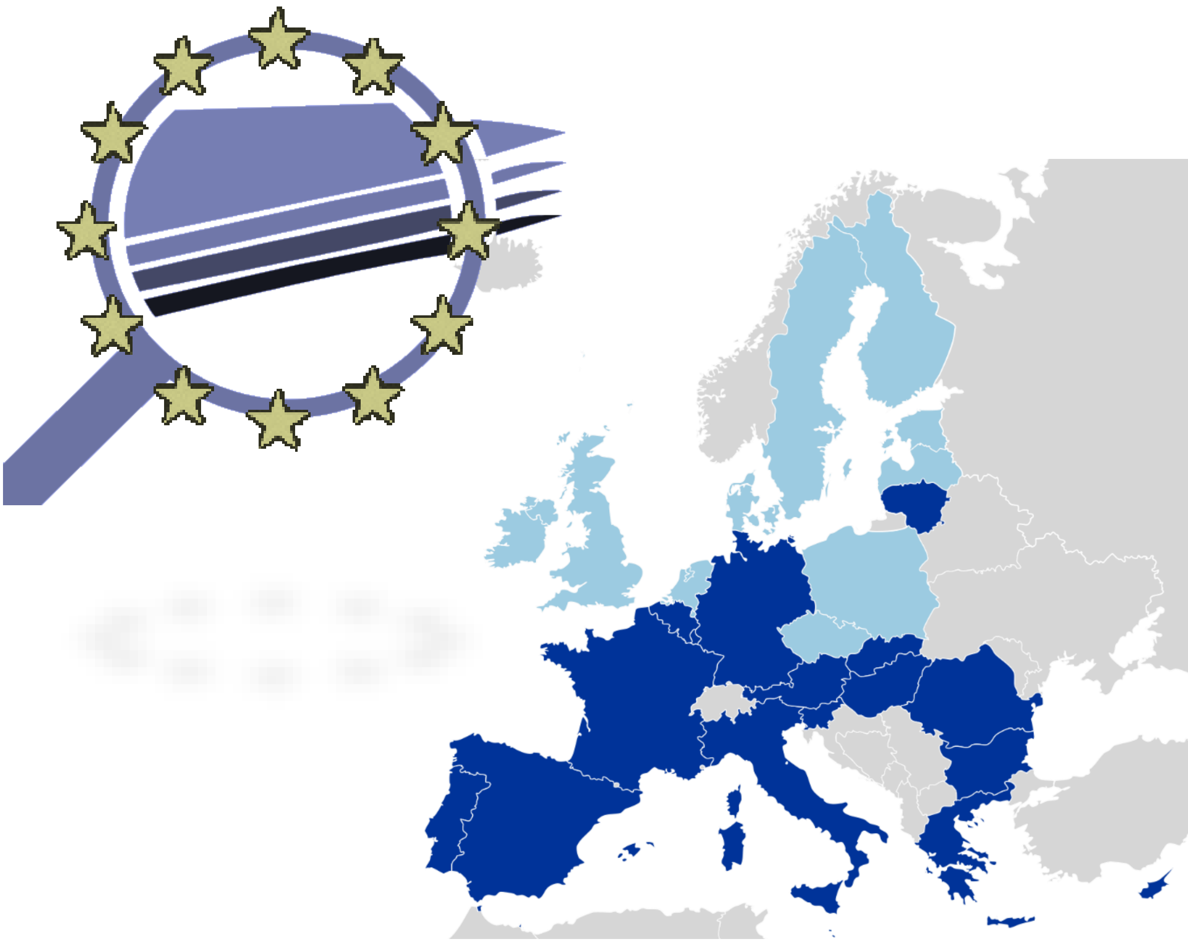
Need-based and spatially explicit agricultural management advice for soil quality improvement



Aleid Teeuwen

March 2020

WAGENINGEN UNIVERSITY & RESEARCH

Need-based and spatially explicit agricultural management advice for soil quality improvement

MSc internship report Soil physics and Land Management

Name student:	Aleid Teeuwen
Student ID:	931114824120
Study:	MSc Plant Sciences
Major:	Natural Resource Management
Chair group:	Soil physics and Land Management
Code number:	SLM-70324
Date:	04.01.2020
Report version:	First draft
Internship supervisors:	Dr. Luuk Fleskens
	Jorge Samuel Mendes de Jesus
University supervisor:	Dr. Jantiene Baartman
Examiner:	Prof. Dr. Coen Ritsema

Disclaimer: This report is part of an education program and hence might still contain (minor) inaccuracies and errors

Contents

1 Acknowledgements

This report was made possible due to the kind guidance of my supervisors Luuk Fleskens and Jantiene Baartman from Soil Physics and Land Management, and due to the additional and dedicated help of Jorge Mendes de Jesus from ISRIC, without whom this work would not have progressed as readily as it did, and without whom I would, most certainly, have despaired many times over the technical challenges which I faced.

2 Abstract

The European Commission have expressed that the approach of the future common agricultural policy (CAP) will be *need-based* and *targeted*. This requires mapping of the heterogeneity of needs within Europe, and it requires that agricultural management practices (AMPs) that address the combination of those needs are promoted through policy. The needs to address threats posed against our agricultural soils, key resources sustaining humans through their delivery of food and other ecosystem services, and the potential quality improvement that may be achieved have, however, not been summarized and mapped for a comprehensive set of indicators. Recently, two methods for selecting agricultural management practices that address multiple indicators in a targeted way have been proposed: the Soil Navigator and the SQApp, both made publicly available as applications. As the SQApp algorithm is spatially explicit, we assessed whether it could be used to support the development of need-based and targeted agricultural policies. We also proposed various ways in which the SQApp algorithm could be improved. We found that many, but not all need-indicators were available at a sufficiently high resolution, coverage and quality. The spatial variation of the indicators suggested that need-based and targeted agricultural management policies should be implemented at a regional or within-regional scale. Of the agricultural management practices advised there were seldomly any practices that were considered to be single best. Instead, two or several AMPs were deemed equally suitable. This precluded the creation of simply, policy-targeted maps. In an attempt to optimize the SQApp algorithm, we assessed whether specifying cropping systems would reduce the number of equally suitable AMPs. This was effective for some cropping systems, but not for the most dominant annual cropping system in Europe: cereals. Adapting the algorithm itself and allowing for a more continuous scoring of AMP suitability did successfully reduce the number of equally suitable AMPs, and revealed that one single AMP, compost application, was recommended almost everywhere.

3 Introduction

Prior to the 1970s, the quality of soils was evaluated on the basis of their suitability for crop growth (Bünemann et al. 2018). This, however, has changed. The multi-functionality of soils is now recognized, and research and policy have adapted accordingly (Schulte et al. 2015, Vrebos et al. 2017). In research, soil quality indicators have been developed to monitor the suitability of soils for functions such as water purification, habitat for biodiversity, carbon sequestration and nutrient recycling (Schulte et al. 2015, Bünemann et al. 2018). Moreover, technical developments in areas such as remote sensing and machine learning have enabled these indicators to be estimated at high spatial resolutions (Chen et al. 2015, Hengl et al. 2017). In policy, all UN member states have committed to monitoring and implementing the sustainability development goals (SDGs), which stress the importance of the abovementioned soil functions (Koch et al. 2013, Keesstra et al. 2016). Furthermore the European Union has expressed deep interest in the potential role of soils and sustainable land management in climate change mitigation and adaptation (IPCC 2019). They have also expressed that the approach of the future common agricultural policy (CAP) will be *need-based* and *targeted* (European Commission 2019).

For agricultural policies to be *need-based* the heterogeneity of needs within Europe must be mapped. For agricultural soils, specifically, need-based policies could target areas where soil quality improvement is high, or where soil threats are severe. Although spatial information about the threats and soil quality indicators already exists (Jones et al. 2003, Panagos et al. 2014, Shangguan et al. 2014), no spatial information can be found concerning the threat posed by combinations of soil threats, or the overall soil quality improvement potential of agricultural soils. In fact, soil quality improvement potential has, to our knowledge, not been mapped at a large spatial scale prior to this study (but see Wills et al. (2017) for a small scale case study). Mapping soil quality improvement potential, both in absolute and relative terms, therefore, was the first challenge tackled in this research.

For agricultural policies to be *targeted*, management should be promoted that i) mitigates all the most severe soil threats, and ii) improves all the soil quality characteristics furthest removed from their potential, optimum state. Till now, however, most research has focused on the effect of management on individual or a few combinations of soil threat/quality indicators only,

resulting in contradictory recommendations (Turpin et al. 2017). With the exception of the Soil Navigator (Debeljak et al. 2019), developed in the LANDMARK project (http://landmark2020.eu/), and the SQApp (Fleskens et al. 2017), developed by iSQAPER (http://www.isqaper-project.eu/), no attempts at combining existing expert knowledge about combined effects of agricultural management practices on multiple soil threat and quality indicators have been published. As the Soil Navigator does not allow for the scaling of management recommendations in space, we will use and assess the SQApp management advice algorithm in order to develop a policy-oriented, spatially explicit system for need-based and targeted agricultural management advice.

We used the SQApp algorithm to map i) overall soil threat severity in Europe, ii) potential for soil quality improvement in Europe and iii) the management practice(s) that are best suited to alleviate soil threats and improve soil quality. In order to assess the recommendations, we also evaluated: iv) how sensitive is our management advice was to crop choice, and v) whether we could optimize the management advice with different methods for weighing on the basis of soil quality indicators and soil threats.

4 Materials and methods

4.1 Data sources and calculation procedures

4.1.1 Soil threat severity

For the calculation of combined soil threat severity, nine soil threats were considered: acidification, water erosion, wind erosion, compaction, salinization, organic matter decline, nutrient depletion, contamination by heavy metals and soil biodiversity decline (Barão and Basch 2017, Fleskens et al. 2017). Indicators were identified for each threat, and indicator values were converted to threat levels according to literature and expert advice[1] (Table 1). The combined soil threat severity at a given location was defined as the average of the highest indicator level of each soil threat:

$$Combined\ soil\ threat\ severity = \frac{\sum_{i=1}^{n} \max(A)}{n}$$

where *n* is the number of soil threats considered, and *A* is an array of the indicator values of soil threat *i*. The number of soil threats considered was dependent on data availability. Threats for which no indicators values were available were ignored.

4.1.2 Soil quality improvement potential

For the calculation of the potential for soil quality improvement, bulk density, cation exchange capacity, electrical conductivity, exchangeable potassium, soil microbial abundance, soil organic carbon content, pH, extractable phosphorus, plant available water storage capacity and total nitrogen content were used as indicators. Since the maximum attainable values of these indicators are affected by climate and soil type (Toth et al. 2016), we were interested in relative, and not absolute soil quality improvement potential.

[1] In order to make this a good report, it needs to be clear where these indicators and indicator thresholds all come from. Currently, that remains vague.

Table 1. Data and thresholds used to calculate soil threat severity. References: (a) Panagos et al. (2015) , (b) Borrelli et al. (2017), (c) Shangguan et al. (2014), (d) Hengl et al. (2017), (e) Lado et al. (2008), (f) Nicholsen & Chambers (2008), (g) (Orgiazzi et al. 2016).

soil threat indicator	**unit**	**soil threat**	**pH range**	**threat level**		
(reference)				low (1)	intermediate (2)	high (3)
water erosion vulnerability* (?)	?	water erosion	Full range	low	intermediate	high
soil loss by water erosion (a)	$t\ ha^{-1}$	water erosion	Full range	0 - 2	2 – 10	> 10
wind erosion vulnerability* (?)	?	wind erosion	Full range	low	intermediate	high
soil loss by wind erosion* (b)	$t\ ha^{-1}$	wind erosion	Full range	0 – 0.5	0.5 – 3	> 3
susceptibility to compaction* (?)	?	soil compaction	Full range			
electrical conductivity** (c)	$dS\ kg^{-1}$	salinization	Full range	0 - 2	2 - 4	> 4
soil organic carbon content* (d)	%	organic matter decl.	Full range	> 2	2 - 1	1 - 0
exchangeable potassium* (c)	$cmol\ kg^{-1}$	nutrient depletion	Full range	> 0.3	0.3 - 0.2	0.2 - 0
Olsen-extracted phosphorus* (c)	$mg\ kg^{-1}$	nutrient depletion	Full range	> 40	40 - 20	20 - 0
total soil nitrogen* (c)	$g\ kg^{-1}$	nutrient depletion	Full range	> 2	2 - 1	1 - 0
pH* (d)		acidification		< 5.5 > 8.0	5.5 – 6.5 8.0 – 7.5	6.5 – 7.5
arsenic**** (e)	$mg\ kg^{-1}$	soil contamination	Full range	0 – 37.5	37.5 – 50	> 50
cadmium**** (e)	$mg\ kg^{-1}$	soil contamination	Full range	0 – 2.25	2.25 – 3	> 3
chromium**** (e)	$mg\ kg^{-1}$	soil contamination	Full range	0 – 300	300 – 400	> 400
Copper (e,f)	$mg\ kg^{-1}$	soil contamination	< 5.5 5.5 – 6.0 6.0 – 7.0 > 7.0	0 – 60 0 – 75 0 – 101.3 0 – 135*****	60 – 80 75 – 100 101.3 – 135 135 – 200*****	> 80 > 100 > 135 > 200*****
lead**** (e)	$mg\ kg^{-1}$	soil contamination	Full range	0 – 225	225 – 300	> 300
mercury**** (e)	$mg\ kg^{-1}$	soil contamination	Full range	0 – 0.75	0.75 – 1	> 1
nickel (e,f)	$mg\ kg^{-1}$	soil contamination	< 5.5 5.5 – 6.0 6.0 – 7.0 > 7.0	0 – 37.5 0 – 45 0 – 56.3 0 – 82.5	37.5 – 50 45 – 60 56.3 – 75 82.5 – 110	> 50 > 60 > 75 > 110
zinc**** (e)	$mg\ kg^{-1}$	soil contamination	Full range	0 – 150	150 – 200	> 200
soil biodiversity index*** (g)		soil biodiversity decl.	Full range	low	intermediate	high

*the classification of these indicators has not been described in Milestone 6.2
**the thresholds of this indicator differs per crop according to Milestone 6.2
***the thresholds of this indicator differs per to pedo-climatic zone according to Milestone 6.2
****the thresholds of this indicator differs according to pH in Milestone 6.2
*****these values do are not the same as the values given in Milestone 6.2

To enable climate and soil type to be taken into account, pedo-climatic zones were defined. A new system for classification was made since existing regional pedo-climatic zonation systems were not comparable and therefore caused conversion issues between systems (Fleskens et al. 2017). This system overlaid World Reference Base (WRB) soil classes (IUSS Working group 2006, Hengl et al. 2017) and Köppen-Geiger climate zones (Peel et al. 2007), resulting in a total of 3422 (118 x 29) unique pedo-climatic zones. Furthermore, two types of land use were incorporated into the zonation system: grassland and cropland, raising the number of unique zones to 6844[2].

Empirical cumulative probability density curves were produced for each soil quality indicator in every pedo-climatic zone. The density curves were based on empirical probability density histograms with 256 bands between the lowest and highest value of each soil quality indicator in every pedo-climatic zone. The cumulative probability (%) corresponding to the actual soil quality indicator value in a given location, was then considered to be the relative performance of that soil quality indicator at that location. The potential improvement of that soil quality indicator at that location was then considered to be the absolute cumulative probability corresponding to the best attainable value minus the relative performance of that indicator (e.g. 7%, Fig. 1) of the soil quality indicator (Table 2).

The overall soil quality improvement potential was then considered to be the average improvement potential of all soil quality indicators. The number of soil quality indicators considered was dependent on data availability. Some soil quality indicators, for instance, were only available for countries within the European Union.

[2] I did not have sufficient time to distinguish on the basis of land use during the internship, but I intend to implement this during the period in which I will work for SLM after the internship.

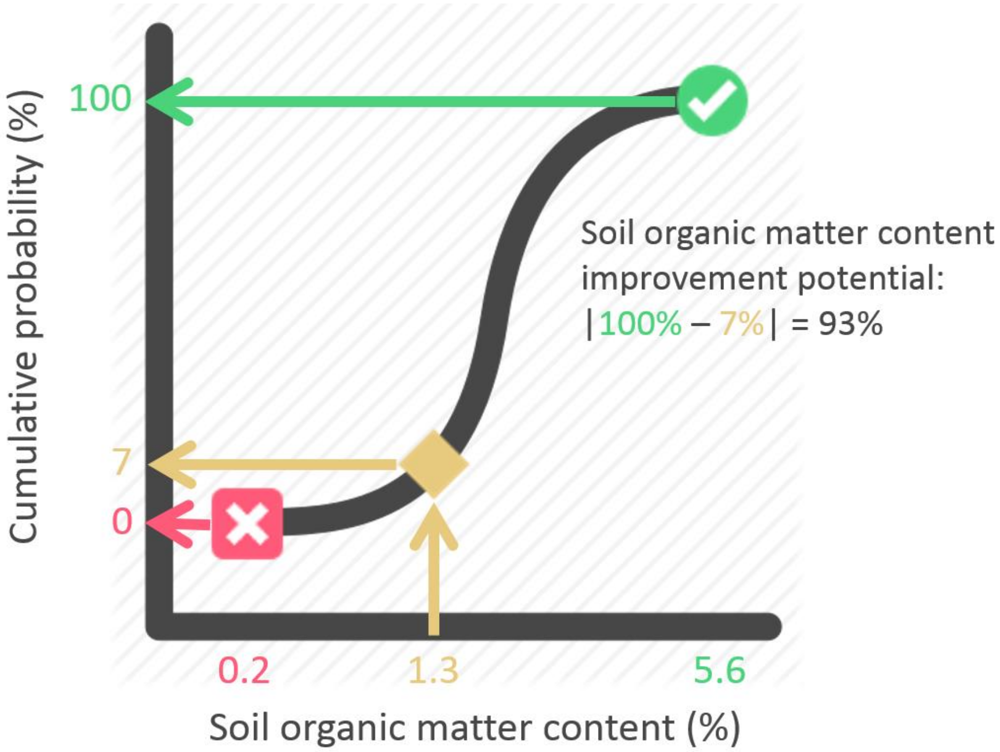


Figure 1. An illustrative example of how the relative improvement potential of a soil quality indicator is calculated. In this example 0.2 is the lowest observed soil organic carbon (SOC) content , and 5.6 is the highest observed SOC content for a specific pedo-climatic zone. 1.3 is the SOC value in our location of interest. Via the cumulative probability curve, we can relate this value to a relative performance of 7%. This means that within this specific pedo-climatic zone, only 7% have a SOC content of 1.3 or lower. The SOC content improvement potential is the absolute cumulative probability linked to the best attainable value (100% linked to 5.6%) minus the relative performance of 7%.

