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Impact of agricultural soil management on Earthworm biomass and SOC

GEO 511 Master's Thesis

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Abstract

Sustainable agricultural management plays a key role in maintaining soil health and associated ecosystem functions. This thesis investigates how long-term agricultural practices influence two major soil health indicators: earthworm biomass and soil organic carbon (SOC). Data from four Swiss long-term field experiments (LTEs) were harmonized using the open-source R package SoilManageR, which standardized management records into comparable indicators such as carbon inputs, soil cover duration, tillage intensity, nitrogen input, and pesticide use. Linear mixed-effects models that account for random effects between the sites were applied to evaluate the effects of management, soil texture, and climate. Earthworm biomass responded strongly to management, with prolonged soil cover and higher carbon inputs increasing abundance, while intensive tillage reduced it. In contrast, SOC levels were mainly governed by inherent soil properties, especially clay content, while management indicators contributed modestly. An alternative SOC-to-clay ratio model revealed additional, though limited, management effects, with carbon input and tillage intensity as the main management drivers of SOC over clay. These findings demonstrate that biological indicators like earthworm biomass are highly sensitive to management and provide early insights into soil health changes, whereas chemical indicators like SOC respond more slowly. The results highlight the importance of harmonized data and standardized indicators when comparing multi-site long-term experiments and emphasize the potential of sustainable management strategies that maintain soil cover, reduce disturbance, and enhance organic inputs.

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1. Introduction and Background

Soils are at the core of sustainable agriculture, providing essential ecosystem services such as nutrient cycling, water regulation, food security, and carbon storage. Management practices play a major role in sustaining or improving these ecosystem services (Powlson et al., 2011; Power, 2010). Agricultural intensification, including frequent tillage, monocultures, and high external inputs, have contributed to extensive and unsustainable soil degradation, pushing ecosystems toward collapse and threatening the long-term habitability of our planet. (Kopittke et al., 2019). At the same time, there are several studies that highlight the potential of different soil management practices such as continuous soil cover using cover crops, reduced disturbance, and organic matter inputs to support soil health (Tully & McAskill, 2020). Understanding how these management practices shape biological and chemical indicators of soil quality is therefore essential.

A valuable source of information to disentangle these relationships are long-term trials or field experiments (LTEs) (Bai et al., 2018). Agroscope, the Swiss center of excellence for agricultural research, maintains or has maintained several long-term agricultural trials in Switzerland to study gradual changes in soil quality and related functions (Agroscope, 2021b). These trials, running over decades, capture processes that cannot be observed in shorter experiments. By applying different management practices such as crop rotation, fertilization, tillage, and farming systems, these trials allow to assess how agriculture influences soil health and ecosystem interactions. LTEs capture the cumulative impact of agricultural practices across multiple rotations, environmental conditions and different sites. They offer repeated measurements of biological and chemical indicators while documenting detailed management histories.

This thesis aims to investigate the relationship between the management of agricultural fields and soil health. The term soil health however is very broad. Maikhuri and Rao (2012) describe it "as the capacity of soil to function as a vital living system within land use boundaries". Soil health and soil quality are often used interchangeably to describe how well soils perform their above mentioned functions. This thesis will be using two different indicators as a representation of soil health. The first one is the abundance of earthworms, which forms an important biological indicator for soil health. Earthworms are "ecosystem engineers": their burrowing and casting builds macropores, stabilizes aggregates, and speeds up organic-matter breakdown and nutrient cycling processes that improve infiltration, aeration, and root growth (Fründ et al., 2010). Because of this tight link to soil functioning, we can use total earthworm abundance/biomass as a practical measure of overall biological activity.

The second indicator analyzed in this thesis is soil organic carbon (SOC). SOC is a central component of soil quality, functionality and health (Lal, 2016). SOC is tightly connected to aggregation, water holding capacity, and the stabilization of nutrients (Mustafa et al., 2020). Its dynamics, however, are shaped by both inherent soil properties, especially texture, and the management of the soil, which can have a significant impact depending on the soil type (Payen et al., 2021; Johannes et al., 2017). Clay content, in particular, strongly governs SOC levels by providing physical and chemical protection of organic matter. While management practices such as increasing carbon inputs and reducing soil disturbance can promote SOC accumulation, these effects often emerge only over longer timescales (Komatsuzaki & Ohta, 2007).

The present study uses data from four LTEs in Switzerland to investigate the relationships between long-term management practices and the two indicators earthworm biomass and soil organic carbon. LTEs provide valuable insights into the effects of specific management practices, they are often analyzed individually, which limits the generalizability of findings across sites and conditions. In this study, I aim to harmonize the management of each trial, to be able to perform meaningful analytics.

Agricultural management influences earthworms and SOC through a variety of well-known dynamics. These assumptions are used to develop a solid foundation for analyzing and explaining our soil health indicators. Carbon inputs from crop residues and organic amendments directly contribute to the formation and stabilization of soil organic matter, thereby supporting SOC accumulation and providing food resources for earthworms (Kong et al., 2005; Marinissen & De Ruiter, 1993). Another factor contributing to soil health is maintaining continuous soil cover through cover crops and optimized crop rotations. Increased soil cover helps regulate soil moisture and temperature, protects against erosion, and creates favorable habitat conditions for soil fauna (Koudahe et al., 2022). Conversely, high soil disturbance through intensive tillage can negatively affect both earthworm biomass and SOC by disrupting soil structure, accelerating decomposition, and increasing carbon losses (Haddaway et al., 2017). The effect on earthworm abundance can have different magnitudes depending on soil types and species (Chan, 2001). Soil texture, particularly clay content, plays a central role in SOC stabilization and can also buffer the effects of management practices (Komatsuzaki & Ohta, 2007). For earthworm populations, climatic factors such as precipitation and temperature additionally influence activity, survival, and reproduction, which is why environmental variability is accounted for alongside management indicators (Singh et al., 2019).

1.1 Research question

My thesis aims to answer the following research question:

How do long-term agricultural management practices affect the soil health indicators earthworm abundance and SOC content across long-term field experiments located in Switzerland?

Specifically, the analysis aims to identify which management, and environmental factors drive earthworm populations across sites and years and determine how SOC levels are shaped by both soil texture and long-term management. To achieve this, not only is the management data considered, but climate data and soil parameters like texture are being used for analyzing earthworm abundance and SOC. Table 1 summarizes the hypotheses tested in this study together with the corresponding variables used for testing. Random effects are used to account for disparity of data, that cannot be explained through the management or climate indicators, such as different soil types at the sites.

Table 1: Hypotheses and corresponding variables

Hypothesis: Improved soil management increases:	**Response Variable**	**Explanatory Variables**	**Random Effects**
Earthworm abundance and biomass	Earthworm biomass	Tillage intensity, C inputs, Soil cover, Soil texture, Temperature, Precipitation	LTE conditions, sampling date
Soil organic carbon content	Soil organic carbon (C_org/SOC)	C inputs, Soil cover, Tillage intensity, Temperature, Precipitation, Soil texture, Pesticide usage	LTE conditions

1.2 Study Design and Approach

The first step is to have a look at the 4 LTEs. What are the goals of each experiment? What data was gathered and what are characteristics of each site, including soil type and climatic conditions? This data needs to be compiled and transformed into a useful format, which enables developing models that can explain both soil health indicators used in this thesis.

The model used is a linear mixed-effects model that can account for random effects between the different sites. Results will show the models using graphs and tables to investigate model performance and the impact of the given indicators on the response variables. Using the results, I will answer the research question in the context of previous research, highlighting the implications for sustainable soil management and the strengths and limitations of the study. The overall goal of this thesis is to contribute to a better understanding of how sustainable management practices can be evaluated and compared. In doing so, it highlights both the potential and the limitations of using long-term experimental data to inform strategies for improving soil health in temperate agro-ecosystems.

2. Study Sites and Data Sources

The data used in this thesis comes from four different Lont-Term Experiments (LTEs) all conducted under the supervision of Agroscope Switzerland. These LTEs are dedicated to studying long term effects of different practices on agricultural systems. Having datasets that stretch over longer periods is crucial to detect changes in soil health und functionality. Some of the experiments started in the 80s and 90s and have already been finished by now. Others are still running in 2025. They all hold valuable information that has not been fully analyzed under different lenses. To properly use the large amounts of data gathered during all these years, most of it must be transformed into a format that allows it to compare the management of each LTE. Here is an overview of the LTEs that were analyzed during this thesis.

2.1 FAST Site Description

The FAST (Farming System and Tillage) trial, established in 2009 by Agroscope in Rümlang (Canton of Zürich, Switzerland) on a calcaric Cambisol, is a long-term field experiment designed to evaluate the agronomic, ecological, and environmental impacts of different farming systems and tillage practices. As a multi-factorial LTE, FAST systematically investigates how conventional and organic farming systems, in combination with plough-based and reduced tillage, influence a wide range of parameters related to soil health, crop productivity, biodiversity, and ecosystem services (Agroscope, 2021a).

The trial employs a split-plot design with two main factors: farming system (conventional vs. organic), and tillage method (ploughing vs. reduced tillage). Each treatment is further subdivided into plots receiving one of three intercropping treatments: no cover crop (fallow), legume cover crops and non-legume cover crops. The rotation spans six years and includes crops in the following order: winter wheat, maize, legumes, winter wheat and a two-year temporary ley. The design includes four replications per treatment and is implemented across two independently managed blocks (FAST I and FAST II) that are shifted by one year, which allows temporal replicates.

The site is located at 485 m. a.s.l with an annual precipitation of 1050 mm and an average temperature of 9.4 °C. The soil type is a calcaric Cambisol with a sandy loam (23% clay, 34% silt, 43% sand, 1.4% org. C). The trial measured physical (density, texture, pore volume), chemical (carbon, nitrogen, available nutrients, nitrous oxide emissions, nitrogen leaching) and biological (earthworms, mycorrhiza, microbial diversity and biomass) soil parameters at regular intervals but not every year. Yields and properties of the crops are measured annually. The experiment is still running in 2025, providing new data every year (Agroscope, 2021).

2.2 Oberacker Site Description

The **Oberacker LTE**, established in 1994 at Inforama Rütti in Zollikofen (Canton of Bern, Switzerland), is a long-term field experiment designed to compare the long-term agronomic and soil-related effects of conventional versus conservation tillage systems under Swiss arable conditions. Managed collaboratively by Agroscope, HAFL (School of Agricultural, Forest and Food Sciences), and the Bern Cantonal Soil Agency (LANAT), the trial provides large datasets regarding soil management in a Swiss climate (Agroscope, 2024)

The trial compares two main tillage systems, conventional ploughing and no-tillage.
The experiment comprises six main plots, each managed continuously under one of the two tillage systems since its inception. The experiment has a six-year crop rotation: Peas, winter wheat, faba beans, winter barley, sugar beet, and silage maize. This design enables yearly data collection for each crop under both tillage systems. In 2009, the trial was expanded to include a fertilization subplot treatment within each tillage regime, comparing a standard

fertilization practice (GRUD/PRIF), and the alternative Kinsey method, which emphasizes base saturation balancing of soil nutrients.

The experiment measures yields and nutrient contents annually and soil properties, like soil PH, SOC, and biological soil properties every 2 years. The site is located at 555 m a.s.l on an eutric Cambisol with sandy loam (18% clay, 23% silt, 59% sand, 1.7% org. C). Annual precipitation and mean Temperature are 1060 mm and 8.8 °C (Agroscope, 2024).

2.3 Chaiblen Site Description

The Chaiblen Long-Term Field Trial (LTE) was conducted at the Agroscope Tänikon research station near Ettenhausen (Canton Thurgau, Switzerland) from 1989 to 2000. The experiment systematically compared three contrasting crop rotation strategies in arable agriculture: a diversified rotation (vielfältig), a wheat-dominant rotation (weizenbetont), and a maize-dominant rotation (maisbetont). For every crop rotation, two different treatments in the form of an integrated (IP) and an intensive approach have been analyzed.

