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José Mário Lobo Ferreira

**Avaliação da Sustentabilidade em Agroecossistemas na Escala de
Estabelecimento Rural com Foco na Qualidade do Solo**

**A Sustainability Assessment Tool for Agroecosystems at the Farm
Scale with a Focus on Soil Quality**

Orientador: Paulo Emílio Lovato

Coorientador: Marcos Alberto Lana

Florianópolis

2026

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A Sustainability Assessment Tool for Agroecosystems at the Farm Scale with a Focus on Soil
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Para Michelle, Alice e Clara

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RESUMO

A avaliação do desempenho ambiental, social e econômico na escala do imóvel rural pode apoiar a gestão de riscos e a transição para sistemas de produção mais sustentáveis, em consonância com os princípios da agricultura conservacionista. São apresentadas a ferramenta Indicadores de Sustentabilidade em Agroecossistemas (ISA) e sua aplicação em 3.296 imóveis rurais em diversas regiões do Brasil. O comportamento dos indicadores foi analisado com o objetivo de identificar aqueles que melhor explicam o índice agregado de sustentabilidade e de avaliar sua sensibilidade a diferentes contextos e à implementação de intervenções de assistência técnica. Os indicadores relacionados à gestão, bem como aqueles relacionados às práticas conservacionistas e ao acesso a serviços públicos apresentaram as associações mais fortes com o índice final de sustentabilidade. Foi observada variabilidade regional nos indicadores gerenciais, bem como naqueles relacionados à conservação do solo e da água e à qualidade da água. As respostas de curto prazo à assistência técnica estiveram principalmente associadas a ajustes na gestão dos imóveis rurais, ao passo que as mudanças de longo prazo relacionaram-se mais fortemente às práticas conservacionistas e ao manejo de resíduos – aspectos ainda pouco reconhecidos como estratégicos pelos produtores. Para fortalecer a capacidade diagnóstica e de monitoramento da ferramenta na escala de talhão e apoiar a adoção de práticas conservacionistas, uma avaliação da qualidade do solo em escala de campo foi integrada à ferramenta ISA. Um parâmetro baseado na temperatura da superfície – uma métrica de sensoriamento remoto de acesso livre – também foi testado para avaliar a qualidade da cobertura do solo, viabilizando análises prospectivas e subsidiando o desenvolvimento de estratégias para adoção de práticas conservacionistas. O uso de indicadores integrados a uma análise de qualidade do solo em escala de campo pode apoiar o planejamento, o monitoramento e a tomada de decisão baseada em evidências por produtores, técnicos e formuladores de políticas públicas.

Palavras-chave: indicadores de sustentabilidade; desenvolvimento sustentável; índice de qualidade do solo; temperatura da superfície; atividade enzimática.

ABSTRACT

The assessment of environmental, social, and economic performance at the farm scale can support risk management and the transition toward more sustainable production systems, in alignment with the principles of conservation agriculture. This study presents the Sustainability Indicators in Agroecosystems (ISA) tool and its application to 3,296 farms across diverse regions of Brazil. Indicator behavior was analyzed to identify those that best explain the aggregated sustainability index, and to evaluate their responsiveness to varying contexts and to technical assistance interventions. Managerial indicators, conservation practices, and access to public services showed the strongest associations with the aggregated sustainability index. Marked regional variability was observed in managerial indicators, as well as in soil and water conservation and water quality indicators. Short-term responses to technical assistance were mainly associated with adjustments in farm management, whereas long-term changes were more strongly related to conservation practices and waste management, which are still not widely recognized as strategic by farmers. To strengthen the tool's diagnostic and monitoring capacity at the field level and support the adoption of conservation practices, a soil quality assessment at the field-site scale was integrated into the ISA tool. A parameter based on land surface temperature – a freely accessible remote sensing metric – was also tested to evaluate soil cover quality, enabling forward-looking analyses and supporting the development of conservation strategies. The use of indicators integrated with a soil quality analysis at the field-scale can support planning, monitoring, and evidence-based decision-making by farmers, technicians, and public policymakers.

Key words: sustainability indicators; sustainable development; soil quality index; land surface temperature; soil enzyme activity.

RESUMO EXPANDIDO

Sustentabilidade é uma noção que admite a chance de que venham a ser conservados - e até recuperados ou regenerados – os sistemas vitais que constituem a condição biogeográfica *sine qua non* da própria evolução da espécie humana e do progresso de suas sociedades, em grande parte “bens comuns” (Veiga, 2025).

Sistemas de produção mais integrados e diversificados, orientados ao aumento da estabilidade e da resiliência, demandam maior complexidade na gestão. Nesse contexto, a aferição do desempenho ambiental, social e econômico na escala do imóvel rural torna-se estratégica para o gerenciamento dos empreendimentos e para a promoção do desenvolvimento rural sustentável. A ferramenta Indicadores de Sustentabilidade em Agroecossistemas (ISA) foi desenvolvida visando integrar essas dimensões, reconhecendo o produtor como agente estratégico na implementação de práticas sustentáveis.

O objetivo deste estudo é apresentar a estrutura da ferramenta ISA, analisar os dados gerados por sua aplicação em diferentes regiões e projetos no Brasil, investigar o comportamento dos indicadores em distintos contextos, bem como sua correlação com o Índice Final, o qual agrega 17 indicadores com pesos iguais, e sua evolução ao longo do tempo em imóveis rurais que receberam assistência técnica. Buscou-se identificar os aspectos que apresentaram avanços, aqueles que permaneceram com baixo desempenho, bem como as possíveis causas e alternativas para a reversão dessas situações.

A base de dados compreendeu cinco programas de assistência técnica distribuídos em diferentes regiões do Brasil. A pecuária constituiu a principal atividade produtiva, com predominância de áreas de pastagem (62%), seguida pela vegetação nativa (25%). A análise de 3.296 imóveis rurais indicou um Índice Final médio classificado como baixo (0,53), com apenas 4,7% dos imóveis atingindo o limiar de sustentabilidade ($\geq 0,7$), enquanto 72% apresentaram desempenho baixo ($\geq 0,5$ e $<0,6$) ou muito baixo ($<0,5$). Os menores resultados estiveram associados, principalmente, à baixa fertilidade do solo, a práticas de gestão subótimas, e a medidas insuficientes de conservação do solo, da água e da biodiversidade. Os resultados variaram entre os programas e regiões, com médias do Índice Final no intervalo de 0,48 a 0,69.

Os indicadores mais dependentes do contexto foram aqueles relacionados a aspectos de gestão do empreendimento, comercialização e inovação, e manejo dos resíduos, e conservação do solo e da água. Observou-se também elevada variabilidade dos resultados entre os estados dentro de um mesmo programa envolvendo 1.192 imóveis rurais, com destaque para o indicador qualidade da água - particularmente em relação à disponibilidade hídrica na região de clima semiárido do Nordeste -, além de diferenças associadas à comercialização e à adoção de práticas inovadoras.

Os indicadores que melhor explicaram o índice de sustentabilidade agregado também estiveram relacionados a aspectos de gestão, conservação do solo, da água e da biodiversidade, e acesso a serviços públicos. Os padrões de correlação variaram entre os contextos, demonstrando a sensibilidade dos parâmetros da ferramenta ISA.

A capacidade de resposta dos indicadores à assistência técnica também variou entre os diferentes contextos analisados. Após um ano de acompanhamento, foram avaliados 1.192 imóveis rurais e, após dois anos, 524 imóveis rurais, abrangendo dois programas de assistência técnica do SENAR em diferentes estados brasileiros. Nesse período, a maior evolução foi observada nos indicadores referentes à gestão do empreendimento, à comercialização e inovação e à fertilidade do solo. O Índice Final médio apresentou um aumento significativo de 5,7% após um ano e de 11,3% após dois anos, enquanto a renda média cresceu 25% e 35%, respectivamente. No programa associado ao rompimento da barragem de Fundão, na bacia do rio Gualaxo do Norte, a avaliação após três anos de assistência técnica, envolvendo 114 imóveis rurais, indicou incremento significativo de 15% no Índice Final médio. Nesse caso, os maiores ganhos estiveram associados à evolução patrimonial e à gestão de resíduos – ambas vinculadas a programas de compensação. No entanto, alguns indicadores permaneceram com desempenho baixo mesmo após os períodos de assistência técnica nos três programas analisados, especialmente aqueles relacionados à ausência de análises de solo de rotina, à gestão inadequada de resíduos e ao controle insuficiente da erosão.

Os indicadores ligados às práticas conservacionistas frequentemente apresentaram progresso mais lento, enquanto as melhorias de curto prazo estiveram principalmente associadas a ajustes de gestão do empreendimento, comercialização e inovação. A adoção de práticas conservacionistas e a incorporação da dimensão

ambiental ao planejamento estratégico e à gestão de riscos continuam sendo desafios significativos.

A integração de indicadores à gestão quotidiana dos sistemas de produção requer atenção à escala de talhão. Parâmetros de monitoramento da qualidade do solo nessa escala foram integrados à ferramenta ISA, com o objetivo de identificar as especificidades de cada área de produção, suas potencialidades e limitações, permitindo também comparar diferentes manejos, tecnologias, insumos e práticas, com base na análise de parâmetros químicos e biológicos e nas informações sobre o manejo, produtividade e rentabilidade. Essa abordagem representa uma estratégia para a transição para modelos de produção mais sustentáveis, facilitando o escalonamento e avaliação das mudanças de manejo adotadas pelos produtores.

A temperatura da superfície e a atividade enzimática são exemplos de parâmetros aplicáveis a diferentes sistemas de produção. A temperatura da superfície, utilizada como indicador da qualidade da cobertura do solo – um dos princípios da agricultura conservacionista –, possibilita a identificação de áreas com baixa cobertura, e pode complementar dados da atividade enzimática do solo.

Para testar a validade desse indicador, foi conduzido um estudo de caso em um imóvel rural na região Centro-Oeste, especificamente no Estado de Goiás. Avaliou-se a relação entre diferentes manejos no sistema de plantio direto, a temperatura da superfície e a atividade enzimática do solo. As práticas analisadas incluíram o cultivo de milho no sistema de Integração Lavoura-Pecuária (ILP), e o plantio ou a sobressemeadura de plantas de cobertura após o cultivo da soja. A temperatura da superfície, obtida por sensoriamento remoto, foi analisada ao longo de um período de nove anos, enquanto as atividades das enzimas β -glicosidase e arilsulfatase no solo foram monitoradas durante seis anos. As diferentes práticas de manejo resultaram em variações significativas da temperatura da superfície (ΔTS), definida como a diferença entre a temperatura das áreas cultivadas e da vegetação nativa.

A introdução de culturas de cobertura após cultivos anuais de ciclo curto – neste estudo, a soja – e a implementação de sistemas integrados de produção (ILP) resultaram em menores valores de ΔTS , fator particularmente relevante em regiões tropicais com estação seca bem definida, por proporcionar uma “ponte verde” entre as safras. Além disso, a maior produção de biomassa associada às culturas de cobertura esteve relacionada à redução de ΔTS , a qual, por sua vez, apresentou

correlação com o aumento da atividade das enzimas arilsulfatase e β -glicosidase, reconhecidas como indicadores de saúde do solo.

Os resultados indicam que a qualidade da cobertura do solo influencia diretamente a atividade enzimática do solo e ressaltam o papel das culturas de cobertura na regulação da temperatura da superfície em ambientes tropicais. A análise de ΔTS , um produto de sensoriamento remoto de fácil acesso, pode ser integrada à estrutura da ferramenta ISA, permitindo a identificação de áreas críticas quanto à qualidade da cobertura do solo e complementando as análises da atividade biológica do solo.

A incorporação da dimensão ambiental ao planejamento estratégico ainda constitui um desafio no processo de adequação dos imóveis rurais, especialmente no que se refere à conciliação entre estabilidade produtiva, resiliência e rentabilidade. O índice de qualidade do solo permite a comparação de novos arranjos e tecnologias na escala de talhão e pode apoiar no desenvolvimento de estratégias para a adoção de práticas conservacionistas. Essa transição rumo a uma produção mais sustentável pode ser implementada de forma gradual, com métricas auxiliando na verificação de sua efetividade. O aprimoramento contínuo da ferramenta ISA permite desenvolver e identificar novas ferramentas de aferição com foco no desempenho ambiental, social e econômico dos imóveis rurais, bem como auxiliar na intensificação ecológica da agricultura e subsidiar políticas de incentivo para a adoção de práticas conservacionistas e a transição para sistemas produtivos mais sustentáveis.

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1 INTRODUCTION

Agriculture is among the human activities that most intimately link our behaviors to natural systems, with bidirectional feedback since the state of natural systems heavily influences agricultural productivity just as agricultural practices regulate the ecosystems in which they take place. Agricultural systems are complex, diverse, and heterogeneous. These characteristics mean that there are various synergies and trade-offs as we attempt to improve their performance (Antle and Ray, 2020).

The conceptual foundations of sustainable agriculture are embedded in broader debates on sustainability and development. Early formulations of regenerative and sustainable agriculture in the 1980s were grounded in ecological interaction principles, emphasizing the interdependence between agricultural practices and natural systems (Harwood, 2020). These debates trace back to the 1970s, when the prevailing conviction was that environmental protection was incompatible with the development ambitions of most nations (Veiga, 2025). The 1971 Report of the Panel of Experts on Development and the Environment, convened by the United Nations in Founex, Switzerland (Doud, 1972), marked the beginning of structured multilateral dialogue aimed at reconciling environmental protection with economic growth. The report also exposed enduring divergences between developed and developing countries, differences that remain relevant today (Veiga, 2025). In the Global South, environmental degradation was framed primarily as a consequence of underdevelopment rather than industrial excess, highlighting the need to integrate development objectives into environmental governance (Mbeva and Makomere, 2025).

The concept of sustainable development was formally articulated in the 1987 Brundtland Report, *Our Common Future*. Its central message – that development and environmental protection are inseparable – represented a conceptual shift away from the growth-versus-conservation dichotomy. Development cannot persist on a degraded environmental base, nor can environment protection succeed if economic systems ignore biophysical limits. Both dimensions are interconnected within a complex web of causes and effects (Brundtland, 1987). This paradigm was consolidated at the 1992 Rio Earth Summit, which provided a comprehensive framework for integrating environmental policies with development strategies. A set of action points for sustainable development was agreed upon at the summit, referred to

as Agenda 21. It also called for the development of sustainability indicators to monitor progress and assess whether conditions were improving or deteriorating (Bell and Morse, 2008). Since then, sustainable development has become the dominant paradigm for reconciling economic and social progress of current as well as future generations within ecological limits (Antle and Ray, 2020).

Subsequent analyses reinforced the structural interdependence between economic growth and ecological integrity. The World Bank's *Inclusive Green Growth* (2012) recognized that economic production is constrained by natural resource stocks and environmental quality, while *Beyond Growth* (2020) emphasized the need to better understand interactions among economic expansion, well-being, inequality reduction, and environmental sustainability (Veiga, 2025). System-based perspectives have also highlighted the central role of information in enabling societal transitions, making it relevant, timely, accurate, and capable of inspiring new rules and goals (Meadows and Randers, 2012). These contributions highlighted that sustainability requires operational metrics capable of guiding decision-making under conditions of complexity and uncertainty.

The concept of rural development must therefore extend beyond social aspects and economic growth to encompass the co-evolution of human and natural systems across spatial and temporal scales, encompassing promotion of complexity, diversity, and interdependence within production systems and across territories (Veiga, 2010). It involves a transition from relative isolation toward diversified territorial structures characterized by stronger institutional networks, productive diversification, and enhanced connectivity (Kageyama, 2010). Within agriculture sciences, the agroecosystem has provided a practical framework for applying sustainable development principles. An agroecosystem is defined as a spatially and functionally coherent unit modified by humans and primarily dedicated to agricultural production, yet not restricted to the site of production, since interactions with other ecosystems in the landscape both influence and are influenced by agricultural activity (Stokes et al., 2023).

As agroecosystems intensify and diversify, their internal complexity increases, demanding robust monitoring frameworks. Indicator selection should align with evaluation objectives and account for spatial and temporal scales, system boundaries, and stakeholder roles (Bell and Morse, 2008). Effective indicators should also capture key ecological functions, be sensitive to various environmental stresses, and integrate

principles such as diversity, stability, and resilience (Qiu et al., 2007). However, balancing information quality, quantity, and collection cost is also essential (Bertocchi et al., 2016), as excessive indicator complexity can undermine interpretation and implementation (Rasmussen et al., 2017).

In Brazil, environmental governance evolved in parallel with these conceptual advances. The creation of the Special Secretariat for the Environment (SEMA) in 1973 and the 1981 National Environmental Policy institutionalized environmental regulation and impact assessment (Ahrens et al., 2007; BRAZIL, 1981). Strategic Environmental Assessment (SEA) subsequently expanded evaluation beyond projects to policies and programs (Ahrens et al., 2007). Within this institutional trajectory and SEA context, the Sustainability Indicators in Agroecosystems (ISA) tool was developed in Minas Gerais to support the agricultural sector in evaluating environmental impacts.

By defining the farm as the basic unit of analysis, ISA recognizes farmers as key agents in advancing the sustainable rural development agenda. The framework integrates target-based, practice-based, and performance-based indicators, enabling agroecosystem diagnosis, monitoring, and strategic planning (Coteur et al., 2020). Its participatory refinement from 21 to 17 indicators aimed to improve communication and balance among social, economic, and environmental dimensions (Figure 1).



Figure 1. ISA tool's 17 indicators.

ISA's environment dimension encompasses the principles of Conservation Agriculture – minimal soil disturbance, permanent cover on the soil surface, and diversification of species in the cropping system (Kassam et al., 2022) – and incorporates biodiversity conservation, driven by concerns over habitat degradation, deforestation, loss of riparian vegetation, and the growing scientific understanding of multiple ecosystem services and functions within agroecosystems, considered central ecological principles supporting farm sustainability. These principles involve habitat maintenance, increased crop and non-crop habitat heterogeneity, nutrient cycling, and

successional dynamics (Storkey et al., 2024). However, despite the importance of long-term sustainability measures, farmers frequently prioritize short-term interventions, such as fertilization, weed and pest control – a tendency often reinforced by time and resource constraints (Kerneck et al., 2021).

As early as the 1980s, studies emphasized that environmental management practices were primarily reactive, focusing on post-impact restoration or damage repair, such as reforestation and habitat recovery (Brundtland, 1987). More recently, the concept of regenerative agriculture (Rodale, 1984) has gained prominence. This approach promotes ecologically centered management practices that enhance and maintain soil health, increase soil organic matter and carbon storage capacity, and reduce dependence on synthetic fertilizers and agrochemicals (Shahmohammadloo et al., 2021).

Soil quality plays a central role in agroecosystem sustainability. Conventional production systems, characterized by intensive input use, including soluble fertilizers and pesticides, have contributed to soil degradation, loss of soil organic matter, erosion, compaction, biodiversity decline, nutrient imbalances, and high input costs (Brown, 2018; Masters, 2021). In contrast, regenerative approaches prioritize restoring soil functions, including nutrient cycling, biological regulation, structure stability, and carbon sequestration. Assessing soil quality requires establishing baselines and selecting sensitive indicators that reflect ecological functioning (Bunemann et al., 2018).

Since its development, ISA has undergone iterative refinement through participatory processes. This thesis advances that trajectory by: (i) detailing the conceptual and methodological construction of ISA; (ii) analyzing its application across 3,296 farms under diverse contexts; (iii) evaluating indicator performance and contribution to the aggregated sustainability index; (iv) assessing responsiveness to different contexts and technical assistance; and (v) incorporating field-scale soil quality assessment, including evaluation of soil cover through land surface temperature. By integrating biological soil indicators with remote sensing metrics, this research strengthens the methodological robustness and practical applicability of ISA, and advances the strategic relevance of sustainability assessment in agroecosystems.

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2 DEVELOPMENT

2.1 CHAPTER I - A SUSTAINABILITY ASSESSMENT TOOL FOR AGROECOSYSTEMS: METHODOLOGY AND PRACTICE

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2.1.1 Abstract

Integrated and diversified production systems require a high level of management complexity. A tool was developed to assess social, economic, and environmental performance at the farm scale, aiming to support agroecosystem governance, recognizing farmers as key agents in advancing the sustainable development agenda in rural areas. The Sustainability Indicators in Agroecosystems tool (ISA) identifies constraints, potentialities, and opportunities through 17 indicators, providing a holistic view of the farm and supporting planning and decision-making processes. Data from 3,296 farms across diverse regions of Brazil were analyzed. This includes follow-up assessments conducted after one to three years of technical assistance. Interpreting the results demands contextualization, particularly in identifying which indicators influence sustainability trajectories depending on regional context, and which best explain variations in the aggregated sustainability index. The ISA tool identified key areas for improvement, related to managerial aspects and conservation practices. The responsiveness of indicators to technical assistance varied over time and with context. Long-term changes were more closely related to conservation practices, which are still not widely perceived as strategic by farmers.

Keywords: Sustainability indicators; Sustainable development; Farm Level Sustainability Assessment; Soil Quality Index.

2.1.2 Introduction

Many technologies adopted in the agriculture sector have led to disconnections between production systems and natural ecosystems, resulting in degradation of natural resources. Food production expansion has been driven by an industrial model characterized by intensification of cultivation via genetic development of high-yielding varieties, specialization in a small number of crop and livestock species and genotypes, dependence on external inputs, and integration with large agribusiness and global markets (Storkey et al., 2024, Marcelino et al., 2024). This model has accelerated biodiversity loss and soil degradation, increasing the vulnerability of agricultural landscapes to the effects of climate change. Moreover, this yield-oriented approach has often compromised food quality while distancing farmers from consumers and weakening their connection with the land (Shahmohamadloo et al., 2021).

Major advancements toward more integrated, diversified, and resilient agroecosystem models incur in increased system complexity, emphasizing the need for monitoring through metrics and parameters that form a comprehensive set of indicators. The effectiveness of these interventions in improving agroecosystem sustainability can be evaluated by monitoring changes in the conditions of the farm and household before and after their implementation (Chopin et al., 2021).

It is also essential to assess whether agroecosystems can assimilate potential impacts while maintaining their productive capacity and resilience over time. Farmers must plan proactively to reduce uncertainties and anticipate opportunities and challenges. Indicators can serve both as diagnostic tools and as instruments for monitoring ongoing transformations, and they can support improvements in highly complex situations (Sala et al., 2015). Thus, a comprehensive assessment of agricultural performance across multiple dimensions is important for moving beyond conventional productivity measures and for more accurately identifying and evaluating the benefits and trade-offs among different agriculture systems (Bicksler et al., 2019).

Agroecosystems operate within, and maintain, interrelations with broader social and ecological systems. Externalities of farm operations should be accounted for in performance evaluations (Talukder and Saifuzzaman, 2016). Each farm represents a unique combination of landscape characteristics, environmental context, and management practices operating at multiple spatial and temporal scales (Storkey

et al., 2024). Therefore, establishing local reference levels and analyzing behavioral trends within agroecosystems are crucial for generating meaningful insights that extend beyond short-term and isolated analyses. Different contexts may lead to varying stages of farm development, as well as differences in farmers' skills, ambitions, and responses to technical and managerial assistance (Alvarez et al., 2014).

Current sustainability assessment tools often rely on practice-based indicators, on the assumption that sustainability performance necessarily improves when specific practices are implemented. In contrast, performance-based indicators, which evaluate the actual effects of farming practices, are considered to have greater scientific adequacy (de Olde et al., 2018). However, the balance between complexity, time suitability, and cost effectiveness is a challenge for scaling up assessments while ensuring scientific soundness. Sustainability frameworks can also be translated into sustainability targets, with which the results of the assessment will be compared (Sala et al., 2015). These targets define a transition process in which practice, result, and outcome-based indicators are all considered; the latter typically monitored over the long-term and may be affected over time by external drivers (Schreefel et al., 2024). It is also essential to ensure that sustainability assessments move beyond descriptive evaluations and compliance analyses.

The Sustainability Indicators in Agroecosystems tool (ISA) was developed in Brazil in 2010 (Ferreira et al., 2012), to evaluate the environmental and socioeconomic performance of agroecosystems, seeking to optimize the balance between sensitivity and cost-effectiveness. In alignment with the principles of the Tool for Agroecology Performance Evaluation (TAPE), the ISA methodology emphasizes broad applicability, theoretical robustness, low data collection costs, partner testing, long-term collaboration, and identification of local reference values with involvement of farmers (FAO, 2018). The spatial scale of ISA tool is the farm. Such a scale facilitates the implementation of policies that support farmers and provide guidance for decision-makers (De Olde et al., 2018).

The ISA tool addresses three interlinked principles of conservation agriculture, defined by the FAO: minimum soil disturbance, permanent soil cover, and crop diversity. ISA's objective is to evaluate the cumulative impacts of management decisions on the farm as a whole. However, sustainability assessments can also take an interrelated approach, applying multidimensional indicators to agricultural systems, by assessing both individual system components and their interactions (Osorio and

Dias, 2024). The tool also evaluates soil quality at the field-site scale, aiming to support farmers in their planning and decision-making processes, providing forward-looking data integrated into sustainability analysis at farm level.