Table 2. Soil quality indicators and optimums used to define relative improvement potential. References: (a) Panagos et al. (2015), (b) Borrelli et al. (2017), (c) Shangguan et al. (2014), (d) Hengl et al. (2017), (e) Lado et al. (2008), (f) Nicholsen & Chambers (2008), (g) Orgiazzi et al. (2016).

Soil quality indicator (reference)	**Unit**	**Best attainable value (optimum)**
Bulk density (d)	kg m^{-3}	Minimum
Cation exchange capacity (d)	cmol kg^{-1}	Maximum
Electrical conductivity (c)	dS kg^{-1}	Minimum
Exchangeable potassium (c)	cmol kg^{-1}	Maximum
Soil microbial abundance (g)		Maximum
Soil organic carbon content (d)	%	Maximum
pH (d)		7
Olsen-extracted phosphorus* (c)	mg kg^{-1}	Maximum
Plant available water storage capacity	mm	Maximum
Total soil nitrogen (c)	g kg^{-1}	Maximum

4.1.3 Management advice

A large range of agricultural management practices (AMPs) were considered as possible means to alleviate soil threats and improve soil quality through improved terrain management, soil management, vegetation management, water management, nutrient management, pest management, pollutant management and grazing management (Table 3).

For a given location, a management advice was created in two steps (Table 4). First, we checked whether the AMP could be applied given the land cover, slope, annual precipitation, landscape position, soil depth, soil texture and stoniness in that location (Table 4). Terraces, for instance, cannot be implemented on grazing land, on slopes shallower than 5%, on flat plains, or on soils that are very shallow, or contain more than 50% sand (Table 4, Appendix 9.1).

Table 3. Agricultural management practices (AMPs) that can mitigate soil threat(s) and/or improve soil quality indicator(s), click on this link to see the full table. If link does not work, navigate to Tables → AMP_reference_table.html. The ids and colours are used to visualise the AMPs in space in the results section.

Show 69 entries   Search:

	id	AMP	colour	type
41	1	Agroforestry	#006400	Vegetation management
6	2	Apply animal manures	#F98300	Nutrient management
2	3	Area closure	#EEEE00	Grazing management
31	4	Avoidance of traffic		Soil management
5	5	Biochar application	#D81500	Nutrient management
17	6	Biological pest control	#008B8B	Pest management
43	7	Buffer zones/landscape elements	#087508	Vegetation management
38	8	Bunds	#68228B	Terrain management
15	9	Chemical disease control	#00A1A2	Pest management

Showing 1 to 69 of 69 entries   Previous 1 Next

Second, we ranked the AMPs according to their combined effect on soil quality (sq) and soil threat (st) indicators. Negative, neutral and positive effects were given values of -1, 0, and 1, respectively (Table 4).

Table 4. Physical characteristics (Step 1) and indicators (Step 2) used to create a location-specific management advice. Press on this step 1 link or this step 2 link, to see the full tables. If links do not work, navigate to Tables → AMP_step1_table.html and Tables → AMP_step2_table.html.

Step 1: check which AMPs may be applied	Step 2: rank AMPs according to their combined effect on the effect on the indicators below
Land cover	**Physical soil quality indicators**
arable land	Bulk density (fine earth) in kg /m3 in depth of 0-30 cm
grazing land	Plant-available water storage capacity (mm) in depth of 0-30 cm
Slope	**Chemical soil quality indicators**
flat (0-2%)	Soil organic carbon content (fine earth fraction) in g per kg in depth of 0-30 cm
gentle (2-5%)	Soil pH x 10 in H2O in depth of 0-30 cm
moderate (5-10%)	Electrical conductivity in soil depth of 0-29cm (dS/m)
rolling (10-15%)	CEC
hilly (15-30%)	Exchangeable potassium in soil depth of 0-29cm (cmol/kg)
steep (30-60%)	Amount of phosphorus using Olsen method (ppm weight)
very steep (>60%)	Total nitrogen in soil depth of 0-29cm (g/kg)
Annual precipitation	
0-250 mm	
250-500 mm	
500 - 750 mm	
750 - 1000 mm	
1000 - 1500 mm	
1500 - 2000 mm	
>2000 mm	
Landscape position	**Biological soil quality indicators**
1 breaks-foothills	Soil microbial abundance (g Cmic/m2)
2 flat plains	Soil macrofauna groups
3 high mountains-deep canyons	
4 hills	
5 low hills	
6 low mountains	
7 smooth plains	
Soil depth	**Soil threats (linked to soil threat indicators)**
very shallow (0-20 cm)	Water erosion (linked to soil loss and erosion vulnerability)
shallow (20-50 cm)	Wind erosion (linked to soil loss and erosion vulnerability)
moderately deep (50-80 cm)	Compaction
deep (80-120 cm)	Contamination (linked to highest ranked heavy metal risk)
very deep (> 120 cm)	Biodiversity decline (linked to soil biodiversity index)
Soil texture	
coarse (sand > 50%)	
fine (clay > 40%)	
medium (other)	
Stoniness	
None (coarse fragments <2%)	
Slightly (coarse fragments 2-10%)	
Moderately (coarse fragments 10-25%)	
Excessively (coarse fragments >25%)	

In order to ensure that the management advice was location-specific, only effects on soil threat indicators with medium or high threat levels, and on soil quality indicators with a relative performance ≤ 33% were considered:

$$AMPi\ rank = \sum^{st\ indicators} effect_{ij} * weight(j) + \sum^{sq\ indicators} effect_{ik} * weight(k)$$

$$weight(j) = \begin{Bmatrix} 0\ j < 3 \\ 1\ j\ \geq 3 \end{Bmatrix} \text{ and } weight(k) = \begin{Bmatrix} 0\ k\ \leq 33\% \\ 1\ k > 33\% \end{Bmatrix}$$

where *AMPi* is a given AMP, *effect*$_{ij}$ is the effect of AMP*i* on soil threat indicator *j*, *effect*$_{ik}$ is the effect of *AMPi* on soil quality indicator *k*, and *weight(j)* and *weight(k)* are 0 or 1 depending on their threat level *j* and relative soil quality performance *k*, respectively.

4.2 Selection of European regions

European regions where local experts involved in the iSQAPER project (http://www.isqaper-project.eu/) were selected for in-depth spatial analysis, as these experts could help us evaluate whether local outcomes were realistic. Eurostat's classification of geo-spatial units for the application of regional policies (NUTS 2) were used to define regional boundaries (Fig. 2) (Eurostat, 2011).

Country	Case study	NUTS 2	Region name
Netherlands	De Peel	NL41	Noord-Brabant
Portugal	Certima	PT16	Centro
Spain	Alicante	ES52 ES62	Valencia Murcia
Greece	Crete	EL43	Crete
Slovenia	Ljubljana	SI04	Zahodna
Hungary	Zala	HU23	Dél-Dunántúl
Romania	Braila	RO22	Sud-Est
Poland	Trzebieszów	PL31	Lubelskie
Estonia	Tartumaa	EE008	Estonia

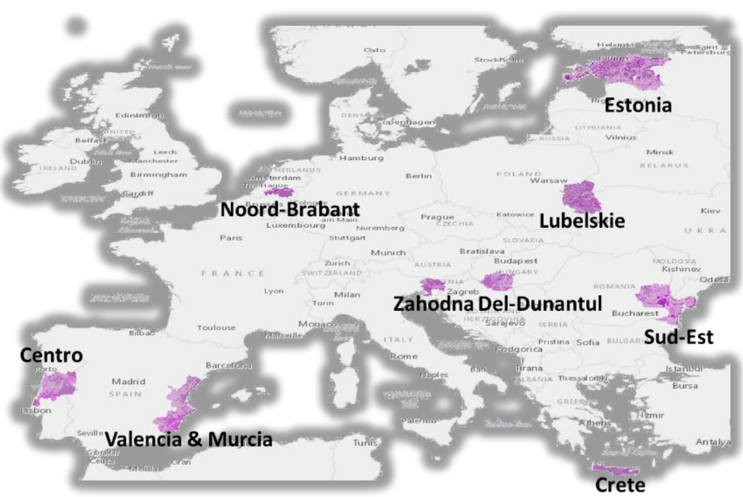


Figure 2. Regions selected for spatial analysis

A full-scale European spatial study was not possible in the scope of this internship, since it required expertise in high performance computation (HPC). Though Wageningen University does host HPC infrastructure (HPC wiki), introduction courses were only provided during the last quarter of the internship.

4.3 Pre-processing of spatial data

All operations on spatial data were implemented in the R environment for statistical computing (R 6.2.0, RStudio Team, 2018). Prior to any other operations, the European maps of soil threat indicators, soil quality indicators, pedo-climatic zones and physical properties were resampled to a resolution of 0.002083 degrees (CRS 84). The projectRaster function from the raster package (Hijmans et al., 2019) was used with nearest neighbour and bilinear interpolation for categorical and continuous variables, respectively.

4.4 Sensitivity and optimization of the SQApp algorithm for management advice

4.4.1 The effect of crop cultivation

Which crops are grown on a specific piece of cropland can be a major determining factor for the types and number of agricultural management practices that can be implemented there. As high-resolution, up-to-date maps on cultivated crops are not available, and would be extremely challenging to maintain updated, we were not able to narrow down the management advice depending on the crop(s) cultivated. Instead we ran a series of scenarios in which we attributed cropland to specific cropping systems: cereal production, root crop cultivation, pasture (intensively managed grassland), rangeland (extensively managed grassland), and permanent crops with and without soil cover (cerealA, rootA, pastureA, rangeA, permcA, permncA, table 3). In those scenarios, only AMPs suited for the specific cropping systems were considered (Appendix 7.2.1).

4.4.2 The effect of the weights attributed to soil indicators

To see how much our management advice would be affected by a different weighting of soil threat and soil quality indicators, we ran two scenarios (Scenario B and C, table 5) in which we used a different type of weighing. Weights were determined as follows:

Scenario B: $weight(j) = \begin{Bmatrix} 0\ if\ j = 1 \\ 1\ if\ j = 2 \\ 2\ if\ j = 3 \end{Bmatrix}$ $weight(k) = \begin{Bmatrix} 0\ if\ k \le 25\% \\ 1\ if\ k \in (25\%, 75\%] \\ 2\ if\ k > 75\% \end{Bmatrix}$

Scenario C: $weight(j) = \begin{Bmatrix} 0\ if\ j = 1 \\ 1\ if\ j = 2 \\ 2\ if\ j = 3 \end{Bmatrix}$ $weight(k) = 2 * \frac{100\% - k}{100\%}$

Table 5. Scenarios used to assess the sensitivity of, and optimize, management advice

Id	Explanation	Threat weights	SQ weights	Comment
A	SqApp as is (baseline)	0 or 1	0 or 1	
cerealsA	SQApp as is with AMP restrictions for cereal production	0 or 1	0 or 1	AMPs unsuitable for cereal production removed from AMP list
rootA	SQApp as is with AMP restrictions for root crop production	0 or 1	0 or 1	AMPs unsuitable for root crop production removed from AMP list
pastureA	SQApp as is with AMP restrictions for pasture	0 or 1	0 or 1	AMPs unsuitable for pasture removed from AMP list
rangeA	SQApp as is with AMP restrictions for rangeland	0 or 1	0 or 1	AMPs unsuitable for rangeland removed from AMP list
permcA	SQApp as is with AMP restrictions for permanent cropping with soil cover	0 or 1	0 or 1	AMPs unsuitable for permanent cropping with soil cover removed from AMP list
permncA	SQApp as is with AMP restrictions for permanent cropping without soil cover	0 or 1	0 or 1	AMPs unsuitable for permanent cropping without soil cover removed from AMP list
B	SQApp with intermediate scores	0, 1 or 2	0, 1 or 2	
C	SQApp with continuous scores	0, 1 or 2	[0, 2]	
1A	SQApp as is with salinity as threat	0 or 1	0 or 1	Electrical conductivity removed as SQ indicator, salinity added as threat indicator
1B	SQApp with intermediate scores with salinity as threat	0, 1 or 2	0, 1 or 2	Electrical conductivity removed as SQ indicator, salinity added as threat indicator
1C	SQApp with continuous scores with salinity as threat	0, 1 or 2	[0, 2]	Electrical conductivity removed as SQ indicator, salinity added as threat indicator
2A	SQApp as is with bias towards threats	0 or 2	0 or 1	
2B	SQApp with intermediate scores with bias towards threats	0, 2 or 4	0, 1 or 2	
2C	SQApp with continuous scores with bias towards threats	0, 2 or 4	[0, 2]	
3A	SQApp as is with bias towards high threats	0, 1 or 5	0 or 1	
3B	SQApp with intermediate scores and bias towards high threats	0, 1 or 5	0, 1 or 2	
3C	SQApp with continuous scores and bias towards high threats	0, 1 or 5	[0, 2]	

4.4.3 The effect of salinity as a soil threat

Preliminary results from the analysis of soil threat severity and soil quality improvement potential revealed that electrical conductivity tended to be low in Europe. Large differences in the relative improvement potential of electrical conductivity, therefore, reflected small absolute differences in electrical conductivity (<2 dS kg^{-1}). As such small differences in electrical conductivity should not affect management advice (Butcher et al 2016), we removed electrical conductivity as a soil quality indicator and considered salinity as a soil threat instead (1A, 1B, and 1C, Table 5).

4.4.4 The effect of weighing soil threats more heavily than soil quality indicators

The thresholds of the soil threats (Table 1) are such that immediate action is required when levels are intermediate or high. Improvement potentials of soil quality indicators, in contrast to soil threats, are relative, and it is not certain that high improvement potential requires immediate action. For this reason, we constructed scenarios that weighed soil threats more heavily than soil quality indicators (2A, 2B, and 2C, Table 5):

Scenario 2A: $weight(j) = \begin{Bmatrix} 0\ j < 3 \\ \mathbf{2\ j\ \geq 3} \end{Bmatrix} \quad weight(k) = \begin{Bmatrix} 0\ k\ \leq 33\% \\ 1\ k > 33\% \end{Bmatrix}$

Scenario 2B: $weight(j) = \begin{Bmatrix} 0\ if\ j = 1 \\ \mathbf{2\ if\ j = 2} \\ \mathbf{4\ if\ j = 3} \end{Bmatrix} \quad weight(k) = \begin{Bmatrix} 0\ if\ k\ \leq 25\% \\ 1\ if\ k \in (25\%, 75\%] \\ 2\ if\ k > 75\% \end{Bmatrix}$

Scenario 2C: $weight(j) = \begin{Bmatrix} 0\ if\ j = 1 \\ \mathbf{2\ if\ j = 2} \\ \mathbf{4\ if\ j = 3} \end{Bmatrix} \quad weight(k) = 2 * \frac{100\% - k}{100\%}$

4.4.5 The effect of weighing severe soil threats more heavily

With a similar rationale as 4.4.4., we also constructed scenarios where severe soil threat levels, only, were weighed more heavily (3A, 3B, and 3C, Table 5):

Scenario 3A: $weight(j) = \begin{Bmatrix} 0\ j < 3 \\ \mathbf{5\ j\ \geq 3} \end{Bmatrix} \quad weight(k) = \begin{Bmatrix} 0\ k\ \leq 33\% \\ 1\ k > 33\% \end{Bmatrix}$

Scenario 3B: $weight(j) = \begin{Bmatrix} 0\ if\ j = 1 \\ 1\ if\ j = 2 \\ \mathbf{5\ if\ j = 3} \end{Bmatrix} \quad weight(k) = \begin{Bmatrix} 0\ if\ k\ \leq 25\% \\ 1\ if\ k \in (25\%, 75\%] \\ 2\ if\ k > 75\% \end{Bmatrix}$

Scenario 3C: $weight(j) = \begin{Bmatrix} 0\ if\ j = 1 \\ 1\ if\ j = 2 \\ \mathbf{5\ if\ j = 3} \end{Bmatrix}\ weight(k) = 2 * \frac{100\% - k}{100\%}$

4.1 Visual assessment of differences between scenarios for AMP advice

In order to compare the different methods for ranking AMPs and the sensitivity of AMP advice to specific cropping systems, the additive scores of each AMP were calculated and mapped for each scenario. To provide a summary of these results, the maps showing the ten highest scores attained additive scores, and (number of) AMPs that attained those highest scores were retrieved. Wherever only one AMP attained the highest score, it was visualised in space. In order to also visualise AMPs that were tied in attaining the highest scores, pie charts were used.

5 Results

5.1 Soil threats in Europe

Our spatial analysis of European soil threat severity revealed that average soil threat severity differed across regions and indicators (Fig. 3). Yet, not all indicators were subject to spatial variation: the range of average soil threat severity ± the standard deviation of the average soil threat severity due to contamination, nutrient depletion, and salinization, were low, high, and low, respectively, in all regions.

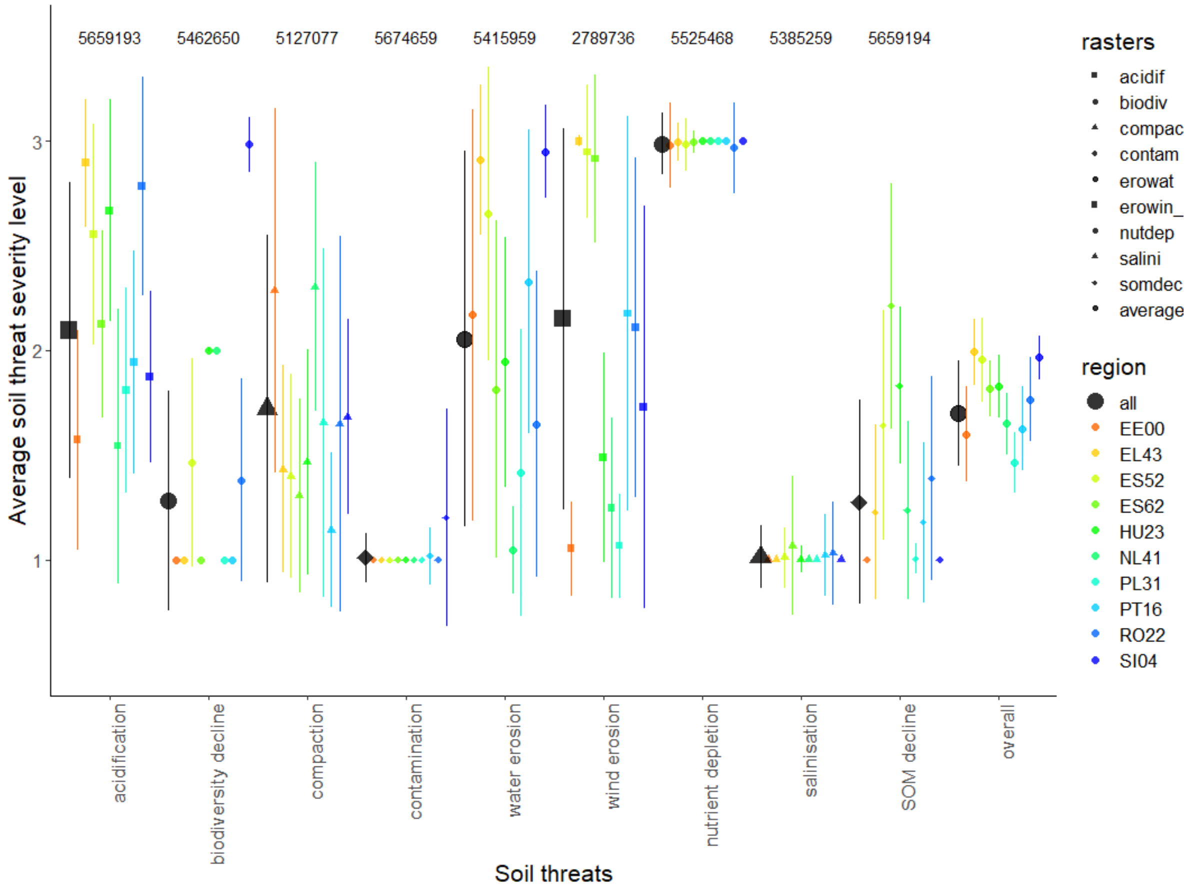


Figure 3. Average soil threat severity level (± standard deviation) per region and soil threat. The number of data points per soil threat for all regions combined is written above each soil threat, and overall averages are shown on in the most-right column.

