Optimisation of nutrient budget in agriculture

D1.3 Quantified measure-impact relationship of selected measures

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Authors	Hongzhen Luo (UGent), Gerard Ros, Maria Anna Antonovardaki, (WU), Salim Belyazid (SU)
Reviewers	Else Bünemann-König (FIBL), DEGAN Francesca (Arvalis), Mengru Wang (WU)
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Preface

Deliverable (D) 1.3 *"Quantified measure-impact relationship of selected measures"* is the final outcome of Task 1.2 Quantify measure-impact relationships in Work Package (WP) 1 of the NutriBudget project, funded by the Horizon Europe programme (project number 101060455). The NutriBudget project aims to develop the prototype of a first-of-its-kind integrated nutrient management platform, called "NutriPlatform", applicable in various regions across Europe. NutriPlatform will operate as a decision-support tool for farmers, advisors, and regional and national authorities. Before the end of the project, "NutriPlatform" (as a stand-alone or integrated into the existing European Commission-promoted Farm Sustainability Tool for nutrient management) will be tested and used by at least 40.000 farmers across Europe.

WP1, titled *"Design Opportunity Map for Effective Measures",* aims to develop a Mitigation Measures Catalogue (MMC) by identifying relevant agronomic mitigation measures across the European Union (EU) that can contribute to agricultural sustainability across different agricultural systems (conventional, organic and agro-ecological), regions and countries. Based on an inventory of effective mitigation measures in Task 1.1, the objective of Task 1.2 is to further quantify the impact of the selected measures on agronomic and environmental selected indicators from WP2/WP3 using meta-analysis. This deliverable presents the final outcome from Task 1.2 meta-analysis for the quantification of measure-impact relationship of selected mitigation measures. The meta-regression models developed in this deliverable will be used in Task 1.3 to support the evaluation of the spatial applicability of the selected measures across European agricultural systems.

Executive summary

Intensification in agriculture, driven by increased machinery and fertiliser use, has substantially boosted food production in Europe. However, the elevated application of nitrogen (N) and phosphorus (P) fertilisers has resulted in severe environmental consequences, impacting biodiversity, climate, water, air quality, and human health. For instance, excessive N leads to increased ammonia and nitrous oxide emissions, contributing to climate change and air pollution, while nutrient runoff or leaching to waterbodies pose risks to water quality, particularly affecting vulnerable populations. Moreover, the decline in biodiversity and soil organic carbon (SOC) further compound food security and environmental challenges. In responding to these issues, the Horizon Europe NutriBudget project aims to develop and implement an integrated nutrient management platform, called NutriPlatform, as a decision support tool to intensify agriculture sustainably, ensuring optimal yields without compromising the environment or human health. Efforts have been made in WP1 to provide an overview of relevant agronomic mitigation measures contributing to agricultural sustainability and impact-specific information (environmental performance related to nutrient use efficiency and losses, among others), which resulted in a catalogue consisting of 22 pre-identified mitigation measures (aiming to be more than 50 by the end of the project).

Based on the inventory of existing agronomic mitigation measures in Task 1.1, Task 1.2 aims to further quantify the impact of the measures on selected indicators from WP2/WP3. These impact indicators have been selected based on interactions with WP2 and WP3, as well as WP4 for measures experimentally investigated in the project's pilot cases. Long-term field experimental data across Europe have been collected from existing research publications and databases for the selected measures. By generating a meta-analysis of the selected measures, this task evaluates their impact response in terms of selected indicators that reflect the relationships between agriculture and the environment regarding nutrient balances, flows and losses.

Deliverable D1.3, presented in this document, is divided in five Chapters. **Chapter 1** provides an introduction to the nutrient challenge in agriculture across Europe, highlighting the importance of developing and implementing effective mitigation measures to improve nutrient use efficiency and nutrient budgets within various agricultural systems, regions and countries. Building on the protocol developed in *D1.2 Quantified measure-impact relationship of selected measures - initial version*, **Chapter 2** summarizes the procedures to establish the meta-regression models with highlights on the progress after submission of *D1.2*. **Chapter 3** presents the characteristics of the collected research data and the results of meta-analyses on the four defined research questions in *D1.2*. A general discussion section is added in **Chapter 4** to explain the specific aspects of each model and interlinks among them. Finally, **Chapter 5** summarises the impact of the selected mitigation measures according to the established models and provides recommendations for the spatial applicability to be evaluated in Task 1.3 (outcome as *D1.5 Algorithms quantifying impacts of measures via field based indicators from satellite derived indices*).

The developed meta-regression (in RQ1-3) and linear regression (in RQ4) models in this deliverable provide quantitative insights for the measure-impact relationship between various agricultural management practices and performance indicators including crop yield, nitrogen use efficiency (NUE), soil pH, SOC, animal productivity, and nutrient recovery/removal from manure, incorporating site-specific factors at European or global scale. The models demonstrated that the impact of management practices shows significant regional variability influenced by local climate, soil properties, and crop type, though substantial variation in responses of the performance indicators remained unexplained stemming from variable experimental conditions and the multifactorial nature of soil and crop systems. Moving forward toward the implementation of these models in Task 1.3 to calculate the nutrient surplus, it is crucial to run multiple scenario analyses based on the defined regional targets, and continuously update the model with new data, especially in the context of European agricultural systems. Nevertheless, these models give data-driven estimates of the impact of management practices on aforementioned performance indicators, thereby supporting the validation of the process-based models developed in WP2. The models established in this deliverable (D1.3) and the outcomes of model implementation in D1.5 will be integrated into broader decision-support frameworks (e.g. the process-based models developed in WP2) to support the decision-making and effective application of the listed mitigation measures (i.e. management practices) by practitioners.

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List of Abbreviations

AIC	Akaike information criterion
ANC	Acid Neutralizing Capacity
CC	Cover Crop
CF	Combined Fertiliser
Clay_sc	Soil Clay Content Scaled
Cr_m	Crop Type Maize
Cr_r	Crop Type Rice
Cr_w	Crop Type Wheat
CT	Conventional Tillage
D	Deliverable
DD	Direct-Drilling
DF	Drip Fertilisation
EE	Enhanced Efficiency Fertiliser
FT	Fertigation
IMP	Application of Biochar
INC	Intercropping
IR	Irrigation
KPI	Key Performance Indicators
lnRR	Natural log of response ratio
LogLik	Natural log of the model likelihood
M	Mowing
MAP_sc	Mean Annual Precipitation Scaled
MAT_sc	Mean Annual Temperature Scaled
MCR	Multi-Crop Rotation
MF	Mineral Fertiliser
ML	Mulching
MMC	Mitigation Measures Catalogue
N_sc	N Application Rate Scaled
N_sq_sc	N Application Rate Squared Scaled
NF	Nitrogen Fertilisation
NT	No-Tillage

NUE	Nitrogen use efficiency
lnRR	Natural log-transformed Response Ratio
OF	Organic Fertiliser
pH_sc	Soil pH Scaled
REML	REstricted Maximum Likelihood
RFP	Right Fertiliser Placement
RFR	Right Fertiliser Rate
RFT	Right Fertiliser Timing
ROM	Log Transformed Ratio of Means
RQ	Research question
RR	Residue Retention
RT	Reduced Tillage
SD	Standard Deviation
SE	Standard Error
SMD	Standard Mean Difference
SOC	Soil Organic Carbon
SOC_sc	Soil Organic Carbon Scaled
ST	Stubble Tillage
TAN	Total Ammonium Nitrogen
TN	Total Nitrogen
TP	Total Phosphorus
WP	Work Package
ZT	Zero Tillage

1. Introduction

Agricultural management practices significantly influence crop production, soil quality, and environmental outcomes. The nutrient status and management of European agricultural systems face several challenges, including maintaining high crop production, soil quality, and mitigating adverse environmental impacts. Addressing these challenges involves efficiency management practices such as optimizing the use of mineral and organic fertilisers, precision farming techniques, crop rotation, cover cropping, and integrated nutrient management systems to enhance crop yields and minimize environmental impacts. For instance, mineral fertilisers provide immediate nutrient availability but can lead to nutrient leaching and greenhouse gas emissions (Young et al., 2021). Conversely, organic fertilisers improve soil health and crop yield (Zhang et al., 2023) but have unpredictable nutrient content and potential for nutrient runoff. Precision farming has the potential to overcome the heterogeneity of agricultural systems and enhance nutrient use efficiency through targeted applications (Guerrero et al., 2021; Nawar et al., 2017), but its adoption varies across Europe. Crop rotation and cover cropping contribute to soil fertility and reduce the need for chemical fertilisers (Young et al., 2021). The integrated nutrient management combines these practices to maximize productivity and sustainability by tailoring approaches to specific local conditions. However, the full impact of these practices remains inadequately understood due to the variability in agricultural systems, complex nutrient dynamics, limited long-term data, inconsistent methodologies, insufficient monitoring, and emerging challenges like climate change.

Addressing the knowledge gaps in nutrient management requires a comprehensive analysis of the long-term field experiments across diverse European agroecological zones to capture sustained impacts on soil health, crop productivity, and environmental outcomes. Standardized methodologies for assessing nutrient management practices are essential for consistent and comparable results, in particular given the fact that their impacts are highly dependent on the site conditions. Integrated modeling approaches that combine process-based models, meta-regression analyses, and scenario simulations can provide actionable insights. Within the NutriBudget project, Task 1.2 is a cornerstone of Work Package (WP) 1, which aims to develop a comprehensive Mitigation Measures Catalogue (MMC) by detailing relevant agronomic measures identified in Task 1.1. Task 1.2 focuses on quantifying the relationships between these measures and their impacts, particularly examining how they affect various agronomic, soil fertility, and environmental indicators outlined in subsequent Work Packages (WP2 and WP3). This task is pivotal in synthesizing and analyzing long-term field experimental data through meta-analysis, providing a deeper understanding of the interplay between agricultural practices and their broader implications. The literature inventory efforts in WP1, combined with the connections to the development of process-based models in WP2 and the establishment of key performance indicators (KPIs) framework in WP3, underscore the project's comprehensive approach to optimizing agricultural practices across different European contexts, aiming to improve nutrient use efficiency and reduce environmental impacts.

Deliverable (D) 1.3, following the established framework and methodology as detailed in *D1.2 Quantified measure-impact relationship of selected measures - initial version*, presents a robust analysis of the meta-analytical findings from Task 1.2. This deliverable develops specific meta-regression models based on the defined research questions (RQs) in *D1.2* to quantify the measure-impact relationship in crop, soil, and animal management systems. The data collected in the MMC during the primary stage of Task 1.1 was used as an important data source for the meta-analysis in this deliverable. Beyond these pre-identified mitigation measures in the MMC, an inventory was conducted to collect extra research data on a broader range of crop, soil and nutrient management practices.

To effectively evaluate the impact of different management practices on nutrient budgets in crop, animal and bioprocessing systems, the following KPIs were selected for the meta-analytical quantification: (i) crop yield, representing the effectiveness of nutrient management in supporting crop productivity, reflecting the direct benefit of nutrient inputs; (ii) nitrogen use efficiency (NUE), assessing how efficiently plants utilize nitrogen, indicating potential reductions in emission, leaching and runoff; (iii) soil organic carbon (SOC), a crucial indicator of soil health, reflecting the capacity of soil to sequester carbon, enhance fertility, and support sustainable agricultural productivity; (iv) soil pH, affecting nutrient availability and microbial activity, serving as a fundamental measure of soil chemical balance; (v) average daily weight gain (ADG), feed conversion ratio (FCR) and protein digestibility of animal feeds (DCP), measuring the efficiency with which livestock convert feed into body mass, highlighting opportunities to optimize animal production systems; and (vi) nutrient (N & P) recovery and removal rates in manure processing, which are essential for understanding nutrient cycling and the environmental impacts of nitrogen use, particularly concerning leaching and emissions. The chosen indicators help quantify nutrient surplus and nutrient use efficiency, which are central to assessing the sustainability of agricultural practices. High yields and NUE suggest that crops are utilizing nutrients efficiently, minimizing waste, and maximizing productivity. Soil pH influences nutrient solubility and availability, thus affecting plant growth and nutrient uptake efficiency. SOC indicates the long-term potential for carbon sequestration and soil health, essential for sustainable nutrient management. Animal ADG, FCR and DCP measure how effectively livestock convert feed into usable body mass and nutrients, reducing resource inputs and waste. The recovery and removal rates of N & P provide insights into the efficiency of nutrient uptake and the potential for nutrient loss, which can lead to environmental degradation. By focusing on these response variables, the meta-analysis can assess how different management practices affect nutrient cycling and identify strategies to improve nutrient use efficiency across diverse European agroecological zones. This comprehensive approach allows for the development of tailored agronomic strategies that enhance sustainability and productivity, helping to mitigate the negative impacts of agriculture on the environment.

The established models reflect the significant regional variability influenced by local climate, soil properties, and crop type, providing nuanced insights into the effectiveness of different management practices. These findings are expected to have substantial impacts within the project, as they will be directly implemented in Task 1.3 to quantify the measure-impacts on European agricultural systems and will be incorporated with the process-based models in WP2 to support decision-making. Beyond the project, the insights from D1.3 will inform the development of tailored agronomic strategies that enhance sustainability and productivity across various agricultural systems in Europe, thus supporting the long-term goals of improved nutrient management and reduced environmental impacts.

2. Methodology

2.1 Overall approach

As stated in *D1.2*, meta-analysis is employed in Task 1.2 to quantify the impact of selected measures on the four identified research questions:

RQ1: What is the impact of the selected mitigation measures (e.g. **crop, soil and fertiliser management**) on **nutrient surplus and nutrient use efficiency by crop?**

RQ2: What is the impact of the selected mitigation measures (e.g. **crop, soil and fertiliser management**) on **soil quality**?

RQ3: What is the impact of the selected mitigation measures (e.g. **animal feed management**) on the **nutrient use efficiency by animals?**

RQ4: What is the impact of the selected mitigation measures (e.g. **manure processing technologies**) on the **N and P recovery from livestock industries?**

The methodology for data collection has been stated in Chapter 2 of *D1.2*. In brief, we used Web of Science (https://www.webofscience.com/), Scopus (https://www.scopus.com/), and Google Scholar (https://scholar.google.com/) to search peer-reviewed publications for our meta-analysis. Specific search terms tailored to our research questions included combinations like "enhanced efficiency fertiliser," "organic fertiliser," "crop rotation," "N_2O emission," "soil organic carbon (SOC)," "livestock feed," and "manure treatment", etc. (see all the search terms listed in *D1.2* Section 2.3.2). The resulting publications were further screened based on the research focus, data availability for the main KPIs and site properties, spatial coverage (mainly focus on European regions), experimental type and duration, following the defined selection criteria in in *D1.2* Section 2.2. For crop and soil systems (RQ1-2), data from both field and pot experiments were included, excluding results from incubation or leaching experiments. In terms of the animal feeding management (RQ3), data were collected mainly from the feeding experiments on pig and poultry, because of the common use of soy-based protein in their feeds. For manure processing management (RQ4), data were collected from different experimental scales including farm level, full or industrial scale, pilot, batch and laboratory scales.

To establish a complete dataset to account for the impact of site conditions, we extracted the following data: crop type, climatic conditions, experimental management (duration of amendments application, in years), soil properties (soil type, texture, initial pH, organic matter/carbon content, bulk density, cation exchange capacity, and base saturation), and amendment properties (type and rate). Collected studies had to meet the following criteria: (1) include a control treatment without implementing the targeted management practice, (2) clearly report inputs and rates of management practice, (3) include target variables such as crop yield, nitrogen uptake, soil pH, SOC, animal productivity, nutrient recovery or removal. (4) report means, standard deviation (SD), or standard error (SE). When SD was missing, SE was converted to SD by multiplying SE by the square root of the number of replicates.

Site factors (climate conditions, soil properties, and local traditional farming practices) data used in this study were obtained from openly accessible data sources when data was missing in original publications, including: (1) climate data, including mean annual temperature (MAT) and mean annual precipitation (MAP), obtained from CRU (http://www.cru.uea.ac.uk/data), (2) soil properties, comprising soil clay content, SOC, and soil pH, extracted from the soil grids provided by ISRIC (http://www.isric.org/explore/soilgrids), and (3) land use data from the Spatial Production Allocation Model (https://www.mapspam.info/data).

The overall approach for the meta-analysis is presented in Figure 1.

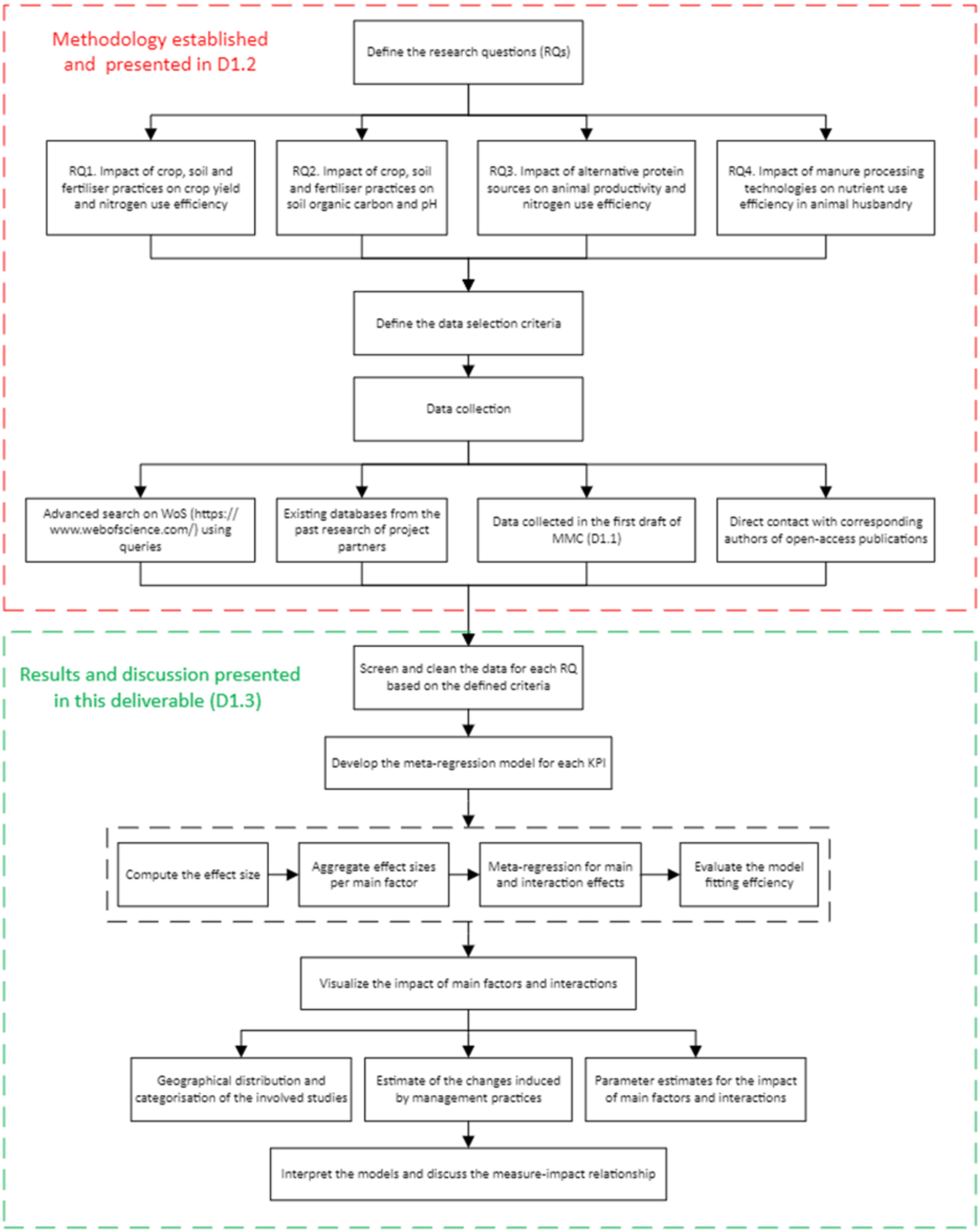

Figure 1. *Methodology developed for the quantification of measure-impact relationship using meta-analysis (details about the methodology refers to D1.2 Quantified measure-impact relationship of selected measures – initial version).*

2.1 Inclusion of global dataset

In the context of measure-impact quantification using meta-analysis, it is crucial to establish robust criteria for data collection to ensure the accuracy and relevance of the findings. One primary criterion for this research is the focus on European data when collecting new observations. This geographical focus aligns with the specific environmental, agricultural, and climatic conditions pertinent to Europe, thereby enhancing the relevance and applicability of the research outcomes to the region. By concentrating on European data, the study can provide targeted insights and recommendations that are directly applicable to European agricultural practices and policymaking. The European context also allows the study to take into consideration the legacy effects of historical land use, agricultural practices, climate and atmospheric deposition. These legacy effects do not only influence the present state of the studied KPIs, but also their eventual responses to management practices and mitigation measures.

However, for some KPIs the use of global data is beneficial for the derivation of empirical (statistical) models quantifying the impact of measures, in particular given the facts that (i) for crop and soil measures (RQ1 and RQ2) there are readily-collected data from open-access databases or existing meta-analytical research focusing on a global scale; (ii) for animal and manure measures (RQ3 and RQ4), the geographical information is usually neither reported nor important for the quantification. Integrating global datasets allows the models to leverage a broader range of data, capturing a wider variety of conditions and practices that may not be fully represented within the available data from European studies alone. Besides, given the novelty of some measures (such as microalgae and duckweed cultivation), there is a lack of available data and more research is still emerging in Europe. Therefore, incorporation of global datasets can enhance the statistical power of the meta-analysis, leading to more comprehensive and reliable conclusions.

Furthermore, the consideration of global datasets is particularly relevant in the context of a changing climate. Climate change is a global phenomenon with varying impacts across different regions, including Europe. By including data from diverse climatic and geographical settings, the research can better account for the variability and potential future scenarios that European agriculture may face by substituting space for time where conditions from outside Europe today can reflect future conditions at European sites. This broader spatial quantification provides a more holistic understanding of the impacts of various measures, enabling the study to anticipate and address the challenges posed by climate change more effectively.

2.2 Statistical analysis

2.2.1 Calculation of effect size

In order to conduct a meta-regression on the original experimental data derived from the primary studies, we first calculated the effect sizes and corresponding variances of the primary studies using three methods (also called effect sizes) based on the means, standard deviations and number of repetitions of the recorded responses or effect indicators, being crop yield, NUE, etc. (Viechtbauer, 2010; Borenstein et al., 2009; Hedges et al., 1999). For each RQ the most appropriate effect sizes were selected given the data availability, population distribution and complexity of the effect size for interpretation. The three effect sizes used in this report include the relative response ratio (lnRR), the mean difference (MD) and the standardized mean difference, as being explained below.

The log transformed ratio of means (lnRR) was calculated as:

$$ln\,RR = ln\,(\frac{X_t}{X_c}), \quad (1)$$

where X_t and X_c are the mean observed effect indicators of the treatment and control group, respectively.

The corresponding variance was calculated as:

$$V_{lnRR} = \frac{{s_t}^2}{n_t {X_t}^2} + \frac{{s_c}^2}{n_c {X_c}^2} \quad (2)$$

where n_t and n_c are the number of the treatment and control, respectively, and s_t and s_c are the standard deviations of the treatment and control, respectively. The change in relative effect indicator (as %) compared to the control due to a management measure was subsequently calculated as:

$$Relative\ change(\%) = \left(e^{\ln RR} - 1\right) \times 100 \quad (3)$$

The ROM method is utilized when the effect of a treatment is expected to be proportional and the data are approximately log-normally distributed. This method is advantageous because the resulted lnRR is dimensionless, allowing for easy comparison across studies with different scales or units, and it normalizes the data, reducing skewness. Therefore, lnRR is calculated for the impact on crop yield in RQ1 (Section 3.1), animal productivity in RQ3 (Section 3.3), and nutrient recovery/removal from manure in RQ4 (Section 3.4). These KPIs often exhibit multiplicative effects in response to management practices and covariates, making lnRR appropriate for capturing these proportional changes. The normalization provided by lnRR also facilitates comparison across different categorial variables such as experimental conditions and technologies, ensuring a consistent measure of treatment impact.

The raw mean difference (MD) due to a change in management, was calculated as:

$$MD = X_t - X_c \tag{4}$$

The corresponding variance was calculated as:

$$V_{MD} = \frac{{s_t}^2}{n_t} + \frac{{s_c}^2}{n_c} \tag{5}$$

The MD method is employed when the effect size is naturally expressed in the same units across studies, or the effect size is already a relative change indicator like NUE. This metric is straightforward and easy to interpret, directly measuring the absolute difference without standardization. Standing between ROM and MD is SMD which is applied when the treatment effect is additive but studies being compared have different measurement scales. In this case, the underlying effect sizes need to be standardized, and the data are normally distributed or can be assumed to be so after standardization.

The standardized mean difference (SMD) was calculated as:

$$SMD = \frac{(X_t - X_c)}{SD_p} \tag{6}$$

$$SD_p = \sqrt{\frac{(n_t - 1){s_t}^2 + (n_c - 1){s_c}^2}{n_t + n_c - 2}} \tag{7}$$

where SD_p is the pooled within-group standard deviation.

In this deliverable, SMD is chosen for the quantification of NUE in RQ1 and for SOC and soil pH in RQ2, because both numerical (e.g. N fertiliser dose, temperature, clay content, etc.) and categorical (management practices such as tillage, cover crop, etc.) variables are considered in the models, while their effect on these KPIs is typically additive rather than multiplicative, and the units of SOC and pH are presented consistently across studies. As such, SMD provides a clear measure of the change in SOC and soil pH due to different management practices over a standardised scale, providing a direct and meaningful measure of treatment impact.

The corresponding variance was calculated as:

$$V_{SMD} = \frac{n_t + n_c}{n_t \times n_c} + \frac{SMD^2}{2(n_t + n_c)} \tag{8}$$

Given that the collected data came from studies applying different research methods, there is non-independence and heterogeneity among the effects (Harrer et al., 2021; Ros et al., 2016). We accounted for the non-independence by using multivariate meta-modeling with restricted maximum-likelihood estimation, as implemented in Metafor (Viechtbauer, 2010). Paper number was used to specify the random-effects structure of the model. Observations of the effect indicators in primary studies were assumed to be independent whereas effects within each study received correlated random effects assuming a symmetric compound structure. Random-effects models can estimate the distribution of individual effect sizes of means, residual heterogeneity and sampling error. It calculates the mean effect size as a weighted mean of individual effect sizes, using the inverse of the sum of the between-study variance (due to variation in experimental conditions) and within-study variance (due to sampling error) as weights (Borenstein et al., 2009).

2.2.2 Effect of site properties controlling effect size

To evaluate the impact of management practices and site conditions (i.e. MAP, MAT, clay content, SOC and soil pH) on the selected effect indicators derived from original field studies, a main factor analysis was performed initially to assess their overall impact and to identify the most relevant variables controlling the impact of the practices applied. The principle behind this approach is based on generalized conclusions derived from a large amount of field studies, allowing the identification of broadly applicable cause-effect relationships. An analysis of variance was then done to evaluate the contribution of each of the assessed management practices and site conditions on the variation of the effect indicators, combined with an analysis of both Akaike's information criteria (AIC) and the *p* value.