Long-term partnerships with universities (UFMG), extension companies (EMATER), and research institutions (Embrapa), alongside collaboration with private corporations and other government institutions have been essential for the development and refinement of ISA. The system has been applied across a range of socioeconomic and environmental settings in Brazil.

The present work has two objectives. The first is methodological, detailing the construction and the framework of the ISA tool. The second is practical, presenting results of ISA application across different contexts. This analysis explores the challenges of universal sustainability assessment, examines how indicators behave across varying contexts and their responsiveness to technical assistance, and identifies which indicators best explain the aggregated sustainability index.

2.1.3 Materials and methods

2.1.3.1 Sustainability Indicators for Agroecosystems (ISA) framework

The ISA tool consists of a questionnaire and a set of parameters (100) that form 17 indicators (Table 1). The tool was designed to assess social, economic, and environmental performance at the farm level, identify critical points and opportunities, and propose corrective measures for management practices that may cause negative environmental impacts. Detailed definitions of each indicator, including parameter descriptions, weighting factors, and measurement units, are provided in the Supplementary Information – Table S1.

Table 1. Sustainability Indicators and the number of parameters for each indicator.

Indicator	Parameters (N°)
I1 Productivity and sales price	2
I2 Income diversity	3
I3 Asset development and indebtedness	6
I4 Access to public services	11
I5 Access to education and training courses	6
I6 Employment quality	10
I7 Business management	8
I8 Commercialization strategies and innovation	4
I9 Waste and residues management	5
I10 Soil fertility	5
I11 Soil erosion and road maintenance	7
I12 Water quality	11
I13 Water contamination risk and pesticide management	10
I14 Soil and water conservation practices	2
I15 Biodiversity conservation practices	3
I16 Natural habitats status	5
I17 Preservation Areas and Conservation Reserve Areas*	2

* Preservation Areas are designed to safeguard riparian zones, preventing soil erosion, filtering runoff, and providing habitats for both aquatic and terrestrial species; Conservation Reserve Areas, whether established through legal requirements or voluntary programs, aim to improve water quality, prevent soil erosion, support wildlife habitats, and enhance ecosystem services.

The environmental dimension comprises the largest share of indicators (I10-I17; 46%), addressing aspects related to soil, water, and biodiversity, followed by the economic (I1-I3; 18%), social (I4-I6; 18%), and managerial (I7-I9; 18%) dimensions, the latter intersecting with the other three.

Quantitative and qualitative data, expressed in different units of measurement, are standardized through a normalization procedure (Andreoli and Tellarini, 2000). For each indicator, an index ranging from 0 to 1 is calculated by comparing on-farm measurements with reference values and applying weighting factors to the corresponding parameters (Table S1). A baseline value standardized at 0.7, considered the sustainability threshold, is based on benchmarks derived from environmental standards, legal requirements, expert consultation, and field validation. Normalization allows for straightforward interpretation by farmers, where zero represents the lowest and one the highest performance value (Rodrigues et al., 2010, Bockstaller et al., 1997, Simon et al., 2022).

The 17 indicators are aggregated into a single index as a simple average, with equal weighting. However, more relevant insights emerge from the specific metrics and parameters within each indicator. Each indicator and corresponding survey data can be further analyzed and systematized to support detailed assessments (e.g., land

ownership, gender equity, economic specialization, income per hectare, soil enzyme activity, pesticide ecotoxicity). The ISA tool is available in an Excel file provided online (https://www.epamig.br/tecnologias_lista/indicadores-de-sustentabilidade-em-agrossistemas-isa/) with free access in both Portuguese and English.

The indicators adopted in the ISA tool follow the SAFA tool categories: performance-based - assessing the results of meeting an objective and the performance of an operation; practice-based - identifying the implementation of best practices; and target-based - focused on plans or policies (Zarbà et al., 2025). Since its early development, the ISA tool has been continuously improved through participatory workshops and feedback from extension technicians and partner institutions, including a structured survey completed by 230 experienced users. Based on data from multiple projects, the framework was refined from 21 to 17 indicators without altering their parameters, aiming to enhance data synthesis and communication, and balance among the three dimensions.

In general, four to eight hours are sufficient to complete a field survey. For each indicator, the weighting factors can be assessed either in the indicator tab (Fig. S1) or in the formula tab. The analyses required to complete the ISA indicators include soil chemical analysis (≈US\$ 14.13) and β -glucosidase and arylsulfatase enzymatic activities, described by Mendes et al. (2019) (≈US\$ 30.04), the latter being optional.

The farm scale, defined as the system boundary, does not account for impacts caused by off-farm activities such as transport, or the manufacturing of fertilizers and agrochemicals, as noted by Van Cauwenbergh et al. (2007) in the SAFE analysis. The pursuit of low cost, rapid assessments restricts the inclusion of more detailed economic assessments, such as production costs and net income, as conducted in the APOIA NovoRural tool (Rodrigues et al., 2018).

Optionally, Soil Quality Index (SQI) is evaluated at field scale in a complementary tab, which can be replicated for multiple plots or production systems within each farm. The evaluation produces an index based on 10 indicators, one of which is optional (soil enzyme activity). Complementary data are collected for each plot, including financial information and plant tissue nutrient analyses interpretation for various crops (Fig. S2).

2.1.3.2 Data collection and analysis

A total of 3,296 farms have been studied to date, encompassing five programs conducted across different states (Figure 2). The spreadsheets were completed between 2016 and 2023. All datasets were standardized to the current ISA version comprising 17 indicators, while maintaining the same 100 parameters from the earlier 21-indicator version.



Figure 2. Geographic distribution by state of technical assistance initiatives focused on livestock production: (A) the National Rural Learning Service (SENAR) under the Forest Investment Program (FIP), funded by the World Bank, comprising 1,978 farms across the states of Maranhão (MA), Tocantins (TO), Bahia (BA), Mato Grosso (MT), Goiás (GO), Mato Grosso do Sul (MS), and Minas Gerais (MG); (B) the SENAR program in Espírito Santo (ES), with 992 farms; (C) the State Rural Extension Company (EMATER) program, with 134 farms in MG; (D) the RENOVA Foundation program, with 114 farms in MG. Additionally, (E) a technical assistance program led by a private company (FAU) was implemented in a region of southern Brazil, in Rio Grande do Sul state (RS), characterized by intensive vegetable, fruit, and grain production, encompassing 78 farms.

To characterize the socioeconomic context of different regions and municipalities, economic complexity was used as one of the parameters (Hidalgo, 2021; Salles et al., 2017), based on DataViva platform (<http://www.dataviva.info/>). Regions or municipalities with more interconnected and centrally positioned productive activities within the economic network were considered to have higher economic complexity.

The responsiveness of the sustainability indicators to the implementation of technical assistance was also evaluated. A second application of the ISA system was performed by SENAR programs (SENAR FIP – A, and SENAR ES - B) after one year of technical assistance on 1,192 farms and after two years on 524 farms. In the Renova Program (D), a second application was conducted after three years of technical assistance, involving 114 farms.

Correlograms were used to assess the correlations between indicators and the Final Index. The strength and direction of relationships were measured using the Spearman's coefficient. For this analysis, the "corrplot" package (Wei and Simko, 2021) was used in the statistical software R (R Core Team, 2023). Boxplots were used to display the minimum and maximum values, first quartile, median, and third quartile of a data series. To identify outliers, lower and upper limits were set at 1.5 times the interquartile range. Indicator values were categorized into six classes, represented by colors: red for the lowest values, yellow for medium values, and green for the highest values. Additionally, an overlapping bar graph was used to visualize the frequency distribution of all indicators in a single graph. Both analyses were performed using "ggplot2" package (Wickham, 2009) in the statistical software R.

2.1.4 Results and discussion

2.1.4.1 Indicators Analysis and Performance Across Different Contexts

The following section presents indicator performance across the five programs and examines how varying contexts influenced results. The 3,296 farms where the ISA was applied encompassed a total area of 223,652 ha, with sizes ranging from 0.2 ha to 6,066 ha (mean = 67.9 ha; median = 26 ha). The predominant production systems were beef cattle (38.7% of the farms), dairy (37.3%), and coffee (17.7%), followed by fruit (1.2%) and vegetable production (0.5%), and other activities (4.6%). On average, pastures occupied 61.8% of the total farm area, while natural habitats (native vegetation) accounted for 25%. Annual crops were minor in this sample, although nationally they represent 15.9% of agriculture land, after grassland/pasture (45%) and native vegetation (30%). Overall, farms occupy 351 million hectares of Brazil's 851 million hectares (IBGE, 2019).

The mean Final Index obtained from the ISA application (0.53) was considered low. Only 4.7% of the farms reached or exceeded the sustainability threshold (≥ 0.7), and 72% had performances classified as low or very low. Indicators associated with the economic and social dimensions (I1-I8) showed higher performance levels (mean = 0.60) than those related to the environmental dimension (I9-I17) (mean = 0.47) (Figure 3). Gabrielli et al. (2023) and da Fonseca et al. (2020) reported similar or higher final index averages using the ISA tool for dairy farms in Minas Gerais (0.57 for 39 smallholder farms and 0.67 for 100 farms, respectively). Although data aggregation reduces detail, it facilitates comparative assessments among farms, programs, and production systems (Andreoli and Tellarini, 2000).

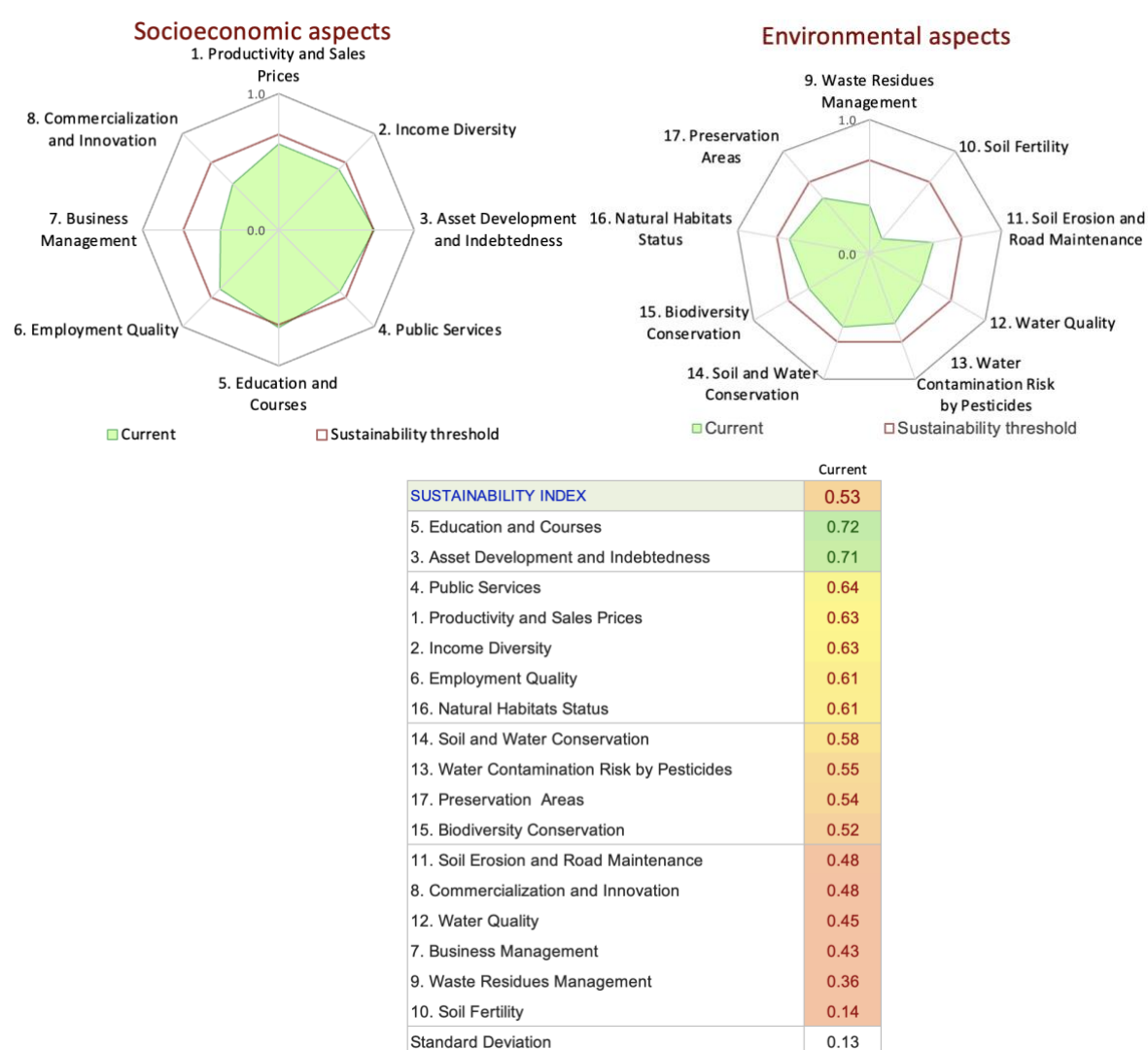


Figure 3. Radial graphs showing the average of 3,296 farms, grouped by socioeconomic and environmental aspects. The red internal line marks the sustainability threshold. The data are also grouped by indicator performance intervals: good (≥ 0.7), medium (≥ 0.6 and < 0.7), low (≥ 0.5 and < 0.6), and very low (< 0.5).

Among the low-performing topics, soil fertility stood out (average = 0.14) due to low fertility values and the absence of soil fertility analysis in 71% of farms, which corresponded to a score of zero. Among farms that did conducted soil analysis, the average soil fertility indicator was 0.49. da Fonseca et al. (2020), applying the ISA tool in 100 dairy farms, reported soil fertility as the lowest-scoring indicator (0.39).

Managerial indicators (including waste and residue management, business management, and commercialization and innovation practices) also showed critical performance, with waste management representing a major challenge for dairy farms. Only 30% of the farms had sewage systems, 41% properly managed household waste, 31% monitored production costs, and 37% maintained cash flow control, while the adoption of innovative technologies or practices reached 40%. These results are consistent with Rodrigues et al. (2010), who identified management as the weakest sustainability dimension, relative to environmental quality, sociocultural values, economic values and landscape ecology, based on an assessment of 177 farms using the Apoia-NovoRural tool.

Conservation practices also showed low performance (0.48-0.58). Insufficient adoption of conservation practices can lead to soil erosion processes, which were identified on 69% of the farms. According to Duff et al. (1992), water-related erosion has long been recognized as a critical problem posing environmental and economic consequences in rural areas.

Regarding biodiversity, native vegetation accounted for 25% of the average farm area. The Conservation Reserve Areas parameter showed comparatively higher performance, largely reflecting compliance with the Brazilian Forest Code, which requires the maintenance of 20-80% of native vegetation on rural properties, depending on the biome. The 2012 revision of the Native Vegetation Protection Law, which introduced the Rural Environmental Cadastre (CAR), has facilitated environmental monitoring and compliance. Farms smaller than four fiscal modules (5-110 ha, depending on the region) are exempt from this requirement (da Silva et al., 2023). At the national level, 39.9% of registered rural land remains under native vegetation, with lower proportions in the Cerrado (37.9%) and Atlantic Forest (24.9%).

Conversely, the Preservation Areas parameter, which evaluates riparian zones protection, showed lower performance despite the adequate overall proportion of natural habitats. The Forest Code requires Permanent Preservation Areas (PPAs),

aiming to create buffer zones along watercourses, springs, and in sensitive topographic areas (steep slopes and hilltops), with widths ranging from 30 to 500 m (da Silva et al., 2023). Although riparian forests are known to reduce runoff and improve water quality (Shahmohamadloo et al., 2021), compliance remains limited. Buffer requirements in Brazil are substantially wider than those adopted in other countries, where widths range from 5 to 15 m (5 m in Germany and France, 10-15 m in Canada and the United States, and variable, often unenforced, standards in China) (Casteloni et al., 2024). A minimum buffer width of 10 m is recommended to maintain ecosystem services such as filtration, erosion control, flood mitigation and the promotion of ecosystem and habitat integrity in water bodies (Marcelino et al., 2024). Landscape simplification and reduced crop rotation have been identified as drivers of farmland biodiversity decline, whereas integrating semi-natural habitats – such as riparian buffer strips or in-field strips of perennial vegetation – can provide resources for functionally important environmental services, including shelter for pollinators and natural enemies (Storkey et al., 2024).

On the topic water contamination risks and pesticide use, 71% of the farms applied pesticides in their production areas, but only 47% of them used protective equipment, just 51% had proper pesticide storage, and only 50% returned the packaging. The average pesticide application rate was 1.45 kg ha^{-1} , varying from 0.5 kg ha^{-1} in the Renova Program (D) to 4.3 kg ha^{-1} in the FAU Program (E). According to FAO (2024), Brazil's total pesticide use in 2022 reached 800,652 tons, equivalent to 3.59 kg ha^{-1} overall. Five crops – soybean, corn, cotton, pasture and sugarcane – account for 87% of the treated area in Brazil, with usage patterns influenced by climate, pest management strategies, and access to technology (Gaboardi et al., 2023).

Indicators related to water, encompassing water quality, soil and water conservation, and water contamination risk, along with waste and residues management, showed greater data dispersion (Figure 4).

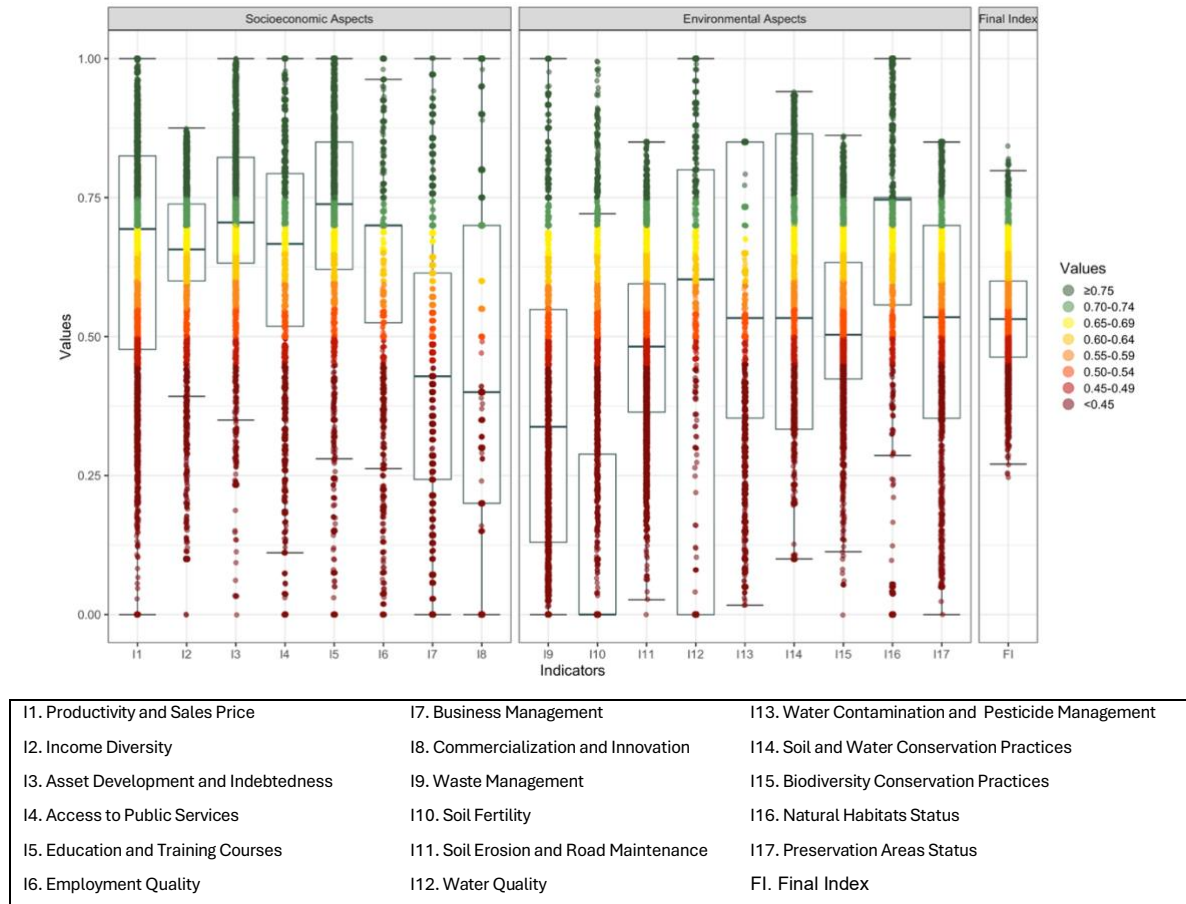


Figure 4. Boxplots of indicators and Final Index from 3,296 farms, showing the minimum and maximum values, first quartile (lower 25%), median (bold line inside the box), and third quartile (upper 25%) of the data series.

Very low values (<0.5) were observed in more than 50% of farms for indicators related to managerial tools (I7-I9) and to soil erosion and road maintenance (I11). Conversely, values above 0.70 were observed in more than 50% of farms for socioeconomic indicators such as productivity, asset development and indebtedness, education and training courses, and employment quality, besides natural habitats status (Fig. S3).

When comparing farms with the highest and lowest Final Index values (top and bottom 25%), the most pronounced differences were observed in managerial activities, including production cost control parameter (sixfold difference between groups) and adoption of innovative techniques parameter (fivefold difference). Erosion processes occurred in 83% of farms with the lowest Final Index and in 46% of those with the highest. The bottom group also had a greater proportion of pastureland and less native vegetation than the best-performing group (Table S2).

Indicator performance varied across the programs, which may reflect farmers' profiles as well as broader biophysical and socioeconomic contexts. Therefore, within each of the five programs, we analyzed how varying socioeconomic conditions affected indicator behavior and the Final Index. The RENOVA program showed the lowest mean Final Index (0.48), reflecting challenges such as severe erosion (in 84% of farms), water stress (66%), low income (USD 148 ha⁻¹ year⁻¹), and degraded preservation areas affected by the Fundão dam rupture from an iron mining exploration. In contrast, the FAU Program (E) achieved a higher mean Final Index (0.68), associated with greater income (USD 2,689 ha⁻¹ year⁻¹), although issues related to water quality and pesticide management remained concerns. The indicators with the highest variability among programs – and thus the most context-dependent – were those related to managerial aspects (I7-I9) and soil and water conservation (Fig. S4).

Indicator variability was also examined by state within the FIP SENAR (A) program, which spans several regions of Brazil (Figure 2). The most context-dependent indicator was water quality (Fig. S5). Regional differences were observed, with lower mean Final Index values in the states of Bahia, Maranhão, and Tocantins, and higher values in Minas Gerais state. Similar patterns were reported by Christo et al. (2025), who applied a quantitative framework to assess sustainability impacts of agricultural production at the municipal level, identifying higher performance in the South and Southeast regions of Brazil and greater economic and social constraints in the North and Northeast. A higher share of public employment in municipalities in this region was also associated with lower economic complexity, potentially affecting socioeconomic aspects in rural areas.

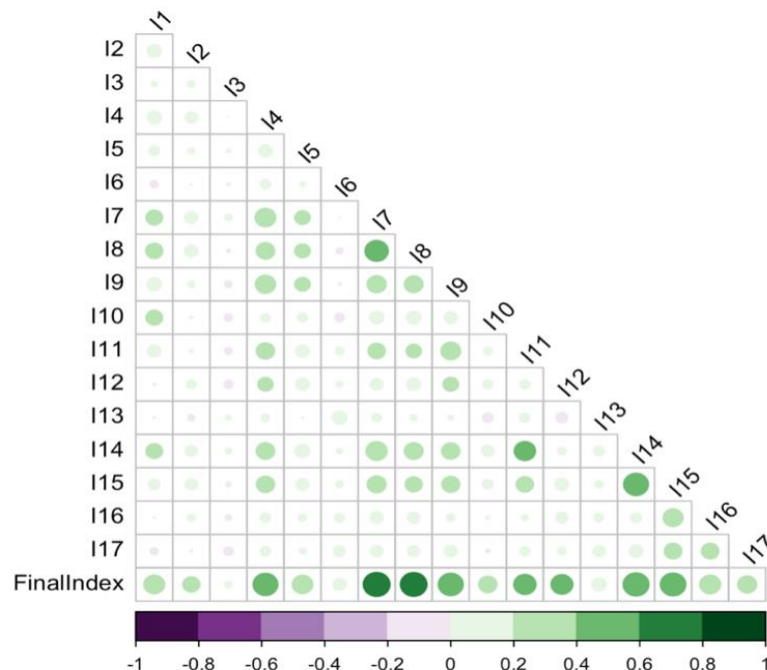
Contextual differences were further evidenced by municipal economic complexity and the proportion of formal employment in public administration (Fig. S6). For example, in the municipality of Brejolândia, in Bahia state (SENAR/FIP program - A), 80.6% of formal jobs were in public administration, compared with 11.4% in São Domingos do Norte, Espírito Santo state (SENAR ES program – B), and 4.4% in the municipality of Novo Hamburgo, in Rio Grande do Sul state (FAU program - E), which showed higher economic complexity. The economic analysis of municipalities provided insights into how the structure of local economies may be reflected in rural areas.

