THE ISSUE OF SCALE WHEN CONSIDERING SYNERGIES AND TRADE-OFFS IN SOIL FUNCTIONS

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1. Introduction

Food production is closely associated with environmental problems such as biodiversity loss, eutrophication, compaction or erosion (Tilman *et al.*, 2001). Governmental and international environmental goals with regard to food security and sustainability require choices regarding land use that promote the first without compromising the latter. As a result, land managers are continuously challenged to maintain or even increase primary productivity while simultaneously decreasing externalities. To aid in this, farmers, scientists, advisory agencies, policy makers and other stakeholders are trying to come up with viable strategies and frameworks to reduce the negative impacts of farming (Garibaldi *et al.*, 2017). One such framework, functional land management, was introduced by Schulte et al. (2014) and puts soils at the forefront of this issue. Soils are the basis of agricultural yield, but they also provide multiple other ecosystem services (or soil functions) that are of great importance to society (Hurni *et al.*, 2015; Bommarco *et al.*, 2018). The functional land management framework highlights five main soil functions of agricultural soils: primary productivity, nutrient cycling, water regulation and purification, climate mitigation and biodiversity and habitat provision (Schulte *et al.*, 2014; Schröder *et al.*, 2016; Sandén *et al.*, 2019; Van de Broek *et al.*, 2019b; van Leeuwen *et al.*, 2019). The delivery of each of these functions depends on the characteristics of the soil, the environmental constraints in the landscape (such as the climate and orography) and the management that is imposed on the system (Coyle *et al.*, 2016). Agricultural soils can provide more than one of these functions simultaneously, but rarely deliver all five functions (Zwetsloot et al., 2020). Sustainability at the landscape level can be achieved if individual fields provide a variety of functions (Fig.1) (Schulte *et al.*, 2015).

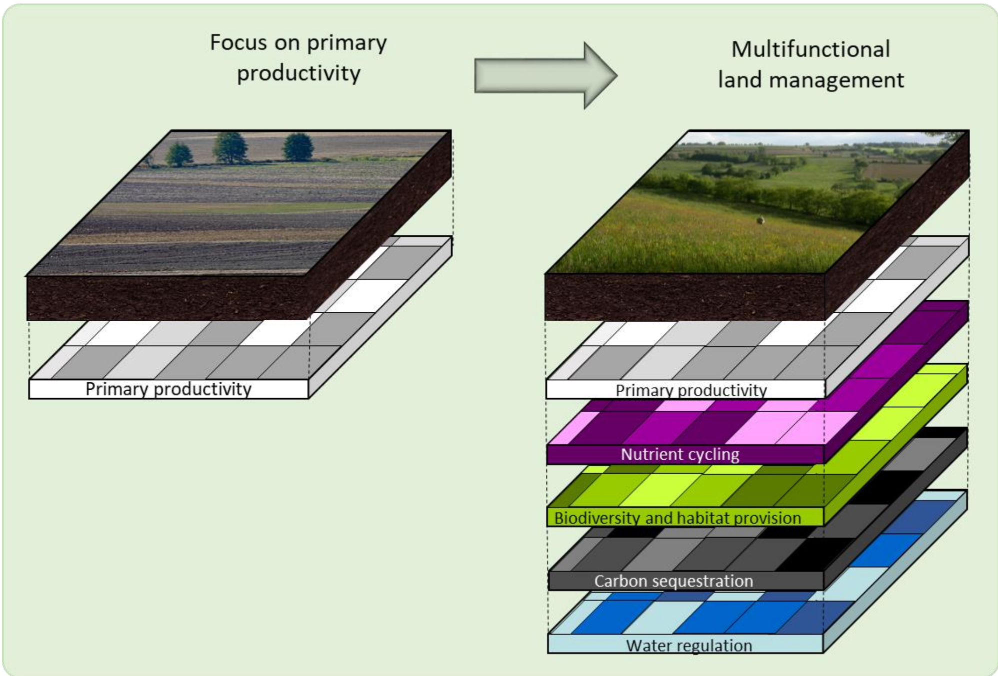

Figure 1. Multifunctional land management aims to shift the focus on primary productivity to the delivery of several soil functions simultaneously at several levels (Schulte et al. 2014).

It is important, therefore, that land managers understand which functions can be delivered by their agricultural systems and where trade-offs exist between soil functions. To this end, the Landmark project, a European-funded research project developed a set of multi-criteria decision models that qualitatively describe the afore-mentioned soil functions (Debeljak et al., 2019). These models were combined into a freely available online tool: The Soil Navigator (www.soilnavigator.eu), a decision support system that predicts the delivery of the five soil functions and provides advice regarding management practices that could improve target functions (Hobbs *et al.*, 2008; Schulte *et al.*, 2014; Schreefel *et al.*, 2020). The Soil Navigator tool has been used to provide an overview of soil multifunctionality both at a European scale, as well as insight into the relationships between soil functions in different agricultural systems spread across five pedoclimatic zones (Zwetsloot *et al.*, 2020). While Landmark provided a significant starting point in the assessment of soil multifunctionality at the field level, it was designed with a pan-European focus and as such had to include a wide range management practices and landscape characteristics to ensure reasonable coverage. When applied within one country, in this case the Netherlands it requires further validation and specification to ensure its applicability and provide a high level of accuracy to local users within their given context.

The goal of this wildcard project was to test the application of the Soil Navigator utilising datasets from within the Netherlands. To enable the assessment of accuracy of the models, and provide insights into potential changes required in the models to better suit the local context.

A third goal was to consider how the Soil Navigator could be utilised within the Netherlands to assess multifunctionality not only at field scale but to establish targets for soil health for different land-use management systems at regional level.

Objectives

The main objectives of this project are to:

- evaluate the delivery of five soil functions, as well as synergies and tradeoffs associated with agricultural production systems in the Netherlands at field level as well as at a regional level using existing datasets,
- evaluate the suitability of the Soil Navigator to evaluate soil functions in the Netherlands, and
- highlight points for potential improvement in the Soil Navigator to better suit the Dutch system.
- investigate possible solutions for the upscaling of information to provide regional scale soil health benchmarks.

In order to carry out these objectives, this project leans on already-existing datasets. Due to the fact that these data were not collected with the purpose of evaluating soil multifunctionality, it is recognised that they are not perfectly suited to this purpose. Therefore, an additional objective to this study will be to:

- evaluate the suitability of existing datasets to evaluate soil multifunctionality, and
- explore potential solutions when the datasets are incomplete.

2. Methods

In order to achieve the main objectives of this study, we obtained datasets from different programs, namely;

1) *Bedrijvennetwerk Bodemmetingen* (BB)

2) *Koeien en Kansen* (K&K) and

3) *Landelijk Meetnet Effecten Mestbeleid* (LMM).

These datasets contained information on the soil physical, chemical and biological characteristics and some aspects related to farm management. The suitability of each of these data sources to assess multifunctionality using the Soil Navigator was examined. When parameters necessary to run the Soil Navigator were missing, we contacted either the project leaders or other experts to find either default values or alternative sources for those missing parameters. Some of these alternative solutions could not be applied within the scope of this project, but are nonetheless noted in this report for future investigations. When the data and time allowed, we calculated multifunctionality of Dutch soils using the Soil Navigator, and explored the synergies and trade-offs between soil functions using correlation plots. From these efforts we also gathered information on potential adjustments to the soil Navigator. When the data or time did not allow, we provide a clear set of next steps to further continue this effort in the future.

