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Soil-related indicators to support agri-environmental policies

Soil erosion
Soil carbon
Soil nutrients and fertility

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Contents

Abstract

The data sets and indicators on soil erosion, soil organic carbon stocks and soil nutrients presented here are the result of modelling activities that took place at the Joint Research Centre, Ispra. The data sets are important advances in the current knowledge of soil properties and processes at continental scale. In addition, the soil erosion, soil carbon and soil nutrient data sets and indicators provide baselines for evaluating the current status of agricultural soils in the European Union and evaluating the impact of agri-environmental policies on land management. Moreover, those data sets can further contribute to proposing and designing management practices to improve the status of agricultural soils, stop land degradation and better target policy interventions. The indicators of soil erosion and soil organic carbon are currently included in monitoring the common agricultural policy (CAP) and the progress towards the Sustainable Development Goals. In addition, here we propose the development of soil nutrient data sets both as individual indicators (phosphorus, nitrogen and potassium) and as a composite indicator of soil fertility. In conclusion, we found that the soil organic carbon changes cannot be identified within the timeline of policy interventions (for example in the CAP the assessment cycle is 7 years).

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Executive summary

This document presents the latest status of soil condition in the European Union (EU), focusing particularly on agricultural land. The document presents the most recent assessment (2016) of soil erosion by water in the EU using the latest state-of-the-art data on management practices and the latest Land Use / Land Cover Area frame Survey (LUCAS). The assessment of soil organic carbon stocks and changes between the two LUCAS surveys (2009, 2015) (https://esdac.jrc.ec.europa.eu/projects/lucas) is addressed with a specific focus on agricultural land. Finally, the report proposes data sets and methods to assess the nutrient status of soils in the EU. To facilitate policy support, we have developed indicators (taking into account policy-relevant requests) based on aggregated data at regional scales (Nomenclature of Territorial Units for Statistics - NUTS2) that compare changes of soil condition in time. The report includes three sections relevant to the evaluation of soil condition and agri-environmental policies: (a) soil erosion, (b) carbon stocks and (c) soil nutrients. Both the key conclusions and the main findings (below) are grouped according to those three sections.

Policy context

Land degradation is a serious issue for society, as it can represent a major threat to food security, climate change mitigation, migration and water scarcity. Through analysis of LUCAS soil data from 2009/12 and 2015, this deliverable contributes to the review of the 2014-2020 Common Agricultural Policy (CAP) by assessing the changes in soil condition under agricultural management. The deliverable assesses the state of soil condition and changes in soil erosion and carbon stocks. Both soil erosion and soil organic carbon are mature indicators used in evaluating CAP's current performance, designing the post-2021 CAP and contributing to other agri-environmental policies: the Sustainable Development Goals (SDGs), seventh environment action programme, soil thematic strategy and Resource Efficiency Scoreboard. In addition, this report provides the latest state-of-the-art status of soil nutrient based on LUCAS and proposes the way forward in developing soil nutrient and soil fertility indicators. The data underpin agri-environmental indicators and SDG indicators.

Key conclusions

The key conclusions related to soil erosion assessment and trends are the following.

- The soil erosion rate does not show a significant decrease between 2010 and 2016 in the EU. The picture is heterogeneous, as most of the regions perform well at applying increased conservation measurements; however, the most erosive ones (e.g. Mediterranean areas) show little progress. This means that the efforts to reduce soil erosion need to be reinforced with more agri-environmentally friendly measures and better targeting of areas with high erosion risk.
- Taking the current trends into account, a stronger set of soil conservation practices (e.g. cover crops, plant residues, reduced tillage, contouring, stone walls, agroforestry) is needed to reduce soil erosion in hotspots. All this modelled work does not yet take account of the effect of climate change, which will probably have a negative impact by increasing soil erosion rates in the EU.
- The current agri-environmental policies need to focus more on hotspot areas, especially on agricultural land where current rates are higher than sustainable ones. In addition, an important step would be to set a policy target of halting severe and very severe or extreme erosion on agricultural land by 2030.

The key conclusions relevant to the estimated soil organic carbon stock changes are the following.

- Changes in soil organic carbon (SOC) content and stocks are not significant in the time interval of 6 years between the two LUCAS surveys (2009-2015). This may raise the issue of whether or not SOC should be estimated at longer intervals (e.g. 10 years) and include a higher number of samples that better represent areas with low density of points and greater uncertainty.
- The impact of management practices to increase SOC may take longer than 10 years to show significant changes. Overall the total SOC changes between LUCAS 2009/12 and 2015 are minimal and account for less than 0.05 % of the total stock of cropland and grassland.
- The impact of climate change should be further investigated, as the first signs show carbon change in cooler areas, which are becoming warmer and dryer. A new model framework integrating machine

learning and biogeochemical modelling is under development at the Joint Research Centre (JRC) to investigate climate and management interactions on carbon cycling.

The key conclusions relevant to soil nutrients are the following.

- Soil nitrogen (N), phosphorus (P) and potassium (K) are assessed for the first time in the EU using measured data for about 22 000 sampled locations. However, one of the main limitations of the NPK mapping is the number of points, which potentially can be increased in future LUCAS surveys or include national surveys.
- The NPK data sets and maps show the potential to develop soil nutrient indicators and monitor them spatially and temporally. Currently, soil erosion and SOC (content, stocks) are mature indicators to support agri-environmental policies in the EU. In the same context, soil nutrient indicators can be developed based on LUCAS NPK data sets to support and monitor agri-environmental policies in future and better manage fertiliser use and avoid nutrient pollution.
- Therefore, optimising the application of phosphorus as a fertiliser is beneficial to both the environment and the economy of the EU. In addition, mapping phosphorus and nitrogen is also important for long-term agri-environmental policies that do not harm our environment and health, and at the same time guarantee optimal fertilisation rates in EU agriculture.

Finally, the major contribution of LUCAS In providing data on measured soil properties (physical, chemical) and databases on landscape features should be underlined. LUCAS proves to be an important asset for monitoring agri-environmental policies in the EU, as it makes it possible to report changes both in land use/cover but also in soil properties (e.g. SOC).

Main findings

The main outputs of the updated 2016 soil erosion assessment are as follows.

- The estimated soil erosion rates in 2016 (2.45 t ha^{-1} yr^{-1}) show a limited decrease of 0.4 % in all lands and 0.8 % in arable land compared with 2010. In the previous decade (2000-2010) the corresponding decrease was larger, as soil erosion decreased by 9 % in all lands and 19 % in arable ones.
- Regarding the conservation practices to reduce soil erosion: (a) the increase in grass margins during 2010-2016 was quite limited (8 %); (b) conservation tillage shows a very limited increase (0.8 %) from 21.6 % to 22.4 %; (c) cover crops are applied to 8.9 % of EU arable land compared with 6.5 % in 2010; (d) in contrast, plant residues show a decrease from 10.6 % in 2010 to 9.1 % in 2016.
- The small overall increase in conservation practices between 2010 and 2016 (implying a decrease in erosion rates) has been offset by a decrease in management practices (leading to an increase in erosion rates) in more sensitive (erosive) areas such as the Mediterranean basin. To summarise, the majority of countries (and regions) perform well, as they are increasing conservation practices; however, the most erosive regions have shown an opposite trend.
- Taking into account that soil formation rates found in the literature are about 1.4-2 t ha^{-1} yr^{-1}, more than a quarter of EU land has erosion rates higher than the 2 t ha^{-1} yr^{-1} threshold. In addition, 6.6 % of EU agricultural land suffers from severe erosion (> 11 t ha^{-1} yr^{-1}).

The main outputs of modelling SOC stocks (content) and changes between LUCAS 2009/12 and LUCAS 2015 are as follows.

- SOC stock estimates, at EU level, are about 7.82 Gt and 4.35 Gt for cropland and grassland, respectively. The results are based on interpolation of the LUCAS topsoil (0-20 cm) data for 2015 on SOC.
- The changes in stocks are not significant, as about 60 % of the SOC changes are below 0.2 % of the average stock. The total change in carbon stocks in grassland was about 0.04 % and in arable land about 0.06 %. Carbon stocks in cropland show a decrease in regions close to the Atlantic Ocean, such as Benelux, Denmark, north Germany, north-west France and Portugal, and in Romania and Bulgaria. In contrast, an increase of carbon stocks is found in areas surrounding the Alps: Czechia, south Germany, south France, north and central Italy, and parts of Austria and Slovakia. This distribution might be due to the effect of climate change, whereby wetter and cooler areas are gradually becoming dryer and warmer, resulting in higher SOC mineralisation.

- About SOC content in all land uses, most (~70 %) SOC changes fall below the limit of ± 4 g kg^{-1} and only 10 % of the area is estimated to have changes higher than ± 12 g kg^{-1}. Moreover, in some of the latter areas, the model uncertainty is high for lack of samples (northern portion of Scandinavia, and Scotland). Sources of uncertainties, particularly high in Finland and Sweden, are probably related to the removal of the litter layer during sampling in woodland. There are other factors that also contribute to increase uncertainty, for example the efficiency of the sampling protocol (differences in sampling location between surveys, difficulties in litter removal) and the fact that sampling was carried out by different surveyors in the two time periods.

The main outputs of soil nutrient mapping using the LUCAS topsoil database are as follows.

- The soil phosphorus (P) map shows the strong correlation with the land use. In particular, the agricultural lands have higher levels of P than natural areas or forests. This is also quite evident in the most intensive agricultural regions of the EU such as the Po plain in Italy, where the levels of P are much higher than the national average. The fertilisation rates in agricultural land influence the P concentration, especially in the wetter climates of north-west Europe.
- The Nitrogen (N), Phosphorus (P) and Potassium (K) datasets are considered baselines to further study the agricultural management practices that can improve the levels of soil nutrients. In addition, further research studies should focus on the processes that influence soil nutrients in agricultural soils: irrigation, increased fertilisation, organic fertilisers, manure application, crop rotation, management practices (tillage, plant residues, cover crops, etc), weather conditions and climate change.
- In conclusion, we have proposed a soil fertility index based on seven available and estimated physical–chemical indicators: available water content, water-filled porosity, pH, SOC, cation exchange capacity, available phosphorus and exchangeable potassium. This index is based purely on soil properties and does not include the influence of climatic conditions (rainfall, temperature, etc.) and management practices (irrigation, tillage, etc.). This first output should be considered a preliminary result to be tested with field experimental data.

Related and future Joint Research Centre work

The JRC Sustainable Resources Directorate (D) and specifically the Land Resources unit, has developed a series of indicators related to soil erosion, SOC and nutrients to support CAP 2014-2020, the SDGs, the Resource Efficiency Scoreboard and the 7th Environment Action Programme (EAP). This work can also support the forthcoming post-2020 CAP, land degradation evaluation, climate adaptation and mitigation, the Biodiversity strategy 2030 and the European Commission political guidelines presented by President von der Leyen in the Green Deal (COM(2019) 640). The legislative proposal for the future CAP (COM(2018) 392) is to shift the focus from compliance to performance. In the future CAP, measures under the green architecture should focus on climate performance, including managing and storing carbon in the soil, and improved nutrient management to improve water quality and reduce emissions.

Quick guide

The document is split into three main chapters in order to better address the soil condition assessment. In Chapter 2, the most up-to-date (2016) assessment of soil erosion by water is presented. This is followed by Chapter 3, where estimates of SOC stocks and changes between the two LUCAS surveys are documented. Finally, Chapter 4 is dedicated to modelling soil nutrients based on N, P and K data sets. Whereas soil erosion and SOC stocks are mature indicators used in agri-environmental policies (CAP, SDGs), the indicator for soil fertility is a proposal to be evaluated by policymakers for future use.

1 Introduction

Globally, soil and environmental challenges (climate change, pollution, desertification, water scarcity and biodiversity decline) are increasing dramatically (Hanjra and Qureshi, 2010). Soil degradation is among the most crucial threats to ecosystem stability, and soils have recently gained more and more social and political visibility. In order to better understand soil's contribution to ecosystem services, we need small- and large-scale modelling and mapping of soil properties and processes.

With the exponential increase of the world population from 1 billion in 1820 to 7 billion in 2012 and projections for 10 billion in 2056, a substantial increase in the demand for food, energy and natural resources (water, air, soil) is expected (Ferreira et al., 2018). Land degradation through human activities is negatively affecting the well-being of at least 3.2 billion people and is pushing the planet towards a mass extinction affecting a sixth of all species.

Human-related activities (deforestation, overgrazing, tillage and unsuitable agricultural practices) and human-induced land use changes are the main reasons for accelerated soil erosion, which has substantial implications for the nutrient and carbon cycles, land productivity and, in turn, worldwide socioeconomic conditions. Soil organic carbon (SOC) is the largest carbon (C) stock in most terrestrial ecosystems (Lal, 2008). Land use changes, and policy frameworks influencing land use could trigger significant changes in SOC levels in the long term. Intensive agriculture and inappropriate land management practices (e.g. overuse of fertilisers and contaminants) may further aggravate the current status of soil nutrients.

New challenges and policy developments after 2015 (among others, the Common Agricultural Policy (CAP), and Sustainable Development Goals (SDGs)) are opportunities for soil scientists and modellers to respond with more accurate assessments of and solutions for how to reduce soil erosion, enhance soil organic carbon, improve soil fertility and, furthermore, reach Zero Net Land Degradation targets by 2030.

2 Soil erosion by water

Global soils are continuously degraded because of population growth, economic development and climate change (Montanarella et al., 2016). Soil erosion is a major form of soil degradation, as more than 1 billion hectares globally are affected by some form of erosion (e.g. water, wind and gully) (Lal, 2003). Human activity and the related land use changes (deforestation and cropland increase) are the main reasons for a 2.5 % increase in soil erosion by water between 2001 and 2012 (Borrelli et al., 2017).

The Status of the World's Soil Resources Report (FAO and ITPS, 2015) found that soil erosion represents the greatest global threat to soil functions (Montanarella et al., 2016), putting food security, water quality and climate change mitigation at risk. New estimates indicate the annual loss to global gross domestic product (GDP) at c.a. USD8 billion, reducing yields by 33.7 million tonnes, and increasing water abstraction by 48 billion m^3 (Sartori et al., 2019). The recent policy report of the Intergovernmental Panel on Climate Change (IPCC) highlights the impact of global mean temperature increase on desertification, land degradation (soil erosion, vegetation loss) and food security (IPCC, 2019). While the problem of soil erosion is acknowledged by such international bodies (the IPCC, United Nations Convention to Combat Desertification (UNCCD) and Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES)), political action at a global level is still missing (Panagos et al., 2019).

In the European Union, policy legislation for soil protection is lacking, as the proposal for a Soil Framework Directive was withdrawn in 2014. However, soil erosion is referred to environmental and agricultural policies (Soil Thematic Strategy, CAP, 2030 Agenda for Sustainable Development, Resource Efficiency Scoreboard).

2.1. Policy framework relevant to soil erosion

Soil erosion is recognised as a threat to soil in the EU's Soil Thematic Strategy and the 7th Environment Action Programme. The Roadmap to a Resource Efficient Europe (COM(2011) 571) sets out a course to reduce soil erosion and requires Member States to implement the actions needed to reduce erosion. The Common Agricultural Policy (CAP) sets requirements to protect utilised agricultural areas against erosion and establishes a framework of standards that aim, among other things, to help prevent soil erosion. The main policy framework (Figure 1) relevant to soil erosion is presented in more detail below.

In the context of the **CAP**, European Commission implementation Regulation 834/2014 lays down rules for the application of the common monitoring and evaluation framework (CMEF) of the CAP. In addition, Regulation 1307/2013 establishes the rules for direct payments to farmers under support schemes within the framework of the CAP. The aim of the CAP is to contribute to the objectives of the Europe 2020 strategy by fostering smart, sustainable and inclusive growth. The European Commission has set up the CMEF to assess the performance of the CAP. The CMEF is a set of rules, procedures and indicators to evaluate the CAP 2014-2020 (income support, market measures, rural development) (CMEF, 2019).

In the EU, one of the main mechanisms to promote more environmentally friendly agriculture was introduced by the CAP reform in 2003, through the **Cross Compliance** mechanism. According to this approach, the farmer support payments were conditional on environmental, animal welfare and food safety standards. This led to the definition of Good Agricultural and Environmental Conditions (**GAEC**), established first by Council Regulation No 1782/2003 and subsequently by Council Regulation (EC) No 73/2009. The prevention of soil erosion and maintenance of soil organic matter were addressed in three GAEC requirements, which each Member State was obliged to address through national/regional standards such as (a) minimal soil cover maintenance (GAEC 4); (b) minimum land management reflecting site-specific conditions to limit soil loss (GAEC 5); and (c) maintenance of soil organic matter level through appropriate practices including a ban on burning arable stubbles (GAEC 6).

The **Soil Thematic Strategy** (COM(2006) 231) is the main EU policy strategy directed at soil protection. The EU and most Member States do not have specific legislation targeting soils, but instead aspects of soil protection are determined by other sectoral policies such as agriculture, forestry, water, waste and land use planning. The Soil Thematic Strategy sought to change this by establishing actions at EU level: integration of soil protection aspects in other sectoral policies, development of the knowledge base through studies and research projects, and raising public awareness about the role that soil plays in the economy and the ecosystem (Ronchi et al., 2019). The Soil Thematic Strategy recognises soil erosion as a major threat to the soil resources of Europe and as one of three priority areas for policy recommendations (Panagos and Montanarella., 2018). Soil erosion requires immediate attention, and irreversible degradation is to be avoided in certain landscapes of Europe. Climate, vegetation cover, land use, topography and soil characteristics as well as conservation practice have a strong impact on soil erosion rates.

The 2030 Agenda for Sustainable Development and its 17 **SDGs** were adopted by the UN in September 2015. The EU is committed to playing an active role to maximise progress towards the SDGs, as outlined in its communication (COM(2016) 739) 'Next steps for a sustainable European future'. In January 2019 the European Commission published the reflection paper 'Towards a sustainable Europe by 2030', contributing to the debate on the shape of Europe and our world in 2030 and beyond. In addition the EU monitors the progress towards the SGDs in an EU context and has established a list of 100 indicators and publishes the annual report 'Sustainable development in the European Union'.

The **Roadmap to a Resource Efficient Europe** is part of the Europe 2020 strategy, the EU's growth strategy for a smart, inclusive and sustainable economy. It supports the shift towards sustainable growth via a resource-efficient, low-carbon economy. The roadmap sets out a framework for the design and implementation of future actions. It also outlines the structural and technological changes needed by 2050, including milestones to be reached by 2020. In the roadmap, it is important to monitor how the land use policies can change practices to reduce soil erosion by water (Panagos and Katsoyiannis, 2019).

2.2. Indicators for European Union policy support

2.2.1. Common Agricultural Policy (CAP) context indicators

The CAP context indicators of the CMEF monitor the socioeconomic and environmental impact of the CAP 2014-2020 by using a set of 45 indicators (socioeconomic, sectoral, and environmental). CAP indicators contribute to the assessment of CAP performance. Soil erosion and soil organic carbon are the two soil-relevant indicators to monitor the impact of the CAP in soils.

CAP context indicator No 42, soil erosion, consists of two sub-indicators: (a) estimated rate of soil loss by water erosion (t ha^{-1} yr^{-1}); (b) estimated agricultural area affected by a certain rate of soil erosion by water (ha). The estimated area is also expressed as a percentage of the total agricultural area. The indicators assess the soil loss by water erosion processes (rain splash, sheet wash and rills) and give indications of the areas affected by a certain rate of soil erosion (moderate to severe, i.e. > 11 t ha^{-1} yr^{-1} in the Organisation for Economic Co-operation and Development (OECD) definition).

Data set: https://ec.europa.eu/info/files/context-indicator-fiches_en

2.2.2. Resource Efficiency Scoreboard

The indicator 'Estimated soil erosion by water – area affected by severe erosion rate' is part of the Resource Efficiency Scoreboard. This is a tool or user interface for presenting key indicators relating to natural resources. It is used to monitor progress towards a resource-efficient Europe on the key thematic objective of 'Land and soils' included in the specific theme 'Nature and ecosystems'. The Roadmap to a Resource Efficient Europe sets the target that the area of land in the EU that is subject to soil erosion of more than 10 t ha^{-1} yr^{-1} should be reduced by at least 25 % by 2020.

Eurostat dedicated section on Europe 2020 – Resource Efficient Europe:

Data set: https://ec.europa.eu/eurostat/databrowser/view/t2020_rn300/default/table?lang=en

2.2.3. Sustainable Development Goals

The indicator 'Estimated soil erosion by water' is part of the EU SDG indicator set. It is used to monitor progress towards SDG 15 and SDG 2. SDG 15, 'Life on land', seeks to protect, restore, and promote the conservation and sustainable use of terrestrial, inland water and mountain ecosystems. This includes efforts and financial resources to sustainably manage forests and halt deforestation, combat desertification, and restore degraded land and soil. In relation to SDG 15, the soil erosion indicator contributes to the sub-theme 'land degradation'.

SDG 2, 'Zero hunger', seeks to ensure access to safe, sustainable and resilient food production. In relation to SDG 2, the soil erosion indicator contributes to the sub-theme 'estimate the environmental impacts of agricultural production'.

