 22 %." Furthermore, the depletion of SOC content in relatively undisturbed ecosystems converted to agricultural land has been documented. For such land conversions, SOC has been found to be depleted by 60% in soils in temperate regions and 75% in soils in the tropics (Lal, 2004; Lal, 2010). Wei, Shao, and Li (2014) estimate that SOC is depleted by 41% in tropical regions, and by 52% in temperate regions.

Soils degradation has been attributed to the widespread adoption of conventional agricultural practices, such as heavily mechanized plowing, monocultures, and extensive farming (Farooq et al., 2015). Tillage and crop residue burning are the practices with the most significant contribution to the degradation of soils (Montgomery, 2007; Farooq et al., 2011). In developing countries, sub-optimal agricultural practices, along with large and growing populations, drive the loss of vegetative cover, causing soils to be less resistant to erosion (Pimentel & Burgess, 2013; Pimentel et al., 2005). The frequent cultivation of soils and the removal of vegetation before crops are planted make croplands particularly susceptible to degradation by increasing soil exposure to wind and rainfall energy (Pimentel & Burgess, 2013). In the last 60 years, soil erosion has caused land to be less productive, leading farmers to abandon at least 430 million ha of arable cropland – almost 30% of the total global cropland area (Kendall & Pimentel, 1994). Lal (2004) calculated that since the beginning of the industrial era, modern agriculture has depleted the global soil C stock by 78 (±12) GtC.

Equally important is the connection between agriculture and associated land-use change that, instead of storing C in global soils, generates GHG emissions. Land use change contributes about 25% of total GHG emissions: 10%-14% from agricultural production (mainly from soils and livestock management), and 12%-17% from land cover change (including deforestation) (Smith et al., 2014; Tubiello et al., 2015). By 2050, emissions from agriculture may increase by 30% (Tubiello et al., 2014). Lal (2008) asserts that agriculture is an "integral solution" to climate change, and that restoring soil C stock through the "judicious land use and adopting BMP" is needed.

Criticisms and limitations of the 4 per 1000 initiative

There are two main criticisms of the 4 per 1000 initiative. The first revolves around the estimation of the value 4 per 1000, which uses a rough estimate of global soil carbon stock from the entire global 2 meter-depth soil profile (149 million km^2). This calculation has been criticized because, in practice, the adoption of BMP that lead to enhanced SOC sequestration is more likely to take place in well-managed lands rather than over the entire global soil cover (Minasny et al., 2017). Therefore, the completion of regionally-specific assessments and the identification of inadequately managed lands is essential to create better-informed programs which intend to increase SOC sequestration. Such initiatives, taken across sufficient land masses, may determine the extent to which the 4 per 1000 initiative is feasible.

The second criticism is related to the limitations of strategies or BMP meant to enhance the levels of soil C (Minasny et al., 2017). Soils with higher initial SOC stock (i.e. grasslands) have a lower capacity to store C – as opposed to soils with lower initial SOC stock. However, in some countries with low initial C stock (e.g. India), it may be difficult to increase SOC levels due to high temperatures or because biomass burning is widely practiced. Additionally, soils have a saturation limit, which also depends on clay and silt content (Hassink, 1997; Six, et al., 2002). As such, these soils can no longer sequester additional C. Another restraint is associated with the period of time during which BMP are adopted. The longer the duration of BMP implementation, the lower the observed SOC levels. Therefore, soil C sequestration could be considered a short-term approach to offset carbon emissions. Furthermore, some regions have extensive agricultural areas (e.g. Australia) where there is a great potential to increase SOC levels if BMP are adopted, unlike countries with limited cropland area (e.g. Belgium, South Korea). Considering these limitations, a one-size-fits-all solution is inappropriate when it comes to implementing the 4 per 1000 initiative.

How do soils gain or lose C? A primer in soil carbon dynamics

Soil is one of the largest pools of carbon on Earth, storing approximately 2.5 GtC. More C is stored in global soils than in both the atmosphere (0.8 GtC) and global vegetation (0.5 GtC) combined (Schwartz, 2014; Lehmann & Kleber, 2015). The content of soil C is determined directly by the growth and death of plant roots, and "indirectly from the transfer of carbon-enriched compounds from roots to soils microbes" (Ontl & Schulte, 2012). Decomposition of biomass from roots, plant litter, animals, and microorganisms by soil microbes releases CO_2 into the atmosphere (as the result of an aerobic or anaerobic reaction – Figure 2). A small fraction of the original carbon stays in the soil to form humus, a material resultant from the natural decay of material, such as leaves, in the soil's top layer (Figure 2). Ontl & Schulte (2012) highlight that humus, unlike plant debris, is more resistant to decomposition (highly recalcitrant), which also means that there is a longer permanence for the carbon stored in the humus. Soil carbon can be sequestered in different ways, including the fixation of atmospheric CO_2 in standing biomass (i.e. trees), long-term biomass products (i.e. timber), living biomass in soils (i.e. microorganisms and perennial roots), recalcitrant organic matter in surface soil (i.e. humus), and inorganic C in subsoil (i.e. carbonates) (Johnson et al., 2007).

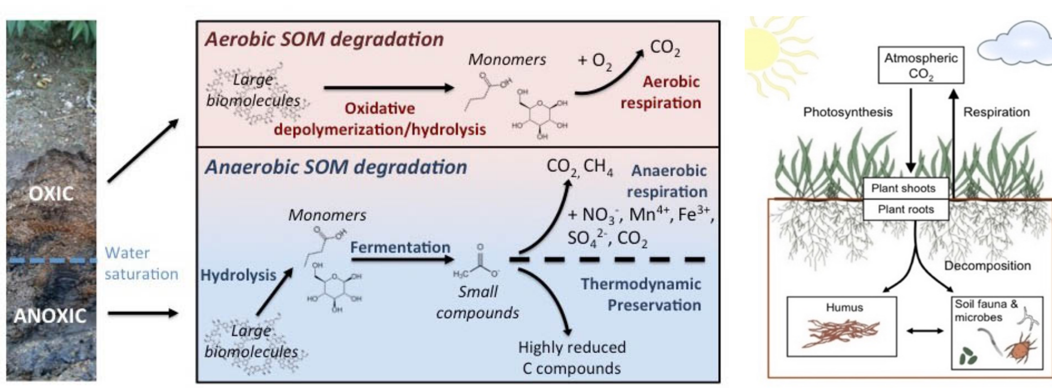


Figure 2. Left) Soil Organic Matter Aerobic and Anaerobic Degradation (Stanford Earth, n.d.) Right) A summarized illustration of a balanced soil carbon dynamic with carbon inputs from photosynthesis and carbon losses by respiration (Ontl & Schulte, 2012).

The impact of environmental conditions, the physical properties of soils, and farm management on SOC content

The stabilization, or destabilization, of C are currently understood as biological, physical, or chemical mechanisms with many processes that "cross these boundaries" (Six, Conant, Paul, & Paustian, 2002). Therefore, the SOC content, and sequestration, in croplands depends on several factors including climatic conditions, physical properties of soils, and farm management history. Climatic conditions affect soil temperature and moisture content, which also affect photosynthesis and decomposition and respiration rates. For instance, regions in northern latitudes, characterized by colder and wetter climates, have higher SOC levels because photosynthesis rates exceed decomposition rates (Ontl & Schulte, 2012). On the other hand, regions with warm temperatures and high precipitation (tropics) present high rates of photosynthesis and decomposition with intermediate SOC levels (Ontl & Schulte, 2012). However, climate alone does not explain all changes in SOC.

Soil type has been found to have a larger effect on soil carbon dynamics than climate (Mathieu, et al., 2015), which highlights the importance of the associations of clay content with organic matter and its role in the stabilization of SOC (Churchman, 2018). Additionally, a soil's physical properties, such as bulk density, water stable aggregation, available water capacity, and infiltration rate, play an important role in maintaining and enhancing SOC levels (Lal, 2007). Furthermore, SOC losses can take place with agricultural activities that have a high level of soil disturbance, which also drive processes such as erosion, leaching, and mineralization. For instance, when tilling is practiced, the physical disturbance "breaks [down] soil aggregates, exposes soil to raindrop impact, releases [SOM], [activates] microbial processes, and increases mineralization of SOM and release of CO_2 to the atmosphere" (Lal, 2007). Soil management then plays a key role in alleviating soil compaction, improving soil structure, increasing infiltration rate, augmenting the available water capacity, and adding or removing SOC.

Potential for Soil Carbon Sequestration

It is important to note that croplands provide a more "immediately practical" role for the enhancement of SOC (Zomer et al., 2017). Unlike forests or grazing lands, croplands are "often intensively managed" (Smith et al., 2008), which could present an opportunity for the adoption of a different management strategy (e.g. AF). Additionally, croplands can, theoretically, sequester up to 88 GtC over the next 50 to 75 years on 1,400 Mha (Lal, 2016). This is equivalent to an annual C sequestration rate of 0.8-1.2 tons of carbon per hectare per year. These amounts may seem small relative to the annual rate of carbon emitted from burning fossil fuels (≈10 GtC). However, at a time when atmospheric carbon dioxide levels have officially passed 400 part per million (ppm) (Kahn, 2016), keeping 1 GtC in the soil sink is equivalent to 0.47 ppm of carbon dioxide (CO_2) in the atmosphere (Lal, 2016).

Increasing the C pool in soils depends on texture and profile characteristics, climatic conditions, and the combination of management practices applied (Paustian et al., 2016). In dry and warm regions, SOC sequestration rates are estimated to vary between 0 and 150 kg C/ha per year (Armstrong, Millar, Halpin, Reid, & Standley, 2003). In humid and cool climates, the rates range from 100 to 1,000 kg C/ha (Grace et al., 1995; Campbell et al., 2000; West & Post, 2002). These rates can be sustained for 20 to 50 years with the uninterrupted use of BMP, or until the soil sink capacity is reached (West & Post, 2002; Sauerbeck, 2001).

Carbon Farming - Best Management Practices for Soil Carbon Sequestration

The implementation of BMP that lead to increased SOC levels is also known as carbon farming. The scope of this research includes BMP with an extensive body of research that have been found to increase soil C stocks. These BMP include, but are not limited to, the retention of crop residues and straw, cover cropping and green manure, the incorporation of organic manures, the adoption of different fertilizer management regimens, and the implementation of agroforestry practices.

Crop Residues and Straw Retention

Crop residue removal is commonly practiced in agriculture to provide inputs for other farming operations (e.g. producing animal feed) and/or to generate additional income (e.g. sale of raw material for biofuel production). Straw and crop residues are also burned or removed to facilitate seed-planting for future crops (Aulakh et al., 2001). However, the excessive removal of crop residue may adversely affect soil processes and properties that lead to decreased SOC levels. This SOC loss can be explained with four processes that take place after crop residue or straw is removed from the fields (Ruis & Blanco-Canqui, 2017). First, SOC is lost from the removal of aboveground biomass. Second, without the presence of crop residues, water and wind erosion is increased with a subsequent loss of SOC (Kenney et al., 2015; Blanco-Canqui et al., 2016a; Blanco-

Canqui et al., 2016b). Third, soil structure is degraded and soil aggregate size is reduced, which leads to faster SOC turnover rates (Six et al., 2000). Fourth, the substrates available for microbes to use new and more efficient C sources for energy are reduced with the removal of crop residues and straw, which increases the loss of SOC (Stetson et al., 2012).

The amount of crop residue removed from the fields also plays a significant role in the loss of SOC. The removal of more than 50 percent of crop residues generally decreases SOC, especially in the long-term, with a loss of SOC ranging between 15 to 50 percent compared to those soils in which crop residues were retained (Blanco-Canqui and Lal, 2009; Raffa et al., 2015). In soils with a crop residue removal rate higher than 50 percent, the average SOC loss was estimated to be 0.87 Mg $ha^{-1}yr^{-1}$ (Megagrams per hectare per year = Megatons per hectare per year), whereas soils with rates below 50 percent accounted for a SOC loss of 0.31 Mg $ha^{-1}yr^{-1}$ (Blanco-Canqui & Lal, 2009; Smith et al., 2012). Therefore, the incorporation of straw has been proposed as a practice that can lead to increased SOC content (Duiker & Lal, 1999; Li et al., 2010).

Liu et al.'s (2014) meta-analysis of 176 published field studies drew relevant conclusions on the effects of the incorporation of straw on SOC in croplands. Both input rate and clay content of the soils were the main factors explaining SOC accumulation. Straw retention significantly increased SOC concentration by 12.8 percent. Additionally, increased SOC levels were positively correlated with OC input (straw return) and crop yield. On the other hand, when applied to soils with high clay content did not lead to higher rates of C. Liu et al. (2014) also found that environmental variables like temperature and precipitation did not have a significant correlation with changes in SOC levels, and soil C saturation is reached after 12 years of continuous straw return. Also, SOC tends to increase more clearly when straw was tilled into the soils compared to straw covering the soil surface, which might be explained by the fact that tilling increases the contact between straw and soils, promoting a higher rate of transformation of straw C into SOC. The SOC loss caused by the removal of crop residues could also be prevented with the incorporation of cover crops and green manure.

Cover Crops and Green Manure

Cover crops are defined as “crops grown primarily for the purpose of protecting and improving soil between periods of regular crop production” (Schnepf and Cox 2006); these crops are sometimes referred to as inter-crops or cash-crops. Green manure refers to a crop used as a soil amendment to provide nutrients for future crops (Cherr, Scholberg & McSorley, 2006). The terms green manure and cover crops are often used interchangeably, however the latter are planted to protect the soil while the former is meant to be tilled back into the soil to enrich the soil with its decomposition. Cover crops and green manure are incorporated between the rows of the regular crop to improve soil health. Some examples of the different types of cover crops include growing mustards and brassicas (e.g. broadleaf species like cabbage), grasses (e.g. wheat, barley), legumes (e.g. hairy vetch, crimson clover), or plant mixtures (Table 1).

There is ample evidence that cover crops and green manure enhance SOC stocks (Poeplau and Don, 2015; McDaniel et al., 2014; Schipanski et al., 2014). However, the reported gains in SOC stocks vary from 0 to 3.50 Mg $ha^{-1}yr^{-1}$ (Blanco-Canqui et al., 2015; Poeplau and Don, 2015). Poeplau and Don’s (2015) meta-analysis found a

Table 1. Examples of Cover Crops (Adapted from Clark & SARE, 2015)

Type of Cover Crop	Species	Relevant Information
Legumes	Clovers, vetch, peas, beans	Fix a lot of nitrogen (N) for subsequent crops. Not good for scavenging N left over after cash crops.
Non-Legumes - Cereals	Rye, wheat, barley, oats, triticale	Useful to scavenging nutrients. Non-legumes are recommended in fields with excess of nutrients.
Non-Legumes – Forage grasses	Annual ryegrass	
Non-Legumes – Broadleaf species	Buckwheat, sunflower, mustards, and brassicas.	
Mixtures	Must be tailored to farm context and needs.	Recommended to multiply and diversify the cover crop benefits.

significant correlation between the time cover crops are introduced and gains in SOC levels with an annual SOC rate of 0.32 (± 0.08) Mg $ha^{-1}yr^{-1}$ are realized. This study also projected an average SOC gain of 0.23 Mg $ha^{-1}yr^{-1}$ using a soil modeling tool called RothC. Ruis and Blanco-Canqui (2017) estimated that the "average SOC increase [was found to be] 0.49 Mg $ha^{-1}yr^{-1}$…in the upper 30 cm of the soil."

Poeplau and Don (2015) drew relevant conclusions from the analysis of environmental and management variables (Table 2). Elevation and sampling depth provided some explanation of changes in SOC stock: increased annual SOC stocks were positively correlated with soil depth, and higher elevation with lower the gains in SOC. There was no evidence of saturation (up to 54 years), however, the number of studies with a duration of over 20 years was small. The constraints due to "limited data from longer term experiments that [might] improve the ability to demonstrate saturation" are acknowledged in this study. Since it is very likely that a cover crop system will reach a saturation, a potential steady state was determined with the RothC carbon modeling software. This new equilibrium was found to be reached after 155 years with half of this new equilibrium being reached after 23 years. Furthermore, significant changes in SOC stock rates were not observed for different tillage management (tilled vs. untilled), functional plant type (legumes vs. non-legumes), and climate (temperate vs. tropic) (Poeaplau & Don, 2015; Ruis & Blanco-Canqui, 2017).

Table 2. Environmental and management practices that provide some explanation to SOC changes after introducing cover crops as green manure (Poeplau and Don, 2015).

Practices with explanatory power	**Practices without explanatory power**	**Practices that could have some explanatory power**
• Time since introduction • Elevation • Sampling depth	• Precipitation • Temperature • Soil type • Soil texture with sand, silt, and clay content • Main crop type or crop rotation • Cover crop type • Cover crop frequency • Amount and type of fertilization • Type of tillage • Number of soil samples • Initial C concentration	Cover crop above and below ground biomass C:N ratio of the cover crop Though these variables might have some explanatory power, they were not included in the meta-analysis because of the following reasons Data was only given in a small number of studies. High variability in the definition of biomass among studies.

Cover crops and green manure also provide other co-benefits to agricultural soils. Some of those benefits include “slow[ing down] erosion,…enhanc[ed] water availability, [and] smother[ing] weeds” (Clark & SARE, 2015), controlling pests and diseases, and increased biodiversity (Lal, 2004). Furthermore, the use of plant mixtures could maximize the potential of cover crops if a careful design considers factors like weather, land management history, current farming operations, type of soil, farming objectives, and the interaction between the chosen plant varieties for cover crops (Pennsylvania State

Extension Agricultural Program, 2017). For instance, Cadavid et al. (1998) found that the incorporation of dry guinea grass (*Panicum maximum*) as mulch led to increased cassava yields for 8 years in Colombian sandy soils. However, there could be negative impacts as well. In Colombian cassava crops, the use of some plant species as green manure have been found to compete strongly for water and nutrients, which has led to decreased cassava yields (Howeler, 2002). A few more examples of cover crops and green manure used in Colombia are provided in Table 3.

Table 3. A few examples of cover crops in Colombian agriculture[1]

Crop - Location	**Cover Crop**	**Reference**
Banana – Santa Marta Region	*Teramus volubilis* (Sw.)*; Callisia cordifolia* (Sw.)*; Desmodium scorpiurus* (Sw.) Des *Desmodium triflorum* (L.) DC	Carbono and Cruz, 2005
Citrics – Department of Meta	*B. brizantha; P. maximum; A. pintoi; D. ovalifolium*	Orduz-Rodriguez et al., 2011
Potato – Department of Boyacá	Forage turnips *Raphanus sativus L.* The legume vicia atropurpurea *Vicia sativa L.* Oats *Avena sativa L.*	Viteri, Martinez, and Bermudez, 2008.

Organic Amendments

Amendments differ widely, in composition and application mode, and include compost, farm yard manure/raw waste/animal manure, green manure (see cover crop and

---

[1] For further information and examples of the use of green manure and cover crops in Colombian and Latin American croplands see Prager Mosquera et al., (2012) and Pound (1999).

green manure section), biosolids, and biofertilizers (Table 4). There is ample evidence that the application of different amendments like farm compost (D'Hose et al., 2014),

Table 4. Definition of different types of amendments

Type of organic amendment	Definition
Farm yard manure/Raw waste/Animal manure	It refers to the decomposed mixture of feces and urine of farm animals along with litter and leftover plant material from bedding or fodder fed to the livestock (TNAU, 2016).
Compost	It refers to a product that is stable, free of pathogens and plant seeds that can be beneficially applied to land and is resultant from the biological decomposition and stabilization of organic substances, under conditions that allow development of thermophilic temperatures as a result of biologically produced heat (Haug, 1993).
Biofertilizer	It is a preparation with inoculate of microorganisms (Bhardwaj et al., 2014). These living or latent cells of efficient microorganisms accelerate certain microbial processes that have been found to improve crop productivity, soil fertility, and the efficiency of the fertilizers
Green manure	A crop used as a soil amendment to provide nutrients for future crops. See cover crops and green manure section.

municipal solid waste compost and farmyard manure (Hemmat et al., 2010), and green manure with industrial waste water (Lin et al., 2008) increase SOC levels. In the same way, different types of animal manure have been found to increase soil C levels. SOC stocks have increased by 3.2 Mg C ha^{-1} after 10 years of poultry litter addition (Sainju et al., 2008), 19.1 Mg C ha^{-1} following 25 years of cattle manure application (Gami et al., 2009), and 3.8 Mg C ha^{-1} after 22 years of pig manure application (Huang et al., 2010). Despite the reported gains in SOC levels, there is also evidence of observed SOC losses (Franzluebber et al., 2001; Angers et al., 2010). A few examples of cases where the addition of organic amendments has led to SOC increases is included in Table 5.

Table 5. Effect of incorporating organic amendments on SOC content – a few examples (Modified from Bhattarcharya et al., 2016). n.a. not available.

Type of Organic Amendment	Location and duration	Effect on SOC	Reference
Farm yard manure, paddy straw, green manure.	Indo-Gangetic plains (India) - 25 years	Increased SOC	Ghosh et al., 2012
Organic manure only, organic manure+inorganic fertilizer, inorganic fertilizer only	Northern China – 18 years	Increased SOC in org.manure + inorg. fertilization	Gong et al., 2009
Organic manure application	Indian Himalayas (India) – 30 years	Increased SOC	Kundu et al., 2007
Manure application	Jilin province (China) – n.a.	Increased POM (Particulate organic matter)	Xie et al., 2014
Green manure application	Qiyang county (China)	Increased SOC	Yang et al., 2014

Maillard and Angers' (2014) meta-analysis of the literature available on the effect of manure[2] application on soil organic carbon stocks found that the changes in SOC stock could not be explained by factors such as climate, manure management system, land use, animal species, soil texture, or initial SOC concentration. Instead, "a dominant effect of cumulative manure-C input[3] on SOC response" was found. Although SOC stocks in tropical countries were lower than in cooler temperate regions, the data to explain whether this trend is caused by either relatively lower cumulative manure-C inputs or

[2] In Maillard and Angers (2014), the term manure refers to compost, mud, sludge, ooze, effluent, waste, manure, dung, slurry, muck slurry, farmyard manure

[3] Maillard and Angers (2014) define manure-C input as a combination of annual manure-C application rate and study duration.

climate is limited. Additionally, the application of cattle manure yielded slightly higher SOC rates than manure from different animal species, but without a significant difference.

Aside from gains in SOC levels, the application of organic manures have additional co-benefits. For instance, soils are protected from erosion and their structure is improved (Altieri & Nicholls, 2013). Furthermore, the use of animal manure and other biosolids enhances aggregation, which favors water retention, microbial activity, and root growth (Carter, 2002; Hao et al., 2004). Additionally, nitrogen management is improved (Smith et al., 2014). However, the poor management or overuse of organic amendments can lead to negative environmental impacts such as increased levels of ammonia in the air and nitrate in groundwater (Bruinsma, 2003). An important factor for the implementation of this BMP is the access that farmers might have to sufficient organic manure or fertilizers for their farming operations, which may be constrained by the lack of either economic or physical resources.

Fertilizer Management – A balanced approach

Goswami (1997) defines the concept of balanced fertilization as the rational use of fertilizers and organic manures to provide nutrients for farming that ensure the efficient use of fertilizers; obtain the best synergistic interaction among all the factors of farming such as water, seeds, and chemical inputs; mitigate the environmental damage through the reduced loss of nutrients; maintain the soil productivity; sustain crop yields in proportion to the biological potential of the crop variety considering the soil-climate and agro-ecological context. Unlike an intensified use of fertilizers that leads to ‘soil mining,’ balanced fertilization aims to build soil health (Mahajan & Gupta, 2009). A balanced fertilization goes beyond the sole application of nitrogen, phosphorous, and potassium (NPK), and also includes the incorporation of organic manure and/or crop residues. "Fertilizers [may] boost yields, [but] they have not restored the soil body" (Jenny, 1980). A balanced fertility management strategy aimed at restoring SOC represents a significantly different approach than one which intensifies the use of chemicals fertilizer amendments and pesticide treatments.

The implementation of fertilizer management practices can either reduce the rate of SOC loss or enhance SOC levels. In low-yielding and nutrient-deficient agricultural systems, fertilizer inputs increase the production of biomass and residue, thus enhancing the amount of C inputs into the soil (Lemke et al., 2010; Eagle and Olander, 2012). In acid soils (e.g. the South American savannah ecosystems - Los Llanos in Eastern Colombia), the application of nitrogen (N) and phosphorous (P) can improve the soils' ability to sink C (Lal, 2008). However, the application of fertilizers may not be the answer in depleted and degraded soils – as shown by modest attempts to increase agricultural production in Africa (Lal, 2008). Despite the fact that organic fertilizers are preferred to increase SOC stocks (Wang et al., 2016), increased crop yields are minimal if the fertilizers are used alone (Manna et al., 2005; Seufert et al., 2012; Wei et al., 2016). The effectiveness of fertilizer application is greater when used with crop residue mulch (Yamoah et al., 2002), trees (Sanchez, 2002), or manure (Han et al., 2016). The different types of fertilizer managements can be categorized into four different groups, which include the unbalanced application of chemical fertilizer (UCF), the balanced application of chemical fertilizers (CF), chemical fertilizers with straw application (CFS), and chemical fertilizers with manure application (CFM) (Han et al., 2016).

Han et al.'s (2016) meta-analysis drew important conclusions on the effect that different fertilizer managements have on SOC levels in croplands. All treatments increased SOC levels, CFM and CFS were identified as the main drivers of SOC gains by an average of 3.5 g kg^{-1} (0.29 g $kg^{-1}yr^{-}1$) and 2.0 g kg^{-1} (0.37 g $kg^{-1}yr^{-1}$) respectively. Likewise, CF and UCF increased SOC levels by 1.7 (0.13 g $kg^{-1}yr^{-1}$) and 0.9 g kg^{-1} (0.07g $kg^{-1}yr^{-1}$) respectively. Increased gains in SOC content under CFM and CFS might be explained by the fact that carbon is added into the soil directly (Liu et al., 2014; Maillard & Angers, 2014) in the form of manure and straw or crop residue. The meta-analysis also found that SOC changes were significantly lower in tropical zones than in cool temperate zones in croplands under CF (1.0, 1.4, and 2.5 g kg^{-1} in tropical, warm, and temperate regions) (Figure 3a). Under CFM, CFS, and UCF, climate was not found to have a significant effect on SOC stocks. Furthermore, croplands in tropical and warm climate zones sequester SOC significantly faster than in cool temperate regions under CFM and CF managements (Figure 3b). The same trend was found under UCF and CFS managements without a significant effect. Also, CF, CFS, and CFM managements sequester C for at least 40 years while UCF treatments reached a saturation level after 20 years. In most cases, croplands in tropical regions reached equilibrium in a shorter period of time than in cooler regions (Table 6).

As the world faces the urgent need to increase the growing demand for food while it deteriorates farming soils (Godfray et al. 2010; Godfray and Garnett 2014), an intensification-approach, along with the expansion of the agricultural land area and the increased area of irrigated land, would only exacerbate "the already severe problems of global warming, depletion of nonrenewable water reserves[,] eutrophication of surface waters, and extinction of not only plants and animals but also those of some fragile soils"

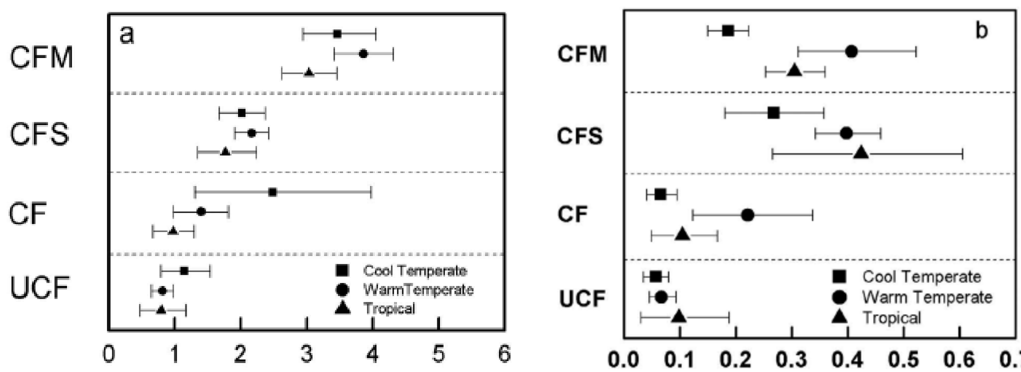


Figure 3. (a) Effects of climate zone on mean changes in SOC (g kg-1) in croplands subjected to different fertilizer management including the unbalanced application of chemical fertilizer (UCF), the balanced application of chemical fertilizers (CF), chemical fertilizers with straw application (CFS), and chemical fertilizers with manure application (CFM). (b) Effects of climate zone on SOC change rates (g kg-1yr-1) subjected to UCF, CF, CFS, and CFM (Han et al., 2016).

Table 6. Time (years) needed to reach equilibrium in croplands under different fertilizer managements (Han et al., 2016).

Climate zone	**Unbalanced Application of Chemical Fertilizers (UCF)**	**Balanced Application of Chemical Fertilizers (CF)**	**Chemical Fertilizers with Straw Application (CFS)**	**Chemical Fertilizers with Manure Application (CFM)**
Cool temperate	NA	NA	46-73	72-117
Warm temperate	18-58	30-69	37-48	50-65
Tropical	NA	19-27	28-47	26-30

(Lal, 2016). The adverse environmental impacts caused by the unbalanced use of fertilizers are widely known, which includes acidification and nutrient loss (Tarkalson et al., 2006; Cai et al., 2015). Despite this wide knowledge, inefficient use of chemical inputs remains a common agricultural practice (Lal, 2004; Lal, 2007; Peñuelas, Sardans, Rivas-ubach, & Janssens, 2012).

Agroforestry

AF is a practice that integrates trees and/or shrubs with crops and/or livestock on the same land-management unit to create both environmental, economic, and social benefits (FAO, 2015; USDA, 2011). FAO breaks agroforestry into three types of systems, while the USDA has five different categories. Despite the different ways AF is categorized, most of these practices adhere to Biardeau et al.'s (2016) brief definition of agroforestry as "the production of livestock or food crops on land that also grow trees." In this thesis, AF is classified into four different groups: alley cropping, agrisilviculture, silvopasture, and one group combining shelterbelts, windbreaks, and riparian buffers (Table 7).

Table 7. Types of agroforestry systems – FAO and USDA (FAO, 2015; USDA, 2011).

FAO	USDA	Classification for this Thesis
• Agrisivilcultural systems • Combination of crops and trees like alley cropping. • Silvopastoral systems • Combination of forestry and grazing of livestock on grasslands or on-farm. • Agrosylvopastoral systems • Integration of trees, animals, and crops.	• Alley cropping • Planting crops between rows of trees. • Forest farming • Growing food under a forest canopy. • Silvopasture • Combination of trees with livestock and their forages on one unit of production. • Riparian Forest Buffers • Areas along rives and streams made up of trees, shrubs, and grasses. • Windbreaks • They protect crops, animals, infrastructure, and soil from wind, snow, dust, and odors.	• Alley Cropping • Agrisilviculture • Silvopasture • Shelterbelts, Windbreaks, and Riparian Buffers.

Studies have shown that AF provide a host of environmental, social, and economic/agricultural production co-benefits (Table 8). The adoption of AF has led to increased land productivity, higher water and resource use efficiency, and croplands being protected from soil erosion (Smith et al., 2014). AF has also been demonstrated to improve "cultural services like recreational, aesthetic, and cultural heritage values" (Torralba et al., 2016). The benefits are manifold, including, but not limited to, wildlife integration, nutrient retention, pollination, pest control, and fire risk reduction. In Europe, AF systems have enhanced biodiversity and ecosystem services when compared to conventional agriculture and forestry plantations (Torralba et al., 2016). Despite the known benefits, barriers such as establishment costs, time and management requirements, and the lack of tree management expertise (Holderieath, Valdivia, Barbieri & Godsey, 2011) often prevent farmers from implementing AF.

Table 8. Environmental and Socio-Economic Benefits of Agroforestry (adapted from Schoeneberger, Bentrup and Patel-Weynand, 2017)

Environmental	Socio-Economic
•Reduced soil erosion from water and wind •improved soil physical condition and fertility •Reduced water pollution, hence improved water quality and protects aquatic ecosystems •Cretes habitat refugia and wildlife integration •Protects biodiversity (pollinators and beneficial insects) •Energy conservation	•Improves future soil productivity •Creates microclimate that improves crop yields and livestock performance and well-being •Creates innovative food-producing systems. Increased farm portfolios and increased economic stability for landowners

Agroforestry potential to sequester SOC

Several studies have found that AF systems have a positive impact on soil carbon sequestration (De Stefano & Jacobson, 2018, Haile et al., 2008; Nair et al., 2009). Enhancement of SOC stocks has been found when land use transition from conventional agricultural practices, pasture/grasslands, and uncultivated/other land-uses to AF. Nair et al. (2010) found that soils in AF systems can sequester between 30 and 300 Mg C ha^{-1}. Dixon (1995) estimated that agroforestry could potentially sequester 1.1 and 2.2 GtC per year for 50 years. Sanchez (2000) posits that AF could restore up to 35 percent of the original C stock lost due to slash-and-burn agriculture. The IPCC estimated that AF systems have the potential to mitigate from 1.1 to 2.2 GtC over a period of 50 years (IPCC, 2007). Also, the conversion of unproductive croplands and grassland into AF could represent the sequestration of almost 0.6 GtC yr^{-1} by 2040 (Jose, 2009). It is worth noting that uncertainties remain in estimating the soil C potential of AF systems.

Although I focus solely on soil C sequestration (belowground biomass) in this research, AF systems can also sequester C aboveground (Lorenz & Lal, 2014). Aboveground biomass refers to the potential that trees have to uptake C in branches, stems, stump, bark, seeds, and foliage. Belowground biomass refers to all living biomass of live roots. AF systems use C for biomass growth, which leads to future C inputs into the soil. As trees grow, nutrients are recovered and fixed, which might lead to increased plant growth and higher SOC stocks (van Noordwijk et al., 1996). Recovered and fixed nutrients may include nitrogen (N), phosphorous (P), calcium (Ca), magnesium (Mg), and potassium (K) (Ajayi et al., 2011). Trees planted as part of an AF system also create microclimates that might lead to conditions where soil moisture and temperature drive higher rates of SOC sequestration (Laganière et al., 2010). Lorenz and Lal (2014) have identified AF practices that increase direct C inputs to the soil such as, but not limited to, returning tree litter to decompose on site or use as mulch, allowing livestock to add organic manure to the soil, and growing woody species during fallow periods.

Alley Cropping

An alley cropping system is a mixed system of trees accompanied by crops in the alleyways (Gold & UMCA, 2011). A few examples of alley cropping systems successfully implemented in different parts of the world include wheat and walnuts in Southern France (Cardinael et al., 2015), coffee plantations with shading trees in Peru (Ehrenbergerová et al., 2016), and rubber and cacao in China (Chen, Liu, Jiang & Wu, 2017). Additional examples include the combination of pecan trees as the main crop with annual crops of wheat and hay in the alleys, mixed systems of apple trees with grass, or intercropped maize with fruit and nut trees and fodder grasses.

In Colombia, several types of alley cropping systems can be found across the country. In Tumaco, a town close to the border with Ecuador, farmers main often establish systems with plantains, cacao, and fruit trees (Ballesteros, Marco, & Ordóñez, 2008). In the eastern state of Casanare, livestock and rubber are important economic activities; the production of rubber is intercropped with a very specific type of maize called *Carare,* which is then used for feed (Rojas et al., 2012). Rubber plants are also planted to provide shade to plantains, which helps control the black sigatoka fungus that affects plantain and banana crops.

Schoeneberger et al. (2017) highlighted different benefits that drive farmers to establish alley cropping systems. First, the movement of nutrients and chemicals is decreased, which leads to the improvement of soil quality by making a better use, and cycling, of nutrients. Furthermore, the habitat for wildlife and beneficial insects is enhanced. Water runoff is reduced as well as soil erosion, and microclimate conditions improve the quality and quantity of crops and forages. Farms adopting alley cropping are also driven by economic incentives. For instance, farmers can diversify their income, increase their productivity, and gain financial rewards in the short and long terms (Gold & UMCA, 2011).

Agrisilviculture

An agrisilviculture system combines the production of agricultural and forest crops. This AF system can include the mix of ginseng, mapley syrup, bee products, shiitake mushrooms, and timber. In north western states in India, poplar, a tree grown for wood and pulp, has been extensively adopted as an agrisilviculture system (Dogra et al., 2014, Chauhan et al., 2015). The use of woody species to provide shelter to cacao plantations is practiced in Costa Rica, with *Cordia alliodora* and *Erythrina poeppigiana* (Norgrove, 2003), and in Uganda, with the hardwood species *Maesopsis eminii* (Chaudhry & Silim, 1980). In Colombia, the Instituto Colombiano Agropecuario (ICA) has made efforts to provide technical training to coffee farmers to adopt agrisilviculture. The purpose of this initiative is to encourage farmers to adopt this AF system to produce biomass to generate energy (ICA, 2017). In this type of AF, the production of agricultural products (e.g. food, botanicals, decoratives, handicrafts) benefit farmers with short-term income, while trees grown for wood products add long-term value (USDA & NAC, 1997).

Silvopasture

Silvopasture is a system that combines trees, forages, and livestock in a single operation. A common misconception of silvopasture is that livestock graze the forests without any control. In this type of system, the farming operation is purposely designed considering facts such as, but not limited to, creating spaces between trees to enable the growth of forages, building temporary fencing to protect young planted trees from livestock, designing the tree planting based on site factors, finding ways to improve water quality and availability, and reducing erosion. Another important factor, especially in places affected by increasing higher temperatures due to climate disruption, is providing shelter for livestock. Heat is a major stressor that negatively affects animal production and welfare (Slimen, Najar, Ghram, & Abdrrabba, 2016). Reduced animal performance then results in economic loss for the farmer (St-Pierre, Cobanov, & Schnitkey, 2003).

