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Quality check of European Datasets contributing to RECARE project

RECARE
Preventing and Remediating degradation of soils in Europe through Land Care

SEVENTH FRAMEWORK PROGRAMME

Deliverable 10.2

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RECARE

Preventing and Remediating degradation of soils in Europe through Land Care

Workpackage 10

Quality check of European Datasets contributing to RECARE project

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Abstract

The aims of this document are the description of the procedures adopted to assess the quality of the data hosted on the JRC data management system and the quality of the data itself. The main aim of the data management platform is to provide data to the users in the project, in particular to case study partners. Other aims are to provide a long term storage and web hosting the data provided by partners and legacy data. Finally the data collected during the project will be made available to external users after the end of the project. The quality check ensures that the data hosted meets the highest quality standards, which is critical for the data management system.

This document is divided into chapters that can be briefly described as follows:

- **Chapter 1: Description of RECARE WP10 and the tasks that should be fulfilled**
- **Chapter 2: Description of the procedures adopted to assess data quality**
- **Chapter 3: Description Results of the data quality check for the hosted data**
- **Chapter 4: Technical description of the metadata and data consistency**

1 WP10 Description and tasks

The aim of the web interface in the European Soil Data Centre is to locate, host and provide relevant information to RECARE partners. The European Soil Data Centre will inventory the data needed by other project partners, and will therefore help find such data within the various databases maintained at the European Soil Data Centre (ESDAC) in JRC. Although these data are generally publicly available, ESDAC will properly crop, resize and readapt data to the needs of partners. The data is then stored into Relational Database Management System (RDBMS) scheme, developed by ESDAC, taking into account the specifications of the Case Studies.

Data is to be provided to users (WP and Case Studies) through an interactive web interface that allows them to explore, visualize and download both baseline data and spatial data hosted in the DMS.

JRC will also assist other WPs, where needed, with GIS analyses and/or modelling, especially those at the European level.

1.1 Access to databases at European level

JRC will, based on requirements specified by other WPs, locate relevant information in the databases hosted by JRC, and will make that information available to RECARE partners. WP10 will inventory which data other WPs need, and will therefore help find such data within the various databases maintained at the European Soil Data Centre (ESDAC) in JRC. Although these data are generally publicly available, WP10 will play a facilitating role where needed. JRC will also assist other WPs, where needed, with GIS analyses and/or modelling, especially those at the European level. The GIS analysis will be performed using ESRI ArcGIS Spatial Analyst and the working scale will be European. Available data that will be managed (exported) in Raster or Shapefile format for the use of RECARE partners are all the datasets relevant to the 8 main threats of the Soil Thematic Strategy: soil erosion (PESERA, RUSLE, soil erodibility, rainfall erosivity), soil organic carbon (OCTOP, LUCAS topsoil, CAPRESE), soil biodiversity threat, statistics on soil sealing, Natural Susceptibility of Soils to Compaction, Saline and Sodic Soils in EU, European Landslide Susceptibility Map and contaminated sites.

The working projection is ETRS LAEA. This will include making such data available in the appropriate formats and projections, supporting upscaling and downscaling of data, and performing GIS analyses that make use of the spatial data available in JRC databases. WP10 will also assist in the upscaling of (modelling) results as part of the EU-wide modelling (Task 8.2) as the output datasets are of European scale and will be hosted in ESDAC. Partner 13 has the technical capabilities to perform upscaling from regional scale to the European one using geostatistical methodologies.

1.2 Development of a Relational Database Management System for the RECARE project

WP10 will inventory which data will be generated in the different WPs. Partner 13 will develop an Relational DataBase Management System (RDBMS) scheme in Oracle taking into account the specifications of the Case Studies. The objective of this data infrastructure is to host the data for soil threats that will be collected in the project. The data infrastructure will also provide links with other soil-related FP7 projects hosted un the European Soil Data Centre (ESDAC) which aims to host those datasets. Spatial and non-spatial data will be included, and will be made available to others after the end of the project. Data generated using WOCAT will be stored in the dedicated WOCAT databases by WPs 3 and 5, and will be available on-line. The RDBMS will not include WOCAT data, but will link to them.

1.3 Templates for the data import/export from the RECARE Case Study sites

The import templates will be developed in Microsoft Excel/Access in order to allow the partners to easily upload their Case Study data. Partner 13 will assist partners to enter their data. Data import software will be develop for performing a first quality check of the provided data and to subsequently upload the datasets in the central Oracle infrastructure. Queries will also be developed for the data export from the central Oracle data infrastructure. Templates were not deemed necessary at this stage as the data management system allows direct data import from excel.

1.4 Web interface for making the data publicly available at the end of the project

Data is to be provided to users (WP and Case Studies) through an interactive web interface that allows them to download both baseline data and spatial data. The web interface allows the partners to navigate and download (and perform other GIS operations) the main datasets hosted in the DMS. The web interface has been developed and incorporated in the ECAS web-portal using the open source CMS (Content Management System) Drupal 7.x.

2 RECARE datasets and quality check type

The identified RECARE threats can be listed as follows, where the data quality check type is indicated if available.

Soil threat	**RECARE WP2 identified threats**	**Data quality check type**
Soil erosion by water	• area affected by soil erosion (km^2) and/or extent of area affected by soil erosion (%) • magnitude of soil erosion/deposition or sediment delivery (tons)	• propagation of uncertainties from input data • map of the standard error of rainfall erosivity • map of soil texture standard error
Soil erosion by wind	• measured soil loss by wind (t ha^{-1} yr^{-1}) • annual/periodic estimates of wind erosion • soils' susceptibility to wind erosion *Proxy indicators* • soil resistance (Ohms) • surface roughness (%) • wind velocity (km hr^{-1}) • soil moisture content (%) • soil cover (%, ha)	• propagation of uncertainties from input data • map of the standard error of rainfall erosivity • map of soil texture standard error
Decline in OM in peat soils	• peat stocks (Mt) *Proxy indicators* • water table (m) • soil moisture content (%) • (soil) temperature (°C) • vegetation type (species)	• quality check not available. Legacy data
Decline in OM in mineral soils	• total carbon stocks to 1 m depth ((t ha^{-1}) • clay/SOC • TOP2 indicators by ENVASSO	• map of soil texture standard error • map of the standard error of soil OC content
Soil compaction	• relative Normalized Density, • air-filled pore volume (%) • penetration resistance (Mpa)	• map of soil texture standard error • map of the standard error of soil OC content
Soil sealing	• sealed area (ha, %) • transition index (TI) • sealed to green areas ratio	• quality check not available. Legacy data
Soil contamination	TOP3 indicators by ENVASSO	• quality check not available. Legacy data
Soil salinization	TOP3 indicators by ENVASSO	• quality check not available. Legacy data
Desertification	TOP3 indicators by ENVASSO	• propagation of uncertainties from input data • map of the standard error of rainfall erosivity • map of soil texture standard

