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# FARManalytics – A bio-economic model to optimize the economic value of sustainable soil management on arable farms

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ABSTRACT

Soil quality is an important determinant of agricultural productivity and environmental quality. Despite its importance, few economic models incorporate sustainable soil management. The objective of this study is to develop and illustrate FARManalytics: a bio-economic model to gain quantitative insight in the economic value of sustainable soil management. First, we defined a comprehensive set of chemical, physical and biological soil quality indicators and quantitative rules on how these indicators respond to farmers' production management over time. Second, we introduce an economic calculation framework that enables accurate calculation of the contribution of different production management decisions towards farm income using Activity-Based-Costing. The set of soil quality indicators and economic calculations serve as the basis for the bio-economic model FARManalytics, which consists of two modules: (1) the *PM calculator*, a module that calculates the impact of current production management on soil quality and farm economics and (2) the *PM optimizer*, a module that uses Mixed-Integer-Linear-Programming to maximize farm incomewithin predefined soil quality indicator constraints. The decision variables are the crop rotation, cover crops, manure & fertilizer application and crop residue management. We illustrate the added value of the model by applying it to an extensive and intensive farm type, both on clay and sandy soil. These farm types are derived from the Farm Accountancy Data Network (FADN) in the Netherlands. FARManalytics demonstrates that it is possible to increase farm income with up to €940 $ha^{-1}$ $year^{-1}$ on clay soil and up to €683 $ha^{-1}$ $year^{-1}$ on sandy soil, while meeting all soil quality targets except subsoil compaction vulnerability. The latter was among the most limiting soil quality indicators for the farm types in this study, together with soil organic matter input, wind erosion vulnerability and plant-parasitic nematodes. FARManalytics integrates the impact of production management decisions on soil quality and economics at farm level. Combined with representative farm types, the bio-economic modeling approach of FARManalytics can provide useful information for policy support. FARManalytics can also be tailored to provide decision support for individual farms, based on data that is commonly available on arable farms at low cost.

## 1. Introduction

Soil quality plays a key role in agricultural productivity and environmental quality (Stevens, 2018). An increasing demand for agricultural products and a decreasing area of agricultural land (Alexandratos and Bruinsma, 2012) lead to increased pressure on our agricultural system, resulting in erosion, soil compaction, loss of soil organic matter, nutrient leaching and pesticide emission (Koch et al., 2013; Squire et al., 2015). Sustainable soil management should help overcome these threats by meeting present productivity needs without compromising soil needs for future generations (adapted from Smith and Powlson, 2007).

Sustainable soil management can be regarded as an economic problem (Stevens, 2018; Kik et al., 2021a): an investment that aims at long-term soil quality and hence farm income, but might reduce short-term profit. Currently, insight in this trade-off between short-term and long-term economic impact is missing, hampering the implementation of SSM. Kik et al. (2021a) define the Economic Value of Land (*EVL*) as the cumulative returns of a piece of land over a period of time.

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Maximum sustainable *EVL* is obtained if a soils' potential is fully utilized in a sustainable way, i.e. soil quality and farm income do not decline over time (Kik et al. 2021a). Following from this, the Economic Value of Sustainable Soil Management (*EVSM*) is defined as the difference between the maximum sustainable *EVL* and the current *EVL* of the farmer. Farmers' production management, i.e., the complete set of physical (e.g. fertilizer and plant protection products) and non-physical inputs (e.g., labor and capital) is the primary determinant of soil quality and hence of *EVL*. Building further on Dury et al. (2012) and Stevens, (2018), Kik et al. (2021a) developed a conceptual framework for modeling *EVSM*.

Optimizing farmers' production management has been included in numerous bio-economic farm models, which are amongst the most widely spread methods to re-design farming systems (Janssen and van Ittersum, 2007). Most of these models use a linear programming framework where profit is one of the most common objectives and constraints typically include availability of resources such as labor, irrigation water and land (Castro et al., 2018; Castro and Lechthaler, 2022). The added value of such models is proven as they allow to evaluate trade-offs and synergies between different production management strategies and thus support the design of alternative systems (Dury et al., 2012; Schreefel et al., 2022). Although many of these models (e.g. Britz et al., 2014; Dogliotti et al., 2005; Groot et al., 2012; Hediger, 2003, Louhichi et al., 2010); Schuler and Sattler, (2010) include some soil quality parameters such as nutrients flows and soil organic matter they typically only make tenuous references to integral concept of soil quality (Schreefel et al., 2022). On the other hand, integrated soil quality assessment tools such as Debeljak et al., (2019) and Ros et al., (2022) often lack an integration of the socio-economic impact of production management decisions at farm-level. Schreefel et al., (2022) make a valuable contribution to bridge this gap by coupling the soil assessment tool Soil Navigator of (Debeljak et al., 2019) to the bio-economic farm model FarmDesign by Groot et al., (2012). In this study, Schreefel et al., (2022) optimize multiple functions of soil using qualitative suggestions of the Soil Navigator for input in FarmDesign. Despite the added value of this approach to understand the socio-economic aspects of sustainable soil management in the farm context, still further advancements have to made to quantitively assess *EVSM*. Therefore, we aim for a quantitative integration of the relation between integral soil quality and production management embedded in a farm's economic context. In such an approach, soil quality has to be included as an integral concept (Bouma, 2014) because ultimately the combination of all soil functions determines long-term soil quality and hence *EVL*. To build further on studies that already include important production management decisions such as cropping plan and crop rotation (Alfandari et al., 2015; Capitanescu et al., 2017; Pahmeyer et al., 2021), additional production management decisions such as cover crops, manure application, fertilizer application and crop residue management have a crucial impact on soil quality and farm economics (Kanellopoulos et al., 2012). The *ex-ante* integral assessment of soil quality as a response to a comprehensive set of production management decisions requires inclusion of a sound set of agronomic decision rules that accurately model the impact of these decisions over time. We build further on the approach of Dogliotti et al.( (2003) to create feasible crop rotations over time, which than serve as the basis for allocation of other production management decisions. The proper implementation of production management decisions is strongly dependent on the farm context (e.g. soil type, climate, cropping plan), which is highlighted by Hannula et al. (2021) and Young et al. (2021). Therefore, we aim for a bio-economic modelling approach that can be tailored at the farm-level using e.g. soil samples and current resource availability so the model is able to suggest concrete alternative production management decisions to reach soil quality targets embedded in the economic context of the farm.

The aim of this study is to integrate soil quality and famers' production management in a bio-economic modeling approach to identify production management strategies that maximize farm income while increasing or preserving soil quality. We define four sub-objectives to reach this aim:

(1) Establish a comprehensive set of chemical, physical and biological soil quality indicators that ensure long-term soil quality in a context of production management optimization to maximize farm profit.
(2) Develop a quantitative economic framework to calculate the contribution of production management elements towards farm income.
(3) Develop a bio-economic model that (*a*) calculates the impact of current production management on soil quality and farm economics and (*b*) optimizes farmers' production management to reach maximum profit.
(4) Illustrate our model by applying it to four representative farm types.

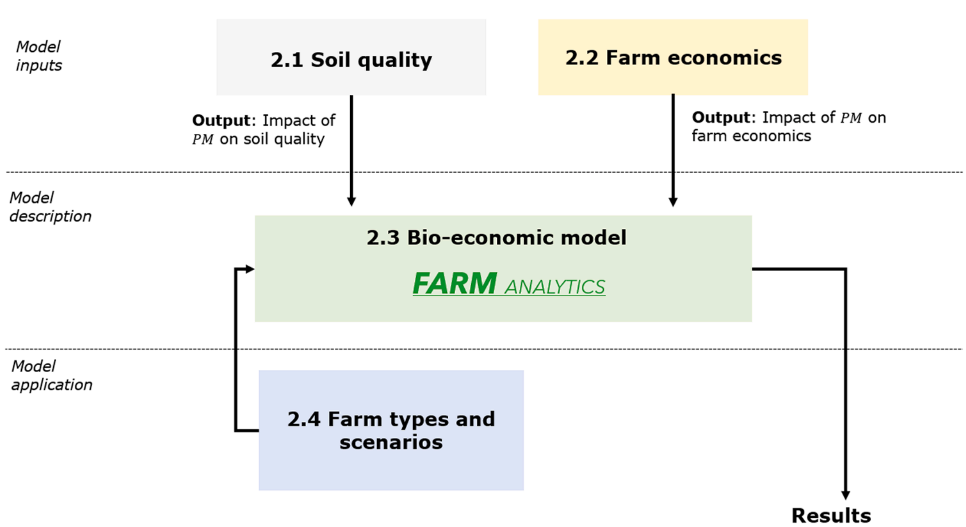


**Fig. 1.** Workflow of the description and application of the FARManalytics bio-economic modeling approach to optimize farmers' production management (*PM*). Numbers refer to section numbers in the chapter Methods.

**Table 1**
– Soil quality indicators and soil quality constraints included in FARManalytics. Indicator minimum thresholds (t_min) or maximum thresholds (t_max) are either based on field experimental evidence (t) or expert judgement (r). Nutrient acronyms: N = Nitrogen, P = Phosphorus, K = Potassium, S = Sulphur, Mg = Magnesium. The values for 11, 14 and 15 rely in part on original development, aside from the mentioned source.