Silvopasture systems have been found to provide economic and environmental benefits (Schoeneberger et al., 2017). For instance, nutrient loss is reduced while higher value products are created. Additionally, the farmer diversifies sources of income from the production of livestock and plant products. Furthemore, this type of AF system could lead to lower feeding costs, reduced vegetation control, improved animal health, and fire protection (Gold & UMCA, 2011). The establishment of silvopasture presents challenges that must be considered by farmers. For instance, adapting and thinning forests to establish silvopasture might significantly add costs in seeds, planting, time, machinery, and labor. Therefore, establishing a silvopasture system in grassland may be more cost-effective than in forests or silvoculture crops. Farmers also have to compensate for the loss of land converted to planting trees that could otherwise be used for grazing. Costs remain an important barrier to the implementation of silvopasture.

This type of AF has been adopted in several places around the world. Silvopasture in Hungary, Scotland, Wales, and Portugal, is claimed to be the most important AF practice (Santiago-Freijanes et al., 2018). In the semi-arid and dry subhumid region of Caatinga in Brazil, livestock production is combined with the use of native trees and shrubs (Pinheiro & Nair, 2018). In Colombia, one example of a silvopasture system includes, but is not limited to, the use of *Leucaena leucocephala* and *Prosopis juliflora* with livestock in the southwestern state of Valle del Cauca (Mahecha et al., 1999). Although cattle is one of the most common animals used in silvopasture, there are systems where sheep, goats, hogs, and bison are used. For example, in the State of Virginia in the United States, a goat and sheep silvopasture system has been adopted in what used to be a 250-acre pine plantation (MacFarland & USDA NACF, 2015).

Shelterbelts, Windbreaks, and Riparian Buffers

Windbreaks, or shelterbelts, consist of planted trees or shrubs that are, mainly, intended to protect wind-sensitive crops. Farmers also establish windbreaks to provide shelter to livestock, enhance crop production, reduce soil erosion, increase bee pollination, and pesticide effectiveness (USDA NACF, 2002). Additional benefits identified in rural communities include protection for structures (e.g. buildings, roads), visual and noise screens, and reduced cooling and heating needs (USDA NACF, 2002). This AF system has also been found to reduce pollen dispersal, which is a big concern for farmers that aim to prevent any cross of genetically engineered material (Auer, Meyes, &

Sagun, 2016). In Colombia, growing blackberries located in places with wind speeds greater than 2 meters per second ($m.s^{-1}$) leads to stressed plants and lower yields. The implementation of windbreaks has been found to reduce air movement to 1.7 $m.s^{-1}$, which has also led to increased water movement through the plants, and cooler leaves in warm weather (Casierra-Posada & Aguilar-Avendaño, 2011).

Riparian buffers are the combination of trees, shrubs, and perennial plants grown adjacent to streams, lakes, or wetlands. Farmers adopt riparian buffers mainly to provide conservation benefits. These systems have been found to enhance the profitability of floodplain plantations (Horton et al., 2018), reduce runoff and pollutants into waterways (Liu et al., 2017), and remove pesticides and maintain groundwater quality (Aguiar et al., 2015). MacFarland et al. (2017) also identified benefits such as the stabilization of eroding banks, protection of cropland and downstream communities from flood damage, creation of recreational spaces, and provision of wildlife habitat and corridors for terrestrial organisms. It is worth noting that large landowners and large monocrop operations might be more willing to implement riparian buffers and windbreaks than other AF practices because they do not require the highly elaborate redesigning of the farm as alley cropping, agrisilviculture, and silvopasture do.

Tillage

Tillage is commonly practiced in agriculture with widely known advantages and disadvantages. Farmers till to overturn soils, prepare seedbeds, and uproot weeds. Tilling provides the seeds with better chances of growing. In some farms, tilling helps to improve the soil structure (e.g. compact soils). Despite its benefits, an extensive use of tillage can also “lead to the deterioration of soil structure, reduced infiltration, accelerated runoff and erosion, water pollution, and degradation of soil and environment” (Lal, 1991). Therefore, farmers aiming to have more sustainable practices decrease the amount of tillage in order to reduce soil disturbance.

Tillage systems include conventional tillage, conservation tillage, and no-tillage. These systems are defined by the percentage of surface residue that is left on the soil surface. Conventional tillage is the most intensive type of tillage where the soil is managed uniformly across the entire farming land using some tools such as, but not limited to, moldboard plows, chisel plows, and disk harrows (SARE, n.d.). For conservation tillage systems, at least 30 percent of plant residues must remain on the field after harvest (USDA, 2017). No-till is the less intensive form of tillage that aims to reduce soil disturbance with the use of no-till seeders.

Although tillage has been widely regarded as an effective practice to increase SOC, there is evidence showing that the impact is actually smaller than formerly thought due to shallow sampling (Luo, Wang & Sun, 2010; Powlson et al., 2014). It has been found that SOC levels increase in the top 0-10 cm layer but that there is a decline in SOC in the 10-40 cm layer (Luo, Wang & Sun, 2010; Angers and Eriksen-Hamel, 2008). This can be explained by the fact that no-tillage discourages the root growth in deeper layers of the soil (Martinez et al., 2008) as well as the downward movement of C from the surface (Duiker and Lal, 2000). Furthermore, the potential of no-till to enhance soil C sequestration has been overstated without taking into consideration a large body of experimental evidence (Powlson et al., 2014). Hence, implementing the aforementioned BMP instead of adopting tillage might lead to enhanced SOC levels, especially those practices where SOC storage is increased by the incorporation of carbon inputs (Poeplau and Don, 2015). Tillage's limited capacity to increase SOC stocks in croplands does not suggest that this practice cannot play an important role in improving food security. On the contrary, making rational use of tillage can lead to a more resilient agricultural system and it should be considered in research looking beyond soil C sequestration rates.

Alternatives practices to increase carbon content in global soils

There are additional practices that have the potential to increase SOC levels but have remained out of the scope of this research due to the lack of extensive scientific literature, the level of scientific development at this point, or their specificity. Some of these practices include the use of plant varieties or species that are capable of increasing carbon inputs due to their greater root mass (Kell, 2012), adopting crop rotations on uncultivated lands (Burney et al., 2010), and irrigating crops with limited water supply (Smith et al., 2008). Additionally, growing perennial crops (crops that do not need to be replanted every year and that can be harvested several times before dying) and improving the grazing management in grasslands (Herrero et al., 2010) can lead to higher contents of SOC. The addition of exogenous inputs like biochar (Hansen et al., 2015) or compost (Paustian et al., 2016) can also increase SOC levels as a result of their slow decomposition which leads to the retention of C for longer periods of time compared to fresh plant residues or un-composted organic matter (Ryals et al., 2015).

Greenhouse gas emissions and agriculture in Colombia

Colombia's most recent reporting of GHG emissions (IDEAM, 2015) concluded that emissions for the year 2012 totaled 178.4 t C, and the main sources are the energy and AFOLU (agriculture, forestry, and other land use) sectors, accounting for 44 and 43 % of the emissions respectively. The agricultural sector is responsible for the emission of 27.9 ton of C per year (Figure 4). The main sources of emissions in the agricultural sector are from grasslands (36.1%), enteric fermentation (27.6%), direct and indirect nitrous

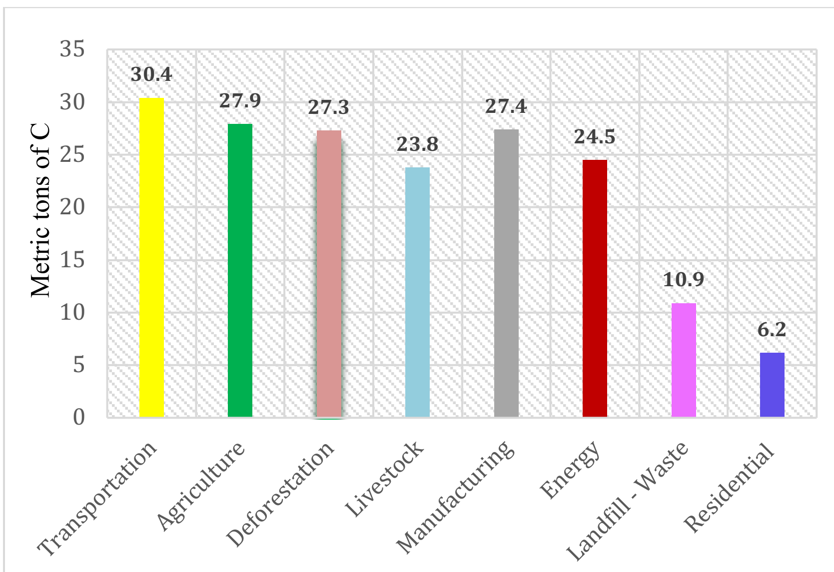


Figure 4. Colombia's greenhouse gas emissions, 2012 (IDEAM, 2012)

oxide (N_2O) emissions from managed croplands (20.3%), and other emissions from croplands (11%). The increased emissions from permanent crops are mostly due to the renewal of crops such as coffee, palm oil, and fruit trees. There was an increase in emissions in permanent crops since the early 2000's, driven mostly by the expansion of palm oil crops.

Climate change policies, laws, and C pricing in Colombia

The Colombian government has demonstrated a commitment in recent years to reducing GHG emission by developing policies and laws to address mitigation and adaptation. The Paris Agreement was ratified by Colombia through Law 1844 of 2017. In 2017, Colombia, Chile, Mexico, and Peru signed the Cali Declaration, reaffirming their commitment to the Paris Agreement of 2015, and their support of pursuing a green growth strategy to address climate change (Alianza del Pacifico, 2017). Decree 298 of 2016 established the National Climate Change System (SISCLIMA), which aims to articulate, formulate, coordinate, monitor and assess policies, norms, plans, projects, and actions related to climate change mitigation and adaption. Additionally, Law 1819 of 2016 established a carbon fuel tax and launched a voluntary exchange carbon market. This law was followed by Decree 926 of 2017 that enables certain regulated businesses to acquire offsets from voluntary standards instead of paying the C tax. In 2017, the National Policy on Climate Change of 2017 was published, which includes, a conceptual framework for climate change plans, disaster management plans, and strategies to reduce emissions. This policy also includes goals mirroring international commitments to keep warming under 2 $^{\circ}$C, targeting 20% reduction in national emissions by 2030. Accordingly, the 2030 emissions should be between 234 and 268 t CO_2 (MINAMBIENTE, 2017a). In 2017, Bill 73 of 2017 was the first public policy proposal that established a framework for climate change mitigation and adaptation in alignment with international commitments (Garcia, 2018). If this bill passes the legislation, important developments would be expected, such as the creation of a national system of climate change adaptation indicators, increasing the amount of protected national lands, strengthening the work for climate change adaptation between the Ministry of

Agriculture and Rural Development and 10 agricultural associations (FEDEARROZ, FENALCE, FEDEGAN, CENIPALMA, ASBAMA, CENICAÑA, CIPAV, Biofuturo, Clayuca, and Biotec), and providing agro-ecological support to farmers in 15 states, among others (MINAGRICULTURA, 2018).

In addition to the laws and decrees proposed and approved in recent years, the Colombian government has also joined other initiatives addressing climate change. In 2015, Colombia joined the Carbon Pricing Leadership Coalition led by the World Bank Group, which is a voluntary partnership that aims to make use of effective carbon pricing policies to achieve meaningful emissions reductions (CPLC, 2018). Additionally, Colombia was one of the countries that joined the 2017 launch of the One Planet Summit. One of this Summit's commitments is to establish a carbon price compatible with the Paris Agreement (One Planet Summit, 2018).

C tax collection began on January 1st 2017. The C price is set at COP$15,000 (about US$5) and it will be adjusted every February to account for the inflation rate from the previous year. Sellers and importers of fossil fuels such as liquified petroleum gas, gasoline, kerosene and jet fuel, diesel, and fuel oil are the industries that are taxed for C emissions. Natural gas is also taxed, but only when it is used for the petrochemical and refinery sectors (MINAMBIENTE, 2017b). Organizations can demonstrate carbon neutrality with the purchase of offsets generated from projects in Colombia, which enable organizations to be exempt from C tax obligations (WBG, 2018). If Bill 73 of 2017 is approved, a national trading system to create allowances will be established (Figure 5a, 5b) and the tax "would serve as a floor price and offset projects could receive allowances that would be sold on the market" (Carbon Trust, EDF & IETA, 2018).

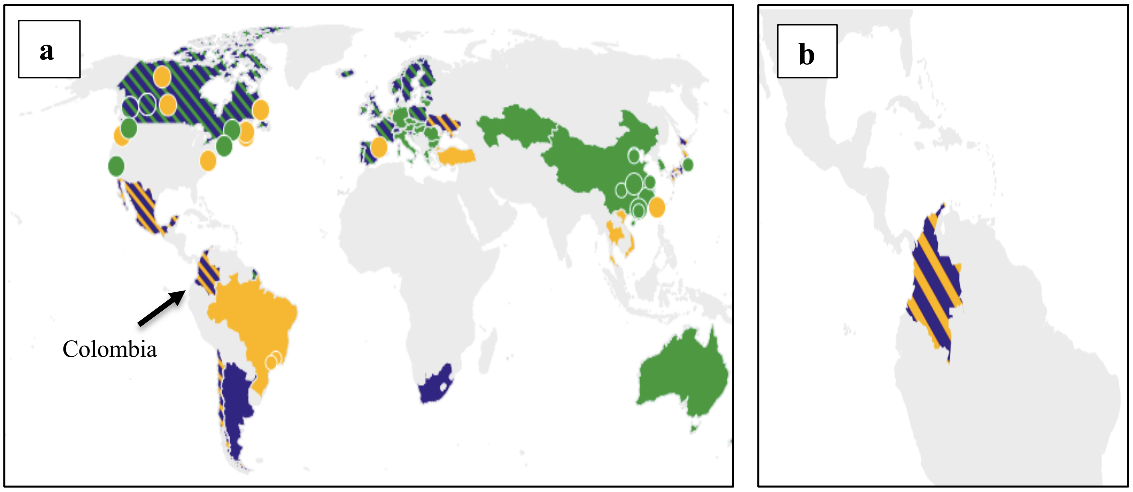


Figure 5. a) National and regional carbon pricing worldwide. b) Colombia has a carbon tax implemented and is considering an emissions trading scheme (ETS) (WBG, 2018). Green: ETS implemented or scheduled for implementation. Yellow: ETS or carbon tax under consideration. Green and Yellow Stripes: ETS implemented or scheduled, tax under consideration. Purple: Carbon tax implemented or scheduled for consideration. Purple and Green Stripes: ETS and carbon tax implemented or scheduled. Yellow and Purple Stripes: Carbon tax implemented or scheduled, ETS under consideration.

Voluntary Carbon Markets (VCM)

VCM is one mechanism with the potential to encourage the adoption of projects to reduce, offset, and avoid C emissions. In this type of market, it is the sellers' and buyers' prerogative to participate in this market. One C offset is equivalent to a metric ton (MT) of carbon dioxide equivalent (CO_2e) that has not been emitted into the atmosphere (Hamrick & Gallant, 2018), and is usually purchased by organizations that have exhausted their internal efforts at reducing greenhouse gas emissions as much as possible. To ensure that the generated offsets are real, additional, measurable, and verifiable, the VCM follows standards such as the Verified Carbon Standard (VCS), the

American Carbon Registry (ACR), the Gold Standard, Plan Vivo, or the Climate Action Reserve (CAR).

VCM projects can potentially generate significant amounts of C reduction or offset. In 2017, the VCM generated its record for highest offsets at 62.7 $MtCO_2e$. In the last 13 years, VCM projects have reduced, sequestered, or avoided over 430 $MtCO_2e$ (Figure 5) (Hamrick & Gallant, 2018). Although the offsets generated during this time remain a very small fraction of the global annual emissions from fossil fuels, two important considerations should be noted. First, the adoption of sustainable practices not only contribute to offset emissions, but they also provide additional co-benefits that might be of significant value for a community, for instance, the creation of new sources of income for farmers that adopt conservation practices or the strengthening of networks between farmers, educational centers, local governments, and markets. Second, it would be highly valuable to explore the additional economic or legal tools that could complement VCM in order to accelerate action to meet ambitious GHG reduction targets and avoid the potential socio-economic disruptions caused by a changing climate.

The impact that the Paris Agreement might have on VCM is considered promising and pursued in this section. In order to reach emission reductions, governments might adopt C pricing schemes, and pursue the complete or partial transition of VCM into a compliance market (domestic, international and centralized, international and decentralized, or the Carbon Offsetting and Reduction Scheme for International Aviation -CORSIA program). Countries might also create new VCM to foster demand for local offsets. This has been the case for countries like France, United Kingdom, Colombia, and Korea. However, reported low C prices and scarce demand remain the main challenges to increasing participation in the VCM (Hamrick & Gallant, 2018). Another important component of the VCM is the highly variable price of C. During a 9 year span, prices fluctuated from under $0.1 to over $70 per ton of C with an average price of $3 to $6 per ton of C (Figure 6)(Hamrick and Gallant, 2018). Several factors influencing this variability including: project costs, buyer's criteria, and the size of purchase - the more offsets you buy the better the price. For Latin America, the average price was reported to be $2.6 per ton of C.

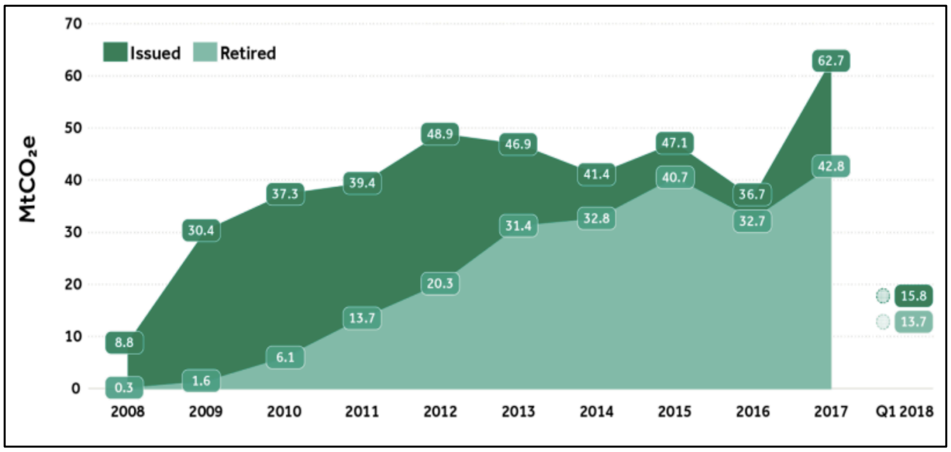


Figure 6. Historical voluntary carbon offset issuances and retirement (Hamrick & Gallant, 2018)

Voluntary Carbon Markets in Colombia

The Fundación Natura, with support from the Food and Agriculture Organization and the Global Environmental Facility (FAO-GEF) through the Inter-American Development Bank (IDB), created the Mechanism for Voluntary Mitigation of GHG (Fundación Natura, 2018). This mechanism was created to achieve two goals. First, the creation of a technological and institutional platform to adopt a market mechanism (Voluntary Emissions Reductions). Second, to facilitate voluntary mitigation activities in Colombia. This platform is still being finalized. The foundation also created a program called Carbono Cero (Zero Carbon) where organizations interested in purchasing GHG offsets submit a C footprint report with emissions reductions targets. The foundation's project portfolio includes low-smoke stoves, reforestation, and avoided deforestation.

One of Fundación Natura's current projects is the 500 hectare establishment of sustainable productive agroforestry systems within an ecological corridor on the Bogotá-Villavicencio highway. This C forestry project for the voluntary market will generate at least 80,000 carbon credits following the VCS standard and CCB Standards over the next 30 years (2017-2047) (Fundación Natura, 2017a; Fundación Natura, 2017b). In addition to the offsets generated, 300 beneficiaries have committed to this initiative for a period of 5 years. Another project is the recovery of degraded areas with agroforestry systems (South Pole Carbon Asset Management Ltd Carbono & Bosques, 2015). This project has two locations with different crediting periods. The Reserva El Silencio has a crediting period of 100 years, while Guacamayas only covers a period of 20 years with the option to extend for another 20 years. This project will generate emission reductions of 745 ton of C per year for 100 years. The fact that there is a foundation that worked closely on the creation of a VCM, and is currently working in the establishment of AF systems, provides a strength to generate marketable GHG offsets.

An examination of the feasibility of the 4 per 100 initiative in Colombia allows for a closer look at how this initiative can inspire decisionmakers to act to increase global SOC levels. Although the development and expansion of modern agriculture has caused the loss of C from global soils, soils and BMP also hold the key to getting C back into soils. Increasing SOC levels is important for mitigating GHG emissions, and to minimizing, or preventing, the potential impacts of climate change. One of the most promising practices is AF, not only because of its potential to sequester carbon in the soil (belowground), but also in the branches and leaves (aboveground). Unlike other BMP, AF proposes a different way of redesigning, and rethinking, a farming operation where other co-benefits (socio-economic and environmental) can be realized. Despite these potential benefits, AF's capability to enhance SOC levels might be influenced by different land use covers (such as forests, conventionally-managed croplands, grasslands, and uncultivated lands) or different climate regions (tropics, temperate, subtropics). Additionally, AF's ability to sequester SOC might also be affected by environmental, physical, or farming conditions. Furthermore, the existence of these practices alone may not be sufficient to convince farmers to change from conventional management strategies, with a higher footprint, to carbon farming. Thus, the creation of market tools like a VCM and the establishment of a C tax might promote an increased adoption of AF systems to generate marketable GHG offsets. This is the case for Colombia, where legislation from 2016 created a C fuel tax and a VCM in alignment with the commitments made as part of the Paris Agreement. These legislative developments makes this South American country a unique case to explore the financial incentive that could be created through the generation of GHG offsets from the adoption of AF. The discussion above leads me to ask the following questions, make the following hypotheses, and establish some specific aims for my research.

Research Question, Hypothesis and Specific Aims

The main research question I will address is whether the 4 per 1000 initiative is feasible in Colombia through the adoption of agroforestry. In order to answer this question, there are three sub-questions I plan to address:

- To what extent is agroforestry in a tropical country like Colombia likely to increase the annual rate of its soil carbon sequestration?
- What types of land use cover should agroforestry systems implement in order to increase soil carbon?
- Given the Colombian context, what mechanism types hold greatest promise for driving higher adoption rates of AF?

My hypothesis relevant to the first sub-question is that significantly higher soil C content will be achieved through the adoption of agroforestry systems in a tropical country like Colombia. I further hypothesize that, controlled for other biotic and abiotic factors, the implementation of AF systems such as agrisilviculture and silvopasture, will lead to higher contents of SOC than alley cropping, shelterbelts, windbreaks, and riparian buffers. I also hypothesize that the conversion of croplands, grasslands, and uncultivated lands to agroforestry systems will lead to a significant higher soil C content. On the other hand, I foresee that the conversion of forests to agroforestry will cause a loss of soil C. My hypothesis for the third sub-question is that a carbon payment scheme involving GHG offsets will be the mechanism that might lead scaling up AF projects in Colombia.

Specific Aims

Using generally available data sources (Web of Science ISI, Proquest Agricultural and Environmental Science Database) testing the above-identified hypotheses requires accomplishing four goals:

- Complete a meta-analysis to identify the soil carbon sequestration rates observed from the adoption of agroforestry practices in different types of land use covers (croplands, grassland, uncultivated land, and forests).
- Identify whether soil C sequestration rates differ significantly among agroecological zones in order to determine the most appropriate soil C sequestration rate for a country like Colombia.
- Evaluate the role that environmental and physical variables such as temperature, precipitation, elevation, latitude, and clay content might play in the sequestration of carbon in soils.
- Establish a SOC baseline, and some measure of its large scale dispersion, for Colombia. This baseline could be mapped for the topsoil (0 to 30 cm.) for either Colombian croplands, grasslands, forests, and/or uncultivated land.

Achieving these goals will provide one or more soil carbon sequestration rates that will be used to create a spreadsheet model to evaluate financial scenarios connecting the potential capacity to store carbon through agroforestry with a potential financial gain from generating marketable greenhouse gas offsets. The following tasks depend on the conclusions drawn from this meta-analysis:

- Identify mechanisms that provide incentives likely to encourage adoption of AF systems in the Colombian context.
- Evaluate the potential financial rewards that could be gained from investing in AF projects aimed to generate GHG offsets over time.

Chapter II.

Methods

Literature search and study selection

In order to find the reported rates of soil C sequestration from the adoption of AF practices, I performed a literature search of peer-reviewed articles in the summer of 2018 from two bibliographic databases: ISI-Web of Science and the ProQuest Agricultural and Environmental Science Database. I made use of the following keywords for the search: (agroforestry OR alley cropping OR agroforestry systems OR silvopasture OR windbreaks OR forest farming) AND (soil organic carbon OR soil carbon sequestration). I then excluded duplicates and records that were not relevant to my research based on their title and/or abstract (Figure 7). I followed the following criteria to assess which articles were eligible to include in my analysis:

- Studies expressed SOC as a mass or stock (Mg C ha^{-1} or Gt C within a defined area) or provided enough information to calculate SOC as a mass or stock. Expressing SOC as a mass or stock is necessary for assessing the potential for climate change mitigation (Powlson et al., 2014).
- Studies provided SOC information for both the non-agroforestry (control) and the AF (treatment) practice to evaluate the SOC response to AF practices. The studies should include a control that was adjacent to the AF system in order to have a similar environmental and soil conditions.

- The literature provided mean annual precipitation (MAP), mean annual temperature (MAT), elevation, age of the AF system, soil clay content, and/or geocoordinates of the evaluated site.

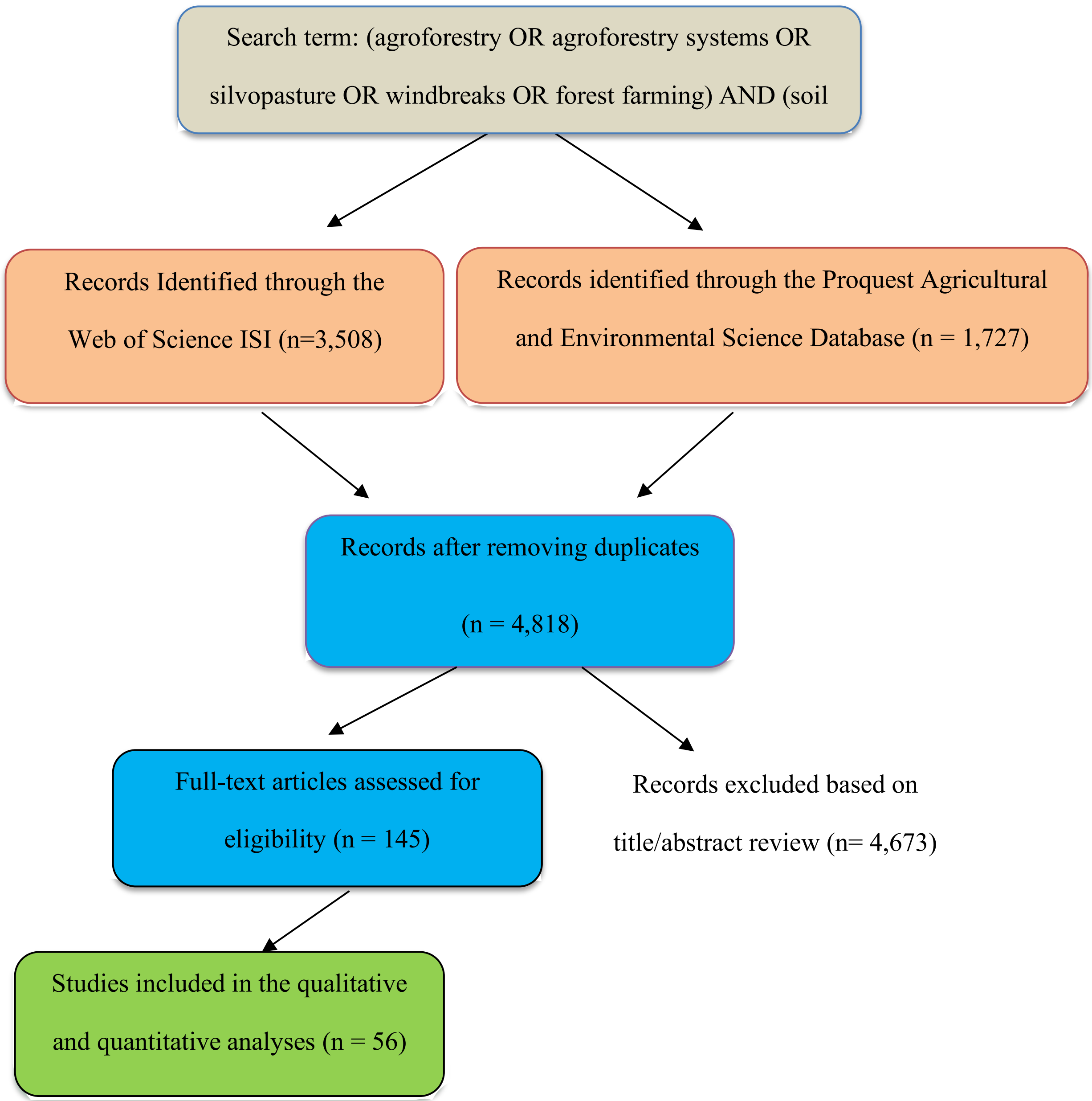


Figure 7. Flowchart illustrating the search strategy and article selection process for studies reporting soil C sequestration in agroforestry systems.

Dataset

A total of 252 observations from 56 studies were included in the dataset for analysis. I also collected the following management, environmental, and soil parameters as potential explanatory variables:

- time since establishment of the AF system (years);
- latitude (degrees);
- mean annual precipitation (MAP) (mm)
- mean annual temperature (MAT) (°C);
- elevation above sea level (m);
- agro-ecological zone;
- soil type;
- sampling depth; and
- clay content (%).

A subset of studies did not report some of these variables. In order to fill in the missing data, I used the reported geocoordinates from the studies in conjunction with several free and open-access online tools. First, I used Google Earth Pro v7.3 (2018) to determine the elevation of the places where the studies were performed. In order to classify the soil type and determine the clay content, I used the recently released global gridded soil information, based on machine learning developed by the International Soil Reference and Information Centre (ISRIC) called SoilGrids250m (Hengl, et al., 2017). I classified soil types according to the World Reference Base for Soil Resources developed by FAO (WRB, 2015). For studies that reported the soil type using a different classification system (e.g. USDA soil taxonomy), I completed my database with either other referenced studies or experts' opinion reporting the equivalent category under WRB, and ultimately if there was any ambiguity, I used the reported geocoordinates in the SoilGrids250m database to classify the soil under the WRB system. For studies in the USA and Australia without MAP or MAT data, I used the NOAA Climate Database (NOAA, 2018) and the Australian Government Bureau of Meterology Database (BOM, 2018). For studies in places without a governmental database available, I used MAP and MAT values from weatherbase.com.

In order to determine the agroecological zone for each study, I used the Global Agro-Ecological Zones (GAEZ v3.0) data portal developed by the International Institute for Applied Systems Analysis (IIASA) and the Food and Agriculture Organization (FAO) (IIASA/FAO, 2012). GAEZ divides the global land into twelve zones: tropics, warm; tropics, cool/cold/very cold; subtropics, warm/moderate cool; subtropics, cool; subtropics, cold; subtropics, very cold; temperate, cool; temperate, cold; temperate, very cold; boreal, cold; boreal, very cold; arctic. About 51 percent of the observations included in this analysis were made in tropical agroecological zones, 30 percent in the subtropics, and around 19 percent remaining in temperate zones.

The sampling depth of reported SOC observations ranged from 2.5 cm to 250 cm. In this analysis, 94 observations accounted for changes in SOC in the topsoil (~30 cm) while 159 observations measured SOC changes in the subsoil (>30 cm). Additionally, 16 types of soils were reported in the studies with vertisols, luvisols, acrisols, and cambisols accounting for about 58 percent of the reported observations of SOC gains in AF systems. The 60 studies reported clay content that ranged from 2 to 75 percent. Additionally, the age of the AF systems included in this analysis varied from 1 to 80 years. Of the 252 total observations, 191 SOC estimations were made in AF systems that were 20 years old or younger, 35 between 20 and 40 years of age, and 26 over 40 years old.

This analysis included reported SOC measurements of agroforestry systems that were established in different types of land use covers such as conventional agriculture, grassland, natural forests, and uncultivated land. The number of observations from cropland and forest converted into AF systems accounted for about 41 and 22 percent of the reported SOC measurements, while observations from grassland and uncultivated land converted into AF accounted for about 23 and 14 percent. More specifically, the largest number of observations were obtained from cropland converted into agrisilviculture (54 observations) followed by forest converted into agrisilviculture (34 observations) and cropland converted into alley cropping systems (28 observations) (Table 9).

Table 9. Number of reported SOC observations in different land uses (top row: forest, conventional agriculture, grassland, uncultivated) converted to agroforestry systems (left column: agrisilviculture, alley cropping, shelterbelt-windbreaks-riparian buffers, and silvopasture).

	Forest	Conventional agriculture	Grassland	Uncultivated	**Total**
Agrisilviculture	34	54	29	31	**148**
Alley cropping	3	28	0	0	**31**
Shelterbelt-Windbreaks-Riparian Buffers	2	12	0	0	**14**
Silvopasture	17	8	30	4	**59**
Total	**56**	**102**	**59**	**35**	**252**

Data analysis and potential explanatory variables

I used a meta-analysis approach in order to determine the effects driven by a change from AF practices to soil carbon in various farming systems (Hedges, Gurevitch, & Curtis, 1999; Stefano and Jacobson, 2018). I followed the methodology provided by Borenstein (2009) to complete a meta-analysis and implement a random-effects model (REM). The REM estimates the mean effect size, known as the summary effect, by assigning more weight to studies with higher precision. In order to run the REM, the within-study and between-study variances are essential. The same methodology was followed to calculate the SOC rate (Mg C ha^{-1} $year^{-1}$). Studies included in this analysis provided variances, or data that could be used to estimate the variance, including standard deviations (SD), standard errors (SE), and samples sizes (n). If only the standard deviation (SD) was reported, I calculated the SE with the following equation:

$$SE = \frac{SD}{\sqrt{n}}$$

In order to calculate the variance for each study, I used the following equation:

$$Variance = [SE^2 \cdot n]$$

When studies reported SOC in percentage or concentration (g kg^{-1} - g of C per kg soil), I used the following equation to calculate the SOC stock (Mg ha^{-1}) (Poeplau and Don, 2015):

$$SOC\ stock = [SOC]\ x\ BD\ x\ D$$

Where [SOC] is the concentration of SOC (%), BD is the bulk density (g cm^{-3}), and D is the soil depth measured (cm).

Since SOC is measured on a physical scale (mass or stock), and is unlikely to be zero, the ratio of the means in the treatment group (AF) and the control group (system before AF) was used as an effect size index. In this research, the effect size index reflects the impact that implementing AF systems has on soil C pools. In experimental ecology, this index is also known as the response ratio (Hedges, Gurevitch, & Curtis, 1999). Since the outcome in this research, which is carbon content in soils, is measured on a true ratio scale, meaning there is a natural scale and there is a natural zero point, the response ratio is truly meaningful. The response ratio would not be adequate for studies measuring outcomes such as test scores or preferences. The response ratio was computed as (Borenstein, 2009; Hedges et al., 1999):

$$RR = \frac{\bar{X}t}{\bar{X}c} = \ln\ (\bar{X}t) - \ln\ (\bar{X}c)$$

Where Xt and Xc are the means of the treatment and control groups respectively. The variance (V) of the log response ratio was calculated as:

$$V_{lnRR} = S_{pooled}^2 \left(\frac{1}{n_c\ (\bar{X}_c^2)} + \frac{1}{n_t\ (\bar{X}_t^2)} \right)$$

Where n_c and n_t are the samples sizes of the treatment and control groups respectively, and S_{pooled} is the pooled standard deviation computed as (Cohen, 1988):

$$S_{pooled} = \sqrt{\frac{(n_c - 1)S_c^2 + (n_t - 1)S_t^2}{n_1 + n_2 - 2}}$$

The standard error was computed as:

$$SE_{lnRR} = \sqrt{V_{lnRR}}$$

Under the random-effects model, the weight assigned to each study is:

$$W_i^* = \frac{1}{V_{Yi}^*}$$

Where V_{Yi}^* is the within-study variance for study *i* plus the between-studies variance, T^2, computed as:

$$V_{Yi}^* = V_{yi} + T^2$$

The parameter tau-squared, T^2, is the variance of the effect size parameters across the population studies computed as:

$$T^2 = \frac{Q - df}{C}$$

Where

$$Q = \sum_{i=1}^{k} W_i Y_i^2 - \frac{\left(\sum_{i=1}^{k} W_i Y_i\right)^2}{\sum_{i=1}^{k} W_i}$$

$$df = k - 1,$$

Where k is the number of studies, and

$$C = \sum W_i - \frac{\sum W_i^2}{\sum W_i}$$

The weight mean, M*, is then computed as

$$M^* = \frac{\sum_{i=1}^{k} W_i^* Y_i}{\sum_{i=1}^{k} W_i^*}$$

that is, the effect size of each treatment multiplied by the weight that the random-effects model assigns to each study, divided by the sum of the weights assigned to the effect size of all the treatments. The variance of the summary effect is computed as the reciprocal of the sum of the weights, as (Borenstein, 2009; Liu et al., 2014):

$$V_{M^*} = \frac{1}{\sum_{i=1}^{k} W_i^*}$$

And the estimated standard error of the summary effect is computed as:

$$SE_{M^*} = \sqrt{V_{M^*}}$$

The 95% lower and upper limits for the summary effect were computed as:

$$LL_{M^*} = M^* - 1.96 \times SE_{M^*}$$

and

$$UL_{M^*} = M^* + 1.96 \times SE_{M^*}$$

A Z-value to test the null-hypothesis (the lack of statistical significance between specified populations) that the mean effect is zero is computed as:

$$Z^* = \frac{M^*}{SE_{M^*}}$$

When the 95% CI value of the response variable did not overlap with 0, I considered the treatment effect on the variable to be significantly different between the control (conventional agriculture) and treatment groups (agroforestry systems) (Gurevitch and Hedges, 2001). A positive effect size indicates a gain in SOC caused by the adoption of an agroforestry system, while an effect size with a negative value indicates a loss of SOC.