		error • map of the standard error of soil OC content
Flooding	• seasonality, magnitude and frequency of precipitation/rainfall intensity • extent of inundated area (ha) • flood frequency (number per year) • loss of crops due to inundation of fields (ha, Euro)	• the threat has not been addressed
Landslides	TOP3 indicators by ENVASSO	• occurrence of landslide activity (ha, km^2 affected per ha or km^2); • volume/weight of displaced material (m^3, km^3, ton of displaced material); • landslide hazard assessment (variable)
Decline in soil biodiversity	TOP3 indicators by ENVASSO	• propagation of uncertainties from input data

For each of the threats a set of field experiments has been implemented as part of WP6.

The aim of the data management system is to provide the WP6 and other project partners with relevant data, in order to provide them with information suitable for the task of identifying and modelling the specific threat of their interest.

For some of the threats a quality check cannot be performed as they are legacy data for which the development steps are not available or fully described or the data sources are not currently available.

In the next chapter a list of specific soil threats and their related datasets, included in the data management system, will be described for reference. At the end of each section dealing with a specific threat, a list of supporting datasets is shown where datasets with uncertainty assessment are underlined.

3 Data quality check procedures for hosted data

The aim of WP10 is to provide a data management system composed of a spatial data database, a database for non-spatial data and of a web interface accessible to RECARE partners, and after the end of the project to others. Evaluating the quality of the hosted data is essential for the project's end users and stakeholders.

RECARE WP2 identified a series of soil threats in Europe with due attention given to the Driving force-Pressure-State-Impact-Response to soil threats. A list of indicators and/or proxy indicators are suggested for each soil threat, such as soil erosion by wind, decline of OM in peat soils, decline of OM in mineral soils and a separate set of indicators for flooding. These indicators have been developed by taking into account the following key issues:

- methodological soundness and data availability,
- measurable and sensitivity to changes,
- policy-relevance and utility for users, and
- geographical coverage of the indicators

Concerning the matter of quality assessment, still the focus is on the databases developed and hosted by JRC, given that most of the project data is to be provided to project partners.

Depending on the type of indicator different methods to assess the quality of the data are available. The methods applied are described in the next paragraphs along with the data they are applicable to.

3.1 Data quality metrics

The following metrics have been used to estimate the quality, in terms of accuracy and precision of the models used to produce JRC based RECARE datasets. These metrics were often used alone, but in some cases they were summarized by other indices.

3.1.1 Measurement quality estimation

Measurement Accuracy: how close a measured value is to the true value (if it is known). If the true value is not known, then the accuracy of measurement can only be estimated.

Measurement Precision: an indication of the reliability and/or repeatability of a measurement, as reflected by the number of significant figures used to represent the measured value.

Measurement Uncertainty/Error: the estimated deviation of a measured value from the true value. The true value may or may not be known. There are three types (sources) of error: measurement mistakes, random errors, and systematic errors.

Random errors result from (hopefully small) uncontrolled variability of the environment, equipment, and/or other subtle aspects of the measurement. The individual measured values randomly deviate high or low of an average value.

Systematic errors result in the consistent deviation of a measurement (on average, either high or low as compared to the true value) due to equipment problems or neglect (or ignorance) of some other important factor in the measurement process.

Measure quality metrics were only tested for the initial dataset (i.e. verifying the accuracy of the measures in the LUCAS dataset). In this sense a thorough validation of the measures and analytical procedures was carried out during the laboratory stage of the LUCAS survey. Using random repeated analyses of the same sample the laboratory could estimate the reliability and repeatability of analytical procedures.

3.1.2 Model quality estimation

Most of the dataset in the LUCAS web platform were obtained through statistical interpolation/extrapolation. In this context, their quality can be assessed through the commonly used statistical procedures and metrics. In particular the following

- **The Mean Value** is the average of the estimated values. The mean is calculated from the sum all A_i (from i = 1 to i = N) and then division of this sum by N.
- **The RMS Deviation** is obtained by taking the square root of the mean of the squared deviations (hence, the RMS-deviation).
- **The Standard Deviation** σ is similar to the rms-deviation, except the 'mean-squared-deviation' is calculated by dividing the 'sum-of-the-squared-deviations' by the so-called "number of degrees of freedom" (DOF), instead of N. Given this we can write a formula for the square of the Standard Deviation (the so-called "variance"): $\sigma^2 = [\Sigma (A_i - \bar{A})^2]/DOF$. For a set of N measurements of the same quantity, the DOF is equal to N-1.
- **The Standard Error** represents an estimate of our uncertainty for the measured mean value (as determined by the number of measurements and the variations in our set of values). The Standard Error is an estimate of the standard deviation of the distribution of mean values expected if the same set of measurements was repeated many times. The Standard Error S is calculated by dividing the Sample Standard Deviation σ by the square root of the number of measurements N. As a formula: $S = \sigma / \sqrt{N}$.

These metrics have been evaluated as figures for the whole dataset, or where possible were mapped for the spatial extent of the dataset.