Since the impact of nutrient, crop and soil management practices on effect indicators may interact, we subsequently analyzed the main and all two-way interactions between management practices and site conditions using a mixed effects model with interaction terms (Harrer et al., 2021):

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i1} x_{i2} + \cdots + u_i + e_i \quad (9)$$

where, y_i is the observed effect size for a given effect indicator, x_{i1} is the value of the first moderator variable for the ith study and x_{i2} is the value of the second moderator variables for the ith study, β_0 is a regression coefficient representing the intercept, β_1 is a regression coefficient indicating how the average true effect size changes for one unit increase in x_{i1}, β_2 is a regression coefficient indicating how the average true effect size changes for one unit increase in x_{i2}, u_i is the variance of the true effect (residual heterogeneity) of study i, e_i is the sampling error of study i, and $x_{i1} x_{i2}$ is the interaction term with coefficient β_3. Numeric variables were standardised to the scale of 0-1 to simplify model parameter selection and interpretation. According to the results of the main factor analysis by an initial model, a generalised full model is established to estimate the mixed effect of management practices and site properties accounting for their interactions. The management practices and site properties showing significant impact on the KPI ($p < 0.05$) are further chosen as the main moderator variables to be included in a refining process with the aims to simply the final model and achieve a more accurate quantification of the measure-impact relationship. However, there could be exemptions that in our hypothesis one certain management practice or site property should show significant impact on the KPI, but it was not reflected by the generalised full model given the collected database. In that case, we still include such a management practice or site property in the refined model to further test our hypothesis. Due to the presence of categorial variables (e.g. crop type, fertiliser type, tillage method, if crop residue, cover crop, irrigation, etc. is included) in the final regression models we skipped the intercept β_0 implying that one of the management practices was considered as baseline to which all other management practices were compared.

To avoid overfitting the regression model, we first checked for unrealistic responses in KPIs due to measures applied, considering observations deviating more than 3 times the SD of the mean response across all studies as being an outlier, and removed them before the regression analysis. We assessed the impact of each factor and its interaction with other variables using analysis of variance. The log-likelihood (LogLik, representing how well the model fits the data) and AIC were used to compare regression models. The best model had high (less negative) LogLik and low AIC values. We also checked the amount of residual heterogeneity according to the Q_E output of the *rma.mv* function in R 4.2.2 software (Viechtbauer, 2010). Q_E tests show whether the variability in the observed effect size (for which the moderators do not account) is larger than the expected sampling variability only, so Q_E represents the heterogeneity which cannot be explained by the model. Smaller values for Q_E reflect a better model performance.

3. Results and discussion

3.1 RQ1: impact of crop, soil and fertiliser measures on crop system

3.1.1 Impact on crop yield

3.1.1.1 Characteristics of the collected data

To evaluate the impact of crop, soil, and fertiliser management practices on crop yield, we created meta-regression models accounting for site properties. The databases for these models contained only crop yield data from European countries being retrieved from existing databases published with original research and other meta-analytical publications (the database is openly shared through the GitHub link in Chapter 4). The site properties data were simultaneously gathered from these publications or retrieved from open datasets described in section 2.1.

For the selection of the crop yield data, three different queries were created based on every practice. The queries included three elements, such as the synonyms of the management practices, synonyms of the indicators, and the keyword of meta-analysis. From the original search, the total number of collected meta-analytical studies based on their title and abstract was N = 80. After screening for online and available databases on European crop yield data this number dropped to N =12. From these 12 meta-analytical studies and the snowballing method, the actual number of experimental studies from which data were inserted in our database reached N = 241 and the paired observations (treatment-control) were assessed to be N = 1227. A thorough check and removal of duplicates was conducted. In this study, we covered all the different climate zones in Europe, as depicted by our primary studies (N = 241) shown in Figure 2.

The management practices can be categorised as crop (crop rotation, cover crop, intercropping, and ley), soil (reduced tillage like ridge or strip, biochar application, residue retention, drilling and mulching), and fertilization (organic fertilisation, drip fertilisation and N or P or K or Mg fertilization) management. Yield data for both treatment and control were collected in kg/ha, and unit transformations were performed when necessary. The numeric site property data were standardized to unit variance.

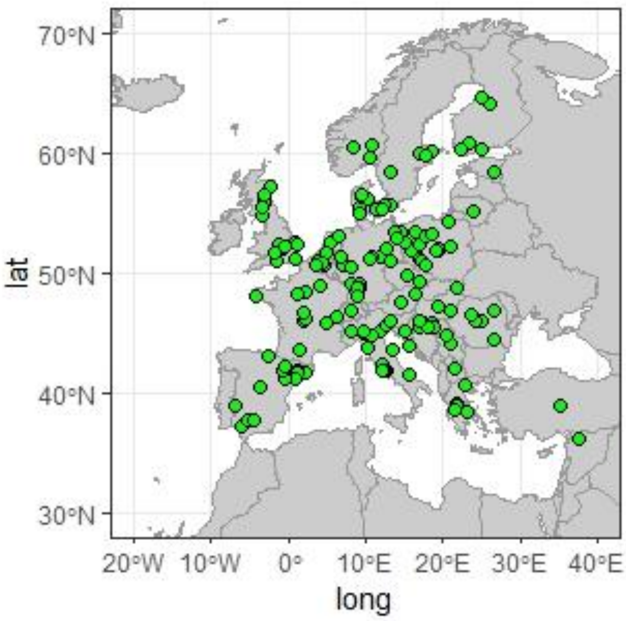

Figure 2. *European map indicating the locations of the 241 primary studies evaluating management practices' effects on crop yield being included in this study.*

It was obvious that soil management practices were the ones dominating in data availability by 72% with a number of 175 studies compared to crop (20%, N = 46) and fertilisation management practices (8%, N = 20). The main reason for this disparity was the limited availability of free and open-access databases. Another factor was that many meta-analytical databases included papers published globally or focused on Asian countries like China, often excluding European countries or mentioning them without providing any data.

3.1.1.2 Quantifying the impact of management and site conditions

Using the “metafor” package in R and the restricted maximum likelihood (REML) estimation we quantified the impact of management practices on crop yield while accounting for site properties and site conditions. We selected the log transformed ratio of means (lnRR) as effect size, provided the relative change in crop yield between the treatment (applied management practices on the field) and the control (no application of practices or conventional applied practices).

The total variation in the response of crop yield due to crop, soil, and fertilisation practices is demonstrated in Figure 3. The lnRR values varied from minus two (a decline of more than 80%) to plus two (an increase of more than 500%). Most of the studies seem to be clustered around zero suggesting a small and neglectable effect on crop yields. However, the presence of both positive (33% of the cases) and negative values (also 30% of the cases) highlights shows that numerous situations occur where management practices can have substantial impacts on crop yield.

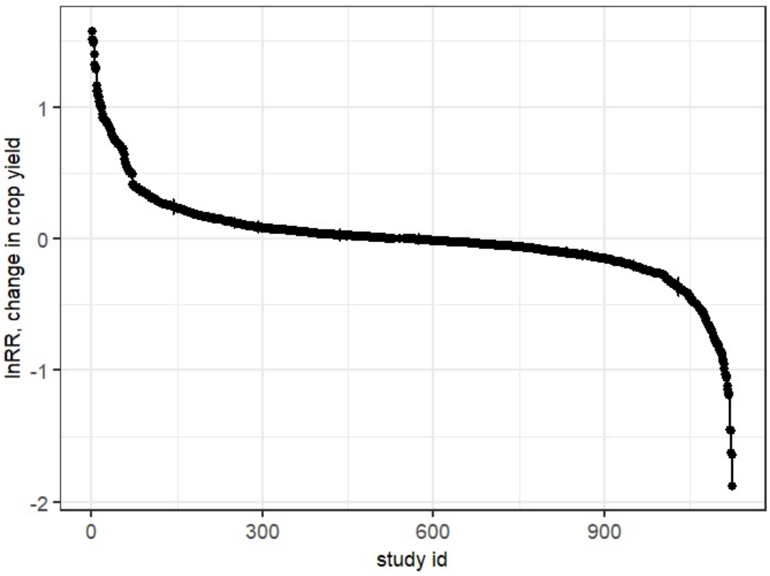

Figure 3. *The observed variation in crop yield changes, presented as the natural log of the response ratio (lnRR), due to crop, soil, and fertiliser management for 1153 observations.*

The initial model based on the impact per main factor

Using a main factor analysis, we showed that most of the management practices had a positive impact on crop yields (Figure 4). Strong and positive impacts were found for stubble tillage (ST), residue retention (RR), nitrogen fertilization (NF), irrigation with fertigation (IR + FT), and solely irrigation (IR) ($P < 0.01$). Negative impacts on crop yield were found for no-till practices (NT) and (multi-) crop rotations (MCR). For all other measures and measure combinations, the impact tended to vary between a 40% reduction to an increase up to 30% ($P > 0.05$).

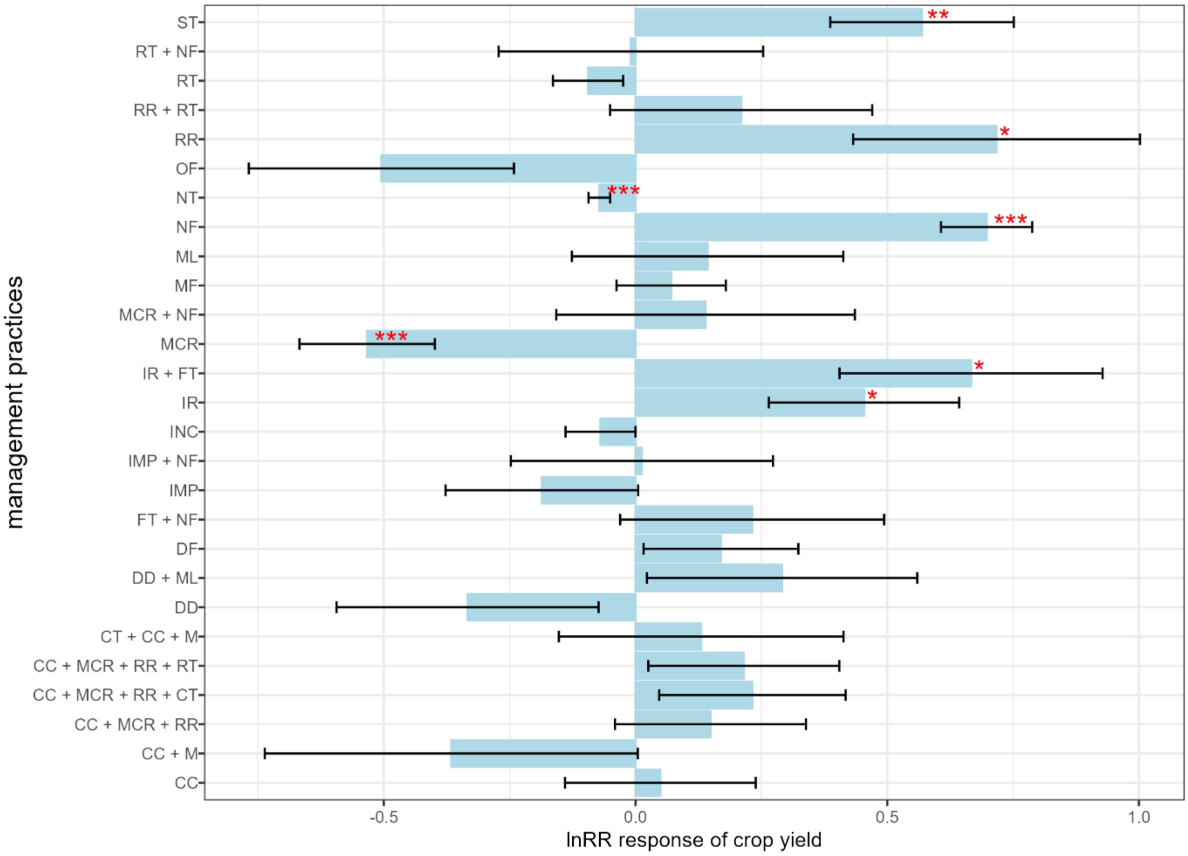

***Figure 4** The lnRR response of crop yields induced by the applied management practices, along with their standard errors. The abbreviations stand for stubble tillage (ST), reduced tillage + nitrogen fertilisation (RT+NF), reduced tillage (RT), residue retention + reduced tillage (RR+RT), residue retention (RR), organic fertilisation (OF), no-tillage (NT), nitrogen fertilisation (NF), mulching (ML), magnesium fertilisation (MF), crop rotation + nitrogen fertilisation (MCR + NF), crop rotation (MCR), irrigation + fertigation (IR+FT), irrigation (IR), intercropping (INC), application of biochar + fertigation (IMP+NF), application of biochar (IMP), fertigation + nitrogen fertilisation (FT+NF), drip fertilisation (DF), direct-drilling + mulching (DD+ML), direct-drilling (DD), conventional tillage + cover crop + mowing (CT+CC+M), cover crop + crop rotation + residue retention + conventional tillage (CC+MCR+RR+CT), cover crop + crop rotation + residue retention + reduced tillage (CC+MCR+RR+RT), cover crop + mowing (CC+M) and cover crop (CC). Asterisks indicate statistically significant differences (*p < 0.05, **p < 0.01 and ***p < 0.001).*

***Table 1.** The site properties evaluated in the models and their description.*

Site properties	Description
Crop type	Rice, vegetables, bean & oilseed crop, cereals, maize, other plant types
Crop residue	Applied (yes), not applied (no), or not mentioned in literature – unknown (U)
Cover crop	Applied (yes), not applied (no), or not mentioned in literature – unknown (U)

Crop rotation	Applied (yes), not applied (no), or not mentioned in literature – unknown (U)
Tillage	Reduced tillage (RT), no-tillage (NT)
Fertiliser type	Inorganic, organic, or not mentioned in literature – unknown (U)
Fertiliser dose	Nitrogen (N), Phosphorus (P), Potassium (K), Magnesium (Mg) in kg / ha
Temperature	The mean annual temperature (°C)
Precipitation	The mean annual precipitation (mm)
Evapotranspiration	The mean annual evapotranspiration (mm)
Total nitrogen	The mean total nitrogen prediction (cg/kg) in the upper soil layer (0 – 5 cm)
SOC	The mean SOC (g/kg) in the upper soil layer (0 – 5 cm)
Clay	The mean clay content (g/kg) in the upper soil layer (0 – 5 cm)
Bulk density	The mean bulk density prediction (cg/cm³) in the upper soil layer (0 – 5 cm)
Cation exchange capacity	The mean cation exchange capacity prediction (mmol(c)/kg) in the upper soil layer (0 – 5 cm)
pH water	The mean pH water in the upper soil layer (0 – 5 cm). Water was used as a solution to extract the pH values and thus it is referred to as pH water.

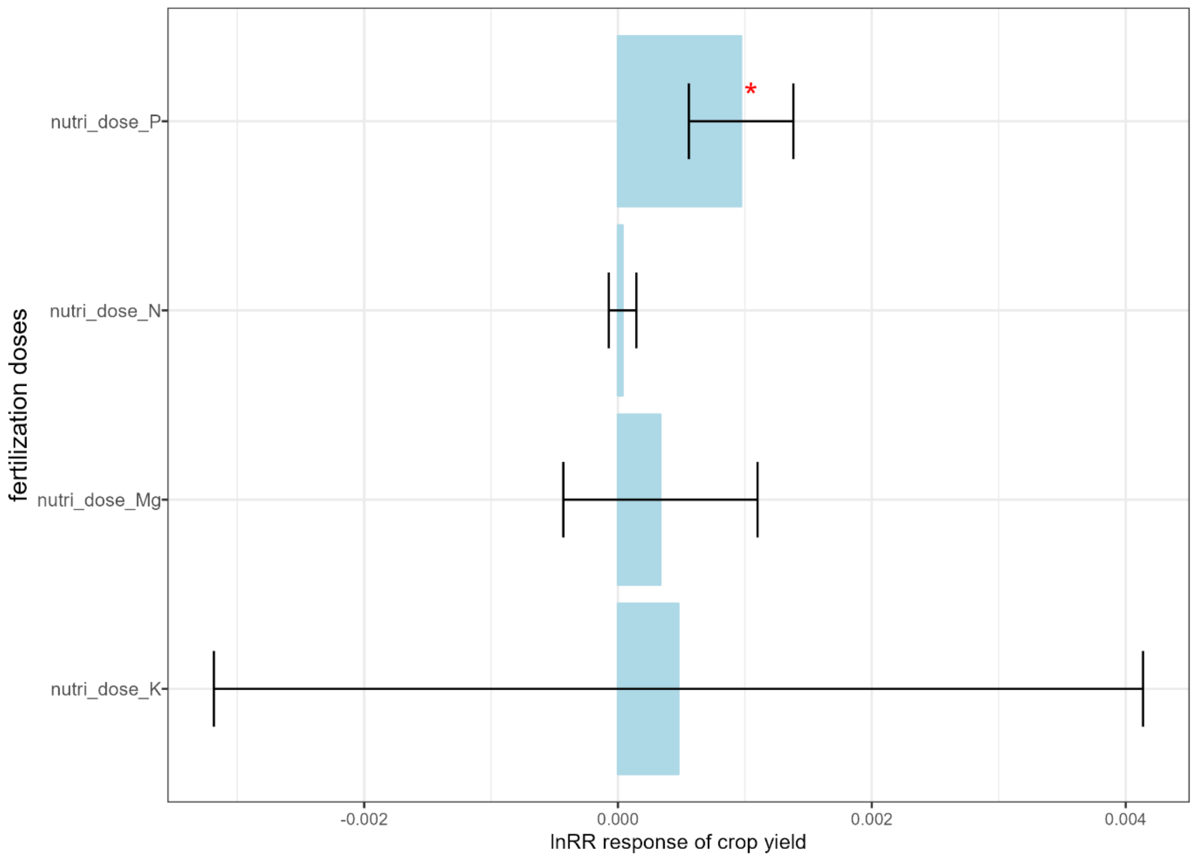

Figure 5. *Effect of fertilisation doses as a covariate on the lnRR response (changes of crop yields) induced by the management practices of soil, crop and fertilisation. In the y-axis the fertilisation doses are exhibited as nutri_dose_P for a phosphorus dose, nutri_dose_N for a nitrogen dose, nutri_dose_Mg for a magnesium dose, and nutri_dose_K for a potassium dose. In the x-axis, the lnRR response is denoted along with the standard error bars and significance is indicated with a p-value less than 0.05 as *.*

In addition to management practices, site properties (Table 1) like fertilisation doses, crop type, soil properties, weather conditions, tillage, crop rotation, and crop residue were also analysed for their impact on the crop yield response to management practices applied (Figure 5-6). These include the fertilizer inputs for phosphorus (P dose), nitrogen (N dose), magnesium (Mg dose), and potassium (K dose) (Figure 5). From these nutrients only the P dose had a significant impact on the management induced change in crop yields, but in any case these impacts were rather small (<1%).

The crop type category included vegetables, rice, maize, cereals, beans and oilseed crops, other arable crops and other plants that do not fall into any of the previous categories (Figure 6). Soil properties included SOC (g/kg), pH water, total nitrogen (cg/kg), clay content (g/kg), cation exchange capacity (mmol(c)/kg), and bulk density (cg/cm^3). Weather conditions included evapotranspiration (mm), precipitation (mm), and temperature (^oC). Fertiliser type was categorised as organic, inorganic, combined, and set to unknown when no information was given. Tillage practices were categorized into reduced tillage, no-tillage, and conventional. Crop rotation was divided into "yes", "no", and "unknown", with "yes" indicating the application of crop rotation, "no" indicating that it was not used, and "unknown" indicating no reference to its application in the examined study. The same principle was applied to crop residue (Figure 6).

As shown in the Figure 6, the impact of management practices on crop yield was strongly different among the crop types, in particular for the arable crops, beans and oil crops as well the "other" crop category ($P < 0.05$). Most of the soil properties had a negative but small impact (<1%) on the crop yield response to management practices ($P<0.05$). Weather conditions demonstrated a positive impact on crop yield, in particular for evapotranspiration and temperature ($P < 0.01$). The type of the fertilizer applied (being organic or inorganic) can have a strong impact on the crop response to management practices ($P > 0.05$), varying from a decline of 5% up to an increase of 15%. Tillage practices had only a minor impact (<5%, $P>0.05$) on the impact of management practices on crop yield. In contrast, crop rotation had a negative impact on the observed management induced change in crop yield ($P<0.01$) though its impact was smaller than 5%. The application of cover crops tended to lower the crop response to management measures, whereas the removal of crop residues led to a decline in the crop yield response of about 10% ($P<0.05$).

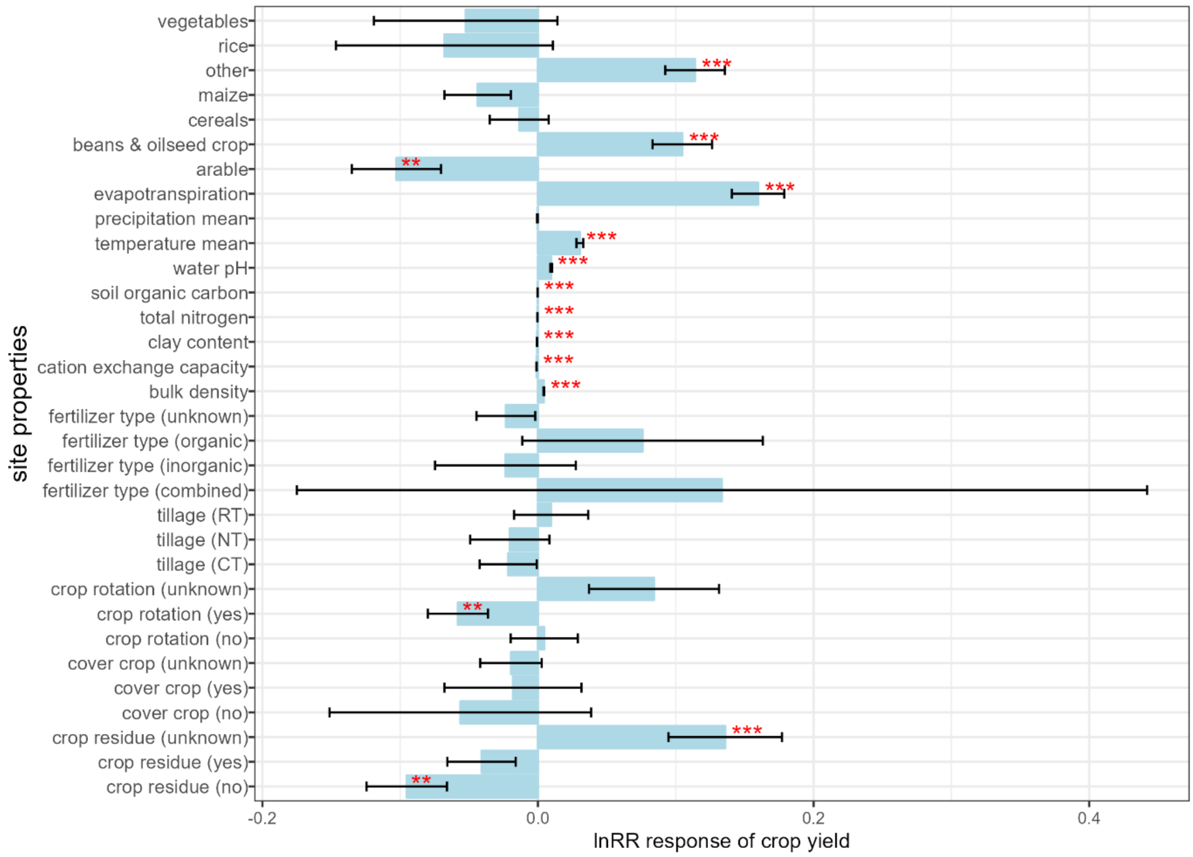

Figure 6. *Effect of site properties on the lnRR response (changes of crop yield) induced by the management practices. Asterisks indicate statistically significant differences (*p < 0.05, **p < 0.01 and ***p < 0.001).*

The generalised full model and refined model

The generalised full model accounted for the interactions among site properties (Table 1) and the management practices being applied to increase crop yields, as grouped in categories (Table 2). The initial created groups of management practices were biochar, combination, crop, drilling, fertilisation, irrigation, mulching, residue, and tillage. From those, most of them displayed positive trends except biochar (-16%), crop (-20%), and tillage (-37%). Notably, none of them showed any significant impact (See Annex 1, Figure A1).While the model estimate and significance of each site property influencing the impact of these management practices varied between a decline of 40% and an increase up to 100% (Annex 1, Figure A1). Notably for the site properties, negative trends were observed for rice, vegetables, all fertilisation types, crop rotations N and K doses, clay, total nitrogen, and pH water. In contrast, the remaining site properties exhibited positive impacts on the crop yield response, in particular for the crop categories beans and oil crops, cereals and other plant types and use of crop rotations, and soil properties such as total nitrogen, and bulk density. These findings acted as an indication for the full generalised model's improvement, and they lead to the creation of the refined one.

Thus, given the initial grouping of management practices showed limited variation and not significant impact on the crop yield response, they were re-grouped based on literature and on our empirical knowledge after the collection of the meta-analytical studies' databases, which suggested that some practices fit into broader categories (Table 2). Regarding site properties, solely the site properties with a significance were selected for the refined model to improve the model's accuracy as have been done in other metamodel and statistical studies (Heinze et al., 2018; Cheng, 2008).

Table 2. *The management practices groups and their included management practices.*

Management practices groups in the **generalised full** model (Figure A1)	**Included practices**	**Management practices groups** in the final **refined** model (Figure 7)
Combination	cover crop + mowing (CC+M), cover crop + (multi-) crop rotation + residue retention (CC+MCR+RR), cover crop + (multi-) crop rotation + residue retention + conventional tillage (CC+MCR+RR+CT), cover crop + (multi-) crop rotation + residue retention + reduced tillage (CC+MCR+RR+RT), cover crop + residue retention + reduced tillage (CC+RR+RT), conventional tillage + cover crop + mowing (CT+CC+M), reduced tillage + nitrogen fertilisation (RT+NF), fertigation + nitrogen fertilisation (FT+NF), irrigation + fertigation (IR+FT), residue retention + reduced tillage (RR+RT), application of biochar + fertigation (IMP+NF), crop rotation + fertigation (MCR+FT), direct-drilling + mulching (DD+ML) direct-drilling + (multi-) crop rotation (DD+MCR), crop rotation + nitrogen fertilisation (MCR + NF)	Combined practice
Fertiliser	organic fertilisation (OF), nitrogen fertilisation (NF), magnesium fertilisation (MF), drip fertilisation (DF)	Fertiliser practice
Biochar	application of biochar (IMP)	Soil practice
Drilling	direct-drilling (DD)	
Mulching	mulching (ML)	
Residue	residue retention (RR)	
Tillage	no-tillage (NT), stubble tillage (ST), reduced tillage (RT)	
Crop	cover crop (CC), intercropping (INC), ley (L), (multi-) crop rotation (MCR)	Crop practice
Irrigation	irrigation (IR)	Irrigation

In the refined model, the significant impact induced by site properties (i.e. soil properties, climatic conditions and existing management) plus their interactions were selected to estimate the crop yield response due to management practices applied (Figure 7). Firstly, the new groups of management practices in the refined model (Table 2) were tested for their impact on crop yield, being the combined practice, crop practice, fertilisation practice, irrigation and soil practice thereby ignoring the effect of site properties. Positive changes were observed for combined management practices and for irrigation practices where most other management practices would decline crop yield. The impact varied from a decline of 40% up to an increase of 28%.