To calculate the effect size in percentage change, the following equation was used:

$$Percentage\ Change = (e^{RR} - 1) \times 100\%$$

I additionally conducted both the linear and the mixed-effects meta-regressions to determine the relationship between the RR and different climatic and physical characteristics such as: MAP, MAT, elevation, age of the agroforestry system, and soil content in conventional agriculture and agroforestry systems. The significance level was set at p = 0.05. I used the metafor Package (Viechtbauer, 2010) in the R statistical software to complete all the statistical analyses.

Establishing a SOC baseline for Colombian croplands

In order to estimate the national mean of SOC stock for Colombian cropland, I used different geospatial datasets and analyzed them with ESRI ArcGIS software (version 10.3; www.esri.com). First, I used the recently released global gridded soil information based on machine learning developed by the International Soil Reference and Information Centre (ISRIC) called SoilGrids250m (Hengl, et al., 2017). From this database, I obtained one global raster layer with the values of SOC stock in tonnes per hectare for the depth interval 0.15-0.30 meters. Additionally, the FAO GLC-Share Land Cover database (Latham, 2014) provided me with a global raster layer where every pixel value represented the percentage of cropland present in the specified location. Third, I obtained a feature layer for the administrative areas for Colombia from the Database of Global Administrative Areas (GADM) (GADM, 2005) that allowed me to clip out the global values and focus solely on the Colombian soil. Due to the fact that soils with high carbon levels are likely to lose SOC under any best management practice (Zomer, Bossio, Sommer & Verchot, 2017); I used one of the global raster layer from SoilGrids250m to identify grid cells with SOC content higher than 400 t C ha^{-1} and exclude them from further analysis. The average soil C stock (t c ha^{-1}) for Colombian croplands estimated in this geospatial analysis along with the soil C sequestration rate from AF systems will help me determine if AF can reach the goal set by the 4 per 1000 initiative:

$$SOC_{rate} \geq \frac{4}{1000} \times SOC_{baseline}$$

Potential C payments of AF systems

I completed a Net Present Value (NPV) analysis with two scenarios including the highest and the lowest soil C sequestration rates obtained for AF practices established in conventional agriculture from the meta-analysis. Additionally, I analyzed different C prices, duration of projects, and interest rates. This NPV analysis including different interest rates can be seen as an opportunity cost, meaning that if an organization invests in the purchase of GHG offsets from an AF project at a given price per ton of C today, the organization can estimate if that investment is adding value to the organization. The results from the NPV analysis also provides the investor with information whether the AF project guarantees a return at a particular interest rate. If the NPV analysis returns a positive result, the investor should not reject the AF project as an option to add value to the organization.

I decided to use different C prices per ton of C in the NPV analysis. These prices represent the offsets that are currently sold at low prices at around COP$10,000 (around US$3 to US$4); offsets sold at the set price of C COP$15,000 (around US$5); and the potential C payments if the C price is set higher at COP$20,000 (around US$6.5) and COP$25,000 (around US$8). Following Winans et al. (2015), I considered three different interest rates 2%, 4%, and 6%. I also included three different project duration including 5 years, 10 years, and 20 years. 5-years represents the time that farmers agree to be part of an AF project. 20 years represents the shortest crediting period found in an AF project intended to generate GHG offset in Colombia (South Pole Carbon Asset Management Ltd Carbono & Bosques, 2015).

In order to complete the NPV, the amount of soil C sequestered by the establishment of AF systems has to be converted into C dioxide equivalent (CO_2e) as:

$$COP_t \, CO_2e^{-1} = (\Delta \, SOC) \times \left(\frac{44}{12}\right) \times \, price \; of \; ton \; of \; C$$

where COP is the abbreviation for Colombian Peso, $\Delta \, SOC$ is the amount of soil C sequestered in the AF systems compared to a cropland managed in a conventional way, and $\left(\frac{44}{12}\right)$ is a conversion factor equivalent to 3.67 ton of CO_2 per hectare of land managed under an AF system in a year (Winans et al., 2015; Chiemela et al., 2018).

Due to the fact that soil C sequestration between both systems will change over time, the market value must be evaluated using the net present value (NPV) approach. The NPV is calculated with a discount rate, which is used to determine the present value of soil C sequestration future cash flow for a period of time. The NPV for soil C sequestration in AF systems was calculated as (Winans et al., 2015):

$$NPV^{soil\ C\ sequestration} = \sum_{t=0}^{T} \frac{1}{(1+r)^t} \times (\Delta SOC)$$

where t represents the time period ranging from zero to T, where T is the duration of the project and r is the discount rate. The ΔSOC is the amount of accrued soil C sequestered during the length of the project (T). The NPV does not include the cost of production or revenues generated. In this analysis, I decided to assess the role of different discount rates 2%, 4%, and 6% (Winans et al., 2016). I also decided to assess two different duration of projects at 10 and 2.

Chapter III.

Results

Responses of soil organic carbon in agroforestry systems in different land uses

The caterpillar plots provide a summary of the observed changes in SOC included in this analysis with their within-study 95% confidence intervals. The summary effects, which is the weighted mean of the RR from all the studies, were calculated with a REM, for both AF systems established in different types of land use covers (Figure 8), and for each type of AF system established in conventional agriculture (Figure 9). The summary effects are plotted as a green rhombus with its confidence intervals. The conversion of forests and conventional agriculture into AF systems had significant opposite effects on SOC stocks. AF systems established in forests led to significant SOC loss ($M^* = -0.11$, $SE_{M^*} = 0.04$, $Z^* = -2.36$, $p = 0.0185$), while in conventional agricultural land, AF led to SOC gains ($M^* = 0.21$, $SE_{M^*} = 0.03$, $Z^* = 6.84$, $p < 0.0001$). The results also reject one of my hypotheses because AF implemented in grasslands ($M^* = 0.02$, $SE_{M^*} = 0.05$, $Z^* = 0.44$, $p = 0.6618$) and uncultivated lands ($M^* = -0.05$, $SE_{M^*} = 0.06$, $Z^* = -0.82$, $p = 0.4121$) did not have a significant impact on SOC. Given these results, my analysis continued to focus on conventional agriculture. All the AF systems had a significant effect on SOC in conventional agricultural land. Silvopasture presented the highest effect ($M^* = 0.46$, $SE_{M^*} = 0.11$, $Z^* = 4.25$, $p < 0.0001$) followed by agrisilviculture ($M^* = 0.22$, $SE_{M^*} =$

0.05, Z* = 4.55, p < 0.0001), shelterbelts-windbreaks- riparian buffers (M*= 0.22, SE_M*= 0.05, Z* = 4.65, p), and lastly alley cropping (M* = 0.13, SE_M* = 0.04, Z* = 3.26, p = 0.0011) (Figure 10) (Appendix A).

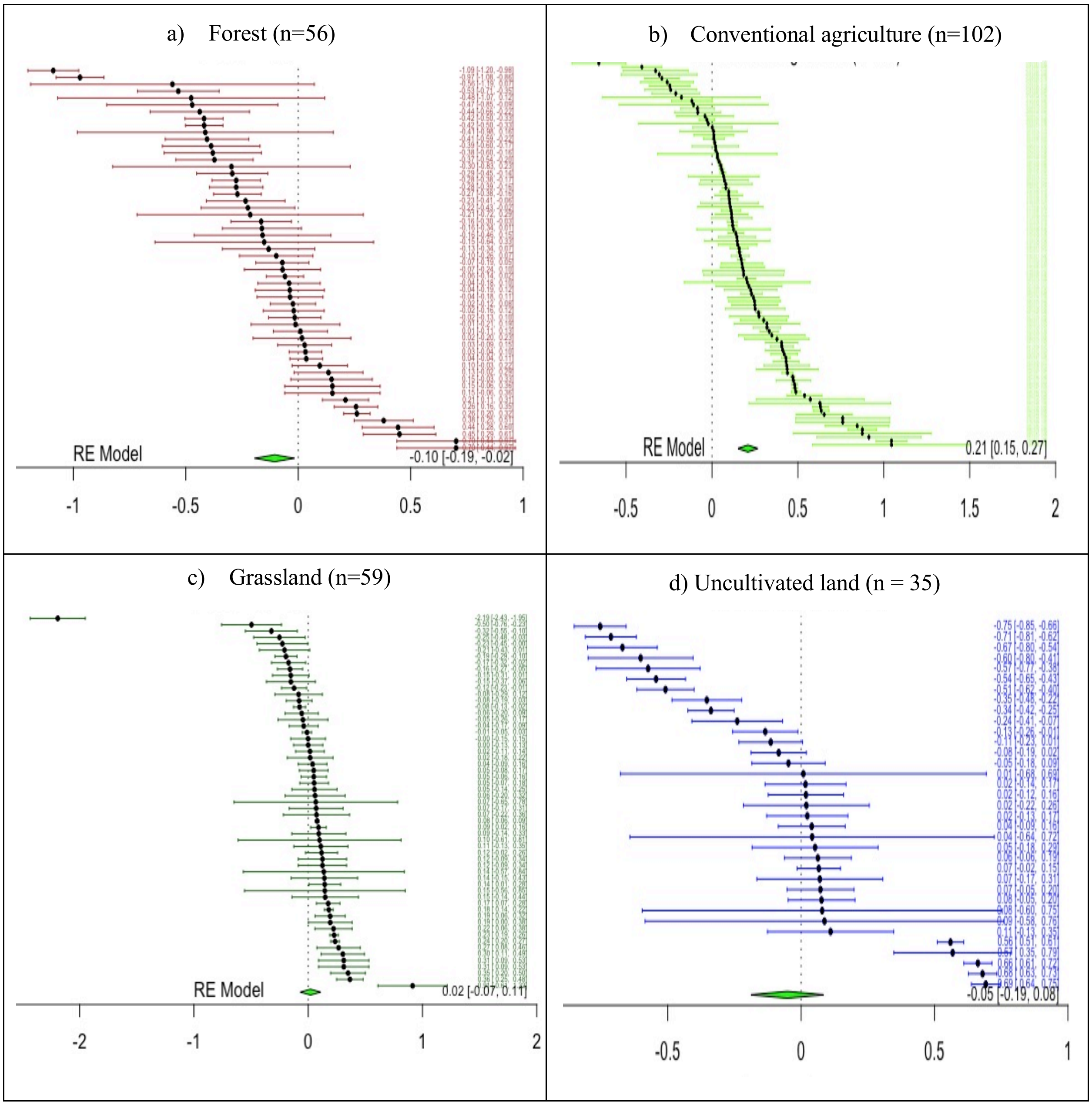


Figure 8. Caterpillar plots - Summary of the meta-analytic literature estimating changes in soil organic carbon after converting (a) forest, (b) conventional agriculture, (c) grassland, and (d) uncultivated land into agroforestry systems. Values on the x-axis are the response ratio (RR = ln SOC AF treatment – ln SOC control) and 95% confidence intervals.

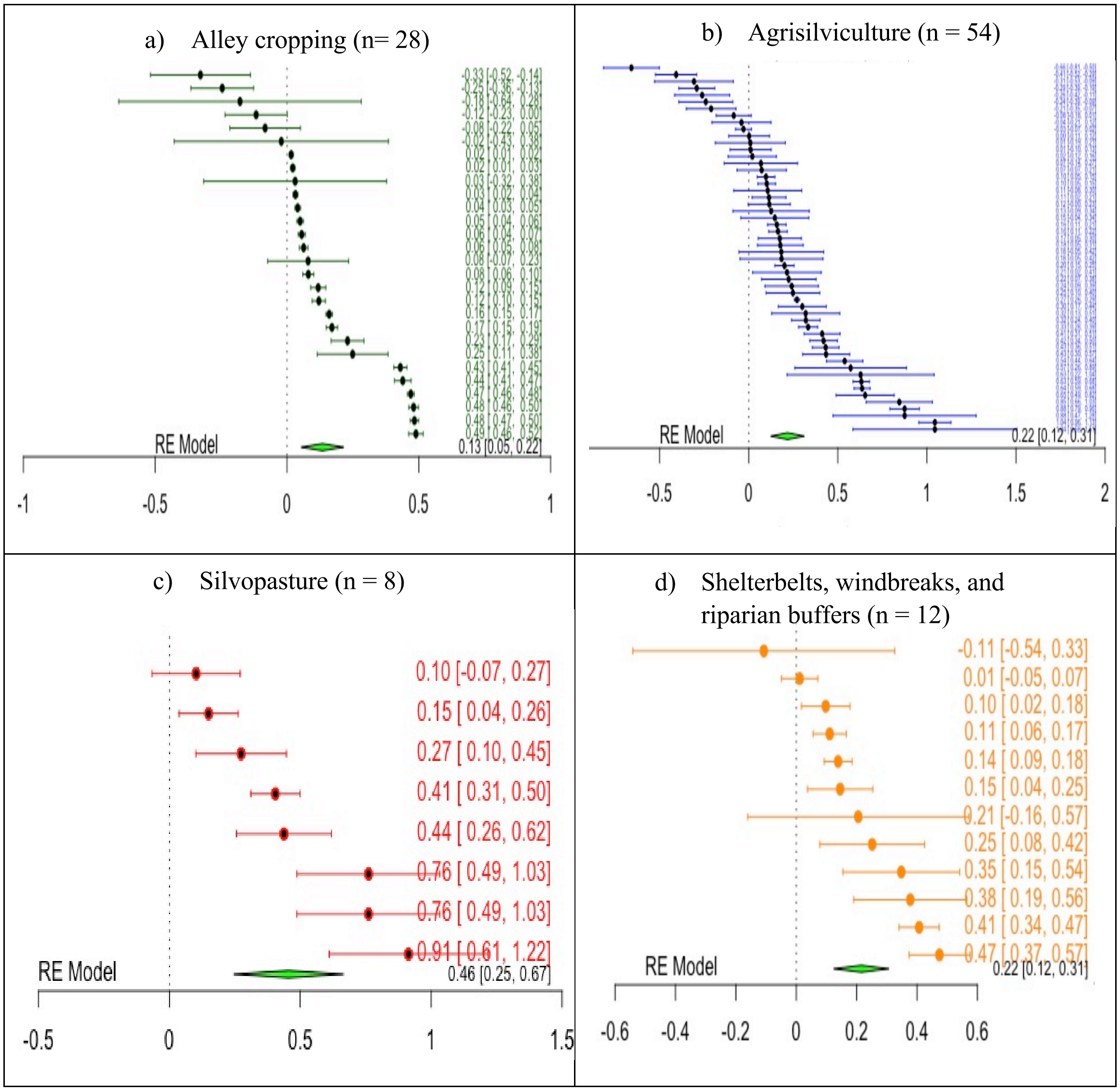


Figure 9. Caterpillar plots - Summary of the meta-analytic literature estimating changes in soil organic carbon after converting conventional agriculture into different agroforestry systems. Values on the x-axis are the response ratio (RR = ln SOC AF treatment – ln SOC control) and 95% confidence intervals.

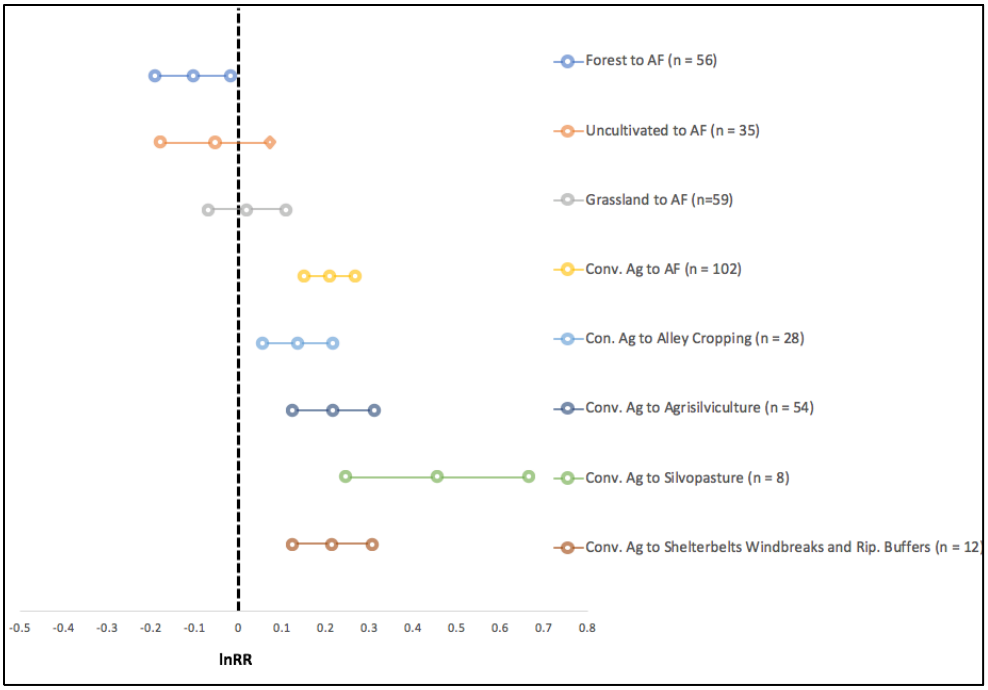


Figure 10. The response ratio (lnRR) for soil organic carbon in different land use covers converted to an agroforestry system. Error bars represent the 95% confidence intervals (CIs); the mean effect size is significantly different from the control when the CIs do not overlap with zero. The sample size is noted in the legend (n).

Responses of soil organic carbon in agroforestry systems in different agroecological zones

AF systems established in very cold temperate regions were found to have no significant effect on soil C stock ($M^* = 0.07$, $SE_M^* = 0.15$, $Z^* = 0.46$, $p = 0.64$). Whereas, the establishment of AF systems in the remaining agroecological zones had a significant effect on soil C. The largest effect on SOC content was found in warm subtropics ($M^* = 0.326$, $SE_M^* = 0.08$, $Z^* = 4.25$, $p < 0.0001$), followed by cold tropics ($M^* = 0.284$, $SE_M^* = 0.02$, $Z^* = 12.03$, $p < 0.0001$), cool temperate regions ($M^* = 0.220$, $SE_M^* = 0.06$, $Z^* = 3.61$, $p = 0.0003$), and warm tropical regions ($M^* = 0.17$, $SE_M^* = 0.05$, $Z^* = 3.14$, $p = 0.0017$) (Figure 11)(Appendix B).

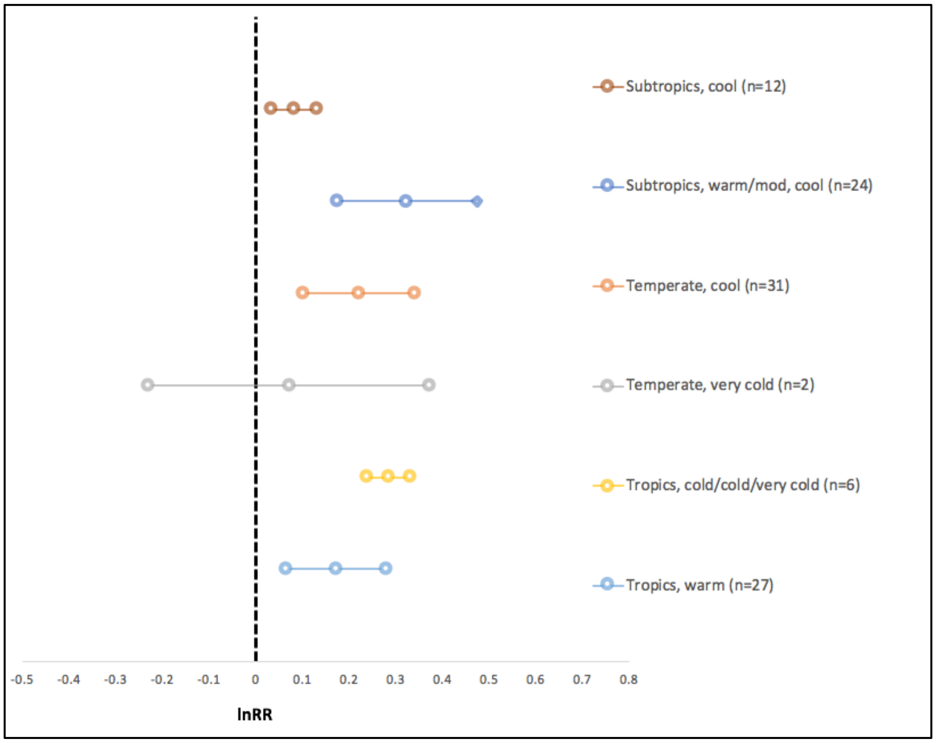


Figure 11. The response ratio (lnRR) for soil organic carbon in different agroecological zones. Error bars represent the 95% confidence intervals (CIs); the mean effect size is significantly different from the control when the CIs do not overlap with zero. The sample size is noted in the legend (n).

Correlations - Linear meta-regressions of environmental, physical, and management variables

The linear meta-regression was completed to identify potential significant correlations between the predictors included in this analysis and the response ratio (Table 10). When observations from all the AF systems were analyzed, precipitation was found to have a significant correlation with the response ratio ($p = 0.0328$, $QM = 4.558$) (Figure 12a). On the other hand, a significant correlation between the remaining variables (age, latitude, precipitation, temperature, elevation, soil type, clay content) and SOC gains was not established. I then separated the data into each AF system (agrisilviculture, alley cropping, silvopasture, and shelterbelts-windbreaks-riparian buffers) to assess potential correlations. The analysis did not find any significant correlation between the predictors and the response ratio in alley cropping systems. On the other hand, temperature was found to be significantly correlated to the response ratio in agrisilviculture ($p = 0.0496$, QM = 3.8538) (Figure 12b), and shelterbelts, windbreaks, and riparian buffers ($p = 0.0453$, QM = 4.006) (Figure 12e). Soil depth ($p < 0.0001$, QM = 23.3202) (Figure 12c) and time ($p = 0.2088$, QM = 1.5799) (Figure 12d) were also found to be significantly correlated to the response ratio in silvopasture systems.

Multiple linear meta-regressions - The role of environmental, physical, and management variables

The multiple linear meta-regression found that predictors like precipitation, temperature, clay, latitude, and soil depth had a significant effect on the content of soil organic carbon in some of the AF systems established in croplands (Table 11). Precipitation was found to have a larger significance in alley cropping systems ($p = 0.0002$, QM = 36.99), followed by the model built for all four types of AF systems together ($p = 0.0285$, QM = 8.56). Temperature was found to have a large significant impact on both alley cropping ($p < 0.001$, QM = 36.99) and agrisilviculture ($p < 0.0001$, QM = 20.93). Another predictor that was found to have a large significant impact was clay in alley cropping systems ($p = 0.0004$, QM = 36.99). Compared to the aforementioned predictors, predictors such as latitude ($p = 0.0029$, QM = 20.93),

Table 10. Linear meta-regression of environmental, physical, and management variables.

	Predictor	*M**	*SE**	*Z*	*p*	*QM*
AF systems	**MAP***	-0.0002	0.0001	-2.1350	**0.0328**	**4.5580**
	MAT	-0.0039	0.0035	-1.0966	0.2728	1.2024
	Elevation	-0.0000	0.0001	-0.1267	0.8992	0.0161
	Latitude	-0.0005	0.0013	-0.3902	0.6964	0.1522
	Clay	-0.0002	0.0025	-0.0731	0.9417	0.0053
	Soil Depth	0.0002	0.0005	0.3516	0.7251	0.1236
	Time	-0.0001	0.0022	-0.0429	0.9658	0.0018
Alley Cropping	MAP	-0.0001	0.0001	-1.0868	0.2771	1.1812
	MAT	0.0096	0.0062	1.5551	0.1199	2.4184
	Elevation	0.0001	0.0001	0.6268	0.5308	0.3929
	Latitude	-0.0013	0.0015	-0.8438	0.3988	0.7120
	Clay	0.0001	0.0001	0.6268	0.9763	0.0009
	Soil depth	0.0003	0.0007	0.5029	0.6150	0.2529
	Time	-0.0025	0.0064	-0.3983	0.6904	0.1587
Agrisilviculture	MAP	-0.0002	0.0001	-1.5233	0.1277	2.3205
	MAT*	-0.0098	0.0050	-1.9631	**0.0496**	**3.8538**
	Elevation	-0.0000	0.0001	-0.5277	0.5977	0.2785
	Latitude	-0.0005	0.0021	-0.2239	0.8228	0.0501
	Clay	0.0006	0.0036	0.1579	0.8745	0.0249
	Soil Depth	-0.0001	0.0007	-0.0930	0.9259	0.0087
	Time	0.0008	0.0047	0.1618	0.8714	0.0262
Silvopasture	MAP	-0.0003	0.0005	-0.7048	0.4810	0.4967
	MAT	-0.0159	0.0126	-1.2569	0.2088	1.5799
	Elevation	0.0001	0.0003	0.4440	0.0007	0.1971
	Latitude	0.0053	0.0042	1.2393	0.2152	1.5359
	Clay	-0.0082	0.0088	-0.9284	0.3532	0.8619
	Soil depth***	0.0067	0.0015	4.3485	**<.0001**	**18.9096**
	Time**	0.0302	0.0110	2.7425	**0.0061**	**7.5211**
Shelterbelts, Windbreaks, and Riparian Buffers	MAP	0.0003	0.0002	1.8757	0.0607	3.5181
	MAT*	0.0134	0.0067	2.0015	**0.0453**	**4.0060**
	Elevation	0.0002	0.0001	1.7103	0.0872	2.9253
	Latitude	-0.0095	0.0050	-1.9146	0.0555	3.6657
	Clay	-0.0104	0.0131	-0.7982	0.4247	0.6372
	Soil depth	0.0087	0.0049	1.7731	0.0762	3.1439
	Time	-0.0022	0.0026	-0.8359	0.4012	0.7047

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

*M** is the summary effect; SE* is the standard error; QM is the test of moderators; MAP is the mean annual precipitation; MAT is the mean annual temperature.

elevation (p = 0.0029, QM = 20.93), and soil depth (p = 0.0369, QM = 20.93) were found to have a lower significance in agrisilviculture.

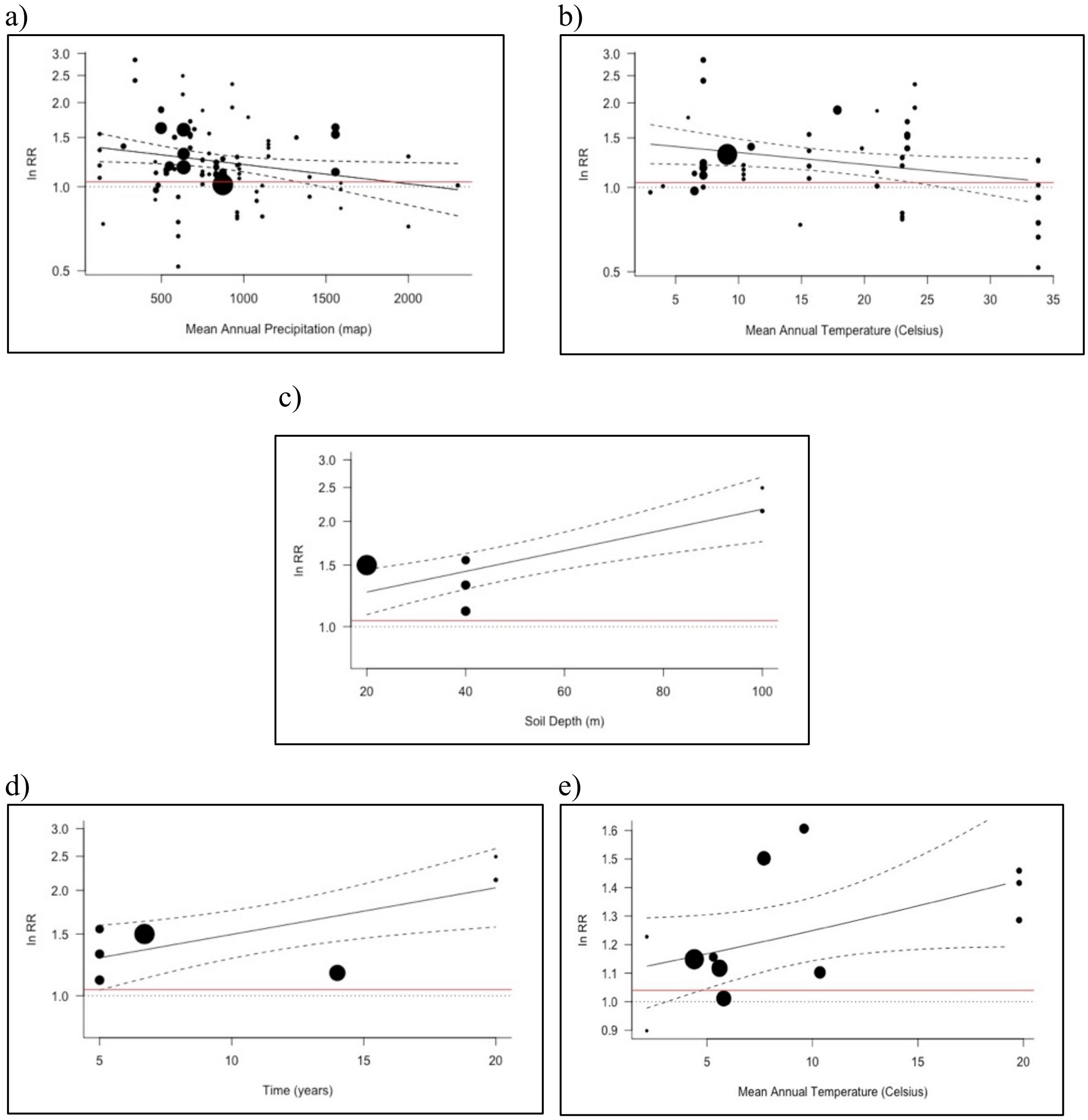


Figure 12. Response ratio (lnRR) plotted against quantitative environmental, physical, and management predictors. (a) MAP in all observations from all types of AF systems, (b) MAT in agrisilviculture, (c) soil depth and (d) time in silvopasture, and (e) MAT in Shelterbelts, Windbreaks, and Riparian Buffers. More precise studies as shown as larger points. A predicted average response ratio as a function of the predictor is also added (with corresponding 95% confidence interval bounds). The dotted horizontal line at ln RR = 1 represents no difference between groups.

Table 11. Multiple meta-regressions of environmental, physical, and management variables.

	Predictors	*M* Summary Effect*	*SE**	*Z*	*p*	*QM*
Agroforestry (All 4 Categories)	**MAP***	-0.0002	0.0001	-2.1907	0.0285	QM (df = 7) = 8.5629
	MAT	-0.0074	0.0049	-1.5328	0.1253	
	Elevation	-0.0000	0.0001	-0.5428	0.5873	
	Latitude	-0.0037	0.0021	-1.7594	0.0785	
	Clay	0.0019	0.0033	0.5774	0.5637	
	Soil Depth	-0.0004	0.0006	-0.6702	0.5027	
	Time	-0.0013	0.0024	-0.5479	0.5837	
Alley Cropping	**MAP*****	-0.0005	0.0001	-3.6908	0.0002	QM (df = 7) = 36.9917
	MAT***	0.0545	0.0108	5.0661	<.001	
	Elevation	0.0000	0.0001	0.3425	0.7319	
	Latitude	0.0010	0.0017	0.5811	0.5612	
	Clay***	-0.0194	0.0055	-3.5232	0.0004	
	Soil Depth	-0.0013	0.0007	-1.9335	0.0532	
	Time	-0.0100	0.0086	-1.1569	0.2473	
Agrisilviculture	MAP	-0.0001	0.0001	-1.0446	0.2962	QM (df = 7) = 20.9333
	MAT***	-0.0234	0.0060	-3.9164	<.0001	
	Elevation*	-0.0003	0.0001	-2.2743	0.0229	
	Latitude**	-0.0188	0.0063	-2.9818	0.0029	
	Clay	0.0074	0.0052	1.4119	0.1580	
	Soil Depth*	-0.0040	0.0019	-2.0863	0.0369	
	Time	0.0016	0.0051	0.3163	0.7517	
Silvopasture	MAP	0.0344	0.0523	0.6583	0.5104	QM (df =4) = 27.8842
	MAT	-0.6276	0.9052	-0.6934	0.4881	
	Elevation	-0.0143	0.0224	-0.6408	0.5216	
	Latitude					
	Clay	-0.2546	0.3504	-0.6394	0.4881	
	Soil Depth					
	Time					
Shelterbelts, Windbreaks, and Riparian Buffers	MAP	-0.0021	0.0015	-1.3795	0.1677	QM (df = 7) = 8.4063
	MAT	0.1019	0.0652	1.5612	0.1185	
	Elevation	0.0000	0.0003	0.0080	0.9936	
	Latitude	-0.0141	0.0186	-0.7564	0.4494	
	Clay	-0.0296	1.3470	1.6334	0.1024	
	Soil Depth	-0.0063	0.0085	-0.7374	0.4609	
	Time	0.0042	0.0044	0.9592	0.3375	

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

*M** is the summary effect; SE* is the standard error; QM is the test of moderators; MAP is the mean annual precipitation; MAT is the mean annual temperature.

SOC content in Colombian croplands

The overlay analysis had two key layers that provided the SOC content (Figure 13) and the cropland cover (Figure 14) in Colombia. After having completed an overlay analysis excluding the highly-carbon dense soils (> 400 Mg C ha^{-1}) and assigning the SOC content values to Colombian cropland (Figure 15), I obtained the total SOC in Colombian croplands using the geospatial analysis in the ESRI ArcGIS software (version10.3; www.esri.com) (Appendix C). The mean SOC in Colombian croplands was the sum of the mean SOC from three different soil layers (0-5, 5-15, and 15-30 cm) (Table 12). The mean SOC was about 103.6 C ha^{-1}, which equals a total stock of approximately 315 Mg C in an agricultural area of 30,359 km^2 (Figure 15).

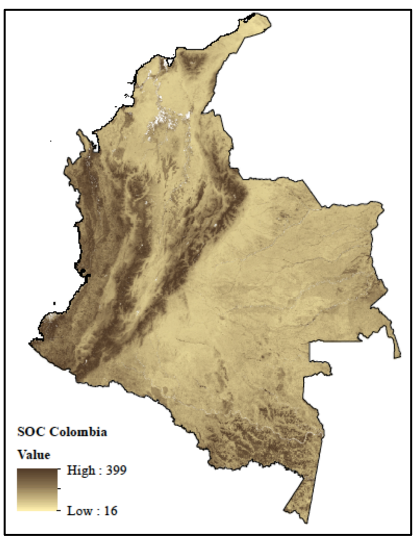


Figure 13. SOC in Colombian Soils. Maps were created based on a geospatial analysis of data obtained from SoilGrids250m(www.soilgrids.org) (Hengl, et al., 2017) and the Database of Global Administrative Areas (GADM) (GADM, 2005), using ESRI ArcGIS software (version10.3; www.esri.com).

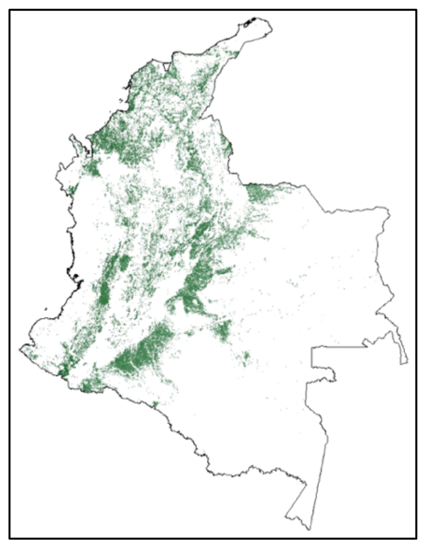


Figure 14. Colombian cropland. Maps were created based on the geospatial analysis of data obtained from FAO GLC-Share Land Cover database (Latham, 2014) and the Database of Global Administrative Areas (GADM) (GADM, 2005), using ESRI ArcGIS software (version10.3; www.esri.com).

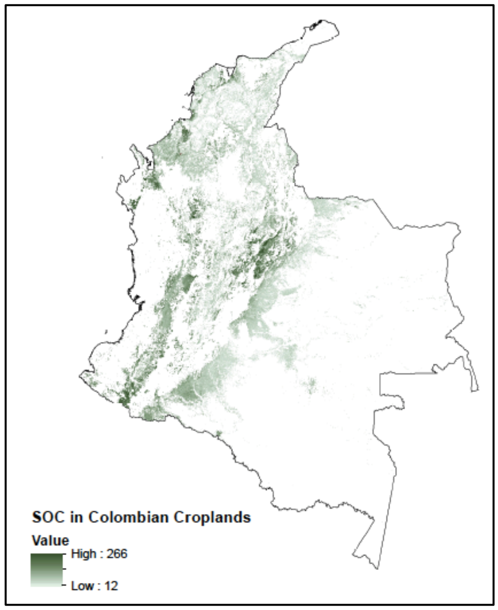


Figure 15. SOC in Colombian Croplands. Maps were created based on the geospatial analysis of data obtained from SoilGrids250m (www.soilgrids.org) (Hengl, et al., 2017), FAO GLC-Share Land Cover database (Latham, 2014) and the Database of Global Administrative Areas (GADM, 2005), using ESRI ArcGIS software (version10.3; www.esri.com).