| Soil quality indicators | | | | | | | | | | Soil quality constraints | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *category* | *nr.* | *indicator* | *acronym* | *source method* | *unit* | *t_min* | *t_max* | *type* | *source constraint* | | *min.* | *max.* |
| *Chemical* | 1 | N balance | Nbal | NDICEA[1] | | | | t | CBAV[2]/Silva[8] | N adv/N sur | Crop N adv.[a] | N surplus (80) |
| | 2 | P Availability Index | PAI | CBAV[2] | (index) | 20/25[a] | 45 | t | CBAV[2] | P adv/P norm | P adv[a] | P norm |
| | 3 | K Availability Index | KAI | CBAV[2] | (index) | 11[b] | 20[b] | t | CBAV[2] | K adv/K bal | K adv[a] | 100 |
| | 4 | S balance | Sbal | CBAV[2] | | | | t | CBAV[2] | S adv/S nur | Supt[a] | S surplus (200) |
| | 5 | Mg Availability Index | MAI | OSI[3] | mg $kg^{-1}$ | 45 | | t | CBAV[2] | Mg adv | Mg adv[b] | |
| | 6 | Acidity | pH | CBAV[2] | | 5[b] | 7[b] | t | CBAV[2] | NV balance | pH advice[b] | |
| | 7 | Cation Exchange Capacity | CEC | OSI/G. Ros[4] | mmol+ $kg^{-1}$ | 100 | | r | OSI/G. Ros[4] | SOM/pH | CEC SOM /pH[c] | |
| *Physical* | 8 | Crumbling Ability | CRA | OSI[3] | (index) | 6 | | t | OSI[3] | CRA_pm_index | 7[e] | |
| | 9 | Wind Erosion Vulnerability | WEV | OSI[3] | (index) | 6 | | t | OSI[3] | WEV_pm_index | 6 | |
| | 10 | Slaking Vulnerability | SV | OSI[3] | (index) | 6 | | t | OSI[3] | SV_pm_index | 7[e] | |
| | 11 | Subsoil Compaction Index | SCI | OD/Terranimo[5] | | | | t | Akker & Bakema[5] | SCI | | 0.2 |
| | 12 | Plant Available Water | PAW | OSI[3] | (mm water) | 50 | | r | OSI[3] | SOM | PAW SOM[d] | |
| | 13 | Soil Organic Matter | SOM | NDICEA[1] | (%/kg $ha^{-1}$) | 2 | | r | OSI[3] | ΔSOM | min ΔSOM[e] | |
| *Biological* | 14 | Plant Parasitic Nematodes | NEM | OD /PPN scheme[6] | | | | r | ODM /PPN scheme[6] | NEM PCI | | 200 |
| | 15 | Soil-Borne Pathogens | SBP | OD/SBP scheme[7] | | | | r | ODM /SBP scheme[7] | SBP PCI | | 200 |

Additional information targets: a: cropping plan dependent, b: cropping plan & soil type dependent, c: CEC depends on pH and SOM content. Constraints are set on pH and SOM, d: PAW can be controlled via SOM. Constraint is set on SOM, e: CRA and SV can be controlled via *PM* decisions and SOM content. Constraints are set both on SOM content and production management decisions directly. f: dependent on SOM required for CEC, CRA, SV, PAW and SOM itself.

References: 1: Van Der Burgt et al., (2006), 2: CBAV, (2022) 3: Ros et al. (2022), 4: Ros (personal communication, March 15, 2022) 5: Bakema and van den Akker (2021), 6: Molendijk (2022), 7: Termorshuizen et al. (2020), 8: Silva et al. (2021)

## 2. Methods

### 2.1. Workflow

The workflow of the description and application of the FARManalytics model is as follows (Fig. 1). First, we explain the soil quality indicators, their target values and quantitative rules how the soil quality indicators respond to production management (Section 2.1). Section 2.2 elaborates on farm economics and explains the contribution of production management decisions to farm income. The output of Section 2.1 and Section 2.2 are datasets and decisions rules with the impact of production management on both soil quality and farm economics, which serve as input for FARManalytics. Section 2.3 describes the actual bio-economic modeling approach of FARManalytics. Lastly, Section 2.4 illustrates the model through a scenario analysis on four standard farm types in the Netherlands.

### 2.2. Model scope

The focus of our study is the farm-level as the farmer is the primary actor in sustainable soil management and decision maker on production management (Kik et al., 2021b). Although our focus is at the farm-level, we only consider the farm activities directly related to crop production, but including inputs such as labour and capital (Fresco and Westphal, 1988). We assume that farms are homogenous in their soil type and production management. We focus on crop yield as the primary output and do not include the options to generate additional farm income through subsidies or provisioning of additional ecosystem services. The temporal scale is the length of one crop rotation. Yields are determined using a target-oriented approach, which implies that yields are static and do not respond to changes in soil quality or production management (van Ittersum, Rabbinge, 1997). We illustrate the approach for the Netherlands, where there is a high demand for agricultural products and intensive land use due to fierce competition for land. This implies that we also use soil quality indicators and data suited for the Dutch context.

### 2.3. Soil quality

A first step towards developing soil quality constraints was to establish a set of soil quality indicators. We first selected soil quality measurements and associated indicators encompassing the various aspects of soil functioning (Rinot et al., 2019). We defined four criteria to select indicators:

1. The set of indicators has to reflect the variation in soil functions contributing to *EVSM* at farm level (Bünemann et al., 2018; Ros et al., 2022).
2. For scalability, data has to be available at large scale and acceptable costs (Rinot et al., 2019). Additionally, the indicator has to account for specific conditions and must be expandable with new indicators or objectives.
3. The evolution of soil quality indicators over time as response to farmers' production management has to be quantifiable (Stevens, 2018).
4. Targets in the form of threshold values have to be available (Rinot et al., 2019). They can be based on experimental evidence, literature or expert judgement.

Based on these criteria and in consultation with the developers of two existing Dutch soil quality indicator sets (the Open Soil Index (OSI) and Soil quality indicators Agricultural soils Netherlands (SAN)(de Haan et al., 2021; Ros et al., 2022)), we arrived at the definitive list of soil quality indicators (de Haan et al., 2021 personal communication, November 8, 2021). Appendix A-1 presents the detailed selection procedure.

We made major adjustments and additions to three indicators. First, we included a more detailed calculation of nitrogen (N) flows compared to either OSI or SAN. N-flows play a key role in crop production and can largely be influenced by production management decisions (Silva et al., 2021). We developed calculation rules for the tactical modeling of N-flows based on the NDICEA model (Van Der Burgt et al., 2006), an empirical N-budget model using first order mineralisation kinetics for soil organic matter that has been validated for Dutch circumstances. Second, we extended the current OSI indicator for subsoil compaction vulnerability based on site specific corrections derived from Rücknagel et al. (2015) and the Terranimo model (Lassen et al., 2013). In its current form, the OSI indicator for subsoil compaction is based on predefined calculations with the SOCOMO model (Van Den Akker, 2004), and its use to assess the impact of changes in production management soil management dynamically, for example annually or across seasons is limited. Terranimo is a dynamic model configured for Dutch circumstances that allowed us to quantify the impact of production management decisions on subsoil compaction vulnerability. Rücknagel et al. (2015) provide guidelines for integrating subsoil compaction vulnerability at cropping plan level. Third, we added an indicator for the development of plant-parasitic nematodes (PPN) and soil-borne pathogens (SBP) based on the Dutch nematode and pathogen schemes (Molendijk, 2022; Termorshuizen et al., 2020). Whereas OSI and SAN only include the current status of nematodes and pathogens, these two schemes allowed us to make a semi-quantitative assessment on their evolution over time as a response to production management.

Table 1 presents the complete set of indictors, clustered as chemical, physical and biological indicators, including threshold values or ranges derived from field experimental evidence (t) or expert judgement (r). The typical soil depth that applies for these indicators is 0.25 – 0.30 m. For each indicator, we also list modeling constraints. Whereas the indicators are used to assess soil quality at a specific location at a certain point in time, the constraints are used to set requirements on the farmers' production management to ensure the indicators stay in or move towards the target range. For the combination of indicators and constraints, one of the following three situations applies: (1) Soil quality indicator **within** target range: formulate constraints for production management to ensure the indicator stays in target range. (2) Soil quality indictor is **below minimum** target: formulate constraints for production management to move the indicator towards the minimum target. (3) Soil quality indicator is **above maximum** target: Formulate constraints for production management to move the indicator towards the maximum target.

For example, with respect to soil organic matter (SOM, nr. 13 in Table 1) the indicator is defined as the percentage of SOM in the topsoil with a minimum target value of 2%. If current SOM content is above the target, the modeling constraint refers to a minimum ΔSOM in kg $ha^{-1}$ $year^{-1}$ to ensure SOM content stays above the target. If the SOM content is below the target value, the required ΔSOM input in kg $ha^{-1}$ $year^{-1}$ has to be higher to move the SOM content towards the target.

Because of trade-offs and synergies between various soil quality indicators it is essential to include their interrelations in modeling (Rinot et al., 2019; Stevens, 2018; Bouma, 2014). An example of an interrelation is the dependency of SOM decomposition on pH. Many soil quality indicators depend on soil inherent properties. For example, the rate of SOM decomposition is dependent on the soil texture. Table 2 presents an overview of indicator interrelations.

After selecting soil quality indicators, we established their relevant interrelations and the relations with production management (Kik et al., 2021a). Farmers' production management is the primary determinant of soil quality. Kik et al. (2021a) provide a basic overview on how production management decisions at a strategic, tactical and operational level influence soil quality. Strategic choices relate to long-term production management decisions, e.g., crop rotation design (Dury et al., 2012). Tactical choices are the choices made within the growing season, e.g., cover crop choice or the manure application regime (Dury et al., 2012). Choices at the operational level are highly dynamic and typically are made on a day-to-day basis, e.g., whether and how much to irrigate during a period of drought. The focus of this study is on the strategic – tactical production management decisions. Table 3 presents the production management decisions included in our bio-economic modeling approach, and Table 4 presents how each of them relate to the soil quality indicators.

Appendix A-3 contains extensive factsheets that explain all calculations, required data and references for every soil quality indicator and their response to production management decisions.

### 2.4. Farm economics

To quantify farm economics we used a business economics approach to calculate profit. We chose to use profit as an economic indicator rather than *EVL* since in the current approach of FARManalytics we do not consider the cumulative returns over time against a discount rate. Kay et al. (2012) define profit at farm-level as the value that remains after subtracting all costs, including opportunity costs for own labour and capital from gross income. For accurate modeling, this implies that both variable and fixed costs of production have to be addressed for all

**Table 2 –**
Interrelations between soil quality indicators. Rows (dependent indicators) show which other indicators impact the considered indicator, e.g. Nitrogen balance (Nbal) is influenced by pH and Soil Organic Matter (SOM). Columns (independent indicators) show the indicators the considered indicator has an impact on e.g. Cation Exchange Capacity (CEC) has an impact on Potassium Availability Index (KAI) and Magnesium Availability Index (MAI). Relations are included as nr. of dependent indicator -> nr. of independent indicator. Interrelations in bold are implemented in the model. See Table 1 for explanation of other acronyms.