Adoption of sustainable practices depends on personal, physical, economic and institutional factors influencing farmers' decisions. Farmers may be in different development stages and possess varying skills and ambitions (Alvarez et al., 2014).

Characterizing the systems under evaluation is a prerequisite for using sustainability as a criterion to guide agriculture transitions. Such characterization should be system-oriented, quantitative, predictive, and diagnostic (Hansen, 1996). Some indicators capture short-term changes, while others evolve over the long term, depending on farmer's priorities and environmental sensitivity.

2.1.4.2 Correlations Between Indicators and the Aggregated Sustainability Index.

According to Spearman's coefficient analysis on the relationships between the Final Index and the indicators, the strongest correlations across 3,296 farms were: Business Management indicator (Spearman's $\rho = 0.64$), Commercialization and Innovation ($\rho = 0.63$), Soil and Water Conservation ($\rho = 0.59$), Biodiversity Conservation ($\rho = 0.58$), Waste Management ($\rho = 0.55$), and Public Services ($\rho = 0.55$) (Figure 5). Four of these indicators (managerial aspects and soil and water conservation practices) were also context-dependent, highlighting their sensitivity to local conditions.



I1. Productivity and Sales Price	I7. Business Management	I13. Water Contamination and Pesticide Management
I2. Income Diversity	I8. Commercialization and Innovation	I14. Soil and Water Conservation Practices
I3. Asset Development and Indebtedness	I9. Waste Management	I15. Biodiversity Conservation Practices
I4. Access to Public Services	I10. Soil Fertility	I16. Natural Habitats Status
I5. Education and Training Courses	I11. Soil Erosion and Road Maintenance	I17. Preservation Areas Status
I6. Employment Quality	I12. Water Quality	Final Index

Figure 5. Correlogram showing correlations between the Indicators and Final Index in 3,296 farms. The size and colors of the circles represent the intensity and direction of the correlation between these variables, respectively, calculated by Spearman's correlation coefficient.

Similar findings were reported by da Fonseca et al. (2020) in 100 dairy farms assisted by SENAR MG using the ISA tool, where strong performance in management, soil fertility, and conservation reserve areas corresponded to higher sustainability. Both studies showed consistent results for managerial indicators. Rodrigues et al. (2010, 2018) also found high correlations between sustainability indices and management-related indicators using the Apoia-NovoRural tool, emphasizing the influence of farmer profile and managerial capacity. Well-organized farmers tend to perform better across economic, social and environmental dimensions.

Some associations between indicators were expected, such as between soil fertility and productivity; and natural habitats and preservation areas, but those were generally weak. Stronger relationships were observed between business management and commercialization and innovation, both linked to technical and organization improvements, between soil and water conservation and biodiversity conservation, reflecting similarities in data collection and ecological overlap, and between soil and water conservation and soil erosion.

Correlation patterns between indicators and the final index varied among the five programs, highlighting managerial aspects for the SENAR FIP (A) program, conservation aspects for SENAR ES (B) and EMATER (C), both presenting landscapes with rugged relief, water quality for RENOVA (D), and water contamination and pesticide for FAU (E), besides commercialization and innovation for both programs. Overall, indicators related to managerial aspects (I7, I8, and I9), conservation practices (I14 and I15), and public services (I4) were the most strongly associated with the Final Index, underscoring the importance of management capability and conservation strategies for improving farm sustainability.

2.1.4.3 Responsiveness of Indicators to Technical Assistance

The ISA was reapplied to 1,192 farms after one year and to 524 farms after two years of technical assistance under the SENAR FIP (A) and SENAR ES (B) programs (Figure 6). The mean Final Index rose from 0.53 to 0.56 after one year (t-

Test, $p < 0.001$) and from 0.53 to 0.59 after two years (t-Test, $p < 0.001$), with the greatest gains related to business management, followed by soil fertility and commercialization and innovation (Fig. S7). Median income per hectare increased by 25% after one year and 35% after two years. Gabrielli et al. (2023), using the ISA tool, also found an increase in the Final Index from 0.55 to 0.65 across 24 dairy farms, after three years, with significant improvements (Wilcoxon test, $p < 0.05$) in productivity, access to public services, business management, commercialization and innovation, and soil and water conservation. In both studies, improvements in managerial, productivity and conservation practices were decisive for enhanced sustainability.

In a third-year assessment, in a different context (Renova Program), improvements were partly driven by compensation measures following the Fundão dam rupture, resulting in a 15% increase in the mean Final Index, from 0.49 to 0.55 after three years (t-Test, $p < 0.001$) (Figure 6). The greatest gains were observed in asset development and indebtedness, business management, and waste residues management (Fig. S7). Farm and municipal profiles in this program revealed structural barriers to rural development, including low municipal economic complexity, limited regional infrastructure, predominance of low-performing livestock systems, an aging farmer population (average 69 years), as well as dependence on government transfer programs, such as pensions, school cash transfer, nutrition cash transfer, and cooking gas transfer.

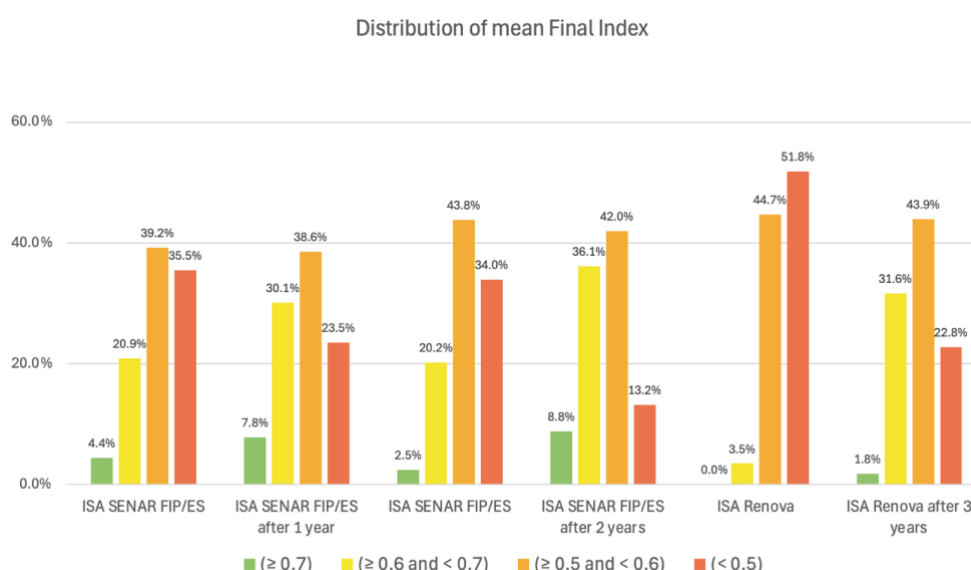


Figure 6. Distribution of Mean Final Index intervals (≥ 0.7 ; $0.6-0.7$; $0.5-0.6$; < 0.5) for ISA data and for programs that received technical assistance.

Across the three programs in which the ISA was reapplied, the strongest correlations with the Final Index were observed for commercialization and innovation, waste management, and public services (Table S3). The analysis of indicator evolution after one and two years of technical assistance in the SENAR program showed that improvements in commercialization and innovation, as well as in business management, were most strongly associated with increases in the Final Index (Fig. S8).

The responsiveness of indicators to technical assistance also varied over time. Environmental indicators linked to conservation practices, including waste management, showed slower progress, reflecting limited incentives, short-term planning horizons, and low integration of environmental management into farm decision-making and risk management (Fig. S9). Managerial tools and soil conservation practices proved to be strategic in enhancing environmental, social and economic performance of farms. The sustainability of agroecosystems depends largely on farmers' management capacity rather than soil-landscape characteristics alone (Qiu et al., 2007). It also involves the ability to collect, store, and use information to guide long-term decisions (Kay et al., 2011).

However, environmental management is often not perceived as strategic, yet its adoption is crucial for improving productivity, reducing costs, and increasing resilience. Major threats to soil – erosion, organic matter loss, compaction, contamination, salinization, and biodiversity loss – remain widespread, with social and economic impacts in the medium and long term (Alaoui et al., 2022). Many farmers still resist adopting conservation practices due to the lack of immediate financial incentives (Duff et al., 1992).

Persistent challenges after the period of technical assistance included the absence of routine soil analysis, inadequate waste management, and insufficient erosion control. Short-term improvements reflected changes in managerial aspects while long-term progress depends on adopting conservation practices. Although not yet widely recognized by farmers as strategic, such practices are essential for enhancing overall sustainability. The indicators were therefore refined to better align with the field-site scale, with a specific focus on soil quality – both to improve the accuracy of ISA indicator completion and to provide metrics that support forward-looking management of production systems. Soil quality index, combined with other

parameters, could help mobilize farmers and technicians in the transition toward more sustainable production systems.

2.1.6 Conclusion

This study examined the principles and processes guiding the development and improvement of the ISA methodology, which reduces system complexity through its indicators while serving as an evidence-based advisory tool. It also incorporates the soil quality index (SQI) at the field-site scale to support farmers and technicians in scaling up management adjustments and adopting a forward-looking approach.

Applications of the ISA across 3,296 farms in diverse contexts and time scales revealed a low mean Final Index and showed that regional specificities affected indicator performance. Regions with low technological development and limited natural resources may require more time and targeted technical support to improve sustainability outcomes, as observed, for example, in farms with low-technology livestock management.

The ISA tool identified key areas for improvement, particularly managerial aspects and the conservation of soil, water, and biodiversity. These aspects showed the strongest relationships with the aggregate sustainability index and can be strengthened through technical assistance focused on management tools and adoption of conservation practices. They also overlapped with aspects expected to improve under technical assistance programs, such as productivity.

Effective planning begins with a sound diagnosis, and progress should be continuously monitored across social, economic, and environmental dimensions. One challenge lies in reconciling generalist indicators, which offer replicability, with indicators that provide greater specificity and accuracy.

Another challenge involves incorporating conservation and managerial practices into strategic planning and risk management, especially for smallholder farmers. Overall, the ISA tool demonstrated its value as a multidimensional management instrument, supporting assessment and monitoring processes across different spatial scales and contexts.

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2.2 CHAPTER II - SOIL QUALITY ASSESSED BY LAND SURFACE TEMPERATURE AND SOIL ENZYME ACTIVITY

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2.2.1 Abstract

Soil quality is crucial for maintaining long-term productivity and food security. Large-scale assessments are often constrained by the high human and financial resources required; however, proxy parameters such as soil enzyme activities and land surface temperatures (LST) can facilitate them. This study investigated how different management practices in no-till crop and livestock production systems affect LST and soil enzymatic activity in regions with a dry season. This on-farm research was conducted in Central Brazil within an agricultural area of approximately 1,900 hectares. Practices aimed at maintaining permanent soil cover, especially during the dry season, were implemented, including no-till systems with maize integrated with livestock production, cover crops sown after soybean harvest, and overseeding of cover crops on soybeans. Crop yield, soil attributes and management practices, along with LST from remote sensing, were assessed over a nine-year period. Soil enzymes β -glucosidase and arylsulfatase activities were measured over a six-year period. Management practices significantly affected Δ LST (difference in land surface temperature between cropping areas and natural vegetation) and arylsulfatase activity. Δ LST had a significant effect on β -glucosidase and arylsulfatase activities. The integrated crop-livestock system and cover crops sown after short-cycle soybean harvest were associated with the lowest Δ LST. This work highlights the significant role of cropping system management, particularly the use of cover crops, in regulating LST in tropical areas. Changes in Δ LST across cropping systems can complement

biological soil analyses by identifying critical areas regarding soil cover quality, a key principle of conservation agriculture.

Keywords: No-till systems; β -glucosidase; arylsulfatase; integrated crop-livestock systems; cover-crops; conservation agriculture; agroecosystems.

2.2.2 Introduction

Due to observed and projected climate change, there is intensifying pressure on agricultural systems to increase food production with lower environmental impacts. One of the key strategies to achieve this goal is to build soil health and enhance soil biological activity using conservation-focused farming practices, such as reducing soil disturbance, building carbon stocks through soil amendments, and protecting the soil (Mooney et al., 2024). Different conservation practices, such as No-Till (NT), cover cropping, crop rotation, and Integrated Crop Livestock System (ICLS), enhance biodiversity and natural biological processes both above and below the soil surface (Kassam et al., 2019). These practices emphasize improving soil cover quality to promote soil thermal regulation, preserve moisture, and increase soil organic carbon (Franchini et al., 2023; Mendes et al., 2018). However, there is scant information on strategies to achieve diversified and permanent soil cover in NT systems, particularly in tropical regions with a dry season. This paper presents results from on-farm research aimed at assessing how different conservation-focused management practices affect land surface temperature and soil enzyme activity (as a proxy for soil quality) on a large-scale grain-producing farm.

Soil health or quality is defined here as “the continued capacity of soil to function as a vital living system, within ecosystem and land-use boundaries, to sustain biological productivity, promote the quality of air and water environments, and maintain plant, animal and human health” (Doran and Zeiss, 2000). Changes in soil chemical or physical properties often affect soil biological activity (Green et al., 2007).

Soil enzymes are used as indicators of soil health due to their relationship to soil biological activity, ease of measurement, and rapid response to changes in soil management (Bandick & Dick, 1999; Acosta-Martínez et al., 2021; Mendes et al., 2024). The activities of different soil enzymes can serve as indicators of soil organic matter (SOM) decomposition (Sinsabaugh et al., 2008), because they catalyze soil

biochemical and nutrient-cycling processes (Stott et al., 2010; Karaca et al., 2010). Moreover, soil chemical, physical, and biological properties affect enzymatic diffusion, substrate turnover, and the proportion of products available for assimilation by cells (Burns et al., 2013; Wallenstein & Burns, 2011).

Since 2020, Brazil has adopted soil bioanalysis (SoilBio) technology, a novel initiative that integrates two key soil enzymes – arylsulfatase and β -glucosidase – into routine commercial soil analysis (Mendes et al., 2019; 2024). This approach enables soil health monitoring by integrating three soil functions: (i) nutrient cycling, based on arylsulfatase and β -glucosidase activities; (ii) nutrient storage, based on soil organic carbon (SOC) and potential cation exchange capacity (CEC); and (iii) nutrient supply, based on concentrations of Ca^{2+} , Mg^{2+} , K^+ , P, pH, $\text{H}+\text{Al}$, Al^{3+} , sum of bases, and base saturation (Mendes et al., 2019; 2021; 2024).

Land Surface Temperature (LST) is a variable applicable at large scales and may influence enzyme activity by regulating microbial activity and SOC decomposition rates (Wang et al., 2022). The soil-atmosphere interface is where the transfer of resources – particularly energy, water, and nutrients – occurs; conditions at the soil surface, particularly temperature and water content, regulate the rate and quantity of such transfers. As land surface temperature rises – and consequently soil temperature – respiration increases, which can deplete soil carbon stocks. In soils with little or no residue input, microorganisms use soil organic matter for energy, thereby reducing long-term soil carbon levels (O'Brien & Hatfield, 2020).

Crop residue cover and cover crops reduce abrupt fluctuations in soil temperature, which reduces evaporation and retains soil water (Blanco-Canqui & Ruis, 2018). NT practices are widely adopted to reduce erosion and increase moisture retention (Six et al., 2002), which helps mitigate these fluctuations in soil temperature. However, even with NT management, the predominance of monocultures and environmental changes can affect several aspects of agroecosystems production, including reduced biodiversity and shifts in temperature and precipitation patterns (Lin, 2011). Long-term experiments have shown that, even with NT management, maintaining constant soil cover and implementing cropping systems with high crop residues inputs are crucial for balancing SOM decay, especially in tropical climate conditions (Mendes et al., 2018).

Therefore, soil quality assessment can improve cropping systems management. The objective of this paper is to investigate at farm scale how different

management practices affect LST and soil enzymatic activity, particularly in regions with a defined dry season. We hypothesize that the cropping system management influences surface temperature, which, in turn, affects soil enzyme activity. Therefore, management practices that provide greater soil cover over time are expected to promote increased enzyme activity and, consequently, higher soil quality.

2.2.3 Materials and methods

2.2.3.1 *Study site*

The study was conducted on a large-scale commercial farm in Central Brazil (-15.210131, -48.444263), located in the Cerrado biome, Goiás state. The regional climate is tropical savanna climate (Aw, Köppen classification), with a five-to-six-month dry season, a mean annual temperature of 22.3°C, and approximately 1,200mm of annual precipitation. The Cerrado biome covers about 2.0 million km², corresponding to 23% of the Brazilian territory (Oliveira et al., 2024). The dominant soil class is dystrophic Ferrasols (WRB), characterized by a deep, intensely weathered profile, high acidity, low nutrient availability, low cation exchange capacity (CEC), high exchangeable aluminum, and strong phosphorus fixation (IUSS Working Group WRB, 2022). Drainage patterns in this biome range from sub-parallel to slightly dendritic and exhibit lower drainage density compared with humid tropical regions (Ab'Saber, 2003).

The farm covers approximately 3,000 ha, including 24% natural vegetation, 50% soybean, 13% maize, and 13% pasture. The study area comprised nine homogeneous field sites (hereafter “plots”), totaling approximately 1,900 hectares. All plots share the same soil class and texture and present similar fertility conditions, as parent material, climate, topography, and original vegetation are comparable across sites, supporting their classification as dystrophic Ferrasols (Table 2).

Table 2. Area (ha), soil chemical properties, soil organic matter (SOM), and clay content in 2025 (0 to 20 cm), mean soybean yield (2017–2025), and a reference pasture (P) from a soil sample in 2004 representing the natural soil fertility of the area.

Plot	Area (ha)	pH (CaCl ₂)	SOM dag kg ⁻¹	Clay content ------(%)-----	V	CEC	Ca ²⁺ -----cmolc dm ⁻³ -----	Mg ²⁺	K ⁺ -----mg dm ⁻³ -----	P	Soybean Yield (Kg ha ⁻¹)
1	225	5.5	3.0	57.0	75.6	7.7	3.6	1.7	239	19.3	3,870
2	130	5.6	3.5	58.0	82.5	9.2	5.0	1.8	301	18.4	3,926
3	169	5.6	3.6	59.0	82.4	8.5	4.3	1.8	319	22.4	3,816
4	320	5.8	3.1	61.3	81.2	7.4	4.2	1.4	180	14.1	4,070
5	338	5.7	2.7	60.6	71.4	7.7	3.2	1.5	306	16.4	4,113
6	222	5.4	3.2	61.3	78.0	7.4	3.5	1.7	258	17.2	3,672
7	112	5.8	3.6	57.0	78.7	8.7	4.0	2.1	292	15.7	3,531
8	227	5.6	2.8	57.2	65.8	7.4	3.1	1.3	194	11.5	3,980
9	150	5.4	2.3	57.4	66.3	6.5	2.7	1.3	213	11.7	3,655
P	40	4.4	3.6	61.3	24.0	8.4	0.7	0.7	224	1.1	

SOM: Soil Organic Matter; CEC: Cation Exchange Capacity; Ca and Mg extracted with 1 M KCl; K and P extracted with Mehlich-1 solution.

According to Sousa & Lobato (2004), for grain production systems in clayey Ferrasols of the Brazilian Cerrado, adequate soil fertility levels are as follows: pH (CaCl₂), 4.9-5.5; cation exchange capacity (CEC), 9.1-13.5 cmolc dm⁻³; Ca²⁺, 1.5-7.0 cmolc dm⁻³; Mg²⁺, 0.5-2.0 cmolc dm⁻³; K, 57-80 mg dm⁻³; and P, 8.1-12 mg dm⁻³. Mean soybean yield in Goiás state was 3,702 kg ha⁻¹ between 2017 and 2025 (CONAB), whereas the farm-level average during the same period was 3,843 kg ha⁻¹.

Improvements in soil fertility and crop nutrition rely on the application of mineral fertilizers, lime, phosphate and silicate rock powders, and biofertilizers, combined with inoculation of *Bradyrhizobium* and *Azospirillum*, among other microorganisms, with the aim of achieving nutritional balance and enhancing biological activity in the soil and rhizosphere.

2.2.3.2 Cropping system management

Annual cropping systems are based on maize and soybean production. Maize is cultivated within Integrated Crop-Livestock Systems (ICLS), consisting of summer maize (*Zea mays*) intercropped with *Brachiaria brizantha* cv. MG4, which is grazed during the subsequent dry season.

Soybean-based systems incorporated cover crops established just after soybean harvest. These systems included either a second maize crop associated with *Brachiaria ruziziensis* or a diversified cover crop mixture composed of *Brachiaria*

ruziziensis, *Crotalaria ochroleuca*, *Crotalaria juncea*, *Pennisetum glaucum*, *Cajanus cajan*, *Fagopyrum esculentum*, and/or *Raphanus sativus*.

Crop system management was defined as follows.

- (i) ICLS: No-till maize intercropped with *Brachiaria brizantha* as a summer crop, followed by grass-based livestock grazing during the dry season.
- (ii) Short C.: No-till short-cycle soybean (< 115 days) as a summer crop, followed by sowing of cover crops.
- (iii) Long C.: No-till long-cycle soybean ($\geq$ 115 days) as a summer crop, followed by sowing of cover crops.
- (iv) Overseeding: Overseeding of *Brachiaria ruziziensis* and/or millet into no-till long-cycle soybean before harvest
- (v) No cover: No-till long-cycle soybean without cover crops during the dry season.

The rainy season in the region typically begins between mid-October and November. As summer crop sowing extends into November-December, particularly with the use of long-cycle soybean cultivars, the window for establishment and development of cover crops or second crop becomes progressively shorter.

Strategies aimed at maintaining a diversified and permanent soil cover have evolved over time (Table 3), supported by the development of seeding equipment capable of establishing a wide range of cover crop species. As a result, areas without cover crops (bare fallow) and areas managed with overseeding have been eliminated, as these practices limit both the quantity and diversity of seeds per unit area.

Table 3. Cover crop management in the study plots from 2017 to 2025: ICLS, Integrated Crop Livestock Systems; Short C., short-cycle soybeans (< 115 days) followed by cover crops; Long C., long-cycle soybeans ($\geq$ 115 days) followed by cover crops; Overseed, *Brachiaria* and/or millet overseeded into standing long-cycle soybeans; No cover, bare fallow.

Plot	2017	2018	2019	2020	2021	2022	2023	2024	2025
1	No cover	Short C.	Overseed	Short C.	Long C.	Short C.	Short C.	Long C.	ICLS
2	Short C.	No cover	Overseed	Overseed	Short C.	Short C.	Short C.	Short C.	Short C.
3	No cover	Overseed	Short C.	Short C.	Short C.	Short C.	Short C.	Short C.	Short C.
4	No cover	Overseed	Overseed	Overseed	ICLS	Long C.	Long C.	Long C.	Long C.
5	No cover	Overseed	Overseed	ICLS	Long C.	Long C.	Long C.	ICLS	Short C.
6	Overseed	No cover	ICLS	Short C.	Long C.	Long C.	ICLS	Long C.	Short C.
7	Overseed	Long C.	Short C.	Overseed	Overseed	ICLS	ICLS	Long C.	Short C.
8	ICLS	Overseed	Overseed	Overseed	Overseed	Long C.	ICLS	ICLS	Long C.
9	Overseed	ICLS	No cover	Overseed	Overseed	ICLS	Short C.	Long C.	ICLS

2.2.3.3 Data collection

Land Surface Temperature (LST)

Thermal images from the Landsat 8 and 9 satellites, with a native spatial resolution of 100 m and an 8-day return period were used. The fusion of Landsat thermal data with Sentinel-2 imagery was applied to enhance the spatial resolution from 100 m to 30 m (Onáčillová et al., 2022). Spectral radiance from the thermal infrared sensor (TIRS) was converted to brightness temperature (K) and land surface temperature using the Planck equation (Eq. 1) (Kramer et al., 2023).

$$T_s = \frac{T_b}{1 + \left(\frac{\lambda T_b}{a}\right) \ln \varepsilon} \quad (1)$$

Where:

T_s = Surface temperature.

T_b = Brightness or apparent temperature recorded by the sensor (Kelvin degrees).

λ = Mean wavelength of thermal infrared radiation.

a = hc/K = 1.438 × 10⁻² m K, where: K = Stefan–Boltzman constant (1.38 × 10⁻²³ J/K).

ln ε = Natural logarithm of surface emissivity.