Data set:

https://ec.europa.eu/eurostat/tgm/table.do?tab=table&init=1&language=en&pcode=sdg_15_50&plugin=1

Metadata: https://ec.europa.eu/eurostat/cache/metadata/EN/sdg_15_50_esmsip2.htm

2.2.4. Agri-environmental indicators (AEI).

The Statistical Office of the EU (Eurostat) makes a detailed overview of an updated set of 28 agri-environmental indicators (AEIs) for the EU, intended to monitor the integration of environmental concerns into the CAP. The AEIs were set up through a Commission communication (COM(2006) 508 final). These AEIs track (a) farm management practices, (b) agricultural production systems, (c) pressures and risks to the environment and (d) the state of natural resources.

In the context of monitoring the status of natural resources, soil erosion is included among the 28 AEIs as AEI 21. It is expressed as mean t ha^{-1} yr^{-1} at different administrative levels: Member State and Nomenclature of Territorial Units for Statistics (NUTS)1/NUTS2/NUTS3. It is used to track the integration of environmental concerns into the CAP at EU, national and regional levels.

AEI fact sheet on soil erosion: https://ec.europa.eu/eurostat/statistics-explained/index.php/Agri-environmental_indicator_-_soil_erosion

List of all AEI indicators and fact sheets: https://ec.europa.eu/eurostat/web/agriculture/agri-environmental-indicators

Data set: https://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=aei_pr_soiler&lang=en

Metadata: https://ec.europa.eu/eurostat/cache/metadata/en/aei_pr_soiler_esms.htm

The CAP contributes to preventing and mitigating soil degradation processes (Matthews, 2013). In particular under Regulation 1305/2013, rural development priorities include agri-environmental measures that offer opportunities for favouring the build-up of soil organic matter, the enhancement of soil biodiversity, the reduction of soil erosion and cross-compliance (which can play an important role in soil protection).

Figure 1. Soil erosion and support to policies.

Source: JRC, 2019

2.3. Indicators for global policy support

2.3.1. Organisation for Economic Co-operation and Development (OECD) Agri-Environmental Indicators

The OECD has developed a database of AEIs, which provides the latest and most comprehensive set of AEIs across 35 OECD countries (plus Norway and Switzerland) from 1990 to 2019. This database builds on the OECD questionnaire and close collaboration with Eurostat and other EU services.

The AEI database can be used as a tool to assist policymakers by describing the current state of and trends in environmental conditions in agriculture that may require policy responses; highlighting where 'hotspots' or new challenges are emerging; comparing trends in performance across time and between countries, especially to assist policymakers in meeting environmental targets, threshold levels and standards, where these have been established by governments or international agreements; developing indicators and a primary data set that can be drawn upon for related activities, for example the development of green growth indicators; and providing information for policy monitoring, evaluation and projecting future trends.

The OECD defines the soil erosion indicator as '% of agricultural land classified as having moderate/high/severe water erosion risk'.

Publication of OECD AEIs: http://www.oecd.org/agriculture/topics/agriculture-and-the-environment/

2.3.2. European Environment Agency (EEA) State of Environment Report

Soil erosion assessment in Europe contributes to the State of the Environment Report (SOER) produced by the European Environment Agency. The newly published SOER refers to the soil erosion assessment and provides aggregated data and statistics both on the current state of soil erosion and for temporal trends (2010-2015 and future projections).

Download: https://www.eea.europa.eu/publications/soer-2020

2.3.3. Other global assessments

The European soil erosion assessment and the indicators derived from it have also been used by the global land assessments of the Inter-Governmental Technical Panel on Soils (FAO/IPTS) and the United Nations Convention to Combat Desertification (UNCCD) (Figure 1).

The soil erosion assessment has been contributed to other policy documents. Among them, we can highlight the UN Environment Programme's *Unlocking the Sustainable Potential of Land Resources: Evaluation Systems, Strategies and Tools* (Herrick et al., 2016) and the IPBES *Regional Assessment Report on Biodiversity and Ecosystem Services for Europe and Central Asia* (Rounsevell et al., 2018).

2.4. Model development

The Revised Universal Loss Equation (RUSLE) (Renard et al., 1997) estimates the mean annual soil loss rates by sheet and rill erosion. The RUSLE model is based on the following equation:

$E = R \times K \times C \times LS \times P$ (1)

where E is the annual average soil loss (t ha^{-1} yr^{-1});

R is the rainfall erosivity factor (MJ mm ha^{-1} h^{-1} yr^{-1});

K is the soil erodibility factor (t ha h ha^{-1} MJ^{-1} mm^{-1});

C is the cover management factor (dimensionless);

LS is the slope length and slope steepness factor (dimensionless);

P is the support practices factor (dimensionless).

According to equation (1), RUSLE consists of a multiplicative equation including five environmental parameters (Figure 3).

A modified version of RUSLE model has been adapted to European conditions and named RUSLE2015, as it was proposed in the literature in 2015 (Panagos et al., 2015). RUSLE2015 improves the quality of estimation by introducing updated, high-resolution (100 m × 100 m) and peer-reviewed input layers of *R*, *K*, *LS*, *C* and *P* applied to control erosion. In addition, RUSLE2015 highlights the dynamic factors (Figure 3), which change in time, and takes into account the conservation practices applied by farmers on the European continent.

As soil physical properties and topography do not change in time, *K* and *LS* remain stable. The rainfall intensity changes from year to year and it is a dynamic factor in the soil erosion modelling. However, rainfall erosivity (*R*) takes into account long-term rainfall intensities, so we have used the 2010 value of *R* (Panagos et al., 2015b).

The dynamic parts of the RUSLE2015 model are the cover management (*C*) and the support practices (*P*) (Figure 3). In more detail, *C* incorporates the changes in land cover and the conservation practices applied in agricultural areas (tillage, cover crops and plant residues). The changes in land cover are either natural (semi-natural areas to forests) or anthropogenic (forests to cropland). Afforestation takes place in areas of land abandonment, while deforestation may take place in areas of agricultural expansion. An additional land cover change that is important for soil loss by water erosion is urbanisation, as the potential erosive area is reducing in time.

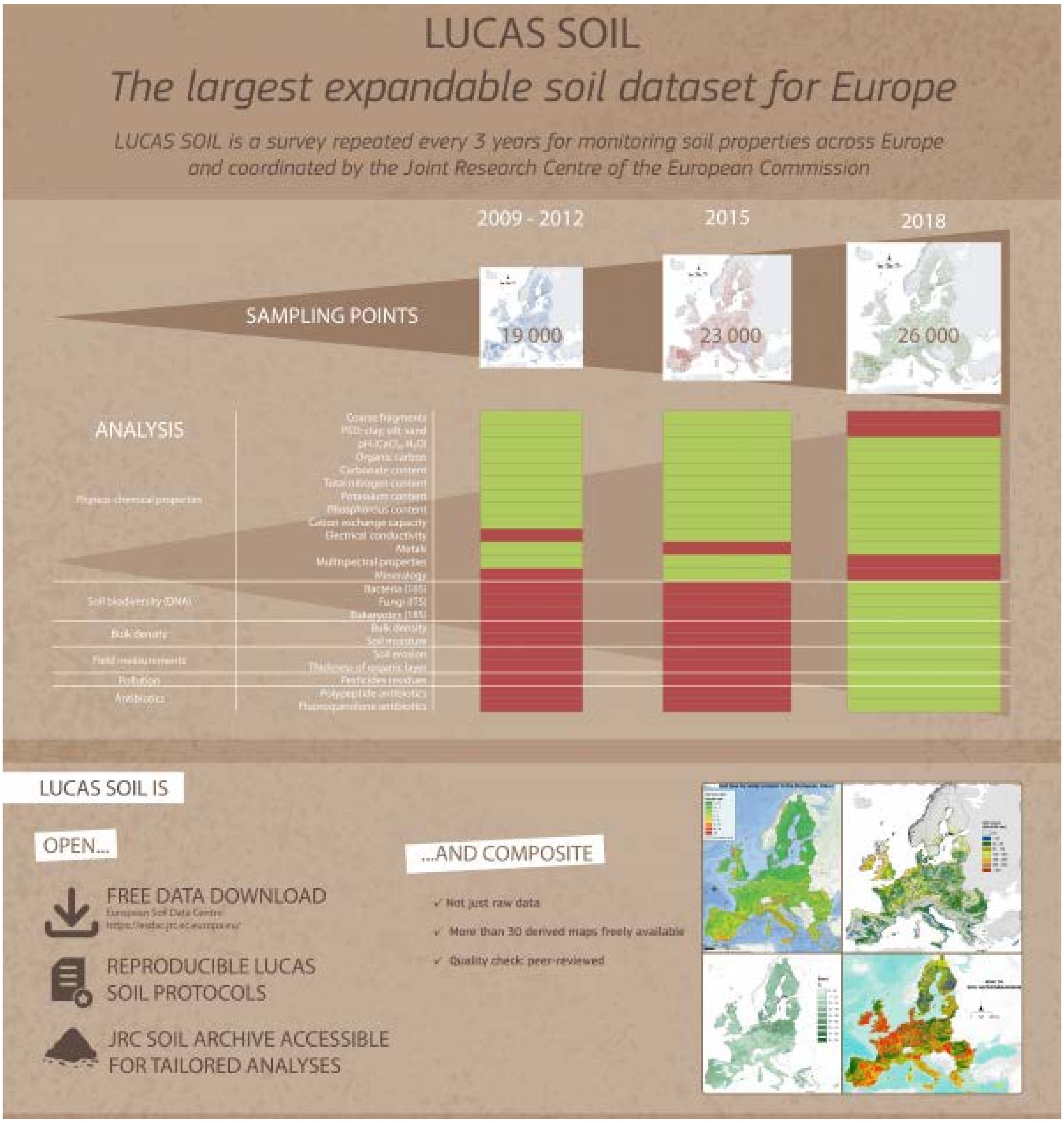
In addition, *P* considers the changes in grass margins and stone walls; those are conservation practices reducing soil erosion by water. The increase or decrease in conservation practices reflects the impact of agri-environmental policies in reducing soil erosion. In conclusion, both the cover management and the support practices quantify the human interventions and the impact of agri-environmental policies (Figure 3). A detailed description of the input factors and the available data is provided in Section 2.4.2.

2.4.1. Data sources

This section describes the main data sources (databases) that have been included in the RUSLE2015 model.

LUCAS 2009-12 topsoil database. The soil erosion studies used the topsoil database from the Land Use/Land Cover Area frame Survey (LUCAS) (known as LUCAS Topsoil), which contains records of the physical and chemical properties of 21 682 soil samples in 27 EU Member States (excluding Croatia) (Figure 2). Topsoil samples (0-20 cm, approximate weight of 0.5 kg) were collected from 10 % of the LUCAS survey points. The density of LUCAS topsoil sample points is around 1 per 199 km^2, corresponding to a grid cell size of around 14 km × 14 km. The laboratory analysis of the physical and chemical properties used standard International Organization for Standardization (ISO) methods including a validation process. The soil samples were taken from the uppermost 20 cm of surveyed soil. More details on both the LUCAS topsoil-sampling scheme and the analysis can be found in published papers (Orgiazzi et al., 2018; Toth et al., 2013). The physical properties used in our soil erodibility model are texture (% silt, % sand, % clay), soil organic matter (%) and coarse fragments (%).

Figure 2. LUCAS Topsoil database.



European Soil Database (ESDB). The ESDB, at 1:1 000 000 resolution (King et al., 1994), is a reference data set for assessing the state of soils in the EU. The ESDB includes, among others, attributes such as texture and soil types expressed as classes.

Stoniness database. During the 2009 LUCAS data collection exercise, the surveyors estimated the percentage of the surface that is covered with stones. Stoniness decreases the soil erodibility factor by a mean of 15 %. Both the % of stones per surveyed point and the decrease of soil erodiblity are recorded in stoniness database. The protective effect of stoniness is strongest in the Mediterranean countries (Greece, Spain, southern France and Portugal), as it reduces erodibility by 20-42 % (Panagos et al., 2014a).

Rainfall Erosivity Database at European Scale (REDES). This has been developed from high temporal resolution (5-minute, 10-minute, 15-minute, 30-minute and hourly) rainfall data collected from 1 675 stations from all EU Member States and Switzerland. A participatory approach has been followed in the data collection, as the records have been collected from countries' meteorological and environmental services with the collaboration of scientists in the domain of rainfall erosivity (Ballabio et al., 2017). REDES includes 29 000 years of data with an average of 17.5 years of data per station. The database has developed a monthly component with more than 18 000 monthly records (Panagos et al., 2016). Recently, the 300 000 erosive individual rainfall events have been also added as a third component of REDES.

European Union Digital Elevation Model (EU-DEM). This provides pan-European elevation data at 1 arc-second, and is a hybrid product based mainly on the Shuttle Radar Topography Mission (SRTM) and Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) Global Digital Elevation Model (GDEM) (Copernicus, 2015). EU-DEM was developed through the Copernicus programme, and its statistical validation documents a relatively satisfactory overall vertical accuracy of 2.9 m root mean square error (EEA, 2014). This resolution of 25 m in EU-DEM is the best available at the European scale.

Corine Land Cover. The Corine Land Cover (CLC) map was developed by image analysis and land use/cover digitalisation of Earth observation data in a geographic information systems (GIS) environment. CLC data sets are available for 1990, 2000, 2006 and 2012 (and released but not validated for 2018). The data sets contain homogeneous data on land cover areas, which are provided in vector format (as polygons). All CLC data sets (CLC, 2019) were established following harmonised procedures based on a common classification system, and can therefore be easily compared. Data are classified into 44 land cover classes, which are grouped under three hierarchical levels. Their nominal scale is 1:100 000 with a minimum mapping unit (MMU) of 25 ha and a change detection threshold of 5 ha. The data are also available in a raster format at a pixel resolution of 100 m, and refer to the year 2006. European validation studies such as LUCAS have shown that the accuracy achieved is above the minimum specified by CLC (85 %) (Buttner, 2014).

Corine Land Cover Change 2006-2012. All land cover/use changes between 2006 and 2012 are integrated using the official data provided by the Copernicus website (https://land.copernicus.eu) (Land Cover Change (LCC) 2006-2012). Land cover and land use change also contributes to changing soil erosion, since there was a shrinkage of arable land (CLC classes 2.1x or raster CLC codes 12, 13 and 14) in the EU between 2006 and 2012 (ca. 750 000 ha). Substantial proportions of former arable land were converted to pasture (CLC code 2.3.1) (equal to ca. 26 % of the change) and non-erosive land (CLC classes 1.1.2, 1.2.1, 1.2.2) (equal to ca. 17 %). For the development of the soil erosion indicators, a hybrid land cover layer was implemented using the 2006 CLC and applying the changes between 2006 and 2012 (Borrelli and Panagos, 2020).

The 2010 soil erosion assessment used the 2006 CLC data set as input for the land cover data. In the updated 2016 soil erosion assessment, we have integrated the official land cover change layer (LCC 2006-2012) provided by Copernicus (https://land.copernicus.eu) and we have developed the hybrid 2012 land cover layer. As the objective of the indicators is to track the change, the most suitable layer is the land cover change between the two periods. The hybrid land cover layer represents the land cover in 2012 avoiding the possible biases due to change of nomenclature.

In addition, Copernicus website with questions and answers (Q&A) states that the ‘Users interested in CLC-changes should always rely on the corresponding CLC-Changes product and never on the difference (intersect) of the two status layers’ (Annex 1). The latest Corine Land Cover, 2018, was not employed, as its validation procedures are still ongoing.

In Annex 1, we provide more information taken from the questions and answers (Q&A) section of the Copernicus website to support our decision and to refer to the best practices in using Corine Land Cover.

Copernicus and derived data set on vegetation density (FCover). The Fraction of Vegetation Cover (FCover) corresponds to the fraction of ground covered by green vegetation. Under the Copernicus programme (Copernicus, 2014), the MERIS (Medium Resolution Imaging Spectrometer) Environmental Satellite sensor derived, after processing, regular standardised biophysical parameter layers over Europe at 300 m resolution covering the period 2011-2012, and at 1 km resolution for about 10 continuous years (2002-2012). The biophysical attributes named ‘BioPar’ are derived from MERIS baseline vegetation model. Among the nine biophysical parameters, FCover is the most appropriate layer representing the percentage (fraction) of the surface covered by any kind of vegetation. The FCover data set is used to weight C factors of a specific land use type, depending on the fractional vegetation cover.

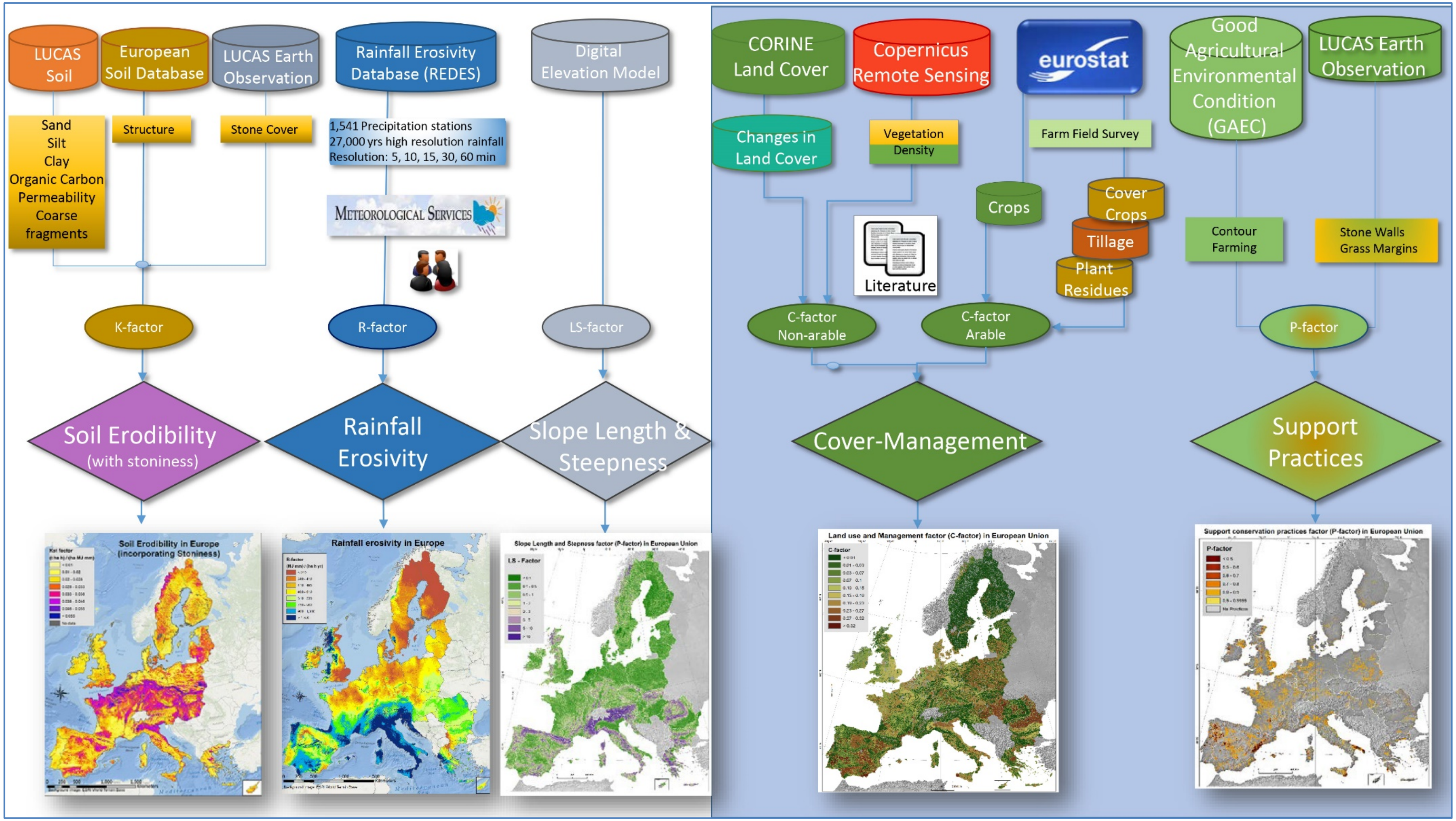
Eurostat statistical data on crops, tillage practices, plant residues and cover crops. The data set of tillage methods includes statistics on tillage practices (conventional tillage, conservation tillage, no till), and the soil conservation data set provides statistics on cover crops and plant residues. The data sets are results of the Farm Structure Survey (FSS) performed by Eurostat. Eurostat collected data from the Farm Structure Survey on Agricultural Production Methods, a survey carried out in 2010 and repeated in 2016, which collected data at farm level on agri-environmental measures. The EU Member States collected information from individual agricultural holdings and, following rules of confidentiality, these data were transmitted to Eurostat and aggregated at the NUTS2 regional level. In this study, the statistical data on tillage practices, cover crops and plant residues are used at the NUTS2 level.

The data are available at: https://ec.europa.eu/eurostat/web/agriculture/data/database

Good Agricultural and Environmental Conditions (GAEC) database. Member States have the flexibility to define the contents of GAEC requirements taking into account the local conditions. In the GAEC database (Angileri et al., 2011; GAEC, 2019), each country has the flexibility to decide the compulsory requirements for farmers to apply contour farming. Among the EU Member States, only 10 have applied contour farming.