Model fitting was evaluated by cross-validation. Cross-validation, is a model validation technique for assessing how the results of a statistical analysis will generalize to an independent data set. It is mainly used in settings where the goal is prediction, and one wants to estimate how accurately a predictive model will perform in practice. In a prediction problem, a model is usually given a training set on which the model is fit, and a testing dataset of unknown data against which the model is tested. The goal of cross validation is to define a dataset to "test" the model in the training phase (i.e., the validation set), in order to limit problems like overfitting, give an insight on how the model will generalize to an independent dataset (i.e., an unknown dataset, for instance from a real problem), etc.

One round of cross-validation involves partitioning a sample of data into complementary subsets, performing the analysis on one subset (called the training set), and validating the analysis on the other subset (called the validation set or testing set). To reduce variability, multiple rounds of cross-validation are performed using different partitions, and the validation results are combined (e.g. averaged) over the rounds to estimate a final predictive model.

One of the main reasons for using cross-validation instead of using the conventional validation (e.g. partitioning the data set into two sets of 70% for training and 30% for test) is that there is not enough data available to partition it into separate training and test sets without losing significant modelling or testing capability. In these cases, a fair way to properly estimate model prediction performance is to use cross-validation as a powerful general technique.

3.1.3 Uncertainty propagation

Some datasets were not obtained directly from statistical modelling. As such it is not possible to directly assess their quality through procedures such as cross-validation (i.e. RUSLE soil erosion map). In these cases, quality assessment and uncertainty mapping can be derived only through uncertainty propagation. In statistics, propagation of uncertainty is the effect of uncertainty of variables used in the model (or random errors) on the uncertainty of a function based on them. When the variables are the values of experimental measurements they have uncertainties due to measurement limitations (which propagate to the combination of variables in the function).

The uncertainty u can be expressed in a number of ways. It may be defined by the absolute error Δx. Uncertainties can also be defined by the relative error $(\Delta x)/x$, which is usually written as a percentage. Most commonly, the uncertainty on a quantity is quantified in terms of the standard deviation, σ, the positive square root of variance, σ^2.

4 Description of the quality check procedures for soil threats

4.1.1 Soil erosion by water

Soil erosion by water in general can be defined as a three-stages process that consists of: (i) the detachment of individual soil particles from the soil surface; (ii) their subsequent transport by water; and, ultimately, (iii) their deposition when water lacks sufficient energy for further transport (Morgan, 2005). The risk of erosion by water has been assessed at the European scale using various models and expert-based approaches.

Data included in the Data Management System (DMS) includes: *(i) PESERA model predictions:* the Pan-European Soil Erosion Risk Assessment (PESERA) model is a process-based and spatially distributed model that was developed to estimate the risk of soil erosion by water across Europe (Kirkby *et al.*, 2004). *(ii) RUSLE model predictions (Figure 3):* Panagos *et al.* (2015) presented a new, extended version of the Revised Universal Soil Loss Equation (RUSLE). JRC has developed the RUSLE 2018 model (fig. 3) and carried out its quality check.

The factors controlling soil erosion are commonly divided into:

(i) erosivity of the erosive agent or its capacity to detach and transport soil particles;

(ii) erodibility of the soil or the inverse of the soil’s resistance against the detachment and transport of its particles;

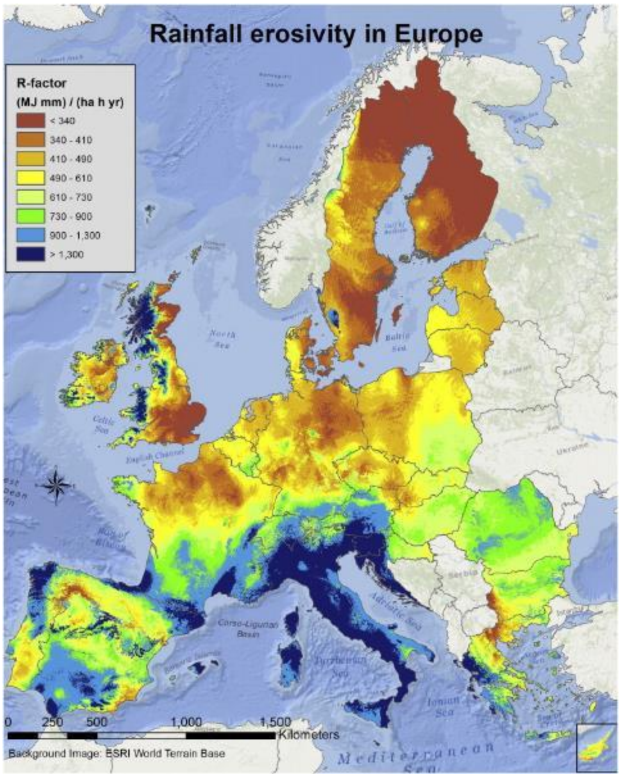


Figure 1 Map of ra
2014)

(iii) plant and litter cover; and

(iv) slope of the terrain (Morgan, 2005).

In order to model these factors, data about climate in particular rainfall erosivity and soil texture is included in the DMS.

Climatic data includes the R-factor, which is the erosivity index of rainfall as estimated by the RUSLE model. The R-factor is a multi-annual average index that measures rainfall's kinetic energy and intensity to describe the effect of rainfall on sheet and rill erosion. However, the erosive forces of runoff due to snowmelt, snow movement, rain on frozen soil, or irrigation are not included in this factor. Besides (R)USLE, the rainfall erosivity can be used as input in other models such as USPED, SEMMED and SEDEM. Further, this dataset could also be interesting for natural hazard predictions such as landslide and flood risk assessment that are mainly triggered by high intensity events.