Diversified	Wheat-dominant	Maize-dominant
Maize, silage	Maize, silage	Maize, silage
Wheat, winter	Wheat, winter	Wheat, winter
Ley, temporary	Barley, winter	Ley, temporary
Ley, temporary	Rapeseed, winter	Maize, silage
Potato, Rapeseed	Wheat, winter	Maize, silage

The site is located at 538 m a.s.l and has an annual Precipitation and temperature of 1189 mm and 8.7 °C. The site is located on a gleyic calcaric cambisol (41% clay, 37% silt, 22% sand, 2.6% org. C). Measurements regarding yields and nutrient content were done annually. Biological soil properties in the form of earthworms were measured every year but only for the last 5 years. Physical and chemical properties were measured twice, in the beginning and at the end of the experimental period.

2.4 Burgrain Site Description

The Burgrain LTE, conducted from 1991 to 2008 near Alberswil (Canton of Lucerne, Switzerland), was a long-term field experiment designed to compare the agronomic, ecological, and environmental performance of three contrasting cropping systems under central Swiss conditions. Managed by Agroscope Reckenholz-Tänikon, the trial aimed to assess the sustainability of organic and integrated farming systems in terms of yield, soil quality, environmental impact, and economic viability (Zihlmann et al., 2010).

The trial compared three main cropping systems: an organic system (Bio), an integrated extensive system (IPe), and an integrated intensive system (IPi). The experiment was laid out in a six-field strip plot design (~4 ha total) with each system applied across replicated strips. The rotation from 1991 to 2002 included potato, maize, winter wheat, summer barley, and temporary leys. From 2003 onward, the crop sequence was adjusted to include winter barley and rapeseed, reflecting regional practice. All treatments used mechanical tillage, with the IPe system adopting reduced tillage from 2003 onward. The extensive system saw less amounts of fertilizers and pesticide usage, but still significantly more than the organic approach. The organic system did without any mineral fertilizers while the others used a combination of mineral and organic in the form of manure and slurry.

The site is located at 580 m a.s.l. on a Cambisol derived from glacial till with loamy texture (approx. 22% clay, 47% silt, 31% sand, 2.0% org. C). Mean annual precipitation and temperature are 1110 mm and 9.4 °C, respectively. The experiment recorded annual crop yields and nutrient contents, while soil physical and biological parameters—such as soil organic carbon (SOC), pH, nutrient levels, compaction, microbial biomass, mycorrhizal colonization, and earthworm populations—were measured at regular intervals. Environmental indicators including nitrate leaching (soil nitrate profiles) and greenhouse gas emissions (N_2O, CO_2, CH_4) were also monitored. Economic performance and eco-efficiency were evaluated through farm-level analyses.

2.5 Overview of LTE Characteristics

Table 2: Overview of the 4 LTEs used in the study

LTE **years**	**Location**	**Soil type** **(%clay/ silt/ sand)**	**Crop rotations and treatments**
Chaiblen **1989-2000**	Tänikon TG 538 m.ü.M 8.7 °C, 1'189 mm	Gleyic,calcaric cambisol (41/37/22)	3 five-year crop rotations, 2 treatments Versatile + integriert/intensiv (Vip, Vis) Cereal focussed + integriert/intensiv (Gip, Gis) Corn focussed + integriert/intensiv (Mip, Mis)
Burgrain **1991-2008**	Alberswil LU 530 m.ü.M 9.0 °C, 1'026 mm	Gleyic cambisol (29/19/52)	2 Six-year crop rotation, 3 treatments Arable focused and forage focused IP intensiv, IP extensiv/notill, organic
Oberacker **1994- today**	Zollikofen BE 555 m.ü.M 9.0 °C, 1'043 mm	Eutric Cambisol sandy loam (18/22/60)	1 Six-year crop rotation (without temporary lay), 2 treatments (tillage, no tillage), 2 fertilizer systems (GRUD/Kinsey)
FAST I + II **(Farming System + Tillage Experiment)** **2009- today**	Rümlang ZH 485 m.ü.M 9.4 °C, 1'059 mm	Calcaric Cambisol sandy loam (22/34/44)	1 Six-year crop rotation (with temporary lay), 4 cropping systems (conventional+(no)tillage and organic+(reduced)tillage) 2 sub treatments (with/without cover crop + norm/half Ninput)

Given that each of the four LTEs described above was designed with a distinct focus, ranging from tillage practices (e.g., FAST and Oberacker) to crop rotation strategies (Chaiblen) and input intensities (Burgrain), it is essential to develop a common data framework for comparative analysis. While these trials share core measurement themes such as yield performance, soil chemistry, and biological indicators, the timing, frequency, and units of measurements vary considerably. Additionally, management practices differ not only between LTEs but also within treatments of the same LTE (e.g., organic vs. integrated, plough vs. no-till), making direct comparison challenging without systematic data transformation.

To address this, all available management information, such as tillage type, fertilization levels, cover cropping, and crop sequence was compiled and standardized into a single, unified format. This harmonized management datasheet ensures that key factors are consistently defined across LTEs, allowing for structured filtering and stratification during analysis. Simultaneously, all measured variables (e.g., SOC, N_min, crop yield, microbial biomass) were consolidated into a single dataset with common variable names, units, and metadata descriptors. This integrated dataset forms the basis for subsequent statistical and multivariate analyses and enables more robust interpretation of long-term trends and cross-experimental interactions. My part in this compiling of data was to clean up and properly transform the management data of the LTE Burgrain while other members from Agroscope focused on the other 3 LTEs.

3. Methods

3.1 SoilManageR Framework

Understanding the effects of agricultural management on soil health requires consistent, comparable metrics across different sites and time periods. However, management practices vary widely, not only between countries but also within regions such as Switzerland, where differences in management practices make comparisons challenging. Even classifications like “organic” or “no-till” include a great deal of variability in how practices are implemented (Heller et al., 2025). SoilManageR addresses this challenge by providing a standardized framework to record and process detailed management data and derive numerical indicators that capture key aspects of soil management. Developed as an open-source R package, it offers a pre-defined data structure and templates for documenting management activities such as tillage, fertilization, sowing, and crop harvesting. Based on these inputs, the package calculates comparable indicators, including carbon inputs, soil tillage intensity (STIR), soil cover duration, nitrogen inputs, and pesticide use. They can be calculated for a specified period, normally per year or crop. Here is how each indicator is calculated.

3.1.1 Carbon Input

The carbon (C) input indicator in the SoilManageR R package quantifies the amount of organic carbon added to the soil per hectare and year (Mg C ha^{-1} $year^{-1}$). It integrates carbon contributions from three primary sources:

- Main crops and crop residues
- Cover crops
- Organic amendments (e.g., manure, slurry, compost)

Here's a breakdown of how each component is calculated, including the formulas used in the package as described in Heller et al. (2025).

The first source of C input is computed using allometric relationships from Bolinder et al. (2007, 2015):

$$C_{total} = C_{main} + C_{residue} + C_{root} + C_{exudates}$$

Where the components start from the left, the carbon in the harvested crop biomass, in above-ground residue (e.g., straw), in the roots and from the plant exudates. Each parameter is calculated using the dry matter yield and different, crop specific parameters derived from various literature (Bolinder et al., 2007/2015; Keel et al., 2017; Wüst-Galley et al., 2020). SoilManageR has a set of standardized dry yield matter for crops and leys in a central European climate. Even if no measurements are available as data input, the package can calculate numerical indicators. This is especially useful if in a dataset, some values are missing, and the user wants a continuous set of indicators per year.

The second source of carbon comes from cover crops. It uses a similar calculation as the main crop, but instead of the actual yield, which is rarely measured in agricultural systems, it uses the time the cover crop is growing (Seitz et al., 2022). There is a minimum and maximum amount of carbon derived from cover crops ranging from a growing period of less than 280 days to more than 240 days. The specific numbers proposed by Seitz et al., (2022) are 1253 kg C/ha as minimum and 1916 kg C/ha for the maximum, with a linear interpolation between the two values.

The last input of carbon comes from organic amendments like manure, compost or slurry.

$$C_{Amendments} = Amount \times DMC \times CC$$

The amount of amendment is multiplied by the dry matter content of it times the carbon content of the dry matter. While SoilManageR provides some default values derived from the Swiss fertilizer recommendations (Sinaj et al., 2017), the calculation increases in accuracy if the user delivers the measured values of the parameters if available.

3.1.2 Tillage Intensity

SoilManageR uses the soil tillage intensity rating STIR developed by the RUSLE2 framework (USDA-NRCS 2023). The calculation of the STIR value uses the speed, area of disturbance, depth, and type of tilling machine as factors. The latter uses different values for the type of disturbance happening to the soil. Some examples would include a factor of 1 for heavy duty tilling (inversion), 0.7 for mixing operations, and 0.15 for compressions using rollers (Heller et al., 2025).

3.1.3 Soil Cover Duration

The soil cover duration indicator in SoilManageR quantifies the number of days per year that the soil is covered by either living plants or plant residues, helping to assess erosion risk and soil protection. Soil cover by different plants is estimated using crop-specific growth curves based on sowing dates and development stages (Mosimann & Rüttimann, 2006), while residue cover is calculated using the decay function of Steiner et al. (2000), which considers mass loss over time and burial from tillage. A minimum threshold of 30% cover is used to count a day as "covered," following Büchi et al. (2016). The model integrates both plant growth dynamics and residue decomposition to provide an annual total of soil cover days (Heller et al., 2025). The package does not account for natural revegetation of bare soils which is hard to capture correctly.

3.1.4 Nitrogen Input

The nitrogen input (kg N/ha) accounts for both the organic and mineral fertilizer applications. While mineral fertilizers have specified amounts of N, the N content of organic amendments is calculated in similar fashion to the carbon contents, by either using standardized values for the different types of organic amendments or using exact, measured values. The nitrogen input into an agricultural system is crucial as it greatly affects yields, soil health and environmental impacts.

3.1.5 Pesticide Usage

The last indicator is the use of pesticides. It is newly developed without much finesse. It calculates the number of times a pesticide (fungicide, herbicide or insecticide) is applied on the field. Even though the indicator lacks the dosage and types of pesticides used, it still provides a meaningful estimate of chemical input intensity. Frequency of application reflects not only the type of management but also indirectly captures system dependency on chemical pest control. This makes it a useful comparative metric for assessing system intensity across farming strategies (e.g., conventional vs. organic, intensive vs. extensive) and for identifying patterns associated with potential environmental risks.

3.2 Management Indicators

Having the proper framework, we can now look at both the distribution and the structure of our data. Evaluating the management data in detail, including examining the correlation structure among indicators, is essential for several reasons. Agricultural long-term experiments often record highly interrelated management practices — for example, tillage intensity will have a significant impact of soil cover. Without explicitly assessing these relationships, models may suffer from multicollinearity, leading to biased or unstable estimates of effects. Using SoilManageR to structure and explore the management data ensures that these relationships are made transparent prior to modeling. Understanding these associations helps identifying redundant or highly collinear variables that might need to be combined, removed, or carefully interpreted in the final models. Exploring the data supports the selection of an appropriate modeling strategy. As a first step, we will be looking at the number of data points as well as typical values.

3.2.1 Burgrain Indicators

For the Burgrain, we have a total of 234 entries with a unique set of identifiers, being year (1996-2008), block (1-7), and treatment (IPi, IPe, Bio). Burgrain shows a notably high maximum nitrogen input of 703 kg N ha^{-1} yr^{-1}, which is consistent with the intensive integrated (IPi) treatment that combined manure and mineral fertilizers in high doses. In contrast, the median nitrogen input of only 131 kg ha^{-1} yr^{-1} demonstrates that the other treatments, especially the organic system, operated at much lower nitrogen levels. Similarly, Burgrain's carbon inputs show a broad range from 814 to over 10,000 kg C ha^{-1} yr^{-1}, reflecting a mixture of high-residue, manure-rich phases in some treatments, and more modest organic inputs in others. However, since Carbon inputs are highly dependent on the harvested crops, the difference can be accounted to crop rotations. Certain years will have more than one harvest event increasing the Carbon inputs per year a lot. Soil cover days remain consistently high across treatments, with a median of 314 days, suggesting all systems maintained good ground cover regardless of input intensity. This is mainly due to good crop rotation with leys as cover crops in between longer periods. The STIR values range widely from 0 to 300, reflecting that while the organic system often used shallower or less frequent tillage, the integrated intensive system relied on conventional ploughing. Again, the high variance can be contributed to crops. A temporary ley that stands for 2 years will have years with no Tillage events while a year with Maize during summer and grain during the winter will have very high STIR values. Pesticide applications have a maximum of 11 but a median of zero, confirming that most treatments, especially organic, applied pesticides rarely, with only the most intensive systems showing high application frequencies.