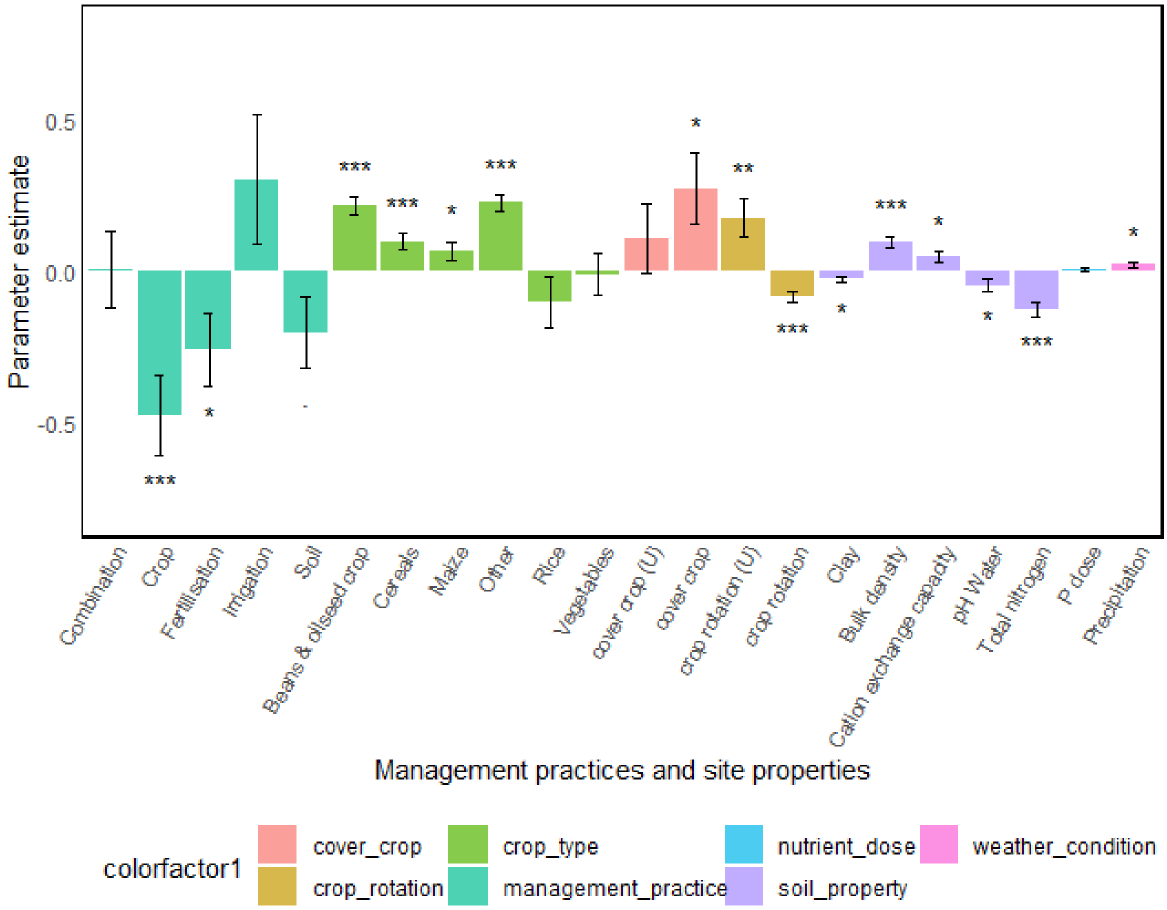

Figure 7. *Parameter estimates of the refined meta-regression model for the effect of the management practices along with the impact of site properties on the changes of crop yield induced by these management practices. The included practices are combined practice, crop practice, fertilisation practice, irrigation and soil practice on crop yield, details of the management practices are presented in Table 2. The presented site properties are the applied (e.g., cover crop) along with those not refferred in the literature (e.g., cover crop (U), in which U stands for unknown). Asterisks indicate statistically significant differences (*p < 0.05, **p < 0.01 and ***p < 0.001). The colour differentiates both the management practices and the site properties from each other, but it also indicates that site properties with the same colour belong in the same group. Thus, green follows the crop type grouping, pink indicates the cover crop, yellow describes the crop rotation, purple the soil properties (clay, bulk density, cation exchange capacity, pH water and total nitrogen), light blue the P dose and fuchsia the weather conditions (precipitation).*

In the final refined model, the included site properties were the crop type, cover crop, crop rotation, soil, and weather conditions (Figure 7). All the crop types except rice and vegetables had a significant impact on the crop yield response to management practices, in particular for the crop categories beans and oilseed crop, cereals, and other plants (P <0.001) and also for maize (P < 0.05). The presence of cover crop was comparable. Crop rotation (-8%) significantly diminished crop yield (p-value < 0.001) while crop rotation (U) significantly increased it (p-value < 0.01). Among soil conditions, only bulk density and cation exchange capacity (4%) showed a positive trend in influencing the yield while the rest showed the opposite. A significance of p-value <0.001 was detected for bulk density and total nitrogen while all the rest soil conditions appeared to have a significance lower than 0.05. Phosphorus dose had a very small but positive impact. An increase in precipitation led to a higher crop response ($P<0.05$).

The generalised full and the refined model demonstrated a better fit when compared with the mean response model across all studies (Table 3). Specifically, the mean response model appeared to be the simplest model with the poorest fit, as indicated by its high AIC (Akaike Information Criterion) values. The generalised full model presented a significant and better fit of data (higher log-likelihood (logLik), lower AIC and AICc (Corrected Akaike Information Criterion) and significant p-value) along with better explanation of variability of the data (lower QE = 88669.5 when compared with the mean response QE = 192858.1). Similarly, the refined model followed the trend of the generalised full model when compared with the mean response model, but performed slightly worse than the generalised model. Nevertheless, the refined model offered practical benefits by using fewer moderators, which allowed for simpler interpretation and provided a clear overview of the current state in crop yield-practices interaction.

***Table 3**. Statistical metrics comparing the relevance of the different models predicting crop yield in response to agricultural practices and site conditions*

Model	logLik	Deviance	AIC	AICc	Moderators p-value
Initial model for main factor analysis	-33420	3853	66844	66844	-
Generalised full model	-31508	63016	63096	63099	< .0001
Refined model	-31541	63082	63128	63129	< .0001

The final refined model highlighted the intricate influence of management practices (Table 2) and site properties on European crop yields and how the site properties (Table 1) affect these influences. Two out of the five management practice groups increased crop yields as expected (Figure 7). However, not all practices showed consistent effects. Crop practices depicted a significant and diminishing impact on crop yields. This effect can be explained by tendencies of some crop practices like cover crops which might hinder arable crop yields like maize and soybean (Deines et al., 2023). Fertilisation management practices, despite their general role in stabilising and significantly boosting crop yields, also demonstrated a similar negative impact on crop yield, contradicting their typical benefits. This is particularly evident with excessive use of fertilisation, such as N fertilisation, which is known to decrease crop yields. This observation also aligns with and explains the negative influence of soil total N on the changes of crop yield due to the direct impact of N fertilisation on total nitrogen (Figure 6). Thus, if the N level is exceeded because of excessive fertilisation then crop yield will consequently decrease. However, in this study, the negative impact of fertilisation can also be explained by the missing data points that already existed from the selected studies' datasets. As it was stated in Kang (2013), missing data can lead to erroneous outcomes by incorporating biases and also diminishing the statistical power of the selected analytical method. Another reason for this negative effect, is the broad grouping of the categories which may hinder the distinction among different doses or types of fertiliser. Similarly, the exclusion of synergistic practices – those that provide positive effects only if they are combined with other practices- from individual categories and their incorporation under one category can further obscure accurate results. For instance, a practice that included both irrigation and fertilisation was categorised under the "combination practices" and not under "irrigation" and "fertilisation practices" individually. This categorisation seemed to enhance simplicity but possibly lead to reduced model accuracy.

Site properties played a significant role in the effect of management practices on crop yields. Soil nitrogen, as mentioned before in the refined model, seemed to decrease crop yields along with clay. Clay content in the soil can present this tendency in high amounts by creating unsuitable conditions like poor draining for plant growth. Crop type as a site property seemed to induce increased or decreased crop yields. Decreased crop yields can be expected for crop types like rice and vegetables if different factors like precipitation are irregular and extreme (Abouhussein, 2012; Jian et al., 2020) s. Certainly, pH (in this study mentioned as pH water) can also influence negatively crop yields due to hindering nutrient movement and causing nutrient immobilization i.e. P in a range below 6.5. However, pH can also be influenced by the addition of N fertilisation, by turning to acidic or alkaline depending on the type of N fertilisation. Bulk density and cation exchange capacity are two other critical soil properties that appeared to positively influence crop yields, indicating that root growth and water movement in soil are highly dependent on them. Additionally, as a site property cover crop presented positive results verifying that cover crops can increase yields by 2.6% on a global scale as stated in Wittwer & Heijden (2020) . Closing, crop rotation presented both negative and positive results leading to the assumption that probably the negative effects resulted from the other factors like soil diseases that are not mentioned in the selected databases.

3.1.2 Impact on nutrient use efficiency

3.1.2.1 Characteristics of the collected data

The impacts of management practices on the nitrogen use efficiency (NUE) as a function of site conditions were evaluated and predicted using a meta-regression model based on 2,436 paired observations from 407 primary studies (Figure 8), following the earlier research of You et al. (2023). This study was designed to evaluate the impact of crop, soil and nutrient management on the NUE. For the current study we focus on the absolute change in NUE (calculated from SMD method). To unravel the impact of site conditions such as soil properties and climatic conditions on the NUE, and the fact that the underlying processes are not that much affected by the climate zone and most data have been collected in the USA and China, we decided to include all these observations in the development of a meta-regression algorithm.

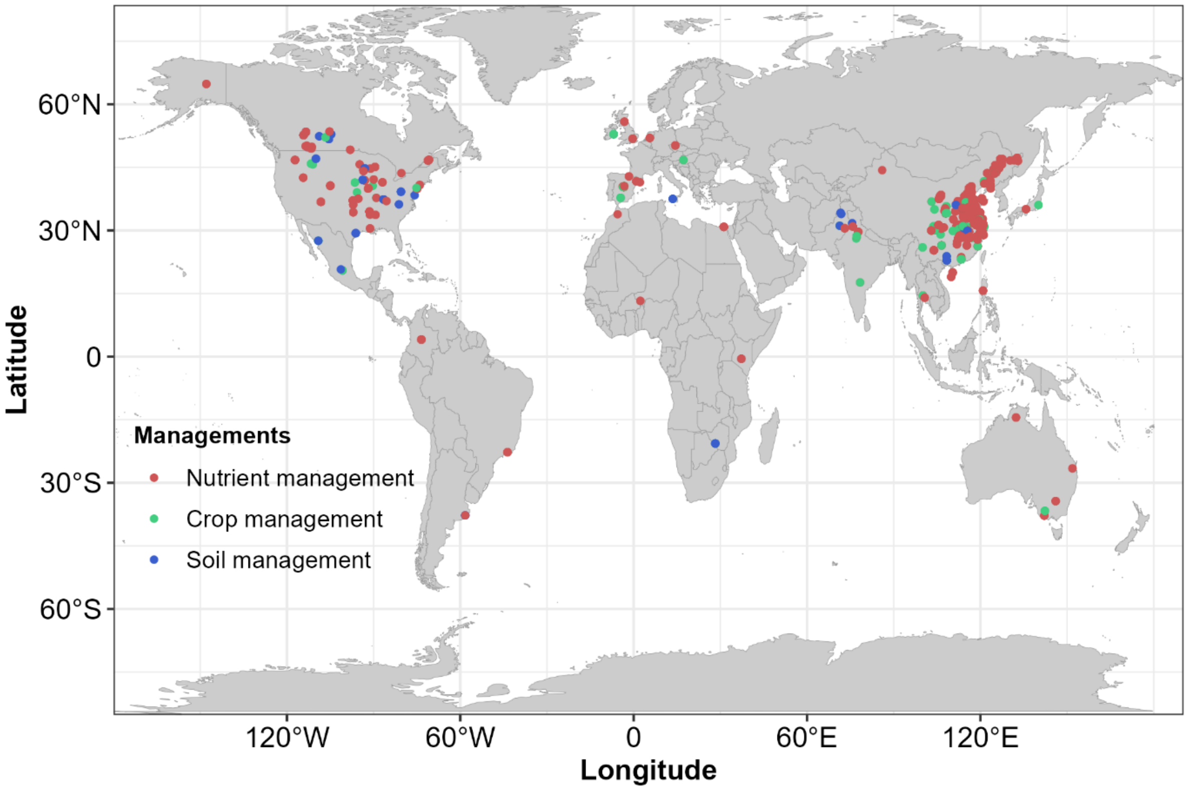

***Figure 8** World map indicating the locations of the 407 primary studies included in the study. Sites are divided in experiments related to impacts of nutrient management (enhanced efficiency fertiliser, combined fertiliser, organic fertiliser, right fertiliser placement, right fertiliser rate and right fertiliser timing), crop management (residue retention, cover cropping and crop rotation) and soil management (zero and reduced tillage). Source: You et al. (2023)*

The total variation in the response of NUE due to crop, soil, and fertilisation practices is demonstrated in Figure 9. The SMD values varied from minus ten to plus ten, a change of more than 40% when retransformed to original scale). Most of the studies seem to be have a positive and significant effect on NUE, having NUE changes exceeding the zero. In about 22% of the cases the management practice adopted led to a decline in the NUE.

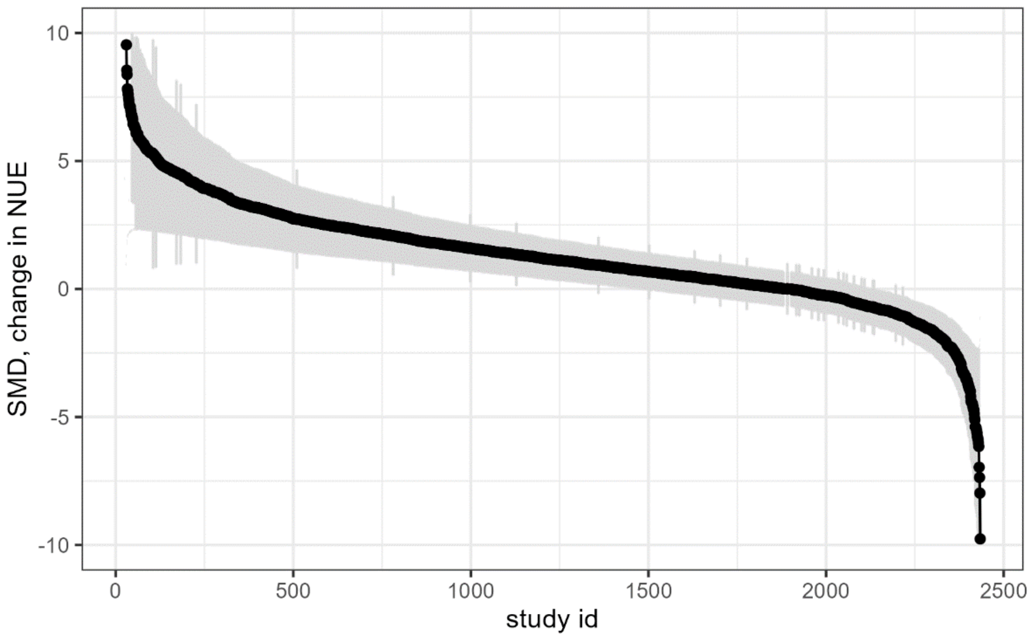

Figure 9. *The observed variation in changes in NUE, presented as the standardized mean difference (SMD) due to crop, soil, and fertiliser management for 2408 observations (28 observations excluded due to extremely high variances).*

3.1.2.2 Quantifying the impact of management and site conditions

Most of the agricultural management practices lead to positive responses in NUE. Using original experimental data, 7 of 12 practices increased the NUE, including the use of efficient fertilisers (the absolute change of NUE is +8%, representing an increase of 8%), combined mineral (+ 5%), the right fertiliser placement (+7%), rate (+10%) and timing (+6%), residue retention (+6%) and cover cropping (+5%). However, the use of organic fertiliser, and zero or reduced tillage generally decrease NUE by 1-2% ($P>0.05$). Hence, there was a consistent increase in absolute NUE up to 10% for most of the management practices applied (Figure 10). Based on the relative response ratio (not shown, but tested in view of similarities with crop yield analysis), the absolute NUE increased by applying enhanced efficiency fertiliser (+9.8%) and combined fertiliser (+6%), using the right fertiliser placement (+7%), rate (+11%) and timing (+7%), as well as residue retention (+8%) and cover cropping (+8%).

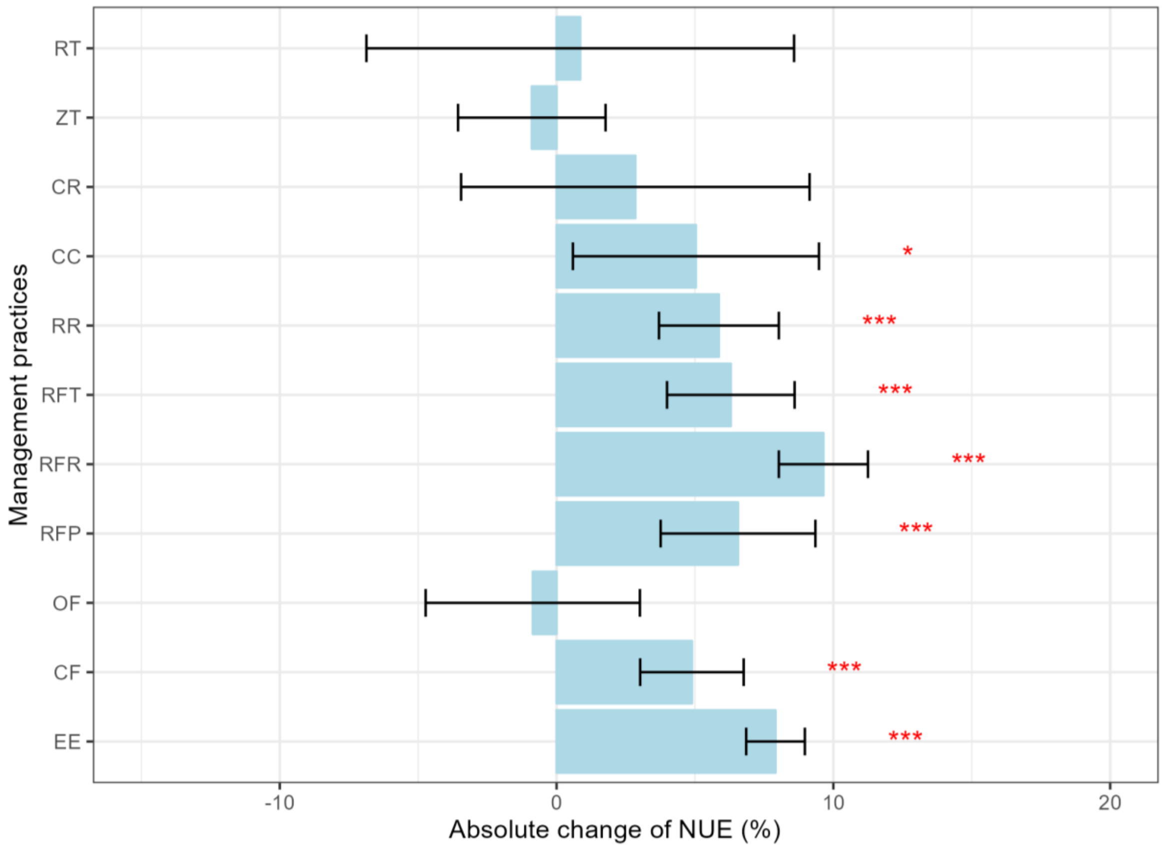

Figure 10. *Changes in nitrogen use efficiency (NUE) in response to agricultural management practices, expressed as the absolute change of NUE as compared to a control/treatment situation. Nutrient management includes enhanced efficiency fertiliser (EE), combined fertiliser (CF), organic fertiliser (OF), right fertiliser placement (RFP), right fertiliser rate (RFR), and right fertiliser timing (RFT). Crop management includes residue retention (RR), cover cropping (CC) and crop rotation (CR). Soil management includes zero tillage (ZT) and reduced tillage (RT). Asterisks indicate statistically significant differences (*$p < 0.05$, **$p < 0.01$ and ***$p < 0.001$).*

When analysing the main influence of controlling site properties, including soil pH, soil organic carbon, temperature and precipitation as well as management practices such as tillage, crop type and fertilizer strategy, it became clear that site management had a strong impact on the observed changes in NUE in response to the adoption of management practices (Figure 10). This implies that the impact of a certain fertilizer measure (e.g. adapting the N rate) on the NUE is controlled by the existing fertilizer practices like placement and timing as well the accompanying site conditions in view of soil and crop management. Together they explain more than 60% of the variation in the averaged NUE of a cropping system. Without accounting for interactions, there was also an impact of soil properties and climatic conditions, but the variation across the dataset is that large that none of them (except for clay) has a significant influence on the NUE. Given the global coverage of the database and the fact that spatial variability in site properties is associated with the variation in management practices being applied already, this requires an in-depth analysis of those interactions (as being done in the next section). In any case, this main factor analysis shows that substantial variation in management induced changes in NUE can be explained by the site properties controlling them.

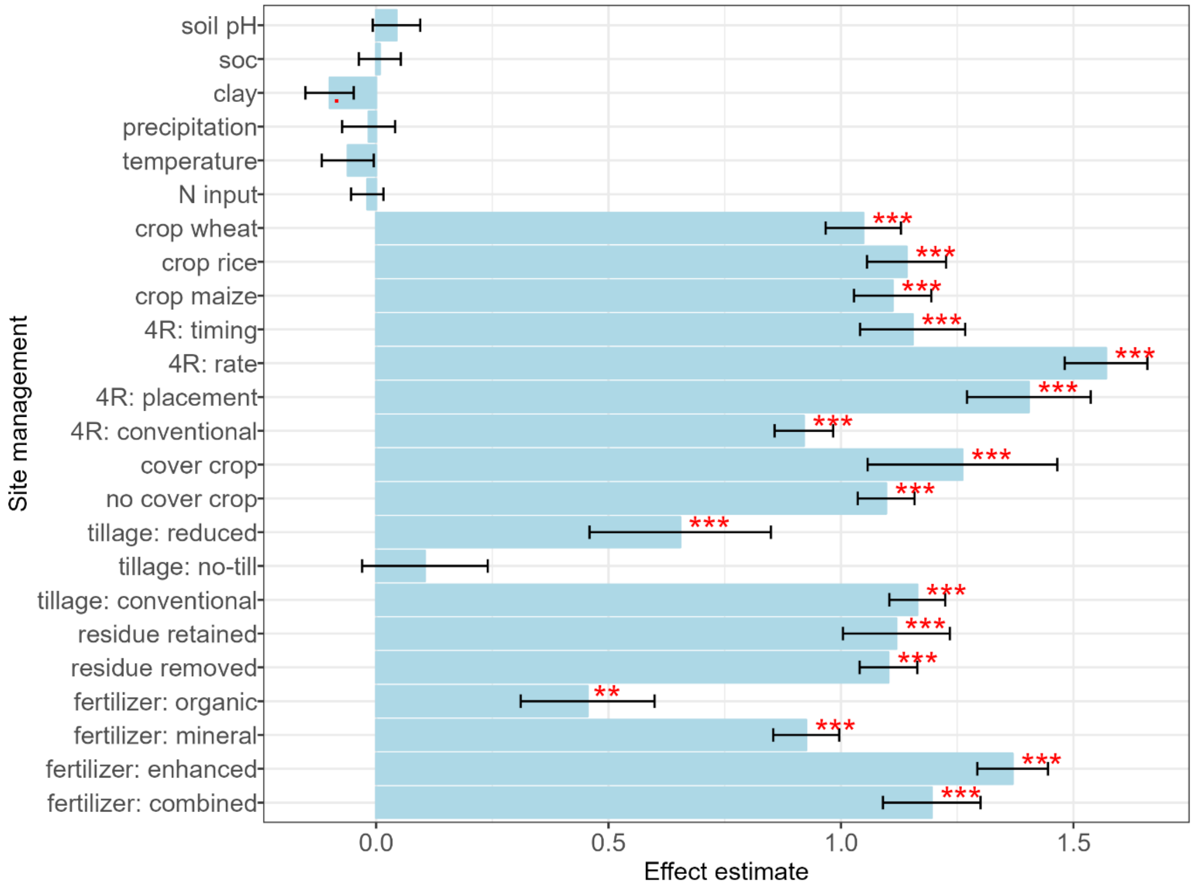

Figure 11*. Effects of climatic, soil, crop and management conditions on NUE responses across all management practices being applied. Impact of categorial variables (being the crop and management conditions) are here visualised for their change in view of a baseline. Numeric variables have been scaled to unit variance. Asterisks indicate statistically significant differences (*p < 0.05, **p < 0.01 and ***p < 0.001).*

The impact of management practices on NUE was strongly affected by site conditions as shown by the meta-analytical studies for categorial clusters of crop, soil and climatic conditions. We found a consistent positive impact of SOC, soil pH and MAP, and a negative impact of N application rate and clay content on NUE when meta-regression models were calibrated on the original field observations (Figure 11, 12). In all cases the nutrient and crop management practices increased NUE, while soil management showed the opposite impact and decreased NUE. The effect of site conditions on the impacts of management on NUE varied with the different practices as shown by the interaction between right fertiliser placement and crop type (maize), and between N application rate and the organic carbon content, as well the interaction between MAP and crop type (maize) (Figure 12). In addition, site conditions including crop type, soil pH, soil clay content, SOC, temperature and precipitation all had an impact on the baseline NUE.

The analysis of 2,436 paired observations from experiments from all over the globe showed that 65% of the variation in management induced NUE changes could be explained by the variation in site conditions (Figure 12). The parameter estimates indicate that selecting the right fertiliser type or using a combination of organic and inorganic fertilisers increases the NUE by 4-8% (Figure 12). Optimizing fertilisation placement, rate and time further increases NUE with 4.3%. NUE was also increased by improved crop residue management (+1.9%) and more diverse crop rotation (+1.6%) but decreased by zero or reduced tillage (-2.9%). As expected, higher N application rates decreased NUE (-0.018% per kg of N added). Changes in NUE varied by crop type (including wheat, maize and rice) as well by variation in clay content (-2.3%) and MAT (-0.4%) whereas the change in NUE was positively correlated to MAP (+1.0%), SOC (+1.2%) and soil pH (+0.3%).