| | | *Independent indicators* | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | *Chemical* | | | | | | | *Physical* | | | | | *Biological* | | | *Inherent* |
| ***Dependent ind.*** | | Nbal | PAI | KAI | Sbal | MAI | pH | CEC | CRA | WEV | SV | SCI | PAW | SOM | NEM | SBP | Soil texture |
| *acronym* | *nr.* | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 |
| Nbal | 1 | | | | | | **6→1** | | | | | | | **13→1** | | | **16→1** |
| PAI | 2 | | | | | | | | | | | | | | | | |
| KAI | 3 | | | | | | | **7→3** | | | | | | | | | |
| Sbal | 4 | | | | | | | | | | | | | **13→4** | | | **16→4** |
| MAI | 5 | | | | | | | **7→5** | | | | | | | | | |
| pH | 6 | | | | | | | | | | | | | **13→6** | | | **16→6** |
| CEC | 7 | | | | | | **6→7** | | | | | | | **13→7** | | | **16→7** |
| CRA | 8 | | | | | | **6→8** | | | | | 11→8 | 12→8 | **13→8** | | | **16→8** |
| WEV | 9 | | | | | | | | | | | | | **13→9** | | | **16→9** |
| SV | 10 | | | | | | | | 8→10 | | | 11→10 | | **13→10** | | | **16→10** |
| SCI | 11 | | | | | | | | | | | | **12→11** | **13→11** | | | **16→11** |
| PAW | 12 | | | | | | | | | | | 11→12 | | **13→12** | | | **16→12** |
| SOM | 13 | | | | | | **6→13** | | | | | | | | | | **16→13** |
| NEM | 14 | | | | | | 6→14 | | | | | | | | | | **16→14** |
| SBP | 15 | | | | | | | | | | | 11→15 | 12→15 | | | | **16→15** |

**Table 3**
– Definition and illustration of farmer' production management decisions included in bio-economic modelling approach FARManalytics. [1]: adapted from Castellazzi et al. (2008) [2]: Ramesh et al. (2019).

| *PM* decision | Definition | Example |
|---|---|---|
| Crop rotation[1] | The set and sequence of crops grown on a field | • Wheat – Potatoes – Wheat – Sugar beets<br>• Wheat - Sugar beets – Potatoes - Corn |
| Cover crop[2] | A close-growing crop that provides soil protection, seeding protection and soil improvement between periods of main crop production | • Yellow mustard planted after winter wheat (1-Aug) and terminated before potato planting (1-Apr). |
| Manure | Organic matter originating from livestock husbandry or composting | • 30 ton $ha^{-1}$ pig slurry applied 1-Mar<br>• 20 ton $ha^{-1}$ compost applied 1-Oct |
| Fertilizer | Application of plant nutrients through natural or synthetically produced fertilizer | • 200 kg Calcium Ammonium Nitrate (27% N) application on 1-May |
| Crop residue management | Decision to sell crop residues to generate revenue or keep them on the field to enhance soil quality | • Sell wheat straw<br>• Keep wheat straw |

production management decisions. Inaccurate attribution of costs and revenues to production management decisions can lead to over- or underestimations. This so-called "cross subsidisation bias" can result in poor management decisions (Gupta and Galloway, 2003; Mattetti et al. 2022). Therefore, we used Activity-Based-Costing (ABC) to accurately attribute fixed costs towards the respective production management decisions (Drury, 2008).

We defined a farm as an entity owning or using a certain area of land. We calculated profit at farm-level as the sum of profit or costs made by each production management decision minus the farm overhead costs:

$$P_{farm} = P_c + P_{cr} - C_{cc} - C_m - C_f - FOC \tag{1}$$

In which:

- $P_c(€)$: Profit from crop production
- $P_{cr}(€)$: Profit from crop residue management
- $C_{cc}(€)$: Costs from cover crop cultivation
- $C_m(€)$: Costs from manure application
- $C_f(€)$: Costs from fertilizer application
- $FOC(€)$: Farm Overhead Costs, general overhead costs that cannot be attributed to production management decisions.

Throughout our approach, we did not consider Farm Overhead Costs. The profit calculated is therefore not the farm profit but defined as "profit on crop enterprise", representing the total profit at farm level excluding costs that cannot be attributed to crops, cover crops, manure, crop residue or fertilizer. In the remainder of this paper we will refer to profit as the profit on crop enterprise.

Fig. 2 visualizes the procedure to calculate profit on crop enterprise:

Because the procedure is the same for all production management decisions, we substituted the indices $c, cc, m, cr, f$ from Eq. 1 with $pm$ in the following calculations. The general procedure to calculate net profit or cost for a specific production management decision is:

$$P_{pm} = \left(R_{pm} - DC_{pm} - OC_{pm}\right)^{*}Area_{pm} \tag{2}$$

In which:

- $R_{pm}$ $(€\ ha^{-1})$: Physical output times price.
- $DC_{pm}(€\ ha^{-1})$: Direct costs of production management inputs, such as seeds and crop protection inputs.
- $OC_{pm}(€\ ha^{-1})$: Total costs (variable + fixed) of field operations and storage & procession operations.
- $Area_{pm}(ha)$: Area of production management decision.

For the production management decisions that do not generate revenue, such as cover crops, manure and fertilizer application, the revenue component of Eq. 2 is set to zero. Total costs for such a production management decision are the sum of direct costs and costs of operations.

Operations costs were calculated according to the following equation:

$$OC_{pm} = ME_{pm} + IB_{pm} + LA_{pm} + EN_{pm} + CON_{pm} \tag{3}$$

In which:

- $ME_{pm}$ $(€\ ha^{-1})$: Mechanization costs, consisting of depreciation, interest, maintenance and insurance. Attributed to the specific

**Table 4 –**
Relations between soil quality indicators and production management. Production management decisions indicated in bold are considered in this study. An "x" represents a quantitative relationship included in the model. A "-" represents a known relationship not yet included in the model. See Table 1 for explanation of soil quality indicators acronyms.

| | | Soil quality indicators | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | *Chemical* | | | | | | | *Physical* | | | | | | *Biological* | |
| | Production management decisions | Nbal | PAI | KAI | Sbal | MAI | pH | CEC | CRA | WEV | SV | SCI | PAW | SOM | PPN | SBP |
| *Strategic dimension* | *Farm set-up* | | | | | | | | | | | | | | | |
| | Production system | x | x | x | x | x | | | | | | | | | | |
| | Mechanization & installation configuration | | | | | | | | | | | x | | | | |
| | Tillage system | - | | | | | | | - | - | - | - | - | - | | |
| | *Land use activities* | | | | | | | | | | | | | | | |
| | **Crop rotation** | x | x | x | x | x | x | | - | - | - | x | | x | x | x |
| | **Cover crops** | x | - | - | - | | | | - | - | - | - | | x | x | x |
| | **Fallow periods** | - | - | - | - | | | | - | - | - | | | | x | x |
| | *Soil management* | | | | | | | | | | | | | | | |
| | **Organic manure** | x | x | x | - | - | x | | | - | | x | | x | | |
| | **Lime (CaO) & Gypsum (CaSO[4])** | | | | x | x | x | | - | | | x | | | | |
| | Field improvements (e.g. drainage) | | | | | | | | - | | - | - | - | | - | - |
| | *Crop management* | | | | | | | | | | | | | | | |
| | Crop cultivar selection | - | | | | | | | | | | | | | x | x |
| | **Crop residue management** | x | x | x | - | | | | | - | - | x | | x | | |
| *Tactical dimension* | **Fertilzer application regime** | x | x | x | x | x | x | | | | | - | | | | |

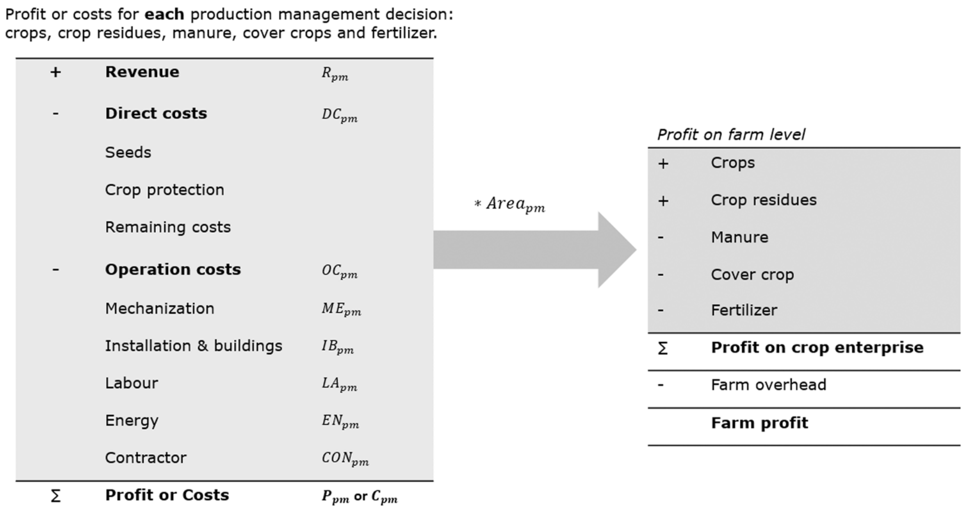


**Fig. 2.** – Outline for the calculation of profit and costs on production management decisions. The sum of total profit or costs on all production management decisions multiplied by their respective area results in profit on crop enterprise, the profit at farm-level excluding overhead costs.

production management decisions based on ABC where usage in hours was used as a costs driver.

- $IB_{pm}$ $(€\ ha^{-1})$: Installation and building costs, consisting of depreciation, interest and maintenance. For example costs of a box storage for potatoes.
- $LA_{pm}$ $(€\ ha^{-1})$: Labour costs, including opportunity costs of own labour.
- $EN_{pm}$ $(€\ ha^{-1})$: Energy costs, costs of energy used in field operations and storage & processing operations.
- $CON_{pm}$ $(€\ ha^{-1})$: Contractors costs, total costs if operations is outsourced to a contractor.