Table 12. Total soil organic carbon stock (Mg ha-1) in Colombian Croplands for the top 30 cm (103.6 Mg C ha^{-1}). Results were estimated based on the geospatial analysis of data obtained from SoilGrids250m (www.soilgrids.org) (Hengl, et al., 2017), FAO GLC-Share Land Cover database (Latham, 2014) and the Database of Global Administrative Areas (GADM) (GADM, 2005), using ESRI ArcGIS software (version10.3; www.esri.com). (Appendix C)

Soil Depth (cm)	**Mean SOC (Mg C ha^{-1})**	**Min**	**Max**	**Standard Deviation**
0-5	23.5	5	93	± 8.88
5-15	37.3	10	183	± 17.13
15-30	42.8	12	266	± 23.40

Soil organic carbon rates in agroforestry systems

Using a REM, a mean (summary effect) is computed by assigning more weight to more precise studies. These weighted means included one rate for the warm tropics agroecological zone, one for all the agroforestry systems established in conventional agricultural lands, and one for each type of agroforestry (Table 13) (Appendix I). The rates varied from 1.35 and 1.16 Mg C per $ha^{-1}yr^{-1}$ for agroforestry systems located in warm tropics and all agroforestry types respectively to about 0.13 Mg C $ha^{-1}yr^{-1}$ in alley cropping systems. Silvopasture was found to have the highest SOC rate (0.46 Mg C $ha^{-1}yr^{-1}$), agrisilviculture and shelterbelts-windbreaks-riparian buffers had similar rates (about 0.22 Mg C $ha^{-1}yr^{-1}$), and alley cropping the lowest.

Considering the SOC stock baseline in Colombian croplands (103.6 Mg C ha^{-1}), an annual increase of 4 per 1000 (4‰) is equivalent to 0.4144 Mg C $ha^{-1}yr^{-1}$. The SOC rate calculated for alley cropping, agrisilviculture, shelterbelts, windbreaks, and riparian buffers did not have a rate that would meet the goal set by the 4 per 1000 initiative. SOC rates calculated for all the reported changes of conventional agriculture converted to AF (n=102), AF in the warm tropics (n=27), and silvopasture (n=8) are likely to meet the goal set by the 4 per 1000 initiative.

Net Present Value – Investing in greenhouse gas offsets in AF projects

After completing the NPV analysis with two different scenarios for a high and a low soil C sequestration rate, I found that the highest return was COP$19,842,417 (around US$6,400) in a 20 year AF project (Figure 16). This calculation used a 2% interest rate, a high soil C sequestration rate of 1.35 Mg C $ha^{-1}yr^{-1}$, and C price of

Table 13. SOC rates (Mg C ha-1yr-1) computed with Random-Effects Model

	SOC rate Mg C ha^{-1} yr^{-1}	*SE Standard Error*	*Number of Observations*
Tropics, warm	1.3533	1.4870	27
Agroforestry, 4 types included	1.1675	0.4163	102
Alley Cropping	0.1346	0.0413	28
Agrisilviculture	0.2179	0.0479	54
Silvopasture	0.4552	0.1071	8
Shelterbelts, windbreaks, and riparian buffers	0.2153	0.0463	12

COP$25,000 per ton in a 20-year-long AF project. When I computed the same analysis for an AF project with a sequestration rate of 0.13 Mg C $ha^{-1}yr^{-1}$, I obtained a return of COP$1,973,538 (roughly US$640) (Figure 17). This is about a ten times difference in return value per hectare of conventional agriculture converted into an AF system that were observed when comparing the high and low scenario of soil C sequestration disregarding the price, interest rate, and duration of project. As proposed by the NPV equation, the cash inflows (in this case the GHG offsets) are proportionate to the return while the interest rates are not. The higher the interest rate used, the lower the returns. Using a 2% interest rate returns a value that is about 60% higher than the ones calculated with a 6% interest rate. Additionally, the longer the project, the higher the amount of C offsets accrued, thus the return.

The different factors previously explained are the reason why return values vary widely. For AF projects lasting 5 years, the return values ranged from COP$55,013 to COP$159,827 in a scenario with a low soil C sequestration rate, while in a high C sequestration scenario the values ranged from COP$553,121 to COP$1,382,802. For AF projects lasting 10 years with a high soil C sequestration, the NPV computes values ranging from COP$1,784,491 to COP$5,822,737. In a lower C sequestration scenario, the NPV varied from COP$177,486 to COP$579,133. For projects with a 20-year period, the lowest NPV were COP$482,184 and COP$4,847,990 for a low and a high soil C sequestration scenario (Appendix J).

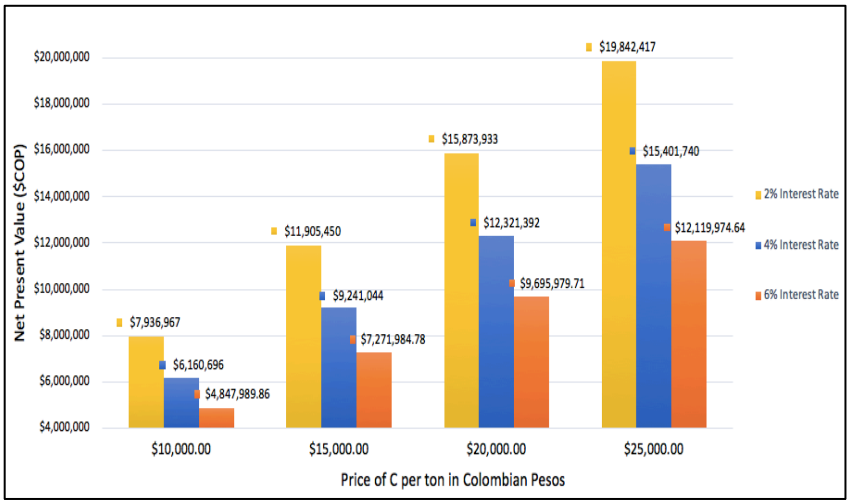


Figure 16. Net present value for a 20 year-long agroforestry project with a high soil C sequestration rate (1.35 Mg C ha-1yr-1) with different carbon prices (COP $10000, $15000, $20000, $25000) and different interest rates (2%, 4%, and 6%).

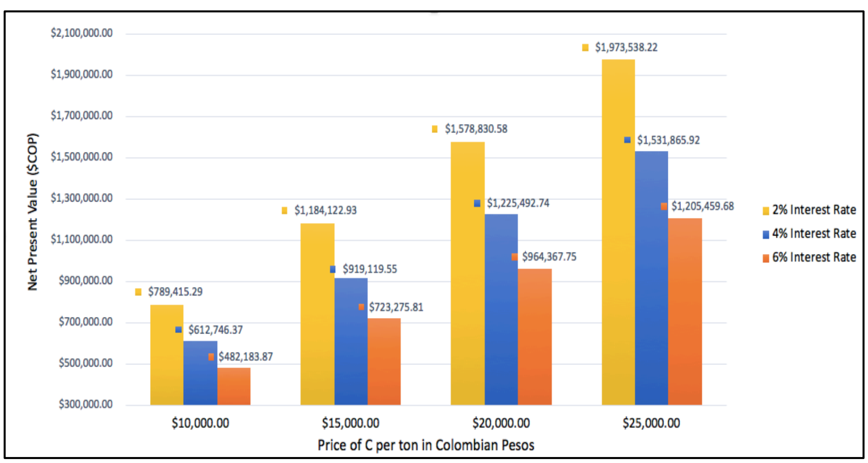


Figure 17. Net present value for a 20 year-long agroforestry project with a low soil C sequestration rate (0.13 Mg C ha-1yr-1) with different carbon prices (COP $10000, $15000, $20000, $25000) and different interest rates (2%, 4%, and 6%).

Chapter IV.

Discussion

Effect of AF on SOC sequestration – Land use

The results of my research indicate that the adoption of AF systems has a significant potential to increase SOC in agricultural land that has been managed in a conventional fashion. I also found that when forests are used to establish AF systems, there is a significant loss of SOC. This effect is aligned with Aguiar et al.'s (2014) finding where AF systems increased SOC but levels were still lower than the SOC stock in natural forests under the same environmental conditions. Additionally, the loss of C when forests are turned into cropland has been reported to reduce levels of SOC by 24% in Canada (Vandenbygaart et al., 2003), 50% in Costa Rica (Veldkamp, 1994), 30 to 50% in Brazil (Machado, 1976; Pöttker, 1977), and 40% in Ghana (Bruun et al., 2015). These findings mirror the ranking that Naair (2009) provided, with forests having the highest content of SOC, followed by agroforestry, tree plantations, and arable crops. The conversion of forests is a pressing issue in Colombia and Latin America as a whole. The main drivers of deforestation in Latin America are the conversion of forests to grasslands (71%) and croplands (14%) (FAO, 2016). It is worth noting that suggesting a conversion of forests to AF systems would not be the right path to mitigate the environmental damage caused by the expansion of agriculture.

My results also showed that AF established in uncultivated land and grasslands did not have a significant effect on SOC. Although authors used the term uncultivated land in their studies, I considered uncultivated land as any land that was not included in the other land use categories (forest, cropland, and grassland). The lack of effect might be explained by the variability on what is included in the uncultivated category. A more refined definition of this category might be needed to improve future research. For grasslands, the effect was positive but not significant. Albrecht et al. (2003) asserts that there has been a long belief that "when trees or shrubs replace…grasslands, there is an automatic increase of C stocks." This is not always the case (Powers, 2004; Chirino et al., 2010). Furthermore, converting grasslands into AF systems might not have a significant effect on SOC gains due to the plant species used in the AF system (Alem and Pavlis, 2014) and/or the presence of perennial grasses or legumes that fix nutrients and increase belowground C inputs in grasslands (Watson, 1963; Vallis, 1972; Boddey et al. 1997; Conant et al. 2001).

Effect of AF on SOC sequestration – Agroecological zones

My analysis found that the establishment of AF systems in conventional agriculture has a positive and significant effect in almost all the different agroecological regions except for those located in very cold temperate regions. Similar effects on SOC have been found in both tropical and temperate regions, where there might be greater C inputs from crop residues in tropical areas but do not translate into greater SOC content because of the higher turnover rate driven by higher temperatures (Oelbermann, Voroney, & Gordon, 2004). Despite the fact that the tropics have a high potential to sink C in their soils due to their severe depletion and degradation, the sequestration rates can be low (Lal, 2004). However, there is a significant potential to offset GHG emissions if the belowground and aboveground C sequestration are accounted for in AF projects. The aboveground C sink potential in the tropics, when compared to other regions, is greater because of its abundant vegetation (Abbas et al., 2017).

The role of environmental, physical, and management predictors

My analysis found that lower SOC levels were significantly correlated with higher precipitation in the reported observations for all the AF systems established in conventional agricultural land. In beech forests, SOC losses of approximately 25% have been observed with annual precipitation greater than 900 mm per year compared to those with precipitation under 600 mm per year (Meier & Leuschner, 2010). Soil moisture and hydrological processes like runoff and ground water infiltration are impacted by precipitation, which also have an impact on SOC levels (Aanderud et al., 2010). SOC content can be affected by water infiltration that might transport substrates from the litter layer to the mineral soil (Lee et al., 2004). On the other hand, precipitation has been found to have an impact on the quantity of C inputs into the soil (Zhou et al., 2008) and the decomposition rate of those inputs (O'Brien et al., 2010).

I also found different correlations between SOC and the mean annual temperature. Higher temperatures were significantly correlated with higher SOC levels in alley cropping, shelterbelts, windbreaks, and riparian buffers. This correlation could be explained by the fact that warmer temperatures drive higher rates of microbial activity, which leads to higher decomposition of organic matter and root turnover (Wotherspoon, 2014). However, higher temperatures were found to be significantly correlated with lower SOC levels in agrisilviculture systems. This result could be explained by a higher soil temperature that leads to higher rates of mineralization and decomposition of organic matter, thus decreasing SOC stocks (Lal, 2004). Harsh environmental conditions with high temperature and low precipitation have been found to limit the amount of C that is supplied to the soils (Batjes, 2001). Also, the young age of the agrisilviculture system or less favorable climatic growing conditions, a combination of both temperature and humidity, both of which could lead to lower aboveground biomass production, which would translate into lower rates of residue incorporation and lower SOC levels below the tree (Mosquera-Losada, Freese, & Rigueiro-Rodriguez, 2011). But, temperature alone may not provide an explanation to changes in SOC content. Temperature affects evapotransporation rate, which also affects soil water content, and decomposition of SOM (Davidson, Trumbore, & Amundson, 2000). Furthermore, features of the AF system can also play a role in changes in SOC stocks. For instance, AF systems with low-tree density have been found to have lower SOC rates compare to high-stem dense systems (Fernández-Nuñez et al., 2010).

Despite extensive research, the effect of temperature sensitivity of soil C decomposition remains a debated topic (Davidson & Janssens, 2006; Reynolds et al., 2017; Tang et al., 2017). It has been argued that “decomposition rates…are not controlled by temperature limitations to microbial activity, and that increased temperature alone will not stimulate the decomposition of forest-derived carbon in mineral soils” (Giardina & Ryan, 2000). Tang et al. (2017) findings have concluded that soil C decomposition in recalcitrant and labile soils are not related to temperature sensitivity. Whereas, Davidson et al. (2000) argue that the key to climatic sensitivity of soil carbon is decomposition rates rather than total ecosystem respiration. A relevant point raised by Davidson et al. (2000) is that in order to explain SOC changes, temperature should not be viewed in isolation.

In agrisilvicultural systems, the amount of SOC content presented a negative correlation with soil depth. This aligns with Batjes and Sombroek's (1997) reported observations of SOC content for different soil types in the tropics and subtropics. The opposite relation was found in silvopasture systems. However, the small amount of observations (n=8) might not capture the real dynamics of the relationship between soil depth and SOC content in this type of AF system.

Potential for soil C sequestration

There are a couple of factors that are necessary to calculate the potential for soil C sequestration through the adoption of AF systems. The first factor is the the soil C sequestration rate that the AF system can achieve in a given unit of cropland. In this research, the range of soil C sequestration rates I estimated for AF practices ranged from 0.135 to 1.35 Mg C ha^{-1}. These calculations are aligned with other reported rates in different AF systems in India (Brahma et al., 2017; Nath et al., 2015; Mangalassery et al., 2014), Kenya (Onim et al., 1990), and the Congo and Nigeria (Paul et al., 2002). However, SOC sequestration rates above 1.5 Mg C ha^{-1}yr^{-1} in tropical countries have also been reported (Dreschel et al., 1991; Impala, 2001; Onim et al., 1990). Given the complexity of soil dynamics, soil C sequestration rates vary with tree species, location, selection of sites where species maximize C sequestration (Brandle et al., 1992; Kort and Turnock, 1999; Hou et al., 2011). In this research, I have decided to use the lowest and the highest soil C sequestration rates to represent a low and a high C sequestration scenarios.

Another important factor to assess the feasibility of the 4 per 1000 initiative is the SOC stock baseline where the AF system will be established. Given a baseline of 103.6 Mg C ha^{-1} for Colombian croplands, any rate under 0.4144 Mg C $ha^{-1}yr^{-1}$ would not lead to an annual increase of soil C of 0.4%. Based on my analysis, silvopasture, and the aggregate data for both AF and AF in tropical countries, are able to provide the soil C sequestration rate needed to achieve the 4 per 1000 goal. Therefore, an increase of 0.4144 Mg C $ha^{-1}yr^{-1}$ in all the Colombian cropland (3,035,900 hectares) represents an increase of 1.26 $x10^{6}$ Mg C yr^{-1}.

Despite the fact that some rates do not meet the 0.4% annual increase, I decided to explore two scenarios with the lowest and the highest soil C sequestration rates (0.135 and 1.35 Mg C $ha^{-1}yr^{-1}$ respectively). Under the low and the high SOC sequestration scenarios, a total of $4.1x10^{6}$ Mg C yr^{-1} and $4.1x10^{5}$ Mg C yr^{-1} can be achieved respectively. Based on the relationship between SOC rates for AF systems and the SOC baseline, future research could explore where AF projects can meet the 4 per 1000 goal. For instance, for a SOC rate equivalent to 0.135 Mg C $ha^{-1}yr^{-1}$ (alley cropping and the lowest SOC rate calculated), the SOC stock of the cropland should be equal to 33.7 Mg C ha^{-1}. For a SOC rate around 0.21 Mg C $ha^{-1}yr^{-1}$ (agrisilviculture and shelterbelts, windbreaks, riparian buffers), the SOC stock should be around 52.5 Mg C ha^{-1}.

Voluntary Carbon Markets in Colombia and NPV

The recent national developments in climate change policies and laws are tied to the commitments made by the Colombian government as part of the Paris Agreement. These latest changes have been shaping a framework to develop and expand a VCM. After a Carbon Tax was passed last year, there was a surge in demand for greenhouse gas offsets. However, since the market is in such an early development stage, there is not enough generation of credits or offsets to meet the demand (M. Hernandez, personal communication June 8, 2018). Additionally, M. Hernandez reported that even though the price of C in Colombia is currently set at COP$15,000 (around US$5), offsets are sold at a price between COP$10,000 and COP%12,000 (around US$3-4). The soil C trade potential for a 20 year-long AF project range from COP$482,184 and COP$4,847,990 (about US$156-1578) per hectare. Considering the fact that the cropland area in Colombia is 30,359 km^2, the potential soil C trade can amount as much as COP$1.5x10^{13}$ (about US$4.8 billion). The C trade potential could even be greater if the aboveground C sequestration is included in a financial analysis.

This market faces several challenges, including the fact that offsets are sold at a price between US$3 and US$5 even though the price is set at US$5. Selling offsets at low prices might allow organizations to be more competitive in the market, but it threatens the profitability of establishing AF projects. Additionally, potential buyers of GHG offsets currently prioritize investing in social responsibility projects over environmental ones. This trend is partly a result of the current national context where the Colombian government and the Revolutionary Armed Forces of Colombia signed a peace accord that ended a 50 year-long armed conflict between. Lal (2004) points out that there is a greater challenge in the tropics to enhancing soil quality due to limitations in institutions, infrastructure, and resource-poor agricultural systems (Lal, 2004). The VCM could offer an alternative path with a two-fold purpose: to incentivize organizations to invest in projects that mitigate their carbon footprint and to engage landholders and farmers in environmentally sound practices that sequester soil C such as agroforestry. Additionally, this is an area where government support could play an important role to strengthen this market through purchasing, ensuring the GHG offsets are sold at a profitable price, extending the C tax to other industrial sectors, the creation of incentives to stimulate the adoption of carbon farming practices, and the creation of programs to educate stakeholders (such as, but not limited to, investors, farmers, landholders, non-profits) and engaging them in the VCM.

Research Limitations

One of the main limitations in this research is the paucity of data. I had to exclude 85 studies because they did not have critical information like the variance, standard error, bulk density, sample size, or age of the AF system. Some studies did not compare the SOC gains in AF systems against a control plot under the same conditions. Inaccurate calculations and high variability of the data might have also introduced errors in the meta-analysis. Like any complex system, soil and AF ecosystems provide inconsistent soil C sequestration rates (Nair, 2011, 2012). There are species that might be more efficient at sinking soil C than others creating higher variability. Furthermore, though the actual area covered by AF systems worldwide can be calculated with the percentage of tree cover on the basis of remote sensing data, the relation between the aboveground biomass C stocks and soil C remain weak (Shi et al., 2018). However, methodologies have been changing over time. The amount and quality of information collected in studies, and the access to new tools and predictive models in the past 10-15 years, is more comprehensive than before. Also, the greater interest for understanding the role of soil in the C cycle and the mitigation of global GHG emissions is rapidly driving many changes in the field.

Another limitation is the use of an estimate average SOC stock per hectare in Colombian croplands. This is not representative of all the cropland in an entire country and perhaps a future question for research is to locate the places with greater potential to sink soil C based on the actual SOC stock in a specific cropland. However, I acknowledge that by using the data obtained from SoilGrids250m (www.soilgrids.org) (Hengl et al., 2017), my aim was to make use of a new open-access tool that could be very helpful for people doing research in places where the information is either very limited or difficult to access.

Questions for further sustainability research

Further research questions to foster the transition of our current activities to more sustainability ones are plentiful. The field of AF and soil C sequestration would gain greatly from further research that links remote sensing technologies, AF national inventories, and the relation to SOC stock. This type of research questions might provide improvements in the quantification of SOC stocks, the creation of more effective monitoring tools, and strengthening the work between different organizations of different nature (such as CATIE, CIRAD, CABI, CIAT, World Agroforestry, IDEAM, MINAGRICULTURA, CVC, DAGMA) to formulate more effective policy and financial instruments for projects aimed to sink C.

Research questions addressing the co-benefits provided by more environmentally sound agricultural practices, such as AF, could be explored. These benefits could also help understand the different goals that communities might be trying to achieve. For instance, the creation of jobs, the protection of clean water, or the empowerment of people affected by environmental injustices. Additionally, co-benefits such as decreased pollution from establishing AF could lead to the formulation of research questions related to nutrient runoff, reduced use of agrichemical inputs, and the role of nitrogen. Further hypotheses can be formulated revolving around the resilience and the health benefits that AF systems can generate. The gap between AF and public health can be bridged with questions about air pollution, food security and nutrition, and/or agricultural productiveness.

Further research questions about how to make a stronger VCM are also relevant. The future of VCM in Colombia, and around the world, is uncertain (Hamrick, Gallant, & Forest Trends, 2018). Research to understand what mechanisms can be created, implemented, or enforced in a given context is essential to make sure this type of market is successfully mitigating GHG offsets. Further research could assess the creation of economic development through the adoption of AF systems or other sustainable agricultural practices. Furthermore, research could explore the role that government can play to scale-up, or complement, VCM. For instance, the "creation of markets through government purchasing…[or]…the direct creation of meaningful, rewarding, and satisfying jobs" (Ashford & Hall, 2018). These types of governmental action could lead to a higher demand for the generation of GHG offsets and creating employment opportunities in rural communities where AF could be implemented.

Conclusions

My research concluded that AF is an effective practice that increases SOC levels in cropland that has previously been managed in a conventional manner. However, AF does not have a significant effect on SOC in grasslands and uncultivated land and the conversion of forests into AF systems generate a SOC loss. The effect of AF on SOC gains was significant in different agroecological zones, except for very cold temperate regions. In order to reach the goal set by the 4 per 1000 initiative in Colombia, the AF system should have a SOC rate of 0.396 Mg C $ha^{-1}yr^{-1}$. Therefore, the rates I estimated for silvopasture, and the aggregates of AF and AF in the tropics met the 4 per 1000 goal. On the other hand, the SOC rates for alley cropping, agrisilviculture, windbreaks, shelterbelts, and riparian buffers did not meet the goal. Despite the low SOC rates calculated for these latter AF systems, it should be noted that this research is focused on soil C, and there is a greater potential to sink C if the aboveground biomass is accounted for.

AF is a promising practice with environmental, social, and economic benefits. The creation of policy and legal frameworks in Colombia to achieve the commitments made in the Paris Agreement have played an important role in the creation of a VCM. AF has the potential to generate value to investors who want to mitigate their GHG emissions. A 20-year AF project with a SOC rate of 1.35 Mg C $ha^{-1}yr^{-1}$ has the potential to generate a value that could be as high as COP$20 million ha^{-1} (around US$6,500 ha^{-1}) if the C price is set at COP$25,000 pesos (around US$8). A more realistic target would be the value returned with the C price set at COP$15,000 at a 2% interest rate resulting in almost COP$12 million ha^{-1} (around US$3,900 ha^{-1}). The salient conclusion from this research is the existence of an incentive to strengthen the Colombian VCM, generate GHG offsets, and create value for investors and for communities through the adoption of AF.

References

Aanderud, Z. T., Richards, J. H., Svejcar, T., et al.. (2010) A shift in seasonal rainfall reduces soil organic carbon storage in a cold desert. *Ecosystems 13:*673–82.

Abbas, F. et al. (2017). Agroforestry: a sustainable environmental practice for carbon sequestration under the climate change scenarios—a review. *Environ Sci Pollut Res (2017) 24:*11177–11191 DOI 10.1007/s11356-017-8687-0

Aguiar, Maria Ivanilda, Silva Fialho, Jamili, Matoso Campanha, Mônica, Senna Oliveira, Teógenes. (2014). Carbon Sequestration And Nutrient Reserves Under Different Land Use Systems. *Revista Árvore [en linea] 2014*, 38 (Enero-Febrero).

Aguiar, TR., Bortolozo, FR., Hansel, FA., Rasera, K., and Ferreira, MT. (2015). Riparian buffer zones as pesticide filters of no-till crops. *Environmental Science and Pollution Research 22(14)* 10618-10626 July 2015. Available at https://doi.org/10.1007/s11356-015-4281-5

Ajayi OC, Place F, Akinnifesi FK, Sileshi GW (2011) Agricultural success from Africa: the case of fertilizer tree systems in southern Africa (Malawi, Tanzania, Mozambique, Zambia and Zimbabwe). *Int J Agric Sustain 9*:129–136. doi:10.3763/ijas.2010.0554

Akpa, S. I. C., Odeh, I. O. A., Bishop, T. F. A., Hartemink, A. E., & Amapu, I. Y. (2016). Total soil organic carbon and carbon sequestration potential in Nigeria. *Geoderma, 271*, 202-215.

Albrecht, & Kandji. (2003). Carbon sequestration in tropical agroforestry systems. Agriculture, Ecosystems and Environment, 99(1), 15-27.

Alem, S. & J. Pavlis. (2014). Conversion of grazing land into Grevillea robusta plantation and exclosure: impacts on soil nutrients and soil organic carbon. *Environ Monit Assess (2014)* 186:4331–4341 DOI 10.1007/s10661-014-3702-0

Al-Kaisi, M., & Yin, X. (2005). Tillage and crop residue effects on soil carbon and carbon dioxide emission in corn- soybean rotations. *Journal of Environmental Quality, 34*(2), 437.

Alianza del Pacifico (2017). Declaracion final de la XII Cumbre de la Alianza del Pacifico. Available at http://www.sice.oas.org/TPD/Pacific_Alliance/Pacific_Alliance_e.asp

Allison, F. E. (1973). *Soil Organic Matter and its Role in Crop Production* Elsevier.

Angers D, Chantigny M, Macdonald J, Rochette P, C^ot_e D (2010) Differential retention of carbon, nitrogen and phosphorus in grassland soil profiles with long-term manure application. *Nutrient Cycling in Agroecosystems, 86*, 225–229.

Armstrong, R. D., Millar, G., Halpin, N. V., Reid, D. J., & Standley, J. (2003). Using zero tillage, fertilisers and legume rotations to maintain productivity and soil fertility in opportunity cropping systems on a shallow vertosol. *Australian Journal of Experimental Agriculture, 43*(2), 141.

Ashford, N.A. & Hall, R. (2018). Achieving global climate and environmental goals by governmental regulatory targeting. *Ecological Economics 152 (2018)* 246-259. https://doi.org/10.1016/j.ecolecon.2018.06.002

Auer, C., Meyer, T., Sagun, V. (2016). Reducing Pollen Dispersal using Forest Windbreaks. *Plant Science Articles 28.* Available https://doi.org/10.1101/204263

Aulakh M S, Khera T S, Doran J W, Bronson K F. (2001). Managing crop residue with green manure, urea, and tillage in a rice-wheat rotation. *Soil Science Society of America Journal, 65*, 820–827.

Chaudhry, M.A., & Silim, S. (1980). Agri-silviculture in Uganda – A case study. Food and Agricultural Organization of the United Nations. Rome, Italy. Available at http://www.fao.org/docrep/n8595e/n8595e05.htm (accessed February 6, 2019)

Ballesteros, W., Marco O., Ordóñez, HR. (2008). Sistemas agroforestales tradicionales en el Consejo Comunitarios del Bajo Mira y Frontera en Tumaco, Nariño, Colombia. *Agroforesteria en las Americas 46* 2008.

Batjes, N. H. (1996). Total carbon and nitrogen in the soils of the world. *European Journal of Soil Science, 47*(2), 151-163.

Batjes NH (2001) Options for increasing carbon sequestration in west African soils: an exploratory study with special focus on senegal. Land Degradation & Development 12:131–142. Available at https://doi.org/10.1002/ldr.444

Batjes, N., & Sombroek, W. (1997). Possibilities for carbon sequestration in tropical and subtropical soils. *Global Change Biology, 3(2),* 161-173.

Benito, E., & Diaz-Fierros, F. (1992). Effects of cropping on the structural stability of soils rich in organic matter. *Soil and Tillage Research; Effects of Cropping on the Structural Stability of Soils Rich in Organic Matter,* (1), 153-161.

Bhardwaj, D., Ansari, M., Sahoo, R., Tuteja, N., 2014. Biofertilizers function as key player in sustainable agriculture by improving soil fertility, plant tolerance and crop productivity. Microb. Cell Fact. 13, 66.

Biardeau, L, Crebbin-Coates R., Keerati, R., Litke, S., Rodriguez, H. (2016). Soil Health and Carbon Sequestration in US Croplands: A Policy Analysis. Natural Resources Conservation Service (NRCS) of the United States Department of Agriculture (USDA) and the Berkeley Food Institute (BFI).

Boddey RM, De Moraes Sa´ JC, Alves BJR, Urquiaga S (1997) The contribution of biological nitrogen fixation for sustainable agricultural systems in the tropics. Soil Biol Biochem 29:787–799. https://doi.org/10.1016/S0038-0717(96)00221-0

BOM (2018). Bureau of Meteorology Australian Government. Maps of Average Conditions. Available at http://www.bom.gov.au/climate/averages/maps.shtml

Borenstein, M., Hedges, L. V., Higgins, J. P. T., Rothstein, H. R. (2011). Introduction to Meta-Analysis. Wiley.

Brevik, E. C. (2010). Soil health and productivity. *Soils, Plant Growth and Crop Production-Volume I*, 106.

Brahma, B., Pathak, K., Lal, R., Kurmi, B., Das, M., Nath, P.C., Nath, A.J., Das, A.K., 2017. Ecosystem carbon sequestration through restoration of degraded lands in north East India. *Land Degrad.* Dev. https://doi.org/10.1002/ldr.2816.

Brandle, J. R., Wardle, T. D., Bratton, G. F. (1992) Opportunities to increase tree planting in shelterbelts and the potential impacts on carbon storage and conservation. In: Sampson RN, Hair D (eds) Forest and Global Change, vol. 1. Opportunities for increasing forest cover. Society of American Foresters, Washington, DC, pp 157–176

Bruun, T., Elberling, B., Neergaard, A., & Magid, J. (2015). Organic Carbon Dynamics in Different Soil Types After Conversion of Forest to Agriculture. *Land Degradation & Development, 26(3)*, 272-283.

Burney, J. A., Davis, S. J., & Lobell, D. B. (2010). Greenhouse gas mitigation by agricultural intensification. *Proceedings of the National Academy of Sciences, 107*(26), 12052-12057. Retrieved from http://library.wur.nl/WebQuery/groenekennis/1962533

Campbell, C. A., Zentner, R. P., Selles, F., Biederbeck, V. O., McConkey, B. G., Blomert, B., & Jefferson, P. G. (2000). Quantifying short-term effects of crop rotations on soil organic carbon in southwestern Saskatchewan. *Canadian Journal of Soil Science, 80*(1), 193-202.

Carbon Pricing Leadership Coalition CPLC (2018). CPLC Partners.

Carbon Trust, EDF & IETA. (2018). Colombia: An Emissions Trading Case Study. The World's Carbon Market. January 2018. Available at https://www.ieta.org/resources/Resources/Case_Studies_Worlds_Carbon_Markets/2018/Colombia-Case-Study-2018.pdf

Cardinael, R., et al. (2015). Impact of alley cropping agroforestry on stocks, forms and spatial distribution of soil organic carbon – A case study in a Mediterranean context. *Geoderma 259-260(2015)* 288-299 Available at http://dx.doi.org/10.1016/j.geoderma.2015.06.015

Casierra-Posada, F. & Aguilar-Avendaño, O.E. (2011). Respuestas fisiologicas y morfológicas de plantas de mora (*Rubus sp.*) sometidas a estres por viento inducido.

Revista Colombiana de Ciencias Horticolas 2(1), 43-53. https://doi.org/10.17584/rcch.2008v2i1.1172

Chambers, A., Lal, R., & Paustian, K. (2016). Soil carbon sequestration potential of US croplands and grasslands: Implementing the 4 per Thousand Initiative. *Journal of Soil and Water Conservation, 71*(3), 74A.

Chauhan SK, Sharma R, Singh B, Sharma SC (2015) Biomass production, carbon sequestration and economics of onfarm poplar plantations in Punjab, India. J Appl Nat Sci 7(1):452–458

Chen, C., Liu, W., Jiang, X., Wu, J. (2017). Effects of rubber-based agroforestry systems on soil aggregation and associated soil organic carbon: implication for land use. *Geoderma 299* (2017) 13-24. Available at http://dx.doi.org/10.1016/j.geoderma.2017.03.021

Cherr, C.M., Scholberg, J.M.S., McSorley, R. (2006). Green manure approaches to crop production: a synthesis. *Agronomy Journal. 98*:302-319. doi:10.2134/agronj2005.0035

Chiemela, S., Nwawulu, Noulèkoun, Florent, Chiemela, Chinedum Jachinma, Zenebe, Amanuel, Abadi, Nigussie, & Birhane, Emiru. (2018). Conversion of degraded agricultural landscapes to a smallholder agroforestry system and carbon sequestration in drylands. *International Journal of Climate Change Strategies and Management, 10(3)*, 472-487.

Chirino, I., Condron, L., McLenaghen, R., & Davis, M. (2010). Effects of plantation forest species on soil properties. In R. J. Gilkes& N. Prakongkep (Eds.), Soil solutions for a changing world (pp. 49–51). Brisbane: Proceedings of the World Congress of Soil Science.

Churchman, GJ. (2018). Game Changer in Soil Science. Functional role of clay minerals in soil. *Journal of Plant Nutrition and Soil Science 181(1)* 99-103 February 2018. Available at https://doi.org/10.1002/jpln.201700605

Cohen, J. (1988). Statistical power analysis for the behavioral sciences (2nd ed.). Hillsdale, NJ: Erlbaum.

Conant, R. T., Paustian, K., & Elliott, E. T. (2001). Grassland Management and Conversion into Grassland: Effects on Soil Carbon. *Ecological Applications, 11*(2), 343-355.

Davidson, E. & Ivan A. Janssens. (2006). Temperature sensitivity of soil carbon decomposition and feedbacks to climate change. *Nature, 440(7081),* 165-173.

Davidson, EA., Trumbore, SE., Amundson, R. (2000). Soil warming and organic carbon content. *Nature, 408(6814)* 789-790 12 December 2000

Decreto 298 de 2016. Ministerio de Ambiente y Desarrollo Sostenible. Bogotá, D.C. February 24, 2016. Available at http://www.funcionpublica.gov.co/eva/gestornormativo/norma_pdf.php?i=68173

Decreto 926 de 2017. Ministerio de Hacienda y Crédito Público. Junio 1 de 2017. Available at http://es.presidencia.gov.co/normativa/normativa/DECRETO%20926%20DEL%2001%20DE%20JUNIO%20DE%202017.pdf de Gruijter, J. J., Mcbratney, A. B., Minasny, B., Wheeler, I., Malone, B. P., & Stockmann, U. (2016). Farm- scale soil carbon auditing. *Geoderma, 265*, 120-130.

De Stefano, A. & Jacobson, M.G. Agroforest Syst (2018) 92: 285. https://doi.org/10.1007/s10457-017-0147-9

Díaz-Zorita, M., & Grosso, G. A. (2000). Effect of soil texture, organic carbon and water retention on the compactability of soils from the Argentinean pampas. *Soil & Tillage Research, 54*(1), 121-126.

Dixon RK (1995) Agroforestry systems: sources or sinks of greenhouse gases? *Agrofor Syst 31*:99–116. doi:10.1007/BF00711719

Dogra AS, Nautiyal S, Nautiyal DP (2014) Contribution of Populus deltoides to farm economy of Punjab. Indian For 140(8):758–762

Drechsel, P., Glaser, B. & Zech, W. Agroforest Syst (1991) 16: 193. https://doi.org/10.1007/BF00119316

Duiker, S. W., Lal, R. (1999) Crop residue and tillage effects on carbon sequestration in a Luvisol in central Ohio. Soil and Tillage Research, 52, 73–81.

Eagle A. J., and L. P. Olander (2012). Chapter 3: Greenhouse Gas Mitigation with Agricultural Land Management Activities in the United States — A Side-by-Side Comparison of Biophysical Potentia. In: Advances in Agronomy. Academic Press, New York, NY, pp. 79 – 179. ISBN: 0065 - 2113.

Ehrenbergerová, L. et al. (2016). Carbon stock in agroforestry coffee plantations with different shade trees in Villa Rica, Peru. *Agroforestry Systems (2016)* 90:433-445. DOI:10.1007/s10457-015-9865-z

FAO. (2015). Agroforestry – Definition. Available at http://www.fao.org/forestry/agroforestry/80338/en/

FAO. 2016. State of the World's Forests 2016. Forests and agriculture: land-use challenges and opportunities. Rome.

Farooq, M., Flower, K. C., Jabran, K., Wahid, A., & Siddique, K. H. M. (2011). Crop yield and weed management in rainfed conservation agriculture. *Soil & Tillage Research, 117*, 172-183.

Farooq, M., & Siddique, K. H. M. (2015). *Conservation Agriculture*. Cham.