Table 3: Indicator values for Burgrain

Burgrain	C_input	N_input	Soil_cover_days	STIR	Pesticide
Min Value	814	0	159	0	0
Max Value	10759	703	366	300	11
Mean	4080	166	300	78	1.6
Median	3450	131	314	64	0

3.2.2 Chaiblen Indicators

Chaiblens data consists of 288 entries with the identifiers year (1989-2000), block (1-4), crop rotation (diversified, wheat dominant, maize dominant), and treatment (intensive, integrated). Chaiblens nitrogen input maximum of 314 kg ha^{-1} yr^{-1} can be attributed to its intensive wheat- or maize-dominant rotations, while the median of 139 kg ha^{-1} yr^{-1} shows that many treatments, particularly diversified systems, and the temporary leys operated at lower nitrogen levels. Carbon inputs vary considerably, from a minimum of 877 to a maximum exceeding 6,000 kg C ha^{-1} yr^{-1}, which again is mainly due to different crop rotations and treatments, with intensive fields having increased yields and subsequently higher C inputs. Soil cover is lower on average (median 248 days) compared to Burgrain, which fits a cereal- and maize-dominant focus with more frequent bare-soil periods. Chaiblens STIR median of 98 suggests moderate to high tillage across many plots, particularly the maize rotations. The pesticide indicator median of 2, with a maximum of 8, suggests that no fully organic trial has been carried out which leads to a higher median number of pesticide uses.

Table 4: Indicator values for Chaiblen

Chaiblen	C_input	N_input	Soil_cover_days	STIR	Pesticide
Min Value	877	0	107	0	0
Max Value	6052	314	366	220	8
Mean	2649	155	238	99	2.0
Median	2320	139	248	98	2

3.2.3 FAST Indicators

FAST is by far the largest dataset. It has 1672 entries with the identifiers year (2009-2023), block (A-D), tillage (conventional vs no-till/ reduced tillage), farming system (conventional vs. organic), and intercropping treatments (fallow, legume cover crops, non-legume cover crops). FAST shows a relatively low mean nitrogen input (96 $kg\,ha^{-1}\,yr^{-1}$) and a maximum of 232, because half the plots receive limited fertilizers because of the organic farming system. The nitrogen inputs are lower compared to the other LTE's, which can be attributed to a change in standard amounts of nitrogen fertilizer usage in the last decades, showing a trend of reducing the amounts of Nitrogen added to arable lands (Harder & Liebisch, 2025) Its carbon input ranges widely (468–8899 $kg\,ha^{-1}\,yr^{-1}$), capturing high-residue legume or cover-crop years in organic treatments, as well as mineral-fertilized conventional rotations. Median soil cover of 272 days is neither very high nor low, mainly because the conventional ploughing and no-till treatment groups are split evenly. The biggest differences compared to the other LTE's can be seen in the STIR value. A median of 23 and maximum of 232 strongly reflect the contrast between reduced tillage and ploughing treatments. The low pesticide application median of zero (and maximum 7) highlights that organic plots did not use pesticides at all, while conventional plots applied them only as needed.

Table 5: Indicator values for FAST

FAST	C_input	N_input	Soil_cover_days	STIR	Pesticide
Min Value	468	0	102	0	0
Max Value	8899	232	366	232	7
Mean	2989	96	261	48	1.0
Median	2250	111	272	23	0

3.2.4 Oberacker Indicators

Oberacker is the second largest dataset with 672 entries with the identifiers being years (1995-2022), block (1-6), tillage system (no-till vs conventional) and fertilization practice (GRUD vs Kinsey). Oberacker shows a relatively low mean nitrogen input (76 $kg\,ha^{-1}\,yr^{-1}$) but with values reaching up to 254 $kg\,ha^{-1}\,yr^{-1}$ in conventional treatments, showing that fertilizer was more modest overall than in other LTEs but still varied by treatment. Carbon input is high (median 4025 $kg\,ha^{-1}\,yr^{-1}$) because of consistent crop residue retention and possible cover-crop inputs, especially in the no-tillage systems. Soil cover days are very high (median 332 days), highlighting the trial's emphasis on no-till systems. The STIR median of 31, ranging up to 322, demonstrates a strong difference between the no-tillage and conventional plough treatments, as expected. Pesticide use shows a median of 3 and a high maximum of 17. No-till systems usually have to rely on herbicide usage to control weeds. The experiment didn't include an organic treatment that would have lowered pesticide use as well.

Table 6: Indicator values for Oberacker

Oberacker	C_input	N_input	Soil_cover_days	STIR	Pesticide
Min Value	863	0	148	0	0
Max Value	9106	254	366	322	17
Mean	4202	76	318	57	3.6
Median	4025	77	332	31	3

3.3 Measured Variables

In comparison to the management data and its corresponding indicators, which are continuous for the whole period, the response variables are measured a lot less frequently. Figure 1 shows how often measurements were taken in each LTE. Because each site had a different scientific focus, the measurements not only differed in topic, but in frequency as well. Earthworm measurements were done on a regular basis in all the sites, which is part of the reasoning on focusing on earthworms as a main topic of this thesis, besides their relevance as a biological indicator for soil health. It is important to mention that usually, not every plot in an LTE was analyzed for every measurement incident. Earthworm populations is a variable that changes rather fast and therefore more recent management events should have a higher impact on EW biomass. I therefore decided to implement a new calculation for each indicator, where more recent events have a higher importance. I implemented a half-life time for every indicator, meaning that for a HL time of 365 days will consider events from a year ago only half. Because this HL time of one year is only a speculation, I calculated each indicator for HL times of 180, 365 and 730 days. The indicators were calculated for the date at which each EW measurement was taken. In the end, 318 different EW measurements were used together with their corresponding management indicators.

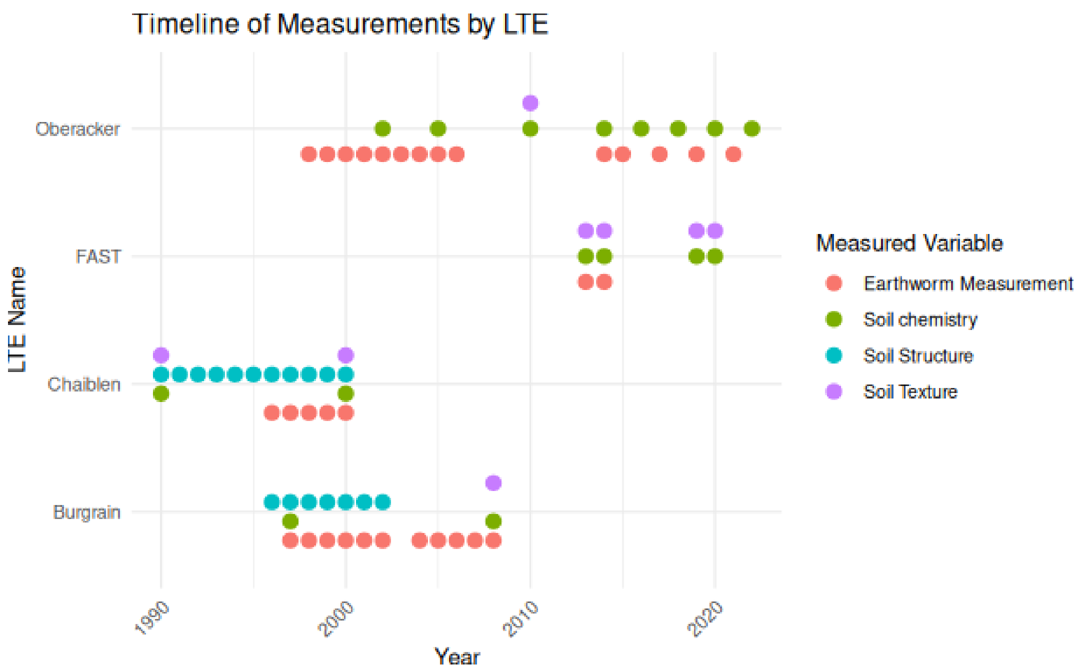

Figure 1: Frequency of measurements taken in each LTE

Soil chemistry and texture were not the focus during data collection, as reflected in the number of measurements taken, but both were fortunately measured at least once per LTE site. For soil texture, the limited number of measurements meant that I calculated averages per plot to provide a representative value, assuming no major changes during the years. Soil chemistry includes several variables, but SOC was the only one consistently measured across all LTEs. It was always measured for every plot and treatment.

3.3.1 Earthworm Data Distribution

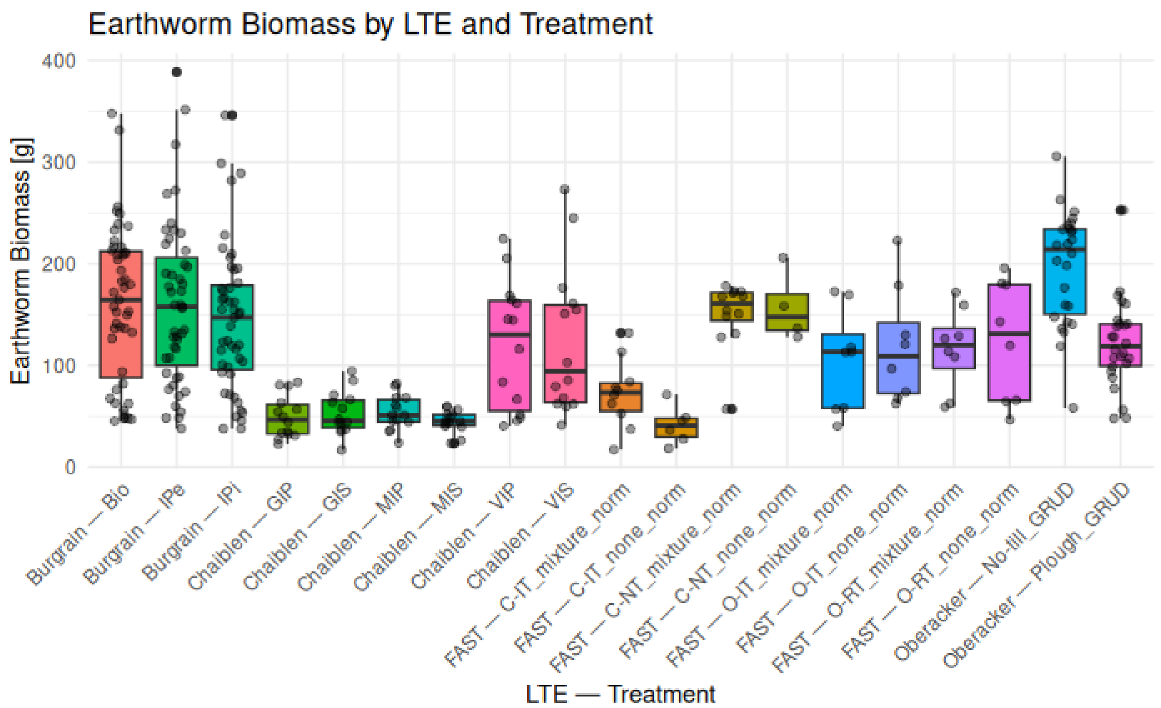

Figure 2: Earthworm biomass sorted by site and treatment

Earthworm biomass varied strongly both between LTE sites and among treatments within sites (figure 2). At some sites, such as Burgrain, median biomass levels exceeded 200 g per sampling unit in the Bio and IPe treatments. FAST showed a wider range of intermediate values, with clear differences between crop rotation and tillage combinations, while Oberacker exhibited some of the highest biomasses, particularly under the No-till treatment, which reached well above 250 g in some samples. In contrast, certain treatments at the same site showed substantially lower values, highlighting strong treatment effects even within a single LTE. One example would be several Chaiblen treatments (e.g., GIP, GIS, MIP), were recorded medians are closer to 50 g. It should be noted that not all EW measurements were taken during the same seasons. While most measurements were taken during fall after harvesting, Chaiblen measured them during spring. This leads to a naturally lower biomass. This seasonality must be considered when modelling the EW biomass, to accurately reflect impact of treatments. Across all sites, variability within treatments was considerable, with some outliers indicating unusually high or low earthworm biomass for given conditions. This heterogeneity reflects both inherent environmental differences between LTEs such as soil type and climate and management-induced variation within sites such as tillage intensity and input levels.

