DISENTANGLING THE CONNECTIONS BETWEEN MANAGEMENT, SOIL HEALTH, AND CROP PRODUCTIVITY AT FIELD AND REGIONAL SCALES

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DISENTANGLING THE CONNECTIONS BETWEEN MANAGEMENT, SOIL HEALTH, AND CROP PRODUCTIVITY AT FIELD AND REGIONAL SCALES

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The expansion of agriculture and unsustainable management strategies have resulted in severe soil depletion, compromising soil functionality, and the ecosystem services it provides. Understanding the drivers of Soil Health (SH) is crucial for developing effective strategies and promoting sustainable management. This research presents the results of four interrelated projects conducted in Uruguay, and New York State, USA. The projects aim to enhance our understanding of SH drivers at different scales and their connection with anthropogenic management and crop productivity.

The research highlights the negative impacts of replacing natural grassland with annually cultivated areas, and underscores the benefits of various conservation practices. It provides a comprehensive set of reference values for evaluating SH indicators in the Pampas region. The study also demonstrates the critical influence of soil organic carbon degradation on cereal productivity losses under annual crop rotations and its relationship with a broader set of SH indicators. To understand the driving force of management in SH, a methodological framework based on the critical zone approach is presented. It proposes using aboveground biomass inputs, which account for 50% of SH variations, as an indicator for potential agronomic management

effects on SH. Management scenarios for the Pampas region are evaluated to showcase the applicability of this approach in assessing sustainable management practices.

Furthermore, high-resolution spatial data, machine learning models, and digital soil mapping techniques are employed to develop SH prediction models and maps, as well as identify the main drivers of SH at a regional scale in New York State, USA. Overall, the findings emphasize the complexity of SH drivers and the need for comprehensive assessments that consider context-specific conditions, which includes an understanding of management effects on biomass fluxes within a land use system and region. Overall, this research contributes to advancing our knowledge of the complex interplay between inherent soil properties and human activities on SH and provides insights into the design of management strategies that promote sustainable soil management.

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who have empowered me to reach new heights in my journey.

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1: INTRODUCTION

1.1. RESEARCH OVERVIEW

The expansion of the agricultural frontier and the accumulated effects of unsustainable management strategies can generate severe soil depletion (Wingeyer et al. 2015a; Beretta-Blanco, Pérez, and Carrasco-Letelier 2019; Novelli, Caviglia, and Piñeiro 2017), compromising soil functionality. Reversing and minimizing soil degradation is needed to optimize soil functioning related to multiple ecosystem services such as food production, carbon sequestration, water quality protection, and the preservation of biodiversity (Keestra et al., 2016).

Soil health (SH) refers to the continued capacity of the soil to function as a vital living ecosystem that sustains plants, animals, and humans (USDA-NRCS 2020). SH can be assessed in many ways, including measuring a comprehensive and hierarchical set of soil physical, biological, and chemical indicators. The status of SH indicators is determined by a complex interplay between inherent soil properties, which settle the baselines soil functional abilities, and anthropogenic activities (Bünemann et al. 2018). This complex interplay between SH drivers obscures the interpretation of SH indicators and drives the need for site-specific evaluations that require intense sampling efforts that may be expensive, time-consuming, and inaccessible for many areas. A deeper understanding of SH drivers is needed to optimize these efforts.

Disentangling the effects of anthropogenic actions and inherent soil properties on SH is needed to fully understand SH status, drivers, and limitations (Miner et al. 2020).

This will contribute to clarifying the often reported confounding benefits of the most promoted conservations or regenerative practices in SH, optimizing the design of sustainable management strategies needed to stop and reverse SH degradation.

This dissertation discusses four interrelated projects that aim to enhance our understanding of SH drivers at different scales, their connection with anthropogenic management, and crop productivity. The projects occurred in two regions, Uruguay, South America, and New York State, USA. The ultimate goal is to provide relevant information for identifying management strategies that promote SH, thereby contributing to global sustainable development goals.

Following this introduction and a discussion of SH conceptual framework, Chapters two to five discuss SH assessment and its impacts on crop productivity within the Uruguayan production context. These are highly relevant for preserving and valuing soils for the South American Pampas. The Pampas experienced the biggest crop production shift globally in the last decades, becoming a central grain production area (Baeza and Paruelo 2020) and threatening one of the world's most extensive natural grassland. Chapter two assesses the impacts of replacing natural grassland with cultivated areas and the benefits of commonly promoted conservation practices (inclusion of perennial grasses and legumes, cover crops, crop diversification, inorganic fertilization, tillage, and pasture duration) on soil biological, chemical, and physical health indicators. Data from three long-term experiments were evaluated and integrated to better understand the potential benefits of sequence intensification, fertilization, and no-tillage in SH under an annual cropping system.

Building on the results presented in chapter two and aiming to elucidate some of the complexities of SH drivers in chapter three, a methodological framework for SH analysis through the lens of the critical zone approach is presented. Estimating aboveground biomass changes is proposed as an intermediate achievable goal to estimate the changes that conservation management can generate in carbon balances and, therefore, SH. Quantitative evidence of aboveground biomass's vital role in SH and potential benefits and limitations are presented. Within this framework, a set of management scenarios for the Pampas regions are evaluated to showcase the potential uses of this approach for the design of more sustainable management practices.

Chapter Four evaluates soil organic Carbon (SOC), the most widely used SH indicator (Bünemann et al. 2018), and assesses the influence of its degradation on cereal productivity and its relationship with a broader set of SH indicators. SOC's critical role in cereal productivity losses under annualized crop rotations was proved by evaluating 56 years of climate, soil, management, and yield data from an Uruguayan long-term experiment.

In chapter five, the conceptual learnings from these studies are applied through a geospatial machine learning approach that focuses on the relationships between climate, inherent soil properties, and land use on SH for the State of New York and regions within the State. High spatial resolution data representing SH drivers, machine learning models, and digital soil mapping techniques were applied to develop SH prediction models and maps and to disentangle the main SH drivers at a regional scale. The potential uses of the generated models for the projection of potential changes in SH associated with regional land were also evaluated.

1.2. SOIL HEALTH CONCEPTUAL FRAMEWORK

The SH concept has become prevalent in soil and environmental sciences relating to the functioning of ecosystem services (Janzen, Janzen, and Gregorich 2021). SH can be considered equivalent to soil quality, yet these concepts are not considered synonyms (J.W. Doran and Parkin 1994). The lack of agreement on a single definition for both SH and soil quality challenges the comparison between concepts. Overall, as an older concept, soil quality has been mainly used to evaluate soil's capability to function with a significant focus on food production and has been assessed mainly by measuring soil chemical properties (Lehmann et al. 2020). SH, which is a newly adopted terminology, usually represents a broad set of soil functions and, therefore, should be assessed by measuring a comprehensive set of soil physical, biological, and chemical indicators.

A criticism of the SH concept is its elusively or ambiguous definition, which can limit research progress. However, this reflects the complexity of the topic that SH aims to represent and the variety of actors adopting the terminology. The more people adopt the SH concept and framework, the harder it will be to agree on a unique definition that integrates different perspectives and priorities. Talking about the health of the soils has proven to promote a deep connection of soils with a bigger audience than the scientific community, as soils are positioned as a living ecosystem. These evoke an instinctive intellectual and emotional response that motivates thoughts and actions arising from a subconscious reflection on our health (Janzen, Janzen, and Gregorich 2021). After all, the term *health* is universally adopted as it relates to human well-being, with the recognition that it needs to be interpreted based on individual circumstances and perspectives.

Furthermore, as SH recognizes soil multifunctionality, it will evolve with the changing social valuation of soil functions. Deciding the value of SH functions involves a value judgment, extending health assessment beyond the laboratory into the social sphere (Janzen, Janzen, and Gregorich 2021; Rapport 1995). Consequently, a rigid and intrinsic definition of SH, considered valid from an academic perspective, is not the ultimate goal. Settling a unique rigid definition of SH and SH assessment might fail to recognize that there is no universally 'optimal' soil nor a universal set of ideal soil characteristics that can feasibly represent all the complex processes in the soil (Bünemann et al. 2018; Lehmann et al. 2020). Like with humans, soil health is contextual, and metrics are tools for assessment that still require interpretation.

From a research perspective, however, a framework that states the minimum requirements for SH assessment should be defined. These should recognize the evolving characteristics of the SH movement, the need for flexibility, and context-specific adaptations, and should also be based on results and research. A certain level of standardization within that flexibility is needed to promote the widespread adoption of SH monitoring and assessment. Some of the recognized requirements for SH assessment include:

1. **Measuring a comprehensive and hierarchical set of soil physical, biological, and chemical indicators**. SH is an abstraction of soil functions that cannot be easily measured. Therefore, SH properties that determine these

functions are assessed by measuring SH indicators. A single indicator usually cannot reflect the complexity of the processes that occur in the soil and determine soil functionality relative to a range of ecosystem objectives. Hence, SH evaluations should integrate a comprehensive set of indicators to reflect multiple physical, chemical, and biological processes in the soil. The targeted processes can vary according to the main soil functions we aim to assess, and the selected SH indicators might be modified accordingly. In this work, it is mainly done in the context of agricultural production environments and their broader environmental impacts. These indicators should be related to soil functions and be relevant to management. Furthermore, to be potentially used by decision-makers, indicators should also be interpretable and inexpensive to collect and measure (John W Doran and Zeiss 2000).

2. **Provide an interpretation framework for the measured indicators:** Measuring SH is only valid if results can be unequivocally interpreted and if reference values are available (Bünemann et al. 2018; Lilburne, Sparling, and Schipper 2004; Sparling and Schipper 2004). The lack of specific benchmarks or interpretation approaches currently limits SH's broader adoption (Yang, Siddique, and Liu 2020). Giving SH indicators a quantitative meaning requires transforming observed values into numerical or categorical scores representing the attribute's relative status (Rinot et al. 2019). Nevertheless, few available approaches provide a clear interpretation scheme for SH indicators (Bünemann et al. 2018), and there is no agreement on the best methodology or references against which SH indicators should be

compared. The Comprehensive Assessment of Soil Health (CASH) of Cornell, which is the framework used in this dissertation, use a peer-based scoring approach based on parameters of the cumulative normal distribution of each indicator over a domain of interest. Developing these scoring functions is challenged by the complexities of site-specific variations in inherent soil properties and land use that drive SH (Bünemann et al., 2018). The definition of the domain should ideally consider the variations in inherent soil properties like texture (Fine, Van Es, and Schindelbeck 2017), climate (Nunes et al. 2021), and land use (Amsili et al., 2023). This requires the generation of a sets of data that are relevant to a production . Alternative approaches, such as the definition of SH Gaps based on the differences between target soil and undisturbed references with similar inherent characteristics, have been proposed (Maharjan, Das, and Acharya 2020). However, knowing the superimposing effect of management in SH, setting pristine conditions as a target for SH establishes unachievable expectations in the potential conditions for the soil under production systems. Furthermore, undisturbed reference areas are not always available.

3. **Provide context-specific references and reflect changes generated by anthropogenic actions**. When evaluating SH, focus is made on understanding anthropogenic actions' effects on soil functional capacity. Having different benchmarks or scores for inherently different soil will allow a better interpretation of the measured values and comparisons of SH among sites. For example, a sandy soil may retain less water than a loamy soil, yet both soils

could be equally healthy in a production environment. Therefore, data of different inherent properties like texture should not be compared directly but rather rated in the context of their different inherent functional capacity. Thereby, the term soil quality refers to the soil's functional capacity, whereas SH refers to the contextual functional capacity, accounting for its inherent potential. The SH concept thus adds the challenge of using context-specific references that account for the effects of inherent soil variations.

Aiming to reflect these minimum requirements in this dissertation, I adopt the term SH defined as "the continued capacity of soil to function as a vital living ecosystem that provides multiple ecosystem services within a given environment" with a focus on the evaluation of dynamic soil properties affected by agronomic management.

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CHAPTER 2: SOIL HEALTH BENEFITS FROM SEQUENCE INTENSIFICATION, FERTILIZATION, AND NO-TILLAGE IN ANNUAL CROPPING SYSTEMS[1]

ABSTRACT

The expansion of annual cropping systems and associated land cover changes may induce soil degradation, compromising the soil's ability to function and provide ecosystem services, also referred to as soil health (SH). Conservation practices may reduce SH decline, yet their benefits are uncertain. The main objectives of this paper were to apply a comprehensive SH assessment framework to evaluate (i) SH differences in natural grasslands and cropping areas, and (ii) how conservation practices lessen SH deterioration. Soils under natural grasslands were compared to cropped soils from three long-term experiments with treatments evaluating the effects of cover crops and/or pastures incorporation; no-tillage; and crop fertilization for Uruguayan Mollisols. Soil chemical (pH, cation exchange capacity, macro, and micro-nutrients), physical (wet aggregate stability, available water holding capacity, penetration resistance), and biological (organic carbon, active carbon, protein, respiration) indicators were measured. SH was significantly lower across all indicators under cropped areas than under natural grasslands, especially when soil fertility is not adequately maintained in cropping systems. Conservation practices

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[1] Rubio, V., Sawchik, J., & van Es, H. (2022). Soil health benefits from sequence intensification, fertilization, and no-tillage in annual cropping systems. *Soil Security, 9*, 100074. https://doi.org/10.1016/j.soisec.2022.100074

lessened SH degradation, particularly soil biological properties, but had confounding benefits. Overall, gains in SH were linked to adequate soil fertility maintenance and longer active plant growth periods associated with including pastures and cover crops in annual cropping system

2.1. INTRODUCTION

The current global shortages in grain supplies is promoting unexpected expansion, intensification, and simplification of annual cropping. Natural grasslands have been converted to annual grain production for centuries due to their high natural fertility and productivity developed under pastures deep rooting systems (Liu et al., 2012). Globally, around 70% of native grasslands have already been converted to cropland or other land uses (Ramankutty et al., 2008).

The South American Pampas, with more than 70 M ha in east-central Argentina, southeastern Brazil, and Uruguay, is one of the world's most extensive natural grassland regions. In the last decade, it experienced the biggest crop production increase globally (Baeza and Paruelo, 2020). This increase is associated with: i) an expansion of the agricultural frontier, limiting remnants of grasslands to marginal areas (Baeza and Paruelo, 2020); and ii) an extraordinary shift from crop pasture rotation to continuous annual cropping systems dominated by soybean (*Glycine max*) monocultures (Wingeyer et al., 2015a). Both have exacerbated soil degradation (Beretta-Blanco et al., 2019; Novelli et al., 2017; Wingeyer et al., 2015[a]). After land conversion, accumulated effects of inadequate management can compromise a soil's ability to provide ecosystem services, also referred to as soil health (SH) (Bünemann et al., 2018; Fine et al., 2017). Grassland soils lost an estimated 50% of their surface soil organic carbon (SOC) contents (Xu et al., 2020), signaling potential limitations for crop growth (Rubio et al., 2021a; van Es and Karlen, 2019). Regenerating grassland soil is critical for securing food production globally and can also contribute to climate change mitigation as the potential C sequestration of these soils is estimated at 10-30% above current global soil carbon stocks (Ghosh, P. K., & Mahanta, 2014; Yang et al., 2019).

Effective conservation management strategies need to be identified to stop and reverse SH degradation and secure soil ecosystem services, but SH is shaped by a complex interplay between agronomic management and inherent soil quality (Fine et al., 2017; Nunes et al., 2020b), as well as economic drivers. Recoupling the traditional crop and pasture rotation might correct the current trend of ecosystem degradation (Carvalho et al., 2021), but economic incentives are generally not favorable. Other strategies like optimization of crop management, adoption of no-tillage, the addition of organic amendments, and the increase in active plant growth periods (diversifying crop rotations or incorporating cover crops) can potentially lessen SH degradation (Dicks et al., 2019; Petersen and Snapp, 2015; Pretty et al., 2018; Wezel et al., 2015).

Moving from conventional tillage to NT systems, however, has inconsistent benefits on surface SOC, the most broadly evaluated SH indicator (Govaerts et al., 2009). Overall, the benefits can be considered minimal (Powlson et al., 2016), but NT has been shown to increase surface SOC in specific cases (e.g., Kinoshita et al., 2017; Nunes et al., 2018; Sharma et al., 2013). Furthermore, when some aspects of SH are enhanced by a conservation practice, others might be weakened. For example, the benefits of NT reducing SOC losses can be offset by an increase in soil compaction (Nunes et al., 2020a; Wander and Bollero, 1999). Also, cover cropping can improve SH by increasing SOC and N contents and by improving soil water holding capacity and structure (Blanco-Canqui et al., 2015; Sainju et al., 2003; Nunes et al., 2018), but it can also reduce nutrient and water availability for subsequent crops (Villamil et al., 2006). These examples highlight the complexities of assessing the suitability and outcomes of different management practices and the importance of comprehensive SH evaluations including biological, physical and chemical properties, which have been limited in the region.

The main objectives of this paper were to apply a comprehensive SH assessment framework to evaluate (i) SH differences in natural grasslands and cropping areas, and (ii) how conservation practices can lessen SH deterioration.. Three long-term field experiments and undisturbed references located in the same soil type and research station in Uruguayan Mollisols, were evaluated. Treatments in these experiments represent regional systems incorporating the most promoted regenerative management practices (fertilization, rotation with perennial pastures, NT, and cover crops) and are contrasted with conventional management.

2.2.MATERIALS AND METHODS

2.2.1. SITE AND EXPERIMENTS

The selected trials are located at La Estanzuela Experimental Station of INIA (Uruguayan National Agricultural Research Institute) in SW Uruguay (34º20 S, 57º41 W, 82 masl). The site has a warm temperate climate, with 50-yr average temperature of 16.6°C (monthly average of 10 °C in July to 23 °C in January). Annual average precipitation is 1100 mm, nearly evenly distributed throughout the year but with high interannual and interseasonal variability. The dominant soil is a Haplic Phaeozem (Vertic, Eutric; World Reference Base; IUSS Working Group, 2015), or Typic Argiudoll (USDA Soil Taxonomy system; Soil Survey Staff, 2010). Soil texture of the surface layer (0-15 cm) is genarally silty clay or silty clay loam, with average values of silt and clay of the experiments of 57% (±2%) and 32% (±2%), respectively. Average initial values of SOC, pH and soil texture are presented in Appendix 2.1.

Three long-term experiments were used to evaluate the impact of different intensification practices on SH. Additionally, samples from nearby undisturbed natural grasslands were evaluated as references of natural conditions. A summary of the experiments is presented in Table 2.1.

Table 2. 1: Treatment descriptions for the three long-term experiments (LTE).

LTE	% pasture	Fertilizer (N+P)	Tillage	Current crop rotation	SII (%)
1	0%	-	CT-NT*	[Barley/Sorghum]-[Wheat/Soybean]-[Fallow/Corn]	52
1	0%	+	CT-NT*	[Barley/Sorghum]-[Wheat/Soybean]-[Fallow/Corn]	52
1	50%	+	CT-NT*	[Barley/Sorghum]-[Wheat/Soybean]-[Fallow/Corn]-3yr.[Pasture]	82
1	66%	+	CT-NT*	[Barley/Red clover]-[Red clover]-[Fallow/Sorghum]-3yr.[Pasture]-[Fallow/Corn]	83
1	33%	+	CT-NT*	[Fallow/Sorghum]- [Wheat/Soybean]-[Red Clover]	74
2	0%	+	MT	[Wheat/Fallow]-[Oat cover crop/Corn]-[Barley/Soybean]	73
2	50%	+	MT	[Wheat/Fallow]-[Oat cover crop/Corn]-[Barley/Soybean]-3yr.[Pasture]	81
2	0%	+	NT	[Wheat/Fallow]-[Oat cover crop/Corn]-[Barley/Soybean]	73
2	50%	+	NT	[Wheat/Fallow]-[Oat cover crop/Corn]-[Barley/Soybean]-3yr.[Pasture]	81
3	0%	+	NT	[Fallow/Soybean]	43
3	0%	+	NT	[Oat cover crop^{early}/Soybean]	82
3	0%	+	NT	[Oat cover crop^{late}/Soybean]	90

*Where: CT: Conventional tillage; NT: No-tillage; *: NT since 2009; MT: Minimum tillage; ([ ]): Crops within one year; (/): Separates winter and summer crops; early: cover crop termination 60 days pre-sowing; late: cover crop termination 30 days pre-sowing. Underlined crops represent soil sampling times for each treatment; SII(%): Average percentage of annual active plant growth since the beginning of the experiment.*

EXPERIMENT 1: Fertilization and Pastures

This trial was established in 1963 to evaluate the effects of fertilizer inputs in continuous annual cropping, and of perennial non-harvested grass-legume pastures (%PS) as part of a rotation with annual crops. Five contrasting treatments were selected for this study (Table 2.1), which were arranged in a randomized complete block design with three staggered blocks. Perennial pastures (a mixture of tall fescue *(Festuca arundinacea* Schreb.), white clover (*Trifolium hybridum* L.), and birdsfoot trefoil (*Lotus corniculatus* L.) are included at 0%, 33%, 50%, and 66% of time in the rotation. Pastures were not grazed and the biomass was cut an average of four to six times a year, and subsequently left on the plots,. All treatments were fertilized, except one with 0% pasture in the rotation without fertilizer. The area of the plots is 5000 m^2 (25*200 m), and the site slope is 2.5 to 3%. More details about the experimental design are found in Grahmann et al. (2020).

Agronomic management included changes over time following the main technological advances of the region, involving a reduction in tillage intensity and time under bare soil. In the early years, conventional tillage (CT; moldboard plowing with secondary tillage) was used. Tillage intensity was reduced in the mid-1990s, and NT was included in 2009. Further details on the effects of treatments on soil properties over time, and on crop productivity were previously reported (Baethgen et al., 2021; Grahmann et al., 2020; Rubio et al., 2018; Rubio et al., 2021).

EXPERIMENT 2: Pastures and tillage

This trial was established in 1996 to evaluate the factorial impacts of crop rotation (continuous cropping vs. crops rotation with pastures at 50%-50%) and tillage practices (NT vs. minimum tillage; Table 1). The area of each experimental plot is 495 m^2 (11x45m), and the slope is less than 1%. The experimental design is a 2x2 factorial laid out in a split-plot randomized design with three staggered replicates. The pasture phase consists of a mixture of tall fescue, white clover, and birdsfoot trefoil. Pastures were not grazed and the residue is cut an average of four times a year and subsequently left on the plots. No changes in cropping sequences or management occurred in this experiment since its initiation.

EXPERIMENT 3: Cover crops in continuous soybean systems

This trial was established in 2004 to evaluate the effects of cover crop inclusion and duration in a continuous soybeans system under NT. The experiment has a 3x2 factorial design, with six replications (not randomized). In this study three of the experimental treatments were evaluated. Oat (*Avena sativa*) was cover cropped with two termination times (early: 60 days pre-sowing, average date September 15; late: 30 days pre-sowing, average date October 15) and contrasted with continuous soybean without winter cover crop (Table 1). The plot size is 132 m^2 (3*44 m), and the slope is less than 1%. No changes in cropping sequences or management occurred in this experiment since its installation.

2.2.2. CROP MANAGEMENT

For all experiments, crop management followed the general practices recommended by INIA for the region. Mineral N and P (urea, diammonium phosphate, monoammonium phosphate, triple superphosphate, and single super phosphate) fertilizers were applied annually at sowing according to soil test recommendations (except one of the 0%PS treatments in Experiment 1 where fertilization was explicitly excluded). All plots were managed to minimize the impacts of weeds, diseases, and pests on yields. Annual crops were harvested for grain, and straw was retained on the plots. Cover crops were not harvested. Pastures were cut to simulate grazing, and forage was left on the plots in all experiments. In Experiments 1 and 2, crops were grown under rainfed conditions. For Experiment 3, supplemental irrigations were performed at sowing in 11 of the 14 evaluated seasons. Irrigations were made between November and January and varied from 12 to 42 mm ha^{-1} $year^{-1}$ (average 19 mm ha^{-1}

year^{-1}). Total irrigation applied since the beginning of the experiment was 264 mm ha^{-1} year^{-1}.

The sequence intensification index (SII), the number of months of the year with living plant roots, was estimated on a monthly basis as proposed by Novelli et al. (2013) to characterize soil use and management (Table 2.1). Average sowing and harvest dates were considered to determine the average growth length in months for each crop: 5.5 for wheat (*Triticum aestivum* L.), barley (*Hordeum vulgare* L.), and flax (*Linum usitatissimum*); 5.2 for sorghum (*Sorghum bicolor* L.) and soybean (*Glycine max*); 6 for corn (*Zea mays* L.); and 4.3 for sunflower (*Helianthus annuus*). For non-harvested perennial pastures nine months of growth was considered for the first year and 12 for the second and third years. Average SIIs for each experiment and treatment are presented in Table 2.1. For experiment 1, the active plant growth increased over time following improvements in crop management in the region, and were similar for most treatments (Appendix 2.2). An exception is the 66%PS treatment which changed from continuous annual cropping (0%PS) after 1983, 37 years prior to soil sampling. For Experiments 2 and 3 SII did not change over the evaluated period.

2.2.3. UNDISTURBED SOIL REFERENCES.

An undisturbed reference area adjacent to each experiment was selected to represent the same soils under natural, uncropped conditions. These areas were covered by natural grasses and, to the best of our knowledge, were never disturbed. Natural grasslands are dominated by C4 grasses with Bermuda grass (*Cynodon Dactylon*), Tall Fescue (*Festuca Arundinacea*) and Dallis grass (*Paspalum dilatatum*) as the main species. In each undisturbed area, three sampling points were selected as replicates for sampling.

2.2.4. SOIL SAMPLING AND ANALYSIS

One four-core composite soil sample per plot was collected on December 2019 from the 0-15 cm depth following CASH protocol (Moebius-Clune et al., 2016). Average maximum penetration resistance from 0 to 15 (PR15) and from 15 to 45 cm depth (PR45) was determined from 15 in-field probings using an Eijkelkamp penetrologer (www.Eijkelkamp.com). One or two different rotation entries were sampled at each block due to the staggered start replications in experiments (underlined crops in Table 2.1).

Disturbed samples were used to determine 18 soil chemical, physical and biological indicators, and gravimetric water content. Ground samples were analyzed for soil chemical properties at the Laboratory of Water, Plants, and Soils of the Experimental Station Alberto Boerger INIA La Estanzuela (Colonia, Uruguay). Briefly, the evaluated properties and the methodologies used were: Soil pH determined potentiometrically (1:2.5 soil/distilled water suspension; Beretta et al., 2014); SOC and total N using dry combustion (900°C) with a LECO analyzer (LECO TrueSpec CN-2000, St. Joseph, USA); Echangeable P colorimetrically using a Bray-I with a 1:10 (w/v) soil/solution ratio and an extraction time of 5 min (Bray and Kurzt, 1945); Exchangeable bases (K, Mg, K, Ca, and Na) by leaching soils with 1 M ammonium acetate (NH4OAc) at pH 7; Extracts analyzed by atomic absorption spectrometry (for Ca and Mg) and atomic emission spectroscopy (for K and Na; Jackson, 1964); micronutrients Fe, Zn, Mn by DTPA extraction and ICP-OES analysis (Andrade et al., 2001). Cation exchange capability (CEC) at pH 7 (mmol kg-1) was calculated from the sum of exchangeable bases and titratable soil acidity at pH 7 (Jackson, 1964). Percent base saturation was calculated based on CEC.

Subsamples were submitted to the Cornell Soil Health Laboratory (Ithaca, NY, USA) for analysis of soil physical and biological properties. Details on the laboratory techniques are available in Moebius-Clune et al. (2016) and Schindelbeck et al. (2016). Briefly, the soil physical indicators were: Plant-available water capacity (AWC) as the water retained between −10 kPa and − 1500 kPa, and assessed gravimetrically by equilibrating soil on ceramic plates in high-pressure chambers (Topp et al., 1997); Wet aggregate stability (WAS) as the proportion of stable aggregates (0.25–2 mm size) after a rainfall simulation (2.5 J of rainfall energy for 300 s); and soil texture using a rapid quantitative method developed by Kettler et al. (2001) where soil samples were fractionated after slaking with 3% sodium hexametaphosphate ($(NaPO_3)n$).
Evaluated soil biological indicators were: Permanganate-oxidizable carbon (POXC, also known as "active carbon") measured as the C oxidized by a dilute potassium permanganate solution ($KMnO_4$) and measured solution absorbance at 550 nm using a hand-held colorimeter (Weil et al., 2003); Autoclaved citrate extractable soil protein (ACE Protein) where proteins were extracted from the soil following a series of centrifugation and autoclaving steps using 0.02 M sodium citrate at pH 7 (Hurisso et al., 2018), and a bicinchoninic acid assay against bovine serum albumin standard curve was used to determine soil protein concentration (Wright, S.F. and Upadhyaya, 1998); Soil respiration (Resp), assessed by trapping and measuring CO_2 emitted by

soil microorganisms over a 4-day room temperature incubation in a sealed chamber with a KOH trap (Schindelbeck et al., 2016).

2.2.5. DATA ANALYSIS

For all the evaluated SH indicators, descriptive statistics and analyses of variance (ANOVA) were performed. The effect of land use (undisturbed soil references vs. experimental area) was evaluated on the full dataset, and heteroscedasticity between the experimental areas, when present, was included and considered uniform for each experimental area (VarIdent). Means separation and multiple comparisons for treatments were computed using the Tukey posthoc test after a significant F-ratio ($p < 0.05$). Regression analyses were performed on the percentage of pastures in the crop rotation (%PS) for fertilized treatments in Experiment 1. Additionally, linear, quadratic, and exponential regressions between SH indicators and SII were performed for the full data set, to explore its association (considering SII equal 100 for the undisturbed references). Exponential regressions are not presented since they didn't generate significant improvements in the regression performance and are more difficult to interpret. The unfertilized treatment of Experiment 1 was excluded from all the regression analyses to avoid confounding effects from nutrient deficiencies. All statistical analyses were performed using RStudio software version 1.0.143 (R core Team, 2019), while spider plots were generated using MS-Excel (Microsoft Corporation, Redmond, WA).

Physical and biological indicators were transformed into a score between 0 and 100 using the CASH scoring algorithms for fine soil textured soils (Fine et al., 2017), which are based on the cumulative normal distribution parameterized by mean and standard deviation values observed in the USA. A more-is-better score was utilized for all evaluated indicators, except penetration resistance where a less-is-better scoring function was used. The scored indicator values were used to represent treatment effects on different soil properties into a single spider plot, allowing for a comprehensive visualization of SH.

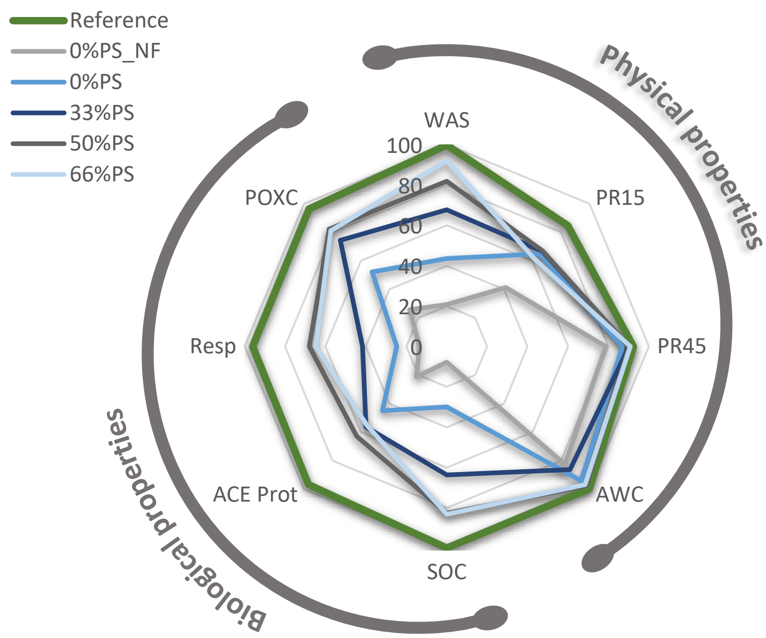
2.3. RESULTS AND DISCUSSION

2.3.1. LAND USE CHANGES

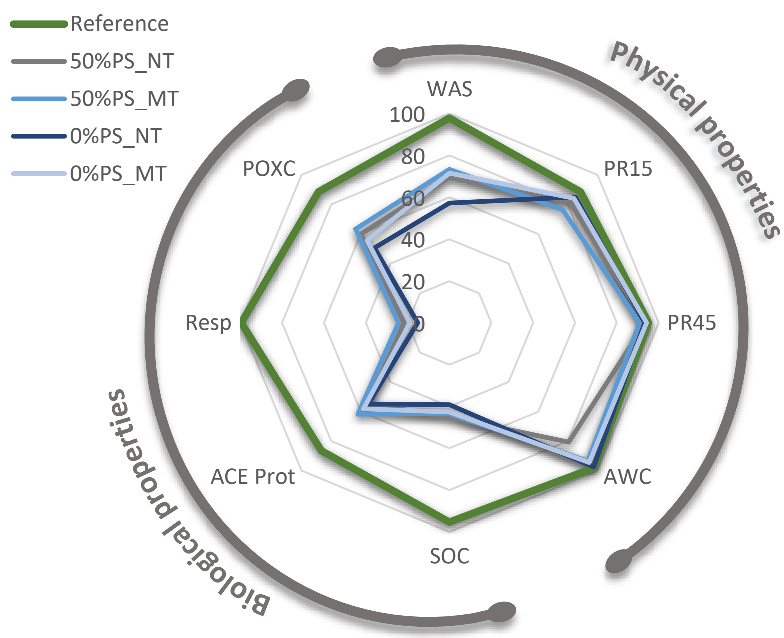
Natural grasslands in the Pampas region have high amounts of SOC and very fertile and healthy soils, but conversion to agricultural production and tillage causes significant SH decline (Table 2.2, Fig. 2.1). This was observed for all measured SH indicators, except Na, suggesting widespread changes in functional capabilities of these soils. Intensive traffic, tillage, and soil erosion have been correlated with soil physical degradation of similar agricultural soils (Alvarez et al., 2017; Botta et al., 2009; Tolon-Becerra et al., 2011). Here, this degradation was observed as a 43% increase in 0-15-cm depth soil penetration resistance and a 44 and 12% average reduction in aggregate stability and AWC, respectively (Table 2.2). AWC was less affected by land use changes than other soil physical indicators, as also measured by others (Amsili et al., 2021; Nunes et al., 2018; van Es and Karlen, 2019), presumably because the gravimetric procedure on disturbed samples removes the beneficial effects undisturbed pastures on lower soil bulk density conditions. The measured soil physical changes may result in reduced root growth, microbial activity, water, and nutrient movement, and increases in soil erosion, and N_2O emissions (Alaoui et al., 2011; Głąb and Gondek, 2014; Mijangos et al., 2006).

The conversion of natural soils to crop production also affects C balances, increasing outputs and reducing inputs, thus negatively impacting soil biological processes. As a result, biological indicators were highly affected by crop conversion where SOC, Resp, ACE Protein, and POXC were reduced by 44, 62, 44, and 28%, respectively. SOC losses were within the estimated range reported for the region by Alvarez (2001). However, the observed loses were higher than the 25-36% and 25% average losses recently reported in agricultural farms in the region by Nicolas et al. (2022) and Rodriguez et al., (2022) perhaps due to the lack of erosion in these relatively flat field sites. Degradation of soil biological properties, among others, may affect nutrient cycling and aggregate stability and result in a broader deterioration of soil chemical and physical processes and crop yields (Rubio et al., 2021a; Tang et al., 2011; Yadav et al., 2021).

a.Experiment 1



b. Experiment 2



c. Experiment 3

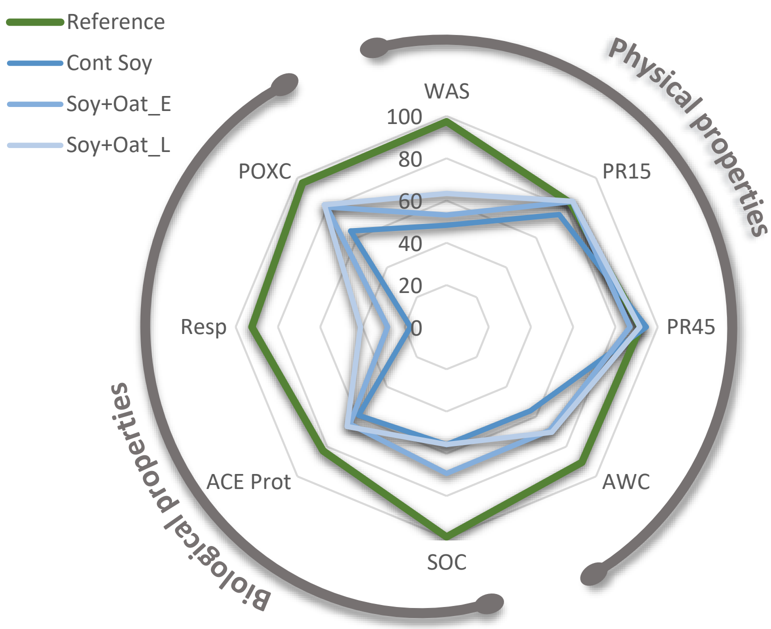


Figure 2. 1*:* Spider plot of soil Physical and biological health indicators, scored from 0 to 100, for experiment 1, 2 and 3 as a function of treatments.

Where; 0%PS_NF: treatment with 0% of the time under non-harvest pastures and no fertilization; 0%PS: treatment with 0% of the time under non-harvest pastures; 33%PS: 33% of the time under non-harvest pastures and 66% under crops; 50%PS: 50% of the time under non-harvest pastures and is 50% under annual crops; 66%PS: 66% of the time under non-harvest pastures and 33% under crops; MT: Minimum tillage treatments; NT : No- tillage; Cont_Soy: Continuous soybean systems; Soy+Oat: Continuous soybean treatments with Oat as winter cover crop; E: Early Oat termination; L: late Oat termination; WAS: Water aggregate stability, PR15: Penetration resistance from 0-15 cm; PR45: Penetration resistance from 15-45 cm;AWC: Available water capacity; SOC: Soil organic carbon; POXC: Permanganate-Oxidizable Carbon or Active Carbon; ACE Prot: ACE Protein; Resp: Respiration

Table 2. 2: Mean soil health indicators for the evaluated experimental farm areas and undisturbed references

*Significance codes: '***': a=0.001 '**' : a=0.01 '*' : a=0.05 '+' : a=0.1 . Where:*

PHYSICAL

	WAS	AWC	PR15	PR45
	--%--	--g/g--	-------*kPa*--------	
Experiments	43.4	0.29	814	1117
References	77.2	0.33	565	1172
Significance	***	***	***	+

BIOLOGICAL

	SOC	POXC	Resp	ACE Protein
	--%--	mg/kg	$mgCO_2/g$	mg/g
Experiments	2.42	661	0.46	6.55
References	4.33	921	1.23	11.8
Significance	***	***	***	***

CHEMICAL

	pH	CEC	Base Sat	N	P	K	Ca	Mg	Na	Mn	Zn	Fe
		meq/100g	--------%-------		mg/kg	---------meq/100g----------				-----mg/kg----		
Experiments	5.58	19.3	75	0.25	37	0.46	10.63	2.71	0.63	48.4	1.06	143
References	6.30	22.6	86.4	0.41	20	1.52	14.01	3.34	0.71	37.1	4.54	167
Significance	***	***	***	***	*	***	***	*	ns	***	***	***

WAS: Water aggregate stability; AWC: Available water capacity; PR15: Penetration resistance from 0-15 cm; PR45: Penetration resistance from 15-45 cm; SOC: Soil organic carbon; POXC: Permanganate-Oxidizable Carbon or Active Carbon; Resp: Respiration; CEC: Cation exchange capability; %Base Sat: Percentage of base saturation

Soil acidification, as well as nutrient deficits and excesses appear as potential concerns associated with the degradation of soil chemical properties. Here, the relative changes generated in soil chemical properties were smaller than those observed in the physical and biological ones. The reduction in soil pH, from 6.30 to 5.58 may be associated with N fertilization, biological N fixation, base cation extraction by crops, and a reduction in SOC (Haynes, 1983) and is consistent with observed regional tendencies (Beretta-Blanco et al., 2019). Soil acidification may reduce potential yields of several crops and, therefore, further exacerbate SOC decline (Liu G, 2015). If soil acidification continues, remediation practices might be needed which may also increase the cost of production.

Crop nutrient extraction and increases in nutrient losses in cropping systems might explain the reduced nutrient availability (Table 2.2). Negative balances are expected for those nutrients that are not generally replenished as fertilizers, like Mg, Zn, Fe, and K. The observed reduction in nutrient availability, especially K and bases, suggests potential future deficiencies. The increase in P levels is associated with excessive fertilization that might increase the risk of P losses to water bodies. The increase in Mn availability is not associated with fertilization, but may have risen with the reduction in soil pH and SOC. Mn-(oxy)hydroxide minerals are associated with SOC stabilization, and lower organic Mn complexes may induce higher availability of Mn detected by soil testing (Franks et al., 2021). Despite being an essential micronutrient, Mn values above 40 mg/kg can be toxic for wheat plants, and therefore this should be monitored in the future (Fageria, 2007).

Overall, our results confirmed the necessity of comprehensive approaches to SH evaluation for assessing anthropogenic soil degradation. The undisturbed soil areas may be used as SH benchmarks against which the condition of Uruguayan agricultural soils are evaluated (Balaguer et al., 2014), and against which potential soil health goals are considered (Maharjan et al., 2020). We corroborated that soil acidification, nutrient losses, and SOC depletion are threats to SH in the Pampas region (Beretta-Blanco et al., 2019; Wingeyer et al., 2015a). Yet, the greatest changes in SH were observed in the traditionally ignored physical and biological SH indicators (Table 2.2

and Fig. 2.1), which may be mostly associated with crop productivity concerns in the region (Ernst et al., 2018; Rubio et al., 2021b).

2.3.2. ROLE OF CONSERVATION PRACTICES

2.3.2.1. Experiment 1: Fertilization and Pastures

All SH indicators showed significant treatment effects, except Ca, Mg, Na, Mn, and CEC (Table 2.3; Fig 2.1). The most depleted SH conditions were observed with unfertilized continuous annual cropping, where severe nutrient deficits limited crop growth (Grahmann et al., 2020). Fertilizer additions prevented significant SH deterioration, mostly with soil biological properties and aggregate stability (Fig 2.1). Fertilizer benefits on SH are presumably associated with higher crop biomass production compared with unfertilized crops, which generates higher root biomass and crop residue cycling, as well as increased soil cover and a reduction in soil erosion (Baethgen et al., 2021). Resulting benefits on SOC and nutrient balances explain the improvements in soil physical and biological properties. Our results corroborate the notion that proper fertilization is critical for sustainable cropping systems (Cassman and Grassini, 2020), yet even with the addition of fertilizers SH under continuous annual cropping was significantly lower than that observed under natural systems (Fig 2.1). Furthermore, additional problems associated with fertilizer additions like soil acidification and external nutrient losses should be avoided.

Supplementary benefits in SH were associated with the inclusion of pastures in the cropping system, presumably due to a reduction in tillage and increased active growth periods, which were particularly important during the first stages of this experiment

(Appendix 2.1). Pastures in the rotation increased biomass inputs and reduced soil erosion losses (Baethgen et al., 2021; Grahmann et al., 2020), which were associated with higher aggregate stability and reduced subsurface penetration resistance. No significant differences in surface water content among treatments were observed at sampling (mean= 30% v/v and, p-value=0,34). Therefore, observed differences in penetration resistance can be associated with changes in soil compaction. Soil biological properties were on average 46% higher and the proportion of time under pastures was significantly correlated with improvements of all the evaluated soil biological indicators (Table 2.3). Furthermore, lower nutrient extractions by crops and a reduction in soil erosion in treatments that include pasture increased the availability of N, K, and Zn. But lower P fertilization rates in pasture-based systems resulted in lower P contents (Grahmann et al., 2020).

Table 2. 3: Factor significance ANOVA of soil physical, biological, and chemical properties for Experiment 1.