2.1 Assessing soil functions

To assess the delivery of the main five soil functions associated with agricultural soils we used the models developed by the Landmark Project (www.landmark2020.eu). Landmark developed five independent multi-criteria decision models, one per studied soil function (Schröder *et al.*, 2016; Debeljak *et al.*, 2019; Sandén *et al.*, 2019; Van de Broek *et al.*, 2019a; van Leeuwen *et al.*, 2019; Wall *et al.*, 2020). These models were created by European expert teams on each of the soil functions, and later evaluated and validated. The models are hierarchical and build up to a final function score of low, medium or high supply. Input variables related to the management, environment and soil properties are first discretized according to defined thresholds specific to climatic zones and land use. The input variables aggregate to the upper level of the model structure through if-then functions and aggregation continues until the top node is reached and an assessment of the performance of a specific function is made. Some nodes in the model have higher weights than others in the final assessment, these weights were initially defined by the experts, but in some cases were refined through the use of data mining techniques (Trajanov et al. 2019). The models were built using The Decision Expert integrative methodology (Bohanec and Rajkovič 1990; Bohanec 2008; Bohanec et al. 2013). The advantage of this methodology is that it allows for quick adjustments to the if-then functions and weights that determine the final assessment. however is that this software. The Decision Support Models which support the final Soil Navigator allow for further investigation into;

1) appropriateness of input parameters

2) thresholds applied to parameters for integration nodes

3) weights applied to super-attributes that define the final functional capacity for a given function model.

The data in this project was assessed using the Soil Navigator online tool which integrates the five function submodels into one framework which harmonises thresholds for parameters across the different modelsSoil Navigator simultaneously (Trajanov et al. 2019).

Field scale data is input manually into the online Soil Navigator tool, and the results are then manually recorded for further analyses. This can be laborious for large datasets and as a result The Soil Navigator is currently being translated into R by researchers at the Jožef Stefan Institute in Slovenia, which would facilitate rapid input and analysis of entire datasets.

2.2 Data sources

Bedrijvennetwerk Bodemmetingen (BB)

The BB (the Soil-Measurements Business Network in English) consists of 16 arable farms spread throughout the Netherlands (Fig. 2). Multiple aspects of soil quality are measured on these farms over time in order to provide better advice for the farmers, enable monitoring over time, and provide advice to improve soil quality (www.beterbodembeheermagazine.nl/wur-najaar-2020/bedrijvennetwerk-bodemmetingen.)

Koeien & Kansen (K&K)

The primary goal of the K&K project (Cows and opportunities in English) is to implement expected environmental legislation on a group of dairy farms. By doing so, the project can visualize the environmental, technical and economic consequences of future legislation at company level (www.koeienenkansen.nl).

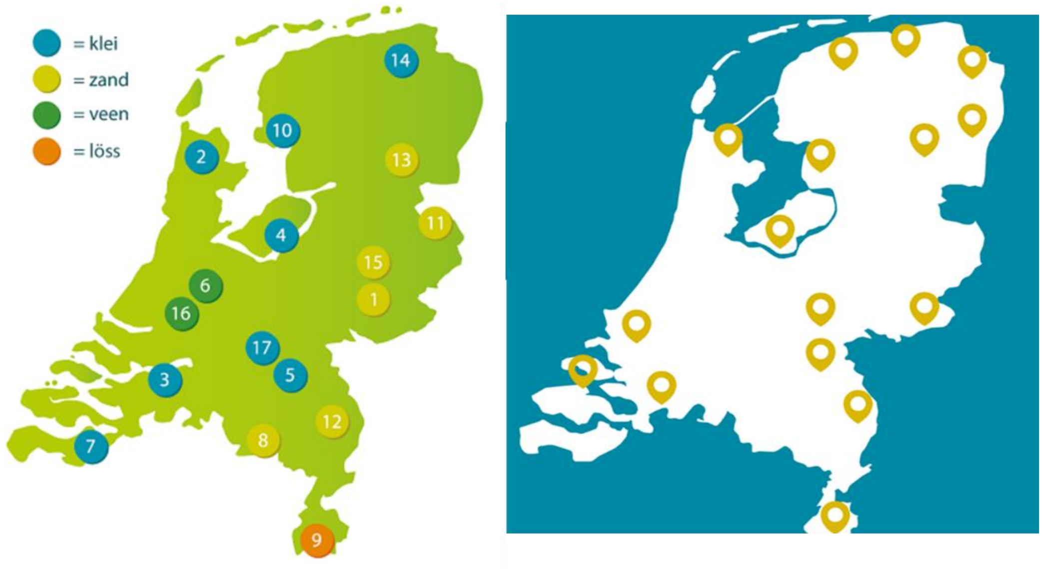

Figure 2. Location of the dairy farms taking part in Koeien & Kansen (Cows and opportunities) on the left hand side and the arable farms that take part in the Bedrijvennetwerk Bodemmetingen (Company network for soil measurements) on the right hand side. Klei: clay soils, zand: sandy soils, veen: peat soils, löss: loess soils.

Landelijk Meetnet Effecten Mestbeleid (LMM)

The LMM (or National Monitoring Network for the Effects of Manure Policy in English) is a program with the aim of monitoring and recording the effects of the manure policy on business management and water quality on Dutch farms. The LMM is jointly managed by the National Institute for Public Health (RIVM) and the Environment and Wageningen Economic Research. The objectives of the LMM are to describe and explain the current quality of groundwater in relation to environmental pressures and policy measures and to research the consequences of changes in agricultural practice and for the quality of recently formed groundwater. Additionally, as part of this monitoring effort, Wageningen Economic Research collects and registers a considerable set of farm level data from all participants in the LMM. These farms are located across the Netherlands and classified into the main 14 farming regions that have been defined by the LMM (Fig. 3). This classification restricts the potential for regionalization, as we were not granted access to more specific geospatial information.

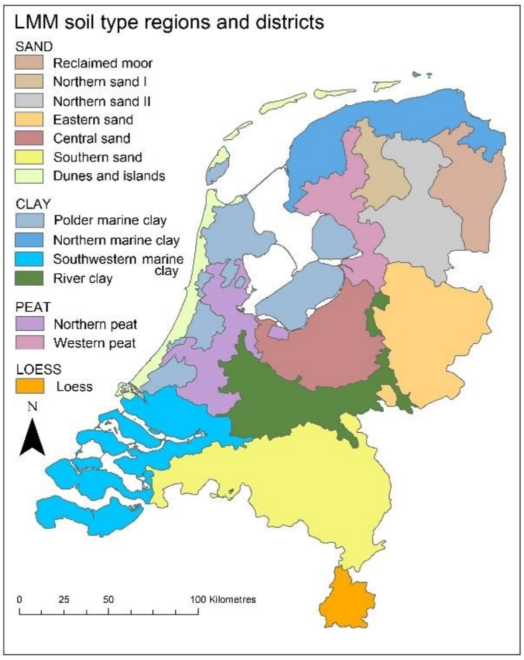

Figure 3. Soil type regions and districts according to the National Monitoring Network for the Effects of Manure Policy (Lukacs *et al.*, 2019).

Soil data and maps

There exists in the Netherlands a breadth of information regarding soil characteristics, many of which is available via the data portal for BIS Nederland (www.bodemdata.nl). Much of this information has recently been used to create high resolution 4-dimensional soil models and maps by the BIS-4D project, in Wageningen University. While most of the information refers to soil physico-chemical parameters, this platform also offers digitalised information on management variables such as crop information at field level for several years, the presence of dikes or the application of manure (A. Helfenstein, personal communication). This means that these data cannot be used on their own to run the Soil Navigator, but rather can complement other existing datasets.