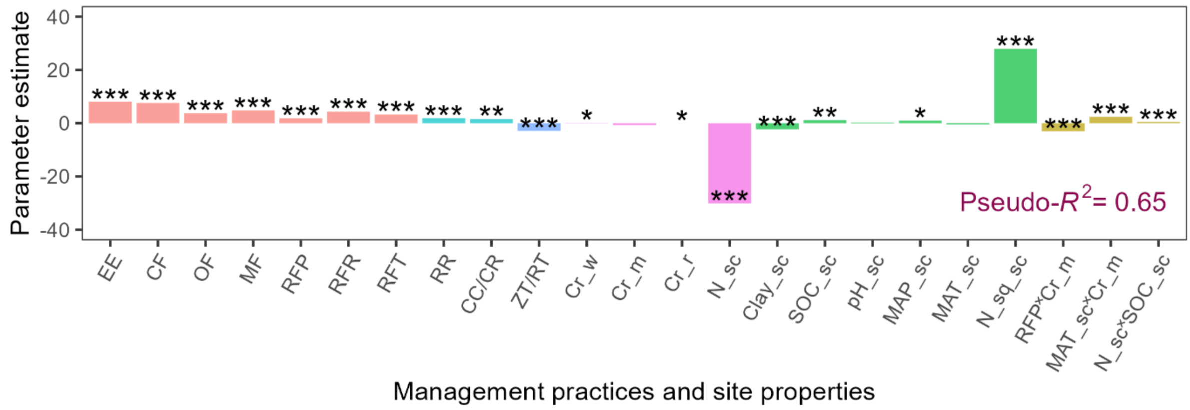

Figure 12. *Parameter estimates for the N recovery efficiency model using SMD method. The multiplication (*) signifies the interaction between variables. Asterisks indicate statistically significant differences (*p < 0.05, **p < 0.01 and ***p < 0.001). The orange bars represent management practices including EE= enhanced efficiency fertiliser, CF= combined fertiliser, OF= organic fertiliser, MF= mineral fertiliser, RFP=right fertiliser placement, RFR= right fertiliser rate, and RFT=right fertiliser timing. The blue bars represent crop management including RR= residue retention, CC= cover cropping, and CR= crop rotation. The light blue bar represents soil management including NT/RT = no tillage or reduced tillage, and the pink bars represents crop type including Cr_w = crop type wheat, Cr_m= crop type maize, Cr_r= crop type rice; the green bars represent site properties including N_sc = N application rate scaled, Clay_sc =soil clay content scaled, SOC_sc =SOC scaled, pH_sc = soil pH scaled, MAP_sc, mean annual precipitation scaled, MAT_sc = mean annual temperate scaled, and N_sq_sc = N application rate squared scaled). The brown bars represent the interactions between right fertiliser placement and crop type maize (RFP*Cr_m), mean annual temperate scaled and crop type maize (MAT_sc*Cr_m), N application rate scaled and SOC scaled (N_sc*SOC_sc). Scaled variables were converted to have unit variance.*

The full generalised model with all explanatory variables included could significantly explain the variation observed in the NUE changes due to management measures applied. When analysing the modelled estimates for the explanatory variables, some of them showed strong intercorrelations (meaning that some unique combinations between these variables existed). Further revising and updating allowed us to remove these dependencies while further reducing the statistical metrices (Table 4) explaining the residual heterogeneity and the variability in NUE by the moderators included (the refined model). We therefore selected the final model as being illustrated in the figure above.

Table 4. *Statistical metrics comparing the relevance of the different models predicting NUE in response to agricultural practices and site conditions.*

Model	logLik	Deviance	AIC	AICc	Moderators p-value
Initial model for main factor analysis	-4698	9397	9401	9401	-
Generalised full model	-4552	9105	9143	9143	< 0.001
Refined model	-4540	9081	9127	9127	< .0001

The results of this study reveal the potential impact of improved nutrient, crop, and soil management practices on NUE as a function of site conditions. As expected, the fertiliser 4R strategies had strong and positive effects on NUE, as these practices ensure that crops receive adequate inputs for N during critical crop growth. Applying the right fertiliser rate is an effective measure to reduce excess N volatilization into the air, runoff into adjacent lands and surface waters, or leaching to groundwater, since the N uptake per unit N applied decreases when N availability is not limiting crop growth. Right timing of fertilisation (e.g., split application and weather dependent application events) can improve the synchronization of the supply of applied N with crop requirements thereby avoiding unnecessary losses, in particular in the beginning and final phase of crop growth. Note that this is a generic finding across all crop types included; for specific crops like wheat the impact of N fertilizers are stronger at the start of stem elongation. Right placement (e.g., fertiliser injection, fertiliser banding) can increase soil N concentration in the root zone and associated uptake rates and reduce ammonia volatilization losses due to limited diffusion rates, in particular for urea or ammonia-based fertilisers. Similarly, higher NUE values were observed after application of enhanced efficiency fertilisers, which can slow N transformation rates and result in the minimization of particular loss paths prior to critical crop growth periods. The positive effect of partial substitution of mineral fertilisers with organic fertilisers on NUE agrees with field observations from long-term experiments given the positive impacts of manure on the structure and nutrient retention capacity of soils. Organic manure additionally provides essential macro- and micronutrients in addition to N and improves the soil microbial activity, thereby providing slow-release N in the later stages of crop growth. Since only part of the manure N is directly available, NUE often declines under full substitution, and a combination of both organic and mineral N is required to match crop demand and N supply throughout the growing season.

The effects of management practices on NUE vary regionally depending on the N application rate, crop type, soil properties and local climate. NUE decreased with an increase in N application rate. This is mainly because N inputs exceeded the N requirements of the crop, which leads to excess N loss to water, soil and air, and the current analysis focuses on agricultural systems that receive sufficient fertiliser inputs for optimum crop yields. Consequently, no experiments were included in which the soil was actively mined due to a higher N uptake than N input. For crop type, the response of NUE to management practices varied greatly between cropping systems, such as lowland rice cropping systems and upland cropping systems, reflecting the variation in crop physiology as well as the associated management practices affecting N uptake. This difference in NUE response to management practices between lowland and upland cropping systems may be related to soil aeration, which is poor in the lowland rice system due to water logging. For soil properties, as expected, soil clay content had a negative effect on NUE. The negative effect of clay content on the impact of measures on the change in NUE was likely due to the low soil microporosity and poor gas exchange capacity with high clay content, implying that measures are likely having a stronger effect on sandy soils. An increase in MAP had a negative effect on NUE because lack of water affects crop growth and grain formation, especially in low rainfall regions, resulting in lower effective N uptake by the crop.

3.2 RQ2: impact of site conditions and amendment measures on soil quality

3.2.1 Characteristics of collected data

Two main soil quality indicators were investigated, soil pH and soil organic carbon (SOC), in response to agricultural regimes and amendment measures. Given the significance of legacy effects from historical land use and atmospheric deposition on SOC and soil pH respectively, the literature search queries were limited to European studies.

A literature search for SOC responses to agricultural practices was conducted in Web of Science which returned 260 studies, that were trimmed down to 127 when considering duplicates that also appear in review papers. The remaining papers were then reviewed first by title then abstract whereby 33 papers were retained. This was again crossed checked for duplicates in review papers, yielding the final literature sample used here. Eventually, data related to SOC responses were collected from 30 individual studies published between 1996 and 2015, with treatment durations ranging from 5 to 41 years, providing insight into both short- and long-term responses. The reviewed studies covered 48 unique locations between latitudes 37.6 in the south and 60.8 in the north, longitudes between 33.3 east and 7.5 west, covering a wide range of climatic conditions.

Similarly, the search for soil pH related studies returned 123 papers, narrowed down to only 20 papers after the title and abstract screening, and an additional paper through snowballing during the data mining process. Therefore, data related to soil pH were collected from 21 individual studies published between 1994 and 2014, covering 55 observations from 28 unique locations (Figure 13). Treatment durations ranged from a single year to 32 years.

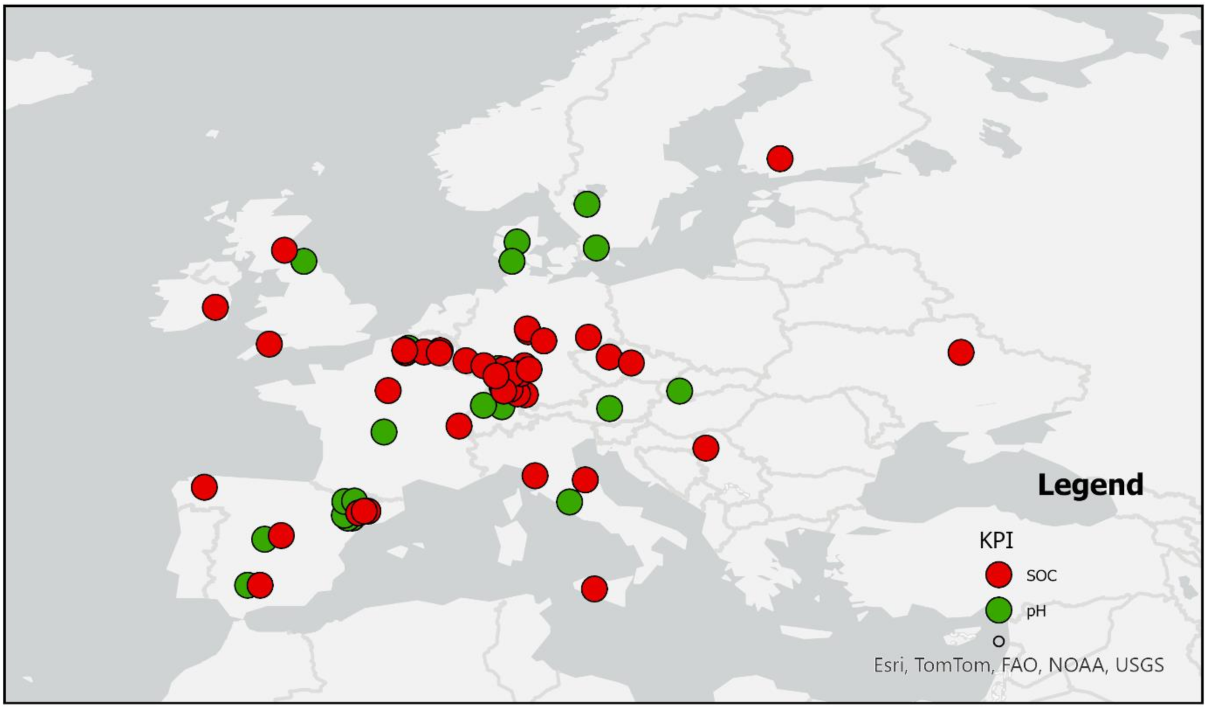

Figure 13. *Geographical distribution of experimental sites used in the analysis of SOC and pH responses to agricultural practices and amendment measures.*

3.2.2 Quantifying the impact of management practices and site properties

3.2.2.1 Soil pH

Soil pH showed a wide range of responses to the reported experimental management practices (Figure 14), with a predominantly positive effect within the investigated studies. Soil pH varies significantly within seasons and a single year, and can also respond strongly to transient events. Acknowledging this short-term temporal variation, we nevertheless keep the focus of our analysis here on the interannual, longer term responses of soil pH to agricultural practices and mitigation measures.

Among all the management practices, liming had obviously the strongest impact on soil pH, with up to nearly three pH units in one instance (Figure 15). Surprisingly, replacing mineral fertiliser with composted or rotted farmyard manure resulted in an impressive increase in soil pH of more than one pH unit. These extreme values are excluded from Figure 14 for visual clarity but included in the analysis. For the majority of the management practices however, 70% of the SMD values lie above 0.8 and below –0.8, indicating large responses to the experimental management practices, while 22% of the reported responses are less than moderate (|SMD| < 0.5).

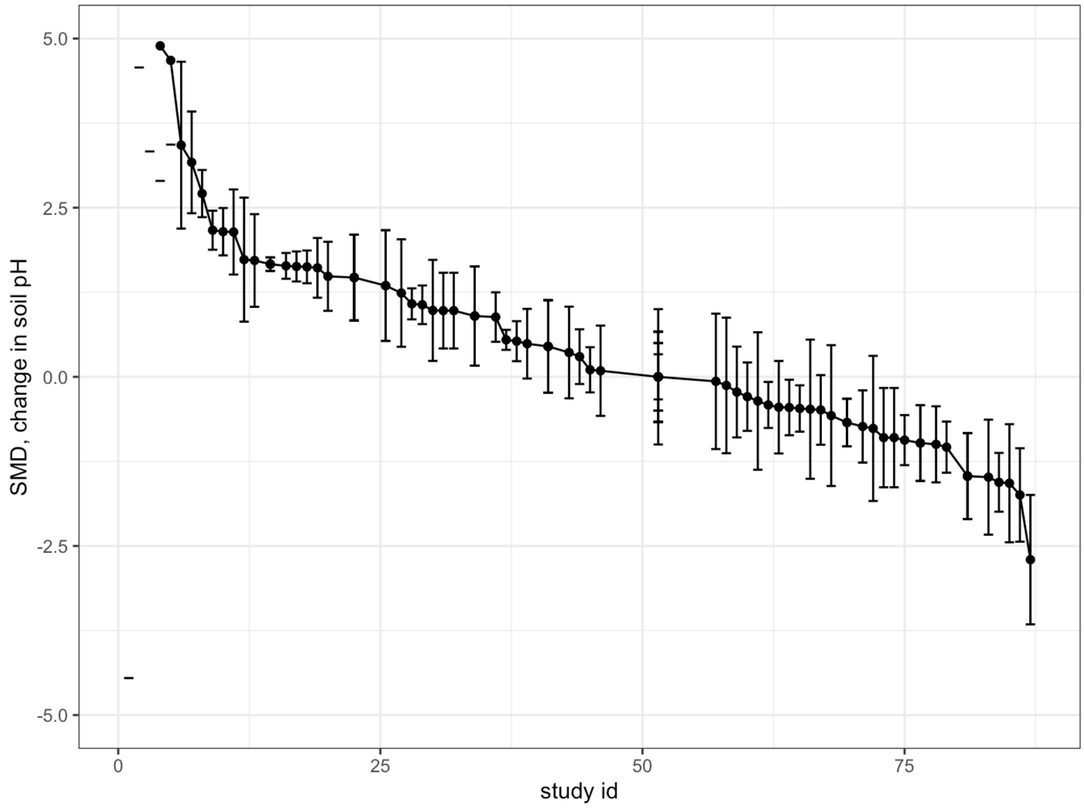

Figure 14. *Hedges' Standardised Mean Difference (SMD) of soil pH in response to agricultural practices among 88 individual entries. Two extreme entries with SMD above 5 are not shown.*

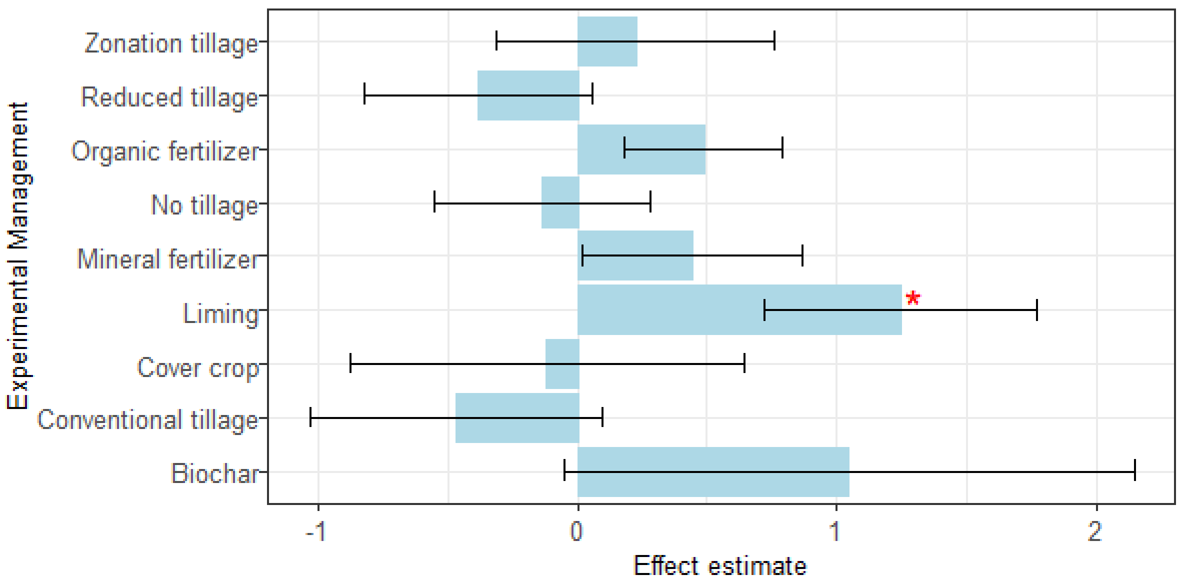

Figure 15. *Estimated effects of experimental management practices on soil pH. The involved management practices are: Zonation Tillage, Reduced Tillage, No Tillage, Conventional Tillage, Organic Fertiliser, No Fertiliser, Cover Crop, Liming, Biochar. Asterisks beside the bars indicate statistically significant differences (*p < 0.05, **p < 0.01 and ***p < 0.001)*

While soil pH is often pre-determined by soil conditions, such as soil mineralogy and texture, it is most strongly regulated by liming (Figure 15). Unlike other amendment methods, liming is usually administered towards a planned target that insures the highest bioavailability of nutrients to the crops. However, pH is also closely linked to other aspects such as soil organic matter content, fertilisation and water availability. The temporal response of soil pH is different for different measures, with liming causing rapid but often short-lived changes, while fertilisation can cause a slow but consistent decline.

The effects of management practices on pH are generally not strongly regulated by site conditions within our dataset (Figure 16), except for initial pH which correlates negatively and significantly with the pH response (higher initial soil pH correlates with weaker response to treatment). Soil organic matter, bulk density, cation exchange capacity and clay content have virtually no significance for the response of soil pH. Climate conditions play a limited role in the responses of soil pH (Figure 16) to the management practices applied, with virtually no effect observed in relation to MAP, and a consistent but non-significant negative effect from MAT and evapotranspiration.

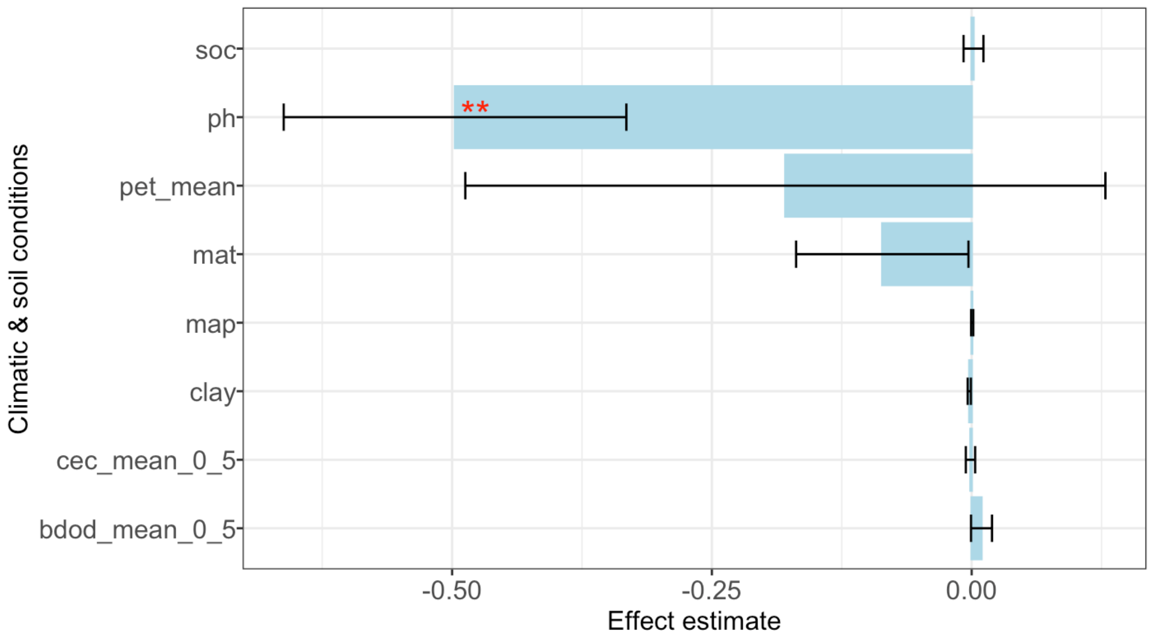

Figure 16. *Effects of climatic and soil conditions on pH responses across all management practices being applied. The involved site properties are: SOC= soil organic carbon, mat=mean annual temperature, map=mean annual precipitation, pet_mean=mean annual potential evapotranspiration, cec_mean_0_5=the average cation exchange capacity in the top 5cm of the soil, dbod_mean_0_5=the average bulk density of fine earth in the top 5cm of the soil. Asterisks indicate statistically significant differences (*p < 0.05, **p < 0.01 and ***p < 0.001)*

Although characterised with high variability, pH responses were predominantly positive under most agricultural management practices at the reported sites (Figure 17). However, significance in correlation was only found between “no tillage” and pH response (p<0.01) and in instances with unknown crop cover management (p<0.05), although the latter is not interpretable. Residue retention correlated weakly with pH response with a p-value<0.1. Although with limited statistical significance, most practices correlated positively with pH response to experimental management practices.

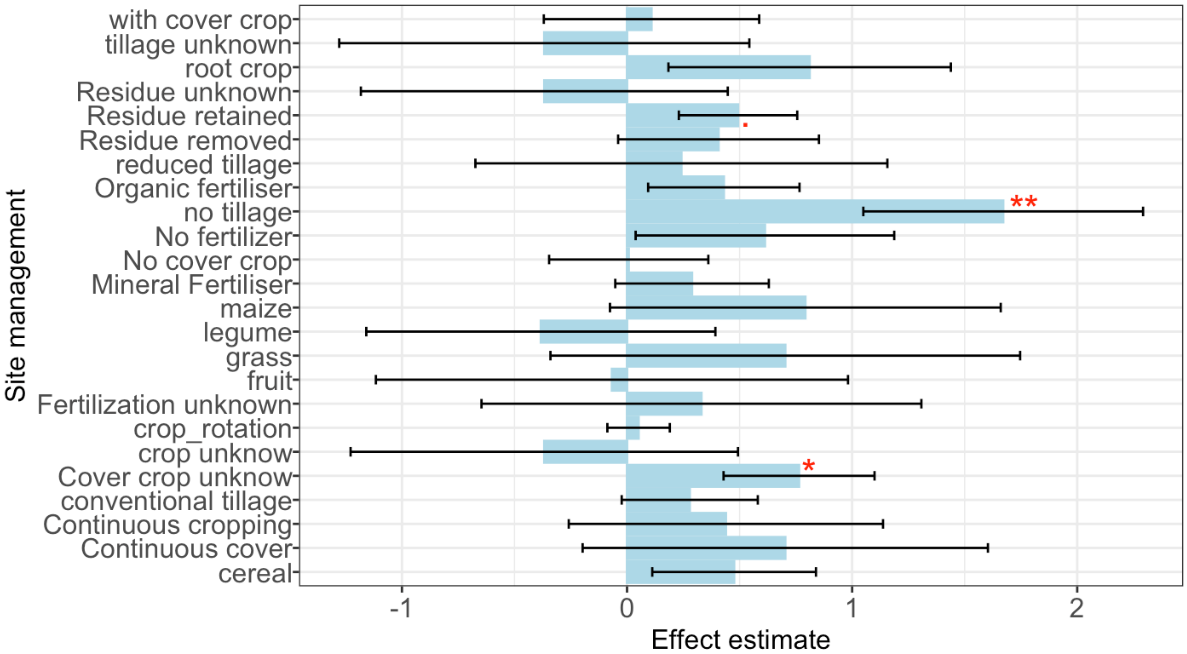

Figure 17. *Effects of site management practices on soil pH response due to management practices applied. Asterisks indicate statistically significant differences (*p < 0.05, **p < 0.01 and ***p < 0.001).*

A generalised full meta-regression model including all independent variables is illustrated in Figures A2. Although the model brings forward the effect of the reviewed experimental management practices as significant, it produces counter intuitive directions of effect on the first sight, as in the case of liming having a significant negative effect of pH. One should however evaluate this value in view of all explanatory variables together, clearly defining the baseline to which the effect of lime is compared. In this case the fertilizer category is defined as the baseline here, leading to a high positive change being corrected by the management measures being applied. A partial dependency analysis or accumulated local effect plot analysis might be beneficial here to elucidate the impact of individual variables, but for the purpose of this study, a detailed analysis of the developed algorithms is not needed. What the model shows however is the consistency among management measures on the one hand, and site properties and agricultural practices on the other. Cumulatively, the model also shows that management is able to match the possibly unintended effects of agricultural practices at the site.

After selecting the most significant independent site condition properties according to the significance observed in the generalised full model, the final model is restricted to initial soil pH, mean annual temperature, tillage, fertiliser type, and crop type, as all these are expected to influence the response of pH to management practices (Figure 18). Results showed that the initial soil pH, the absence of tillage and grassland land use are the most significant factors regulating the response of pH. The refined model produces much more intuitive results that are more in line with the partial hypotheses behind each management practices aimed at amending pH.

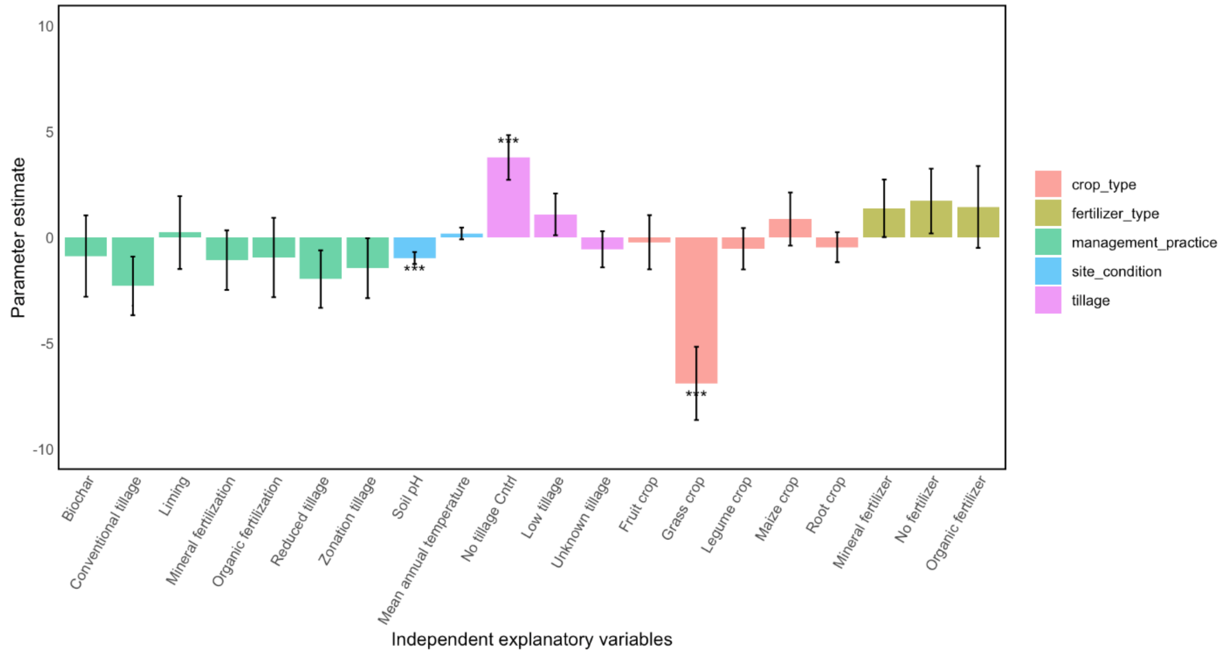

Figure 18. *Final refined meta-regression model of pH response to management practices and site conditions. Asterisks indicate statistically significant differences (*p < 0.05, **p < 0.01 and ***p < 0.001).*

The refined model had the lowest AIC of the tested alternatives. Both the generalised and refined models have significantly lower AIC and AICc compared to the mean response model, supporting the choice of the respective independent variables included (Table 5). The logLik and the test of moderators p-value both indicate an improvement of the models after the restriction of the predictors. The p-value shows a limited but significant level of prediction only for the refined model.