Faulkner, Edward H (Edward Hubert). (1943). *Plowman's folly.* Norman: University of Oklahoma.

Fernández-Núñez E, Rigueiro-Rodríguez A, & Mosquera-Losada MR. (2010). C allocation dynamics one decade after afforestation with Pinus radiata D. Don and Betula alba L. under two stand densities in NW Spain. Ecol Eng 36:876–890

Franzluebbers, A. J., Stuedemann, J. A., Wilkinson, S. R. (2001) Bermudagrass management in the Southern Piedmont USA: I. Soil and surface residue carbon and sulfur. *Soil Science Society of America Journal, 65*, 834–841.

Friedrich, T., Derpsch, R., & Kassam, A. (2012). Overview of the Global Spread of Conservation Agriculture. *Field Actions Science Reports. the Journal of Field Actions,* (Special Issue 6) Retrieved from http://factsreports.revues.org.ezp-prod1.hul.harvard.edu/1941

Fundación Natura (2017a). Portafolio de Proyecto de Carbono Forestal MVC Colombia.

Fundación Natura (2017b). Corredor Ecologico Vial Bogotá-Villavicencio. Video https://www.youtube.com/watch?v=XYRC08eRN5o

Fundacion Natura (2018). Portafolio de Proyecto de Carbono Forestal. MVC Colombia.

GADM. GADM Database of Global Administrative Areas. (2005). Data downloaded from: http://gadm.org

Garcia, Guillermo (2018). Colombia, con ley para el cambio climatico. Ola Politica. Julio 12, 2018. Available at http://olapolitica.com/opinion/colombia-con-ley-para-el-cambio-climatico/

Ghosh, S., Wilson, B., Ghoshal, S., Senapati, N., Mandal, B., 2012. Organic amendments influence soil quality and carbon sequestration in the Indo-Gangetic plains of India. *Agric. Ecosyst. Environ*. 156, 134-141.

Giardina, C. P. & Ryan, M. G. (2000). Evidence that decomposition rates of organic carbon in mineral soil do not vary with temperature. *Nature, 404(6780),* 858-861.

Google Earth Pro version 7.3 (2018). Retrieved from https://www.google.com/earth/desktop/

Gold, M. & University Missouri Center for Agroforestry [UMCA]. (2011). Agroforestry for ecosystem services. 2011 Annual Report: Research, Education, and Outreach.

Gong, W., Yan, W., Wang, J., Hu, T., Gong, Y., 2009. Long-term manure and fertilizer effects on soil organic matter fractions and microbes under a wheatemaize cropping system in northern China. *Geoderma 149*, 318-324.

Grace, P. R., Oades, J. M., Keith, H., & Hancock, T. W. (1995). Trends in wheat yields and soil organic carbon in the Permanent Rotation Trial at the Waite Agricultural Research Institute, South Australia. *Australian Journal of Experimental Agriculture, 35*(7), 857-864.

Haider, K. (1999). Von der totenorgnischensubtanzzum humus. *Pflanzener-Nähr, 162*, 363-371.

Haile SG, Nair PKR, Nair VD (2008) Carbon storage of different soil-size fractions in Florida silvopastoral systems. *J Environ Qual 37*:1789. https://doi.org/10.2134/jeq2007.0509

Hamrick, K., M. Gallant, and Forest Trends (2018). Unlocking potential – State of the Voluntary Carbon Markets 2017 Overview. Available at https://www.forest-trends.org/publications/voluntary-carbon-markets/

Han, P., Zhang, W., Wang, G., Sun, W., & Huang, Y. (2016). Changes in soil organic carbon in croplands subjected to fertilizer management: A global meta-analysis. Scientific Reports, 6, 27199.

Hansen, V., Müller-Stöver, D., Ahrenfeldt, J., Holm, J. K., Henriksen, U. B., & Hauggaard-Nielsen, H. (2015). Gasification biochar as a valuable by-product for carbon sequestration and soil amendment. *Biomass and Bioenergy, 72*, 300-308.

Haug, T.H. (1993). The practical handbook of compost engineering. Boca Raton, Flor: Lewis.

Hedges, L., Gurevitch, J., & Curtis, P. (1999). THE META-ANALYSIS OF RESPONSE RATIOS IN EXPERIMENTAL ECOLOGY. Ecology, 80(4), 1150-1156.

Hengl, T., Mendes de Jesus, J., Heuvelink, G. B.M., Ruiperez Gonzalez, M., Kilibarda, M. et al. (2017) SoilGrids250m: global gridded soil information based on Machine Learning. PLoS ONE 12(2): e0169748. doi:10.1371/journal.pone.0169748

Hassink, J. (1997). The capacity of soils to preserve organic C and N by their association with clay and silt particles. *Plant and Soil, 191*(1), 77-87.

Heisler, J. L., Weltzin, J. F. (2006) Variability matters: towards a perspective on the influence of precipitation on terrestrial ecosystems. *New Phytol 172:*189–92.

Hernandez, M. (2018, June 8th). Personal Interview.

Herrero, M., Thornton, P. K., Notenbaert, A. M., Wood, S., Msangi, S., Freeman, H. A., Rosegrant, M. (2010). Smart investments in sustainable food production: revisiting mixed crop-livestock systems. *Science (New York, N.Y.), 327*(5967), 822-825.

Holderieath, J., C. Valdivia, C. Barbieri and L. Godsey. 2011. Exploring landowners' connections to carbon markets in rural Missouri—Interest, feasibility, and transaction costs. In Ashton, S.F., S.W. Workman, W.G. Hubbard and D.J. Moorhead (eds.). Agroforestry: A Profitable Land-Use. Proceedings, 12th North American Agroforestry Conference, Athens, GA, 4-ˇ9 June 2011. pp.151-158.

Horton, AJ., Lazarus, ED., Hales, TC., Constantine, JA., Bruford, MW., Goossens, B. (2018). Can riparian forest buffers increase yield from oil palm plantations? *Earth's Future (6)*8 1082-1096. Available at https://doi.org/10.1029/2018EF000874

Hou, Q., Young, L. J., Brandle, J. R., Schoeneberger, M. M. (2011) A spatial model approach for assessing windbreak growth and carbon stock. *J Environ Qual 40:*842–852

Instituto Colombiano Agropecuario (ICA). (2017). Agricultores del Tolima se capacitan en la conservacion y produccion de sistemas agroforestales y plantaciones forestales. September 19, 2017. Available at https://www.ica.gov.co/noticias/todas/agricultores-del-tolima-se-capacitan-en-la-conserv.aspx (accessed February 6, 2019).

IDEAM, PNUD, MADS, DNP, Cancillería. (2015). Inventario Nacional de Gases de Efecto Invernadero (GEI) de Colombia. Tercera Comunicación Nacional de Cambio Climático. IDEAM, PNUD, MADS, DNP, Cancillería, FMAM. Bogotá, Colombia. Available at http://www.cambioclimatico.gov.co/en/inventario-nacional-de-gases-efecto-invernadero

IIASA/FAO, 2012. Global Agro-ecological Zones (GAEZ v3.0). IIASA, Laxenburg, Austria and FAO, Rome, Italy. Available at http://pure.iiasa.ac.at/id/eprint/13290/1/GAEZ_Model_Documentation.pdf

Impala, 2001. First annual report of IMPALA Project, covering the period October 2000–December 2001, Nairobi, Kenya, 68 pp.

IPCC AR4 SYR. (2007), Core Writing Team; Pachauri, R.K; and Reisinger, A., ed., *Climate Change 2007: Synthesis Report*, Contribution of Working Groups I, II and III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, IPCC, ISBN 92-9169-122-4

Jose S. (2009). Agroforestry for ecosystem services and environmental benefits: an overview. Agroforestry Systems 76: 1-10.

IUSS Working Group WRB. 2015. World Reference Base for Soil Resources 2014, update 2015 International soil classification system for naming soils and creating legends for soil maps. World Soil Resources Reports No. 106. FAO, Rome.

Jenny, H., Raychaudhuri, S.P., 1960. Effect of Climate and Cultivation on Nitrogen and Organic Matter Reserves in Indian Soils. ICAR, New Delhi, India

Johnson, J.M.-F., Franzluebbers, A.J., Lachnicht Weyers, S., Reicosky, D.C. 2007. Agricultural opportunities to mitigate greenhouse gas emissions. *Environmental Pollution* 150, 107-124.

Kahn, B. (2016). Earth's CO_2 Passes the 400 PPM Threshold – Maybe Permanently. *Scientific American*. Available at https://www.scientificamerican.com/article/earth-s-co2-passes-the-400-ppm-threshold-maybe-permanently/

Kell, D. B. (2012). Large- scale sequestration of atmospheric carbon via plant roots in natural and agricultural ecosystems: why and how. *Philosophical Transactions of the Royal Society of London. Series B, Biological Sciences, 367*(1595), 1589.

Kendall, H. W., & Pimentel, D. (1994). Constraints on the Expansion of the Global Food Supply. *Ambio, 23*(3), 198-205.

Kimble, J. M., Rice, C. W., Reed, D., Mooney, S., Follett, R. F., & Lal, R. (2007). *Soil Carbon Management* CRC Press.

Knox, S. H., Sturtevant, C., Matthes, J. H., Koteen, L., Verfaillie, J., & Baldocchi, D. (2015). Agricultural peatland restoration: effects of land- use change on greenhouse gas (CO2 and CH4) fluxes in the Sacramento- San Joaquin Delta. *Global Change Biology, 21*(2), 750.

Kort, J., Turnock, R. (1999) Carbon reservoir and biomass in Canadian prairie shelterbelts. *Agrofor Syst 44:*175–186.

Kundu, S., Bhattacharyya, R., Prakash, V., Ghosh, B.N., Gupta, H.S., 2007. Carbon sequestration and relationship between carbon addition and storage under rainfed soybeanewheat rotation in a sandy loam soil of the Indian Himalayas. Soil Tillage Res. 92, 87-95.

Laganiere J, Angers DA, Pare D (2010) Carbon accumulation in agricultural soils after afforestation: a meta-analysis. *Glob Chang Biol 16*:439–453. https://doi.org/10.1111/j.1365-2486.2009.01930.x

Lal, R. (2004). In Lal R. (Ed.), *Soil Carbon Sequestration Impacts on Global Climate Change and Food Security*

Lal, R. (2007). Soil Physical Properties and Erosion. In Kimble et al., 2007. (Eds), Soil Carbon Management Economic, Environmental, and Societal Benefits (165-178). CRC Press.

Lal, R. (2008). Carbon sequestration in soil. *CAB Reviews: Perspectives in Agriculture, Veterinary Science, Nutrition and Natural Resources, 3*(30), 20 pp.

Lal, R. (2010). Managing Soils and Ecosystems for Mitigating Anthropogenic Carbon Emissions and Advancing Global Food Security. *Bioscience, 60*(8), 708-721.

Lal, R. (2016). Beyond COP 21: Potential and challenges of the "4 per Thousand" initiative. *Journal of Soil and Water Conservation, 71*(1), 25A.

Langdale, G. W., West, L. T., Bruce, R. R., Miller, W. P., & Thomas, A. W. (1992). Restoration of eroded soil with conservation tillage. *Soil Technology, 5*(1), 81-90.

Latham, J., Cumani, R., Rosati, I. & Bloise, M. *FAO Global Land Cover (GLC-SHARE) Beta-Release 1.0 Database, Version 1.0 - 201*4. 1–40 (Land and Water Division, FAO, 2014). Data downloaded from: http://www.fao.org/geonetwork/srv/en/main.home?uuid=ba4526fd-cdbf-4028-a1bd-5a559c4bff38

Lee, X. H., Wu, H. J. Sigler J et al. (2004) Rapid and transient response of soil respiration to rain. *Glob Change Biol 10:*1017–26.

Lemke, R. L., Vandenbygaart, A. J., Campbell, C. A., Lafond, G. P., & Grant, B. (2010). Crop residue removal and fertilizer N: Effects on soil organic carbon in a long- term crop rotation experiment on a Udic Boroll. *Agriculture, Ecosystems and Environment, 135*(1), 42-51. doi: 10.1016 / j.agee.2009.08.010, ISSN: 01678809.

Ley 1819 de 2016. Impuesto sobre la Renta de las Personas Naturales. Bogotá D.C. Diciembre 29 de 2016. Available at http://www.funcionpublica.gov.co/eva/gestornormativo/norma.php?i=79140

Ley 1844 de 2017. Acuerdo de Paris. Bogotá, D.C. Julio 14 de 2017. https://redjusticiaambientalcolombia.files.wordpress.com/2017/07/ley-1844-de-2017-acuerdo-paris-cambio-climatico.pdf

Li , Z.P., Liu, M.,Wu, X. C. et al. (2010) Effects of long-term chemical fertilization and organic amendments on dynamics of soil organic C and total N in paddy soil derived from barren land in subtropical China. Soil and Tillage Research, 106, 268–274.

Liu, C., Lu, M., Cui, J., Li, B. & Fang, C. Effects of straw carbon input on carbon dynamics in agricultural soils: a meta-analysis. Global Change Biol, doi: 10.1111/gcb.12517 (2014).

Liu, Y., Engel BA., Flanagan, DC., Gitau, MW., McMillan, SK., Chaubey, I. (2017). A review on the effectiveness of best management practices in improving hydrology and water quality: Needs and opportunities. *Science of the Total Environment (601-602)*2017 580-593. Available at http://dx.doi.org/10.1016/j.scitotenv.2017.05.212

Lorenz, K., & Lal, R. (2014). Biochar application to soil for climate change mitigation by soil organic carbon sequestration. Journal of Plant Nutrition and Soil Science, 177(5), 651-670.

MacFarland, K. & USDA National Agroforestry Center in Forestry (NACF). (2015). Virginia is for lovers – and silvopasture. USDA. Available at https://www.usda.gov/media/blog/2015/09/17/virginia-lovers-and-silvopasture (accessed February 4, 2019).

MacFarland, K., Straight, R., Dosskey, M. (2017). Riparian Forest Buffers: An Agroforestry Practice. USDA. Available at https://www.fs.usda.gov/nac/documents/agroforestrynotes/an49rfb01.pdf (accessed February 5, 2019).

Machado, J.A., 1976. Efeito do sistema convencional de cultivo na capacidade de infiltracão de agua no solo. Master´s thesis. Departamento de Solos, UFSM (Universidade Federal de Santa Maria). Santa Maria, Brazil, 114p. (in Portuguese)

Mahajan, A. and Gupta, R.D. (2009) Balanced Use of Plant Nutrients. In: Mahajan A., Gupta R.D. (eds) Integrated Nutrient Management (INM) in a Sustainable Rice—Wheat Cropping System. Springer, Dordrecht

Mahecha, L., Rosales, M., Molina, C., Molina, J. (1999). Experiencias en un Sistema silvopastoril de Leucaena *Leucocephala-cynodon plectostachyus-Proposis juriflora* en el Valle del Cauca, Colombia. Agroforesteria para la Produccion Animal en Latinoamerica. 325-336. Available at http://www.fao.org/livestock/agap/frg/agrofor1/Mahech20.PDF (accessed February 2, 2019).

Mangalassery, S., Dayal, D., Meena, S.L., Ram, B., 2014. Carbon sequestration in agroforestry and pasture systems in arid north western India. *Curr. Sci. 107,* 1290–1293.

Manna M C, Swarup A, Wanjari R H, Ravankar H N, Mishra M N, Singh Y V, Sahi D K, Sarap P A. 2005. Long-term effect of fertilizer and manure application on soil organic carbon stock, soil quality and yield sustainability under sub-humid and semi-arid tropical India. *Field Crops Research, 93*, 264–280.

Marongwe, L. S., Kwazira, K., Jenrich, M., Thierfelder, C., Kassam, A., & Friedrich, T. (2011). An African success: the case of conservation agriculture in Zimbabwe. *International Journal of Agricultural Sustainability, 9*(1), 153-161. doi:10.3763/ijas.2010.0556

Mathieu, JA., Hatté, C., Balesdent, J., & Parent E. (2015). Deep soil carbon dynamics are driven more by soil type than by climate: a worldwide meta-analysis of radiocarbon profiles. *Global Change Biology 21*, 4278-4292. DOI: 10.1111/gcb.13012

Meier, I. C., Leuschner, C. (2010) Variation of soil and biomass carbon pools in beech forests across a precipitation gradient. *Glob Change Biol 16:*1035–45.

MINAGRICULTURA. (2018). Informe de Gestión 2017 (Ley 1474 de 2011, Articulo 74). Bogotá, D.C, enero de 2018. Available at https://www.minagricultura.gov.co/planeacion-control-gestion/Gestin/PLANEACION/Informe_de_Gesti%C3%B3n_(Metas_Objetivos_Indicadores_Gestion)/INFORME%20DE%20GESTI%C3%93N%202017%20.pdf

MINAMBIENTE (2017a). Politica Nacional de Cambio Climático - PNCC. Política nacional de cambio climático / Luis Gilberto Murillo, Ministro (2016 - :); [Eds.] Dirección de Cambio Climático: Florián Buitrago, Maritza; Pabón Restrepo, Giovanni Andrés; Pérez Álvarez, Paulo Andrés; Rojas Laserna, Mariana; Suárez Castaño, Rodrigo. ---- Bogotá, D. C.: Colombia. Ministerio de Ambiente y Desarrollo Sostenible, 2017.

MINAMBIENTE (2017b). Principales preguntas frente al impuesto nacional al carbono y la solicitud de no causacion por carbono neutralidad. ABC Decreto 926 de 2017.

Minasny, B., Malone, B. P., McBratney, A. B., Angers, D. A., Arrouays, D., Chambers, A., Winowiecki, L. (2017). Soil carbon 4 per mille. *Geoderma, 292*, 59-86.

Ministerio Ambiente Desarrollo Sostenible. (2013). Política de Gestión Integral del Suelo. *Revista de Derecho,* (26), 110-136. Retrieved from http://dialnet.unirioja.es/servlet/oaiart?codigo=2347094

Montgomery, D. R. (2007). Soil erosion and agricultural sustainability. *Proceedings of the National Academy of Sciences, 104*(33), 13268.

Mosquera-Losada M.R., Freese D., & Rigueiro-Rodriguez A. (2011). Carbon Sequestration in European Agroforestry Systems. In BM. Kumar and P.K.R. Nair (eds). *Carbon Sequestration Potential of Agroforestry Systems: Opportunities and Challenges, Advances in Agroforestry* 8. Springer Science+Business Media B.V. 2011. Available at https://doi.org/10.1007/978-94-007-1630-8_3

Nair PKR, Kumar BM, Nair VD (2009a) Agroforestry as a strategy for carbon sequestration. *J Plant Nutr Soil Sci Fur Pflanzenernahrung Und Bodenkd 172*:10–23. https://doi.org/10.1002/jpln.200800030

Nair PKR, Nair VD, Kumar BM, Showalter JM (2010) Carbon sequestration in agroforestry systems. *Adv Agron 108*:237–307. doi:10.1016/S0065-2113(10)08005-3

Nair, P. K. R. (2011) Methodological challenges in estimating carbon sequestration potential of agroforestry systems. In: Kumar BM, Nair PKR (eds) Carbon sequestration potential of agroforestry systems. Springer, Dordrecht, pp 3–16

Nair, P. K. R. (2012) Carbon sequestration studies in agroforestry systems: a reality-check. *Agrofor Syst 86:*243–253. https://doi.org/10.1007/s10457-011-9434-z

Nath, A.J., Lal, R., Das, A.K., 2015. Ethnopedology and soil quality of bamboo (Bambusa sp.) based agroforestry system. *Sci. Total Environ. 521-522:*372–379. https://doi.org/10.1016/j.scitotenv.2015.03.059

NOAA (2018). Climate Data Online (CDO). Available at https://www.ncdc.noaa.gov/cdo-web/

Norgrove, L. (2003). Agrisilviculture systems: Timber – food crop system in the humid tropics. *Journal for Interdisciplinary and Cross-Cultural Studies 3* 2003.

O'Brien, S. L., Jastrow, J. D., Grimley, D. A., et al. (2010) Moisture and vegetation controls on decadal-scale accrual of soil organic carbon and total nitrogen in restored grasslands. *Glob Change Biol 16:*2573–88.

Oelbermann, M., Voroney, R. P., Gordon, A. M. (2004) Carbon sequestration in tropical and temperate agroforestry systems: a review with examples from Costa Rica and southern Canada. *Agri Ecosys Environ 104:*359–377. doi:10.1016/j.agee.2004.04.001

One Planet Summit (2018). Commitments. Available at https://www.oneplanetsummit.fr/en/commitments-15

Onim, J.F.M., Mathuva, M., Otieno, K. et al. Agroforest Syst (1990) 12: 197. https://doi.org/10.1007/BF00123474

Ontl, T. A. & Schulte, L. A. (2012) Soil Carbon Storage. *Nature Education Knowledge* 3(10):35

Paul, K. I., Polglase, P. J., Nyakuengama, J. G., Khanna, P. K. 2002. Change in soil carbon following afforestation. *Forest Ecology and Management 168:* 241–257.

Paustian, K., Lehmann, J., Ogle, S., Reay, D., Robertson, G. P., & Smith, P. (2016). Climate-smart soils. *Nature, 532*(7597), 49-57.

Pimentel, D., & Burgess, M. (2013). Soil Erosion Threatens Food Production. *Agriculture, 3*(3), 443-463.

Pimentel, D., Hepperly, P., Hanson, J., Douds, D., & Seidel, R. (2005). Environmental, Energetic, and Economic Comparisons of Organic and Conventional Farming Systems. *Bioscience, 55*(7), 573-582.

Pinheiro, FM., & Nair PKR. (2018). Silvopasture in the Caatinga biome of Brazil: A review of its ecology, management, and development opportunities. *Forest Systems 27(1)* 2018. Available at https://doi.org/10.5424/fs/2018271-12267

Poeplau, C., and A. Don. 2015. Carbon sequestration in agricultural soils via cultivation of cover crops-A meta-analysis. Agric. Ecosyst. Environ. 200:33–41. doi:10.1016/j.agee.2014.10.024

Pöttker, D. Efeitos do tipo de solo, tempo de cultura e da calagem sobre a mineralização da matéria orgância em solos do Rio Grande do Sul. Porto Alegre, Universidade Federal do Rio Grande do Sul, 1977. 128p. (Tese de Mestrado)

Powers, J. S. (2004). Changes in soil carbon and nitrogen after contrasting land-use transitions in northeastern Costa Rica. Ecosystems, 7, 134–146. doi:10.1007/s10021-003-0123

Powlson, D. S., Stirling, C. M., Jat, M. L., Gerard, B. G., Palm, C. A., Sanchez, P. A., & Cassman, K. G. (2014). Limited potential of no-till agriculture for climate change mitigation. *Nature Climate Change, 4(8),* 678-683.

Proyecto de Ley 73 de 2017 – Bill 73 2017 (2017). Proyect to de Ley de Cambio Climático. Bogotá, D.C. Agosto 9 de 2017. http://jacevedo.imprenta.gov.co/documents/10280/3796703/669.pdf/fefdeb55-a45f-4937-88cb-97e4e187982b

Reynolds, L.L., Lajtha, K., Bowden, R.D. et al. *Biogeochemistry (2017) 136*: 249. https://doi.org/10.1007/s10533-017-0384-z

Rice, C., White, P., & Fabrizzi, K. (2007). Benefits of Soil Organic Carbon to Physical, Chemical, and Biological Properties of Soil. In Kimble, John. Rice, Charles. Reed, Debbie., S. Mooney & R. L. Follet Rattan. (Eds.), *Soil Carbon Management* (pp. 155-162) CRC Press. Retrieved from http://www.crcnetbase.com/doi/abs/10.1201/9781420044096.ch7

Rojas, JR., Bonadie, JR., Reis, W. de Castro, A., Martinez, A., Jaimes, Y. (2012). Sistemas agroforestales con caucho – el caso de Brasil y Colombia. Corporacion Colombiana de Investigacion Agropecuaria, CORPOICA. Bucaramanga, 2012.

Rosell, R.A., Galantini, J.A., 1998. Soil organic carbon dynamics in native and cultivated ecosystems of South America. In: Lal, R., Kimble, J., Follett, R., Stewart, B.A. (Eds.), Management of Carbon Sequestration in Soil. CRC, Boca Raton, FL, pp. 11–33.

Ruddiman, W. F., Ellis, E. C., Kaplan, J. O., & Fuller D. Q. (2015). Defining the epoch we live in. *Science, 348*(6230), 38-39.

Ruis, S., & Blanco-Canqui, H. (2017). Cover Crops Could Offset Crop Residue Removal Effects on Soil Carbon and Other Properties: A Review. Agronomy Journal, 109(5), 1785-1805.

Ryals, R., Hartman, M. D., Parton, W. J., Delonge, M. S., & Silver, W. L. (2015). Long-term climate change mitigation potential with organic matter management on grasslands. *Ecological Applications, 25*(2), 531-545.

Sauerbeck, D. R. (2001). CO2 emissions and C sequestration by agriculture–perspectives and limitations. *Nutrient Cycling in Agroecosystems, 60*(1), 253-266.

Sanchez PA (2000) Linking climate change research with food security and poverty reduction in the tropics. Agric Ecosyst Environ 82:371–383

Sanchez, P. A. *Science 295*, 2019 (2002).

Santiago-Freijanes, JJ., et al. (2018). Agroforestry development in Europe: Policy issues. *Land Use Policy 76(2018)* 144-156. Available at https://doi.org/10.1016/j.landusepol.2018.03.014

Schertz, D. L., Moldenhauer, W. C., Livingston, S. J., Weesies, G. A., & Hintz, E. A. (1989). Effect of past soil erosion on crop productivity in Indiana. *Journal of Soil and Water Conservation; Effect of Past Soil Erosion on Crop Productivity in Indiana,* (6), 604-608.

Schnepf, M., and C. Cox, eds. 2006. Environmental Benefits of Conservation on Cropland: The Status of Our Knowledge. Ankeny, Iowa: Soil and Water Conservation Society.

Schoeneberger, M. M., Bentrup, G., Patel-Weynand, T. (eds) (2017) Agroforestry: enhancing resiliency in U.S. agricultural landscapes under changing conditions. Gen Tech Rep WO-96. USDA Forest Service, Washington DC

Schwartz, J. (2014). Soil as Carbon Storehouse: New Weapon in Climate Fight? *Yale Environment 360.* Retrieved from https://e360.yale.edu/features/soil_as_carbon_storehouse_new_weapon_in_climate_fight accessed June 11, 2018.

Seufert V, Ramankutty N, Foley J A. 2012. Comparing the yields of organic and conventional agriculture. *Nature, 485*, 229–232.

Shi, L., W. Feng, J. Xu, Y. Kuzyakov. (2018). Agroforestry systems: Meta-analysis of soil carbon stocks, sequestration processes, and future potentials. *Land Degradation and Development 2018*; 1-12.

Six, J., Conant, R., Paul, E., & Paustian, K. (2002). Stabilization mechanisms of soil organic matter: Implications for C-saturation of soils. *Plant and Soil, 241*(2), 155-176.

Slimen, IB., Najar, T., Ghram, A., & Abdrrabba, M. (2016). Heat stress effects on livestock: molecular, cellular and metabolic aspects, a review. *Journal of Animal Physiology and Animal Nutrition 100* (3) 401-412 June 2016.

Smith P., M. Bustamante, H. Ahammad, H. Clark, H. Dong, E. A. Elsiddig, H. Haberl, R. Harper, J. House, M. Jafari, O. Masera, C. Mbow, N. H. Ravindranath, C. W. Rice, C. Robledo Abad, A. Romanovskaya, F. Sperling, and F. Tubiello. (2014). Agriculture, Forestry and Other Land Use (AFOLU). In Edenhofer, O., R. Pichs-Madruga, Y. Sokona, E. Farahani, S. Kadner, K. Seyboth, A. Adler, I. Baum, S. Brunner, P. Eickemeier, B. Kriemann, J. Savolainen, S. Schlömer, C. von Stechow, T. Zwickel and J.C. Minx (Ed.), *Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge, United Kingdom and New York, NY, USA.: Cambridge University Press.

Smith, P., Martino, D., Cai, Z., Gwary, D., Janzen, H., Kumar, P, Smith, J. (2008). Greenhouse gas mitigation in agriculture. Philosophical Transactions of The Royal Society B-Biological Sciences, 363(1492), 789-813.

South Pole Carbon Asset Management Ltd & Carbono & Bosques (2015). Recovery of degraded areas with agroforestry systems in Colombia. Available at https://www.vcsprojectdatabase.org/#/project_details/1429

St-Pierre, NR. Cobanov, B., & Schnitkey, G. (2003). Economic losses from Heat Stress by U.S. Livestock Industries. *Journal of Dairy Science 86* E52-E77. June 2003. Available at https://doi.org/10.3168/jds.S0022-0302(03)74040-5

Stanford Woods Institute for the Environment. (2012). Natural Capital Project. Retrieved from https://woods.stanford.edu/research/centers-programs/natural-capital-project

Stanford Earth. (n.d.). Soil Carbon Dynamics. Soil and Environmental Biogeochemistry. Retrieved from https://pangea.stanford.edu/soils/soil-carbon-dynamics

Stockmann, U., Padarian, J., McBratney, A., Minasny, B., de Brogniez, D., Montanarella, L., Field, D. J. (2015). Global soil organic carbon assessment. *Global Food Security, 6*, 9-16.

Tang, J., Cheng, H., Fang, C. (2017) The temperature sensitivity of soil organic carbon decomposition is not related to labile and recalcitrant carbon. *PLoS ONE 12(11):* e0186675. https://doi.org/10.1371/journal.pone.0186675

Tate, K.R., 1992. Assessment based on a climosequence of soils in tussock grasslands of soil carbon storage and release in response to global warming. *J. Soil Sci. 43,* 697–707.

TNAU (2016). Organic Farming: Organic Inputs and Techniques – Manures. Available at http://agritech.tnau.ac.in/org_farm/orgfarm_manure.html

Torralba, M., Fagerholm, N., Burgess, P.J., Moreno, G., Plieninger, T. (2016). Do European agroforestry systems enhance biodiversity and ecosystem services? A meta-analysis. *Agriculture, Ecosystems and Environment 230*: 150-161. http://dx.doi.org/10.1016/j.agee.2016.06.002

Tubiello, F. N., Salvatore, M., Ferrara, A. F., House, J., Federici, S., Rossi, S., . . . Smith, P. (2015). The Contribution of Agriculture, Forestry and other Land Use activities to Global Warming, 1990-2012. *Global Change Biology.*

Tubiello, F.N., Salvatore, M., Cóndor Golec, R.D., Ferrara, A., Rossi, S., Biancalani, R., Federici, S., Jacobs, H., Flammini, A. (2014). *Agriculture, Forestry and Other Land Use Emissions by Sources and Removals by Sinks:1990–2011 Analysis*. Rome: FAO Statistics Division.

University of Missouri, 1930. A Study on the Influence of Climate upon the Nitrogen and Organic Matter Content of the Soil (Res. Bull. 152). Agric. Exp. Stn., Columbia, MO.

USDA. (2011). USDA Agroforestry Strategic Framework. Accessed at https://www.usda.gov/sites/default/files/documents/FactSheet_final_8-1-11.pdf

USDA & NAC. (1997). Forest Farming: An Agroforestry Practice. Agroforestry Notes. Forest Farming – 1. November, 1997. Available at https://www.fs.usda.gov/nac/documents/agroforestrynotes/an07ff01.pdf

USDA NACF. (2002). Agroforestry Notes – Windbreaks: An Agroforestry Practice. March 2002. AF Note-25. Available at https://www.fs.usda.gov/nac/documents/agroforestrynotes/an25w01.pdf (accessed February 6, 2019).

Vallis, I. (1972) Soil nitrogen changes under continuously grazed legume-grass pastures in subtropical coastal Queensland. *Aust J Exp Agric 12*:495–501

Vandenbygaart, B., Gregorich, E. G., Angers, D. (2003). Influence of agricultural management on soil organic carbon: a compendium and assessment of Canadian studies. August 2003. *Canadian Journal of Soil Science 83 (4)*:363-380

Van Noordwijk, M., Lawson, G., Soumare, A., Groot, J. J. R., Hairiah, K. (1996) Root distribution of trees and crops: competition and/or complementarity. In: Ong CK, Huxely P (eds) Tree-crop interactions, a physiological approach. CAB International, Wallingford, pp 319–364

Veldkamp, E. 1994. Organic Carbon Turnover in Three Tropical Soils under Pasture after Deforestation. *Soil Sci. Soc. Am. J. 58*:175-180.

Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. Journal of Statistical Software, 36(3), 1-48. URL: http://www.jstatsoft.org/v36/i03/

Viscarra Rossel, R., Webster, R., Bui, E., & Baldock, J. (2014). Baseline map of organic carbon in Australian soil to support national carbon accounting and monitoring under climate change. *Global Change Biology, 20*(9), 2953-2970.

Wardle, D. A., Bardgett, R. D., Klironomos, J. N., Setälä, H., van der Putten, Wim H, & Wall, D. H. (2004). Ecological linkages between aboveground and belowground biota. *Science (New York, N.Y.), 304*(5677), 1629-1633.

Watson, E. R. (1963) The influence of subterranean clover pastures on soil fertility. I. Short-term effects. *Aust J Agric Res 14*:796–807

Wang, J. Z., Lu, C. A., Zhang, W. J., Feng, G., Wang, X. J., Xu, M. G. 2016. Decomposition of organic materials in cropland soils across China: A meta-analysis. Acta Pedologica Sinica, 53, 16–27. (in Chinese)

Wei, X., Shao, M., Gale, W., & Li, L. (2014). Global pattern of soil carbon losses due to the conversion of forests to agricultural land. *Scientific Reports, 4*, 4062.

Wei, W., Yan, Y., Cao, J., Christie, P., Zhang, F., Fan, M. 2016. Effects of combined application of organic amendments and fertilizers on crop yield and soil organic matter: An integrated analysis of long-term experiments. *Agriculture, Ecosystems and Environment, 225,* 86–92.

West, T. O., & Post, W. M. (2002). Soil organic carbon sequestration rates by tillage and crop rotation. *Soil Science Society of America Journal, 66*(6), 1930-1946.

Wilhelm, W., Johnson, J., Hatfield, J., Voorhees, W., & Linden, D. (2004). *Crop and soil productivity response to corn residue removal: A literature review*.

Winans, K., Tardif, S., Lteif, A., & Whalen, A. (2015). Carbon sequestration potential and cost-benefit analysis of hybrid poplar, grain corn and hay cultivation in southern Quebec, Canada. Agroforestry Systems, 89(3), 421-433.

Winans, K. S., Whalen, J. K., Rivest, D., Cogliastro, A. & Bradley, R. L. (2016). Carbon Sequestration and Carbon Markets for Tree-Based Intercropping Systems in Southern Quebec, Canada. Atmosphere, 7(2).

Wotherspoon, A. (2014). Quantification of Carbon Gains and Losses for Five Tree Species in a 25-year-old Tree-Based Intercropping System in Southern Ontario, Canada. Thesis presented to the University of Guelph. Available at https://atrium.lib.uoguelph.ca/xmlui/handle/10214/7850

World Bank Group WBG (2018). Carbon Pricing Dashboard. Available at https://carbonpricingdashboard.worldbank.org/

Xie, H., Li, J., Zhu, P., Peng, C., Wang, J., He, H., Zhang, X., 2014. Long-term manure amendments enhance neutral sugar accumulation in bulk soil and particulate organic matter in a Mollisol. Soil Biol. *Biochem. 78*, 45-53.

Yamoah, C. F., et al., Field Crops Res. 75, 53 (2002).

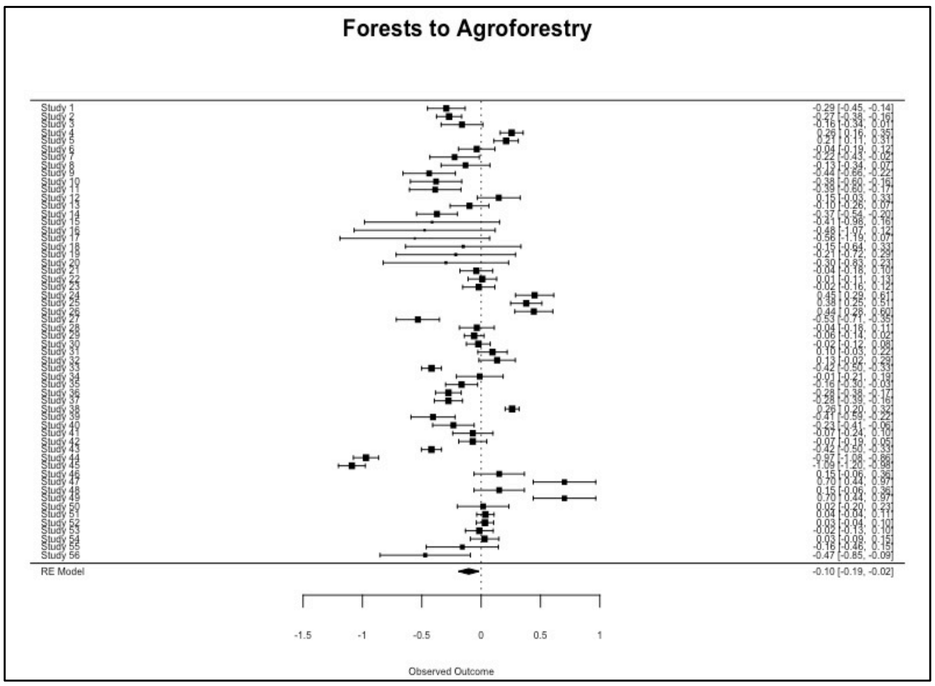
Yang, Z.P., Zheng, S.X., Nie, J., Liao, Y.L., Xie, J., 2014. Effects of long-term winter planted green manure on distribution and storage of organic carbon and nitrogen in water-stable aggregates of reddish paddy soil under a double-rice cropping system. J. Integ. Agric. 13, 1772-1781.