2.3. Evaluation of the datasets' suitability

The first step was to combine all variables needed as input parameters into the Soil Navigator into a single master dataset (Appendix). This list of parameters was shared with the collaborating teams, who provided the matching data where available, or a set of measured attributes that could be used as proxies for these input parameters. When proxies were provided, we provide information on how to work with these to calculate soil functions. In some cases parameters were not measured in the datasets used in this study, proxy variables were also not available. In such cases, we first contacted the project leaders for their expert opinion, and followed up with online searches for databases, maps and relevant literature. We also contacted additional experts in the field to investigate potential sources for the missing information.

2.4 Exploration of potential changes to the Soil Navigator

A key objective of this study was to explore parameter input, threshold and weights which should be adjusted to further validate the Soil Navigator for the Dutch agricultural system. To do so, we first observed the results obtained from assessing soil multifunctionality at field level on the 32 fields from the BB. We specifically looked at whether discretization according to the threshold values proposed in the Soil Navigator separated the fields into different categories or not. If discretization did not separate the fields, variability in the Dutch system might not be captured. In such cases new thresholds could be explored, or that variable may be redundant in the Dutch context.

In the second step we observed whether the final assessments of soil functions divided the fields according to performance into high, medium or low performing fields, or whether they produced only one assessment for most fields. For example, if using the Soil Navigator on 32 fields in the Netherlands provided the assessment that all fields have high nutrient cycling, this could be indicative that the model does not capture the variability of nutrient cycling in the Netherlands, or that nutrient cycling is uniform over the studied area. A solution to increase the sensitivity to the model is to either change the weights of different parts of the models, to add variables that might increase the predicting powers of the model, or to eliminate variables that are redundant in the given system. In fact, these tasks were undertaken by the authors of the Soil Navigator using machine learning techniques, but without a specific focus on the Dutch system (Sandén *et al.*, 2019; Wall *et al.*, 2020). Specifically, the authors used data mining to find parts of the model that were redundant or to alter the weights that experts had assigned to particular nodes of the model in order to increase the model's predictive capacity. In the case that we find a lack of classification ability by the model, we will use classification trees to identify the input variables with the most significant explanatory power for the dataset, using soil function performance as a response variable. We choose to use classification trees (Breiman *et al.*, 2017) for this endeavour as it serves several purposes simultaneously: it provides an importance factor for each explanatory variable, and it provides thresholds used at each split of the tree that could then be used to re-assess the thresholds used in the Soil Navigator functions (Henderson et al., 2005). The goodness of fit of the classification tree is given as a probability of correct or incorrect classifications. We will use the 'rpart' package in R (Therneau *et al.*, 2015; R Core Team, 2019). In order to carry out this effort, the response variable needs to first be discretized. This discretization will be discussed further in the text, as it is dependent on the results of the first exploration.

3. Results and discussion

3.1. Suitability of existing datasets

A common disadvantage of using existing datasets, is that these were gathered for purposes other than the assessment of multifunctionality using the Soil Navigator. The first step in completing this exercise was to explore the suitability of each dataset to the calculation of soil functions. To do so, we compiled the input variables necessary to run the Soil Navigator (Appendix 1), and compared them to the variables included in the aforementioned datasets.

Bedrijvennetwerk Bodemmetingen

This project provided data from two fields for each farm (a total of 32 fields) on the management as well as several soil physical, chemical and biological characteristics. These data were provided as separate written reports for each field. Information relevant to this study was extracted from each of these reports and put into an excel sheet. Numeric variables were discretized according to the thresholds provided on the Soil Navigator.

When the use of drainage and liming had been catalogued, we included it in the analysis, otherwise these attributes were left blank. The information on the residues left on the field was missing. When slurries were applied we assumed that they were incorporated in the soil (as is mandated by law).

Koeien en kansen

The K&K database comprises of field level information from numerous dairy farms in the Netherlands. We were granted access to information regarding the chemical, soil and physical characteristics of 5 farms, two located on sandy soils, two on clay soils and one on loess. These data were provided on separate excel sheets, depending on the information contained in them. Each field on these farms was sampled over several years. Soil samples for these farms were taken most often at 10 cm depth. However, between 1999 and 2000 the samples were taken at either 5 or 10 cm. Depending on what was sampled the depth is sometimes different, for example the samples that refer to N or P content are often at a depth different than that reported for the rest of the sampling. While we had time to select fields that had been consistently sampled over time, and connect the information on these excel sheets such that each record corresponded to a specific field on a specific year, we did not have sufficient time to input these data into the Soil Navigator.

Additionally, while some information regarding management was gathered for the main purpose of the project, some of the information was missing. Missing variables were for example the species diversity of the grassland , how often it was reseeded, or information regarding irrigation practices. We prepared questionnaires to contact the farmers to collect further information, but unfortunately this could not be completed before the end of the project date. We further modified the land management questionnaires that were created by the Landmark project to gather management information from land managers at farm scale instead of field level. In order to facilitate information gathering at farm scale, the questionnaire should be filled out for three types of fields: those closest to the stables, and therefore the more intensively managed fields; those furthest from the main farm buildings; and those reserved for arable crops. Farmers are asked first to classify their fields into these three categories, and then provide the necessary information for these three types of fields, as well as an overview of the area covered by each of these types of fields.

Landelijk Meetnet Effecten Mestbeleid

Due to a number of miscommunications, the complete dataset (including the location of the farms in the 14 regions outlined on Figure 3) was only received at the end of December, meaning there was very little time to clean the dataset, carry out regionalization of the data and calculate soil functions. We have however attempted to give an overview of the available data, as well as steps to follow in regionalisation in the future. The dataset provided extended from 2006 until 2019. The same farms were monitored on more than one occasion, but some farms were dropped from the campaign and others added into the monitoring campaign during this period. To assess multifunctionality of Dutch farms at a regional level we propose selecting data from all available years. If a farm has been sampled over several years, we propose to include only one record in the analyses (randomly selected), in order to ensure an independent dataset. This process was completed for the data received and we excluded five farms, as they were either classified into two regions in different years (two records) or appeared to be classified as dairy farms and grasslands depending on the year of sampling (three records). This selection resulted in a total of 617 farms (Table 2).

Table 2. Number of farms in the LMM across different regions and land use types.

Soil type	Region	Land use type	
		Arable	Dairy
Sand	Reclaimed moor	22	14
	Northern sand I	1	30
	Northern sand II	11	48
	Eastern sand	3	83
	Central sand	2	26
	Southern sand	27	59
	Dunes and islands		2
Clay	Polder marine clay	15	10
	Northern marine clay	12	55
	Southwestern marine clay	17	10
	River clay	1	30
Peat	Northern peat		10
	Western peat		39
Loess	Loess	28	30

In section 3.6 we propose further steps to calculate multiple soil functions using the LMM data in combination with soil information when necessary.

Missing variables

Weather variables, thickness of the organic layer, drainage class, salinity levels, groundwater table depth, soil crusting, altitude and slope and some aspects regarding soil management were missing from all datasets.