LUCAS. The Land Use / Land Cover Area frame Survey includes ground observations on both land use/cover and landscape features for over 300 000 observation points visited by surveyors in 2015. The LUCAS 2012 data set was used for the development of the soil erosion indicator in 2010, and the LUCAS 2015 data set was used for the updated version of the soil erosion indicator in 2016. LUCAS includes points at a mean density of one point every 16 km^2. During the surveys, the surveyor collects and records land use/cover data and walks eastwards along a transect of a 250 m line recording the sequence of land cover types and linear landscape features. Among them, stone walls and grass margins are useful inputs for the development of soil erosion indicators.

Figure 3. RUSLE2015 model for estimation of soil erosion indicators in the European Union (shaded parts are the dynamic soil erosion components).



Source: Panagos et al., 2015 (adapted in 2019 for the soil erosion indicator).

2.4.2. Input factors

The main drivers of soil erosion are (a) soil properties, (b) rainfall and climatic conditions, (c) topography, (d) land cover and crop management and (e) conservation practices. Those drivers are represented by factors in the RUSLE model, equation (1). The five main input factors (Figure 3) in the RUSLE2015 model are described in detail.

Soil erodibility

The greatest obstacle to soil erosion modelling at larger spatial scales is the lack of data on soil characteristics. One key parameter for modelling soil erosion is the soil erodibility, expressed as ***K-factor*** in the widely used models such as the Universal Soil Loss Equation and its revised version (RUSLE). This factor is related to soil properties such as:

- organic matter content,
- soil texture,
- soil structure,
- permeability,
- stoniness.

The modelling of *K-factor* takes into account the following data sources: the LUCAS 2009-12 topsoil database, the ESDB and Stoniness database.

The JRC generated the first harmonised high-resolution soil erodibility map (with a grid cell size of 500 m × 500 m) for the 28 EU Member States (Panagos et al., 2014a). Soil erodibility was calculated for the LUCAS survey points using the monograph of Wischmeier and Smith (1978). A cubist regression model was applied to correlate spatial data such as latitude, longitude, remotely sensed features and terrain features in order to develop a high-resolution soil erodibility map. The mean *K* for Europe was estimated at 0.032 $t\ ha\ h\ ha^{-1}\ MJ^{-1}\ mm^{-1}$ with a standard deviation of 0.009 $t\ ha\ h\ ha^{-1}\ MJ^{-1}\ mm^{-1}$. The resulting soil erodibility data set compared well with published local and regional soil erodibility data. However, the incorporation of the protective effect of surface stone cover, which is usually not considered for soil erodibility calculations, resulted in an average 15 % decrease in the factor. The exclusion of this effect in *K*-factor calculations is likely to result in an overestimation of soil erosion, particularly for the Mediterranean countries, where the highest percentages of surface stone cover were observed. Recent research findings have also addressed the relationship between soil organisms and soil erosion as earthworm abundance has an overall negative effect on the erodibility of soil (Orgiazzi and Panagos, 2018).

In response to a number of requests from non-EU users, we also make available the extrapolated data sets covering Norway, Switzerland, Balkan states, Moldova and Ukraine.

Data: https://esdac.jrc.ec.europa.eu/content/soil-erodibility-k-factor-high-resolution-dataset-europe

Rainfall erosivity

Among the factors used within RUSLE models (Wischmeier and Smith, 1978), rainfall erosivity is of high importance, as precipitation is the driving force of erosion and has a direct impact on the detachment of soil particles, the breakdown of aggregates and the transport of eroded particles by runoff. Rainfall erosivity, expressed as **R-factor** is the kinetic energy of raindrops' impact and the rate of associated runoff. R-factor is a multiannual average index that measures rainfall's kinetic energy and intensity to describe the effect of rainfall on sheet and rill erosion. R-factor sums up the rainfall erosivity of all erosive events. For each erosive event, we have estimated the product of kinetic energy of a rainfall event (*E*) and its maximum 30-minute intensity ($mm\ h^{-1}$).

Compared with past assessments, the European *R* factor (Panagos et al., 2015b) in RUSLE2015 has taken into account:

- precipitation duration,
- magnitude,
- intensity.

Input data sources: Rainfall Erosivity Database at European Scale (REDES).

The time-series precipitation data of more than 75 % of EU Member States cover the decade 2000-2010. Gaussian process regression (Rasmussen and Williams, 2006) has been used to interpolate the R-factor station values of REDES in a European rainfall erosivity map at 500 m resolution. The significant covariates affecting the R-factor interpolation are total precipitation, seasonal precipitation, precipitation of driest/wettest months, average temperature, elevation and latitude/longitude. The mean R-factor for the EU plus Switzerland is 722 MJ mm ha^{-1} h^{-1} yr^{-1}, with the highest values (> 1 000 MJ mm ha^{-1} h^{-1} yr^{-1}) in the Mediterranean and regions around the Alps while the lowest values (500 MJ mm ha^{-1} h^{-1} yr^{-1}) are found in the Nordic countries (Panagos et al., 2015b).

The European Soil Data Centre (ESDAC) makes available many data sets relevant to rainfall erosivity: (a) REDES, (b) the *R* factor data set, (c) erosivity density, (d) monthly rainfall erosivity in Europe, (e) seasonal erosivity estimations, (f) future projections of rainfall erosivity (2050) and (g) indicators of rainfall erosivity.

Data: https://esdac.jrc.ec.europa.eu/content/rainfall-erosivity-european-union-and-switzerland

Slope length and steepness

Topography is taken into account in the RUSLE2015 model with the combination of L-factor and S-factor. S-factor measures the effect of slope steepness, while L-factor defines the impact of slope length. The combined ***LS-factor*** describes the effect of topography on soil erosion.

The LS calculation was performed using the original equation proposed by Desmet and Govers (1996) and implemented using the System for Automated Geoscientific Analyses (SAGA), which incorporates a multiple-flow algorithm and contributes to a precise estimation of flow accumulation. The LS-factor data set was calculated using a high-resolution (25 m × 25 m) Digital Elevation Model (EU-DEM) for the whole European Union, resulting in an improved delineation of areas at risk of soil erosion compared with lower-resolution data sets. This combined approach of using GIS software tools with high-resolution digital elevation models has been successfully applied in regional assessments in the past, and is now being applied for first time at the European scale.

The application of the methodology resulted in the first topographic mapping of LS-factor at 25 m resolution for the European Union (Figure 3). The highest values are observed in mountain areas such as the Alps (Slovenia, Austria, Italy and France), the Pyrenees (Spain), the Apennines (Italy), the Carpathian mountains (Romania) and the Pindos mountain range (Greece). The mean LS-factor value for the whole European Union is 1.63, with a range of 0 to 99 (Panagos et al., 2015c).

Input data sources: EU-DEM at 25 m resolution.

Data: https://esdac.jrc.ec.europa.eu/content/ls-factor-slope-length-and-steepness-factor-eu

Cover management factor

Land cover and management influence the magnitude of soil loss and are represented by **C-factor** in equation (1). Cover management is the factor that policymakers and farmers can most readily influence in order to help reduce soil loss rates. For the estimation of C-factor, JRC has developed the Land Use and Management (LANDUM) model (Panagos et al., 2015d).

The LANDUM model estimates annual C-factor values in arable and non-arable land (forests, semi-natural areas, natural grassland) following two different approaches. Lands such as bare rocks, wetlands, beaches, glaciers, water bodies and artificial areas are not taken into consideration, given their negligible effect from a soil erosion perspective. In arable land, the factor is estimated using crop statistics (% of land per crop) and data on management practices such as conservation tillage, plant residues and winter crop cover (provided by European census data). Maintaining crop residues on soil surfaces not only protects the soils from splash erosion but also increases infiltration rates (Unger and Vigil, 1998) and reduces surface runoff (Greenland, 1975), resulting in less soil loss. In their experimental field, Campbell et al. (1979) found that crop residues decrease soil loss by around 12 %. Cover crops reduce soil loss by improving soil structure and increasing infiltration, protecting the soil surface, scattering raindrop energy and reducing the velocity of the movement of water over the soil surface (Smith et al., 1987). Wall et al. (2002) and Bazzoffi (2007) have estimated the reduction in *C-factor* due to the application of cover crops to be around 20 %.

The crop composition of an agricultural area is an important input in estimating the water erosion risk. An area with a high proportion of more erosive crops (sugar beets, potatoes, tobacco, maize) is more susceptible to water erosion than an area with a high proportion of less erosive crops (rice, wheat, barley, permanent crops, etc.) (Figure 4).

In forests or grassland, the cover protection is dense and the soil is protected through the whole year. Thus, forest and grassland have the lowest mean C-factor (Figure 4). The factor in non-arable land was estimated by weighting the range of values found in the literature according to fractional vegetation cover, which was estimated based on the remote sensing data set FCover (fraction of ground covered by green vegetation) from Copernicus.

The methodology is designed to be a tool for policymakers to assess the impact of different management practices and land use change in soil erosion by water. In addition, the effect of future land use change and crop rotation scenarios can be estimated as well. The impact of land use changes (deforestation, arable land expansion, afforestation) and the effect of policies (such as the Common Agricultural Policy and the Renewable Energy and Water Framework Directives) can potentially be quantified with the proposed model.

Input data sources: Corine Land Cover 2012 (hybrid layer developed by JRC), Corine Land Cover Changes 2006-2012, Copernicus vegetation density layer, Eurostat statistical data on crops, tillage practices, plant residues and cover crops.

Data: https://esdac.jrc.ec.europa.eu/content/cover-management-factor-c-factor-eu

(the updated C-factor for 2016 will be released at the same web address)

Support practices

The support practice factor (P-factor) is rarely taken into account in soil erosion risk modelling at sub-continental scale, as it is difficult to estimate for large areas and there is a lack of available data sets. P-factor considers three management practices for reducing soil erosion by water: contour farming, stone walls and grass margins (Panagos et al., 2015e).

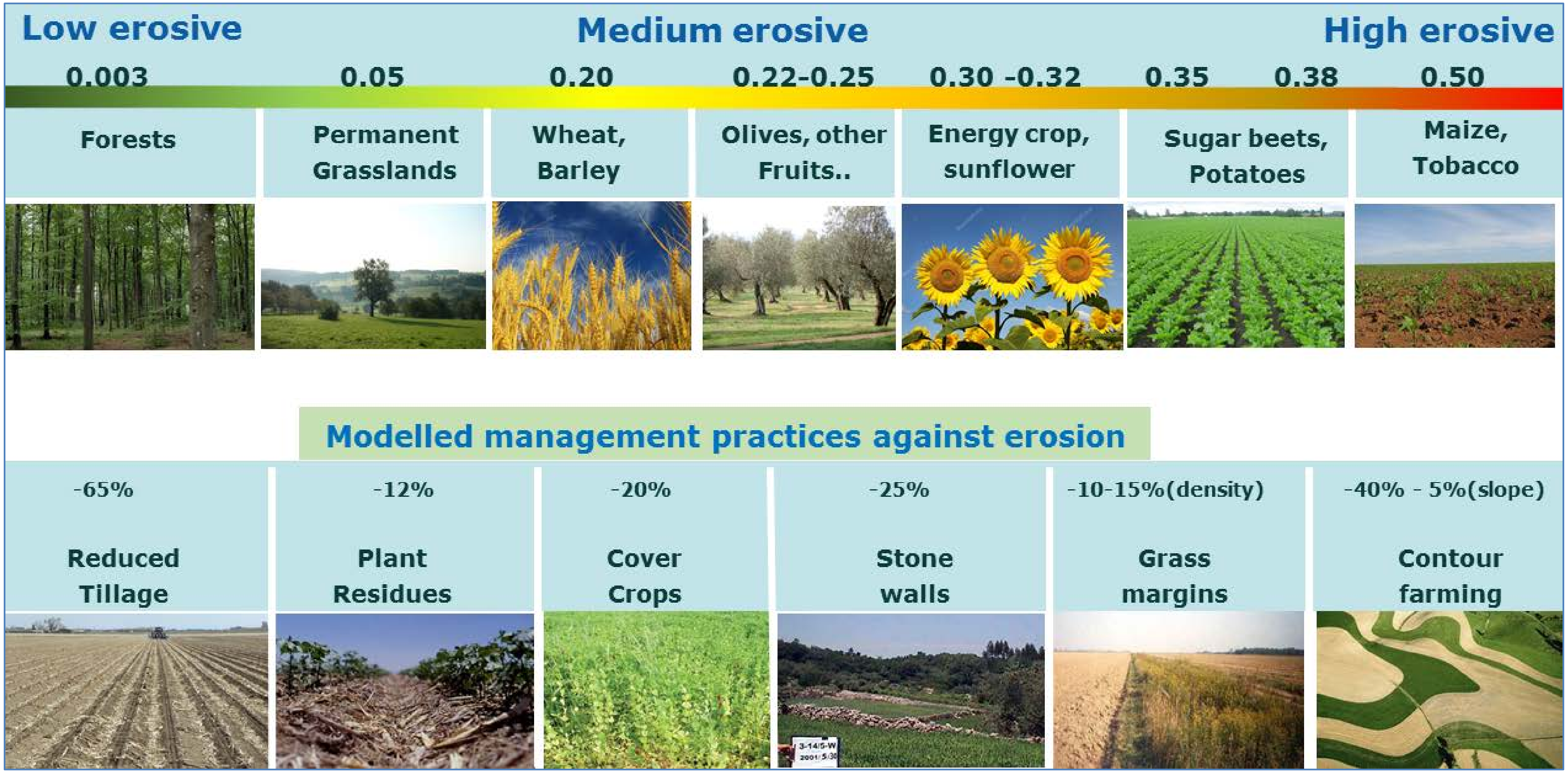
The contouring may reduce soil erosion from 5 % to 40 % depending on the slope application. Stone walls are considered effective for reducing slope length and as a consequence soil erosion. Dry stone walls (or terraces) are widespread landscape features in the Mediterranean and especially in the islands. Depending on their status (partially degraded, good condition) they may trap sediments and reduce soil erosion by between 20 % and 35 %. In addition, small landscape elements such as hedges or buffer strips should not be removed, as they protect habitats and reduce runoff volumes. Haan et al. (1994) considered grass margins one of the most effective measures for reducing sediment delivery, and experimental results showed a concrete reduction of inflowing sediments. Depending on the density of grass margins, they can reduce runoff and as a consequence soil erosion by 10-15 % (Figure 4).

Input data sources: LUCAS 2015 (stone walls, grass margins), GAEC database.

Data: https://esdac.jrc.ec.europa.eu/content/support-practices-factor-p-factor-eu

(the updated P-factor for 2016 will be released at the same web address)

Figure 4. The importance of land cover (less versus more erosive) with the C-factor values in the bar (dark green to red) and the effect of management practices in reducing erosion (minus signs show the percentage decrease).

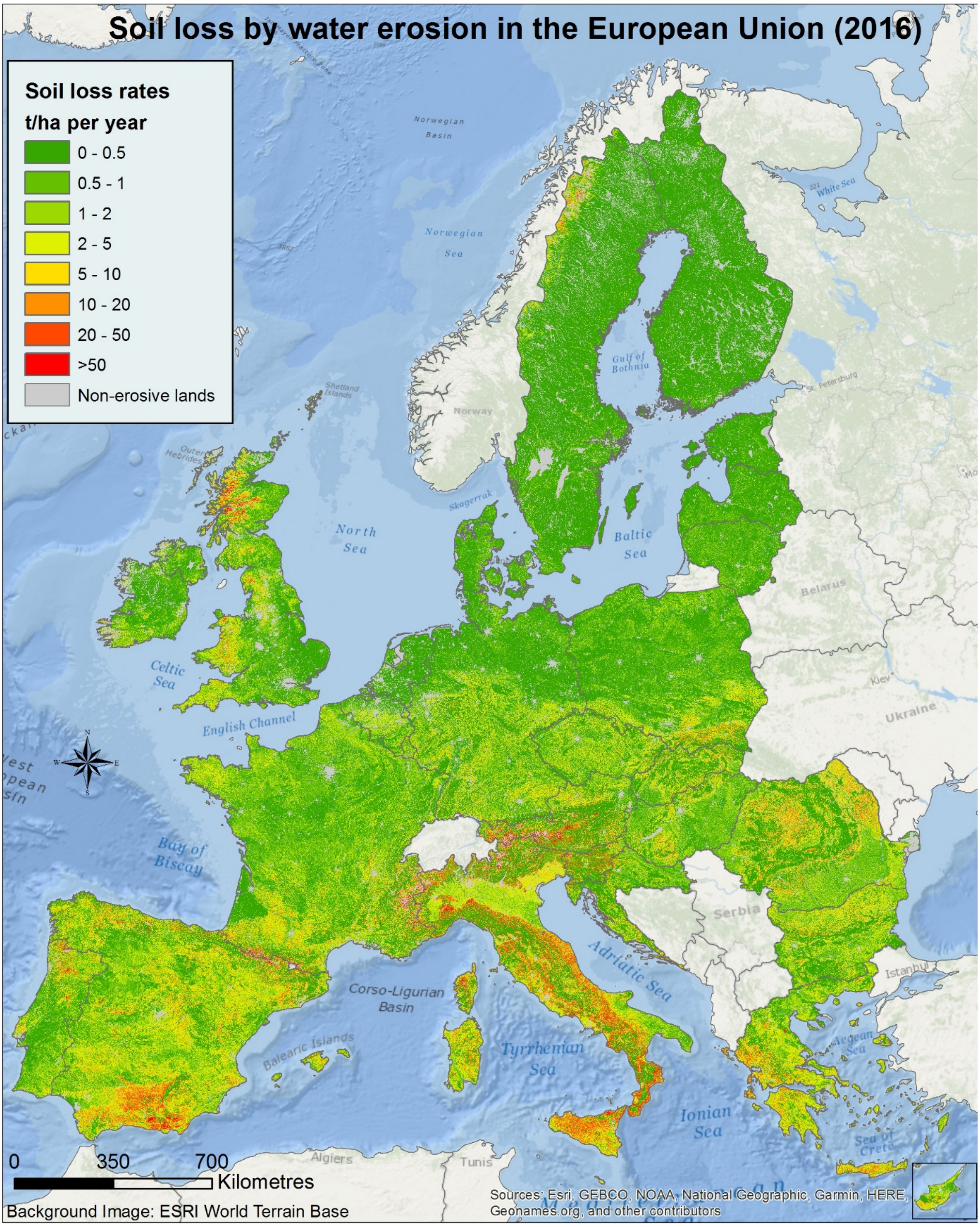


Source: JRC, 2019

2.5. Soil loss by water erosion assessment 2016

The potentially erosive area is about 3 912 × 10^3 km^2, which is about 89.6 % of the continental EU area (Figure 5). The erosive areas are defined based on Corine Land Cover and include all the agricultural areas (CLC classes 2.x), forests (CLC classes 3.1.x – x represents all the sub-classes 3.1.1, 3.1.2, 3.1.3), scrub and herbaceous areas (CLC classes 3.2.x), sparsely vegetated areas (CLC class 3.3.3) and burnt areas (CLC class 3.3.4).

Figure 5. Soil loss by water erosion assessment 2016.



The non-erosive areas include land covers not prone to soil erosion (cities, urban areas, bare rocks, glaciers, wetlands, lakes, rivers and marine waters). In practice, we do not consider the artificial surfaces (CLC classes 1.x), beaches and dunes (CLC class 3.3.1), bare rocks (CLC class 3.3.2), glaciers (CLC class 3.3.5), wetlands (CLC classes 4.x) and water bodies (classes 5.x). The non-erosive area has been slightly increased compared with 2010, mainly because of urbanisation.

The mean soil erosion rate in the EU-28 for 2016 is estimated as 2.45 t ha^{-1} yr^{-1}, which is close to the 2010 mean erosion rate (2.46 t ha^{-1} yr^{-1}). This decline of 0.4 % in 6 years is much smaller than the reduction in the period 2000-2010 (–9 %).

The spatial patterns of the 2016 EU soil erosion map (Figure 5) are similar to those of 2010. The differences between the two data sets are more obvious when they are compared with the aggregated data. By aggregating the data at regional level, we developed the indicator 'Estimated mean soil erosion rate as t ha^{-1} yr^{-1}' (Figure 6). For soil loss by water erosion, the estimated total is about 960 million tonnes, slightly decreased (by about 10 million tonnes) compared with 2010 (Panagos et al., 2015).

The modelled soil erosion data set includes uncertainties, which are mainly inherited from input factors. The major sources of uncertainty are found in some highly erosion-prone Corine land cover classes (e.g. sparsely vegetated areas) that demonstrate high variability between Mediterranean regions (badlands) and northern Europe (mixed vegetation with rocks). As the second source of uncertainty, we consider the input data on management practices, which are available not at farm level but at regional level (NUTS2). However, the results of RUSLE2015 have been verified successfully with the national soil erosion data sets collected for the European Environment Information and Observation Network (EIONET) and put in the EIONET-Soil database. This includes estimates for soil erosion risk at 1 km pixel size for eight Member States: Belgium, Bulgaria, Germany, Italy, the Netherlands, Austria, Poland and Slovakia (Panagos et al., 2014b). In addition to this verification, authors have also successfully compared the RUSLE2015 outputs with plot erosion rates (Alewell et al., 2019).

2.5.1. Mean estimated soil erosion by water

The Indicator 'estimated soil erosion by water' aggregates the detailed data set of 100 m × 100 m resolution (Figure 5) at different NUTS levels. This indicator fits both the CAP context indicator and the SDGs, Resource Efficiency Scoreboard and AEIs described above.