### 2.5. Bio-economic model FARManalytics

The bio-economic modeling approach 'FARManalytics' consists of two modules, *PM* calculator and *PM* optimizer. In the *PM* calculator, the production management decisions on crop rotation, cover crops, manure, fertilizer and crop residues are considered as fixed inputs to be made by the user. In the *PM* calculator, these decision variables are linked to soil quality and economic data (see Section 2.1 and Section 2.2) to calculate the impact of current production management on soil quality indicators and farm economics. The key feature of the *PM* calculator is that this module allows to gain insight in whether current production management keeps soil quality indicators in their target range. The module *PM* optimizer is an optimization model that selects the production management (crop rotation, cover crops, manure,

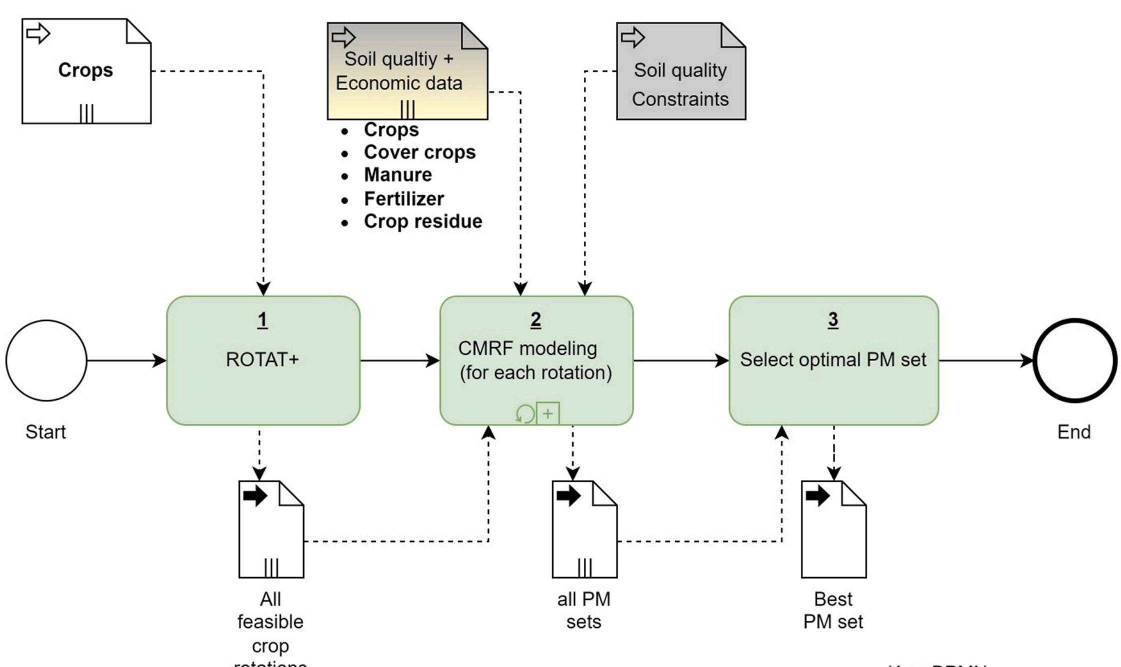


**Fig. 3.** Business Process Model and Notation (BPMN) diagram of the PM optimizer module in the bio-economic model approach FARManalytics. PM stands for Production Management, ROTAT+ is a crop rotation generator, and CMRF modeling stands for cover crops, manure, crop residues and fertilizer optimization within a crop rotation using mixed-integer linear programming.

fertilizer, crop residue management) achieving the soil quality targets from Section 2.1 while earning highest profit on crop enterprise.

Fig. 3 presents an outline of the *PM* optimizer in a Business Process Model and Notation (BPMN) diagram.

The *PM* optimizer has three processes included (Fig. 3). In process one, crop rotations are generated using ROTAT+ (Dogliotti et al., 2003). The input for ROTAT+ is a list with crops and agronomic data such as planting dates, harvest dates, maximum crop frequency and minimum period of return. Based on agronomic rules e.g., maximum crop frequency and minimum period of repeat between the same crops, ROTAT+ generates all feasible crop rotations.

In process two, the choice of cover crops, manure application, crop residue management and fertilizer application (CMRF) is optimized within each feasible rotation. The input is a dataset with the impact on soil quality and economics for crops, cover crops, manure, crop residues and fertilizer. For example, the nitrogen uptake of a crop, the nematode host function of a cover crop, the P content of manure and revenues generated by selling the crop residue wheat straw. First, within the CMRF modeling the soil quality and economic data of the crops in the crop rotation are initialized. Second, the other production management decisions within each crop rotation are optimized with a Mixed-Integer-Linear-Programming (MILP) model. The objective function of the model is to maximize profit on crop enterprise over time of one rotation.

The decision variables in the MILP model are the following:

- Cover crops *(binary):* Plant cover crop *cc* in year *t*.
- Manure application *(continuous):* Quantity of manure type *m* in year *t*.
- Crop residues (*binary*): Sell or keep crop residues *cr* of crop *c* in year *t*.
- Fertilizer (*continuous*): Quantity of fertilizer type *f* in year *t*.

The model contains three types of constraints:

- *Agronomic* constraints ensure the agronomic feasibility of the chosen solution. An example of these constraints is the cover crop constraints that ensure cover crops can only be planted between crops if there is sufficient growing time in between. Another example are manure constraints that ensure manure only applied at desired times and in feasible quantities.
- *Legal* constraints limit the usage of N from animal manure, total N and total P according to the Dutch nutrient legislation.
- *Soil quality* constraints (Table 1): constraints on production management to ensure soil quality targets are achieved, with the underlying assumption that if soil quality constraints are met soil quality is preserved. Because of their dynamic nature, the N, S and pH constraints are applied yearly, whereas other soil quality constraints are applied over the length (in years) of the rotation.

Process three in Fig. 3 is to select the best production management set. The result of process two is collection of all production management sets: feasible crop rotations with optimized cover crop, manure, fertilizer and crop residue choices and the consecutive impact on soil quality and economics. Within this collection, the optimal production management set is the set that has highest profit while meeting the soil quality constraints.

The number of feasible crop rotations generated by ROTAT+ can impede the computational feasibility of process 2. Therefore, we implemented a heuristic: within the ROTAT+ output we select the rotations with the highest crop profit at rotational level. This set goes through process 2: If an optimal solution is found, calculations stop. If no optimal solution is found, we select a further set of rotations with highest profit ranks and run process 2 again. This procedure is repeated until a feasible solution is found or until all feasible rotations are processed

### 2.6. Farm types and scenarios

To illustrate the model, we defined four standard farm types based on the Dutch Farm Accountancy Data Network (FADN), managed by Wageningen Economic Research and KWIN AGV 2022 (van der Voort, 2022). KWIN AGV is a Dutch handbook containing quantitative standards for arable farming. Yields, prices, costs of inputs and costs of assets where all determined based on KWIN AGV 2022. For the land costs, we took the long-term land rent price from KWIN AGV 2022. We evaluated the impact of production management on soil quality and profit for two arable farm types (intensive, extensive) on two different but representative soil types (clay, sand) (Table 4). For each soil type an extensive and intensive current production management regime has been defined. The extensive production management focuses more on preserving soil quality with an extensive crop rotation, the use of cover crops where possible and input of cattle slurry and solid manure. The intensive production management focuses on short-term profit with an intensive crop rotation, a limited number of cover crops and preferential use of pig and cattle slurry as manure.

We defined the following scenarios:

We designed the following scenarios, which were applied on every farm type:

- Baseline (*b*): Continuation of current production management (Table 5) during one complete rotation.
- Profit tactical (*pt*): Optimization of production management choices in the tactical dimension without soil quality constraints, except for crop nitrogen requirements and legal nutrient norms. Optimization in the tactical dimension only refers to potential changes in the cover crops, manure, crop residues and fertilizer.
- Soil quality tactical (*st*): Similar to the profit scenario but including all soil quality constraints as defined in Table 1. However, this scenario does not consider changes in crop rotation.
- Soil quality strategic (*ss*): Optimization of production management in the strategic dimension including soil quality constraints and potential changes in crop rotation and cropping plan. For both the extensive and intensive farm types, changes in crop rotation can be made based on the crops that are currently on the intensive farm types because this farm type has the highest diversity of crops. In the extensive *ss* scenarios, a minimum share of 50% of crops in the rotation has to be cereals (incl. corn) whereas this is minimum 25% in the intensive scenarios.

In the baseline scenario, the *PM* calculator of FARManalytics is used to assess the impact of current management (Table 5) on soil quality and economics. The other scenarios (profit tactical, soil quality tactical and soil quality strategic) involve optimization and use the *PM* optimizer module. We distinguish a soil quality tactical scenario and a soil quality strategic scenario because of the substantial difference in time by which the proposed changes in production management can be implemented. The changes in the soil quality tactical scenarios can usually be implemented on short notice without the need to drastically alter the farm setup. For example, planting other cover crop species usually only implies ordering other cover crop seeds from the supplier. In contrast, changing the cropping plan might require a farmer to invest in new capital assets such as machinery or installations.

An additional soil cover constraint is applied in all scenarios except the profit tactical scenarios. This constraint ensures that the soil is covered by either a crop or a cover crop for a specified percentage of the time of the rotation. For clay soil this is 75%, and for sandy soil 70%. Additional constraints were set on cover crops regarding the frost vulnerability and regrowth scores. Both scores are in the range of zero to five. A score of zero implies a that a cover crop regrows after termination or is not vulnerable to frost. In contrast, a score of five means that a cover crop does not regrow and is highly susceptible to frost. Since regrowth and frost resistance are often undesirable, only cover crops with a score of four or five were withheld.

In the scenario analysis, we did not apply the P-advice constraint as the P-norm was lower for all farm types. Since the P-norm then becomes the limiting factor, it was not possible to implement the P-advice

**Table 5 –**
Current production management decisions on four different Dutch farm types to illustrate the FARManalytics bio-economic modeling approach.

| *PM decisions* | *Farm types*<br>**Clay extensive** | **Clay intensive** | **Sand extensive** | **Sand intensive** |
|---|---|---|---|---|
| *Crop rotation* | WP-WW-SB-WW-WP-WW-SB-WW | WP-WW-SO-SB-WP-WW-CA-SB | WP-SC-WB-SB-WP-SC-WB-SB | WP-WB-SB-CA-WP-SC-SB-SO |
| *Cover crops* | (WW) -> Winter radish | (WW) -> Yellow Mustard | (WB) -> White radish<br>(SB year 4) -> Winter rye | (WB) -> White radish<br>(SC) -> Winter rye<br>(SB year 3) -> Winter rye<br>(SO) -> Yellow mustard |
| *Crop residue management* | Keep wheat straw | Sell wheat straw | Keep barley straw | Sell barley straw |
| *Manure & lime* | WW crop: 40 ton ha$^{-1}$ CS<br>WW autumn: 20 ton ha$^{-1}$ CSM | WP spring:25 ton ha$^{-1}$ PS<br>WW crop:27.5 ton ha$^{-1}$ PS<br>WW autumn:20 ton ha$^{-1}$ CS | WP spring:30 ton ha$^{-1}$ CS<br>SC spring:30 ton ha$^{-1}$ CS<br>SC autumn:20 ton ha$^{-1}$ GFTC<br>WB autumn:12.5 ton ha$^{-1}$ CSM<br>SB spring:30 ton ha$^{-1}$ CS | WP spring:35 ton ha$^{-1}$ CS<br>SB spring:35 ton ha$^{-1}$ CS<br>CA spring:30 ton ha$^{-1}$ CS<br>SC spring:35 ton ha$^{-1}$ CS<br>SO spring:30 ton ha$^{-1}$ CS |
| *Fertilizer (kg N/P/K/S/Mg ha$^{-1}$)* | | | | |
| **WP**: ware potatoes | 167 N/135 K/68 S/20Mg | 140 N/135 K/68 S/16Mg | 108 N/14 P/111 K | 122 N/18 P/111 K |
| **SB**: sugar beets | 108 N/16Mg | 108 N/16Mg | 59 N | 59 N |
| **SO**: seed onions | | 133 N/147 K/68 S/14Mg | | 93 N/25 P/108 K |
| **CA**: carrots | | 59 N/107 K/68 S/4Mg | | 76 N/25 P/78 K |
| **WW**: winter wheat | 108 N/16Mg | 95 N/14Mg | | |
| **WB**: winter barley | | | 143 N/90 K/47 S | 143 N/90 K/47 S |
| **SC**: silage corn | | | 49 N/36 K | 49 N/18 P/36 K |

Crops: WP = ware potatoes, SB = sugar beets, CA = carrots, SO = seed onions, WW = winter wheat, WB =winter barley, SC = silage corn. Manure: PS = pig slurry, CS = cattle slurry, CSM = cattle solid manure, GFTC = GFT compost. Fertilizer: N = Nitrogen, P = $P_2O_5$, K = $K_2O$, S = $SO_3$, Mg = MgO

constraint. Furthermore, we also did not apply the SCI constraint because with the current crops cultivated on the farms the threshold value could never be met.