PHYSICAL

	WAS	AWC	PR15	PR45
	--%--	---g/g---	---------*kPa*---------	
0%PS_NF	19d	0.28c	1262a	1462 a
0%PS	30cd	0.31ab	903b	1213b
33%PS	44bc	0.29bc	869b	1089bc
50%PS	52ab	0.33a	876b	1089bc
66%PS	61a	0.33a	958b	1055c
Treatment	**	*	**	**
%Pasture	**	ns	ns	*
Regression coefficient	0.47	-	-	-0.33

BIOLOGICAL

	SOC	POXC	Resp	ACE Protein
	--%--	mg/kg	$mgCO_2/g$	mg/g
0%PS_NF	1.50d	444c	0.27c	3.50d
0%PS	2.0c	560b	0.39bc	5.70c
33%PS	2.5b	710a	0.54b	6.39b
50%PS	2.89a	731a	0.75a	7.12a
66%PS	2.88a	728a	0.73a	6.51b
Treatment	***	***	***	***
%Pasture	***	*	**	*
Regression coefficient	0.01	2.67	0.01	0.02

CHEMICAL

	pH	CEC	Base sat	N	P Bray	K	Ca	Mg	Na	Mn	Zn	Fe
		meq/100g	---------%---------		mg/kg	------------ meq/100g----------				---------mg/kg---- -----		
0%PS_NF	6.23a	16.13	86.0a	0.15 d	3.2d	0.57b	10	2.58	0.77	39.44	0.47b	52c
0%PS	5.43b	16.3	73.1b	0.20 c	33a	0.39c	8.98	1.84	0.74	59.45	0.52b	132b
33%PS	5.34b	18.8	72.2b	0.26 b	26ab	0.46c	10.31	2.24	0.71	49.23	0.50b	130b
50%PS	5.51b	18.3	73.2b	0.28ab	14c	0.64b	10.05	2.11	0.58	55.28	0.78a	152a
66%PS	5.53b	18.2	73.4b	0.29a	18bc	0.74a	9.72	2.35	0.67	51.35	0.83a	140ab
Treatment	**	ns	*	***	***	***	ns	ns	ns	ns	*	***
%Pasture	ns	ns	ns	***	**	**	ns	ns	ns	ns	*	ns
Regression coefficient	-	-	-	0.0014	-0.26	0.01	-	-	-	-	0.01	-

Significance codes: '***': α=0.001 '**' : α=0.01 '*' : α=0.05 '+' : α=0.1 . Where: 0%PS_NF, 0% of the time under pastures and no fertilization; 0%PS, 0% of the time under non-harvest pastures and N, P fertilization; 33%PS: 33% of the time under non-harvest pastures and 66% under crops and N, P fertilization; 50%PS: 50% of the time under non-harvest pastures and 50% under crops and N, P fertilization; 66%PS: 66% of the time under non-harvest pastures and 33% under crops, and N, P fertilization; WAS:

Water aggregate stability; AWC: Available water capacity; PR15: Penetration resistance from 0-15 cm; PR45: Penetration resistance from 15-45 cm; SOC: Soil organic carbon; POXC: Permanganate-Oxidizable Carbon or Active Carbon; Resp: Respiration; CEC: Cation exchange capability; %Base Sat: Percentage of base saturation.

2.3.2.2. Experiment 2: Pastures and Tillage

Most of the evaluated SH indicators were not affected by tillage, pasture inclusion, or their interaction in Experiment 2 (Table 2.4; Fig 2.1), although an increase in Fe content in NT systems was observed ($p < 0.01$). In addition, the inclusion of pastures slightly reduced AWC ($p<0.05$) and increased surface penetration resistance ($p<0.1$) when compared to 0%PS systems. Different outcomes with pasture incorporation were observed compared to Experiment 1 (Tables 2.3 and 2.4), presumably related to (i) the baseline continuous cropping systems in Experiment 1 having a lower SII and using more intensive tillage than in Experiment 2, therefore, pasture additions generated a larger relative benefit in SII in Experiment 1 than 2 (average change form 53 to 80% and from 73 to 81% respectively), and (ii) a 3% slope combined with intensive tillage during the first years of Experiment 1 promoting greater soil erosion losses than the 1% slope with minimum/no-tillage in Experiment 2. These, combined with the shorter duration of Experiment 2 and lower accumulation of treatment effects in C balances, can explain the lack of benefits from pasture inclusion. Comparably, no benefits of pasture incorporation on SOC were observed for a long-term experiment in Northwest Uruguay on a cropping system with 83% SII and a slope lower than 1% (Salvo et al., 2010).

The conversion from minimum to NT system did not affect the evaluated SH indicators in Experiment 2 (Table 2.4). Similar insignificant effects of NT on SOC had been related to poorly drained (Paustian et al., 1997) and fine textured soils (Fiorini et al., 2020), conditions both present in this experiment. Furthermore, the main benefits of NT systems over conventional or minimum tillage systems on sloping soils may be associated with decreasing soil erosion (Verhulst et al., 2010; Sun et al., 2015), which is also the main reason for NT adoption in the Pampas region. Yet, with a slope lower than 1%, the advantages of NT were minimal for this site. Additional benefits of NT may be associated with diminished C mineralization by reducing disruption of aggregates and soil microorganisms' access to previously protected C pools (Six et al., 2000). Still, our results indicate that continuous NT might not be the most beneficial strategy for SH preservation under low erosion risk conditions, as also concluded by Luo et al. (2010). No significant benefits of NT on SOC had been reported in 40% of 78 cases compiled by Govaerts et al., (2009), which might explain the apparent lack of effects of NT on soil physical and biological properties (Blanco-Canqui and Ruis, 2018). Neither pasture incorporation nor tillage and their interaction affected surface soil water content at sampling (mean= 20%v/v, p-value=0.455). Therefore, this variable did not affect the observed effects of treatment on penetration resistance.

Table 2. 4: Factor significance ANOVA of soil physical, biological, and chemical properties for Experiment 2

PHYSICAL

	WAS	AWC	PR15	PR45
	--%--	-----g/g-	-------------*kPa*------	----
0%PS_MT	47	0.31	538	869
0%PS_NT	39	0.33	510	889
50%PS_MT	47	0.31	703	1048
50%PS_NT	44	0.28	607	903
Tillage	ns	ns	ns	ns
PS	ns	*	+	ns
Tillage*PS	ns	ns	ns	ns

BIOLOGICAL

	SOC	POXC	Resp	ACE Protein
	--%--	mg/kg	mg CO_2/g	mg/g
0%PS_MT	2.21	608	0.33	6.53
0%PS_NT	2.15	578	0.29	6.31
50%PS_MT	2.22	647	0.39	6.81
50%PS_NT	2.25	599	0.35	6.45
Tillage	ns	ns	ns	ns
PS	ns	ns	ns	ns
Tillage*PS	ns	ns	ns	ns

CHEMICAL

	pH	CEC	Base Sat	N	P Bray	K	Ca	Mg	Na	Mn	Zn	Fe
		meq/100g	-----------%	--------	mg/kg	-----------meq/100g---	------			---------mg/kg-------		
0%PS_MT	5.50	20.3	76.3	0.22	27	0.40	11.54	3.02	0.64	54.52	0.55	106
0%PS_NT	5.73	18.8	71.5	0.23	21	0.39	9.69	2.66	0.70	59.15	0.63	132
50%PS_MT	5.41	19.7	75.1	0.23	23	0.55	10.46	3.1	0.69	56.18	0.67	110
50%PS_NT	5.38	19.5	73.1	0.23	25	0.39	10.03	3.08	0.75	54.72	0.55	134
Tillage	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	**
PS	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns
Tillage*PS	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	*	ns

Significance codes: ‘***’: α=0.001 ‘**’ : α=0.01 ‘*’ : α=0.05 ‘+’ : α=0.1. Where: 0%PS_NF, 0% of the time under pastures and no fertilization; 0%PS, 0% of the time under non-harvest pastures and N, P fertilization; 33%PS: 33% of the time under non-harvest.Where: ; 0%PS, treatment with 0% of the time under non-harvest pastures and N, P fertilization; 50%PS 50% of the time under non-harvest pastures and 50% under crops and N, P fertilization; MT: represent minimum tillage treatments; NT: represent no-tillage treatments; WAS: Water aggregate stability; AWC: Available water capacity; PR15: Penetration resistance from 0-15 cm; PR45: Penetration resistance from 15-45 cm; SOC: Soil organic carbon; POXC: Permanganate-Oxidizable Carbon or Active Carbon; Resp: Respiration; CEC: Cation exchange capability; %Base Sat: Percentage of base saturation.

2.3.2.3. Experiment 3: Cover crops in continuous soybean systems

Four SH indicators were significantly affected by the inclusion of an oat cover crop in a continuous soybean system (Table 2.5; Fig 2.1c). SOC changes would be expected after 15 years (McClelland et al., 2021), but there were no significant differences between treatments. However, changes were detected in more labile C fractions like POXC and respiration (Table 2.5), suggesting that these indicators are more sensitive to changes in management than total SOC. Also, in agreement with previous studies, greater aggregate stability was measured in the cover crop treatments (e.g., Hermawan and Bomke, n.d.; Villamil et al., 2006), although these differences were not statistically significant.

The late-terminated cover crop treatment had lower penetration resistance in the surface layer than the continuous soybean treatment but higher in the deeper soil layer (Table 2.5). The lack of soil water content differences among treatments at sampling (mean= 35%g/g, p-value= 0.484) suggest that cover crops reduce surface soil compaction. However, lower water contents in late terminated cover crops treatments, when high evapotranspiration is expected, might have confounded the observed differences in subsurface penetration resistance (Duiker, 2002).

Table 2. 5: Factor significance ANOVA of soil physical, biological, and chemical properties for Experiment 3.

PHYSICAL

	WAS	AWC	PR15	PR45
	---%----	--g/g---	--------*kPa*----------	
Cont_Soy	34	0.239	724 a	848 b
Soy+Oat_E	35	0.257	531 b	1172 a
Soy+Oat_L	42	0.259	517 b	1020 ab
Treatment	ns	ns	*	*
Cover crop	ns	+	*	*

BIOLOGICAL

	SOC	POXC	Resp	ACE Protein
	%	mg/kg	$mgCO_2$/g	mg/g
Cont_Soy	2.41	623b	0.31b	6.88
Soy+Oat_E	2.62	734ab	0.42ab	7.34
Soy+Oat_L	2.40	776a	0.53a	7.28
Treatment	ns	*	**	ns
Cover crop	ns	**	**	ns

CHEMICAL

	pH	CEC	Base Sat	N	P Bray	K	Ca	Mg	Na	Mn	Zn	Fe
		meq/100g	----------%------	-----	mg/kg	-------------meq/100g---------	-----			----------mg/kg------	----	
Cont_Soy	5.58	18.6	74	0.25	72	0.43	10.3	2.53	0.61	45.9	2.05	153
Soy+Oat_E	5.59	20.1	76	0.27	73	0.39	11.2	3.13	0.56	43.1	1.83	156
Soy+Oat_L	5.55	20.5	75	0.24	54	0.39	11.2	3.01	0.77	50.6	1.32	162
Treatment	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns
Cover crop	ns	+	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns

Significance codes: '***': α=0.001 '**' : α=0.01 '*' : α=0.05 '+' : α=0.1.Where: Cont_Soy: Continuous soybean systems; Soy+Oat: Continuous soybean treatments with Oat as winter cover crop; E: Early Oat termination; L: late Oat termination; WAS: Water aggregate stability; AWC: Available water capacity; PR15: Penetration resistance from 0-15 cm; PR45: Penetration resistance from 15-45 cm; SOC: Soil organic carbon; POXC: Permanganate-Oxidizable Carbon or Active Carbon; Resp: Respiration; CEC: Cation exchange capability; %Base Sat: Percentage of base saturation.

2.3.3. SEQUENCE INTENSIFICATION INDEX

Overall, lower SH was observed under less intensive plant growth conditions (Figs. 2.2, 2.3, and 2.4). In the combined dataset the relationship between SH and SII was significant for all SH indicators, except PR45 and Na (Table 2.6). Changes in SII explained between 58 and 73% of the variation observed in SH indicators, mostly modeled as quadratic increases. Indicators with high correlation with SII were Resp> SOC> Total N> Zn>POXC> WAS> ACE protein. When undisturbed reference soils were excluded, the relationship between SII and SH indicators was generally weaker (Table 2.6). Yet, a significant relationship of SII with soil biological indicators, PR15, and WAS was observed in farmed areas reaffirming that these indicators are the most sensitive to land-use changes (Amsili et al., 2020; Nunes et al., 2018). Intensive cropping sequences that maximize SII by minimizing fallow periods and increasing biomass production therefore appear associated with SH improvements. Lower correlation of SII with soil chemical indicators is explained by the addition of fertilizers. Additional benefits of more intense cropping systems that were previously documented include higher radiation and water use efficiencies; reduction in nutrient losses; increasing richness and diversity of soil microbial communities; reduced soil erosion; weed and disease suppression; and improved pollination (Caviglia and Andrade, 2010a; de la Fuente et al., 2021; Villamil et al., 2006).

Table 2. 6: Lineal Regression analysis between soil health indicators and the sequence intensification index

	With reference sites		Without reference sites	
	Significance	*R^2.adj*	*Significance*	*R^2.adj*
PHYSICAL				
WAS	***	0.59	+	0.14
AWC	**	0.15	ns	-
PR15	**	0.25	+	0.05
PR45	ns	-	ns	-
BIOLOGICAL				
SOC	***	0.69	+	0.06
POXC	***	0.61	***	0.39
ACE.Prot	***	0.58	+	0.08
Resp	***	0.73	**	0.19
CHEMICAL				
pH	**	0.21	ns	-
CEC	***	0.27	+	0.06
%Base Sat	**	0.17	ns	-
N	***	0.67	+	0.07
P	**	0.04	+	0.05
K	***	0.51	ns	-
Ca	**	0.23	ns	-
Mg	**	0.18	ns	-
Mn	+	0.18	ns	-
Na	ns	-	ns	-
Zn	**	0.63	**	0.10
Fe	**	0.45	**	0.28
CASH_FB	*****	**0.74**	*****	**0.34**

Significance codes: '***': α=0.001 '**' : α=0.01 '*' : α=0.05 '+' : α=0.1.Where: WAS: Water aggregate stability; AWC: Available water capacity; PR15: Penetration resistance from 0-15 cm; PR45: Penetration resistance from 15-45 cm; SOC: Soil organic carbon; POXC: Permanganate-Oxidizable Carbon or Active Carbon; ACE Prot: ACE Protein; Resp: Respiration; CEC: Cation exchange capability; %Base Sat: Percentage of base saturation; CASH_FB: integrated physical and biological soil health index.

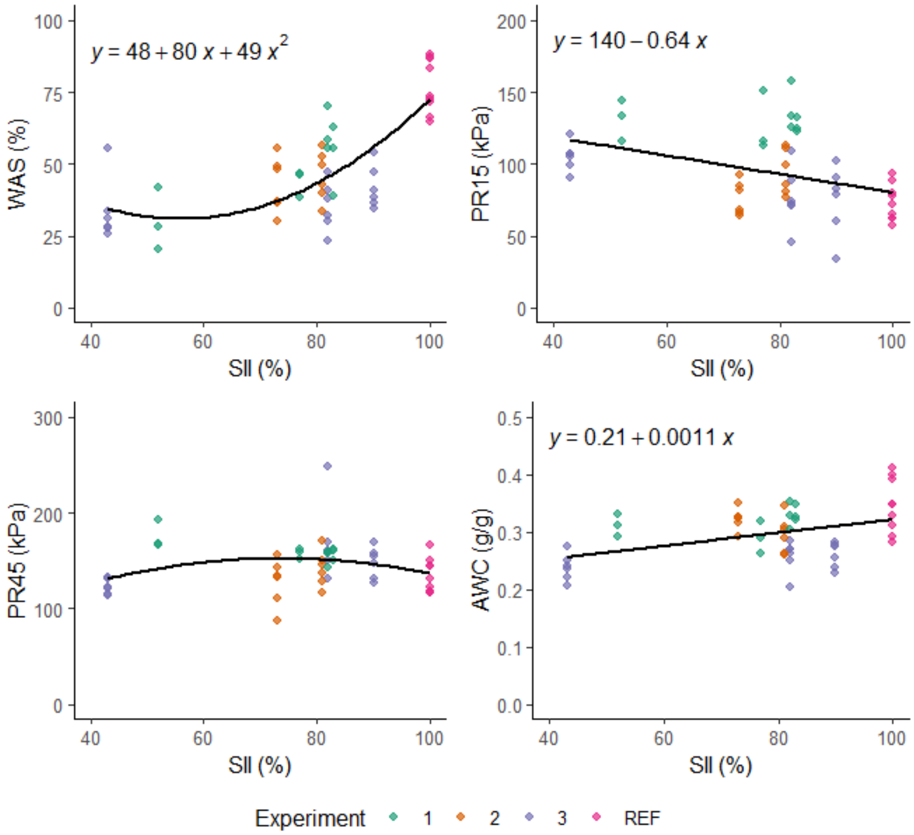


Figure 2. 2: Physical Soil health indicators as a function of Sequence Intensification Index (SII).

When: The best regression equation is presented when significant. WAS: Water aggregate stability, PR15: Penetration resistance from 0-15 cm; PR45: Penetration resistance from 15-45 cm; AWC: Available water capacity.

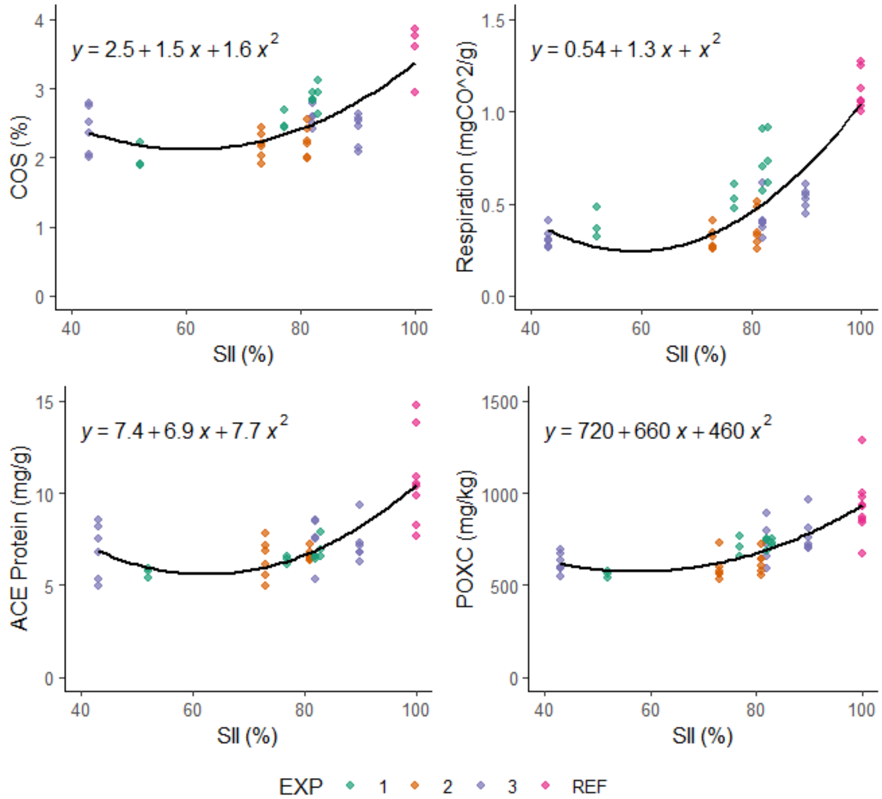


Figure 2. 3: Biological Soil health indicators as a function of Sequence intensification index (SII).

When: The best regression equation is presented, when significant. SOC: Soil organic carbon; POXC: Permanganate-Oxidizable Carbon or Active Carbon; ACE Prot: ACE Protein; Resp: Respiration.

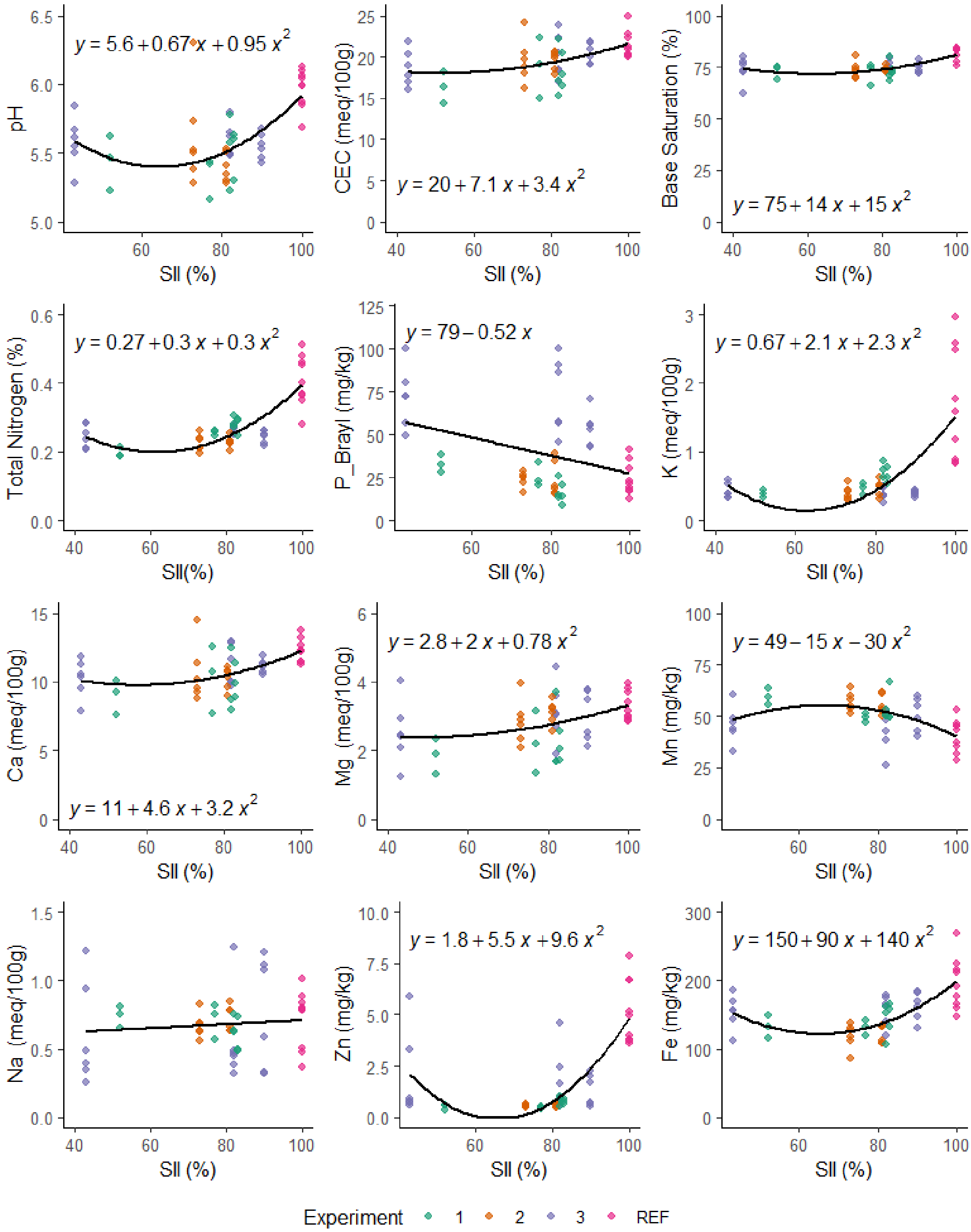


Figure 2. 4*:* Chemical Soil health indicators as a function of Sequence intensification index (SII).

When: The best regression equation is presented when significant. CEC: Cation exchange capability; %Base Sat: Percentage of base saturation

2.3.4. CONSIDERATIONS FOR CROPPING SYSTEM SUSTAINABILITY

In the Pampas region, where the economic outcomes of crop production increasingly depend on soybean production, unbalanced cropping with a low proportion of winter covers and low SII are common under unregulated conditions (Caviglia and Andrade, 2010, Wingeyer et al. 2015). The need for intensifying cropping systems that maximize crop yields and SII was previously demonstrated for enhancing aggregate stability (Novelli et al., 2017; Tourn et al., 2019). Here this is reported for a broader set of physical, biological, and chemical properties (Figs. 2.2-2.4) and reinforces the value of crop polycultures (Kremen and Merenlender, 2018; Bowles et al., 2020; Guzman et al., 2021, Heggens- taller et al. 2008), cover crops (Pinto et al., 2017; Sekaran et al., 2021; Villarino et al., 2021) and rotation with perennial forage crops (Carvalho et al., 2021; Franzluebbers et al., 2014).

Our results show that different strategies can be used to mitigate SH degradation in annual cropping areas, but they do not support the idea that the sustainability benefits of these practices are universally applicable to all production environments (Tables 2.3 and 2.4). Even in the same research area, pasture incorporation had significant SH benefits in one experiment and no effects in the other (Fig. 2.1). With a low erosion risk, under minimum or no-tillage, and high SII (as evaluated in Experiment 2), similar SH levels can be achieved with continuous cropping systems and with 50% perennial pastures systems. However, including pastures in annual cropping systems with low SII and moderate/high erosion risk was an effective conservation strategy (Experiment 1). Similarly, increasing SII by incorporating cover crops into a continuous soybean system showed positive SH benefits. SH indicators had a similar response to SII among the different experiments (Figs. 2.2- 2.4), despite potential additional SH benefits of perennial pastures through reduction in tillage frequency, increased C inputs from roots and rhizodeposits, and the incorporation of legumes (Baethgen et al., 2021; Franzluebbers et al., 2014; Franzluebbers and Gastal, 2018; Six et al., 2000).

Overall, these results highlight the importance of crop sequence intensification on the benefits of conservation practices in SH. Yet, a deeper understanding of the main drivers of long-term benefits of increasing SII is needed. Despite the lack of observed benefits associated with NT under low-erosion risk, this practice is still important for cropping system sustainability on erosion-prone lands in Uruguay.

2.4.CONCLUSIONS

This study included a comprehensive evaluation of SH under different cropping systems. Our results confirm the serious negative effects of annual cropping on SH relative to perennial grassland, highlighting the importance of regenerative practices to lessen SH deterioration. Good nutrient management is critical as it allows for greater biomass production and cycling. Additional conservation practices may result in different outcomes even under the same climatic conditions, parent material, and soil type. This suggests against a simple set of practices for SH improvement, and also indicates that local conditions must be considered. For example, the inclusion of perennial pastures can increase SII and improve SH (Experiment 1), but this may not be pronounced in intensive cropping systems with low erosion risk (Experiment 2).

Yet, increasing crop sequence intensification appears to have a consistent positive impact on SH even without the inclusion of perennial species (Experiment 3), which may be achieved through cover crops. Overall, increasing the active plant growth period and maintaining high yields through good nutrient management were the most promising and generalizable management practices to improve SH in cropping systems.

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CHAPTER 3: QUANTIFYING SOIL ORGANIC CARBON CRITICAL ROLE IN CEREAL PRODUCTIVITY LOSSES UNDER ANNUALIZED CROP ROTATIONS[2]

ABSTRACT

Understanding the impact of soil degradation on crop productivity is essential for decision-makers to predict agronomic, economic, and environmental outcomes of agricultural operations. Soil organic carbon (SOC) is affected by the cropping system and impacts soil health through other soil physical, chemical, and biological properties. Data from a 56-year long-term experiment in Uruguay's Pampa region were analyzed to quantify soil degradation impacts on wheat (*Triticum aestivum* L.), and barley (*Hordeum vulgare*) yields. Increasing degrees of soil degradation were generated by six rotations with variable annual crop and pasture proportions (0%, 33%, 50%, and 66% pasture). Yield records (n=368) and annual values of 14 explanatory variables containing soil, climatic, and management indicators were evaluated using least squares and random forest regressions. Rotation-induced SOC variation ranged from 1.2 to 2.6%, and robust relationships between SOC, soil physical, chemical, and biological properties were established. Over time yields increased in crop pasture systems but plateaued for the annualized crop rotation (0%

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[2] Rubio, V., Diaz-Rossello, R., Quinke, J.A., & van Es, H. M. (2021). Quantifying soil organic carbon ' s critical role in cereal productivity losses under annualized crop rotations. *Agriculture, Ecosystems and Environment*, *321*(October 2020). https://doi.org/10.1016/j.agee.2021.107607

pasture). Yield improvements due to agronomic technology advances partly mask soil degradation effects. SOC losses generate a reduction in yields, even when the SOC level was above 2%, and no critical levels of SOC were established. SOC interacted with climate indicators to impact yield. This analysis confirms the central role of SOC in yield outcomes beyond nutrient availability, and its potential to represent a wide range of soil functions. Our findings indicate that crop rotations with a higher percentage annual vs. perennial crops negatively impact SOC, associated soil properties, and yield potential.

3.1. INTRODUCTION

There is a general recognition that soil organic matter - also measured as organic carbon (SOC) - is an indicator that encapsulates and regulates most physical, biological, and chemical soil properties (Bünemann et al., 2018; Schjønning et al., 2018). Agricultural practices have depleted SOC levels by 25 to 75% in most soils of the world (Lal, 2011). This degradation has been exacerbated in the last two decades in Uruguay – as in many other areas of the South American Pampas region- by a shift from crop pasture rotation (CPR) systems to continuous annual cropping (CAC) systems(Alvarez and Steinbach, 2009; Beretta-Blanco et al., 2019; Wingeyer et al., 2015).

Negative impacts of CAC systems in crop yields had been recognized in the region (Ernst et al., 2020; O. R. Ernst et al., 2018). Yet, benchmarks that allow farmers, agricultural professionals, and policymakers to predict the potential losses in productivity associated with soil degradation are limited. Establishing quantitative relations between soil health and crop yield is challenging due to several confounding factors related to different climatic conditions, soil properties, and crop management practices. While many studies show positive relationships between SOC and crop yield (e.g., Oldfield et al., 2019; van Es and Karlen, 2019), others claim that, with sufficient fertilizer, SOC does not affect crop performance (Hijbeek et al., 2017; Loveland and Webb, 2003; Oelofse et al., 2015). Therefore, it has been recognized that the lack of specific SOC target levels is one of the main barriers for its use in sustainable management (Herrick, 2000; NRC, 2010).

SOC contents are affected by both inherent and anthropogenic factors. For example, soils stabilize C through mineral-organic bonds; therefore, soil with higher clay and silt contents tend to have higher SOC, all else being equal (Six et al., 2002). Nunes et al. (2020) used an extensive soil database from across the USA and found significant differences among eight regions, which were attributed to soil and climate effects. Differences were also observed among cropping systems, tillage types, and use of cover crops where systems with less soil disturbance and more carbon cycling/return showed higher SOC levels. Therefore, evaluation of SOC effects on yields across different soil types and regions cannot be linked to degradation from land use or easily isolated from other yield controlling factors. Furthermore, the effects of SOC can be confounded, among others, with variations in other soil properties, climate, management practices, and their complex interactions (Schjønning et al., 2018). Strategies to experimentally increase or decrease SOC, like the removal of the topsoil (Robbins et al., n.d.; Tanaka and Aase, 1989), or the addition of organic amendments

(Hijbeek et al., 2017) have been used. These strategies do not represent the actual processes involved in soil degradation and associated to the intensification of the main cropping systems in the Pampas region.

The evaluation of long-term experiments (LTE) has been identified as the best way to evaluate the impacts of contrasting food production systems and management practices on soil properties that might change slowly over time, such as SOC (Johnston and Poulton, 2018). Long term evaluations are needed to assess variation in soil quality and to represent the effect of interannual climatic variation on yields. Results from numerous LTEs had report changes in SOC that could be related to changes in crop yields. Still, the soil data in those experiments are often insufficient to quantify the relationship. Also, different statistical approaches might be needed to determine the main factors controlling yields and to establish quantitative relations. The complex intercorrelations between variables limit the performance of classical statistical methods, like linear models, which assume independence between variables and little or no correlations (Draper and Smith, 1998). Nonparametric regression techniques like Random Forests allow for a more accurate analysis for modeling complex relationships between predictors and the target variables (Breiman, 2001). This approach has been proven appropriate for the prediction of crop yields (Hoffman et al., 2019) and the isolation of specific variable effects (Hoffman et al., 2017).

Wheat (*Triticum aestivum* L.) and barley (*Hordeum vulgare* L.) are among the most widely grown cereal crops (FAOSTAT, 2020). Given its essential role in the human diet, cereal yields can be considered an appropriate indicator of land production capacity (Bindraban et al., 2000). Using a unique LTE data set from Uruguay that includes annual soil, weather and yield data, this study aims to: i) evaluate the influence of soil degradation generated by land use on cereal productivity; and ii) explore the existence of a critical level of SOC in a Mollisols of the Pampas region.

3.2.MATERIALS AND METHODS

3.2.1. EXPERIMENTAL SITE

The study was conducted at the research station “La Estanzuela” situated at the National Institute of Agricultural Research (INIA) in SW Uruguay (34º20 S, 57º41 W, 82 m asl) which is located in the South American Pampas region. The climate at the site is humid subtropical, with a 50-yr average temperature of 16.6 °C. Annual average precipitation is 1100 mm, almost evenly distributed throughout the year, but with large interannual variability. The dominant soil at the site is classified as a Haplic Phaeozem (Vertic, Eutric; World Reference Base) or smectitic Vertic Argiudoll in the USDA Soil Taxonomy system (Soil Survey Staff, 2010). Soil surface clay and silt contents are 351 and 562 g kg^{-1}, respectively (silty clay loam texture class), and the slope is 2.5-3%.

3.2.2. FIELD EXPERIMENT

The data set analyzed in this study was generated from a LTE established in 1963 to evaluate the effects of rotation and N and P fertilization on continuous cropping systems (Grahmann et al., 2020; Moron, 2003). The experiment has seven treatments arranged in a randomized complete block design with three replications, and the plot size is 0.5 ha (25 x 200 m). Six of these treatments were analyzed here, where an unfertilized treatment was excluded. Selected treatments compare continuous annual cropping systems (CAC) with crop pasture rotations (CPR) with different durations and species (Table 3.1). For this study, treatments with the same amount of pasture in the rotation were combined in the analysis (same nomenclature in Table 3.1).

Prior to the experiment the site was under continuous agriculture for more than 40 years (mostly wheat-fallow). Treatment description and dominant crop and pasture rotation is presented in Table 3.1. Over time the experiment experienced changes following the main technological modifications of the region (for more details see Moron, 2003). In 1974 the replications were staggered to incorporate year effects into the experimental design. Barley was incorporated to the crop sequence in 1983 replacing flax (*Linum usitatissimum*). In that year, the treatment with 66% of the time under pastures was incorporated by replacing a CAC system. In 2009 no-tillage was implemented in all treatments replacing conventional tillage practices. A detailed analysis of long-term changes of SOC and soil chemical properties for this LTE was recently done by Grahmann et al. (2020). Soil chemical conditions at the beginning of the experiment (1964) and for the last rotation period presented as a function of time under pastures treatment are presented in Appendix 3.1.

Table 3. 1: Proportion of time under pasture, fertilization management, and crop rotation per treatment

Treatment nomenclature	Proportion of pasture in the rotation	Dominant crop rotation (1983-2014)
0%PS	0%	**<u>Barley</u>**/Sorghum-**<u>Wheat</u>**/Sunflower

50%PS	50%	**<u>Barley</u>**/Sorghum-**<u>Wheat</u>**/Sunflower -Legume pasture (3 yr)-Corn
66%PS*	66%	**<u>Barley</u>**/Red Clover (1 yr)-Sorghum-Mixed pasture (3 yr)-Corn
50%PS	50%	**<u>Barley</u>**/Sorghum-**<u>Wheat</u>**/Sunflower-Mixed pasture (3 yrs)-Corn
0%PS	0%	Oat/Soyean-**<u>Wheat</u>**/SunFlower-Soybean
33%PS	33%	Sorghum - **<u>Wheat</u>**/SunFlower- Red Clover

**this treatment was under continuous cropping till 1983*

Crop management follow the general management practices recommended by INIA technicians for the region. Wheat and barley were sown between May and June and harvested in December. Mineral N (urea) and P (diammonium phosphate, monoammonium phosphate, triple super phosphate and single super phosphate) fertilizers were applied annually according to soil test recommendations at sowing. N re-fertilization was made considering plant N test at Zadoks 22 and 30 (Zadoks et al., 1974). Annual crops were harvested for grain, and straw was retained on the plots. Pastures were cut to simulate grazing and forage was left on the plots.

3.2.3. CROP DATA

The similarity between wheat and barley species regarding phenological behavior, yield potential and agricultural practices allowed us to jointly analyze both crops and improve the robustness of the analysis. The evaluated data set contains a total of 368 yield records (kg ha^{-1}), 68% corresponding to wheat and 32% to barley. Records were available or generated for crop sowing, flowering and harvest dates, days until flowering, and N and P fertilization rates. Average annual crop N and P fertilization per decade are presented in Table 3.3. The yield of Sorghum that immediately preceded the evaluated crops was incorporated in the analysis, and a value of cero was assign for other previous crops. Previous reports on negative allelopathic effects of Sorghum over wheat and barley (Roth et al., 2000) motivate the incorporation of this variable.

Table 3. 2 Average mineral N and P fertilizer inputs per crop as a function of percentage of time under pastures per decade

period	**0%PS**	**33%PS**	**50%PS**	**66%PS**
		N (kg ha^{-1})		
1965-1975	41.1	50.3	35.0	36.5
1976-1985	45.7	42.8	40.1	45.0
1986-1995	37.1	41.8	35.2	53.1
1996-2005	35.1	41.8	26.3	42.5
2005-2019	127.8	88.5	131.9	50.7
Average	**60**	**52**	**59**	**44**
		P (kg ha^{-1})		
1965-1975	45.3	48.2	45.0	45.3
1976-1985	24.1	27.0	28.8	25.6
1986-1995	40.4	43.4	36.3	50.1
1996-2005	18.6	21.4	14.4	5.3
2005-2019	22.7	16.0	24.6	15.3
Average	**30**	**31**	**27**	**29**

Even though the experiment has an annual staggered design (since 1974) not all phases of the rotation were present in all years. Thus, the comparison between treatments is modestly unbalanced, especially when involving treatments with longer pasture phases and less years with winter crops. Consequently, these data required a multivariate analysis.

3.2.4. SOIL DATA

One composite sample per plot was collected yearly in April or May from each plot from 20 random cores in the center of the plot from the 0-to-15 cm depth. Dry samples were analyzed for SOC, total N (Ntot), pH in water (1:2.5 soil/distilled water suspension; Beretta et al., 2014), and phosphorous Bray-I (Bray and Kurzt, 1945)

(PBray). Between 1964 and 2011, SOC was measured using $K_2Cr_2O_7$ and heat as described by Tinsley (1950). Beginning in 2012, SOC was measured using dry combustion (900°C) using a LECO analyzer (Wright and Bailey, 2001). Values obtained with the LECO were corrected to be comparable with Tinsley values using a locally calibrated correction factor of 0.81. Ntot was determined after sulfuric acid digestion, distillation with micro Kjeldahl, and titration as described by Bremner (1965). From 2012 onwards, total N was also measured by dry combustion (900°C) (Wright and Bailey, 2001).

Ammonium acetate exchangeable K was determined annually since 1990 according to Jackson (1964). Potentially mineralizable nitrogen (PMN) was determined anually since 2010 by anaerobic incubation at 40°C for 7 days. Soil was prevously sieved at field moisture, following the methodology recommended by Bundy and Meisinger (1994). Soil bulk density (BD) was determined from undisturbed soil samples taken at two soil depths (0-7.5 cm and 7.5-15 cm) in three occasions, 1979, 2007-2009 (in each year, one block was measured) and 2018 in all experimental plots. Additional measurements of DB were performed in tratments 0%PS (Barley/Sorghum-Wheat/Sunflower crop rotation), 50%PS and 66%PS treatments. For these same treatments, aggregate stability was determined in 2015 from 0-20 cm depth according to the Le Bissonnais (1996) method (Rubio et al., 2019).

3.2.5. WEATHER DATA

Daily weather data was collected since 1965 at the site (available at http://www.inia.uy/gras). Accumulated precipitation, average maximum and minimum temperatures, radiation, and precipitation during the crop critical periods (defined as

15 days before and after flowering in which weather has the biggest impact on yield; Fischer (1985) were analyzed. Additionally, the average photothermal quotient (Q) for this period was estimated as the relationship between radiation and average temperature minus base temperature for wheat and barley (which is 4.5°C).

3.2.6. DATA ANALYSIS

Scatter plots between SOC and all soil properties measured in the long-term experiment were constructed and evaluated with linear regression models. The model with higher r^2 was selected. Treatments with the same amount of time under pasture and fertilization (Table 3.1) were grouped for the evaluation of effects on yields. Yield evolution over time was evaluated using a linear regression model between year and observed yields. First and second order regression were evaluated and the one with highest r^2 values was selected. Yields for all treatment groups were corrected to account for the effect of technology progress using average annual yield progress of the country. The correction factor was estimated by fitting a linear regression model between average wheat and barley national yields (FAOSTAT Online Database, 2020) and year for the time period evaluated in the experiment. The estimated yield progress was 46 kg ha^{-1} year $^{-1}$ ($p < 0.0001$, $r^2 = 0.75$) and yields were therefore corrected to a 2018 basis as:

$$\text{Observed yield} + [(2018 - \text{year of evaluation}) * 46].$$

3.2.6.1. Random Forest (RF).

RF classification and regression models were used to evaluate and quantify SOC impacts on crop yields. RF is a recursive partitioning machine learning method that generates an ensemble of regression trees (Breiman, 2001). Trees are constructed on a random subset of the data (bagged samples), using only a random subset of predictor variables for split point selection at each node (Liaw and Wiener, 2002). Among other benefits these models allow for the evaluation of nonlinear relations between the predictors and better representation of complex interactions among variables. They are also highly robust to noise and irrelevant features, and have shown low bias and variance (Breiman, 2001; Hoffman et al., 2019).

The impact of 14 explanatory variables on corrected yields was evaluated. The studied variables were; soil (SOC, Ntot, pH, PBray); management (N and P fertilization rates, days until flowering, sowing year, yield of sorghum in case it was the previous crop); weather conditions in the crop critical period (mean temperature, radiation, accumulated precipitation, Q) and weather during vegetative crop growth (accumulated precipitation). Redundant features were identified as those with correlation coefficients greater than 0.65. In this data set SOC and N, as well as Q and radiation were highly correlated. The importance of these features was determined building a RF model that included all evaluated variables. SOC and Q were more important attributes than Ntot and Radiation. Therefore, these last two features were not incorporated in the estimation of the final RF model.

The default values of 500 for number of trees and 5 for node size were used.

The error rate of model predictive ability was tested generating an out of the bag validation technique which splits the data set into a calibration and a validation subset with each point left out of the bag approximately 36% of the times (Liaw and Wiener, 2002). Variable importance was estimated based on the changes of regression prediction errors with each specific variable in the out-of-bag validation. To identify most important variables the criteria that least agree with each other were selected. These were: 1. The number of times the variable appears as a root; 2. The mean increase in mean square error after that variable is permuted; 3. The probability (p-value) of the one side binomial test; 4. The number of nodes that used that variable for splitting. Variable importance ranking including all variables created considering node minimal depth and mean in which that variable is presented.

Averaged responses for all trees were considered for the estimation of partial dependence of fitted yield values to SOC variations, with predictions limited to the observed data range. Interactions and correlations between predictors were identified through systematic use of partial dependence and RF interaction frame. RF analysis was performed using the "randomForest" (Liaw and Wiener, 2002) and "randomForestExplainer" packages in R (Paluszynska, 2017). The model performance was assessed using coefficient of determination (R^2) and root mean square prediction error (RMSE).

3.3. RESULTS

3.3.1. SOIL ORGANIC CARBON AND ITS RELATIONSHIP WITH OTHER SOIL PROPERTIES

The percentage of time under pasture caused divergence in SOC over time (Fig. 3.1). Overall, SOC ranged from 1.2 to 2.6. Comparing the first and last cycles of rotation (Table 3.2), SOC decreased 20% for the 0%PS treatment where final SOC reached 1.6%. Conversely, treatments with 33%PS, 50%PS and 66%PS increased SOC by 0.66%, 10.75% and 12.33%, respectively.

Increases in SOC were associated with increases in Ntot and exchangeable K contents with Spearman correlation r=0.79 and 0.49, respectively (Fig. 3.2). SOC was weakly correlated with PBray and pH having a negative relation (r=-0.28 and -0.43, respectively). Furthermore, SOC was negatively correlated with BD (r=-0.91) and positively correlated with aggregate stability (r=0.81, Fig. 3.2). More details on treatment effects on soil physical properties in this experiment can be found in Rubio et al. (2018). Additionally, SOC was positively associated with biological activity measured as N mineralization potential (exponential), as well as CEC (quadratic; Fig. 3.2).