Table 5. *Statistical metrics comparing the relevance of the different models predicting soil pH in response to agricultural practices and site conditions*

Model	logLik	Deviance	AIC	AICc	Moderators p-value
Initial model for main factor analysis	-138	275	279	280	--
Generalised full model	-107	214	252	268	0.3295
Refined model	-96	192	238	267	0.0076

The developed models revealed that, for soil pH, the most significant determinants were the initial alkalinity of the soil, and the physical soil disturbance practices, highlighting two important properties of this KPI: firstly, pH is an aggregated indicator of soil chemical balances (Schecher and Driscoll, 1987; Sato and Ohkishi, 1993), and is regulated by strong buffering processes over the entire range of the pH scale (de Vries et al., 1989). At the lower scale, aluminium oxides can be mobilised to buffer proton concentrations (Gustafsson et al., 2018), while at intermediate pH, cation exchange is able to absorb protons and release base cations to regulate the Acid Neutralizing Capacity (ANC) of the soil solution, and finally at higher pH, typical of alkaline soils, carbonate and silicate dissolution are able to consume protons. The prominence of these processes is often represented in the baseline pH, thereby the prominence of the latter confirmed in our analysis. Secondly, difference in the physical disturbance of the soil, represented by “no tillage” and “grass crops”, strongly affect the dynamics of organic matter in the soil, the former by reducing the mixing of organic matter from the topsoil and residue into deeper layers, and the latter by providing a constant input of litter and organic exudates. The decomposition of organic matter in the soil produces organic radical that interfere negatively with the ANC, and consequently pH (Chapman et al., 2008). Tillage makes more organic matter available to a wider proportion of the soil and brings mineral rich and often more alkaline conditions that promote the activity of decomposer microbes closer to the surface (Liu et al. 2006). These two pathways would enhance decomposition and thereby have a negative impact of pH, as confirmed by our meta-regression models. Undisturbed soils under grasslands, on the other hand, receive a steady flow of fresh litter and exudates, which can act as primers and substrate for decomposition (Kuzyakov et al., 2000, Mary et al., 1993; Fu and Cheng, 2002), thereby producing more organic radicals, reducing the ANC, and negatively affecting pH. These processes are obviously known to agronomists (Bolan et al., 2003), prompting the use of liming in substantial amounts to maintain pH at optimal levels for nutrient bioavailability. It is therefore surprising that our results do not highlight the role of liming as strongly, which could be due to the low number of liming experiments included in the meta-analysis compared to the relatively large variance of the observed KPI changes. The results therefore indicate that measures to mitigate pH should be adapted to site conditions and consider the strong buffering processes that regulate the long-term responses of soil pH.

3.2.2.2 Soil organic carbon

Data for changes in SOC under different tillage management practices and a range of agricultural practices and site conditions were collected from 30 different studies in Europe, providing 329 distinct observations (Figure 19). Special focus was put on tillage for its prominence in affecting SOC above other practices (Man et al., 2022; Khan et al., 2007; Francaviglia et al, 2023). However, due to the strong interactions between tillage regimes and other factors, we include a wide range of agricultural practices and site conditions in the multivariate analysis in this study. Of the 329 observed SDM, 199 were at least moderate (|SMD|>0.5), of which 151 were large (|SMD|>0.8). Nearly twice as many entries categorised as having moderate or large SMD were positive compared to negative.

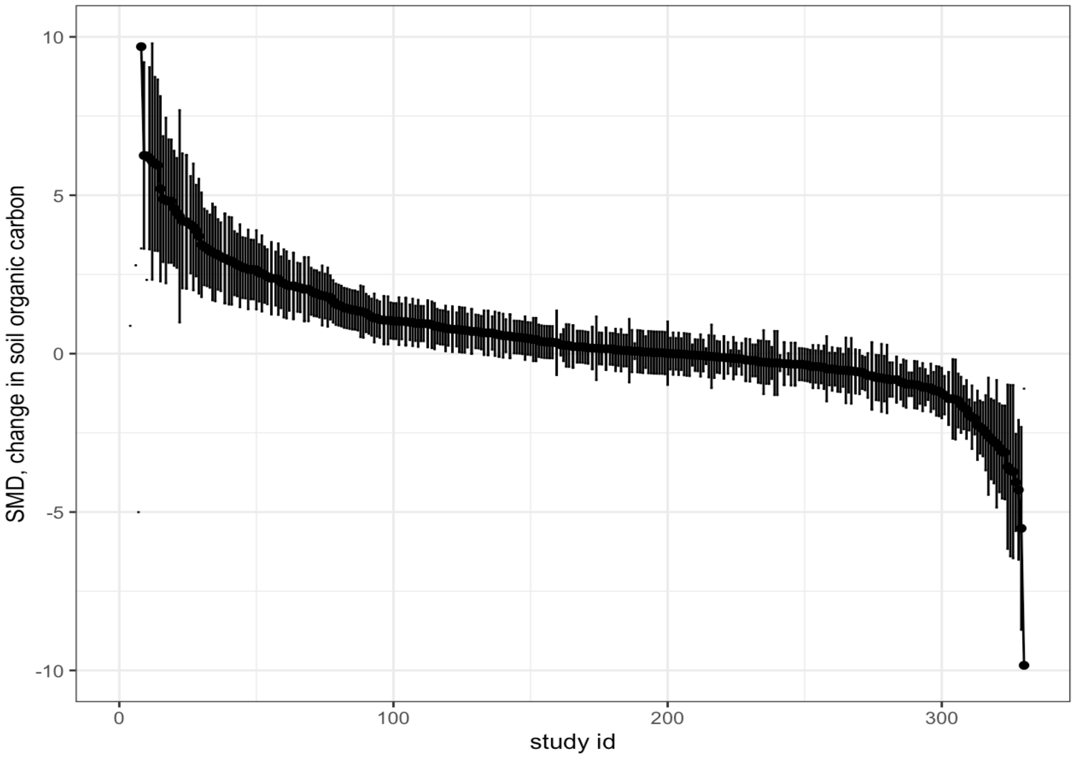

Figure 19. *SMD values of SOC response to agricultural practices among 329 unique observations. Five observations with extreme SMD values above 10 are not shown.*

Expectedly, SOC responds positively and significantly to reduced tillage and no tillage treatments (Figure 20-21). However, stronger and significant estimates are found for residue management, the use of fertiliser, the maintenance of cover crops and the choice of crop. Surprisingly, climatic and soil conditions do not seem to correlate with the tillage and fertilizer induced changes in SOC, being the main management measures included in the database, except for soil bulk density which has a small but significant effect. This implies that the management impacts are rather consistent over the different climate zones.

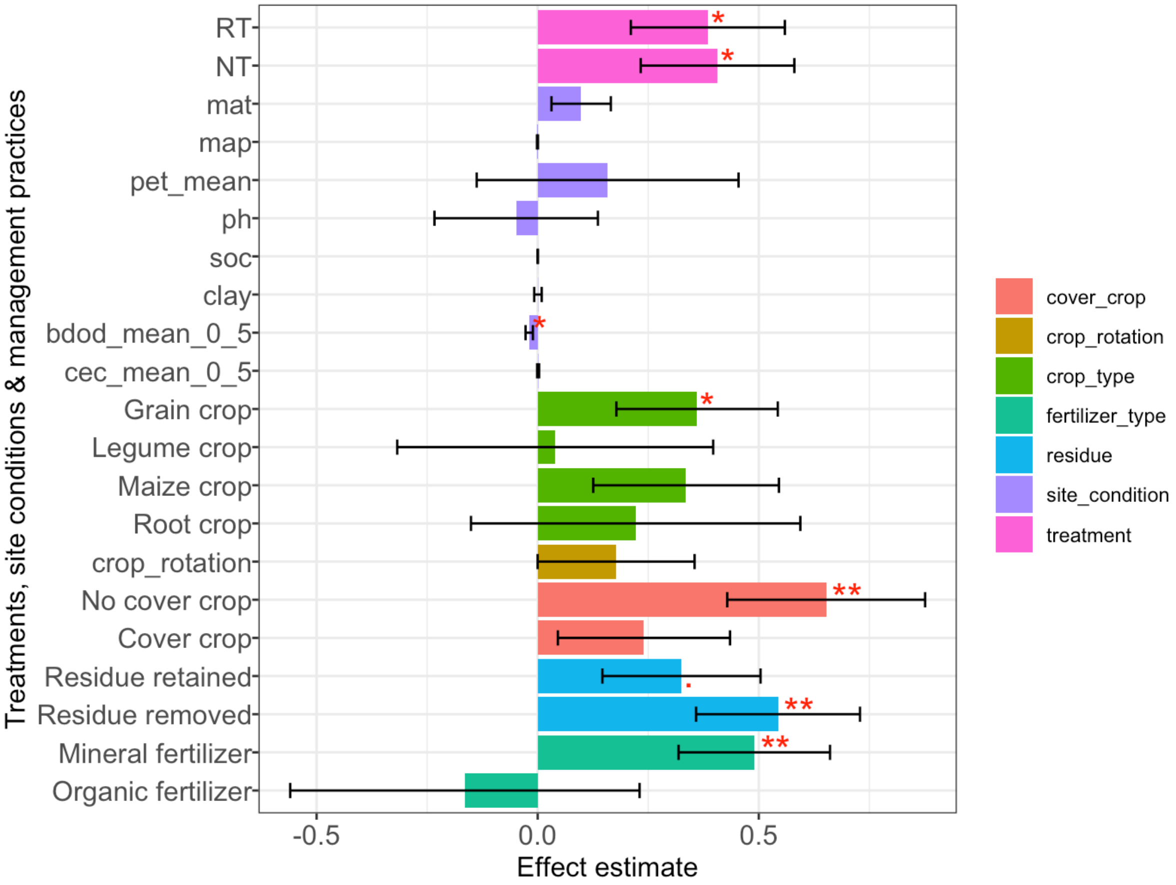

Figure 20. *Effect estimates of site conditions and management on SOC (a main factor analysis). Management practices including RT = reduced tillage, NT = no tillage, mat = mean annual temperature, map = mean annual precipitation, pet_mean = mean annual potential evapotranspiration, cec_mean_0_5 = the average cation exchange capacity in the top 5cm of the soil, dbod_mean_0_5 = the average bulk density of fine earth in the top 5cm of the soil. SOC refers to the initial content of soil organic carbon before treatment, as a covariate. Asterisks indicate statistically significant differences (*p < 0.05, **p < 0.01 and ***p < 0.001).*

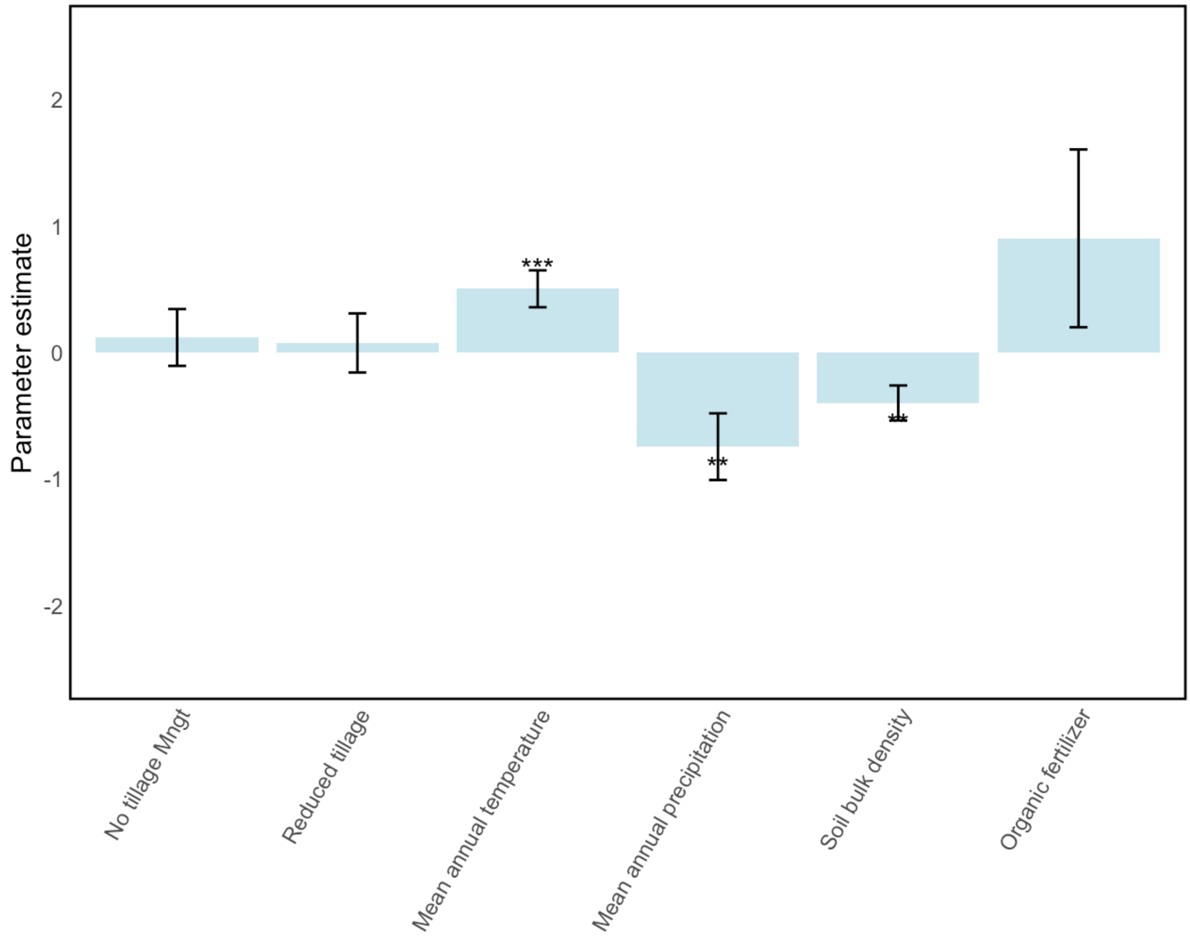

Figure 21. *Refined meta-regression model explaining the change in SOC and restricted to six independent explanatory variables including management practices (tillage) and site properties.*

SOC is primarily responsive to tillage regimes, and because tillage alternatives vary in depth, SOC is often reported for different soil depths. Like pH, SOC is dependent on the history of a site, at least in the original background state, and can be significantly affected by agriculture, with a strong distinction between grasslands, for grazing for example, and arable land. On arable land, the fate of the residue seems to have a clear impact on SOC as it regulates the input of organic matter into the soil. Finally, there is a clear difference in SOC between mineral and organic fertilisation regimes, with the latter likely sustaining higher inputs and thereby higher stocks of SOC.

Table 6. *Statistical metrics comparing three models predicting changes in SOC.*

Model	logLik	Deviance	AIC	AICc	Moderators p-value
Initial model for main factor analysis	-537	1076	1079	1079	--
Generalised full model	-265	530	564	568	0.17
Refined model	-355	711	725	725	0.0006

Compared to the quantification of measure-impact on soil pH, the developed meta-regression models were less reliably able to capture and explain changes in SOC, despite relying on a denser dataset than pH. However, some aspects of the analysis were able to inform about the original hypothesis that tillage regimes are the prominent driver in regulating SOC (Stockmann et al. 2013). When considered independently, reduced tillage and no tillage significantly contributed to increasing SOC according to our analysis, even though not as strongly as other factors such as the use of fertiliser or the management of crop residue. Yet obviously these measures are never isolated on the field, and the more relevant multivariate analysis shows the expected direction of effect from tillage regime but does not confirm their significance. Instead, climate factors, soil density and the input of organic matter through organic fertiliser are the predominant explanatory variables that emerge from our analysis. Climate, and in context the microclimatic conditions of the soil, determine the decomposition rates of soil organic matter in complex ways that can give rise to counterintuitive outcomes (Canesa et al., 2021). Temperature is expected to increase the rates of decomposition (Kirschbaum, 1995), but it can also arguably correlate positively with higher growth rates, thereby higher rates of litter input, at the same time as it drives higher evaporation rates (through increasing the vapor pressure difference between plants/soil and the air) thereby retarding decomposition through water deficit. These three pathways have opposite effects, and in the case of our meta-analysis produce a net positive effect where higher temperatures correlate with higher SOC ($p<0.001$). Similarly, precipitation acts through multiple simultaneous pathways on SOC, though perhaps most importantly as the main regulator of decomposition in the well drained soils in agricultural soils (unless we consider rice paddies). This could explain the significant negative effect precipitation has on SOC. Finally, soil bulk density is a strong predictor of the mineral fraction of the soil (higher density for higher mineral fraction), and can be seen at an indicator of the initial organic matter content of the studied sites, although this was not confirmed with the indicator for SOC.

3.3 RQ3: impact of alternative protein source on pig and poultry nutrient use efficiency

3.3.1 Characteristics of collected data

The following indicators are selected to quantify the impact of alternative protein source on the productivity and nutrient use efficiency in pig and poultry system:

Average daily weight gain (ADG) is calculated as the average daily increase of an animal's body weight, reflecting the efficiency of converting dietary protein into body mass (Degola and Jonkus, 2018; Keto et al., 2021). It is a critical indicator of animal productivity and health. Higher ADGs indicate more efficient growth and overall better productivity, suggesting that the protein source in the animal's diet is being effectively utilized for growth, thus indicating better nutrient use efficiency.

Digestibility of Crude Protein (DCP) represents the proportion of protein in the diet that is digested and absorbed by the animal, based on differences of crude protein (or 6.25*nitrogen) measured in the diet and faeces (Huuskonen et al., 2014). A high DCP indicates that a greater proportion of the consumed protein is available for growth and maintenance, leading to improved animal performance and productivity. Efficient protein digestibility ensures that the nutrients are optimally used, minimizing waste and enhancing the conversion of dietary protein into animal body protein (Lestingi 2024). This leads to reduced nitrogen excretion, which is beneficial for both animal health and environmental sustainability.

Feed Conversion Ratio (FCR) is the ratio of feed intake to the weight gain of the animal. It is a critical metric in determining the efficiency with which an animal converts feed into body mass (Khan 2018). A lower FCR indicates less feed is required for the animal to gain a unit of body weight, or more of the consumed protein is converted into animal biomass rather than being wasted (higher nutrient use efficiency). Therefore, it is used as a direct indicator of the cost-effectiveness of the protein source in the diet (Chojnacka et al., 2021).

In total 230 observations were collected for these three indicators from 20 publications on animal feeding management using either soybean-based products or alternative protein sources such as insect, microalgae, duckweed, rapeseeds, legumes (such as faba bean and yellow lupine), and grass juice that are locally produced. The numbers of observations involved for each of the alternative protein sources were summarized in Figure 22. Since most of the animal feeding experiments happened indoor and the feeding strategies were mainly affected by the animal type and growing stage, the site properties of the animal experiments (longitude, latitude, and climate conditions such as temperature and precipitation) were usually not available from the publications, thus they were not listed as covariance in this meta-analysis. Instead, the effect of animal type (pig or poultry) and growing stages (starting, growing, finishing/fattening, or whole growing state) were explored with the effect of supplemental rate and category of alternative protein sources.

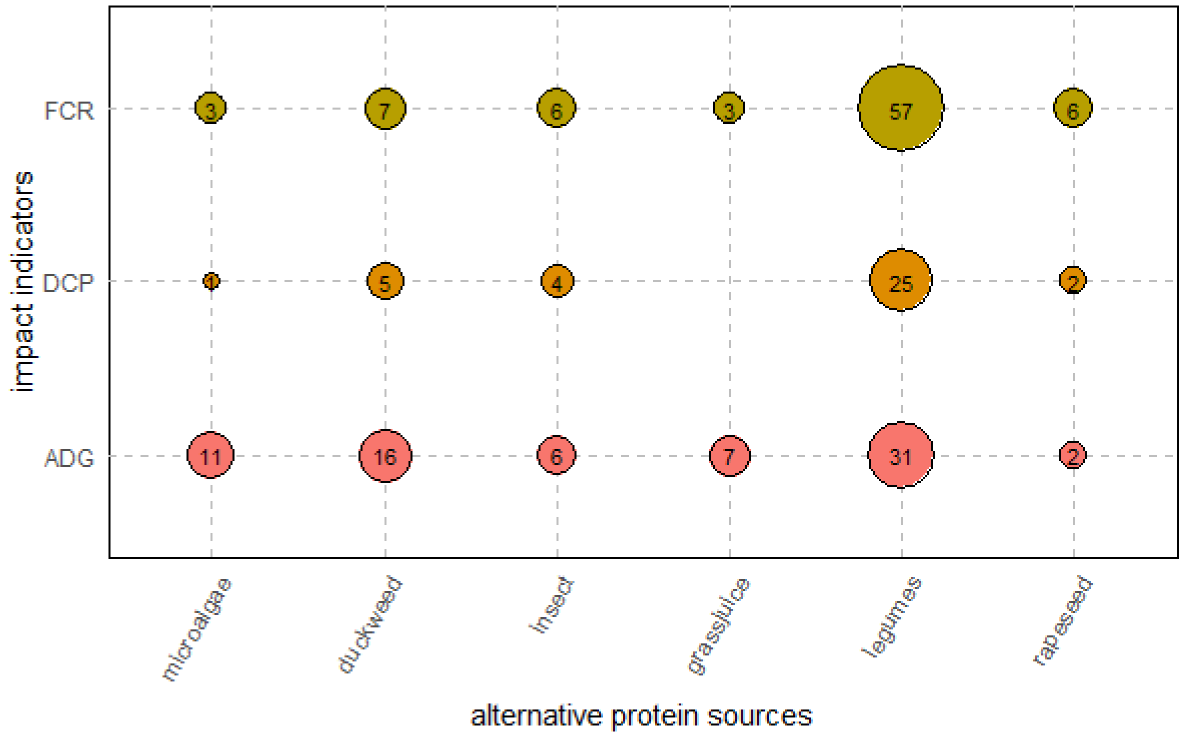

Figure 22. *Bubble chart of included studies for the meta-analysis quantifying the impact of alternative protein sources on pig and poultry productivity. Each axis intersection in the matrix represents the number of studies reporting an effect size for the corresponding measure using alternative protein sources and the key performance indicators, where the bubbles are proportional to the number of observations. Colours represent the type of indicators from top to bottom: FCR = feed conversion ratio, DCP = digestibility of crude protein, ADG = average daily weight gain.*

3.3.2 Quantifying the impact of alternative protein sources

The impact of the alternative protein sources on ADG, DCP and FCR was quantified using the “metafor” package in R to fit a random-effects model using restricted maximum likelihood (REML) estimation. The effect size was calculated as the natural logarithm of the ratio of the mean of the treatment group (alternative protein sources) to the mean of the control group (soybean), i.e. log-transformed response ratio (lnRR). Meta-regression modelling results were presented in forest and bar plots differentiating the management practices (e.g. supplemental rates and categories) and the influencing factors (animal type, growth stage).

3.3.2.1 Impact of alternative protein sources on ADG

Figure 23 displays the distribution of the observed changes of ADG induced by alternative protein sources in animal feed (lnRR) across 65 studies. It revealed that majority of the changes are neutral (lnRR ≈0), which is consistent with the high uncertainty on the model estimates in Figure 24, implying that only limited effects were visible for the different categories of alternative protein sources (supplement_category) or animal type and stages. Nevertheless, the supplemental rate of the alternative protein source showed a significantly ($p < 0.001$) negative estimate, suggesting a higher supplemental rate of alternative protein may lead to a 4.9% decrease in the ADG.

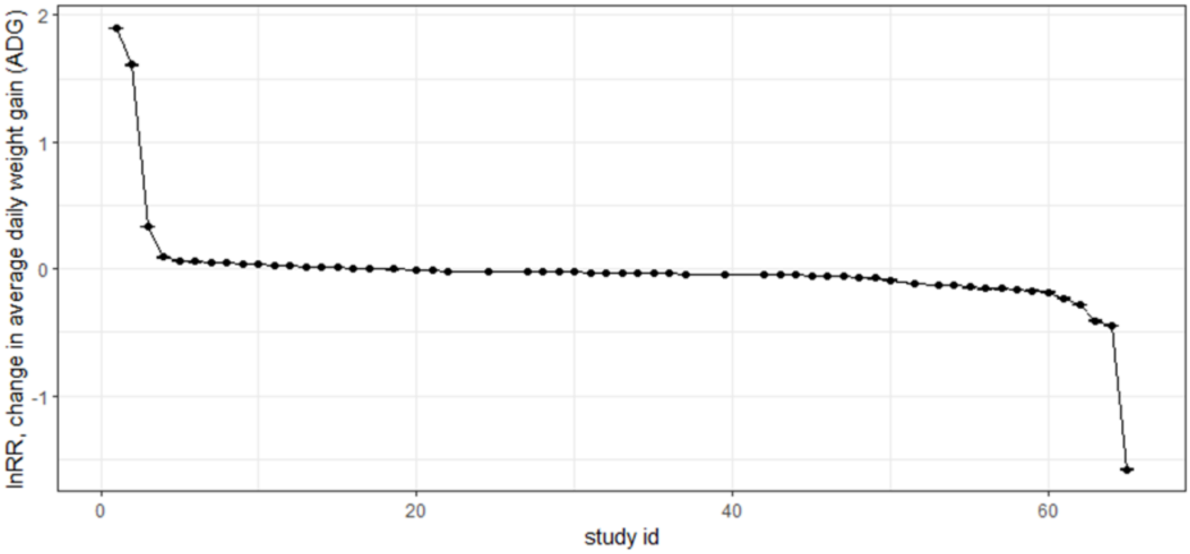

Figure 23. *Observed variation in changes of average daily weight gain (ADG) due to the substitute of alternative protein sources for 65 studies.*

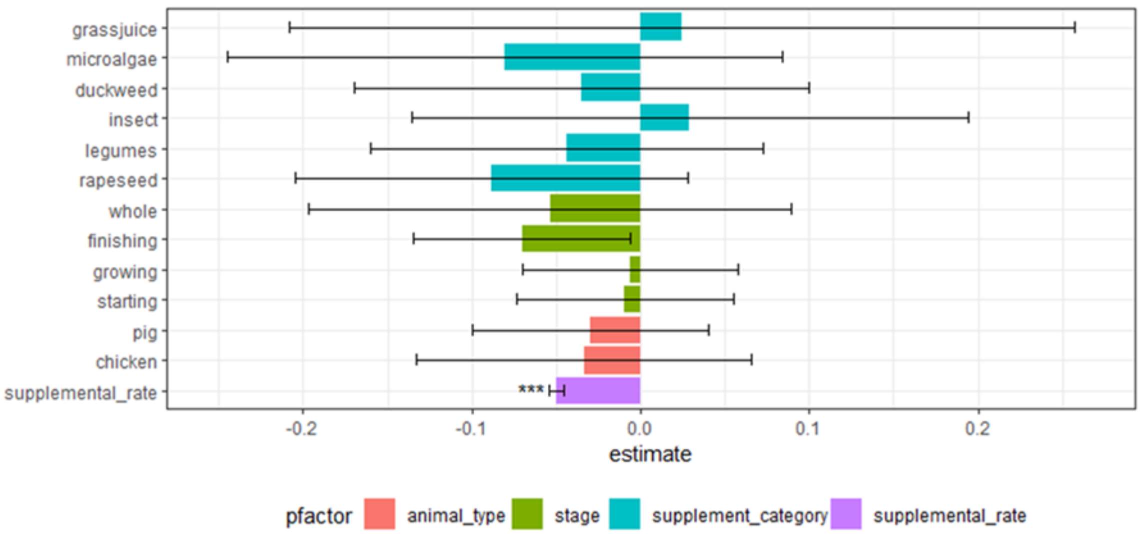

Figure 24*. Effect of the alternative protein sources (supplemental_rate and supplement_category) and other influencing factors (animal_type and stage) on the average daily weight gain (ADG) of animals. Asterisks indicate statistically significant differences (*p < 0.05, **p < 0.01 and ***p < 0.001). The blue bars represent the impact of supplement categories including grass juice, microalgae, duckweed, insect, legumes, and rapeseed. The red bars represent the impact of animal type including pig and chicken. The green bars represent the impact of animal growth stage including starting, growing, finishing, and whole growth period. The purple bar represents the impact of supplemental rate of the alternative protein source ranging from 0-100%.*

The meta-regression model per factor was further refined taking into consideration of the interactions between supplemental rate and categories of the alternative protein sources (Figure 25). These estimates from the refined meta-regression model showed significant negative impact (-0.95) of the supplemental of alternative protein sources with increasing rates. However, various positive impact was observed for the supplement of duckweed, legumes and rapeseed, with significance (p< 0.01) observed when duckweed is used. When the alternative protein sources were computed with the supplemental rates, the model estimated positive impact of the interactions ranging from 79%-219%, with significance observed for the different supplemental rates of insects, legumes, grass juice, and rapeseed. Besides, the alternative protein supplement also showed significantly negative impact (-0.09) on ADG for the starting period of animal growth.