Zhou, G. Y., Guan, L. L., Wie, X. H., et al. (2008) Factors influencing leaf litter decomposition: an intersite decomposition experiment across China. *Plant Soil 311:*61–72.

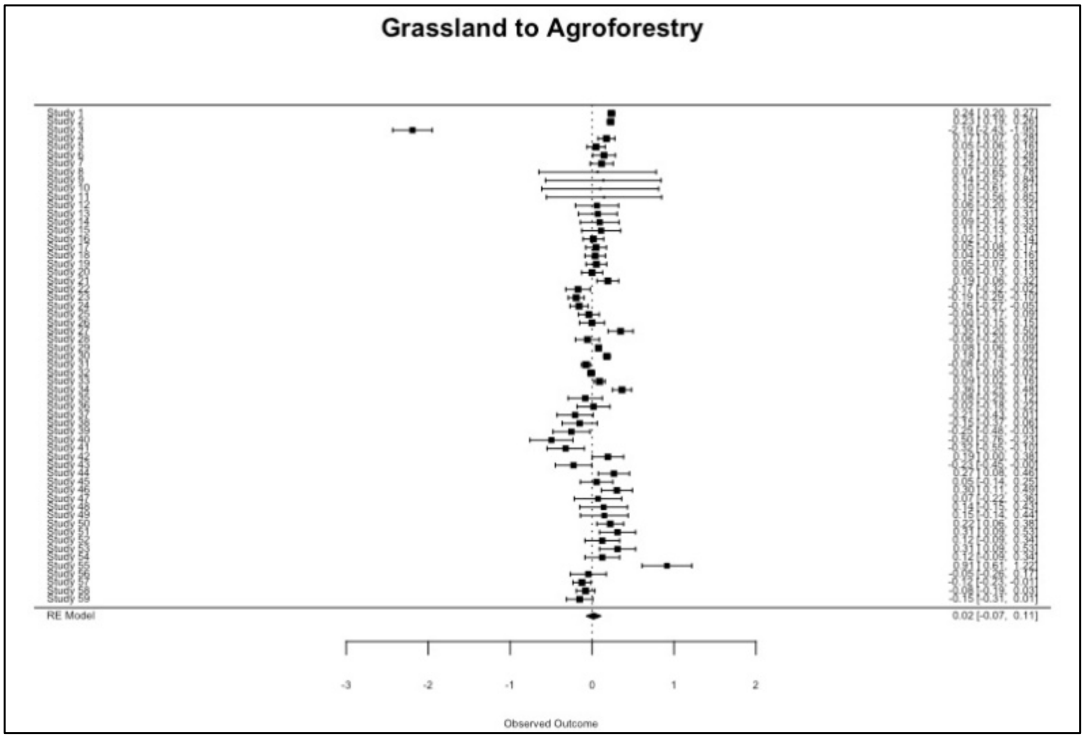
Zomer, R.J., Bossio, D.A., Sommer, R., Verchot, L.V., 2017. *Global Sequestration Potential of Increased Organic Carbon in Cropland Soils.* Scientific Reports 7: DOI http://dx.doi.org/10.1038/s41598-017-15794-8

Appendix

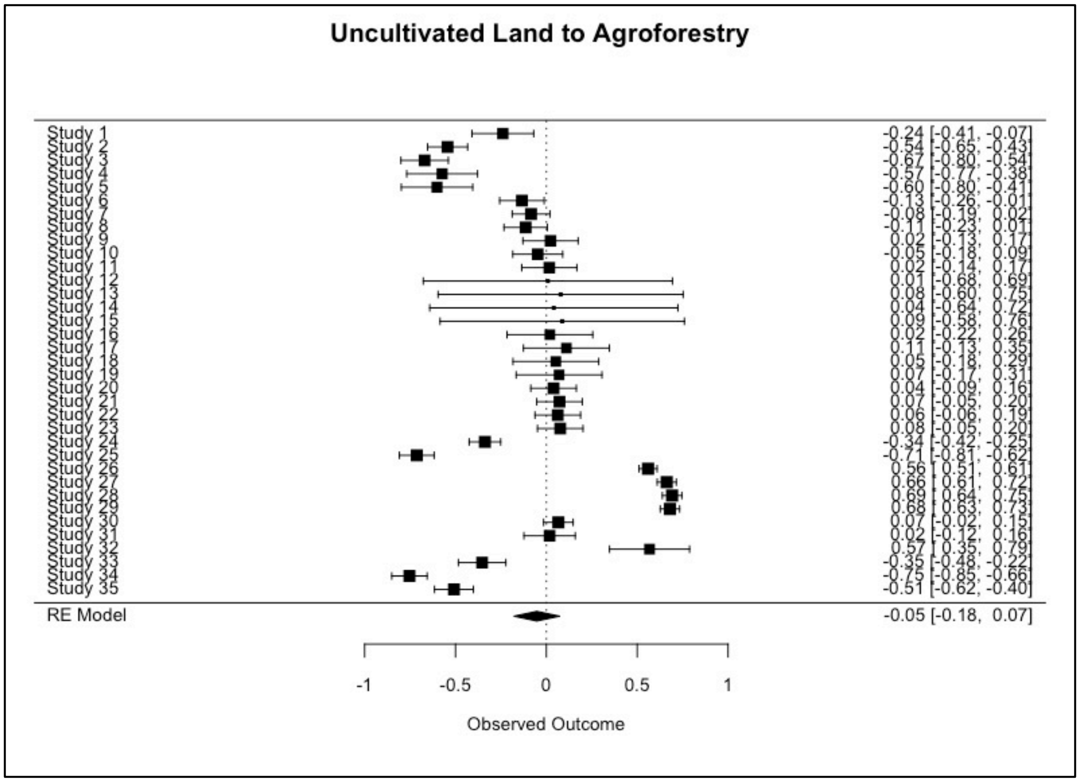
Appendix A. Random effects model to test the effect of the conversion of different land uses (forest, grassland, uncultivated land, conventional agriculture) to agroforestry systems



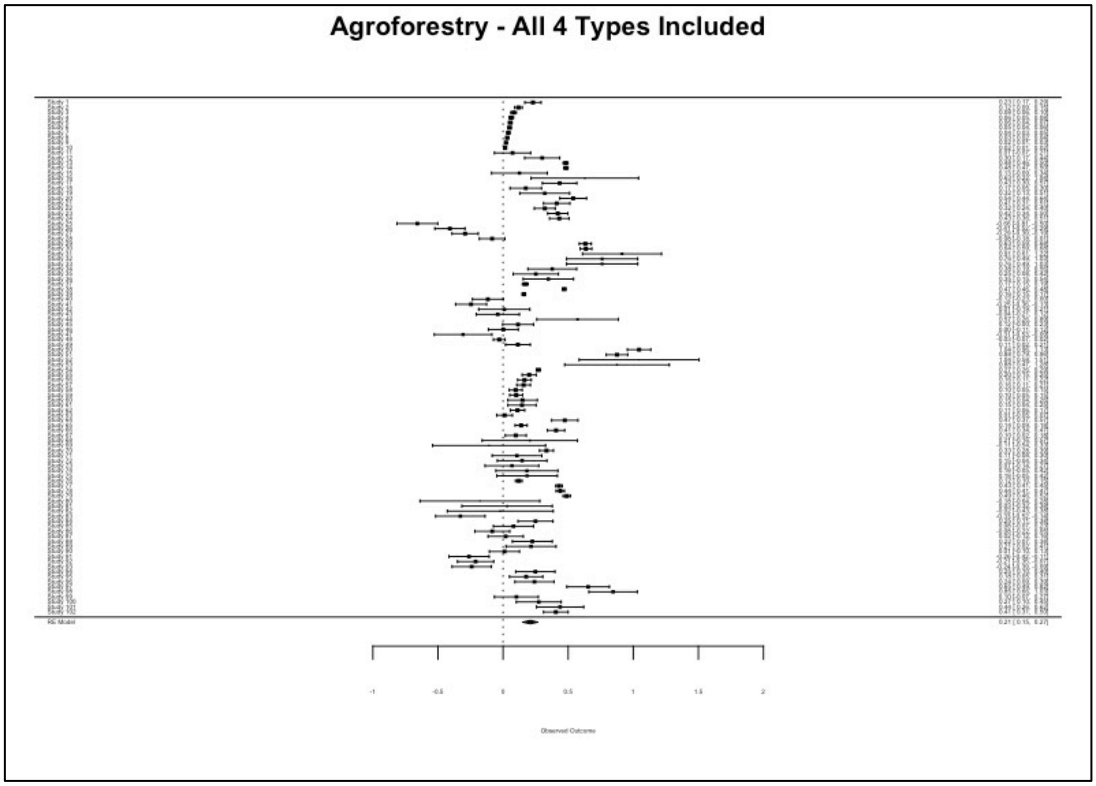

```
Random-Effects Model (k = 56; tau^2 estimator: HE)

tau^2 (estimated amount of total heterogeneity): 0.0982 (SE = 0.0221)
tau (square root of estimated tau^2 value):      0.3134
I^2 (total heterogeneity / total variability):   95.45%
H^2 (total variability / sampling variability):  21.96

Test for Heterogeneity:
Q(df = 55) = 1298.8475, p-val < .0001

Model Results:

estimate      se     zval    pval    ci.lb    ci.ub
 -0.1045  0.0444  -2.3563  0.0185  -0.1915  -0.0176  *

---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```



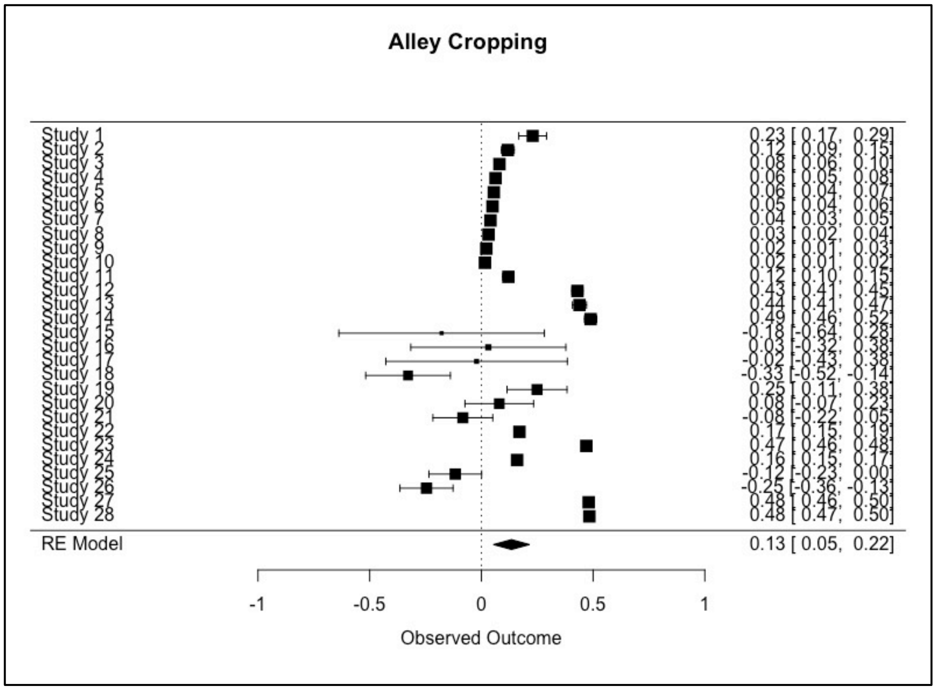

```
Random-Effects Model (k = 59; tau^2 estimator: HE)

tau^2 (estimated amount of total heterogeneity): 0.1112 (SE = 0.0245)
tau (square root of estimated tau^2 value):      0.3334
I^2 (total heterogeneity / total variability):   98.15%
H^2 (total variability / sampling variability):  53.96

Test for Heterogeneity:
Q(df = 58) = 803.6272, p-val < .0001

Model Results:

estimate      se     zval     pval    ci.lb    ci.ub
  0.0200  0.0458   0.4374   0.6618  -0.0697   0.1098

---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```



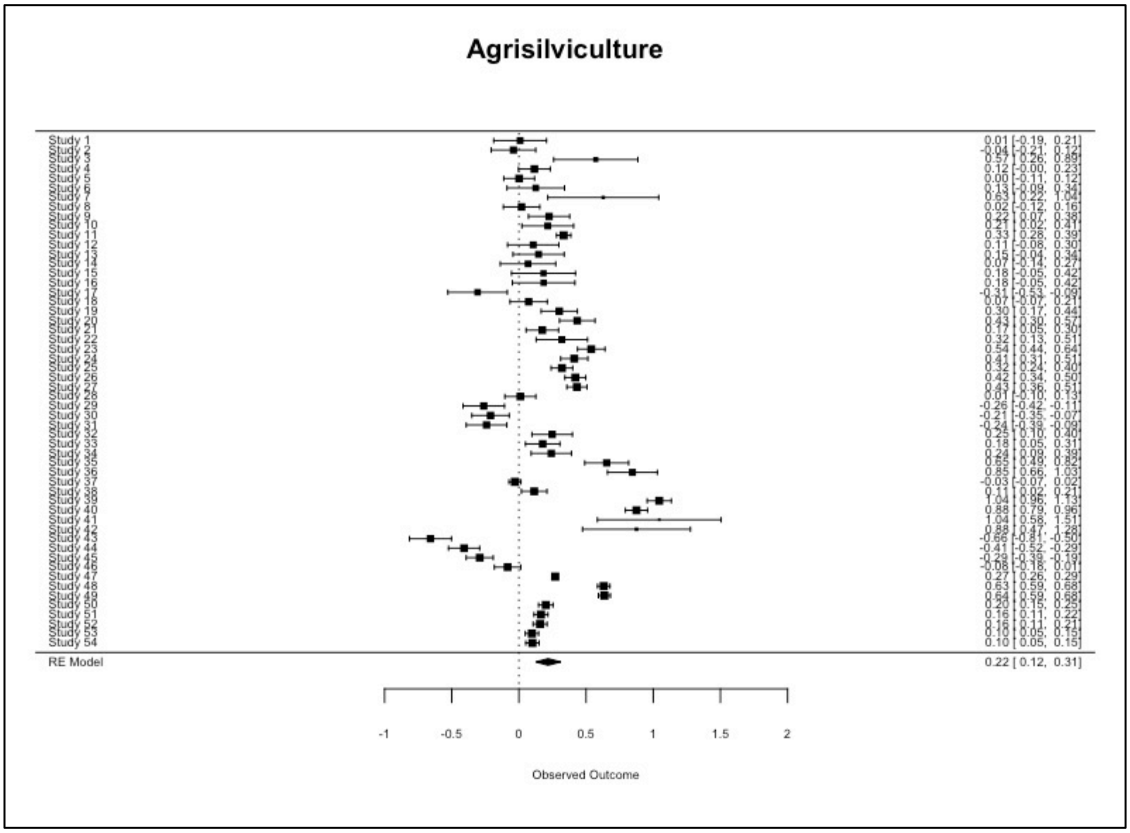

```
Random-Effects Model (k = 35; tau^2 estimator: HE)

tau^2 (estimated amount of total heterogeneity): 0.1314 (SE = 0.0374)
tau (square root of estimated tau^2 value):      0.3624
I^2 (total heterogeneity / total variability):   97.73%
H^2 (total variability / sampling variability):  44.01

Test for Heterogeneity:
Q(df = 34) = 2888.2466, p-val < .0001

Model Results:

estimate      se     zval    pval    ci.lb   ci.ub
 -0.0527  0.0642  -0.8202  0.4121  -0.1785  0.0732

---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```



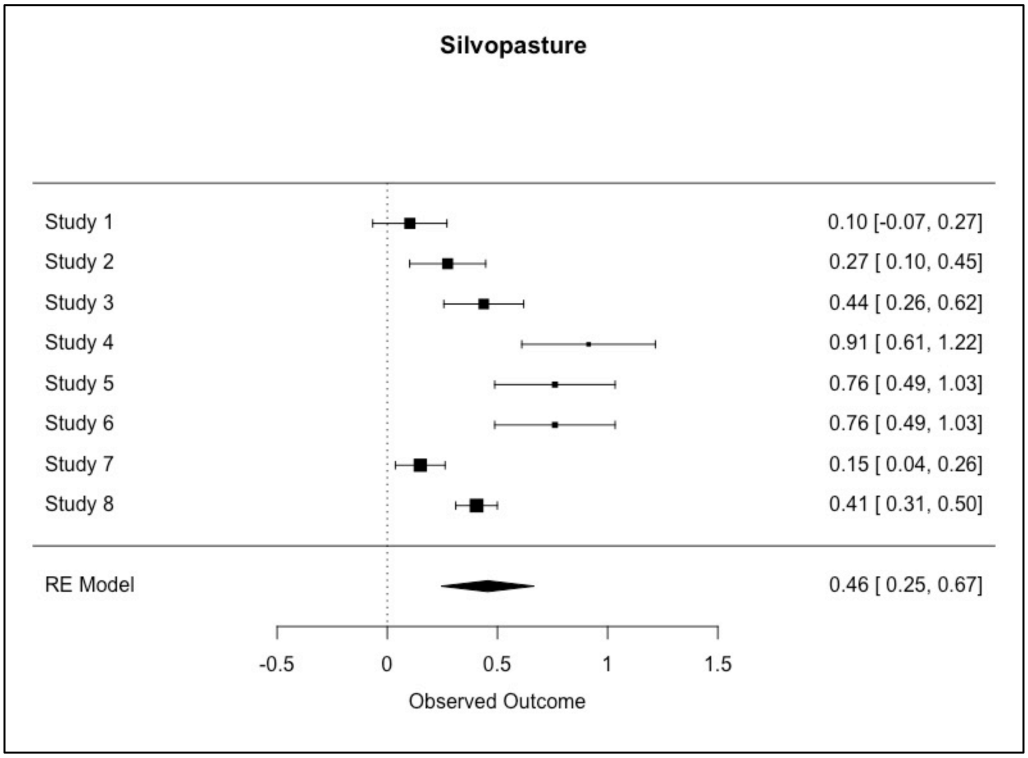

```
Random-Effects Model (k = 102; tau^2 estimator: HE)

tau^2 (estimated amount of total heterogeneity): 0.0888 (SE = 0.0137)
tau (square root of estimated tau^2 value):      0.2979
I^2 (total heterogeneity / total variability):   99.71%
H^2 (total variability / sampling variability):  349.54

Test for Heterogeneity:
Q(df = 101) = 13468.0512, p-val < .0001

Model Results:

estimate      se    zval    pval   ci.lb   ci.ub
  0.2092  0.0306  6.8420  <.0001  0.1493  0.2691  ***

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```



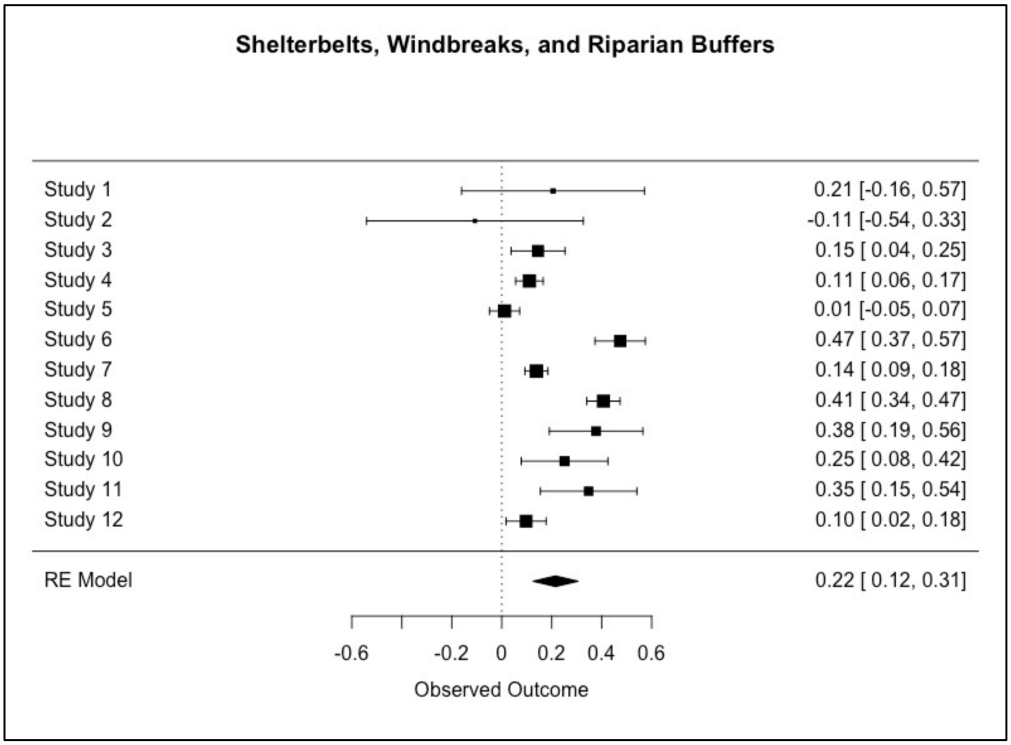

```
Random-Effects Model (k = 28; tau^2 estimator: HE)

tau^2 (estimated amount of total heterogeneity): 0.0441 (SE = 0.0141)
tau (square root of estimated tau^2 value):      0.2100
I^2 (total heterogeneity / total variability):   99.82%
H^2 (total variability / sampling variability):  562.47

Test for Heterogeneity:
Q(df = 27) = 10338.5508, p-val < .0001

Model Results:

estimate      se    zval    pval   ci.lb   ci.ub
  0.1346  0.0413  3.2566  0.0011  0.0536  0.2156   **

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```




```
Random-Effects Model (k = 54; tau^2 estimator: HE)

tau^2 (estimated amount of total heterogeneity): 0.1171 (SE = 0.0243)
tau (square root of estimated tau^2 value):      0.3423
I^2 (total heterogeneity / total variability):   98.68%
H^2 (total variability / sampling variability):  75.70

Test for Heterogeneity:
Q(df = 53) = 2164.5950, p-val < .0001

Model Results:

estimate      se    zval    pval   ci.lb   ci.ub
  0.2179  0.0479  4.5473  <.0001  0.1240  0.3119  ***

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

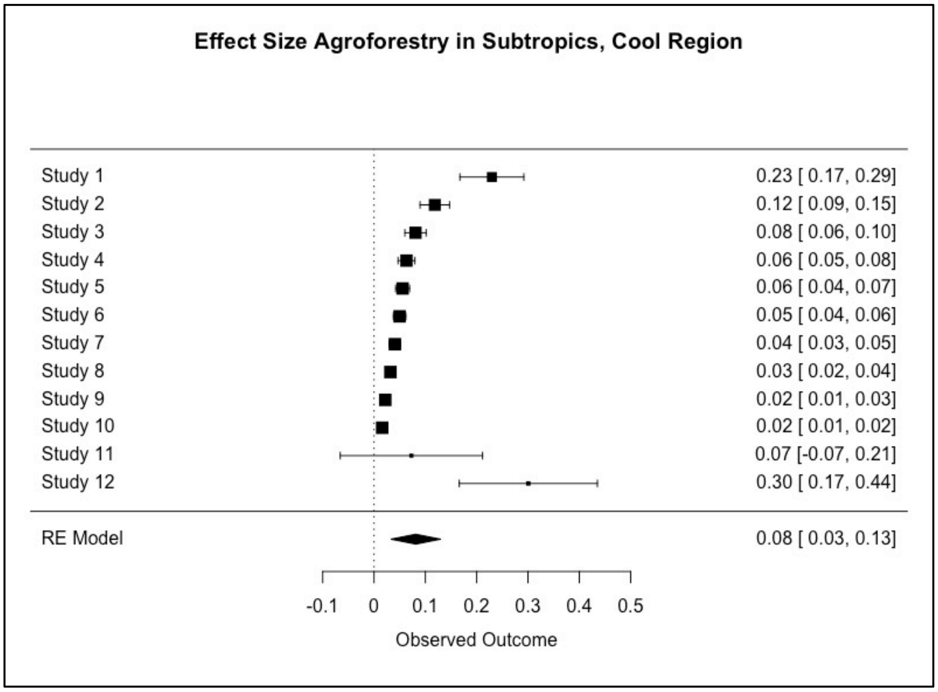



```
Random-Effects Model (k = 8; tau^2 estimator: HE)

tau^2 (estimated amount of total heterogeneity): 0.0810 (SE = 0.0496)
tau (square root of estimated tau^2 value):      0.2845
I^2 (total heterogeneity / total variability):   92.01%
H^2 (total variability / sampling variability):  12.51

Test for Heterogeneity:
Q(df = 7) = 54.0066, p-val < .0001

Model Results:

estimate      se    zval    pval   ci.lb   ci.ub
  0.4552  0.1071  4.2487  <.0001  0.2452  0.6652  ***

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

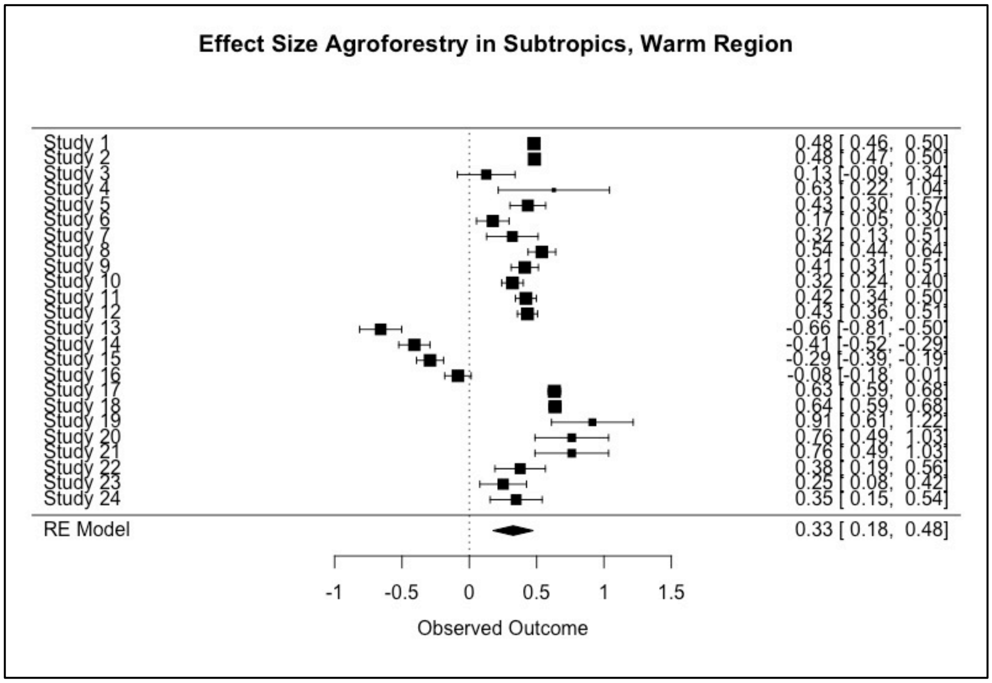



```
Random-Effects Model (k = 12; tau^2 estimator: HE)

tau^2 (estimated amount of total heterogeneity): 0.0198 (SE = 0.0141)
tau (square root of estimated tau^2 value):      0.1407
I^2 (total heterogeneity / total variability):   90.97%
H^2 (total variability / sampling variability):  11.07

Test for Heterogeneity:
Q(df = 11) = 130.7038, p-val < .0001

Model Results:

estimate      se     zval     pval    ci.lb    ci.ub
  0.2153  0.0463  4.6474  <.0001  0.1245  0.3061  ***

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

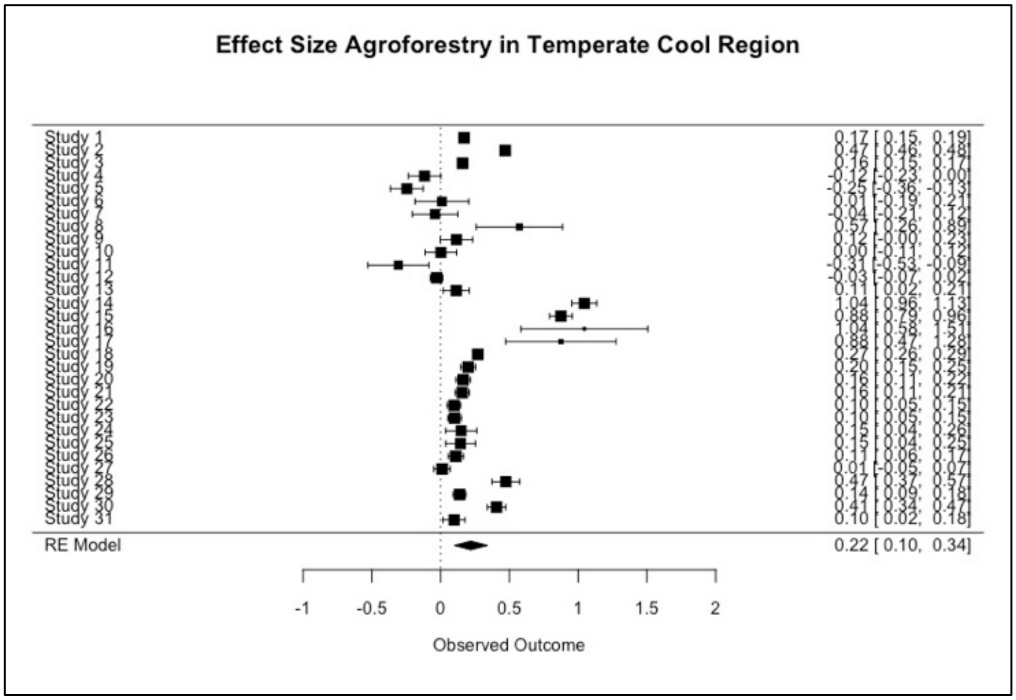
Appendix B. Random effects model to test the effect of agroecological zones in conventional agricultural land converted to agroforestry systems.



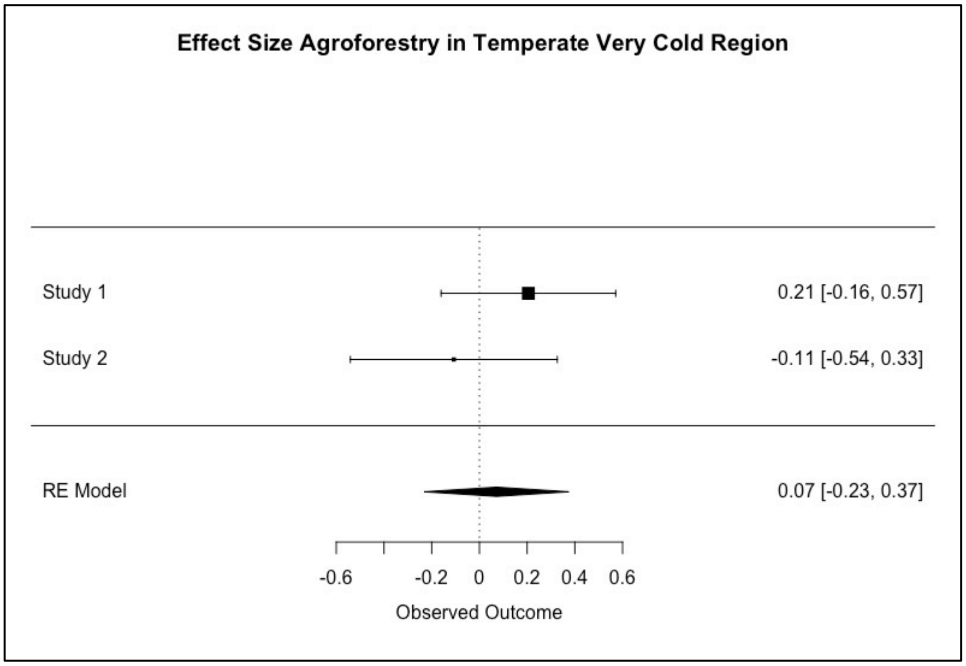

```
Random-Effects Model (k = 12; tau^2 estimator: HE)

tau^2 (estimated amount of total heterogeneity): 0.0067 (SE = 0.0034)
tau (square root of estimated tau^2 value):      0.0821
I^2 (total heterogeneity / total variability):   99.30%
H^2 (total variability / sampling variability):  141.95

Test for Heterogeneity:
Q(df = 11) = 163.3364, p-val < .0001

Model Results:

estimate      se    zval    pval   ci.lb   ci.ub
  0.0813  0.0248  3.2760  0.0011  0.0326  0.1299  **

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```



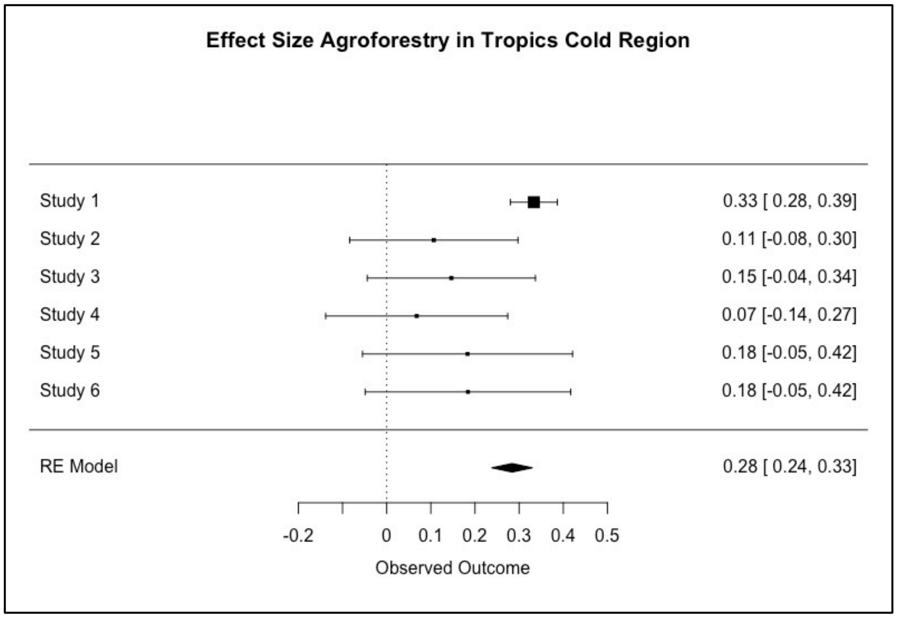

```
Random-Effects Model (k = 24; tau^2 estimator: HE)

tau^2 (estimated amount of total heterogeneity): 0.1341 (SE = 0.0420)
tau (square root of estimated tau^2 value):      0.3661
I^2 (total heterogeneity / total variability):   99.33%
H^2 (total variability / sampling variability):  148.24

Test for Heterogeneity:
Q(df = 23) = 946.0236, p-val < .0001

Model Results:

estimate      se     zval     pval    ci.lb    ci.ub
  0.3259  0.0767   4.2462   <.0001   0.1755   0.4763  ***

---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```



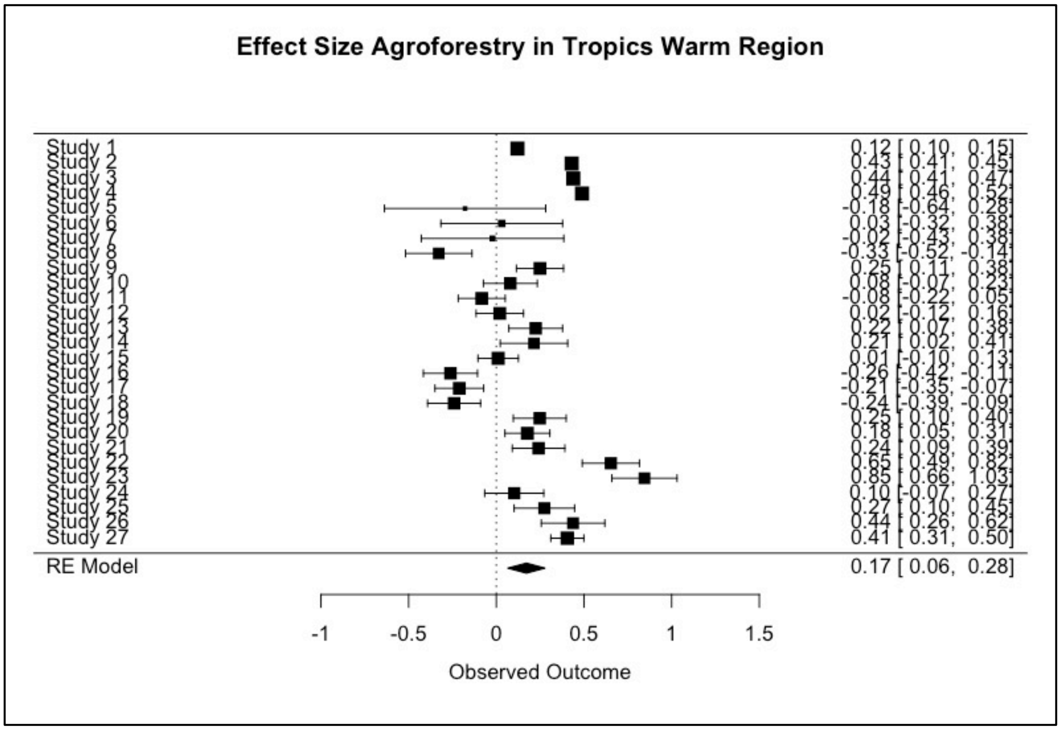

```
Random-Effects Model (k = 31; tau^2 estimator: HE)

tau^2 (estimated amount of total heterogeneity): 0.1100 (SE = 0.0302)
tau (square root of estimated tau^2 value):      0.3317
I^2 (total heterogeneity / total variability):   99.64%
H^2 (total variability / sampling variability):  280.65

Test for Heterogeneity:
Q(df = 30) = 2528.5787, p-val < .0001

Model Results:

estimate      se    zval    pval   ci.lb   ci.ub
  0.2200  0.0610  3.6091  0.0003  0.1005  0.3394  ***

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```