## 3. Results

The results section is structured as follows: First we show the results of the crop profit calculation for the farm type 'clay intensive'. Subsequently, we show the results of the scenario calculations and discuss the results in the order baseline – profit tactical – soil quality tactical – soil quality strategic. Finally, we show a trade-off curve for the key soil quality indicator Soil Organic Matter vs. profit.

### 3.1. Crop profit

Table 6 shows the results of the crop profit calculation on the farm type 'clay intensive'. The profit for winter wheat is negative, i.e. −€233 ha$^{-1}$, which is not surprising as in the Netherlands winter wheat is mainly cultivated as a break crop. Break crops are cultivated to benefit soil quality in the first place, not as a cash crop (Robson et al., 2002). The net profit for ware potatoes is just slightly positive, i.e. €20 ha$^{-1}$, despite the relatively high revenue of €8080 ha$^{-1}$, as the costs of crop inputs (€2240 ha$^{-1}$), field operations (€2226) and storage operations (€2494) have a negative impact on the financial returns. With a profit of €2683 ha$^{-1}$, onions are the most profitable crop: crop revenue is approximately €2000 ha$^{-1}$ higher than for potatoes, while the total costs are comparable. Despite a revenue of only €3900 ha$^{-1}$, sugar beets are the second most profitable crop with a profit of €933 ha$^{-1}$. This can be explained by the low field operation costs and the absence of storage and processing costs. Although the revenue for carrots is almost three times the revenue of sugar beets, the profit is only 50% of that of sugar beets. A costly harvest leads to high field operations costs for carrots (>

**Table 6**
Crop profit for crops cultivated on a hypothetical arable farm of 100 ha on clay soil in the Netherlands.

| **Crop** | **Unit** | **Ware potatoes** | **Winter wheat** | **Seed onions** | **Sugar beets** | **Carrots** |
|---|---|---|---|---|---|---|
| *Revenues* | | | | | | |
| *Crop yield* | kg ha$^{-1}$ | 50500 | 10000 | 54300 | 97500 | 85500 |
| *Crop price* | € kg$^{-1}$ | 0.16 | 0.21 | 0.18 | 0.04 | 0.14 |
| *Total crop revenue* | *€ ha$^{-1}$* | 8080 | 2080 | 9883 | 3900 | 11,799 |
| *Direct costs* | | | | | | |
| Seeds | € ha$^{-1}$ | 1440 | 107 | 800 | 282 | 990 |
| Crop protection | € ha$^{-1}$ | 800 | 330 | 960 | 354 | 480 |
| Total direct costs | *€ ha$^{-1}$* | 2240 | 437 | 1760 | 636 | 1470 |
| Crop gross margin | *€ ha$^{-1}$* | 5840 | 1643 | 8123 | 3264 | 10,329 |
| *Operation costs crop cultivation* | € ha$^{-1}$ | | | | | |
| Labour | € ha$^{-1}$ | 494 | 100 | 338 | 156 | 713 |
| Energy | € ha$^{-1}$ | 212 | 80 | 189 | 118 | 212 |
| Mechanization | € ha$^{-1}$ | 1520 | 257 | 1074 | 352 | 1045 |
| Contractor work | € ha$^{-1}$ | 0 | 339 | 577 | 605 | 1745 |
| Total operation costs crop cultivation | *€ ha$^{-1}$* | 2226 | 776 | 2177 | 1231 | 3714 |
| *Operation costs storage & processing* | | | | | | |
| Inputs storage | € ha$^{-1}$ | 515 | | 116 | | 0 |
| Labor | € ha$^{-1}$ | 50 | | 50 | | 125 |
| Energy | € ha$^{-1}$ | 132 | | 282 | | 1074 |
| Mechanization | € ha$^{-1}$ | 314 | | 314 | | 641 |
| Installations & buildings | € ha$^{-1}$ | 1483 | | 1401 | | 3224 |
| *Total operation costs storage & processing* | *€ ha$^{-1}$* | 2494 | 0 | 2162 | 0 | 5063 |
| *Land costs* | *€ ha$^{-1}$* | 1100 | 1100 | 1100 | 1100 | 1100 |
| **Crop profit** | **€ ha$^{-1}$** | **20** | **-233** | **2683** | **933** | **451** |

€2000 ha$^{-1}$), on top of high storage & processing costs due to the use of expensive box storage and mechanical cooling. The results of the crop profit calculation show that the comprehensive economic calculations yield interesting differences in the financial returns between crops that would not have become clear based on a simple gross margin approach. For example, the gross margin of ware potatoes (€8080 − €2240 = €5840) is substantially higher than the gross margin of sugar beets (€3900 − €636 = €3264) while the ultimate profit of sugar beets is €903 higher.

Table 7 shows the main results for profit and the soil quality constraints for the baseline scenarios and the soil quality strategic scenario for all four farm types.

### 3.2. Baseline scenario

The baseline results follow from calculation of the current produc-

**Table 7 –**

Profit and related soil quality indicators outcomes for scenarios. With regard to soil quality indicators we show minimum (t_min, in grey) and maximum thresholds (t_max, yellow) and calculation results. If the thresholds are not met, results are underlined and indicated in red.

| | | | | Farm types & scenerarios | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Indicators | | | | CE | | CI | | SE | | SI | |
| *theme* | *indicator* | *type* | *unit* | *b* | *ss* | *b* | *ss* | *b* | *ss* | *b* | *ss* |
| Profit | crop | result | (€ ha$^{-1}$) | 1222 | 1683 | 1672 | 1803 | 697 | 1087 | 1113 | 1252 |
| | cover crop | result | (€ ha$^{-1}$) | -178 | -70 | -80 | -138 | -89 | -102 | -163 | -102 |
| | manure | result | (€ ha$^{-1}$) | -10 | 32 | 58 | 35 | -6 | -43 | 29 | -44 |
| | crop residue | result | (€ ha$^{-1}$) | 0 | 180 | 75 | 90 | 0 | 100 | 31 | 75 |
| | fertilizer | result | (€ ha$^{-1}$) | -256 | -107 | -264 | -81 | -201 | -84 | -218 | -97 |
| | land | result | (€ ha$^{-1}$) | -1100 | -1100 | -1100 | -1100 | -600 | -600 | -600 | -600 |
| | total | result | (€ ha$^{-1}$) | -322 | 618 | 361 | 609 | -199 | 358 | 192 | 484 |
| N legal | N manure legal | t max | (kg ha$^{-1}$) | 170 | 170 | 170 | 170 | 170 | 170 | 170 | 170 |
| | N manure applied | result | (kg ha$^{-1}$) | 134 | 133 | 112 | 146 | 107 | 109 | 118 | 109 |
| | N total legal | t max | (kg ha$^{-1}$) | 248 | 221 | 209 | 218 | 152 | 141 | 161 | 153 |
| | N total applied | result | (kg ha$^{-1}$) | 199 | 144 | 177 | 133 | 157 | 112 | 161 | 118 |
| N | N advice | t min | (kg ha$^{-1}$) | 216 | 203 | 194 | 195 | 178 | 156 | 174 | 167 |
| | N available | result | (kg ha$^{-1}$) | 258 | 205 | 248 | 205 | 216 | 163 | 233 | 178 |
| | N surplus | t max | (kg ha$^{-1}$) | 80 | 80 | 80 | 80 | 80 | 80 | 80 | 80 |
| | N surplus | result | (kg ha$^{-1}$) | 69 | 30 | 92 | 35 | 49 | 11 | 78 | 31 |
| P | P advice | t min | (kg ha$^{-1}$) | 83 | 88 | 80 | 80 | 77 | 80 | 71 | 73 |
| | P norm | t max | (kg ha$^{-1}$) | 60 | 60 | 60 | 60 | 60 | 60 | 60 | 60 |
| | P applied | result | (kg ha$^{-1}$) | 58 | 60 | 59 | 60 | 61 | 60 | 57 | 60 |
| K | K advice | t min | (kg ha$^{-1}$) | 151 | 144 | 206 | 187 | 216 | 188 | 232 | 210 |
| | K applied | result | (kg ha$^{-1}$) | 203 | 146 | 166 | 187 | 255 | 201 | 225 | 210 |
| | K surplus | t max | (kg ha$^{-1}$) | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| | K surplus | result | (kg ha$^{-1}$) | 52 | 2 | -40 | 0 | 39 | 13 | -7 | 0 |
| S | S uptake | t min | (kg ha$^{-1}$) | 32 | 35 | 36 | 35 | 36 | 38 | 38 | 35 |
| | S applied | result | (kg ha$^{-1}$) | 44 | 40 | 52 | 42 | 25 | 39 | 24 | 36 |
| | S surplus | t max | (kg ha$^{-1}$) | 200 | 200 | 200 | 200 | 200 | 200 | 200 | 200 |
| | S surplus | result | (kg ha$^{-1}$) | 12 | 5 | 17 | 7 | -12 | 0 | -13 | 1 |
| Mg | Mg advice | t min | (kg ha$^{-1}$) | 0 | 0 | 0 | 0 | 74 | 74 | 74 | 74 |
| | Mg applied | result | (kg ha$^{-1}$) | 83 | 38 | 39 | 45 | 56 | 79 | 35 | 76 |
| pH | NV advice | t min | (NV ha$^{-1}$) | 0 | 0 | 0 | 0 | 164 | 150 | 162 | 146 |
| | NV applied | result | (NV ha$^{-1}$) | 0 | 0 | 0 | 0 | 0 | 219 | 0 | 219 |
| CRA | CRA required | t min | (index ha$^{-1}$) | 6 | 6 | 6 | 6 | 6 | 6 | 6 | 6 |
| | CRA score | result | (index ha$^{-1}$) | 8 | 8 | 8 | 8 | 8 | 8 | 8 | 8 |
| WEV | WEV required | t min | (index ha$^{-1}$) | 6 | 6 | 6 | 6 | 6 | 6 | 6 | 6 |
| | WEV score | result | (index ha$^{-1}$) | 8.6 | 8.6 | 8.6 | 8.6 | 6.2 | 6.7 | 6.4 | 6.6 |
| SV | SV required | t min | (index ha$^{-1}$) | 7 | 7 | 7 | 7 | 7 | 7 | 7 | 7 |
| | SV score | result | (index ha$^{-1}$) | 9.1 | 9.1 | 9.1 | 9.1 | 7.8 | 7.8 | 7.8 | 7.8 |
| SCI | SCI required | t max | (index ha$^{-1}$) | 0.2 | 0.2 | 0.2 | 0.2 | 0.2 | 0.2 | 0.2 | 0.2 |
| | SCI score | result | (index ha$^{-1}$) | 0.27 | 0.2 | 0.39 | 0.36 | 0.33 | 0.26 | 0.43 | 0.37 |
| SOM | SOM lim. factor | | (-) | SOM | SOM | SOM | SOM | CEC | CEC | CEC | CEC |
| | SOM required | t min | (kg ha$^{-1}$) | 1915 | 1915 | 1915 | 1915 | 4564 | 4564 | 4564 | 4564 |
| | SOM input | result | (kg ha$^{-1}$) | 4765 | 2854 | 1881 | 2937 | 4074 | 4564 | 2662 | 4564 |
| NEM | max NEM PCI | t max | (€ PRL ha$^{-1}$) | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | Meloidogyne Chitwoodi | result | (€ PRL ha$^{-1}$) | 0 | 0 | 0 | 0 | 58 | 146 | 296 | 196 |
| | Pratylenchus Penetrans | result | (€ PRL ha$^{-1}$) | 0 | 0 | 0 | 0 | 20 | 153 | 233 | 176 |
| SBP | max SBP PCI | t max | (€ PRL ha$^{-1}$) | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | Rhizoctonia Solani | result | (€ PRL ha$^{-1}$) | 0 | 101 | 101 | 126 | 7 | 46 | 157 | 76 |
| | Scliortinia | result | (€ PRL ha$^{-1}$) | 0 | 0 | 0 | 27 | 0 | 0 | 137 | 14 |
| | Verticilium Dahlae | result | (€ PRL ha$^{-1}$) | 0 | 0 | 3 | 0 | 0 | 0 | 4 | 0 |