- Weather variables – Using data downloaded from the Royal Dutch Meteorological Agency (KNMI), we collected weather information from all weather stations in the Netherlands. We calculated the distance from the location of interest to the closest weather station and extracted the relevant information from this dataset for the year in which soil samples had been taken.
- Tillage and residues left in the field – Specific information on tillage as well as the proportion of residues left in the field was never available, and we relied on the expert opinion of the project leaders regarding the tillage and residue management.
- Expected yield is a property that would commonly be known to the land manager, as they would probably know the performance of the field under assessment. This information was not recorded by any of the projects, although primary productivity was. We chose to leave this characteristic blank, as we did not always know how the field performed compared to other years.
- Crop failure per 20 years – As per Vazquez *et al.* (2020), we assumed that crop failure, defined by the Landmark team as the number of times in the past 20 years that a field failed to produce any yield, was zero, unless so indicated by the data sources.
- Thickness of the soil organic layer – The Soil Navigator requires information regarding the thickness of the organic layer, with thresholds between 10-30 cm. This information was not gathered in the projects that take part in this study. Past efforts to qualify soil functions in the Netherlands assumed a medium value (Vazquez *et al*. 2020).
- Altitude and slope degree – The altitude and slope of each field were not documented, but were assessed using the ‘Actueel hoogtebestand Nederland’ online tool (http://www.ahn.nl/). Altitude was taken from the middle of the field, and slope was assessed by creating a segment between two opposite points in the field. The maximum input and slope were used as input for the soil Navigator. While this method was suitable when assessing a small number of fields (BB), it is time consuming, and would be difficult to apply to whole farms.
- Soil crusting or capping – This is more relevant to arable crops than grasslands in the Netherlands, and therefore this attribute was only included in the assessment of soil functions for arable crops in the BB project. Here we assumed that soil crusting was not a problem in any of the fields (J. de Haan, personal communication) due to the fact that soil crusting is not a major issue in Dutch agriculture.
- Groundwater level: The Soil Navigator provides two thresholds to groundwater table, and fields have either high, medium or deep groundwater table. In the Netherlands the water table is often manipulated such that it is not stable in time. While there are online tools for obtaining the groundwater table level on a given moment, we applied two different methods to calculate the groundwater table. For BB, and due to the more

limited number of records, we used information obtained from Dinoloket (www.dinoloket.nl/ondergrondgegevens). Here we looked up for each field the closest assessment of groundwater table in and around that location and took into account temporal and spatial variations to come up with an average value for the groundwater depth. For LMM we used the ground water classification ('Grondwatertrappen'). 'Grondwatertrappen' are classes of the depths of the groundwater table between which the groundwater table fluctuates on average (Basisregistratie Ondergrond Catalogus Model grondwaterspiegeldiepte (geostandaarden.nl)). For the LMM, we obtained the average maximum and minimum groundwater levels for the 14 regions established in this project from the groundwater table maps of the Netherlands available in the National Key Registry of the Subsurface (https://www.broloket.nl/ondergrondmodellen).

- Drainage class – In the Soil Navigator drainage class is intended to be an observation made by the land manager. We followed Vazquez *et al.* and assumed that clay content would play an important role in the infiltration capacity of the soil. When clay content was below 27% we assumed a well-drained soil, between 27-40% we assumed a moderately drained soil, and when clay content was above 40% we assumed a poorly-drained soil.
- Salinity – Salinity in the Soil Navigator is expressed as the content of salt in the 0 to 25 cm soil layer, expressed in ECe dS/m. This measure is not included in standard soil tests in the Netherlands. However, to evaluate the potential for damage due to salinity, the Netherlands monitors the chloride concentration (mg Cl/l) in the groundwater. The results have been published on a map of the depth at which the fresh ground water can be found, considering freshwater to be any concentration below 1000 mg Cl/l (de Louw *et al.*, 2015). We used this map to classify those areas that would be considered 'high' in salinity when the chloride concentration in the groundwater was too high at a depth between -5 to 5 m. The map, as well as the data underlying this map can be downloaded from the National Georegister[1].

Discussion and future recommendations

While there is a multitude of data available in the Netherlands (for example the sources used for this study), there are issues related to using these data. First, these data were collected with different purposes, which means that often information required by the Soil Navigator is missing. This is particularly true in the case of management related data. For example information related to soil drainage, tillage, number of months that the cows are housed, number of times the grass is mowed per year or the percentage cover of legumes. Second, the data are often from older datasets, which could mean a change in manager, management style or a significant change in the size of the farm since the data was collected. The land manager may not know what specific management practices which were applied on a given field a number of years prior, or may only be able to provide an approximate assessment of farm level management practices. Thirdly, when datasets include personal information, and in

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[1] https://nationaalgeoregister.nl/geonetwork/srv/dut/catalog.search#/metadata/64909141-3f9f-40d0-b7cc-98ff58ea2610

order to protect the participants, data sharing policies become very restrictive and significantly hinder the amalgamation of existing datasets.

A combination of remote sensing and digital soil mapping may offer a partial solution to the issue of missing management data. Remote sensing has been used by researchers to assess tillage regimes, residue management and agricultural water management (Daughtry *et al.*, 2006; Hively *et al.*, 2018; Meijninger *et al.*, 2018), to assess altitude average slope angle on a given area (Warren *et al.*, 2004), and for assessments of soil crusting (Shoshany *et al.*, 2013). The expected yield of a given field can also be identified using remote sensing to identify areas of relatively low and high yields in time (Lobell *et al.*, 2006). Crop failure could also be derived from remote sensing data, but this might require a re-evaluation of the definition of crop failure to expand a lower number of years (from 20 to 10) and to include not just fields that did not produce any crops to fields that experienced a "significant reduction in yield" of for example 50%. This value reflects the maximum yield reduction catalogued in the Netherlands since 1976 (Prins *et al.*, 2018).

This solution may not cover all management practices included in the assessment of soil functions. For example soil liming may be harder to assess using remote sensing. We suggest that projects monitoring soil parameters start including information on soil management. A good starting point would be the questionnaires designed for the monitoring campaign carried out by Zwetsloot et al. (2021). In cases such as K&K, in which farmers may have to provide information on a multitude of fields and year, we propose dividing the farm into areas that are similarly managed, and filling out the questionnaire for each area separately. The farmer should provide a list of which fields belong to which management area. This, however means that temporal assessments of soil functions would be done with no variation in management practices, and based solely on changes in environmental and soil related variables.

Another issue regarding working with pre-existing datasets is the difficulty in gathering these datasets. This is due, in part, to the gathering of spatially explicit personal information. In such cases, the WUR maintains a strict policy that suggests collecting as little personal data as possible, and analyzing the data only after having received consent from the participants involved. If the data is used for purposes other than those established in the project definition, participants need to be informed, and will be able to rescind their participation from the new study. The collaborating partners were more than willing to share these data, as they considered our aims were in line with those that the projects were initially designed for, the final decision regarding data sharing was not always with our direct partners, but had to be made by other external parties. This made data gathering an arduous process. The LMM, for example cannot be published or even extracted from the working environment of Wageningen Economic research unless it has been averaged in groups of 10 farms. In this project, we were granted information only at the rough spatial scale of soil region (Fig. 2) and we could not have assessed multifunctionality at any finer spatial scale than that. This means that rather than calculating soil functions per farm, and then applying regionalization rules to the results, such as the approach taken by Schreefel et al. (in review), we had to first average the input variables of several farms, and then calculate

3.3 Evaluation of soil functions

We assessed soil functions on 32 fields in the Netherlands, all belonging to the BB. Most fields scored high on at least two functions (25 fields). Seven scored high on only one soil function, and none scored high on all five soil functions. Half of the fields studied scored low for only one soil function (16) and none scored low for all five soil functions. Most often, primary productivity and nutrient cycling are provided at a high level (Figure 4a, e). Climate mitigation and biodiversity and habitat provision are most often delivered at a medium level (Figure 4b, c). Water regulation is assessed as low in most of the studied arable fields.