3.3.2 SOC Data Distribution

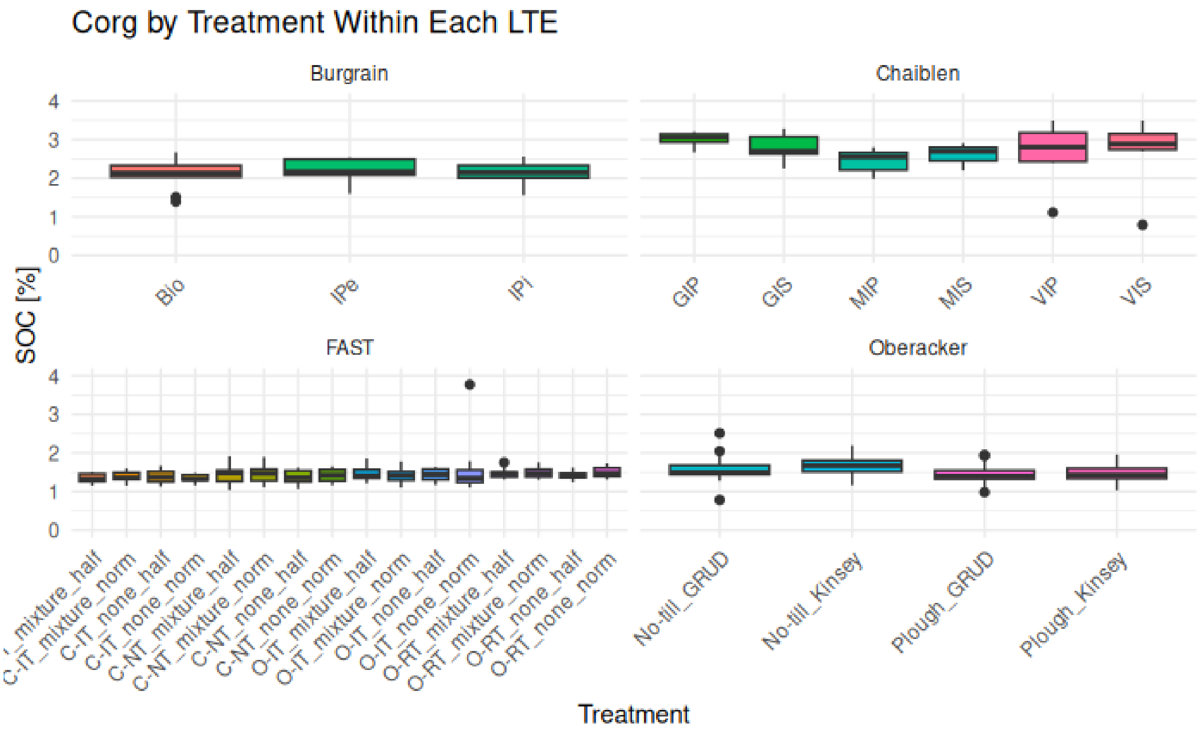

Figure 3: SOC values in percent per site and treatment

SOC content showed distinct differences between LTE sites and small differences among treatments within sites (figure 3). At Burgrain, SOC values were relatively high and consistent, with medians around 2% across the Bio, IPe, and IPi treatments, and only minor variation between treatments. Chaiblen displayed the biggest range of SOC, with medians spanning from about 2.5% to above 3% depending on the treatment, indicating treatment-specific differences in organic carbon levels. FAST had the lowest SOC values overall, with medians close to 1% across all treatments and very limited between-treatment variation. In Oberacker, SOC levels were intermediate, with medians near 2% for both No-till and Plough treatments, and only small differences between the GRUD and Kinsey management variants. Within most treatments, variability was moderate, but still visible enough to be explained through different management. Figure 3 shows three very clear outliers in FAST and Chaiblen. Given the rest of the measurements were very consistent, I assumed the outliers to be measurement errors and did not include them in the final analysis.

3.3.3 Climate Data

The next set of data needed to perform analysis is climate data. Climate data for the analysis is obtained by combining gridded meteorological datasets with the geographic coordinates of the LTE sites. Daily meteorological variables, air temperature, precipitation, and relative sunshine duration, were taken from MeteoSwiss gridded data (Meteoswiss, 2025). It should be noted that the dataset is an unofficial product and contains occasional gaps, which were interpolated. The data should therefore be interpreted with caution. Daily records were assigned to calendar years and seasons (winter, spring, summer, fall), and meteorological data merged to produce a complete daily dataset per LTE. From this, annual and seasonal climate summaries are calculated, including mean temperature and total precipitation. This is a tradeoff, because in a perfect world, I would have the aggregated data preceding a measurement event (e.g EW measurement) or even daily data. However, working with such huge datasets is not feasible for this type of work. Consequently, I calculated data per year, but also per season to get some seasonal variability still. These aggregated datasets provided climate indicators for subsequent modelling.

3.3.4 Covariance of Indicators

Another important factor to consider when deciding on how to analyze our data is the covariance between indicators. Before looking at actual data, we already expect that certain indicators, like soil cover and STIR are dependent while others like STIR and N_input should be independent of each other. The question is by what degree and how the covariance can be explained and ultimately if it is suitable to use all the indicators when explaining our response variables. First, we will look at correlations between all our data to get a better understanding of each indicator, before looking directly at data used in explaining EW and SOC and look for differences.

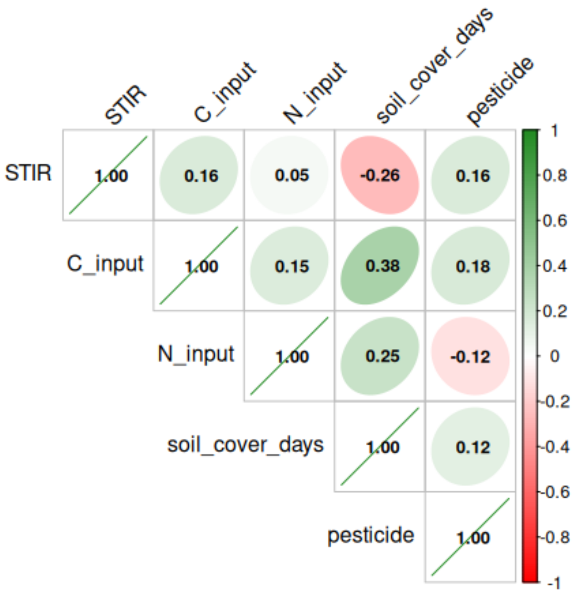

Figure 4: Correlation matrix of entire dataset

The first notable correlation is between soil cover and STIR, as expected being a negative correlation. The effect however is not very drastic, because heavy duty tilling before a sowing event does not decrease soil cover very much and may even promote faster sprouting and earlier growth. Soil cover shows significant positive correlations with both N and C input. Higher fertilization rates indicate better growth and a higher soil cover. On the other hand, cover cropping not only increases soil cover drastically, but it also increases C inputs. We can also see that pesticide usage has no strong correlations, indicating the indicator to be somewhat independent of the others.

3.3.5 Earthworm Indicators

Now we will have a look at the indicators used to explain the Earthworms present in agricultural soil. The main thing to look out for is whether certain indicators have a very high correlation and should therefore not both be used to try and explain the earthworm biomass. We can see the biggest correlation between C input and soil cover of 0.48. This is not problematic when developing a model to estimate the EW biomass.

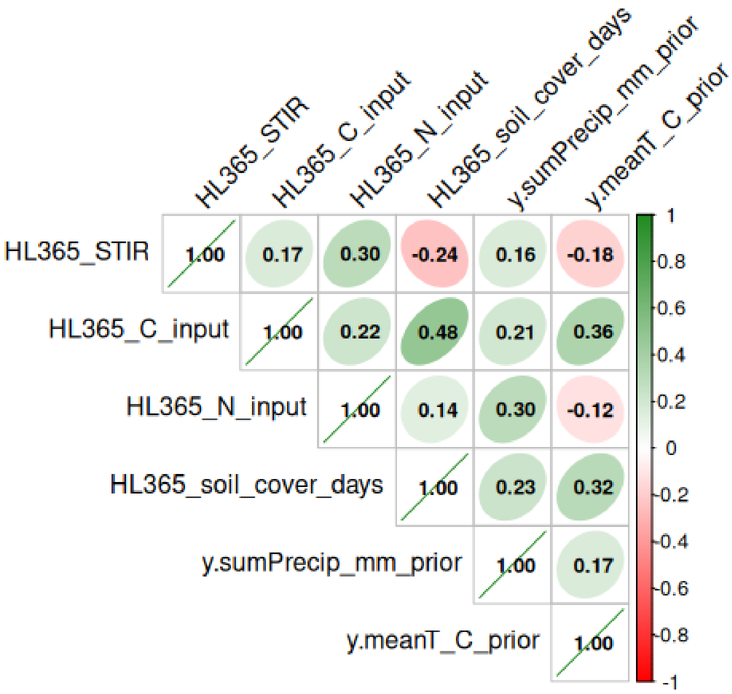

Figure 5: Correlation matrix of indicators that are relevant for the earthworm analysis

3.3.6 SOC Indicators

The correlations between the indicators used for explaining SOC levels are shown in the following matrix. We can see that we have higher correlations than before, especially between soil cover and carbon input. This is likely due to cover crops that have a large impact on both variables. The value of 0.64 could be concerning regarding modelling, but it is not critically high. When modeling, we must consider this correlation and check whether it opposes struggles in the end.

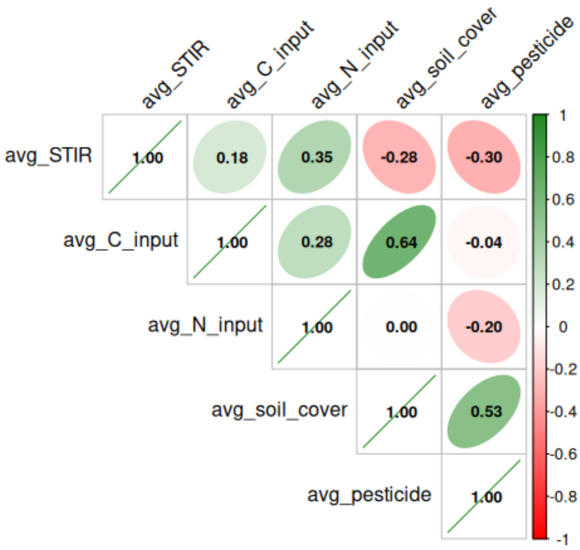

Figure 6: Correlation matrix of indicators used to analyze SOC

3.4 Model Selection

Having prepared the management and climate indicators and assessed their relationships for potential collinearity, the next step is to determine the most suitable statistical framework for analyzing the data. The structure of the dataset is hierarchical and unbalanced, with repeated measurements taken within plots, plots nested within blocks, and blocks within LTE sites. In addition, the sampling frequency of the response variables is substantially lower than that of the management indicators, which are available continuously over the entire experimental period. The question is to use a linear model or something else. Since the goal of this thesis is not only to predict our response variables, but to understand the influence of each predictor, linear models offer an improved interpretability. Given the limited sample size, especially with the SOC measurement, more complex models run the risk overfitting. This combination of nested design, unbalanced sampling, and smaller sample size makes linear mixed-effects models (LMMs) particularly appropriate.