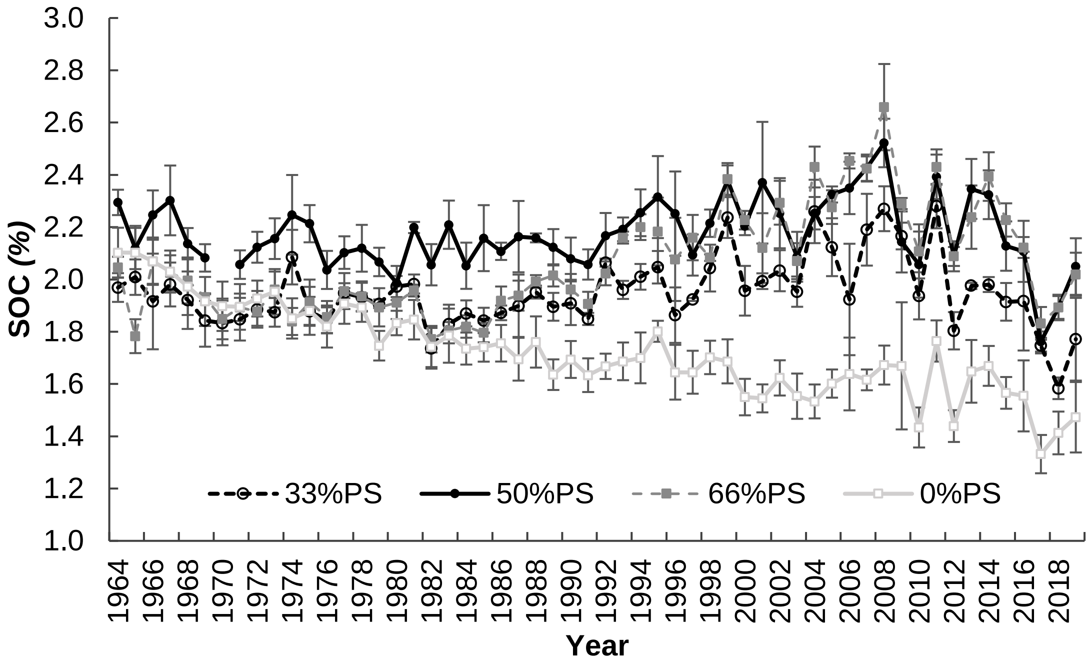

Figure 3. 1: *Soil organic carbon (SOC) evolution, from 0-15 cm depth at INIA long term experiment, as affected by percentage of time (%PS) under pasture and fertilization treatment.*

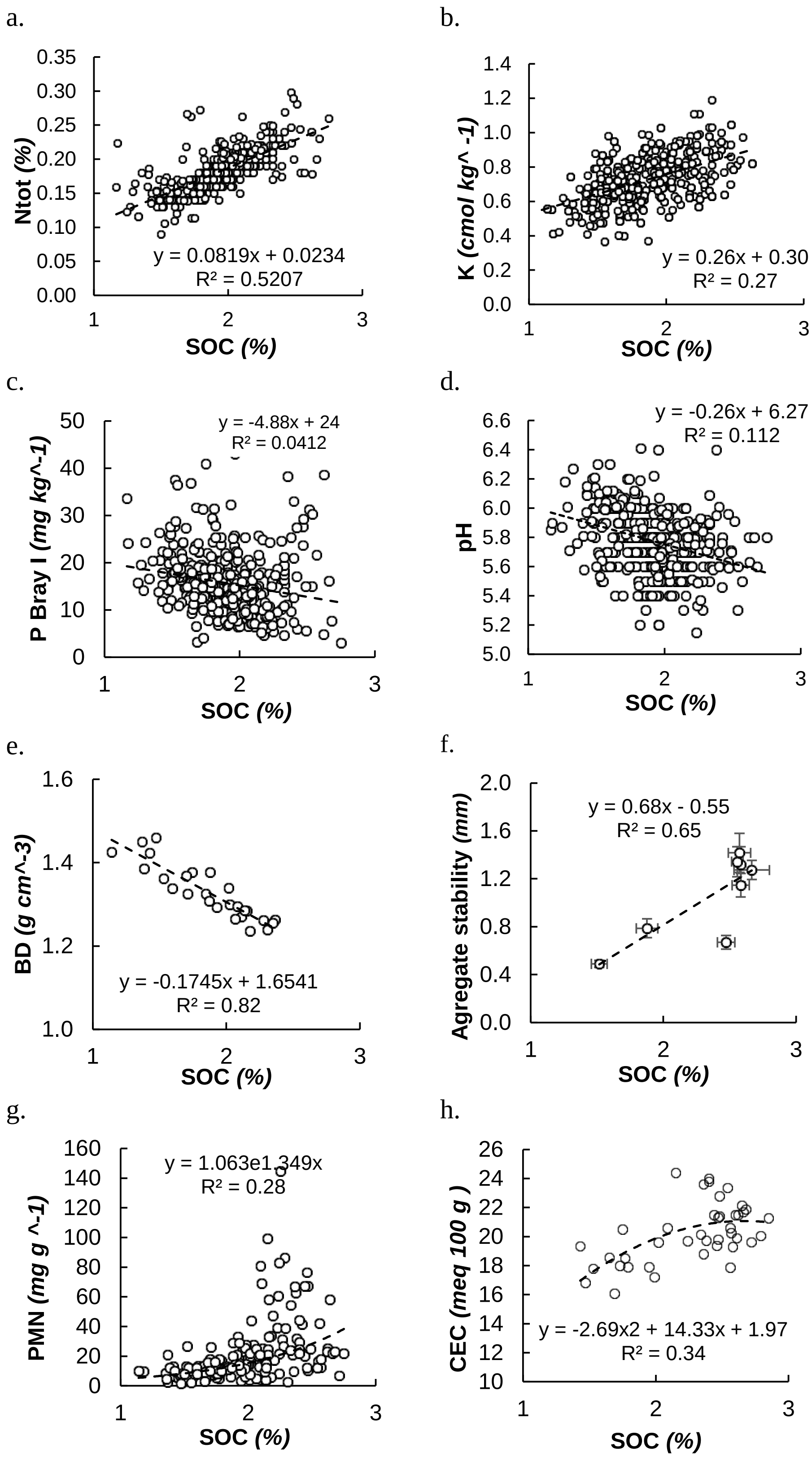
a.
Ntot (%)
y = 0.0819x + 0.0234
R² = 0.5207
SOC (%)
b.
K (cmol kg^ -1)
y = 0.26x + 0.30
R² = 0.27
SOC (%)
c.
P Bray I (mg kg^-1)
y = -4.88x + 24
R² = 0.0412
SOC (%)
d.
pH
y = -0.26x + 6.27
R² = 0.112
SOC (%)
e.
BD (g cm^-3)
y = -0.1745x + 1.6541
R² = 0.82
SOC (%)
f.
Agregate stability (mm)
y = 0.68x - 0.55
R² = 0.65
SOC (%)
g.
PMN (mg g ^-1)
y = 1.063e1.349x
R² = 0.28
SOC (%)
h.
CEC (meq 100 g)
y = -2.69x2 + 14.33x + 1.97
R² = 0.34
SOC (%)

Figure 3. 2: Relationship between soil organic carbon (SOC) and a. Total N (Ntot); b. K (cmol kg $^{-1}$); c. P; d. Soil pH; e. bulk density (BD, g cm $^{-3}$), f) aggregate stability (mm), and g) Nitrogen mineralization potential (PMN, mg g $^{-1}$) and h)Cation exchange capability (CEC, meq 100 g^{-1})

3.3.2. YIELD TRENDS

Average barley and wheat yields were 2,564 and 2,164 kg ha^{-1}, respectively, which are 33% higher than the national yield average for wheat and 14% (FAOSTAT Online Database, 2020). In the last ten years of the experiment the averege yields were 5,137 kg ha^{-1} for the 66%PS treatment, 4,092 kg ha^{-1} for 50%PS, 3,883 kg ha^{-1} for 33%PS and 2,796 kg ha^{-1} for 0%PS, showing a strong relationship between the %PS and cereal yield (Fig. 3.3).

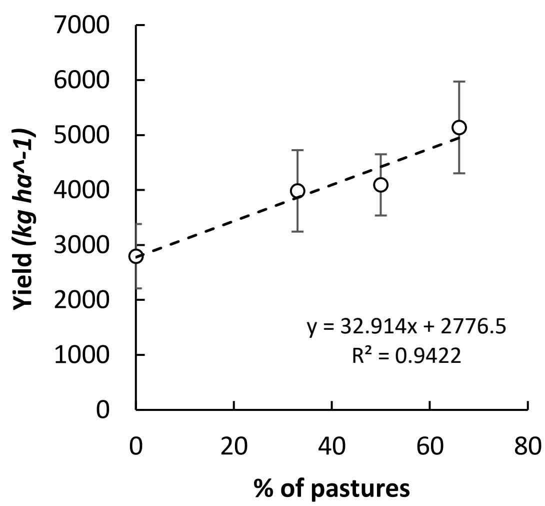

Figure 3. 3: Average wheat and barley yields as a function of time under pasture in the rotation from 2009 to 2019

A positive annual trend was observed in all treatments (Fig. 3.4). On average the annual yield increase was similar to nationwide observations, representing 2.2% of initial yield values (FAOSTAT Online Database, 2020). The annual trend varied among treatments but was linear for those that included pastures. A concave quadratic equation was the best fit for the 0%PS treatment which showed a maximum in 2013, indicating that soil limitations prevented further yield increases despite the improving crop genetic potential.

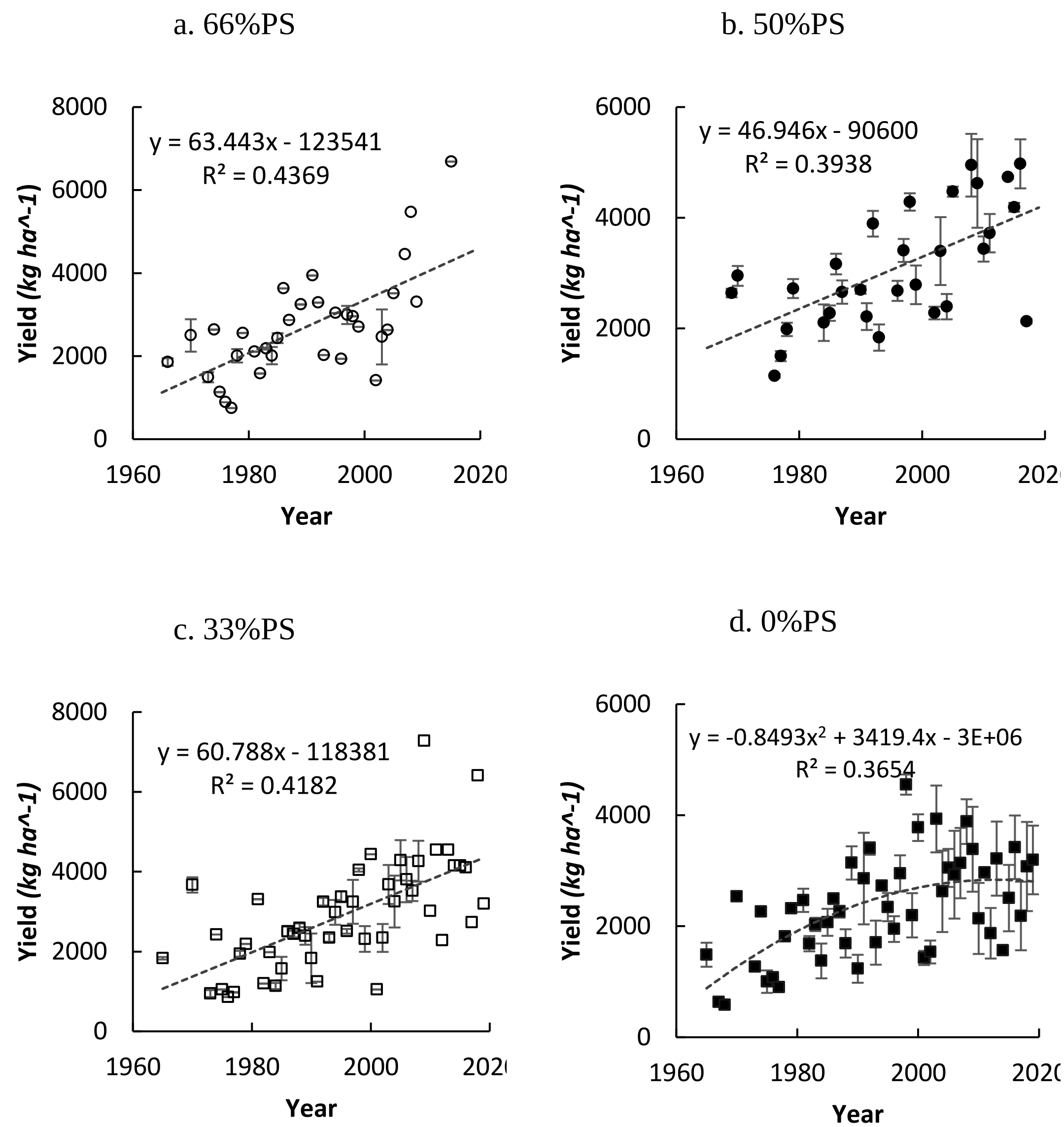

Figure 3. 4*:* Wheat and barley yield trend in the long the experiment. Each plot represents treatments with a different proportion of the time under pastures (%PS).

3.4.Random Forest model

The predictive performance of the RF model for year-corrected yield showed a good performance of RF models with both the complete data set (r=0.96) and the out of the bag validation (0.64; Fig. 3.5). RMSE of the model was 348 kg ha^{-}1 for calibration and 784 kg ha^{-1} for the validation test where 40.34% of the variance in yields was explained.

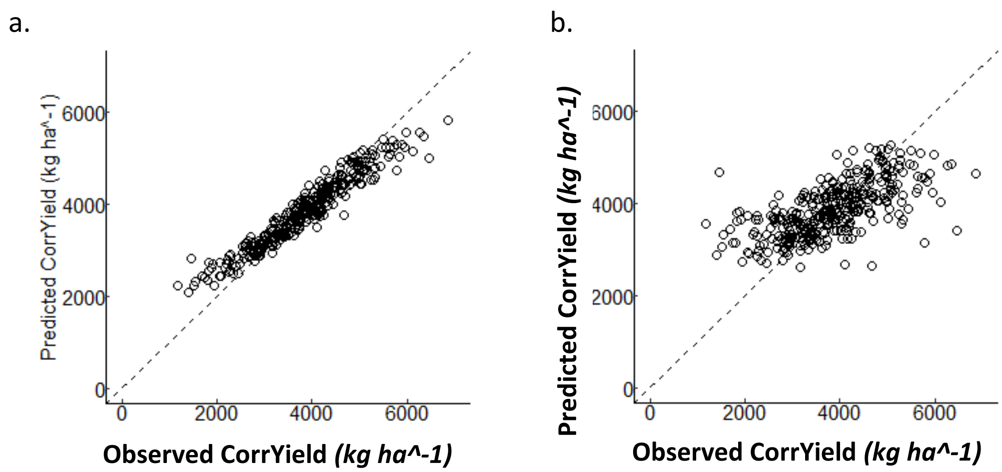

Figure 3. 5*:* Scatter plot of observed vs predicted year-corrected yields (CorrYield) with random forest model for: a) calibration; and b) out of the bag validation data sets.

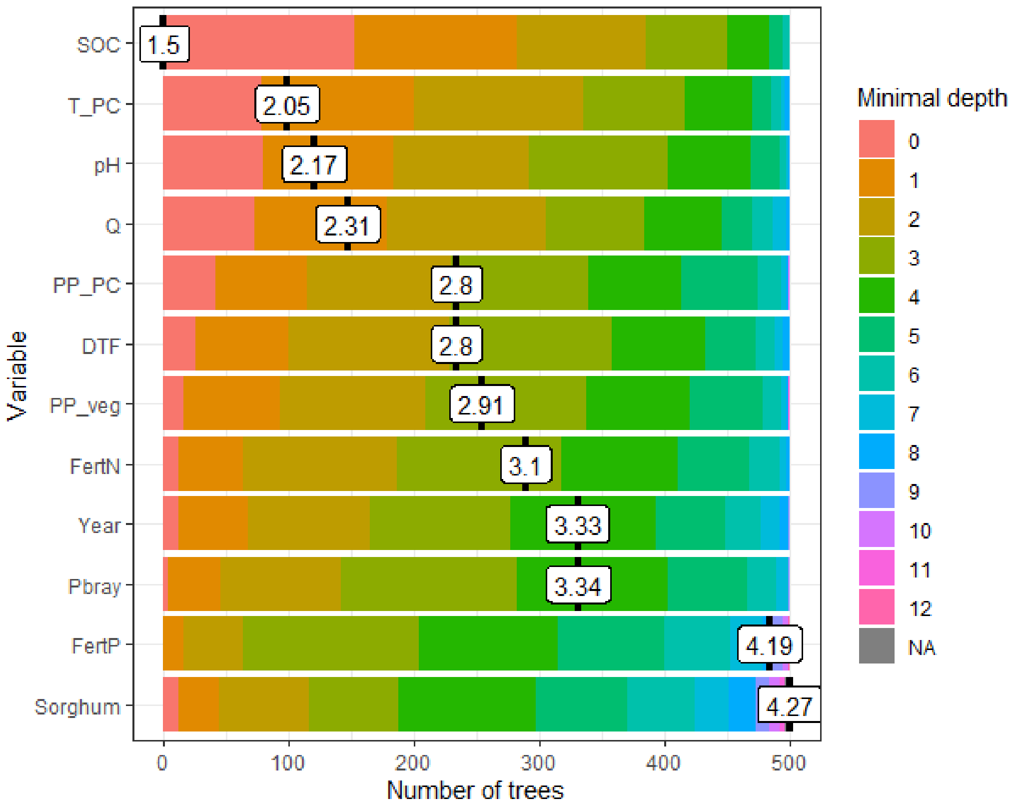

Figure 3. 6:: Variable importance ranking of random forest model for yield prediction, estimated as the average minimal depth of presence in the trees

Where: *SOC: Soil organic carbon; pH: Soil pH; PBray: Phosphorous Bray I; FertP: Phosphorus fertilization; FertN: Nitrogen fertilization; DTF: Number of days between sowing and flowering; Sorghum: Yield of Sorghum harvest pre wheat/barley sowing; T_PC: Average temperature during critical period of yield definition (PC), defined as 15 day pre and post flowering; PP_PC: Accumulated precipitation in PC; PP_veg: Accumulated precipitation till flowering; Q: Average Photothermal coefficient in PC.*

A high degree of agreement between the different criteria in the ranking of the most important variables for yield definition was observed. Combining four of the available variable importance criteriums the top ranked predictor variables for yield were a mixture of soil and climate-related variables: SOC, mean temperature, Q, and soil pH (Fig. 3.6).

The effects of the five most important soil-related variables on yields showed that SOC had a strong positive relationship and pH had a negative relationship (Fig. 3.7). Higher yield losses were associated with a decrease in SOC from 2.6% to 1.2%, representing a reduction of about 1000 kg ha^{-1}. The increase in soil pH generated a reduction in yield of about 500 kg ha^{-1}, which is somewhat counterintuitive considering that the pH values were generally below-optimum (<6.5).   FertN, PBray and FertP did not show clear trends with yields (not shown). The interaction frame showing the most important interactions among variables is presented in Appendix 3.2.

Multi-prediction partial dependence plots showing the most important interactions of SOC effects on yield showed strong interactions of SOC with climatic variables (temperature and Q; Fig. 3.8). Having good climatic conditions allowed the achievement of high yields mostly on sites with higher SOC levels. Similarly, low pH and high SOC were associated with high yields. Dependence plots for FertN and PBray did not show interactions, i.e., higher yields were associated with higher SOC independent of nutrient conditions.

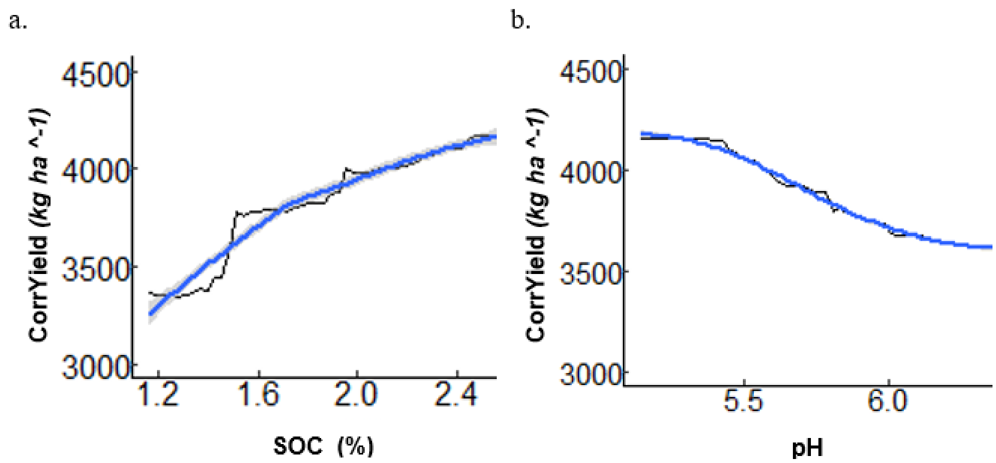

Figure 3. 7: Partial dependence plot between year-corrected yields (CorrYield) and a) soil organic carbon (SOC), and b) soil pH from the random forest model.

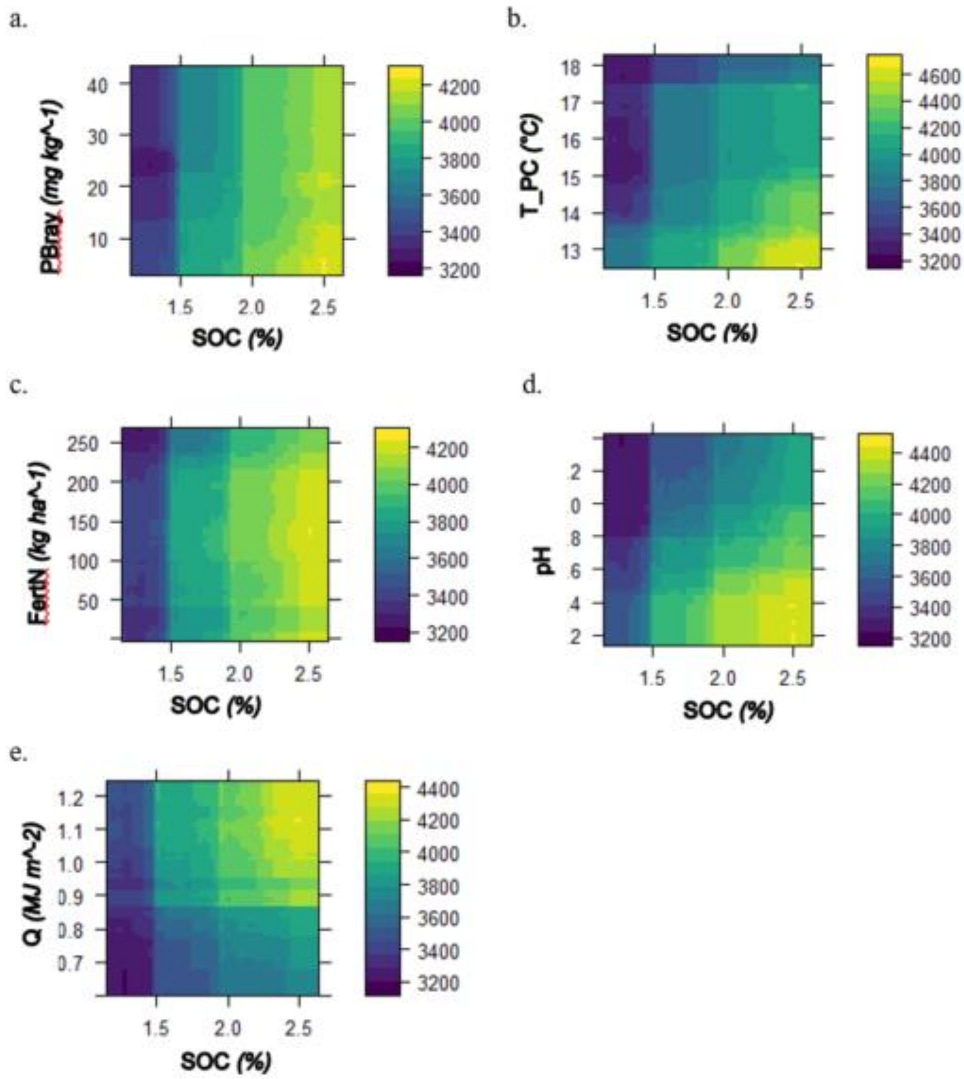

Figure 3. 8: Multi-predictor partial dependence plots showing effects on yield of the interaction between soil organic carbon (SOC(%)) and: a) Phosphorous Bray I (PBray); b) Average temperature during the critical period of yield definition defined as 15 days pre- and post-flowering (T_PC); c) Nitrogen fertilization (FertN); d) Soil pH (pH);e) average Photothermal coefficient during the critical period of yield definition

3.4.DISCUSSION

Contrasting time under pasture generated considerable variations in SOC through the course of the field experiment (Fig.3.1). CPR treatments had lower nutrient extraction, soil erosion, and tillage intensity than CAC systems (Grahmann et al., 2020). The addition of long-term treatment trends and SOC inter-annual variability allowed the evaluation of a wide range of SOC, varying from -42% to +25% of the initial SOC levels. The observed depletion of SOC associated with CAC systems was correlated with a reduction in N content. Considering that N in soil is mostly in the organic form, a tight correlation between C and N is expected. C:N ratios generally vary between 10 and 15 (Murphy, 2015), and in this study, the observed ratio was on average 11.56, suggesting normal C cycling. The positive correlation observed here between C and K is likely associated with the smaller grain extraction of CPR systems that have less cropping frequency. The same decreasing tendency in K content is observed at a national level and associated with an increase in cropping frequency and higher soil erosion losses (Beretta-Blanco et al., 2019). Higher SOC in CPR was also associated with higher CEC and, therefore, nutrient retention potential (Fig 3.2). Thus, despite the strong effect of clay minerals in these soils, reductions in SOC in more intense cropping systems might be related to reduced CEC.

The association of SOC with nutrients is also determined by the fertilization strategy, and the results of this study might do not necessarily represent the overall relationship expected for cropping systems with different proportions of crop or pasture in their rotations. However, the strategy of nutrient management followed here for N, P, K, and CEC bases fairly represent the most common practices, and the main tendencies of change observed in the region (Beretta-Blanco et al., 2019; Wingeyer et al., 2015).

SOC is one of the main soil binding agents, and its positive relationship with aggregate stability has been recognized for a long time, notwithstanding the mineral effects like those from Fe and Al hydroxides and Ca carbonates that were not present in this soil. It has been proposed that no effect on aggregation should be expected when SOC reaches certain levels (Tisdall and Oades, 1982); however, these levels are not clearly defined in the literature. Here a linear association between SOC and aggregate stability was observed. Active and continued root growth during the pasture phase might explain part of the observed results. An association of SOC with BD is expected if the lower SOC reduces aggregation and structural integrity in the face of mechanical stresses. In this study, a very tight relationship between SOC and BD was observed (Fig. 3.2). Additionally, other factors like more intense tillage operations and higher traffic intensities associated with contrasting management practices on CAC and CPR systems might explain these associations.

An exponential relation between SOC and PMN was observed, lower SOC contents were associated with disproportionately lower PMN values. This indicates higher losses of the labile C and N pools, measured through PMN, in relation to the most stable pools in thus systems with less proportion of pastures (Franzluebbers et al., 1996). Therefore, values of SOC below 2% are associated with C that exists in excess of the more stable mineral-bound fractions. Similar outcomes had been observed in a survey of commercial farms in Uruguay where an average reduction in SOC of 20% was related to decreases of PMN of 41.5% (Moron et al., 2012). The decrees in PMN is associated with a degradation of soil biological health, a reduction in N available for plants, and slower SOC cycling (Bünemann et al., 2018; Knoepp et al., 2000). These results agree with the fact that reductions in N supply might be one of the first consequences of the elimination of pastures from cropping systems (O. Ernst et al., 2018)

Overall, CAC systems resulted in the degradation of soil quality and cereal yields when compared with CPR. SOC losses represent the detrimental effects of CAC in soil chemical (pH, Ntot, P, and K), physical (bulk density and aggregate stability) and biological properties (nitrogen mineralization potential). These properties are related to the capacity of soil to retain and provide water and nutrients to crops, and to reduce negative environmental impacts (Arshad and Martin, 2002; Drobnik et al., 2018; Moebius-Clune et al., 2016). Therefore, these results confirm that SOC is a crucial indicator and that summarizes a broader assessment of soil quality (Horn and Peth, 2009).

3.4.1. SOIL DEGRADATION AND TECHNOLOGICAL PROGRESS

An increase in yield associated to technological improvement was observed for all treatments; however, the rates of change varied (Fig. 3.2). The rate of yield increases was constant for CPR treatments, but decreased over time in CAC and reached a maximum in the year 2013. Since the improvements in crop genetic and management practices were the same for all treatments, the cumulative soil degradation counteracted the technological yield gains. Therefore, the adverse effects of soil degradation can limit yield enhancement but can also be hidden by technological progress. This study corroborates the importance of using a yield correction factor to eliminate technological improvements when analyzing LTE datasets.

3.4.2. YIELD DRIVERS

A high proportion of corrected yield variability was explained by integrating climatic, management, and soil chemical properties in a RF model. RF performance was superior to the linear model predictions (results non shown), confirming the advantages of this nonparametric data mining approach for yield evaluations (Hoffman et al., 2019, 2017). Caution is warranted by interpreting the outcome of the model calibration step as model performance in the out of the bag validation process was significantly worse, even when it involved a single experimental site analysis. As previously reported (Hoffman et al., 2017), an overestimation of small yields and an underestimation of large yields was observed (observed values in respect to 1:1 line in Fig. 3.5).

SOC had the highest predictive value for yield (Fig. 3.6), yield reductions associated to SOC losses represented 28% of average yields achieved (Fig. 3.7). Our results confirm that SOC can be used to summarize a wide range of soil functions related with crop production, and to represent the impacts of land degradation associated to CAC systems.

Further reductions in yield associated with CAC were represented by soil pH, which was the third most important variable for yield definition. A change of pH from 5.2 to 6.4 was associated with a 14% yield reduction relative to average values (Fig. 3.6). Considering that the optimum soil pH level reported for wheat and barley is about 6.8

(Rabuffetti, 2017), the opposite effect was expected. This suggests that the observed outcome is not associated with a direct consequence of pH on yield, but rather by the impact of another variables or effects that are correlated with pH but were not identifiable in this experiment.

The second most important variable in yield definition was the average temperature during the critical period, and the average photothermal coefficient was the fourth one. Globally, climatic conditions are estimated to explain about 35% of wheat yields variability, being the temperature one of the most important factors (Ray et al., 2015). Low temperatures and high radiation levels promote high growth rates and long grain development periods allowing the achievement of high yields (Ahmed and Hassan, 2011; Giulioni et al., 1997). Furthermore, these climatic conditions are associated with a lower pressure of diseases and therefore have a substantial indirect effect on yield (Díaz Rosello et al., 2015). However, in soil with low SOC contents, high yields were not achieved even under favorable climatic conditions (Fig. 3.8). This results also indicate that the detrimental effects of soil degradation are more important under years with high yield potentials.

The weak interaction observed in this study between N and SOC (Fig. 3.8) seems to contradict previous results observed by Ernst et al. (2018 and 2020) where the addition of extra N fertilization rates reduced detrimental effects of CAC systems. However, in this study, where N fertilization doses are defined considering treatments effects on N in soil and climatic conditions, important N limitations on yields are not expected. Although our data cannot be used to evaluate N related yield limitation associated to

CAC systems evidence about the existence of non-N yield limitations are provided, in accordance with these same authors.

3.4.3. IS THERE A CRITICAL LEVEL OF SOC?

For a long time, it has been recognized that limitations on yield start below 2% of SOC, and this value is often conceived as a critical level (Kemper and Koch, 1966, Greenland et al. 1975, Kravchenko and Bullock, 2000; Pan et al., 2009; Zvomuya et al., 2008). A global metanalysis recently supported this for wheat and maize (Oldfield et al., 2019). In this study, the evidence was mixed. Yield, BD, and aggregate stability were linearly correlated with SOC and did not show a breaking point at the 2% level. i.e., the benefits of increasing SOC continued above 2% of SOC. But CEC and PMN showed nonlinear patterns where values appeared to plateau or exponentially increase, respectively, near the 2% SOC level. When previous studies suggested that SOC losses have a negative effect on soil structure only below 2% (Kemper and Koch, 1966, Greenland et al. 1975), here negative effects on soil BD and aggregate stability were observed above this value. Considering that SOC effects on soil properties and yields are conditioned among others by soil texture, climate, and the composition of the carbon in the soil (Six et al., 2002; Loveland and Webb, 2003; Murphy, 2015) the existence of a unique critical value of SOC is not probable and also not supported by our data. Similarly, SOC should not be considered as a uniform component, and differences in its chemical form and turnover rates condition its role. Therefore, the relation between SOC and yields could be different if the differences in SOC are generated by amendment additions, or if soils of diverse regions are compared. In all, this LTE offered insights that are difficult to achieve, even with other LTEs, because of the frequency of historical soil sampling and the number of measured properties.

3.5.CONCLUSIONS

The expansion of CAC systems has led to soil degradation challenging the achievement of sustainable intensification goals. SOC is an appropriate indicator to summarize the impact of this degradation over yields, reflecting the deterioration of soil physical, chemical, and biological properties. SOC decline was strongly associated with negative yield impacts that were not overcome by improved production technologies but were nevertheless masked by them. The negative impacts of SOC depletions were more remarkable under favorable weather conditions with higher yield potentials. In conclusion, these results open opportunities to give value to soil degradation in the economic functions of the local agro-ecosystems and help inform policy decisions.

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CHAPTER 4: BIOMASS INPUTS DRIVE IMPACTS OF AGRONOMIC MANAGEMENT ON SOIL HEALTH[3]

ABSTRACT

Identifying effective management practices to conserve and regenerate soil health (SH) is critical for sustainable development, but confounding effects of management are often reported. Aboveground biomass can be used as a guide to assess whether agronomic management practices can generate changes in carbon balances and therefore SH. Data on soil physical, biological, and chemical SH indicators from three Uruguayan long-term experiments on Pampas region Mollisols were used to (i) present quantitative evidence showcasing the importance of evaluating SH through biomass inputs, (ii) assess potential limitations of this approach, and (iii) illustrate the proposed framework for different scenarios of land management. Management effects in aboveground biomass inputs explained 50% of the changes generated in soil physical and biological health indicators. Significant improvements in SH can be achieved by reducing yield gaps and intensifying cropping sequences. However, the benefits of increasing crop diversification, incorporating perennial crops, or reducing tillage may be limited to situations where these practices increase biomass production.

[3] Rubio V, Nuñez A, Berger A., & van Es, H. M. Biomass inputs drive impacts of agronomic management on soil health. To be submitted to Environmental Research Letters

4.1. INTRODUCTION

The recent acknowledgment of soil's central role in food security, water quality, biodiversity preservation, climate change, and other sustainability issues has put its health status on the sustainability agenda. Soil health (SH) refers to the capacity of the soil to function as a vital living ecosystem that sustains plants, animals, and humans(USDA-NRCS 2020). Many management strategies potentially contribute to improving SH and thereby agricultural sustainability. However, inconsistent effects on the direction and magnitude of SH changes are often reported.

These variable responses to agronomic management practices (e.g., tillage, cover crops, diversification, and inclusion of perennial grasses) have been linked to variations in inherent soil conditions (Fiorini et al. 2020; Ghimire et al. 2019), time since the adoption of the management practice (e.g., Poeplau and Don, 2015 for cover crops; Blanco-Canqui and Ruis, for tillage), agro-climatic conditions, and interaction with other management strategies (Luo, Wang, and Sun 2010; Rajan Ghimire et al. 2018; Dimassi et al. 2014). While many of these factors can significantly impact the absolute values of SH, overall, they provide limited explanation for the diverse responses in SH to the same management strategy (Poeplau and Don 2015a; Jian, Du, and Stewart 2020).

Rather than the management practice itself, or the variations in inherent soil properties, recent evidence suggests that the positive effects of management on SH might be limited to those situations where net increases in carbon (C) inputs are achieved (Page, Dang, and Dalal 2020). This is related to the fact that C and nutrient balances are primary mechanisms of soil functions (Guo and Lin 2016). Therefore, understanding SH status and its changes requires envisioning SH through the lens of a critical zone approach (Yoder et al. 2022; Banwart et al. 2019), meaning that they should be analyzed in the context of C and nutrient fluxes within the system, as well as horizontal fluxes outwards.

While a detailed estimation of C fluxes, can be complex, an intermediate achievable goal is to estimate the changes that management generates in aboveground biomass inputs. Higher aboveground biomass inputs can be associated with more continuous plant growth and soil cover, higher root biomass, greater residue mass incorporation, and lower erosion losses, all factors that can improve SH. Therefore, producing and retaining higher plant biomass can promote physical, chemical, and biological properties (Blanco-Canqui and Lal 2009), but most studies that evaluate management effects on SH do not report the associated changes in biomass. A recent meta-analysis, encompassing 581 independent experiments, to elucidate cover crop benefits on SOC, the most extensively measured SH indicator, reported that only 28 studies registered biomass changes. Therefore, the relationships between biomass inputs and SH is still mostly undetermined (Mirzaei et al. 2021).

We hypothesize that the potential benefits of agronomic management on SH can be evaluated through the accumulated changes in aboveground biomass, attempting a critical zone approach. Our objectives are to use data on SH indicators from three Uruguayan long-term experiments on Pampas region Mollisols to (i) present quantitative evidence showcasing the importance of evaluating SH through biomass inputs, (ii) assess potential limitations of this approach, and (iii) illustrate the proposed framework for different scenarios of land management.

4.2.MATERIALS AND METHODS

This study builds on SH data recently published by Rubio et al. (2022) and evaluates a methodological approach to estimate changes in SH as it relates to biomass inputs. Here we present only a brief description of the experiments and SH determination methodologies, while details can be found in Rubio et al. (2022).

4.2.1. SITES AND EXPERIMENTS

We evaluate three experiments located at La Estanzuela Experimental Station (INIA, the Uruguayan National Agricultural Research Institute) in SW Uruguay (34º20 S, 57º41 W, 82 masl). The site has a warm temperate climate with an average temperature of 16.6°C. Annual average precipitation is 1100 mm, almost evenly distributed throughout the year, but with considerable interannual variability. The dominant soil type is a Typic Argiudoll (USDA Soil Taxonomy), and the soil texture class of the surface layer (0-15 cm) is silty loam or silty clay loam.

Table 4. 1: Treatment descriptions for three long-term experiments.

Exp	**%Pasture**	**Tillage**	**Current crop rotation**
1	0% PS	CT-NT*	[Barley/<u>Sorghum</u>]-[Wheat/<u>Soybean</u>]-[Fallow/<u>Corn</u>]
1	50% PS	CT-NT*	[Barley/<u>Sorghum</u>]-[Wheat/<u>Soybean</u>]-[Fallow/Corn]-3yr.[<u>Pasture</u>]
1	66% PS	CT-NT*	[Barley/<u>Red clover</u>]-[<u>Red clover</u>]-[Fallow/Sorghum]-3yr.[<u>Pasture</u>]-[Fallow/<u>Corn</u>]

1	33% PS	CT-NT*	[Fallow/Sorghum]- [Wheat/Soybean]-[Red Clover]
2	0% PS	MT	[Wheat/Fallow]-[Oat cover crop/Corn]-[Barley/Soybean]
2	50% PS	MT	[Wheat/Fallow]-[Oat cover crop/Corn]-[Barley/Soybean]- 3yr.[Pasture]
2	0% PS	NT	[Wheat/Fallow]-[Oat cover crop/Corn]-[Barley/Soybean]
2	50% PS	NT	[Wheat/Fallow]-[Oat cover crop/Corn]-[Barley/Soybean]- 3yr.[Pasture]
3	0% PS	NT	[Fallow/Soybean]
3	0% PS	NT	[Oat cover crop ^{early}/Soybean]
3	0% PS	NT	[Oat cover crop ^{late}/Soybean]

*PS: non-harvested pastures; CT: Conventional tillage; NT: No-tillage; *: NT since 2009; MT: Minimum tillage. ([ ]): Separate different years in the rotation; (/): Separate winter and summer crops; early: early termination 60 days pre-sowing; late: late termination 30 days pre-sowing. Underlined crops represent sampling time in each experiment and treatment. Barley:*
Hordeum vulgare L.; *Wheat: Triticum aestivum* L.; *Sorghum: Sorghum bicolor; Soybean: Glycine max; Corn: Zea mays; Red clover: Trifolium pratense; Oat: Avena sativa.*

The evaluated experiment and treatments are presented in Table 4.1 and are further detailed in Rubio et al. (2022). Briefly:

- Experiment 1 was established in 1963 to research perennial pasture duration in cropping systems. We evaluate four contrasting treatments, arranged in a randomized complete block design with three staggered replications. The plot size is 5000 m^{2,} and the site slope is about 2.5 to 3%.
- Experiment 2 was established in 1996 to study crop rotation and tillage effects in cropping systems. We evaluate four randomized treatments arranged in a

2x2 factorial with three staggered replicates. The plot size is 495 m^2, and the slope is less than 1%.

- Experiment 3 was established in 2004 to investigate the effects of cover crop incorporation and duration in a continuous soybeans (*Glycine max)* system under NT. We evaluate three treatments arranged in a partially randomized six-block design. The plot size is 132 m^2, and the slope is less than 1%.

In all experiments, crop management followed INIA's technical recommendations for the region. Annual crop fertilization with mineral N and P was performed at sowing according to soil test recommendations. Annual crops were harvested for grain, and straw was retained on the plots. Oats (*Avena sativa*) were sown as cover crops. Perennial pastures were composed by a mixture of tall fescue (*Festuca arundinacea* Schreb.), white clover (*Trifolium hybridum* L.), and birds´-foot trefoil (*Lotus corniculatus* L.) and managed by cutting leaving the biomass in the fields in all experiments. Crops and pastures were grown under rainfed conditions without additional irrigation, except soybeans in Experiment 3 where supplemental irrigation was applied equally to all treatments at sowing.

4.2.2. SOIL SAMPLING AND ANALYSES

One four-core composite soil sample per plot was collected on December 2019 from the 0–15 cm depth following the CASH protocol (Schindelbeck et al. 2022; Moebius-Clune 2016). Average maximum penetration resistance from 0 to 15 (PR15) and 15 to 45 cm (PR45) depths was determined from 15 in-field probings using an Eijkelkamp penetrologger (www.Eijkelkamp.com). Different rotation entries were sampled at each block due to the staggered start replications in experiments (underlined crops in Table 4.1). A total of 18 soil chemical, physical and biological indicators were assessed. Soil chemical properties measured at the Laboratory of Water, Plants, and Soils of INIA La Estanzuela (Colonia, Uruguay) were: soil pH (Beretta et al., 2014); SOC and total N (LECO TrueSpec CN-2000); exchangeable P (Bray and Kurzt 1945); exchangeable bases (K, Mg, Ca, and Na) at pH 7; cation exchange capability (CEC) at pH 7 (Jackson 1964); and percent base saturation.

Subsamples were submitted to the Cornell University Soil Health Laboratory (Ithaca, NY, USA) for analysis of soil physical and biological properties. Details on the laboratory techniques are available in Moebius-Clune et al. (2016) and Schindelbeck et al. (2022). Evaluated soil physical indicators were: plant-available water capacity (AWC) (Topp et al. 1997); wet aggregate stability (WAS); and soil texture (Kettler, Doran, and Gilbert. 2001). Evaluated soil biological indicators were: permanganate-oxidizable C (POXC)(Weil et al 2003); autoclaved citrate extractable soil protein (ACE Protein) (Hurisso et al. 2018); and soil respiration (Resp) (Schindelbeck et al 2022).