```
Random-Effects Model (k = 2; tau^2 estimator: HE)

tau^2 (estimated amount of total heterogeneity): 0.0069 (SE = 0.0691)
tau (square root of estimated tau^2 value):      0.0832
I^2 (total heterogeneity / total variability):   14.19%
H^2 (total variability / sampling variability):  1.17

Test for Heterogeneity:
Q(df = 1) = 1.1654, p-val = 0.2804

Model Results:

estimate      se     zval     pval    ci.lb   ci.ub
  0.0716  0.1546   0.4630   0.6434  -0.2315  0.3746

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

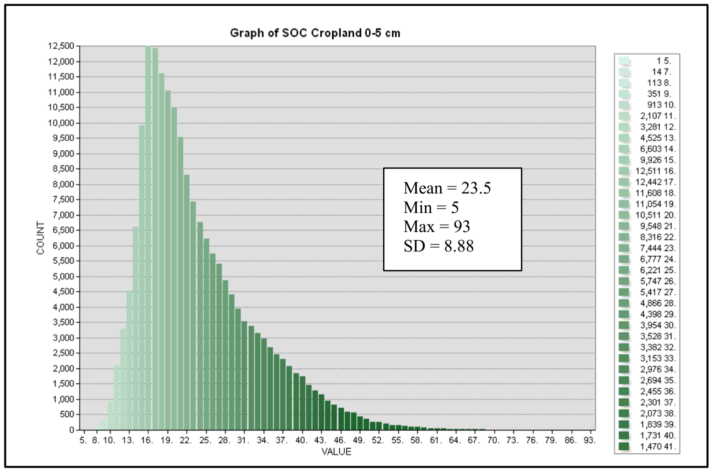


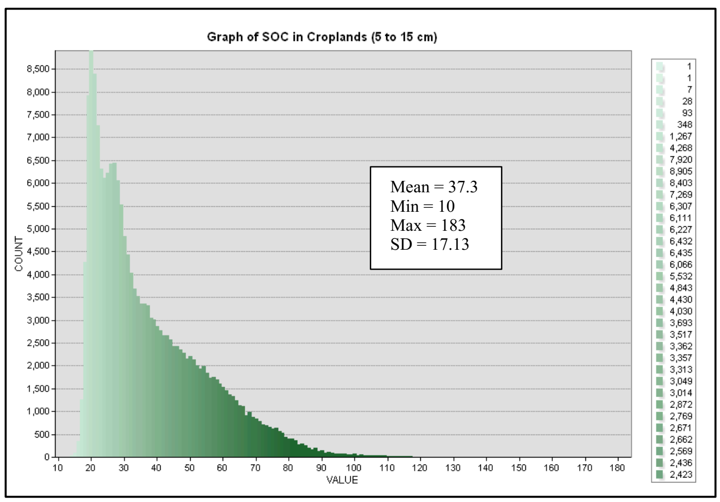

```
Random-Effects Model (k = 6; tau^2 estimator: HE)

tau^2 (estimated amount of total heterogeneity): 0 (SE = 0.0068)
tau (square root of estimated tau^2 value):      0
I^2 (total heterogeneity / total variability):   0.00%
H^2 (total variability / sampling variability):  1.00

Test for Heterogeneity:
Q(df = 5) = 14.2400, p-val = 0.0142

Model Results:

estimate      se     zval    pval   ci.lb   ci.ub
  0.2840  0.0236  12.0322  <.0001  0.2378  0.3303  ***

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

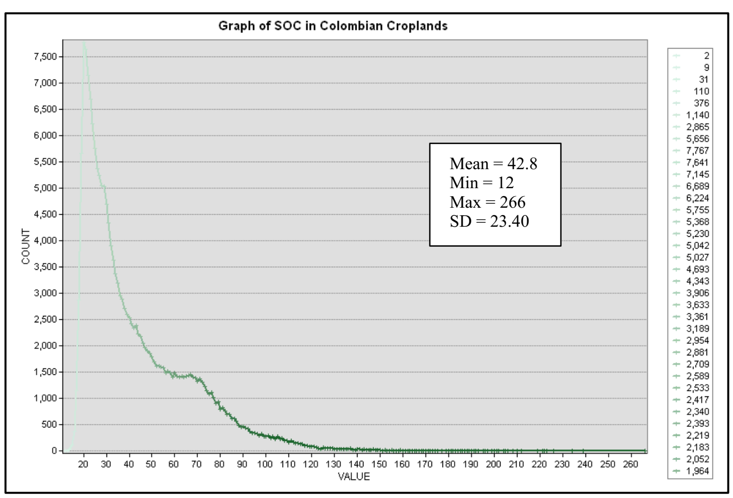



```
Random-Effects Model (k = 27; tau^2 estimator: HE)

tau^2 (estimated amount of total heterogeneity): 0.0730 (SE = 0.0231)
tau (square root of estimated tau^2 value):      0.2702
I^2 (total heterogeneity / total variability):   98.27%
H^2 (total variability / sampling variability):  57.80

Test for Heterogeneity:
Q(df = 26) = 891.5480, p-val < .0001

Model Results:

estimate      se     zval     pval    ci.lb    ci.ub
  0.1717  0.0548  3.1359  0.0017  0.0644  0.2791   **

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

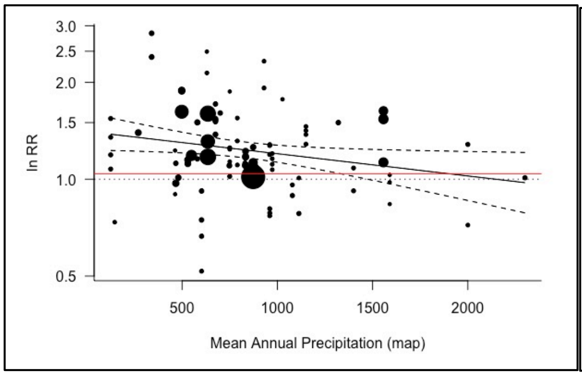
Appendix C. Mean soil organic carbon in Colombian cropland for the topsoil



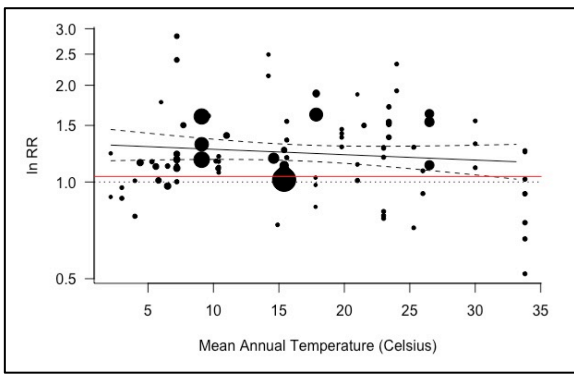




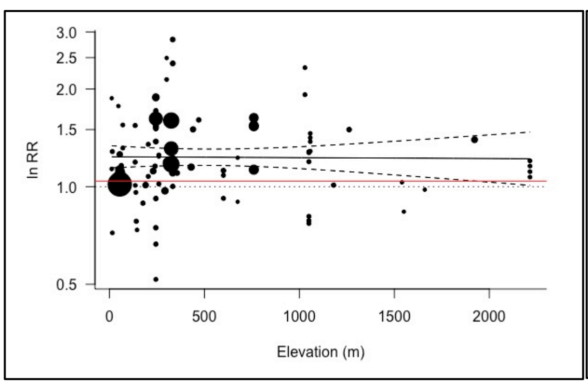
Appendix D. Linear meta-regressions for climatic, physical, and management variables in conventional agricultural land converted to agroforestry systems (all 4 types of AF included).



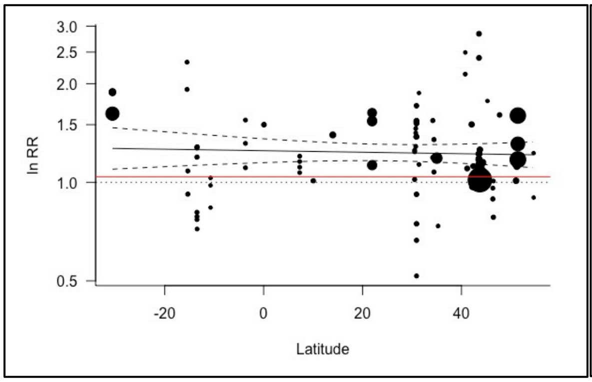

```
Mixed-Effects Model (k = 102; tau^2 estimator: HE)

  logLik  deviance       AIC       BIC      AICc
-20.1902  480.0078   46.3804   54.2553   46.6253

tau^2 (estimated amount of residual heterogeneity):     0.0844 (SE = 0.0131)
tau (square root of estimated tau^2 value):             0.2906
I^2 (residual heterogeneity / unaccounted variability): 99.70%
H^2 (unaccounted variability / sampling variability):   328.49
R^2 (amount of heterogeneity accounted for):            4.88%

Test for Residual Heterogeneity:
QE(df = 100) = 12615.8095, p-val < .0001

Test of Moderators (coefficient(s) 2):
QM(df = 1) = 4.5580, p-val = 0.0328

Model Results:

         estimate      se     zval    pval    ci.lb    ci.ub
intrcpt    0.3432  0.0696   4.9319  <.0001   0.2068   0.4796  ***
map       -0.0002  0.0001  -2.1350  0.0328  -0.0003  -0.0000    *

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```



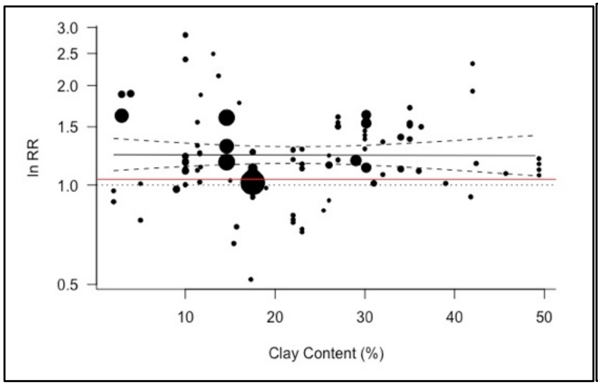

```
Mixed-Effects Model (k = 102; tau^2 estimator: HE)

  logLik  deviance       AIC       BIC      AICc
-21.9937  483.6148   49.9873   57.8622   50.2322

tau^2 (estimated amount of residual heterogeneity):     0.0883 (SE = 0.0137)
tau (square root of estimated tau^2 value):             0.2972
I^2 (residual heterogeneity / unaccounted variability): 99.71%
H^2 (unaccounted variability / sampling variability):   342.92
R^2 (amount of heterogeneity accounted for):            0.52%

Test for Residual Heterogeneity:
QE(df = 100) = 13464.7089, p-val < .0001

Test of Moderators (coefficient(s) 2):
QM(df = 1) = 1.2024, p-val = 0.2728

Model Results:

         estimate      se     zval    pval    ci.lb    ci.ub
intrcpt    0.2734  0.0661   4.1389  <.0001   0.1439   0.4029  ***
mat       -0.0039  0.0035  -1.0966  0.2728  -0.0108   0.0031

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```



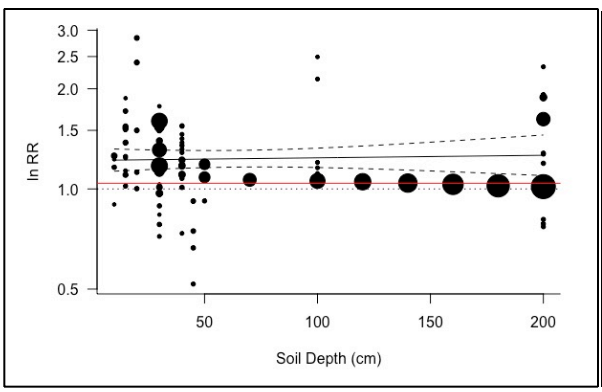

```
Mixed-Effects Model (k = 102; tau^2 estimator: HE)

  logLik  deviance       AIC       BIC      AICc
-22.6448  484.9170   51.2895   59.1644   51.5344

tau^2 (estimated amount of residual heterogeneity):     0.0896 (SE = 0.0139)
tau (square root of estimated tau^2 value):             0.2993
I^2 (residual heterogeneity / unaccounted variability): 99.71%
H^2 (unaccounted variability / sampling variability):   345.78
R^2 (amount of heterogeneity accounted for):            0.00%

Test for Residual Heterogeneity:
QE(df = 100) = 9560.9175, p-val < .0001

Test of Moderators (coefficient(s) 2):
QM(df = 1) = 0.0161, p-val = 0.8992

Model Results:

         estimate      se     zval    pval    ci.lb    ci.ub
intrcpt    0.2129  0.0420   5.0639  <.0001   0.1305   0.2952  ***
elev      -0.0000  0.0001  -0.1267  0.8992  -0.0001   0.0001

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```



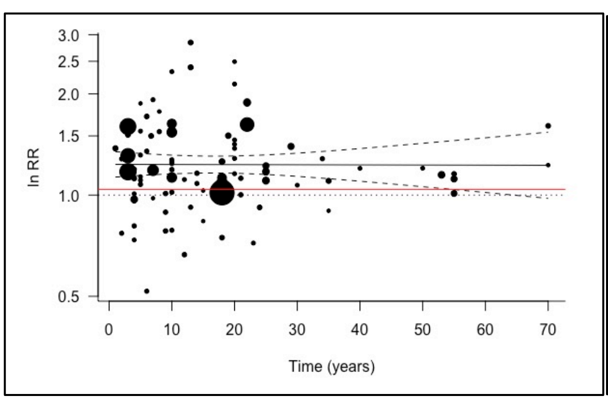

```
Mixed-Effects Model (k = 102; tau^2 estimator: HE)

  logLik  deviance       AIC       BIC      AICc
-22.5828  484.7930   51.1656   59.0405   51.4105

tau^2 (estimated amount of residual heterogeneity):     0.0897 (SE = 0.0139)
tau (square root of estimated tau^2 value):             0.2995
I^2 (residual heterogeneity / unaccounted variability): 99.71%
H^2 (unaccounted variability / sampling variability):   344.31
R^2 (amount of heterogeneity accounted for):            0.00%

Test for Residual Heterogeneity:
QE(df = 100) = 9324.0163, p-val < .0001

Test of Moderators (coefficient(s) 2):
QM(df = 1) = 0.1522, p-val = 0.6964

Model Results:

        estimate      se     zval    pval    ci.lb   ci.ub
intrcpt   0.2218  0.0446   4.9740  <.0001   0.1344  0.3092  ***
lat      -0.0005  0.0013  -0.3902  0.6964  -0.0030  0.0020

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```




```
Mixed-Effects Model (k = 102; tau^2 estimator: HE)

  logLik  deviance       AIC       BIC      AICc
-22.6514  484.9302   51.3027   59.1776   51.5476

tau^2 (estimated amount of residual heterogeneity):     0.0896 (SE = 0.0139)
tau (square root of estimated tau^2 value):             0.2994
I^2 (residual heterogeneity / unaccounted variability): 99.71%
H^2 (unaccounted variability / sampling variability):   349.67
R^2 (amount of heterogeneity accounted for):            0.00%

Test for Residual Heterogeneity:
QE(df = 100) = 12721.5893, p-val < .0001

Test of Moderators (coefficient(s) 2):
QM(df = 1) = 0.0053, p-val = 0.9417

Model Results:

        estimate      se     zval    pval    ci.lb   ci.ub
intrcpt   0.2133  0.0638   3.3413  0.0008   0.0882  0.3384  ***
clay     -0.0002  0.0025  -0.0731  0.9417  -0.0052  0.0048

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

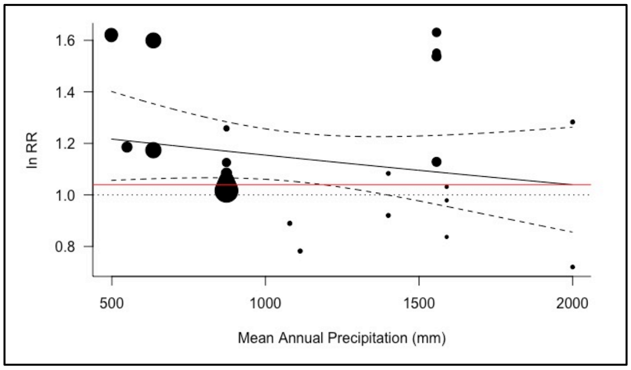



```
Mixed-Effects Model (k = 102; tau^2 estimator: HE)

  logLik  deviance       AIC       BIC      AICc
-22.5906  484.8087   51.1813   59.0562   51.4262

tau^2 (estimated amount of residual heterogeneity):     0.0896 (SE = 0.0139)
tau (square root of estimated tau^2 value):             0.2993
I^2 (residual heterogeneity / unaccounted variability): 99.70%
H^2 (unaccounted variability / sampling variability):   330.82
R^2 (amount of heterogeneity accounted for):            0.00%

Test for Residual Heterogeneity:
QE(df = 100) = 11906.6505, p-val < .0001

Test of Moderators (coefficient(s) 2):
QM(df = 1) = 0.1236, p-val = 0.7251

Model Results:

           estimate      se    zval    pval    ci.lb   ci.ub
intrcpt      0.1980  0.0442  4.4754  <.0001   0.1113  0.2847  ***
soildepth    0.0002  0.0005  0.3516  0.7251  -0.0008  0.0012

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

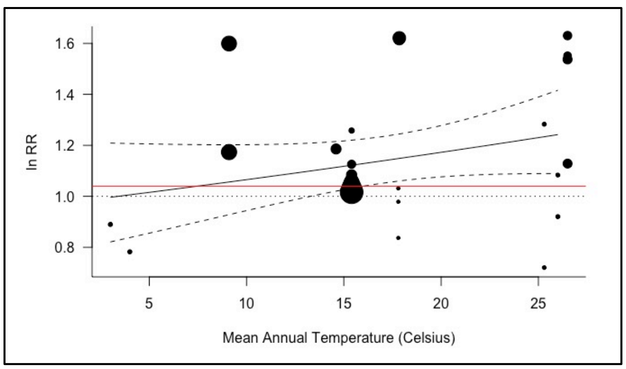



```
Mixed-Effects Model (k = 102; tau^2 estimator: HE)

  logLik  deviance       AIC       BIC      AICc
-22.6583  484.9440   51.3166   59.1915   51.5615

tau^2 (estimated amount of residual heterogeneity):     0.0897 (SE = 0.0139)
tau (square root of estimated tau^2 value):             0.2996
I^2 (residual heterogeneity / unaccounted variability): 99.71%
H^2 (unaccounted variability / sampling variability):   344.83
R^2 (amount of heterogeneity accounted for):            0.00%

Test for Residual Heterogeneity:
QE(df = 100) = 12459.2196, p-val < .0001

Test of Moderators (coefficient(s) 2):
QM(df = 1) = 0.0018, p-val = 0.9658

Model Results:

        estimate      se     zval    pval    ci.lb   ci.ub
intrcpt   0.2108  0.0478   4.4065  <.0001   0.1170  0.3046  ***
time     -0.0001  0.0022  -0.0429  0.9658  -0.0044  0.0042

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

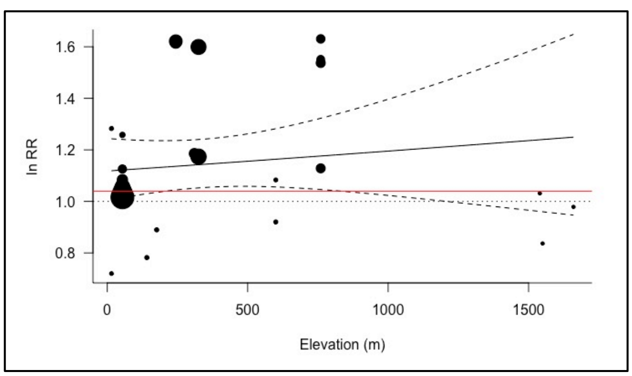
Appendix E. Linear meta-regressions for climatic, physical, and management variables in conventional agricultural land converted to alley cropping



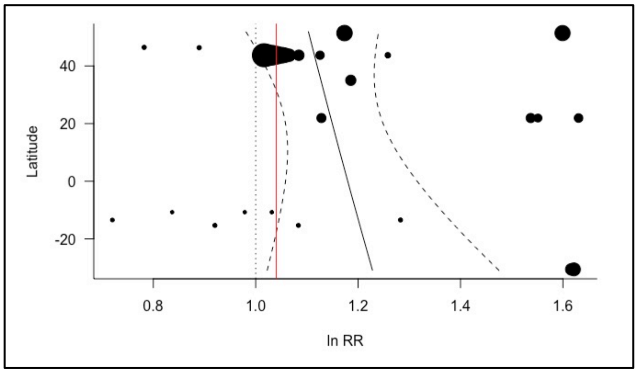

```
Mixed-Effects Model (k = 28; tau^2 estimator: HE)

  logLik  deviance       AIC       BIC      AICc
  3.2922  162.8906   -0.5844    3.4122    0.4156

tau^2 (estimated amount of residual heterogeneity):     0.0426 (SE = 0.0139)
tau (square root of estimated tau^2 value):             0.2064
I^2 (residual heterogeneity / unaccounted variability): 99.82%
H^2 (unaccounted variability / sampling variability):   548.23
R^2 (amount of heterogeneity accounted for):            3.42%

Test for Residual Heterogeneity:
QE(df = 26) = 9945.0081, p-val < .0001

Test of Moderators (coefficient(s) 2):
QM(df = 1) = 1.1812, p-val = 0.2771

Model Results:

         estimate      se     zval    pval    ci.lb   ci.ub
intrcpt    0.2473  0.1111   2.2258  0.0260   0.0295  0.4651  *
map       -0.0001  0.0001  -1.0868  0.2771  -0.0003  0.0001

---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```



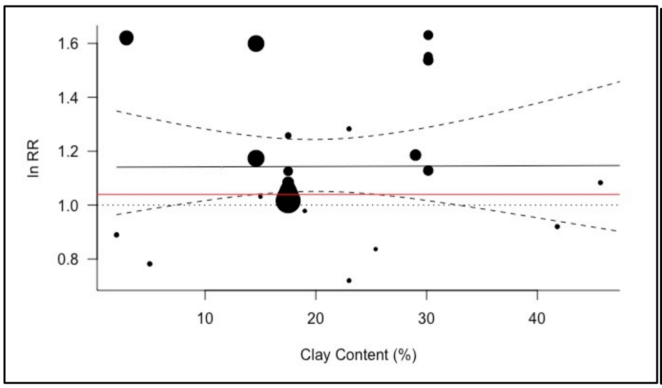

```
Mixed-Effects Model (k = 28; tau^2 estimator: HE)

  logLik  deviance       AIC       BIC      AICc
  3.9076  161.6598   -1.8152    2.1814   -0.8152

tau^2 (estimated amount of residual heterogeneity):     0.0423 (SE = 0.0139)
tau (square root of estimated tau^2 value):             0.2057
I^2 (residual heterogeneity / unaccounted variability): 99.81%
H^2 (unaccounted variability / sampling variability):   538.95
R^2 (amount of heterogeneity accounted for):            4.12%

Test for Residual Heterogeneity:
QE(df = 26) = 10230.8545, p-val < .0001

Test of Moderators (coefficient(s) 2):
QM(df = 1) = 2.4184, p-val = 0.1199

Model Results:

         estimate      se     zval    pval    ci.lb   ci.ub
intrcpt   -0.0326  0.1152  -0.2835  0.7768  -0.2584  0.1931
mat        0.0096  0.0062   1.5551  0.1199  -0.0025  0.0217

---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```



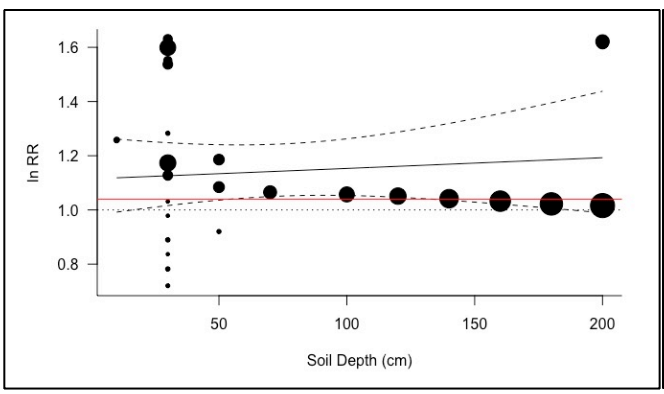

```
Mixed-Effects Model (k = 28; tau^2 estimator: HE)

  logLik  deviance       AIC       BIC      AICc
  2.8807  163.7135    0.2385    4.2351    1.2385

tau^2 (estimated amount of residual heterogeneity):     0.0469 (SE = 0.0148)
tau (square root of estimated tau^2 value):             0.2166
I^2 (residual heterogeneity / unaccounted variability): 99.83%
H^2 (unaccounted variability / sampling variability):   593.84
R^2 (amount of heterogeneity accounted for):            0.00%

Test for Residual Heterogeneity:
QE(df = 26) = 5445.8037, p-val < .0001

Test of Moderators (coefficient(s) 2):
QM(df = 1) = 0.3929, p-val = 0.5308

Model Results:

         estimate      se    zval    pval    ci.lb   ci.ub
intrcpt    0.1116  0.0555  2.0094  0.0445   0.0027  0.2204  *
elev       0.0001  0.0001  0.6268  0.5308  -0.0001  0.0003

---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```



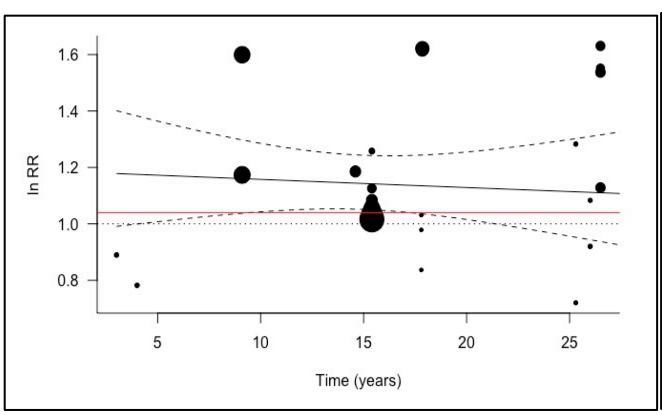

```
Mixed-Effects Model (k = 28; tau^2 estimator: HE)

  logLik  deviance       AIC       BIC      AICc
  3.0549  163.3652   -0.1098    3.8868    0.8902

tau^2 (estimated amount of residual heterogeneity):     0.0458 (SE = 0.0147)
tau (square root of estimated tau^2 value):             0.2140
I^2 (residual heterogeneity / unaccounted variability): 99.83%
H^2 (unaccounted variability / sampling variability):   578.32
R^2 (amount of heterogeneity accounted for):            0.00%

Test for Residual Heterogeneity:
QE(df = 26) = 6551.6133, p-val < .0001

Test of Moderators (coefficient(s) 2):
QM(df = 1) = 0.7120, p-val = 0.3988

Model Results:

         estimate      se     zval    pval    ci.lb   ci.ub
intrcpt    0.1651  0.0558   2.9610  0.0031   0.0558  0.2744  **
lat       -0.0013  0.0015  -0.8438  0.3988  -0.0043  0.0017

---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```




```
Mixed-Effects Model (k = 28; tau^2 estimator: HE)

  logLik  deviance       AIC       BIC      AICc
  2.6976  164.0798    0.6048    4.6014    1.6048

tau^2 (estimated amount of residual heterogeneity):     0.0460 (SE = 0.0149)
tau (square root of estimated tau^2 value):             0.2144
I^2 (residual heterogeneity / unaccounted variability): 99.83%
H^2 (unaccounted variability / sampling variability):   589.84
R^2 (amount of heterogeneity accounted for):            0.00%

Test for Residual Heterogeneity:
QE(df = 26) = 9421.0967, p-val < .0001

Test of Moderators (coefficient(s) 2):
QM(df = 1) = 0.0009, p-val = 0.9763

Model Results:

         estimate      se    zval    pval    ci.lb   ci.ub
intrcpt    0.1318  0.0912  1.4447  0.1486  -0.0470  0.3105
clay       0.0001  0.0041  0.0297  0.9763  -0.0079  0.0081

---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

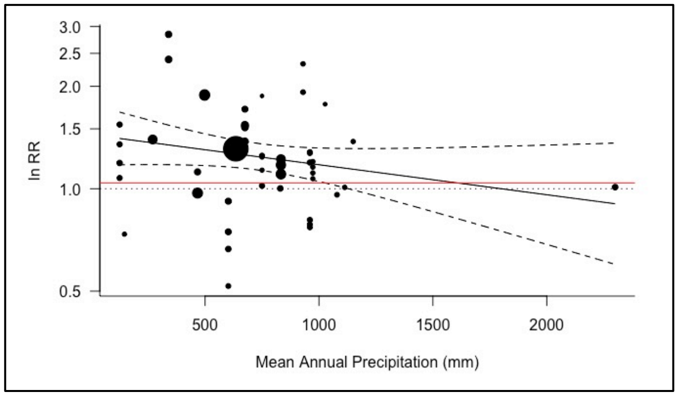



```
Mixed-Effects Model (k = 28; tau^2 estimator: HE)

  logLik  deviance       AIC       BIC      AICc
  2.8320  163.8110    0.3360    4.3326    1.3360

tau^2 (estimated amount of residual heterogeneity):     0.0450 (SE = 0.0146)
tau (square root of estimated tau^2 value):             0.2120
I^2 (residual heterogeneity / unaccounted variability): 99.82%
H^2 (unaccounted variability / sampling variability):   544.34
R^2 (amount of heterogeneity accounted for):            0.00%

Test for Residual Heterogeneity:
QE(df = 26) = 8916.3188, p-val < .0001

Test of Moderators (coefficient(s) 2):
QM(df = 1) = 0.2529, p-val = 0.6150

Model Results:

           estimate      se    zval    pval    ci.lb   ci.ub
intrcpt      0.1096  0.0646  1.6963  0.0898  -0.0170  0.2362  .
soildepth    0.0003  0.0007  0.5029  0.6150  -0.0010  0.0016

---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

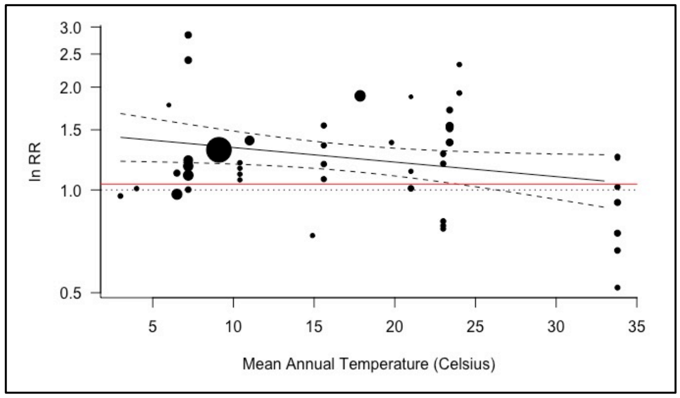



```
Mixed-Effects Model (k = 28; tau^2 estimator: HE)

  logLik  deviance       AIC       BIC      AICc
  2.7782  163.9186    0.4436    4.4402    1.4436

tau^2 (estimated amount of residual heterogeneity):     0.0458 (SE = 0.0148)
tau (square root of estimated tau^2 value):             0.2140
I^2 (residual heterogeneity / unaccounted variability): 99.82%
H^2 (unaccounted variability / sampling variability):   565.01
R^2 (amount of heterogeneity accounted for):            0.00%

Test for Residual Heterogeneity:
QE(df = 26) = 8707.8415, p-val < .0001

Test of Moderators (coefficient(s) 2):
QM(df = 1) = 0.1587, p-val = 0.6904

Model Results:

         estimate      se     zval    pval    ci.lb   ci.ub
intrcpt    0.1722  0.1041   1.6531  0.0983  -0.0320  0.3763  .
time      -0.0025  0.0064  -0.3983  0.6904  -0.0151  0.0100

---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

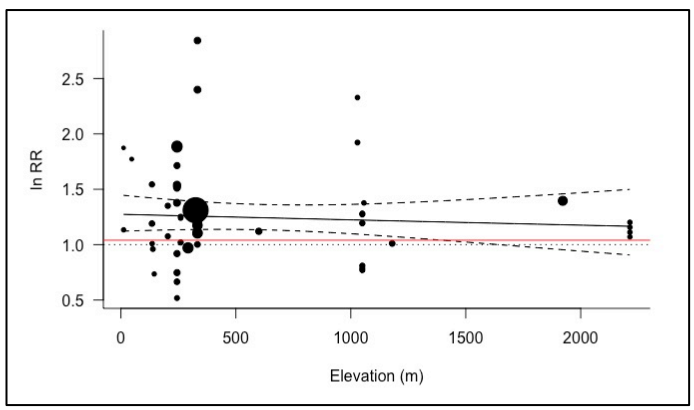
Appendix F. Linear meta-regressions for climatic, physical, and management variables in conventional agricultural land converted to agrisilviculture



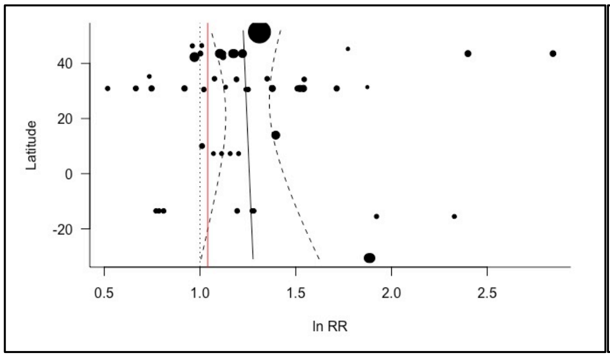

```
Mixed-Effects Model (k = 54; tau^2 estimator: HE)

  logLik  deviance       AIC       BIC      AICc
-17.8177  237.5637   41.6354   47.6024   42.1154

tau^2 (estimated amount of residual heterogeneity):     0.1135 (SE = 0.0239)
tau (square root of estimated tau^2 value):             0.3369
I^2 (residual heterogeneity / unaccounted variability): 98.64%
H^2 (unaccounted variability / sampling variability):   73.31
R^2 (amount of heterogeneity accounted for):            3.08%

Test for Residual Heterogeneity:
QE(df = 52) = 1927.2961, p-val < .0001

Test of Moderators (coefficient(s) 2):
QM(df = 1) = 2.3205, p-val = 0.1277

Model Results:

         estimate      se     zval    pval    ci.lb   ci.ub
intrcpt    0.3661  0.1082   3.3827  0.0007   0.1540  0.5782  ***
map       -0.0002  0.0001  -1.5233  0.1277  -0.0005  0.0001

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```



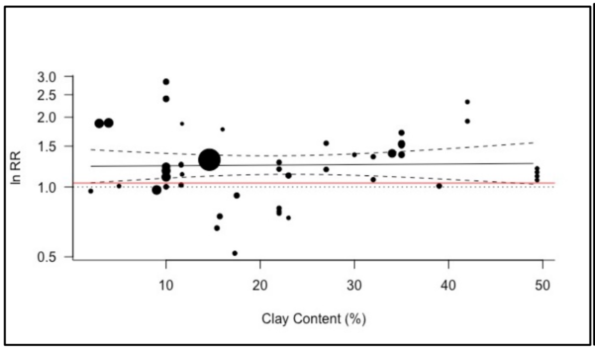

```
Mixed-Effects Model (k = 54; tau^2 estimator: HE)

  logLik  deviance       AIC       BIC      AICc
-17.0252  235.9788   40.0505   46.0174   40.5305

tau^2 (estimated amount of residual heterogeneity):     0.1098 (SE = 0.0231)
tau (square root of estimated tau^2 value):             0.3314
I^2 (residual heterogeneity / unaccounted variability): 98.54%
H^2 (unaccounted variability / sampling variability):   68.33
R^2 (amount of heterogeneity accounted for):            6.27%

Test for Residual Heterogeneity:
QE(df = 52) = 2163.6430, p-val < .0001

Test of Moderators (coefficient(s) 2):
QM(df = 1) = 3.8538, p-val = 0.0496

Model Results:

         estimate      se     zval    pval    ci.lb    ci.ub
intrcpt    0.3845  0.0969   3.9676  <.0001   0.1946   0.5744  ***
mat       -0.0098  0.0050  -1.9631  0.0496  -0.0196  -0.0000    *

---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```



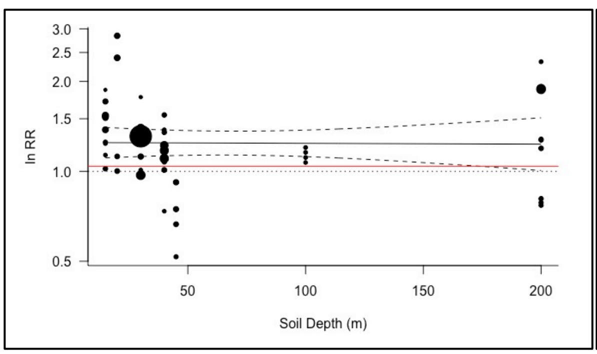

```
Mixed-Effects Model (k = 54; tau^2 estimator: HE)

  logLik  deviance       AIC       BIC      AICc
-18.9106  239.7496   43.8213   49.7882   44.3013

tau^2 (estimated amount of residual heterogeneity):     0.1186 (SE = 0.0248)
tau (square root of estimated tau^2 value):             0.3444
I^2 (residual heterogeneity / unaccounted variability): 98.67%
H^2 (unaccounted variability / sampling variability):   75.36
R^2 (amount of heterogeneity accounted for):            0.00%

Test for Residual Heterogeneity:
QE(df = 52) = 2157.4807, p-val < .0001

Test of Moderators (coefficient(s) 2):
QM(df = 1) = 0.2785, p-val = 0.5977

Model Results:

         estimate      se     zval    pval    ci.lb   ci.ub
intrcpt    0.2426  0.0671   3.6165  0.0003   0.1111  0.3741  ***
elev      -0.0000  0.0001  -0.5277  0.5977  -0.0002  0.0001

---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```



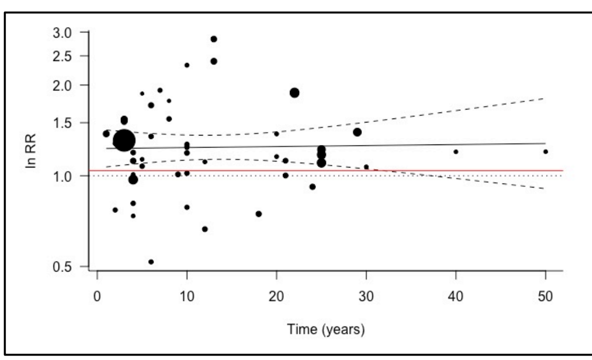