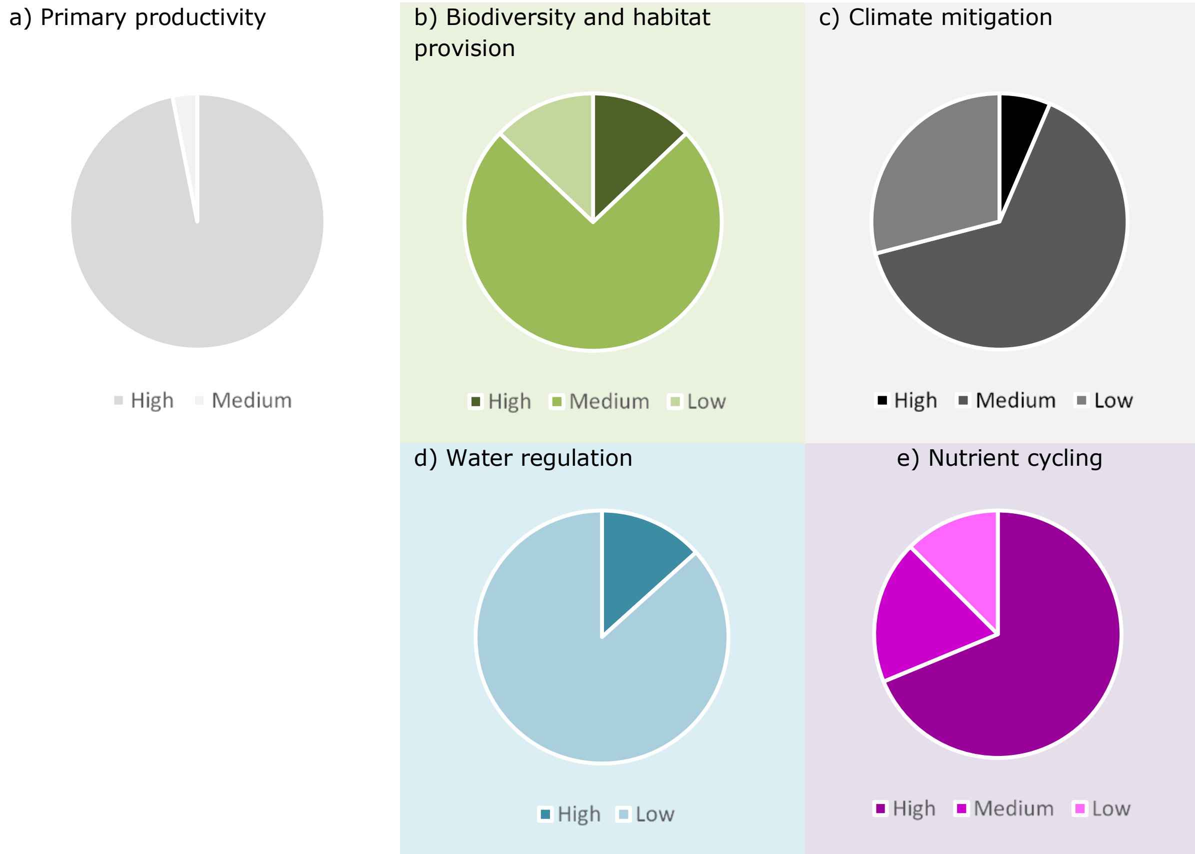

Figure 4. Percentage of high, medium and low scores for five soil functions, assessed in 32 arable fields in the Netherlands.

The scores associated with primary productivity are a result of medium environmental conditions (precipitation, temperature, altitude and slope degree), combined with an overall high score for the cropping system (Table 2). According to the models, the low scores attained in water regulation are mainly due to a low capacity for water storage, as well as a high potential for N leaching and P losses through run-off.

As can be seen in Fig. 5, there is very little variation in the assessment of potential primary productivity in arable fields in the BB dataset across the Netherlands. In fact, this reflects the fact that the Netherlands has high cereal yield per hectare compared to other countries in the

European Union[2], and it agrees with the results of Vazquez *et al.* 2020 who also observed a large proportion of high scores in primary productivity. Climate regulation, biodiversity and habitat provision and nutrient cycling show a larger variability of results.

Table 2. Number of arable fields within the *Bedrijvennetwerk Bodemmetingen* project that scored high, medium or low in the five main agricultural soil functions as well as the next lower tiers that make up each soil function.

	High	Medium	Low
Primary productivity	**31**	**1**	**0**
Environmental conditions	0	32	0
Soil conditions	10	20	2
Cropping system	32	0	0
Management practices	8	3	18
Water regulation	**5**	**0**	**27**
Water storage	0	2	30
Drainage and N leaching	23	6	3
Runoff and P loss	31	0	1
Biodiversity and habitat provision	**4**	**24**	**4**
Nutrients	11	20	1
Biology	0	5	27
Structure	1	11	20
Hydrology	25	6	1
Nutrient cycling	**22**	**6**	**4**
Mineralisation	4	18	10
Nutrient recovery	10	14	8
Nutrient harvest index	30	2	0
Climate regulation	**2**	**19**	**10**
Carbon sequestration	18	11	3
Reduction of N2O emissions	0	7	25
Reduction of CH4 emissions	32	0	0

Water regulation and purification was almost always low (table 2). These results relate to the low score in the 'runoff and P loss' attribute. In fact, the Netherlands is one of the countries with the largest surpluses of P in the soil (Smit *et al.*, 2010; van Dijk *et al.*, 2016), and one with the largest inputs of animal manure (Schroder *et al.*, 2010). Schroder *et al.* (2010) provide a good overview of measures that can be taken to reduce P losses, such as namely adjusting the amount, timing and placement of manure applications or increasing the use of cover cops and catch crops. However, the water regulation function may need further adjustments. None of the fields scored medium, and we observed a trade-off between the attributes in the model, such that high 'water storage' never occurred with high 'drainage and

[2] https://agri4cast.jrc.ec.europa.eu/DataPortal/Resource_Files/PDF_Documents/35.pdf

N leaching' or high 'runoff and P loss', and the latter were strongly correlated (Table 2). This could mean that there were simply no fields with a medium water regulation capacity amongst our samples, but we suggest further testing.

3.4. Synergies and trade-offs

Using the results obtained in the previous section, we created correlation plots to investigate the relationship between soil functions. Our results do not point towards any strong trends, other than the negative relationship between water regulation and primary productivity (Fig. 5).