4.2.3. ESTIMATION OF CUMULATIVE ABOVEGROUND BIOMASS INPUTS

Cumulative aboveground biomass inputs per plot were estimated based on measured yields from the beginning of each experiment to the sampling date (Dec. 2019). Crop yields were measured for each crop in four 50*1.5 m areas along the center of each plot for Experiment 1; for Experiments 2 and 3, the entire plot was harvested. The estimated harvest index values were: 0.45 for soybean; 0.5 for corn; 0.35 for sunflower; 0.5 for sorghum; 0.4 for barley; 0.43 for wheat produced after 1970, and

0.23 for wheat before 1970 (Bolinder et al., 2007; Gholinezhad and Bernousi, 2009). Non-harvested biomass was assumed to have been left in the field and cycled back to the soil. For pastures, aboveground biomass was measured by cutting, drying, and weighing the biomass in four areas of 2.5 m^2 located at the center of each experimental plot, 6-10 times a year. The same procedure was used to estimate total biomass accumulated and returned to the soil by cover crops at termination time.

4.2.4. DATA ANALYSIS

A composite SH index was estimated for each plot as the unweighted mean of scored soil physical and biological indicators. Scored indicators between 0 and 100 were calculated using the CASH laboratory scoring algorithms (Fine et al 2017) based on the cumulative normal distribution of observed SH values in the studied USA.

Treatment effects on accumulated aboveground biomass input and the composite SH index were evaluated for each experiment through analysis of variance (ANOVA). Mean separation was computed using Tukey's posthoc test after a significant F-ratio ($p < 0.05$). For each experiment, the treatment that does not apply any conservation practice (a priori worst management scenario) was selected as a reference, corresponding to 0%PS for Experiment 1, 0%PS_MT for Experiment 2, and Cont_soy for Experiment 3. The effects of conservation practices on SH and accumulated aboveground biomass were estimated as the change from the reference treatment. Linear regression analyses were performed to evaluate how cumulative biomass related to individual SH indicators and to the composite SH index.

4.2.5. HYPOTHETICAL MANAGEMENT SCENARIOS

Based on established relations with biomass inputs, four hypothetical management scenarios were used to evaluate potential changes in SH after 12 years compared with a continuous soybean system baseline. The four alternative scenarios were: 1. eliminating soybean yield gaps; 2. scenario 1 plus the inclusion of cover crops; 3. replacing continuous soybean with a soybean-corn (*Zea mays* L.) rotation with cover crops; and 4. replacing six years of crops in scenario 3 for a perennial pasture ("ley" farming). All scenarios were evaluated for two yield levels, current yield (mean yield scenario) and potential yield, to assess potential gradients of response.

Average national yields from 2009 to 2019 (DIEA 2020) were used for the estimation of biomass inputs for the mean yield scenarios. Average yields of the top five cultivars in the National Cultivar Evaluation Experiments from the same period (Instituto Nacional de Semillas (INASE) were used for the potential yield (eliminated yield gap) scenario. These yields, obtained under small plot experiments, might overestimate the attainable yields at the farm level but represent maximum achievable yields for the environment under best management practices. Mean and potential biomass for cover crops and pastures were defined based on the reports for mean and top 10% dairy farmers from La Cooperativa Nacional de Productores de Leche (CONAPROLE) estimated with remote sensing data (Gabriel Oleggini et al 2017). Yield values for each scenario are presented in Appendix 1. The regression function between changes in biomass and the composite SH index was used to estimate potential changes in SH.

4.3. RESULTS AND DISCUSSION

4.3.1. EFFECT OF BIOMASS PRODUCTION ON SOIL HEALTH

4.3.1.1. Treatment effects on composite soil health

A general pattern across the three experiments exists where increased composite SH scores are associated with management practices that improved productivity and increased aboveground biomass inputs into the system (Fig. 4.1). For Experiment 1, including perennial pastures into a continuous crop rotation with low baseline biomass inputs (3.59 Mg ha^{-1} yr^{-1}) significantly increased biomass inputs and SH (p-value < 0.0001). Yet for Experiment 2, pasture incorporation did not increase biomass or SH (Fig. 4.1b). Compared to Experiment 1, the reference treatment of Experiment 2 includes a more intense cropping sequence with a higher proportion of C_4 crops. This resulted in high baseline biomass inputs (6.05 Mg ha^{-1} yr^{-1}), which were not increased by including perennial pasture (p-value = 0.26). The observed discrepancy shows that even under similar inherent conditions the same management practice can generate dissimilar results, requiring a more in-depth understanding of its impact on C inputs. Further supporting the close relationship between biomass inputs and SH, expanding the perennial pasture duration from 33% to 55% in Experiment 1 resulted in additional increases in biomass and SH. Similarly, cover crop inclusion and its duration on a continuous soybean system significantly raised aboveground biomass and SH in Experiment 3. But no benefits were observed by increasing pasture duration beyond 50% in Experiment 1 where no further rise in biomass inputs were generated (50%_PS vs 66%_PS). Overall, specific management practices successfully increased SH only when there was a change in biomass production and retention.

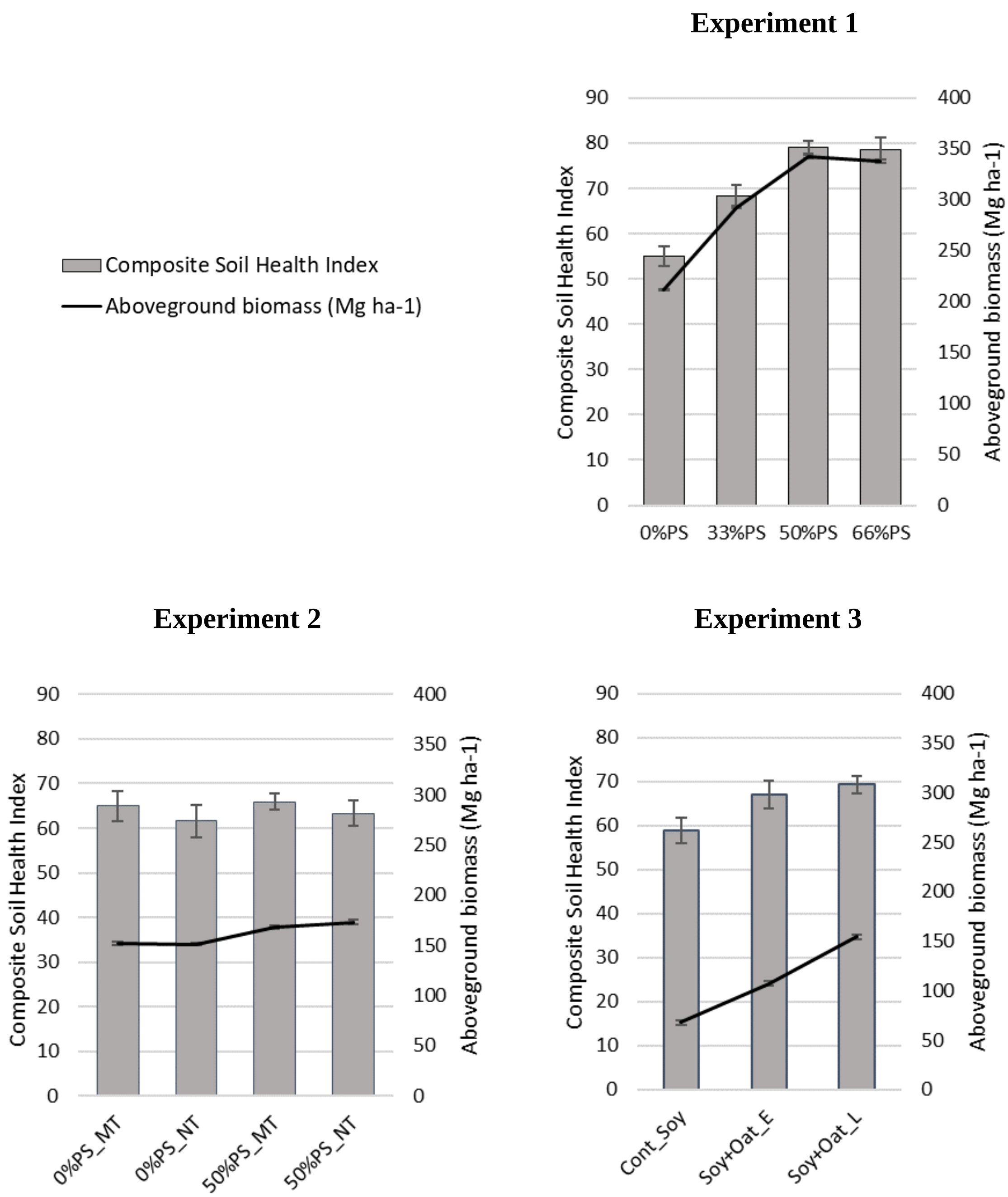

Figure 4. 1. Composite Soil health physical and biological index and accumulated aboveground dry biomass inputs during the experiment from crops and pasture and cover crops phases per treatment as a function of treatment.

Where: %PS, refers to the percentage of time under perennial non-harvest pastures; MT: to minimum tillage treatments; NT: to no-tillage treatments; Cont_Soy: to continuous soybean systems; Soy+Oat: to continuous soybean treatments with Oat as winter cover crop terminated early (E) or late (L) in the growing season.

These results support the notion of a dominant effect of management-induced changes in aboveground biomass on resulting changes in SH. This helps explain why the same management practice may or may not impact SH, independently of crop diversity, perenniality, or tillage system (Figs. 4.2-4.5).

A key aspect of our analysis is the evaluation of cumulative biomass changes. SH indicators reflect the status of the soil given the accumulation of processes over time, thus different experiments with contrasting length, histories and trajectories can be brought together by evaluating SH changes resulting from the variations in cumulative biomass. This approach eliminates the effects of SH variations associated with initial conditions, baseline biomass inputs, and contrasting experimental durations facilitating the integration of different experiments. Such potential SH benefit assessments could be done at low cost by using vegetation indices derived from remote sensing data, which can robustly estimate aboveground biomass production (Meng et al 2013, Dong et al 2020).

4.3.2. BIOMASS EFFECTS ON SOIL HEALTH INDICATORS

Overall, aboveground biomass inputs explained variations in physical, biological, and chemical SH indicators (Figs. 4.2-4.5). Changes in aboveground biomass explained up to 50% of the variation in the composite physical and biological SH index (Fig 4.2).

Increasing biomass inputs promotes microbial activity and fosters SOC sequestration (Xie et al 2022). SOC gains may explain the overall SH benefits since SOC controls a broader set of SH indicators (e.g.,Bünemann et al., 2018; Rubio et al., 2021a; Schjønning et al., 2018). This strong correlation between biomass inputs and a broad set of SH indicators helps explain the similar responses of a set of ecosystem services to the variations in vegetation indices estimated from remote sensing data (José M. Paruelo 2016, Staiano et al 2021).

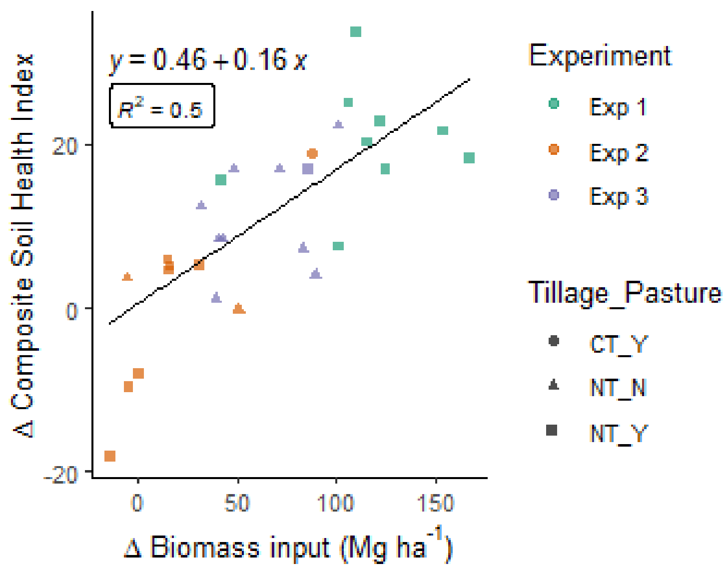

Figure 4. 2: Variations in the composite Soil Health Index as a function of the change in above-ground biomass.

Where: Δ, refers to the variation with respect to the reference treatment; Tillage=CT, represents conventional tillage treatments; Tillage=NT, represents no-tillage treatments; Pasture=Y; represents treatments incorporating perennial pastures in the cropping sequence; and Pastures=N, represents treatments that do not incorporate pasture in the cropping systems.

Increases in biomass were specifically correlated with improvements in total and active C, Resp, WAS, surface and subsurface penetration resistance, total N, CEC, and % base saturation (Figs. 4.3-4.5). AWC was not related to the changes in biomass, as it has known low sensitivity to land use effects compared to soil texture differences (Amsili et al 2021, Nunes et al 2021, van Es and Karlen 2019). Chemical indicators related to soil nutrient content had low correlations with changes in biomass. This can be explained by the effects of synthetic fertilization additions and crop nutrient extractions on soil nutrient contents that are not reflected by biomass inputs.

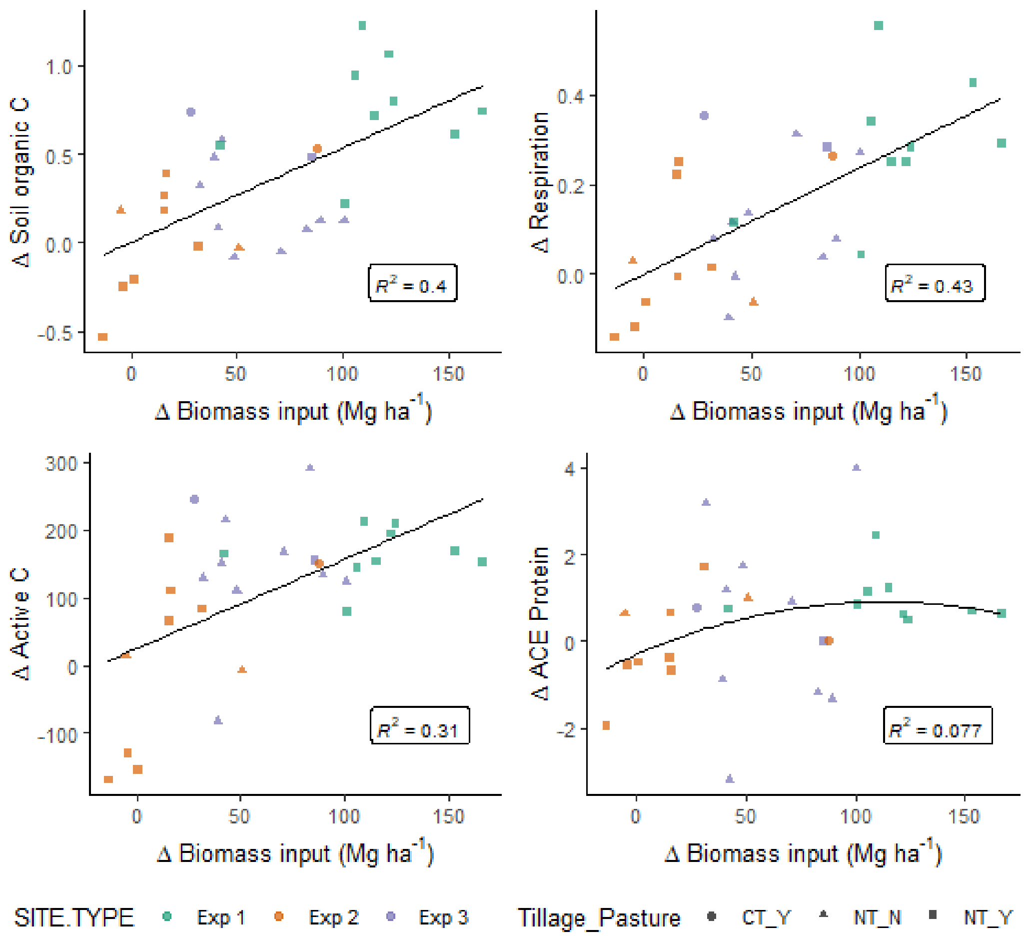

Figure 4. 3: Variation in biological soil health indicators as a function of the variations in above-ground biomass.

Where: Δ, refers to the variation with respect to the reference treatment; Tillage=CT, represents conventional tillage treatments; Tillage=NT, represents no-tillage treatments; Pasture=Y; represents treatments incorporating perennial pastures in the cropping sequence; and Pastures=N, represents treatments that do not incorporate pasture in the cropping systems.

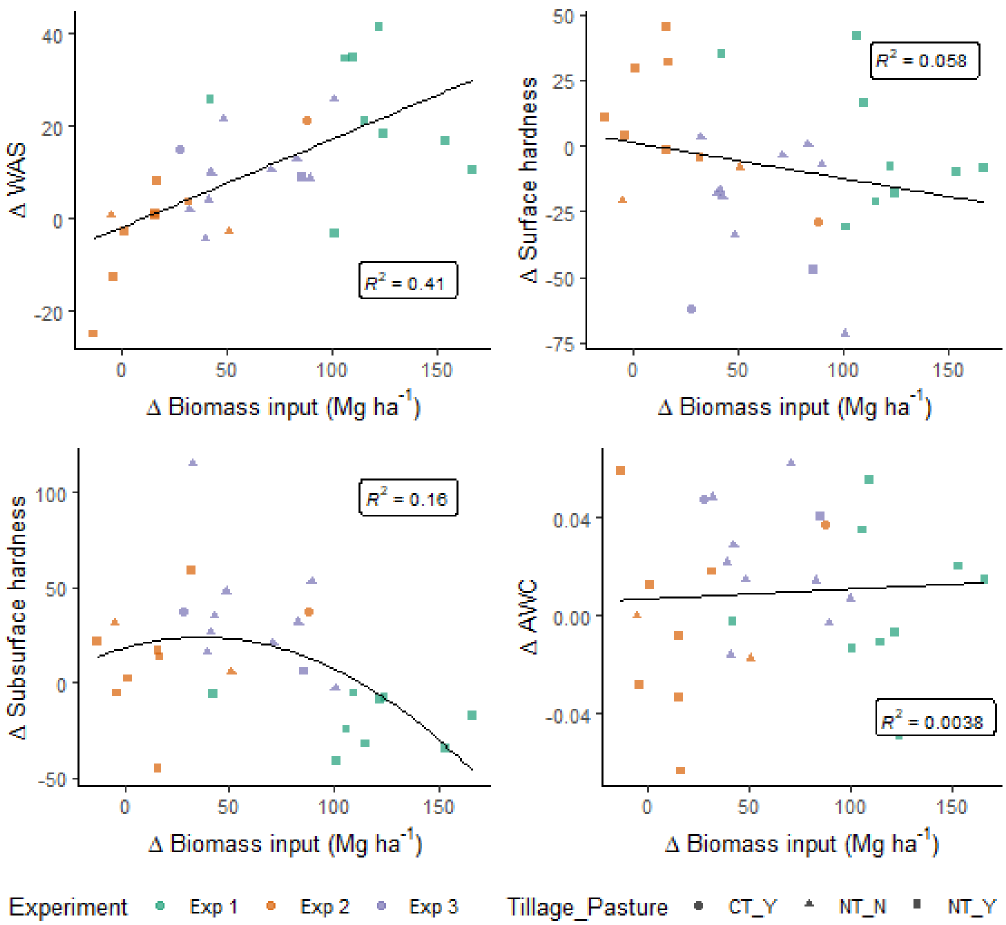

Figure 4. 4: Variation in physical soil health indicators as a function of the variations in above-ground biomass.

Where: WAS, refers to the water aggregate stability; AWC, to available water capacity; Δ, represents the variation with respect to the reference treatment; Tillage=CT, represents conventional tillage treatments; Tillage=NT, represents no-tillage treatments; Pasture=Y; represents treatments incorporating perennial pastures in the cropping sequence; and Pastures=N, represents treatments that do not incorporate pasture in the cropping systems.

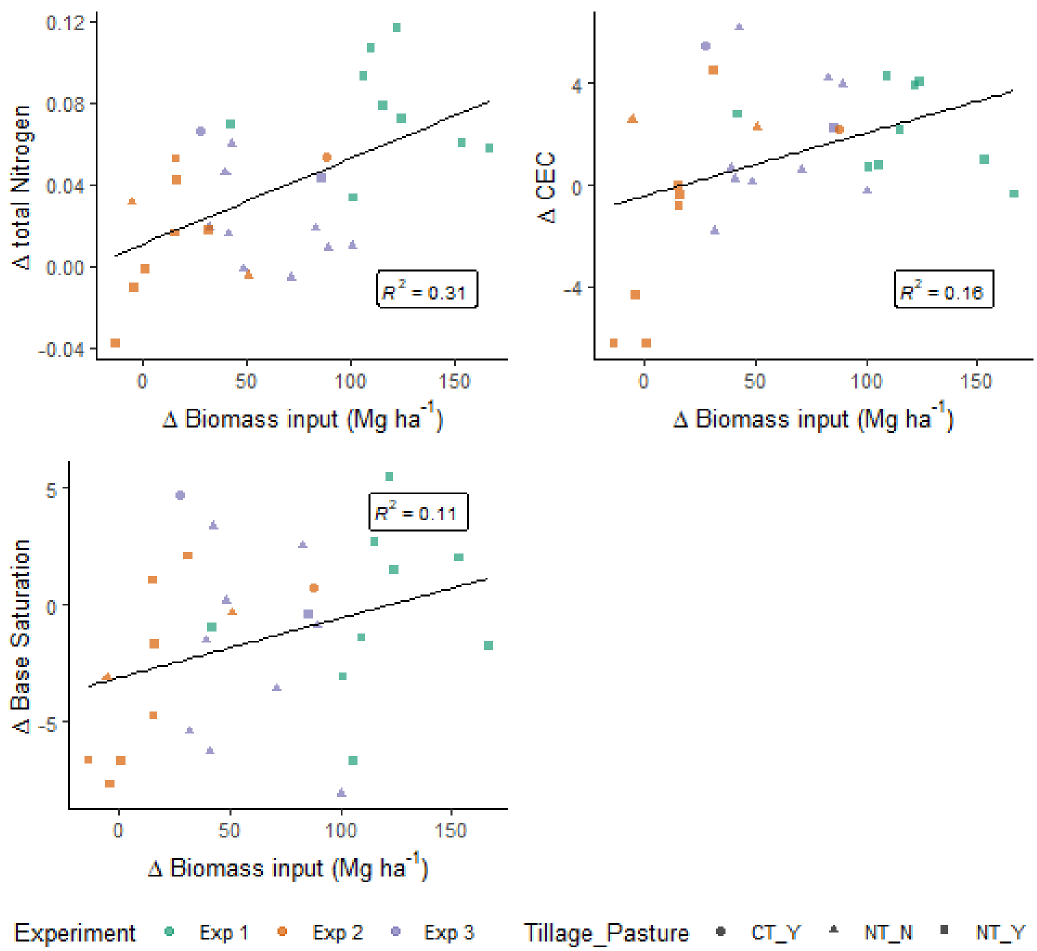

Figure 4. 5: Variation in chemical soil health indicators as a function of the variations in above-ground biomass.

Where: Only indicators with significant correlations are represented; CEC, represents the cation exchange capability; Δ, represents the variation with respect to the reference treatment; Tillage=CT, represents conventional tillage treatments; Tillage=NT, represents no-tillage treatments; Pasture=Y; represents treatments incorporating perennial pastures in the cropping sequence; and Pastures=N, represents treatments that do not incorporate pasture in the cropping systems.

Interestingly, under similar aboveground biomass inputs, we did not observe additional benefits on SH due to a higher proportion of perennial pastures. This was unexpected since the inclusion of perennial pastures reduces tillage frequency, and increases C inputs from roots, rhizodeposits, and crop diversification (Baethgen et al., 2021; Franzluebbers and Gastal, 2018; Kögel-Knabner et al., 2022), all factors that increase C use efficiency and residence time of stabilized C (Lal 2018). Different results could be expected when evaluating subsoil responses to management, where 20 % of total management effects in SOC had been reported (Skadell et al. 2023). Biomass source material (crop type) did not affect the relationship between aboveground biomass and SH, which suggests that biomass quantity is more important than quality for SH and C balances (Berti et al 2016).

The relationship between SH indicators and biomass inputs was not affected by tillage system (minimum vs. no-till; Experiment 2). Tillage benefits are generally associated with decreased C losses through soil erosion and CO_2 mineralization (Ogle et al 2012, Palm et al 2014) , but erosion was not a major concern in the tillage experiment due to the very low slope of the site (< 1%). Different results can be expected for sites with higher erosion rates. Ours therefore align with previous observations that the positive effects of no-till adoption on SOC depend in part on changes to C balances (Ogle et al 2012), i.e., those benefits may be limited if there is no significant erosion concern or change in yield.

A second step in evaluating SH from the critical zone approach is determining the amount of biomass needed to generate a specific level of change in SH. Here, all the evaluated indicators showed a linear relationship to biomass input variations in the range of observations, except for ACE Protein and subsurface penetration resistance. However, as observed for SOC, benefits from agronomic management and biomass cycling are expected to be finite and reach an equilibrium (Six et al 2002), and will also be limited by the maximum net primary productivity of each location. More significant and faster benefits are expected in degraded soil with higher SOC saturation deficits (Baethgen et al 2021; Pravia et al 2019), which was not observed here for ACE Protein, which is a very labile component of SOM yet R^2 values were low for this particular indicator.

In all, this study shows the prevailing effect of above-ground biomass inputs for a broad set of conservation practices and SH indicators. This information can explain the variable results observed among different long-term experiments involving conservation practices and highlights the importance of maximizing crop productivity to maintain SH in agroecosystems. In this context, even maintaining high yield potentials and associated biomass inputs through synthetic fertilizer applications appears to result in SH and SOC benefits (Rubio et al., 2022; Skadell et al., 2023).

4.3.3. PREDICTING SH CHANGES UNDER DIFFERENT MANAGEMENT SCENARIOS

The strength and magnitude of aboveground biomass input effects on SH indicators for Mollisols in Uruguay allows for the assessment of SH changes from hypothetical agronomic management alternatives. The generated scenarios can represent expected management changes for the Pampas region, a major global grain export area. Here, production was traditionally performed in rotation with perennial pastures which limited overall SH degradation (Grahmann et al., 2020; Moron, 2003) . However, early 2000's commodity prices promoted the expansion of soybean monocultures, reaching 67% of the cultivated area (Wingeyer et al 2015). No-tillage and higher-yielding grain crops, and other agronomic advances may have limited the severity of SH loss, but the greater shift from perennial pastures to a low-biomass monoculture crop overall resulted in significant soil degradation (Beretta-Blanco et al 2019, Nicolas et al 2022).

4.3.3.1. Reducing yield gap and incorporating cover crops.

Fig. 4.6 shows the biomass inputs and SH effects of several agronomic management alternatives, with horizontal bars represented the range of outcomes between current and optimal (no gap) yield levels. The low biomass returns of soybean monocultures represented in our baseline scenario can explain the recent soil degradation observed in the Pampas, while improvements in biomass inputs are possible without changing the crop rotation. Simply reducing the soybean yield gap (yields increase from 2.2 to 6.5 Mg ha^{-1}) generates benefits in SH (up to 8.6 points of increase for the composite SH Index with scale 0-100; Fig. 4.6). Incorporating cover crops in a continuous soybean rotation can further boost cumulative aboveground inputs. Variations in the magnitude of cover crop benefits in C sequestration, microbial activity, and soil physical properties have been broadly reported (Poeplau and Don 2015b, Jian et al 2020a, Muhammad et al 2021). Here, estimated cover crop benefits for the composite SH Index can vary between 6 and 21 depending on biomass productivity (Fig. 4.6), highlighting the importance of maximizing biomass. Cover crop benefits can be achieved without changing the main cash crop in the rotation and without affecting its yield (Pinto et al 2017;Vendig et al 2023). Similar responses can be expected by incorporating a winter cash crop (double cropping; data not shown), with the additional advantage of adding extra income.

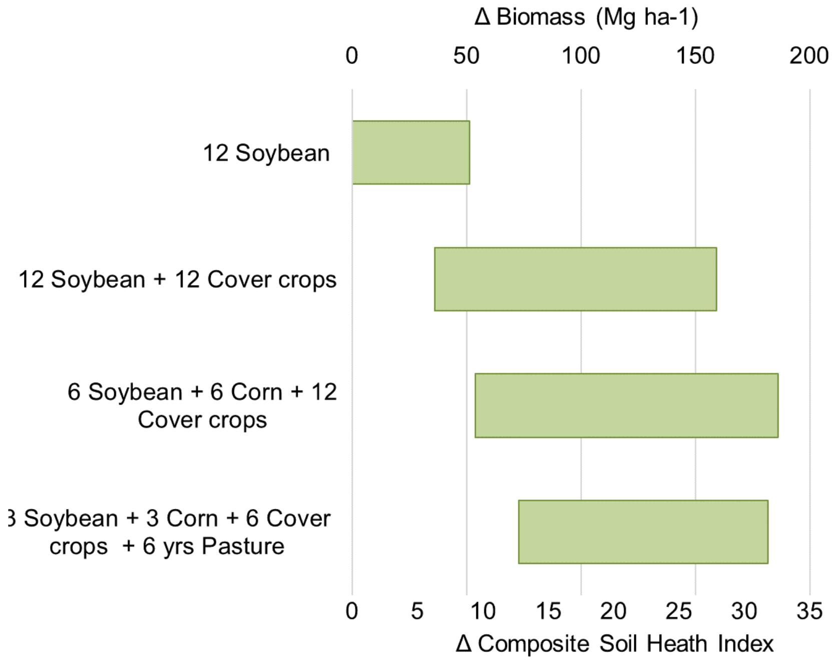

Figure 4. 6: Impact of cropping system changes on above-ground biomass inputs and composite soil health index: 12-year estimates compared to a continuous soybean system with national average yields.

Where; Δ, represents the expected variation; and the low end of the variation range assumes current yield levels, and the high end assumes potential yield levels.

4.3.3.2. Alternative rotations

Further increases in SH may be achieved if corn, a crop with higher biomass returns to the soil than soybean, replaces 50% of the soybeans. This change can raise composite SH scores between 9 and 22 compared to continuous soybean. Higher biomass inputs and SH can explain the benefits of corn-soybean rotations over soybean monocultures in crop yield at ~ 23% for the Brazilian Pampas (Pott et al 2023) .

Re-incorporating pastures into crop rotations has been proposed to improve the sustainability of cropping systems in the Pampas (Carvalho et al 2021). Our results show that this strategy would generate lower cumulative biomass input and expected

SH benefits than those generated by a continuous corn-soybean rotation with cover crops under the high-yield scenario (closed yield gaps), even if 100% of pastures biomass is returned to the soil (Fig. 4.6). Overlaps among scenarios are explained by varying yield levels (from current to closed yield gap), and show how only productive pastures and crops generate the expected benefits in SH. Low biomass production of pastures during the establishment year and biomass depletion over time generates a disadvantage when compared with intensive and productive annual crops (Ojeda et al. 2018). However, the incorporation of pastures can generate greater changes in biomass and SH under the average yield scenario, meaning that this strategy may have lower risks.

While the economic incentives for integrated crop-pasture systems might not be favorable, our results show that other techniques like optimization of rotations with high-biomass crops, minimizing yield gaps yields, and increasing active plant growth periods (cover crops) can potentially reach similar and even higher biomass inputs and SH levels than systems that include pastures. Our approach, however, does not account for other potential concerns associated with continuous annual cropping systems like increased energy, water, fertilizer, or pesticide uses, soil erosion, or compaction which might have negative environmental impacts that are not reflected by the indicators evaluated here.

4.4. CONCLUSIONS

Understanding the impacts of management practices on aboveground biomass is key to predicting potential effects on SH. Aboveground biomass quantity, rather than origin, is a strong determinant of conservation practices' benefits. Notably, soybean production, which in recent years has greatly expanded in South America under monoculture, produces limited post-harvest residue biomass. Including high-biomass annual crops (e.g., corn) and perennials into rotations, eliminating yield gaps, and including cover crops can enhance biomass inputs and improve SH. Although aboveground biomass can be easily estimated and measured it is rarely reported, but further evaluations of SH-biomass relationships will provide valuable insights on the potential benefits of different cropping and conservation strategies. Furthermore, given the expanding technologies available for remotely sensing biomass production (e.g., satellite-based NDVI), the presented relationships may be used to estimate SH changes on larger scales.

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CHAPTER 5: MAPPING SOIL HEALTH AT REGIONAL SCALE: DISENTANGLING DRIVERS AND PREDICTING SPATIAL LAND USE EFFECTS[4]

ABSTRACT

Soil health (SH) is usually represented by measuring dynamic soil indicators that vary considerably in time and space based on the interactions of factors such as soil type, current and historic land use and management strategies including cropping system, and crop productivity. Hence, SH indicators are typically difficult to generalize and costly to assess at broad geographic scales. Digital soil mapping based on machine learning (ML) can integrate SH observations with remotely sensed data and may provide a promising alternative for efficiently predicting SH at scale, especially if short and mid-term management data are included into the models. Four soil biological (soil organic matter, POXC, Protein, and respiration) and two physical (water aggregate stability and available water capacity) indicators as well as a composite SH index were evaluated to 1) establish associations between climate, inherent soil properties, land use, and management to SH indicators in NY State; 2) develop data-driven models for predicting and mapping SH indicators at the regional scale; and 3) estimate SH impacts from hypothetical scenarios of regional land use change. The approach proved to be a valuable strategy for mapping dynamic SH

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indicators (average R^2=0.58), except available water capacity (R^2=0.28) for which limitations in the precision of model covariates associated with soil texture limit its evaluation. Anthropogenic actions explained on average 42% of the variations in SH indicators. Land use systems and management practices that increase biomass return to the soils are associated with better SH conditions. Land use changes can have minor mean effects in SH at the regional scale. However, SH improvements generated by the incorporation of pasture-hay into annual cropping systems can be considerable for some specific areas within the region. Overall, the geospatial application of ML models to map SH provides insights into SH variability and drivers that can support efficient management interventions helping target solutions to sites where higher benefits are expected.

5.1. INTRODUCTION

Soil health (SH) is defined as the capacity of the soil to function as a vital living ecosystem that sustains plants, animals, and humans (USDA-NRCS, 2020) . To evaluate SH, a comprehensive set of functional indicators should be measured (Moebius-Clune et al., 2016). However, the inherent cross-scale and temporal variability of SH indicators challenges diagnostics and gaining understanding of its drivers (Karlen et al., 2001).

SH is a major component of rational and regenerative land use, which is increasingly receiving attention from policymakers. The State of New York recently passed a Soil Health and Climate Resiliency Act (Senate: S4722A/House: A5386A, 2021), which endeavors to assist farmers to adapt to climate change and to contribute to greenhouse gas mitigation goals by improving SH. It also mandates science-based SH standards to assist in farm planning and goal setting. The development of these standards requires a comprehensive understanding of the status of SH and pathways for improvement to set meaningful and attainable goals. This leads towards an evidence-based strategy for prioritizing land management strategies and geographic targeting.

SH is defined by a complex interplay between inherent soil properties, land use, and management practices (Moebius-Clune et al., 2016). Inherent properties generally remain static over time and are defined by the long-term effect of soil-forming factors (i.e., time, climate, parental material, topography, and biology). Dynamic properties, represented by SH indicators, change on annual or decadal time scales, and are affected by shorter-term land use strategies and management practices. Different SH reference values have been developed for soil with contrasting inherent properties based on attributes such as texture (Fine et al., 2017 Nunes et al., 2020; Nunes et al., 2023). Nevertheless, the nature of the relationships between climate, inherent soil properties, and land use or management strategies in determining SH status remains largely unknown.

Digital Soil Health Mapping with Machine Learning

Digital soil mapping (DSM) integrates point-based soil measurements with remotely-sensed spatial data, with the latter serving as environmental covariates in machine learning (ML) and other statistical modeling frameworks such as regression kriging that are used for DSM. DSM has demonstrated accuracy and cost-effectiveness in mapping inherent soil properties at scale in certain regions (Searle et al., 2021). Many studies had been performed to map SOM, despite being a dynamic soil property most studies don't incorporate recent land use and management data for its evaluation, and do not consider sampling date for the determination of model covariates. Therefore, SOM is indeed evaluated as a static soil property. With the exception of SOM, the use of DSM use for mapping dynamic soil properties has been limited (FAO / Global Soil Partnership, 2018), and comprehensive SH evaluations had not been performed.

The lack of available land use and management covariates at scale may limit DSM utility for mapping SH indicators, particularly for properties that are more sensitive to short-term agronomic factors than SOM, including commonly-measured indicators like permanganate oxidizable carbon, protein, and respiration (Nunes et al., 2018). In the US, emerging data products are addressing these limitations including the Crop-specific Land Cover Data (CLD) digital map created by the National Agricultural Statistics Service (NASS) of the US Department of Agriculture. CLD provides an annual land use classification by identifying crop types at 30 m spatial resolution (USDA, 2020). Within a given region, specific crops often have similar management practices (e.g., tillage and fertilization) and, therefore, their presence and frequency might have similar cumulative medium-term effects in SH. Furthermore, crop sequences can be grouped to identify the main land use system, e.g., continuous cash grain systems can be differentiated from dairy systems since dairies usually alternate the annual cash grains with perennial pastures or hay. Significant variations in SH indicators among land use systems have already been identified in New York State (Amsili et al., 2021). On the extremes, annual systems with low biomass residues (e.g., vegetables) typically have lower SH indicators than perennial pastures with permanent soil cover and high levels of in situ biomass recycling.

Another promising data product to use as covariates in DSM are the short- and medium-term time series of vegetation indices, which can provide information related to vegetation growth, indicating its productivity and active growth periods. These in turn influence the quantity and quality of biomass that can potentially be returned to soil as residues, as well as by root decomposition following harvest, which are the energy drivers related to many SH indicators. Normalized Difference Vegetation Index (NDVI) values reflect the phenology and growth of crops and might reflect differences in management that cannot be accounted by the main land use type and crop.

Modeling interpretability and SH drivers

Utilizing DSM for evaluating SH indicators will not only contribute to predicting SH at large scales, but can also enhance our comprehension of the underlying SH drivers (Beucher et al., 2022; Padarian et al., 2020; Samek et al., 2019). Recent advances in ML interpretability generated by the use of SHapley Additive exPlanations (SHAP) values developed by Lundberg Scott M. and Lee Su-In., (2017) allow us to unravel the complex patterns between prediction covariates and predicted properties and evaluate the contribution of each covariate to the final model for each observation. Promising results have been reported for predicting soil organic matter (SOM), yielding useful insights into its drivers, and patterns of spatial variation (Wadoux et al., 2023).

Higher datasets on SH indicators, better model interpretability, and the increasing availability of high-resolution data on environmental covariates increase the potential utility of DSM for prediction and understanding soil properties. In this study, we incorporate three land-use-related factors in our DSM models to predict SH, including (i) the main land-use systems, (ii) the frequency of different crops within these systems, and (iii) their productivity based on NDVI values. We hypothesize that combining land use and cropping systems information with more traditional covariates in DSM will strengthen the prediction of dynamic physical and biological SH indicators, while permitting us to anticipate the impacts of future land use changes on soil health.

The objectives of this study are to 1) quantify relationships between climate, inherent soil properties, and land use for SH indicators across NY State; 2) develop data-driven models for predicting and mapping SH indicators at the regional scale; and 3) use predicted SH maps to estimate impacts from hypothetical regional land use change scenarios.

5.2. MATERIALS AND METHODS

5.2.1. DATASET AND STUDY AREA

The Comprehensive Assessment of Soil Health (CASH; Moebius-Clune et al., 2016) was developed to assess sets of physical, biological and chemical indictors. We evaluated samples voluntarily submitted for CASH analysis by agricultural professionals and farmers to the Cornell Soil Health Laboratory, between 2014-2021.

Samples were presumably collected following the instructions given by Moebius-Clune et al. (2016), representing the soil surface layer from 0-15 cm. Our analysis focused on the evaluation of continuous annual grain cropping systems, continuous perennial pastures or hay, rotations that incorporate annual crops and perennials, and mixed systems that cultivate annual grains, processing vegetables, and pastures (see section 3.2). Soil orders other than Entisols, Alfisols, or Inceptisols were not evaluated since they were not sufficiently represented in the dataset.

To correct potential biases, we cleaned the dataset eliminating outlier observations for slope (>10%) and SOM (> 7.4%, 7.6%, and 8.1% for coarse, medium, and fine soil, respectively). The sample location, which was provided by the client, was individually checked, eliminating samples with obvious errors in geotagging. Finally, only samples that included all CASH indicators were tested, resulting in a final dataset of 827 samples (Fig. 5.1).

Our study evaluated two different geographic domains, the larger one (35,120 km^2; 827 samples) representing all the Major Land Resource Areas (MLRA) (USDA, Natural Resources Conservation Service, 2022) within New York State where agriculture takes place. The smaller domain (17,954 km^2; 579 samples) which is a subset of the first, encompassing the glaciated landscapes and gently rolling hills of the 'Ontario-Erie Plain and Finger Lakes Region' MLRA, and as well as the valleys and ridges of the 'Glaciated Allegheny Plateau and Catskill Mountains' MLRA. Overall, samples were well-distributed throughout the evaluated regions (Fig.5.1).

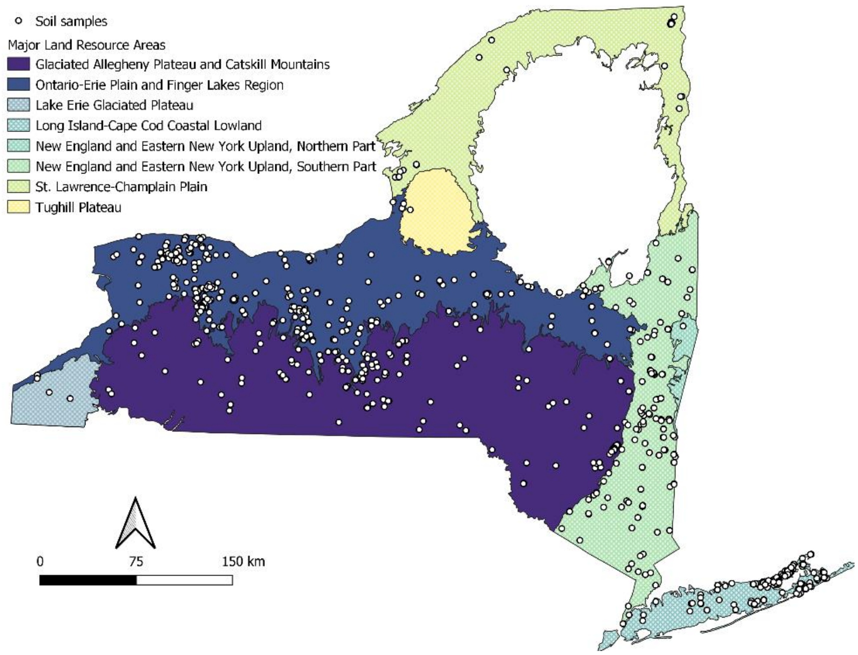


Figure 5. 1: Locations of the study areas and spatial distribution of the soil health observations.

5.2.2. SOIL HEALTH INDICATORS

Each sample was analyzed at the Cornell Soil Health laboratory (Ithaca, NY) for a set of soil physical and biological indicators. Details on the laboratory techniques are found in Moebius-Clune et al., (2016) and Schindelbeck et al., (2022). Briefly, the evaluated indicators were:

- Total soil organic matter (SOM) determined using loss on ignition (LOI) method at 500°C and was estimated using Storer's (1984) Eq. 1.

  $SOM = (LOI \times 0.7) \times 0.23$ [1]

- Permanganate-oxidizable carbon (POXC) measured as the C oxidized by a dilute potassium permanganate solution (KMnO4) through solution absorbance at 550 nm using a hand-held colorimeter (Weil et al., 2003).
- Autoclaved citrate extractable soil protein (ACE Protein) determined by extracting soil proteins following a series of centrifugation and autoclaving steps using 0.02 M sodium citrate at pH 7 (Hurisso et al., 2018), and a bicinchoninic acid assay against bovine serum albumin standard curve to determine soil protein concentration.
- Soil respiration (Resp) assessed by trapping and measuring CO_2 emitted by soil microorganisms over a 4-day room temperature incubation in a sealed chamber with a KOH trap (Schindelbeck et al., 2016).
- Plant-available water capacity (AWC) measured as the water retained between −10 kPa and − 1500 kPa, and assessed gravimetrically by equilibrating soil on ceramic plates in high-pressure chambers (Topp et al., 1997)
- Wet aggregate stability (WAS) measured as the proportion of stable aggregates (0.25–2 mm size) after a rainfall simulation (2.5 J of rainfall energy for 300 s).
- Composite Soil Health Index (SH Index; scale 0-100) calculated as the un-weighted arithmetic mean of all the scored values of individual SH indicators (also scale 0-100) calculated in turn from observed values using their cumulative normal distribution as proposed by Fine et al., (2017).