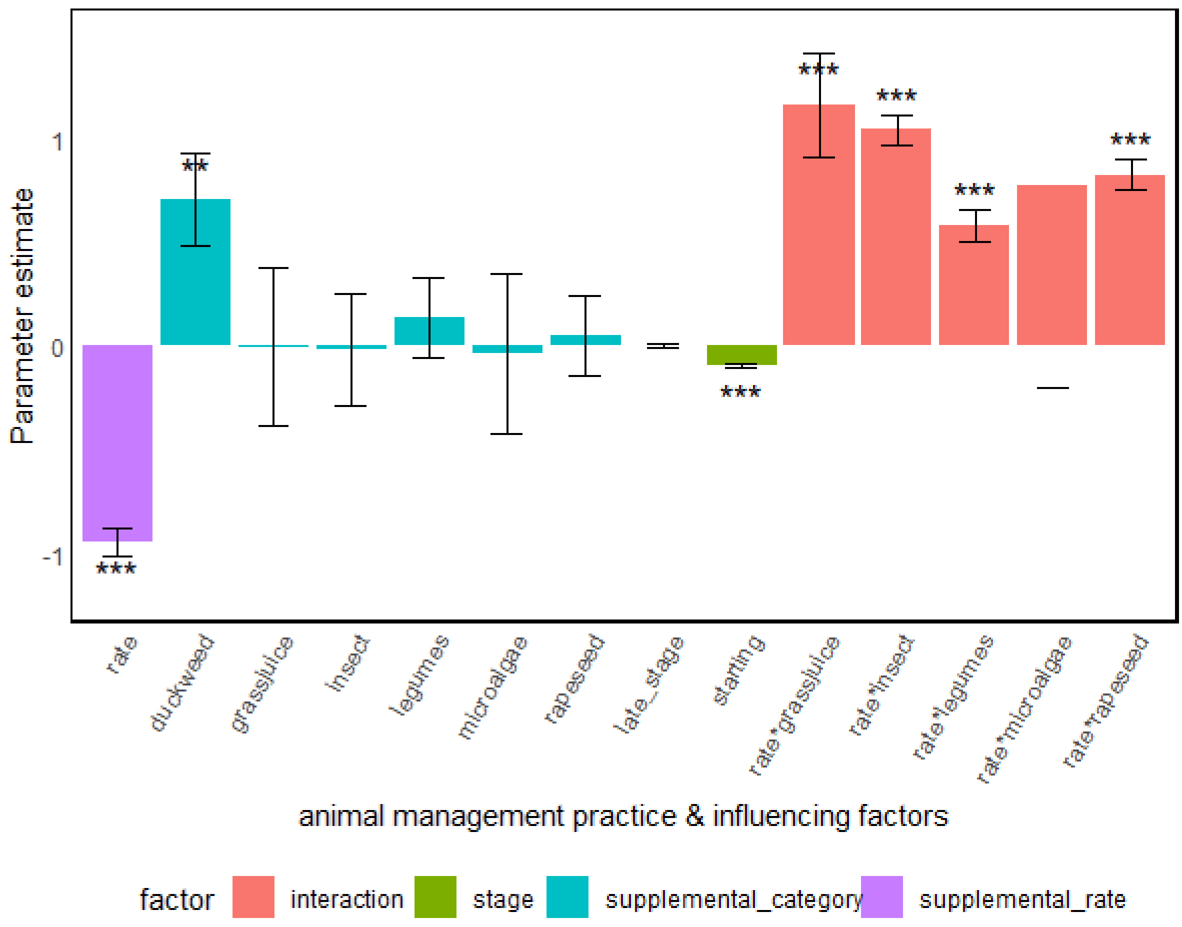

Figure 25. *Parameter estimate of the alternative protein sources (supplemental_rate and supplement_category) and other influencing factors (animal_type (only pig included) and stage) effect on the average daily weight gain (ADG) of animals. The multiplication (*) signifies the interaction between variables. Asterisks indicate statistically significant differences (*p < 0.05, **p < 0.01 and ***p < 0.001). The purple bar represents the impact of supplemental rate of the alternative protein source ranging from 0-100%. The blue bars represent the impact of supplement categories including grass juice, microalgae, insect, legumes, and rapeseed. The green bars represent the impact of animal growth stage including starting and late stages (growing, finishing, and whole growth period). The red bars represent the interactions between supplemental rate and different supplemental categories.*

3.3.2.2 Impact of alternative protein sources on DCP

Referring to the impact of alternative protein sources on DCP, 14 studies were included in the computation of lnRR (Figure 26), with 4 studies showing positive changes and the rest showing negative changes. Among these studies, data is only available for pigs, therefore animal type is not considered as a covariance in this estimation. Similar to the impact on ADG, when categorising the estimated effect based on the different stages, alternative protein supplemental rate and categories (Figure 27), only insect showed a positive effect (2%), while significance was only observed in the estimates for the effect of whole growth stage (-13%) and supplemental rate (-2%).

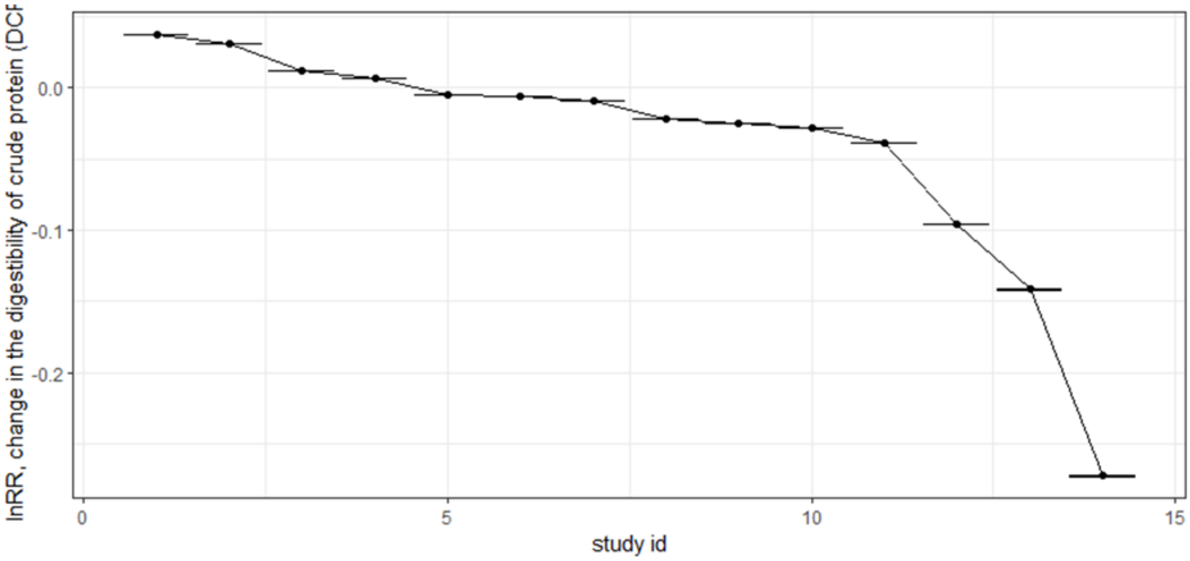

Figure 26. *Observed variation in changes of the digestibility of crude protein (DCP) due to the substitute of alternative protein source for 14 studies.*

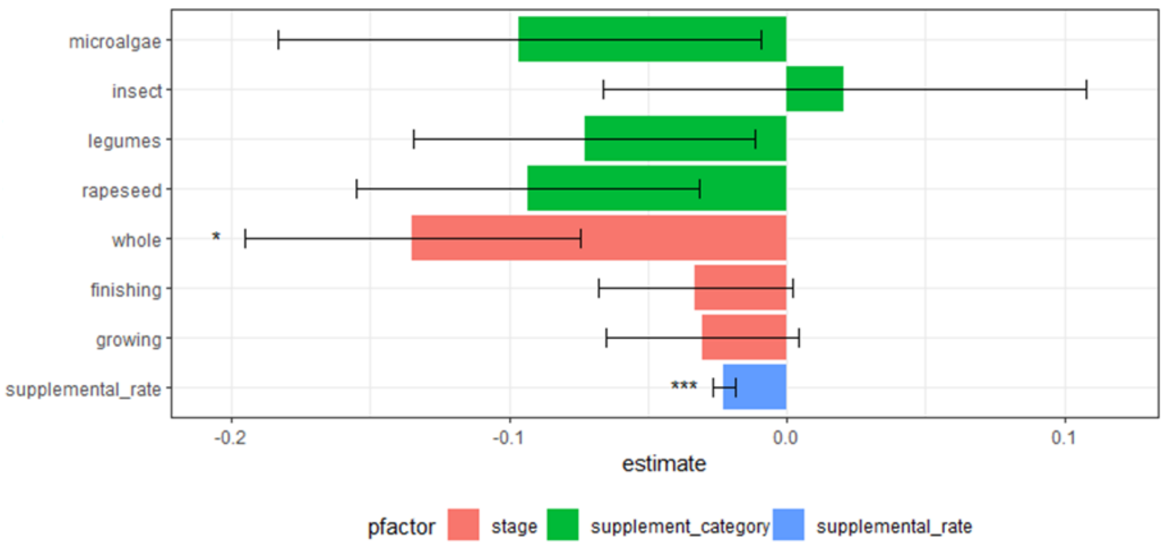

Figure 27. *Effect of the alternative protein sources (supplemental_rate and supplement_category) and other influencing factors (animal_type and stage) on the digestibility of crude protein (DCP) in the animal feed. Asterisks indicate statistically significant differences (*p < 0.05, **p < 0.01 and ***p < 0.001). The green bars represent supplement categories including microalgae, insect, legumes, and rapeseed. The red bars represent animal growth stage including growing, finishing, and whole growth period. The blue bar represents supplemental rate ranging from 1-100%.*

In the refined model considering the interactions between supplemental rate and supplement categories, the supplemental rate and legumes as alternative protein source showed a positive impact on the DCP, while supplementing with insect, microalgae or rapeseed lead decrease in DCP of the animal feed (Figure 28). The significant negative interactions between supplemental rate and legumes as well as between supplemental rate and rapeseed also suggested that a higher supplement of legumes and rapeseed as alternative protein sources may lead to a higher decrease in the DCP. Besides, the negative impact was estimated higher when alternative protein was used over the whole growth period (-0.14), as compared to supplements at growing stage (-0.003).

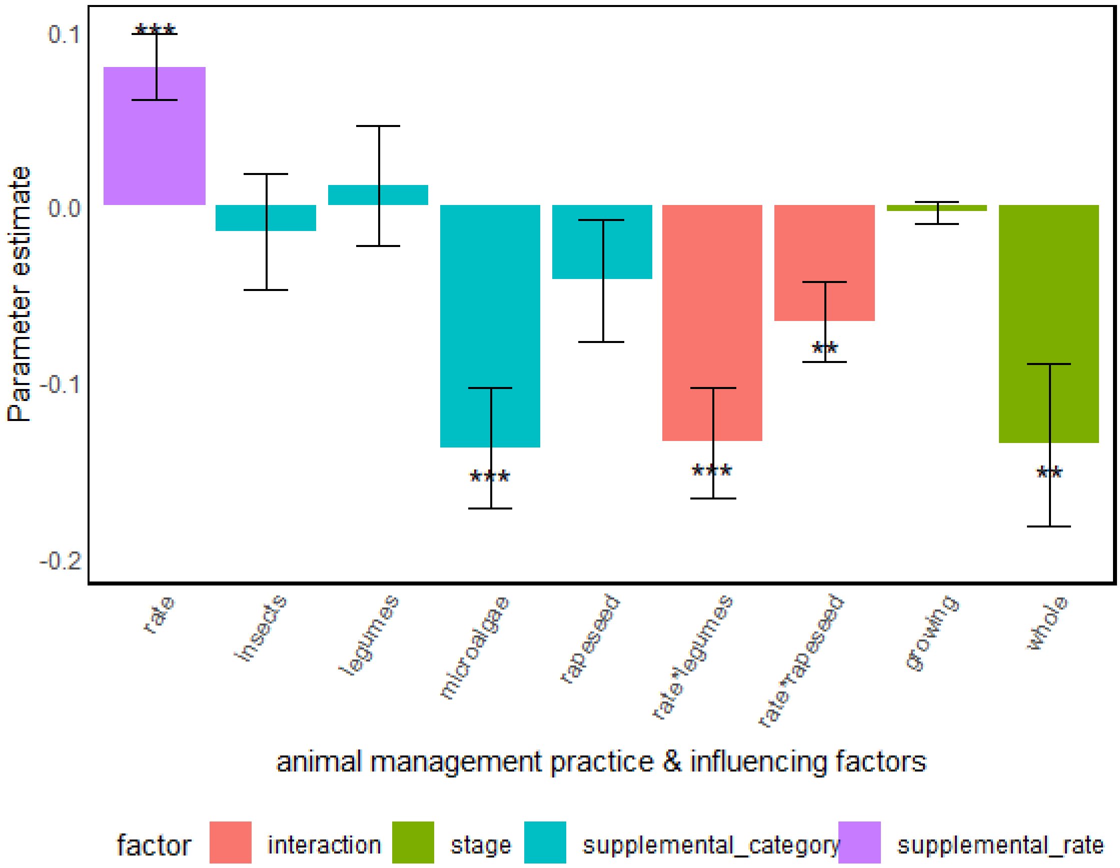

Figure 28. *Parameter estimate of the alternative protein sources (supplemental_rate and supplement_category) and other influencing factors (animal_type and stage) effect on the digestibility of crude protein (DCP) in the animal feed. The multiplication (*) signifies the interaction between variables. Asterisks indicate statistically significant differences (*p < 0.05, **p < 0.01 and ***p < 0.001). The purple bar represents the impact of supplemental rate of the alternative protein source ranging from 0-100%. The blue bars represent the impact of supplement categories including microalgae, legumes, and rapeseed. The green bars represent the impact of animal growth stage including growing and whole growth period. The red bars represent the interactions between supplemental rate and different supplemental categories.*

3.3.2.3 Impact of alternative protein sources on FCR

The changes in FCR induced by supplement of alternative protein sources were calculated across 65 studies (Figure 29). The data reveal that the lnRR is above 0 in 42 studies, suggesting that the introduction of alternative protein sources have a positive effect on the FCR in most cases. The effect sizes (estimates) confirmed this positive effect over the different supplement categories including microalgae (4%), duckweed (8%), and legumes (4%), the different stages including growing (4%), finishing (7%) and whole growth stage (0.2%) both for pig (2%) and chicken (8%) (Figure 30). A significantly positive estimate (27%) was observed for the supplemental rate ($p < 0.001$), suggesting that higher supplemental rates of alternative protein sources may lead to an increased FCR, implying less efficient feed conversion.

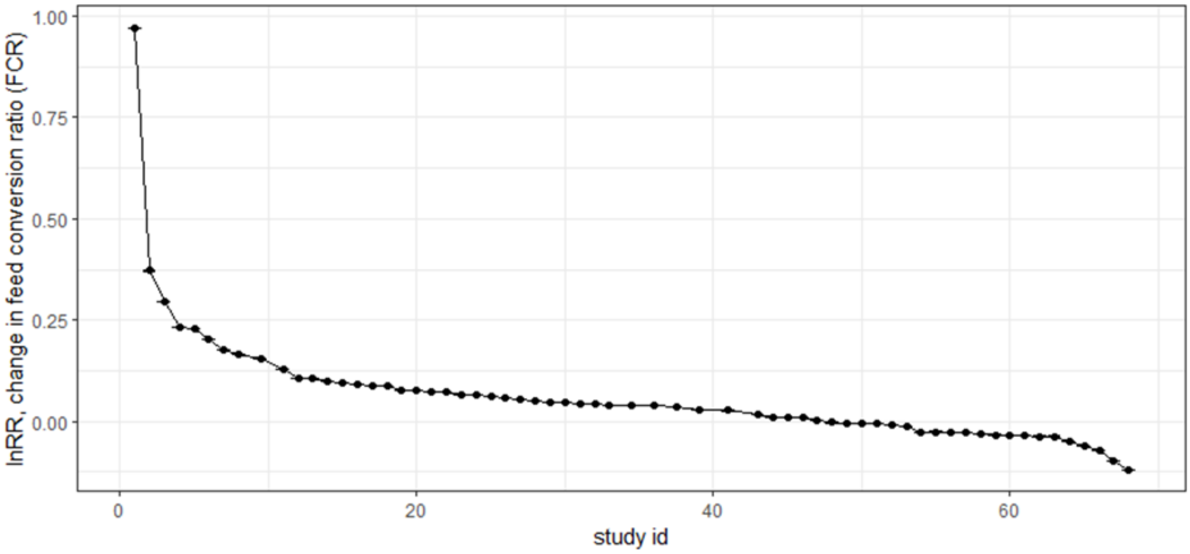

Figure 29. *Observed variation in changes of the feed conversion ratio (FCR) due to the substitute of alternative protein source for 82 observations.*

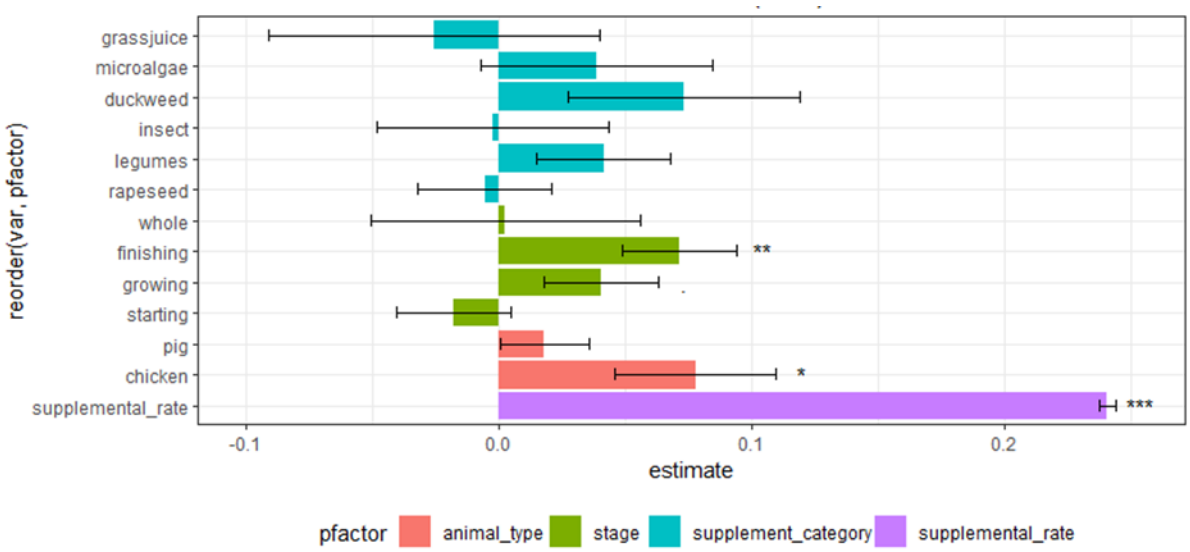

Figure 30. *Effect of the alternative protein sources (supplemental_rate and supplement_category) and other influencing factors (animal_type and stage) on the feed conversion ratio (FCR). Asterisks indicate statistically significant differences (*p < 0.05, **p < 0.01 and ***p < 0.001). The purple bar represents the impact of supplemental rate of the alternative protein source ranging from 0-100%. The blue bars represent the impact of supplement categories including grass juice, microalgae, duckweed, insect, legumes, and rapeseed. The green bars represent the impact of animal growth stage including starting, growing, finishing, and whole growth period.*

Elaborating the interactions between the categories of alternative protein sources and supplemental rate as well as the animal growth stages, the refined meta-regression model revealed that these three factors explained 62% of the changes of FCR (Figure 31). Overall, the supplement of alternative protein led to decreased FCR (i.e. improvements in nutrient use efficiency) when quantifying based solely on specific supplement categories (including grass juice, microalgae, and legumes) or when counting the interactions between supplemental rate and type of alternative protein sources. However, the significant positive impact of the supplemental rate (1.57) on FCR suggested that regardless of the type of alternative protein sources, a higher supplemental rate still led to higher FCR, i.e. lower nutrient use efficiency. Furthermore, the animal growth stage also shows significantly positive impact on FCR, particularly during the starting and growing period. Specifically, supplementing insect at growing stage showed significantly positive impact (0.05) on the FCR, probably due to the negative impact observed on DCP by supplemental of insect (Figure 28) as compared to other sources.

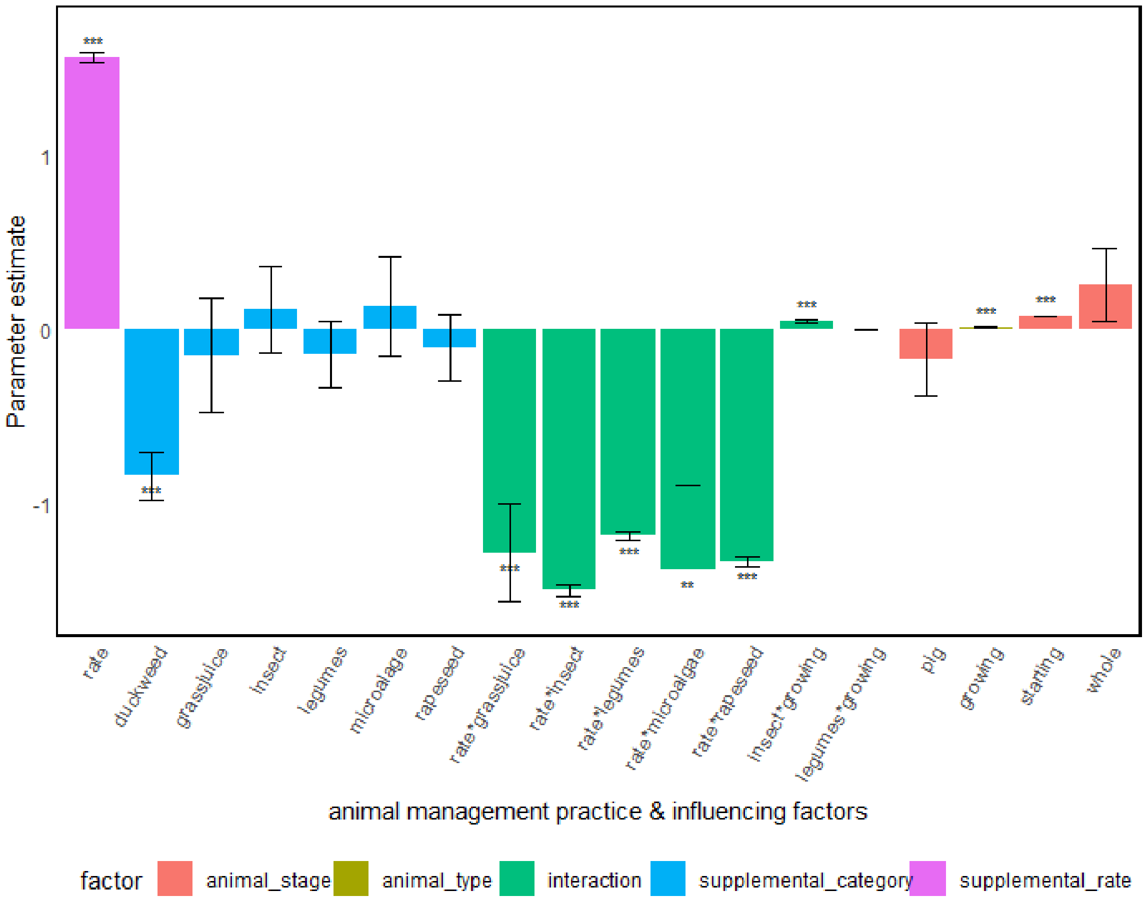

***Figure 31**. Parameter estimate of the alternative protein sources (supplemental_rate and supplement_category) and other influencing factors (animal_type and stage) effect on the feed conversion ratio (FCR). The multiplication (*) signifies the interaction between variables. Asterisks indicate statistically significant differences (*p < 0.05, **p < 0.01 and ***p < 0.001). The purple bar represents the impact of supplemental rate of the alternative protein source ranging from 0-100%. The blue bars represent the impact of supplement categories including grass juice, microalgae, insect, legumes, and rapeseed. The green bars represent the impact of animal growth stage including starting, growing, and whole growth period. The red bars represent the interactions between supplemental rate and different supplemental categories.*

3.3.3 Performance of the developed regression models

Table 7 presented the statistics from the meta-regression models developed for the impact of supplementing alternative protein at different rates and categories on the ADG, DCP and FCR respectively, taking into consideration the influence of animal types (pig and poultry) and growth stages (starting, growing, finishing, or as whole growth period). The significance (p < 0.0001) observed in the test of moderators reveals that the selected factors (supplemental rate, supplement categories, animal type, animal growth stage) significantly account for the variability in the induced changes of the three performance indicators. A small value of AIC and the Log.lik in the refined model confirm that the refined models, which include moderators, provide significantly better fits compared to the generalised full model, emphasizing the role of the selected factors in explaining the observed variability. However it is also worth noting that, based on the significant test for residual heterogeneity (p < 0.0001), there is still substantial unexplained variability, probably derived from factors that were not included in the models, such as the duration of the animal feeding experiments, the overall composition of the diets used in the studies, the nutrient content and quality of the alternative protein in each supplemental category, as well as animal housing management practices. This complexity underscores the importance of considering a broad range of potential moderators and covariates in meta-analyses to account for as much variability as possible and to identify the true effects of the interventions being studied.

Table 7. *Parameters and statistics of the linear regression models to quantify the impact of supplemental rate (0-100%) and supplement categories of alternative protein sources (duckweed, microalgae, grass juice, rapeseed, legumes, insect) on the ADG, DCP and FCR on the influences of animal type (pig and chicken) and animal growth stages (starting, growing, finishing and the whole growth period). The multiplication (*) signifies the interaction between variables. Asterisks indicate statistically significant differences (*p < 0.05, **p < 0.01 and ***p < 0.001).*

KPI	Number of observations	Test for Residual Heterogeneity	Test of Moderators	AIC (generalised full model; refined model)	Log.lik (generalised full model; refined model)
ADG	65	$Q_E = 6313, p < 0.0001$	$Q_M = 751, p < 0.0001$	4311; 4072	-2143; -2021
DCP	14	$Q_E = 139, p < 0.0001$	$Q_M = 143, p < 0.0001$	115; 118	-50; -49
FCR	68	$Q_E = 11798, p < 0.0001$	$Q_M = 12889, p < 0.0001$	10380; 7741	-5178; -3851

3.4 RQ4: efficiency of manure processing technologies on N and P efficiency

Depending on the purpose of manure processing, nutrient recovery rate and removal rate were calculated to evaluate the management efficiency. The nutrient removal rate refers to the proportion of nutrients that are eliminated from the manure during processing, preventing them from re-entering the agricultural cycle. This process primarily aims to reduce the environmental impact of excess nutrients, such as eutrophication of water bodies and greenhouse gas emissions. In contrast, the nutrient recovery rate pertains to the proportion of nutrients that are extracted and converted into usable forms during manure processing. The goal here is to recycle these nutrients back into the agricultural system, promoting sustainable nutrient management and reducing the dependence on synthetic fertilisers.

