Optimisation of nutrient budget in agriculture

D1.4 Algorithms quantifying impacts of measures via field based indicators from satellite derived indices - initial version

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Disclaimer: *The wording "from satellite derived indices" in the title of D1.4 "Algorithms quantifying impacts of measures via field based indicators from satellite derived indices - initial version" does not fully cover the data sources that are used in this deliverable. The focus of D1.4 is on the application of the models on EU scale based on existing databases, which are partially satellite-derived. Meaning, data used in D1.4 is not based only on the satellite derived indices.*

Preface

Deliverable 1.4 *"Algorithms quantifying impacts of measures via field based indicators from satellite derived indices - initial version"* is part of outcomes from Task 1.3 in work package (WP) 1 of NutriBudget project, funded by 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", in various regions across Europe. The NutriPlatform will operate as a decision-support tool for farmers, advisors and regional authorities. Before the end of the project, the "NutriPlatform" (as a stand-alone or integrated in the existing European Commission promoted Farm Sustainability Tool for nutrient management) will be tested and used by at least 40.000 farmers across Europe.

The WP1 *"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. The objective of Task 1.3 is to derive predictive models or decision trees to predict the response of Key Performance Indicators (selected from WP3) given the site properties of the farm, region or country thereby assessing the applicability as well efficiency of measures to alter the KPIs.

This deliverable, as an initial version of the Task 1.3 results, aims to establish a protocol for application of meta-analytical regression models (deliverable D1.2 from Task 1.2) to quantify the measure-impact relationship of selected mitigation measures to improve specific agronomic and environmental indicators selected in WP2/WP3, linked to crop yield, soil health (e.g. soil organic carbon (SOC) content / sequestration), soil water retention, air quality (e.g. ammonia emissions) and water quality (e.g. nutrient surplus and nutrient use efficiency). The protocol also presents an approach to identify the most appropriate and effective measures given the current agronomic and environmental performance of farms and fields. The protocol in this deliverable will guide the actual application of developed meta-regression models in a later stage of Task 1.2 and support the calibration and validation of predicted measure impacts by the empirical and process based models from WP2.

Executive Summary

Intensification in agriculture, driven by increased machinery and fertilizer use, has substantially boosted food production in Europe. However, the elevated application of nitrogen (N) and phosphorus (P) fertilizers 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, decline in biodiversity and soil organic carbon further compound food security and environmental challenges. In responding to these issues, the Horizon Europe NutriBudget project aims to develop and implement integrated nutrient management platform, called NutriPlatform, as a decision support tool to intensify agriculture sustainably, ensuring optimal yields without compromising the environment or public 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 use efficiency, nutrient losses…), which resulted in an user-friendly catalogue consisting 22 pre-identified mitigation measures (aiming to be more than 50 by end of the project).

Based on the inventory of existing agronomic mitigation measures in Task 1.1, and the meta-regression models build to estimate their impact on selected Key Performance Indicators in Task 1.2, Task 1.3 aims to apply these meta-regression models on an European scale while accounting for the spatial variability in soil properties, climatic conditions and management measures already applied. By applying these spatial explicit meta-regression models, one can identify the most effective measures to increase the agronomic and environmental performance of farming systems across Europe.

Deliverable D1.4 is divided in four Chapters. **Chapter 1** provides a general introduction to the nutrient challenge in agricultural 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. **Chapter 2** describes the methodology to apply developed meta-analytical regression models on European scale and to identify appropriate measures, including an overview of existing databases (partly satellite derived) to tailor the calculated impacts on field, farm and regional scale. Three examples from previous studies following this methodology are presented in **Chapter 3** illustrating how agronomic measures can be optimised in view of targets for SOC sequestration (example 1), crop yield, soil organic matter and the nitrogen surplus (example 2) and targets for nutrient efficiency, water retention and nutrient buffering in view of leaching and runoff (example 3). Lastly **Chapter 4** describes and summarizes the expected outcomes, potential risk and mitigation strategies.

In general, D1.4 (Task 1.3, WP1) reports on:

- A **developed protocol to apply meta-regression models** that estimate the impact of agronomic farm and field measures on the desired status of soil surpluses of carbon and nutrients in view of targets for soil quality, water quality, climate, biodiversity and crop production, taken into account the site properties controlling those impacts. The actual application and spatial visualisation of these impacts are foreseen in Deliverable 1.5, Task 1.3, WP1.
- The **protocol that presents an approach to identify the most appropriate and effective measures** in view of the key performance indicators selected in WP3 and being used by the models in WP2. It will be used to finetune and calibrate the model-based assessment to develop roadmaps with various measures to improve the sustainability of agriculture (moving form current to desired status) as foreseen in WP2.
- The **protocol that allows the estimation of site specific impacts of agronomic measures** in view of agronomic and environmental targets for indicators selected in WP2/3. These indicators are linked to crop yield and desired carbon and nutrient budgets in view of soil health

(e.g. soil organic carbon (SOC) content / sequestration), soil water retention, air quality (e.g. ammonia emissions) and water quality (e.g. nutrient surplus and nutrient use efficiency).

- The **protocol that facilitates the identification of appropriate measures** by combining estimates of the actual carbon and nutrient budgets, spatial explicit regional targets for those budgets, the impact of measures on those budgets and the optimisation across multiple agronomic and environmental targets into an overall score reflecting the integrative farm and field performance in view of these targets.
- The **protocol application that is illustrated with three examples** derived from previous European or national projects focussing on optimising agricultural management in view of multiple targets: one on carbon sequestration, one on agronomic yield benefits and N use efficiency and one on farm measures to improve water availability and buffering capacity in view of water quality.

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List of Abbreviations

AB	Abstract
D	deliverable
DoA	Description of the Action
EU	European Union
FaST	Farm Sustainability Tool
FSWP	Farm Soil and Water Plan
GHG	GreenHouse Gasses
KPI	Key Performance Indicators
MD	Mean difference
MMC	Mitigation Measures Catalogue
N	Nitrogen
NCU	Nitrogen Calculation Unit
NUE	Nutrient use efficiency
NUTS	Nomenclature of Territorial Units for Statistics
P	Phosphorus
RQ	Research question
SD	Standard deviation
SMD	Standard mean difference
SOC	Soil Organic Carbon
SPAM	Spatial Production Allocation Model
TI	Title
TS	Topic
WP	Work package

1. Introduction

Agricultural management practices play a pivotal role in shaping the sustainability of agriculture with respect to crop production, soil quality, and environmental health. Numerous practices have been demonstrated to positively impact crop yield and soil fertility while mitigating nutrient losses and enhancing carbon sequestration. However, these practices also exhibit negative consequences, including decreased nutrient use efficiencies and increased emissions of greenhouse gases. The escalating nutrient losses to air and water pose significant challenges, leading to issues such as air pollution, water pollution, eutrophication, biodiversity loss, and soil degradation. Mitigating the adverse effects of nutrient pollution hinges on the judicious use of agricultural practices, necessitating a focus on impacts and improvements in nutrient use efficiencies, particularly nitrogen (N) and phosphorus (P).

Agronomic measures optimising the carbon and nutrient budgets in agriculture result in improved nutrient use efficiency of applied fertilisers, enhance crop yield and soil health together with minimised nutrient losses to air and water. The number of studies examining impacts of agronomic measures are rapidly increasing, confirming their key role in improving sustainability, including studies examining the impact of crop diversification and cover crops, reduced tillage, and precision fertilisation practices (Bolinder et al., 2020; Eagle et al., 2017a; Haddaway & Rytwinski, 2018). Because agricultural management practices are part of sustainable intensification, it is key that we understand their effects on crop growth, soil nutrient status and environmental quality. For example, practices such as diversified crop rotations and improved nutrient management through 4R practices, that is, applying fertilizer according to the right type, right amount, right timing and right placement (Venterea et al., 2016), could help maintain crop yields while reducing nutrient surpluses and associated losses (Eagle et al., 2017b; Tonitto et al., 2006). Although agricultural intensification might negatively impact SOC contents (Luo et al., 2010), measures such as residue management, reduced tillage and optimized rotation schemes can sequester carbon, becoming influential in climate change mitigation and increasing soil fertility (Haddaway et al., 2014; Lugato et al., 2014). Various best management practices have been recommended based on goals for soil quality, nutrient surpluses and water use (Antonopoulos et al., 2018). Nevertheless, the existing body of research has a notable limitation—it tends to be confined to individual agricultural practices and single indicators. When only single measures and impacts are considered, this can lead to suboptimal outcomes due to adverse impacts on other indicators (pollution swapping) while also the potential benefits on other indicators are not accounted. The consequence is a gap in our comprehension of the intricate dance of potential trade-offs and co-benefits that might unfold across a tapestry of indicators.

Moreover, the impacts of practices are highly contingent on site-specific properties (Abdalla et al., 2016; Qin et al., 2015), emphasizing the need for a more nuanced and tailored approach to agricultural optimization. These site properties, ranging from crop type and soil characteristics to climatic conditions such as precipitation and temperature, serve as dynamic influencers on the outcomes of agricultural interventions. For instance, a practice like minimal tillage might manifest higher emissions of N_2O in tropical climates compared to subtropical ones, underlining the significance of climate considerations. Similarly, the emission patterns of N_2O might diverge between arable croplands in wet sites and dry sites due to climate disparities. These variations underscore the necessity of accounting for these site-specific factors to bolster the predictive accuracy of the impacts of agricultural practices across locations.