Table 5.1 summarizes the basic statistics for the evaluated SH indicators for the complete final dataset (large domain). Basic statistical parameters were similar for both domains, and the respective histograms of SH indicators are presented in the

Appendix 5.1. A natural logarithmic transformation was applied to indicators that exhibited skewness values higher than 0.5 (SOM, ACE Protein, Resp, and WAS) to enhance the accuracy of the statistical analyses. The composite SH Index had a range of values from 9 to 99 on a theoretical scale of 0-100, indicating that a wide range of SH conditions existed within the study areas (Table 5.1).

Table 5. 1: Descriptive statistics of the evaluated soil health indicators for NY State

	SH Index	SOM	POXC	ACE Protein	Resp	AWC	WAS
	------------%------------		------------mg/kg-----------		mgCO2/kg	----%----	---g/g---
Mean	54	3.07	535	6.5	0.58	0.22	33.7
Min	9	0.20	20	0.42	0.01	0.05	2.6
Max	99	7.57	1259	20.06	2.16	0.39	100
SD	21	1.27	198	2.72	0.28	0.05	23.6
Relative SD	39	42	36	40	49	23	66
Skewness	0.31	0.73	0.24	1.48	1.46	-0.1	0.84
Kurtosis	2.25	3.35	3.17	6.36	6.28	3.54	2.66

Where: SH Index: Composite Soil Health Index; SOM: Soil organic Mater; POXC: Permanganate-Oxidizable Carbon; ACE: ACE Protein; Resp: Respiration; AWC: Available water capacity; WAS: Water aggregate stability.

5.2.3. MODEL COVARIATES FOR PREDICTING SH AT SCALE

A set of 26 high-resolution publicly-available covariates with known effects in SH were selected for this study. Table 5.2 describes each variable, including data source and spatial resolution. Variables were grouped into three categories according to the factors they represent: (1) Climate, (2) Soil & Topography, and (3) land use & management. The first two are standard for DSM; the latter aims to represent historical and recent land use and management strategies to strengthen the use of DSM to predict dynamic soil properties. We consider a system as a land use sequence over a period of years as opposed to a single year to account for the legacy of past management. Here we characterized the land use and management by looking at the main land use system, the proportion of the mean crops in the rotation, and NDVI.

Crop frequencies can help elucidate the differences within the land use systems, and NDVI values can elucidate variations on management and productivity within the same crop. A six-year period prior to sampling was selected since this is the typical duration of the crop rotations associated with dairy farms in the region and the maximum period of available data. The evaluated periods went from 2008-2013 for samples submitted in 2014 to 2016-2021 for samples submitted in 2022.

The production system and the percentage of time under different crop types were determined by evaluating the USDA's cropland data layer (CDL) (USDA, National Agricultural Statistics Service Cropland Data Layer, 2023). We considered CDL values from 2017-2022 to generate current SH maps. For the determination of the production system, CDL information was first grouped into four categories of production systems: (i) annual grain cropping systems (Annual_Grain_sys); (ii) rotating annual crops and pastures or hay, which mostly represent cropping systems associated with dairy farms (Grain_Past_Hay_sys) and where the annual grain is primarily corn (*Zea mays* L.) for silage; (iii) continuous perennial pastures, or hay (Past_Hay_sys), and (iv) rotations between annual grains, processing vegetables and pastures (Annual_Grain_Veg_sys). The complete list of crops in each category is presented in Appendix 5.2. A summary of the average proportion of time under the evaluated crops, pasture, and hay for each production system and the predicted areal extent are presented in Appendix 5.3. Categorical variables, including USDA Soil Taxonomy soil order and production system, were converted into dummy variables.

Table 5. 2: Model covariates variable description, sources, and spatial resolution

Name	Description	Source	Spatial resolution
Climate			
Mean_Temp	Historic mean annual temperature (˚C) (2000-2017)	MODIS	1 km
Precipitation	Historic mean accumulated annual precipitation (mm)		1 km
Soil & Topography			
Soil_Order*	Inceptisols, Entisols, and Alfisols	Gridded Soil Survey Geographic Database (gSSURGO)	30 m
Drain_class	Ordinal values: 1= Very poorly drained, and 7= Excessively drained		
Slope	Slope gradient in percent	NASADEM_HGT/001 dataset (NASA, 2021)	30 m
Clay	Percent clay for 5-10 cm depth.	POLARIS Probabilistic Remapping of SSURGO (Chaney et al., 2019)	30 m
Silt	Percent silt for 5-10 cm depth		
pH	pH for 5-10 cm depth		
Organic_Matter_P	Percent SOM for 5-10 cm depth		
Bulk_Density $^{\Delta}$	Bulk density (g/cm3) for 5-10 cm depth		
Land Use & Management			
Production system*	Annual_Grain_sys, Grain_Past_Hay_sys, Past_Hay_sys, and Annual_Grain_Veg_sys.	Cropland Data Layer USDA National Agricultural Statistics Service Cropland Data Layer (2023)	30 m
Past_Hay_perc	Percent perennial grasses and legumes in pastures or hay areas		
Alfalfa_leg_ perc $^{\Delta}$	Percent perennial legumes mostly alfalfa used for hay production		
Crop_perc	Percent annual grain crops		
Corn_perc $^{\Delta}$	Percent corn		
Soy_perc $^{\Delta}$	Percentage of soybean		
Wheat_Barley_perc $^{\Delta}$	Percentage of wheat and barley		
Rye_Oat_perc $^{\Delta}$	Percentage of rye and oats		
Veg_perc	Percentage of processing vegetables		
Annual_NDVI	Mean NDVI value 1 yr pre sampling		30 m

Mean_NDVI	Mean NDVI value 6 yr pre sampling	Landsat-7 image courtesy of the U.S. Geological Survey

*Where: *represent categorical variables which are treated as dummy variables in the XGBoost models; $^{\Delta}$ represents variables that were not included in the final optimized predictions models; Soybean: Glycine max; Wheat: Triticum aestivum L.; Barley: Hordeum vulgare; rye: Lolium multiflorum L Oat: Avena sativa.*

5.2.4. DSM WORKFLOW

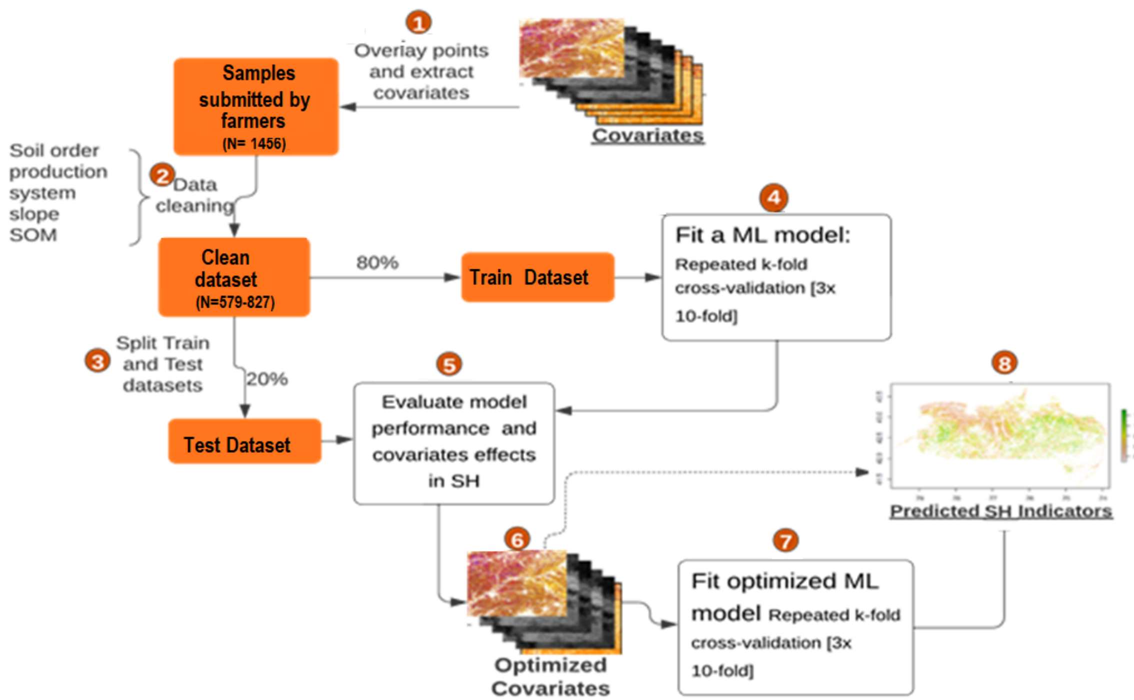


Figure 5. 2: Workflow and modeling approach summary

5.2.4.1.Model calibration

We evaluated five models per indicator and spatial domain. Four were partial models and one was a complete model including all covariates. The first three partial models evaluated the effects of Climatic, Soil & Topography, and Land Use & Management separately. The fourth partial model assessed the combined effect of Climatic and Soil & Topography related covariates.

The modeling approach (Fig 5.2) used extreme Gradient Boosting (xgBoost), an optimized boosting algorithm that builds models from individual "weak learners" in an interactive way. Data were initially divided into training (80%) and validation (20%) datasets. Model training was performed using a repeated 10-fold cross-validation scheme as a resampling method, with the Caret Package in the R statistical software (R Core Team, 2018). This procedure was repeated five times using different splits, reducing the variance in the estimates of the model's performance, and making it more reliable than a simple random division of the dataset into calibration and validation datasets. Model hyperparameters were optimized using a grid search approach considering all possible combinations. The tuned parameters and their evaluated values are presented in Appendix 5.4. For each SH indicator, the best combination of model parameters was selected based on the lowest root mean square error (RMSE) as the performance metric.

5.2.4.2.Model performance evaluation

Model performances were tested on the validation datasets as an independent measurement. The percentage of variance explained by the models and the RMSE normalized by the interquartile range of the predicted SH variable (NRMSE) were estimated. The Lin's concordance correlation coefficient (LCCC) was estimated to evaluate the fit of the observed and predicted values in the independent dataset to the 1:1 line (Lin L, 1989), assessing model predictive capacity. The correlation between observed and predicted values, histograms of model residuals, and the spatial distribution of the residuals were also evaluated to assess model performance (Appendix 5.5, 5.6). All analyses were carried out using R statistical software (R Core Team, 2018). All algorithms were implemented in the ‘Caret’ and ‘xgboost’ (Kuhn, 2008) packages.

5.2.4.3. Variable importance and contribution to the models

To evaluate the importance and functional form of the association between covariates and SH indicators, we evaluated SHAP values. These represent the contribution of each feature to the final model prediction accounting for the interaction with other covariates, by using concepts from cooperative game theory (Christopher Molnar, 2022). The main advantage of this approach is that all possible feature combinations and their selection orders are evaluated to estimate the SHAP values, since the order in which a model sees features can affect its predictions. Also, SHAP values can be computed for individual observations, providing additional insight into model performance and drivers of SH in diverse settings. All evaluations were performed using the SHAPforxgboost R package (Yang Liu and Allan Just, 2020)

5.2.5. SPATIAL PREDICTION OF SOIL HEALTH INDICATORS

The original covariate resolution spanned from grid cell sizes of 30*30 m to 1 km, and all variables were therefore aligned to 100 m grid by resampling with a near neighbor or bilinear interpolation. Covariates were then transformed into a common spatial domain corresponding to the extent of NY State. Predictions of SH indicators for 2023 were performed considering the six years prior to 2023 for the land use-related data layers (CDL, and NDVI related covariates). The coordinate reference system used in this study was WGS 1984 UTM zone 40 (EPSG:32640).

For SH predictions, full models were optimized by removing the less important variables and aiming to reduce model overfitting. Covariates that showed a consistently low contribution, as measured by their SHAP values on the initial models, were eliminated from the optimized models. The eliminated variables were bulk density and variables representing the individual contributions of annual grain crops (Alfalfa_leg_perc, Corn_perc, Soy_perc, Wheat_Barley_perc, Rye_Oat_perc). Both annual and mean NDVI were maintained in the final model as they had a high contribution to the final models, despite being highly correlated. The final prediction models included 20 covariates consistent across physiographic domains and individual SH indicators. Log-transformed indicators were back-transformed for mapping.

5.2.6. PREDICTING SOIL HEATH CHANGES UNDER LAND USE CHANGE

To illustrate a potential use of the models, we estimated SH under a hypothetical land use change scenario for areas in Central New York that despite spatial proximity currently have different land use characteristics. Seneca County has a high prevalence of annual grain production, while lands in neighboring Cayuga County are mostly part of integrated crop-livestock dairy farms. The latter system has been proven to increase SH. The scenario consisted of replacing all continuous annual grain crops systems (Annual_Grain_sys) in the areas with integrated annual crops and pastures and hay systems (Grain_Past_Hay_sys). The land use and management parameters were defined by estimating the average values of all the land use related covariates for the region under Grain_Past_Hay_sys. The mean values of land use model covariates for Grain_Past_Hay_sys and Annual_Grain_sys are presented in Table 5.3.

Table 5. 3: Mean land use covariates for annual grain systems and annual grain pasture and hay systems for Seneca County.

	Annual_Grain_sys	**Grain_Past_Hay_sys**
Annual_NDVI	0.175	0.216
Mean_NDVI	0.1996	0.2325
Crop_perc	94%	57%
Corn_perc	46%	30%
Soy_perc	39%	24%
Wheat_Barley_perc	8%	4.7%
Oat_Rye_perc	1.2%	1.1%
Past_Hay_Perc	0%	34%

Where: Annual_Grain_sys: annual grain cropping systems; Grain_Past_Hay_sys: integrated annual crops and pastures and hay systems.

5.3. RESULTS AND DISCUSSION

5.3.1. MODEL PERFORMANCE

Table 5.4 summarizes the performance of the five evaluated models for the state of New York (large domain) and for the subregion of Ontario-Erie Plain, Finger Lakes Region, Glaciated Allegheny Plateau and Catskill Mountains domain for each SH indicator. Significant variations were observed among models, domains, and indicators. The results demonstrate that given a sufficiently large dataset dynamic physical and biological SH indicators can be predicted at a regional scale, specifically if a comprehensive set of covariates are included in the models.

5.3.1.1. Geographic domain and model performance

The models performed slightly better over the smaller domain than the larger one for most indicators and models except AWC. Increasing the evaluated area is usually associated with a reduction in sample density (0.032 samples km^{-2} to 0.024 samples km^{-2} in this study, but within the commonly reported sampling densities for DSM of soil carbon) (Chen et al., 2022). The lower sample density in the larger domain may explain the overall reduction in model accuracy, which on average represented a decrease in R^2 and LCCC of 0.6 compared to the smaller domain.

Spatial patterns of model covariates and changes in soil processes in spatial and scale domains can also explain the differences in the relative performances of the partial models among domains. Which might indicate the need for specific models for different sub-regions.Yet, similarities in mean, range, and distribution of SH indicators among domains suggest that both represent a similar range of SH variations (Appendix 5.1). This may also be associated with the decision to focus on Entisols, Inceptisols, and Alfisols.

Table 5. 4 Model performance for the validation data set over the different study domains and SH indicators presented as R2 and normalized root mean square error (NRMSE) and the Lin's concordance correlation coefficient (LCCC).

	Large Domain					**Small Domain**				
	Climate	Soil & topography	Land Use	Climate and soil & topography	Full Model	Climate	Soil & topography	Land Use	Climate and soil & topography	Full Model
R^2										
SH index	0.47	0.45	0.42	0.56	0.59	0.57	0.49	0.58	0.59	0.74
ln_SOM	0.46	0.51	0.39	0.51	0.60	0.58	0.5	0.51	0.68	0.69
POXC	0.39	0.36	0.27	0.41	0.44	0.43	0.44	0.44	0.47	0.52
ln_ACE	0.28	0.31	0.27	0.37	0.42	0.45	0.35	0.44	0.5	0.55
ln_Resp	0.30	0.40	0.34	0.48	0.52	0.37	0.25	0.39	0.43	0.50
AWC	0.29	0.33	0.09	0.39	0.45	0.20	0.11	0.21	0.20	0.28
ln_WAS	0.47	0.33	0.41	0.49	0.60	0.55	0.50	0.57	0.65	0.69
NRMSE										
SH index	0.51	0.52	0.53	0.47	0.45	0.50	0.56	0.51	0.50	0.40
ln_SOM	0.55	0.55	0.58	0.53	0.47	0.51	0.55	0.55	0.45	0.45
POXC	0.61	0.63	0.67	0.60	0.58	0.66	0.65	0.65	0.63	0.60
ln_ACE	0.73	0.73	0.73	0.69	0.67	0.72	0.77	0.72	0.67	0.64
ln_Resp	0.73	0.68	0.72	0.55	0.61	0.61	0.68	0.61	0.59	0.55
AWC	0.65	0.63	0.75	0.62	0.57	0.86	0.92	0.84	0.86	0.82
ln_WAS	0.49	0.55	0.52	0.48	0.42	0.55	0.57	0.52	0.49	0.46
LCCC										
SH index	0.64	0.59	0.58	0.69	0.72	0.72	0.66	0.71	0.73	0.84
ln_SOM	0.65	0.63	0.56	0.68	0.74	0.75	0.69	0.70	0.82	0.82
POXC	0.54	0.52	0.41	0.57	0.60	0.62	0.59	0.59	0.65	0.69
ln_ACE	0.47	0.45	0.41	0.52	0.57	0.62	0.50	0.62	0.66	0.70
ln_Resp	0.50	0.55	0.51	0.64	0.67	0.59	0.47	0.60	0.65	0.70
AWC	0.47	0.50	0.23	0.58	0.60	0.37	0.27	0.38	0.39	0.47
ln_WAS	0.63	0.49	0.57	0.65	0.74	0.67	0.60	0.68	0.73	0.76

SH Index: Composite Soil Health Index; SOM: soil organic matter; ; POXC: permanganate-oxidizable carbon; ACE: ACE Protein; Resp:respiration; AWC: available water capacity; WAS: water aggregate stability.

5.3.1.2. Performance of partial models

The relative performance of the partial models varied between the two domains of analysis. Here even the smaller domain represented a relatively large area with significant climatic differences, which explained a high proportion of SH variations. In the larger domain, climatic-only models performed similarly to soil & topography models and outperformed management-only models. Similar average performance was observed between climate and management-only models in the smaller domain, but they outperformed soil and topography models. The more significant improvement with management-related models in the smaller domain agrees with previous studies showing that management covariates are more influential in smaller areas as the environmental covariates tend to be more uniform (Emadi et al., 2020).

Among the partial models, those including a combination of climatic and soil & topography covariates had the highest performance, with an average R^2 value of 0.46 and 0.50 for the larger and smaller domains, respectively. Our results confirm the critical role of inherent soil properties and climatic variables in defining SH indicators. Their estimated effects are similar to those reported for POXC, Resp, and SOC at the continental scale, assessing 124 long-term experiments located across North America (Liptzin et al., 2022). However, for WAS, our study showed a much higher effect of inherent soil properties and climate than that previously reported, where they only explained 18% of WAS variability (Bagnall et al., 2022). A possible cause may be correlations between management, soil, and climate covariates included in our model.

Correlations between the covariates incorporated in our models affect the relative performance of the partial models and obscure the identification of individual covariate effects. Covariates correlations (Appendix 5.4) represent a main confounding factor in this study and any DSM approach. These should be carefully considered when interpreting generated information as climate and soil types often define land use. For example, a combination of favorable inherent soil and climate characteristics in the Ontario-Erie Plain and Finger Lakes MLRA has been associated with more intensive annual grain and processing vegetable agriculture relative to other areas for more than 100 years (Cline and R.L. Marshall, 1976; Nobe et al., 1960), resulting in overall lower SH outcomes.

5.3.1.3. Full model performance

Full models outperformed all partial models, highlighting the importance of incorporating explicit covariates representing all the main soil-forming factors for predicting soil properties. Incorporating land use and management-related covariates generated only modest improvements in model performance, increasing the variance explained 6% when compared to no-management models. The fact that soil and climate variables are asociations with managments might explain the small improvements in model performance. Model improvement due to land use and management incorporation were expected to be higher for dynamic SH indicators, but this was not observed. Management related variables did explain a higher proportion of the variations of the indicators that are more sensitive to management (see section 5.3.2).

Covariate correlations incorporating all relevant variables in the models elucidate individual covariate effects. The included land use and management practices allowed us to elucidate the effect of cropping systems, crop rotation and crop productivity. This goes beyond the traditional DSM approaches which only minimally differentiate among contrasting land uses, e.g., forest vs annual grain (Zhang et al., 2022), and do not represent more detailed effects from crop rotations or productivity.

The performance of the complete models varied significantly among SH indicators, with AWC the lowest with R^2 = 0.28 and other indicators with R^2 values ranging from 0.5 to 0.74 and LCCC values from 0.70 to 0.84. NRMSEs were greater than 0.5 for POXC, ln_ACE, and ln_Resp, which can be considered high for this type of analysis. The lack of systematic errors or clear spatial patterns on the residual distribution observed in the study indicates an accurate model performance across a wide range of SH values and locations (Appendix 5.5 and 5.6). Yet, modest underestimations of high SH values and overestimations of low values were observed for individual indicators (Appendix 5.5), which is characteristic of most modeling approaches and reflects limitations of predicting extreme values with tree-based machine learning methods. This limitation was not evident when evaluating the composite SH_index, which already represents an average of the scored values of individual SH indicators, therefore attenuating extreme observations in individual SH indicators.

SOC/SOM and AWC are, among the evaluated indicators, the only ones previously mapped using DSM techniques with 126 and 20 mapping efforts, respectively (Chen et al., 2022). Among these, average R^2 values were 0.49 for surface SOC/SOM and 0.34 for AWC. Our models performed significantly better for SOM but had a lower performance for AWC. The lower performance for AWC was unexpected since AWC is measured on disturbed soil samples and recognized as easy to predict (Amsili, 2023 in preparation), especially with soil texture related covariates (Libohova et al., 2018).

In our models, texture is derived from the POLARIS dataset which has its own associated errors (Chaney et al., 2019). Specifically, POLARIS approximates SSURGO map unit composition by disaggregating polygons so that the particular pixel may not accurately represent the map unit component at the observation location.

Estimating SH properties from estimate rather than directly measured soil data implies inevitable uncertainties. The R^2 between texture values measured in our samples and the extracted values from POLARIS for silt and clay were 0.26 and 0.46, respectively (Appendix 5.8), similar to those reported by Chaney et al. (2019) for clay but much lower for silt (R^2=0.58). Limited representation of landscape variations of soil properties by DSM products, like POLARIS, might constrain the accuracy of these maps at fine resolution (30 m) (Rossiter et al., 2022). Replacing POLARIS estimations with measured texture values generated minor changes in models' performance for most SH variables (Appendix 5.9), but was improvement was significant for SOM (R^2=0.67 to 0.78) and AWC (R^2=0.28 to 0.41) which confirms the importance of texture for these indicators. Interestingly, these two indicators are most affected by the accuracy of the texture-related variables, but had been previously shown to be less affected by short-midterm management. Overall, potential improvements to the generated models are associated with a better prediction of important model covariates.

5.3.2. COVARIATE IMPORTANCE AND IMPACT IN SH INDICATORS

The use of SHAP values increased the interpretability of ML models, bringing insight into relationships between SH indicators and model covariates for the region. Fig. 5.3 represents covariates importance as its relative SHAP values for each indicator in the smaller domain. Although they varied among indicators, the functional forms remain robust, illustrated by SHAP dependence plots for the 14 most important covariates for the composite SH index in the smaller domain (Fig. 5.4). Additionally, Fig. 5.5 summarizes the importance and relationships of the top six covariates and SH indicators. Further details on SHAP dependence plots for both extents are in Appendix 5.10 and 5.11.

The consistency observed in the SHAP dependence plots among indicators suggests that the processes and factors that positively impact one SH indicator tend to have a beneficial effect on other indicators as well, suggesting interdependencies among different aspects of SH. Climate-related covariates had the most significant effects for most SH indicators ,where increases in the average Mean_Temp from 7 to 12 ^{o}C led to lower SH. This is consistent with reports for soil carbon and carbon-related variables at regional, continental, and global scales (Lamichhane et al., 2019). Among others, increases in mean temperature are associated with higher mean annual C oxidation rates (Lamichhane et al., 2019). Precipitation had a quadratic relation with SH, positive up to 1100-1200 mm, and possibly negative at higher levels (with limited observations >1200 mm). Higher annual precipitation may be associated with a more positive C balance through higher plant productivity and OM inputs combined with less C oxidation due to more prevalent anaerobic microsites, which together can promote SOM accumulation (Jackson et al., 2017).

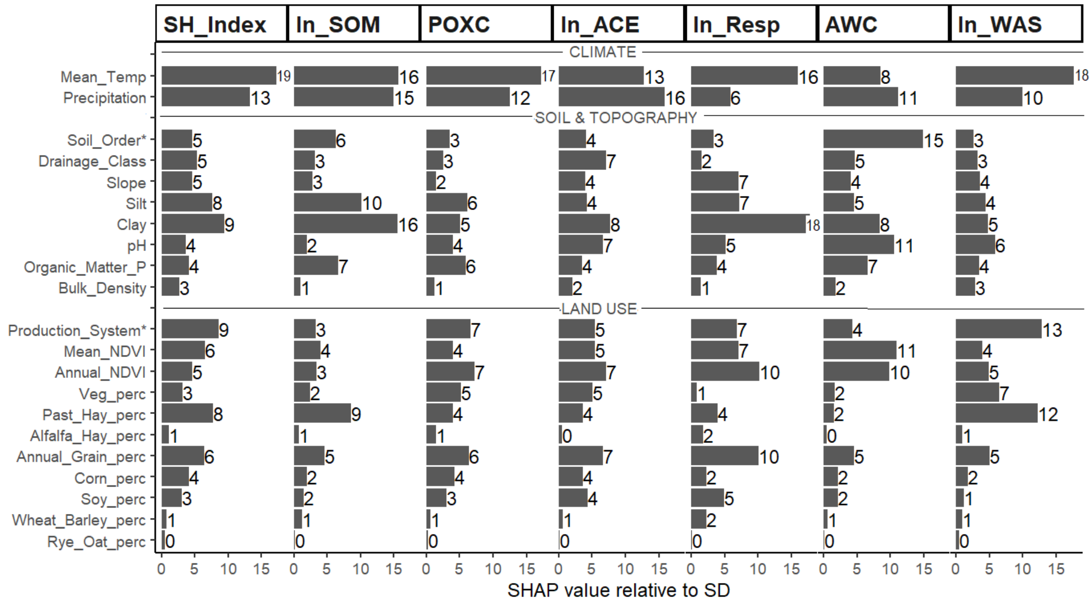


Figure 5. 3: SHAP (SHapley Additive explanation) values for each covariate and soil health indicator relative to its standard deviation

Where: SH Index: Composite Soil Health Index; SOM: Soil organic Mater; ; POXC: Permanganate-Oxidizable Carbon; ACE: ACE Protein; Resp: Respiration; AWC: Available water capacity; WAS: Water aggregate stability. Addition of SHAP values of each dummy covaraite reprecenting the factor.*

Among the soil and topography variables, clay and silt contents most significantly influence the majority of SH indicators. For this study, increased clay contents from 7 to 25%, and silt contents from 35 to 55% were associated with higher SH values, with limited observations outside these ranges. Higher SH indicator values in finer-textured soils have been broadly recognized, motivating the development of texture-specific soil health indicator values (Amsili et al., 2023; Fine et al., 2017; Nunes et al., 2021, 2020).

The average order of importance for the remaining soil and topography-related indicators was: Soil pH> the integrated effect of Soil_Order >

Organic_Matter_p>Drainage_Class> Slope> Bulk_Density. Soil pH had a positive quadratic relationship with SH, with an optimal value around 6, coincident with the optimal range for plant growth.

Increasing Organic_Matter_p, from 2 to 4%, positively impacted SH indicators, with limited observations outside this range. A higher contribution of Organic_Matter_p to the models was expected, especialy for the estimation of ln_SOM. The low contribution shows that POLARIS maps do not reflect current conditions, as the R^2 values between POLARIS SOM and measured values in our dataset was only 0.14 (Appendix 5.8c). Similar results are expected for most of the available SOM/SOC maps, as they do not incorporate a dynamic component to reflect the current state. This is significant given the high interest in these propoertires in the context of current climate discussions.

Management was the main driver for most SH indicators when analyzing the combined effects of model covariates by category, on average 42% of the accumulated SHAP effects (range 32 to 51%). This suggests a prevalent role of anthropogenic processes in SH which follow the expected tendencies giving our current knowledge of management effects on SH. The greatest effects were observed for WAS and Resp, similar to Amsili et al., (2021) who also found that these two indicators responded more to variations in cropping system than texture. The lowest management effects were observed for AWC and SOM which are more afected by soil and topography-related covariates, although management covariates still explained 39 and 32% their variability, respectively. The greater influence of soil and topography-related covariates in AWC and SOM models explains why POLARIS inacuracies had greater negative impacts and models had less sensitivity to management when compared to other SH indicators.

From the management or land use-related covariates, the integrated effect of the production system had the highest average influence in our models. It was followed by more specific covariates Annual_grain_perc> Annual_NDVI>Mean_NDVI> Past_Hay_Perc> Veg_perc. Those representing the percentage of individual crops or pastures had the lowest effects.

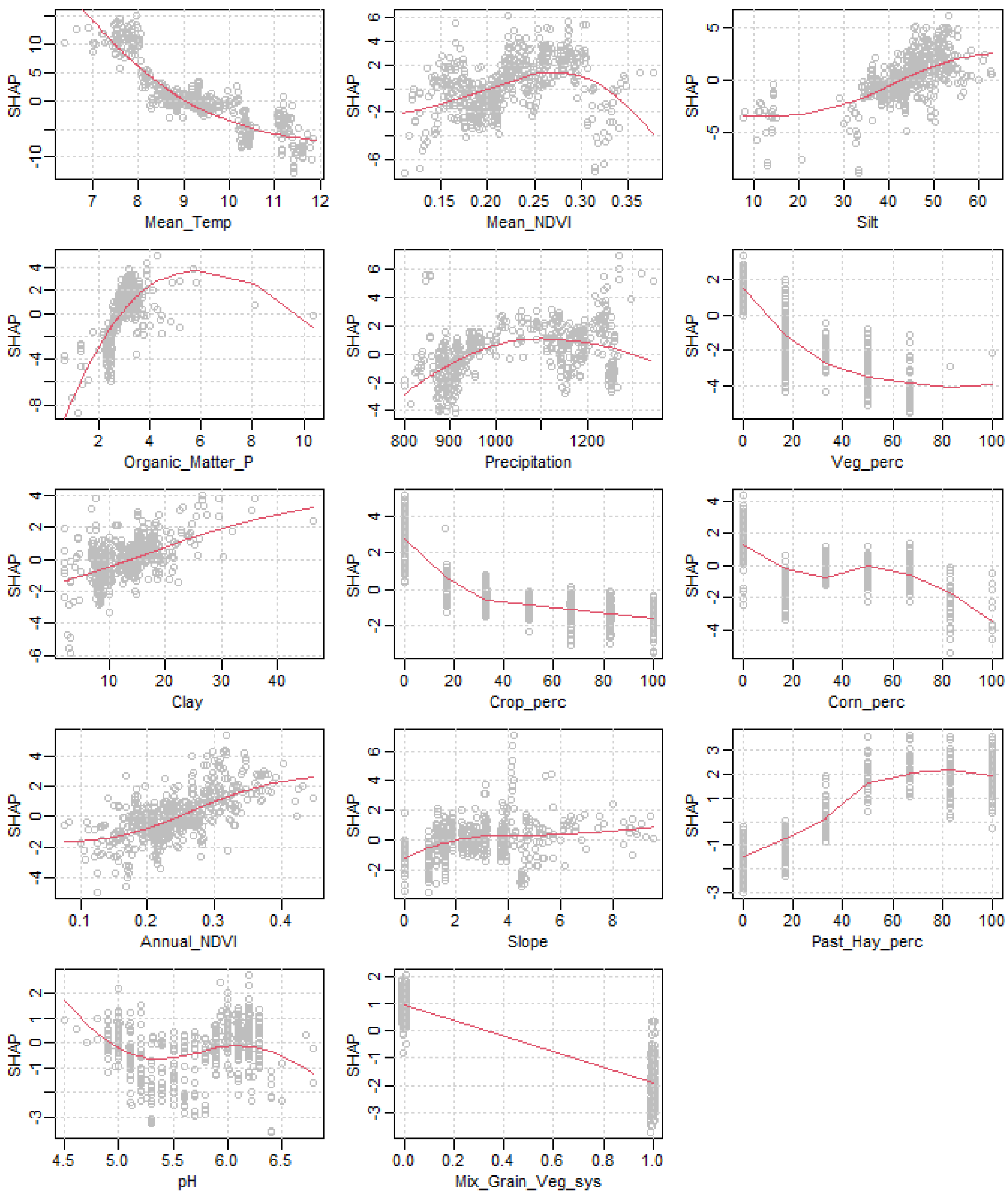


Figure 5. 4: SHAP dependency plots for the 14 most important covariates in the definition of the composite soil health index for the smaller domain.

Overall, the land use-related variables that had a positive effect on SH may be associated with practices that promote higher biomass production and return to the soil through residues or manure. This supports a recent result that aboveground biomass returns can explain up to 50% of the variations in SH in long-term experiments on Mollisols in South America (Rubio et al., 2023 in preparation). Here, this benefit is reflected by the positive effects of annual and mean NDVI values in SH. NDVI is directly and positively related to primary vegetation productivity and active plant growth periods that can enrich SOM and SH (Paul, 2016).

While for SOM it has been reported that covariates that represent long periods of NDVI can be more influential than a single year snapshot of this (Wilson and Lonergan, 2013), here annual NDVI had a higher average ranking than mean NDVI for POXC and Resp. The higer average importance of Annual_NDVI (1 yr pre-soil sampling) vs Mean_NDVI (6 yr pre-soil sampling), reflects short term management effects in SH, but may also be a confounding factor with cropping system that is not captured. For example, corn grain and corn grown for silage have similar NDVI profiles but result in different biomass cycling after harvest, while the latter is more likely rotated with a perennial forage crop and receives manure applications. This supports the need to include short term management covariates for SH modeling.

Furthermore, the strong positive SH effect of the Past_Hay_sys may reflect the benefits of higher production and return of biomass. This is not only associated with higher plant productivity of grasslands when compared to most annual crops, but may also reflect the effects of common manure applications. The lack of management-related data surrounding fertilization, harvesting, and manure application practices represents a limitation in our ability to represent management effects in biomass flows, and therefore SH. However, we assumed that the similarities in management strategies among farmers within the same systems might somehow reflect some of these strategies. The important role of land use system in our models, which represent crop productivity with NDVI values, shows that land use effects reflect more than the short- mid term effects of biomass production.

The third most important variable associated with land use was the Annual_Grain_perc. The higher the percentage of annual grains in the system, the lower SH, while Past_Hay_perc had a positive relationship with SH. Veg_perc was also negatively related to SH. These suggest that within the mixed systems that integrate annual crops with pastures is beneficial for SH.

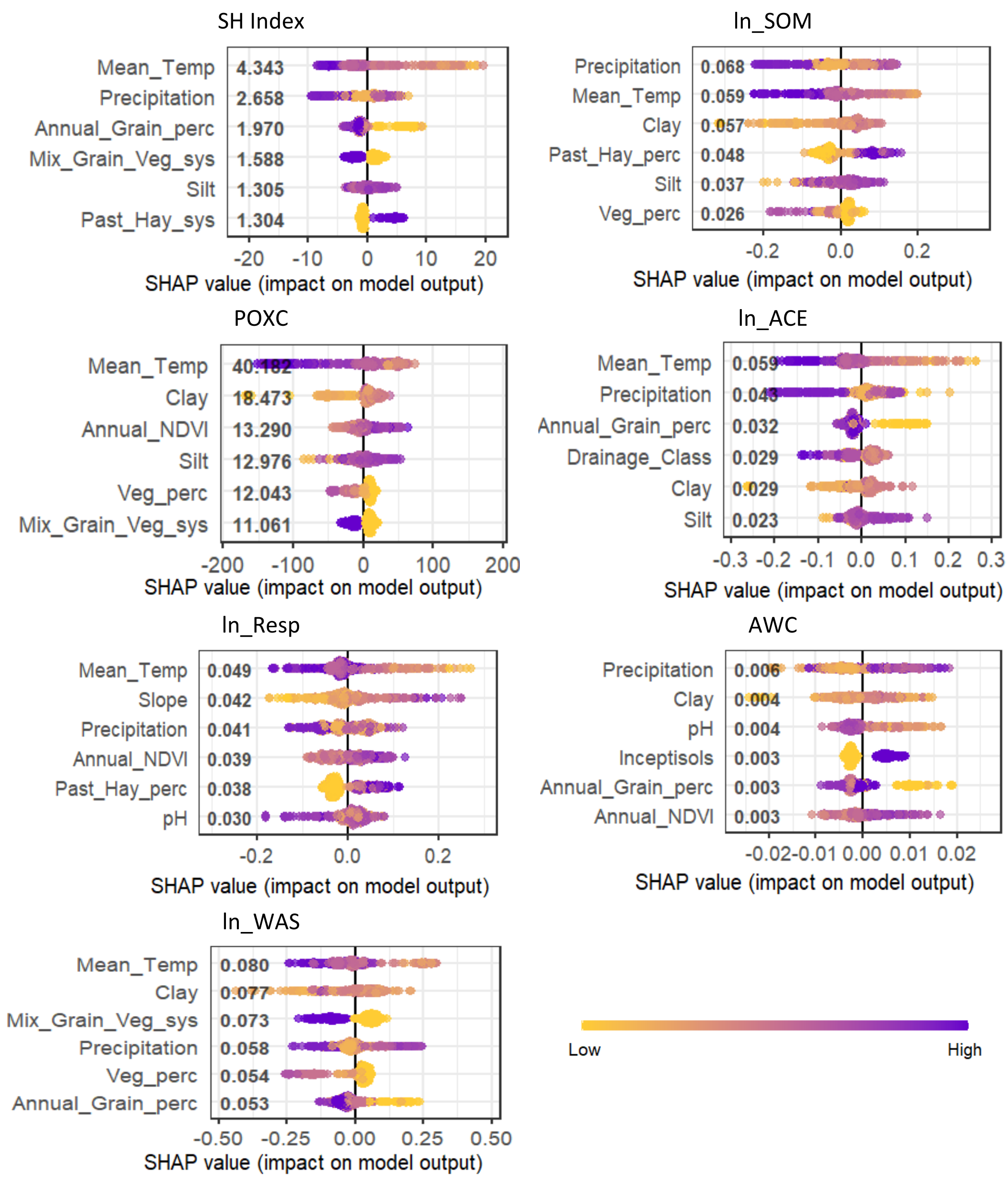


Figure 5. 5: SHAP (SHapley Additive explanation) summary plot representing the top six contributing covariates to the XGBoost models for the determination of SH indicators in area two.

Where: Each point represents an observation from the original dataset. The y-axis indicates the covariable name in order of importance from top to bottom, the value next to them is the mean SHAP value; X-axis is the SHAP value that indicates the change in log-odds; The gradient color indicates the original value for that variable.

5.3.3. SPATIAL PREDICTIONS AND MAPPING

All evaluated SH indicators were mapped for the smaller domain with the full optimized models at 100 x 100 m resolution. The mean spatial predictions and model performance parameters for all the evaluated individual indicators are presented in Fig 5.7. The prediction of the composite SH Index is presented in Fig 5.6. Pruning low predictors from the model did not significantly reduce model performance (average R^2 reduction of 0.015) (Fig 5.6).

SH indicators varied greatly throughout the study domain at regional scale and also among neighboring farms located with different land use or management. Overall, higher SH values were observed in the Glaciated Allegheny Plateau, and the Catskill Mountains than in the Ontario-Erie Plain and Finger Lakes region. Ontario MLRA had a higher mean annual temperature and pH, and lower precipitation and silt content than the Allegheny Plateau region. The Ontario MLRA is regarded as a more favorable agricultural environment but therefore also has a higher proportion of annual grain and vegetable crops, whereas the Alleghany region has a higher proportion of pastures. Paradoxically, SH outcomes are on average less positive for the inherently more favorable agricultural production environment (soil, climate, etc.), because it is *ipso facto* also more associated with cropping systems that result in lower SH.

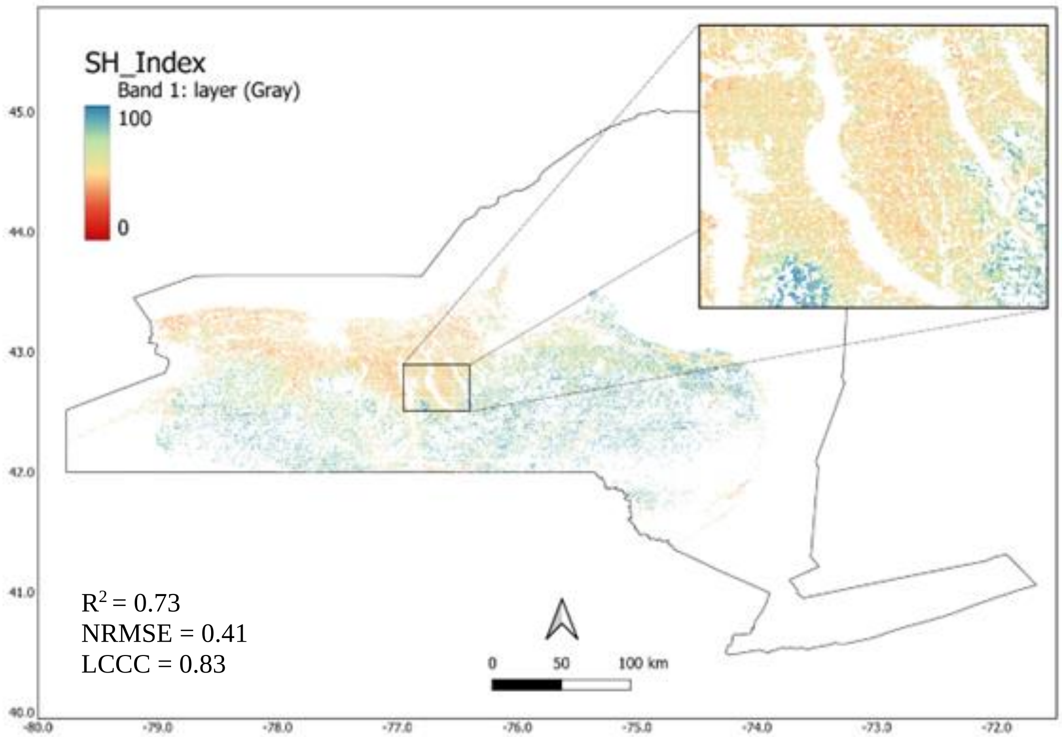
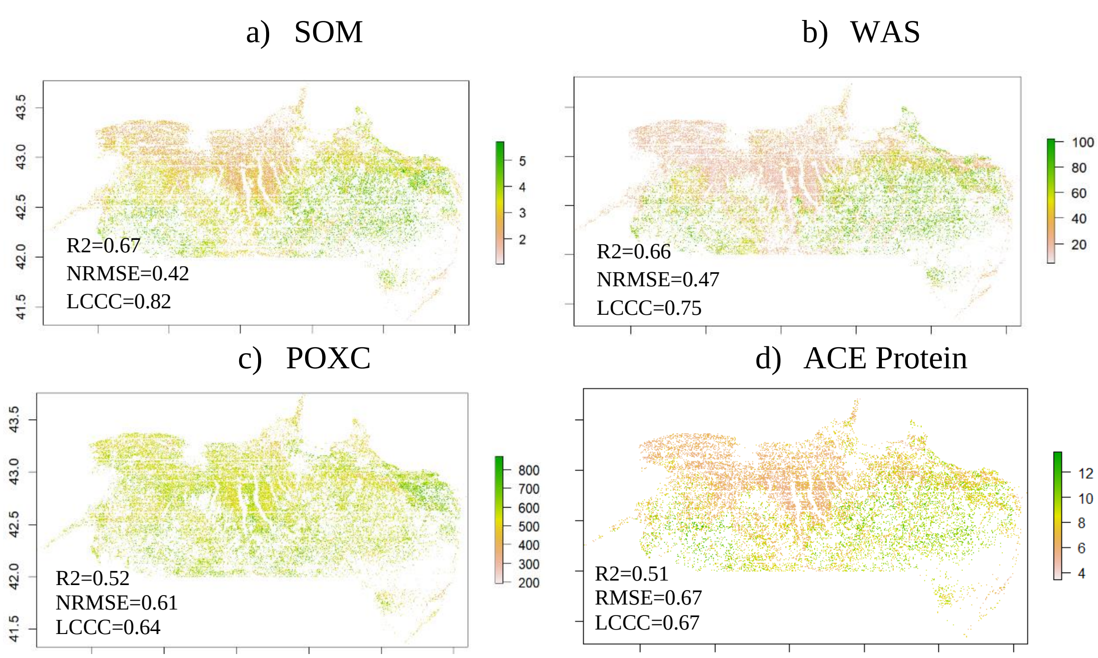


Figure 5. 6: Composite Soil Health Index prediction for extent two



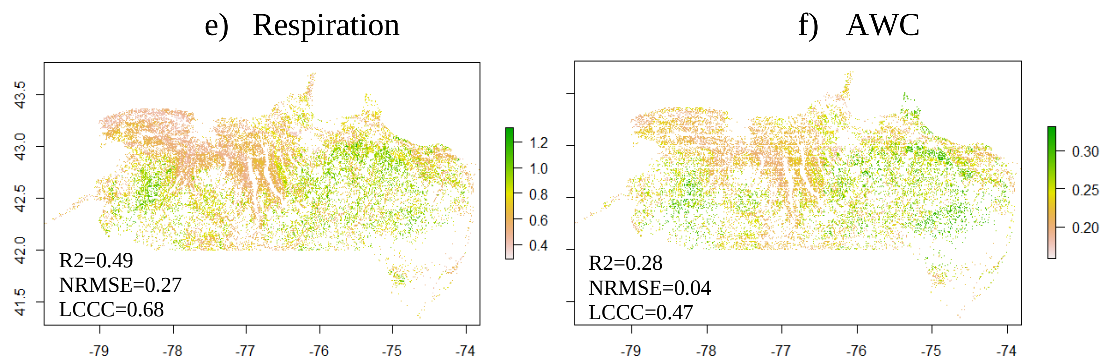


Figure 5. 7: Prediction maps of biological and physical SH indicators, based on the complete model over the small domain.