The geographical distribution of the mean erosion rates show an increase of mean rates in 8 countries and a decrease in 20 countries (Table 1). Among the latter, there are significant positive signs of increase in conservation practices in Austria, Germany, Denmark, Estonia, France and Portugal. Unfortunately, Bulgaria shows a decrease in management practices to reduce soil erosion, which has had the effect of increasing the mean soil erosion rate to 2.18 t ha^{-1} yr^{-1} (+ 5.9 %). Three Mediterranean countries with high erosion rates (from higher rates to lower), Italy (8.59 t ha^{-1} yr^{-1}), Greece (4.19 t ha^{-1} yr^{-1}) and Spain (4.0 t ha^{-1} yr^{-1}) show an increase in mean rates of at least 1.5 % compared with 2010. If those four countries had maintained the same level of management practices as in 2010, then the mean soil erosion rate in the EU-28 could have been reduced to 2.43 t ha^{-1} yr^{-1} (–1.3 %).

The changes of soil erosion in the period 2010-2016 at regional level show a heterogeneous picture. The north-west European regions performed well, as there was a decrease in mean erosion rates, while in the Mediterranean ones the high erosion rates were worsening.

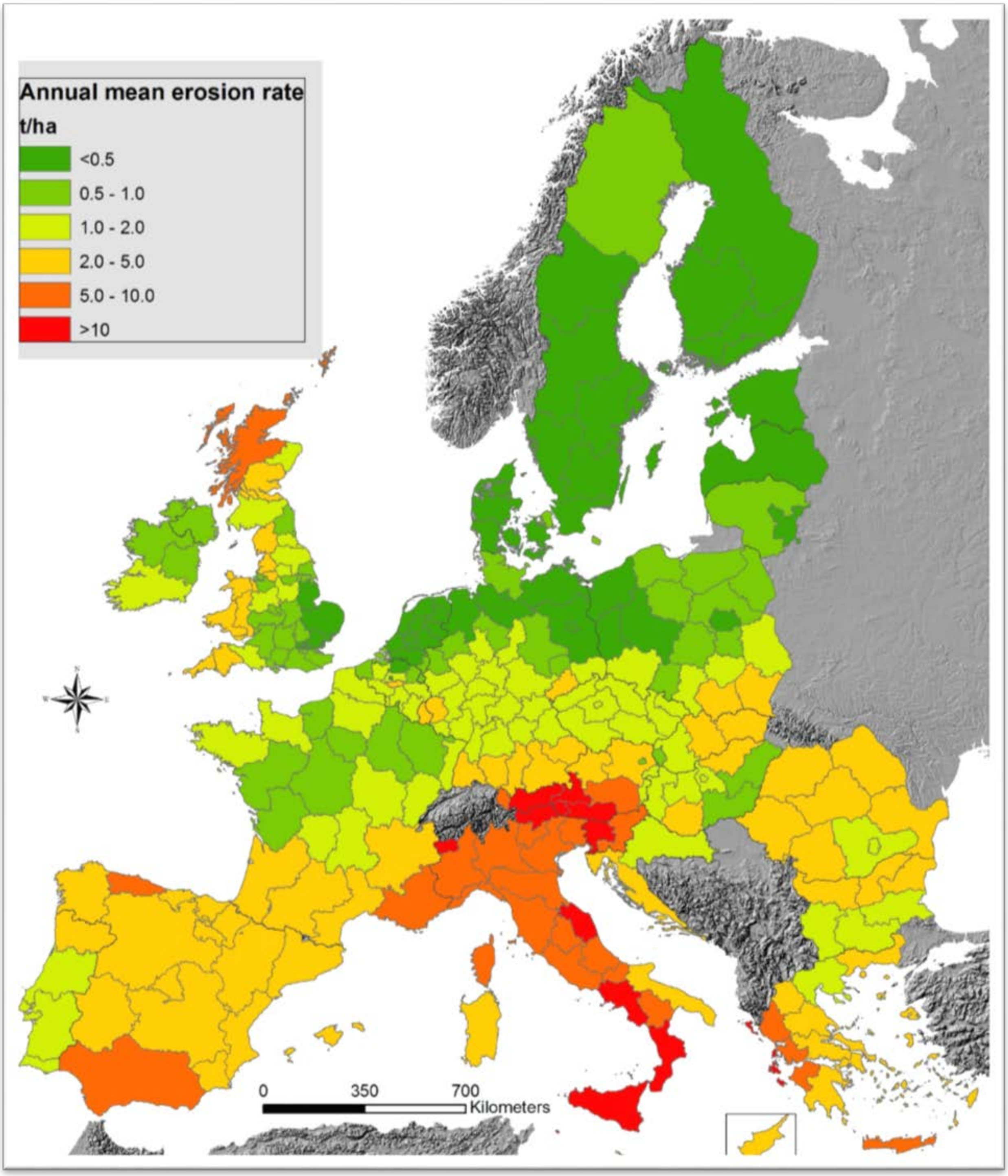
Table 1. Mean estimated soil erosion rates for the development of the SDG indicator (reference years 2010, 2016)

Member State	**Country Codes**	**2010 (t ha^{-1} yr^{-1})**	**2016 (t ha^{-1} yr^{-1})**	**Change (%)**
Austria	AT	7.19	7.19	–0.1
Belgium	BE	1.22	1.22	0.1
Bulgaria	BG	2.05	2.18	5.9
Cyprus	CY	2.89	2.99	3.3

Czechia	CZ	1.65	1.63	–0.7
Germany	DE	1.25	1.23	–1.9
Denmark	DK	0.50	0.47	–5.7
Estonia	EE	0.21	0.19	–6.8
Greece	EL	4.13	4.19	1.6
Spain	ES	3.94	4.00	1.5
Finland	FI	0.06	0.06	–0.4
France	FR	2.25	2.20	–2.4
Croatia	HR	3.16	2.41	–23.7
Hungary	HU	1.62	1.61	–0.8
Ireland	IE	0.96	0.95	–1.1
Italy	IT	8.46	8.59	1.5
Lithuania	LT	0.52	0.51	–0.5
Luxembourg	LU	2.07	2.07	–0.2
Latvia	LV	0.32	0.33	2.2
Malta	MT	6.02	4.47	–25.7
Netherlands	NL	0.27	0.26	–2.5
Poland	PL	0.96	0.99	2.3
Portugal	PT	2.31	2.17	–6.0
Romania	RO	2.84	2.80	–1.6
Sweden	SE	0.41	0.40	–1.6
Slovenia	SI	7.43	7.46	0.3
Slovakia	SK	2.18	2.16	–0.9
United Kingdom	UK	2.38	2.37	–0.2
European Union	**EU**	**2.46**	**2.45**	**–0.4**

The soil erosion rates are also aggregated at different levels: NUTS0, NUTS2 and NUTS3. This allows better comparability between different regions. As an example, Figure 6 provides the mean soil erosion rates at regional level (NUTS2).

Figure 6. Estimated mean soil erosion rates (2016) – SDG indicator.



2.5.1. Agricultural area under severe erosion

This Indicator 'estimated agricultural area affected by severe soil erosion' uses a specific land cover mask to focus only on agricultural area. Based on the requirements given by the Directorate-General for Agriculture and Rural Development (DG AGRI), the classification of soil erosion data was based on Corine Land Cover classes (2012): total agricultural area (Corine raster codes 12-22 and 26), arable and permanent crop area (Corine raster codes 12-17 and 19-22) and permanent meadows and pasture (Corine raster codes 18, 26). Then, the threshold of 11 t ha^{-1} yr^{-1} is applied to map the agricultural areas under severe erosion. Table 2 aggregates the area under severe erosion both as a number of hectares (in 1,000) and as a percentage of the total agricultural land.

The JRC provides the soil erosion indicator to DG AGRI for different NUTS levels. Using the latest version (2016 data set), the JRC has developed factsheets for NUTS0 (country), NUTS1, NUTS2 (region) and NUTS3 (province) levels. An example of those factsheets is provided in Table 2 for NUTS0. The other three factsheets are provided to DG AGRI but it is not possible to fit them in this document given the large number of provinces (1 324), regions (271) and NUTS1 areas (100).

Table 2. CAP context Indicator: agricultural area (%) under severe erosion, 2016

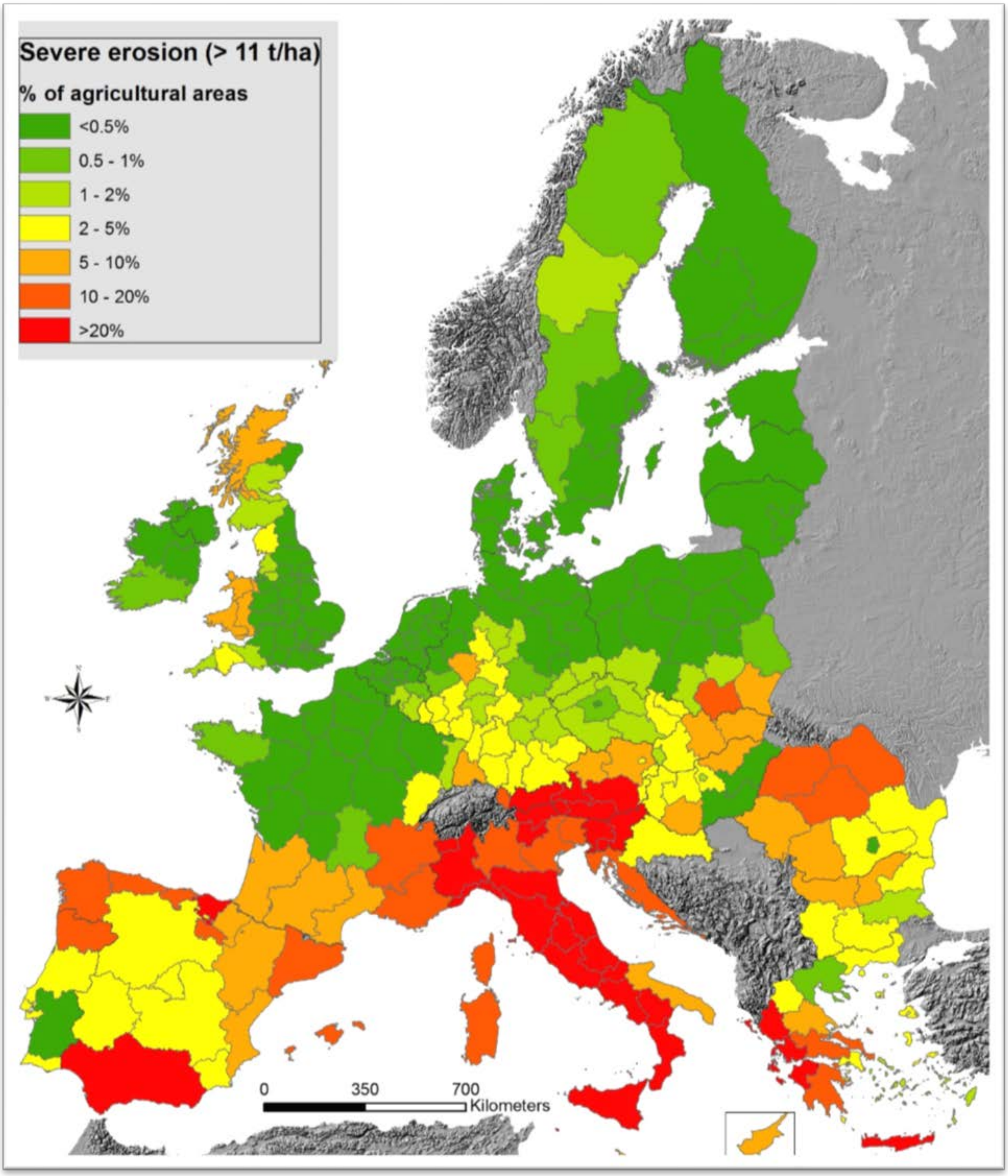
Soil erosion by water		Agricultural areas at risk of soil erosion by water					
Member State	Tonnes ha^{-1} yr^{-1}	Estimated agricultural area (1,000 ha) affected by moderate to severe water erosion (> 11 t ha^{-1} yr^{-1})			Estimated agricultural area (%) affected by moderate to severe water erosion (> 11 t ha^{-1} yr^{-1})		
		Total agricultural area	Arable and permanent crop area	Permanent meadows and pasture	Total agricultural area	Arable and permanent crop area	Permanent meadows and pasture
		1 000 ha			% of total area in each category		
EU-28	**2.45**	**14 119.2**	**11 979.9**	**2 139.2**	**6.6**	**7.2**	**4.5**
AT	7.19	660.9	211.9	449.1	19.9	10.8	33.3
BE	1.22	7.2	6.7	0.4	0.4	0.5	0.1
BG	2.18	246.0	231.6	14.4	4.0	4.4	1.8
CY	2.99	34.5	34.4	0.1	7.4	7.9	0.3
CZ	1.63	68.1	65.6	2.5	1.5	1.8	0.3
DE	1.23	301.6	267.3	34.2	1.4	1.6	0.8
DK	0.47	0.1	0.1	0.0	0.0	0.0	0.0
EE	0.19	0.0	0.0	0.0	0.0	0.0	0.0
EL	4.19	652.8	599.9	53.0	10.2	11.6	4.3
ES	4.00	2 714.8	2 478.5	236.3	9.8	10.1	7.2
FI	0.06	0.1	0.1	0.0	0.0	0.0	0.0
FR	2.20	937.2	639.9	297.3	2.8	2.7	3.0
HR	2.41	162.3	131.2	31.1	6.4	6.6	5.7
HU	1.61	177.1	173.3	3.8	2.8	3.2	0.4
IE	0.95	16.8	7.3	9.5	0.4	0.7	0.3
IT	8.59	5 610.0	5 081.0	528.9	32.8	33.3	28.1
LT	0.51	0.8	0.8	0.0	0.0	0.0	0.0
LU	2.07	4.6	4.4	0.2	3.3	4.3	0.5
LV	0.33	0.3	0.3	0.0	0.0	0.0	0.0
MT	4.47	1.4	1.4	0.0	8.9	8.9	0.0
NL	0.26	0.1	0.1	0.0	0.0	0.0	0.0
PL	0.99	278.4	277.4	1.1	1.4	1.7	0.0
PT	2.17	225.6	222.9	2.7	5.2	5.4	1.3
RO	2.80	1 264.2	1 103.7	160.6	9.1	10.1	5.6
SE	0.40	12.8	11.7	1.1	0.3	0.3	0.2
SI	7.46	307.4	242.7	64.7	42.2	41.1	47.2
SK	2.16	160.5	153.1	7.4	6.7	7.3	2.5
UK	2.37	273.7	32.7	241.0	1.7	0.5	2.7

Note: Data calculated using RUSLE model. EU, national and regional data: 2012 (CLC2012). Corine Land Cover classes: total agricultural area (12-22 and 26), arable and permanent crop area (12-17 and 19-22) and permanent meadows and pasture (18 and 26).

More than 14.1 million ha of agricultural land (including pasture and grassland) is under threat of severe erosion. This represents 6.58 % of the total agricultural area in the EU. This is similar to the situation in 2010, when the proportion of severe erosion was 6.62 %. The area of arable lands and permanent crops have a higher proportion of severe erosion than pasture and grassland.

Slovenia and Italy are the Member States with the highest proportions of severe soil erosion in agricultural areas (42 % and 32.8 %). In addition, some Mediterranean Member States (Greece, Spain, Malta and Cyprus) plus Austria and Romania have shown relatively high percentages of agricultural land affected by severe erosion (higher than the mean EU-value). Nine Member States, mainly Nordic and other northern European ones (DK, EE, LV, LT, FI, SE, BE and IE) have less than 0.5 % of their agricultural areas affected by severe erosion (Figure 7).

Figure 7. Percentage of agricultural area affected by severe erosion – CAP Context Indicator 42.

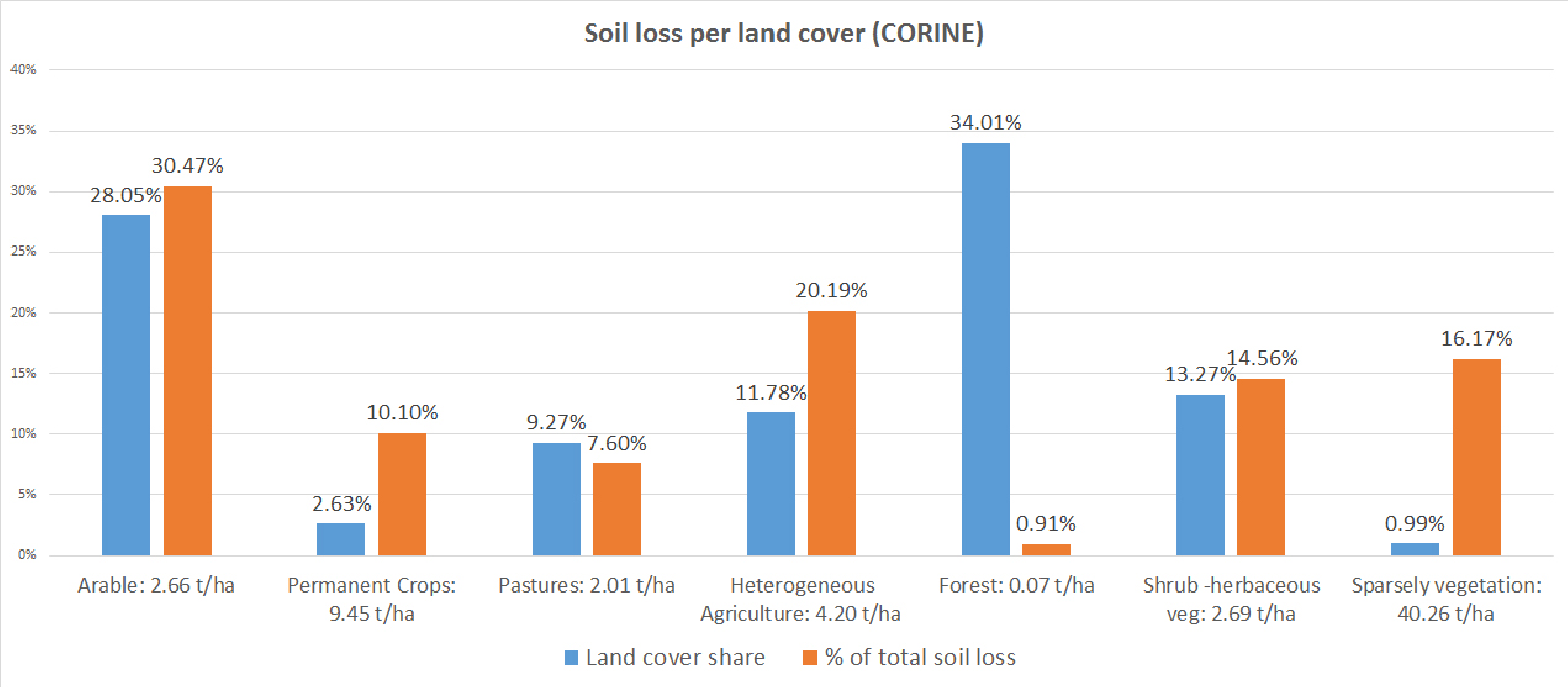


2.5.2. Soil erosion rates by type of land cover

The mean rate of soil loss for the 110 million ha of arable land of the EU (2.67 t ha^{-1} yr^{-1}) is 10 % higher than the overall soil loss rate (2.45 t ha^{-1} yr^{-1}). Permanent crops have a high mean soil loss rate (9.45 t ha^{-1} yr^{-1}), as most of the vineyards and olive trees are located in hilly Mediterranean areas with high rainfall erosivity. The mean annual soil loss rate in pastures is 2 t ha^{-1} yr^{-1}, mainly due to higher vegetation densities and, as a consequence, lower C-factor. The heterogeneous agricultural areas have a higher overall mean rate of soil loss (4.2 t ha^{-1} yr^{-1}) than do arable land areas, although their C-factor is lower. This disparity is due to the differences in topography (which influence the LS-factor), as the arable land is typically located in flat or gently sloping areas.

The forest and semi-natural Corine land cover/use classes are very heterogeneous in terms of soil loss estimates. Although they occupy around 34 % of the EU's erosive land, forests have by far the lowest rate of soil loss (0.07 t ha^{-1} yr^{-1}), contributing to less than 1 % of the total soil loss in Europe (Figure 8). Areas covered with shrub and herbaceous vegetation have a mean soil loss rate of 2.69 t ha^{-1} yr^{-1}. Very high soil loss rates (40 t ha^{-1} yr^{-1}) have been estimated for sparsely vegetated areas, which are mainly badlands in high attitudes with scattered vegetation. Those sparsely vegetated areas explain the high rates of soil loss in southern Spain and Italy. However, this is the most uncertain land cover group, because of the uncertainty of the *C* factor and the ambiguity in the Corine Land Cover classification.

Figure 8. Rates of mean soil loss by land cover group and corresponding percentages of soil loss (reference year 2016).