When zooming in on Centro (PT16, Fig. 4), we see the spatial data used to calculate the averages above (Fig. 3). We also note that the availability and resolution of the data differ substantially, with the compaction grid being very course, and wind erosion and compaction data missing for large areas of land (Fig. 4, see also Appendix 9.3.1) . For zoomed in data of

the other regions, or of the indicators used obtain soil threat levels, see Appendix 9.3.2 and 8.3.3, respectively.

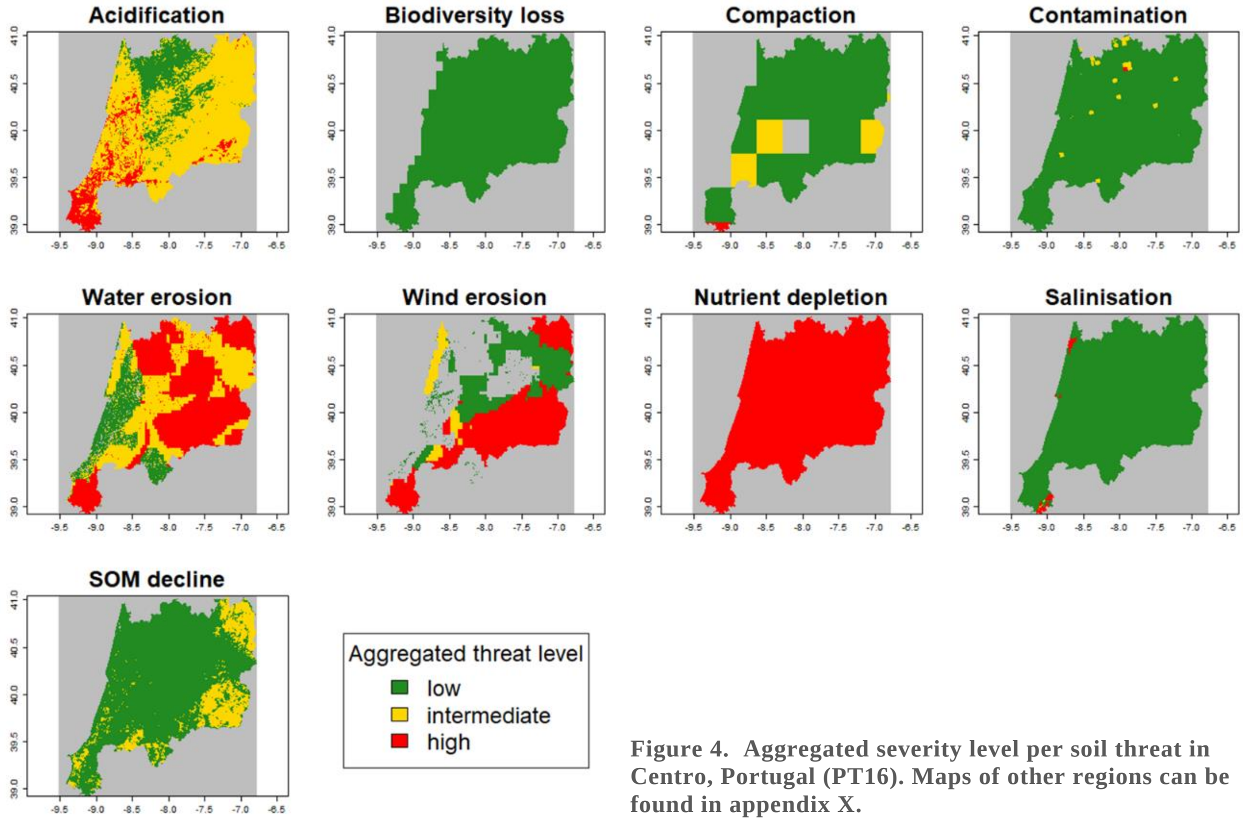


Figure 4. Aggregated severity level per soil threat in Centro, Portugal (PT16). Maps of other regions can be found in appendix X.

The average soil threat severity was subject to less spatial variation (Fig. 3, Fig. 5). On average, the threat level was 1.70 ± 0.25 (low to intermediate). Crete (EL43), Zahodna (SI04) and Valencia (ES52) had the highest threat levels, amongst others due to high levels of acidification (Crete and Valencia), wind erosion (Crete and Valencia), water erosion (Crete and Zahodna), biodiversity decline (Zahodna) and contamination (Zahodna) (see Appendix 9.3.3).

In some maps, the effects of the low-resolution indicators are readily visible. In Lubelskie, Poland, for instance, we see a block pattern with three different shades of green. Low, intermediate and high compaction levels, created the dark green, green and light green blocks, in this instance.

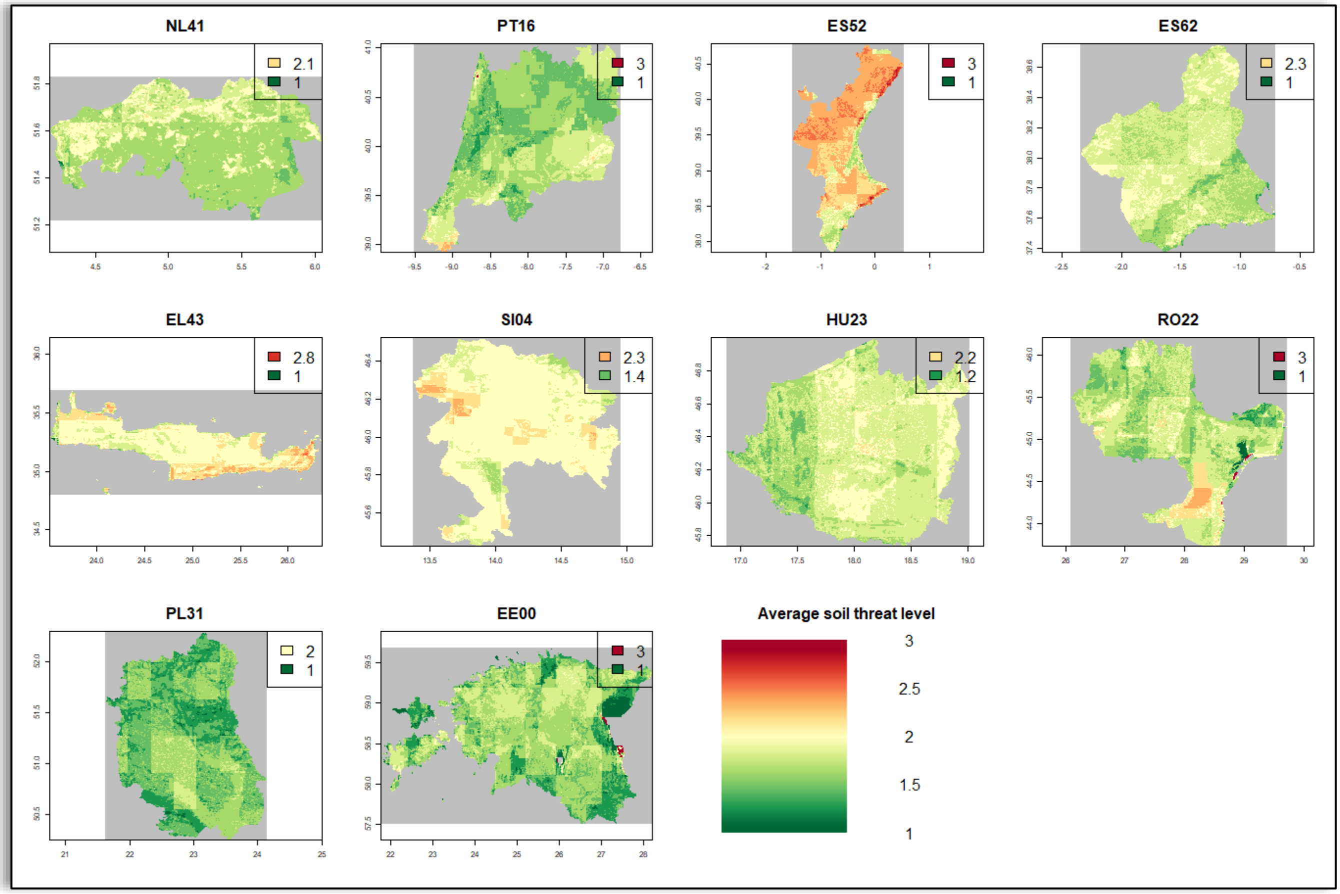


Figure 5. Average soil threat severity level for each of the 10 selected regions. Minimum and maximum averages are displayed in the upper left corners.

5.2 Soil quality improvement potential in Europe

Our spatial analysis revealed that most, but not all, soil quality indicators in most, but not all regions, were no more than one standard deviation away from 50% improvement potential (Fig. 6). Notably high relative improvement potentials for CEC were found in the Netherlands, for bulk density in Greece, for nitrogen in the Netherlands and Greece, for SOC in all regions except Estonia, and for water holding capacity in Greece (Fig. 6). Notably low relative improvement potentials for CEC were found in Estonia, Greece, Romania and Slovenia, for bulk density in Poland, for potassium in Estonia, Spain and Romania, for microbial abundance in the Netherlands, for phosphorus in the Netherlands and Poland, and for pH in Greece and Spain (Fig. 6).

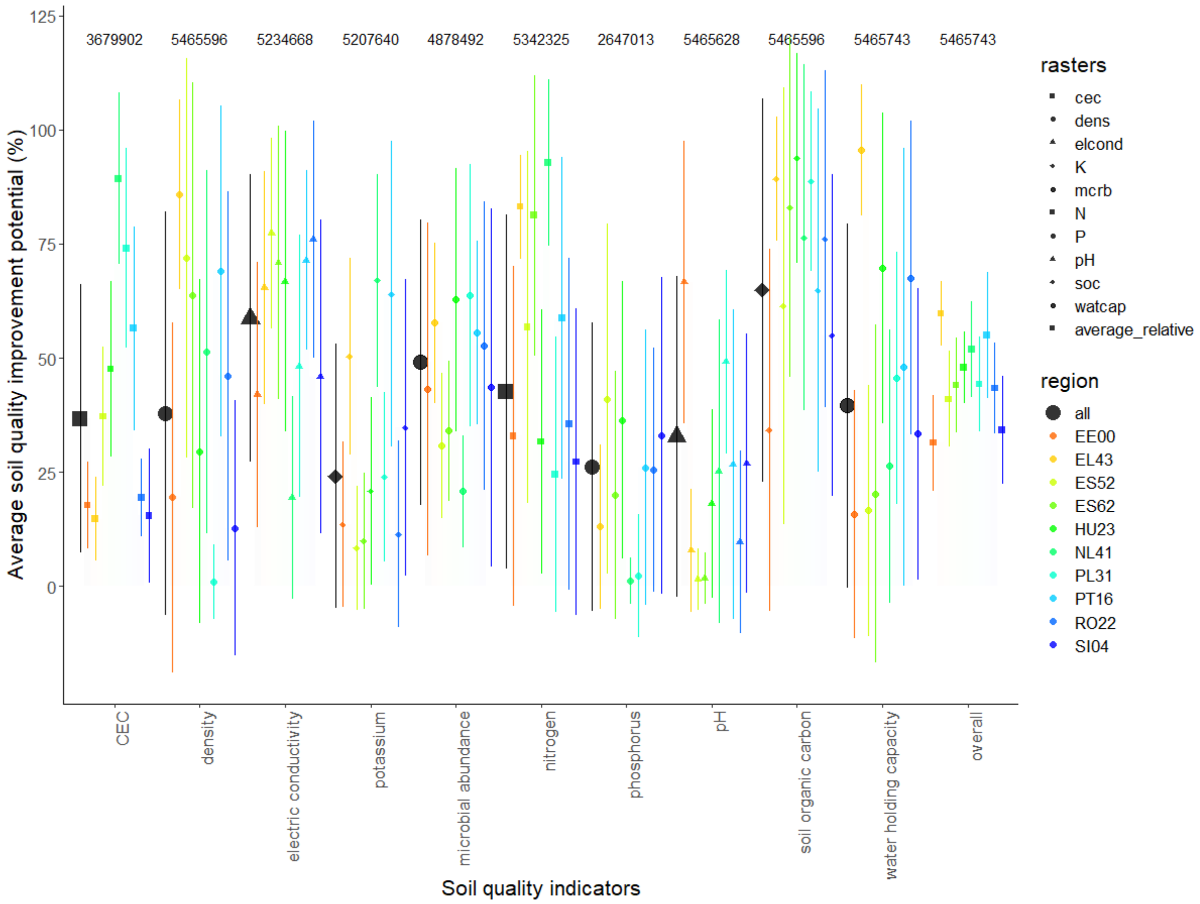


Figure 6. Average soil quality improvement potential (± standard deviation) per region and soil quality indicator. The number of data points per soil threat indicator for all regions combined is written above each soil threat, and overall averages are shown on in the most right column (overall).

Average soil quality improvement potential, however, did not vary much from region to region (Fig. 6, Fig. 7). With average improvement potentials of 34% and 31%, respectively, Slovenia and Estonia had the highest average relative soil quality, whilst Greece and Portugal had the lowest average relative soil quality, with 60% and 55% average improvement potential, respectively (Fig. 6, Fig. 7).

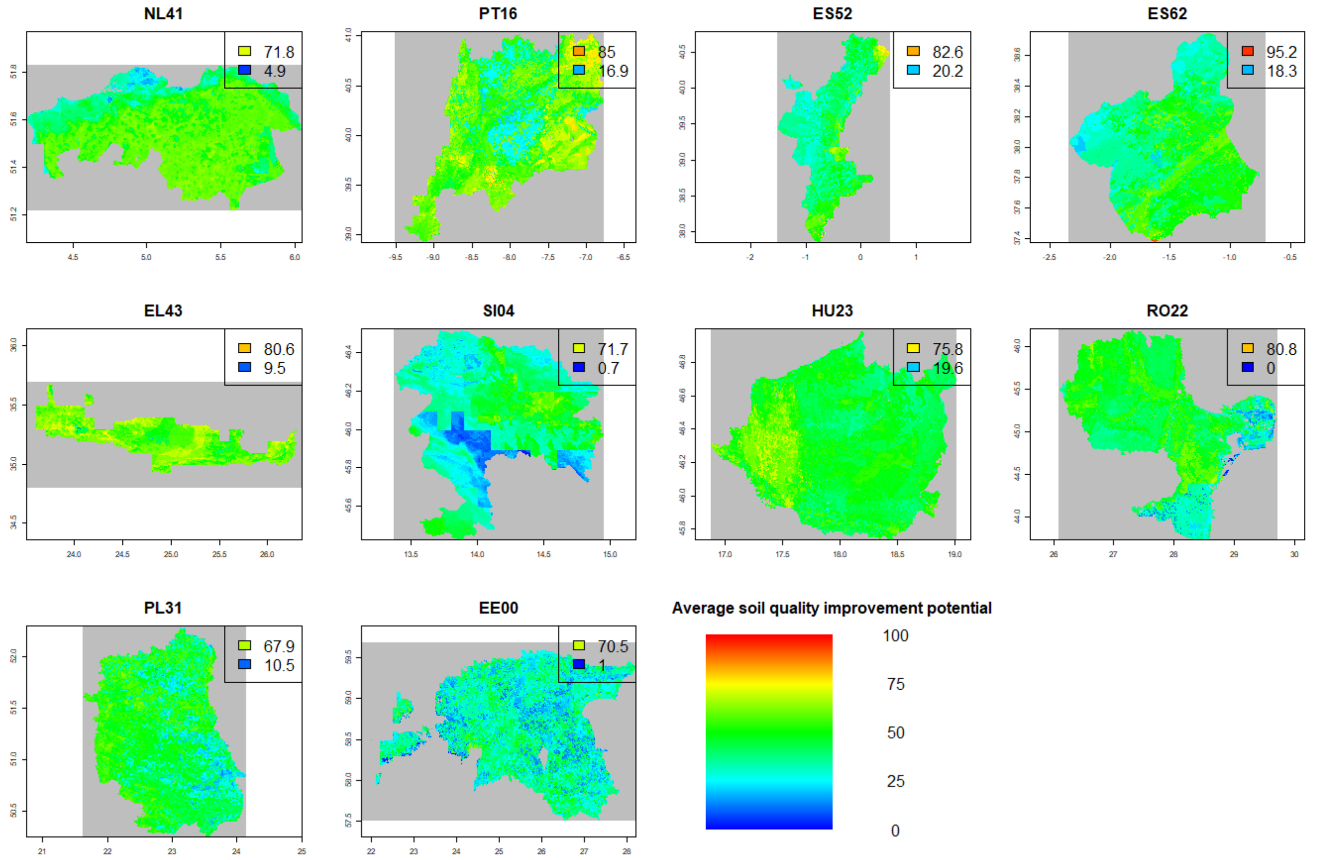


Figure 7. Average relative improvement potential (%) in the selected 10 regions. Minimum and maximum averages improvement potential are displayed in the upper left corners.

When zooming in on Centro, Portugal (PT16), looking at bulk density as a soil quality indicator, we see that the actual bulk density values are between 1200 and 1650 kg m^{-3} (Fig. 8a). Given the climate and soil type, however, it should be possible to reduce the bulk density considerably in many places. In the Southern part of Centro, we can see that the potential achievable bulk density is ~800 kg m^{-3} (Fig. 8b). This results in an absolute improvement potential of ~400 kg m^{-3} in the southern part of Centro, and between 0 and 400 kg m^{-3} in the northern part of Centro (Fig. 8c). In relative terms, however, we see that actual bulk density tends to be very high in the western and eastern parts, and very low in the central parts of Centro (Fig. 8d). The improvement potential follows the same trend (Fig. 8f). To see maps of other soil quality indicators or regions, see Appendix 9.4.2.