Where: SOM: Soil organic Mater (%); WAS: Water aggregate stability (%); POXC: Permanganate-Oxidizable Carbon (mg/kg);ACE Protein (mg/g); Respiration (mgCO2/g); AWC: Available water capacity (g/g). For full size map please see Appendix 5.16-21

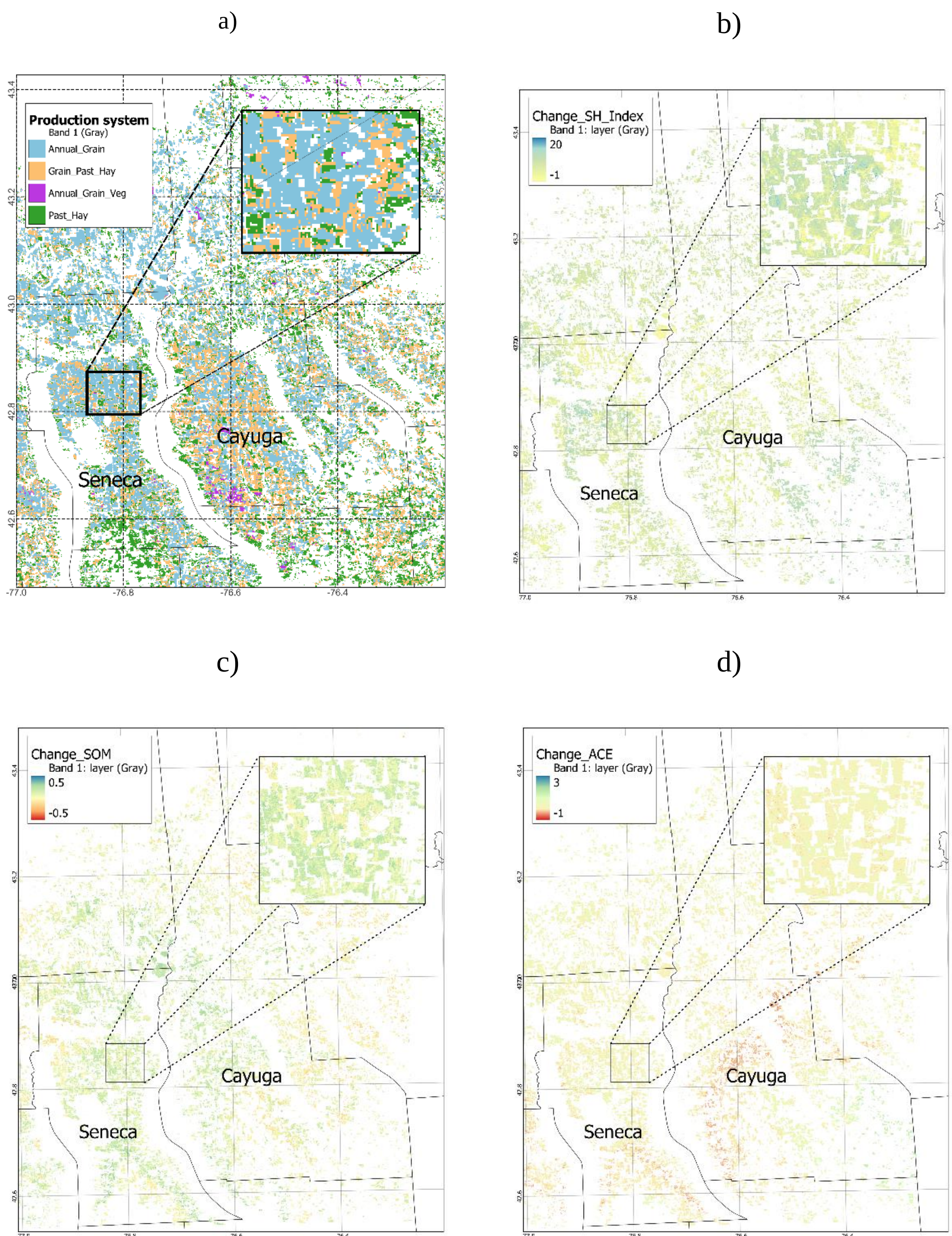
5.3.4. SCENARIO MODEL APPLICATION

Mapping SH indicators helps establish SH references and can guide regional resource policies and land use strategies (Searle et al., 2021). For example, our maps suggest a framework that includes separate SH data interpretation and benchmarking by MLRA (data non shown). The generated models can be used to simulate future conditions of SH in New York under different scenarios of land use change in the context of climate and soil resources. Yet, land use is also defined by economics, including access to markets, cultural, and social factors. Cayuga and Seneca Counties have similar natural characteristics, but the latter has a high proportion of annual cropping systems, whereas Cayuga has a higher proportion of dairies that rotate annual grains with perennial hay lands/pastures. Given the observed SH benefits of integrated systems, we evaluated the potential changes in SH generated by hypothetically replacing annual grain systems with integrated pasture hay grains. Predicted SH changes were small on average, especially with compared with the uncertainty of our model (Appendix 5.6) there was a wide range of outcomes with spatial structure to the distribution of predicted changes (Table 5.5, Fig. 5.7). For some SH indicators like POXC, there is a potential benefit from the land use change in some areas with fine soil texture, suggesting interactions between management and inherent soil properties that were not easily identified from SHAP values. These complex relationships between land use, inherent and baseline soil properties, and climate that are being captured by the model and can be used to further increase our understanding of SH drivers.

Table 5. 5: Summary table of the estimated changes in soil health evaluated as the mean, max, min, and SD.

	SH index	*SOM*	*POXC*	*ACE*	*RESP*	*AWC*	*WAS*
mean	6.7	0.07	2.2	0.30	0.01	0.010	4.91
max	21,0	0.50	106,0	2.04	0.16	0.042	21.20
min	-7.2	-0.35	-70,1	-0.66	-0.16	-0.016	-4.61
sd	3.3	0.10	20,3	0.30	0.04	0.012	2.79

Where: SH Index: Composite Soil Health Index; SOM: Soil organic matter; ; POXC: Permanganate-oxidizable carbon; ACE: ACE protein; Resp: respiration; AWC: available water capacity; WAS: water aggregate stability.


a)
b)
c)
d)
Production system
Band 1 (Gray)
Annual_Grain
Grain_Past_Hay
Annual_Grain_Veg
Past_Hay
Seneca
Cayuga
Change_SH_Index
Band 1: layer (Gray)
20
-1
Change_SOM
Band 1: layer (Gray)
0.5
-0.5
Change_ACE
Band 1: layer (Gray)
3
-1

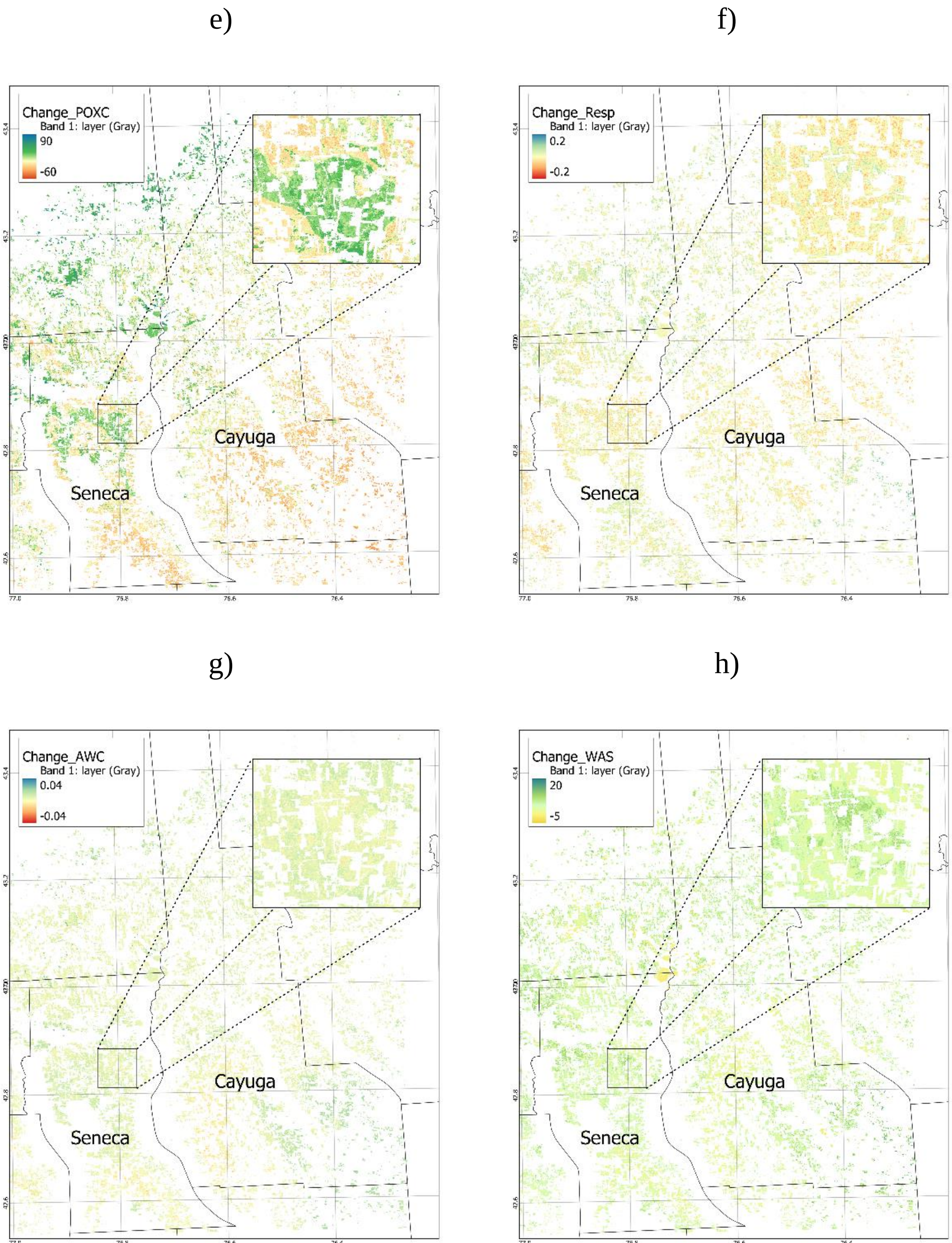


Figure 5. 8: Hypothetical changes for SH indicator values: a) Current land use systems; b) Projected land use systems; c) Changes in soil health indicators generated by land use changes.

5.4. CONCLUSIONS

This study provides a comprehensive and data-driven approach that contributes to our understanding of the drivers and current status of a comprehensive set of SH indicators in different regional domains in NY State. Despite potential limitations with inaccuracies on soil sample geolocations and model covariates, detailed management information, and number of SH data, results prove that models including climate, soil, topography, and short and mid-term management covariates can predict dynamic SH indicators with good accuracy. SHAP values can be used to disentangle the role of the different covariates in SH. The important role of management in SH was proven, which highlights the importance of promoting land use systems and management practices that enhance biomass production and return to soils. It also emphasizes that DSM approaches that do not include agronomic variables miss important drivers of SH. The generated models were able to accurately predict SH over unknown areas, which can help make informed decisions for SH conservation. These maps can be used as baseline for evaluating the efficiency of conservation plans and to guide SH strategies over different areas within the state. Also, the hypothetical land use change scenario illustrates how the generated models can be applied in that context. Overall, the inclusion of land use and management covariates with traditional DSM and ML approaches is a promising tool for exploration of SH characterization and enhancement efforts.

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CHAPTER 6: GENERAL CONCLUSION

Enhancing SH and mitigating soil degradation requires an understanding of SH status and drivers. The research findings presented in this study contribute to advancing our knowledge on the effects of inherent and anthropogenic factors on SH, and on the complex interplay among them, increasing our overall comprehension of SH dynamics at different scales. This information can support informed decisions and facilitate the design of agronomic management strategies that promote sustainable soil management and help understand the consequences of soil degradation in cropping systems. One of the main conclusions of this research is that soil health is impacted by inherent soil characteristics (unchangeable), land use system characteristics (limited change possible), and agronomic management (most changeable).

Chapters two to four represent one of the first comprehensive SH evaluations in the Pampas region. By evaluating SH in undisturbed areas and long-term experiments, which represent agricultural systems with and without the application of the most promoted conservation practices, the sensibility of the CASH indicators for Mollisols in the Pampas was evaluated. Chapter two provides quantitative evidence confirming the serious negative effects of cropping on SH relative to natural grassland areas. This highlights the importance of promoting the conservation of grassland biomes which are highly threatened natural ecosystem’s globally, with less than 30% of its original area remining undisturbed. In fact, the inherently high SH and functioning of natural grasslands makes them attractive to conversion to grain production under increasing global demand.

In chapter three the negative effects SH degradation generated by annualized cropping systems, and assessed through SOC declines, on crop yield was proved and quantified. Results confirm the connections between SH and soil functions demonstrating that SH degradation effects in food production cannot be overcome by fertilization or improved production technologies.

Chapter two also provides evidence on how management practices can mitigate soil degradation; thereby minimizing yield losses. Practices that increase crop sequence intensification, like the inclusion of perennial pastures or cover crops in low intensity annual cropping systems have consistent benefits on SH; however, no benefits of tillage reduction were observed in sites with low erosion risk. Our results emphasize the complexity of SH drivers, showing that the same management can have different outcomes, even under identical climatic conditions, parent material, and soil type. This advises against a simple set of practices for SH improvement.

At the field scale, the effects of agronomic management can be elucidated if SH changes are evaluated through the lens of biomass inputs to the system. In chapter four, a methodological framework for the evaluation of SH based on aboveground biomass is proposed, and quantitative evidence is presented on the importance biomass quantity, rather than origin, on conservation practices' benefits. Practices that increase biomass returns to the soil like reducing yield gaps, including high-biomass annual crops, cover crops, and perennials into rotations can enhance SH. SH-biomass relationships explained 50% of the variations in soil physical and biological indicators. Therefore, evaluating these relationships can provide valuable information for understanding and evaluating the potential benefits of different cropping systems and agronomic management approaches on SH. Yet, further evaluations are needed to prove its value for different soils, climates, and management conditions.

The results presented in chapters 2 to 4 can be used as a first approximation for the interpretation SH values and the design of soil conservation strategies for Argiudolls under agriculture and integrated systems in the Uruguayan Pampas region. This information can be used to further promote and develop comprehensive SH evaluations in the region needed for guiding on-farm agronomic management decisions. Given the wide range of soil degradation present in the evaluated experiments the measured SH values provide a starting point for interpretation of SH indicators in the region. Yet, further evaluations are necessary to encompass more soil types and land uses. It is noted that the presented results may not accurately represent less traditional cropping areas including Alfisols at the east of Uruguay. Additionally, the expected SH conditions and limitations for beef production systems under natural grasslands is not reflected. Therefore, less traditional cropping areas and land uses different than annual cropping should be considered separately and may require further tailored approaches.

At the regional scale, variations on inherent soil conditions, climate, and management drive SH, and these factors should be considered in evaluating and interpreting SH indicators. In chapter five, high spatial resolution covariates that represent the main SH driving factors were integrated to interpret their role on the definition of SH at the regional scale for the state of New York, USA. Digital soil mapping techniques and machine learning models showed a high potential for the prediction and mapping of dynamic soil properties. In this approach SH drivers were represented by the main land use system, crop frequency and medium- and short-term pre sampling estimations of crop productivity (NDVI), which allowed for the evaluation and representation of management effects on SH. Largely, results show that better SH conditions are expected under management situations that return higher biomass inputs to the soil, which supports the findings observed in chapter four for Uruguayan conditions.

This research opened a set of opportunities for advancing our knowledge in SH and optimizing regional SH conservation strategies by proving the possibility of accurately modeling and mapping SH indicators over large areas. Here, the generated models for predicting SH changes was evaluated testing a hypothetical management scenario. While temporal SH variations should be further validated, this scenario analysis provides insights into the expected changes in SH and its spatial variability, helping identify areas that should be prioritized in regional soil conservation plans. Furthermore, given that many soil functions happen at regional scale, e.g., the conservation of water quality, spatial SH estimations can be linked to a broader set of soil functions, which is still a challenge in SH research.

Overall, the insights presented in this dissertation have enriched our understanding of the intricate relationship between SH drivers. Moreover, they have provided compelling evidence on the significance of preserving SH for enhancing crop productivity in the Pampas region. The research emphasizes that biomass inputs into the soil plays a prominent role in driving SH at both field and regional scales. Hence, it is recommended to adopt a comprehensive perspective on agronomic management effects on SH, especially in the context of biomass production and associated C inputs and outputs.

APPENDIX

7.1.APPENDIX CHAPTER 3

Appendix 3 1: Soil chemical properties (0 to 15 cm depth) at the establishment of the long-term experiment (1963) and for the last rotation period (2014 to 2019).

Year	Treatment	pH	SOC (%)	Ntot (%)	P Bray I (ppm)	K (cmol kg^{-1})
1963	All	5.9	2.08	0.19	7.1	0.87
Last rotation period (2014-2019)	0 %PS	5.76	1.50	0.17	27.9	0.52
	33%PS	5.66	1.86	0.22	18.0	0.63
	50%PS	5.56	2.02	0.24	17.1	0.61
	66%PS	5.60	2.07	0.23	15.0	0.76

0%PS: continuous agriculture with fertilizer; 33%P: crop pasture rotation (CPR) with 33% of the time under pasture; 50%PS: CPR with 50% of the time under pasture; 66%PS: CPR 66% of time under pastures; pH: Soil pH in water; SOC: Percentage of soil organic carbon (0-15); Ntot: percentage of nitrogen in soil (0-15 cm); P Bray I: Phosphorous content in soil; K: Exchangeable K.

Appendix 3. 2: Number of observations, average corrected yields and standard deviation from 1963 to 2018 as a function of percentage of pasture and fertilization

Treatment group	N° of data	CorreYield	Estandar desviation
66PS%	37	3633 A	986
50PS%	58	3968 A	1027
33PS%	47	3653 A	1286
0PS%	111	3186 B	1028
0%PS_NF	59	1626 C	440

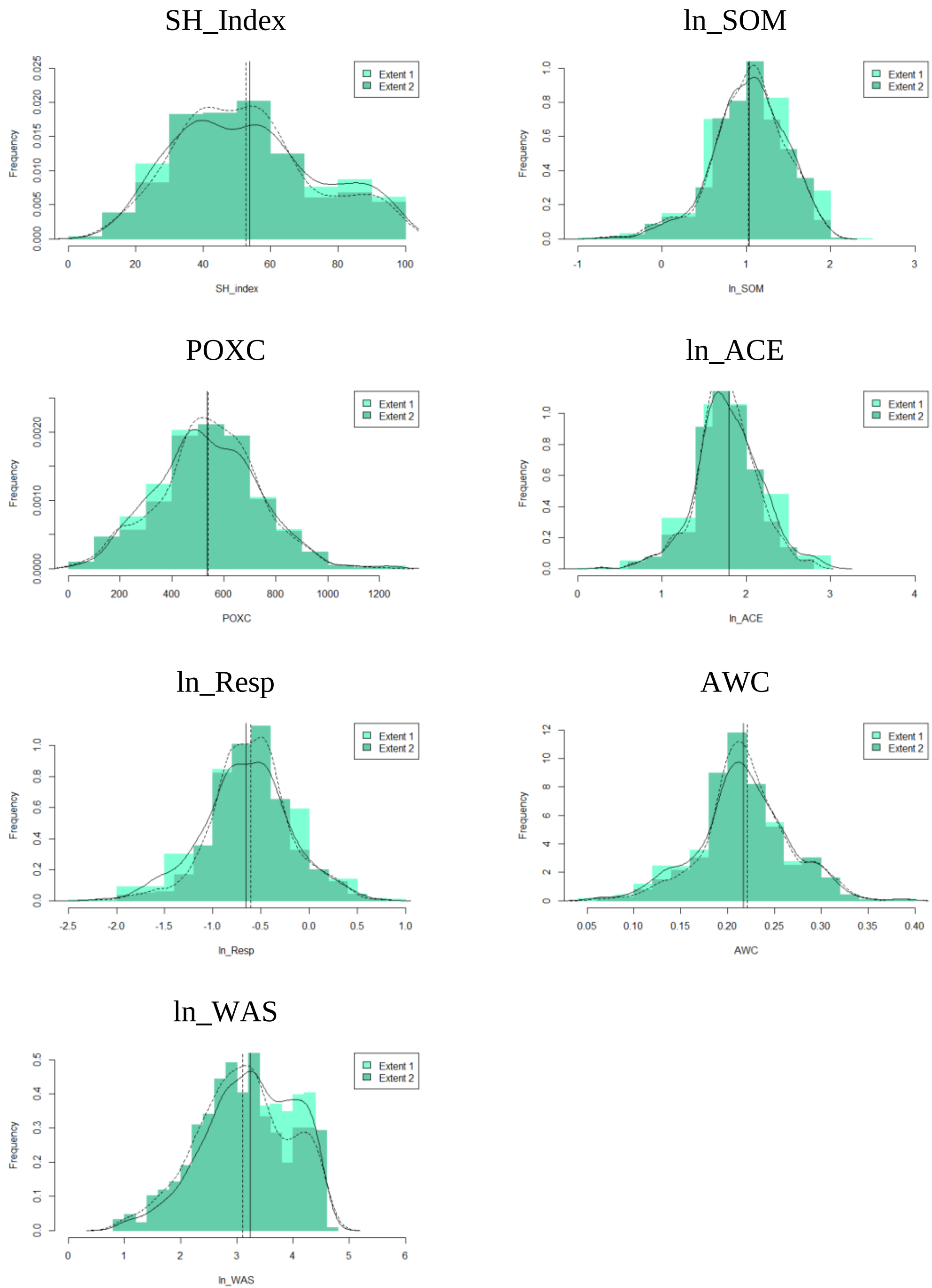
0%PS_NF: Continuous agriculture without fertilizer input; 0%PS: continuous agriculture with fertilizer; 33%PS: Crop pasture rotation (CPR) with 33% of the time under pasture; 50%PS: CPR with 50% of the time under pasture; 66%PS: CPR 66% of the time under pastures, CorrYield: Yield corrected to 2018. Different letters in the same columns indicate significant differences among treatments.

7.2.APPENDIX CHAPTER 4

Appendix 4. 1: Average and high crop yields and biomass production used in the management scenario analysis for crops and pastures, respectively.

	Current mean yield	High yield
	----------------------Mg ha^{-1}-----------------------	
Soybean	2	6.5
Cover crop	3	9
Corn	5	11
Pastures	10	17

7.3. APPENDIX CHAPTER 5



Appendix 5.1: Distribution frequency of soil health indicators for the large and small domains.

Where: Vertical lines represent mean values. The complete line represents Extent one, and the dotted line Extent two. SH Index: Composite Soil Health Index; SOM: Soil *organic Mater; ; POXC: Permanganate-Oxidizable Carbon; ACE: ACE Protein; Resp: Respiration; AWC: Available water capacity; WAS: Water aggregate stability.*

Appendix 5.2:

CDL code	CDL crop	New category	new code
0			0
1	Corn	Crop	100
2	Cotton	Crop	100
3	Rice	Crop	100
4	Sorghum	Crop	100
5	Soybeans	Crop	100
6	Sunflowers	Crop	100
7			0
8			0
9			0
10	Peanuts	vegetables	10000
11	Tobacco	vegetables	10000
12	SweetCorn	vegetables	10000
13	PoporOrnCorn	vegetables	10000
14	Mint	vegetables	10000
15	Developed_MedIntensity	urban	10000000
16			0
17			0
18			0
19			0
20			0
21	Barley	Crop	100
22	DurumWheat	Crop	100
23	SpringWheat	Crop	100
24	WinterWheat	Crop	100
25	OtherSmallGrains	Crop	100
26	DblCropWinWht_Soybeans	Crop	100
27	Rye	Crop	100
28	Oats	Crop	100
29	Millet	Crop	100
30	Speltz	crop	100
31	Canola	Crop	100
32	Flaxseed	vegetables	10000
33	Safflower	vegetables	10000
34	RapeSeed	vegetables	10000
35	Mustard	vegetables	10000
36	Alfalfa	legume	100000
37	OtherHay_NonAlfalfa	pasture	1000

38	Camelina	vegetables	10000
39	Buckwheat	Crop	100
40			0
41	Sugarbeets	vegetables	10000
42	DryBeans	vegetables	10000
43	Potatoes	vegetables	10000
44	OtherCrops	Crop	100
45	Sugarcane	Sugarcane	100000000
46	SweetPotatoes	vegetables	10000
47	MiscVegs&Fruits	vegetables	10000
48	Watermelons	vegetables	10000
49	Onions	vegetables	10000
50	Cucumbers	vegetables	10000
51	ChickPeas	vegetables	10000
52	Lentils	vegetables	10000
53	Peas	vegetables	10000
54	Tomatoes	vegetables	10000
55	Caneberries	vegetables	10000
56	Hops	vegetables	10000
57	Herbs	vegetables	10000
58	Clover_Wildflowers	vegetables	10000
59	Sod_GrassSeed	grass	1000
60	Switchgrass	grass	1000
61	Fallow_IdleCropland	Crop	100
62			0
63			0
64			0
65			0
66	Cherries	fruticulture	10
67	Peaches	fruticulture	10
68	Apples	fruticulture	10
69	Grapes	fruticulture	10
70	ChristmasTrees	ALG	1
71	OtherTreeCrops	ALG	1
72	Citrus	fruticulture	10
73			0
74	Pecans	fruticulture	10
75	Almonds	fruticulture	10
76	Walnuts	fruticulture	10
77	Pears	fruticulture	10
78			0
79			0
80			0
81			0

82			0
83			0
84			0
85			0
86			0
87			0
88			0
89			0
90			0
91			0
92	Aquaculture	non agriculture	1000000
93			0
94			0
95			0
96			0
97			0
98			0
99			0
100			0
101			0
102			0
103			0
104			0
105			0
106			0
107			0
108			0
109			0
110			0
111	OpenWater	non agriculture	1000000
112			0
113			0
114			0
115			0
116			0
117			0
118			0
119			0
120			0
121	Developed_OpenSpace	urban	10000000
122	Developed_LowIntensity	urban	10000000
123	Developed_MediumIntensity	urban	10000000
124	Developed_HighIntensity	urban	10000000

125			0
126			0
127			0
128			0
129			0
130			0
131	Barren	urban	10000000
132			0
133			0
134			0
135			0
136			0
137			0
138			0
139			0
140			0
141	DeciduousALG	ALG	1
142	EvergreenALG	ALG	1
143	MixedALG	ALG	1
144			0
145			0
146			0
147			0
148			0
149			0
150			0
151			0
152	Shrubland	urban	10000000
153			0
154			0
155			0
156			0
157			0
158			0
159			0
160			0
161			0
162			0
163			0
164			0
165			0
166			0
167			0
168			0

169			0
170			0
171			0
172			0
173			0
174			0
175			0
176	Grass_Pasture	pasture	1000
177			0
178			0
179			0
180			0
181			0
182			0
183			0
184			0
185			0
186			0
187			0
188			0
189			0
190	WoodyWetlands	ALG	1
191			0
192			0
193			0
194			0
195	HerbaceousWetlands	ALG	1
196			0
197			0
198			0
199			0
200			0
201			0
202			0
203			0
204	Pistachios	fruticulture	10
205	Triticale	Crop	100
206	Carrots	vegetables	10000
207	Asparagus	vegetables	10000
208	Garlic	vegetables	10000
209	Cantaloupes	vegetables	10000
210	Prunes	fruticulture	10
211	Olives	fruticulture	10
212	Oranges	fruticulture	10

213	HoneydewMelons	vegetables	10000
214	Broccoli	vegetables	10000
215	Avocado	fruticulture	10
216	Peppers	vegetables	10000
217	Pomegranates	fruticulture	10
218	Nectarines	fruticulture	10
219	Greens	vegetables	10000
220	Plums	fruticulture	10
221	Strawberries	vegetables	10000
222	Squash	vegetables	10000
223	Apricots	fruticulture	10
224	Vetch	legume	100000
225	DblCropWinWht_Corn	Crop	100
226	DblCropOats_Corn	Crop	100
227	Lettuce	vegetables	10000
228	DblCropTriticale_Corn	Crop	100
229	Pumpkins	vegetables	10000
230	DblCropLettuce_DurumWht	vegetables	10000
231	DblCropLettuce_Cantaloupe	vegetables	10000
232	DblCropLettuce_Cotton	vegetables	10000
233	DblCropLettuce_Barley	vegetables	10000
234	DblCropDurumWht_Sorghum	Crop	100
235	DblCropBarley_Sorghum	Crop	100
236	DblCropWinWht_Sorghum	Crop	100
237	DblCropBarley_Corn	Crop	100
238	DblCropWinWht_Cotton	Crop	100
239	DblCropSoybeans_Cotton	Crop	100
240	DblCropSoybeans_Oats	Crop	100
241	DblCropCorn_Soybeans	Crop	100
242	Blueberries	vegetables	10000
243	Cabbage	vegetables	10000
244	Cauliflower	vegetables	10000
245	Celery	vegetables	10000
246	Radishes	vegetables	10000
247	Turnips	vegetables	10000
248	Eggplants	vegetables	10000
249	Gourds	vegetables	10000
250	Cranberries	fruticulture	10
251			0
252			0
253			0
254	DblCropBarley_Soybeans	Crop	100

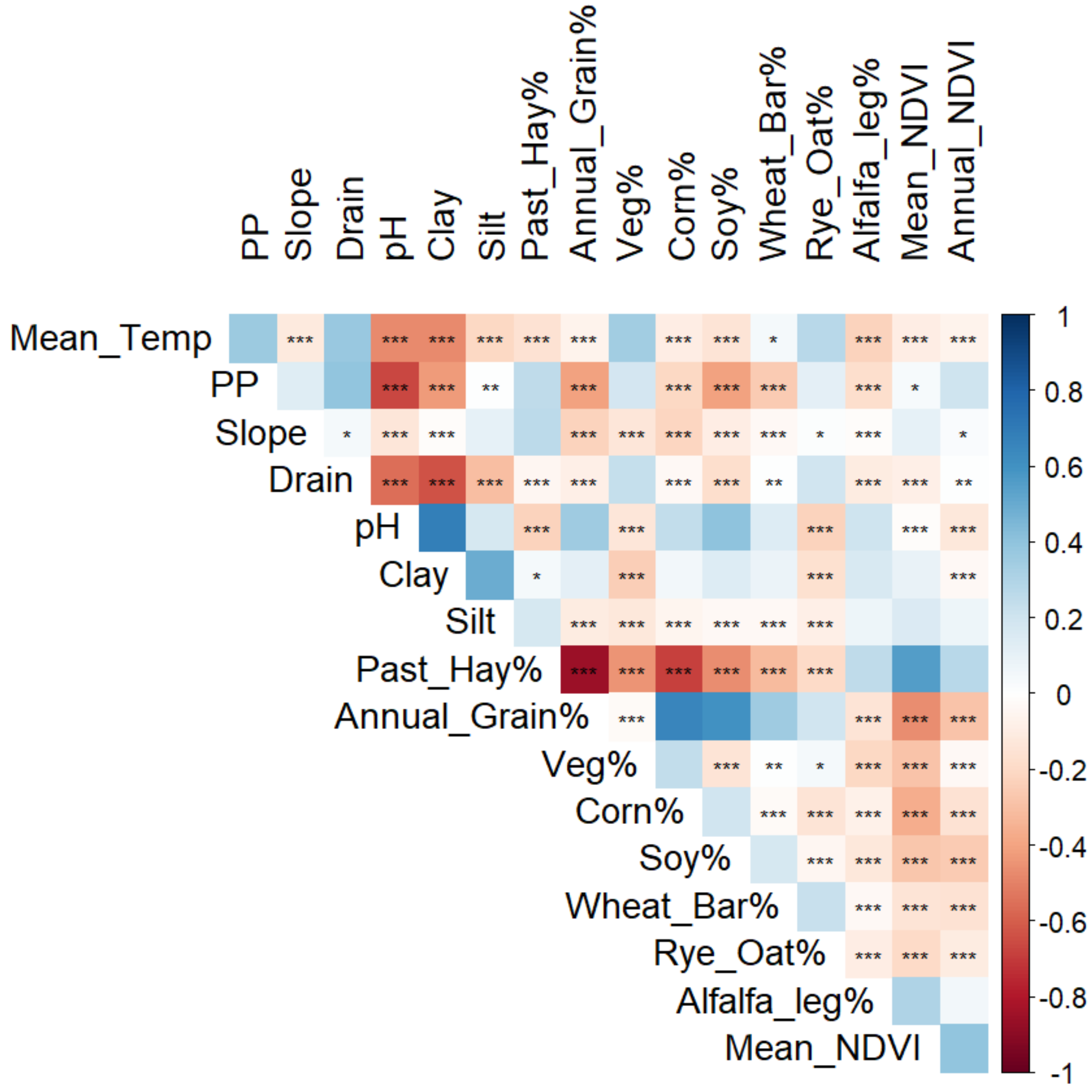
Appendix 5.2: Percentage of time under different crops and pastures per land use systems

Production system	Corn	Soybean	Wheat and Barley	Annual grains	Rye and oat	Pasture and hay	Processing vegetables
							%
Crop_sys	50	24	9	95	2	3	1
Crop_Past_Hay_sys	28	6	3	48	2	49	1
Mix_Veg_sys	37	7	6	55	5	9	35
Past_Hay_sys	1	0	0	1	0	91	1

Appendix 5.3: Tunned hyperparameters of the XGBOOST model and evaluation range

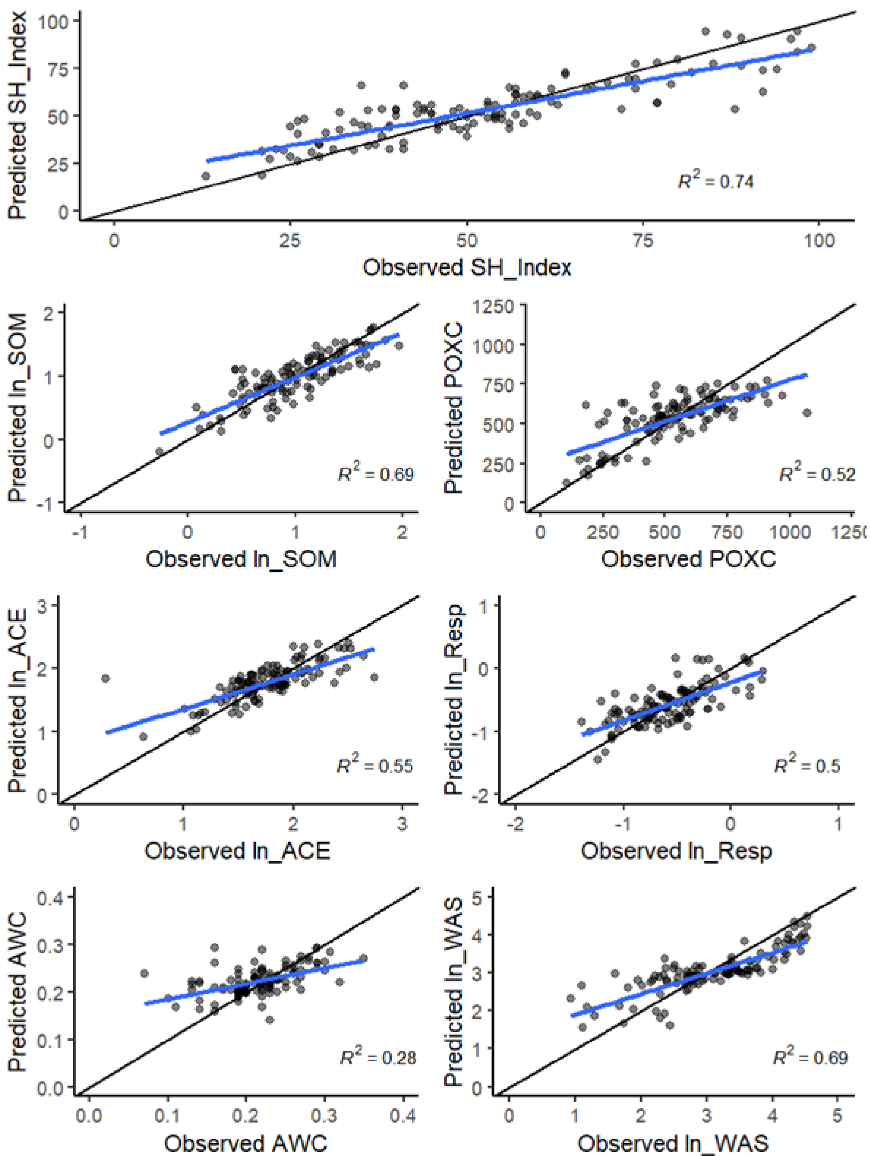
Hyperparameter	Definition	Evaluated range
Max_depth	The depth of the tree	6:8
Min_child_weight	The minimum sum of weights of all observations	c(2.0, 2.25, 2.5)
Colsample_by_tree	The number of variables supplied to a tree	c(0.3, 0.4, 0.5)
subsample	The number of samples supplied to a tree	c(0.5, 1)
eta	Learning rate	0.05, 0.075, 0.1

Appendix 5. 4: Pearson correlations between model covariates



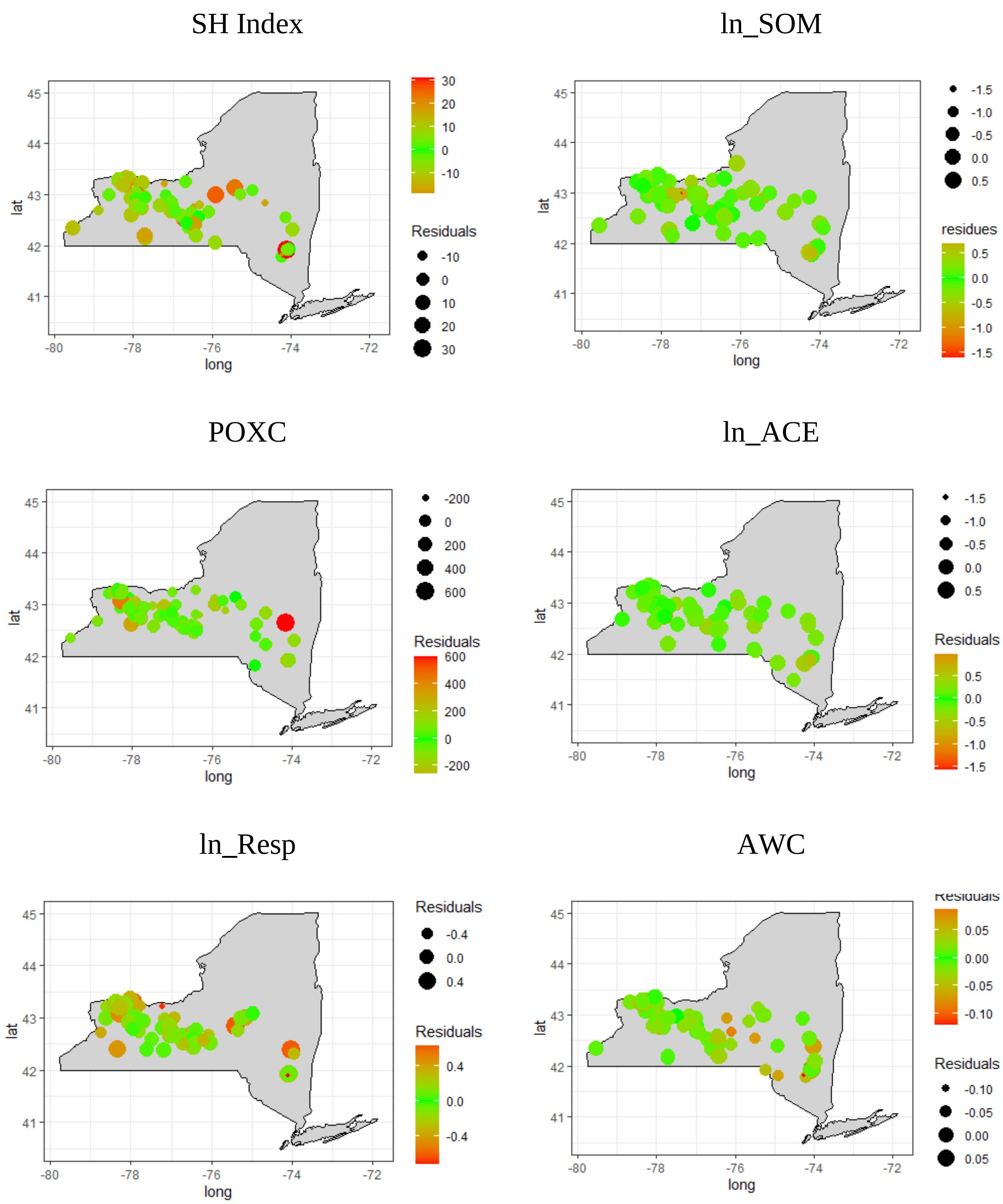
Where: *** :p-value=0.001, **; p-value=0.01,: *= p-value= 0.05;

Appendix 5.5 : Model fitting results for the validation dataset presented as the Observed vs. Predicted values and r-squared for the complete model in the smaller domain

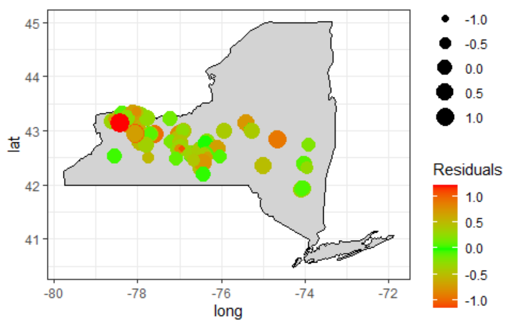


Where: SH Index: Composite Soil Health Index; SOM: Soil organic Mater; POXC: Permanganate-Oxidizable Carbon; ACE: ACE Protein; Resp: Respiration; AWC: Available water capacity; WAS: Water aggregate stability.

Appendix 5. 6: Spatial distribution of residuals from the complete model in the smaller domainfor each soil health indicator.