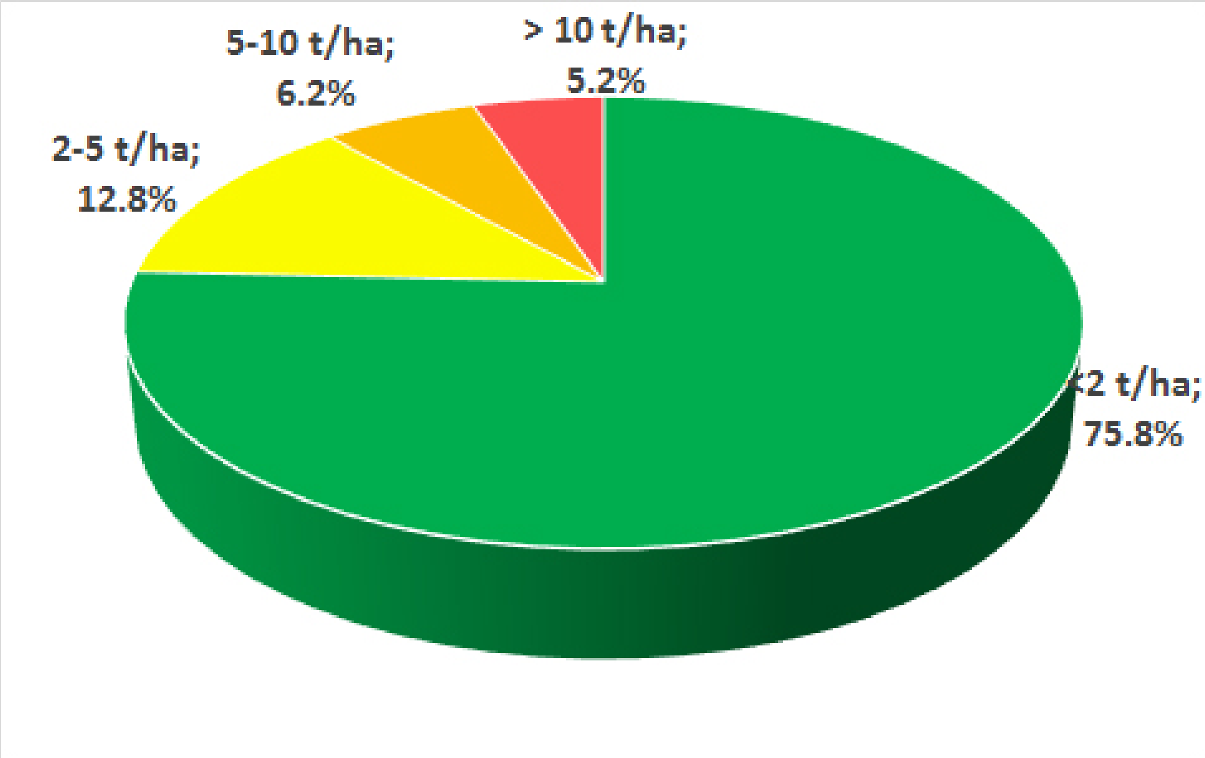


2.5.3. Soil erosion rates per different classes

The soil loss rates of about 76 % of the total European land area are less than 2 t ha^{-1} yr^{-1}. This threshold is considered to be sustainable, given the generally accepted soil formation rates (Verheijen et al., 2009). The remaining 24 % of the European land area, which has soil loss rates above 2 t ha^{-1} yr^{-1}, contributes almost 87 % of the total soil loss in the EU (Figure 9).

Soil protection measures should definitely be taken in the 5.2 % of the European land area that suffers from severe soil loss (mean rates > 10 t ha^{-1} yr^{-1}) and contributes to 52 % of the total soil loss in the EU. An example of such a measure is the afforestation or re-vegetation of sparsely vegetated areas that have very high soil loss rates. Other proposed soil erosion control measures include the increase of areas under cover crops, the application of plant residues and grass margins in arable land.

Figure 9. Distribution of erosion classes.



2.6. Concluding remarks on soil erosion

Soil erosion estimates are of high importance for a number of EU policies such as the CAP, Soil Thematic Strategy, the Resource Efficiency Scoreboard and other related initiatives (e.g. SDGs) (Panagos and Katsoyiannis, 2019). Potentially, the soil erosion indicators may also be included in assessing ecosystem services, biodiversity loss (Biodiversity Strategy 2030) and sediment pollution (Water Framework Directive).

The estimated soil erosion rates in 2016 show a limited decrease of 0.4 % in all lands and 0.8 % in arable land compared with 2010. In the decade 2000-2010 the corresponding decrease was significant, as soil erosion decreased by 9 % in all lands and 19 % in arable land (Figure 10).

The increase of grass margins in the period 2010-2016 was quite limited (8 %) (Borrelli and Panagos, 2020). The conservation tillage show a very limited increase (0.8 %) from 21.6 % to 22.4 %. The cover crops are applied to 8.9 % of EU arable land, compared with 6.5 % in 2010. In contrast, the plant residues show a decrease from 10.6 % in 2010 to 9.1 % in 2016. This last figure is worrying, as this decrease may be attributed to the increased use of plant residues as biomass for renewable energy.

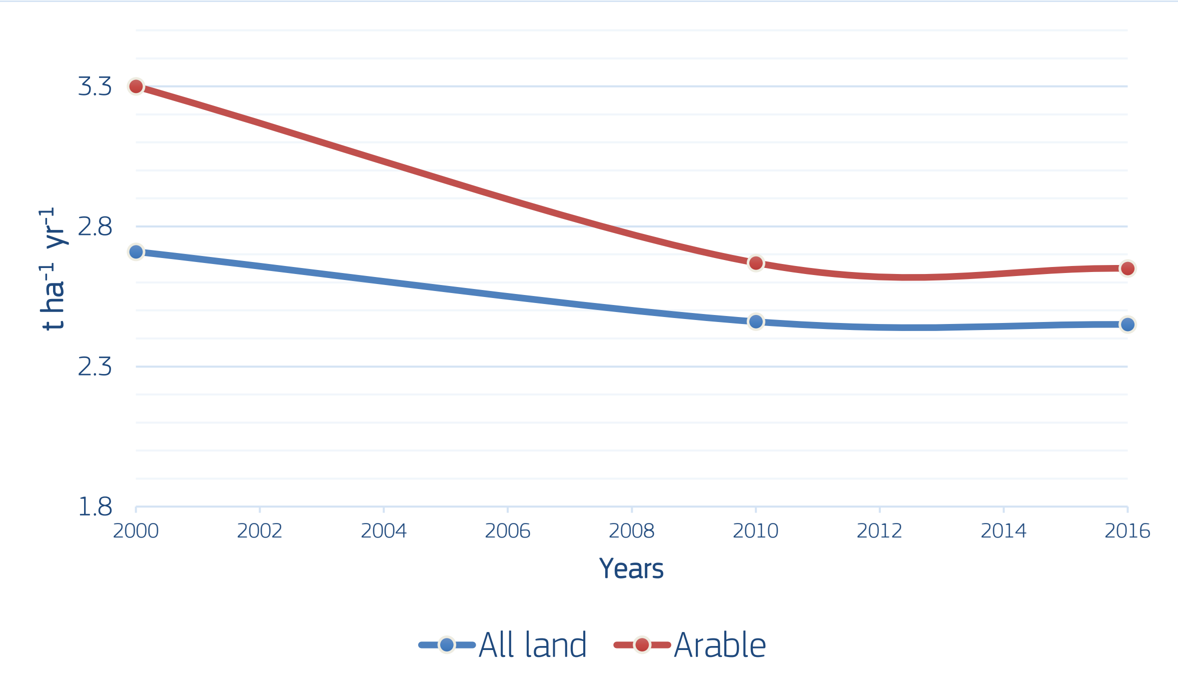
Taking into account the geographical distribution of changes, the small mean increase in management practices at European scale (implying a decrease in C and P-factor) has been offset by a decrease in management practices (and as a consequence an increase in C and P-factor) in more sensitive (erosive) areas such as the Mediterranean basin. In a nutshell, the majority of Member States (and regions) perform well as they increase conservation practices; however, the most erosive regions have shown deterioration.

The soil formation rates found in the literature are about to 1.4-2 t ha^{-1} yr^{-1} (Verheijen et al., 2009). As noted above, almost a quarter of the EU's land has erosion rates higher than the threshold of 2 t ha^{-1} yr^{-1}. In addition, 6.6 % of the EU's agricultural land suffers from severe erosion. It is evident that a stronger package of soil conservation practices (e.g. cover crops, plant residues, reduced tillage, contouring, stone walls, agro-forestry) is needed to reduce soil erosion in hotspots. All of this does not yet take into account the effects of climate change, which will have an undesirable impact in increasing soil erosion. Extreme intense rainfall may be expected to increase by 18 % on average in the EU by 2050 (Panagos et al., 2017).

The current agri-environmental policies in place need to focus on hotspots and reduce soil erosion rates in agricultural land where current rates are higher than sustainable. In addition, an important step would be to set a policy target of halting severe and very severe/extreme erosion on agricultural land by 2030.

The focus on soil erosion processes is mainly on water erosion in the EU, as this is the most dominant threat. However, both scientists and policymakers should not ignore soil losses due to wind erosion (Borelli et al., 2017b), harvest erosion (Panagos et al., 2019) and gully erosion (Vanmaercke et al., 2016).

Figure 10. Trends in mean soil erosion on all lands and arable land, EU.



3 Carbon stocks based on LUCAS topsoil

The Land Use/Land Cover Area Frame Survey (LUCAS) is a project to monitor land use and land cover changes across the EU. The survey is performed every 3 years; the latest published LUCAS data set dates back to 2015. It now covers all the 28 current and former EU Member States and includes field observations at more than 273 000 points. Soil samples are taken in about 10 % of the surveyed locations every 6 years. The first LUCAS soil survey was done in 2009, collecting 19 969 topsoil samples (0-20 cm) from 25 of the EU-28, excluding Bulgaria, Croatia and Romania (Orgiazzi et al., 2018). In the 2012 survey, 2 034 topsoil samples were collected from Bulgaria and Romania, following the standard procedure of 2009. The overall sampling density of this European soil survey is nearly one soil sample every 196 km^2 (Panagos et al., 2013), which means one sample about every 14 km × 14 km.

The LUCAS topsoil data set is the most comprehensive and harmonised soil data set at European scale, which allows pan-EU studies on the distribution of physical properties (clay, silt and sand) (Ballabio et al., 2016), soil erodibility (Panagos et al., 2014a), SOC (de Brogniez et al., 2015) and the modelling of diffuse pollution with heavy metals such as copper (Ballabio et al., 2018). The number of points selected is based on a stratification in order to cover all possible land uses (based on Corine land cover classes) and country surface (Carre et al., 2013). Orgiazzi et al. (2018) described in detail the soil-sampling procedure and the standards that the surveyors should follow. The soil samples were analysed for the percentage of coarse fragments, particle size distribution (silt, clay, sand), pH, organic carbon, calcium carbonate, soluble phosphorus, total nitrogen, extractable potassium, cation exchange capacity (CEC) and multispectral properties (Tóth et al., 2013). Because of problems in labelling, tagging, geo-referencing and mismanagement, 321 soil samples were excluded from the LUCAS Topsoil database, resulting in 21 682 total records.

The sample analysis was performed by a single laboratory, contributing to data comparability by avoiding uncertainties due to analysis based on different methods or different calibrations in multiple laboratories. In a first phase, LUCAS topsoil samples were analysed for their physical and chemical properties following ISO standard procedures. In a later stage, an additional analysis for heavy metals was performed. The main source of information for carbon stocks is the LUCAS topsoil data set.

The quality assessment of LUCAS Topsoil databases 2009-2015 has been performed in additional technical reports (Hiederer, 2018, 2020). This quality assessment found that the results from the laboratory analysis of LUCAS Topsoil are valuable to characterise European topsoil conditions (Hiederer, 2020).

3.1. Modelling carbon stock changes between 2009 and 2015

Changes in soil carbon stocks were assessed by fitting a boosted trees model on the measured SOC concentrations of the samples taken in the 2009/2012 and 2015 LUCAS surveys.

Gradient-Boosting Machines (GBMs) aim to minimise the loss function (a measure of difference between the observed and predicted values) by combining a sequence of base learner models. A common optimisation method to find a minimum is gradient descent, which involves going down a gradient to reach a minimum. The key idea behind GBMs is to sequentially add a new base learner model to the ensemble sequence such that the new model is the model with the greatest correlation with the negative of the loss function's gradient calculated using the current ensemble sequence predictions.

The GBM algorithm is a boosting algorithm that sequentially combines decision trees such that each additional tree is trained with more weighting placed on correctly predicting data points that the previous decision trees misclassified. In simple terms, each new tree aims to correct the mistakes of the previous trees. GBMs have been successfully implemented across a range of classification tasks but are known to have performance issues when there is noise present in the data.

The hyper-parameters of the GBM control the complexity of the learning function. A GBM with a high max depth (maximum number of interactions between independent variables), high ntree (number of trees) and low observations per node (minimum number of data points required for each end node) is more complex and, thus, more prone to overfitting. Therefore, limiting the max depth or ntree or increasing the observations per node can effectively perform regularisation and reduce the chance of overfitting.

The grid search for the hyper-parameters investigated in our models were ntree = 10, 50, 125 and 200; max depth = 2, 4, 6, 8 and 10; the minimum observations per node = 2, 10, 50 and 100. The GBM model was chosen to have a Bernoulli distribution and the chosen model had the hyper-parameters ntree = 125, max depth = 4 (up to four variable interactions were used by the model) and observations per node = 50.

3.2. Methodology and data sources

To support the spatial predictions of soil properties, a series of data sets or covariates were selected according to their possible influence on soil chemical properties. The spatial resolution of the covariates was set to 250 m, as a compromise between the resolution of the Moderate-resolution Imaging Spectro-radiometer (MODIS) data (500 m), the finer resolution of EU-DEM (25 m) and the coarser WorldClim climatic (1 km) data sets (Fick and Hijmans, 2017). Overall, 100 numeric and 99 dummy covariates were considered in the first steps of the analysis. The dummy covariates were obtained from the coding of the categorical variables classes (Corine, parent material type) into dichotomous variables.

3.2.1. MODIS and derived data

A series of MODIS image products for 2009 was collected (MOD13Q1, in particular the MODIS global vegetation indices; Didan, 2015). These products are characterised by a spatial resolution between 250 and 500 m and a temporal resolution of 16 days. The products include blue, red and near- and mid-infrared reflectance, centred at 469 nm, 645 nm, and 858 nm, respectively. The reflectance is used to determine the MODIS daily vegetation indices, such as the Normalised Difference Vegetation Index (NDVI) and the Enhanced Vegetation Index (EVI).

The NDVI is defined as $NDVI = (NIR - RED)/(NIR + RED)$, where NIR and RED stand for the spectral reflectance measurements acquired in the near-infrared and visible (red) regions, respectively. The NDVI has been used to estimate a large number of vegetation properties from its value, such as biomass, chlorophyll concentration in leaves, plant productivity and fractional vegetation cover.

The EVI index is defined as:

$$EVI = g \cdot \frac{NIR-RED}{NIR+c1 \cdot RED-c2 \cdot BLUE+L} \qquad (2)$$

where g is the gain factor, NIR, RED, and BLUE are the surface reflectances in the corresponding spectral bands, L is the canopy background adjustment, and c1 and c2 are coefficients for the aerosol resistance term, which uses the blue band to correct for aerosol influences on the red band. The coefficients adopted by the MODIS-EVI algorithm are l = 1, c1 = 6, c2 = 7.5 and g = 2.5.

Phenological indices were derived from MODIS data using a first-order harmonic model on the EVI and NDVI multitemporal data. The harmonic uses discrete Fourier processing that decomposes temporal curves in a linear trend plus amplitude, variance and phase metric terms. The harmonic model can be defined as:

$$\widehat{Y_t} = \alpha_0 + \sum_{j=1}^{m} \alpha_j \, cos\left(\frac{j2\pi t}{l}\right) + \beta_j \, sin\left(\frac{j2\pi t}{l}\right) \qquad (3)$$

where $\widehat{Y_t}$ is the vegetation index value, t is the time value for a given pixel, l is the cycle length (yearly), m is the order of the trigonometric polynomial and coincides with the number of harmonics of the expansion (set as 1 in this study), and α_j and β_j are the Fourier coefficients.

Harmonic analysis using Fourier series has been used to model the temporal changes in the vegetation cover using satellite data for several decades (Menenti et al., 1993; Moody and Johnson, 2001; Olsson and Eklundh, 1994) and provides better spatial information on the different types of vegetation cover than using composite images alone.

In addition, a Principal Component Analysis (PCA) transformation of the full MODIS 16-day images time series was performed for each band in order to extract relevant features. The PCA projects the time-correlated input images into uncorrelated principal components ordered according to their variance. Thus, the first few components account for most of the time-related variation in each MODIS band.

3.2.2. Terrain parameters

EU-DEM (Bashfield and Keim, 2011) was used to derive land features at a resolution of 25 m × 25 m for the EU.

Both EU-DEM and the derived surface parameters were then rescaled to 250 m. The derivation of land surface parameters was made using the System for Automated Geoscientific Analyses GIS software. Among the various parameters derived and tested, the most relevant were multi-resolution valley bottom flatness and multi-resolution ridge top flatness (Gallant and Dowling, 2003), slope, slope height and vertical distance to channel network.

3.2.3. Land cover

The Corine Land Cover map was developed by image analysis and digitalisation of earth observations. Corine Land Cover data sets are also available in a raster format comprising 44 classes. The nominal scale of Corine is 1:100 000 with an MMU of 25 ha and a change detection threshold of 5 ha. The Corine Land Cover data set was used as input for land use/cover. The reliability of Corine 2000 version at 95 % confidence level is 87.0 ± 0.7 %, according to the independent interpretation performed on the LUCAS data (Buttner, 2014).

3.2.4. Climate data

Monthly temperature averages and extremes, and monthly average precipitation values, were obtained from the WorldClim (http://www.worldclim.org/) data set at a spatial resolution of 1 km^{2}. These data layers are the interpolated values of average monthly climate data collected from numerous weather stations. The approach uses a thin plate smoothing spline with latitude, longitude and elevation as independent variables to locally interpolate data (Hijmans et al., 2005). Climatic data were included explicitly in the model in the form of monthly values of minimum and maximum temperatures and monthly cumulated rainfall rates. The bioclimatic variables (temperature and precipitation indices) of WorldClim were also included in the analysis. Given the high collinearity of climate data, a careful feature selection procedure was applied in the model-training stage.

3.2.5. Legacy soil data and parent material geochemistry

In the first stage of this study, the ESDB (Panagos et al., 2012) was considered as a possible covariate to characterise soil properties. In this context, the ESDB was utilised as a multinomial variable by identifying and labelling soil types. However, the use of the ESDB soil data was found to provide little improvement to the model outcome and was then removed from the analysis. Nonetheless, the data within the ESDB were used to create a map of the parent material geochemistry that was included in the model.

3.3. Map of soil organic carbon stock changes between 2009/2012 and 2015

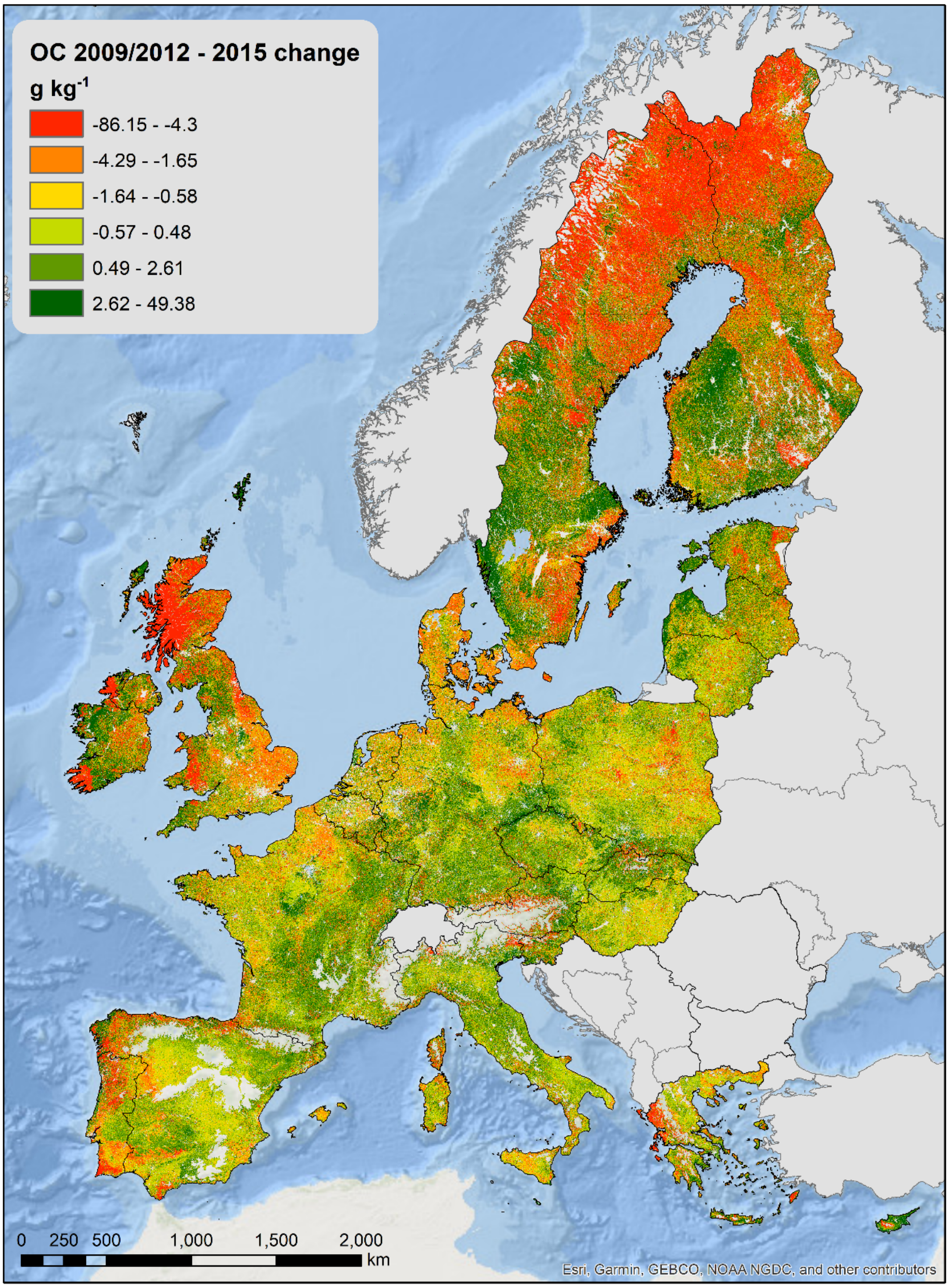
The results presented here should be considered a preliminary modelling comparative analysis between the two main LUCAS surveys. As such, besides the uncertainties due to sampling strategy, surveyors' accessibility and possible laboratory biases, the spatial maps include the uncertainties of modelling and the problems inherited from data about covariates (land cover, climate and terrain). There are additional studies that are performed based only on the point data or the SOC content (%). However, this study focuses exclusively on the carbon stocks based on a spatial interpolation model and not on simple statistical aggregation.