Images from the Landsat 8 and 9 satellites, acquired by the Operational Land Imager (OLI and OLI-2) sensors for path/row 221-071, were obtained from the United States Geological Survey repository (EarthExplorer). Monitoring was conducted in July, during the dry season, which allowed the selection of cloud-free images and reduced atmospheric interference with surface radiation. Land surface temperature was derived using the Raster Calculator tool in the open-source software QGIS (Quantum Geographic Information System), version 3.22, by applying the following equation (Eq. 2):

$$TS = (1321.08 / \ln(774.89 / (3.3420 \cdot 10^{-4} \cdot \text{BAND10} + 0.110000) + 1)) - 273.15 \quad (2)$$

Where:

TS = surface temperature.

BAND10 = thermal band (TIRS).

The temperature of each production system (plot) was extracted using the Zonal Statistics plugin available in QGIS, which integrates raster data (land surface temperature) with the corresponding vector layers of the sampled plots. Image pre-processing was performed using the Semi-Automatic Classification plugin within QGIS, and the areas corresponding to plots under different production system practices were converted into shapefiles.

To ensure comparability among management practices across years, the land surface temperature difference (Δ LST) was calculated as the difference between the LST of each plot and the mean LST of two native vegetation fragments within the farm, which were used as land surface cover reference areas.

Enzymes analysis

In the first year, ten locations were randomly selected within each plot, and soil samples were collected using a soil probe. At each location, seven subsamples were taken – six between sowing rows and one within the row – resulting in a total of 70 subsamples per plot at the 0–10 cm depth. In subsequent years, soil samples were collected in the vicinity of the same locations.

β -glucosidase and arylsulfatase enzymatic activities were determined following the method described by Tabatabai (1994), which is based on the colorimetric quantification of p-nitrophenol released by soil enzymes when 1.0 g of soil is incubated with a buffered solution containing synthetic chromogenic p-nitrophenyl substrates (Mendes et al., 2019). Soil organic carbon (SOC) content was determined using the Walkley-Black method (Nelson and Sommers, 1996), and calculated according to Jackson (1958).

Cover crop biomass

Cover crop biomass was assessed between 2023 and 2025 using 0.5 m $\times$ 0.5 m sampling frames. Three frames were sampled per plot each year. Above-ground

plant material was clipped, oven-dried at 80°C to constant mass, and weighed. Measurements of cover crop dry matter production were conducted in July, coinciding with the dates of the satellite images used for LST assessment.

2.2.3.4 Data analysis

Considering the structure of the dataset, mixed-effects modelling with restricted maximum likelihood (REML) estimation method (Zuur et al., 2009) was applied to analyze: (i) the relationships between crop management practices and Δ LST; (ii) the relationship between Δ LST and soil enzymes β -glucosidase and arylsulfatase; and (iii) the relationships between crop management practices and the activities of β -glucosidase and arylsulfatase. Plots were treated as random factors in the model. Normality and homogeneity of variances were verified on standardized residuals (Zuur et al., 2009). Tukey's tests were applied to identify specific differences between crop management practices. All analyses were conducted in R (R Core Team, 2023) using the packages nlme (Pinheiro et al., 2018), ggplot2 (Wickham, 2009), emmeans (Lenth, 2024) and multcomp (Hothorn et al., 2008) (Supplementary information A - scripts and results, and Table S4).

For the analysis of crop management practices and Δ LST, the dataset comprised 81 observations spanning nine years and nine plots. Analyses of Δ LST and enzyme activities, as well as crop management practices and enzyme activities, were based on 54 observations across six years and nine plots. A linear mixed-effects model was employed to assess the relationships between SOM and the activities of β -glucosidase and arylsulfatase, using 45 observations collected over five years across nine plots. In addition, the relationship between soybean yield and enzyme activities was evaluated using 43 observations spanning six years and nine plots; maize production was not included in this analysis.

A four-quadrant model was used to evaluate trends in soil carbon dynamics (loss, increase, or stability) across the nine plots over five years (2020, 2022, 2023, 2024, and 2025). The model is based on the relationship between SOC and the average activities of β -glucosidase and arylsulfatase per unit of SOC (average specific enzyme activity – ASEA) which standardizes enzyme activity according to SOC levels (Chaer et al., 2023). Threshold values for SOC and ASEA were used to define the four quadrants. The model assumes that the balance between ASEA and SOC may shift

due to the higher sensitivity of soil enzymes and the influence of agricultural management practices that either improve or degrade soil quality (Chaer et al., 2023).

2.2.4 Results

Crop management practices had a significant effect on Δ LST ($F = 11.62$; $p < 0.001$). Cropping systems with earlier establishment of soil cover, such as ICLS and short-cycle soybeans followed by cover crops, exhibited lower Δ LST values, whereas overseeding, no cover systems, and long-cycle soybeans were associated with the greatest increases in LST over the nine-year observation period (Figure 7).

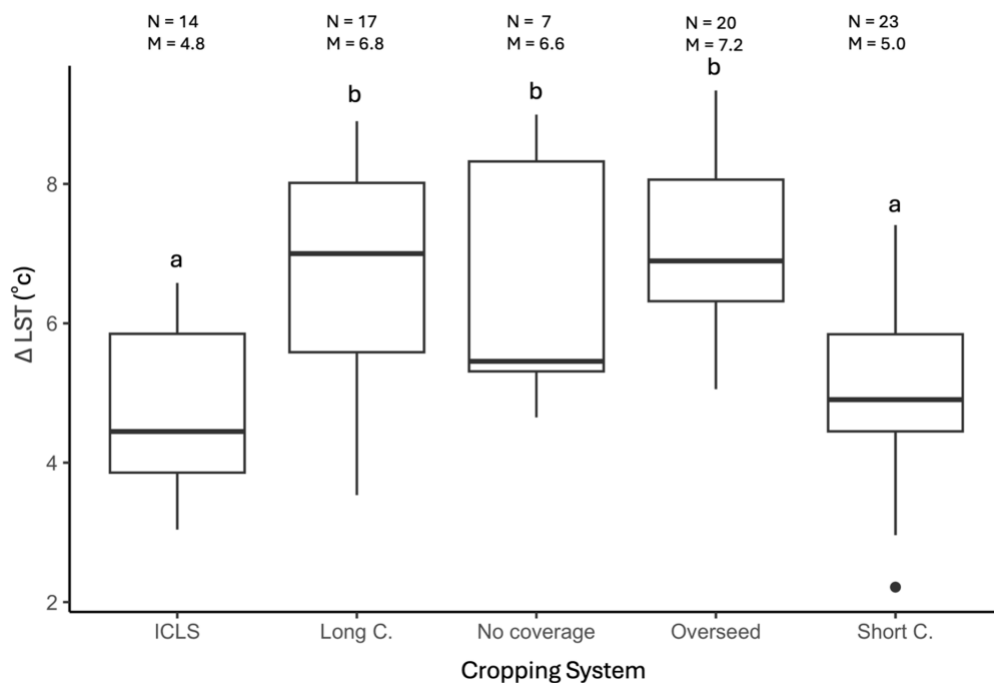


Figure 7. Boxplots of changes in Land Surface Temperature (Δ LST) in areas with different cover crop management practices: ICLS, Integrated Crop Livestock Systems; Long C., long-cycle soybeans (≥ 115 days) followed by cover crops; No cover, bare fallow; Overseed, *Brachiaria* and/or millet overseeded into standing long-cycle soybeans; Short C., short-cycle soybeans (< 115 days) followed by cover crops. Different letters indicate significant differences based on Tukey's test; n denotes the number of observations, and M represents the mean of Δ LST ($^{\circ}\text{C}$) across nine years and nine plots.

Across the nine plots (1,900 ha), the mean LST over the nine-year period was 27.8°C , with a maximum of 35.3°C and a minimum of 18.8°C . In contrast, the two native vegetation fragments exhibited a mean LST of 21.7°C , with maximum and minimum values of 26.6°C and 12.6°C , respectively. The mean Δ LST between cropped

plots and native vegetation was 6.1°C, reflecting interannual differences in field crop surface temperatures relative to native vegetation reference areas (Figure 8).

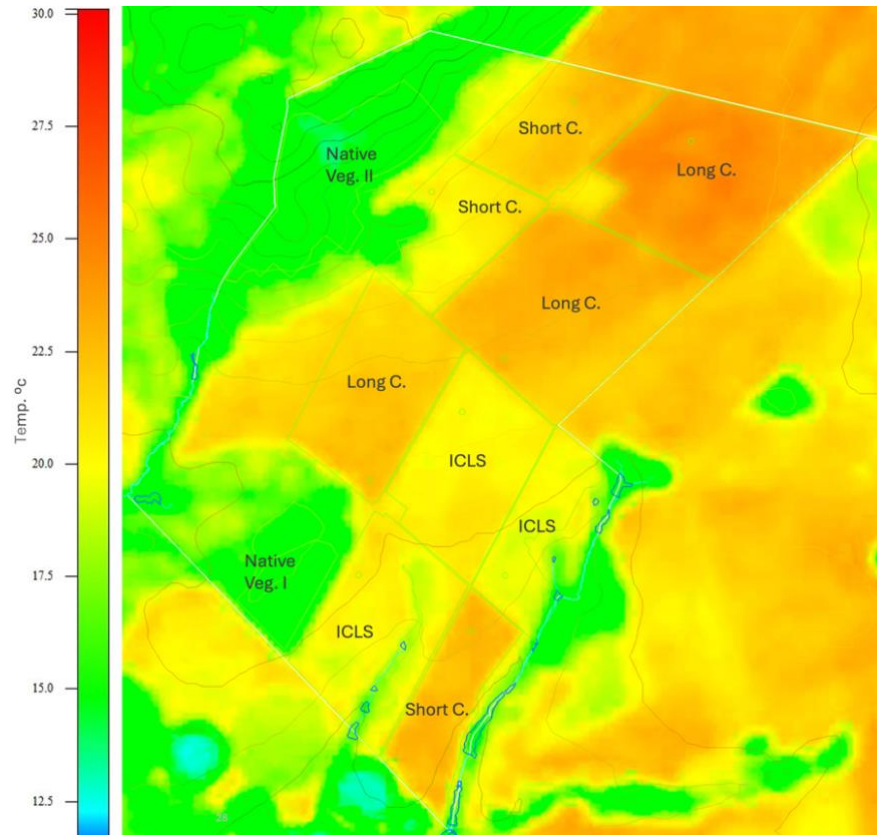


Figure 8. Land surface temperature (LST) image derived from the Landsat 8 thermal infrared band (TIRS), illustrating LST patterns in the study area in July 2023 under different crop management practices and native vegetation fragments: ICLS, Integrated Crop Livestock Systems; Long C., long-cycle soybeans followed by cover crops; Short C., short-cycle soybeans followed by cover crops.

Cover crop biomass, measured between 2023 and 2025, had a significant effect on ΔLST ($\beta = -0.35$; $t = -5.67$; $p < 0.001$), indicating that greater biomass production was associated with lower surface temperatures (Figure 9). During this period, crop management systems also significantly affected ΔLST ($F = 12.31$; $p = 0.0006$). The mean ΔLST between cropped plots and native vegetation over the three-year period was 5.6°C. The ICLS exhibited the highest mean cover crop biomass among the evaluated systems (Table 4).

Table 4. Cover crops and grass mean biomass (dry mass) and mean Δ LST, both measured in July (dry season) under long-cycle soybean followed by cover crops (Long C.), short cycle soybean followed by cover crops (Short C.), and Integrated Crop Livestock System (ICLS) across three years and nine plots.

Cropping System	Mean Biomass (ton ha ⁻¹)	Mean Δ LST (°C)
Long C.	5.75 a	7.28 b
Short C.	7.38 a	4.98 a
ICLS	12.56 b	4.41 a

Means followed by equal letters in the columns do not differ by the Tukey's test at 5% probability

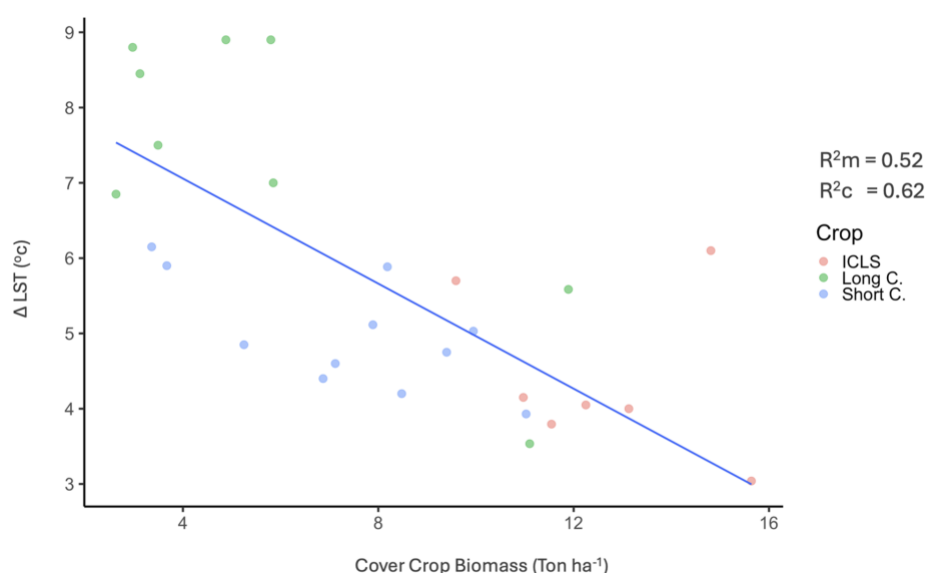


Figure 9. Relationship between cover crop biomass and Δ LST across three years and nine plots ($P=0.0009$), with identification of crop management practices: ICLS, Integrated Crop Livestock Systems; Long C., long-cycle soybeans followed by cover crops; Short C., short-cycle soybeans followed by cover crops (R^2m – marginal – focuses on fixed effects; R^2c – conditional – include both fixed and random effects).

Δ LST significantly affected soil enzyme activities. β -glucosidase activity showed a stronger negative correlation with Δ LST ($\beta = -8.03$; $t = -3.83$; $p = 0.0004$) than arylsulfatase activity ($\beta = -4.87$; $t = -2.22$; $p = 0.031$) (Figure 10).

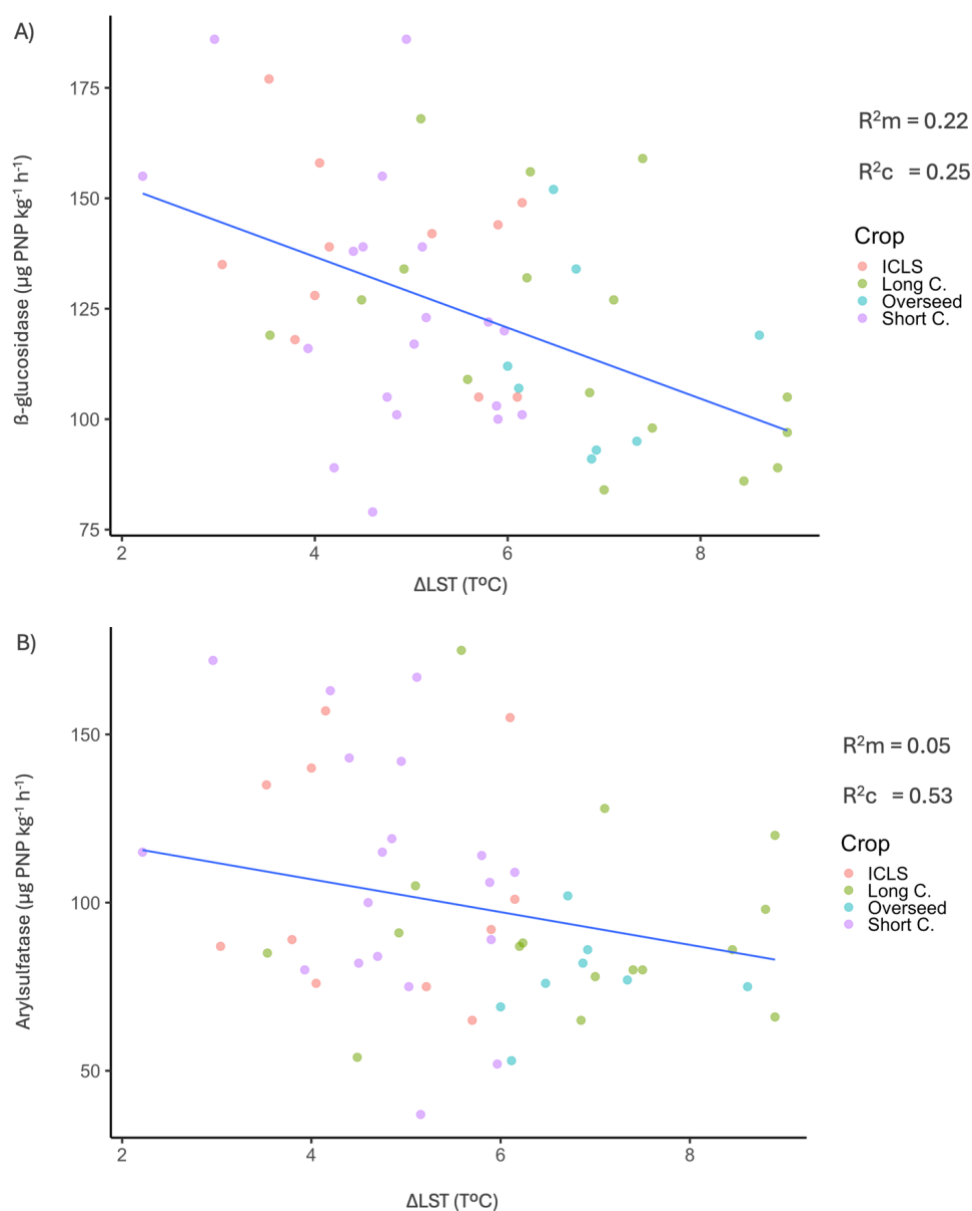


Figure 10. Relationship between ΔLST and soil enzymes activities: (A) β -glucosidase and (B) arylsulfatase evaluated across six years and nine plots, with identification of crop management practices: ICLS, Integrated Crop Livestock Systems; Long C., long-cycle soybeans followed by cover crops; Overseed, *Brachiaria* and/or millet overseeded into standing long-cycle soybeans; Short C., short-cycle soybeans followed by cover crops.

Crop management practices affected arylsulfatase activity ($F = 6.81$; $p = 0.0008$), whereas no significant effect was observed for β -glucosidase activity ($F = 1.53$; $p = 0.22$) (Figure 11).

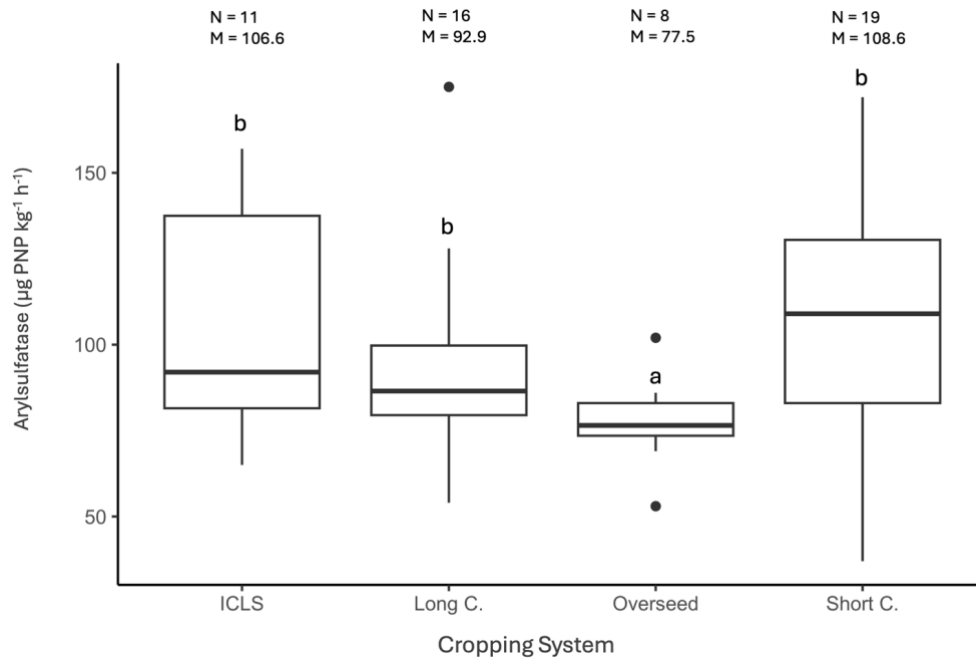


Figure 11. Boxplots showing arylsulfatase responses to cover crop management practices: ICLS, Integrated Crop Livestock Systems; Long C., long-cycle soybeans followed by cover crops; Overseed, Brachiaria and/or millet overseeded into standing long-cycle soybeans; Short C., short-cycle soybeans followed by cover crops. Different letters indicate significant differences based on Tukey's test; n denotes the number of observations, and M represents the mean of arylsulfatase enzyme activity (mg p-nitrophenol kg⁻¹ soil h⁻¹) across six years for each cropping system.

β -glucosidase activity was positively associated with SOM at the 0–10 cm depth ($\beta = 39.76$; $t = 3.80$; $P = 0.0006$; $R^2_m = 0.23$; $R^2_c = 0.37$), while no association was detected between SOM and arylsulfatase activity ($\beta = 8.78$; $t = 0.79$; $p = 0.44$). No significant relationships were observed between soybean yield and β -glucosidase ($p = 0.35$) or arylsulfatase activity ($p = 0.83$).

A four-quadrant model was applied to evaluate the relationship between SOC and average specific enzyme activity (ASEA) for the years 2020, 2022, 2023, 2024, and 2025 (SOC data at 0–10 cm depth were not available for 2021). ASEA, calculated as the mean activity of arylsulfatase and β -glucosidase per unit of SOC, was positively associated with SOC during this period ($\beta = 0.02$; $t = 3.22$; $P = 0.0028$; $R^2_m = 0.19$; $R^2_c = 0.19$). For 2020, an improvement in ASEA and stable SOC levels were observed; both variables remained above threshold values considered adequate to achieve 50% of maximum yield (15.55 for SOC and 4.3 for ASEA) according to Chaer et al. (2023) (Figure 12).

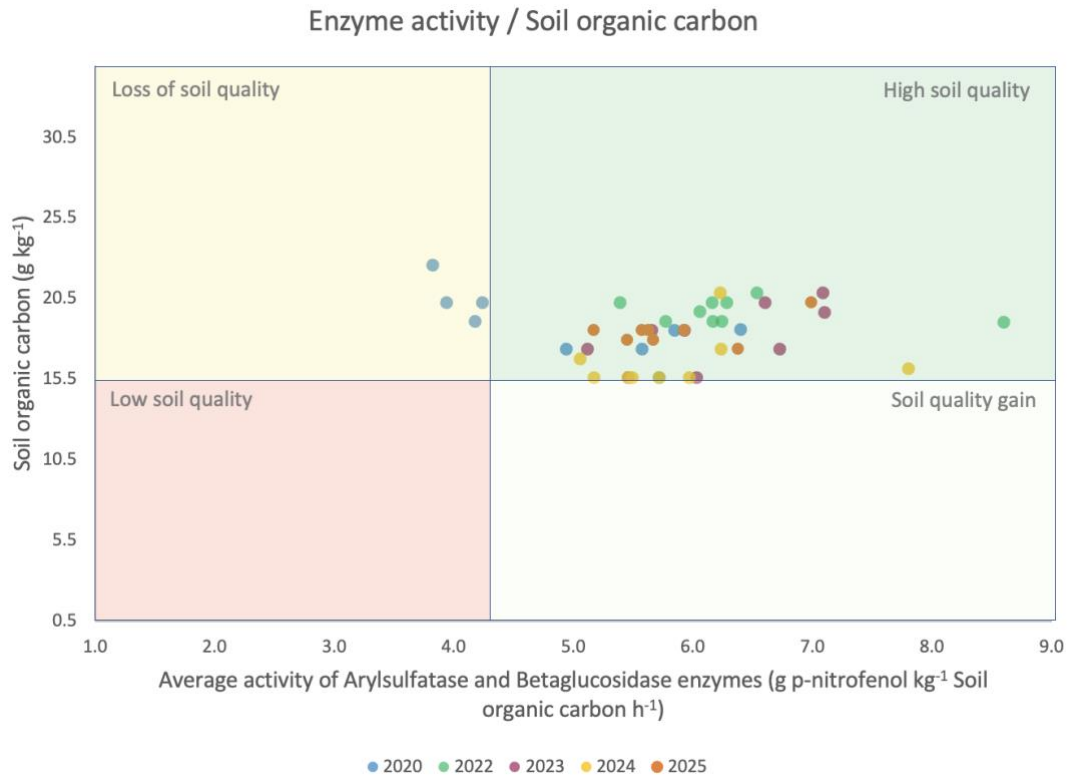


Figure 12. Scatter plot illustrating the relationship between SOC and average specific enzyme activity (ASEA) for nine plots (0-10 cm depth) in 2020, 2022, 2023, 2024 and 2025. Quadrants with high SOC/high ASEA and low SOC/low ASEA represent stable patterns indicative of high-quality and low-quality soils, respectively. Quadrants characterized by low ASEA/high SOC and high ASEA/low SOC represent transitional states associated with biological degradation (carbon loss) and regenerative processes (carbon gain), respectively, following Chaer et al. (2023).