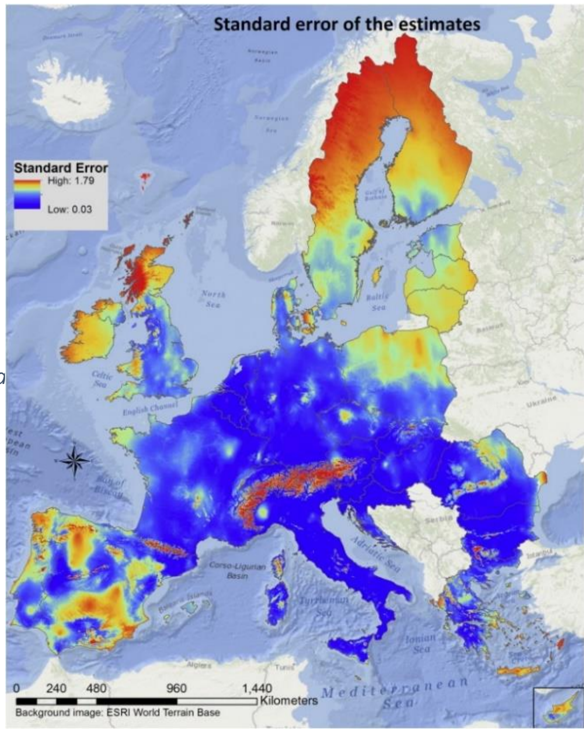


Figure 2 Uncertainty of the R-factor prediction calculated with the GPR spatial interpolation model.

The R-factor values calculated from precipitation data of different temporal resolutions were normalised to R-factor values with temporal resolutions of 30 min using linear regression functions. Precipitation time series ranged from a minimum of 5 years to a maximum of 40 years. The average time series per precipitation station is around 17.1 years, the most datasets including the first decade of the 21st century. Gaussian Process Regression (GPR) has been used to interpolate the R-factor station values to a European rainfall erosivity map at 1 km resolution.

The RUSLE is a purely deterministic model in which the product of physical measures is used to derive the amount of soil loss. As such, a rigorous assessment of uncertainties is not feasible, nor would it be meaningful, unless the uncertainties of the input layers and their propagation in the model scheme were quantified. Accordingly, the estimation of the uncertainty in the RUSLE model outputs remains in most case an unaddressed issue. A thorough quantification of uncertainty associated to the RUSLE model was provided only in a few local-scale studies, mainly dealing with a single model factor such as rainfall, soil type and topography.

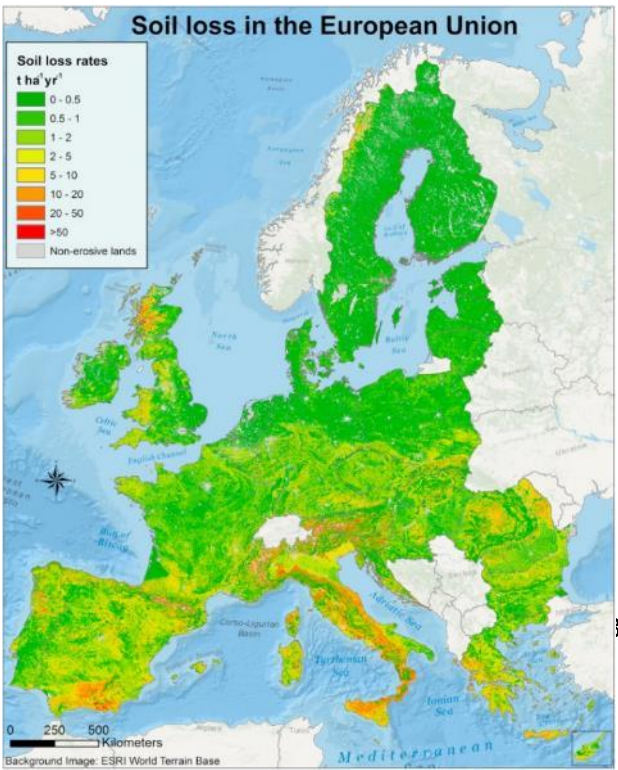
In this study a different approach was followed representing the uncertainty as a probability distribution through the use of a Bayesian modelling technique. The idea is to use the data distribution to estimate the uncertainty in the prediction. Given that the RUSLE is based on the product, for simplicity all the layers were log-transformed. Next, each of the input layers was treated as a spatial random field. A random field is a stochastic process defined in terms of expectation and covariance, once these two parameters are estimated, different simulation of the field can be created. Each of the simulation has the same parameters, but differs due to the stochasticity of the process. By combining a large number of simulations, one could, in principle, estimate how the uncertainty propagates to the model output (soil loss). As deriving spatially continuous simulations for each of the layers is impractical, a simulation approach based on Gibbs sampling and an additive model was used.

The model is expressed as:

$$z\,(S_0) = z(R) + z(LS) + z(K) + z(C) + e(s)$$

where the z() values are realization of each of the log-transformed model input layers and e(s) is the spatial component of the model.

A Markov Chain Monte Carlo (MCMC) algorithm, was used to derive realizations of z(S0) (soil loss) by simulating from the multivariate normal distribution with zero mean and covariance matrix Vb, where Vb is the Bayesian covariance matrix of the fitted model. MCMC was applied using the JAGS software through R interface.



4.1.2 Rainfall erosivity uncertainty assessment

The application of the Gaussian Process Regression (GPR) spatial interpolation model allowed us to derive not only the R-factor but also the standard error of the estimate. In this study, the map of standard error (fig. 2) was directly used to estimate the uncertainty of the prediction model. Using the standard error to estimate the dispersion of prediction errors, the highest uncertainty was found to be in north-western Scotland, north-western Sweden and northern Finland due to the relatively small number of precipitation stations and high diversity of environmental features. The model prediction was also found to have increased uncertainty levels in the Southern Alps and the Pyrenees. Medium uncertainty is noticed in Spain, northern Poland, the west of Ireland, North Cyprus and the Aegean islands due to a lack of stations. In general, the model had a good prediction rate with low standard errors in the majority of the study area.

According to the log statistics of the European Soil Data Centre, those spatial layers are highly requested for modelling activities in erosion by water and wind, biodiversity modelling, water capacity, crop growth, vegetation, soil conservation, moisture, land use, ecological analysis, groundwater vulnerability and hydrology.