The implementation of practices requires therefore a comprehensive understanding of the impacts of agricultural management practices on crop productivity, soil health and water quality. Therefore, research efforts are needed to assess the effectiveness of management practices and their interactions in different agricultural systems, landscapes, and climatic conditions (as being quantified in WP1 and WP2). In addition, the adoption of these practices by farmers and stakeholders depends on their economic feasibility, social acceptability, and institutional support. This calls for scientific underpinned decision support tools that integrates these aspects. A range of approaches has been used to assess the applicability and impact of measures including experimental evidence from individual research (Rozemeijer et al., 2010), and data-driven statistical (Young et al., 2021; Djodjic et al., 2002) and process-based models (de Vries et al., 2023). Each of these methods has its limitations regarding site specificity and all are highly data demanding.

Among these methods, meta-analytical models have advantages for spatial explicit modelling since these models can potentially assess the averaged impacts of agronomic measures on crop yield, soil organic matter levels, nutrient surpluses and nutrient losses while accounting for site properties controlling these impacts (Haddaway et al., 2017; Meurer et al., 2018). Though the dependency of these indicators on agro-ecological site properties is known from ample evidence from field experiments and modelling studies, their impact on the effectiveness of agronomic measures are often ignored in meta-analysis studies, thereby hampering the guidance and actual implementation of agronomic measures on farm and field level. Zooming into the specifics of the NutriBudget project, WP1 aims to develop a mitigation measures catalogue (MMC) by identifying relevant agronomic measures across the EU. Task 1.2, quantifying measure-impact relationships focuses on the evaluation of the measures identified in Task 1.1. This includes the quantification of their impact on specific indicators from subsequent work packages (WP2 and WP3) taking into account the agroecological conditions controlling their impacts.

When meta-regression models become available, thereby connecting the tailor-made response of key performance indicators (KPIs) to applied measures (described in deliverable D1.2), one can also develop spatial explicit maps guiding the selection of appropriate measures to improve the performance of farming systems on these KPIs. When applying these models on European scale this WP aims to provide spatial explicit maps for the best management practices to be applied in view of the agronomic and environmental targets. And this is exactly the Task 1.3 being described as "*This task will design (and apply) meta-models to extrapolate the findings of T1.2 (meta-regression models linking impacts to indicators) and site property data to all other agricultural fields across Europe, and integrates this outputs in decision support algorithms assessing both the applicability and efficiency of measures depending on agro-ecological site specific factors (where efficiency is defined in relation to multiple objectives of sustainable agriculture)."* The value of this quantification extends far beyond the project's confines; it stands as a critical informational repository for policymakers, researchers, and stakeholders navigating the realms of nutrient management and environmental sustainability within the agricultural sector.

Note that this deliverable, related to Task 1.3, focuses mainly on a methodological approach to apply meta-regression models using open (satellite) derived data sources to estimate the impact of measures on KPIs for sustainable agriculture, slightly deviating from the deliverable description in the Document of Action (DoA) for D1.4 "*Algorithms quantifying impacts of measures via field based indicators from satellite derived indices (e.g. compaction, yield (stress), timing agronomic events, runoff risks, etc) spatial are modelled, and the code is shared via github and made available via an API for further use – initial version*" where activities of WP3 (Deliverable D3.3) summarized as "*Report and github-repo with algorithms for derivation of KPI from sensing data (T3.3), allowing other WPs to make use of the developed spatial explicit indicators for application on-farm level across EU*" were mixed up. We therefore focussed on the original task described for the application of meta-regression models on European scale (Task 1.3) and designed a field and farm specific upscaling protocol, as being described in this report.

2. Methodology

2.1 Optimising management measures across farming systems

To assess the actual farm performance in view of agronomic and environmental targets, an integrative KPI framework has been designed to monitor the transition from the current to the desired status to have optimised farming systems in equilibrium with maximum agricultural performance and minimal environmental pressure (Ros et al., 2023a). As such, this framework will guide the actual decision support as well the identification of appropriate roadmaps to reach the desired status for soil surpluses of carbon and nutrients in view of targets for soil quality, water quality, climate, biodiversity and crop production. The KPIs selected include site specific thresholds for carbon and nutrient budgets in view of agronomic and environmental targets. Since farmers can adjust their management to improve their agronomic and environmental impact, Task 1.3 aims to deliver site specific decision support for the best measures to be applied in order to reach the desired targets. Here we describe the actual framework to guide the selection of appropriate measures that improves the performance of farming systems on these KPIs.

2.1.1 Model framework

To guide the appropriate selection of effective measures in view of the agronomic and environmental targets (quantified in KPIs), five steps need to be taken:

- **set regional targets (step 1)** for the carbon and nutrient budgets in view of targets for effect indicators, such as soil health, including soil carbon and phosphorus status and associated crop yields, air quality, such as ammonia emissions for quality of nature, and water quality, including nitrate leaching (in view of and groundwater quality), and nutrient runoff to surface water (in view of aquatic ecological biodiversity).
- **quantify the actual carbon and nutrient budgets as compared to targets (step 2)** expressed as distance to target, defined as Key Performance Indicators (KPIs) for agronomic or environmental effects for all soil types, land uses and farming systems across Europe thereby defining the actual risks (i.e. losses or decline in soil nutrient status).
- **quantify the potential impact of measures (step 3)** to minimize undesired carbon and nutrient losses or accumulation in soil given their applicability and effectiveness, thereby taken into account the site conditions controlling these risks.
- **quantify the actual and possible KPIs (step 4)** for all fields and farms after **identification of appropriate measures that need to be taken** to reach the desired status for those KPIs.
- aggregate the actual performance over the various KPIs into one **integrative score** reflecting the overall farm and field performance in view of the desired targets (step 5).

The five steps are conceptually visualised in Figure 1., shortly summarized below and subsequently discussed in more detail in the sections 2.1.2 to 2.1.5.

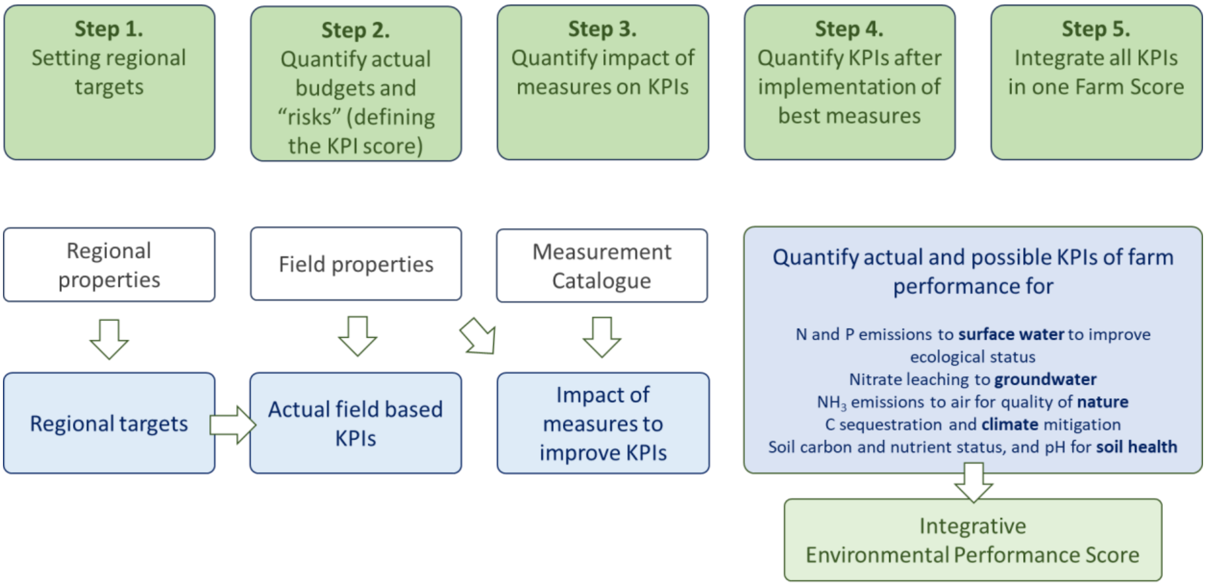

***Figure 1**. Model framework to assess the environmental impact of farming systems and to select the most appropriate measures to maximize the sustainability of farming in view of targets for surface water quality, groundwater nitrate concentration, ammonia emission for nature, carbon sequestration for climate mitigation, and soil nutrient status and pH for improvement of soil health.*

Set regional targets (step 1)

First, one has to quantify the targets to be achieved. In the NutriBudget project we aim to reduce the nutrient emissions from agriculture with spatial explicit targets for groundwater quality (originating from the Nitrates Directive), surface water quality (originating from the Water Framework Directive), ammonia emissions (originating from the Birds and Habitats Directive), and greenhouse gas emissions (originating from the ambitions to reduce the emissions from agriculture and to mitigate part of the greenhouse gases (GHG) emissions by carbon sequestration, the Paris Agreement). At the same time there is the objective to produce sufficient food (an agronomic and economic objective) and to maintain soil health whereas the latter objectives are less quantitative in policy documents but clearly defined in agronomic recommendation systems. Ros et al. (2023a) propose to use inversed modelling to link these environmental and agronomic targets to spatial explicit targets (and also limits) for carbon and nutrient budgets, being the difference between the input and crop uptake (for all nutrients) or decomposition (for carbon). This results for each region in five farm and field specific targets:

1. a critical N budget in view of desired nitrate levels in groundwater
2. a critical N and P budget in view of desired N and P runoff and leaching to surface water
3. a critical N input in view of maximum NH_3 emissions from soil, storages and stables
4. a target value for N, P, K, S, Ca, Mg, Cu and Zn budget as well the pH in view of soil quality
5. a critical C budget in view of desired C sequestration for mitigating climate change

In WP2 this proposal will be implemented in the process-based models so that for each field and site across Europe, specific targets are defined for the desired carbon and nutrient budgets.