The map presented in Figure 11 shows the changes in SOC concentration as predicted by the GBM model. The map depicts the changes as colour classes divided into quantiles of the predicted difference between SOC measured in 2009/2012 and 2015 (i.e. 2015 – 2009 values). It should be noted that changes in SOC are quite small given the short time interval, most (~70 %) of the SOC changes fall below the limit of ± 4 g kg^{-1} and only 10 % of the area is predicted to have changes greater than ± 12 g kg^{-1}. Moreover, many of the areas where the change is predicted to be greater than ± 12 g kg^{-1} are areas where the model uncertainty is high for lack of samples (Scotland and northern Scandinavia).

Changes in SOC concentration seem to be mostly due to climate and cover, with increases related to the presence of forest or permanent grassland. Decreases seem to be related to areas more affected by climate change, with warmer and drier conditions that favour organic matter mineralisation.

SOC stocks were calculated using a pedotransfer function using soil texture and SOC as inputs. The actual volume of the fine earth fraction was calculated by subtracting the volume of the coarse fragments from the soil volume. The resulting stocks are given in kilograms per hectare (kg ha^{-1}) aggregated at NUTS2 level in Figure 12. As for the concentrations, the values for the stock changes are quite small considering that, on average, the maximum change in stock represents about 2 % of the average SOC stock. The changes in stock are not significant, as about 60 % of the SOC changes are below 0.2 % of the average stock.

Figure 11. SOC concentration change between 2009/12 and 2015 (2015 – 2009 values) as modelled by Gradient-Boosting Machines (GBMs).

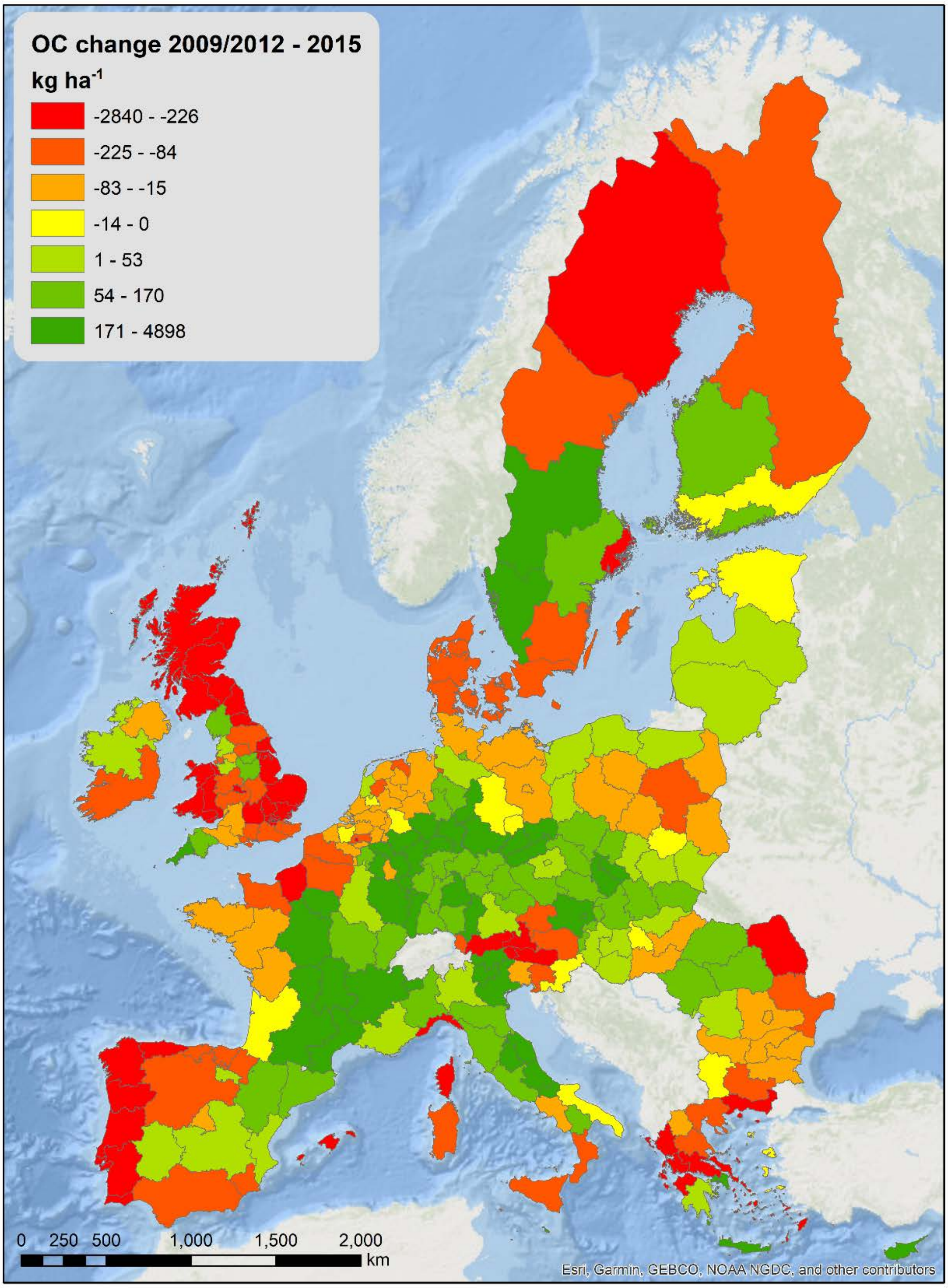


The soil stocks are estimated (Lugato et al., 2014; Poeplau et al., 2017) using the SOC content (%), the bulk density and the depth:

$$SOC_{Stock} = SOC\ cont\ (\%) \times Bulk\ Density \times Depth \qquad (4)$$

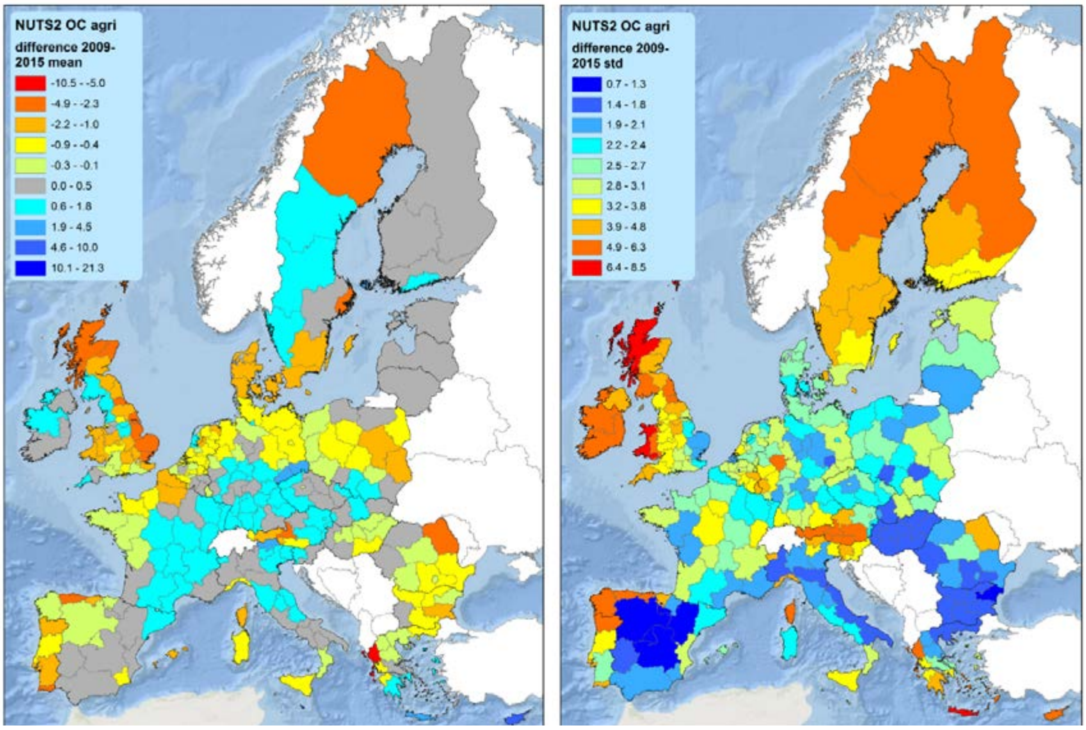
The SOC content is modelled based on LUCAS 2015, the bulk density is taken from the recent estimation of physical properties (Ballabio et al., 2016) and the soil depth is 20 cm.

Figure 12. Changes in mean carbon stocks between 2009/12 and 2015 (20015 – 2009 values) at NUTS2 level.



Results of changes in organic carbon (OC) content include uncertainty given the large values of standard error demonstrated in cropland, woodland and grassland (Figure 13). In most of the NUTS2 regions in the UK and in northern Finland and Sweden, the large standard error values in cropland and grassland were mainly due to the reduced number of points per region. In Finland and Sweden, the problems with the removal of litter layer during sampling contributed to the large standard errors in woodland. Other factors also contributed to large standard errors, for example the efficiency of the sampling protocol (differences of sampling location between surveys, difficulties in litter removal), the fact that sampling was carried out by different surveyors or that the analyses were carried out by different technicians or with different instruments in the laboratory during each survey. The impact of these factors on OC and nitrogen contents and other soil properties should be reduced as we carry out more surveys and have more data to fine-tune comparison between surveys.

Figure 13. Changes in OC content and standard deviation between LUCAS 2019/2012 and 2015 surveys at NUTS2 level in cropland.



3.4. Carbon stocks and changes 2009/12-2015 in cropland and grassland

The SOC stocks in Figure 12 refer to all land cover types (cropland, pasture/grassland, forests, semi-natural areas, wetlands, etc.). However, monitoring performance for the purpose of the CAP shows that only the land cover classes falling under cropland and grassland are actively managed. For this reason, assessing the total SOC stocks and their changes in cropland and grassland is critical to evaluate the effect of the CAP on soil degradation.

Figure 14 depicts the stocks (in tons per hectare) of SOC in cropland (left panel) and their estimated changes between the two LUCAS surveys of 2009/2012 and 2015. As expected, the larger stocks (in terms of tons per hectare) are in the wetter and cooler parts of the EU, in particular in Ireland, UK and Scandinavia. Nevertheless, just a small part of the EU SOC stock is actually accounted for by these areas, as their relative area occupied by cropland is relatively small (for instance UK cropland has about half as much soil carbon as France's) compared with central Europe (Table 3).

Changes in SOC stocks are quite small and account for less than 1 % of the stock. The spatial distribution of the stock changes evidences decreasing stocks in the cropland soils of the NUTS2 regions closer to the Atlantic Ocean, including Portugal, the north of Spain, north-west France, Benelux, northern Germany and Denmark (ordered from south to north); decreases are also present in Bulgaria, Poland and Romania. The area surrounding the Alps shows generally increasing stocks (except in part of Austria). In particular, SOC stocks in cropland increase in southern France, most regions of Germany, Czechia, parts of Slovakia and Austria, and most regions of north central Italy (regions around the Alps). This distribution might be due to the effect of climate change, whereby wetter and cooler areas are gradually becoming dryer and warmer, resulting in the mineralisation of SOC.

Figure 15 depicts the stocks (in tons per hectare) of SOC in grassland (left panel) and their estimated changes between the two LUCAS surveys of 2009/2012 and 2015. The distribution of both stocks and stock changes is quite similar to that for cropland, supporting the hypothesis that climate is the main driver of these changes.

Figure 14. Soil Organic Carbon (SOC) stocks in cropland and changes in SOC between 2009/12 and 2015 (20015-2009 values) at NUTS2 level.

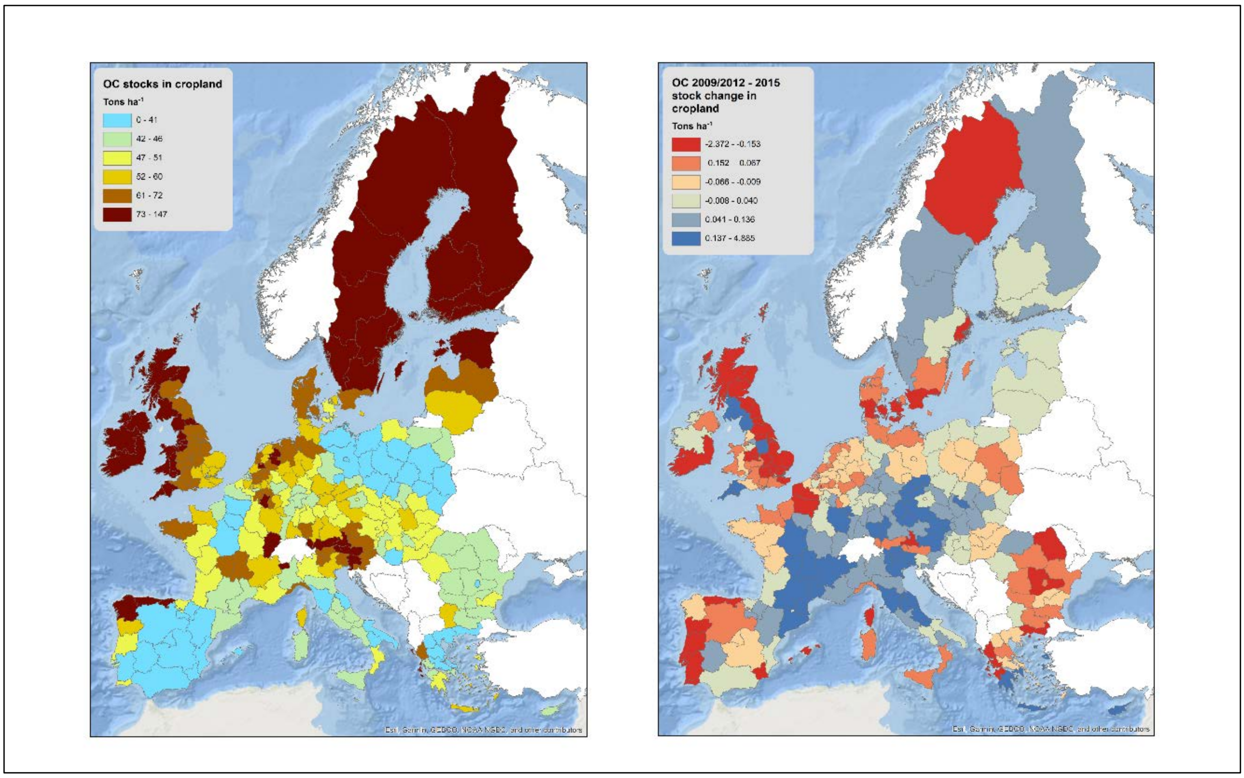
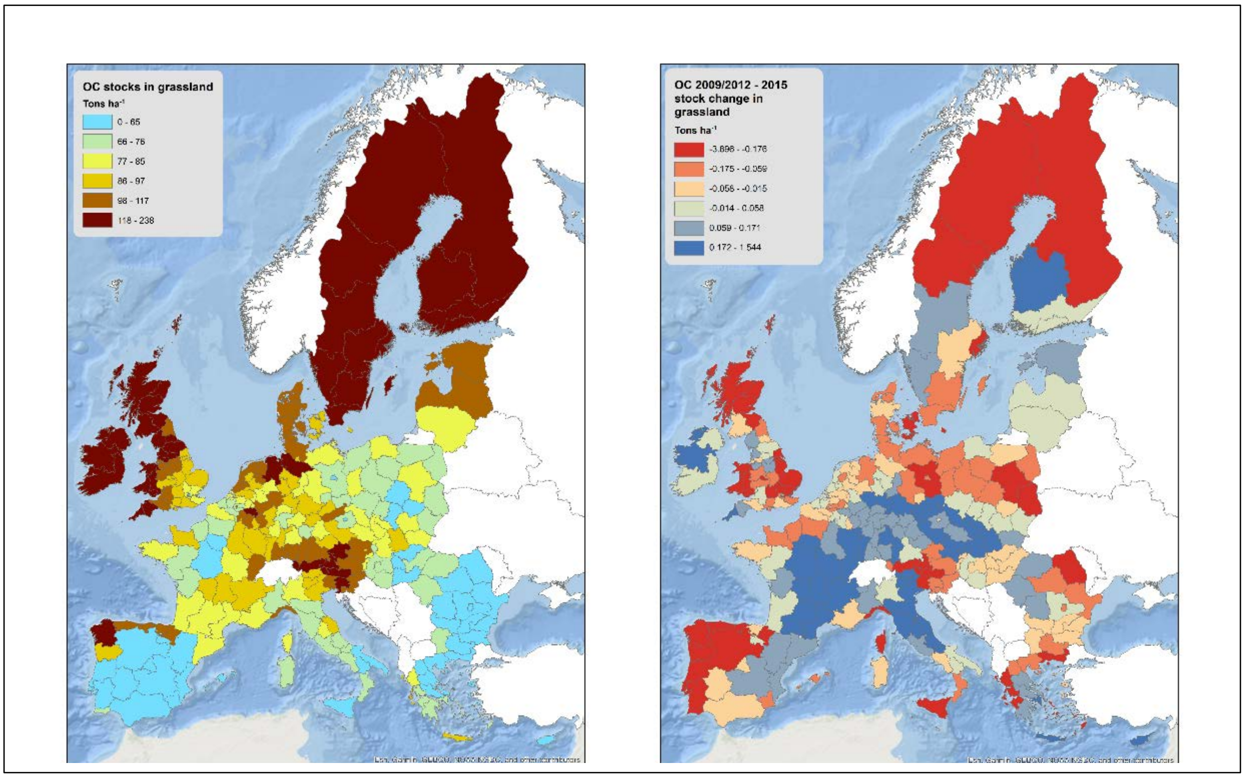


Figure 15. Soil Organic Carbon (SOC) stocks in grassland and changes in SOC between 2009/12 and 2015 (2015 – 2009 values) at NUTS2 level.



The total amount of SOC in cropland, grassland and the changes for each Member State are given in Table 3, plus the totals for the whole EU. In general the amount of SOC depends on the country size and the percentage of area occupied by the specific land cover, as these quantities can vary by several orders of magnitude, whereas SOC concentrations in soils have a more moderate variation among countries. For example, the UK has the largest stock of SOC in grassland among current and former EU Member States, while France has the largest stock in cropland. In addition, the changes in the stocks between 2009 and 2015 shown in Table 3 mostly depend on the size of the stock, so the UK has the largest change in grassland stocks, but France and Italy have the same change in cropland although Italy has a smaller cropland area.

Table 3. Soil Organic Carbon (SOC) stocks for grassland and cropland (million tons) and changes between 2009/2012 and 2015 (thousand tons).