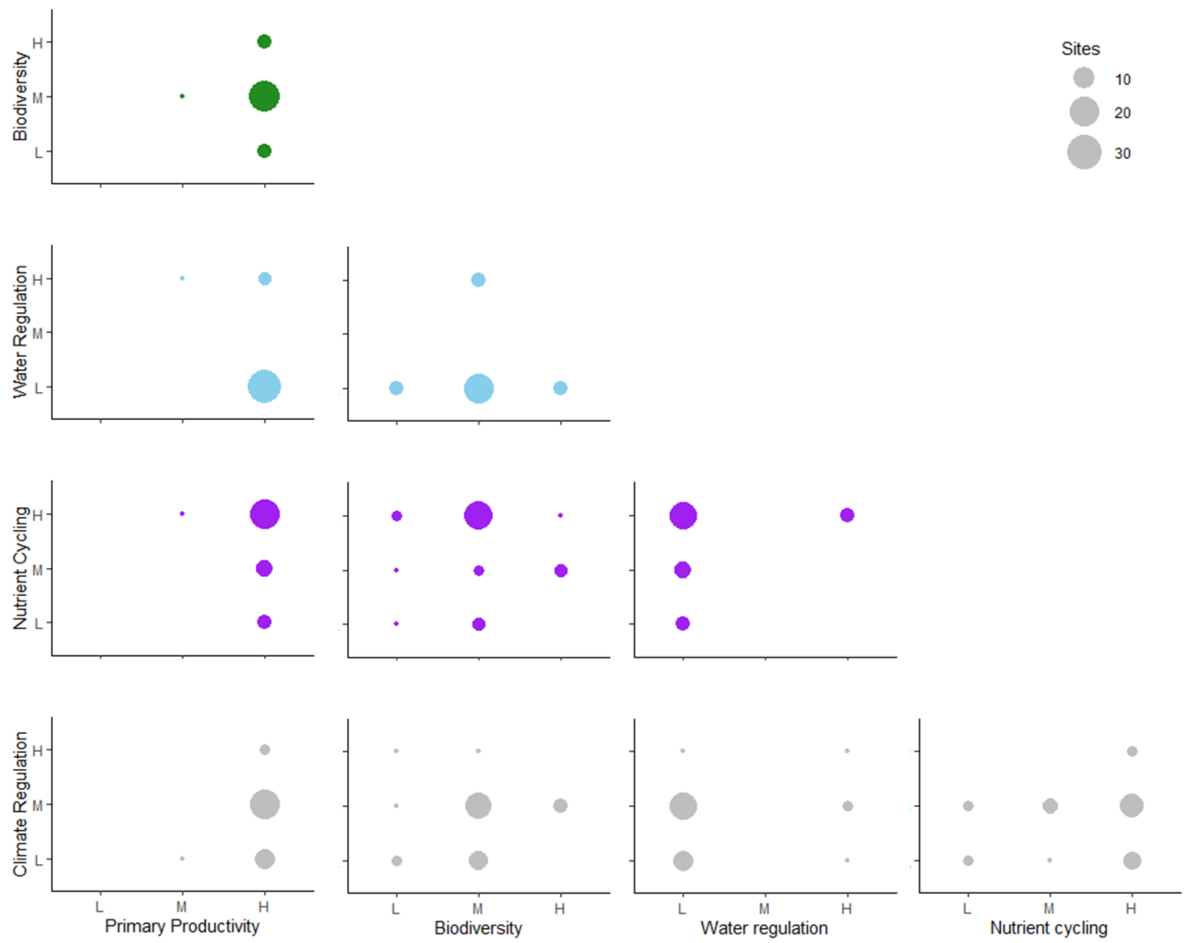

Figure 5. Relationship between high (H), medium (M) and low (L) scores for five soil functions, assessed in 32 arable fields in the Netherlands. The size of the circle represents the number of fields.

Zwetsloot *et al*. (2020) found interesting synergies and trade-offs between soil functions, for example, they found a trade-off between climate regulation and biodiversity and habitat provision in the Atlantic north climatic zone. We did not observe such a relationship. Vazquez *et al*. (2020) found a strong positive relationship between nutrient cycling and primary productivity that coincided with a negative relationship with biodiversity and habitat provision. This was also not observed in this case, where we observed that most fields scored a medium level of biodiversity and habitat provision. While this assessment was interesting, 32 sites is still a small number to properly understand the relationships between soil functions, Zwetsloot *et al*. (2020) for example found diverging trends depending on pedo-climatic zone. Similarly, one could expect that some trade-offs would be more likely to occur on sandy or clayey soils. Therefore, we suggest that this effort is repeated once more sites have been assessed.

3.5. Adjustments to the Soil Navigator

To better understand synergies and trade-offs between soil functions in the Netherlands, and to help farmers in their decision making, it may be useful to further split the current “high” primary productivity bracket into more classes. We applied classification trees to rank the importance of different variables in explaining the yield classes, and to explore new thresholds that would increase the explanatory potential of the data. As a response variable, we used a discretized value for yield. Using information regarding yield for each field in the BB project, we classified it into “high”, when it was 15% higher than the reported average yield for that crop in the Netherlands on the year the samples were taken (2019), “low” when yield was 15% lower than the country wide average, or “medium” when yield was in the 15% bracket (CBS, 2021). The choice of this 15% threshold follow the findings of Silva *et al.* (2020), who observed a 15% coefficient of variation in the yield of Dutch crops.

We grew two trees: one including the variables included in the Soil Navigator given that they were not correlated and that they included variability into the dataset (Fig 6); the other tree was grown using variables that were outside of the scope of the Soil Navigator, but that were measured for the BB (Fig 7). The ‘depth of the organic horizon’ and ‘soil crusting’ were not included in the analyses as they did not include any variability to the dataset. Weather variables were strongly correlated, and temperature and rainfall specifically were negatively correlated, so we included only yearly rainfall in the analyses. Similarly, slope and altitude were correlated, and only altitude was included in the analyses.

However, with only 32 fields the results from this effort were not good, as none of the generated classification trees were successful at estimating the yield classification. The first attempt yielded only a root, meaning that no information was gained by splitting the data. In fact this initial tree did not classify the data into ‘low’. By forcing the tree to result in three classes we produced a second tree in which the splits could accurately classify the yield scores (fig 7), but was overfitted, meaning that it would likely not yield good results if used with a different dataset (cross validation error = 1.12). The results indicate that changes to the thresholds for magnesium content in the soil, pH, bulk density and annual precipitation could lead to improvements in classification, but more data is needed.

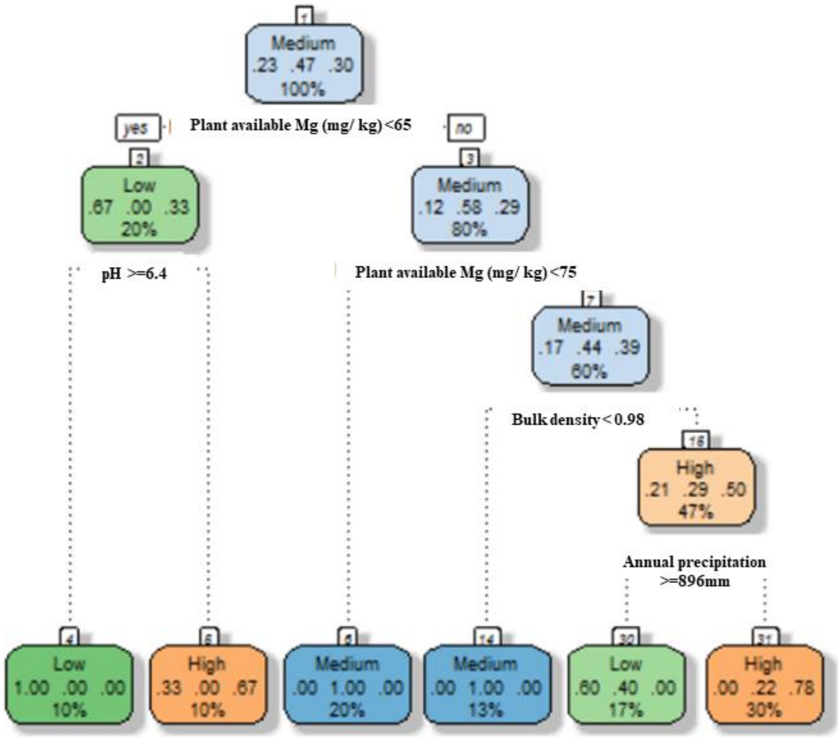

Figure 6. Classification tree obtained using variables included in the Soil Navigator. The letters in bold indicate the splitting values. The lowest part of the tree indicates the end classification, and the percentage of data allotted to each class.

Adding information outside of the Soil Navigator also did not yield a tree with a good cross validation error (1.06), indicating a strong over-parametrization. This means that these results might not be applicable to other datasets. The results indicate that biological components of the dataset, particularly the microbial biomass (Totaal.ug.g) and the abundance of plant parasitic nematodes of the Meloydogines family can aid in splitting the data into yield classes (Fig. 7). Annual precipitation and the use of organic amendments can also aid in splitting these data.