Quantify the actual carbon and nutrient budgets (step 2)

The second step includes the quantification of the actual carbon and nutrient budgets, as well the associated losses to air and water for all farming systems across Europe taken into account the actual natural and anthropogenic element inputs and their fate in the soil and environment. This quantification is done with process-based models (WP2) and data-driven meta-analytical regression models (Tasks 1.2. and 1.3). Adding more carbon or nutrients than needed results in unnecessary surpluses, which may sometimes even lead to adverse environmental impacts for soil health, water quality, biodiversity and climate. Since the selected KPIs evaluates these budgets in view of critical limits or target values, they also quantify the “distance to target” showing how much the carbon and nutrient budgets have to change to meet the desired targets for soil, water, nature, and climate. More details are given in 2.1.3 as well in section 2.2.

Quantify the potential impact of measures (step 3)

Third, farmers can reduce the risk of undesired accumulation of carbon and nutrients (and associated losses) on field and farm level by applying measures that minimize the distance to target, either via direct adaptation of the inputs or via measures affecting the pathways how nutrient are leaving the agroecosystem. To quantify the impact of measures on the carbon and nutrient budgets (and potentially the associated losses) one needs to know i) whether a measure is applicable on a given site, ii) how a measure affects the carbon and nutrient inputs, or existing loss routes to the environment, and thereby the carbon and nutrient budgets (being the KPIs used in Nutribudget).

Identify appropriate measures and quantify actual and possible KPIs (step 4)

Combining the targets (step 1), the actual risks (step 2) and the impact of measures (step 3) allows one to assess the environmental impact of farming systems on field, farm and regional level for all selected KPIs. Knowing where and how measures affect the risks in view of the desired targets, one can identify which (combination of) measures need to be taken to reach these targets.

Evaluation integrative farm performance (step 5)

Knowing the actual situation on field and farm level for the carbon and nutrient budgets in view of the desired budgets to reach the targets as well the measures taken to minimise the risks of carbon and nutrient losses, the final farm performance can be derived by quantification of the total distance to target from the individual KPIs, each being defined as a dimensionless distance to target.

The five different steps are discussed in more detail in the next sections.

2.1.2 Setting regional targets

In Europe, N deposition hampers the achievement of a favourable conservation status within regions being defined as Natura 2000 sites in view of the Birds and Habitats Directive. In terrestrial ecosystems, excessive levels of reactive forms of atmospheric N leads to the loss of biodiversity by favouring nutrient-demanding species. High levels of reactive atmospheric N originate from the emissions of ammonia (NH_3) and nitrogen oxide (NO_X), and policies have been implemented to reduce these emissions to improve the ecological condition of nature areas. Even though the word nitrogen is not explicitly mentioned in the Birds and Habitats Directive, the current ecological condition is strongly controlled by N deposition, implying that a reduction in N deposition is needed for all terrestrial ecosystems where current N deposition exceeds a critical N deposition level (critical load). This in turn requires a strong reduction in NH_3 and NO_X emissions. Despite a general reduction in ammonia emissions by 24% since 1990, predictions up to 2020 indicate that the risk of exceeding critical loads remains high, irrespective of the implementation of current policies and measures to reduce N emissions (Eurostat, 2023). In a recent publication, De Vries et al. (2021) applied a spatially explicit N balance model for the EU to derive boundaries for N losses to water and air and associated N surpluses and inputs to protect water quality and aquatic biodiversity (see below) but also terrestrial biodiversity. This implies that for each unique combination of soil type, land use and geohydrological settings a target is available for the acceptable N inputs and surplus. A similar approach will be applied in WP2 of the NutriBudget project to define spatial explicit targets for the nitrogen budget to restore and improve the biodiversity in nature areas by minimising aqueous and gaseous N export from agricultural land (and potentially also from stables and manure storage facilities).

Increased N and P concentrations in surface water lead to eutrophication, characterized by excessive plant and algal growth and oxygen depletion, which negatively affects aquatic biodiversity. Critical concentrations for dissolved total nitrogen, indicating a risk for eutrophication range between 1.0 and 2.5 mg N L^{-1}, though this range goes as low as 0.3 mg N L^{-1}, following the guidelines of the WFD to achieve a good water quality. This range is based on (i) an extensive study on the ecological and toxicological effects of inorganic N pollution (Camargo and Alonso, 2006), (ii) an overview of maximum allowable N concentrations in surface waters in national surface water quality standards (Liu et al., 2012), (iii) different European objectives for N loads (Laane, 2005), and (iv) critical limits for total dissolved N concentration in surface waters discharging into the North Sea and the Baltic Sea (Kunkel et al., 2017). Critical N runoff rates from agricultural soils can subsequently be calculated by multiplying the critical N concentration in runoff with the precipitation surplus, multiplied with runoff fraction as done by de Vries et al. (2023). With respect to P runoff, the P concentrations in surface waters should stay below the upper limit of good ecological status (EC, 2000), ranging from 0.04 to 0.53 mg L^{-1}. Spatial explicit critical thresholds for both N and P budgets will therefore be quantified for all agricultural systems in Europe in WP2.

The critical nitrate concentration in groundwater was set to the WHO drinking water limit of 50 mg NO_3 L^{-1}, which is also the threshold stated in the EU Nitrates Directive (EC, 1991). This limit is based on epidemiological evidence for methemoglobinemia in infants (WHO, 2011). As a proxy for NO_3 concentration in groundwater itself, one can use the concentration in water leached from the soil profile to groundwater as the critical limit. In several countries (e.g. the Netherlands) this concentration is used as an early warning concentration since during the transport in the saturated zone the nitrate concentration can be lowered via denitrification or via mixing water flows. As with runoff, critical N leaching rates from agriculture can be calculated by multiplying the critical N concentration in leachate to groundwater with the share of precipitation surplus leached to groundwater (see De Vries et al., 2021). Also here, these critical thresholds can be translated into acceptable N surpluses and N inputs (see above), as will be done in WP2. The leaching of carbon via dissolved organic carbon or other nutrients needs to be minimized as well, but no critical concentrations have been defined yet given that these nutrients have limited effect on human or environmental quality.

Regarding the agronomic soil health critical limits and target values have been identified for soil pH and all nutrients except for N given its dynamic nature. The fate of N is largely controlled by the inputs whereas the fate of other nutrients is largely controlled by the soil processes controlling their sorption / fixation to the mineral phase. In the classic agronomic concept of “build-up-and-maintenance” the desired surplus (or budget or accumulation) of phosphorus, potassium, calcium, magnesium, sulphur, copper and zinc depends on the size of the plant available nutrient pool in soil. Agronomic thresholds do not exist for pollutants like Cd and As, whereas critical inputs or surpluses can be defined based on its concentration in soil solution and the associated crop uptake on the one hand or on the impact on soil organisms on the other. Using long-term field experiments critical soil concentrations have been determined for various crops to derive the optimum soil nutrient concentration where the crop yield is not limited by deficiencies. When the soil concentration is in the optimum range, then it is sufficient to replace the crop nutrient uptake by fertilization (so crop input equals crop removal plus some unavoidable losses). In the case that the soil is deficient, then one need to fertilize more than the plant actually removes, resulting in a build-up of the soil nutrient pool. In the case that the soil is enriched with nutrients above the agronomic optimum, then the fertilizer input should be lower than crop removal, implying a net mining of the soil nutrient pool. Note that the optimum soil nutrient level might deviate across soil types, climatic conditions and crops. In reality the methodology to assess this optimum soil nutrient level also varies across countries. Given the agronomic knowledge base, and the foreseen standardization in the Nutribudget project, a series of critical thresholds (or target values) will be determined for the aforementioned nutrients.