Farm type & scenario acronyms: C = clay, S = Sand, I = intensive, E = extensive, _b = baseline, _ss = soil quality strategic
Soil quality indicators: N = Nitrogen, P = Phosphorous, K = Potassium, S = Sulphur, Mg = Magnesium, CEC = Cation Exchange Capacity, CRA = Crumbling Ability, WEV = Wind Erosion Vulnerability, SV = Slaking Vulnerability, SCI = Soil Compaction Index, PAW = Plant Available Water, SOM = Soil Organic Matter, PPN = Plant Parasitic Nematodes, SBP = Soil-Borne Pathogens.

tion management in Table 5 with the *PM* calculator module of FARManalytics. In all baseline scenarios the legal norm for P-application is lower than the P-advice (Table 7). In all baseline scenarios the Subsoil Compaction Index (SCI) exceeds the threshold value but extensive farms (*CE* and *SE*) have a better SCI score compared to intensive farms (*CI* and *SI*). This can be explained by the higher share of cereals that have a lower SCI impact. Besides P-advice and SCI, *CE_b* fulfils all soil quality thresholds. Additional concerns in *CI_b* are the high N-surplus and the low input of K. In *SI_b* and *SE_b*, the input of Sulphur (S), Magnesium (Mg) and Neutralizing Value (NV) is insufficient as S and Mg fertilization and liming (input of NV) are not in the current production management. Due to the very low Cation Exchange Capacity (CEC) of the sandy soil, an input of 4564 kg SOM $ha^{-1}$ is required to rise the CEC. Farms on sandy soils do not fulfil this threshold, although the input of SOM is substantially higher in *SE_b* compared to *SI_b*. Cultivating crops vulnerable for *M.chitwoodi* and *P.penetrans* causes the target value for these nematodes to be exceeded in *SI_b*. In both *CE_b* and *SE_b*, total profit is negative (Table 7).

### 3.3. Profit tactical scenario

The profit tactical scenario (*pt)* results from optimization of production management with the *PM* optimizer module of FARManalytics without soil quality constraints applied. Table 8 lists the production management choices for all scenarios. Table 9 breaks down the profit in its underlying components for all scenarios on all farm types. In the profit tactical scenario there are no soil quality constraints apart from the crop nitrogen requirements. Excluding cover crops results in a profit increase between €80 $ha^{-1}$ and €178 $ha^{-1}$ (Tables 7 and 9). The results also show the economic importance of pig slurry: its inclusion results in a profit increase of €10 to €93 and it helps to reduce fertilizer use (e.g., €188 $ha^{-1}$ higher profit due to reduced fertilizer use in *CI_p* compared to *CI_b*). Crop residues are always sold to generate additional profit compared to the baseline, yielding €150 $ha^{-1}$ on clay soil and €62 $ha^{-1}$ on sandy soil. In all profit scenarios, total profit increases substantially compared to all baseline scenarios, However, this is at the expense of soil quality. For example in scenario *SI_p*, the input of SOM is only 1187 kg $ha^{-1}$ whereas the threshold is 4564 kg $ha^{-1}$.

### 3.4. Soil quality tactical scenario

In the soil quality tactical scenario (*st*) the *PM* optimizer module of FARManalytics maximizes profit while fulfilling soil quality thresholds by changing cover crop choice, manure & fertilizer application and crop residue management. Cover crops are planted to achieve the soil cover requirement. On sandy soil, winter radish and *A. strigosa* are the preferred cover crops: winter radish is a non-host for the nematode *M. chitwoodi* and *A. strigosa* is a non-host for the nematode *P. penetrans*. By choosing these cover crops, the model is able to fulfill the soil cover constraint without violating the nematode constraint. Cattle slurry is preferred over pig slurry as it allows a higher input of K and SOM. This results in a decrease in profit generated with manure compared to the profit tactical scenarios, e.g. €29 $ha^{-1}$ in *CE_st* compared to €68 $ha^{-1}$ in *CE_pt*. On sandy soil, applying additional compost helps to meet the SOM target value. Because input of compost is a cost, profit generated with manure application decreases with respectively €45 $ha^{-1}$ for *SE_st* and €101 $ha^{-1}$ for *SI_st* compared to the baseline. Model results show a substantial decrease in fertilizer usage. The application of N fertilizer is reduced with approximately 50% in all *st* scenarios. P and K fertilizer are barely used anymore. Subsequently, profit increases in the range of €78 $ha^{-1}$ in *SE_st* up to €181 $ha^{-1}$ in *CI_st* compared to baseline. S and Mg fertilizer are applied on sandy soil to reach the target values. Betacal, available as a waste stream from sugar beet processing, is applied to increase and maintain pH at low costs. Even with soil quality constraints, crop residues are sold in all scenarios to generate additional profit.

### 3.5. Soil quality strategic scenario

The soil quality strategic scenario also allows for changes in the crop rotation. In *CE_ss* a 5-year rotation with sugar beets, seed onions and winter wheat is preferred. Within the 50% space for intensive crops, sugar beets and seed onions have the highest profit. In *CI_ss* 75% of the rotation can include intensive crops. Compared to the baseline, this scenario changes by increasing the frequency of seed onions and lowering the frequency of ware potatoes and sugar beets. A similar pattern can be observed in *SE_ss* and *SI_ss*. In *SE_ss*, silage corn is still cultivated despite its low revenue because there is no better alternative: 50% of the rotation must be filled with extensive crops and two consecutive cultivations of winter barley are not allowed. The ability to choose other crop rotations substantially increases the profit while soil quality thresholds (except SCI) can be achieved: Profit is €105 ha-1 in *CE_ss* while in *CE_st* profit is €618 $ha^{-1}$.

To illustrate the models' capability for more in-depth analyses, Table 9 includes ΔSOM against profit for all scenarios. The baseline scenarios for clay extensive and sand extensive perform well on ΔSOM but poorly on profit. This is exactly the other way around for the profit tactical scenarios on clay intensive and sand intensive: these scenarios result in high profit but low ΔSOM. ΔSOM is a limiting factor on sandy soil, but not on clay soil as all the optimized scenarios on sandy soil are exactly on the target value. These results show that when the model is able to change more production management decisions (i.e., crop rotation in soil quality strategic scenarios), the trade-off between ΔSOM and profit can be overcome. For all farm types, the ΔSOM target can be met while increasing profit compared to the baseline scenarios.

## 4. Discussion & conclusions

The objective of this study was to develop and illustrate FARManalytics, a bio-economic modeling approach to maximize economic returns while preserving soil quality. FARManalytics is illustrated for scenarios on four standard farm types in the Netherlands.

### 4.1. Model outcomes and model behaviour

For FARManalytics to provide added value, it should provide credible outcomes with regard to soil quality indicators and farm economics in different scenarios.

#### 4.1.1. Baseline scenario

The model is able to calculate the impact of current farmers' production management on soil quality and profit on crop enterprise on different soil types and scenarios. For example, the farm types "clay intensive" and "sand intensive" have a higher profit but a lower score on the soil quality indicators soil organic matter (SOM) input and subsoil compaction vulnerability compared to the farm types clay extensive and sand extensive. The model calculates correctly that crop and soil requirement differ per soil type i.e., higher levels of SOM, lime and nutrients on sand compared to clay.

#### 4.1.2. Profit tactical scenario

When farmers optimize their management for short-term profit few soil quality constraints are applied, only legal nutrient norms and a requirement for sufficient nitrogen (N) input are taken into account. As expected, cover crops are not implemented as they have a negative direct impact on profit and in the absence of soil quality constraints there is no incentive to do so. Pig slurry is the preferred manure type, as it is available at a price premium for the arable farmer. This is confirmed by substantial decreases in fertilizer use because except for N, for which there are no minimal nutrient input requirements. Crop residues are always sold to generate additional revenue.