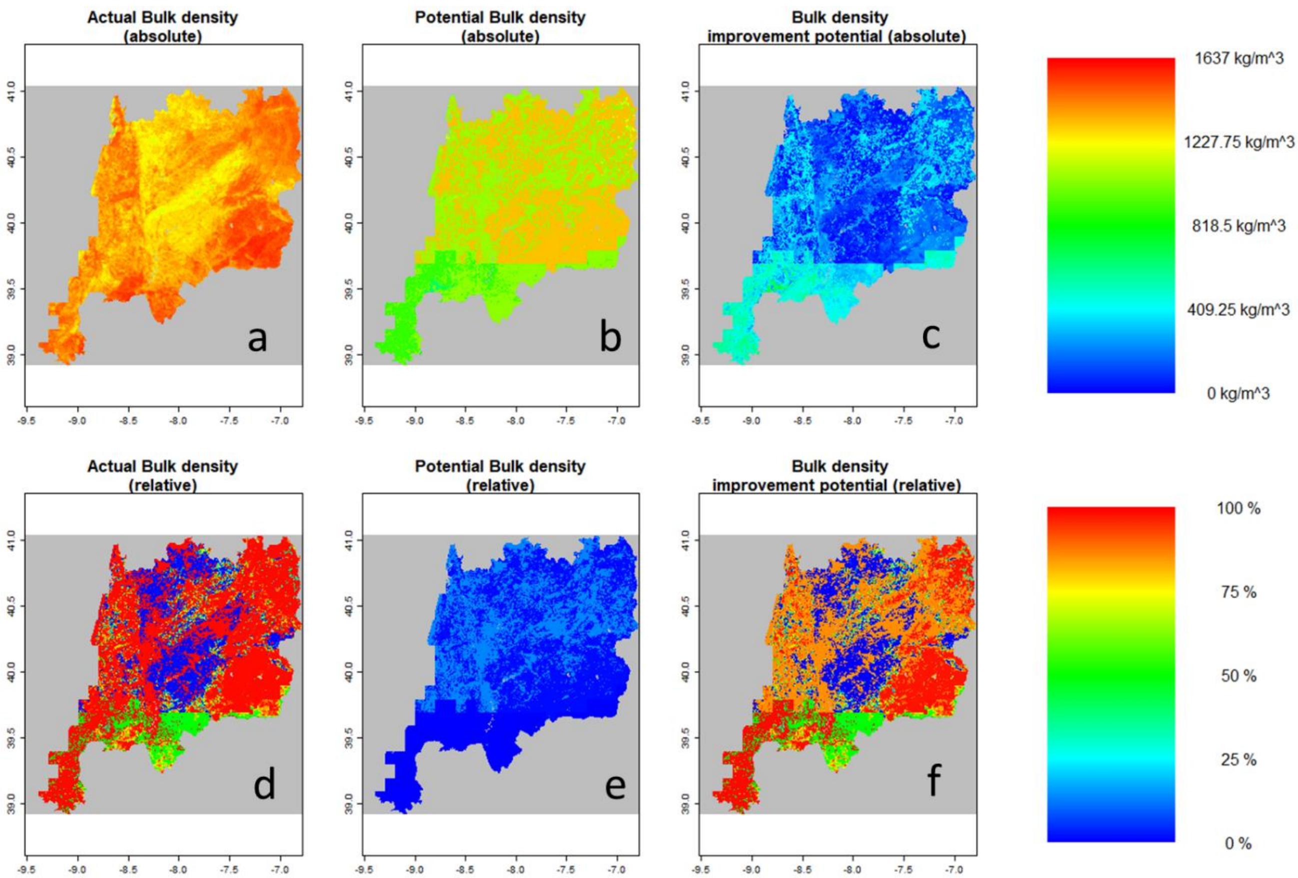


Figure 8. An example of the absolute (a) and relative (d) actual bulk density values (current state), absolute (b) and relative (e) potential bulk density values (optimum values, or capability), and the absolute (c) and relative (f) bulk density improvement potential. Potential bulk density values depend on climate and soil characteristics.

5.3 Agricultural management recommendations

5.3.1 Agricultural management recommendations obtained using the SQApp algorithm

Additive scores

The additive scores used to rank AMPs in the SQApp algorithm, were found to differ in space and vary among AMPs (Fig 9, Fig 10). The highest obtained additive scores ranged from 8 in Hungary (HU23), Murcia (ES62), Poland (PL31) and Estonia (EE00), to 11 in Valencia (ES52) (Fig. 11).

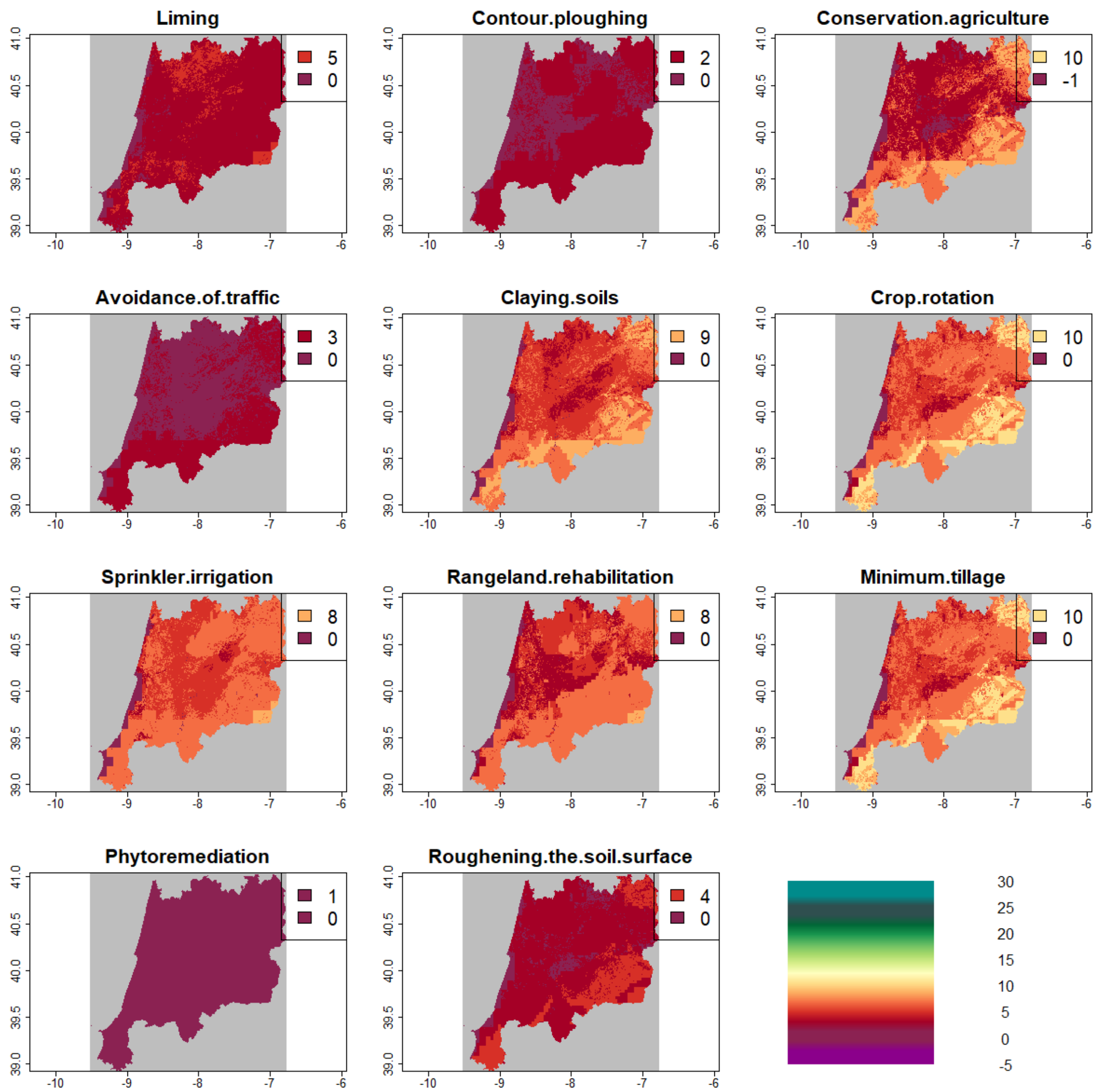


Figure 9. The additive scores obtained by eleven randomly selected AMPs in Centro, Portugal (PT16), using the SQApp algorithm (scenario A). The numbers in the upper corners of each map show the maximum and minimum scores obtained by each AMP and their associated colour.

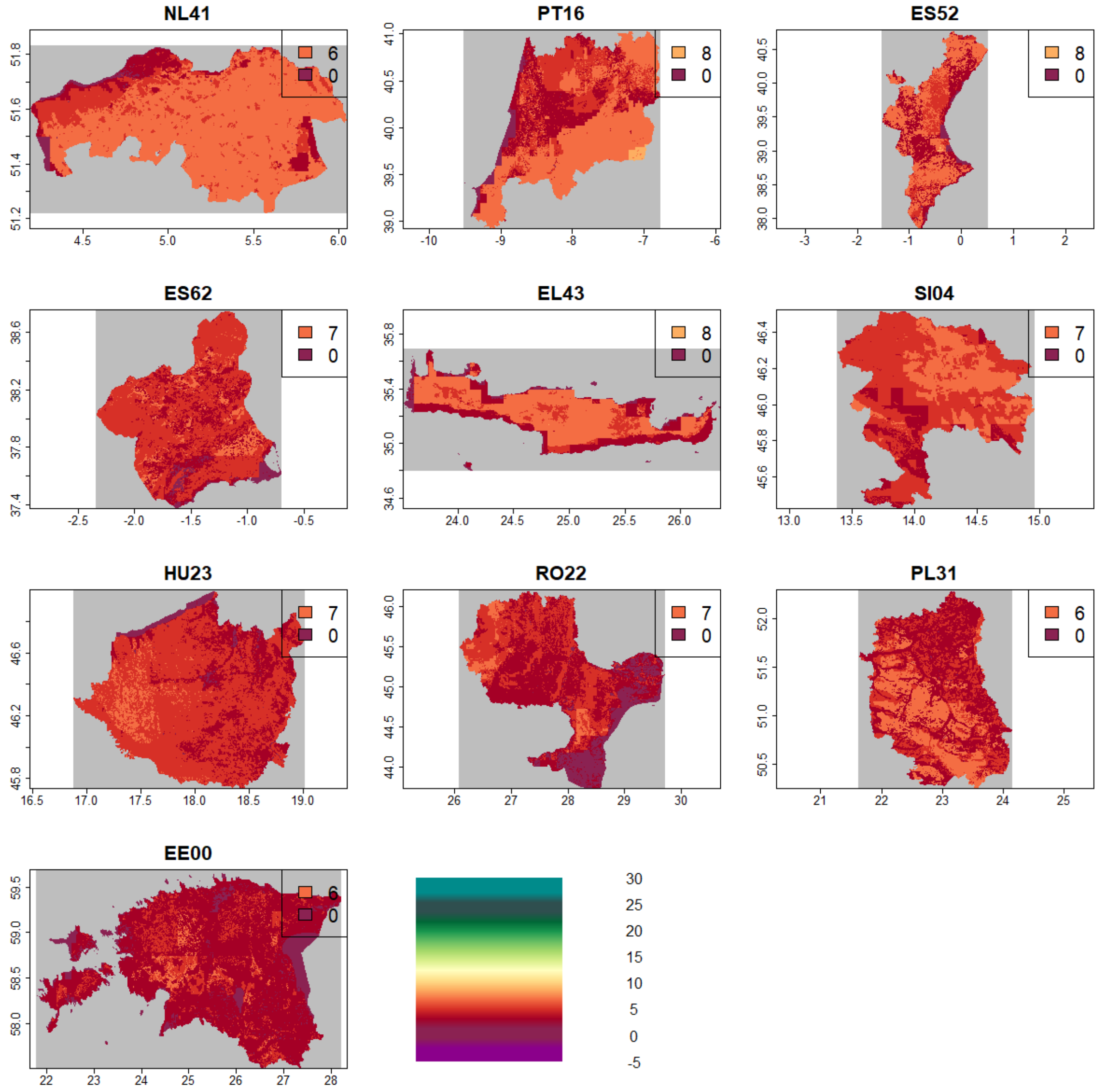


Figure 10. The additive scores obtained by one AMP (agroforestry) in each of the selected European regions, using the SQApp algorithm (scenario A). The numbers in the upper corners of each map show the maximum and minimum scores obtained by each AMP and their associated colour.

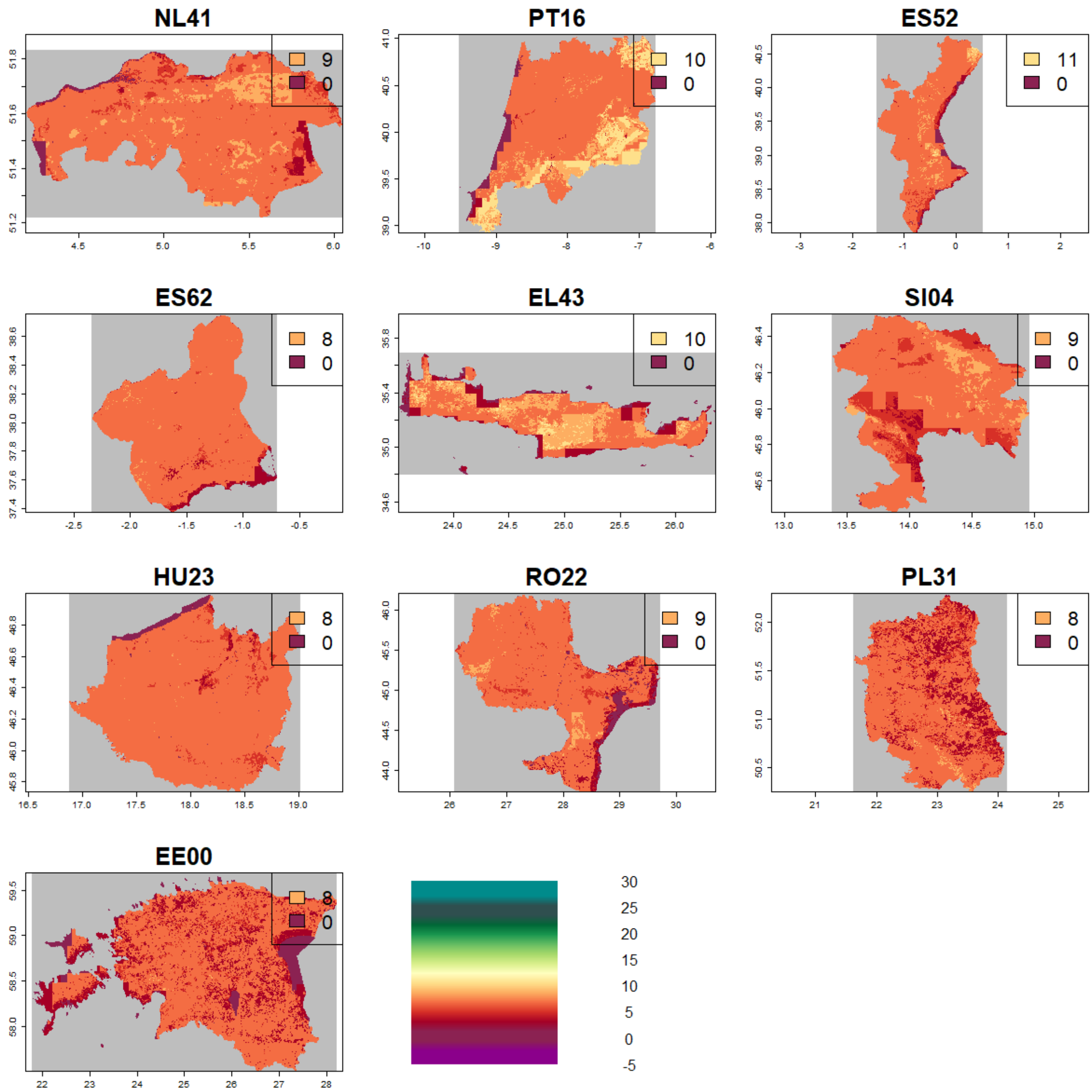


Figure 11. The highest obtained additive scores in each selected European regions, using the SQApp algorithm (scenario A). The numbers in the upper corners of each map show the maximum and minimum scores obtained by each AMP and their associated colours.

The number of AMPs achieving those highest scores ranged from 1 to 69 (even in lakes, management advice would be produced). Areas where one AMP was the single best practice were rare, as were areas where more than ten AMPs obtained the highest attainable additive score (Fig. 12). Where there were single best practices, these were either biochar application, compost application or sprinkler irrigation (Fig. 13).