Targets for SOC have been derived as a function of clay content for mineral soils (Körschens et al., 1998). Using long-term experiments starting in 1902, they proposed critical limits for SOC for optimum crop production, ranging from 0.5% SOC at 4% clay to 1.75% SOC at 38% clay. This approach takes into account the fact that one uniform threshold for SOC is likely not appropriate (Goulding et al., 2013; Loveland and Webb, 2003; Oldfield et al., 2019) and that clay particles stabilizes and protect organic matter in soil from decomposition (Goulding et al., 2013). Recently, Ros & de Vries (2024) designed a more comprehensive framework to define critical thresholds for SOC in mineral soils in view of chemical, physical and biological functions that soils can supply. The spatial explicit quantification of these thresholds is also done in WP2. Note that SOC targets for peat soils and drained organic soils used for agriculture might be derived differently since SOC is already at maximum but the losses are highly dependent on drainage levels. On the other hand one can discuss whether this high SOC as such is needed for agronomic soil quality or mainly to mitigate climate change. This implies separate SOC targets in view of agronomy and C sequestration for climate mitigation.

In summary, spatial explicit thresholds and targets will be defined by inversed modelling and agronomic algorithms for nitrogen, phosphorus, potassium, calcium, magnesium, sulphur, copper and zinc budgets in WP2, taken into account the policy regulations and ambitions regarding clean air, water and a healthy biodiversity.

2.1.3 Quantify the actual carbon and nutrient budgets and associated risks

To know whether additional measures need to be implemented to reduce the environmental impact of farming, one needs to know the current fate and budgets of carbon and nutrients on farm and field level. This quantification is usually done with empirical or process-based models. In WP2 a spatial explicit process-based model will be developed, being applicable from field to European scale, allowing the quantification of the current carbon and nutrient stocks, and their change over time in response to management and agroecosystem properties such as soil type, land use, geohydrology and climate. The meta-regression models developed in WP1 are used to calibrate and validate the model results of WP2 and delivers insights that are not implemented in WP2 such as the crop response to measures.

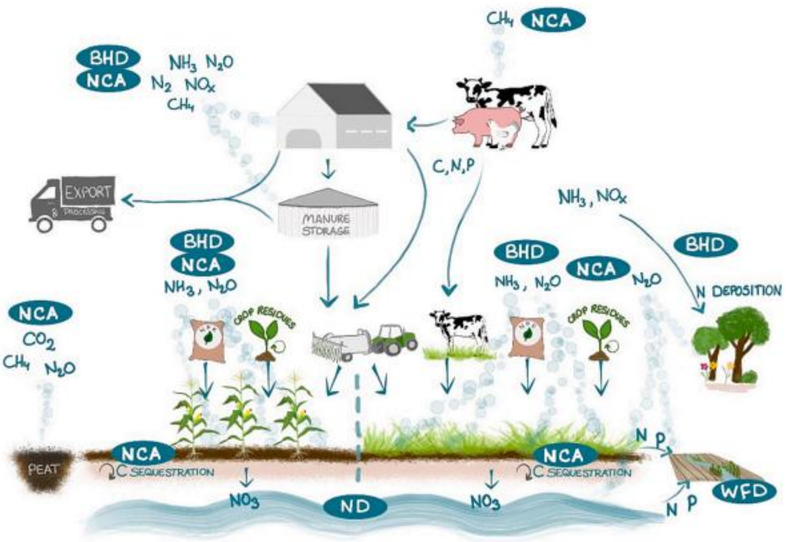

Figure 2. *Simulated nitrogen, phosphorus and carbon flows and emissions in agriculture, deposition in nature and the relation with the European agreements and directives (WFD = Water Framework*

Directive, ND = Nitrate Directive, BHW = Bird and Habitat Directive, NCA = National Climate Agreements following Fit for 55[1]*). Source: Kros et al. (2024).*

2.1.4 Quantify the potential impact of measures

There is a growing interest in and urgent need for optimized farm and field management practices to reduce the impact of agriculture on soil, air and water quality. These practices include a wide range of interventions, such as precision agriculture, conservation tillage, cover cropping, integrated pest management, and nutrient management planning (Young et al., 2020; 2021). These interventions aim to minimize the use of agrochemicals, increase nutrient-use efficiency, and improve soil health, thereby reducing the risk of water pollution. Recent meta-analytical studies also showed that the impacts of improved measures are highly affected by site conditions including field morphology and hydrological connectivity (affecting the risk of surface runoff), soil physical and chemical quality (affecting the fate of nutrients) and the land use associated management practices. Phosphorus leaching from agricultural soils is, for example, affected by the water depth (wet conditions favour the dissolution and subsequent leaching of P), the level and distribution of P over labile, reactive and stable P species and the aluminium and iron oxides affecting the retention capacity of P in soils (Van Doorn et al., 2023). The adsorption behaviour of phosphorus is often described by a Langmuir isotherm whereas the maximum adsorption capacity and the binding strength might be affected by pH, soil texture and fertilizer history. Similarly, N emissions are affected by the rooting depth of crops, the N input dose, the groundwater depth and the quality of the soil organic matter driving the mineralization rate of soils. As a consequence, the impact of agronomic measures will be affected by these properties as well, challenging the selection of appropriate measures on field and farm scale.

Where WP2 focusses on the use of process-based models to assess the fate of carbon and nutrients in soil and the environment, empirical and data-driven (meta-analytical regression) models, assessing the impact of agronomic measures on the fate of carbon and nutrients and thereby on soil, air and water quality, are developed in WP1. Meta-analysis is a statistical methodology that integrates information from numerous independent studies to conduct a comprehensive examination of the overall effect or relationship between variables as well their dependency on so called co-variates. It entails the systematic collection and analysis of data across multiple studies, facilitating the derivation of robust conclusions and the formulation of generalizations. In essence, a meta-analysis consistently concentrates on the analysis of the influence of a given treatment (or measure to be taken), denoted as X, on a specific variable, denoted as Y. The primary inquiry revolves around elucidating how variable Y undergoes changes attributable to the application of treatment X. The quantified alteration is commonly referred to as an "effect size," representing either a relative or absolute change. Analogous to conventional regression models, meta-analysis also enables the estimation of the impact of covariates such as site properties through the amalgamation of effect sizes. For example, You et al. (2023) estimated the maximum improvement in the Nitrogen Use Efficiency (NUE, being estimated as the fraction of the effective N-input via fertilizer, manure, deposition and fixation taken up by the crop) due to application of crop, soil and fertilizer management measures for all croplands worldwide while taken into account the agro-ecological conditions controlling the impact of N fertilizers. Similarly, Lessmann et al (2021) predicted how much carbon can be sequestered in the soil by adoption of crop, soil and fertilizer management measures. For a series of measures (being summarized in the Measurement Catalogue (Task 1.1) meta-regression models will be built to predict their impact on selected KPIs associated with the occurring carbon and nutrient budgets. These measures encompass a spectrum of practices spanning fertilizer, soil, crop, animal feeding and housing, as well as manure processing management.

[1] The Fit for 55 package is a set of proposals to revise and update EU legislation and to put in place new initiatives with the aim of ensuring that EU policies are into line with the climate goals agreed by the Council and the European Parliament.

In summary, both process-based (from WP2) as data-driven meta-regression models (from WP1), or even a combination of both (e.g. a data driven and site specific estimate of the NUE can be used to improve the quality of process based models), can be used to quantify the impact of measures on the fate of carbon and nutrients in any agroecosystem. To guide farmers in their decision to select the most effective and appropriate measures, two key parameters need to be assessed for each measure: (i) where is the measure applicable (depending on farming system, soil type, climatic conditions, and so on), and (ii) how does the measure affect the carbon and nutrient budgets or the associated losses (in view of the desired targets for these indicators).

2.1.5 Identify appropriate measures and derive farm score

Once for a single field, farm or region the targets are known (step 1), and the actual budgets or losses or risks are quantified (step 2), and the potential impact of measures are known (step 3), then one can also identify the most effective measure or measure combination to bridge the gap between the current and desired status for the selected KPIs.

Since the sustainability of farming is evaluated in view of multiple objectives (e.g. crop yield, soil health, water quality, etc.), we need to apply a goal-oriented optimisation approach to identify the most appropriate measures to be applied. Given the actual distance to target for the set of indicators, one can apply site-specific weighing functions to estimate how the gap (being the distance to target) changes when a measure is adopted, being different for indicators that need to be minimized or maximized. We give below two examples where the impact of a measure on crop yield (Y) and N surplus (N_{sp}) is evaluated in view of a target using linear scoring functions:

$$sY = \boldsymbol{max}\left(0.1\,, 1 - \boldsymbol{min}\left(1\,, \frac{(1+dY)*Y_{ref}}{Y_{target}}\right)\right) \qquad (1)$$

$$sN_{sp} = \boldsymbol{max}\left(0.1\,, \boldsymbol{max}\left(0\,, \frac{(1+dN_{sp})*N_{sp,ref}}{N_{sp,critical}} - 1\right)\right) \qquad (2)$$

where sY and sN_{sp} are the site-specific weighted scores for yield and N surplus (a value between 0 and 1), and dY and dN_{sp} are the estimated change in crop yield and N surplus due to the implementation of a measure, respectively, Y_{target} and $N_{sp,critical}$ represent the target yield, and critical level of N surplus, respectively, and Y_{ref} and $N_{sp,ref}$ refer to the reference, or actual value for crop yield and N surplus.