**Table 8**
- Production Management choices made by bio-economic modeling approach FARManalytics for scenarios on arable farm types in the Netherlands. Farm types: CE = Clay extensive, CI = Clay intensive, SE= Sand extensive, SI = Sand intensive. Scenarios: b= baseline, pt = profit tactical, st = soil quality tactical, ss = soil quality strategic. Crop acronyms: WP = Ware potatoes, SB= Sugar beets, CA = Carrots, SO= Seed onions, WW = Winter wheat, WB = Winter barley, SC = Silage corn. Cover crop acronyms: WR = Winter radish, OVP = Mixture of oats, vetch and phacelia, YM = yellow mustard, AV = Avena Strigosa, RY = Winter rye a = autumn termination, s = spring termination. Manure: PS= Pig slurry, CS = Cattle slurry, CSM = Cattle Solid Manure, GFTC = GFT compost, GRC = Green compost. Lime: BET = Betacal flow (Liquid lime-rich waste stream available from sugar beet processing)

| | | | | Covercrops | | | | | | | | | | Crop residues *(s: sell/ k: keep)* | | | | | | | | | | Manure (*avg. ton ha$^{-1}$ y$^{-1}$*) | | | Lime | Fertilizer (*avg. kg ha$^{-1}$ y$^{-1}$*) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Nr | Farm | Scenario | Crop rotation (-) | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | type 1 | type 2 | type 3 | *(avg. ton ha-1 y-1)* | N | P | K | S | Mg |
| 1 | CE | b | WP-WW-SB-WW-WP-WW-SB-WW | | $WR_a$ | | $WR_a$ | | $WR_a$ | | $WR_a$ | | | | k | | k | | k | | k | | | CS: 20 | CSM: 10 | | | 130 | 0 | 34 | 7 | 18 |
| 2 | CE | pt | WP-WW-SB-WW-WP-WW-SB-WW | | | | | | | | | | | | s | | s | | s | | s | | | CS: 7.5 | PS: 12.5 | | | 77 | 0 | 0 | 0 | 0 |
| 3 | CE | st | WP-WW-SB-WW-WP-WW-SB-WW | | $OVP_s$ | | $OVP_s$ | | | | | | | | s | | s | | s | | s | | | CS: 31.7 | PS: 3.2 | | | 64 | 0 | 0 | 3 | 3 |
| 4 | CE | ss | SO-WW-SB-WW-WW | | $OVP_s$ | | | | | | | | | | s | | s | s | | | | | | CS: 19.2 | PS: 8 | | | 65 | 0 | 0 | 2 | 2 |
| 5 | CI | b | WP-WW-SO-SB-WP-WW-CA-SB | | $YM_a$ | | | | $YM_a$ | | | | | | s | | | | s | | | | | CS: 10 | PS: 13.1 | | | 110 | 0 | 69 | 14 | 14 |
| 6 | CI | pt | WP-WW-SO-SB-WP-WW-CA-SB | | | | | | | | | | | | s | | | | s | | | | | CS: 7.5 | PS: 12.5 | | | 48 | 0 | 0 | 0 | 0 |
| 7 | CI | st | WP-WW-SO-SB-WP-WW-CA-SB | | $OVP_s$ | $AV_s$ | | | $OVP_s$ | | $AV_s$ | | | | s | | | | s | | | | | CS: 40 | | | | 48 | 0 | 0 | 4 | 4 |
| 8 | CI | ss | WP-WW-SO-SB-WP-CA-WW-SO-SB-WW | | $OVP_s$ | $AV_s$ | | | | $OVP_s$ | | | $AV_s$ | | s | | | | s | | | s | | CS: 29.6 | PS: 4.0 | | | 45 | 0 | 6 | 3 | 3 |
| 9 | SE | b | WP-SC-WB-SB-WP-SC-WB-SB | | | $WR_a$ | | | | $WR_a$ | | | | | | k | | | | k | | | | CS: 22.5 | CSM: 3.1 | GFTC: 5 | | 90 | 3 | 59 | 4 | 0 |
| 10 | SE | pt | WP-SC-WB-SB-WP-SC-WB-SB | | | | | | | | | | | | | s | | | | s | | | | PS: 15.4 | | | | 44 | 0 | 0 | 0 | 0 |
| 11 | SE | st | WP-SC-WB-SB-WP-SC-WB-SB | $AV_s$ | | $OVP_s$ | | | | $AV_s$ | | | | | | s | | | | s | | | | CS: 28.5 | GRC: 11.0 | | BET: 1.3 | 48 | 0 | 32 | 16 | 15 |
| 12 | SE | ss | SB-SC-WB-SO-WB-SB-WB-SC-SO-WB | | | $AV_s$ | | $AV_s$ | | | $AV_s$ | | | | | s | | s | | s | | | s | CS: 27.2 | GFTC: 1.6 | GRC: 9 | BET: 1.3 | 39 | 0 | 0 | 18 | 15 |
| 13 | SI | b | WP-WB-SB-CA-WP-SC-SB-SO | | $WR_a$ | | | | $RY_s$ | $RY_s$ | $YM_s$ | | | | s | | | | | | | | | CS: 29.4 | | | | 90 | 13 | 67 | 2 | 0 |
| 14 | SI | pt | WP-WB-SB-CA-WP-SC-SB-SO | | | | | | | | | | | | s | | | | | | | | | PS: 15.4 | | | | 35 | 0 | 0 | 0 | 0 |
| 15 | SI | st | WP-WB-SB-CA-WP-SC-SB-SO | | $WR_s$ | | | $AV_s$ | $AV_s$ | $AV_s$ | | | | | s | | | | | | | | | CS: 25 | GRC: 13.3 | | BET: 3.7 | 48 | 0 | 40 | 16 | 15 |
| 16 | SI | ss | WP-WB-SO-SB-WP-CA-WB-SO-WB-SB | | $AV_s$ | | | | | $AV_s$ | | $AV_s$ | | | s | | | | | s | | s | | CS: 14.3 | GRC: 8.7 | GFTC: 1.5 | BET: 1.3 | 45 | 0 | 10 | 14 | 13 |

*4.1.3. Soil quality tactical scenario*

In the tactical scenario, soil quality constraints are applied and the model is allowed to change the cover crops, manure, fertilizer and crop residue management within the existing rotation. The model can meet the soil quality targets without implementing relatively costly (ca. €250 ha$^{-1}$) cover crops. This contradicts current common practice in Dutch arable farming where cover crops such as winter wheat are grown after all early harvested crops. Farmers' might perceive additional benefits from cover crops than those currently included in our soil quality indicator set. The agronomic benefits of cover crops are also broadly acknowledged in literature including soil organic matter build-up, minimal nutrient losses and improved soil structure (Hao et al., 2023; Adetunji et al., 2020). The types of cover crops themselves are credible: on clay soil oats, vetch and phacelia are preferred as they are vulnerable to frost, do not regrow and provide up to 75 kg N ha$^{-1}$ for the following crop. On sandy soil, winter radish and *A. strigosa* are preferred as they do not host problematic plant-parasitic nematodes. Regarding manure, cattle slurry and compost are preferred over inorganic fertilizers and pig slurry. Cattle slurry is freely available and a valuable source of nutrients and SOM. Additional compost is applied on sandy soil, as it can provide more organic matter per unit phosphorous (P), where the P application is legally limited by manure regulations. Taking all soil quality constraints into account, the model is still able to substantially reduce fertilizer use. These results differ greatly from the current practice in the baseline scenario. Regarding N, one explanation is that the model considers, contrary to current practice, all possible sources of N (i.e. deposition, soil mineralization and mineralization from manure). However, N losses such as volatilization, leaching and denitrification during the growing season are not taken into account which may lead to an overestimation of the amount of available nitrogen. Given the organic matter and nutrient inputs via manure and compost, in combination with the relatively high contents in the soil, P and potassium (K) fertilizer are not needed. Even with all soil quality constraints in place, crop residues of winter wheat and winter barley can be sold in all scenarios. Selling these crop residues results in additional profit (€250 - €300 ha$^{-1}$) while the associated removal of nutrients and SOM can be compensated by other management choices (i.e. applying manure or growing cover crops). Nevertheless, this result is remarkable: on Dutch farms it is common practice to keep the crop residues on the field for their perceived benefits on soil quality.

*4.1.4. Soil quality strategic scenario*

Changing the cropping plan or crop rotation had a substantial impact on the profit at farm level, particularly when onions were included. This finding illustrates the added value of our economic calculation framework for crop profit, which is in line with the conclusions drawn by Mattetti et al. (2022) who state that "the existence of robust and reliable cost is of outmost importance for making informed decisions". Our findings correspond to those of others, e.g. Alfandari et al. (2015) and Capitanescu et al. (2017), who show that the crop rotation is of major importance for both agronomical and economic performance. Despite the pivotal role of the cropping plan, inclusions of other production management decisions such as cover crops, manure, fertilizer and crop residues are crucial to meet soil quality thresholds (Dogliotti et al., 2005). For example, soil organic matter can be optimized by applying manure or compost and growing cover crops. The soil quality threshold can never be met solely based on changes in the cropping plan.