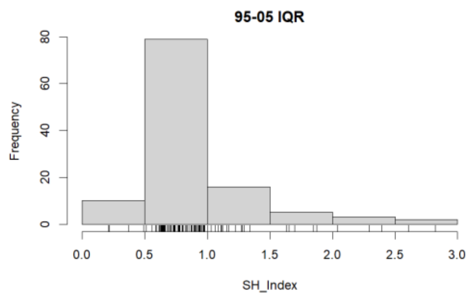
ln_WAS



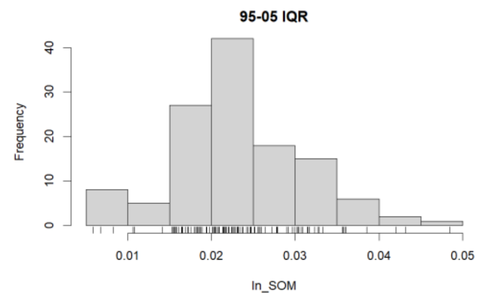
SH Index: Composite Soil Health Index; ln_SOM: logarithmic transformation of Soil organic Mater; POXC: Permanganate-Oxidizable Carbon; ln_ACE: logarithmic transformation of ACE Protein; ln_Resp: logarithmic transformation of Respiration; AWC: Available water capacity; ln_WAS: logarithmic transformation of Water aggregate stability.

Appendix 5.7: Uncertainty in soil health indicators prediction using full models in the small domains.

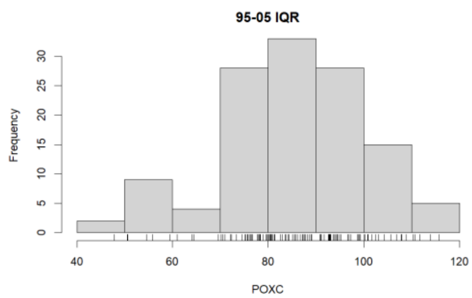
SH_Index



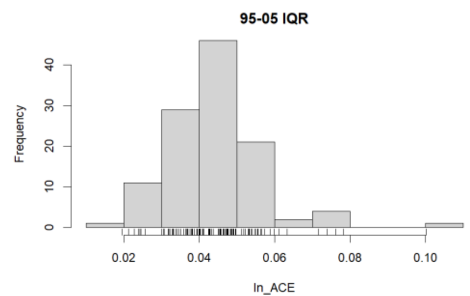
ln_SOM



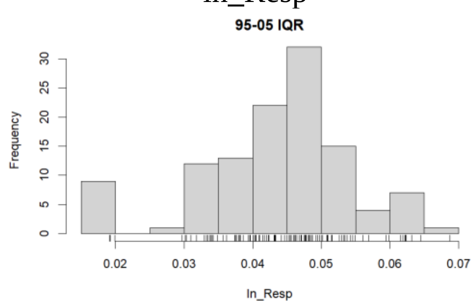
POXC



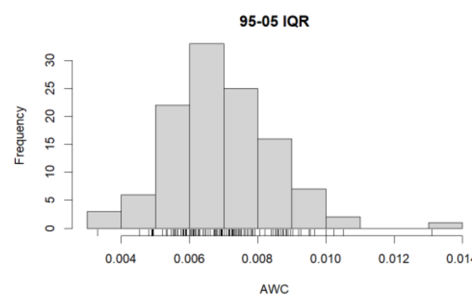
ln_ACE



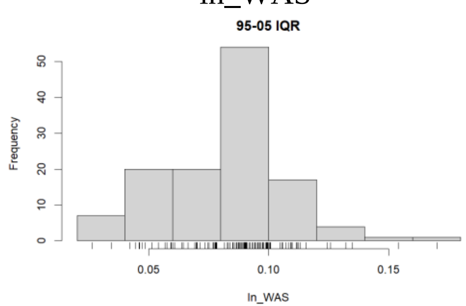
ln_Resp



AWC



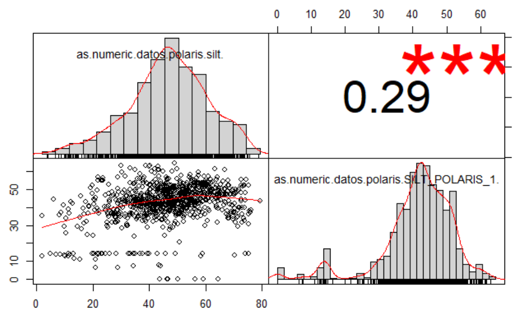
ln_WAS



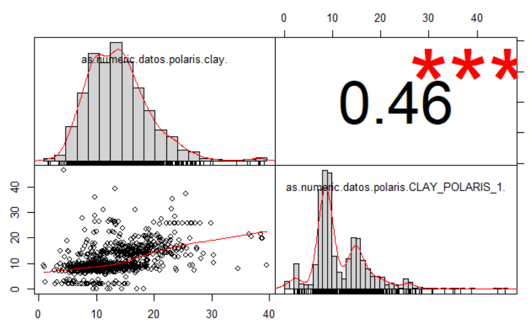
Where: SH Index: Composite Soil Health Index; SOM: Soil organic Mater; ; POXC: Permanganate-Oxidizable Carbon; ACE: ACE Protein; Resp: Respiration; AWC: Available water capacity; WAS: Water aggregate stability.

Appendix 5.8: Correlation analysis between measure silt (a) and clay (b) values and extracted data from POLARIS

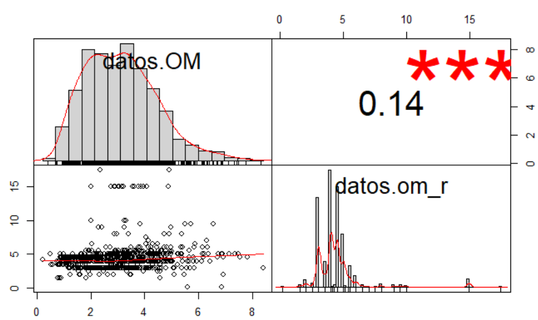
a)



b)



c)



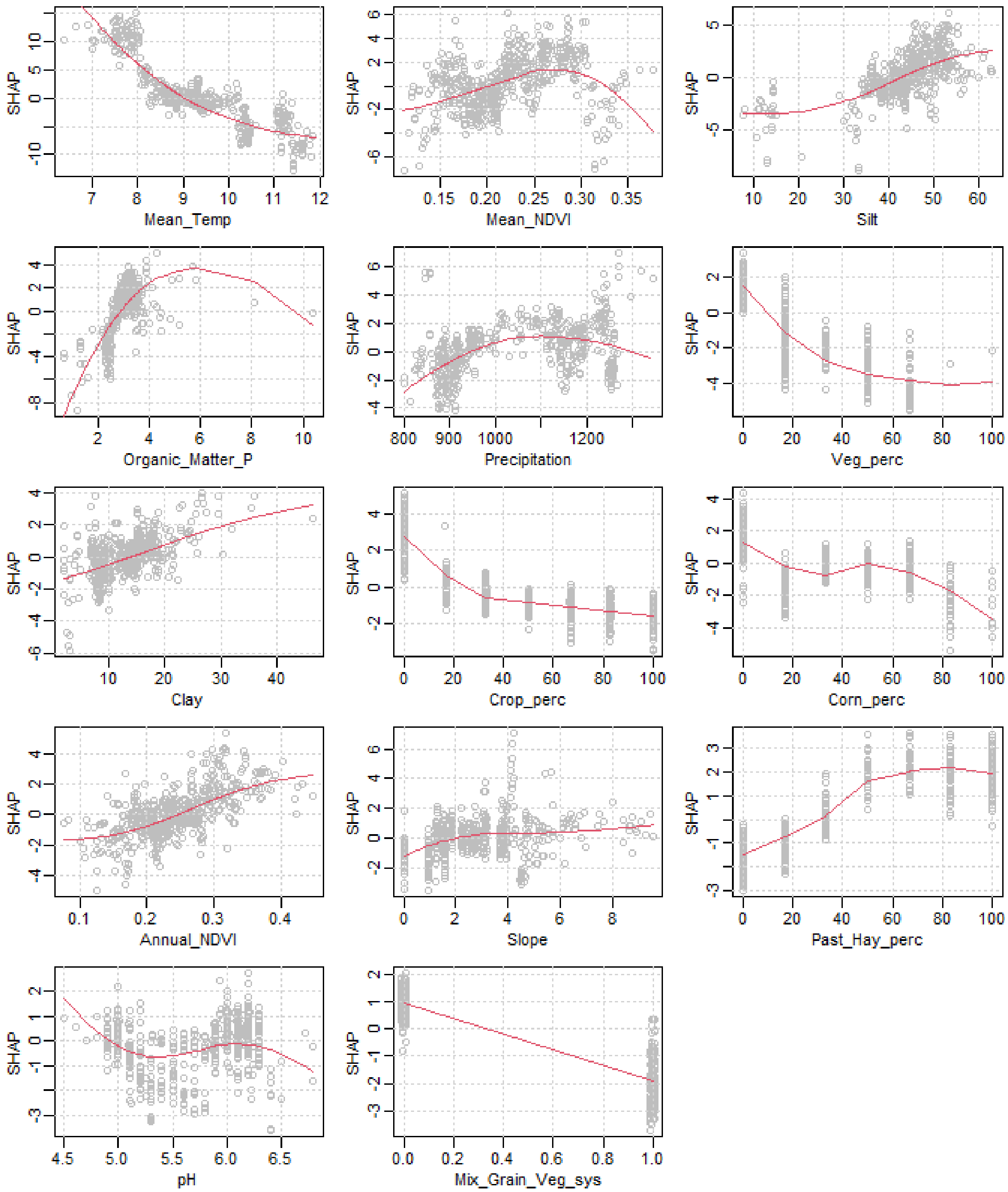
Appendix 5.9: Soil & topography and full model performances with measured and POLARIS estimated silt and clay variables.

	--Measured silt and clay--		-------POLARIS data ------	
	Soil & Topography	Full model	Soil & Topography	Full Model
----------R2----------				
SH index	0.48	0.72	0.49	0.74
ln_SOM	0.6	0.78	0.5	0.67
POXC	0.43	0.57	0.44	0.52
ln_ACE	0.38	0.54	0.35	0.55
ln_Resp	0.29	0.54	0.25	0.5
AWC	0.4	0.41	0.11	0.28
ln_WAS	0.41	0.73	0.5	0.69
----------RMSE----------				
SH index	0.47	0.35	0.56	0.40
ln_SOM	0.47	0.36	0.55	0.45
POXC	0.57	0.50	0.65	0.60
ln_ACE	0.63	0.54	0.77	0.64
ln_Resp	0.59	0.46	0.68	0.55
AWC	0.63	0.62	0.92	0.82
ln_WAS	0.56	0.39	0.57	0.46
----------LCCC----------				
SH index	0.65	0.83	0.66	0.84
ln_SOM	0.76	0.87	0.69	0.82
POXC	0.6	0.71	0.59	0.69
ln_ACE	0.54	0.69	0.50	0.70
ln_Resp	0.52	0.72	0.47	0.70
AWC	0.6	0.61	0.27	0.47
ln_WAS	0.54	0.8	0.60	0.76

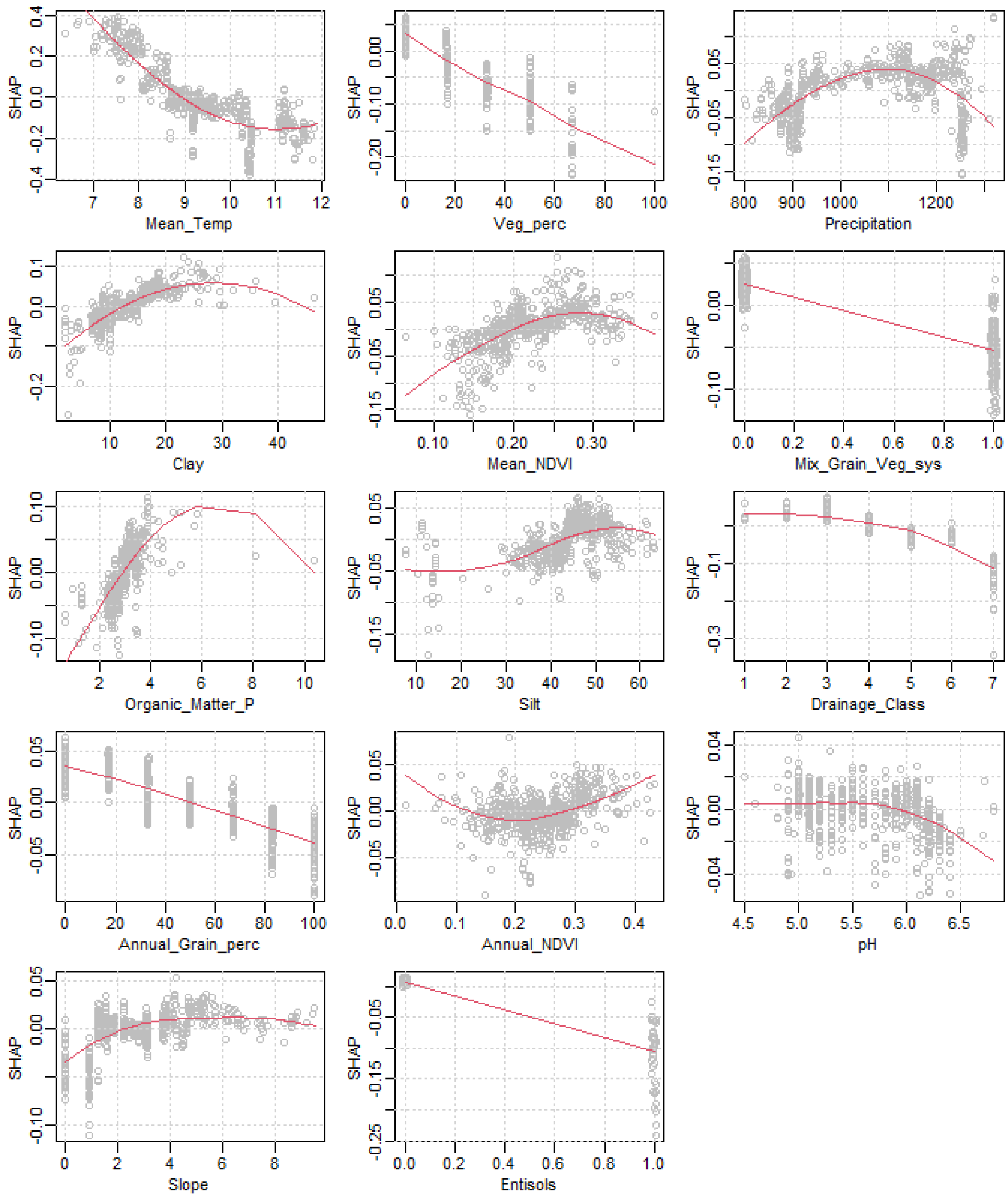
SH Index: Composite Soil Health Index; ln_SOM: logarithmic transformation of Soil organic Mater; POXC: Permanganate-Oxidizable Carbon; ln_ACE: logarithmic transformation of ACE Protein; ln_Resp: logarithmic transformation of Respiration; AWC: Available water capacity; ln_WAS: logarithmic transformation of Water aggregate stability.

Appendix 5. 10: SHAP dependency plots for soil health indicators in over the smaller domain

a) **SH_Index**

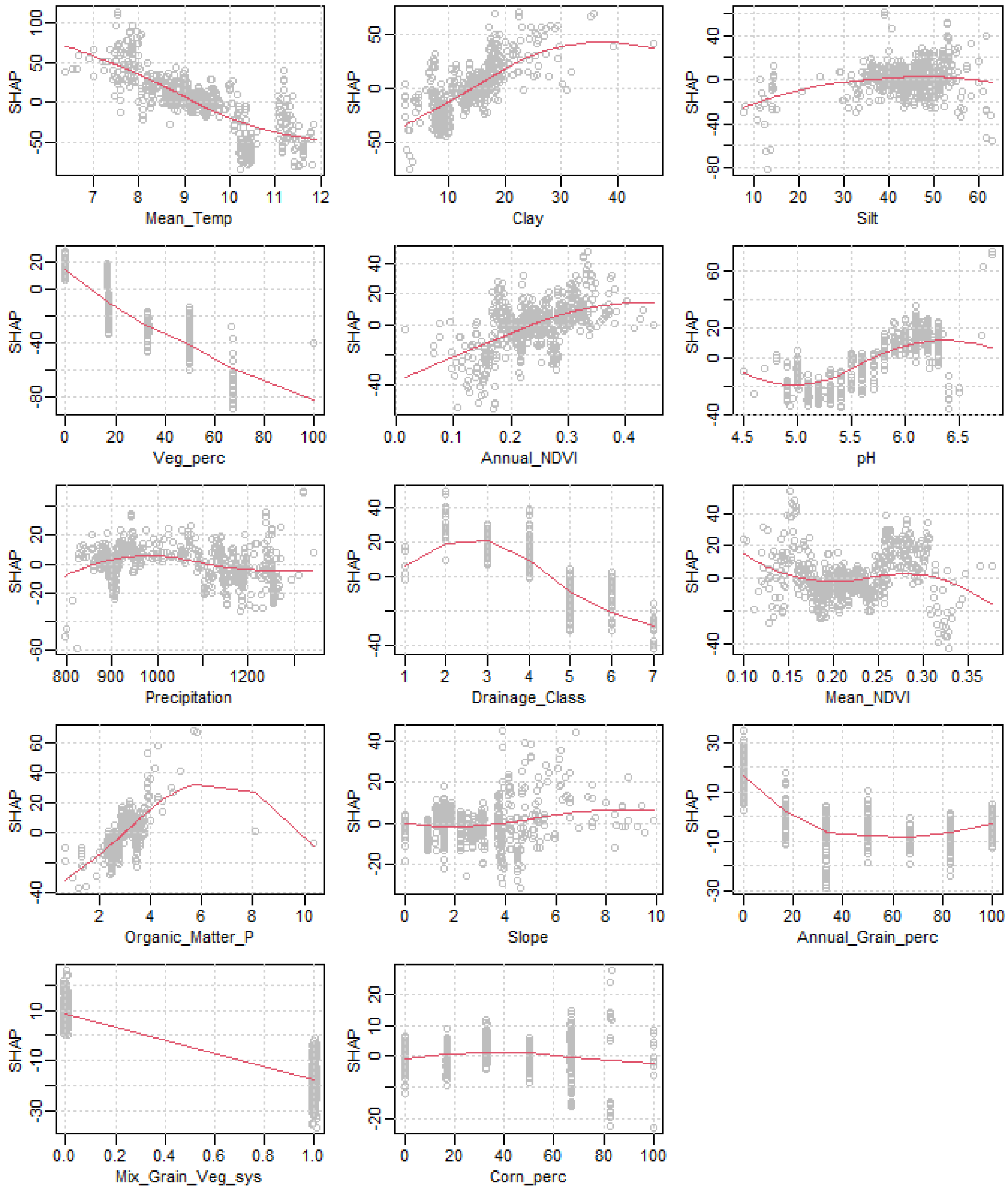


b) ln_SOM

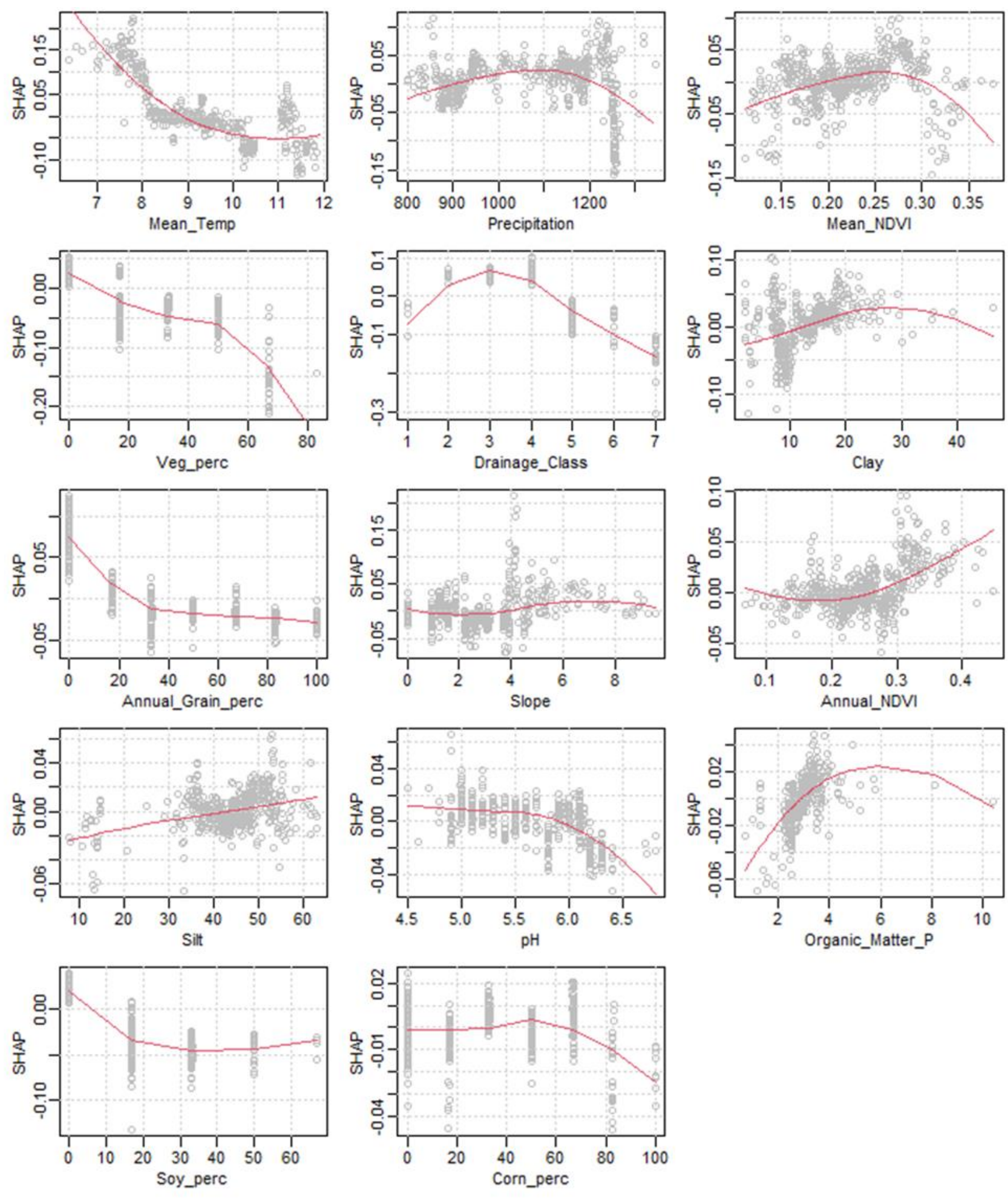


SHAP
Mean_Temp
Veg_perc
Precipitation
Clay
Mean_NDVI
Mix_Grain_Veg_sys
Organic_Matter_P
Silt
Drainage_Class
Annual_Grain_perc
Annual_NDVI
pH
Slope
Entisols

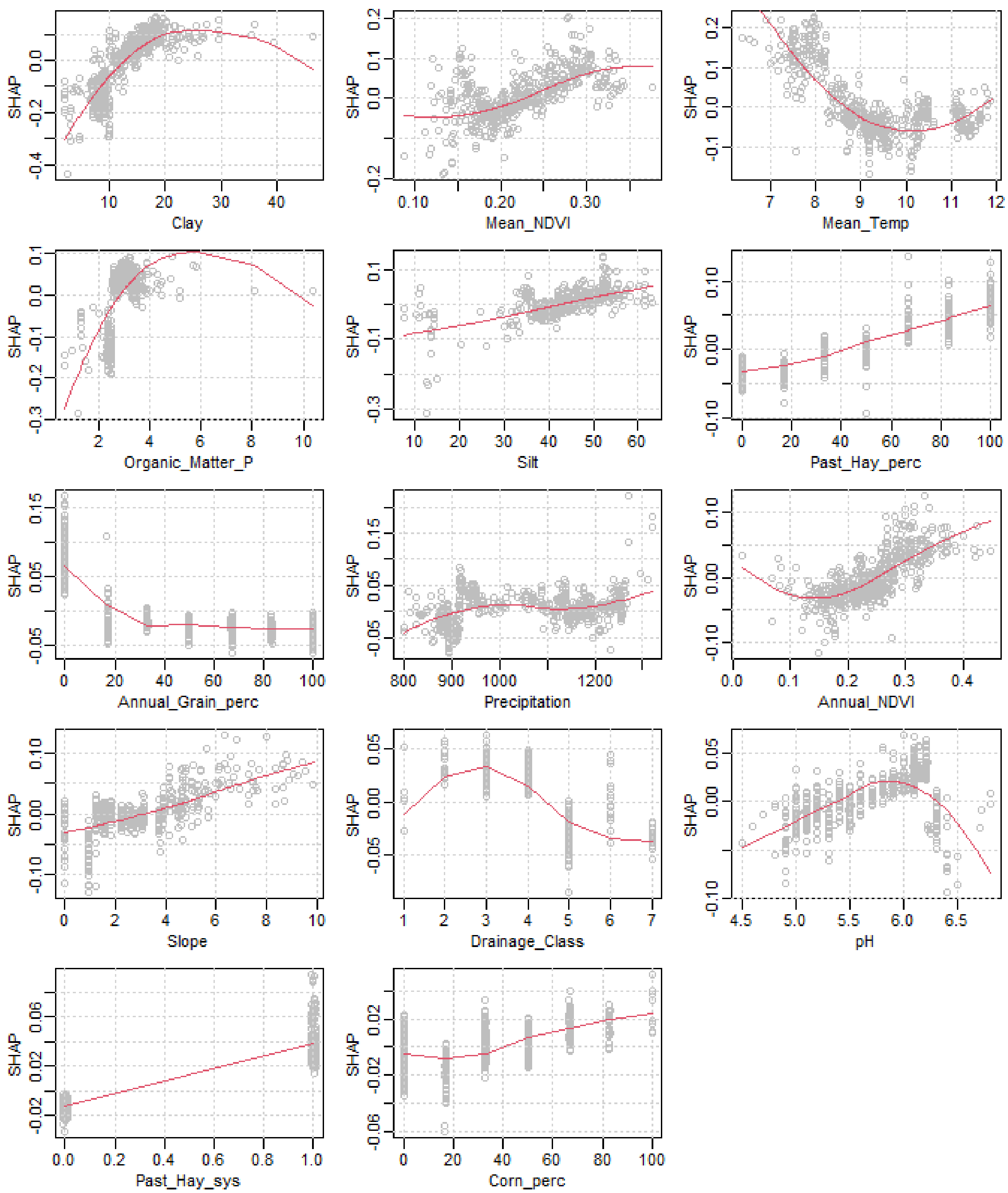
c) POXC


SHAP
Mean_Temp
Clay
Silt
Veg_perc
Annual_NDVI
pH
Precipitation
Drainage_Class
Mean_NDVI
Organic_Matter_P
Slope
Annual_Grain_perc
Mix_Grain_Veg_sys
Corn_perc

d) ln_ACE

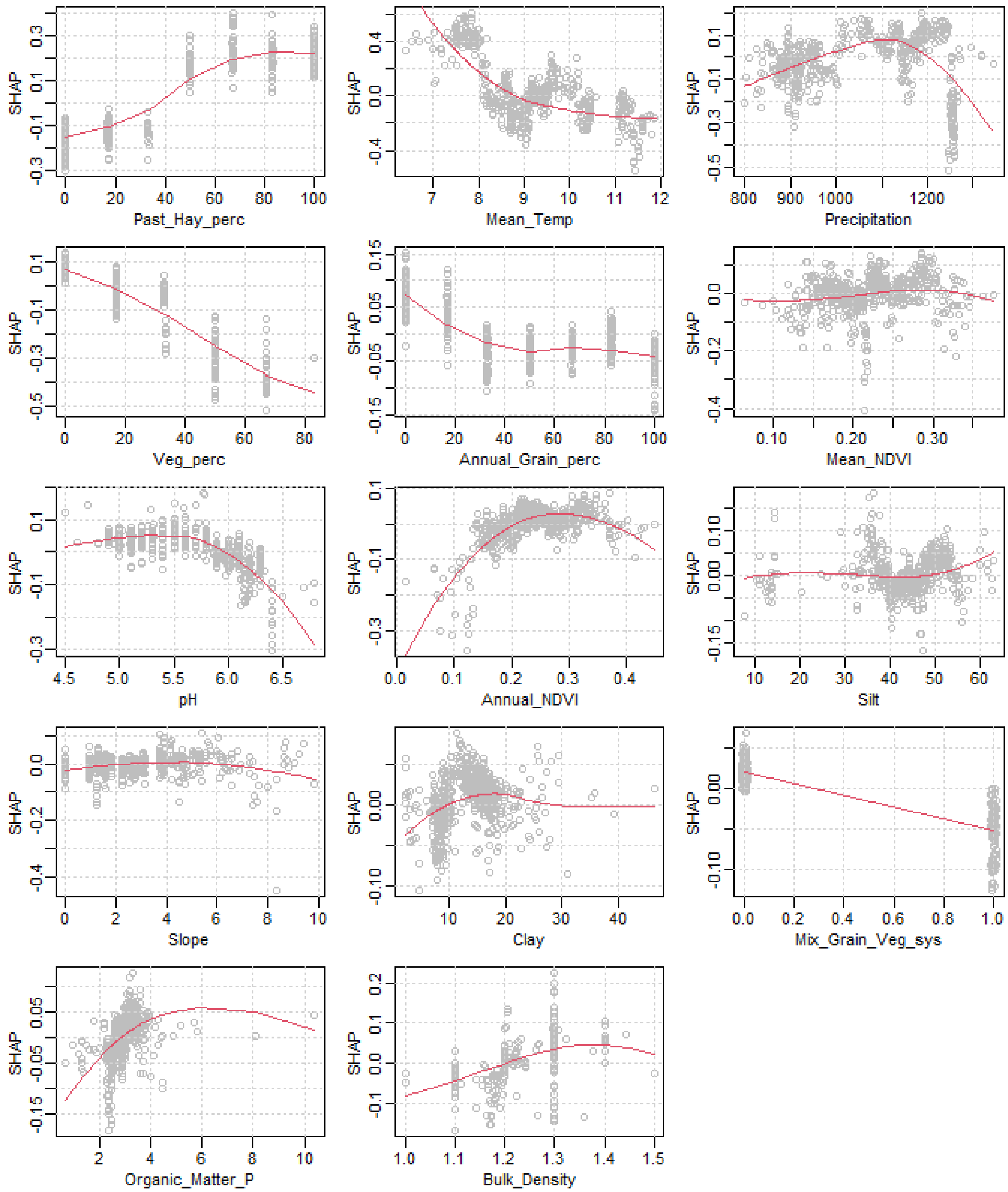

SHAP
Mean_Temp
Precipitation
Mean_NDVI
Veg_perc
Drainage_Class
Clay
Annual_Grain_perc
Slope
Annual_NDVI
Silt
pH
Organic_Matter_P
Soy_perc
Corn_perc

e) ln_Resp
f)

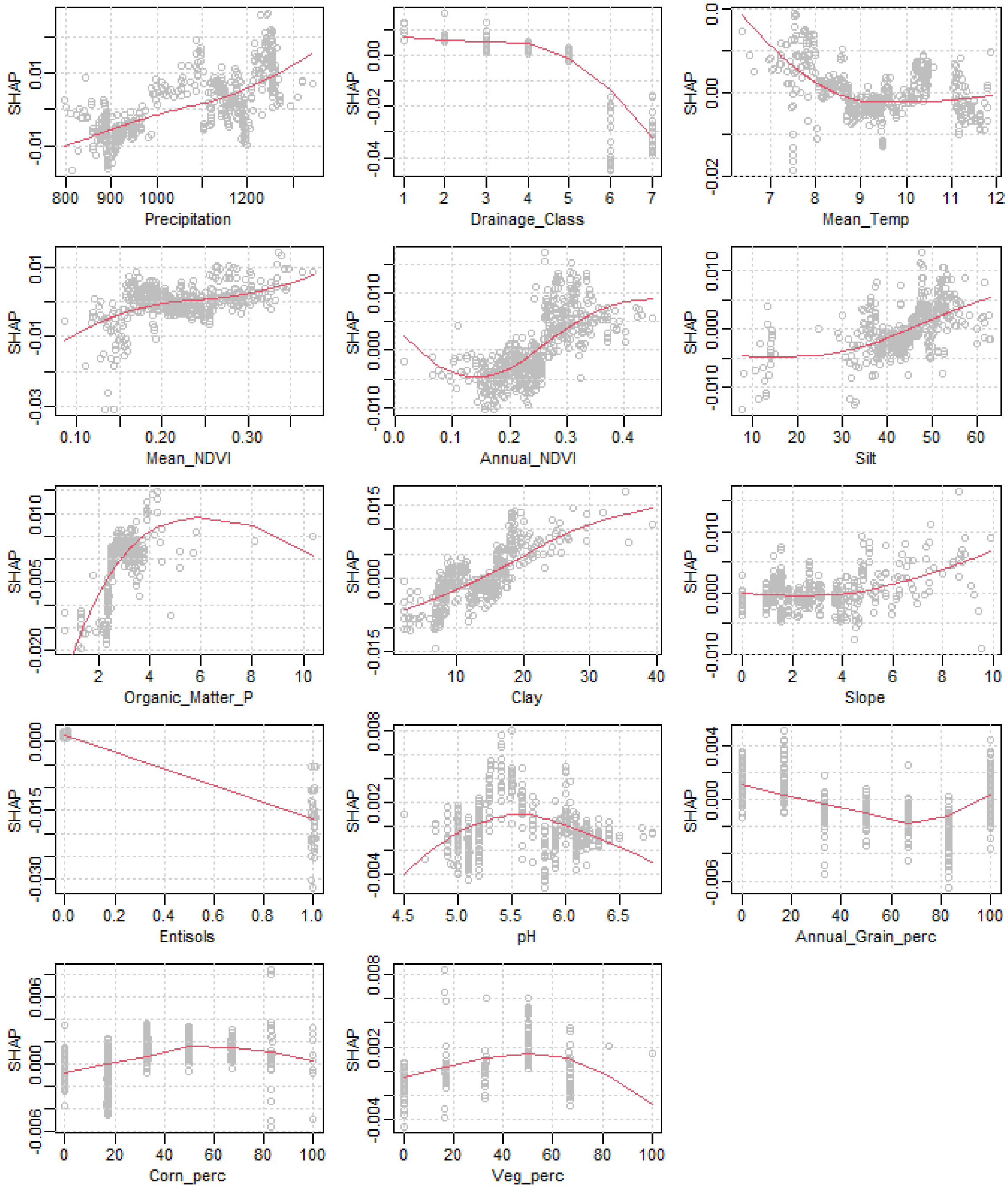


SHAP
Clay
Mean_NDVI
Mean_Temp
Organic_Matter_P
Silt
Past_Hay_perc
Annual_Grain_perc
Precipitation
Annual_NDVI
Slope
Drainage_Class
pH
Past_Hay_sys
Corn_perc

ln_WAS


SHAP
Past_Hay_perc
Mean_Temp
Precipitation
Veg_perc
Annual_Grain_perc
Mean_NDVI
pH
Annual_NDVI
Silt
Slope
Clay
Mix_Grain_Veg_sys
Organic_Matter_P
Bulk_Density

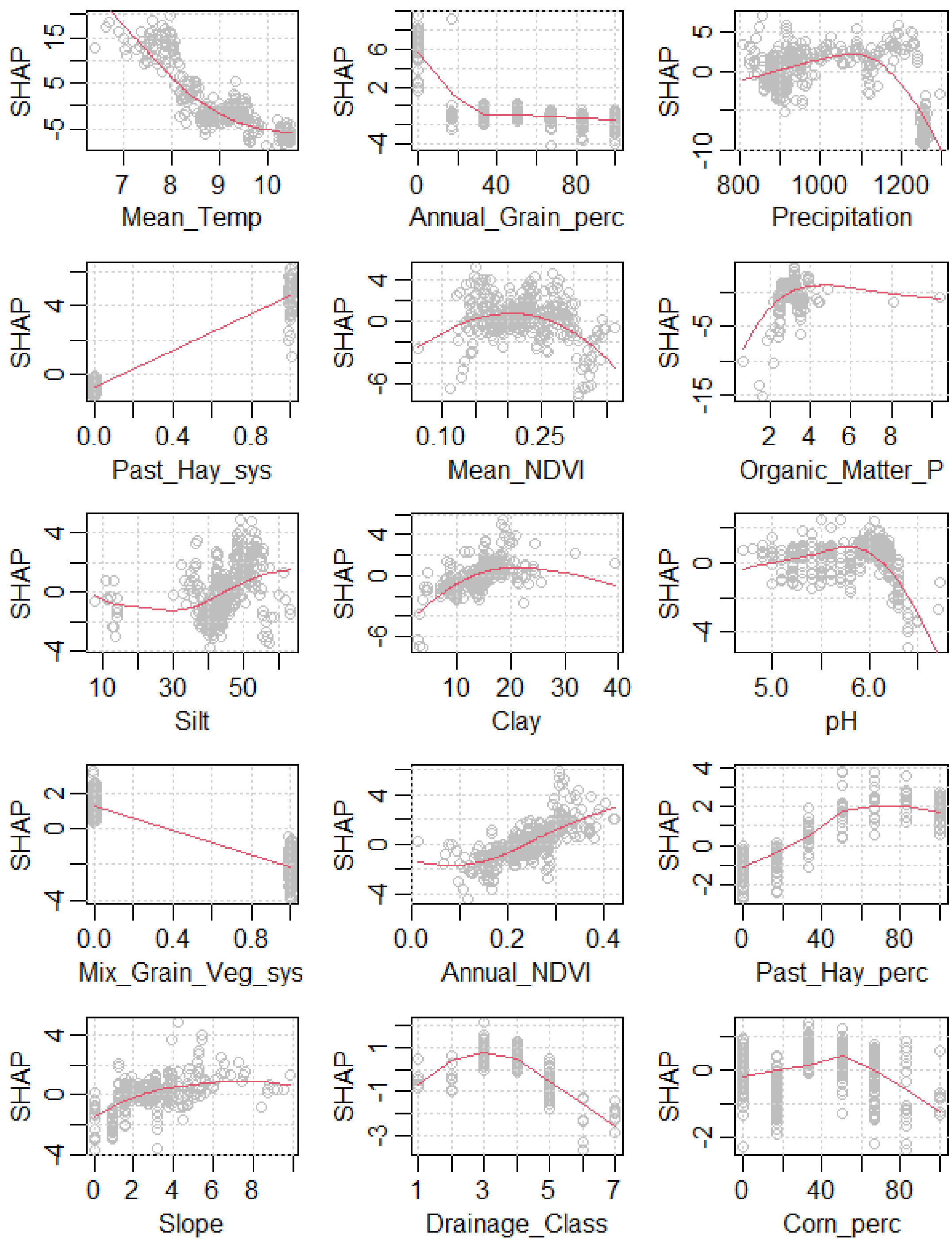
g) AWC



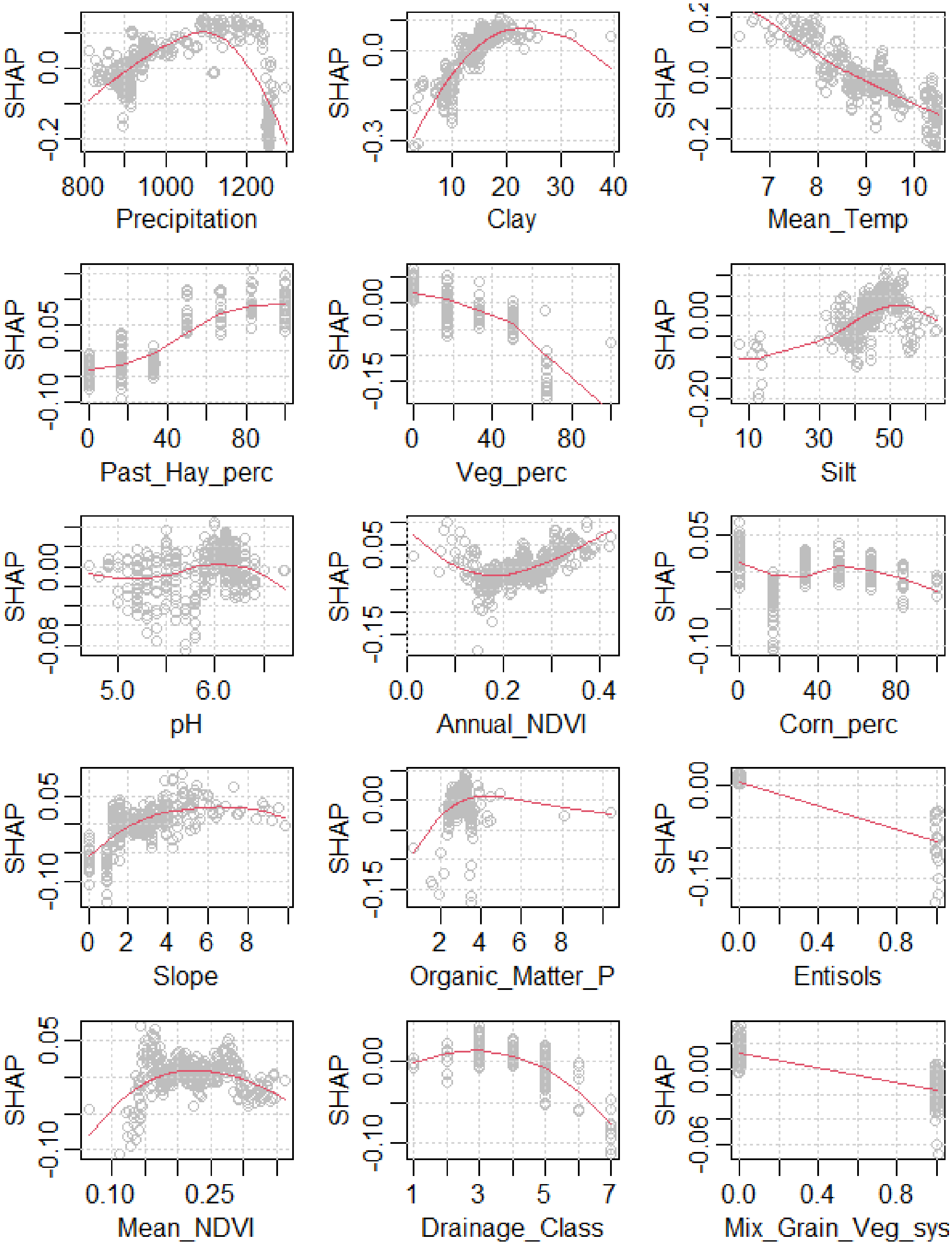
SH Index: Composite Soil Health Index; ln_SOM: logarithmic transformation of Soil organic Mater; POXC: Permanganate-Oxidizable Carbon; ln_ACE: logarithmic transformation of ACE Protein; ln_Resp: logarithmic transformation of Respiration; AWC: Available water capacity; ln_WAS: logarithmic transformation of Water aggregate stability.