Data provided and hosted for soil erosion by water

1. Climatic data
    1.1. Rainfall erosivity map of Europe
2. Soil data
    2.1. Soil texture maps
        2.1.1. Soil coarse fragments maps
        2.1.2. Soil organic carbon maps
3. Maps of soil erosion
    3.1. PERSERA map of soil erosion
    3.2. RUSLE map of soil erosion[1]

Figure 3 Map of soil loss by water erosion (RUSLE) (Panagos et al., 2015)

[1] Through uncertainty propagation

4.1.3 Soil texture

One of the key attributes of the European Soil Database is the soil texture along with soil coarse fragments content. It is determined by the proportion of sand, silt and clay (%) and it is expressed as a texture class (Jones et al., 2005).

Texture was predicted using Multivariate Additive Regression Splines (MARS); this procedure constrains the prediction of every single particle size class to a physically meaningful range. Texture data was transformed using the additive log-ratio. Table 1 shows prediction performance for model fitting (R^2), k-fold cross validation (k-CV R^2) and independent sample validation (CV R^2). Independent sample validation was performed by selecting 5000 random samples (by a stratified random sampling) and using them to validate the model fitted on the remaining ~ 15,000 samples; in this case the metrics used to evaluate model performance is RMSE. The k-fold cross-validation was performed for a k = 5 and repeated 100 times using different random splits in order to obtain more stable estimates by averaging.

Table 1 Prediction performances for texture and coarse fragments mapping from the LUCAS database using multivariate MARS.

	CV-RMSE	R^2	k-CV R^2	CV R^2	CV R^2 ESDB
Clay	7.70	0.93	0.65	0.50	0.51
Silt	12.60	0.92	0.62	0.47	0.49
Sand	17.30	0.93	0.60	0.49	0.48
Coarse f.	19.22	0.73	0.52	0.40	0.39

The best predicted variable was the clay content, whilst silt content was less well predictable. However the differences are substantially negligible. Coarse fragments were treated as an independent variable and predicted by a different MARS model, as such the metrics for coarse fragments are presented in a different line of Table 1. Model fitting resulted in very good performance metrics both in fitting and cross-validation (Table 1), with only the prediction of coarse fragments performing quite differently from the others.

Table 1 also depicts the change of CV R^2 when soil units from the European Soil Database (ESDDB) are added as dummy variables (CV R2 ESDB), it should be noted that being the GCV term in MARS comparable to Akaike Information Criterion (Barron and Xiao, 1991) the fitting procedure of the model already selects the most efficient model. It is thus the model that selects the most informative variables or excludes the least informative. In this context we found that MARS models consistently rejected data from soil units. We will discuss this aspect below.

Fig. 5 depicts the k-fold cross validation results by plotting the predicted versus observed values for the three variables for both the fitting and the validation sets. The variable colour scale in the same plot depicts the normalized standard deviation for a given observation as estimated through the 100 repetitions. From Fig. 5 we can see that the fitted values present a quite low dispersion with most of the values within the value of the standard deviation. In general the errors are homoscedastic, this contributes to the high R^2 values of Table 1. However it is possible to notice a slight bias as the values are consistently over predicted for high observed values and under predicted for the lower ones. k-fold errors are more dispersed as usual with some quite large deviation, this is expected as cross validation tests the generalization capacity of the model on new samples. Nevertheless model performance is still quite good with most of the samples falling within the value of the standard deviation.