*4.1.5. Synthesis*

Nutrient management, soil compaction and soil organic matter input pose major challenges for soil quality in the Netherlands (Mandryk et al., 2014; Ros et al., 2022; Silva et al., 2021). Numerous studies recommend production management decisions based on models, field experiments or statistical analysis. For example:

**Table 9**
– Farm profit broken down in its different underlying components vs. input of soil organic matter (ΔSOM) for scenarios on arable farm types in the Netherlands. Scenarios with a total negative profit or scenarios that do not achieve the ΔSOM target are underlined and indicated in red.

| Scenarios | | | Profit or costs *(€ ha⁻¹ year⁻¹)* | | | | | | | ΔSOM (kg ha⁻¹ jaar⁻¹) | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Nr | Farm | Scenario | Crop | Cover crop | Manure | Crop residue | Fertilizer | Land | Total profit | min. target | result |
| 1 | CE | *b* | 1222 | -178 | -10 | 0 | -256 | -1100 | <u>-322</u> | 1915 | 4765 |
| 2 | CE | *pt* | 1222 | 0 | 68 | 150 | -123 | -1100 | 217 | 1915 | 2080 |
| 3 | CE | *st* | 1222 | -88 | 29 | 150 | -108 | -1100 | 105 | 1915 | 3285 |
| 4 | CE | *ss* | 1683 | -70 | 32 | 180 | -107 | -1100 | 618 | 1915 | 2845 |
| 5 | CI | *b* | 1672 | -80 | 58 | 75 | -264 | -1100 | 361 | 1915 | <u>1881</u> |
| 6 | CI | *pt* | 1672 | 0 | 68 | 75 | -76 | -1100 | 639 | 1915 | <u>1678</u> |
| 7 | CI | *st* | 1672 | -172 | 28 | 75 | -83 | -1100 | 420 | 1915 | 3290 |
| 8 | CI | *ss* | 1803 | -138 | 35 | 90 | -81 | -1100 | 609 | 1915 | 2937 |
| 9 | SE | *b* | 697 | -89 | -6 | 0 | -201 | -600 | <u>-199</u> | 4564 | <u>4074</u> |
| 10 | SE | *pt* | 697 | 0 | 77 | 62 | -71 | -600 | 165 | 4564 | <u>1324</u> |
| 11 | SE | *st* | 697 | -129 | -51 | 62 | -123 | -600 | <u>-144</u> | 4564 | 4564 |
| 12 | SE | *ss* | 1087 | -102 | -43 | 100 | -84 | -600 | 358 | 4564 | 4564 |
| 13 | SI | *b* | 1113 | -163 | 29 | 31 | -218 | -600 | 192 | 4564 | <u>2662</u> |
| 14 | SI | *pt* | 1113 | -42 | 77 | 31 | -55 | -600 | 524 | 4564 | <u>1187</u> |
| 15 | SI | *st* | 1113 | -172 | -72 | 31 | -130 | -600 | 170 | 4564 | 4564 |
| 16 | SI | *ss* | 1252 | -102 | -44 | 75 | -97 | -600 | 484 | 4564 | 4564 |

Farm types: CE = clay extensive, CI = clay intensive, SE = sand extensive, SI = sand intensive.
Scenarios: b = baseline, p = profit tactical, st = soil quality tactical, ss = soil quality strategic

- Silva et al. (2021) studied the impact of different nutrient sources (fertilizer, manure) on N uptake efficiency and N surplus.
- Hanse et al. (2011) studied the impact of subsoil compaction on sugar beet yield and found that lower soil stress caused by lower axle load and less field operations reduce the occurrence and impact of soil compaction.
- Hijbeek et al. (2018) studied farmer intentions to adopt production management decisions such as input of animal manure or compost, cereal crops in crop rotation and cover cropping to increase SOM content.

All these studies focus on management recommendations for a specific indicator on field level. However, the decision-making process at the farm level must take all soil quality aspects into account in a specific socio-economic context (Schreefel et al., 2022). FARManalytics allows to make decisions with a holistic view on soil quality and the inclusion of socio-economic aspects can help to select production management decisions that ensure the long-term preservation of soil quality while maintaining a financially robust strategy. This is illustrated in the sand soil quality scenarios, where an ambitious SOM threshold has to be met: the solution provided by FARManalytics is to use a combination of compost and slurry and still sell crop residues. The input of compost and slurry ensures sufficient input of SOM and nutrients, while selling crop residues increases the profit.

### 4.2. Model evaluation

FARManalytics is a bio-economic modeling approach that integrates the impact of production management choices on soil quality and economics at farm level. However, the current set-up of FARManalytics has some limitations.

#### 4.2.1. Soil quality indicator selection

Compared to some other studies, on soil quality indicators, our study contains a limited number of physical and especially biological indicators (Dominati et al., 2010; Greiner et al., 2017; Jónsson and Davídsdóttir, 2016). Bünemann et al. (2018) review studies with a more extensive set of physical indicators (e.g., penetration resistance, hydraulic conductivity and aggregate stability) and biological indicators (e.g., soil respiration, earthworms, and microbial diversity). The main reasons why we did not include these indicators are: (1) their evolution over time as a result from production management could not be calculated, (2) indicator data is not available or (3) threshold values are not available. Bünemann et al. (2018) and Ros et al. (2022) also described this limitation.

#### 4.2.2. Soil quality indicator set-up

The current indicator set is based on Dutch national circumstances, calculations and samples. We believe this approach is justifiable, as agronomy is always controlled by local site conditions and no commonly accepted international set of soil quality indicators is available. Besides arable farming, the indicator set can also be used in other types of farming, e.g. dairy, vegetable and flower production (see Ros et al., 2022). However, it is likely that in its current form the set of soil quality indicators does not generalize outside the Netherlands. The indicator set can, however, be adapted to other site conditions: indicators and constraints can be supplemented or replaced by more representative ones for other countries to do comparable analyses (as illustrated by Ros et al., 2022). For some quality indicators (e.g., Cation Exchange Capacity and plant parasitic nematodes), thresholds are based on expert judgement. Broader application and validation would be encouraged to generate field experimental evidence. Detailed limitations and recommendations for every soil indicator are provided in the soil quality factsheets in Appendix A-3.

#### 4.2.3. Target-oriented approach

FARManalytics uses a target-oriented approach in which the required value of soil quality indicators and production management is derived from a target yield level that does not respond dynamically to the environment (van Ittersum, Rabbinge, 1997). However, one of the key questions that remains is: how do crop yield and future profit respond to changes in soil quality? Answering this question requires detailed production functions where yield is a function of soil quality. Although such functions exist for individual components, such as nitrogen and are included in crop models e.g. Jones et al., (2003), to the best of our knowledge such functions are currently not able to capture soil quality and its interrelations as a whole. We recommend that such functions are based on long-term field experiments. Examples where such functions can be based on can be found in Bongiorno et al. (2019), Schrama et al. (2018) and Korthals et al. (2014).

#### 4.2.4. Production management decisions

Although the current set-up covers the most crucial production management decisions, the model can be extended to include additional decisions. First, we suggest including crop cultivar selection, as different cultivars of the same crop can have substantially different impacts on soil quality. Second, more detailed decisions regarding machinery used in field operations could be included as a means to control the limiting indicator subsoil compaction vulnerability.

#### 4.2.5. Farm heterogeneity & economics

The economic outcomes of FARManalytics are strongly dependent on economic input variables, e.g. the crop profit. These economic input variables can vary strongly between farms and deviate substantially from the average number we used in the standard farms. This can explain why i.e. the crop profit on potatoes in Table 6 is only €20 $ha^{-1}$, while potatoes are considered one of the most important cash crops in the Netherlands. Three main factors can explain these variation. First, the farm set-up. For example economies of scale and geographical location can lead to lower production costs compared to average numbers and other farmers. Second, opportunity costs: Whereas our approach calculates opportunity costs on own labour and capital, farmers often neglect them. This might lead to a positive bias towards labour and capital intensive crops. Third, crop yield & price: Crop yield and price can vary substantially between farms and over years, which implies that some farmers can gain higher earnings compared to average numbers and other farmers.

#### 4.2.6. Risks & uncertainty

FARManalytics is a static and deterministic model with the objective to maximize profit. However, in reality dynamics (e.g., weather circumstances) and uncertainty (e.g., fluctuating input- and output prices) are of pivotal importance (Ridier et al., 2016; Lien and Hardaker, 2001). Farmers might be willing to implement production management with lower returns, but also at lower risks and uncertainty (Dury et al., 2012). A first step to gain more insight in the risks and uncertainty involved in production might be to do a sensitivity analysis on model inputs and run different worst- and best-case scenarios (Kleijnen, 1994). A more thorough solution is to explore the options for stochastic or robust optimization (Najafabadi et al., 2019; Yue et al., 2022).

### 4.3. Implications for use of model

Our study proves that integrating soil quality and economics at farm level contributes to solving the socio-economic challenge of sustainable soil management. FARManalytics can be used as a decision support system in the following contexts:

- *Policy impact analysis:* FARManalytics provides insight in the impact of current management on farm economics and long-term soil quality based on a reasonable number of input variables that are commonly available. When combined with representative farm types such as the farm types in this study, this can yield valuable information on where issues with soil quality will arise. FARManalytics can provide alternative production management decisions that increase farm level profit while preserving soil quality. These results can provide insight in the effectiveness of different production management decisions on soil quality and farm profit, and can therefore inform policy on sustainable soil management.
- *Farm-level decision support*: FARManalytics can be tailored to individual farms for a thorough economics analysis, informing decisions to increase short-term income. One example, from the scenarios in this study is to cultivate more seed onions instead of ware potatoes. When tailored to individual farms, FARManalytics can also provide insight in the expected development of soil quality and profit. Common strategies to achieve sustainable soil management while earning highest profit for the scenarios in this study are (1) optimizing the crop rotation, (2) reducing fertilizer use and (3) selling crop residues. Optimal alternative strategies are strongly dependent on the initial soil status and economic situation of the farm, but FARManalytics can be tailored to fit the specific circumstances of farms. For credible results at farm-level it is of outmost importance that the input data is complete and matches local and farm conditions.

The following potential future developments could further improve FARManalytics:

- Inclusion of more physical and biological indicators. Availability of sound soil quality indicators and subsequent agronomic advice hampers further extension of the model.
- Integration stand-alone tools: FARManalytics provides integral insight in crops, cover crops and manure and fertilizer application at a level of detail comparable to other stand-alone tools. Integrating more tools into FARManalytics will make FARManalytics more userfriendly for bio-economic modeling of individual farms.
- Link to farm management systems: Many of the inputs for FARManalytics are already registered in a farm management systems. Direct integration would make FARManalytics modeling more straightforward.

### 4.4. Conclusions

- FARManalytics, a bio-economic model proved to be helpful to provide quantitative insight in the economic aspects of sustainable soil management at farm level.
- Subsoil compaction vulnerability, soil organic matter input and plant-parasitic nematodes are identified as the main soil quality issues.
- Profit can increase with up to €940 $ha^{-1}$ $year^{-1}$ on clay soil and with €683 $ha^{-1}$ $year^{-1}$ on sandy soil by appropriate management.
- The main shortcoming of the model are the limited number of physical and biological soil quality indicators included and the static and deterministic modeling approach.
- FARManalytics for standard farm types can inform policy impact analysis. If required data are available, FARManalytics can be tailored to individual farms.

## CRediT authorship contribution statement

**H.W. Saatkamp:** Writing – review & editing, Supervision, Conceptualization. **M.P.M. Meuwissen:** Writing – review & editing, Supervision. **G.H. Ros:** Writing – review & editing, Methodology, Conceptualization. **G.D.H. Claassen:** Writing – review & editing, Supervision, Conceptualization. **M.C. Kik:** Writing – original draft, Software, Methodology, Conceptualization. **A.B. Smit:** Writing – review & editing, Supervision, Conceptualization.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data Availability

Data will be made available on request.

## Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.eja.2024.127192.

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