The main advantage of using a linear mixed-effects model in this study is that it fits both the structure of the data and the goals of the analysis. In a linear model, each coefficient tells us how much the response variable changes, on average, when a predictor changes by one unit, while keeping the other predictors constant. This makes the results easy to interpret and to communicate, which is important in this thesis where the focus is on explaining relationships rather than only predicting outcomes.

Mixed-effects models are especially useful here because the data are hierarchical: repeated measurements are taken within plots, plots are grouped in blocks, and blocks are part of different LTE sites. This means that measurements from the same plot or site are more similar to each other than to those from other plots or sites. The model handles this by adding random effects, which allow each group (e.g. each site or plot) to have its own baseline level. This is where partial pooling comes in. Plots or sites with few measurements "borrow strength" from those with more data, so their estimates are more stable than if they were modelled completely separately, but still distinct enough to reflect their own data (Bolker, 2015).

Another big benefit is that mixed-effects models can use all the data, even if the number of observations is not the same for every plot or year, which is the case here. Many other approaches would either require perfectly balanced datasets or drop incomplete cases, leading to a loss of valuable information. Linear models also make it easier to check whether the model assumptions are met, such as whether the relationships are roughly straight-line (linear) and whether the residuals are normally distributed. While other modelling approaches, like more flexible non-linear models or machine learning methods might capture complex patterns, they often require much larger datasets, make it harder to interpret the role of each variable, and do not naturally handle the kind of grouped, unevenly sampled data used here. In short, a linear mixed-effects model is a good match because it can deal with the data structure, make full use of the available information, and produce clear, interpretable results that are directly linked to the scientific questions.

Choosing the right random effects is very important when developing the model. A random effect that is obvious and should always be present is the site. Different types of soil characteristics or past management history could largely influence both earthworms and SOC. Depending on the site, there will be similar differences between blocks and even different plots, for example if a block is located on a slope. To account for this, the models will include random effects for LTE site, block (nested within site), and plot (nested within block and site). This structure allows each set of random effects to have its own baseline response while still estimating the overall effects of the explanatory variables. In R, the contribution of random effects can be evaluated by inspecting the variance components or by comparing marginal and conditional R^2 values. This helps to assess the influence of the random effects on the response variable and to decide whether the chosen random structure is appropriate or can be simplified.

3.4.1 Backwards Selection

To arrive at a concise and interpretable model, I will use a backwards (step-down) selection procedure for the fixed effects. This begins with a full model containing all candidate predictors justified by our hypothesis, ensuring that potentially important variables are not excluded prematurely. Predictors are then removed sequentially, starting with the least contributive, and the fit of the reduced model is compared to the previous one using the Akaike Information Criterion (AIC). The process continues until no further removal leads to an improvement in AIC, resulting in a final model that retains only those variables with the strongest support from the data (Zhang, 2016). This approach has the advantage of starting from a comprehensive model and reducing it systematically, thereby providing a clear, reproducible selection pathway. Compared with automated systems, this approach helps discuss why certain explanatory variables fail to predict the response variable. It also allows for targeted refinement of the temporal weighting of retained management indicators using half-life (HL) tuning, which can be done after the main variable selection without introducing an unmanageable number of model combinations. Nevertheless, backwards selection is not without drawbacks: the final model may depend on the starting set of variables and the sequence of removals, and repeated testing can inflate Type I error rates. Furthermore, small changes in AIC may not be practically meaningful, so model simplification will be guided by both statistical and ecological considerations. By using linear mixed-effects models together with a clear, step-by-step backwards selection process, the analysis aims to remain relevant and easy to interpret, while still being complex enough to capture the key relationships between long-term management, climate conditions, and the biological and soil chemical indicators in this study.

3.4.2 Earthworm Model

For the Earthworm model, I log-transformed earthworm biomass before fitting linear models because biomass values are strictly positive and, in our data, were right-skewed with variability increasing as the mean increased. Taking logs compresses large values, stabilizes the variance, and makes the residuals closer to normal (Changyong, 2014). It also reflects the ecology of the system, where many drivers act multiplicatively (e.g., moisture × organic matter), so a log scale linearizes these relationships. The initial model uses all the explanatory variables defined in the hypothesis (i.e soil cover, C_input, STIR, clay, Precip, Temp). Using backwards selection, the goal is to achieve a model that can explain earthworm biomass with significant predictors.

The random-effects structure in the earthworm biomass model was chosen to reflect both the spatial and temporal dependencies in the data. This means that all plots measured in the same site during the same year share a common baseline, reflecting environmental influences such as local weather conditions, background soil status, and other site-specific factors in that year. Although climate variables such as annual precipitation and mean temperature are included as fixed effects in the model, it is still important to account for site–year as a random effect. The measured climate indicators capture broad, continuous drivers, but they cannot fully describe all the conditions that differ between years at a given site, like short-term weather extremes, soil moisture dynamics, or site-specific events that are not captured in the averaged climate variables. Treating site–year as a random effect therefore controls for these unmeasured sources of variation that affect all plots within the same site in a given year. This prevents the unexplained year-to-year differences from inflating the residual error or biasing the estimated effects of the fixed predictors. In other words, the fixed climate variables model the general influence of temperature and precipitation, while the random site–year effect absorbs the remaining annual fluctuations that are specific to each site but not explicitly measured. It is important to note that the model tries to explain the biomass first by using the explanatory variables and afterwards accounts for random effects. Using this random effects structure ensures that the model does not think each year at a given site behaves the same.

The second random effect used specifies a random intercept for blocks nested within LTE treatments. This accounts for systematic differences between blocks, such as subtle variations in topography, soil texture, or drainage, that could influence earthworm biomass independently of the measured management indicators. Together, these random effects account for similarities between measurements taken in the same site and year, as well as within the same treatment blocks. This avoids treating dependent observations as independent and makes the fixed effect estimates more reliable.

3.4.3 SOC Model

For the SOC model, I decided to use the last measurement taken in each plot and describe it with the management indicators leading to the point of measurement. Because SOC is a slowly changing soil property, it primarily reflects the cumulative impact of management practices over many years. The continuous management indicators available for the entire period capture long-term patterns in the management, making them well suited for explaining variation in SOC. For the model, the yearly averages for every indicator were used as explanatory variables.

Taking the most recent SOC measurement as a response variable ensures comparability across sites. Earlier measurements could be influenced by historic management or prior land use, which might not be relevant to the long-term management regimes applied during the LTEs. The most recent measurements, by contrast, represent the accumulated influence of experimental treatments and are less affected by these initial conditions. The only problem is the different running times for each LTE, ranging from 11 to 28 years. These differences should in theory be explained through the random effects of the model. Since the time corresponds to the LTE itself, using LTE as a random effect is sufficient to explain the variance. From a practical perspective, using a single, latest measurement avoids over-representing sites with more frequent sampling and simplifies the statistical analysis, while still retaining the essential long-term signal needed for modelling.

While climate factors can contribute to SOC, our approach will result in only 4 distinct values for both Precipitation and temperature, each corresponding to an LTE. Because the LTEs are all located in relatively similar climatic regions, these values are very close to one another and are therefore unlikely to explain much of the variation in SOC. Furthermore, any site-level climatic differences will already be accounted for through the random effect of LTE in the model.

4. Results

4.1 Earthworm Model Results

The modelling began with a full specification including soil cover days, C input, STIR, soil texture (clay), seasonal precipitation, and mean seasonal temperature, with random intercepts for site–year and treatment–block combinations. Stepwise removal of predictors showed that both temperature and clay content contributed little to explaining earthworm biomass. Annual precipitation also had only a weak effect and was dropped ($p \approx 0.20$). This selection was based on the p-levels of each predictor, by always removing the predictor with the worst significance level. The AIC of the model only increased slightly when removing each predictor, but more importantly it did not worsen the model. C input was found to be only marginally significant ($p \approx 0.055$) and its exclusion did not improve model fit. Based on this and an ecological reasoning of being a food source for soil organisms, it was retained in the final model. This model now includes STIR, soil cover and C input.

Next, I checked if changing the half-life time for every predictor used in the compiled model would result in an improved model accuracy. Soil cover with a 365-day half-life performed best, while both shorter (180 days) and longer (730 days) half-life worsened the fit. The same applied when changing the half-life time of STIR. For C input, HL180 and HL365 produced similar results with a slight edge towards HL365. HL730 led to a clear decline in model performance. The final model therefore included soil cover (HL365), C input (HL365), and STIR (HL365) as fixed effects, alongside the random effects of site–year and treatment–block.

Table 7: Residuals of earthworm model

Residual Distribution	Value
Minimum	–2.96
1st Quantile (Q1)	–0.54
Median	0.06
3rd Quantile (Q3)	0.58
Maximum	2.14

Table 8: Statistics for the fixed effects of the EW model

Fixed effect	Estimate	Std. Error	df	t value	p-value
Intercept	1.456	0.123	222	11.85	< 0.001
Soil cover days (HL365)	0.00144	0.00023	279	6.17	< 0.001
C input (HL365)	0.000016	0.000008	252	1.93	0.055
STIR (HL365)	–0.00085	0.00021	305	–3.97	< 0.001

Table 9: Statistics for the random effects of the EW model

Group (random intercept)	Variance	Std. Dev.
Block within treatment	0.0108	0.104
Site–year	0.0289	0.170
Residual	0.0156	0.125

Table 10: R^2 values for EW model

Metric	Value
Marginal R^2 (fixed)	0.24
Conditional R^2 (full)	0.79

Table 11: Unique contribution of each predictor to the final EW model

Predictor	Unique contribution	Average shared	Individual	% of total
HL365 soil cover days	0.1173	0.0556	0.1729	72.4 %
HL365 C input	0.0313	–0.0149	0.0164	6.9 %
HL365 STIR	–0.0024	0.0518	0.0494	20.7 %

The final mixed-effects model provided a good fit to the data, with a low AIC (–229.8) and residual variance smaller than the variance explained by site–year and block effects. The full model has an R^2 value of 0.79. Only using the fixed effects would result in a value much lower of 0.24. Soil cover shows a strong positive effect, STIR a strong negative effect, and C input a marginal positive trend. Soil cover is the strongest contributor to the model accounting for 72.4 percent. Having a look at the correlation of the fixed effects, the highest is between STIR and soil cover (0.539). The inclusion of site–year and block random intercepts effectively reduced unexplained variance and ensuring that fixed-effect estimates were not biased. Residual diagnostics indicated no major deviations from model assumptions, supporting the relevance of the model. Figure 7 shows how well the model predicts the biomass compared to the observed values. As a comparison, figure 8 shows the same predicted values but without the correction for the random effects which clearly worsens the fit.