Given the nutrient status in control management was already counted in the calculation of the recovery or removal rate (%), an effect size as changes induced by the manure processing management is not necessary for the impact quantification in this research question. Accordingly, absolute values were presented for nutrient recovery/removal rates (%), and this will not affect the overall quantification. Moreover, research on manure processing management is usually performed in single batch given the variability in nutrient composition of manure collected over time and economical concerns particularly for scale-up tests (pilot or full-scale). Consequently, standard deviations were usually not reported for the nutrient recovery and removal rates, and therefore linear regressions are developed to quantify the impact of manure processing management on different nutrients (TN, TAN, NH_3, TP) recovery/removal efficiency at various scales (lab, batch, pilot and full industrial scales).

3.4.1 Manure processing for nutrient recovery

Technologies for nutrient recovery are designed to extract valuable nutrients from manure and convert them into usable products:

- **Solid fraction and liquid fraction:** Resulted from **solid-liquid separation** which is commonly used as the primary process for manure treatment. There are various types of separation installations such as screens, centrifuges, and screw or belt presses (Hjorth et al., 2010; Zhang et al., 2022). Being on-farm, it is practical and efficient in decoupling soluble nutrients from suspended matters including colloidal particles, fine solids, fiber, etc. (Bustamante et al., 2013; Hjorth et al., 2010; Khoshnevisan et al., 2021). Depending on the characteristics of manure and the implemented device, the resulted solid and liquid fractions show various potential to be used as fertilisers, soil improvers or raw materials for further nutrient recovery.
- **Ammonium salts (including ammonium sulphate and nitrate):** Recovered from manure or animal houses through **acid scrubbing** with or without a preliminary **stripping** process. The

theory lies in the equilibrium of N in the form of the ammonium ion (NH_4^+) with the unionized (free) ammonia (NH_3), which can be pushed towards gaseous strippable NH_3 with increasing pH and/or temperature (Brienza et al., 2020, Jiang et al., 2014). The recovered ammonium salts can be used as biobased fertilisers to replace synthetic fertilisers.

- **Algae and duckweed:** Both algae and duckweed are photoautotrophic plants that use solar energy to reduce inorganic nutrients to organic matter thus producing biomass (Acién Fernández et al., 2018; Lambert et al., 2022). With supply of light and/or extra CO_2, algae and duckweed can be cultivated in bioreactors to absorb nutrients from manure, which can then be harvested and used as biofertiliser or animal feed. Microalgae and duckweed biomass can also contribute to biogas production when co-digested with manure.
- **Permeate and concentrate:** Effluents of **membrane filtration** which is usually used for sequential concentration of nutrients in liquid fractions after primary solid-liquid separation (Vaneeckhaute et al., 2017). The driving force for membrane filtration can be a difference in pressure (such as microfiltration, ultrafiltration, nanofiltration, forward/reverse osmosis), concentration (gas permeable membrane filtration, membrane distillation), temperature or electric potential, depending on the different type of membranes (Bera et al., 2022).
- **Struvite:** Struvite is a white orthorhombic crystalline compound, which is composed of Mg^{2+}, NH_4^+, and PO_4^{3-} ($MgNH_4PO_4 \cdot 6H_2O$) in equal molar amounts (Korchef et al., 2011). **Struvite precipitation** is a chemical process where magnesium, ammonia, and phosphate react to form struvite crystals, which can be used as a slow-release fertiliser (Muhmood et al., 2018).

3.4.1.1 Characteristics of the collected data

Figure 32 displays a bubble plot summarizing the nutrient recovery rate (%) of various end products from manure processing. The plot categorizes nutrient recovery rates for three types of nutrients: Total Phosphorus (TP), Total Ammonium Nitrogen (TAN), and Total Nitrogen (TN). The size of each bubble represents the number of observations involved in the meta-analysis for each nutrient and end product. In total 433 observations were collected from 37 publications. Among the collected observations for TN recovery, 73% (129 observations) was about microalgae and struvite, 94% (127 observations) of the observations for TAN recovery was about microalgae and ammonium salts (including ammonium nitrate and ammonium sulphate), while 83% (100 observations) of the observations for TP recovery was about microalgae and struvite, suggesting microalgae cultivation, stripping and scrubbing, and struvite precipitation are highly promising technologies for nutrient recovery from manure.

The very limited data on nutrient recovery rates from membrane filtration (end products as permeate and concentrate) means that conclusions drawn from this data are highly uncertain. This uncertainty can affect the credibility of using permeate as a nutrient recovery method and may lead to hesitation or lack of adoption by practitioners due to insufficient evidence of its effectiveness.

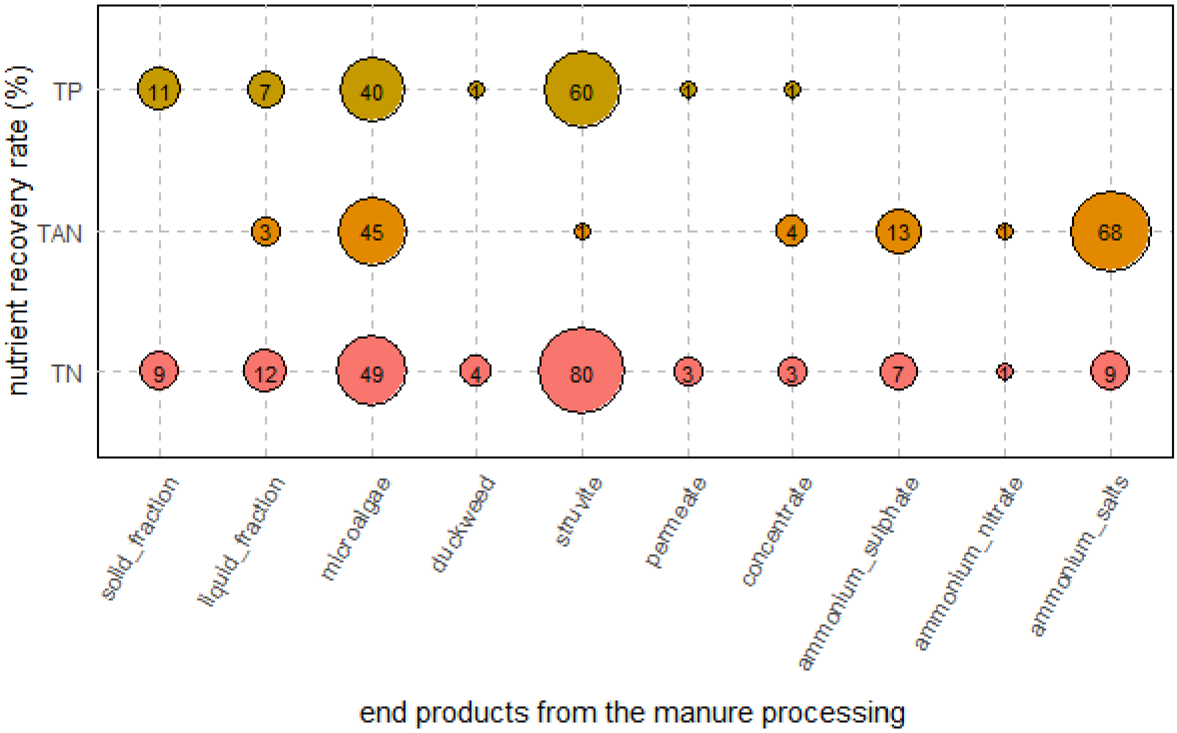

Figure 32*. *Bubble chart of included studies for the meta-analysis quantifying the impact of manure processing technologies on nutrient recovery rate. Each axis intersection in the matrix represents the number of studies reporting an effect size for the corresponding end products from manure processing practices and the nutrient recovery rate (%), where the bubbles are proportional to the number of studies. Colors represent the type of indicators from top to bottom: TP = recovery of total phosphorus, TAN = recovery of total ammonium nitrogen, TN = recovery of total nitrogen.

3.4.1.2 Visualizing the main impact of manure processing

Figure 33 illustrates the nutrient recovery rates for various end products derived from different manure processing technologies, focusing on TN, TAN and TP. Physical separation showed a high TP recovery rate (60%) in the solid fraction, while a high TN (73%) and TAN (83%) recovery in the liquid fraction. Both microalgae cultivation and struvite precipitation achieved averagely high recovery for all the three nutrient indicators (TN 73%-77%, TAN 70%-86%, TP 64%-88%). Membrane filtration's concentrate showed high recovery rate of TP (85%) but moderate recovery for both TN and TAN (42%-56%). Duckweed cultivation showed a relatively low nutrient recovery (TN 21% and TP 39%). Among the various ammonium salts derived from stripping and scrubbing technologies, ammonium sulphate (59) achieved a higher TAN recovery than ammonium nitrate (32%).

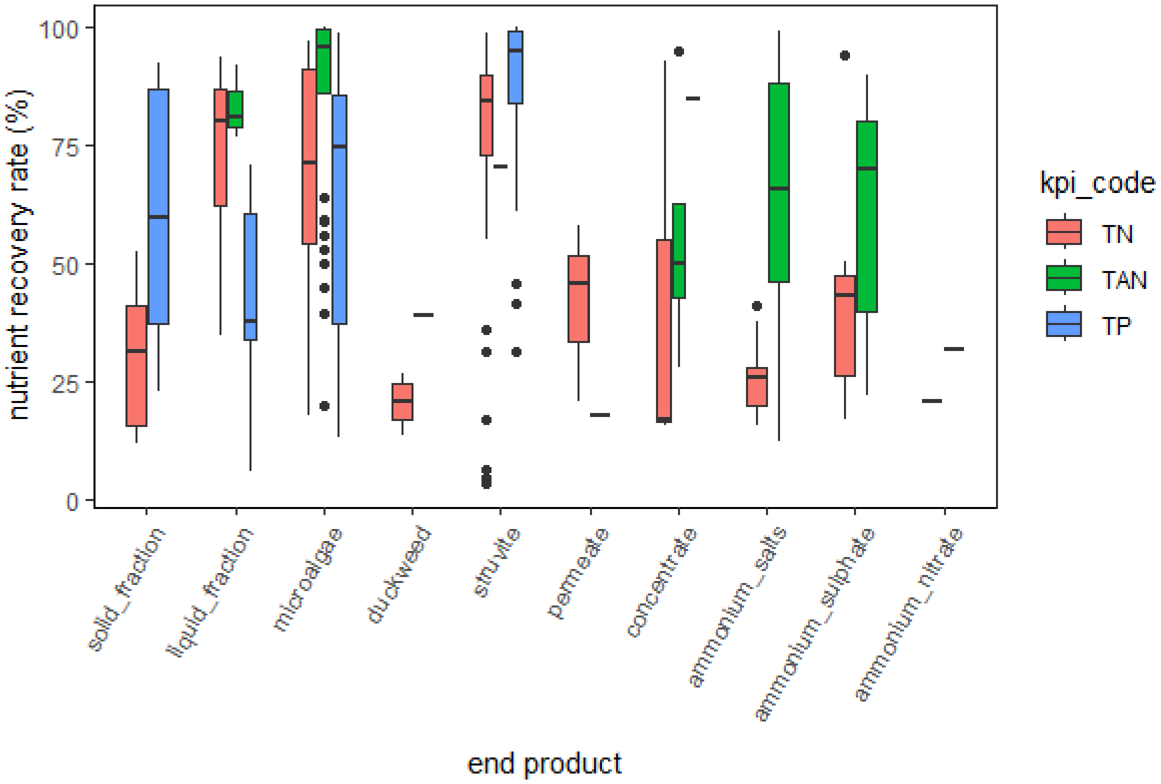

***Figure 33**. Absolute values of the nutrient recovery rate (%) in the end products resulted from single or integrated nutrient recovery technologies differentiated for nutrients. The end products include solid fraction and liquid fraction of manure/digestate from physical separation, microalgae from microalgae cultivation, struvite from precipitation, permeate and concentrate from membrane filtration, ammonium salts/sulphate/nitrate from stripping and scrubbing. Colours represent the type of indicators from top to bottom: TP = recovery of total phosphorus, TAN = recovery of total ammonium nitrogen, TN = recovery of total nitrogen.*

When categorized by different scales of the recovery process (full scale, pilot, batch, and laboratory), physical separation was tested in pilot and full-scale operations, the nutrient recovery rates vary between 43%-88% in the solid and liquid fractions (Figure 34). Data for nutrient recovery of microalgae or duckweed cultivation and struvite precipitation are only available at laboratory or pilot scale. Microalgae cultivation and struvite precipitation showed high nutrient recovery rates at both laboratory (75%-82%) and pilot scales (61%-69%). The duckweed cultivation showed a low mean recovery of around 24% in pilot operations. Results for membrane filtration was collected for full-scale operation, demonstrating moderate recovery rates in both permeate (36%) and concentrate (54%). The stripping and scrubbing technology showed a decreasing recovery rate when scaling up from laboratory (91%) to pilot (55%-72%) and full-scale (46%). Notably, the resulted ammonium nitrate exhibited a low nutrient recovery (27%). However, it is worth noting that only two studies were included for ammonium nitrate, which may suggest a bias in the quantification.

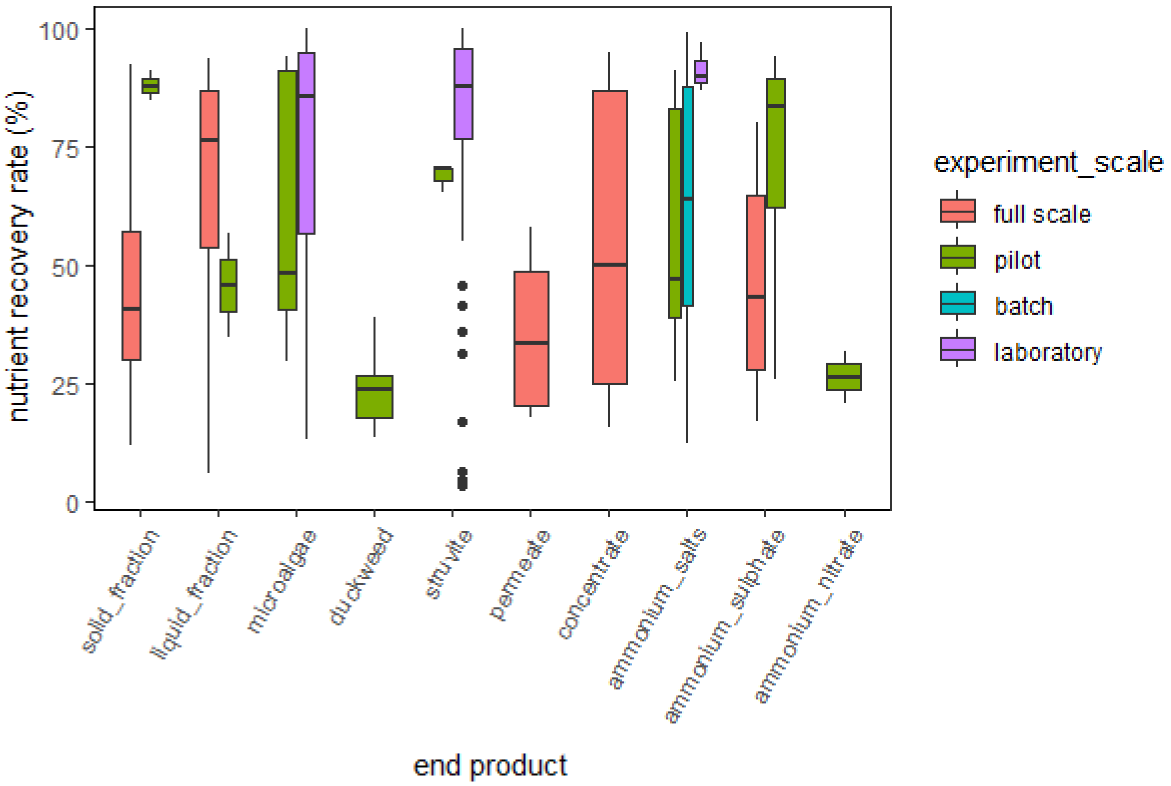

Figure 34. *Absolute values of the nutrient recovery rate (%) in the end products resulted from single or integrated nutrient recovery technologies differentiated for experimental scales. The end products include solid fraction and liquid fraction of manure/digestate from physical separation, microalgae from microalgae cultivation, struvite from precipitation, permeate and concentrate from membrane filtration, ammonium salts/sulphate/nitrate from stripping and scrubbing. Colours represent the different scales of recovery process, including full scale (operational environment such as industry serving for commercial purpose), pilot (industrially relevant environment), batch (continues lab experiment), laboratory (single lab experiment).*

The nutrient recovery rates vary across different manure processing technologies (thus in end products) and the scale of the recovery process. Technologies such as struvite precipitation and ammonia stripping and scrubbing stand out for their high recovery rates, particularly at larger scales, suggesting their potential for efficient nutrient recovery in industrial applications. Struvite precipitation is highly effective for P recovery, with consistently high recovery rates. However, it is less effective for N recovery. Stripping and Scrubbing show high recovery rates for both TN and TAN, particularly when sulphate acid is used as scrubber resulting in ammonium sulphate as end products. This suggests that stripping and scrubbing are highly efficient for N recovery from manure. Physical separation of manure results in higher P recovery in the solid fraction and higher N recovery in the liquid fraction, with generally high recovery rates at full-scale operation, emphasizing their effectiveness in practical applications. Microalgae cultivation at both laboratory and full-scale shows promising results for both N and P recovery in the microalgae biomass, though with considerable variability, which might be attributed to differences in cultivation conditions and algae species. The concentrate obtained from membrane filtration shows moderate recovery rates for both nitrogen and ammonium nitrogen, while the permeate has very low nutrient recovery rates, indicating that nutrients are more concentrated in the retentate.

3.4.1.3 Linear regression model for the nutrient recovery

Linear regression models (see Chapter 4 the link to R script and database used for the RQ4 models) were developed to quantify the individual impact of animal farming systems (pig, poultry, cattle, dairy, or mix), manure processing technologies (or type of end products), experimental scales, as well as the interactions between manure processing technologies (or type of end products) and experimental scales on nutrient recovery rate (%). Results were presented in Table 8.

The developed models explain 94%, 94%, and 91% of the variability in TN, TAN, and TP recovery rates, respectively. All models have significant *F*-statistics and very low *p*-values, indicating that the predictors used in these models are significantly related to the recovery rates of the respective nutrients.

Table 8. *Parameters and statistics of the linear regression models to quantify the impact of manure processing and experimental scale on the recovery rate (%) of TN, TAN, and TP in manure derived from different animal farming systems (pig, poultry, cattle, dairy, or mix).*

Nutrient	Number of observations	Multiple R^2	Adjusted R^2	*F*-statistic	*p*-value
TN	177	0.94	0.93	130.10	<0.001
TAN	135	0.94	0.92	53.72	<0.001
TP	121	0.91	0.90	56.15	<0.001

3.4.2 Manure processing for nutrient removal

Technologies employed for nutrient removal from manure focus on reducing the nutrient load before disposal or further processing. For example, nitrification-denitrification (NDN) is the main and common process for removal of organic matter and reduces N and P content in waste streams including animal manure and derivatives. Constructed wetland are engineered systems that use natural processes involving wetland vegetation, soils, and their associated microbial assemblages to remove nutrients from manure effluent (Vymazal et al., 2021). Some technologies such as physical separation (including centrifugation, screw press, ect.), microalgae and duckweed cultivation, membrane filtration and distillation (including ultrafiltration, reverse osmosis, gas permeable membrane filtration) are commonly used in nutrient recovery from manure (see section 3.4.1), but also integrated in the post treatment to remove residue nutrients. In terms of nutrient removal, acidification and ammonia scrubbing refers mainly to the reduction of NH_3 emissions in animal houses or manure storage by using acid (scrubber).

3.4.2.1 Characteristics of the collected data

In this deliverable, a total of 206 observations (Figure 35) were collected from 51 publications, among which, data for removal of NH_3 was mainly collected from research on acidification (44%) and ammonia scrubbing (56%), while TP removal data was mainly collected from research on microalgae (35%) and constructed wetland (42%). Among the collected observations for TN removal, 35% (24 observations) was about press filtration, 56% (36 observations) was about microalgae cultivation and constructed wetland. Also, of the 80 observations for TAN removal, 42.5% was about constructed wetland.

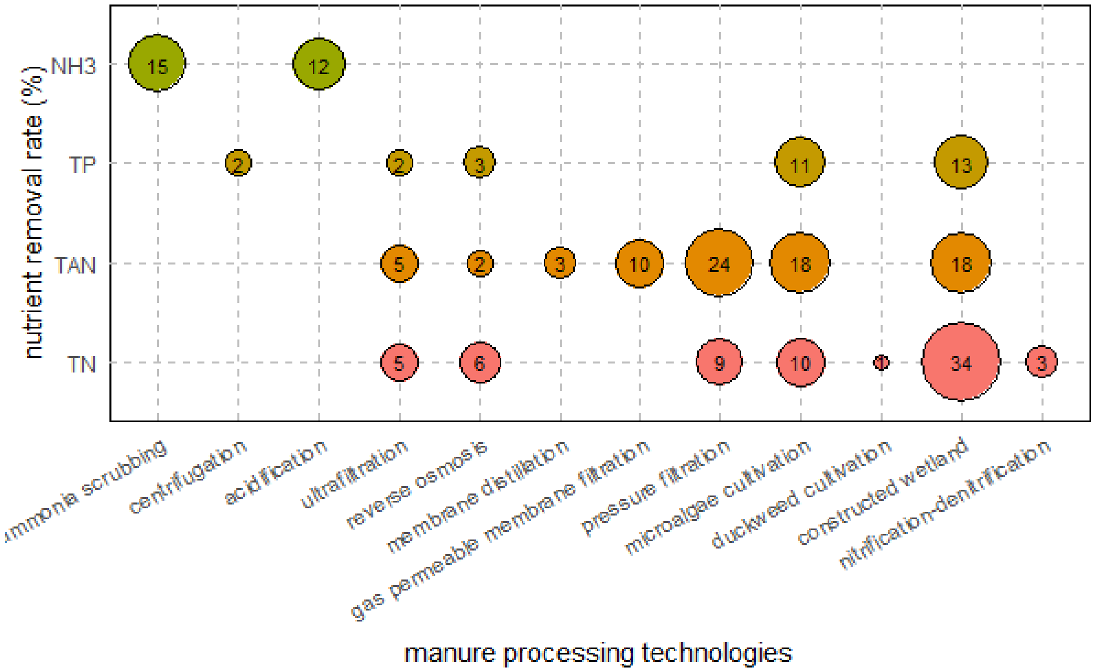

Figure 35. *Bubble chart of included studies for the meta-analysis quantifying the impact of manure processing technologies on nutrient removal rate. Each axis intersection in the matrix represents the number of studies reporting an effect size for the corresponding manure processing technologies and the nutrient removal rate (%), where the bubbles are proportional to the number of studies. Colours represent the type of indicators from top to bottom: NH3 = reduction of ammonia emissions, TP = removal of total phosphorus, TAN = removal of total ammonium nitrogen, TN = removal of total nitrogen.*

3.4.2.2 Visualizing the impact of main factors and interactions

Figure 36 illustrates the nutrient removal rates for various manure processing technologies, focusing on TN, TAN, TP, and NH_3. Both acidification and ammonia scrubbing demonstrated a very high NH_3 removal rate (averagely 76%-77%), highlighting its effectiveness in mitigating ammonia emission from animal house and manure storage. The conventional manure treatment process, i.e. nitrification and denitrification, revealed high removal of TN (72%) as compared to ultrafiltration (34%), constructed wetland (56%), duckweed cultivation (43%). However, in terms of TP removal, data is not available from nitrification and denitrification, while it remained high (averagely 62% -90%) in other processing technologies including centrifugation, ultrafiltration, reverse osmosis, microalgae cultivation and constructed wetland. Removal of TAN was highest in membrane distillation (82% ± 10%) microalgae cultivation (84%), and gas permeable membrane filtration (79%). While other membrane filtration (including ultrafiltration, press filtration and reverse osmosis) showed a relatively low TAN removal rate (34%-59%), revealing a comparable removal capacity as constructed wetland (60%).

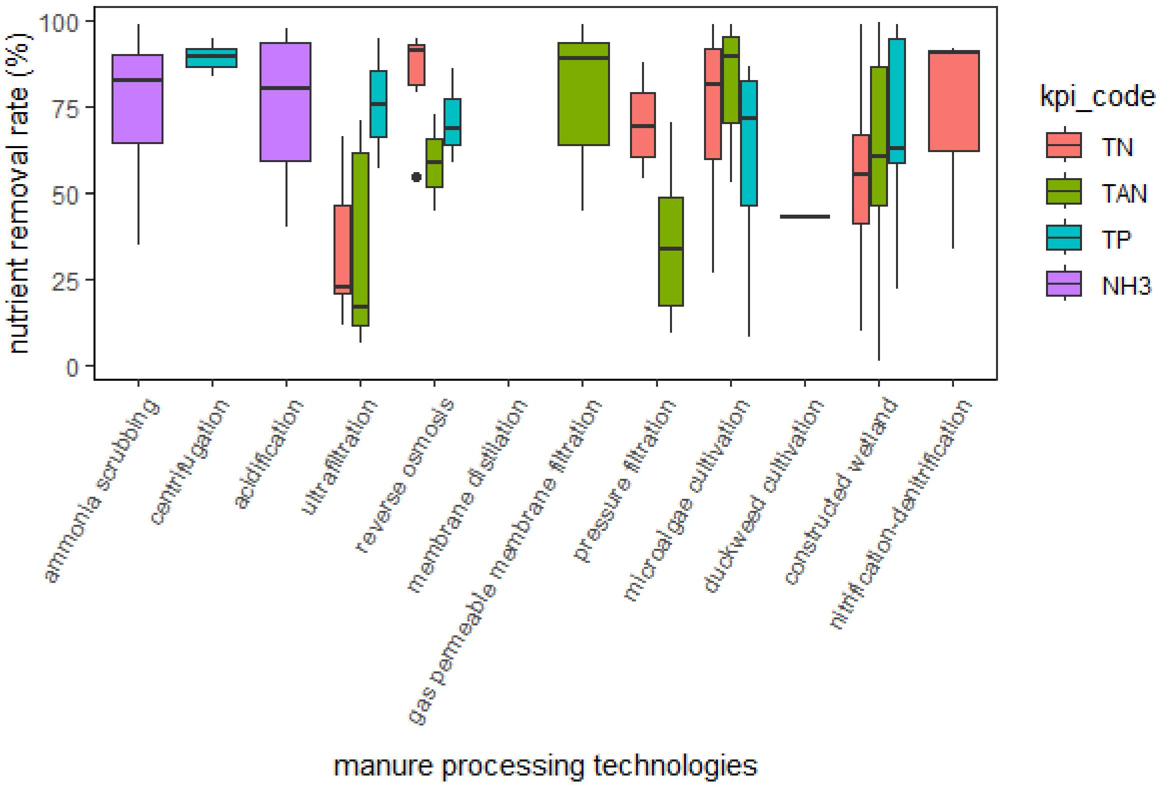

Figure 36. *Absolute values of the nutrient removal rate (%) through manure processing technologies differentiated for nutrients. The technologies include ammonia scrubbing, centrifugation, acidification, ultrafiltration, reverse osmosis, porous polypropylene membrane filtration, pressure filtration, gas permeable membrane filtration, microalgae/duckweed cultivation, constructed wetland, nitrification and denitrification. Colours represent the type of indicators from top to bottom: TN = recovery of total nitrogen, TAN = recovery of total ammonium nitrogen, TP = recovery of total phosphorus, NH3 = ammonia emissions.*

Differentiated in experimental scales (Figure 37), acidification showed a slightly higher and more stable NH_3 emission reduction in laboratory (77%) than at farm (68%). The same trend was observed for constructed wetland, with a higher removal rate at laboratory (63%) and pilot scales (80%) as compared to full scale (59%). However, this is not necessarily applied to other technologies, for example, ultrafiltration illustrated a higher nutrient removal rate at full scale (66%) than at laboratory (15%), while the removal rate of microalgae cultivation was higher with lower variations in pilot scale (75%) than in laboratory (62%). The collected data also revealed that the current studies for membrane distillation, pressure filtration and gas permeable membrane filtration focus mostly on laboratory scale, suggesting a need for up-scaling research.