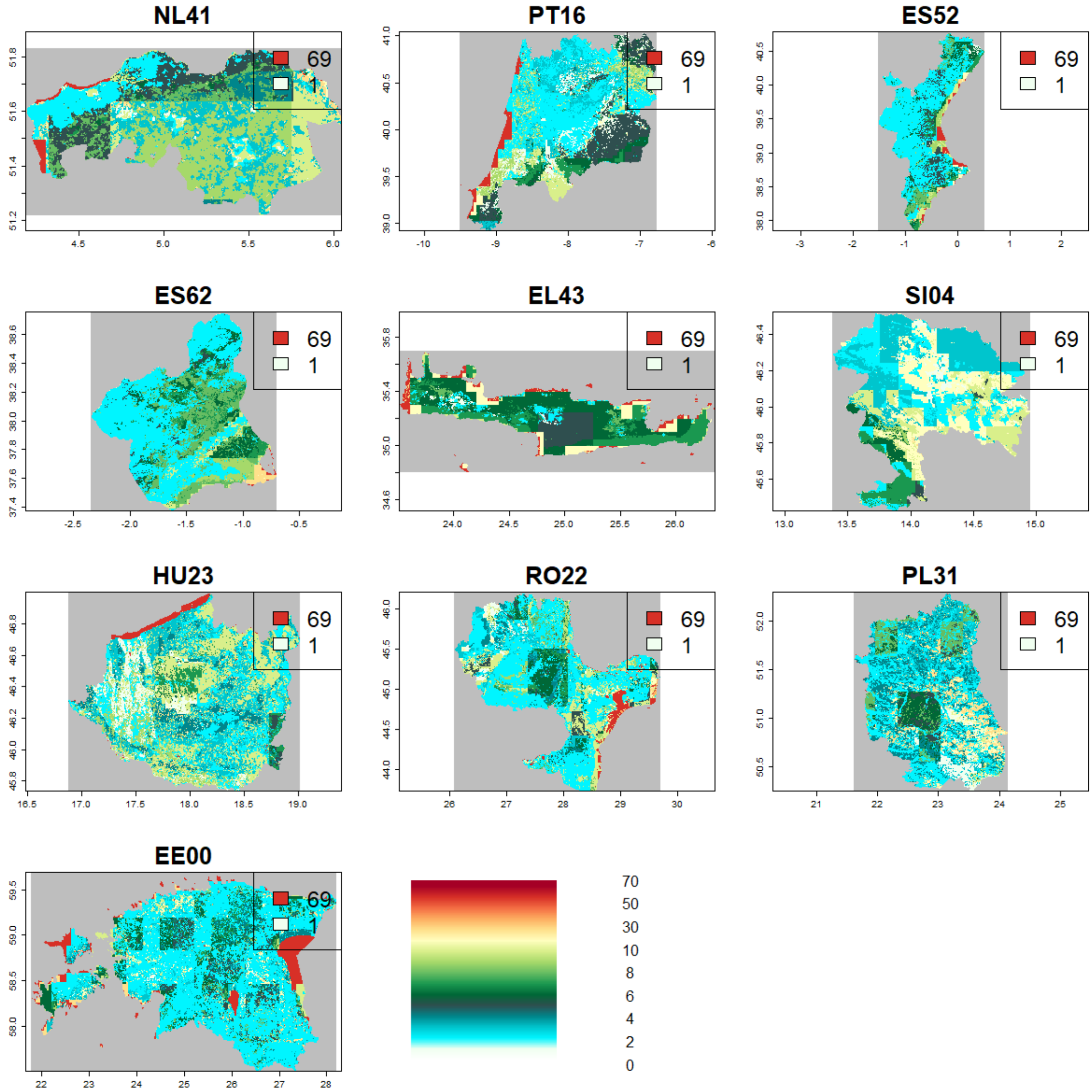


Figure 12. Number of AMPs obtaining the highest attainable score in each of the selected European regions, using the SQApp algorithm (scenario A). The numbers in the upper corners of each map show the maximum and minimum number of best AMPs and their associated colours.

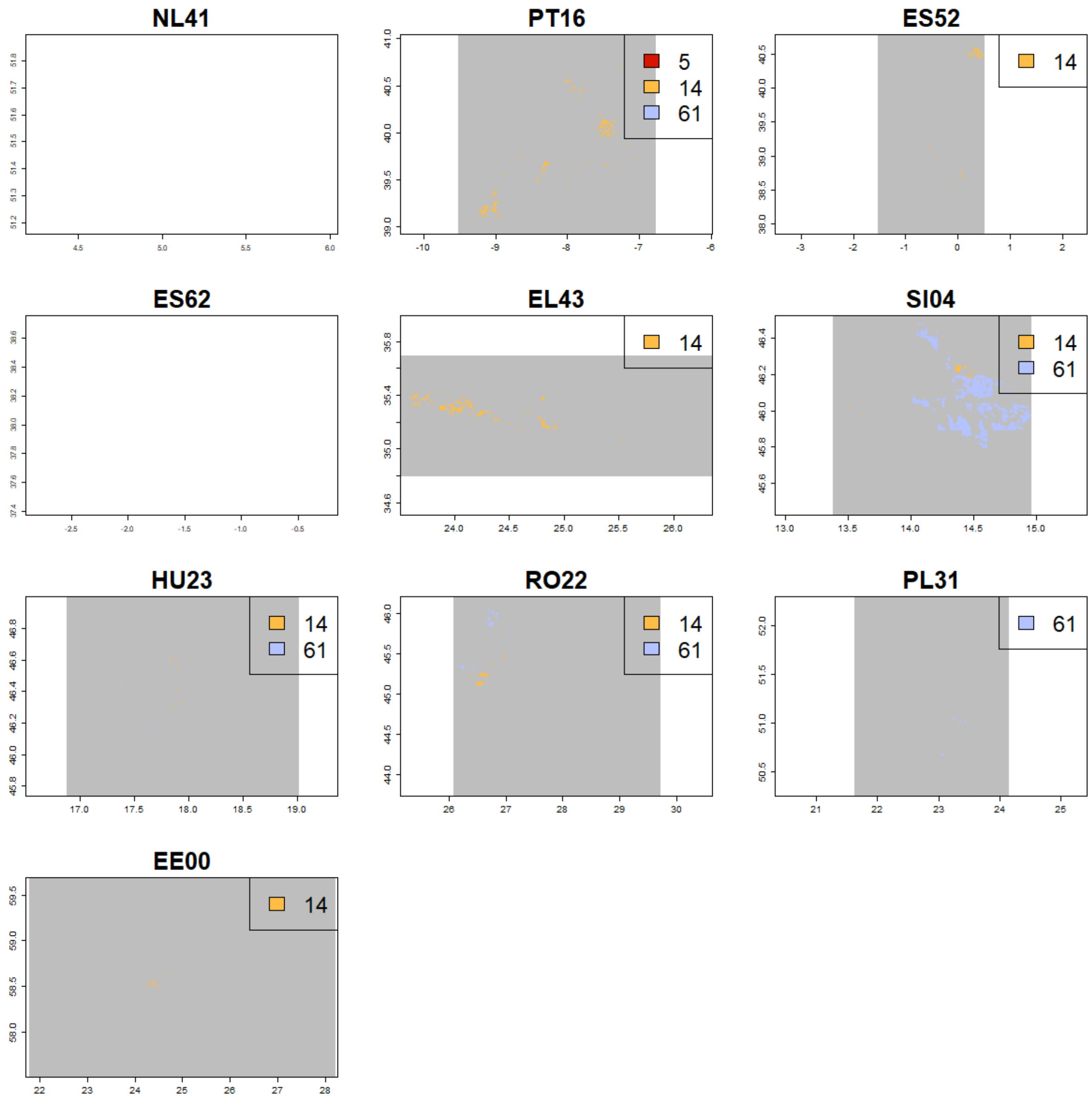


Figure 13. AMPs obtaining the highest attainable score alone in selected European regions, using the SQApp algorithm (scenario A): Biochar application (5), Compost application (14) and Sprinkler irrigation (61). In the Brabant (NL41) and Murcia (ES62), there were no single best practices.

Looking at all AMPs achieving the highest scores and not only the AMPs achieving the highest scores alone, we see that a great diversity of AMPs were recommended, amongst which the most common were compost application (14), crop rotation/diversification (20), growing halophytes (28), minimum-tillage (44), no-tillage (45) and straw interlayer burial (62) (Fig. 14). Moving away from the highest scores to the second highest and down to the tenth highest scores, the diversity of management practices being recommended increased (Fig. 14).

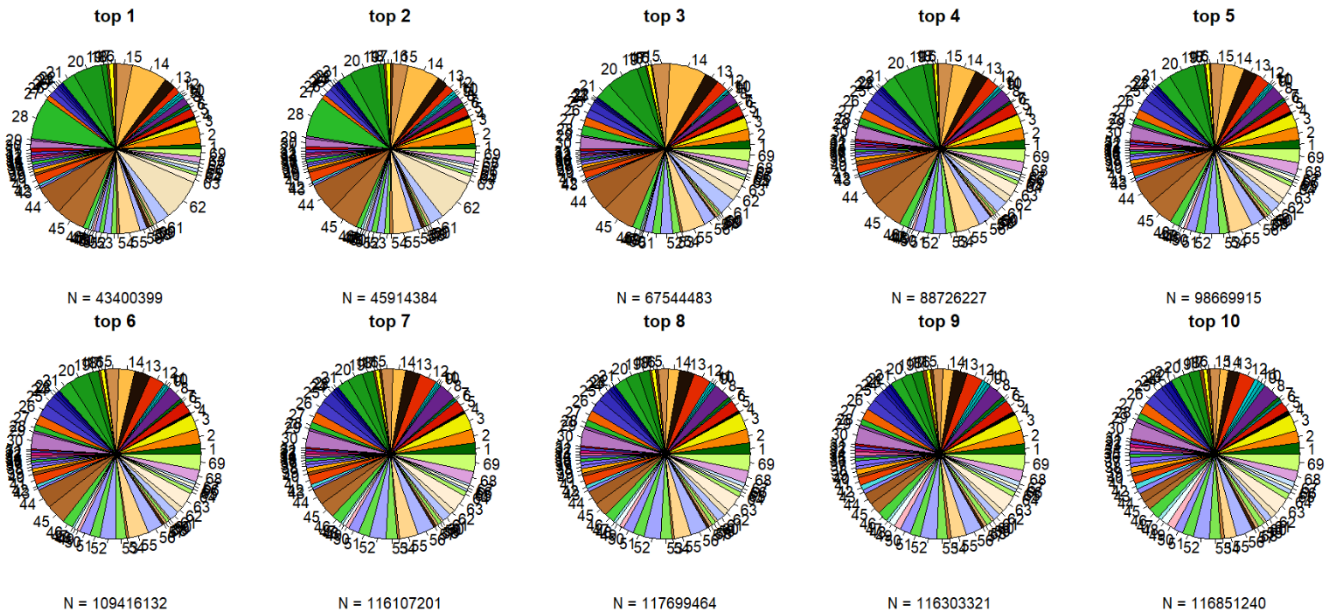


Figure 14. The frequency at which AMPs obtained the highest attainable scores (top 1), second highest attainable scores (top 2), third highest (top 3), and onwards to the tenth highest attainable scores (top 10), in all the selected European regions combined, using the SQApp algorithm (scenario A). See table 3 for AMP descriptions.

5.3.2 The effect of cropping system on the recommendation of AMPs

Restricting the array of possible AMPs to those suitable for specific cropping systems only, did not have much effect on the highest achieved additive scores for the cropping systems: cereals, root crops, or permanent crops with or without soil cover (Fig. 15). The highest attained scores in the scenarios where the land use was assumed to be pasture or rangeland, however, were often lower than in the other cropping systems scenarios, as well as in the baseline scenario where no cropping system was assumed (Fig. 15). This trend was similar in all European regions (Appendix 9.5.2).

The number of AMPs obtaining the highest attainable scores in the scenarios where specific cropping systems were assumed, differed according to cropping system. Assuming the cropping system was cereals or root crops, did not reduce the number of AMPs obtaining the highest attainable scores much, but assuming the cropping system was pasture, rangeland, or permanent crops did (Fig. 16). This trend was similar in other all European regions (Fig 16, Appendix 9.5.3).

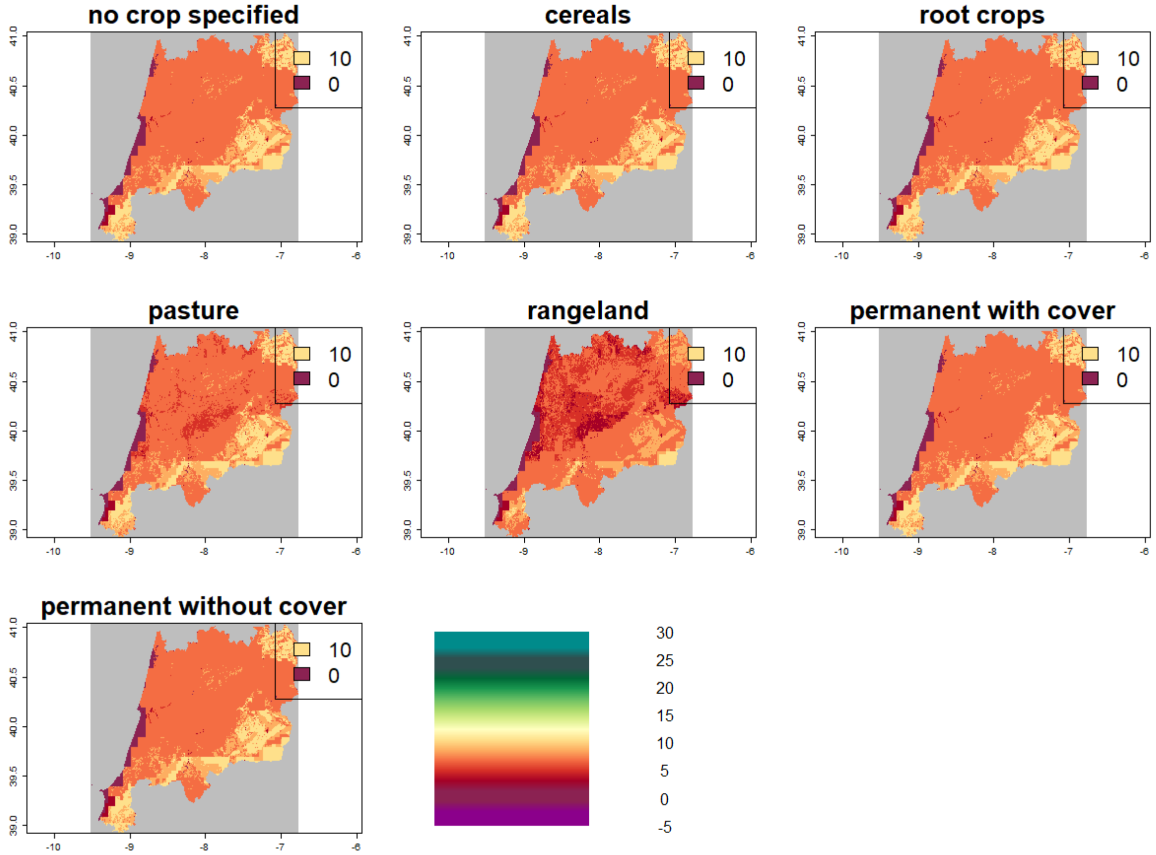


Figure 15. The highest attained scores for the baseline scenario (no crop specified), and the scenarios where specific cropping systems were assumed and only AMPs suitable for those cropping systems were considered. The numbers in the upper corners of each map show the maximum and minimum scores obtained by each AMP and their associated colours.

Where there were single best practices, these were biochar application, compost application or sprinkler irrigation assuming cereals or root crops; compost application, controlled and rotational grazing or sprinkler irrigation assuming pasture; animal manure application, controlled and rotational grazing or integrated nutrient management assuming rangeland, and compost application, growing halophytes and sprinkler irrigation, assuming permanent crops were grown with and without soil cover (Fig. 17).

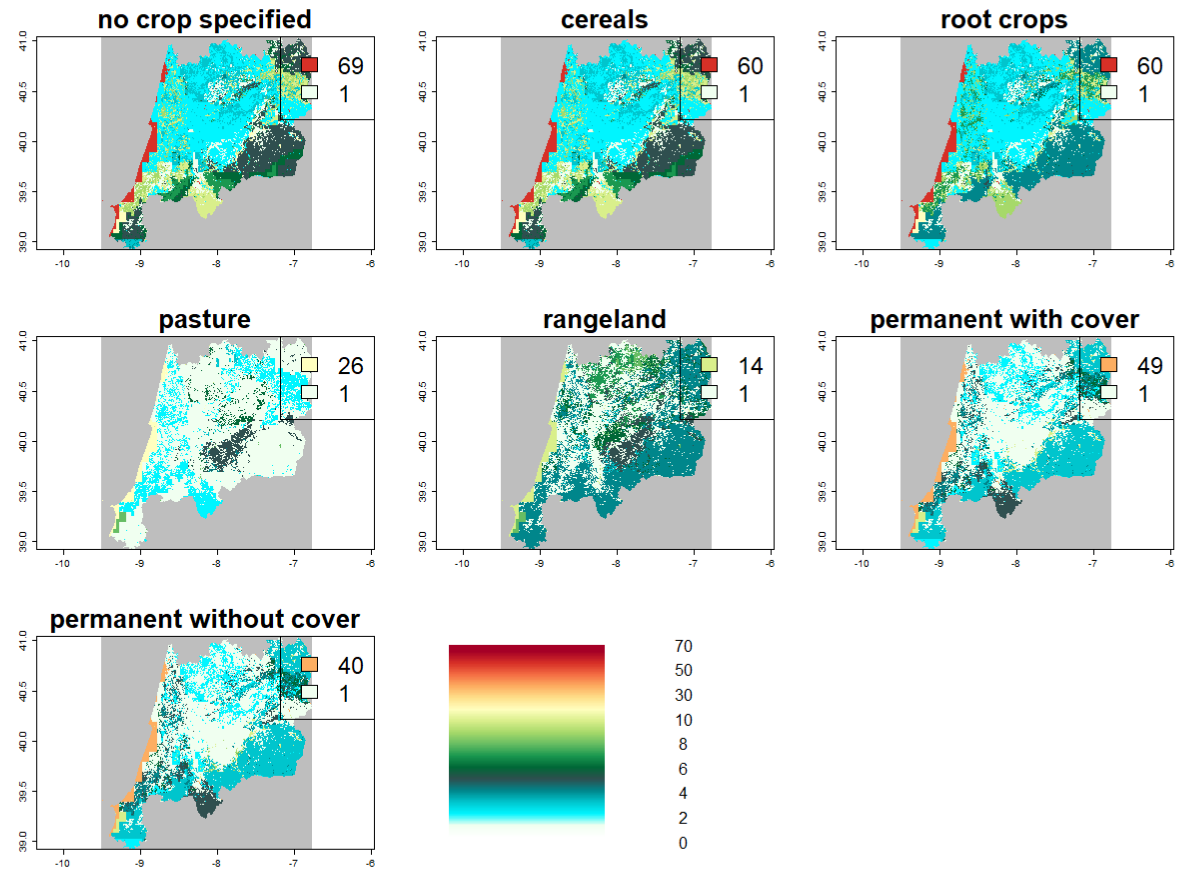


Figure 16. Number of AMPs obtaining the highest attainable score in Centro, Portugal (PT16), using the SQApp algorithm (scenario A), assuming the cropping system to be cereal or root crop production, pasture or rangeland, or production of permanent crops with or without soil cover. The numbers in the upper corners of each map show the maximum and minimum number of best AMPs and their associated colours.

Looking at all AMPs achieving the highest scores and not only the AMPs achieving the highest scores alone, we see that a great diversity of AMPs were recommended (Fig. 18). When assuming cereals or root crops were produced, the most common agricultural management practices were the same as in the absence of any cropping system assumption. Assuming permanent crops were grown, also resulted in many of the same management practices being recommended as in the absence of any cropping system assumption, with the exception of crop rotation and straw interlayer burial. Assuming the land was pasture or rangeland, however, management practices such as animal manure application (2), area closure (3), bunds (8), sprinkler irrigation (61) and vegetative strips (69) were more commonly recommended (Fig. 18). In rangeland specifically, rangeland rehabilitation (53) was also a commonly recommended practice. Moving away from the highest scores to the second highest and down to the tenth highest scores, the diversity of management practices being recommended increased (Fig. 18).