Precipitation showed up as an explanatory variable on both classification trees. In fact, previous studies in NL have highlighted the importance of soil moisture and water availability during the growing season on yield (Hack-ten Broeke *et al.*, 2016; Silva *et al.*, 2020). Additionally, Hack-ten Broeke *et al.* (2016) pointed to salinity as a predictor of productivity, a factor that was included into the analysis, and yet was not picked as an explanatory variable. There are important differences here. Both studies mentioned above used a large amount of data, and their conclusions are therefore much more broadly applicable than those obtained during this exercise. But these can inform changes to the weights in the models underlying the Soil Navigator. The sowing and harvest dates were also found to explain a part of the variation in yield (Silva *et al.*, 2020), a factor that we could unfortunately not include in our analysis, but that could also be derived from remote sensing data in a future attempt for large scale assessment of soil functions and adaptations to the Soil Navigator.

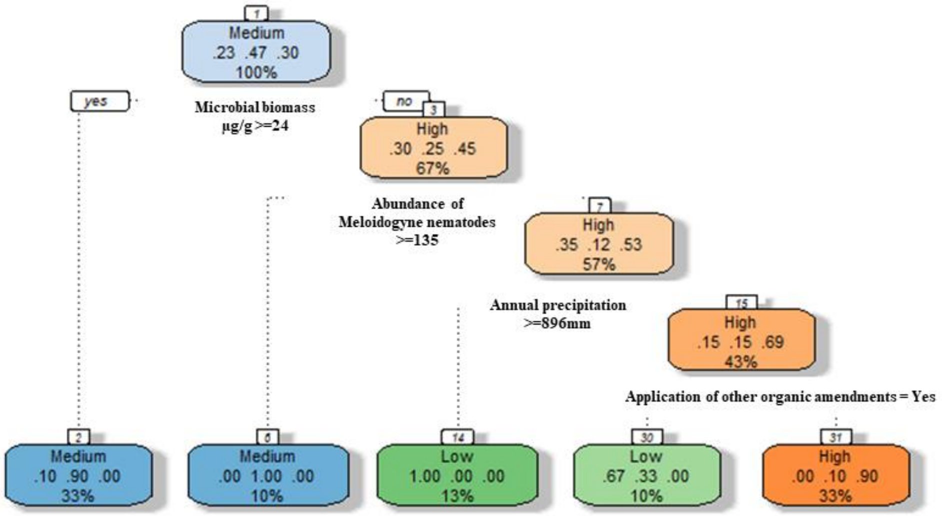

Figure 7. Classification tree obtained using variables obtained by the *Bedrijvennetwerk Bodemmetingen* project. The tree was pruned using a cp=0.7.

Other adjustments could be made to the Soil Navigator to aid in its use in the Netherlands. These changes could be especially useful in facilitating research using the Soil Navigator, as well as informing policy at larger spatial scales. Instead of using groundwater level, we suggest the use of the grondwatertrap classes. Salinity and depth of the organic layer could also be adjusted to reflect already existing maps in the Netherlands (see section 3.1). For example, the Soil Organic matter map documents the percentage of organic matter at 30 cm in the Netherlands (van Tol-Leender *et al.*, 2019). These changes would require for the selection of new thresholds that would reflect the role of organic matter and salinity to the different soil functions, using the same units as those used in the maps. Applying these changes could allow for a link to existing maps and resources when using the Soil Navigator, such that the user would be provided with a larger amount of information, but could adjust it if necessary.

Another important step to allow for large scale applications of the Soil Navigator is creating a possibility to analyze records in batch. This effort is already on the way, and being carried out by researcher at the Jožef Stefan Institute, Slovenia. Achieving these steps would allow for the exploration of larger numbers of data, including for example temporal trends. The LMM and K&K which have collected data for many years provide a good starting point to assess temporal patterns in soil functions, so long as they were combined with remote sensing efforts (see for example the Groenmonitor at www.groenmonitor.nl), and using soil maps to compliment the information.

Some thresholds in the discretization of data could be revisited, particularly, ‘Precipitation from October to February’, and from ‘March to August’, ‘average annual temperature’, and the ‘average temperature in the first growing month’. The thresholds used to classify these values do not help classify the sites, and may in fact be redundant, as they were strongly correlated.

3.6. Steps toward regional assessments of soil functions

The strategy to follow to assess multifunctionality of soil functions at a regional level using the Soil Navigator depends strongly on whether the assessment of multifunctionality can be done in batch or not. If not, then we suggest to first select all input variables for the Soil Navigator and calculate summary statistics for each numeric input variable and region. The regions selected may be restricted by agreements surrounding the available data, for example in our analyses, regions were pre-defined by the LMM, and it was impossible to deviate from these regions. Nominal variables, such as the use of irrigation, tillage or the use of pesticides, will need to become a numeric, and then translated again to nominal. For example, one could calculate the total area -within a region- that uses pesticides. This should then be turned into a proportion of the region that receives pesticides. When this proportion is larger than 60%, we consider that the pest disease in this region is managed through the use of pesticides. 60% is an arbitrary threshold, but other methods could be used to select thresholds. We would instead suggest to use using Jenks' natural breaks optimization to calculate three groups from all the data obtained (Jenks, 1967). In fact, rather than use a yes/no classification, such as that required by the Soil Navigator, we could make the most of the LMM data, which includes the amounts of fertilizers applied per hectare for all farms sampled. We could, therefore calculate the average amount of fertilizer used per hectare per region, and then divide these values into high pesticide use regions and low pesticide use regions.

In the case that the procedure can be automatized, Wageningen Economic Research would still need to allow for us to be able to download information into their working environment, such as the code that automatizes the Soil Navigator, as well as access to the various mapping environments that provide additional information about the soil system. Neither of these was possible for the duration of this project. If these barriers can be surpassed, we could calculate soil multifunctionality following a different but more thorough procedure:

1. Calculate multifunctionality for each of the farms included in the LMM. This would result in a number of representative farms for each region being assessed. Each farm is classified according to their land use and whether they are an organic or conventional farming system, and when possible an indication of the intensity of land use (something the LMM already provides).
2. From this, we can obtain an typical score for functionality for each type of farming system and each region.
3. The functionality score for each region should be representative of the percentage cover and the functionality score of each type of farming system, by applying a weight to the functionality score that reflects this coverage.

More practical aspects need to be addressed when adjusting the LMM to be used on the Soil Navigator. Below we present a list of specific issues to address.

- Artificial drainage and irrigation: The LMM collects the proportional area that is drained (or irrigated) in a given farm. We propose the use of Jenks' natural breaks optimization to calculate thresholds of high and low irrigation.
- Number and identity of crops in rotation: Crop rotation in the Soil Navigator is meant to reflect a temporal diversity in cropping rotation. This, however, is difficult to extract from the LMM database, since the information exists in terms of total area planted with a given crop or type of crop, and not at field level. Vazquez et al. (2020) proposed the use of the Shannon-Wiever diversity index (Shannon, 1948) to calculate the spatial crop diversity of each farm such that $H' = \Sigma\, p\mathrm{i} \times \ln (p\mathrm{i})$, where pi is the proportional abundance of crop *i*. However, the Soil Navigator platform requires information regarding the actual crop types, and the score for the related attribute is calculated from it. To account for this, we propose inclusion of functional diversity of crops such that the spatial diversity of crops at farm levels includes an assessment of the diversity of crop types (and not just species), and that farms with a diversity of crop types receive a higher score than those with very little functional variation.
- Salinity –We suggest the use of the map reflecting the salinity of the ground water (de Louw *et al.*, 2015) as a proxy for salinity in the soil. The authors of this map suggest not to use it for local assessments of salinity, since there is too much local variability, but it could be used when assessing regional salinity levels. All farms within a given region would therefore receive a similar classification for salinity.