Similarly, Ros et al. (2022) used quadratic and logistic scoring functions to assess the contribution of individual soil functions to soil health in view of its potential to sustain crop production. By using these scoring function all changes in carbon and nutrient budgets can be evaluated in view of a threshold or limit, thereby standardizing each indicator to the same unit, being a “distance to target”.

Importance of user preferences

In reality not all targets are equally important, or at least, there is discussion on their relevance among policy makers, farmers associations, non-governmental organisations and other stakeholders in the agricultural sector. If needed, one can apply user weighing criteria to finetune the desired measures (or combination of measures) in view of the desired targets. For example, the LANDMARK project investigated user objectives in relation to soil health, agronomy and environmental indicators by conducting surveys of different types of stakeholders (e.g. growers, policymakers, researchers, etc.). Stakeholders were asked to prioritize different agronomic indicators or functions (crop production/soil quality / environmental buffering, etc.) by assigning a total of 15 points over a limited number of indicators (Sturel et al., 2018). This results in an average priority of different indicators based on the type of stakeholder (e.g. a grower may prioritize an increase in crop yield more compared to a researcher who may prioritize environmental goals).

To identify the most appropriate and effective measure or combination of measures, the estimated change in the distance to target for a series of indicators due to the adoption of these measures can be calculated for each field given site conditions such as soil type, crop type and climatic conditions and the current practices already applied. This can be done for all single measures as well for all potential combinations. The contribution of single measures and each combination of measure (*m* = 1 to *m* = *n*) in reaching the desired targets for the selected *k* indicators together (summarised as $SCORE_M$) can be calculated as follows:

$$SCORE_m = \sum_{X=1}^{X=k} \left(u_X * \sum_{m=1}^{m=n} \left(sX_1 + \cdots + \frac{sX_n}{n} \right) \right) \Big/ \sum_{X=1}^{X=k} (u_X)$$

where for each combination of measures the total change in the distance to the targets (sX, a value between 0 and 1) is multiplied by an user priority u_X (varying between 0 and 1) for the indicator to obtain an integrative score reflecting the total distance to target ($SCORE_M$). In the case that a measure or measure combination changes the indicator up to the desired target or down to the required critical limit, the total summed distance to target is equal to zero, implying that extra measures are not needed.

Note that in this approach we assume that the effects of management practices are not additive when applied together. We use therefore a simplified weighing procedure where the additionality declines with the order of the measures when sorted from highest to lowest impact (Lessmann et al., 2021). This implies that the impact of combining measures progressively diminish with the number of measures applied.

Given the fact that this integrative score can be calculated for all single measures as well for each combination of measures, this approach allows one to (1) prioritize these measures in view of the best single measure to meet the targets, (2) rank the *n* individual measures in view of their contribution to meet the targets, and (3) find the best combination of measures where we limit ourselves in NutriBudget to the best combination of two and three measures.

2.2 Key Performance Indicators

The impact of the measures is quantified for a limited number of Key Performance Indicators being outlined in subsequent work packages (WP2 and WP3).

As stated in D1.1_Mitigation Measures Catalogue - first draft version, indicators relevant to the agronomic and environmental impact of mitigation measures have been categorized as follows: agro-ecosystem properties, pressure indicators, effect indicators, and performance indicators. Among them, four of the performance indicators (listed in Table 1) are selected as the main focus of the quantification in Tasks 1.2 up to 1.5, which will also be simulated by process-based models developed in WP2.

Table 1. *Key performance indicators selected.*

Class	Key Performance Indicator	Description	Relevant agro-pillars
P3	Carbon and Nutrient Surplus Gap	Gap between current and target/critical nutrient surplus, derived as the soil carbon and nutrient status gap (indicator P1) divided by a target time plus unavoidable or critical losses.	• Crop production • Animal husbandry • Agro-processing
P5	Nutrient Use Efficiency	The ratio of nutrient uptake divided by the nutrient inputs	• Crop production • Animal husbandry
P8	Farmgate C, N and P Efficiency Gap	Gap between current and target farm gate balances for C, N and P.	• Crop production • Animal husbandry

			• Agro-processing
P9	Soil Quality Index (focus on SOC and pH)	An index reflecting the distance to target for optimum soil health given the OSI framework (or adapted version of it)	• Crop production

Note that the carbon surplus gap is always a target value in view of soil quality (a target C surplus when the soil C is below a target value while above a target value there is not target to be attained) while the nitrogen surplus gap it is always a critical value in view of air or water quality (e.g. a critical N surplus in view of acceptable NH_3 emissions to air or NO_3 losses to water. For phosphorus, it can be a target value (a required P surplus when the soil P status is below a target value) or a critical value (a required negative surplus when the soil P status is above a target value requiring mining).

For a more detailed description of these indicators we refer to deliverable 3.1 entitled '*Overview of existing indicators used in national and European policies and market initiatives in relation to agronomic and environmental aims*'.

2.3 Upscaling results of measures

As mentioned above, impacts of agricultural management practices are affected by contextual factors including site properties and current management practices. This implies that one needs the relevant site properties on high spatial resolution across Europe in order to assess the impact of measures on the selected KPIs. The impacts of the various management practices will be assessed in a spatially explicit approach and upscaled to EU reduction potentials for the identified KPIs by multiplying the relative impacts (%) with the potential area where the practice can be applied. This will be done by applying derived meta-regression model using European datasets on current farming practices (see 2.3.1) combined with data on site properties, i.e. climate conditions and soil properties (2.3.2), considering the potential area where the practice can be applied , corrected for the areas where it is already practiced (2.3.3)

2.3.1 Current and potential management practices

Since the impacts strongly depend on the actual management practices being applied, one can derive spatial explicit maps of current practices, following the procedures outlined by Lessmann et al. (2021). This includes spatially explicit data from the Koeppen Geiger classification map (Peel et al., 2007), the spatial production allocation model (SPAM) for land use (Wood-Sichra et al., 2005) or remote sensing derived cropping maps (Ghassemi et al., 2022), maps on N fertilizer application rates (from WP2 or Lu & Tian, 2016; Lu & Qin, 2017), N manure production and application rates on cropland and grassland (from WP2 or from Xu et al., 2019; Zhang et al., 2017), the global tillage system dataset (Porwollik et al., 2019) and FAO and Eurostat databases on cropping systems, crop residue retention, and crop residue burning. Combing these maps allows the identification of potential areas for application of agronomic measures related to fertilization (such as enhanced efficiency fertilizer, combined fertilizer, organic fertilizer, fertilizer placement, fertilizer rate, fertilizer timing, and biochar), residue retention, cover cropping, and crop rotation (all crop management), and zero and reduced tillage (all soil management). Information on mineral fertilizer and manure application can also be taken from MITERRA-Europe at an appropriate resolution, such as the 40.000 so called Nitrogen Calculation Units (NCUs), which are NUTS3[2] subdivisions. NCUs amount to approximately 40,000 polygons (clusters of 1km x 1km pixels) that represent unique combinations of soil type, administrative region, slope class and altitude class (De Vries et al., 2011b).

[2] Nomenclature of Territorial Units for Statistics or NUTS (French: Nomenclature des unités territoriales statistiques) is a geocode standard for referencing the administrative divisions of countries for statistical purposes

2.3.2 Site properties

Site factors (climate conditions, soil properties, and land use) data can be obtained from openly accessible data sources, including: climate data (mean annual temperature and mean annual precipitation) obtained from Climate Research Unit (http://www.cru.uea.ac.uk/data), soil properties, comprising soil clay content, soil organic carbon, and soil pH, extracted from the soil grids provided by ISRIC or LUCAS databases, and land use data from the Spatial Production Allocation Model. Other data-sources include spatial maps available on high resolution for Europe for erosion, carbon saturation capacity, compaction, soil biodiversity and groundwater depth, soil hydraulic properties, SOC stocks, soil nutrients and pH, all available at Joint Research Centre.

2.3.3 Upscaling approach accounting for the applicability of measures

Below, some examples are given how the upscaling approach can account for the applicability of measures, focusing on nutrient management (changes in the combination of organic and mineral fertilizer, enhanced efficiency fertilizers and improved fertilizer placement and fertilizer timing), crop management (biodiversification) and soil management (tillage), thereby accounting for some constraints that need to be accounted for when upscaling the meta-analytical predictions to European scale.

One important constraint related to the use of organic residues, manure, sludge or compost is that the expected change in soil pools (as being estimated my meta-regression models) can never exceed the total amount of these products being available in a region. For example, when predicting the change in SOC stocks due to the amendment of soils with manure one can make use of models calibrated on long-term experimental data. The change in SOC stocks across Europe however can never exceed the total amount of carbon excreted minus the carbon decomposed during storage or deposited on grassland. This implies that the benefits of manure amendment only occur in those areas where currently a part of the manure is wasted and not recycled yet.

The current and potential application of enhanced efficiency fertilizers, improved fertilizer placement, and fertilizer timing, can be estimated based on the agricultural technology level as given by the SPAM dataset. SPAM includes a global map of cropland being categorized depending on technology level, including the categories low technology, high technology, irrigated or rainfed. We classified grid cells as “low technology level” when the cropland area with low technology level was more than 50% of the total cropland area. In those areas, we assumed that there is full potential for the application of enhanced efficiency fertilizers (including synthetic inhibitors or coated fertiliser) and for optimising the timing and placement of fertilisers to reduce the nitrogen losses to air and water. Inversely, we assumed that these three measures are fully practiced, and thus are not effective, in the areas with high technology level given the higher incomes and higher pressures on and regulations for environmental targets in agriculture.