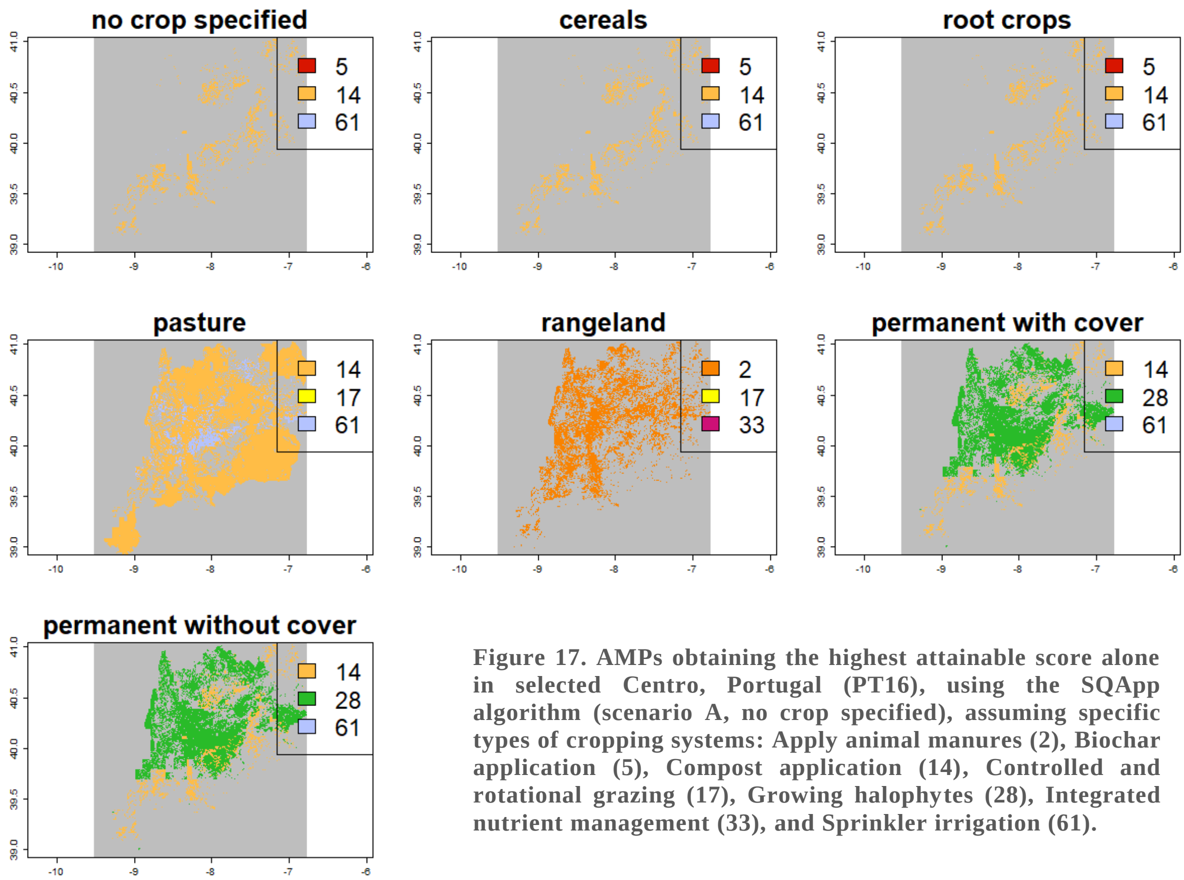


Figure 17. AMPs obtaining the highest attainable score alone in selected Centro, Portugal (PT16), using the SQApp algorithm (scenario A, no crop specified), assuming specific types of cropping systems: Apply animal manures (2), Biochar application (5), Compost application (14), Controlled and rotational grazing (17), Growing halophytes (28), Integrated nutrient management (33), and Sprinkler irrigation (61).

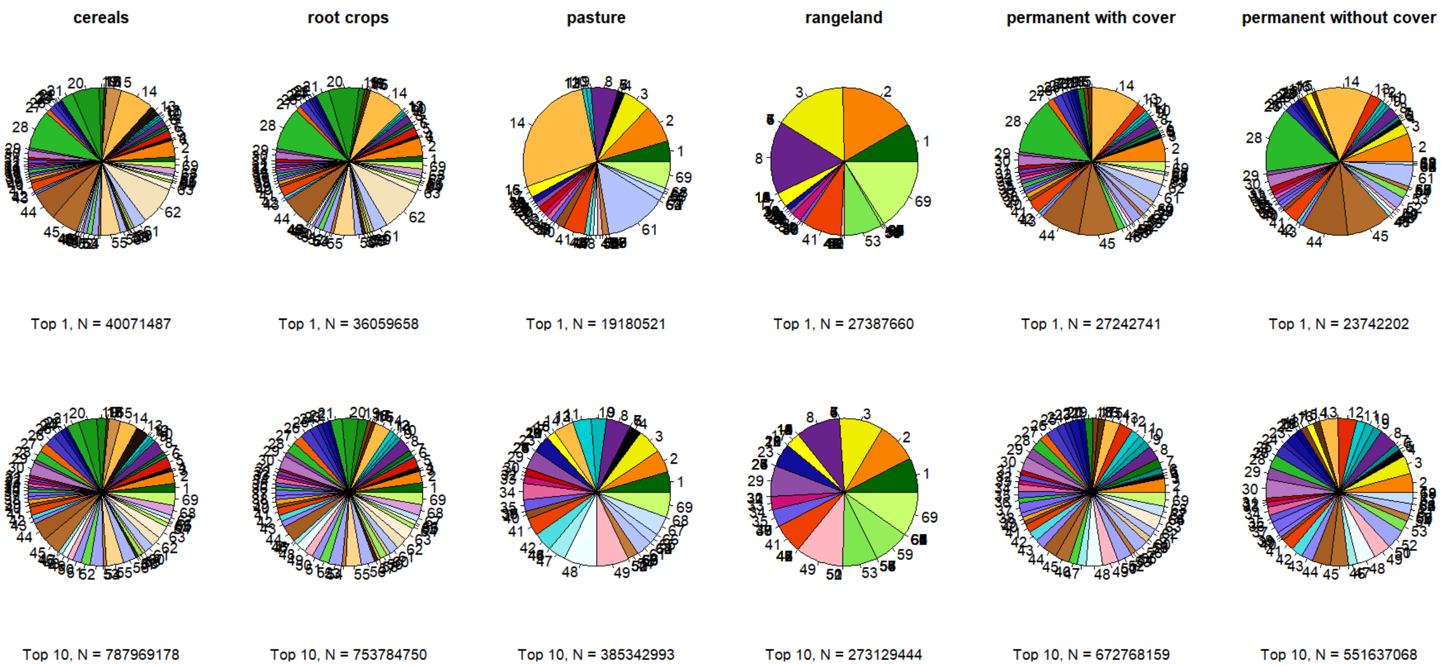
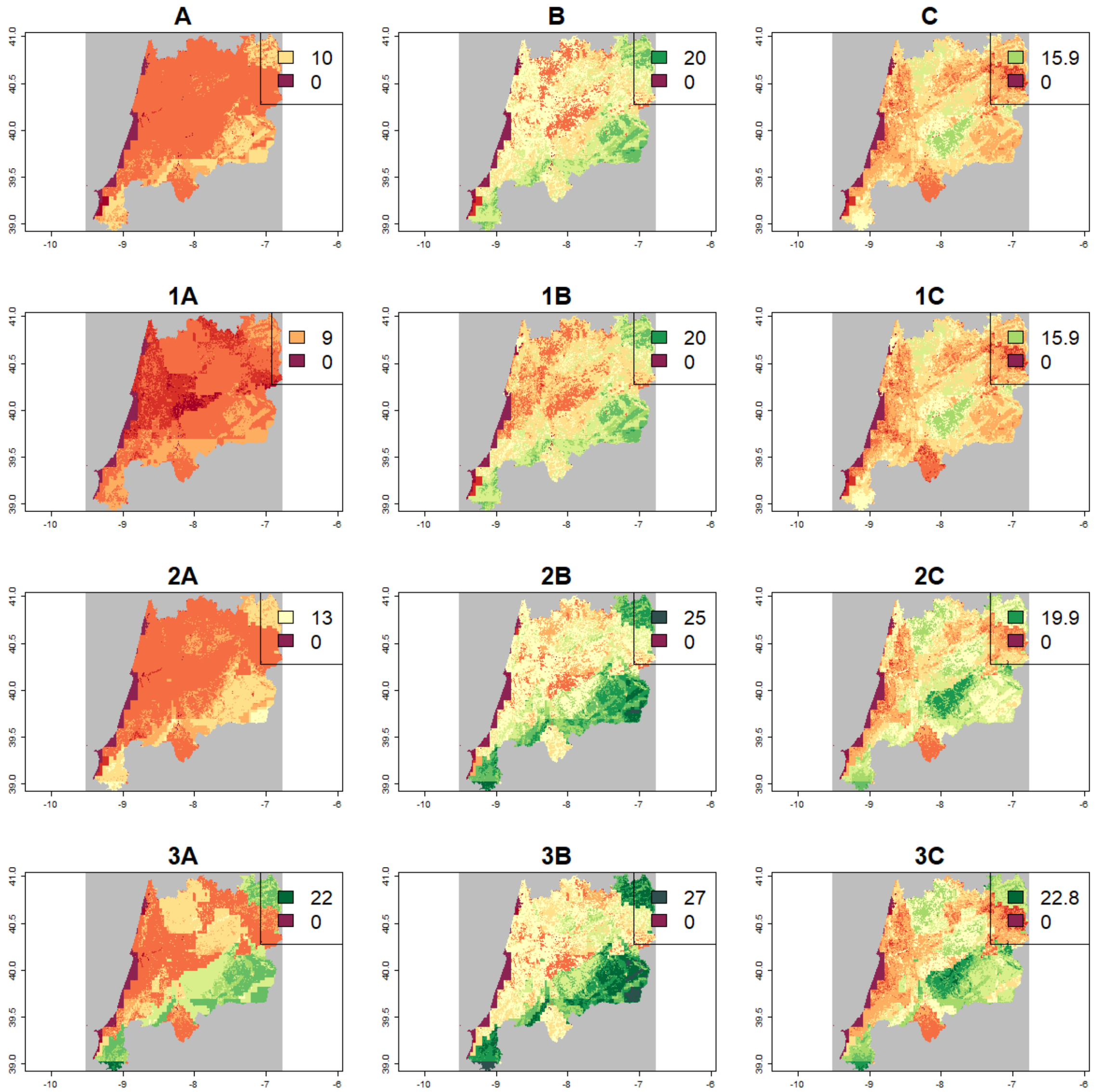


Figure 18. The frequency at which AMPs obtained the highest attainable scores (top 1), or one of the ten highest attainable scores (top 10), in all the selected European regions combined, using the SQApp algorithm (scenario A), assuming specific types of cropping systems. See table X for AMP descriptions.

5.3.3 The effect of different weighing methods on AMP recommendations

Weighing soil threat and soil quality indicators differently, greatly affected the highest achieved additive scores (Fig 19, Appendix 9.4.2). Visually, scenarios B, B1, B2, and B3, and C, C1, C2, and C3 were subject to greater spatial variation (Fig 19). This trend was similar in all European regions (Appendix 9.4.2).



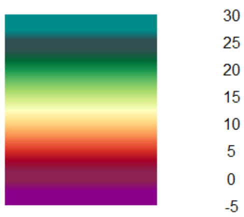
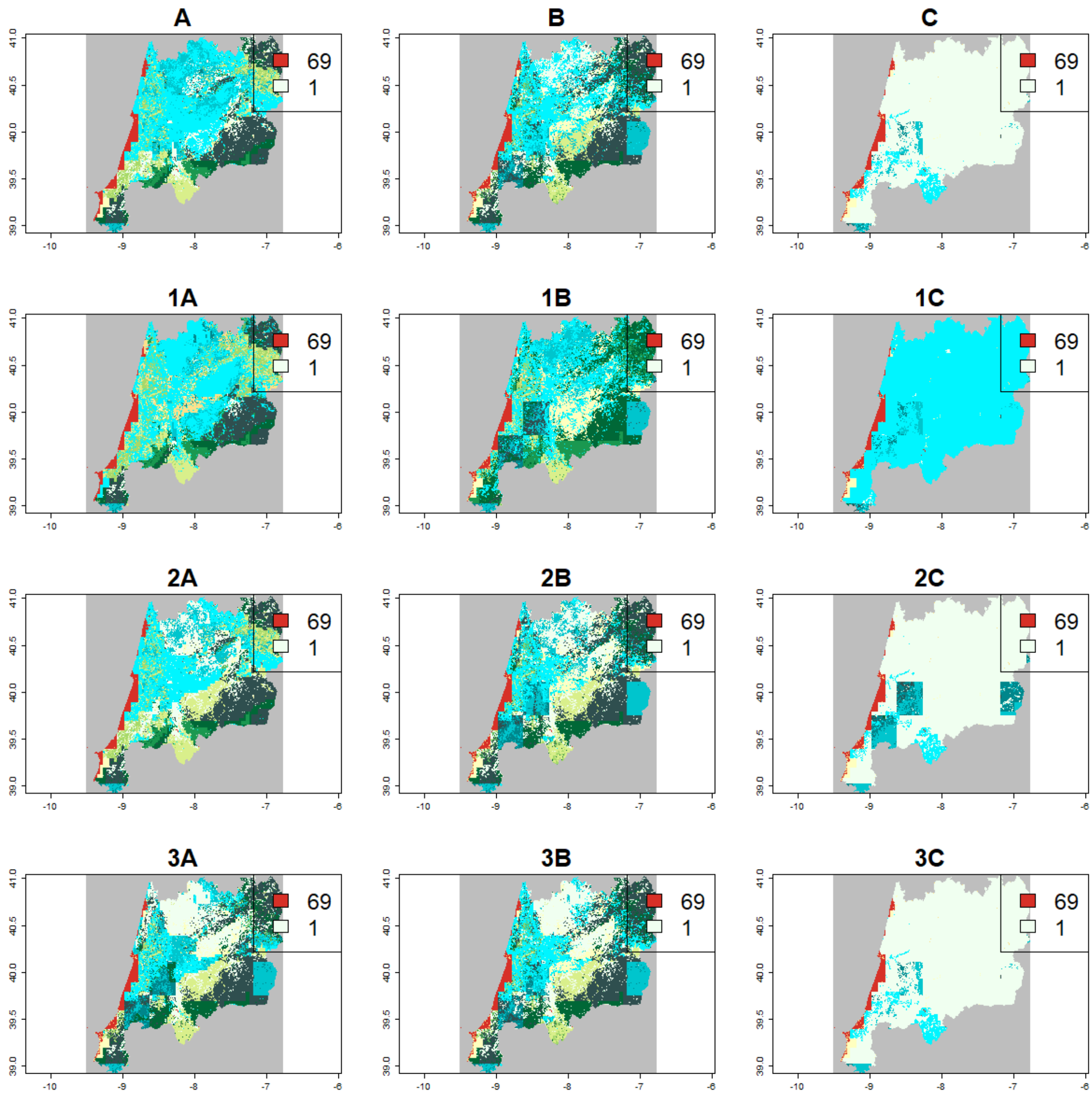


Figure 19. The highest attained scores for the baseline scenario (A), and the scenarios where different weighing methods were used to create AMP recommendations. See table X for description of scenarios. The numbers in the upper corners of each map show the maximum and minimum scores obtained by each AMP and their associated colours.

The number of AMPs obtaining the highest attainable, differed according to scenario. While accounting for salinity as a threat instead of a soil quality indicator (1A-1C), did not reduce the

number of AMPs obtaining the highest attainable scores much, allowing for continuous weights according to soil quality improvement potential (C-3C) did (Fig. 20). Though not to the same extent, weighing (severe) soil threats more heavily than soil quality indicators (2A-2C and 3A-3C), also reduced the number of AMPs obtaining the highest attainable scores. This trend was similar in other all European regions (Fig 20, Appendix 9.5.3).



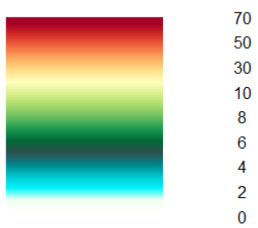


Figure 20. Number of AMPs obtaining the highest attainable score in Centro, Portugal (PT16), using the SQApp algorithm (scenario A), and the scenarios where different weighing methods were used to create AMP recommendations. See table X for description of scenarios. The numbers in the upper corners of each map show the maximum and minimum number of best AMPs and their associated colours.

Where there were single best practices, compost application dominated, occasionally losing to biochar application (5), buffer zones (7), liming (40) and sprinkler irrigation (Fig. 21).

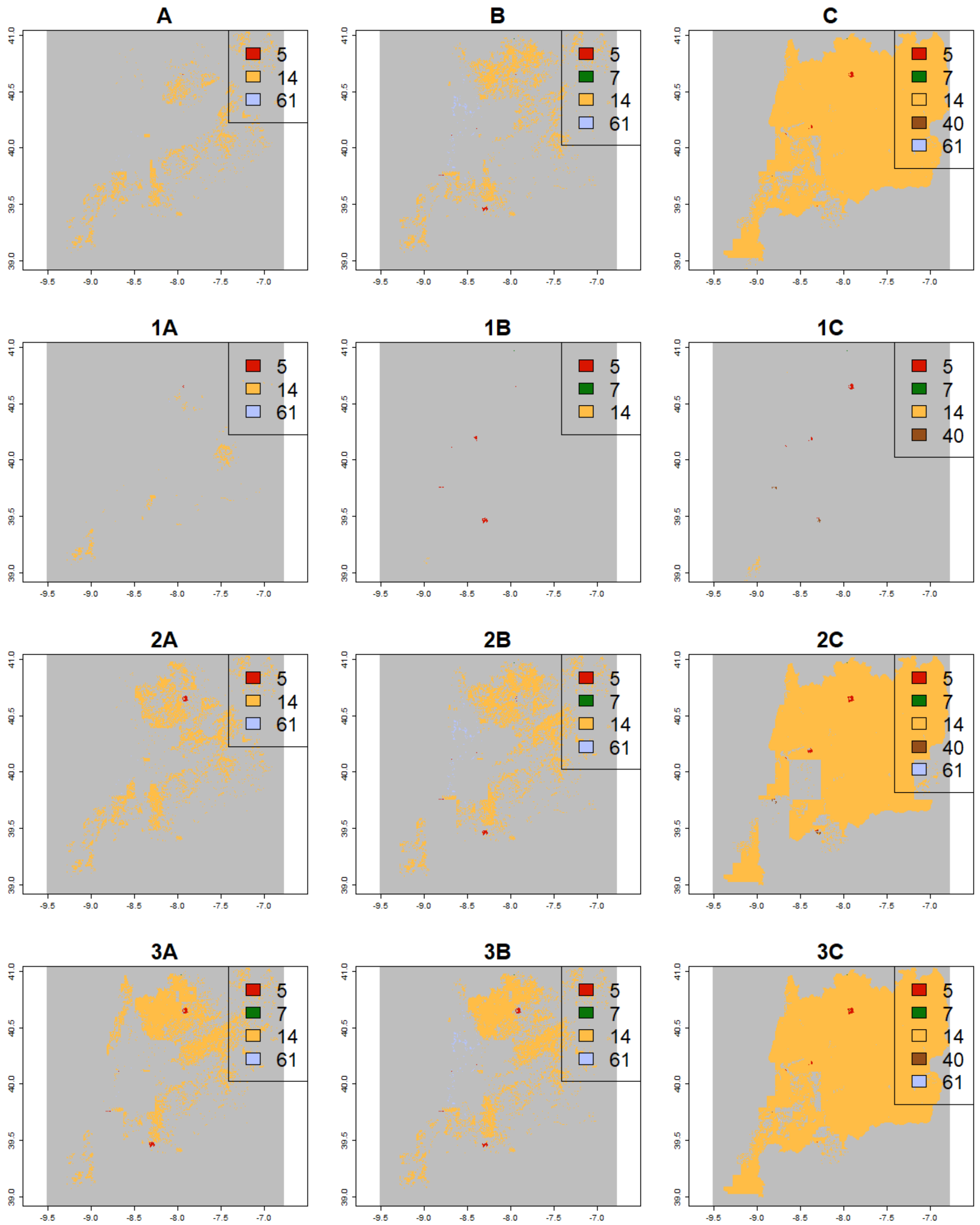


Figure 21. AMPs obtaining the highest attainable score alone in selected Centro, Portugal (PT16), using the SQApp algorithm (scenario A), and the scenarios where different weighing methods were used to create AMP recommendations. See table X for description of scenarios: Biochar application (5), Buffer zones/landscape elements (7), Liming (40), and Sprinkler irrigation (61).