Similarly, we do not have information on the groundwater level for each field, and we would suggest, as we did in section 3.1 to use the *grondwatertrap* class that is most dominant for each farm (information that is present in the LMM). Alternatively, there exists maps of the ground water table depth (mean lowest and highest) are available at a resolution of 50 by 50 m (BRO Grondwaterspiegeldiepte 2021; www.broloket.nl/ondergrondmodellen)

4. Conclusions

Zwetsloot *et al*. (2019) suggest that good soil quality is achieved when fields are providing three or more soil functions at a medium to high level. With this suggestion in mind, this scoping project shows that Dutch agricultural fields have adequate soil quality. However, there is a clear trend for low water regulation and high primary productivity. These results highlight the importance of assessing multifunctionality to highlight those functions which agricultural systems support and where trade-offs occur with the wider environment. This project also assessed the importance of understanding the multifunctional capacity of soils both at a local (field) scale and also at a larger regional scale. By doing so we can understand not just the number of functions being supported at field scale but also whether there is a diversity of functions being provided at the landscape level and how these relate to land management and landscape.

This scoping study provides an indication of multifunctionality of soils in NL, but follow up research would further our understanding of the synergies and trade-offs between functions, and help us better understand the results obtained in the water regulation model. A way to do this may be to explore using elements of the Waterwijzer Landbouw (WaterVision

Agriculture), a tool for assessing effects of water management on agricultural production in the Netherlands, which is widely used by water boards, provinces and municipalities, as well as farmer organizations (https://waterwijzerlandbouw.wur.nl/).

Additionally, we suggest to further collaboration with team working on an indicator set for quality of agricultural soils in the Netherlands: 'BLN' (Bodemindicatoren voor Landbouwgronden in Nederland) (https://edepot.wur.nl/550065). This minimum dataset was launched in 2019 and is embraced by the Dutch National Program for Agricultural soils, a policy strategy to have all agricultural soils sustainably managed in 2030. The indicator set is currently further developed in the Public-Private Partnership 'Beter Bodembeheer' and the national program Smart Land Use. The set uses the results of the other indicator sets and soil quality assessment tools in the Netherlands (Open Bodemindex, BodemConditieScore, Soil-Health-Index and BedrijfsWaterWijzer). Its development is also embedded in the EJP SOIL programme. We believe that the Soil Navigator can provide further structure to this indicator set, by contextualizing results in the shape of soil functions. The soil navigator tool would then be applicable for use by farmers but also in research to under changes in the condition of soil health in the Dutch National Program for Agricultural Soils.

This project, and in particular the evaluation of the suitability of the Soil Navigator to evaluate soil functions in the Netherlands, suffered strongly from limitations due to data sharing. Collaboration within Wageningen UR and associated data providers, such as the RIVM on data sharing should be further supported. This is often hampered due to the funding source of the research programme and the privacy obligations associated with data sharing. Another limiting factor in applying the Soil Navigator was the need to input all data manually into the Soil Navigator. While procedures have been put in place to run several fields simultaneously, these measures are currently not freely available and this will be resolved in Spring of 2022.

Lastly, of the models making up the Soil Navigator, only the Biodiversity and Habitat provision model includes soil biology as a factor, yet soil organisms play an fundamental role in soil functioning (Bardgett and van der Putten, 2014; Ferris and Tuomisto, 2015). The initial objective of the Soil Navigator, was to provide an assessment of soil functions to farmers and land managers who may not have access to biological information. Another issue in including biodiversity into each of the soil function models is disentangling the impact that different groups have on each soil function. The classification tree presented in figure 7 suggests that biological measurements may aid in the assessment soil primary productivity in the fields belonging to the BB. A recent publication by Zwetsloot *et al.* (2021) provides valuable information that could be used to bring biological measurements into the Soil Navigator. This publication provides a link between soil organisms and soil functions, and the authors have also created an online tool specifically designed to aid researchers in selecting which organisms to monitor in order to better understand soil functioning (www.biosisplatform.eu) (Zwetsloot et al., 2021).

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Appendix

Input variable	Type	Function
Bacterial biomass	Biological	BD
Earthworm abundance	Biological	BD
Earthworm richness	Biological	BD
Enchytraeid abundance	Biological	BD
Enchytraeid richness	Biological	BD
Fungal biomass	Biological	BD
Microarthropod abundance	Biological	BD
Microarthropod richness	Biological	BD
Nematode abundance	Biological	BD
Nematode richness	Biological	BD
Altitude	Environment	PP
Annual precipitation	Environment	ALL
Annual temperature	Environment	CR, BD
Average daily temperature in first month of growing season (oC)	Environment	NC
Groundwater table depth	Environment	PP, NC, WR, BD
Number of days with daily average temperatures above 5◦C	Environment	PP, NC
Precipitation - Cropping season	Environment	WR
Precipitation - Wet season	Environment	WR
Precipitation in first month of growing season	Environment	NC
Slope	Environment	PP
Artificial drainage	Management	NC, WR, CR, BD
Biological pest management	Management	PP
Catch crops	Management	BD
Chemical pest management	Management	PP, BD
Cover crop	Management	NC, WR
Crop failure risk	Management	NC
Crop residue management	Management	WR
Crop type (Water used by crop type)	Management	WR
Drained peatland	Management	CR
External C inputs	Management	CR
Fraction of annual yield harvested via grazing	Management	NC
Grassland	Management	CR
Grassland in rotation	Management	BD
Incorporation of by-product (e.g. manure, compost, sludge)	Management	NC
Irrigation	Management	PP, NC, WR, BD
Irrigation frequency	Management	WR
Irrigation rate	Management	WR
Irrigation type (H2O efficiency)	Management	WR
Labile Carbon input	Management	WR
Liming	Management	BD
Manure application	Management	CR
Manure type	Management	BD
Mineral N fertilisation	Management	PP, NC, WR, BD

Input variable	Type	Function
Mineral P fertilisers input	Management	WR
N fertilization (Organic & Mineral)	Management	CR
N offtake by crop	Management	WR
NH4 content in manure	Management	CR
Nitrification inhibitors	Management	CR
NPP yield	Management	CR
Number of crops in rotation	Management	PP, BD
Organic N fertilisation	Management	PP
Organic N fertilisation (manure)	Management	WR
Organic P input	Management	WR
Percentage of catch groups, cover crops, green maure (CaC/CoC/GM)	Management	PP
Percentage of legumes in rotation	Management	PP
Physical pest management	Management	PP
Share of catch or cover crops	Management	CR
Share of crop residues left in the field after harvest (%)	Management	NC, CR
Share of legumes (number of years out of 5 previous years - excluding present year)	Management	NC
Stocking rate	Management	PP, WR
Tillage	Management	CR, BD
Type of crops in rotation	Management	BD
Yield	Management	PP
Bulk density	Soil	PP,NC, WR, BD
C:N ratio	Soil	PP, BD
Cation exchange capacity (CEC)	Soil	PP
Clay content	Soil	PP, WR
Mg	Soil	PP
N:P ratio	Soil	BD
pH	Soil	PP, NC, BD
Plant available K	Soil	PP
Plant available P	Soil	PP
Salinity	Soil	PP
Soil organic matter	Soil	PP, WR, CR, BD
Soil P status	Soil	PP, WR, CR, BD
Soil texture	Soil	PP, WR, CR, BD
Soil type	Soil	PP, WR, CR, BD
Thickness of organic layer	Soil	
Drainage class	Soil	
Rooting depth	Soil	
Soil crusting	Soil	