The measure of fertilizer rate is particularly relevant for areas where the current NUE is low. Using the NUE predictions coming from WP2 one can assume that measures optimising the fertilizer dose are only applicable in areas where NUE is smaller than 0.5. For biochar and other soil improvers, one can assume that it can be applied everywhere given the urgency to improve soil health across Europe, although its availability might be limited due to the absence of sufficient biomass and high energy costs.

Using the crop intensity maps generated by Liu et al. (2021) and Zhang et al. (2021), one can estimated where biodiversification of the crop rotation can be applied as measure. The original dataset describes the cropping intensity distribution using satellite date from the period 2001 to 2019 at 250 m resolution. All grid cells where the cropping intensity is lower or equal than 1 are considered as potential areas where crop rotation (more variation in crops over time) can be applied as measure to reduce N losses. Insight in the current application of tillage and the potentially suitable area to apply zero tillage (Conservation Agriculture) was derived from a global tillage system dataset. Areas identified with high-intensity tillage and intermediate intensity tillage have the potential to be converted to zero or reduced tillage. We considered all grid cells (on 0.5 x 0.5 degree) where the area with conservation agriculture (no-till) was smaller than 50% of the total cropland area as being relevant for application the measure of no-till or reduced tillage. Information on tillage and cropping practices can be improved based on data from Eurostat farm structure survey databases on management and practices (Eurostat, 2016), where total hectares of arable land area on which each management measure is applied is provided at the level of NUTS2 statistical units[3] (Eurostat, 2020). Current tillage and cropping practices can be derived from downscaling Eurostat data to NCUs, where management information from the NUTS2 level is assigned to the finer spatial resolution of the NCU level.

[3] NUTS 1: major socio-economic regions, NUTS 2: basic regions for the application of regional policies, NUTS 3: small regions for specific diagnoses

3. Three illustrations

To illustrate the value of the proposed framework, we show here three (published) examples where data-driven approaches including meta-regression models were applied to find the most appropriate selection of measures to improve the sustainability of agriculture. These three examples include i) an example of the work of Lessmann et al. (2021) where the potential C sequestration in soil was quantified for a series of measures, ii) and example of the INSPIRATION project that was designed to develop data driven decision support algorithms for crop, soil and water management in view of targets for crop yield, SOC and N surpluses (Young et al., 2021), and iii) an example from the Dutch Farmer oriented Soil and Water Plan, a running decision support tool developed in the Netherlands to guide the appropriate selection of measures to improve soil health, nutrient efficiency and ground and surface water quality (Ros et al., 2019). Note that these three examples are highly focussed on either one indicator or a subset of environmental issues to be solved, thereby missing the integrative view of the meta-regression and process-based models build in the NutriBudget project. Nevertheless these examples already show as a proof of principle the high potential of this approach to guide farmers on field and farm level to select the most appropriate measures improving the sustainability of farming.

3.1. Example 1. Carbon sequestration

In October 2021, Lessmann et al. published their research on the potential of improved cropland management to increase SOC stocks worldwide. To create spatially explicit insights in the impact of climate-smart practices, Lessmann et al. (2021) combined global meta-analytical models for the impact of improved management practices on SOC sequestration with spatially explicit data on current management practices and potential areas for the adoption of these measures. Relevant measures included (a) fertilization practices, i.e., use of organic fertilizer compared to inorganic fertilizer or no fertilizer, (b) soil tillage practices, i.e., no-tillage relative to high or intermediate intensity tillage, and (c) crop management practices, i.e., use of cover crops and enhanced crop residue incorporation.

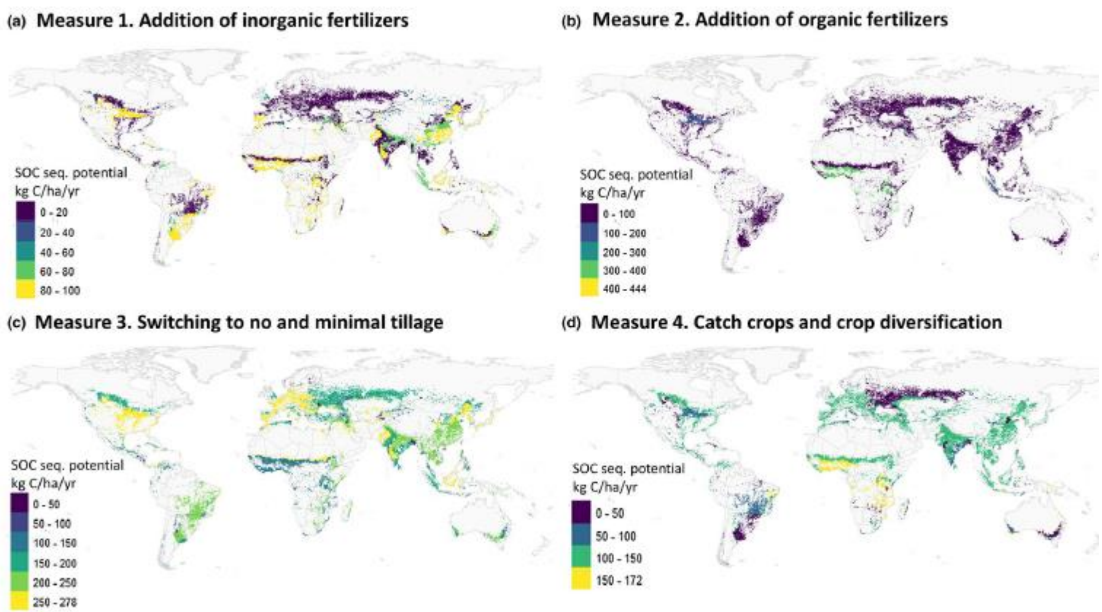

Figure 3. *The soil organic carbon (SOC) sequestration potential (in kg C / ha arable land / year) estimated in the top 20–30 cm soil depth for four agronomic measures (a) addition of inorganic fertilizers, (b) addition of organic fertilizers, (c) switching to no and minimal tillage and (d) catch crops and crop diversification as estimated from meta-analytical field experiments and extrapolated to all arable agro-ecosystems given the climate zone, soil tillage practices, and crop rotation system. Note: the legend differs per map.*

They showed that the estimated global C sequestration potential varies between 0.44 and 0.68 Gt C yr^{-1}, assuming maximum complementarity among all measures taken. A more realistic estimate, not assuming maximum complementarity, is from 0.28 to 0.43 Gt C yr^{-1}, being on the lower end of the current range of 0.1–2 Gt C yr^{-1} found in the literature. One reason for the lower estimate is the limited availability of manure that has not yet been recycled. Another reason is the limited area for the adoption of improved measures, considering their current application and application limitations. They found large regional differences in carbon sequestration potential due to differences in yield gaps, SOC levels, and current practices applied (see Figure 3.). The highest potential is found in regions with low crop production, low initial SOC levels, and in regions where livestock manure and crop residues are only partially recycled.

3.2. Example 2. Optimising yield, SOC and N surplus

In 2022, Young et al. described first results of their decision support tool designed for optimisation of crop yields, SOC and N surpluses by agricultural management measures across Europe. In the IFS study they focussed on the impact of fertilizer strategies on these three indicators.

In their study they build upon an agronomic dataset synthesized from published meta-analyses on long-term field experiments (Young et al., 2021) to unravel the impact of 4R strategies and crop diversification and crop yield, SOM and nitrogen surpluses given their dependency on site properties. The N surplus is hereby defined as the difference between the N supplied and the N removed by crop uptake. SOC and N surplus were chosen as indicative of impacts on environmental targets because SOC is one of the key drivers affecting soil fertility due to its role in soil nutrient supply, water retention and carbon sequestration whereas N surplus is indicative for all nutrient losses to the environment (higher surpluses leads to higher losses). Site properties included are soil texture, soil organic matter levels, bulk density, carbon to nitrogen ratio, clay content, and pH. They particularly explore the impact of nutrient management strategies in order to (i) assess how the effect of a measure varies for different indicators and under local conditions, (ii) evaluate the performance of measures at meeting multiple agronomic objectives, and (iii) map the expected impact of measures in various European regions, focusing on present trade-offs and synergies.

Current crop yield targets were based on FAO actual yields per crop at the national scale while the sub-national variation was derived from the Global Yield Gap Atlas, scaled to the mean crop yields per NCU (see De Vries et al., 2020). Current clay and SOC values in the topsoil were generated from WISE, SPADE1 and EFSDB databases, which jointly contain about 3.600 soil profiles, irregularly distributed over Europe (Heuvelink et al., 2016). Data for clay and soil organic matter contents at NCU level were derived with a multivariate regression kriging model accounting for the spatial structure of soil properties and their dependency on explanatory variables such as soil type and land cover (Heuvelink et al., 2016). Target limits for SOC were assessed as a function of clay content. Current N surpluses at NCU level were estimated as the total N input by animal manure, fertilizer, biosolids, biological N fixation and atmospheric deposition minus the N that is removed by crop harvesting. More details are described by De Vries et al. (2020). Critical limits for N surpluses at NCU level were derived as a function of N input and precipitation surplus.