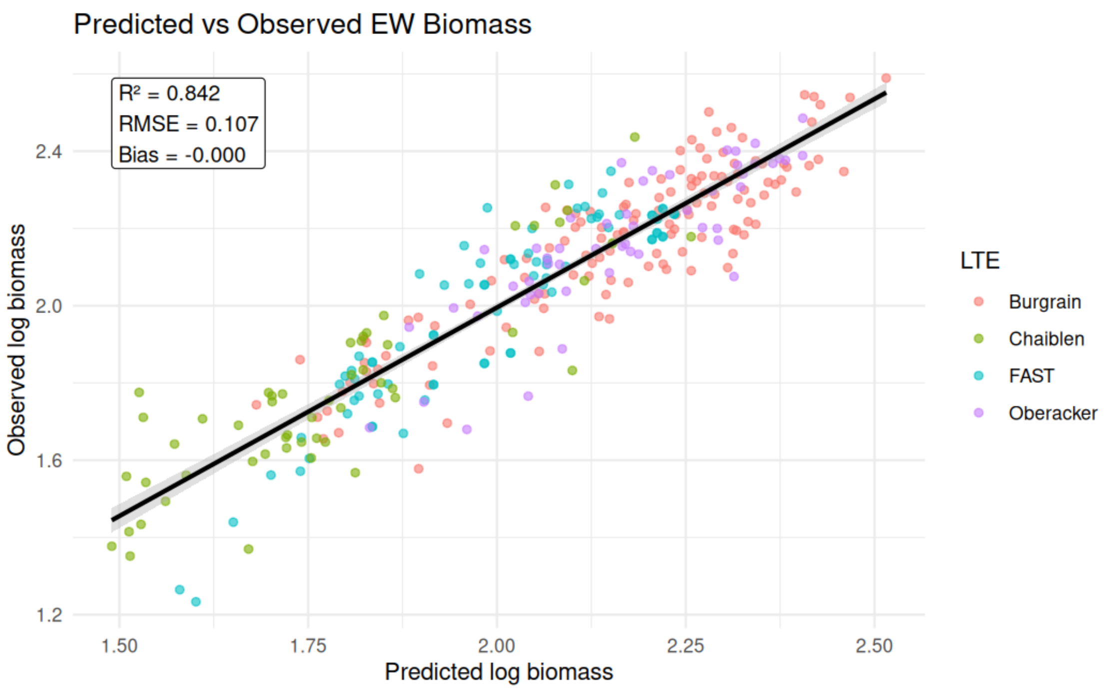

Figure 7: Comparison between model predictions and actual values

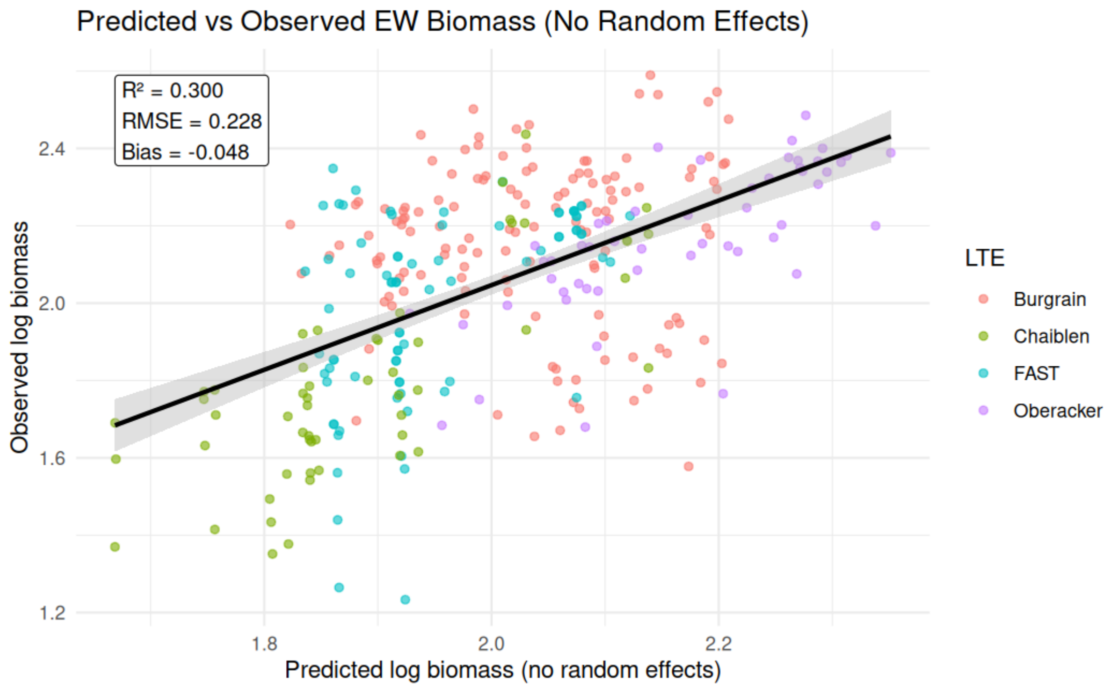

Figure 8: Comparison between predicted and observed EW values, without the correction for random effects

The effect plots illustrate the partial relationships between each explanatory variable included in the final model and earthworm biomass. Each figure shows the fitted regression line (blue) with a 95% confidence band (shaded area). The yellow dots represent the predicted values plus the residuals (i.e., the observed values corrected for the other variables in the model. This visualization isolates the effect of each predictor on earthworm biomass while holding other predictors constant.

These plots are included to provide a visual representation of how the model translates the explanatory variables into estimated changes in earthworm biomass. This visual representation helps interpret the results and see if outliers occur, like it is the case with high STIR and both high and low C input values. These values should be interpreted with caution, as neither the x-axis nor the y-axis represents directly comparable real-world quantities. The EW biomass is log-transformed, and the predictors are changed through the implementation of half-life times.

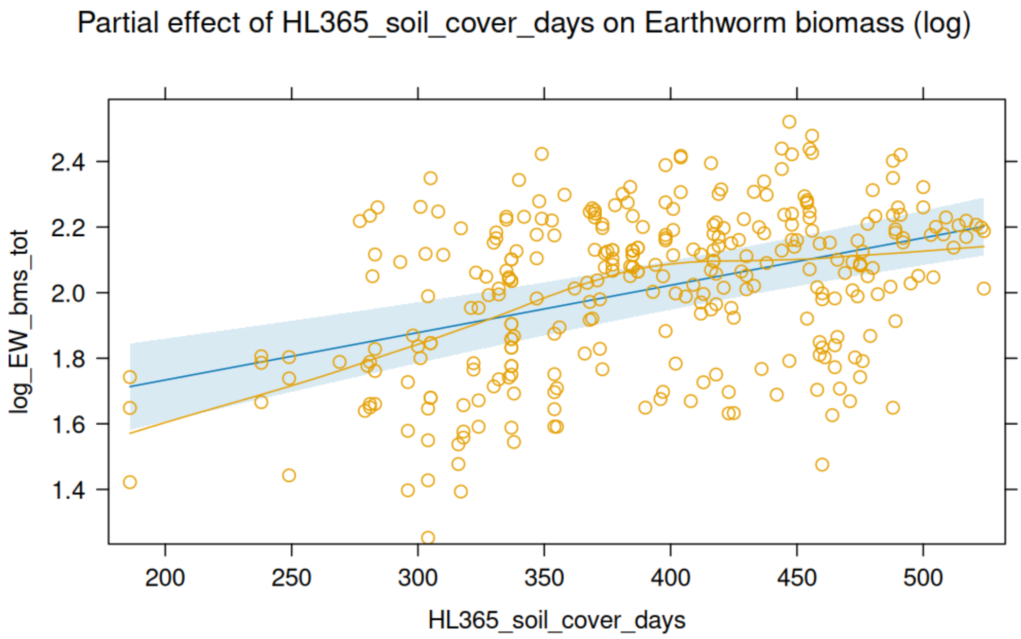

Figure 9: Partial effects of soil cover in EW model

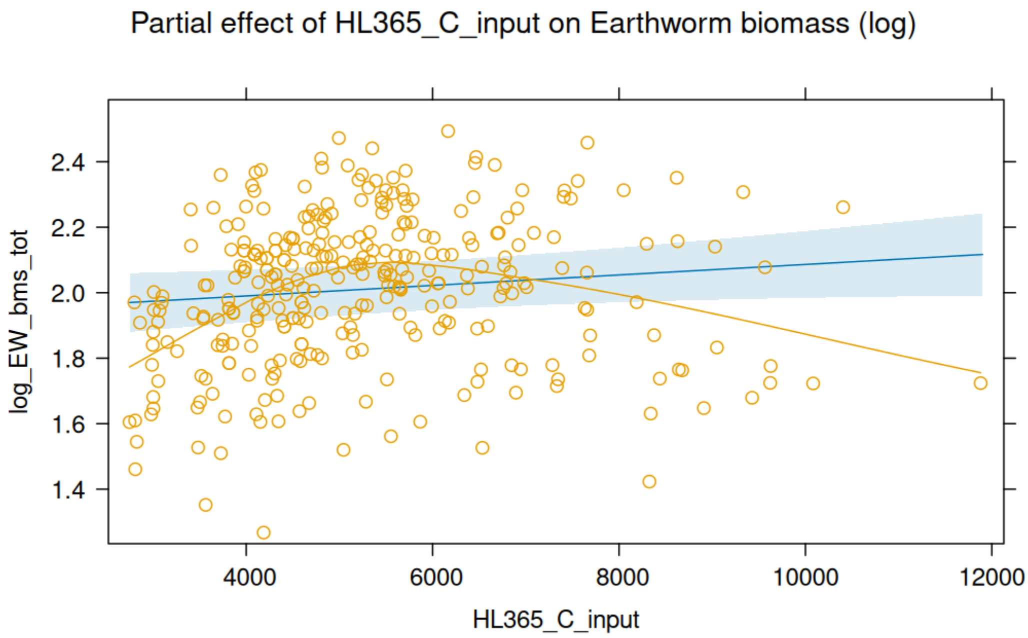

Figure 10: Partial effects of carbon input in EW model

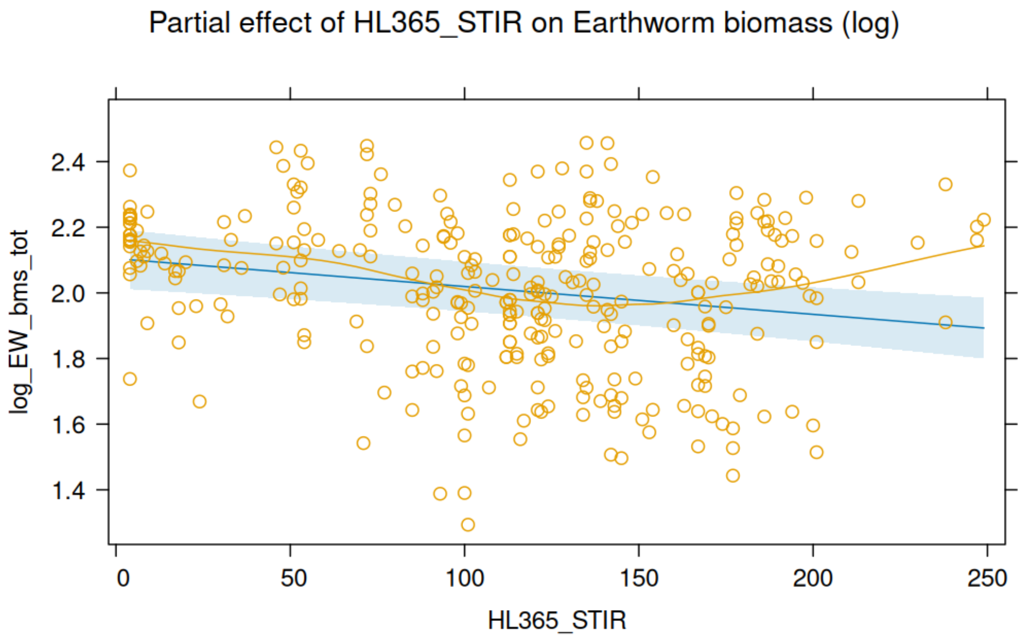

Figure 11: Partial effect of tillage intensity in EW model

4.2 SOC Model Results

The initial model for SOC included the management indicators STIR, carbon input, soil cover, nitrogen input, and pesticide use, alongside soil texture (clay content) as a fixed effect, and LTE as a random effect to account for site-level variation. As explained in the model selection, climate factors were not included in this approach. During backwards model selection, nitrogen input was removed first due to its non-significant effect, followed by soil cover, which showed no explanatory power for SOC ($p > 0.6$). STIR was then dropped as the next weakest predictor, leaving a final model that retained carbon input, clay content, and pesticide use as fixed effects. The inclusion of LTE as a random effect ensured that differences between sites, including variance in temperature and precipitation, were accounted for, rather than being absorbed by the fixed predictors. The final model had the following attributes shown in tables 12 to 16.