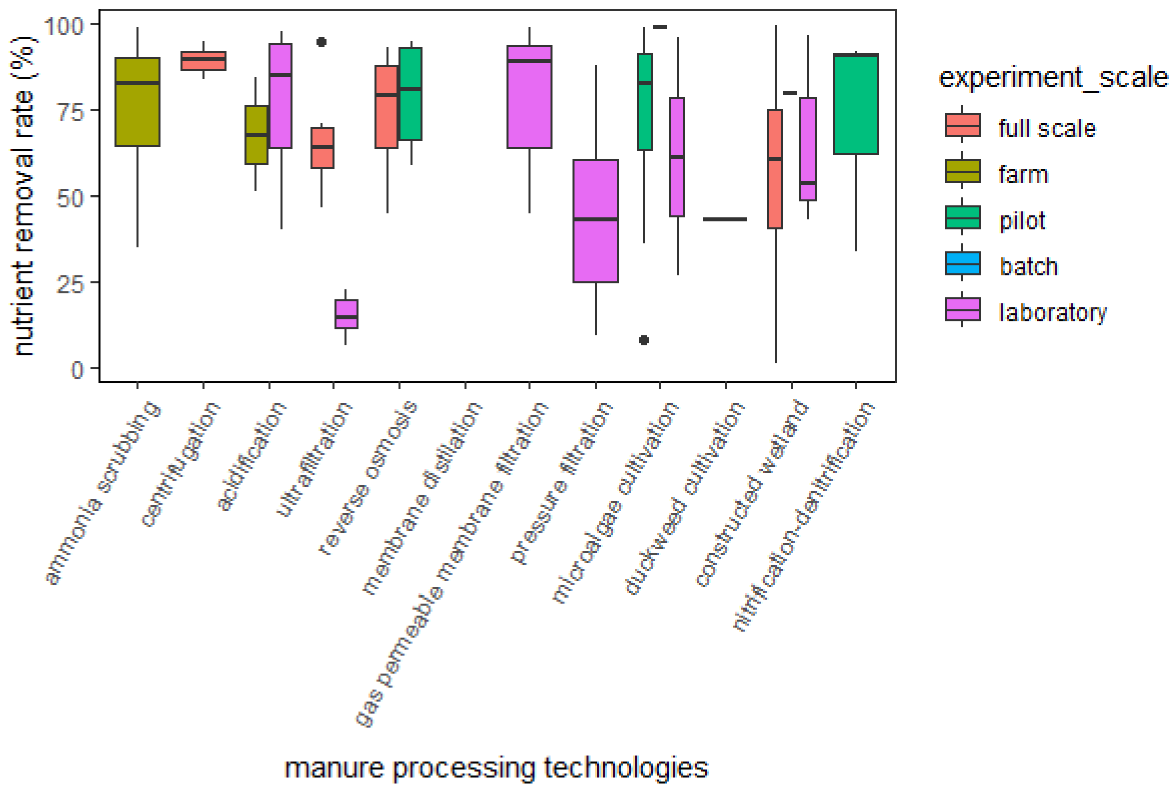

Figure 37. *Absolute values of the nutrient removal rate (%) through manure processing technologies differentiated in experimental scales. The involved technologies include ammonia scrubbing, centrifugation, acidification, ultrafiltration, reverse osmosis, porous polypropylene membrane filtration, pressure filtration, gas permeable membrane filtration, microalgae/duckweed cultivation, constructed wetland, nitrification and denitrification. Colours represent the different scales of recovery process, including full scale (operational environment such as industry serving for commercial purpose), pilot (industrially relevant environment), batch (continues lab experiment), laboratory (single lab experiment).*

3.4.2.3 Linear regression model for nutrient removal

Similar as in the section 3.4.1.3, linear regression models (Table 9) were also developed to quantify the individual impact and interactions of manure processing technologies and experiment scales on the removal rate (%) of NH_3, TN, TAN and TP, respectively. The models showed high explanatory power for all the four types of concerned nutrients, with multiple and adjusted R^2 values all above 0.9, and they are statistically significant overall. Linking to the significant ($p<0.001$) and high explanation power ($R^2>0.9$) of the models developed for nutrient recovery rate (Table 8), it is suggested that both the nutrient recovery and removal rate were mainly affected by the type of feedstock, the manure processing technologies and the operational scales. Therefore, the linear regression models developed in this study can be used to predict and evaluate the impact of manure processing technologies and experimental scales on the recovery or removal rate (%) of NH_3, TN, TAN, and TP in manure derived from different animal farming systems (pig, poultry, cattle, dairy, or mix). However, calibration and validation are needed with an externed database to including a higher number of results derived from various experimental scales, such as nutrient recovery/removal through full-scale microalgae/duckweed cultivation, nutrient removal through membrane filtration at pilot and full-scale operation.

Table 9. *Parameters and statistics of the linear regression models to quantify the impact of manure processing technologies and experimental scales on the removal rate (%) of NH_3, TN, TAN, and TP in manure derived from different animal farming systems (pig, poultry, cattle, dairy, or mix).*

Nutrient	**Number of observations**	**Multiple R^2**	**Adjusted R^2**	***F*-statistic**	***p*-value**
NH_3	27	0.94	0.93	130.1	<0.001
TN	68	0.94	0.92	53.72	<0.001
TAN	80	0.91	0.90	56.15	<0.001
TP	31	0.94	0.91	33.03	<0.001

4. General discussion

The databases and R scripts used to develop the regression models for the four defined RQs are openly shared on Github through the following link: https://github.com/gerardhros/nutribudget.

The meta-regression models established in RQ1, which included key site properties such as crop type, cover crop presence, crop rotation, soil, and weather conditions, effectively quantified the impact of crop, soil and fertiliser management practices on crop yield and NUE. The analysis revealed that most crop types, except rice and vegetables, significantly influenced crop yield, with beans, oilseeds, cereals, and maize showing particularly strong responses. Cover crops had a comparable effect, while crop rotation had a nuanced impact, decreasing yield in some cases but increasing it significantly under certain conditions. Soil properties such as bulk density and cation exchange capacity showed positive correlations with yield, though other soil factors like total nitrogen negatively influenced crop outcomes. Additionally, increased precipitation positively affected yield, indicating the critical role of local climate in management outcomes. Regarding NUE, the 4R strategies—applying the right fertiliser rate, timing, and placement—proved particularly effective in enhancing NUE by optimizing nitrogen availability and minimizing losses. Enhanced efficiency fertilisers and partial substitution with organic fertilisers also improved NUE, though full substitution could reduce efficiency. However, the effects of these management practices on NUE vary regionally due to differences in nitrogen application rates, crop types, soil properties, and local climate conditions. Refining the meta-regression model by selecting only the significant moderator variables offered a better fit for predicting crop yield responses than the generalised full model. Its simpler structure provided practical benefits by allowing for easier interpretation of the complex interactions between management practices and crop-related indicators.

Regarding the impact of crop, soil, and fertiliser management practices on SOC and soil pH, the models were able to predict responses of soil pH to management and site conditions, but were less reliable in predicting changes in SOC. The performance of the meta-regression models for soil pH was significantly influenced by the initial alkalinity of the soil and physical soil disturbance practices. The initial alkalinity plays a crucial role in regulating pH through various buffering processes, such as the mobilization of aluminium oxides, cation exchange, and carbonate and silicate dissolution. Physical disturbance, such as no-tillage and grass cropping, affects the dynamics of organic matter and its decomposition, influencing soil pH. Despite these comprehensive analyses, the role of liming was not prominently highlighted, potentially due to the limited number of liming experiments in the meta-analysis. The findings suggest that mitigation measures for pH should be tailored to specific site conditions, accounting for these strong buffering processes. In contrast, the meta-regression models for soil organic carbon (SOC) exhibited less reliability in capturing changes despite using a larger dataset. Although reduced tillage and no-tillage practices independently increased SOC, their significance was diminished in multivariate analyses, which highlighted climate factors, soil density, and organic matter inputs as predominant determinants. The complex interplay of these factors, such as temperature influencing decomposition rates and precipitation regulating soil moisture, led to counterintuitive outcomes. For instance, higher temperatures were associated with increased SOC, while higher precipitation had a negative impact. Soil bulk density also emerged as a significant predictor, indicating the importance of the mineral content and initial organic matter levels of the sites studied. These findings underscore the multifaceted nature of SOC dynamics and the challenges in modelling them accurately, particularly on the large scale.

Three meta-regression models were also established to quantify the impact of alternative protein source in animal feeding on the animal productivity, using ADG, DCP and FCR as indicators. Overall, a higher supplemental rate of soybean protein using alternative protein sources resulted in a reduction in ADG and feed use efficiency (increased FCR), likely because of imbalanced amino acid profiles or anti-nutritional factors present in some alternative proteins. For example, many plant-based proteins (such as legumes) lack one or more essential amino acids, which can limit growth when provided in excess without proper supplementation (Zacharias, 2016). Conversely, a higher supplemental rate of the alternative protein showed positive impact on the DCP, suggesting a potential reduction of N excretion in the urine and faeces. This increase in crude protein digestibility with higher supplementation rates may occur because some alternative proteins contain high levels of soluble or easily degradable protein fractions, which are quickly digested. However, this does not necessarily translate into improved growth performance if the absorbed amino acids are not utilized effectively due to other limiting factors, such as imbalances in amino acid profiles. Among all the six alternative protein sources, duckweed stood out with a significantly positive impact on the ADG and significantly negative impact on FCR, microalgae showed a significantly negative impact on the DCP. The interactions between supplemental rate and type of alternative protein source showed significant impact on all the three indicators (positive on ADG while negative on DCP and FCR), suggesting that the importance of optimizing the supplemental rate when a novel protein source is used to substitute the soy-based protein in animal feed. Additionally, the timing to apply alternative protein also plays an important role in the animal performance, for instance, replacing soy-based protein with alternative proteins throughout the entire growing season could lead to cumulative negative effects on daily weight gain and feed conversion efficiency. These results highlight the importance of optimizing the timing and rate of alternative protein inclusion to maximize their benefits while minimizing potential drawbacks.

Given the nature of the available data in RQ4 for the nutrient recovery/removal rate from manure management practices (see section 3.4), the measure-impact was quantified through linear regression models taking into consideration the interactions with the experimental scales and the impact of manure origin (i.e. animal type). Results revealed that the established linear regression models can well explain the variability between studies (multiple and adjusted $R^2 > 0.9$, $p < 0.001$). Microalgae cultivation, struvite precipitation generally showed high TN and TP recovery rate (> 75%), but most data is collected through laboratory experiments, suggesting a need for further research at pilot and full scale. Stripping and scrubbing showed high TAN recovery rate both at laboratory and pilot scale, while a decrease was observed at full-scale operation. When referring to nutrient removal technologies, microalgae cultivation and constructed wetland reflected similar efficiency in removal of TN as the conventional nitrification and denitrification treatment. Meanwhile, these two technologies showed a significant removal of TAN and TP at either laboratory, pilot or full scales. Ammonia scrubbing and acidification were typically used in mitigating NH_3 emission from animal house, showing high removal of NH_3 (>75%) at farm level.

5. Conclusions and recommendations

Following the methodology developed in *D1.2*, meta-regression or linear regression models were developed in this deliverable to quantify the measure-impact relationship in crop, soil and animal management systems. The results are as follows:

- **RQ1**: the impact of crop, soil, and fertiliser management practices on crop yield and NUE was quantified through meta-regression models using the ROM and SMD effect size, respectively. The results showed that the crop management (including cover crop, intercropping, crop rotation, ley) and fertilisation management (including organic fertilisation, N and Mg fertilisation, drip fertilisation) showed significantly negative impact on crop yield, most likely due to a main contribution of the negative impact induced by crop rotation and organic fertilisation. While for NUE, the fertilisation management, including enhanced efficiency fertilisers and partial substitution with organic fertilisers, had the most positive impact. The impact of management practices varied regionally, influenced significantly by annual precipitation, crop type, soil properties, and local climate.
- **RQ2**: the impact of management practices on soil pH and SOC was quantified through meta-regression models using the SMD effect size. For soil pH, physical soil disturbance practices and the initial alkalinity of the soil showed the most significant influence, with no-tillage and grass crops negatively impacting pH. The models were less reliable in predicting changes in SOC, but identified climate factors, soil density, and organic matter inputs as significant determinants.
- **RQ3**: the impact of alternative protein sources on animal productivity was quantified through meta-regression models using the ROM effect size. The results showed that higher supplemental rates of alternative protein sources reduced ADG and FCR but improved DCP. The impact differed for pig and poultry at various growth stages, with a generally higher negative impact on the feed digestibility and use efficiency when alternative protein sources are used at early growth stages (starting) or over the whole growth.
- **RQ4**: the impact of manure processing practices on nutrient recovery and removal was quantified through linear regression models. The results revealed that microalgae cultivation and struvite precipitation had high TN and TP recovery rates in laboratory experiments. Stripping and scrubbing technologies showed high TAN recovery across all scales, but efficiency decreased at full scale. Constructed wetlands and microalgae cultivation were effective in removing TN, TAN, and TP, while ammonia scrubbing and acidification effectively reduced NH3 emissions at the farm level.

Despite the incorporation of comprehensive steps to address data heterogeneity in the development of meta-regression models, including data harmonization, incorporating site-specific factors, model refinery by subgrouping main factors, the developed models revealed different levels of unexplained variance (heterogeneity). This heterogeneity might be induced by the variability in experimental conditions, measurement techniques, and site-specific characteristics across different studies introducing a high level of noise, making it difficult for the models to capture the true effect of management practices on the KPIs. Additionally, the inherent complexity and multifactorial nature of soil and crop systems mean that a wide range of interacting variables influence the outcomes, which can be challenging to model accurately. This also implies that the uncertainty should be counted when using these meta-regression models to guide the model calibration and model assessment of measures-impact in WP2.

To effectively apply these models in practice, which is highlighted in Task 1.3 considering the current nutrient status of European agricultural systems, scenario analysis can be a useful tool to acknowledge and accommodate the inherent variability at a large scale. By running multiple scenarios that account for different assumptions and conditions, stakeholders can better understand the range of possible outcomes and make more informed decisions. Note that the model error is assumed to be random, implying that over- and underestimations might cancel out when applied on regional scale. Besides, the model outputs will be integrated as part of a broader decision-support framework rather than relying on them in isolation. For instance, while the models can indicate general trends and potential impacts of specific management practices, local agricultural advisors and stakeholders should interpret these results in the context of their specific conditions and experiences. Furthermore, it is important to continuously refine and update the models as new data becomes available. Furthermore, clear communication about the limitations and uncertainties associated with the model predictions is essential. Users of these models should be made aware of the potential for variability and the reasons behind it. This transparency can help to manage expectations and foster trust in the models as useful, though not infallible, tools for decision-making.

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Annexes

Annex 1 The generalised full model estimations for the impact of management practices and site properties on crop yield, soil pH and SOC

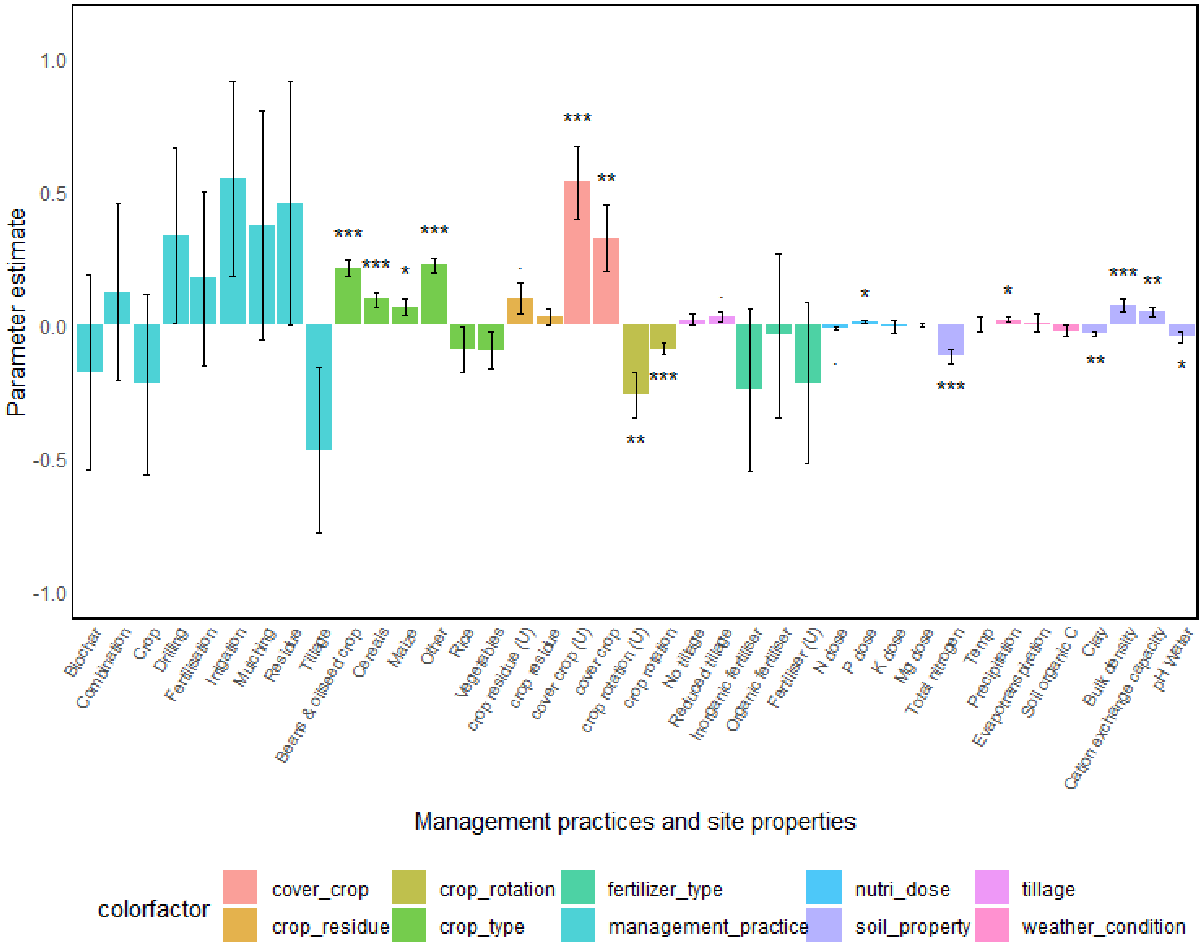

Figure A1. *Parameter estimate for the impact of management practices on crop yields along with the impact of site properties on the changes of crop yield induced by these management practices. This Figure depicts the grouping of the management practices for the general full model based on the significant impact per factor (Figure 5-6). The colour differentiates both the management practices and the site properties groups from each other, but it also indicates that factors with the same colour belongs in the same group. The combination group includes examples of practices involving more than two factors, as detailed in Table 1. Asterisks indicate statistically significant differences (*p < 0.05, **p < 0.01 and ***p < 0.001).*

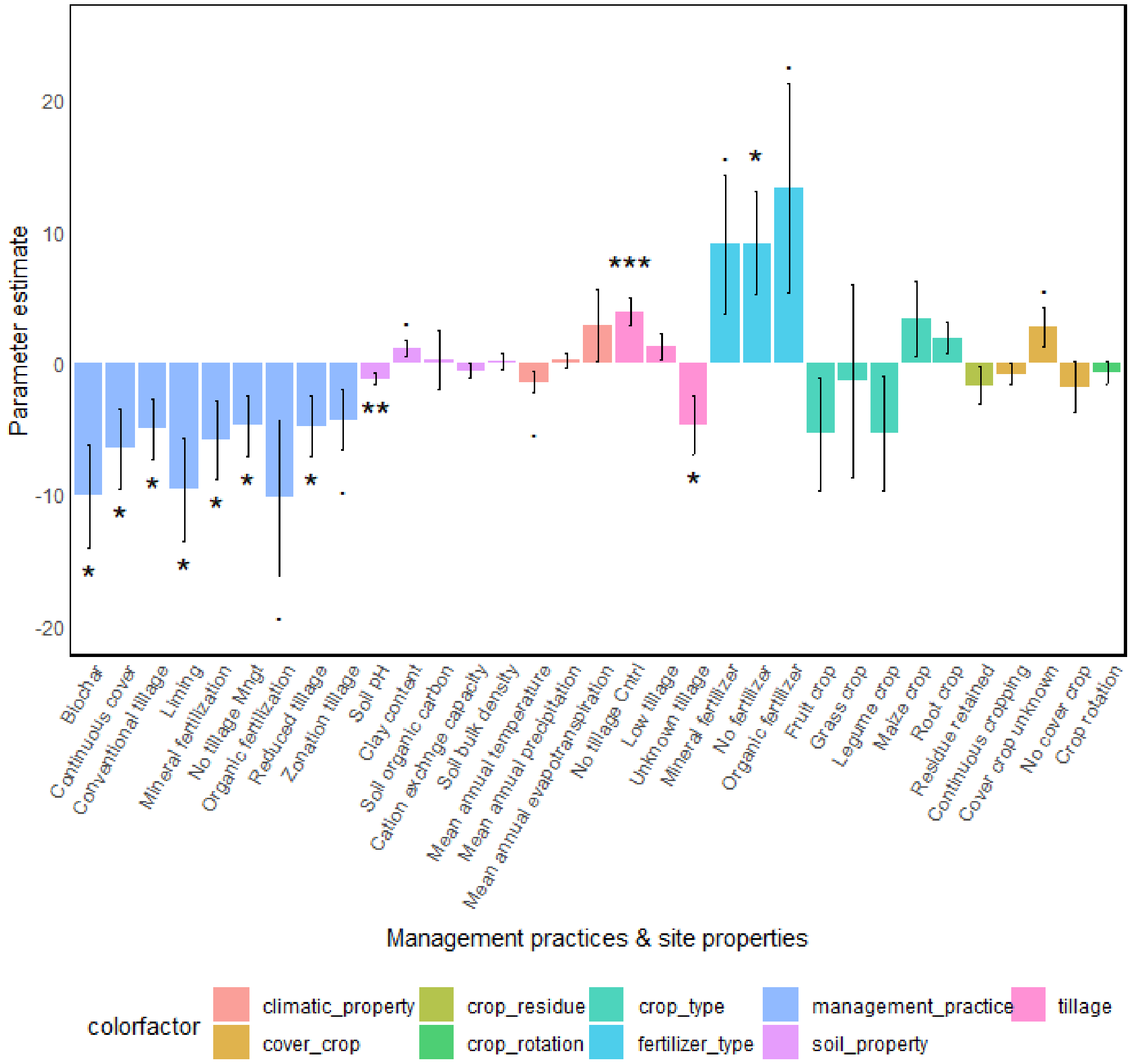

Figure A2. *Parameter estimates of all management practices and site properties included in the meta-regression model for the impact on soil pH. Asterisks indicate statistically significant differences (*p < 0.05, **p < 0.01 and ***p < 0.001).*

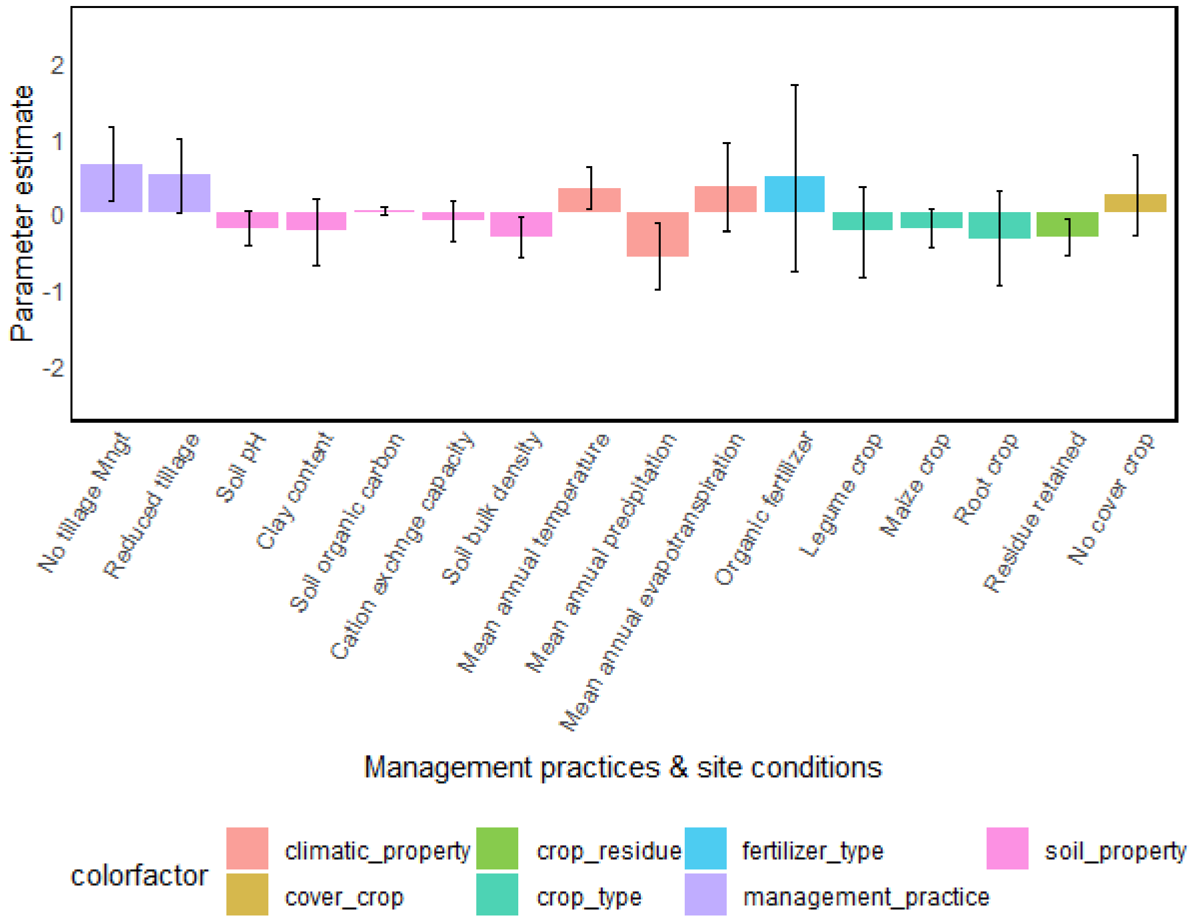

Figure A3. *Generalised full model for the impact of management practices and site properties on SOC, the results showed that all the included explanatory variables have no significant explanatory power. Asterisks indicate statistically significant differences (*p < 0.05, **p < 0.01 and ***p < 0.001).*

Optimisation of nutrient budget in agriculture

Project Coordinators:

Prof. Erik Meers, Erik.Meers@UGent.be
Dr. Ivona Sigurnjak, Ivona.Sigurnjak@UGent.be
Ghent University, Sint Pietersnieuwstraat 25, Ghent 9000, Belgium.

The Consortium:

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