Member State	Country codes	Total OC stock in grassland (million tons)	OC stock change 2009/2012 and 2015 in grassland (thousand tons)	Total OC stock in cropland (million tons)	OC stock change between 2009/2012 and 2015 in cropland (thousand tons)
Austria	AT	64.2	–54.0	115.4	280.3
Belgium	BE	35.4	7.5	80.5	–39.7
Bulgaria	BG	40	–38.8	244.3	–346.5
Cyprus	CY	1.5	40.7	19.7	414.5
Czechia	CZ	71.1	209.4	178.4	350.1
Germany	DE	629.5	341.0	705.5	293.1
Denmark	DK	6.9	–4.9	202.2	–434.6
Estonia	EE	37.8	23.0	83.1	0.1
Greece	EL	57	–272.0	207.6	–579.2
Spain	ES	190.6	–304.8	804.8	–104.2
Finland	FI	3	–37.2	335.6	113.9
France	FR	717.2	1 057.2	1 180.0	859.2
Hungary	HU	61.3	–32.8	252.8	–102.0
Ireland	IE	528.6	362.8	107.2	–64.1
Italy	IT	55.9	25.9	672.8	859.2
Lithuania	LT	30.6	4.6	191.9	10.3
Luxembourg	LU	3.5	–1.7	7.1	–8.7
Latvia	LV	75.2	4.1	124.7	–2.8
Malta	MT	—	—	0.6	71.3
Netherlands	NL	102.2	–33.1	86.6	–89.6
Poland	PL	197.3	–217.5	632.0	–282.3
Portugal	PT	10.8	–123.0	173.1	–1 678.4
Romania	RO	173.8	–616.1	488.4	–2 814.4
Sweden	SE	60.2	–207.3	325.6	–92.9
Slovenia	SI	14.9	–7.9	43.4	39.6
Slovakia	SK	23.8	41.6	103.0	113.3
United Kingdom	UK	1 160.1	–1 962.1	453.0	–1 633.3
Total		4 352.4	–1 795.2	7 819.3	–4 867.8

The total SOC stocks for grassland in the EU-27 (estimates for Croatia are not included) are about 4.35 Gt while for cropland this estimate is about 7.82 Gt. The values refer to the top 20 cm of the soil. In total, the top 20 cm of the EU-27's agricultural land stores about 12.17 Gt of SOC. Previously modelled results have estimated the SOC stock at about 17.63 Gt but the measured soil depth was 0-30 cm and the area was much larger, including all EU Member States plus Albania, Bosnia and Herzegovina, Croatia, Montenegro, North Macedonia, Norway and Serbia (Lugato et at al., 2014.)

The total SOC change between LUCAS 2009/12 and 2015 in grassland is about 1.8 million tons (Table 3), which is a decrease of about 0.04 %. In the same line, the SOC change in cropland is estimated at about 4.8 million tons of SOC, which is a decrease of about 0.06 %. Overall, the total SOC change between LUCAS 2009/12 and 2015, as shown in Table 3, is minimal and accounts for less than 0.05 % of the total stock.

Neither trend is significant, because the carbon stock changes are estimated over a very short period (6 years).

3.5. Concluding remarks on carbon stocks

Under current climatic and agri-environmental conditions, SOC does not change significantly in 6 years. It should be noted that changes in SOC are quite small given the short time interval. This raises the question of making LUCAS topsoil survey intervals longer (e.g. 10 years) and orienting funding towards an increased number of points in under-represented areas.

Most (~70 %) of the SOC changes fall below the limit of ± 4 g kg^{-1} and only 10 % of the area is predicted to have changes bigger than ± 12 g kg^{-1}. Moreover, many of the areas where the change is predicted to be higher than ± 12 g kg^{-1} are areas where the model uncertainty is high for lack of samples (northern portions of Scandinavia and of Scotland).

The changes in SOC stocks are not significant, as about 60 % of EU agricultural areas experienced SOC stock changes below 0.2 % between 2009/12 and 2015. The estimation of SOC content had uncertainties such as the large standard errors in Finland and Sweden, and the problem with the removal of the litter layer during sampling, which contributed to the large standard errors in woodland. There are other factors that also contributed to large standard errors, for example the efficiency of the sampling protocol (differences in sampling location between surveys, difficulties in litter removal) and the fact that sampling was carried out by different surveyors.

The total change in carbon stocks in grassland was about 0.04 % and in arable land about 0.06 %. Carbon stocks show a decrease in cropland in regions close to the Atlantic Ocean, such as Benelux, Denmark, northern Germany, north-west France and Portugal, and in Bulgaria and Romania. In contrast, an increase in carbon stocks is found in areas surrounding the Alps, such as Czechia, southern Germany, southern France, northern and central Italy, and parts of Austria and Slovakia. This distribution might be due to the effect of climate change, whereby wetter and cooler areas are gradually becoming dryer and warmer, resulting in the mineralisation of SOC (Lugato et al., 2018). In a nutshell, the changes in SOC content and SOC stocks are not significant in such a short period as 6 years.

4 Soil nutrients

Using the ca. 22 000 soil samples from LUCAS, the JRC analysed a full range of soil properties – including Nitrogen (N), Phosphorus (P), Potassium (K) – and their influencing factors. This new research activity (Ballabio et al., 2019) provides a comprehensive overview of the distribution of chemical properties (including pH, cation exchange capacity, calcium carbonate, C/N ratio, N, P and K) in the soils of 26 EU Member States (Croatia was not included because soil samples were not taken in 2009/12; Cyprus was not included because we were missing input layers for developing the soil nutrient maps), an area covering more than 4.5 million km^2.

The number of points selected is based on a stratification in order to cover all possible land uses (based on Corine land cover classes) and country surface (Carre et al., 2013). Topsoil-sampling locations were selected to be representative of European landscape features, so a Latin hypercube stratified random sampling was applied to design the survey (Carré and Jacobson, 2009). The features taken into account for the stratified random sampling were Corine Land Cover 2000 and the Shuttle Radar Topography Mission (SRTM) together with the latter's derived slope, aspect and curvature.

The sample analysis was performed by a single laboratory, contributing to data comparability by avoiding uncertainties due to analysis based on different methods or different calibrations in multiple laboratories. In a first phase, LUCAS topsoil samples were analysed for their physical and chemical properties following ISO standard procedures (Orgiazzi et al., 2018). In order to assess the relation between environmental features and soil chemical properties distribution, Gaussian Process Regression (GPR)(Rasmussen and Williams, 2006) was utilised for inference and mapping. A detailed description of the spatial interpolation model can be found in the publication of Ballabio et al. (2019).

Phosphorus and potassium levels were higher in cropland and grassland than in woodland in all Member States in both the 2009/2012 and the 2015 surveys. This is because of the larger nutrient supply to grassland and arable land from fertilisation. Both P and K contents showed a positive linear relationship between 2009/2012 and 2015 surveys in all Member States, except for K in Sweden. This means that K and P data in 2009/2012 and 2015 moved in the same direction, despite the presence of points with large differences in their contents between surveys. The absence of a positive linear relation for K in Sweden is linked to difficulties in accurately removing the needle-type litter of coniferous forests, a key source of K for the soil.

As explained before, better training of surveyors is needed to ensure accurate removal of the litter layer in woodland, especially in coniferous forests. This would minimise errors in the laboratory analysis due to the sampling and would improve the comparability of the data between surveys. Sweden had the largest proportion of revisited points in woodland (81 %), of which 56 % were in coniferous forests. Thus, the impact of incorrect litter removal on the analysis of K was greater in this Member State.

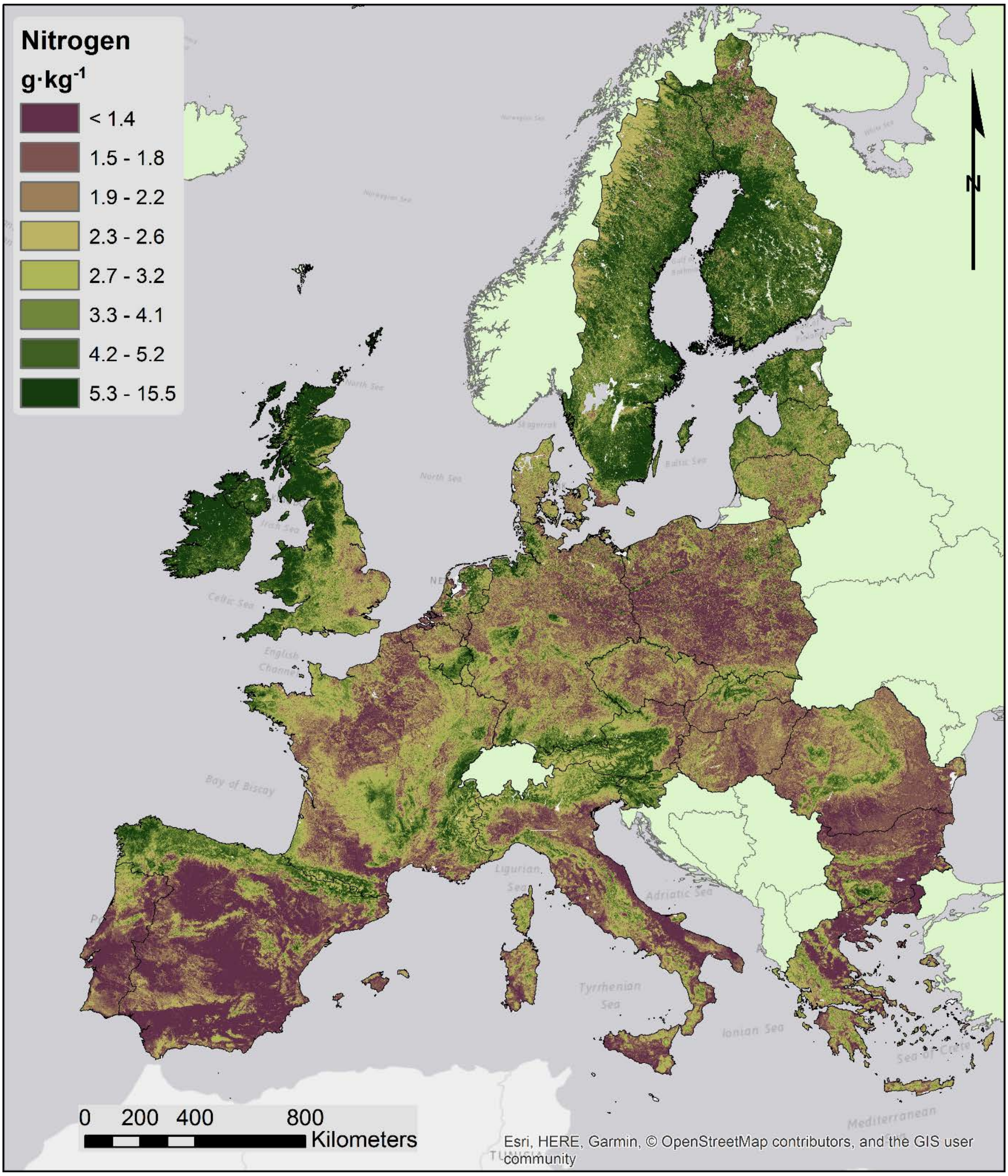
4.1. Soil Nitrogen

Among all the essential nutrients, Nitrogen (N) is required by plants in the largest quantity and is important for soil fertility and soil quality (Reeves, 1997). Nitrogen is the most frequent limiting factor in crop productivity (Smil, 1999). The spatial distribution of nitrogen in the soil is affected not only by natural ecological processes but also by intensive human activities (K. Wang et al., 2013). This is an important challenge for accurate predictive mapping at regional scales.

The distribution of topsoil nitrogen (Figure 16) is highly correlated with SOC, given that nitrogen is a major component of soil organic matter. While the C/N ratio can vary, some carbon-rich soils are also nitrogen rich, at least in terms of absolute quantities. Given this relation, it is quite clear that vegetation cover and climate are the main drivers in the distribution of nitrogen. As the map in Figure 16 shows, forests and grassland areas tend to have higher nitrogen content (Table 4). Forests in Scandinavia and in mountain areas are clearly outlined by the map (Ballabio et al., 2019). Climate also acts as a main driving force influencing nitrogen content along the Atlantic area; in particular, Ireland and the United Kingdom show higher N concentrations due to a fresh and humid climate, which favours organic matter accumulation. Soil texture also plays a role in stabilising organic matter and thus nitrogen. Areas with coarser soils, such as most of Poland, tend to have less nitrogen even if other conditions are favourable (e.g. vegetation, climate).

While the nitrogen concentration is relevant to assessing stocks and potential N_2O emissions, the ratio between carbon and nitrogen can better represent the differences in the organic matter composition. Where higher rates correspond to more oligotrophic soils, typical of coniferous forests, or to peatland soils, lower rates are typical of more balanced nutrient-rich soils.

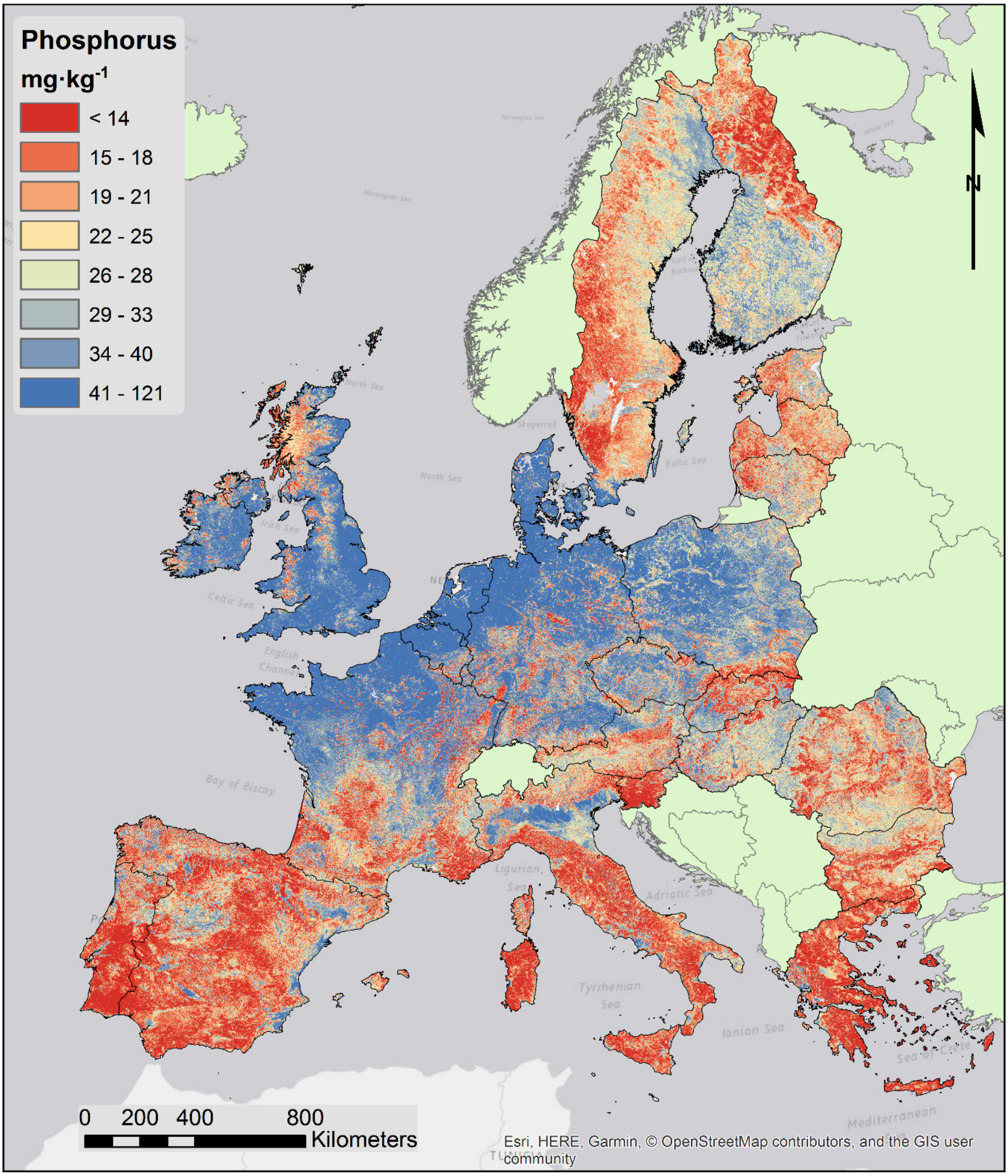
Figure 16. Topsoil nitrogen concentrations.



4.2. Soil Phosphorus

Phosphorus is mainly derived from the weathering of minerals in parent rock material. It is usually the second most limiting nutrient for terrestrial primary production (Cordell et al., 2009). In agricultural areas fertilisation can result in higher levels of P, especially in highly productive areas where high input of P fertilisers is reported (Tóth et al., 2014). Modern agriculture is highly dependent on P fertilisers, and P supply is strategically critical at global level.

Figure 17. Topsoil phosphorus concentrations.



The map of soil phosphorus (Figure 17) shows a clear trend in which land use appears to have a strong influence. In particular, most of the agricultural areas have higher levels of P. This is quite evident in areas such as the

River Po plain (Italy) where levels of P diverge from the national average. In general, areas with natural land cover and those with a prevalence of permanent crops correspond to lower levels of P (Ballabio et al., 2019).

The geological background seems to have a quite small influence, whereas climate is much more relevant; this is probably because of higher fertilisation rates in wetter climates. The P map produced in this study also confirms models of P fertilisation load (Potter et al., 2010).

In should be noted that phosphorus is a limited resource with significant reserves in just a few countries (China, Morocco, Russia, South Africa, etc.), none of which is in the EU. Therefore, optimising the use and application of phosphorus as a fertiliser is beneficial to both the environment and the economy of the EU. Mapping phosphorus concentration in soils is crucial for designing long-term agri-environmental policies that do not harm our environment and health, and at the same time guarantee optimal fertilisation rates in agriculture. The reforms of the CAP, with a shift to decoupled payments and away from direct support linked to production of specific crops, have already led to a strong reduction in fertiliser use.

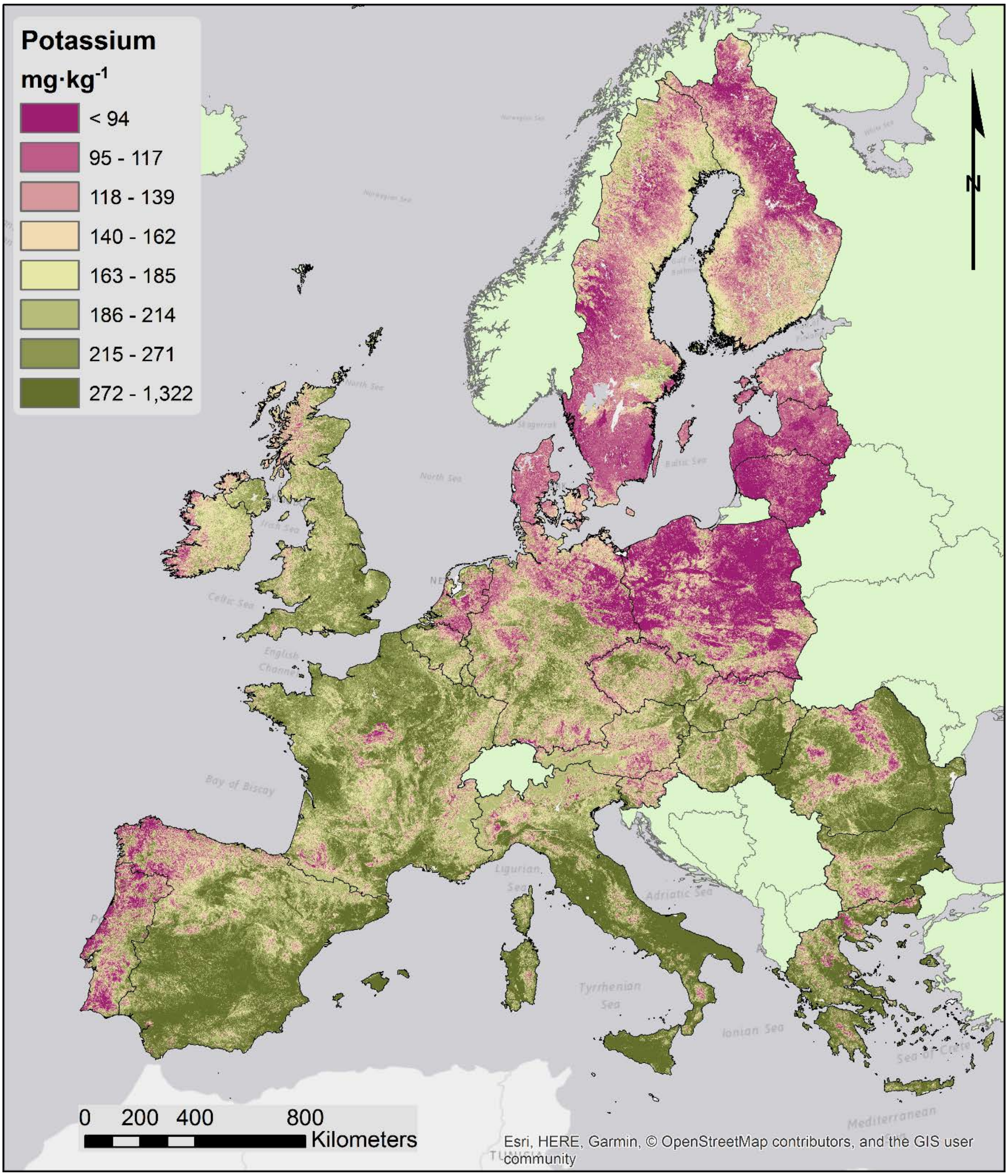
Therefore, this data set (Figure 17) can be used as the most up-to-date baseline to study the impact of CAP measurements and development programmes in Member States in reducing nutrient pollution (nitrogen, phosphorus) from agriculture in order to meet the commitments of the Water Framework Directive.

4.3. Soil Potassium

Potassium has different functions for plant life; it is a constituent of enzymes and acts as a regulator of drought tolerance and water use (M. Wang et al., 2013). In the soil, the principal sources of potassium are feldspars and micas, which release K during weathering (Hillel, 2008). In the soil itself, potassium appears in three forms: in the circulating solution; as an exchangeable ion adsorbed to the surface of clay particles; and in organic matter. Given the wide distribution of K-containing minerals and the fact that it is prevented from leaching by cation exchange, its depletion from the soil is quite uncommon.