Looking at all AMPs achieving the highest scores and not only the AMPs achieving the highest scores alone, we see that a great diversity of AMPs were recommended in all scenarios (Fig. 22). Practices that were dominant in all scenarios, were: animal manure application (2), compost application (14), crop rotation/diversification (20), deep rooting crops (21), and minimum tillage (44) and no-tillage (45). The relative dominance of these practices did, however, vary according to scenario. This is not necessarily caused by a variation in absolute dominance, though; dominance of crop rotation, for instance, can be seen to decrease as the number of best practices (N) increases. However, for crop rotation/diversification, deep rooting crops, minimum-tillage, and no-tillage, the absolute number of times the highest attainable scores were obtained, clearly differs between scenarios. The relative dominance of these practices, seem to depend largely on the absence/presence of other dominant practices.

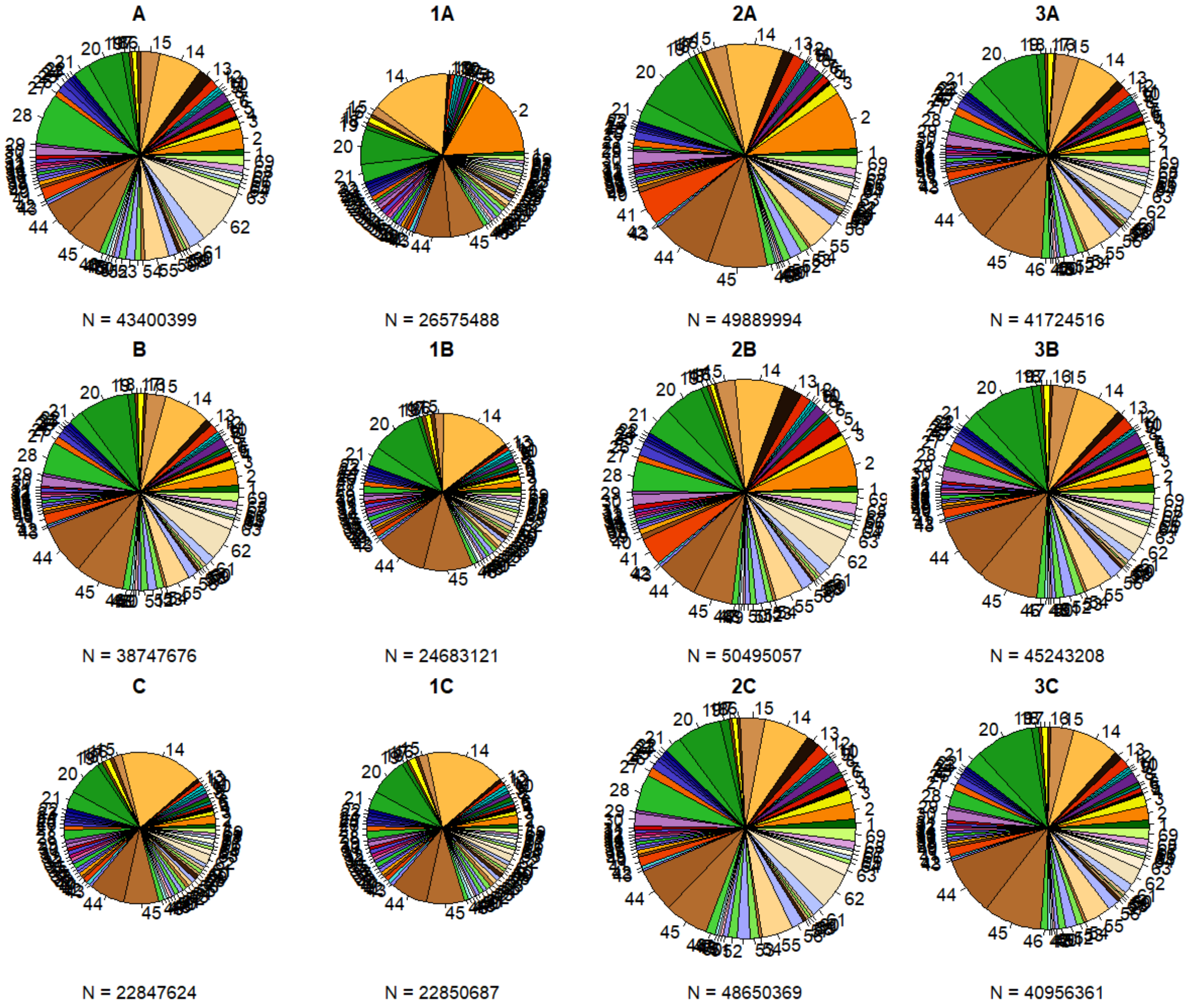


Figure 22. The frequency at which AMPs obtained the highest attainable scores, in all the selected European regions combined, using the SQApp algorithm (scenario A), and the scenarios where different weighing methods (1A-3C) were used to create AMP recommendations. The number of AMPs achieving the highest attainable score for all locations combined is given below each pie-cart (N). The area of each pie ∝ N. See table X for description of scenarios and table Y for description of AMPs.

Agricultural practices that were dominant in some, but not all scenarios were: growing halophytes (28), liquid manure and slurry application (41), retaining crop residues (55), and straw interlayer burial (62) (Fig. 22). The dominance of growing halophytes and straw interlayer burial was absent from the scenarios where salinity was not considered to be a relative (soil quality) indicator, but an soil threat with absolute thresholds defining soil threat severity (1A-2C). It was also reduced in the scenarios where a continuous weighing method was used (scenarios C-3C) and where soil threats were weighed more heavily than soil quality indicators (2A-2C and 3A-3C). Slurry application, was especially dominant in scenarios 2A and 2B, i.e. where a stepwise (not continuous) weighing method was used and the effect of AMPs on soil threats weighed more heavily than on soil quality indicators. Retaining crop residues was a dominant practice in all scenarios but C and 1A-1C, i.e. it's dominance was impeded by a continuous weighing of the effect of AMPs on soil quality indicators and by regarding salinity as a threat indicator.

6 Discussion

In this study we aimed to facilitate the development of need-based and spatially explicit agricultural policies for soil quality improvement, by mapping i) overall soil threat severity in Europe, ii) potential for soil quality improvement in Europe and iii) the management practice(s) that are best suited to alleviate soil threats and improve soil quality.

Soil threats

Mapping overall soil threat severity provided valuable insights:

i) The frequency of high threat levels due to nutrient depletion was very high in all selected European regions

ii) The frequency of intermediate and high threat levels due to contamination and salinization was very low in all selected European regions

iii) The frequency of the remaining soil threats varied between and within the selected European regions.

The implications of these results for policy makers, is that improved nutrient management is urgently needed in all European regions, and could be addressed through a common set of guidelines, regulations or laws. Mitigation of other soil threats, such as biodiversity loss, soil organic matter depletion and acidification, would be better addressed through regional and sub-regional guidelines, regulations and laws.

Mapping soil threats did, however, also reveal that the completeness and resolution at which soil threat data are available is poor for some soil threat indicators. Amongst these indicators were: soil compaction susceptibility, soil biodiversity index, soil loss due to wind erosion, wind erosion vulnerability, and water erosion vulnerability. Moreover, tests done by (Luuk reference about in-field testing of the SQApp) revealed that the estimates for the indicators: total nitrogen, exchangeable potassium and Ohlsen-extracted phosphorus were very inaccurate. While incomplete data may result in ineffective policies, too coarse data and data of poor quality can potentially lead to ill-informed policies, that may potentially cause soil quality to decrease rather than improve (Turpin 2017). Therefore, investments in research and soil monitoring are essential for the further development of need-based and spatially explicit policies. Future research should reassess the management advice given here with improved information on the mentioned indicators[3].

Agricultural management advice

Using the SQApp algorithm, we found that a great diversity of agricultural management practices were recommended (Fig. 14). We were, however, not able to visualise these in space, as there was rarely one agricultural management practice that was the best (Fig. 13). This means that, as of now, we are not able to assess how suitable or spatially varied the agricultural practices recommended using the SQApp algorithm were. Two methods that partially overcame this weakness were presented: i) narrowing down the array of AMPs to the AMPs applicable in a specific cropping system only, and ii) optimizing the method used to weigh the soil threat and soil quality indicators.

[3] We will do this for nitrogen, phosphorus and potassium in the future.

We found that narrowing down the array of AMPs was effective for pasture, rangeland, and permanent crops with, and without soil cover. Narrowing down the array of AMPs applicable in cereals and root crops, was ineffective (Fig 17). As cereals are the dominant crop on arable land in Europe (Eurostat 2017), this is problematic. Expanding the range of possible additive scores through different weighing methods was, however, found to be effective (Fig 21, scenarios C, 2C and 3C).

For weighing methods C, 2C and 3C, and the land use scenarios pasture and rangeland, respectively, one single AMP was recommended almost everywhere (Fig. 17, Fig 21). For the rangeland scenario, this AMP was application of animal manure, and in C, 2C and 3C, and the pasture scenario, it was compost application. The positive effect that these practices both have on all indicators except electrical conductivity, soil compaction and heavy metal contamination, explains their dominance, but may be questioned. Bai et al. (2016) for instance, found no long-term effect of organic matter addition soil pH. Moreover, the expected magnitude of the (positive) effect of an AMP on a soil threat or soil quality indicator, is not yet[4] included in the SQApp algorithm. This introduces a systematic bias towards well-rounded practices, even though the positive effect of these well-rounded practices on each indicator might be small. It also reduces the possible spatial differentiation of the management advice.

For the scenarios where the land use was assumed to be permanent crops, growing halophytes was most often found to be the single best practice. This outcome can be explained by the high positive effect (+6) attributed that the growing of halophytes is thought to have on electrical conductivity[5]. As long as there are less than six indicators that need to be addressed, not including electrical conductivity (or salinity in scenarios 1A-1C), this means that growing halophytes will get the best score if electrical conductivity does need to be addressed. Whether electrical conductivity actually needs to be addressed in these instances, however, may be questioned. As electrical conductivity tended to be low almost everywhere (<2 dS kg^{-1}, Fig. 23), large relative improvement potentials reflected small absolute improvement potentials in

[4] This is, however, planned for the future

[5] In an early stage of the development of the SQApp, an exception was made for the weighing of AMPs targeted specifically at addressing soils with high electrical conductivity. Instead of attributing a positive +1 effect on electrical conductivity, with additional +1, 0 or -1 effects as applicable on other indicators, it was decided that a positive +6 effect would be attributed to electrical conductivity and no effect (0) would be attributed to other indicators.

electrical conductivity. Such small absolute electrical conductivity values are no threat to soil quality (Butcher et al 2016). The dominance of the recommendation to grow halophytes (in order to address high relative electrical conductivity improvement potentials), is therefore misleading. So was the relative dominance of straw interlayer burial (Fig. 22).

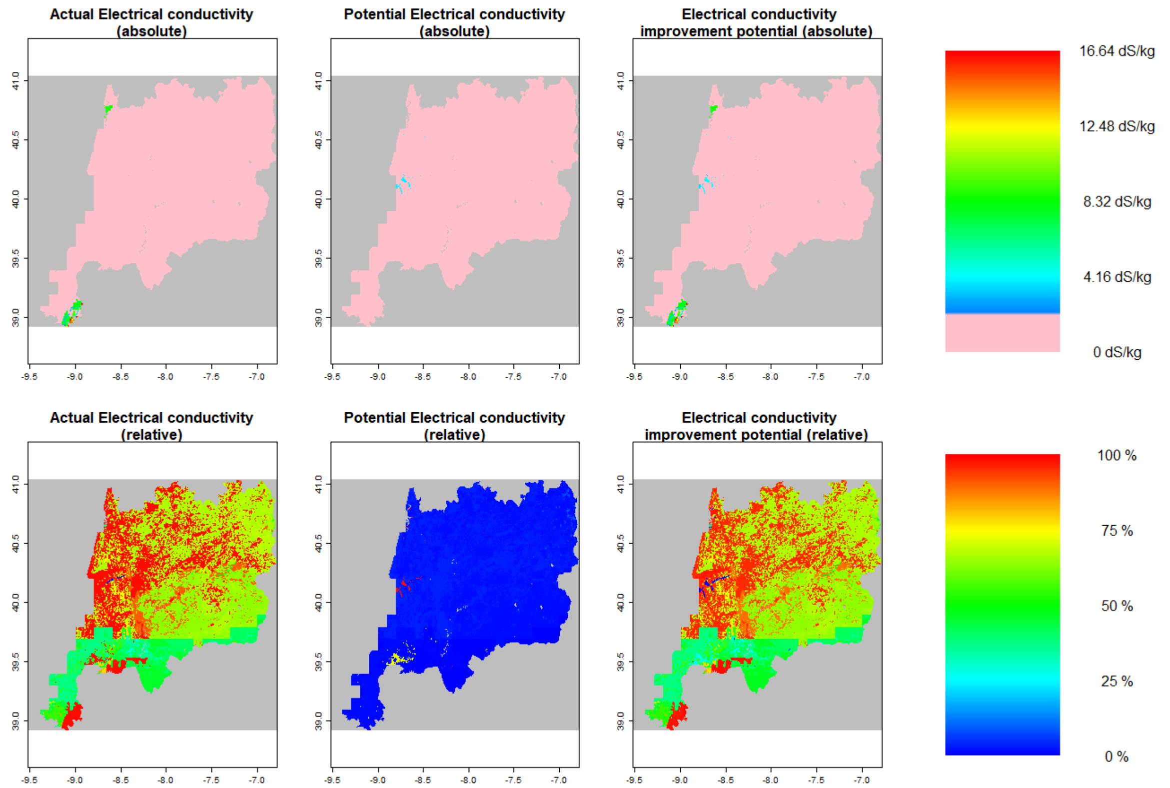


Figure 23. Electrical conductivity in Centro, Portugal. Where the absolute electrical conductivity is below 2.00 dS/kg (i.e. where salinity is a problem according to Butcher et al., 2016), is given a pink colour.

Recommendations for optimization of the SQApp algorithm

In order to avoid the current bias towards well-rounded AMPs and AMPs addressing high, but still unimportant relative electrical conductivity improvement potentials, we recommend to:

i) Consider the effect of AMPs on electrical conductivity/salinity not in relative, but in absolute terms where thresholds are used to indicate whether the electrical conductivity needs to be addressed or not[6]. With this in place, and with a

[6] An underdeveloped, but interesting thought: Could one not, simply, consider all soil threat/quality indicators in both absolute and relative terms, and subsequently give the effect of AMPs on indicators which need addressing in absolute terms a (much) higher weight than indicators that need addressing in relative terms? Then the agricultural management advice would still be targeted to specific soils and climates, but one would make very sure that soil threats that urgently needed to be addressed were addressed.

weighing method in place that attributes more weight to soil threats than soil quality indicators, we suggest that there will be no need to attribute high (+6) positive weights to the effect of certain AMPs on electrical conductivity.

ii) Select and further developing a weighing method that allows for a (more) continuous scoring of AMPs so that the number of AMPs obtaining the highest attainable score is reduced and may be visualised in space. Additionally, one could make interactive, multi-layered maps (using r-packages such as leaflet, ggigraph, plotly or tmap) where users may scroll over, or click on the map in order to see which AMPs are recommended in a certain area.

iii) Improve the table containing the effects of AMPs on soil threat and soil quality indicators (positive = +1, neutral = 0 or negative = -1), so that not only the presence and direction of an effect is indicated, but also its magnitude. We suggest starting by indicating whether positive effects are large (in which case they might be attributed a large positive effect = +2). We assume this will lessen the bias towards well-rounded practices substantially.

In order to improve the general quality of the management advice, we recommend to:

iv) Make sure no AMPs are recommended on non-agricultural land, especially water bodies.

v) Replace low-resolution indicators, low-coverage indicators and low-quality indicators and background data:

- Low-resolution data: soil compaction, global biodiversity index, precipitation, Koppen climate zone
- Low-coverage data: soil loss due to wind erosion, wind erosion vulnerability, water erosion vulnerability, soil compaction, Koppen climate zone and CEC and phosphorus
- Low-quality data: phosphorus, nitrogen and potassium

7 Conclusion

This study assessed whether need-based and targeted agricultural management advice could be mapped and used as tools for European policy development. We found that many, but not all need-indicators (i.e. soil threat indicators and soil quality indicators), were available at a sufficiently high resolution, coverage and quality. The spatial variation of the indicators suggested that need-based and targeted agricultural management policies should be implemented at a regional or within-regional scale. This study selected the SQApp algorithm as a tool to create need-based and targeted agricultural management advice. Our assessment of the agricultural management practices advised revealed that there were seldomly any practices that were considered to be single best. Instead, two or several AMPs were deemed equally suitable. Though this is not necessarily conceptually flawed, it precludes the creation of simply, policy-targeted maps. In an attempt to optimize the SQApp algorithm, we assessed whether specifying cropping systems would reduce the number of equally suitable AMPs. This was effective for some cropping systems, but not for the most dominant annual cropping system in Europe: cereals. Adapting the algorithm itself and allowing for a more continuous scoring of AMP suitability did successfully reduce the number of equally suitable AMPs, but revealed that one single AMP, compost application, was recommended almost everywhere. The cause of the dominance of this AMP was a systematic bias towards well-rounded AMPs (i.e. AMPs that have a positive, though possibly small, effect on many indicators) that was built into the SQApp algorithm. We suggest that this bias may be overcome by distinguishing between small and large positive effects.