2.2.5 Discussion

The results showed that earlier sowing of cover crops, as observed in the ICLS and short-cycle soybean systems, led to improved soil cover quality and, consequently, lower Δ LST values (Figure 7). The findings also indicated that cover crop biomass significantly influences Δ LST, with higher biomass associated with lower Δ LST (Figure 9). This effect can be attributed to the longer growth period of cover crops before the onset of the dry season and subsequent soil moisture depletion, which ultimately leads to plant senescence. As biomass accumulates, the combined effects of surface insulation, increased roughness, and higher albedo (Tahooni et al., 2023; Gu et al., 2007) contribute to reduced soil temperatures (Blanco-Canqui and Ruis, 2020).

The amount of biomass produced by cover crops depends not only on the length of the growing season and rainfall, but also on factors such as seeding rate, fertilization, tillage practices, and species composition (Ruis et al., 2019). In this context, the use of cover crop mixtures allows the inclusion of species better adapted to local climate conditions and with complementary functional roles, thereby increasing biodiversity.

The adoption of NT management combined with short-cycle soybean cultivars (< 115 days) enables the establishment of a second crop or a diversified cover crop mixture before the end of the rainy season, thereby increasing diversity and biomass production. Soybean cultivars with different maturity cycles are staggered to reduce yield loss risks associated with climatic variability, such as drought during the grain-filling period. However, late-maturing soybean cultivars followed by second crops or cover crops sown at the end of the rainy season may be more susceptible to yield losses under erratic rainfall conditions (Mendes et al., 2018). Therefore, research aimed at improving soil cover quality in regions with pronounced dry seasons should also focus on the breeding and management of robust, drought-tolerant cover crop species/varieties capable of producing substantial biomass within a short time frame. The inclusion of perennial components, such as grasses (*Brachiaria* and related species of the *Urochloa* genus), and their integration with livestock following maize harvest in ICLS, has been shown to enhance drought tolerance and promote high biomass production (Mendes et al., 2018; Souza et al., 2024).

Proper livestock management within ICLS is crucial to maximize biomass production, nutrient cycling, and SOM accumulation. Muniz et al. (2021) demonstrated a significant effect of cropping system on biomass production at the time of soybean sowing in an ICLS, reporting values of 4.9 tons ha⁻¹ for *B. brizantha*, 4.3 tons ha⁻¹ for *Panicum maximum* cv. Tamani, and 3.4 tons ha⁻¹ for maize grown in succession to soybean. Accordingly, the adoption of cover crop mixtures, short-cycle cultivars, and ICLS aims to maximize biomass production and improve soil cover quality.

Satellite-based observations of land surface temperature (LST) have become an important tool for assessing climate variability and land surface overheating, particularly in urban environments (Onačillová et al., 2022). They are also valuable in agricultural landscapes, where they can be used to estimate soil cover quality during the dry season (Figure 8). LST data have supported environmental planning and the development of sustainable rural-based economy zones (Abu Haider et al., 2021).

According to Heinemann et al. (2020), the use of Δ LST enables the assessment of temperature variability across spatial units, facilitating the identification of hotspots and their potential drivers. Surfaces with high land surface emissivity, such as bare soil, exposed rocks, and sealed areas (e.g., urban heat islands), typically exhibit diurnal temperature amplitudes (Heinemann et al., 2020). In contrast, vegetated surfaces or areas where cover crop residues are maintained generally show reduced temperature variability (Suti et al., 2021). The use of native vegetation fragments as reference areas for LST normalization (Figure 8) reduces sensitivity to interannual climatic variability and differences in biomass production. A potential limitation of the Δ LST approach is the availability of suitable reference areas with native vegetation. While regulations in some countries, such as Brazil, require farms to maintain a proportion of undisturbed land, comparable reference areas may be absent in other regions, particularly in semi-arid landscapes. In such cases, it becomes necessary to define the maximum acceptable distance between productive areas and reference vegetation to ensure reliable Δ LST estimates. In regions with a well-defined dry season or frequent heat waves, soil cover quality emerges as a key factor influencing soil biological activity, which is closely linked to enzyme-mediated processes.

Δ LST had a significant effect on β -glucosidase and arylsulfatase activities (Figure 10), corroborating the findings of Passinato et al. (2021). Those authors showed a negative relationship between mean annual air temperature and the activities of β -glucosidase and arylsulfatase, based on a principal component analysis (PCA) that integrated soil attributes, altitude, climate variables, and crop yield across 54 conservation agriculture field sites. Each enzyme has an optimum temperature range, and temperatures exceeding this threshold can lead to enzyme denaturation and reduced activity (Wang et al., 2022). Cover crop cultivation during the dry season can also prevent or reduce direct solar radiation reaching the soil surface. Plant residues, cover crops, and green manures promote soil thermal regulation, moisture conservation, and increases in soil organic carbon (Franchini et al., 2023; Blanco-Canqui & Ruis, 2018). Additionally, appropriate cover crop management can improve soil aggregation, enhance water infiltration, reduce long-term compaction risks, and strengthen nutrient cycling and soil temperature regulation (Ruis et al., 2019; Ruis et al., 2020; Blanco-Canqui and Ruis, 2020; e Silva et al., 2023).

Microbial-driven SOM decomposition is regulated by both the quantity and quality of SOM components, which are influenced by temperature. In addition, low soil

water content under high temperatures is expected to reduce extracellular enzyme activity due to desiccation and a limited supply of plant-derived substrates (Hou et al., 2016). Reduced plant residue inputs caused by drought stress during the growing season may further decrease enzyme activity. Changes in residue availability can, in turn, affect soil microbial community composition and associated enzyme activities (de Carvalho et al., 2024).

Both β -glucosidase and arylsulfatase are closely linked to SOM dynamics. Soil sulfatases are primarily of microbial origin, and since carbon substrates largely regulate microbial growth in soil, carbon availability is a key controlling factor. β -glucosidase is an extracellular hydrolytic enzyme involved in the degradation of cellulose, one of the most abundant carbon polymers in soils (Cregut et al., 2009; Wallenstein and Burns, 2011). Analysis of the relationship between SOM and enzymes activities revealed a significant effect of SOM on β -glucosidase activity. Microbial decomposition of SOM depends on enzyme-mediated processes, including those driven by β -glucosidase, acid phosphatase, and arylsulfatase (de Camargo et al., 2024). Many enzymes involved in SOM turnover belong to the hydrolase class and play a central role in the cycling of soil carbon (C), nitrogen (N), phosphorus (P) and sulfur (S) (Piotrowska-Długosz et al., 2023). Consequently, SOM is one of the main factors affecting β -glucosidase (Štursová et al., 2011) and arylsulfatase activities (Mendes et al., 2021). β -glucosidase is considered a sensitive indicator of changes in soil and residue management, often indicating shifts in SOC before they are evident in total organic carbon measurements. This enzyme plays a key role in plant residue decomposition and in supplying readily available carbon substrates as simple sugars to soil microbial communities (Stott et al., 2010).

SOM quantity and quality, along with C and N inputs, are, therefore, central controls on soil microbial biomass and activity. Organic amendments such as manure, cover crops, and composted materials can stimulate microbial biomass by increasing labile organic matter pools. However, further research is needed to clarify how SOM quantity and composition, as well as nutrient inputs, regulate microbial community structure, enzyme activities, and the subsequent transformations of C, N, P, and S (Bowles et al., 2014). In this study, activities of arylsulfatase and β -glucosidase were positively associated with soil organic carbon, reinforcing the close coupling between soil thermal conditions, organic matter dynamics, and enzyme-mediated processes (Supplementary Information A).

No significant relationships between soybean yield and β -glucosidase or arylsulfatase were observed. Similar results were reported by Serafim et al. (2023), who found no significant relationship between enzyme activity and yield in samples collected at the end of the soybean cycle from a highly productive area under long-term NT, with yields ranging from 3.4 Mg ha⁻¹ to 5.0 Mg ha⁻¹. In contrast, studies conducted across areas with a wider range of grain yields and SOC contents have reported significant positive relationships between increased soil enzymatic activity and soybean yield (Lopes et al., 2013; Lopes et al., 2018; Passinato et al. 2021). In the present study, the absence of significant relationships between soil enzyme activities and soybean yield is likely a consequence of the uniformly high yield levels observed across all plots, with a mean soybean yield of 3.7 Mg ha⁻¹ over nine years. In addition, the relationship between enzyme activity and yield may be affected not only by soil health attributes but also by soybean cultivar characteristics, including growth cycle length, regional adaptation, and climatic conditions, particularly precipitation. Further research across different regions and management systems, with a focus on soil cover quality, is needed to build a more comprehensive database that may enable deeper exploration of the relationships among management practices, Δ LST, and soil enzyme activity. Gaps also remain concerning soil compaction, organic matter dynamics, water infiltration, and soil aggregate stability, especially when accounting for cost, accessibility, and scalability constraints. Further research is needed to investigate the parameters used in this study across similar and contrasting contexts.

The significant effect of cropping systems on arylsulfatase activity (Figure 11) suggests that soil cover quality influences microbial metabolic processes and, consequently, enzyme activity. Soil enzyme activities integrate the legacy of past management as well as current strategies aimed at maintaining soil cover during the dry season. As noted by Stott et al. (2010), enzyme activity reflects long-term fluctuations in microbial biomass rather than instantaneous population sizes. Balota et al. (2004) reported higher arylsulfatase activity under NT compared with conventional tillage and a decline in activity with increasing soil depth. Similarly, Nogueira & Melo (2003) associated reductions in arylsulfatase activity with lower SOM content along the soil profile, hypothesizing that SOM constitutes the main reservoir of sulfate esters, which serves as substrates for the enzyme.

Different crops and soil management practices, including crop rotation, fertilization, and tillage, can determine soil enzyme activity (Yu et al., 2023). Hok et al. (2018) observed that both arylsulfatase and β -glucosidase respond to changes in soil management and are closely linked to soil carbon dynamics. Higher activities of arylsulfatase and β -glucosidase have been reported under ICLS compared with NT systems, particularly during the cropping cycle, highlighting the positive contribution of perennial grass components in integrated systems (Barbosa et al., 2023). In addition, high residue biomass in NT systems can increase microbial biomass carbon and nitrogen, thereby enhancing β -glucosidase activity (Carlos et al., 2021). In the present study, no significant effect of system management on β -glucosidase activity was detected.

The interactions among soil microorganisms, extracellular enzymes, and SOM are shaped by agricultural management practices. In this context, LST data derived from freely available satellite imagery provide valuable insights into land use dynamics and soil cover quality over large spatial scales. Variations in LST (Δ LST) across cropping systems have the potential to monitor soil cover conditions, identify critical areas, and complement soil enzyme analyses, which are often more sensitive to management-induced changes than SOM measurements alone. Integrating soil enzyme activity data with LST information can support soil quality monitoring, evaluation of management practices, and decision-making aimed at achieving high productivity while conserving soil natural resources. Moreover, this integrated approach provides complementary information to physical and chemical indicators for assessing soil quality in complex agroecosystems.

2.2.6 Conclusion

This on-farm study confirms and quantifies the influence of crop management practices on land surface temperature differentials (Δ LST). Early establishment of cover crops, use of short-cycle soybean cultivars, and production systems such as Integrated Crop-Livestock Systems (ICLS) contribute to lower Δ LST, which is particularly relevant in tropical regions with a well-defined dry season.

The study also demonstrates that enhanced biomass production from cover crops is linked to reduced Δ LST, which, in turn, is associated with increased activity of arylsulfatase and β -glucosidase enzymes – well-proven indicators of soil health.

Overall, these findings highlight the central role of cropping system management, especially the use of cover crops, in regulating LST in tropical dry-season environments. Integrating Δ LST data with soil enzyme activity measurements offers a complementary approach for monitoring soil quality and supporting the optimization of agricultural management practices.

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3 FINAL REMARKS

Sustainability assessment is a complex and dynamic field that can support the active role of farmers in rural development. One of the central contributions of the ISA tool is its ability to communicate environmental, social, and economic performance through 17 indicators comprising 100 parameters, while reconciling analytical depth with time and cost effectiveness. The application of the ISA tool in five programs across different regions of Brazil, involving 3,296 farms, revealed a low mean Final Index, mainly attributed to low soil fertility, suboptimal management practices, and insufficient soil, water, and biodiversity conservation measures. Assessment results varied among programs and regions. Correlation patterns also varied across contexts, demonstrating the sensitivity of the ISA tool's parameters and highlighting context-dependent dynamics.

The responsiveness of indicators to technical assistance also varied over time. Environmental indicators linked to conservation practices along with waste management often showed slower progress. Strengthening business organization and other managerial aspects, supported by technical assistance, represents an important step toward improving farm efficiency. However, the adoption of conservation practices and the incorporation of the environmental dimension into strategic planning and risk management remain significant challenges. Regions with low technological development and limited natural resources may also require more time and different technical support strategies to improve sustainability outcomes.

Integrating indicators into the daily management of production systems requires attention to the field scale. Soil is considered a foundational component of the system; its regeneration depends on maintaining the interdependence and balance among biological, physical, and chemical attributes that ensure soil quality and ecological functionality, thereby sustaining productive potential over time. Soil quality monitoring parameters at this scale were incorporated into the ISA tool, recognizing the uniqueness of each field site.

The soil quality index enables the assessment of impacts and performance related to soil parameters, production costs, nutrient balance, and productivity. This approach represents an effective strategy for transitioning toward more sustainable production models, facilitating the scaling up of management changes and enabling

comparisons across technologies, management strategies, inputs, and conservation practices. Monitoring these attributes can support farmers, technicians, and policymakers in addressing the challenge of incorporating the environmental dimension into strategic planning. Assessing soil quality through chemical, physical, and biological attributes is highly complex. The challenge lies in identifying and developing accessible, replicable, and sensitive metrics and indicators that enable scalability while maintaining a solid scientific basis.

Land surface temperature (LST) and soil enzyme activity are examples of parameters applicable across different production systems. Results indicate that soil cover quality influences soil enzyme activity. For the first time in this context, Δ LST – defined as the difference in land surface temperature between cropping areas and natural vegetation – was used to analyze correlations with soil enzyme activity.

The introduction of cover crops following short-cycle crops and the implementation of Integrated Crop-Livestock Systems contributed to lower Δ LST – a crucial factor in tropical regions with a well-defined dry season. Furthermore, greater biomass production from cover crops was associated with reduced Δ LST, which, in turn, correlated with higher arylsulfatase and β -glucosidase enzyme activities – recognized indicators of soil health. These findings highlight the critical role of cover crops in regulating land surface temperature in tropical environments. Δ LST analysis – an easily accessible remote sensing product – can be integrated into the ISA tool framework to identify critical areas regarding soil cover quality, a key principle of conservation agriculture, while complementing soil biological analyses. Nevertheless, important gaps remain in soil quality assessment – particularly regarding compaction, organic matter dynamics, water infiltration, and aggregate stability - especially under constraints related to cost, accessibility, and scalability. Further research is needed to investigate the parameters used in this study across similar and contrasting contexts.

Metrics for assessing environmental and socioeconomic performance can also support the development of incentive policies – such as reduced rural insurance premiums and differentiated credit lines – aimed at promoting conservation practices. Agroecosystems are open and dynamic systems that require ongoing monitoring and adjustments. Regeneration is a continuous and cyclical process of improvement and adaptation.

Based on the analysis presented in this thesis, the challenge of improving environmental, social, and economic performance becomes evident. The use of

metrics to evaluate the effectiveness of new production systems and technologies is essential for transforming production models and supporting farmers, technicians, and policymakers. Relevant, accurate, and up-to-date information also plays a central role in inspiring new strategies and objectives. The soil quality index enables comparison across technologies and management approaches, and the data generated by the ISA tool can inform and support incentive policies for the adoption of conservation practices and the advancement of the sustainable development agenda.

4 SUPPLEMENTARY INFORMATION

Table S1. Summary of the definitions of the 21 Sustainability Indicators, including their parameters, weighting factors, and measurement units.

Indicator	General definition	Parameters	Weighting factor	Measurement units
1 Productivity and Sales Price	Assesses annual gross income and compare average productivity and market price with regional or local benchmarks.	1. Average productivity. 2. Average selling price.	1. (1) 2. (1)	1. Kg/ha, Ton./ha, L/ha/year, Kg/ha/year. 2. \$/unit
2 Income Diversity	Assign different weights based on income source (on-farm or off-farm) and income type. Also evaluate the economic specialization rate.	1. On-farm activities. 2. Off-farm activities. 3. Pension, retirement, financial aid, or other sources.	1. (2) 2. (1) 3. (0.3)	\$
3 Asset Development and Current Indebtedness	Evaluate farm asset value and analyze growth or decline over a defined period. Compare total indebtedness with estimated farm asset value.	1. Land value. 2. Buildings. 3. Equipment. 4. Animal/Grain stocks. 5. Increase in Agriculture / Irrigation area. 6. Total indebtedness in relation to total farm asset value.	1. (0.7) 2. (1) 3. (1) 4. (1) 5. (1) 6. (1)	1 – 5. Evolution (%). 6. (%)
4 Access to Public Services	Verify access to basic services. Verify also the production of own staple food (only for smallholder farmers).	1. Water. 2. Electricity. 3. Roads. 4. Healthcare. 5. School transportation. 6. Security. 7. Internet. 8. Public waste collection. 9. Vegetables, grains, tubers. 10. Orchard. 11. Milk, eggs, meat.	1. (1) 2. (1) 3. (1) 4. (1) 5. (1) 6. (1) 7. (1) 8. (1) 9. (1) 10. (1) 11. (1)	(1) satisfactory; (0.5) partial; (0) absent.
5 Access to Education and Training Courses	Assess the educational status of the farmer, family, and permanent workers, and participation in short-/medium-term courses.	1. Fewer than nine years of schooling. 2. Primary school. 3. Secondary school. 4. College/University. 5. Short-term courses. 6. Long-term courses.	1. (0.7) 2. (1) 3. (1.2) 4. (1.5) 5. (0.5) 6. (0.8)	Number of people.
6 Employment Quality	Verify compliance with labor laws (70% of final result) and adherence to recommended labor standards for permanent	1. Employee registration. 2. Overtime payment. 3. Above minimum wage.	1. (1) 2. (1) 3. (1) 4. (1) 5. (1) 6. (1)	Number of workers.

	and temporary employees (30%).	4. Food supplementation. 5. Housing assistance. 6. Education assistance. 7. Profit sharing. 8. Accident insurance. 9. Leisure access. 10. Space for food production.	7. (5) 8. (3) 9. (1) 10. (3)	
7 Business Management	Assess the use of cash-flow, production cost records, financial credit, technical assistance, participation in organizations, and compliance with environmental regulations.	1. Cash flow. 2. Production costs. 3. Technical assistance. 4. Participation in Associations. 5. Environmental compliance. 6. Investment credit. 7. Production credit. 8. Commercialization credit.	1. (1) 2. (1) 3. (1) 4. (1) 5. (2) 6. (0.4) 7. (0.4) 8. (0.2)	(1) satisfactory; (0.5) partial; (0) absent.
8 Commercialization Strategies and Innovation	Verify if the farmer seeks market information, accesses value-added or institutional markets, and adopts innovative/environmentally sound techniques.	1. Market information. 2. Certified products. 3. Adoption of innovative techniques. 4. Capacity to innovate.	1. (0.4) 2. (0.4) 3. (0.3) 4. (0.4)	Yes/No (1 or 0).
9 Waste and Residues Management	Evaluate sewage and farm waste disposal, including management or reuse of organic waste and treatment of liquid/gaseous effluents.	1. Sewage disposal. 2. Garbage disposal. 3. Organic solid residues. 4. Liquid effluents. 5. Gaseous effluents.	1. (1) 2. (1) 3. (1) 4. (1) 5. (1)	1. Sewage collector, biodigester tank. 2. Garbage collected, buried or burned. 3. Composting/reuse of organic residues (%). 4 and 5. Adequate treatments of effluents (%).
10 Soil Fertility	Evaluate soil fertility and biological activity (enzymes arylsulfatase and β -glucosidase).	1. Organic matter. 2. Phosphorus. 3. Base Saturation. 4. Arylsulfatase activity (optional) 5. β -glucosidase activity (optional).	1. (1) 2. (1) 3. (1) 4. (1) 5. (1)	1. dag kg ⁻¹ . 2. mg dm ⁻³ , Mehlich ⁻¹ . 3. (%) 4 - 5. mg p-nitrophenol kg ⁻¹ h ⁻¹ .
11 Soil Erosion Processes, Road Maintenance and Conservation	Estimate the extent, intensity, and trend of erosion process. Evaluate drainage structures, runoff systems, and on-farm road condition/maintenance.	1. Area (% of total area). 2. Degradation stage. 3. Erosion trend. 4. Road slope. 5. Runoff structures. 6. Potholes. 7. Erosion grooves.	1. (0.5) 2. (0.5) 3. (0.2) 4. (1) 5. (1) 6. (1) 7. (1)	1. ha. 2. Initial, intermediary, advanced stages. 3. decreasing, stable, increasing. 4 - 7 (%)
12 Water Quality	Evaluate aquatic ecosystems using a rapid protocol. Optional analyses: pH, nitrate, coliform, turbidity.	1. Type of occupation of riverbanks. 2. Anthropogenic changes. 3. Vegetation shading. 4. Erosion signals next to banks. 5. Water clarity. 6. Water odor.	1. (4) 2. (2) 3. (4) 4. (4) 5. (3) 6. (2) 7. (4) 8. (1) 9. (3) 10. (2)	1. Land use categories. 2. Presence/absence. 3. Absence/partial/total. 4. Absent/moderate/accentuated. 5. Transparent/tea color/opaque. 6. None/sewage/oil. 7. Stones, gravel/mud, sand/cement, channeled.

		7. Characterization of river bottom. 8. Water pH (optional). 9. Thermotolerant Coliform (optional). 10. Total Nitrate (optional). 11. Water turbidity (optional).	11. (4)	8. pH 9. (UFC 100 mL ⁻¹). 10. (mg L ⁻¹ NO ₃). 11. UNT.
13 Water Contamination Risk and Pesticide Management	Assess risk of water contamination by pesticides, considering pesticide properties (mobility, persistence, toxicity) and field vulnerability (soil clay content, distance to water course, management). Assess compliance with legal requirements for protective measures, storage, and proper disposal of pesticide/veterinary packaging.	Toxicity Index (1. Fish Lethal Concentration LC50, 2. Acceptable Daily Intake - ADI). Leaching Index (3. Soil Adsorption Coefficient K _{oc} , 4. Degradation half-life (Disappearance Time - DT _{1/2}). Field vulnerability (5. Clay %; 6. Distance to water; 7. Soil management). 8. Personal protective equipment. 9. Proper storage. 10. Package return.	1. (1) 2. (1) 3. (1) 4. (1) 5. (1) 6. (1) 7. (1) 8. (1) 9. (1) 10. (1)	1. 96h LC50 mg l ⁻¹ . 2. mg kg ⁻¹ day ⁻¹ . 3. 1/ log ₁₀ (K _{oc}) - mL g ⁻¹ . 4. log ₁₀ (T _{1/2}) - days. 5. % clay. 6. Distance (m). 7. No-till, plowed soil. 8. Number of people. 9. Yes/No (1 or 0). 10. Yes/No (1 or 0).
14 Soil and Water Conservation Practices	Evaluate adoption of soil conservation practices and adequacy of water conservation.	1. Soil conservation practices. 2. Water storage and conservation practices.	1. (2) 2. (1)	1. High, moderate, incipient, critical situation. 2. Sufficient, insufficient, critical situation.
15 Biodiversity Conservation Practices	Evaluate adoption of practices to promote biodiversity. Farm-scale diversity is also measured by Shannon-Weaver index.	1. Biodiversity conservation practices. 2. Farm diversity index. 3. Proportion (over 70%) of monocultures bordering the farm.	1. (0.6) 2. (0.4) 3. (0.1)	1. High, moderate, incipient, critical situation. 2. Shannon-Weaver Index. 3. Yes/No (1 or 0).
16 Natural Habitats: Physiognomy and Status	Assess conservation status of natural habitats (successional stage), number of fragments, and protection from grazing and/or fire.	1. Native vegetation area. 2. Successional stage. 3. Number of fragments. 4. Connectivity. 5. Protection from grazing/fire.	1. (1) 2. (1) 3. (1) 4. (1) 5. (1)	1. % total area. 2. Early, middle, advanced stage. 3. Fragment index. 4 and 5. Yes/No (1 or 0).
17 Preservation Areas (PA) status and Conservation Reserve Areas (CRA) status	Assess land use/occupation and conservation status of PA surrounding springs and water bodies. Determine whether remaining native vegetation meets CRA requirements.	1. % of PA protected/preserved. 2. CRA area requiring restoration.	1. (1) 2. (1)	1. (%) 2. hectares

1 PRODUCTIVITY AND SALES PRICES					
1.1 Estimated gross annual income on the farm (descending order)					
	Choose an option	Annual estimated value (\$)			
Activity 1 (higher income)	Bovine milk	\$77.385,16	64,6%		
Activity 2	Livestock	\$19.434,63	16,2%		
Others activities	Others	\$3.533,57	2,9%		
*Agricultural, livestock and/or forestry activities carried out at the farm					
1.2 Productivity of the main activities					
	Activity 1	Activity 2	Activity 3		
Activities (select)	Bovine milk			Weighting factor	
Units of measurement (select)	L of milk/ha/year			> 20%	0,9
Current mean productivity	11.500,0			Production or sale price = local	0,7
Mean selling price (\$/un.)	\$0,39			< 20%	0,5
Mean local productivity	5.000,0			< 40%	0,3
Mean local price (\$/un.)	\$0,38				
Result	0,86	Reference: Depontti (2002); Mattos Filho (2004); Lopez e Ridaura (2001).			