Table 12: Statistics of each predictor for the SOC model

Predictor	**Estimate**	**Std. Error**	**df**	**t value**	**p-value**
Intercept	–0.117	0.180	29.7	–0.65	0.520
Avg. C input	0.000173	0.000032	50.7	5.46	1.5e–06
Clay	0.0472	0.00383	30.4	12.33	2.3e–13
Avg. pesticide	0.0670	0.0165	67.0	4.05	1.3e–04

Table 13: Unique contribution for fixed effects of SOC model

Predictor	**Unique contribution**	**Average shared**	**Individual**	**% of total**
Avg. C input	0.2313	–0.1418	0.0895	14.6 %
Clay	0.6017	–0.1431	0.4586	74.9 %
Avg. pesticide	0.1868	–0.1226	0.0642	10.5 %

Table 14: Statistics of random effect of SOC model

Group	**Effect**	**Variance**	**Std. Dev.**
LTE : Block	Intercept	0.01895	0.138
Residual	—	0.05143	0.227

Table 15: Residual distribution of SOC model

Statistic	Value
Minimum	–5.29
Q1	–0.52
Median	–0.03
Q3	0.53
Maximum	2.95

Table 16: R^2 values for the SOC model

Metric	Value
Marginal R^2 (fixed)	0.61
Conditional R^2 (full)	0.72

The final model for soil organic carbon (SOC) retained carbon input, clay content, and pesticide use as fixed effects, with LTE and block structure included as random effects. Residuals were approximately centered around zero, with most values between –0.5 and 0.5, though a few larger deviations were observed (table 15). The random structure indicated modest variability at the block-within-LTE level, while residual variation remained the largest source of unexplained variance (table 14). Figures 12 to 14 show the partial effects on SOC of each predictor.

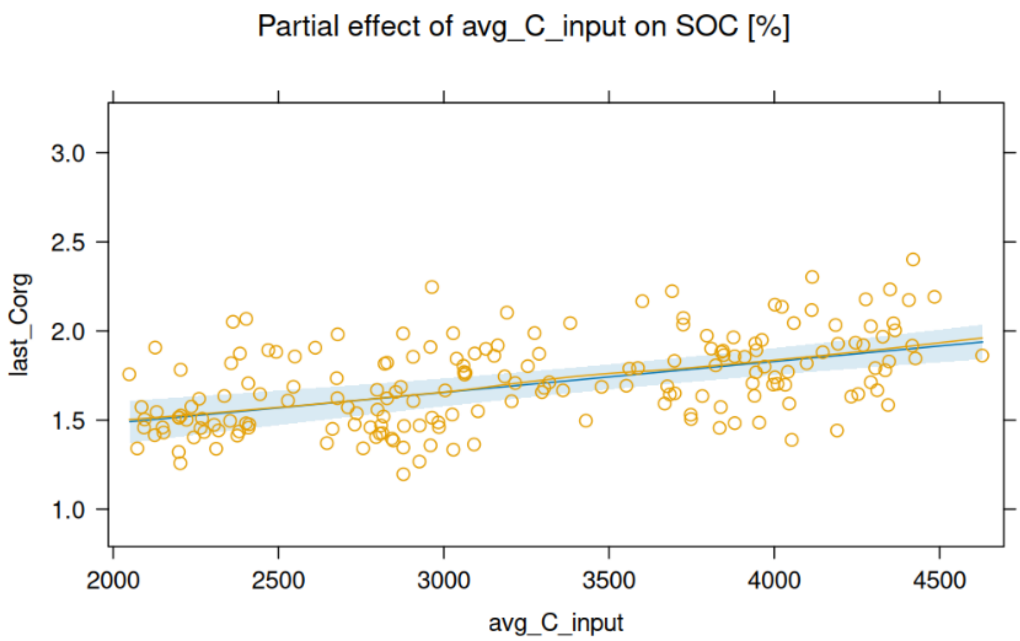

Figure 12: Partial effect of carbon input on SOC

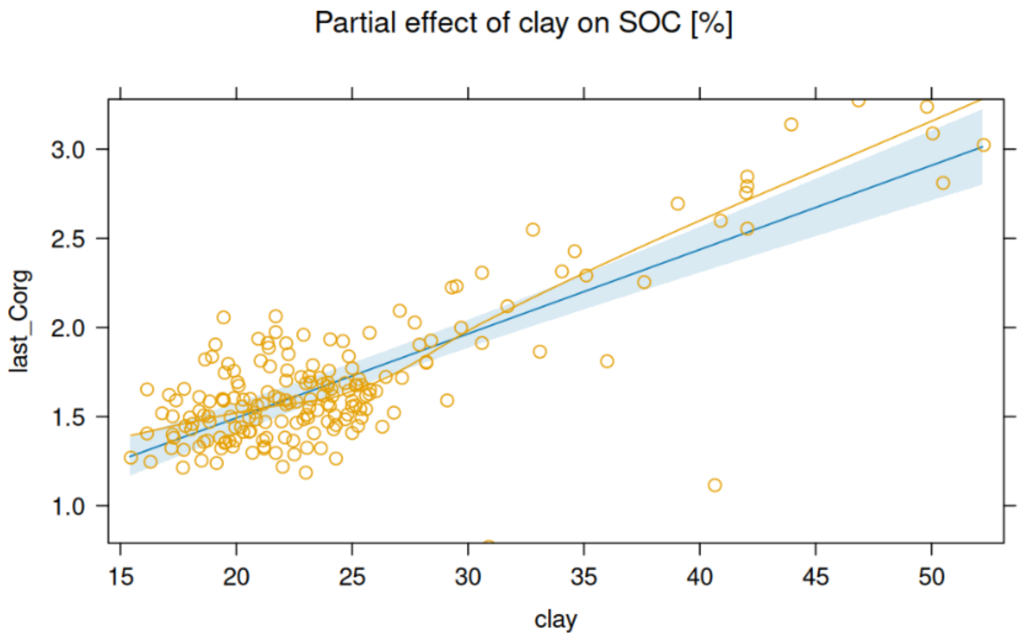

Figure 13: Partial effect of clay on SOC

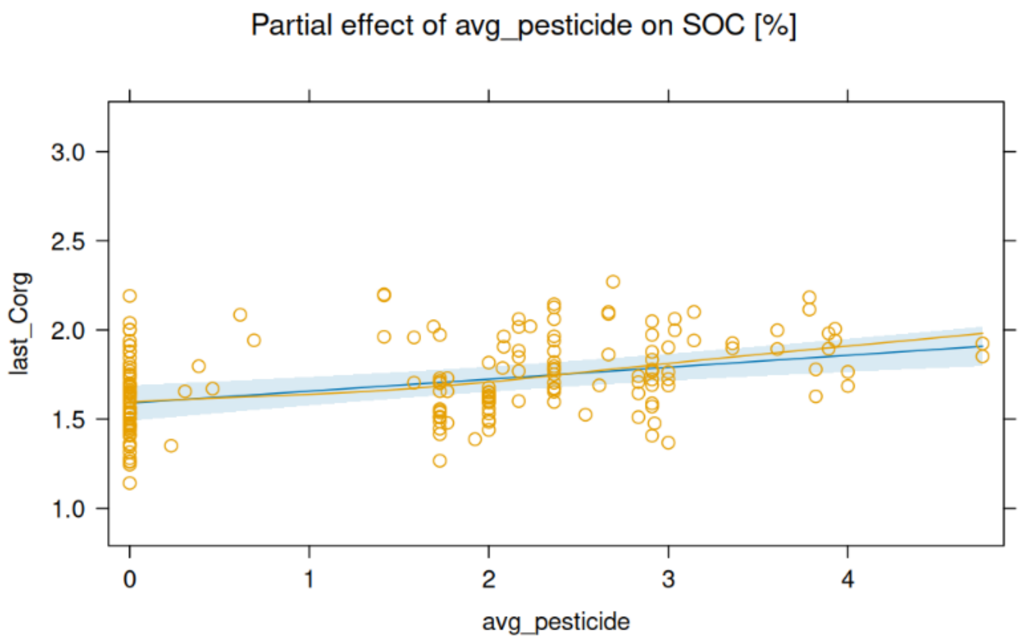

Figure 14: Partial effect of pesticied use on SOC

Among the fixed effects, clay emerged as the dominant predictor of SOC, showing a highly significant positive relationship and explaining the majority of the final model (table 13). Carbon input also showed a positive effect, with a smaller but still meaningful contribution, while pesticide use had a moderate positive association. Taken together, these predictors explained 61% of the variance in SOC through fixed effects alone, and 72% when including the random structure (table 16). Hierarchical partitioning confirmed the dominance of clay (≈75% of explained variance), with additional contributions from carbon input (≈15%) and pesticide use (≈10%). Because clay is such a dominant predictor of SOC, I tried a different approach to capture more of the indicator effect. The approach was to use SOC/clay as a dependent variable.

4.3 SOC to Clay Ratio Model

With the new approach, we are left with soil cover, STIR, pesticide, N input, and C input. Backwards selection removed pesticide (p=0.70), soil cover (p=0.79), and N input (p=0.57) as explanatory indicators in that order. The final model therefore explains SOC/clay with STIR and C input. Quantiles are distributed evenly around 0 as seen in table 20. The model shows clear negative correlations between STIR and SOC/clay and significant positive correlation between C input. The model shows no problematic correlation between the two predictors, and both have similar unique contribution to the fixed effects with STIR having a slight edge (56.1% vs 43.9%). The random effect of LTE explained a substantial share of the variance, while the fixed effects together accounted for a modest proportion (marginal $R^2 \approx 0.06$; conditional $R^2 \approx 0.65$; table 21).

Table 17: Statistics of each predictor in the SOC/ clay model

Predictor	Estimate	Std. Error	df	t value	p-value
Intercept	0.0643	0.00743	10.7	8.65	3.7e–06
Avg. STIR	–9.5e–05	2.35e–05	183.7	–4.04	7.9e–05
Avg. C input	4.39e–06	1.47e–06	184.3	2.99	0.00318

Table 18: Unique contribution of each predictor in the SOC/clay model

Predictor	Unique contribution	Average shared	Individual	% of total
Avg. STIR	0.0518	–0.0161	0.0357	56.1 %
Avg. C input	0.0439	–0.0160	0.0279	43.9 %

Table 19: Random effects of the SOC/clay model

Group	Effect	Variance	Std. Dev.
LTE	Intercept	0.000158	0.0126
Residual	—	0.000095	0.00975

Table 20: Residuals of the SOC/clay model

Statistic	Value
Minimum	–3.96
Q1	–0.53
Median	–0.12
Q3	0.57
Maximum	3.47

Table 21: R^2 values of the SOC/clay model

Metric	Value
Marginal R^2 (fixed)	0.064
Conditional R^2 (full)	0.648

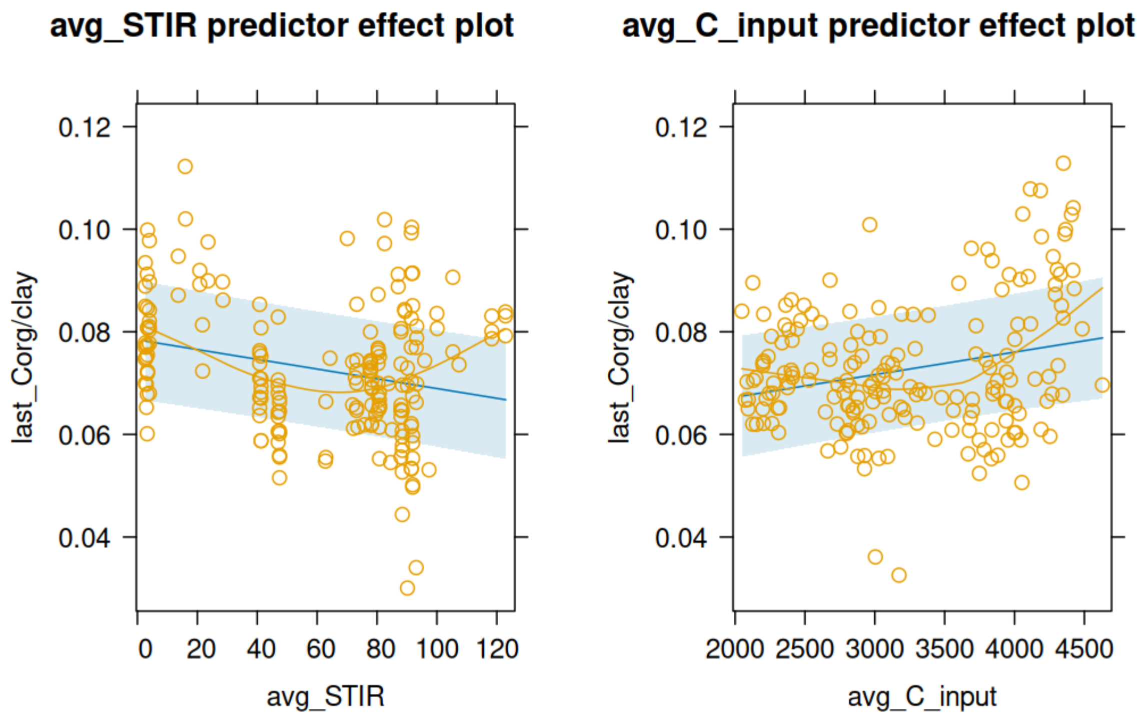

Figure 15: Partial effects of the two predictors STIR and C input of the SOC/clay model

Table 22 shows a summary for all the predictors of each model, how much they contribute and to what extent they explain the variables, as seen by the R^2 values.