Using existing meta-analytical models, the impact of the following measures was quantified: (i) combined fertilization where organic and inorganic fertilizers are applied in various combinations to supply sufficient nutrients for crop growth as well to improve soil health by organic matter inputs, (ii) organic fertilization where inorganic fertilizers are completely replaced by organic ones, (iii) the use of enhanced efficiency fertilizers including controlled release fertilizers and the use of inhibitors to avoid nitrogen losses during the growing season, (iii) right fertilizer rate where the nutrient dose is adjusted to crop nutrient uptake and unavoidable losses, (iv) right fertilizer timing where the nutrient dose is split over multiple gifts to avoid or minimize the occurrence of losses, and (iv) the right fertilizer placement where the default broadcasted application technique is replaced by other techniques such as banding, injecting or incorporation.

Given the differences between actual and desired status for crop yield, SOC and N surplus, it is not surprising that the best measures are focusing on reducing the N surplus. The measure having the biggest impact on N surplus is the adaptation of fertiliser type where the use of controlled release fertilisers or inhibitors have the highest potential to reduce the N surplus. As a consequence, the use of enhanced efficiency fertilisers is recommended in the majority of NCUs throughout Europe. Right fertiliser timing and rate are the two second most chosen measures (each 5.9% of cases), and the order of effectiveness of other measures follows as: right fertilizer time (3.7%), combined organic and inorganic fertilization (2.8%), and organic fertilization (2.6%).

For illustration we show some of the modelled outcomes in Figure 4. These include calculated targets for crop yield (being defined as the current situation divided by the water limited target yield) and the predicted change in crop yield (in Mg ha^{-1}) when the best measure (selected per grid cell, being a NCU) was implemented. For each NCU also the best measure can be identified to increase crop yield, lower the N surplus and to increase SOC (not shown).

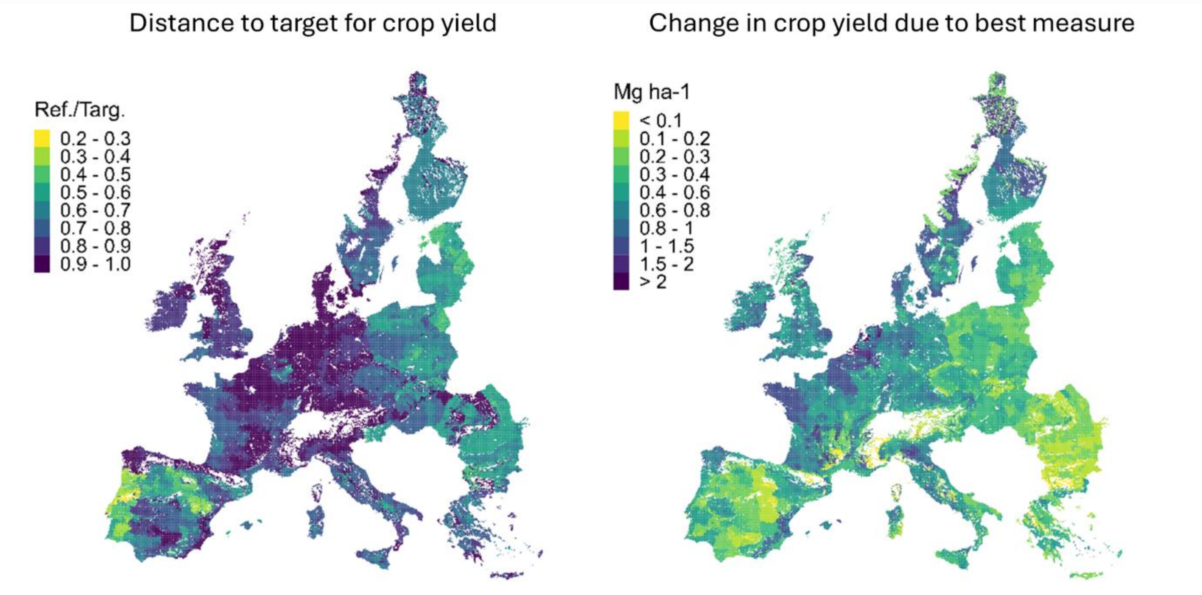

Figure 4. *The calculated distance to target for crop yield, the recommended best measure to improve crop yield, SOC and N surplus as well the calculated change in crop yield due to that specific measure.*

3.3. Example 3. FSWP

The Farmer oriented Soil and Water Plan (FSWP) was developed in 2018 by the Nutrient Management Institute in collaboration with Wageningen University, research institutes, farm advisors and farmer associations (Ros et al., 2019). The decision support tool integrally evaluates the contribution of agricultural field properties and field management to five environmental targets (nitrate leaching to groundwater, nitrogen and phosphorus losses to surface waters, water retention and nutrient use efficiency) and provides recommendations for farming practices. The FSWP is an [open-source modular framework]() in which soil properties, field derived risks and management advice are linked hierarchically. The FSWP leverages the existing knowledge base on measure impact relationships, open data and routine laboratory soil data, enabling its application with limited costs. The FSWP is a generic framework that can be adopted for specific regions depending on data availability and existence of environmental targets.

Regional environmental targets used in the FWSF are based on national and regional environmental policy documents. These targets encompass the (1) Nitrate Directive (EC, 1991), (2) the ecological targets for the surface water given the Dutch implementation of the Water Framework Directive (EC, 2000), (3) associated critical nitrogen and phosphorus loading (Groenendijk et al., 2016), (4) the targets for sufficient groundwater recharge and water buffering, (5) and the ambition to close nutrient cycles by avoiding inefficient fertilizer applications. To achieve these targets, the FSWP firstly quantifies the targets in a spatially explicit fashion on a scale varying from zero (no target present) to one (huge target present) for all five aforementioned environmental targets. After that, the impact of each agricultural field in controlling the nitrate leaching, nutrient loading to surface water, the water recharge and buffering and high nutrient use efficiency is quantified in so called potential field risk indicators that also vary from zero (no risk) to one (maximum risk). Farmers can reduce the risk on field and farm level by applying measures that reduce the potential risk for all five targets while accounting for site properties and the effectiveness and applicability of available measures. Combining the targets, field risk indicators and impact of measures allows one to assess the environmental impact of farming systems on field, farm and regional level.

Based on a review of scientific and grey literature, the applicability and effectiveness of measures on water retention, nutrient emissions and nutrient efficiency, more than 180 measures have been selected. The measures can be categorised as i) soil improvement, ii) land and crop management, iii) fertilizer management, iv) ditch and water management, and v) farmyard measures. Using an expert judgement procedure, each measure is assessed in view of applicability, costs and its effect on nitrate leaching to groundwater, nitrogen and phosphorus loading to surface water (via runoff and drainage), water retention in soil and the nutrient efficiency of fertilizers. For the applicability, each measure is evaluated whether it can be applied depending on crop category (15 crop types), farming system (arable, vegetable, husbandry, tree nurseries, bulbs), soil type (clay, sand, loess, and peat), soil wetness (dry, moist, and intermediate), drainage system (drains included, undrained), slope (steeper than 2% or flat), and distance to surface water (surrounded by ditches or not). The effectiveness is evaluated using a 5-grade classification system varying from minus two to plus two, where the effectiveness is assessed in view of the aforementioned five targets. The impact of a measure on phosphorus loading to surface water additionally depends on the phosphorus saturation degree whereas the impact on the nitrogen loss to surface water and groundwater depends on the soil wetness. The costs for implementing a measure on field or farm level are classified into three categories including i) no costs and potentially beneficial, ii) limited costs, iii) expensive.

To optimise the best combination of measures, three subsequent steps are taken. First, the actual field risks for the five targets are calculated by adapting the potential risks given the regional target via a logistic conversion function, implying that the field based risks increase when substantial efforts are needed to improve the regional targets, and that the risks decrease when regional targets are already achieved. Second, the actual field risk is subsequently adapted when measures have been taken to reduce the risk given their applicability and effectiveness. The effectiveness of measures is assumed to be linearly dependent on the distance to target, implying that measures have much higher impact in cases where substantial effort is required to reach the target. Since the impact of each measure on target is quantified, it is subsequently possible to estimate the total integrated impact of measure on field, farm and regional level by averaging the total distance to target for the five indicators selected.

The FSWP framework was applied for all fields in the region 'the Achterhoek', being an area in the Southeastern part of the Netherlands, mainly cultivated by animal husbandry. Most common crops include grassland and maize cultivated on sandy soils. The pH is in most of the soils within agronomic target values and the organic matter content often exceeds the 2%. The majority of the fields are characterised by high phosphorus levels and high risk for subsoil compaction and water limitation. The area struggles with challenges for surface water quality (mainly phosphorus), groundwater quality (nitrate leaching), severe yield reductions by drought stress during the growing season and low nutrient use efficiencies due to a long history of overfertilization (with P) and high potential for nitrate leaching. Around 114.400 hectare (55.000 fields) is cultivated by farmers. The five risk indicators of the FSWP were quantified for each agricultural field and used to select the best measures to be improve the environmental and agronomic impact of these fields.