```
Mixed-Effects Model (k = 54; tau^2 estimator: HE)

  logLik  deviance       AIC       BIC      AICc
-19.0405  240.0092   44.0809   50.0479   44.5609

tau^2 (estimated amount of residual heterogeneity):     0.1195 (SE = 0.0250)
tau (square root of estimated tau^2 value):             0.3457
I^2 (residual heterogeneity / unaccounted variability): 98.54%
H^2 (unaccounted variability / sampling variability):   68.65
R^2 (amount of heterogeneity accounted for):            0.00%

Test for Residual Heterogeneity:
QE(df = 52) = 1886.6772, p-val < .0001

Test of Moderators (coefficient(s) 2):
QM(df = 1) = 0.0501, p-val = 0.8228

Model Results:

         estimate      se     zval    pval    ci.lb   ci.ub
intrcpt    0.2293  0.0696   3.2924  0.0010   0.0928  0.3657  ***
lat       -0.0005  0.0021  -0.2239  0.8228  -0.0047  0.0037

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```




```
Mixed-Effects Model (k = 54; tau^2 estimator: HE)

  logLik  deviance       AIC       BIC      AICc
-19.0542  240.0366   44.1083   50.0753   44.5883

tau^2 (estimated amount of residual heterogeneity):     0.1196 (SE = 0.0250)
tau (square root of estimated tau^2 value):             0.3458
I^2 (residual heterogeneity / unaccounted variability): 98.69%
H^2 (unaccounted variability / sampling variability):   76.62
R^2 (amount of heterogeneity accounted for):            0.00%

Test for Residual Heterogeneity:
QE(df = 52) = 2157.9951, p-val < .0001

Test of Moderators (coefficient(s) 2):
QM(df = 1) = 0.0249, p-val = 0.8745

Model Results:

         estimate      se     zval    pval    ci.lb   ci.ub
intrcpt    0.2056  0.0925  2.2238  0.0262   0.0244  0.3868  *
clay       0.0006  0.0036  0.1579  0.8745  -0.0064  0.0076

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

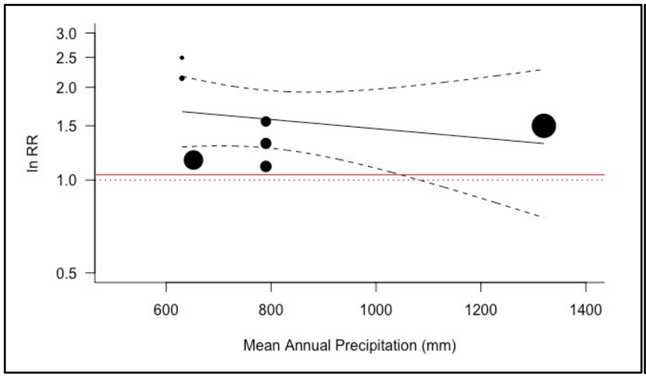



```
Mixed-Effects Model (k = 54; tau^2 estimator: HE)

  logLik  deviance       AIC       BIC      AICc
-19.0590  240.0463   44.1180   50.0850   44.5980

tau^2 (estimated amount of residual heterogeneity):     0.1194 (SE = 0.0250)
tau (square root of estimated tau^2 value):             0.3455
I^2 (residual heterogeneity / unaccounted variability): 98.63%
H^2 (unaccounted variability / sampling variability):   73.01
R^2 (amount of heterogeneity accounted for):            0.00%

Test for Residual Heterogeneity:
QE(df = 52) = 1941.1521, p-val < .0001

Test of Moderators (coefficient(s) 2):
QM(df = 1) = 0.0087, p-val = 0.9259

Model Results:

           estimate      se     zval    pval    ci.lb   ci.ub
intrcpt      0.2226  0.0686   3.2423  0.0012   0.0880  0.3571  **
soildepth   -0.0001  0.0007  -0.0930  0.9259  -0.0015  0.0013

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

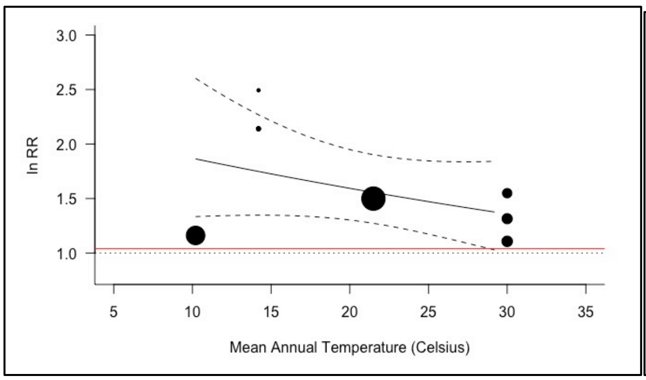



```
Mixed-Effects Model (k = 54; tau^2 estimator: HE)

  logLik  deviance       AIC       BIC      AICc
-19.0526  240.0335   44.1052   50.0721   44.5852

tau^2 (estimated amount of residual heterogeneity):     0.1195 (SE = 0.0250)
tau (square root of estimated tau^2 value):             0.3457
I^2 (residual heterogeneity / unaccounted variability): 98.48%
H^2 (unaccounted variability / sampling variability):   65.86
R^2 (amount of heterogeneity accounted for):            0.00%

Test for Residual Heterogeneity:
QE(df = 52) = 2160.5347, p-val < .0001

Test of Moderators (coefficient(s) 2):
QM(df = 1) = 0.0262, p-val = 0.8714

Model Results:

         estimate      se     zval    pval    ci.lb   ci.ub
intrcpt    0.2082  0.0777  2.6780  0.0074   0.0558  0.3606  **
time       0.0008  0.0047  0.1618  0.8714  -0.0085  0.0100

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

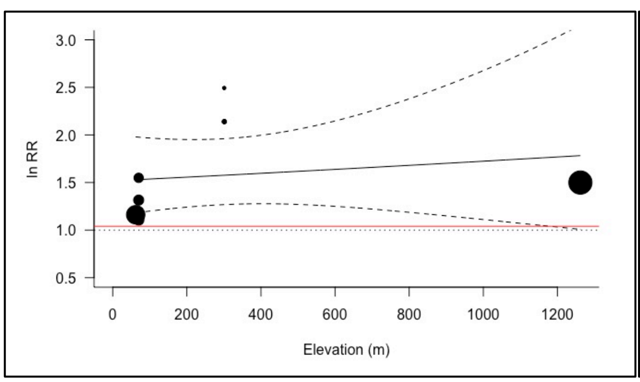
Appendix G. Linear meta-regressions for climatic, physical, and management variables in conventional agricultural land converted to silvopasture



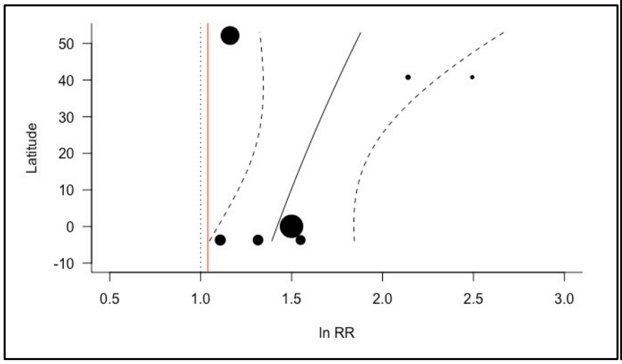

```
Mixed-Effects Model (k = 8; tau^2 estimator: HE)

  logLik  deviance       AIC       BIC      AICc
 -0.9922   25.2061    7.9844    8.2227   13.9844

tau^2 (estimated amount of residual heterogeneity):     0.0849 (SE = 0.0564)
tau (square root of estimated tau^2 value):             0.2914
I^2 (residual heterogeneity / unaccounted variability): 90.19%
H^2 (unaccounted variability / sampling variability):   10.20
R^2 (amount of heterogeneity accounted for):            0.00%

Test for Residual Heterogeneity:
QE(df = 6) = 52.9175, p-val < .0001

Test of Moderators (coefficient(s) 2):
QM(df = 1) = 0.4967, p-val = 0.4810

Model Results:

         estimate      se     zval    pval    ci.lb   ci.ub
intrcpt    0.7288  0.4022   1.8119  0.0700  -0.0596  1.5172  .
map       -0.0003  0.0005  -0.7048  0.4810  -0.0013  0.0006

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```



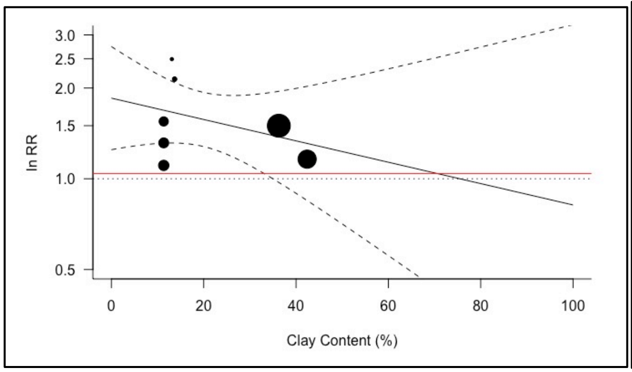

```
Mixed-Effects Model (k = 8; tau^2 estimator: HE)

  logLik  deviance       AIC       BIC      AICc
 -0.3494   23.9204    6.6987    6.9371   12.6987

tau^2 (estimated amount of residual heterogeneity):     0.0696 (SE = 0.0471)
tau (square root of estimated tau^2 value):             0.2639
I^2 (residual heterogeneity / unaccounted variability): 90.22%
H^2 (unaccounted variability / sampling variability):   10.23
R^2 (amount of heterogeneity accounted for):            14.00%

Test for Residual Heterogeneity:
QE(df = 6) = 53.9101, p-val < .0001

Test of Moderators (coefficient(s) 2):
QM(df = 1) = 1.5799, p-val = 0.2088

Model Results:

         estimate      se     zval    pval    ci.lb   ci.ub
intrcpt    0.7830  0.2814   2.7825  0.0054   0.2315  1.3346  **
mat       -0.0159  0.0126  -1.2569  0.2088  -0.0406  0.0089

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```



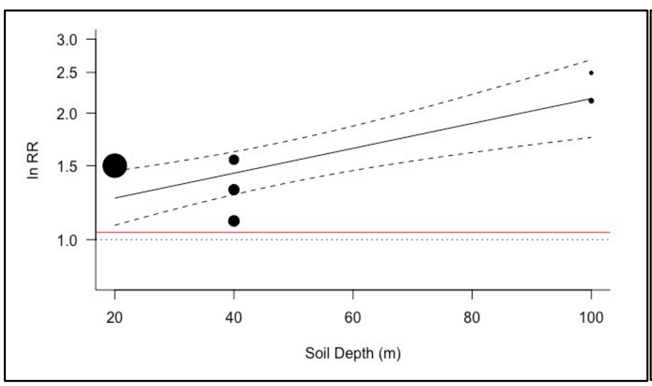

```
Mixed-Effects Model (k = 8; tau^2 estimator: HE)

  logLik  deviance       AIC       BIC      AICc
 -1.2061   25.6339    8.4122    8.6505   14.4122

tau^2 (estimated amount of residual heterogeneity):     0.0916 (SE = 0.0605)
tau (square root of estimated tau^2 value):             0.3027
I^2 (residual heterogeneity / unaccounted variability): 90.79%
H^2 (unaccounted variability / sampling variability):   10.86
R^2 (amount of heterogeneity accounted for):            0.00%

Test for Residual Heterogeneity:
QE(df = 6) = 48.5746, p-val < .0001

Test of Moderators (coefficient(s) 2):
QM(df = 1) = 0.1971, p-val = 0.6571

Model Results:

         estimate      se     zval    pval    ci.lb   ci.ub
intrcpt    0.4175  0.1443   2.8924  0.0038   0.1346  0.7004  **
elev       0.0001  0.0003   0.4440  0.6571  -0.0004  0.0007

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```



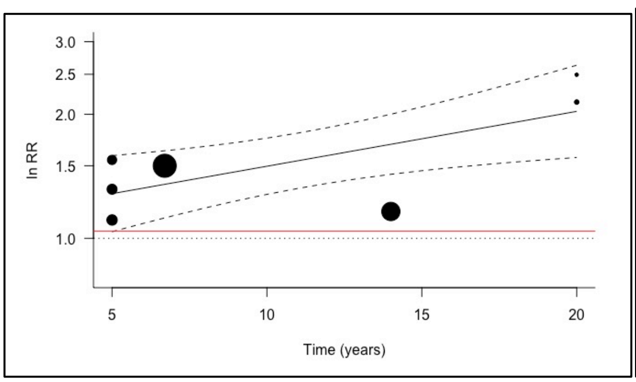

```
Mixed-Effects Model (k = 8; tau^2 estimator: HE)

  logLik  deviance       AIC       BIC      AICc
 -0.3720   23.9657    6.7440    6.9823   12.7440

tau^2 (estimated amount of residual heterogeneity):     0.0698 (SE = 0.0472)
tau (square root of estimated tau^2 value):             0.2642
I^2 (residual heterogeneity / unaccounted variability): 89.59%
H^2 (unaccounted variability / sampling variability):   9.60
R^2 (amount of heterogeneity accounted for):            13.79%

Test for Residual Heterogeneity:
QE(df = 6) = 53.9009, p-val < .0001

Test of Moderators (coefficient(s) 2):
QM(df = 1) = 1.5359, p-val = 0.2152

Model Results:

         estimate      se    zval    pval    ci.lb   ci.ub
intrcpt    0.3508  0.1297  2.7054  0.0068   0.0967  0.6050  **
lat        0.0053  0.0042  1.2393  0.2152  -0.0031  0.0136

---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```




```
Mixed-Effects Model (k = 8; tau^2 estimator: HE)

  logLik  deviance       AIC       BIC      AICc
 -0.7774   24.7765    7.5548    7.7931   13.5548

tau^2 (estimated amount of residual heterogeneity):     0.0811 (SE = 0.0542)
tau (square root of estimated tau^2 value):             0.2847
I^2 (residual heterogeneity / unaccounted variability): 91.37%
H^2 (unaccounted variability / sampling variability):   11.59
R^2 (amount of heterogeneity accounted for):            0.00%

Test for Residual Heterogeneity:
QE(df = 6) = 48.9129, p-val < .0001

Test of Moderators (coefficient(s) 2):
QM(df = 1) = 0.8619, p-val = 0.3532

Model Results:

         estimate      se     zval    pval    ci.lb   ci.ub
intrcpt    0.6167  0.2043   3.0187  0.0025   0.2163  1.0171  **
clay      -0.0082  0.0088  -0.9284  0.3532  -0.0254  0.0091

---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

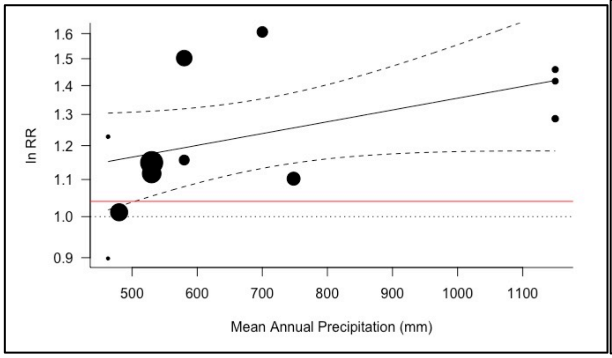



```
Mixed-Effects Model (k = 8; tau^2 estimator: HE)

  logLik  deviance       AIC       BIC      AICc
  4.3644   14.4929   -2.7288   -2.4905    3.2712

tau^2 (estimated amount of residual heterogeneity):     0.0109 (SE = 0.0134)
tau (square root of estimated tau^2 value):             0.1045
I^2 (residual heterogeneity / unaccounted variability): 61.30%
H^2 (unaccounted variability / sampling variability):   2.58
R^2 (amount of heterogeneity accounted for):            86.51%

Test for Residual Heterogeneity:
QE(df = 6) = 23.3203, p-val = 0.0007

Test of Moderators (coefficient(s) 2):
QM(df = 1) = 18.9096, p-val < .0001

Model Results:

           estimate      se    zval    pval    ci.lb   ci.ub
intrcpt      0.0990  0.0855  1.1575  0.2471  -0.0686  0.2666
soildepth    0.0067  0.0015  4.3485  <.0001   0.0037  0.0097  ***

---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

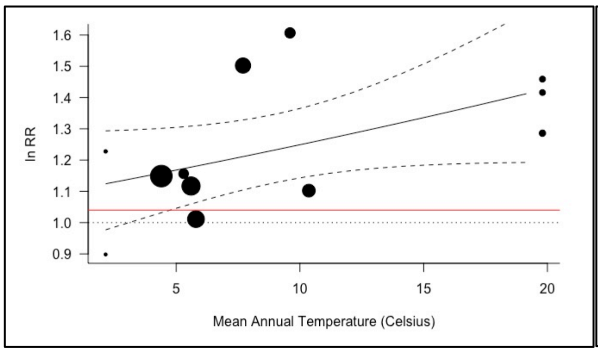



```
Mixed-Effects Model (k = 8; tau^2 estimator: HE)

  logLik  deviance       AIC       BIC      AICc
  1.9558   19.3102    2.0884    2.3268    8.0884

tau^2 (estimated amount of residual heterogeneity):     0.0313 (SE = 0.0248)
tau (square root of estimated tau^2 value):             0.1769
I^2 (residual heterogeneity / unaccounted variability): 81.47%
H^2 (unaccounted variability / sampling variability):   5.40
R^2 (amount of heterogeneity accounted for):            61.36%

Test for Residual Heterogeneity:
QE(df = 6) = 46.4146, p-val < .0001

Test of Moderators (coefficient(s) 2):
QM(df = 1) = 7.5211, p-val = 0.0061

Model Results:

         estimate      se    zval    pval    ci.lb   ci.ub
intrcpt    0.0983  0.1419  0.6932  0.4882  -0.1797  0.3764
time       0.0302  0.0110  2.7425  0.0061   0.0086  0.0518  **

---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

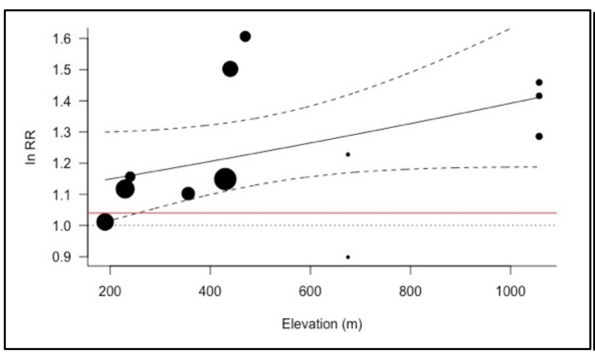
Appendix H. Linear meta-regressions for climatic, physical, and management variables in conventional agricultural land converted to shelterbelts, windbreaks, or riparian buffers



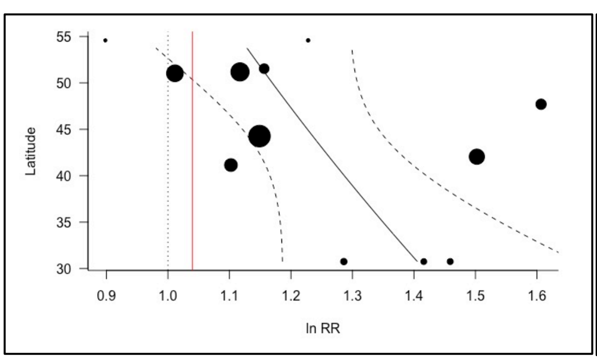

```
Mixed-Effects Model (k = 12; tau^2 estimator: HE)

  logLik  deviance       AIC       BIC      AICc
  6.2411   32.5202   -6.4823   -5.0276   -3.4823

tau^2 (estimated amount of residual heterogeneity):     0.0136 (SE = 0.0122)
tau (square root of estimated tau^2 value):             0.1164
I^2 (residual heterogeneity / unaccounted variability): 87.63%
H^2 (unaccounted variability / sampling variability):   8.09
R^2 (amount of heterogeneity accounted for):            31.59%

Test for Residual Heterogeneity:
QE(df = 10) = 107.1094, p-val < .0001

Test of Moderators (coefficient(s) 2):
QM(df = 1) = 3.5181, p-val = 0.0607

Model Results:

         estimate      se    zval    pval    ci.lb   ci.ub
intrcpt    0.0029  0.1195  0.0246  0.9804  -0.2314  0.2372
map        0.0003  0.0002  1.8757  0.0607  -0.0000  0.0006  .

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```



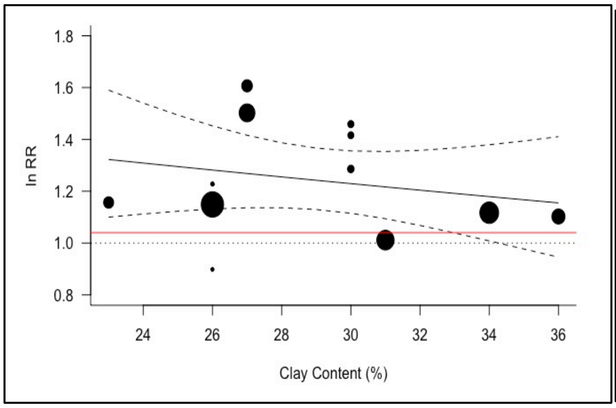

```
Mixed-Effects Model (k = 12; tau^2 estimator: HE)

  logLik  deviance       AIC       BIC      AICc
  6.3680   32.2665   -6.7360   -5.2813   -3.7360

tau^2 (estimated amount of residual heterogeneity):     0.0128 (SE = 0.0117)
tau (square root of estimated tau^2 value):             0.1129
I^2 (residual heterogeneity / unaccounted variability): 86.78%
H^2 (unaccounted variability / sampling variability):   7.56
R^2 (amount of heterogeneity accounted for):            35.62%

Test for Residual Heterogeneity:
QE(df = 10) = 105.5939, p-val < .0001

Test of Moderators (coefficient(s) 2):
QM(df = 1) = 4.0060, p-val = 0.0453

Model Results:

         estimate      se    zval    pval    ci.lb   ci.ub
intrcpt    0.0889  0.0736  1.2080  0.2271  -0.0554  0.2332
mat        0.0134  0.0067  2.0015  0.0453   0.0003  0.0266  *

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```



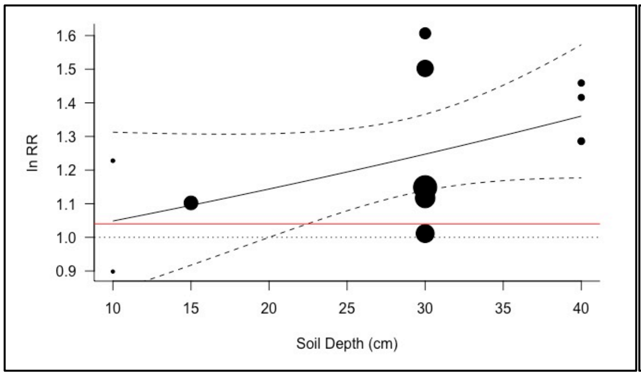

```
Mixed-Effects Model (k = 12; tau^2 estimator: HE)

  logLik  deviance       AIC       BIC      AICc
  6.2320   32.5385   -6.4639   -5.0092   -3.4639

tau^2 (estimated amount of residual heterogeneity):     0.0173 (SE = 0.0141)
tau (square root of estimated tau^2 value):             0.1315
I^2 (residual heterogeneity / unaccounted variability): 89.91%
H^2 (unaccounted variability / sampling variability):   9.91
R^2 (amount of heterogeneity accounted for):            12.69%

Test for Residual Heterogeneity:
QE(df = 10) = 90.6633, p-val < .0001

Test of Moderators (coefficient(s) 2):
QM(df = 1) = 2.9253, p-val = 0.0872

Model Results:

         estimate      se    zval    pval    ci.lb   ci.ub
intrcpt    0.0909  0.0848  1.0724  0.2835  -0.0753  0.2571
elev       0.0002  0.0001  1.7103  0.0872  -0.0000  0.0005  .

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```



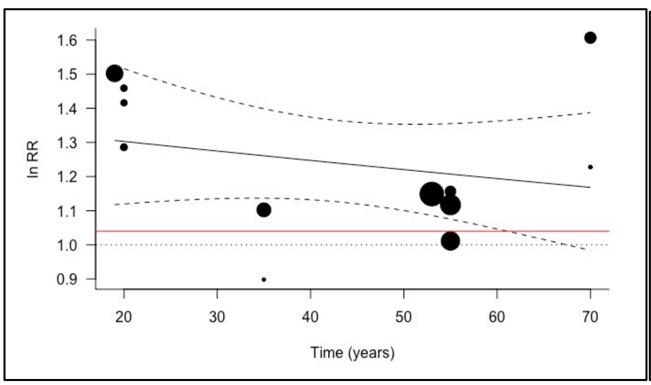

```
Mixed-Effects Model (k = 12; tau^2 estimator: HE)

  logLik  deviance       AIC       BIC      AICc
  6.2719   32.4587   -6.5437   -5.0890   -3.5437

tau^2 (estimated amount of residual heterogeneity):     0.0132 (SE = 0.0118)
tau (square root of estimated tau^2 value):             0.1151
I^2 (residual heterogeneity / unaccounted variability): 86.84%
H^2 (unaccounted variability / sampling variability):   7.60
R^2 (amount of heterogeneity accounted for):            33.18%

Test for Residual Heterogeneity:
QE(df = 10) = 99.5605, p-val < .0001

Test of Moderators (coefficient(s) 2):
QM(df = 1) = 3.6657, p-val = 0.0555

Model Results:

         estimate      se     zval    pval    ci.lb   ci.ub
intrcpt    0.6339  0.2226   2.8476  0.0044   0.1976  1.0702  **
lat       -0.0095  0.0050  -1.9146  0.0555  -0.0193  0.0002   .

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```




```
Mixed-Effects Model (k = 12; tau^2 estimator: HE)

  logLik  deviance       AIC       BIC      AICc
  5.1083   34.7858   -4.2167   -2.7620   -1.2167

tau^2 (estimated amount of residual heterogeneity):     0.0221 (SE = 0.0158)
tau (square root of estimated tau^2 value):             0.1486
I^2 (residual heterogeneity / unaccounted variability): 90.99%
H^2 (unaccounted variability / sampling variability):   11.10
R^2 (amount of heterogeneity accounted for):            0.00%

Test for Residual Heterogeneity:
QE(df = 10) = 111.1460, p-val < .0001

Test of Moderators (coefficient(s) 2):
QM(df = 1) = 0.6372, p-val = 0.4247

Model Results:

         estimate      se     zval    pval    ci.lb   ci.ub
intrcpt    0.5192  0.3837   1.3531  0.1760  -0.2329  1.2713
clay      -0.0104  0.0131  -0.7982  0.4247  -0.0360  0.0152

---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```




```
Mixed-Effects Model (k = 12; tau^2 estimator: HE)

  logLik  deviance       AIC       BIC      AICc
  6.0967   32.8091   -6.1934   -4.7387   -3.1934

tau^2 (estimated amount of residual heterogeneity):     0.0139 (SE = 0.0115)
tau (square root of estimated tau^2 value):             0.1179
I^2 (residual heterogeneity / unaccounted variability): 87.72%
H^2 (unaccounted variability / sampling variability):   8.15
R^2 (amount of heterogeneity accounted for):            29.85%

Test for Residual Heterogeneity:
QE(df = 10) = 121.7707, p-val < .0001

Test of Moderators (coefficient(s) 2):
QM(df = 1) = 3.1439, p-val = 0.0762

Model Results:

           estimate      se     zval    pval    ci.lb   ci.ub
intrcpt     -0.0399  0.1490  -0.2678  0.7889  -0.3319  0.2521
soildepth    0.0087  0.0049   1.7731  0.0762  -0.0009  0.0182  .

---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```




```
Mixed-Effects Model (k = 12; tau^2 estimator: HE)

  logLik  deviance       AIC       BIC      AICc
  5.1505   34.7014   -4.3011   -2.8463   -1.3011

tau^2 (estimated amount of residual heterogeneity):     0.0216 (SE = 0.0154)
tau (square root of estimated tau^2 value):             0.1470
I^2 (residual heterogeneity / unaccounted variability): 91.33%
H^2 (unaccounted variability / sampling variability):   11.54
R^2 (amount of heterogeneity accounted for):            0.00%

Test for Residual Heterogeneity:
QE(df = 10) = 104.0520, p-val < .0001

Test of Moderators (coefficient(s) 2):
QM(df = 1) = 0.7047, p-val = 0.4012

Model Results:

         estimate      se     zval    pval    ci.lb   ci.ub
intrcpt    0.3086  0.1210   2.5509  0.0107   0.0715  0.5457  *
time      -0.0022  0.0026  -0.8395  0.4012  -0.0073  0.0029

---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Appendix I. Soil organic carbon rates calculated under the random-effects model

Results per region

```
Test for Residual Heterogeneity:
QE(df = 96) = 816861.7186, p-val < .0001

Test of Moderators (coefficient(s) 2:6):
QM(df = 5) = 1.1733, p-val = 0.9474

Model Results:

                                     estimate      se     zval    pval    ci.lb   c
intrcpt                                0.3868  1.2372   0.3126  0.7545  -2.0381  2.
agzoneSubtropics, warm/mod, cool       0.9557  1.5154   0.6307  0.5282  -2.0143  3.
agzoneTemperate, cool                  0.6019  1.4572   0.4131  0.6796  -2.2541  3.
agzoneTemperate, very cold            -0.3765  3.2765  -0.1149  0.9085  -6.7983  6.
agzoneTropics, cold/cold/very cold     0.3743  2.1432   0.1747  0.8613  -3.8264  4.
agzoneTropics, warm                    1.3533  1.4870   0.9101  0.3628  -1.5612  4.

---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Results for all AF systems included

```
Random-Effects Model (k = 102; tau^2 estimator: HE)

  logLik   deviance        AIC        BIC       AICc
-290.7235  1021.0745   585.4471   590.6970   585.5683

tau^2 (estimated amount of total heterogeneity): 17.6705 (SE = 2.4877)
tau (square root of estimated tau^2 value):      4.2036
I^2 (total heterogeneity / total variability):   100.00%
H^2 (total variability / sampling variability):  69388.93

Test for Heterogeneity:
Q(df = 101) = 1408640.9344, p-val < .0001

Model Results:

estimate      se    zval    pval   ci.lb   ci.ub
  1.1675  0.4163  2.8043  0.0050  0.3515  1.9834  **

---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Alley Cropping

```
Random-Effects Model (k = 28; tau^2 estimator: HE)

tau^2 (estimated amount of total heterogeneity): 0.0441 (SE = 0.0141)
tau (square root of estimated tau^2 value):      0.2100
I^2 (total heterogeneity / total variability):   99.82%
H^2 (total variability / sampling variability):  562.47

Test for Heterogeneity:
Q(df = 27) = 10338.5508, p-val < .0001

Model Results:

estimate      se    zval    pval   ci.lb   ci.ub
  0.1346  0.0413  3.2566  0.0011  0.0536  0.2156  **

---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Agrisilviculture

```
Random-Effects Model (k = 54; tau^2 estimator: HE)

tau^2 (estimated amount of total heterogeneity): 0.1171 (SE = 0.0243)
tau (square root of estimated tau^2 value):      0.3423
I^2 (total heterogeneity / total variability):   98.68%
H^2 (total variability / sampling variability):  75.70

Test for Heterogeneity:
Q(df = 53) = 2164.5950, p-val < .0001

Model Results:

estimate      se    zval    pval   ci.lb   ci.ub
  0.2179  0.0479  4.5473  <.0001  0.1240  0.3119  ***

---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Silvopasture

```
Random-Effects Model (k = 8; tau^2 estimator: HE)

tau^2 (estimated amount of total heterogeneity): 0.0810 (SE = 0.0496)
tau (square root of estimated tau^2 value):      0.2845
I^2 (total heterogeneity / total variability):   92.01%
H^2 (total variability / sampling variability):  12.51

Test for Heterogeneity:
Q(df = 7) = 54.0066, p-val < .0001

Model Results:

estimate      se    zval    pval   ci.lb   ci.ub
  0.4552  0.1071  4.2487  <.0001  0.2452  0.6652  ***

---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Shelterbelts, Windbreaks, and Riparian Buffers

```
Random-Effects Model (k = 12; tau^2 estimator: HE)

tau^2 (estimated amount of total heterogeneity): 0.0198 (SE = 0.0
tau (square root of estimated tau^2 value):      0.1407
I^2 (total heterogeneity / total variability):   90.97%
H^2 (total variability / sampling variability):  11.07

Test for Heterogeneity:
Q(df = 11) = 130.7038, p-val < .0001

Model Results:

estimate      se    zval    pval   ci.lb   ci.ub
  0.2153  0.0463  4.6474  <.0001  0.1245  0.3061  ***

---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Appendix J. Net Present Value calculations for AF projects with a high and low soil C sequestration rate with different interest rates and duration of projects.

				Discount Rates (%)			Duration of Project (years)			
C Seq Rate (Mg C ha-1 yr-1)	CO2e Seq (Mg CO2e ha-1 yr-1)	C Price (COP$/t C)	Soil C Price (COP$/t CO2e ha yr)	2	4	6	5	10	20	NPV
1.35	4.96	$ 10,000.00	$ 49,621.00	■			■			$ 642,777.16
				■				■		$ 2,329,094.89
				■					■	$ 7,936,966.65
					■		■			$ 595,774.15
					■			■		$ 2,034,076.34
					■				■	$ 6,160,695.84
						■	■			$ 553,120.94
						■		■		$ 1,784,490.67
						■			■	$ 4,847,989.86
0.13	0.49	$ 10,000.00	$ 4,935.33	■			■			$ 63,930.94
				■				■		$ 231,653.12
				■					■	$ 789,415.29
					■		■			$ 59,256.00
					■			■		$ 202,310.41
					■				■	$ 612,746.37
						■	■			$ 55,013.69
						■		■		$ 177,486.47
						■			■	$ 482,183.87
1.35	4.96	$ 15,000.00	$ 74,431.50	■			■			$ 964,165.74
				■				■		$ 3,493,642.33
				■					■	$ 11,905,449.98
					■		■			$ 893,661.23
					■			■		$ 3,051,114.51
					■				■	$ 9,241,043.77
						■	■			$ 829,681.42
						■		■		$ 2,676,736.00
						■			■	$ 7,271,984.78
0.13	0.49	$ 15,000.00	$ 7,403.00	■			■			$ 95,896.48
				■				■		$ 347,479.68
				■					■	$ 1,184,122.93
					■		■			$ 88,884.06
					■			■		$ 303,465.61
					■				■	$ 919,119.55
						■	■			$ 82,520.59
						■		■		$ 266,229.71
						■			■	$ 723,275.81
1.35	4.96	$ 20,000.00	$ 99,242.00	■			■			$ 1,285,554.32
				■				■		$ 4,658,189.77
				■					■	$ 15,873,933.31
					■		■			$ 1,191,548.31
					■			■		$ 4,068,152.68
					■				■	$ 12,321,391.69
						■	■			$ 1,106,241.89
						■		■		$ 3,568,981.34
						■			■	$ 9,695,979.71
0.13	0.49	$ 20,000.00	$ 9,870.67	■			■			$ 127,861.98
				■				■		$ 463,306.25
				■					■	$ 1,578,830.58
					■		■			$ 118,512.08
					■			■		$ 404,620.82
					■				■	$ 1,225,492.74
						■	■			$ 110,027.46
						■		■		$ 354,972.95
						■			■	$ 964,367.75
1.35	4.96	$ 25,000.00	$ 124,052.50	■			■			$ 1,606,942.90
				■				■		$ 5,822,737.22
				■					■	$ 19,842,416.63
					■		■			$ 1,489,435.38
					■			■		$ 5,085,190.85
					■				■	$ 15,401,739.61
						■	■			$ 1,382,802.36
						■		■		$ 4,461,226.67
						■			■	$ 12,119,974.64
0.13	0.49	$ 25,000.00	$ 12,338.33	■			■			$ 159,827.00
				■				■		$ 579,132.81
				■					■	$ 1,973,538.22
					■		■			$ 148,140.06
					■			■		$ 505,776.02
					■				■	$ 1,531,865.92
						■	■			$ 137,534.28
						■		■		$ 443,716.18
						■			■	$ 1,205,459.68

Shaded areas indicate the discount rate and the duration of the project used in the calculation of the net present value (NPV). For instance: the first row is the NPV for an AF project with a sequestration rate of 1.35 Mg C ha^{-1} yr^{-1}, with a set C price of COP$10,000 with a discount rate of 2% for a 5-year long project.