Table 22: Summary of all the models and their predictors

Model	**Significant Predictors**	**Estimate**	**Unique Contribution (%)**	**R^2 Marginal**	**R^2 Conditional**
Earthworm Biomass	Soil cover (HL365)	+0.00144	72.4%	0.24	0.79
	C input (HL365)	+0.000016	6.9%		
	STIR (HL365)	–0.00085	20.7%		
SOC	Clay	+0.0472	74.9%	0.61	0.72
	C input	+0.000173	14.6%		
	Pesticide	+0.0670	10.5%		
SOC/clay	STIR	–9.5e–05	56.1%	0.064	0.65
	C input	+4.39e–06	43.9%		

5. Discussion

This study investigated how long-term agricultural management practices influence two key soil health indicators earthworm biomass and SOC, using data from four Swiss long-term field experiments (LTEs). SoilManageR allowed the data to be harmonized across all sites which resulted in consistent comparison of the management. The results demonstrate that management practices significantly affect earthworm biomass. Higher carbon inputs from crop residues and organic amendments, as well as prolonged soil cover, were associated with increased earthworm abundance, whereas greater soil disturbance had a strong negative effect. Climatic variables, such as precipitation and temperature, contributed little to explaining variability. For SOC, the analysis revealed that soil texture, particularly clay content, was the strongest predictor of variation across sites. However, management still had an impact on carbon content. Using SOC over clay as response variable isolated the effects of management, which were only marginal. This discussion will explain why certain parameters had to be excluded from the final model and what the main drivers of EW and SOC are.

5.1 Earthworm Predictors

The results show that soil cover has the strongest impact of earthworm abundance. Earthworms are sensitive to soil moisture and temperature (Johnstone et al., 2024). Continuous soil cover can help reduce evaporation and buffer temperature extremes by shading the soil. Earthworms thrive under a stabile habitat (Chauhan, 2014). Having more continuous soil cover greatly contributes to this habitat stability. Uncoincidentally, the second strongest predictor, STIR, greatly relates to this stability. Soil disturbance can physically harm individuals and destroy egg cocoons and expose individuals to predators like birds (Crittenden et al., 2014). Apart from this direct impact, indirect mechanisms like disrupting burrows, altering pore connectivity, and exposing organic matter to rapid decomposition decrease earthworm abundance on a longer timeframe. Carbon inputs is the last predictor used in my model. While less significant, it still showed that providing a food source in different forms, either through plant material, exudates or other organic compounds positively influenced earthworm biomass.

While these indicators are all correlated, like STIR and soil cover or carbon inputs and soil cover through higher cover crop residues, the correlation between them is not statistically problematic. They all have a unique contribution explained above. However, some predictors that were expected to influence earthworms did not have a significant effect. Even though earthworms are sensitive to changes in temperatures and soil moisture (Johnstone et al., 2014), both the temperature and the precipitation indicators were dropped during model selection. Averaging both variables over a period of three months drastically excludes weather extremes, such as dry periods, heavy rainfall or high temperatures. Using the random effect structure of year within LTE captured site-specific and temporal differences in weather conditions better than using the climate variables. Defining the climate variables in a way that can account for these extreme weather situations is challenging. One approach would be to count the number of days with temperature or precipitation extremes defined by a 90^{th} percentile for the norm of the given day/month. With precipitation, this does not fully capture soil moisture as previous days should be considered. Therefore, a metric for soil moisture must be included. Frost is another factor not respected in the data, especially frost and thaw cycles can influence earthworms significantly (Patricio Silva et al., 2014). Conclusively, there would be ways to implement climate data differently, but each with its challenges. Regarding the scope of the thesis and the emphasis on management, the approach chosen can be justified.

Soil texture did not contribute to the final model, likely because it is too simple to fully describe habitat conditions preferred by the earthworms. Random effects did a much better job in capturing these complex differences compared to soil texture. Keeping the half-life time at 365 days gave the best model, which could be a consequence of the backwards model selection which already started with the indicators HL365. Given the high p-values of the indicators that failed to be included and the high correlation between the same indicators of different half-life times, the results likely stayed the same.

5.2 SOC Predictors

The model for SOC revealed that soil texture, particularly clay content, was the strongest predictor of SOC levels across the four LTEs. This finding is consistent with well-established mechanisms showing that clay-rich soils provide both physical protection of organic matter within aggregates and chemical stabilization through interactions with mineral surfaces (Cai et al., 2016; Six et al., 2002; Johannes et al., 2017). Sites with higher clay content therefore have an inherently greater potential to accumulate and retain SOC, which explains why a substantial portion of the variability in SOC across LTEs could be attributed to clay content.

Nevertheless, management practices still contributed to SOC variation, albeit to a lesser degree than for earthworm biomass. Higher carbon inputs from crop residues and organic amendments were associated with increased SOC stocks, which aligns with previous findings showing that organic inputs are a key driver of SOC build-up (Lal, 2016; Powlson et al., 2011). In contrast, pesticide usage showed a negative effect on SOC levels in the final model. There is increasing evidence that repeated pesticide applications can indirectly affect SOC by altering microbial activity and decomposition dynamics (Sim et al., 2022). These effects may accumulate over time, particularly in LTEs with continuous pesticide exposure. However, more plausible is the explanation that pesticide usage is a good indicator for the type of agricultural management system. Conventional systems often use more mineral fertilizers compared to manuring and they do heavier tillage. These mechanisms are known to influence SOC stocks to a significant degree (Sheoran et al., 2019) and pesticide usage summarizes these practices to a certain degree.

The management indicators soil cover and soil disturbance were excluded from the final model during backward selection, suggesting that their direct effects on SOC are less significant, or that they are better summarized through the other indicators (e.g pesticide usage). This seems surprising, given that a high tillage intensity is normally associated with a decrease in SOC (Haddaway et al., 2017). Another reason could be that measurable shifts in SOC stocks emerge only after decades of consistent management and our timeframe of a dozen years was still too short (Johnston et al., 2009). Unfortunately, we don’t know the history before the experimental setups started and whether SOC levels are settled in or still undergoing bigger changes.

5.3 SOC to Clay Ratio Model

SOC is highly correlated to the soil texture, in particular clay. This is seen in literature (Johannes et al., 2017) and based on the previous model. Using SOC/clay as a response variable gave a better insight into the management’s effects. While this alternative approach increased the relative importance of carbon inputs and STIR, the total explained variance decreased considerably compared to the original model ($R^2m \approx 0.06$ vs. $R^2m \approx 0.61$). SOC/clay Is a different indicator of soil health than just organic carbon. It gives more information about the structure of soils (Rabot et al.,2024). A good soil structure requires a SOC:clay ratio of > 0.1 and less than 0.075 is considered a bad soil structure (Johannes et al., 2017). Looking at the results and in particular figure 15, the median of the modelled data ranges from 0.8 to 0.7, decreasing with higher STIR and increasing with larger C inputs. These relations make sense ecologically, but they do not capture the full picture, hence the low explained variance for the fixed effects. There are still a lot of variables which are not accounted for in my model such as microbial activity, chemical properties like pH and mineral composition and soil types in general. Furthermore, SOC/clay as an indicator inherently integrates measurement uncertainty from both SOC and clay values. Together, these factors create variability in SOC/clay that is not explained by the fixed effects of management alone, highlighting the complexity of SOC dynamics even under well-controlled experimental conditions.

5.4 Evaluation of SoilManageR

A key strength of this study lies in the use of the SoilManageR R package, which enabled the harmonization of the detailed management histories across the four LTEs into standardized indicators. This approach allowed us to combine data from sites with different management systems, machinery used, compositions of organic fertilizers, rotations, and measurement frequencies into a consistent framework, making cross-site comparisons possible. Without this harmonization, the multi-site analysis conducted here would not have been feasible. The way each indicator is set up works great for sites located in a Swiss or central European climate.

However, the use of SoilManageR also introduces some limitations that should be considered when interpreting the results. First, the package derives management indicators from available records, which may vary in detail and accuracy between LTEs, leading to potential inconsistencies in calculated variables. Second, SoilManageR simplifies highly complex management systems into aggregated metrics such as total carbon input or cumulative soil disturbance, which inevitably reduces information about timing, interactions, and short-term effects. For example, differences in the quality of organic inputs (e.g., compost vs. slurry vs. crop residues) or the seasonality of soil cover are not taken into consideration. Finally, SoilManageR depends on consistent assumptions when converting management data into numerical indicators, and while this improves comparability across sites, it reduces nuanced dynamics thar are specific to site or management practices.
Overall, SoilManageR provides a powerful tool for integrating and analyzing management data across long-term experiments, but the step from complex practices to simple management indicators provides a source of uncertainty.

6. Conclusion

This thesis investigated how long-term agricultural management practices influence two key indicators of soil health: earthworm biomass and SOC, using data from four Swiss long-term field experiments. By harmonizing detailed management histories through the SoilManageR R package, this study integrated data from sites with contrasting soils and farming systems into a single analytical framework. Linear mixed-effects models were then applied to analyze the effects of management, inherent soil properties, and environmental conditions on earthworms and SOC.

Earthworm biomass was shown to be strongly influenced by management indicators. Increased carbon inputs and extended soil cover promoted larger earthworm populations, while higher soil disturbance had a negative effect. These findings highlight the importance of management strategies that maintain soil quality by providing good conditions for soil macrofauna. In contrast, SOC levels were dominated by inherent soil properties, particularly clay content, which explained a large portion of the variation across LTEs. Carbon inputs positively affected SOC accumulation and pesticide use had a negative impact which is explained through the correlation between organic farming systems and lower pesticide usage. The alternative SOC/clay model showed a more ecologically meaningful result, with carbon inputs (positively correlated) and STIR (negatively correlated) as relevant indicators. However, these fixed effects only explained roughly 6% in the final model. This highlights the complexity of carbon stabilization processes and the role of unmeasured biological and chemical drivers not considered in the model.

Taken together, these results demonstrate that biological indicators such as earthworm biomass are highly responsive to management and provide early insights into the effects of farming practices, whereas chemical indicators like SOC are less susceptible to management and need longer timeframes and further information to show effects. This highlights the value of combining biological and chemical perspectives when assessing soil health. The findings also illustrate the potential and limitations of integrating multi-site datasets using harmonized management indicators. While SoilManageR enabled a comprehensive cross-site analysis, uncertainties remain due to simplifications of complex practices, historical legacies, and incomplete measurements. Future studies should integrate additional biological and chemical indicators, account for extreme climatic events, and expand analyses to more diverse sites and management systems.

Overall, this thesis demonstrates that long-term management strategies emphasizing continuous soil cover, reduced disturbance, and sufficient organic inputs can simultaneously enhance soil biological activity and promote sustainable carbon storage, thereby contributing to improved soil health and resilience.

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Personal Written Decleration

I hereby declare that the submitted thesis is the result of my own, independent work. All external sources are explicitly acknowledged in the thesis. Portions of the text and assistance in phrasing were supported by OpenAI's ChatGPT, a language model, but all interpretations, conclusions, and final edits are my own.

27.08.2025 Zurich

Signature *Date & Place*