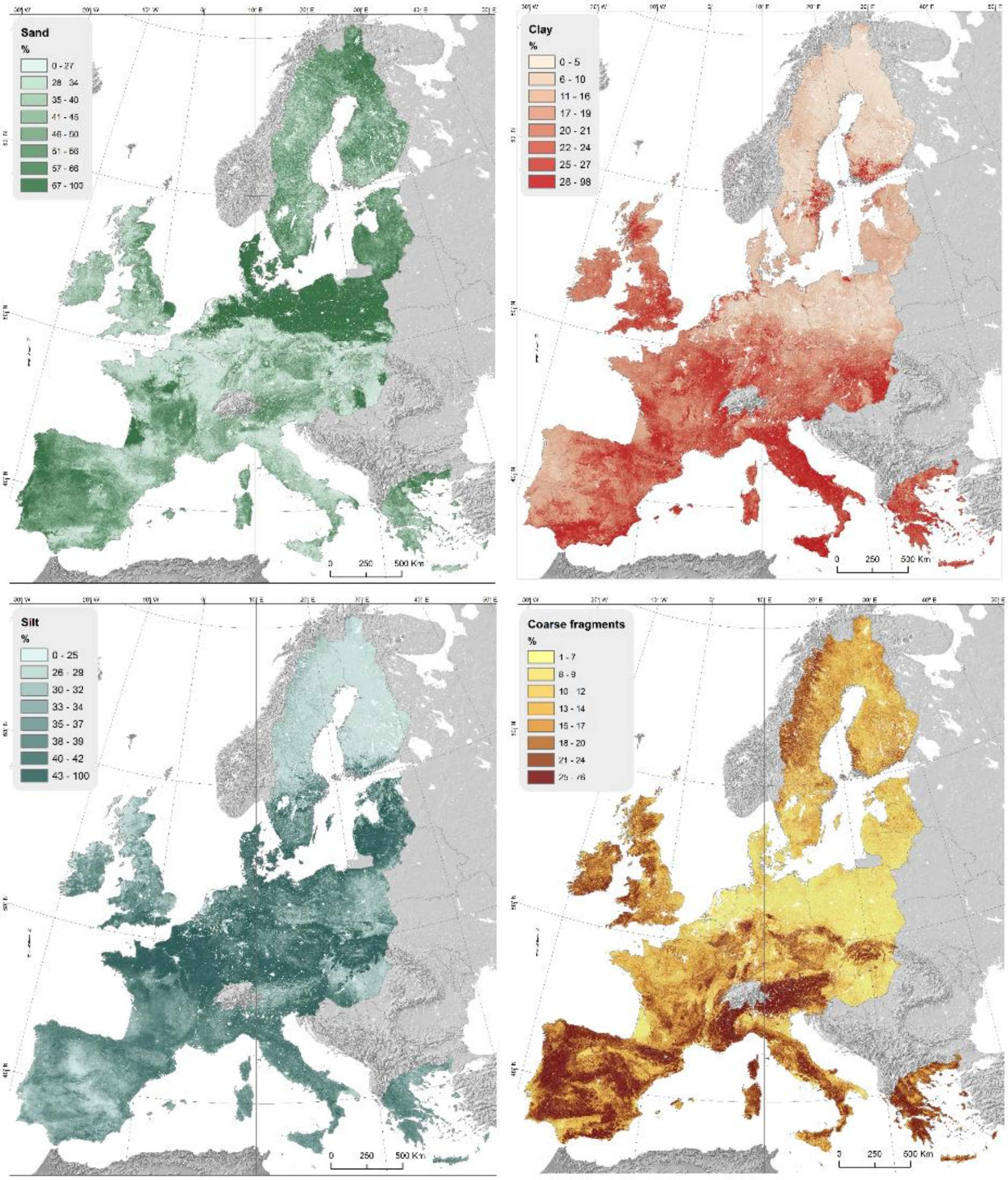


Figure 4 Topsoil (0-20cm) Sand, Silt, Clay and coarse fragments content (%) modelled by Multivariate Additive Regression Splines (Ballabio et al, 2016)

A map of model standard deviation (Fig. 6) was also produced. As the MARS models the variables as an ensemble, the resulting standard deviation map was obtained as an averaged composite of the standard error of the three variables. Areas above 1000 m evidence the high uncertainties and evidence the difficulty in predicting undersampled areas. In general the map depicts a quite low model standard deviation in relatively homogeneous areas such as plains. Regions with a more diverse morphology are in general less well predicted (western Scotland, Pyrenees, Apennines, western Greece, etc.). In this case topography seems to be the main controlling factor in determining model performance. In general the worst performance is obtained in mountain and hilly areas, this can be explained by the fact that these areas have a high diversity in terms of terrain, land cover and substrate, whilst being sampled with the same density as the rest of Europe, resulting in a larger model deviation. Areas above 1000 m of altitude show the highest uncertainties which are of the same order of the predicted values (up to and above 100%).

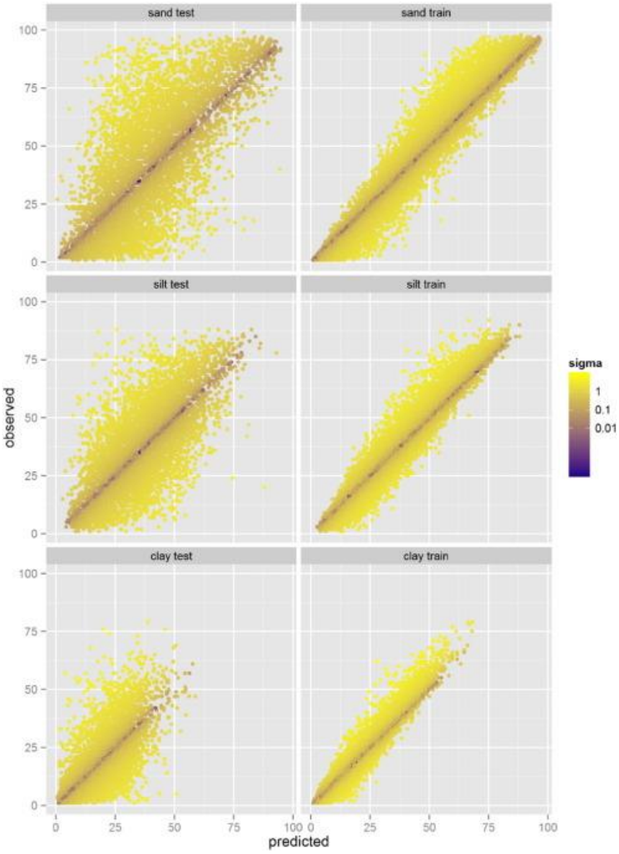


Figure 5 Model accuracy tested by cross-validation.

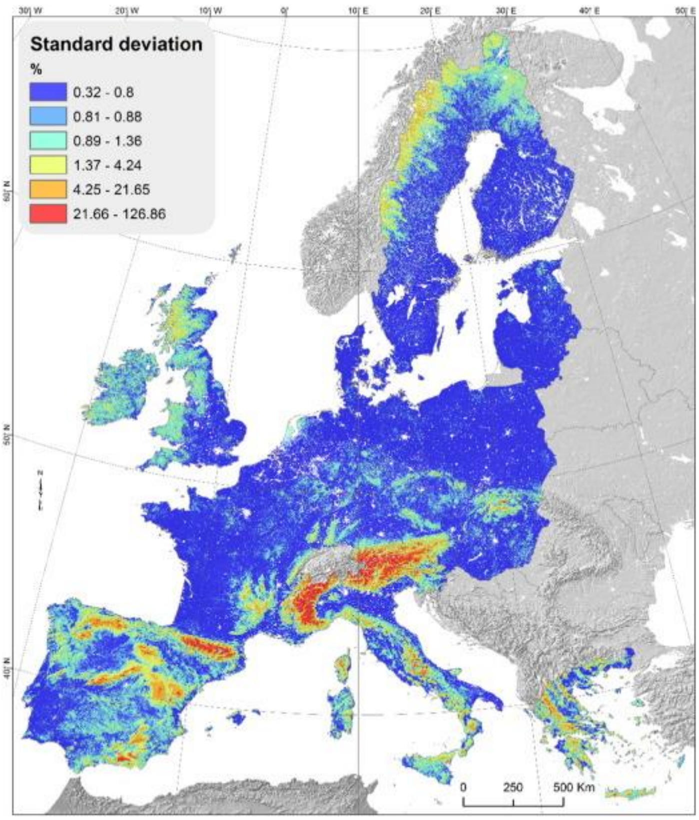


Figure 6 Averaged standard deviation of the Multivariate Additive Regression Splines model