Appendix 5.11: Shap dependency plots for soil health indicators in extent two

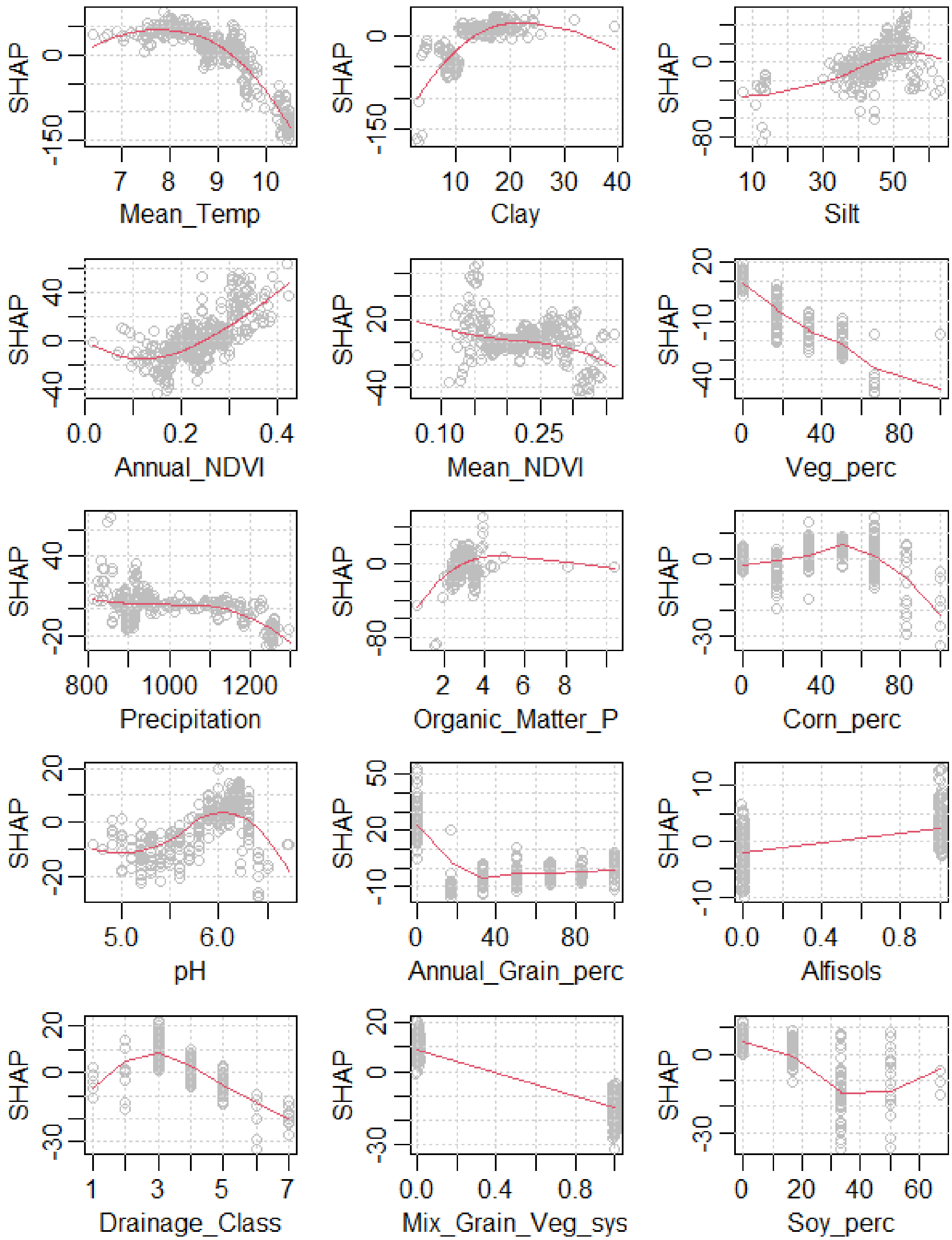
a) **SH_Index**



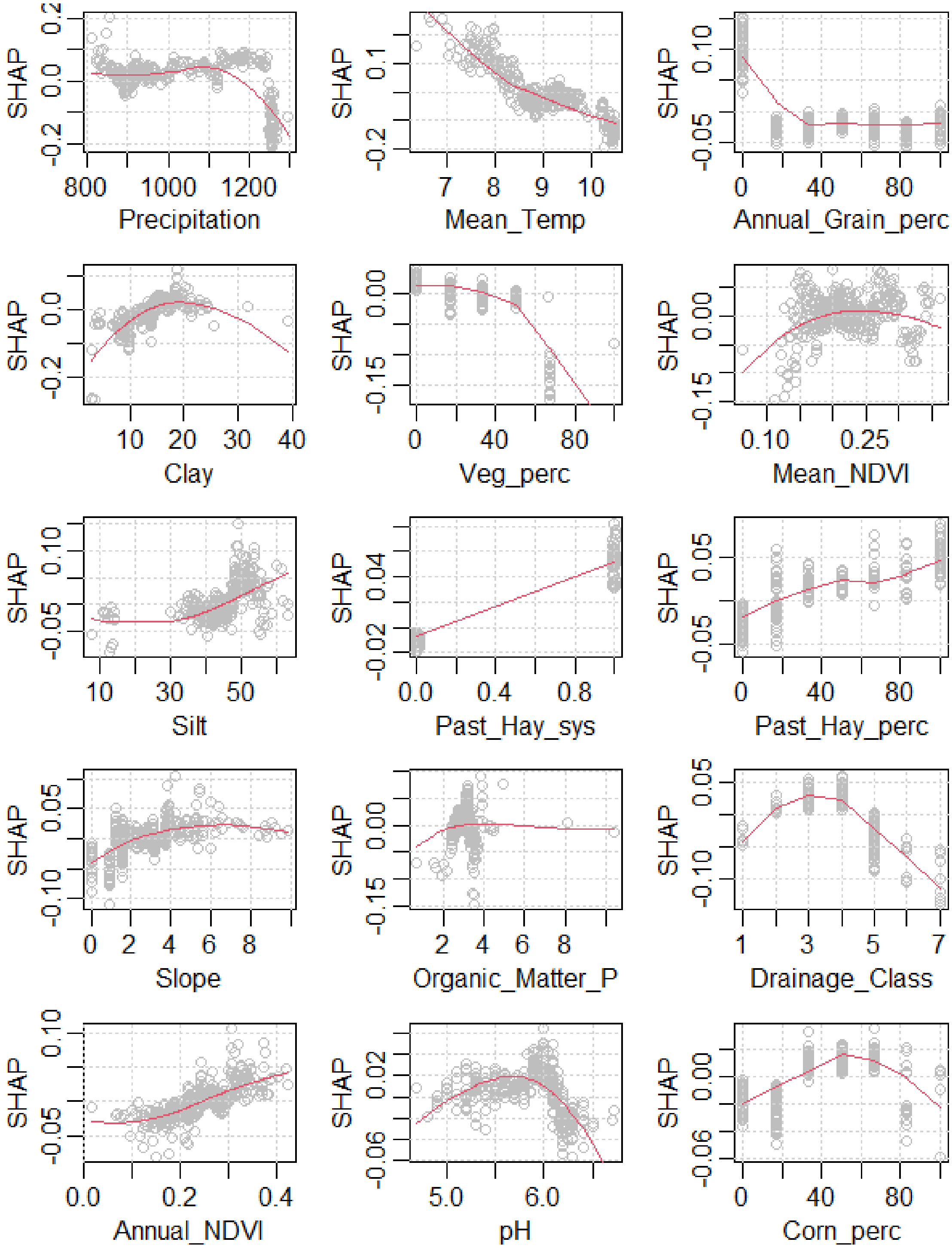
b) ln_SOM


SHAP
0.0
-0.2
800
1000
1200
Precipitation
SHAP
0.0
-0.3
10
20
30
40
Clay
SHAP
0.2
0.0
-0.2
7
8
9
10
Mean_Temp
SHAP
0.05
-0.10
0
40
80
Past_Hay_perc
SHAP
0.00
-0.15
0
40
80
Veg_perc
SHAP
0.00
-0.20
10
30
50
Silt
SHAP
0.00
-0.08
5.0
6.0
pH
SHAP
0.05
-0.15
0.0
0.2
0.4
Annual_NDVI
SHAP
0.05
-0.10
0
40
80
Corn_perc
SHAP
0.05
-0.10
0
2
4
6
8
Slope
SHAP
0.00
-0.15
2
4
6
8
Organic_Matter_P
SHAP
0.00
-0.15
0.0
0.4
0.8
Entisols
SHAP
0.05
-0.10
0.10
0.25
Mean_NDVI
SHAP
0.00
-0.10
1
3
5
7
Drainage_Class
SHAP
0.00
-0.06
0.0
0.4
0.8
Mix_Grain_Veg_sys

c) POXC

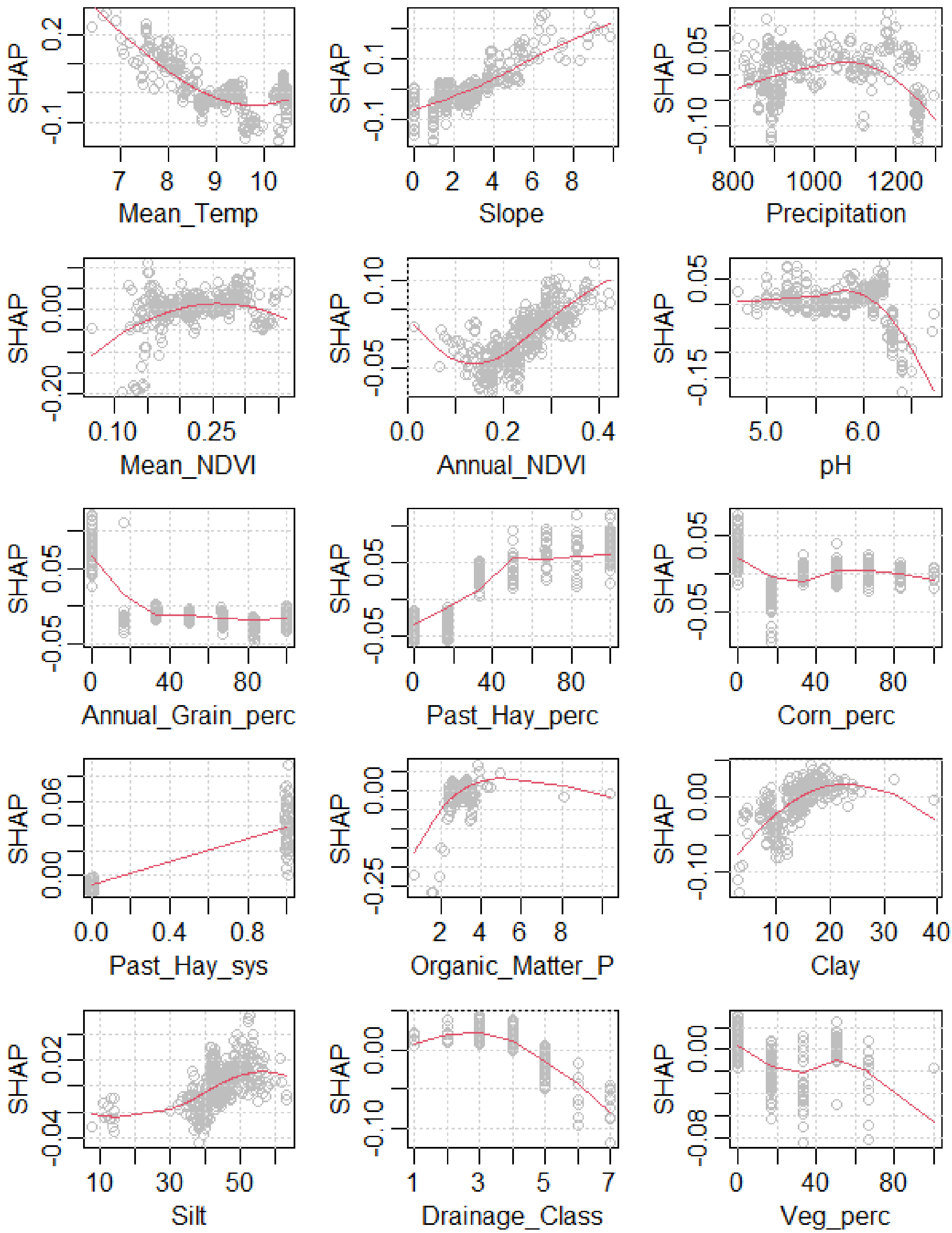

SHAP
Mean_Temp
Clay
Silt
Annual_NDVI
Mean_NDVI
Veg_perc
Precipitation
Organic_Matter_P
Corn_perc
pH
Annual_Grain_perc
Alfisols
Drainage_Class
Mix_Grain_Veg_sys
Soy_perc

d) ln_ACE



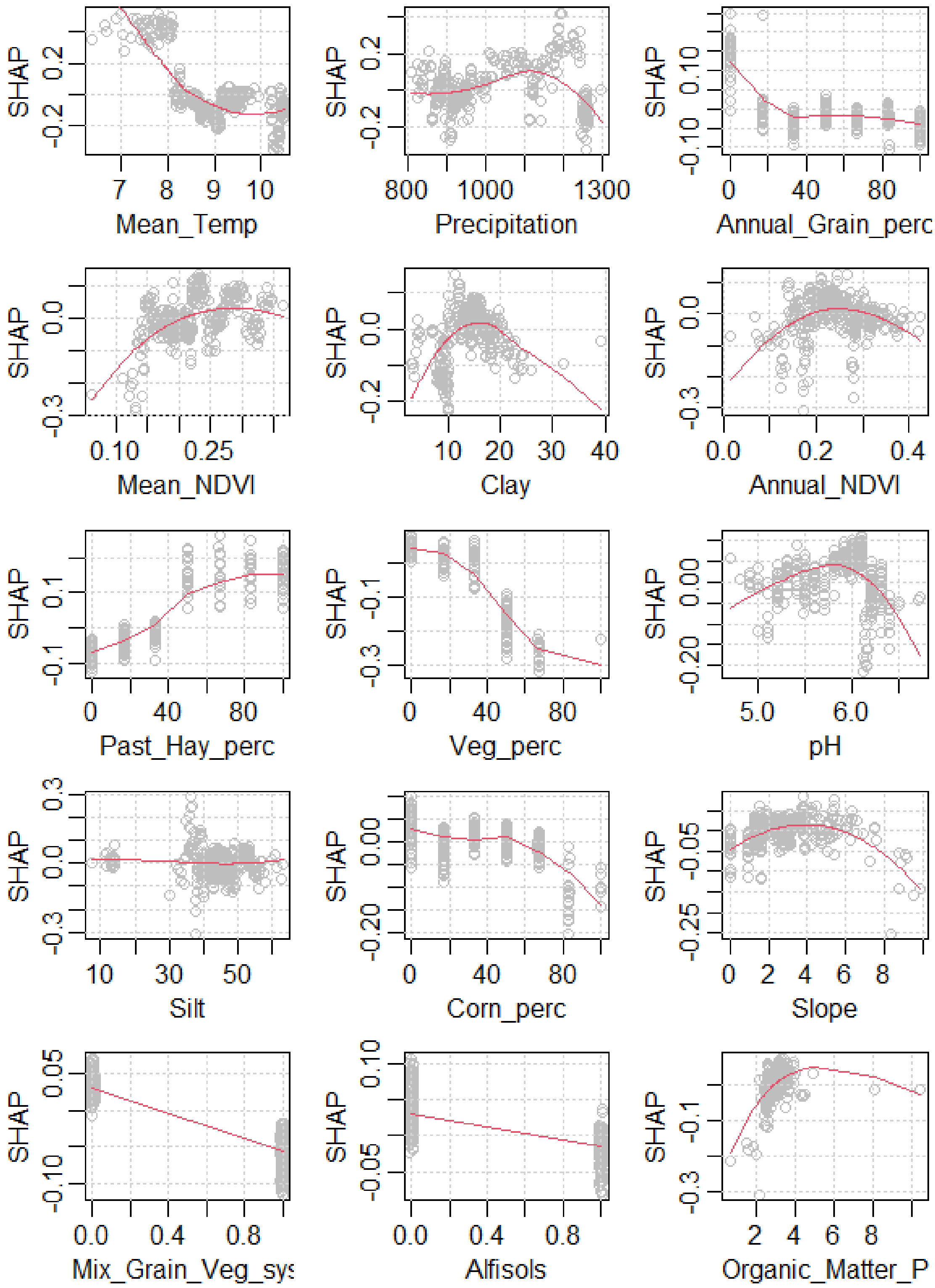
SHAP
Precipitation
Mean_Temp
Annual_Grain_perc
Clay
Veg_perc
Mean_NDVI
Silt
Past_Hay_sys
Past_Hay_perc
Slope
Organic_Matter_P
Drainage_Class
Annual_NDVI
pH
Corn_perc

e) ln_Resp

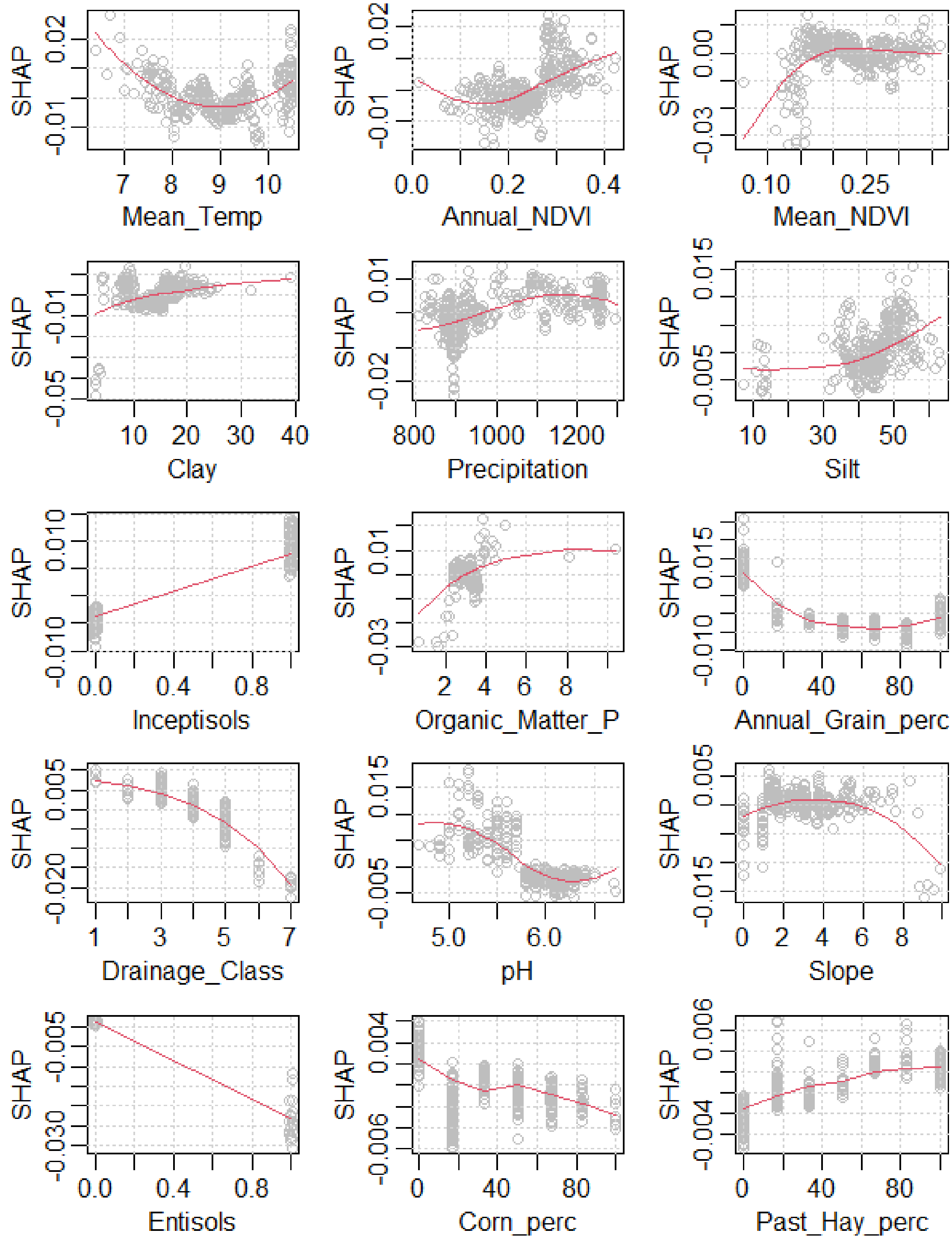


SHAP
Mean_Temp
Slope
Precipitation
Mean_NDVI
Annual_NDVI
pH
Annual_Grain_perc
Past_Hay_perc
Corn_perc
Past_Hay_sys
Organic_Matter_P
Clay
Silt
Drainage_Class
Veg_perc

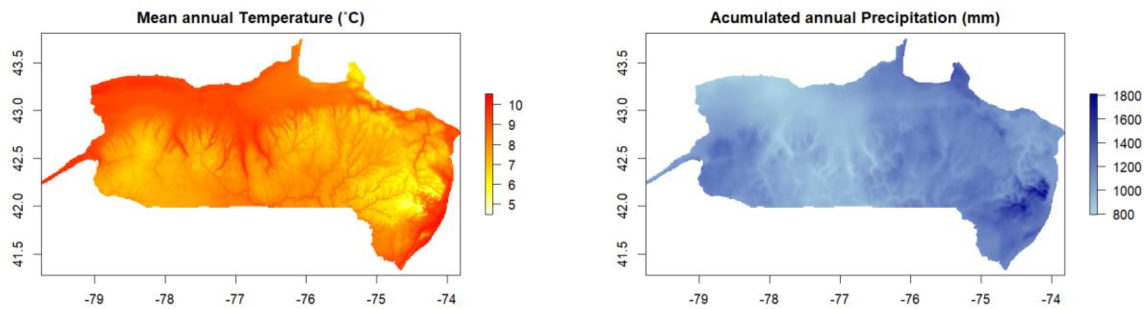
f) ln_WAS


SHAP
Mean_Temp
Precipitation
Annual_Grain_perc
Mean_NDVI
Clay
Annual_NDVI
Past_Hay_perc
Veg_perc
pH
Silt
Corn_perc
Slope
Mix_Grain_Veg_sys
Alfisols
Organic_Matter_P

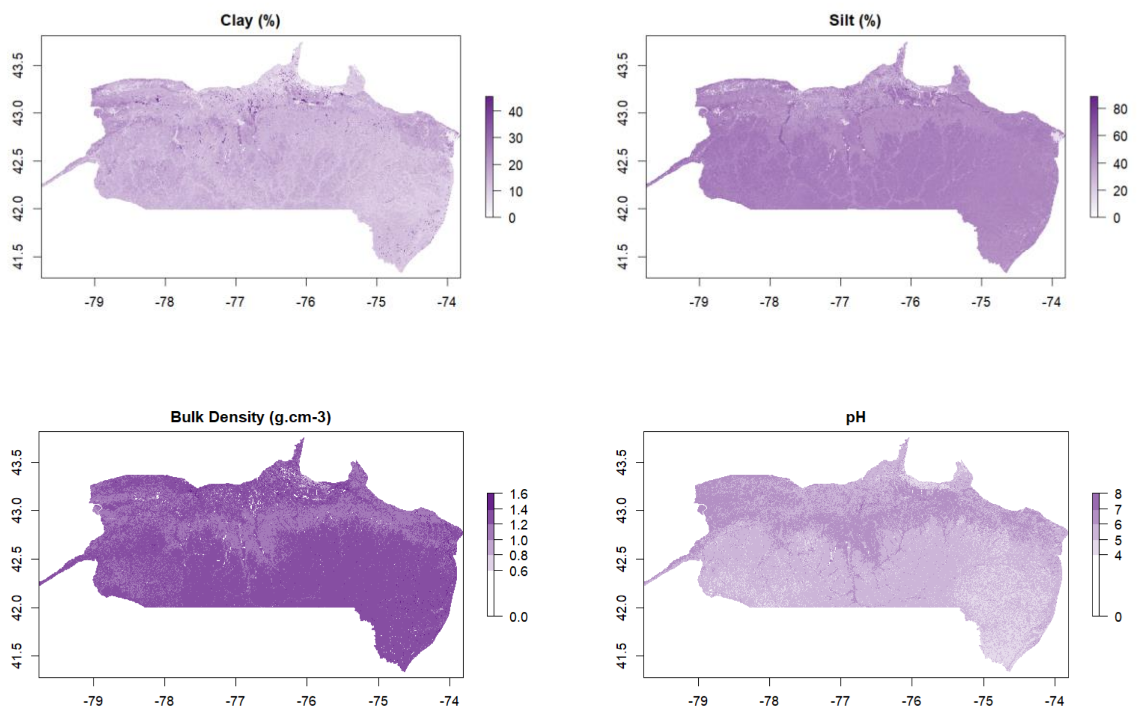
g) AWC



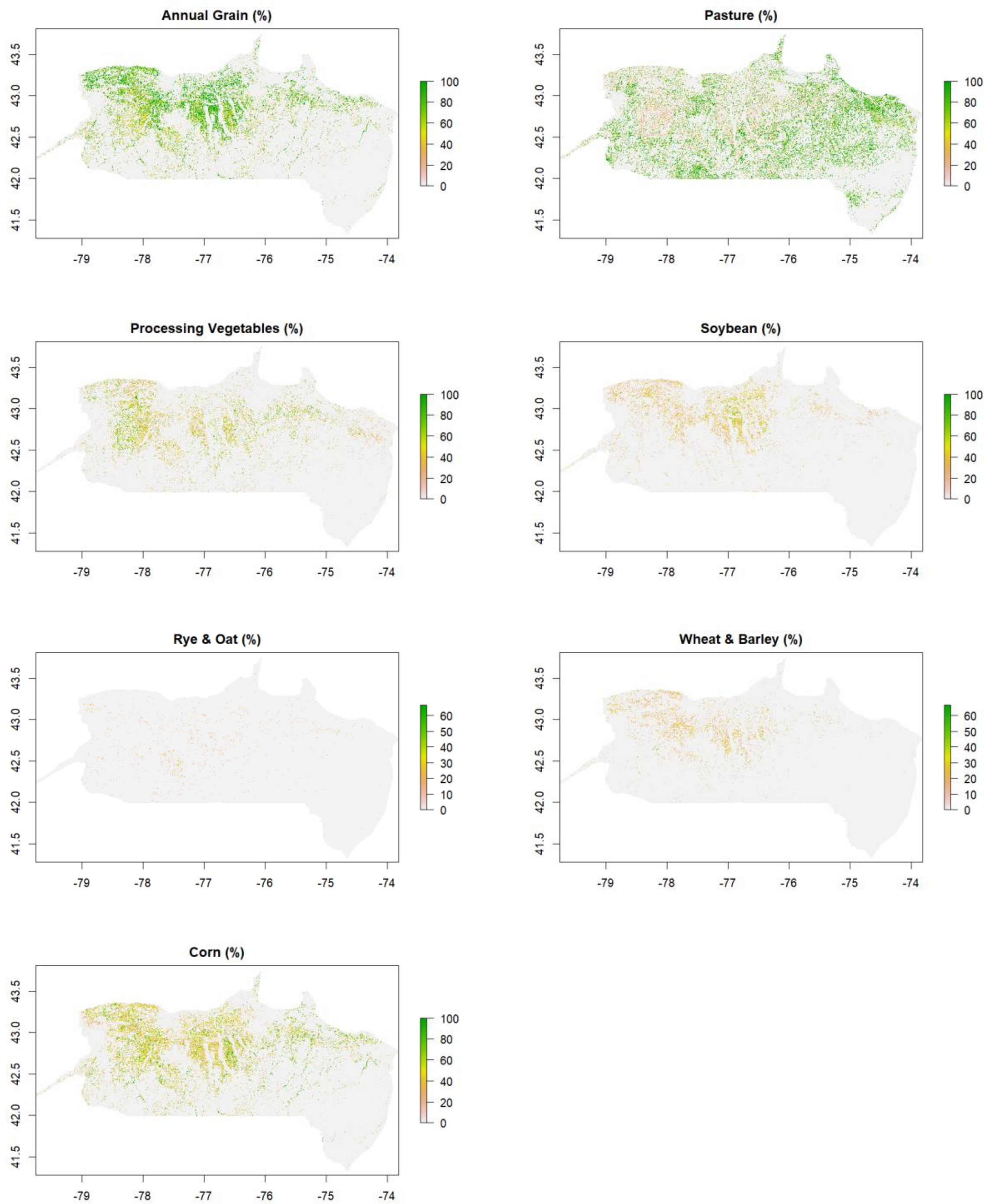
SH Index: Composite Soil Health Index; ln_SOM: logarithmic transformation of Soil organic Mater; POXC: Permanganate-Oxidizable Carbon; ln_ACE: logarithmic transformation of ACE Protein; ln_Resp: logarithmic transformation of Respiration; AWC: Available water capacity; ln_WAS: logarithmic transformation of Water aggregate stability.



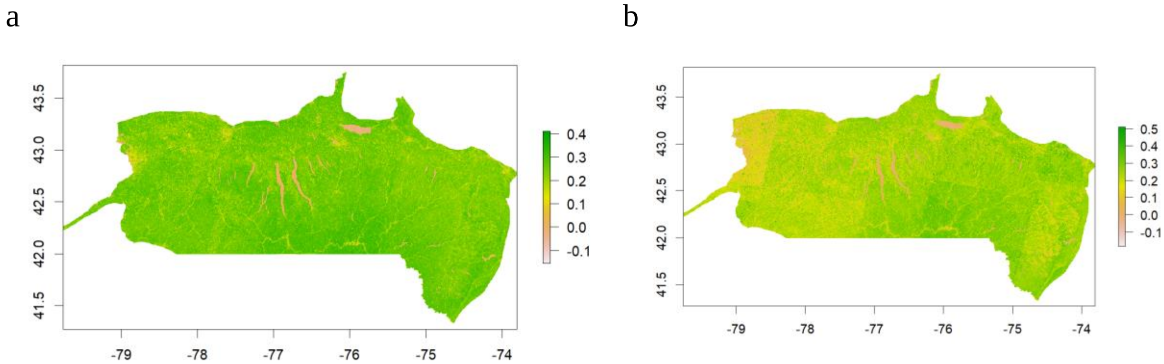
Appendix 5.11: Climate related model covariates over the evaluated smaller domain



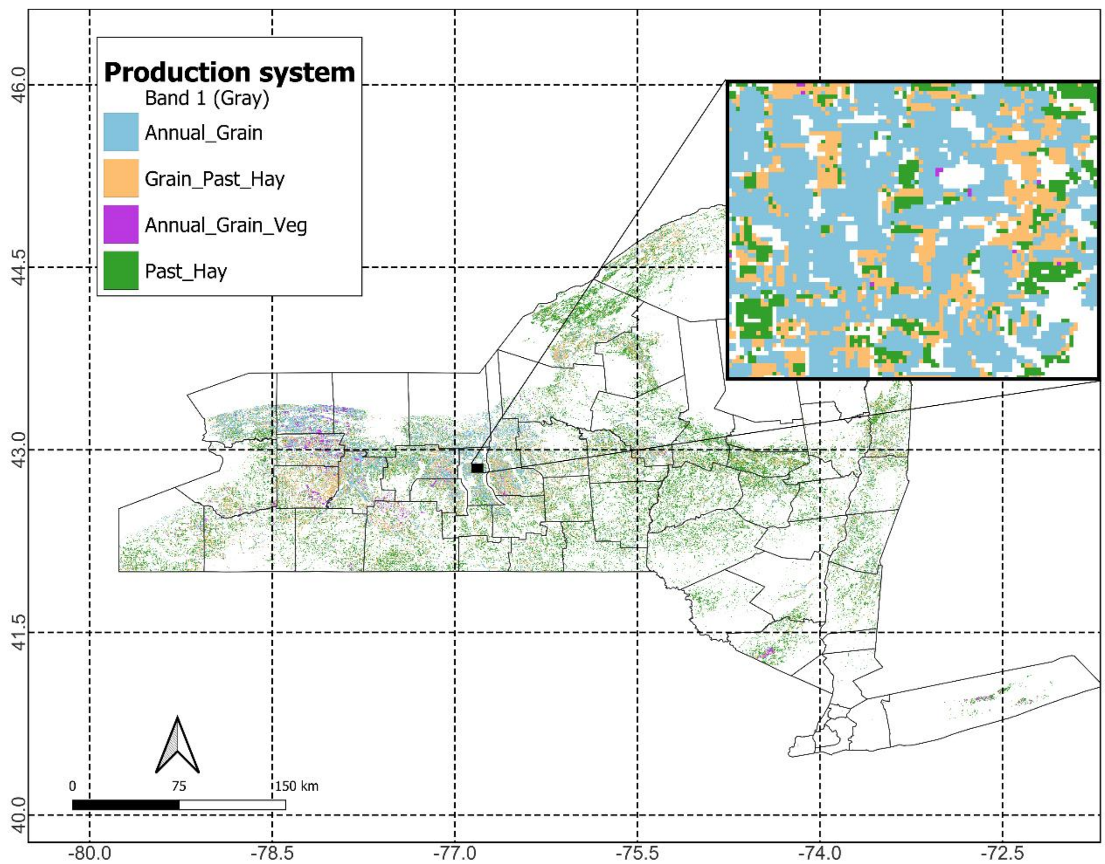
Appendix 5.12: Soil related model covariates over the evaluated smaller domain



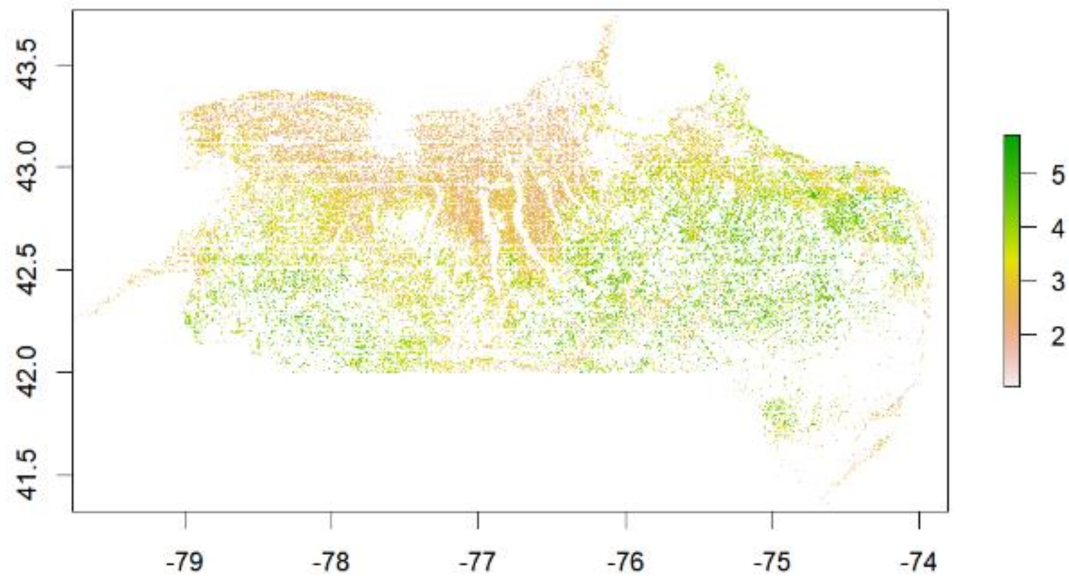
Appendix 5.13: Land use related model covariates over the evaluated smaller domain



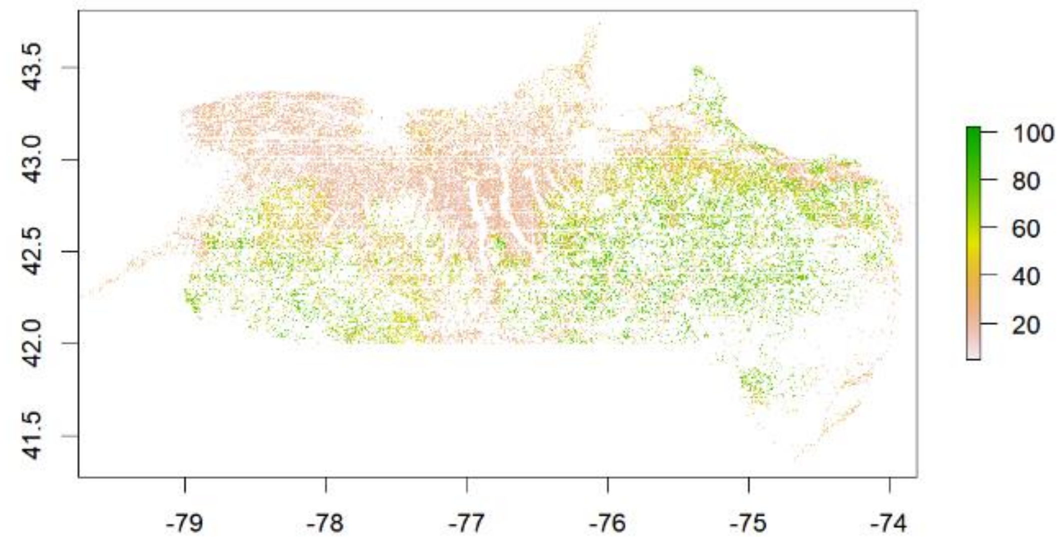
Appendix 5.14: Six year (a) and one year (b) mean NDVI over the evaluated smaller domain



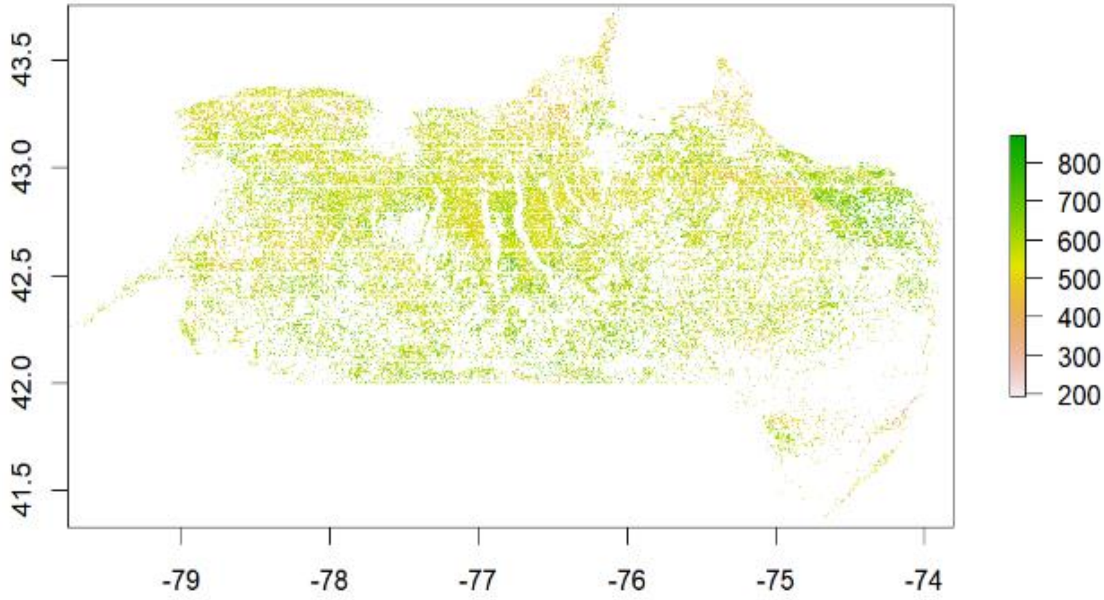
Appendix 5.15: Land use systems



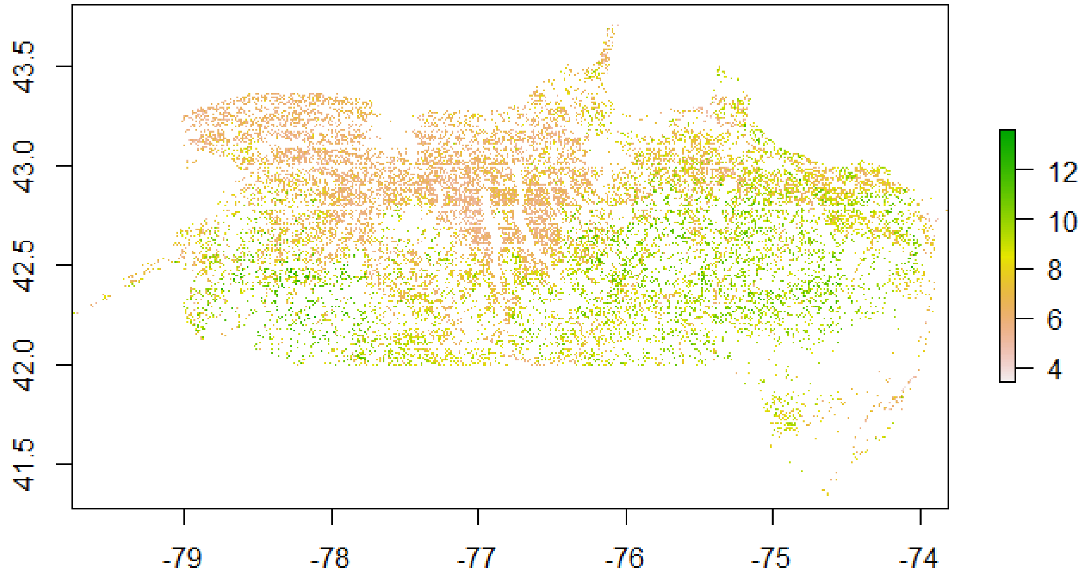
Appendix 5.16: Predicted Soil organic matter, based on the complete model over the small domain



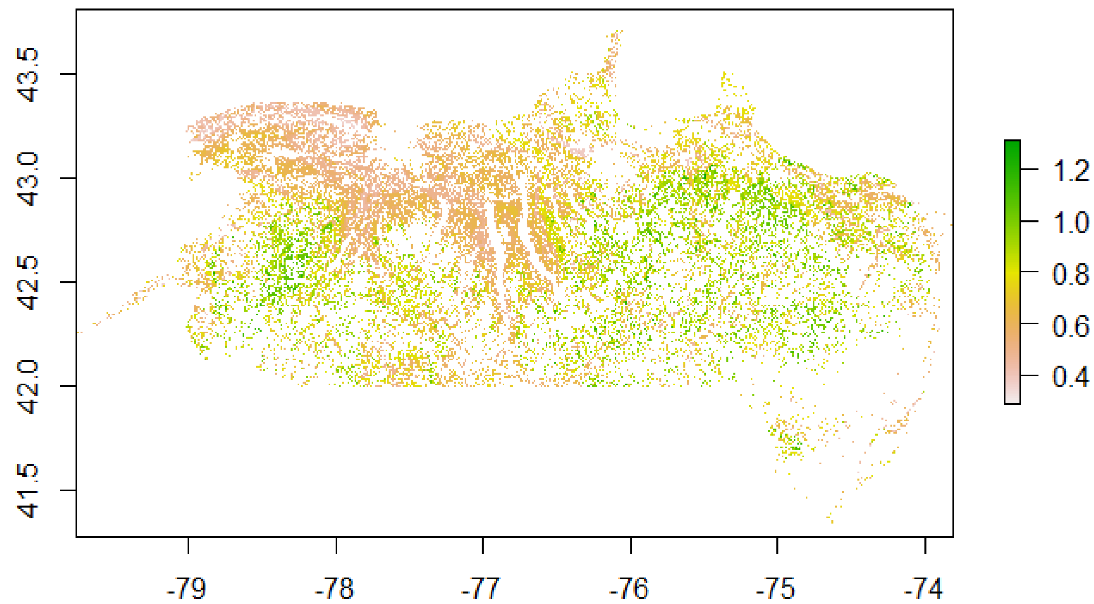
Appendix 5.17: Predicted water aggregate stability, based on the complete model over the small domain.



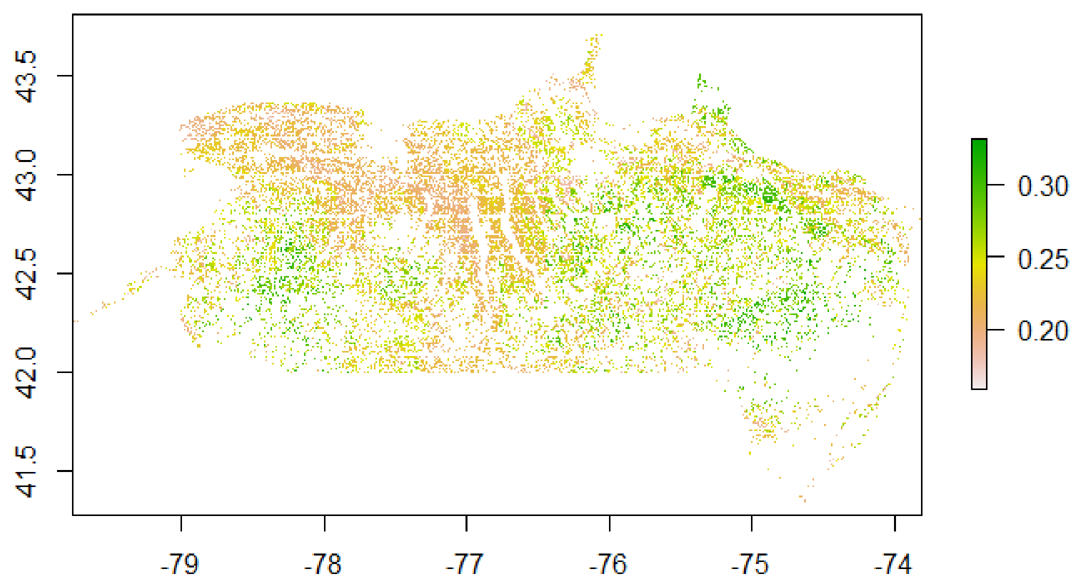
Appendix 5.18: Predicted Permanganate-Oxidizable Carbon, based on the complete model over the small domain.



Appendix 5.19: Predicted ACE Protein, based on the complete model over the small domain.



Appendix 5.20: Predicted Respiration, based on the complete model over the small domain.



Appendix 5.21: Predicted Available water capacity, based on the complete model over the small domain.