Fig. S1. Example of Indicator 1 applied on a dairy farm in 2021

SQI **0.76**

Soil Fertility

Soil Organic Matter (SOM) (dag kg ⁻¹)	3.6
Phosphorus (mg dm ⁻³)	15.7
Calcium (cmolc dm ⁻³)	4.0
Magnesium (cmolc dm ⁻³)	2.1
Potassium (mg dm ⁻³)	291.7
pH	5.9
Aluminium (cmolc dm ⁻³)	0.0
Cation Exchange Cap. (CEC) (cmolc dm ⁻³)	8.7
Base Saturation (%)	78.7
K/CTC (%) (reference 3 - 5%)	8.6
Ca/CTC (%) (reference 40 - 60%)	46.0
Mg/CTC (%) (reference 15 - 20%)	24.1

Nutrients (Input)

N (Kg/ha)	10.0
P (Kg/ha)	75.0
K (Kg/ha)	30.0

Yield (Plot)

Main agricultural activity	Soybeans
Unit	Kg/ha
Yield / productivity	5,040

Economic analysis (Plot)

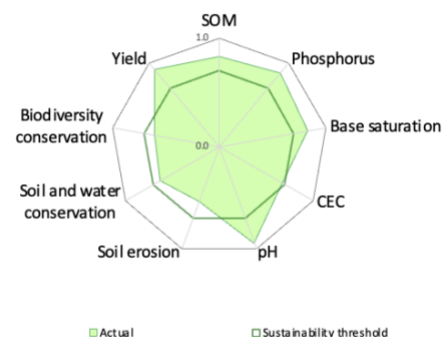
Total Inputs (\$/ha)	\$486
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Foliar analysis

P (g/kg)	2.3	Low
K (g/kg)	16.1	Adequate
N (g/kg)	28.0	Low
S (g/kg)	2.1	Low
Ca (g/kg)	15.3	High
Mg (g/kg)	5.2	High
B (mg/kg)	45.4	Adequate
Zn (mg/kg)	65.1	Adequate
Fe (mg/kg)	952.0	High
Mn (mg/kg)	96.0	Adequate
Cu (mg/kg)	12.4	High

Plot description Plot 8
Data 20/3/25
Area 112.0

SQI



Soil erosion (Plot)

Area	7.0
Degradation stage	Initial
Degradation process trend	Reduction

Soil cover quality / pesticides

Number of species Cover Crops	4
Pesticides (L/ha)	7.8

Soil Biology

Arylsulfatase (mg p-nitrophenol kg ⁻¹ h ⁻¹)	106
β-glucosidase (mg p-nitrophenol kg ⁻¹ h ⁻¹)	103
Biological soil quality index	0.77

Soil Quality (Plot)

	Plot 8
SOM	0.83
Phosphorus	0.88
Base saturation	0.83
CEC	0.67
pH	0.95
Soil erosion	0.54
Soil and water conservation	0.63
Biodiversity conservation	0.60
Yield	0.92
Biological soil quality index	0.77
Soil Quality Index	0.76

Fig. S2. Soil Quality Index (SQI) report containing soil fertility parameters, nutrient inputs (nitrogen, phosphorus, and potassium), yield, production costs, SQI parameters, cover crops diversity (number of species), annual pesticide use per hectare, erosion processes, and soil biology analysis.



Fig. S3. Relative frequency (%) of indicators and Final Index for 3,296 farms. *Farms without soil fertility analysis (71% of the total) were excluded from this assessment of soil fertility levels (I10), as the absence of analysis results in a value of zero.

Table S2. Mean values of parameters for the 25% of farms with the lowest and highest ISA Final Index.

Parameters	824 Farms (Lowest ISA)	824 Farms (Highest ISA)
Farmer age (years)	52	51
Farm area (ha)	40	81
Access to land (Owner)	67%	77%
Land use and cover - pasture	70%	56%
Land use and cover - native vegetation	21%	25%
Income composition - pension	15%	6%
Income composition – activities outside farm	16%	12%
Income composition – activities on the farm	69%	82%
Gross Income (\$/ha/year)	\$ 548	\$ 1,538
Regular accesses to school transportation	59%	88%
Education level (College/University)	7%	22%
Farmers participation in short-term courses	14%	36%
Access to technical assistance	31%	70%
Farmer participation on rural association	26%	59%
Analysis of production costs	10%	60%
Adoption of innovative techniques	13%	67%
Composting and reuse of organic solid waste	15%	54%
Pesticide operation	68%	73%
Personal protective equipment - pesticides	20%	75%
Soil Organic Matter (dag kg ⁻¹)*	2.1	2.1
Base Saturation*	31%	46%
CEC (cmolc dm ⁻³)*	4.1	5.3
Advanced erosion processes	7%	2%
Intermediate erosion processes	32%	10%
Initial erosion processes	44%	34%
Problems with water quality	23%	14%
Critical situation - water conservation	6%	0.6%
Critical situation - soil conservation	7%	0.3%
Critical situation - road conservation	28%	11%
Critical situation - biodiversity conservation	7%	0.6%
Final Index	0.41	0.66

* Results considering the farms with soil analysis (46% of the farms with the highest ISA Final Index didn't have soil analysis; 86% of the farms with the lowest Final Index didn't have soil analysis).

	SENAR FIP 1,978	SENAR ES 992	EMATER 134	RENOVA 114	FAU 78	Max/Min Variation
SUSTAINABILITY INDEX	0.52	0.54	0.64	0.48	0.69	0.21
9. Waste Residues Management	0.31	0.43	0.43	0.26	0.73	0.48
7. Business Management	0.41	0.44	0.67	0.23	0.61	0.44
14. Soil and Water Conservation	0.57	0.61	0.68	0.28	0.71	0.43
8. Commercialization and Innovation	0.45	0.48	0.81	0.39	0.61	0.42
10. Soil Fertility	0.06	0.24	0.44	0.42		0.38
4. Public Services	0.62	0.67	0.74	0.48	0.81	0.33
13. Water Contamination Risk by Pesticides	0.61	0.42	0.58	0.72	0.61	0.31
15. Biodiversity Conservation	0.51	0.54	0.57	0.39	0.70	0.31
12. Water Quality	0.36	0.57	0.66	0.58	0.63	0.30
11. Soil Erosion and Road conservation	0.47	0.51	0.50	0.41	0.67	0.26
17. Preservation and Conservation Reserve Areas	0.59	0.45	0.59	0.46	0.68	0.24
1. Productivity and Sales Prices	0.59	0.67	0.82	0.64	0.72	0.23
16. Natural Habitats	0.63	0.54	0.70	0.63	0.77	0.22
2. Income Diversity	0.63	0.64	0.68	0.47	0.62	0.21
3. Asset Development and Indebtedness	0.71	0.72	0.64	0.56	0.66	0.16
6. Employment Quality	0.64	0.57	0.56	0.50	0.66	0.15
5. Education and Courses	0.68	0.78	0.72	0.68	0.79	0.11

Fig. S4. Average profile and indicator performance of farms across the different programs analyzed (n = 3,296). The FAU program did not use the soil analysis interpretation due to differences in soil classes and interpretation methods

	500 BA	72 GO	155 MA	988 MG	71 MS	29 MT	163 TO	Max/Min Variation
SUSTAINABILITY INDEX	0.46	0.51	0.48	0.56	0.54	0.54	0.50	0.10
12. Water Quality	0.03	0.55	0.02	0.55	0.33	0.62	0.46	0.60
8. Commercialization and Innovation	0.32	0.38	0.50	0.51	0.57	0.53	0.48	0.25
4. Public Services	0.50	0.61	0.58	0.67	0.75	0.69	0.62	0.25
6. Employment Quality	0.67	0.66	0.42	0.67	0.67	0.60	0.62	0.25
14. Soil and Water Conservation	0.51	0.43	0.66	0.63	0.59	0.64	0.42	0.24
9. Waste Residues Management	0.17	0.23	0.38	0.39	0.34	0.15	0.26	0.23
7. Business Management	0.29	0.30	0.42	0.49	0.50	0.41	0.32	0.21
13. Water Contamination Risk by Pesticides	0.63	0.65	0.47	0.62	0.64	0.45	0.59	0.20
17. Preservation and Conservation Reserve Areas	0.54	0.63	0.58	0.62	0.68	0.50	0.54	0.18
3. Asset Development and Indebtedness	0.79	0.62	0.61	0.71	0.67	0.71	0.67	0.17
16. Natural Habitats	0.59	0.58	0.68	0.63	0.59	0.73	0.68	0.15
1. Productivity and Sales Prices	0.62	0.66	0.62	0.59	0.51	0.61	0.53	0.15
5. Education and Courses	0.65	0.69	0.58	0.71	0.68	0.70	0.73	0.15
10. Soil Fertility	0.04	0.12	0.02	0.08	0.06	0.15	0.03	0.13
11. Soil Erosion and Road conservation	0.42	0.37	0.50	0.49	0.50	0.40	0.46	0.13
2. Income Diversity	0.63	0.67	0.65	0.64	0.66	0.68	0.56	0.12
15. Biodiversity Conservation	0.47	0.48	0.56	0.53	0.49	0.52	0.46	0.10

Fig. S5. Average profile and indicator performance of farms across the different Brazilian states analyzed (n = 1,978).

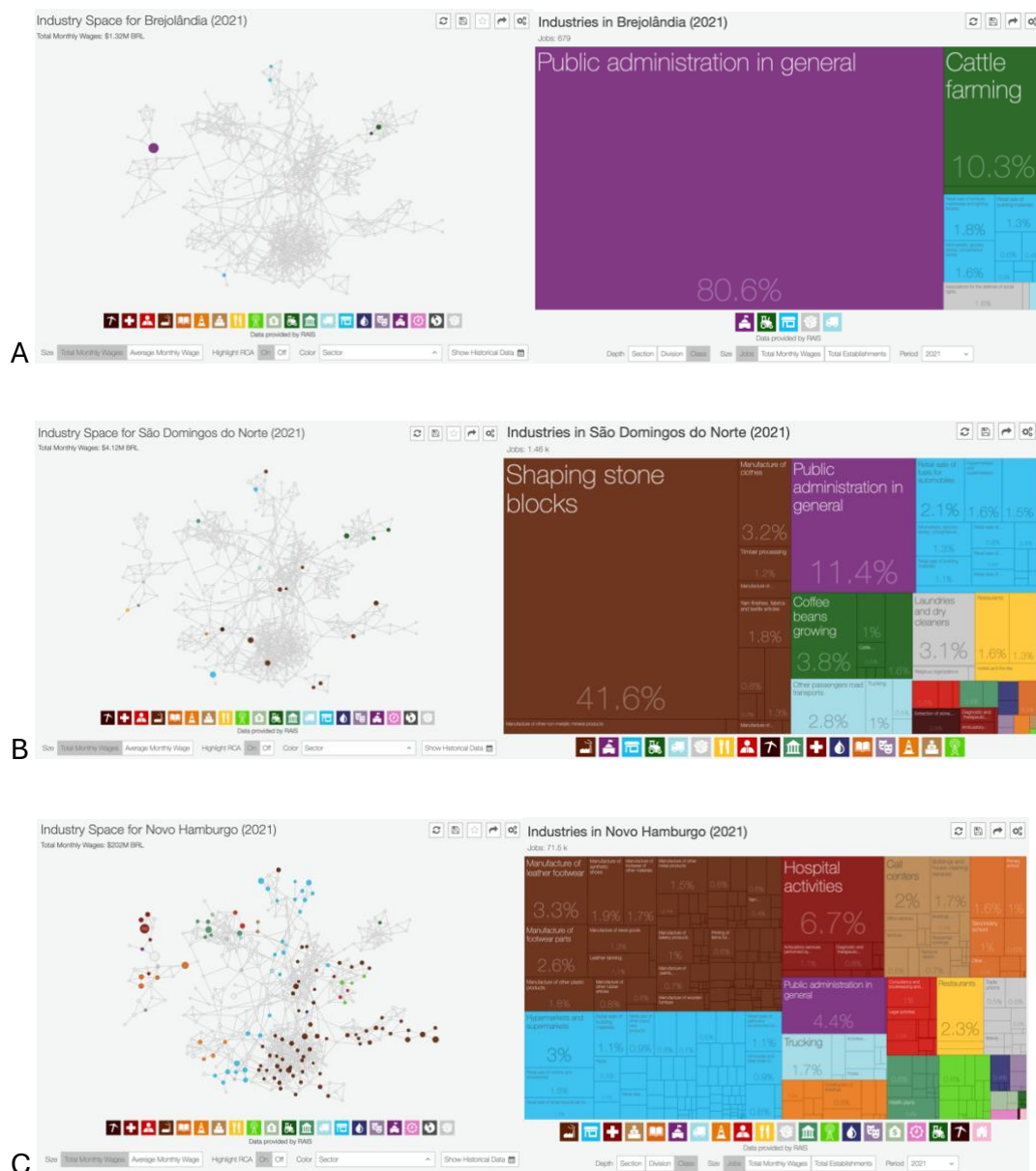
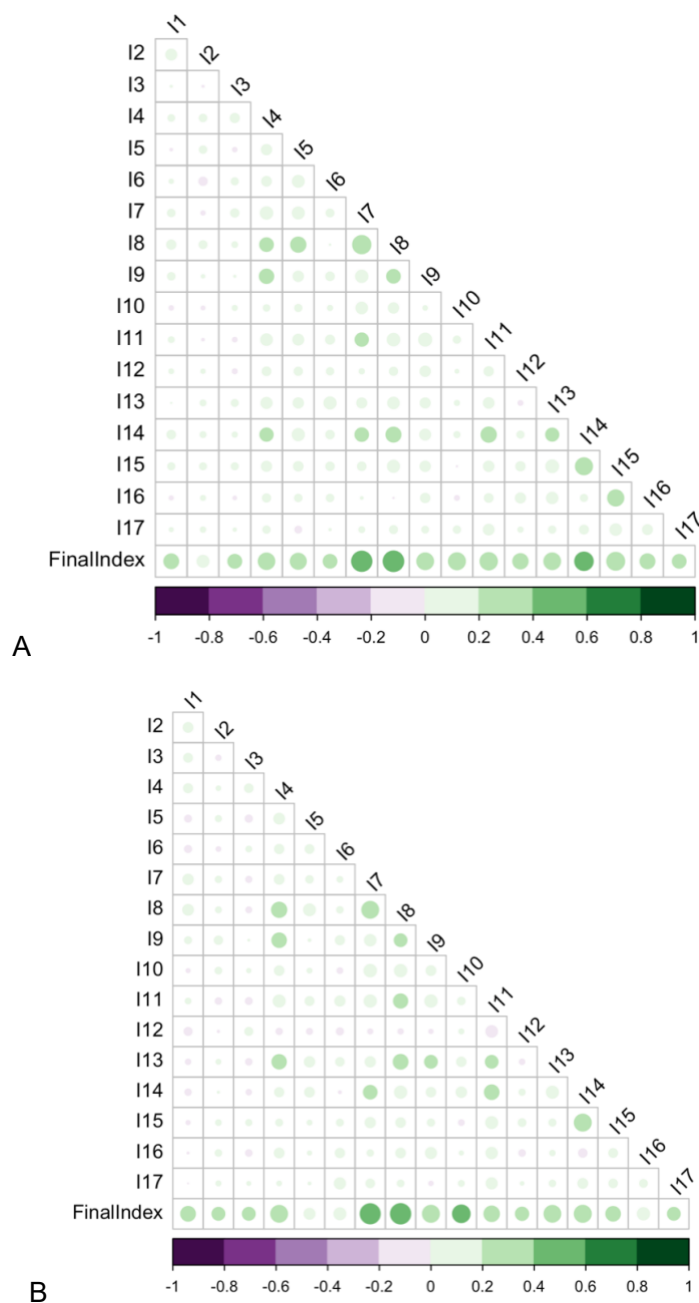


Fig. S6. Economic complexity and formal jobs generated by economic classification are presented for: (A) the municipality of Brejolândia (10.6 thousand inhabitants) in the state of Bahia (FIP program); (B) São Domingos do Norte (8.07 thousand inhabitants) in the state of Espírito Santo (SENAR/ES program); and (C) Novo Hamburgo (239 thousand inhabitants) in the state of Rio Grande do Sul (FAU Program). Jobs generated by the local government are highlighted in purple (Source: <https://www.dataviva.info/>).

	Current	Historical I		Current	Historical I
SUSTAINABILITY INDEX	0.56	0.52	SUSTAINABILITY INDEX	0.59	0.53
5. Education and Courses	0.73	0.70	5. Education and Courses	0.76	0.73
3. Asset Development and Indebtedness	0.71	0.72	3. Asset Development and Indebtedness	0.74	0.76
2. Income Diversity	0.65	0.64	4. Public Services	0.67	0.63
1. Productivity and Sales Prices	0.65	0.60	1. Productivity and Sales Prices	0.66	0.58
4. Public Services	0.64	0.61	7. Business Management	0.65	0.44
6. Employment Quality	0.63	0.62	2. Income Diversity	0.65	0.63
16. Natural Habitats Status	0.63	0.60	6. Employment Quality	0.63	0.60
14. Soil and Water Conservation	0.62	0.57	16. Natural Habitats	0.62	0.59
13. Water Contamination Risk by Pesticides	0.60	0.58	14. Soil and Water Conservation	0.60	0.54
7. Business Management	0.57	0.40	8. Commercialization and Innovation	0.59	0.48
17. Preservation Areas	0.56	0.55	12. Water Quality	0.57	0.49
8. Commercialization and Innovation	0.56	0.45	13. Water contamination risk by Pesticides	0.56	0.53
15. Biodiversity Conservation	0.53	0.51	15. Biodiversity Conservation	0.53	0.50
11. Soil Erosion and Road Maintenance	0.48	0.47	17. Preservation Areas	0.52	0.51
12. Water Quality	0.44	0.41	11. Soil Erosion and Road conservation	0.51	0.49
9. Waste Residues Management	0.36	0.32	9. Waste Residues Management	0.43	0.39
10. Soil Fertility	0.21	0.08	10. Soil Fertility	0.27	0.12
Standard Deviation	0.12	0.14	Standard Deviation	0.10	0.13

	Current	Historical I
SUSTAINABILITY INDEX	0.55	0.48
3. Asset Development and Indebtedness	0.79	0.56
13. Water Contamination Risk by Pesticides	0.75	0.73
5. Education and Courses	0.70	0.68
16. Natural Habitats Status	0.65	0.64
12. Water Quality	0.61	0.58
6. Employment Quality	0.58	0.51
1. Productivity and Sales Prices	0.58	0.64
10. Soil Fertility	0.56	0.42
17. Preservation Areas	0.54	0.46
4. Public Services	0.53	0.48
8. Commercialization and Innovation	0.53	0.38
2. Income Diversity	0.50	0.47
15. Biodiversity Conservation	0.44	0.39
11. Soil Erosion and Road Maintenance	0.43	0.41
9. Waste Residues Management	0.42	0.26
14. Soil and Water Conservation	0.41	0.28
7. Business Management	0.41	0.23
Standard Deviation	0.11	0.13

Fig. S7. Evolution of average index values between the first ISA application (historical - baseline) and the second ISA application (current – follow-up) for (A) 1,192 farms after one year of technical assistance, (B) 524 farms after two years, and (C) 114 farms after three years of technical assistance in a different context (Renova Program).



I1. Productivity and Sales Price	I7. Business Management	I13. Water Contamination and Pesticide Management
I2. Income Diversity	I8. Commercialization and Innovation	I14. Soil and Water Conservation Practices
I3. Asset Development and Indebtedness	I9. Waste Management	I15. Biodiversity Conservation Practices
I4. Access to Public Services	I10. Soil Fertility	I16. Natural Habitats Status
I5. Education and Training Courses	I11. Soil Erosion and Road Maintenance	I17. Preservation Areas Status
I6. Employment Quality	I12. Water Quality	Final Index

Fig. S8. Correlation matrix showing the relationship between the evolution of indicators and the Final Index across the two ISA applications: A - after one year of technical assistance (N = 1,192 farms); B - after two years of technical assistance (N = 524 farms). The size and color of the circles represent the strength and direction of the correlations, calculated using Spearman's correlation coefficient.

Table S3. Correlations between indicators and the Final Index (Spearman's ρ) for 3,296 farms (first application), 1,192 farms (first and second applications, one year apart), 524 farms (first and second applications, after two years), and 114 farms in the Renova program (first and second applications, after three years).

Data	N° farms	Indicators (Spearman's ρ)					
ISA 1 General	3,296	I7 (0.64)	I8 (0.63)	I14 (0.59)	I15 (0.58)	I9 (0.55)	I4 (0.55)
ISA 1 SENAR	1,192	I8 (0.62)	I4 (0.56)	I14 (0.55)	I9 (0.54)	I7 (0.53)	I15(0.53)
ISA after 1 year	1,192	I8 (0.59)	I4 (0.56)	I9 (0.55)	I14 (0.54)	I15 (0.53)	I7 (0.52)
ISA 1 SENAR	524	I8 (0.63)	I7 (0.59)	I14 (0.52)	I9 (0.51)	I4 (0.50)	
ISA after 2 years	524	I9 (0.55)	I8 (0.54)				
ISA 1 Renova	114	I8 (0.62)	I2 (0.55)				
ISA after 3 years	114	I8 (0.64)					

I1. Productivity and Sales Price	I7. Business Management	I13. Water Contamination and Pesticide Management
I2. Income Diversity	I8. Commercialization and Innovation	I14. Soil and Water Conservation Practices
I3. Asset Development and Indebtedness	I9. Waste Management	I15. Biodiversity Conservation Practices
I4. Access to Public Services	I10. Soil Fertility	I16. Natural Habitats Status
I5. Education and Training Courses	I11. Soil Erosion and Road Maintenance	I17. Preservation Areas Status
I6. Employment Quality	I12. Water Quality	

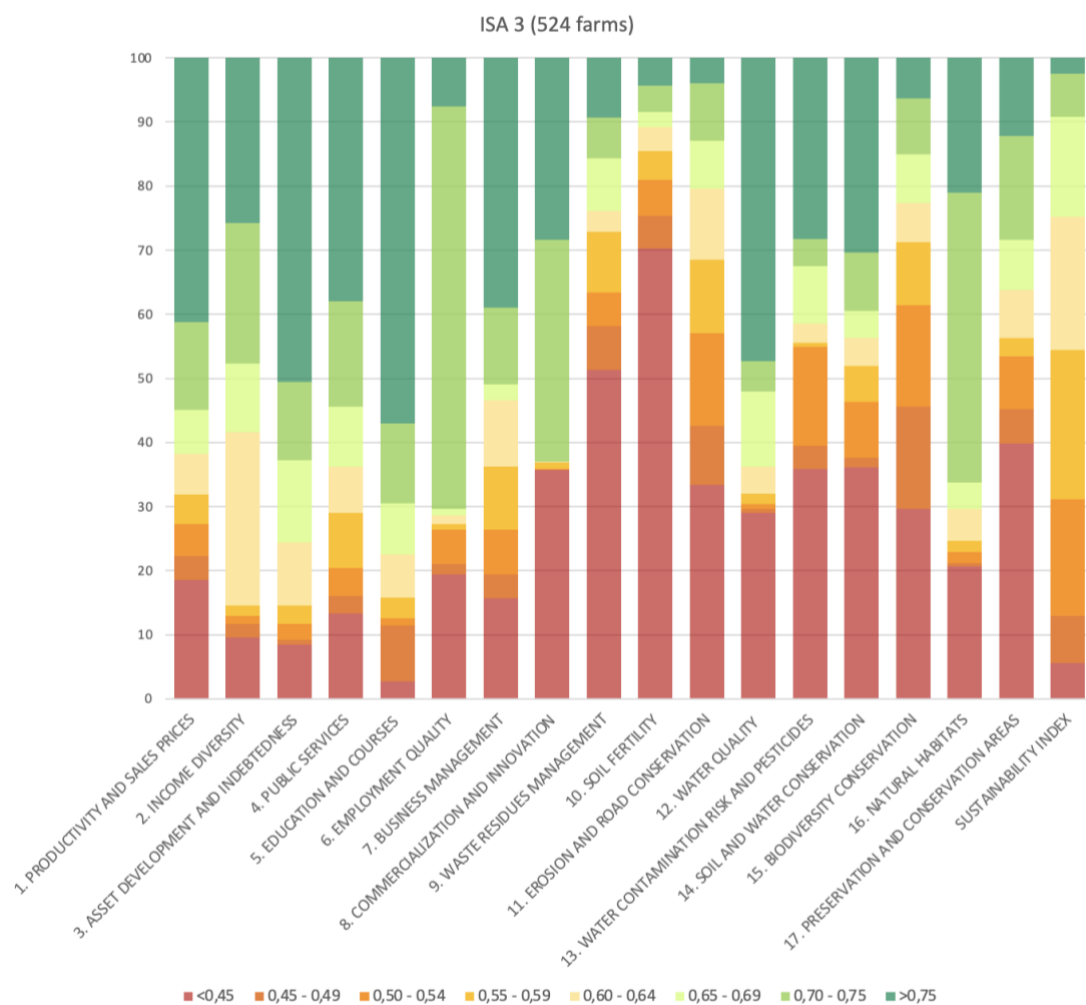


Fig. S9. Relative frequency (%) of indicators and Final Index for 524 farms after two years of technical assistance.