4.1.4 Soil erosion by wind

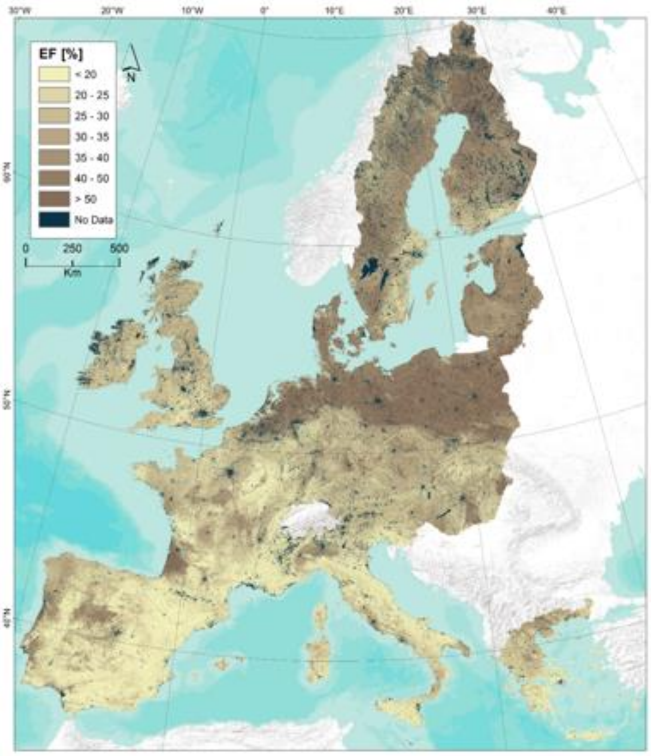


Figure 7 Map of wind erosion susceptibility of European soils (500m spatial resolution) based on the estimation of the wind-erodible fraction of soil (EF) (Fryrear et al., 2000).

Soil erosion by wind is a serious environmental problem (Lal, 1994) causing severe soil degradation in arid, semi-arid and agricultural areas (Woodruff and Siddoway, 1965; Kalma *et al.*, 1988). Wind erosion occurs where 1) the soil is loose, finely divided and dry; 2) where the soil is smooth and bare; and 3) wind is strong.

In early 2014, the JRC proposed an integrated mapping approach to estimate soil susceptibility to wind erosion (Borrelli *et al.*, 2014a). The wind-erodible fraction of soil (EF) is one of the key parameters for estimating the susceptibility of soil to wind erosion (Fryrear *et al.*, 1994; Fryrear *et al.*, 2000). It was computed for 18,730 geo-referenced topsoil samples (from the Land Use/Land Cover Area frame statistical Survey – LUCAS - dataset). The prediction of the spatial distribution of the EF (Figure 7) and a soil surface crust index drew on a series of related but independent covariates, using a digital soil mapping approach (Cubist-rule-based model to calculate the regression, and Multilevel B-Splines to spatially interpolate the Cubist residuals) (Goovaerts, 1998). The spatial interpolation showed a good performance with an overall R^2 of 0.89 (in fitting). Spatial patterns of the soils' susceptibility to wind erosion in line with the state of the art in the literature were achieved.

A cross validation was carried out to evaluate the performance of the spatial prediction approach. The extremely limited number of studies that report soil erodible fraction estimations or similar types of soil erodibility by wind assessment did not allow for the application of further validation procedures for the calculated values of soil erodibility. Furthermore, we compared our findings with previous for the geographical areas where soil susceptibility to wind erosion had been reported (i.e., Geest area of Lower Saxony, Southern Great Plains of Hungary and the Dutch provinces of Groningen and Drenthe).

The outcomes of the proposed modelling approach were subjected to a validation procedure to assess the model performance. A subset of the literature locations suffering from wind erosion reported by Borrelli et al. (2016) was employed. Out of 156 locations accurately georeferenced in GIS, 90 were found to be located within EU-28 arable land. In the European arable land, 85 of the 90 locations reported in literature (94.4%) were classified by the GIS-RWEQ model as being susceptible to erosion.

Data provided and hosted for wind soil erosion

1. Climatic data
    1.1. Map of wind intensity for Europe
2. Soil data
    2.1. Soil texture maps
        2.1.1. Soil coarse fragments maps

2.1.2. Soil organic carbon maps

3. Maps of soil erosion

3.1. Map of estimated wind erosion[2]

[2] Through uncertainty propagation

4.1.5 Decline in Soil organic matter data quality check

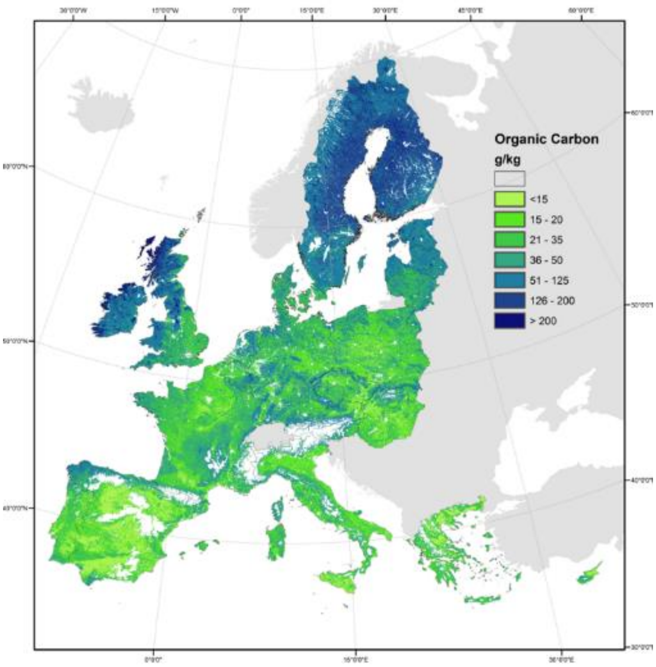


Figure 8 Map of Soil Organic Carbon (de Brogniez et al., 2015)

Soil, after the oceans, is the largest pool of carbon in the biosphere. The SOC pool is about twice the size of the atmospheric carbon pool and about three times the size of the biota carbon pool. The global SOC pool to a depth of 1m is estimated at 1,500 billion tonnes (Batjes, 1996), ranging from 30 t ha^{-1} in arid climates to 800 t ha^{-1} in permafrost-affected regions (Lal, 2004).