In Figure 5 the total distance to target in view of C sequestration as well the evaluation of soil health in view of optimum threshold for crop production are visualised for all agricultural fields in the regio.

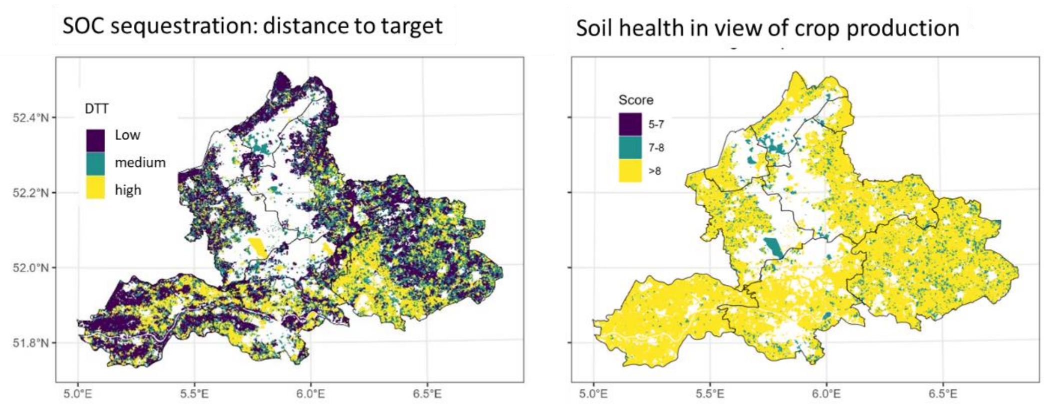

Figure 5. *Two examples of the field based calculated distance to target in view of carbon storage in the soil (left) and the soil pH and nutrient contents required for optimum crop production (right) for the region Achterhoek in the Netherlands. Source: Ros et al. (2023b).*

In addition, the top-5 measures are identified per field and aggregated for the region giving guidance for policy support and regional farmer advisory services. Figure 6 illustrates the recommend measures to improve the water quality for surface water and groundwater, the nutrient use efficiency and the water retention in soil on field level. Most of the measures identified were related to the optimisation of nitrogen fertilizers (category fertilization 4R) and the improvement and maintenance of drainage systems and adaptation of water flow regulating equipment to increase water infiltration (category drainage and ditch). In contrast, end-of-pipe solutions to reduce phosphorus losses (e.g. iron-coated filters on drainage pipes) or measures to improve soil structure (e.g. no-tillage, compost addition, etc.) were less effective to contribute to a more sustainable farm management on these fields.

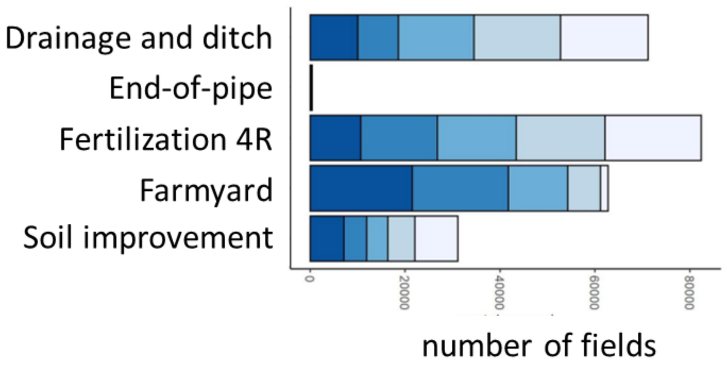

Figure 6. *Occurrence of most recommended measure, clustered per category, required to improve water quality, crop production, water retention and nutrient use efficiency in the Achterhoek region in the Netherlands.*

4. Expected outcomes and potential challenges

The principal deliverable arising from Task 1.3 encompasses spatial maps with estimated changes in carbon and nutrient budgets across Europe in view of the desired targets for soil quality (health) and for water quality and air quality in view of biodiversity and the identification of appropriate and effective measures to improve the current performance of agricultural farms. It visualises and applies the developed meta-regression models from Task 1.2 for all farming systems across Europe thereby accounting for the spatial variability in site conditions and management. These maps will assist in the development of roadmaps to improve the agricultural sustainability in such a way that the current carbon and nutrient budgets are tailored to the site conditions to that both agronomic and environmental targets are achieved. The current deliverable describes and illustrates a robust upscaling protocol to apply these meta-regression models on high spatial resolution. The final results will be delivered in *D1.5 Algorithms quantifying impacts of measures via field based indicators* which is anticipated to be finalized and submitted by August 2024.

Quantifying the impact of agricultural practices over time and space using literature based meta-regression models comes with inherent risks that can impact the validity and reliability of the study findings. One significant risk lies in the heterogeneity of the datasets sourced from various studies, as differences in experimental designs, geographical locations, and climatic conditions may introduce variability not well explained by the meta-analytical models calibrated in Tasks 1.2 and 1.3. Heterogeneity can obscure true effect sizes and lead to misleading conclusions. Another potential risk is the uncertainty on the predicted occurrence of current management measures. Since the actual area where measures are applied are not monitored, the protocol here helps to estimate these areas but these are often based on data on relative coarse resolution.

The impact of the uncertainty in meta-regression models on the outcome of the NutriBudget project can be strongly limited by the application of proper statistical mitigation techniques and by combining it with results from process based models being developed in WP2. The meta-regression models and identification of appropriate measures are meant to guide and evaluate the outcomes of the process based models developed in WP2 by delivering quantitative estimates of management induced impacts while accounting for site properties. The estimates of the meta-regression models thereby avoid unrealistic estimates that might occur from the process based models since these regression models are based from observations done in field trials. Note that meta-regression models automatically correct for high uncertainties in observations done in field trials, and that appropriate statistical methods will be applied during the calibration of meta-regression models to avoid structural errors. For this, the meta-regression models are evaluated on publication bias and on model and residual heterogeneity before being applied.

In addition, the outcomes of the meta-regression and process based models will be applied via an user friendly decision support tool developed in WP5. Where the model based assessments of farming systems across Europe (being a deliverable of WP2) are done with open source available data from farming systems and site conditions, the outcomes of the decision support tool (DST) are based on farm derived input data. This also implies that potential uncertainty on open source input data is much lower when applied in the DST. Uncertainties on input data do not substantially affect the conclusions on European or farming system scale given the fact that uncertainties usually cancel out (You et al., 2023; de Vries et al, 2023).

Note that publication bias might also affect the quality of the meta-analytical regression models, but common correction algorithms are applied to avoid structural biases in the predicted impact of measures on selected KPIs (see D1.2). The data driven estimates of measures as well the identification of best measure combinations will therefore support the calibration and reliable quantification via the processed based models developed and tested in WP2 and indirectly support the design and impact assessment of the roadmaps evaluated in WP2.

5. Conclusions

This report (D1.4, Task 1.3, WP1) describes the approach and methodology to apply meta-regression models on local, regional and European scale, thereby facilitating the decision support of agronomic measures to improve the carbon and nutrient budgets in view of agronomic and environmental targets. The actual application and spatial visualisation of these impacts are foreseen in D1.5, Task 1.3, WP1.

First, we highlight the importance of developing and implementing effective mitigation measures to improve nutrient use efficiency and nutrient budgets within various agricultural systems, regions and countries.

Second, we develop a protocol to apply developed meta-analytical regression models on European scale to estimate the impact of agronomic farm and field measures, taken into account the site properties controlling those impacts and the targets to be achieve, and to identify appropriate measures, including an overview of existing databases (partly satellite derived) to tailor the calculated impacts on field, farm and regional scale.

Third, we present three examples from previous studies illustrating how agronomic measures can be optimised in view of targets for SOC sequestration (example 1), crop yield, soil organic matter and the nitrogen surplus (example 2) and targets for nutrient efficiency, water retention and nutrient buffering in view of leaching and runoff (example 3).

The main conclusions are that the developed protocol:

- **presents an approach to identify the most appropriate and effective measures** in view of the key performance indicators selected in WP3 and being used by the models in WP2. As such, it will be used to finetune and calibrate the model-based assessment to develop roadmaps with various measures to improve the sustainability of agriculture (moving form current to desired status) as foreseen in WP2.
- **allows the estimation of site specific impacts of agronomic measures** in view of agronomic and environmental targets for indicators, linked to crop yield and desired carbon and nutrient budgets in view of soil health (e.g. soil organic carbon (SOC) content / sequestration), soil water retention, air quality (e.g. ammonia emissions) and water quality (e.g. nutrient surplus and nutrient use efficiency).
- **facilitates the identification of appropriate measures** by combining estimates of the actual carbon and nutrient budgets, spatial explicit regional targets for those budgets, the impact of measures on those budgets, and the optimisation across multiple agronomic and environmental targets into an overall score reflecting the integrative farm and field performance in view of these targets.

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Optimisation of nutrient budget in agriculture

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