Table S4. Database containing plot identification; year; soybean cycle description (short-cycle and long-cycle) and ICLS; cover crop management, number of species, sowing date and cumulative rainfall during the cover-crop growing season; land surface temperature (LST) and Δ LST (difference between plot temperature and native vegetation temperature); soil organic matter (SOM) at 0-10 and 0-20 cm; soybean yield; arylsulfatase and β -glucosidase activities; and enzyme index. Statistics analysis.

Plot	Year	Crop typology	Cover-crops management	Cover-crops - n° of species	Cover-crops biomass dry matter (ton ha ⁻¹)	Cover-crops sowing (date)	Cumulative rain fall (cover-crops)	Cumulative rain (summer crop oct-may)	LST °C	Δ LST °C	SOM 0-10	SOM 0-20	Soybean yield (kg/ha)	Arylsulfatase (mg p-nitrofenol kg ⁻¹ solo h ⁻¹)	β -glucosidase (mg p-nitrofenol kg ⁻¹ solo h ⁻¹)	Enzymes Index
1	2017	Long C.	No cover	0		No cover		1,297	28.38	5.5		3.7	4,440			
2	2017	Short C.	No-till	2		02/02/17	548	1,348	26.40	3.5		3.8	3,114			
3	2017	Long C.	No cover	0		No cover		1,113	27.58	4.7			3,138			
4	2017	Long C.	No cover	0		No cover		1,092	28.21	5.3			3,528			
5	2017	Long C.	No cover	0		No cover		1,166	28.26	5.3			3,528			
6	2017	Long C.	Overseeding	1		02/22/17	220	1,297	27.98	5.1			3,978			
7	2017	Long C.	Overseeding	1		02/22/17	174	1,139	28.38	5.5		3.2	3,642			
8	2017	Maize	ICLS	1		ICLS	591	1,297	26.74	3.8			9,600(corn)			
9	2017	Long C.	Overseeding	1		02/22/17	209	1,191	28.66	5.7		3.1	3,654			
1	2018	Short C.	No-till	2		02/12/18	355	1,268	28.65	4.9		2.6	3,222			
2	2018	Long C.	No cover	0		No cover		1,232	31.69	7.9		2.0	3,672			
3	2018	Long C.	Overseeding	1		02/28/18	330	1,190	30.46	6.7		2.4	3,792			
4	2018	Long C.	Overseeding	1		02/22/18	359	1,190	30.13	6.4		2.3	3,888			
5	2018	Long C.	Overseeding	1		02/28/18	288	1,153	31.76	8.0		2.2	3,888			
6	2018	Long C.	No cover	0		No cover		1,258	32.74	9.0		2.6	3,600			
7	2018	Long C.	No-till	1		03/28/18	175	1,215	31.76	8.0		2.8	3,132			
8	2018	Long C.	Overseeding	0		03/04/18	68	1,059	31.42	7.7		2.3	3,708			
9	2018	Maize	ICLS	1		ICLS	526	953	28.49	4.7		2.0	5,700(corn)			
1	2019	Long C.	Overseeding	1		03/13/19	342	1,424	35.01	9.0	2.5	3.3	3,762			
2	2019	Long C.	Overseeding	2		03/08/19	324	1,459	34.17	8.2	3.1	2.8	3,414			
3	2019	Short C.	No-till	2		02/22/19	423	1,189	33.10	7.1	3.4	2.7	2,970			
4	2019	Long C.	Overseeding	1		02/12/19	455	1,189	35.31	9.3	2.7	2.5	3,900			
5	2019	Long C.	Overseeding	1		02/12/19	459	1,264	35.30	9.3	2.6	2.9	3,606			
6	2019	Maize	ICLS	1		ICLS	579	1,430	32.55	6.6	2.8	2.6	7,602(corn)			
7	2019	Short C.	No-till	1		02/11/19	445	1,355	33.38	7.4	3.1	3.3	2,580			
8	2019	Long C.	Overseeding	1		02/06/19	566	1,461	33.86	7.9	2.6	2.9	4,182			
9	2019	Long C.	No cover	1		No cover	314	1,400	34.69	8.7	2.7	3.0	3,114			
Plot	Year	Crop typology	Cover-crops management	Cover-crops - n° of species	Cover-crops biomass dry matter (ton ha ⁻¹)	Cover-crops sowing (date)	Cumulative rain fall (cover-crops)	Cumulative rain (summer crop oct-may)	LST °C	Δ LST °C	SOM 0-10	SOM 0-20	Soybean yield (kg/ha)	Arylsulfatase (mg p-nitrofenol kg ⁻¹ solo h ⁻¹)	β -glucosidase (mg p-nitrofenol kg ⁻¹ solo h ⁻¹)	Enzymes Index
1	2020	Short C.	No-till	2		02/26/20	179	1,311	29.18	5.2	3.5	3.6	4,062	37	123	0.60
2	2020	Long C.	Overseeding	2		03/13/20	344	1,256	30.14	6.1	3.3	3.4	4,464	53	107	0.62
3	2020	Short C.	No-till	2		03/09/20	355	1,271	29.83	5.8	3.0	3.3	3,714	114	122	0.81
4	2020	Long C.	Overseeding	2		03/18/20	357	1,139	32.64	8.6	3.0	3.3	4,176	75	119	0.71
5	2020	Maize	ICLS	1		ICLS	732	1,253	29.24	5.2	3.2		8,820(corn)	75	142	0.74
6	2020	Short C.	No-till	2		03/05/20	467	1,245	29.99	6.0	3.0	3.3	3,684	52	120	0.62
7	2020	Long C.	Overseeding	1		03/14/20	300	1,255	31.37	7.3	3.5	3.7	3,954	77	95	0.67
8	2020	Long C.	Overseeding	2		03/19/20	339	1,327	30.95	6.9	2.7	3.4	3,966	86	93	0.70
9	2020	Long C.	Overseeding	2		03/19/20	333	1,268	30.90	6.9	3.9	3.2	4,050	82	91	0.68
1	2021	Long C.	No-till	2		03/25/21	102	1,098	27.36	4.9		3.7	4,518	91	134	0.80
2	2021	Short C.	No-till	2		02/18/21	340	1,156	24.65	2.2		2.2	3,690	115	155	0.87
3	2021	Short C.	No-till	2		02/09/21	425	1,238	25.40	3.0		2.7	3,678	172	186	0.96
4	2021	Maize	ICLS	1		ICLS	544	1,228	25.96	3.5		3.3	9,180(corn)	135	177	0.93
5	2021	Long C.	No-till	3		03/05/21	230	1,098	26.92	4.5		4.8	4,668	54	127	0.64
6	2021	Long C.	No Till	2		03/25/21	142	1,064	28.67	6.2		3.1	4,254	88	156	0.79
7	2021	Long C.	Overseeding	0		03/19/21	68	1,092	28.91	6.5		3.1	4,410	76	152	0.78
8	2021	Long C.	Overseeding	1		03/18/21	84	1,111	28.44	6.0		3.5	4,086	69	112	0.69
9	2021	Long C.	Overseeding	1		03/18/21	72	1,098	29.15	6.7		2.7	4,110	102	134	0.82
1	2022	Short C.	No-till	2		02/22/22	184	1,212	19.00	4.7	3.4	2.3	3,792	84	155	0.81
2	2022	Short C.	No-till	5		03/04/22	113	1,341	18.80	4.5	3.3	2.3	4,506	82	139	0.77
3	2022	Short C.	No-till	5		03/10/22	108	1,436	19.25	5.0	3.3	2.5	4,572	142	186	0.94
4	2022	Long C.	No-till	4		03/24/22	75	1,481	19.40	5.1	3.6	2.9	4,098	105	168	0.87
5	2022	Long C.	No-till	3		03/24/22	61	1,290	20.50	6.2	3.5	2.2	3,954	87	132	0.75
6	2022	Long C.	No-till	1		03/27/22	39	1,147	21.70	7.4	3.3	2.6	2,904	80	159	0.77
7	2022	Maize	ICLS	1		ICLS	427	1,192	20.45	6.2	3.5	2.5	8,160(corn)	101	149	0.84
8	2022	Long C.	No-till	1		04/02/22	37	1,215	21.40	7.1	3.5	3.1	3,270	128	127	0.86
9	2022	Maize	ICLS	1		ICLS	417	1,215	20.20	5.9	3.3	2.9	8,160(corn)	92	144	0.82

Plot	Year	Crop tipology	Cover-crops management	Cover-crops - n° of species	Cover-crops biomass dry matter (ton ha ⁻¹)	Cover-crops sowing (date)	Cumulative rain fall (cover-crops)	Cumulative rain (summer crop oct-may)	LST °C	Δ LST °C	SOM 0-10	SOM 0-20	Soybean yield (kg/ha)	Arylsulfatase (mg p-nitrofenol kg ⁻¹ solo h ⁻¹)	β-glucosidase (mg p-nitrofenol kg ⁻¹ solo h ⁻¹)	Enzymes Index
1	2023	Short C.	No-till	4	3.36	03/01/23	246	1,162	21.20	6.2	3.2	2.2	3,636	109	101	0.77
2	2023	Short C.	No-till	5	5.25	03/04/23	255	1,207	19.90	4.9	3.2	2.6	4,034	119	101	0.78
3	2023	Short C.	No-till	4	6.87	02/26/23	266	1,207	19.45	4.4	2.9	3.4	4,240	143	138	0.88
4	2023	Long C.	No-till	2	3.49	03/31/23	109	1,245	22.55	7.5	3.0	2.6	4,616	80	98	0.68
5	2023	Long C.	No-till	4	2.63	03/11/23	187	1,230	21.90	6.9	2.7	2.3	4,230	65	106	0.63
6	2023	Maize	ICLS	1	12.25	ICLS	368	1,179	19.10	4.1	3.0	2.7	8,580(corn)	76	158	0.76
7	2023	pasture 18m	ICLS	1	13.13	ICLS	373	1,253	19.05	4.0	3.5	2.6	pasture	140	128	0.87
8	2023	Maize	ICLS	1	10.97	ICLS	387	1,192	19.20	4.2	3.6	2.4	9,180(corn)	157	139	0.90
9	2023	Short C.	No-till	4	3.67	02/21/23	341	1,127	20.95	5.9	2.7	1.8	3,862	89	100	0.72
1	2024	Long C.	No-till	1	2.97	04/03/24	49	1,104	32.40	8.8	2.7	2.1	2,922	98	89	0.72
2	2024	Short C.	No-till	3	7.12	03/06/24	296	1,225	28.20	4.6	2.7	2.5	3,726	100	79	0.69
3	2024	Short C.	No-till	3	8.48	03/06/24	291	1,318	27.80	4.2	2.8	2.1	3,972	163	89	0.79
4	2024	Long C.	No-till	3	5.85	03/16/24	257	1,277	30.60	7.0	2.7	2.5	4,080	78	84	0.62
5	2024	Maize	ICLS	2	9.59	ICLS	570	1,191	29.30	5.7	2.9	1.6	7,980(corn)	65	105	0.62
6	2024	Long C.	No-till	3	4.88	04/16/24	1	1,100	32.50	8.9	2.7	2.9	2,100	66	105	0.64
7	2024	Long C.	No-till	3	5.80	04/17/24	0	1,057	32.50	8.9	3.0	2.7	1,974	120	97	0.69
8	2024	pasture 18m	ICLS	1	14.81	ICLS	488	1,059	29.70	6.1	3.6	1.8	pasture	155	105	0.74
9	2024	Long C.	No-till	3	3.12	04/09/24	8	1,064	32.05	8.5	2.7	1.4	3,138	86	86	0.61
1	2025	Maize	ICLS	1	15.64	ICLS	478	1,034	26.9	3.0	3.1	3.0	9,480(corn)	87	135	0.79
2	2025	Short C.	No-till	4	9.40	02/27/25	289	1,115	28.6	4.8	3.2	3.5	4,716	115	105	0.79
3	2025	Short C.	No-till	4	7.89	03/05/25	193	1,139	29.0	5.1	2.9	3.3	4,872	167	139	0.90
4	2025	Long C.	No-till	2	11.10	03/17/25	265	1,120	27.4	3.5	3.1	3.1	4,278	85	119	0.74
5	2025	Short C.	No-till	4	11.03	02/19/25	275	1,069	27.8	3.9	3.1	2.7	4,920	80	116	0.70
6	2025	Short C.	No-till	4	9.95	02/26/25	234	1,026	28.9	5.0	3.0	3.2	4,866	75	117	0.69
7	2025	Short C.	No-till	4	8.19	02/25/25	247	1,060	29.8	5.9	3.2	3.6	5,040	106	103	0.77
8	2025	Long C.	No-till	4	11.89	02/23/25	190	1,043	29.5	5.6	3.5	2.8	4,668	175	109	0.85
9	2025	Maize	ICLS	2	11.55	ICLS	462	1,122	27.7	3.8	3.2	2.3	8,820(corn)	89	118	0.76

A. Scripts and results

A.1 - Analysis of Crop management (System) x Land Surface Temperature (LST).

```
library(readxl) # to import data from Excel.
library(nlme) # for mixed models.
library(ggplot2) # for charts.
library(RVAideMemoire) # for model validation charts.
library(emmeans) # for multiple comparison of means.
dados$Crop<-as.factor(dados$Crop)
dados$Block<-as.factor(dados$Block)
```

Mixed Model with plots(blocks) as a random effect

```
m1 <- lme(Tdiff ~ Crop, random =~1 | Block, method="REML", data = dados)
summary(m1)
```

Linear mixed-effects model fit by REML

Data: data1

AIC	BIC	logLik
291.3233	307.6384	-138.6617

Random effects:

Formula: ~1 | Block

	(Intercept)	Residual
StdDev:	6.452813e	-05 1.372201

Fixed effects: Tdiff ~ Crop

	Value	Std.Error	DF	t-value	p-value
(Intercept)	4.768571	0.3667362	68	13.002730	0.0000
SystemLong C.	1.994958	0.4952336	68	4.028317	0.0001
SystemNo coverage	1.855000	0.6352057	68	2.920314	0.0047
SystemOverseed	2.426429	0.4781655	68	5.074454	0.0000
SystemShort C.	0.186646	0.4651475	68	0.401262	0.6895

Correlation:	(Intr)	CrpLC.	CrpNcv	CrpOvr
SystemLong C.	-0.741			
SystemNo coverage	-0.577	0.428		
SystemOverseed	-0.767	0.568	0.443	
SystemShort C.	-0.788	0.584	0.455	0.605

Standardized Within-Group Residuals:

Min	Q1	Med	Q3	Max
-2.35281073	-0.70949619	-0.03659624	0.73239996	1.78893797

Number of Observations: 81

Number of Groups: 9

Anova

anova (m1)

	numDF	denDF	F-value	p-value
(Intercept)	1	68	1548.4861	<.0001
System	4	68	11.6213	<.0001

Model validation

```
plotresid(m1, shapiro = T)
Shapiro-Wilk normality test
data: model.res
W = 0.98047, p-value = 0.253
E <- resid(m1)
x1<-dados$System
plot(E~x1)
abline(h=0)
```

#comparison of means

```
library(mvtnorm)
library(survival)
library(MASS)
library(TH.data)
library(multcomp)
library(multcompView)
library(nlme)
library(emmeans)
library(dplyr)

tukey<-emmeans(m1, list(pairwise ~ System), adjust = "tukey")
tukey_results <- cld(tukey, Letters = letters)
tukey_results
```

Crop	emmean	SE	df	lower.CL	upper.CL.	group
ICLS	4.77	0.367	8	3.92	5.61	a
Short C.	4.96	0.286	8	4.30	5.62	a
No coverage	6.62	0.519	8	5.43	7.82	b
Long C.	6.76	0.333	8	6.00	7.53	b
Overseed	7.20	0.307	8	6.49	7.90	b

Degrees-of-freedom method: containment

Confidence level used: 0.95

P value adjustment: tukey method for comparing a family of 5 estimates

significance level used: alpha = 0.05

#boxplot

```
p<- ggplot(dados, aes(System, LST))
p + geom_boxplot() + theme_classic()
```

A.2.1 - Analysis of Land Surface Temperature (LST) x β -glucosidase enzyme activity (Glu).

```
dados_beta$Crop<-as.factor(dados_beta$Crop)
dados_beta$Block<-as.factor(dados_beta$Block)
library(dplyr)
library(reshape)
```

Mixed Model with plots(blocks) as a random effect (Tdiff = Δ LST)

```
m1_beta <- lme(Beta ~ Tdiff, random =~1 | Block, method="REML", data = dados_beta)
summary(m1_beta)
```

Linear mixed-effects model fit by REML

Data: data		
AIC	BIC	logLik
494.3145	502.1195	-243.1572

Random effects:

Formula: ~1 | Block

	(Intercept)	Residual
StdDev:	5.020935	23.4216

Fixed effects: Beta ~ Tdiff

	Value	Std.Error	DF	t-value	p-value
(Intercept)	168.87767	12.362263	44	13.66074	0e+00
Tdiff	-8.02926	2.096034	44	-3.83069	4e-04

Correlation:

	(Intr)
Tdiff	-0.957

Standardized Within-Group Residuals:

Min	Q1	Med	Q3	Max
-2.0908950	-0.7186907	-0.2063563	0.7008395	2.3250296

Number of Observations: 54

Number of Groups: 9

Model validation

```
plotresid(m1, shapiro = T)
Shapiro-Wilk normality test
data: model.res
W = 0.96757, p-value = 0.1505
E <- resid(m1)
x1<-dados_beta$LST
plot(E~x1)
abline(h=0)
```

Graphic

```
F0<-fitted(m1_beta, level=0)
preditora <- dados_beta$Tdiff #replace the covariate here
label_preditora<-"Temperature difference"
```

```

Y=dados_beta$Beta; legendaY="Beta"
g1=ggplot(data=dados_beta, aes(x = preditora, y = Y)) +
  geom_point(aes(col=Crop), alpha=0.6, size=4) +
  theme_classic(base_size = 25)+
  ylab(legendaY) + xlab(label_preditora)+
  labs(colour="Crop")
g1
g1 + stat_smooth(aes(y = F0), linetype = "solid",
  se = F, method = "lm")
ggsave("Beta1.png", width=8, height=6, dpi=400)

```

#R² using piecewiseSEM

```

library(piecewiseSEM)
modelList <- psem(
  m1_beta <- lme(Beta ~ Tdiff, random =~1 | Block, method="REML", data = dados_beta)
)
summary(modelList)
Structural Equation Model of modelList
Call:
lme4::lmer(Beta ~ Tdiff, data = dados_beta, method = "REML")
AIC:
494.314

```

Tests of directed separation:

No independence claims present. Tests of directed separation not possible.

Global goodness-of-fit:

Chi-Squared = 0 with P-value = 1 and on 0 degrees of freedom

Fisher's C = NA with P-value = NA and on 0 degrees of freedom

Coefficients:

Response	Predictor	Estimate	Std.Error	DF	Crit.Value	P.Value	Std.Estimate
Beta	Tdiff	-8.0293	2.096	44	-3.8307	4e-04	-0.4719 ***

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

Individual R-squared:

Response	method	Marginal	Conditional
Beta	none	0.22	0.25

A.2.2 - Analysis of Land Surface Temperature (LST) x Arylsulfatase enzyme activity (Aryl).

```

dados_ari$Crop<-as.factor(dados_ari$Crop)
dados_ari$Block<-as.factor(dados_ari$Block)

```

Mixed Model with plots(blocks) as a random effect

```

m1_ari <- lme(Aryl ~ Tdiff, random =~1 | Block, method="REML", data = dados_ari)
summary(m1_ari)

```

Linear mixed-effects model fit by REML

Data: dados

AIC	BIC	logLik
505.3341	513.139	-248.667

Random effects:

Formula: ~1 | Block

	(Intercept)	Residual
StdDev:	22.91721	22.86686

Fixed effects: Aryl ~ Tdiff

	Value	Std.Error	DF	t-value	p-value
(Intercept)	126.41615	14.862877	44	8.505497	0.0000
Tdiff	-4.87215	2.191285	44	-2.223423	0.0314

Correlation:

(Intr)

LST -0.832

Standardized Within-Group Residuals:

Min	Q1	Med	Q3	Max
-2.39644149	-0.46917773	-0.03654006	0.66267160	2.15066596

Number of Observations: 54

Number of Groups: 9

Model validation

plotresid(m1, shapiro = T)

Shapiro-Wilk normality test

data: model.res

W = 0.98224, p-value = 0.6006

E <- resid(m1_ari)

x1 <- dados_ari\$Tdiff

plot(E~x1)

abline(h=0)

R² using piecewiseSEM

modellList <- psem(

 m1_beta <- lme(Aryl ~ Tdiff, random = ~1 | Block, method="REML", data = dados_ari)

)

summary(modellList)

Structural Equation Model of modellList

Call:

Aryl ~ Tdiff

AIC

505.334

Tests of directed separation:

No independence claims present. Tests of directed separation not possible.

Global goodness-of-fit

Chi-Squared = 0 with P-value = 1 and on 0 degrees of freedom

Fisher's C = NA with P-value = NA and on 0 degrees of freedom

Coefficients:

Response	Predictor	Estimate	Std.Error	DF	Crit.Value	P.Value	Std.Estimate
Aryl	Tdiff	-4.8722	2.1913	44	-2.2234	0.0314	-0.2328 *

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05

Individual R-squared:

Response	method	Marginal	Conditional
Aryl	none	0.05	0.53

A.2.3 - Analysis of Land Surface Temperature (LST) x Biological Index (Arylsulfatase and β -glucosidase).

```
dados$Crop<-as.factor(dados$Crop)
dados$Block<-as.factor(dados$Block)
```

Mixed Model with plots(blocks) as a random effect

```
m1_BI <- lme(BI ~ Tdiff, random =~1 | Block, method="REML", data = dados)
summary(m1_BI)
```

Linear mixed-effects model fit by REML

Data: data

AIC	BIC	logLik
-101.4067	-93.60177	54.70337

Random effects:

Formula: ~1 | Block

	(Intercept)	Residual
StdDev:	0.04252833	0.07115771

Fixed effects: BI ~ Tdiff

	Value	Std.Error	DF	t-value	p-value
(Intercept)	0.9226184	0.04144659	44	22.260416	0e+00
LST	-0.0302363	0.00762317	34	-3.966374	4e-04

Correlation:

(Intr)
Tdiff -0.91

Standardized Within-Group Residuals:

Min	Q1	Med	Q3	Max
-2.27894158	-0.69973806	0.04612555	0.86916517	1.62732557

Number of Observations: 54

Number of Groups: 9

Model validation

```
plotresid(m1, shapiro = T)
Shapiro-Wilk normality test
data: model.res
W = 0.96768, p-value = 0.1522
E <- resid(m1)
x1<-dados$LST
```

```
plot(E~x1)
abline(h=0)
```

R² using piecewiseSEM

```
library(piecewiseSEM)
modellList <- psem(
  m1_BI <- lme(BI ~ Tdiff, random =~1 | Block, method="REML", data = dados)
summary(modellList)
Structural Equation Model of modellList
Call:
  BI ~ Tdiff
  AIC
-101.407
```

Tests of directed separation:

No independence claims present. Tests of directed separation not possible.