8 References

Bai, Z., Caspari, T., Gonzalez, M. R., Batjes, N. H., Mäder, P., Bünemann, E. K., de Goede, R., Brussaard, L., Xu, M. Ferreira, C. S. S., Reintam, E., Fan, H., Mihelic, R., Glavan, M. & Toth, Z. (2018). Effects of agricultural management practices on soil quality: A review of long-term experiments for Europe and China. Agriculture, ecosystems & environment, 265, 1-7.

Barão, L., and G. Basch. 2017. Identification of parameter/indicator set for testing and evaluating the impact on soil quality and crop production parameters.

Borrelli, P., E. Lugato, L. Montanarella, and P. Panagos. 2017. A new assessment of soil loss due to wind erosion in European agricultural soils using a quantitative spatially distributed modelling approach. Land degradation & development **28**:335-344.

Bünemann, E. K., G. Bongiorno, Z. Bai, R. E. Creamer, G. De Deyn, R. de Goede, L. Fleskens, V. Geissen, T. W. Kuyper, P. Mäder, M. Pulleman, W. Sukkel, J. W. van Groenigen, and L. Brussaard. 2018. Soil quality – A critical review. Soil Biology and Biochemistry **120**:105-125.

Butcher, K., Wick, A. F., DeSutter, T., Chatterjee, A., & Harmon, J. (2016). Soil salinity: A threat to global food security. Agronomy Journal, 108(6), 2189-2200.

Chen, J., J. Chen, A. Liao, X. Cao, L. Chen, X. Chen, C. He, G. Han, S. Peng, and M. Lu. 2015. Global land cover mapping at 30 m resolution: A POK-based operational approach. ISPRS Journal of Photogrammetry and Remote Sensing **103**:7-27.

Debeljak, M., A. Trajanov, V. Kuzmanovski, J. Schröder, T. Sandén, H. Spiegel, D. P. Wall, M. Van de Broek, M. Rutgers, and F. Bampa. 2019. A field-scale decision support system for assessment and management of soil functions. Frontiers in Environmental Science **7**:115.

European Commission. 2019. The post 2020 Common Agricultural Policy: Environmental benefits and Simplification. **Agriculture and Rural Development**.

Eurostat. 2017. Main annual crop statistics, extracted 04.01.2019 from: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Archive:Main_annual_crop_statistics&oldid=332968

Fleskens, L., C. Ritsema, B. Zhanguo, V. Geissen, X. Yang, and J. Mendes de Jesus. 2017. Pilot Soil Quality Assessment Tool.

Hijmans, R. J., van Etten (2013). Raster package in R. URL: https://www.rspatial.org/raster/RasterPackage.pdf

Hengl, T., J. M. de Jesus, G. B. Heuvelink, M. R. Gonzalez, M. Kilibarda, A. Blagotić, W. Shangguan, M. N. Wright, X. Geng, and B. Bauer-Marschallinger. 2017. SoilGrids250m: Global gridded soil information based on machine learning. PLoS one **12**:e0169748.

IPCC. 2019. Climate Change and Land.

IUSS Working group, F. 2006. World reference base for soil resources.

Jones, R. J., G. Spoor, and A. Thomasson. 2003. Vulnerability of subsoils in Europe to compaction: a preliminary analysis. Soil and Tillage Research **73**:131-143.

Keesstra, S. D., J. Bouma, J. Wallinga, P. Tittonell, P. Smith, A. Cerdà, L. Montanarella, J. N. Quinton, Y. Pachepsky, and W. H. Van Der Putten. 2016. The significance of soils and soil science towards realization of the United Nations Sustainable Development Goals. Soil.

Koch, A., A. McBratney, M. Adams, D. Field, R. Hill, J. Crawford, B. Minasny, R. Lal, L. Abbott, and A. O'Donnell. 2013. Soil security: solving the global soil crisis. Global Policy **4**:434-441.

Lado, L. R., T. Hengl, and H. I. Reuter. 2008. Heavy metals in European soils: a geostatistical analysis of the FOREGS Geochemical database. Geoderma **148**:189-199.

Orgiazzi, A., R. D. Bardgett, and E. Barrios. 2016. Global soil biodiversity atlas. European Commission.

Panagos, P., P. Borrelli, J. Poesen, C. Ballabio, E. Lugato, K. Meusburger, L. Montanarella, and C. Alewell. 2015. The new assessment of soil loss by water erosion in Europe. Environmental science & policy **54**:438-447.

Panagos, P., K. Meusburger, C. Ballabio, P. Borrelli, and C. Alewell. 2014. Soil erodibility in Europe: A high-resolution dataset based on LUCAS. Science of the total environment **479**:189-200.

Peel, M. C., B. L. Finlayson, and T. A. McMahon. 2007. Updated world map of the Köppen-Geiger climate classification. Hydrology and earth system sciences discussions **4**:439-473.

RStudio Team. (2015). RStudio: integrated development for R. RStudio, Inc., Boston, MA URL: http://www.rstudio.com.

Schulte, R. P. O., F. Bampa, M. Bardy, C. Coyle, R. E. Creamer, R. Fealy, C. Gardi, B. B. Ghaley, P. Jordan, H. Laudon, C. O'Donoghue, D. Ó'hUallacháin, L. O'Sullivan, M. Rutgers, J. Six, G. L. Toth, and D. Vrebos. 2015. Making the Most of Our Land: Managing Soil Functions from Local to Continental Scale. Frontiers in Environmental Science **3**.

Shangguan, W., Y. Dai, Q. Duan, B. Liu, and H. Yuan. 2014. A global soil data set for earth system modeling. Journal of Advances in Modeling Earth Systems **6**:249-263.

Toth, G. L., X. Song, T. Hermann, and B. Toth. 2016. HIERARCHICAL AND MULTI-SCALE PEDOCLIMATIC ZONATION.

Turpin, N., H. Ten Berge, C. Grignani, G. Guzmán, K. Vanderlinden, H.-H. Steinmann, G. Siebielec, A. Spiegel, E. Perret, and G. Ruysschaert. 2017. An assessment of policies affecting Sustainable Soil Management in Europe and selected member states. Land Use Policy **66**:241-249.

Vrebos, D., F. Bampa, R. Creamer, C. Gardi, B. Ghaley, A. Jones, M. Rutgers, T. Sandén, J. Staes, and P. Meire. 2017. The impact of policy instruments on soil multifunctionality in the European Union. Sustainability **9**:407.

Wills, S., C. Williams, C. Seybold, L. Scheffe, Z. Libohova, D. Hoover, C. Talbot, and J. Brown. 2017. Using soil survey to assess and predict soil condition and change. Pages 123-135 Global soil security. Springer.

9 Appendices

9.1 Back-ground information on AMP selection step 1

In order to test whether AMPs could be recommended or not, we checked whether the land cover, annual precipitation, bedrock depth, soil texture, stoniness of the soil, landscape positioning and slope were compatible with the AMP. We used SoilGrids (Hengl et al. 2017) data and data from Chen et al. (2014) for the physical characteristics (Table 6). These were classified (Table 7) and indications of compatibility (1) or incompatibility (0) were indicated per class for each AMP (Table 4).

Table 6. Raster layers used to create management practice map. References: e = Hengl et al., 2017, h = Chen et al., 2014, ? = I do not know

limitations disaggr. id	limitations disaggregated	limitations aggr. id	limitations aggregated	folder	reference	nature	unit	original resolution
1	cropland	1	land cover	land cover	h	binary		0.00208
2	annual precipitation	2	precipitation	meteo	?	continuous	mm	0.00208
3	bedrock depth	3	bedrock depth	soil grids	e	continuous	cm	0.00208
4	clay content	4	soil texture	soil grids	e	continuous	%	0.00208
5	stoniness	5	stoniness	soil grids	e	continuous	%	0.00208
6	grassland	1	land cover	land cover	h	binary		0.00208
7	landscape positioning	6	landscape positioning	geomorphology	?	categorical		0.00208
8	slope	7	slope	geomorphology	?	continuous	%	0.00208
9	sand content	4	soil texture	soil grids	e	continuous	%	0.00208

Table 7. Thresholds used to categorize conditional limitations. See table 6 for units.

Limitation	Categorical classes						
	1	2	3	4	5	6	7
land cover*	cropland	grassland					
precipitation	0 - 250	250 - 500	500 - 1000	1000 - 1500	1500 - 2000	> 2000	
bedrock depth	0 - 20	20 - 50	50 - 80	80 - 120	>120		
soil texture	sand > 50%	clay > 40%	other				
stoniness	0 - 2	2 - 10	10 - 25	> 25			
landscape positioning	1	2	3	4	5	6	7
slope	0 - 2	2 - 5	5 - 10	10 - 15	15 - 30	30 - 60	> 60

9.2 Background information on cropping system scenarios

A table with a value 1 if an AMP was applicable in a specific cropping system and a value 0 otherwise was used to select AMPs for each cropping system scenario (Table X).

Table 8. Data used to specify whether AMPs may be applied in specific cropping systems. Press this link to see the full table. If link does not work, navigate to Tables → AMP_cropping_scenarios.html.

Show 69 entries Search:

	AMP	colour	Cropping_system	AMP_applicable
1	Agroforestry	#006400	permanent crops with soil cover	0
2	Agroforestry	#006400	Cereals	1
3	Agroforestry	#006400	Oleaginous crops	1
4	Agroforestry	#006400	Root crops	1
5	Agroforestry	#006400	Open field vegetables	0
6	Agroforestry	#006400	Arable_Other	1
7	Agroforestry	#006400	Maize	1
8	Agroforestry	#006400	Permanent_crop_Other	0
9	Agroforestry	#006400	permanent crops without soil cover	0
10	Agroforestry	#006400	Indoor vegetables	0
11	Agroforestry	#006400	Permanent_cover_Olives/nut trees	0
12	Agroforestry	#006400	Fruit trees	0
13	Agroforestry	#006400	Leguminous crops	1
14	Agroforestry	#006400	Permanent_cover_Vineyards	0

9.3 Additional soil threat figures

9.3.1 Data availability

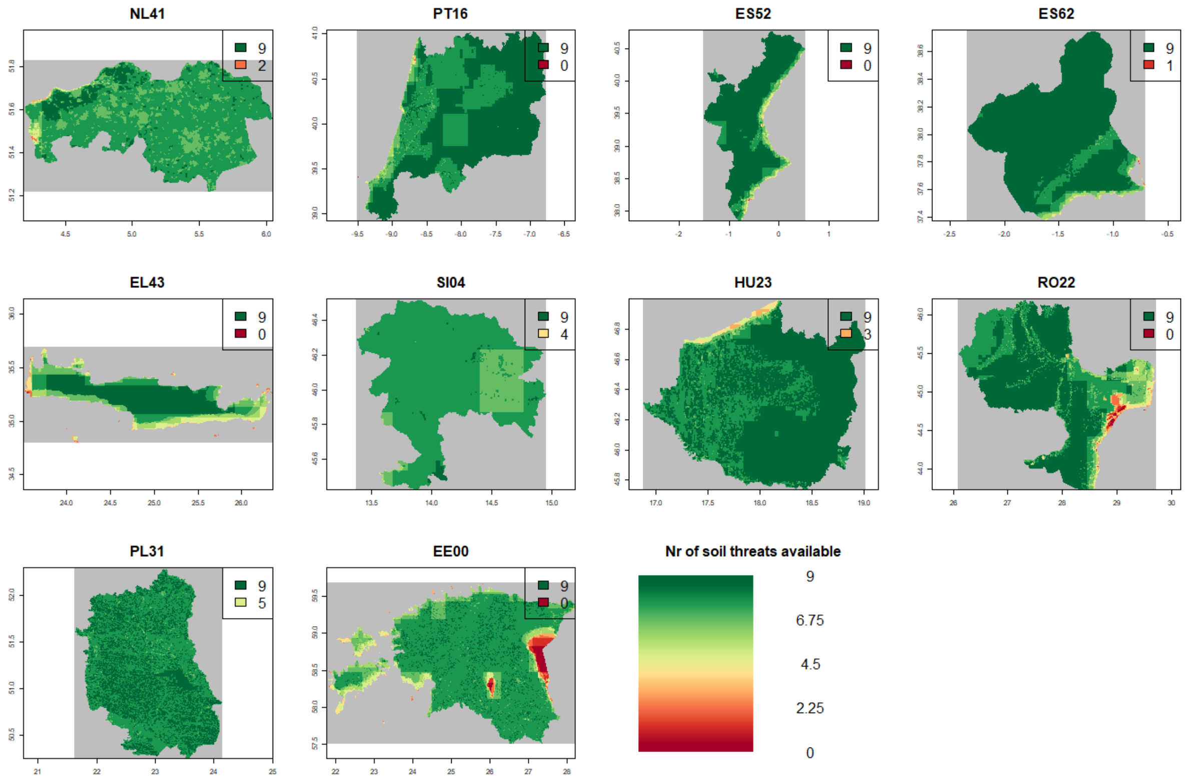


Figure 24. Number of soil threats for which soil threat indicators are available, in each selected region. The numbers in the upper corners of each map show the maximum and minimum number of soil threat indicators available and their associated colours.

9.3.2 Soil threat level of all soil threat indicators per region

To see the soil threat severity levels per soil threat indicator in all selected regions, navigate to Figures → SoilThreatIndicators → SoilThreatLevel_Region_IndicatorGrid.

9.3.3 Threat level of all threats levels per region

To see the soil threat severity levels per aggregated soil threat indicator in all selected regions, navigate to Figures → SoilThreatIndicators → AggregatedSoilThreatLevel_Region_IndicatorGrid.

9.4 Additional soil quality figures

9.4.1 Data availability

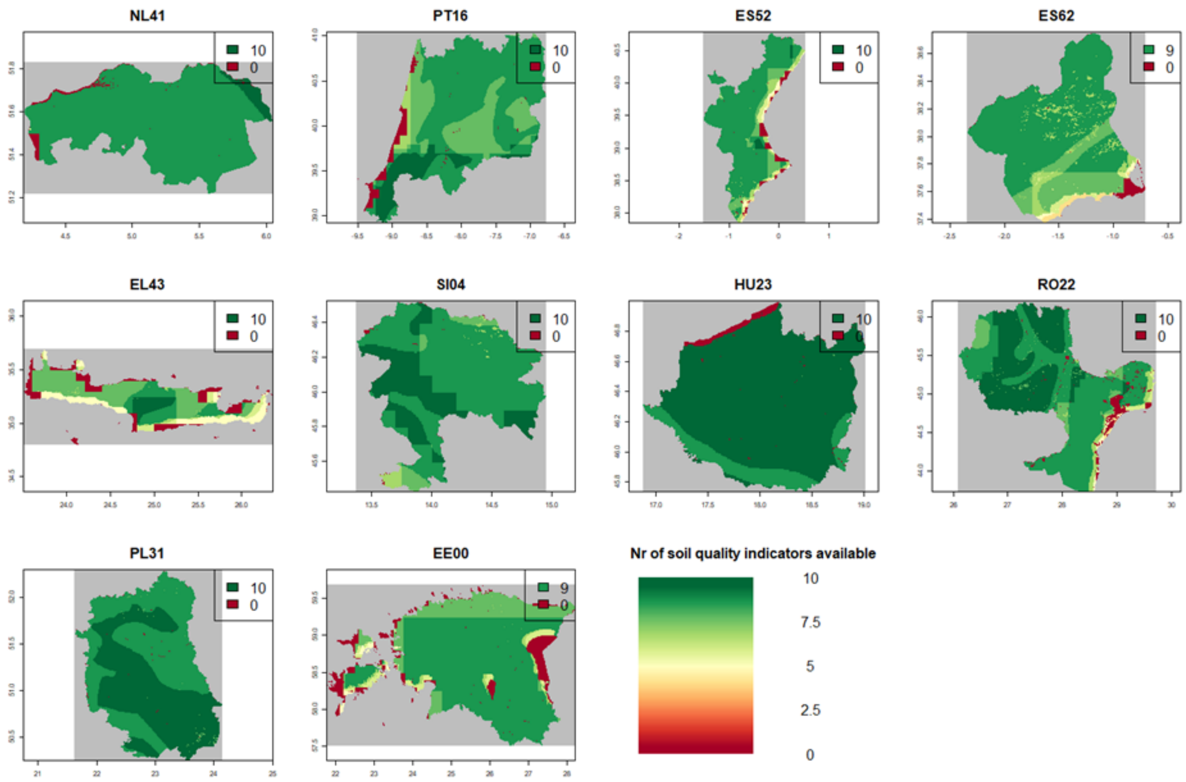


Figure 25. Number of available soil quality indicators available, in each selected region. The numbers in the upper corners of each map show the maximum and minimum number of soil quality indicators available and their associated colours.

9.4.2 Relative and absolute soil quality improvement potential

To see the relative and abosulte current and optimal soil quality values and improvement potential values for each indicator and region, navigate to Figures → SoilQualityIndicators

9.5 Additional agricultural management practice figures

9.5.1 Additive scores of each agricultural management practice

To see the additive scores of each agricultural management practice in each region, per scenario, navigate to Figures → AgriculturalManagementPractices → AdditiveScores_AMP&Region_ScenarioGrid. To see the additive scores of each agricultural

management practice in each scenario, per region, navigate to Figures → AgriculturalManagementPractices → AdditiveScores_AMP&Scenario_RegionGrid.

9.5.2 Highest – tenth highest attainable additive scores

To see the highest, second highest, down to tenth highest attainable additive scores, navigate to Figures → AgriculturalManagementPractices → HighestAdditiveScores_Region&Ranking_ScenarioGrid and Figures → AgriculturalManagementPractices → HighestAdditiveScores_Region&Scenario_RankingGrid

9.5.3 Number of best practices

To see the number of best practices for each scenario, per region, navigate to Figures → AgriculturalManagementPractices → NrOfHighestAMPs_Scenario&Ranking1_RegionGrid.

9.5.4 Single best practices

To see the single best practices for each scenario and region, navigate to Figures → AgriculturalManagementPractices → SnglBestAMPs_Region&Ranking_ScenarioGrid, Figures → AgriculturalManagementPractices → SnglBestAMPs_Region&Scenario_RankingGrid, or Figures → AgriculturalManagementPractices → SnglBestAMPs_Scenario&Ranking1_RegionGrid