Soil potassium distribution (Figure 18) is mostly driven by parent material chemistry and climate. In particular, lower than average K concentrations are typical of the sandy soils of north-eastern Europe, and of the relatively young soils of Scandinavia. Moreover, Portugal and north-western Spain also exhibit lower levels of potassium, probably due to leaching. In general, soils with higher clay content are better able to retain K, so the two variables show similar spatial distributions (Ballabio et al., 2016).

Figure 18. Topsoil potassium concentrations.



4.4. Concluding remarks on soil nutrients

The soil phosphorus map shows the strong influence of land use. In particular the agricultural land has higher levels of P than natural areas or forests (Table 4). This is also quite evident in the most intensive agricultural regions in the EU, such as the River Po plain in Italy, where the levels of P are much higher than the national mean value. The fertilisation rates in agricultural land influence the P concentration especially in the wetter climates of north-west Europe.

Topsoil nitrogen is highly correlated with SOC (Ballabio et al., 2019). In addition to this, vegetation (higher values in forests and grassland), climate (higher values in humid climates) and soil texture play an important role in nitrogen distribution. Soil potassium distribution is driven by parent material (low K in sandy soils; higher K in clay soils) and climate.

Table 4. Mean estimated values of soil nutrients for each group of land uses based on LUCAS

Land uses	**Nitrogen (N)** (g kg^{-1})	**Phosphorus (P)** (mg kg^{-1})	**Potassium (K)** (mg kg^{-1})
Agricultural land (Corine codes: 12-17, 19-22)	1.84	32.35	230.49
Pasture/grassland (Corine codes: 18, 26)	2.87	33.68	197.01
Forests (Corine codes: 23-25)	2.11	20.22	156.92
All the rest	2.19	24.41	187.96
Total	**2.11**	**27.20**	**195.07**

With about 22 000 sampled locations, the LUCAS soil database is unique for its number of available observations, its spatial coverage and its temporal resolution. However, one of the main limitations of the NPK mapping is the number of points, which potentially can be increased in future LUCAS campaigns or in national surveys. The data sets presented above show the potential to develop soil nutrient indicators and monitor them spatially and temporally. Currently, soil erosion and SOC (content, stocks) are the mature indicators to support agri-environmental policies in the EU. In the same context, we are developing additional data sets (nitrogen, phosphorus and potassium) investigating the main drivers influencing their spatial distribution and temporal trends.

5 Soil fertility

This chapter addresses a purely research issue, which can be further developed into a soil fertility indicator. While soil erosion and SOC stocks are mature indicators used in agri-environmental policies (CAP, SDGs), the indicator for soil fertility is a proposal to be evaluated by policymakers for future use. The evaluation of soil fertility (and soil quality) implies the selection of key parameters to measure physical, chemical and biological soil properties. Current approaches propose to apply nonlinear scoring techniques to a minimum data set of soil parameters (physical, chemical, biological) and combine the scores in a weighted composite indicator (Andrews et al., 2002).

A bi-factorial quality index based on fuzzy logic has been tested and applied in the literature to assess the overall soil quality and its evolution in the cropping systems (Morari et al., 2008). In order to attain an overall comparison of the different cropping systems, the index combines a soil quality index (SQI) and a soil quality trend index. The former varies from 0 (poor quality) to 1 (high quality) and is calculated applying fuzzy logic to a set of selected soil parameters. The resulting index combination allows the sustainability of a given cropping system with its management practice to be quantified. The approach is based on fuzzy logic and was used to develop this Soil Quality Index (SQI):

(a) Selection of soil parameters was influenced by local conditions. However, other parameters such as soil depth, even if they are critical indicators (Doran and Jones, 1996), were not chosen because they are missing for the whole study area or are homogeneous or do not limit the crop production (Morari et al., 2008). The following physical–chemical indicators were selected: available water content (AWC), water-filled porosity (WFP, ratio between water content at 33 kPa and total porosity), pH, soil organic carbon (SOC), cation exchange capacity (CEC), Olsen phosphorus (Pav) and exchangeable potassium (Kex) (Table 5). A pedotransfer function (Wosten et al., 2001), using texture and SOC as independent variables, was applied to estimate AWC and WFP.

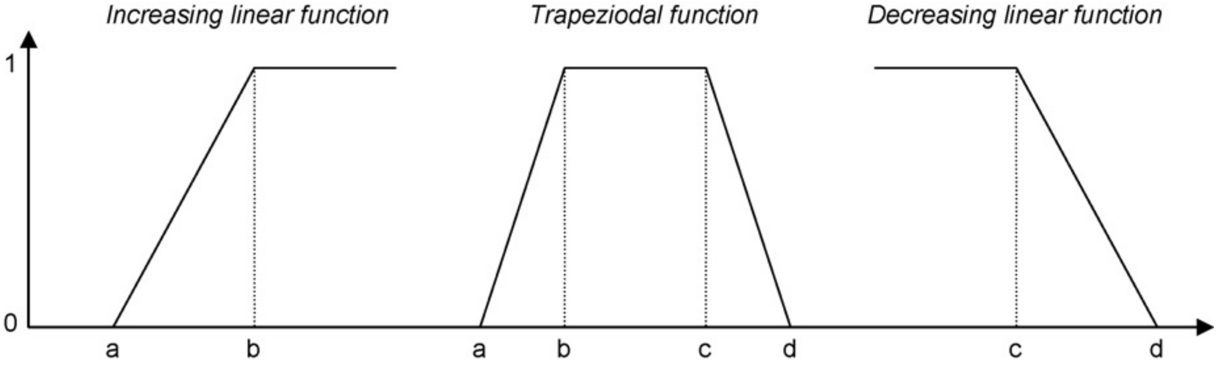
(b) Definition of the membership functions and fuzzification of the parameters applied the linear membership formulation proposed by Zimmerman (1985). Depending on the indicator considered, these functions can be of three types: increasing linear function (ILF), "more is better'; decreasing linear function (DLF), "less is better"; and trapezoidal function (TF), "optimum" (Figure 19). Thresholds and limits of the functions were selected according to Karlen et al. (2003) and local experiments (e.g. Giardini and Morari, 2004) (Table 5). A single function was applied for each parameter.

Table 5. Thresholds and limits of the functions used to calculate the soil quality index (SQI).

Thresholds	**Parameters**						
	SOC(Mg ha^{-1})*	**CEC** (meq. 100g^{-1})	**pH**	**P$_{av}$**(mg kg^{-1})	**K$_{ex}$**(mg kg^{-1})	**WFP**	**AWC**
	TF	**ILF**	**TF**	**TF**	**ILF**	**TF**	**ILF**
a	9	5	4.5	7.5	45	0.15	0.1
b	20	15	6	30	400	0.55	0.3
c	40		7	75		0.75	
d	100		9	600		0.95	
Weights	0.18	0.17	0.10	0.14	0.13	0.14	0.14

* SOC stock at 0-10 cm.

Figure 19. Fuzzy membership functions used in the soil quality index (SQI) calculation.



Source: Morari et al., 2008

(c) Aggregation of the fuzzy set and calculation of the SQI applied the following weighted linear combinations of the indicators (Karlen et al., 2003; Mendoza and Prabhu, 2003):

$$SQI = \sum w_i \mu_i \quad (5)$$

where μ_i is the fuzzy membership value of the *i*th parameter, the *i*th parameter is one of the parameters in Table 5 and w_i is the weight of each parameter as expressed in Table 5. The SQI is dimensionless with values ranging from 0 to 1.

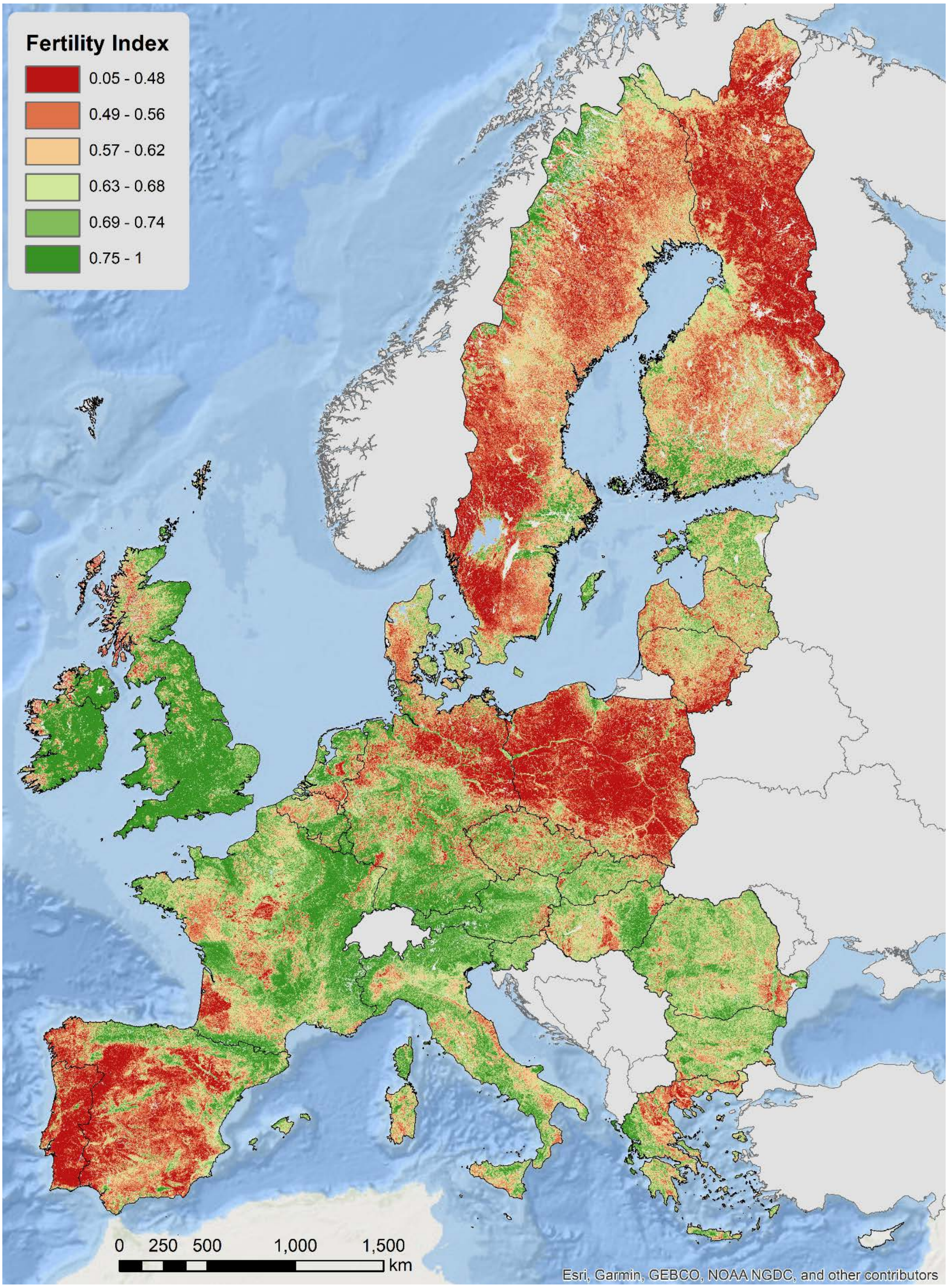
(d) The SQI's capacity to represent the productive and habitability functions of the soil was evaluated. It is quite difficult to get the trends in this index, as we do not have time series data available at this continental scale.

The SQI is orientated towards a specific function of the soil: the capacity to sustain plant production. No target variables (e.g. N leaching or erosion) were available to test the capacity of the index to represent the soil's environmental functions (Andrews et al., 2002). However, the trapezoidal functions used for some parameters (e.g. SOC and Pav) indirectly consider also the negative effects that the high concentration levels can have on the environment and thus allowed a more integrated evaluation of the soil quality.

The outcome of the SQI is shown in Figure 20, where the index is used to represent the fertility of the soil. It is important to consider that the index is based only on soil parameters, so the effects of other parameters influencing crop productivity such as climate (e.g. temperature, rainfall) and management (e.g. irrigation) are not considered.

The map in Figure 20 depicts higher fertility in the areas where agriculture is more developed. This is not unexpected, as historically the more suitable soils were claimed for crop production. In general, a large part of the EU has fertile soils. Most of the limitations due to soil texture are in Poland and north-eastern Germany. Other limitations are due to soil chemical properties, as in the cases of Portugal (having generally acid soil) and Scandinavia (limited by both texture and chemical properties).

Figure 20. Map of soil fertility index.



In conclusion, we have proposed a soil fertility index based on seven available physical–chemical indicators: AWC, WFP, pH, SOC, CEC, Olsen phosphorus (Pav) and exchangeable potassium. This index is based purely on soil properties and does not include the influence of climatic conditions (rainfall, temperature, etc.) and management practices (irrigation, tillage, etc.). This first output should be considered a preliminary result to be tested with field experiments on site.

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List of abbreviations and definitions

AEI	agri-environmental indicator
AWC	available water content
CAP	common agricultural policy
CEC	cation exchange capacity
CLC	Corine Land Cover
CMEF	common monitoring and evaluation framework
Corine	coordination of information on the environment
ESDB	European Soil Database
EU-DEM	European Union Digital Elevation Model
Eurostat	Statistical Office of the European Union
EVI	Enhanced Vegetation Index
FCover	Fraction of ground covered by green vegetation
GAEC	good agricultural and environmental conditions
GDP	gross domestic product
GIS	geographic information systems
GBM	gradient-boosting machine
IPBES	Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services
IPCC	Intergovernmental Panel on Climate Change
ISO	International Organization for Standardization
JRC	Joint Research Centre
LANDUM	Land Use and Management (Model)
LUCAS	Land Use / Land Cover Area frame Survey
MERIS	Medium Resolution Imaging Spectrometer
MMU	minimum mapping unit
MODIS	Moderate-resolution Imaging Spectro-radiometer
NDVI	Normalised Difference Vegetation Index
NUTS	Nomenclature of Territorial Units for Statistics
NPK	nitrogen, phosphorus, potassium
OC	organic carbon
OECD	Organisation for Economic Co-operation and Development
PCA	principal component analysis
Q&A	questions and answers
REDES	Rainfall Erosivity Database at European Scale
RUSLE	Revised Universal Loss Equation
SDG	Sustainable Development Goal
SOC	soil organic carbon
SQI	soil quality index
UN	United Nations

WFP	water-filled porosity

List of boxes

List of tables

List of figures

Annexes

Annex 1: Copernicus Q&A for the best use of Corine Land Cover and the derived layers of CLC 2006-2012

Q: I want to use land cover changes derived from CORINE Land data between 2006 and 2012. Should I use the difference between the two status layers or the CLC-Changes dataset instead?
A: Users interested in CLC-changes should always rely on the corresponding CLC-Changes product and never on the difference (intersect) of the two status layers. The CLC-Changes product includes the real land cover changes mapped directly, at a higher resolution of 5-ha MMU, while the difference (intersect) includes the difference of two generalised lower resolution (25-ha MMU) datasets. The consequence of the 'change mapping first' methodology (see: CLC 2006 Technical Guidelines at: http://land.copernicus.eu/user-corner/technical-library) – and eventually that of the different MMUs – is that the difference between two consecutive status layers (e.g. CLC 2006 and CLC 2012) will differ from the corresponding CLC-Changes layer (e.g. CLC-Change 2000-2006). The magnitude of difference depends on the size distribution of change polygons. If there are many changes in the size range of 5-25 ha, the difference will be significant. If all changes were larger than 25 ha, then there would be no difference. In addition, the new CLC status layer includes revisions (correction) of the previous status layer. The revisions cannot be distinguished from actual land cover changes when intersecting two status layers.

Q: Comparing the CLC data of 2006 and 2012 in Germany we see a remarkable decrease of classes 242 (complex cultivation patterns) and 243 (land principally occupied by agriculture with significant natural presence) and increases in class 231 (pastures). Can you explain the reason?
A: In CLC 2012 Germany has changed the CLC production methodology. The standard photo-interpretation (applied in CLC 1990, CLC 2000 and CLC 2006) has been replaced by a non-standard methodology based on using existing national data, the Digital Land Cover Model for Germany (DLM-DE). The concept of the DLM-DE embodies the integration of national topographic reference data (ATKIS Basis-DLM) with remote sensing data and covers the needs of the federal authoritative bodies. Verification of CLC in many countries showed that a common mistake in standard CLC photo-interpretation is the overestimation of areas such as 'complex cultivation patterns' (CLC class 242) and 'land principally occupied by agriculture with significant natural presence' (CLC class 243). Pure classes often can be separated or joined to neighbours, i.e. there is a need to reduce the coverage of 242 and 243. DLM-DE data (1 ha resolution) are much more detailed, than the standard European CLC (25 ha resolution). As DLM-DE does not contain mixed classes like 242 and 243, these classes were formed in CLC 2012_DE as part of the complex generalisation process. Although we do not have final validation results yet, we assume that the accuracy of CLC 2012_DE, compared to CLC 2006_DE is better, because of the improved methodology. For the two totally different methodologies applied in 2006 and 2012, CLC 2006 and CLC 2012 in Germany should not be compared.

Annex 2: Corine Land Cover Classes (grid codes and class CLC codes)

GRID CODE	CLC Class	Level 1	Level 2	Level 3
1	1.1.1	Artificial surfaces	Urban fabric	Continuous urban fabric
2	1.1.2	Artificial surfaces	Urban fabric	Discontinuous urban fabric
3	1.2.1	Artificial surfaces	Industrial, commercial and transport units	Industrial or commercial units
4	1.2.2	Artificial surfaces	Industrial, commercial and transport units	Road and rail networks and associated land
5	1.2.3	Artificial surfaces	Industrial, commercial and transport units	Port areas
6	1.2.4	Artificial surfaces	Industrial, commercial and transport units	Airports
7	1.3.1	Artificial surfaces	Mine, dump and construction sites	Mineral extraction sites
8	1.3.2	Artificial surfaces	Mine, dump and construction sites	Dump sites
9	1.3.3	Artificial surfaces	Mine, dump and construction sites	Construction sites
10	1.4.1	Artificial surfaces	Artificial, non-agricultural vegetated areas	Green urban areas
11	1.4.2	Artificial surfaces	Artificial, non-agricultural vegetated areas	Sport and leisure facilities
12	2.1.1	Agricultural areas	Arable land	Non-irrigated arable land
13	2.1.2	Agricultural areas	Arable land	Permanently irrigated land
14	2.1.3	Agricultural areas	Arable land	Rice fields
15	2.2.1	Agricultural areas	Permanent crops	Vineyards
16	2.2.2	Agricultural areas	Permanent crops	Fruit trees and berry plantations
17	2.2.3	Agricultural areas	Permanent crops	Olive groves
18	2.3.1	Agricultural areas	Pastures	Pastures
19	2.4.1	Agricultural areas	Heterogeneous agricultural areas	Annual crops associated with permanent crops
20	2.4.2	Agricultural areas	Heterogeneous agricultural areas	Complex cultivation patterns
21	2.4.3	Agricultural areas	Heterogeneous agricultural areas	Land principally occupied by agriculture, with significant areas of natural vegetation
22	2.4.4	Agricultural areas	Heterogeneous agricultural areas	Agro-forestry areas
23	3.1.1	Forest and semi natural areas	Forests	Broad-leaved forest
24	3.1.2	Forest and semi natural areas	Forests	Coniferous forest
25	3.1.3	Forest and semi natural areas	Forests	Mixed forest
26	3.2.1	Forest and semi natural areas	Scrub and/or herbaceous vegetation associations	Natural grasslands
27	3.2.2	Forest and semi natural areas	Scrub and/or herbaceous vegetation associations	Moors and heathland
28	3.2.3	Forest and semi natural areas	Scrub and/or herbaceous vegetation associations	Sclerophyllous vegetation
29	3.2.4	Forest and semi natural areas	Scrub and/or herbaceous vegetation associations	Transitional woodland-shrub
30	3.3.1	Forest and semi natural areas	Open spaces with little or no vegetation	Beaches, dunes, sands
31	3.3.2	Forest and semi natural areas	Open spaces with little or no vegetation	Bare rocks
32	3.3.3	Forest and semi natural areas	Open spaces with little or no vegetation	Sparsely vegetated areas
33	3.3.4	Forest and semi natural areas	Open spaces with little or no vegetation	Burnt areas
34	3.3.5	Forest and semi natural areas	Open spaces with little or no vegetation	Glaciers and perpetual snow
35	4.1.1	Wetlands	Inland wetlands	Inland marshes
36	4.1.2	Wetlands	Inland wetlands	Peat bogs

37	4.2.1	Wetlands	Maritime wetlands	Salt marshes
38	4.2.2	Wetlands	Maritime wetlands	Salines
39	4.2.3	Wetlands	Maritime wetlands	Intertidal flats
40	5.1.1	Water bodies	Inland waters	Water courses
41	5.1.2	Water bodies	Inland waters	Water bodies
42	5.2.1	Water bodies	Marine waters	Coastal lagoons
43	5.2.2	Water bodies	Marine waters	Estuaries
44	5.2.3	Water bodies	Marine waters	Sea and ocean

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