Global goodness-of-fit:

Chi-Squared = 0 with P-value = 1 and on 0 degrees of freedom

Fisher's C = NA with P-value = NA and on 0 degrees of freedom

Coefficients:

Response	Predictor	Estimate	Std.Error	DF	Crit.Value	P.Value	Std.Estimate
BI	Tdiff	-0.0291	0.0067	44	-4.35	1e-04	-0.4888 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05

Individual R-squared:

Response	method	Marginal	Conditional
BI	none	0.23	0.43

A.3.1 - Analysis of Cover Crop System management (System) x β -glucosidase enzyme activity (Glu)

```
dados$Crop<-as.factor(dados$Crop)
dados$Block<-as.factor(dados$Block)
```

Mixed Model with plots(blocks) as a random effect

```
m1 <- lme(Beta ~ Crop, random =~1 | Block, method="REML", data = dados)
summary(m1)
anova(m1)
```

Linear mixed-effects model fit by REML

Data: dados

AIC	BIC	logLik
490.9899	502.462	-239.4949

Random effects:

Formula: ~1 | Block

	(Intercept)	Residual
StdDev:	0.815339	26.27444

Fixed effects: Beta ~ Crop

	Value	Std.Error	DF	t-value	p-value
(Intercept)	136.38293	7.928621	42	17.201343	0.0000
CropLong C.	-17.88896	10.293205	42	-1.737939	0.0895
CropOverseed	-23.47382	12.210863	42	-1.922372	0.0614
CropShort C.	-11.45601	9.963355	42	-1.149815	0.2567

Correlation:

	(Intr)	CrpLC.	CrpOvr
Crop Long C.	-0.769		
Crop Overseed	-0.648	0.499	
Crop Short C.	-0.795	0.612	0.516

Standardized Within-Group Residuals:

Min	Q1	Med	Q3	Max
-1.7460910	-0.7752718	-0.0941770	0.5274343	2.3204049

Number of Observations: 54

Number of Groups: 9

anova(m1)

num	DF	denDF	F-value	p-value
(Intercept)	1	42	1187.6253	<.0001
Crop	3	42	1.5267	0.2216

Model validation

plotresid(m1, shapiro = T)

Shapiro-Wilk normality test

data: model.res

W = 0.96206, p-value = 0.08525

E <- resid(m1)

x1<-dados\$System

plot(E~x1)

abline(h=0)

tukey<-emmeans(m1, list(pairwise ~ System), adjust = "tukey")

tukey_results <- cld(tukey, Letters = letters)

tukey_results

Crop	emmean	SE	df	lower.CL	upper.CL	group
Overseed	113	9.30	8	91.5	134	a
Long C.	118	6.58	8	103.3	134	a
Short C.	125	6.04	8	111.0	139	a
ICLS	136	7.93	8	118.1	155	a

Degrees-of-freedom method: containment

Confidence level used: 0.95

P value adjustment: tukey method for comparing a family of 4 estimates

significance level used: alpha = 0.05

A.3.2 - Analysis of Crop management (Crop) x Arylsulfatase enzyme activity (Aryl)

```
dados$Crop<-as.factor(dados$Crop)
dados$Block<-as.factor(dados$Block)
```

Mixed Model with plots(blocks) as a random effect

```
m1 <- lme(Aryl ~ Crop, random =~1 | Block, method="REML", data = dados)
summary(m1)
anova(m1)
```

Linear mixed-effects model fit by REML

Data: dados

AIC	BIC	logLik
482.1923	493.6645	-235.0962

Random effects:

Formula: ~1 | Block

	(Intercept)	Residual
StdDev:	26.81251	19.91145

Fixed effects: Aryl ~ Crop

	Value	Std.Error	DF	t-value	p-value
(Intercept)	110.27683	10.975366	42	10.047668	0.0000
Crop Long C.	-6.91359	8.096542	42	-0.853894	0.3980
Crop Overseed	-41.40903	9.548580	42	-4.336669	0.0001
Crop Short C.	-9.00312	9.268296	42	-0.971389	0.3369

Correlation:

		(Intr)	CrpLC.	CrpOvr
Crop	Long C.	-0.426		
Crop	Overseed	-0.350	0.437	
Crop	Short C.	-0.463	0.510	0.424

Standardized Within-Group Residuals:

Min	Q1	Med	Q3	Max
-2.3477554	-0.6960536	-0.1052347	0.6457475	2.0263979

Number of Observations: 54

Number of Groups: 9

```
anova(m1)
```

num	DF	denDF	F-value	p-value
(Intercept)	1	42	112.20175	<.0001
Crop	3	42	6.81262	8e-04

Model validation

```
plotresid(m1, shapiro = T)
```

Shapiro-Wilk normality test

data: model.res

W = 0.98766, p-value = 0.8497

```
E <- resid(m1)
```

```
x1<-dados$System
```

```
plot(E~x1)
```

```
abline(h=0)
```

#comparison of means

```
tukey<-emmeans(m1, list(pairwise ~ Crop), adjust = "tukey")
tukey_results <- cld(tukey, Letters = letters)
tukey_results
```

Crop	emmean	SE	df	lower.CL	upper.CL	.group
Overseed	68.9	11.8	8	41.8	96	a
Short C.	101.3	10.6	8	76.9	126	b
Long C.	103.4	10.5	8	79.2	128	b
ICLS	110.3	11.0	8	85.0	136	b

Degrees-of-freedom method: containment

Confidence level used: 0.95

P value adjustment: tukey method for comparing a family of 4 estimates

significance level used: alpha = 0.05

A.3.3 - Analysis of Crop management (Crop) x Biological Index (Arylsulfatase and β -glucosidase).

```
dados$Crop<-as.factor(dados$Crop)
dados$Block<-as.factor(dados$Block)
```

Mixed Model with plots(blocks) as a random effect

```
m1 <- lme(SQI ~ Crop, random =~1 | Block, method="REML", data = dados)
summary(m1)
anova(m1)
```

Linear mixed-effects model fit by REML

Data: dados

AIC	BIC	logLik
-82.4839	-71.01176	47.24195

Random effects:

Formula: ~1 | Block

	(Intercept)	Residual
StdDev:	0.04851526	0.07757993

Fixed effects: Aryl ~ Crop

	Value	Std.Error	DF	t-value	p-value
(Intercept)	0.8078387	0.02922487	42	27.642170	0.0000
CropLong C.	-0.0644518	0.03124585	42	-2.062731	0.0454
CropOverseed	-0.1058187	0.03690559	42	-2.867280	0.0064
CropShort C.	-0.0413427	0.03386208	42	-1.220916	0.2289

Correlation:

		(Intr)	CrpLC.	CrpOvr
Crop	Long C.	-0.622		
Crop	Overseed	-0.514	0.453	
Crop	Short C.	-0.663	0.540	0.450

Standardized Within-Group Residuals:
 Min Q1 Med Q3 Max
 -1.98930999 -0.54483958 -0.07284147 0.77672313 1.70091360

Number of Observations: 54

Number of Groups: 9

```
anova(m1)
num      DF    denDF      F-value    p-value
(Intercept)  1     42      1542.5687    <.0001
Crop         3     42       3.0621     0.0384
```

Model validation

```
plotresid(m1, shapiro = T)
```

Shapiro-Wilk normality test

data: model.res

W = 0.98032, p-value = 0.5141

```
E <- resid(m1)
```

```
x1 <- dados$System
```

```
plot(E~x1)
```

```
abline(h=0)
```

#comparison of means

```
tukey <- emmeans(m1, list(pairwise ~ Crop), adjust = "tukey")
```

```
tukey_results <- cld(tukey, Letters = letters)
```

```
tukey_results
```

Crop	emmean	SE	df	lower.CL	upper.CL	.group
Overseed	0.702	0.0333	8	0.625	0.779	a
Long C.	0.743	0.0264	8	0.683	0.804	ab
Short C.	0.766	0.0262	8	0.706	0.827	ab
ICLS	0.808	0.0292	8	0.740	0.875	b

Degrees-of-freedom method: containment

Confidence level used: 0.95

P value adjustment: tukey method for comparing a family of 4 estimates

significance level used: alpha = 0.05

A.4.1 - Analysis of Soil Organic Matter (SOM) x β -glucosidase enzyme activity (Glu)

```
dados$Block <- as.factor(dados$Block)
```

Mixed Model with plots(blocks) as a random effect

```
m1 <- lme(Glu ~ SOM, random = ~1 | Block, method="REML", data = dados)
```

```
summary(m1)
```

Linear mixed-effects model fit by REML

Data: dados

AIC	BIC	logLik
401.8831	408.9279	-196.9416

Random effects:

Formula: ~1 | Block

	(Intercept)	Residual
StdDev:	9.710276	20.74047

Fixed effects: Glu ~ SOM

	Value	Std.Error	DF	t-value	p-value
(Intercept)	-6.71848	33.30107	35	-0.20175	0.8413
SOM	39.76273	10.46476	35	3.79968	0.0006

Correlation:

(Intr)

SOM -0.991

Standardized Within-Group Residuals:

Min	Q1	Med	Q3	Max
-2.4847780	-0.5501394	-0.1339202	0.8677494	2.4248847

Number of Observations: 45

Number of Groups: 9

Model validation

```
plotresid(m1, shapiro = T)
```

Shapiro-Wilk normality test

data: model.res

W = 0.97612, p-value = 0.4716

```
E <- resid(m1)
```

```
x1<-dados$Block
```

```
plot(E~x1)
```

```
abline(h=0)
```

R² using piecewiseSEM

```
modellist <- psem(
```

```
  m1 <- lme(Glu ~ SOM, random =~1 | Block, method="REML", data = dados)
```

```
)
```

Run summary

```
summary(modellist)
```

Global goodness-of-fit:

Chi-Squared = 0 with P-value = 1 and on 0 degrees of freedom

Fisher's C = NA with P-value = NA and on 0 degrees of freedom

Coefficients:

Response	Predictor	Estimate	Std.Error	DF	Crit.Value	P.Value	Std.Estimate
Beta	SOM	39.7627	10.4648	35	3.7997	6e-04	0.5045 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05

Individual R-squared:

Response	method	Marginal	Conditional
Beta	none	0.23	0.37

A.4.2 - Analysis of Soil Organic Matter (SOM) x Arylsulfatase enzyme activity (Aryl)

```
dados$Block<-as.factor(dados$Block)
```

```
# Mixed Model with plots(blocks) as a random effect
```

```
m1 <- lme(Aryl ~ SOM, random=~1 | Block, method="REML", data = dados)
```

```
summary(m1)
```

Linear mixed-effects model fit by REML

Data: dados

AIC	BIC	logLik
415.2862	422.331	-203.6431

Random effects:

Formula: ~1 | Block

	(Intercept)	Residual
StdDev:	25.36687	21.41028

Fixed effects: Aryl ~ SOM

	Value	Std.Error	DF	t-value	p-value
(Intercept)	70.99516	36.32298	35	1.9545520	0.0587
SOM	8.77532	11.15664	35	0.7865557	0.4368

Correlation:

(Intr)

SOM -0.969

Standardized Within-Group Residuals:

Min	Q1	Med	Q3	Max
-2.37227392	-0.38867129	0.04900689	0.66149839	1.80653624

Number of Observations: 45

Number of Groups: 9

```
# Model validation
```

```
plotresid(m1, shapiro = T)
```

Shapiro-Wilk normality test

data: model.res

W = 0.95751, p-value = 0.09811

```
E <- resid(m1)
```

```
x1<-dados$Block
```

```
plot(E~x1)
```

```
abline(h=0)
```

A.4.3 - Analysis of Soil Organic Matter (SOM) x Δ Land Surface Temperature (Δ LST).

```
dados$Crop<-as.factor(dados$Crop)
dados$Block<-as.factor(dados$Block)
```

Mixed Model with plots(blocks) as a random effect

```
m1 <- lme(Tdiff ~ SOM, random =~1 | Block, method="REML", data = dados)
summary(m1)
Linear mixed-effects model fit by REML
```

Data: dados

AIC	BIC	logLik
170.0803	177.1251	-81.04017

Random effects:

Formula: ~1 | Block

	(Intercept)	Residual
StdDev:	0.0001520176	1.498574

Fixed effects: Tdiff ~ SOM

	Value	Std.Error	DF	t-value	p-value
(Intercept)	9.178853	2.2918767	35	4.004951	0.0003
SOM	-1.070426	0.7233499	35	-1.479817	0.1479

Correlation:

(Intr)

SOM -0.995

Standardized Within-Group Residuals:

Min	Q1	Med	Q3	Max
-1.882144807	-0.669630607	-0.001719226	0.512244513	1.956808963

Number of Observations: 45

Number of Groups: 9

Model validation

```
plotresid(m1, 104shapiro = T)
Shapiro-Wilk normality test
data: model.res
W = 0.97193, p-value = 0.3397
E <- resid(m1)
x1<-dados$System
plot(E~x1)
abline(h=0)
```

R² using piecewiseSEM

```
modellList <- psem(
  m1 <- lme(Tdiff ~ SOM, random =~1 | Block, method="REML", data = dados)
)
summary(modellList)
```

Structural Equation Model of modelList

Call:

Tdiff ~ SOM

AIC

170.080

Tests of directed separation:

No independence claims present. Tests of directed separation not possible.

Global goodness-of-fit:

Chi-Squared = 0 with P-value = 1 and on 0 degrees of freedom

Fisher's C = NA with P-value = NA and on 0 degrees of freedom

Coefficients:

Response	Predictor	Estimate	Std.Error	DF	Crit.Value	PValue	Std.Estimate
Tdiff	SOM	-1.0704	0.7233	35	-1.4798	0.1479	-0.2201

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05

Individual R-squared:

Response	method	Marginal	Conditional
Tdiff	none	0.05	0.05

A.5.1 - Analysis of Δ Land Surface Temperature (Δ LST) x Cover Crops Biomass.

```
dados_beta$Crop<-as.factor(dados_beta$Crop)
```

```
dados_beta$Block<-as.factor(dados_beta$Block)
```

Mixed Model with plots(blocks) as a random effect

```
m1_beta <- lme(Tdiff ~ Biomass, random =~1 | Block, method="REML", data = dados_beta)
```

```
summary(m1_beta)
```

Linear mixed-effects model fit by REML

Data: dados

AIC	BIC	logLik
98.94731	103.8228	-45.47365

Random effects:

Formula: ~1 | Block

	(Intercept)	Residual
StdDev:	0.553147	1.141004

Fixed effects: Tdiff ~ Bio

	Value	Std.Error	DF	t-value	p-value
(Intercept)	8.452813	0.5792737	17	14.592089	0
Biomass	-0.348896	0.0615290	17	-5.670432	0

Correlation:

(Intr)

Bio -0.869

Standardized Within-Group Residuals:

Min	Q1	Med	Q3	Max
-1.1218188	-0.7381541	-0.2081314	0.5756347	2.0291714

Number of Observations: 27

Number of Groups: 9

Model validation

```
plotresid(m1, 106shapiro = T)
Shapiro-Wilk normality test
data: model.res
W = 0.91418, p-value = 0.02865
E <- resid(m1)
x1<-dados$Bio
plot(E~x1)
abline(h=0)
```

R² using piecewiseSEM

```
modellList <- psem(
  m1 <- lme(Tdiff ~ Bio, random =~1 | Block, method="REML", data = dados)
)
summary(modellList)
Structural Equation Model of modellList
Call:
  Biomass ~ Tdiff
  AIC 98.947
```

Tests of directed separation:

No independence claims present. Tests of directed separation not possible.

Global goodness-of-fit:

Chi-Squared = 0 with P-value = 1 and on 0 degrees of freedom

Fisher's C = NA with P-value = NA and on 0 degrees of freedom

Coefficients:

Response	Predictor	Estimate	Std.Error	DF	Crit.Value	P.Value	Std.Estimate
Tdiff	Biomass	-0.3489	0.0615	17	-5.6704	0	-0.7687 ****

Signif. codes: 0 '****' 0.001 '***' 0.01 '**' 0.05

Individual R-squared:

Response	method	Marginal	Conditional
Tdiff	none	0.52	0.62

A.5.2 - Analysis of Crop management (System) x Biomass

```
dados$Crop<-as.factor(dados$Crop)
dados$Block<-as.factor(dados$Block)
```

Mixed Model with plots(blocks) as a random effect

```
m1 <- lme(Biomass ~ Crop, random =~1 | Block, method="REML", data = dados)
summary(m1)
anova(m1)
```

Linear mixed-effects model fit by REML

Data: dados

AIC	BIC	logLik
133.6448	139.535	-61.82238

Random effects:

Formula: ~1 | Block

	(Intercept)	Residual
StdDev:	0.0001766841	2.775199

Fixed effects: Bio ~ System

	Value	Std.Error	DF	t-value	p-value
(Intercept)	12.562429	1.048927	16	11.976459	0.0000
CropLong C.	-6.814317	1.398569	16	-4.872350	0.0002
CropShort C.	-5.180519	1.341792	16	-3.860897	0.0014

Correlation:

	(Intr)	SysLC.
SystemLong C.	-0.750	
SystemShort C.	-0.782	0.586

Standardized Within-Group Residuals:

Min	Q1	Med	Q3	Max
-1.44923251	-0.79093782	-0.09437488	0.56143387	2.21421532

Number of Observations: 27

Number of Groups: 9

> anova(m1)

	NumDF	denDF	F-value	p-value
(Intercept)	1	16	234.59852	<.0001
Crop	2	16	12.63826	5e-04

plotresid(m1, 107shapiro = T)

Model validation

Shapiro-Wilk normality test

data: model.res

W = 0.96188, p-value = 0.4075

E <- resid(m1)

x1<-dados\$System

plot(E~x1)

abline(h=0)

#comparison of means

tukey<-emmeans(m1, list(pairwise ~ System), adjust = "tukey")

tukey_results <- cld(tukey, Letters = letters)

tukey_results

p<- ggplot(dados, aes(System, Bio))

p + geom_boxplot() + theme_classic()

```
raw_means <- dados %>%
  group_by(System) %>%
  summarize(mean_Bio = mean(Bio))
print(raw_means)
```

System	emmean	SE	df	lower.CL	upper.CL .	group
Long C.	5.75	0.925	8	3.61	7.88	a
Short C.	7.38	0.837	8	5.45	9.31	a
ICLS	12.56	1.050	8	10.14	14.98	b

Degrees-of-freedom method: containment

Confidence level used: 0.95

P value adjustment: tukey method for comparing a family of 3 estimates

significance level used: alpha = 0.05

A.5.3 - Analysis of Crop management (Crop) x Land Surface Temperature (Δ LST) (2023 – 2025)

```
dados$Crop<-as.factor(dados$Crop)
dados$Block<-as.factor(dados$Block)
```

Mixed Model with plots(blocks) as a random effect

```
m1 <- lme(Tdiff ~ Crop, random =~1 | Block, method="REML", data = dados)
summary(m1)
anova(m1)
```

Linear mixed-effects model fit by REML

Data: dados

AIC	BIC	logLik
96.05159	101.9419	-43.02579

Random effects:

Formula: ~1 | Block

	(Intercept)	Residual
StdDev:	5.642955e	-05 1.268115

Fixed effects: Tdiff ~ Bio

	Value	Std.Error	DF	t-value	p-value
(Intercept)	4.405000	0.4793024	16	9.190441	0.0000
CropLong C.	2.875000	0.6390698	16	4.498726	0.0004
CropShort C.	0.577727	0.6131257	16	0.942266	0.3601

(Intr)	CrpLC.
CropLong C.	-0.750
CropShort C.	-0.782 0.586

Standardized Within-Group Residuals:

Min	Q1	Med	Q3	Max
-2.9532025	-0.3993042	-0.1835222	0.8219072	1.3366297

Number of Observations: 27

Number of Groups: 9

	numDF	denDF	F-value	p-value
(Intercept)	1	16	526.2857	<.0001
Crop	2	16	12.3091	6e-04

Model validation

```
plotresid(m1, shapiro = T)
Shapiro-Wilk normality test
data: model.res
W = 0.91325, p-value = 0.02723
E <- resid(m1)
x1<-dados$Bio
plot(E~x1)
abline(h=0)
```

Crop	emmean	SE	df	lower.CL	upper.CL .	group
ICLS	4.41	0.479	8	3.30	5.51	a
Short C.	4.98	0.382	8	4.10	5.86	a
Long C.	7.28	0.423	8	6.31	8.25	b

A.6.1 - Analysis Betaglucosidase enzyme activity (Glu) x Yield

```
dados$Crop<-as.factor(dados$Crop)
dados$Block<-as.factor(dados$Block)
```

Mixed Model with plots(blocks) as a random effect

```
m1 <- lme(Yield ~ Beta, random =~1 | Block, method="REML", data = dados)
summary(m1)
```

Linear mixed-effects model fit by REML

Data: dados

AIC	BIC	logLik
672.0062	678.8605	-332.0031

Random effects:

Formula: ~1 | Block

	(Intercept)	Residual
StdDev:	0.08055235	669.7008

Fixed effects: Beta ~ Yield

	Value	Std.Error	DF	t-value	p-value
(Intercept)	3575.622	471.0442	33	7.590841	0.0000
Beta	3.618	3.8224	33	0.946653	0.3507

Correlation:

(Intr)
Yield -0.976

Standardized Within-Group Residuals:

Min	Q1	Med	Q3	Max
-2.9156482	-0.4540527	0.1387400	0.5605182	1.6300973

Number of Observations: 43

Number of Groups: 9

Model validation

```
plotresid(m1, shapiro = T)
Shapiro-Wilk normality test
data: model.res
W = 0.92093, p-value = 0.005758
E <- resid(m1)
x1<-dados$Block
plot(E~x1)
abline(h=0)
```

A.6.2 - Analysis Arylsulfatase enzyme activity (Aryl) x Yield

```
dados$Block<-as.factor(dados$Block)
```

Mixed Model with plots(blocks) as a random effect

```
m1 <- lme(Yield ~ Aryl, random =~1 | Block, method="REML", data = dados)
summary(m1)
Linear mixed-effects model fit by REML
```

Data: dados

AIC	BIC	logLik
673.2271	680.0814	-332.6136

Random effects:

Formula: ~1 | Block

	(Intercept)	Residual
StdDev:	0.08071765	676.6122

Fixed effects: Aryl ~ Yield

	Value	Std.Error	DF	t-value	p-value
(Intercept)	3945.488	326.5846	33	12.081062	0.000
Aryl	0.675	3.1952	33	0.211201	0.834

Correlation:

	(Intr)
Yield	-0.949

Standardized Within-Group Residuals:

Min	Q1	Med	Q3	Max
-3.0334464	-0.4312289	0.1210082	0.7300508	1.5119159

Number of Observations: 43

Number of Groups: 9

Model validation

```
plotresid(m1, shapiro = T)
Shapiro-Wilk normality test
data: model.res
W = 0.91146, p-value = 0.002838
E <- resid(m1)
```

```
x1<-dados$Block
plot(E~x1)
abline(h=0)
```

A.7 - Biological Index (Arylsulfatase and β -glucosidase)(BI) x Soil Organic Carbon (SOC)

```
dados$Crop<-as.factor(dados$Crop)
dados$Block<-as.factor(dados$Block)
```

Mixed Model with plots(blocks) as a random effect

```
m1 <- lme(BI ~ SOC, random =~1 | Block, method="REML", data = dados)
summary(m1)
Linear mixed-effects model fit by REML
```

Data: dados

AIC	BIC	logLik
-81.13541	-74.09061	44.5677

Random effects:

Formula: ~1 | Block

	(Intercept)	Residual
StdDev:	0.04123678	0.07073236

Fixed effects: Aryl ~ Yield

	Value	Std.Error	DF	t-value	p-value
(Intercept)	0.3854799	0.11420518	35	3.375327	0.0018
SOC	0.0197621	0.00614611	35	3.215388	0.0028

Correlation:

	(Intr)
Yield	-0.988

Standardized Within-Group Residuals:

Min	Q1	Med	Q3	Max
-2.5528738	-0.5429000	0.2254727	0.6181591	1.4962441

Number of Observations: 45

Number of Groups: 9

Model validation

```
plotresid(m1, shapiro = T)
Shapiro-Wilk normality test
data: model.res
W = 0.95462, p-value = 0.07614
E <- resid(m1)
x1<-dados$Block
plot(E~x1)
abline(h=0)
```

Call:

Biomass ~ Tdiff

AIC 175.731

Tests of directed separation:

No independence claims present. Tests of directed separation not possible.

Global goodness-of-fit:

Chi-Squared = 0 with P-value = 1 and on 0 degrees of freedom

Fisher's C = NA with P-value = NA and on 0 degrees of freedom

Coefficients:

Response	Predictor	Estimate	Std.Error	DF	Crit.Value	PValue	Std.Estimate
SOC	BI	8.8561	2.7917	35	3.1723	0.0031	0.4355 **

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05

Individual R-squared:

Response	method	Marginal	Conditional
Tdiff	none	0.19	0.19