SOM decline has been widely recognised as a major threat for sustainable soil management because of the pivotal role played by the organic material on many soil functions, like food and biomass production, storage and filtering, biological habitat and gene pool, etc.

Soil organic carbon decline strongly depends on physical, chemical and biological drivers of both natural and human origin. Since most of these drivers are the same as the ones that influence the composition of terrestrial ecosystems, SOM and ecosystem types show strong correspondences to one another

- Climate (precipitation, temperature, solar radiation, etc.)
- Topography
- Soil type and properties (e.g. soil texture, soil temperature, moisture, pore structure)
- Land cover/vegetation type

Part of these factors are the same that have been provided for the estimation of soil erosion

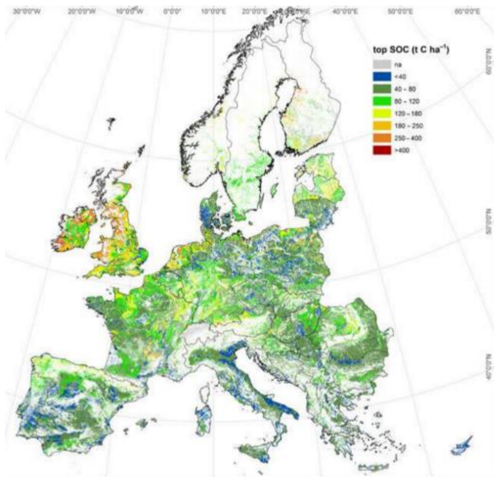


Figure 9 Soil organic carbon (SOC) stock in the top-soil layer (0–30 cm) of European agricultural soils (Source: Lugato et al., 2014.)

Data provided and hosted for soil organic carbon decline

1. Climatic data
   1.1. Map of temperature and rainfall intensity for Europe
2. Soil data
   2.1. Soil texture maps
      2.1.1. Soil coarse fragments maps
      2.1.2. Soil texture maps
      2.1.3. Soil organic carbon maps
3. Maps of Soil Organic Carbon
   3.1. Map of Soil Organic Carbon
   3.2. Map of Soil Organic Carbon stocks in agricultural fields[3]

[3] Through uncertainty propagation

4.1.6 Quality check for Soil Organic Carbon map

The quality of the SOC map for Europe (fig. 8) was thoroughly checked. The initial dataset was split into a calibration (85%) and a validation (15%) set by Latin hypercube sampling. The stratification was conditioned by the following variables: elevation, slope, net primary productivity, temperature, PP0, latitude, longitude, measured OC content and CORINE land cover. Knowing that land cover has a large impact on OC content, we developed a statistical model on samples for which observed land cover (from the LUCAS survey) and CORINE land-cover inventory were in agreement to avoid using wrong land-cover classes to calibrate the model. However, using observed land cover (LUCAS) instead of mapped/predicted (CORINE) land cover has potentially the consequence of under-estimating the prediction error variance (Kempen et al., 2010). To check this, we fitted a model on the entire dataset and found no differences in cross-validation results. A generalized additive model (GAM) was fitted on the calibration set. To prevent an 'over-fit', thin plate regression splines were fitted by maximum penalized likelihood. A backward stepwise approach was then followed to select the best set of covariates and to determine the relative influence of each of the covariates on the overall prediction capabilities of the model. The Akaike Information Criterion (AIC) and the deviances explained were calculated and compared for each of the models created (Akaike, 1974). The selected model was then applied to the points of the validation set. Predicted and measured OC content were compared and both root mean square errors (RMSE) and normalized root mean square error (RMSE divided by the observed data range; NRMSE) were calculated. The coefficient of determination was calculated for the validation procedure.

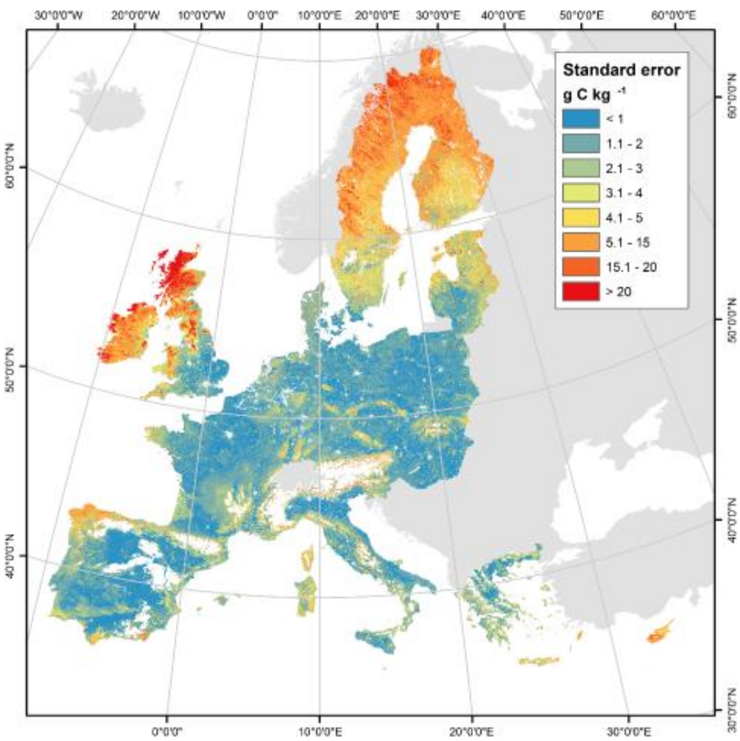


Figure 10 Standard error map for SOC distribution

Large standard errors are observed in northern latitudes but also in inland wetlands or moors and heathlands (Figure 10). Few samples were taken in the highlands of Scotland, in Wales, in south-western Ireland or in northern Sweden and Finland, where OC variation tends, moreover, to be very large (Figure 9). In all these areas, OC predictions have large standard errors. Mountain ranges such as the Alps (Italy, France and Austria), the Carpathians (the Czech Republic, Slovakia and Poland), the Apennines (Italy), the Central Massif and the Vosges (France) and the Pindus (Greece) had large standard errors in their areas below 1000 m altitude. Areas where a large standard error is estimated should be considered with caution. In contrast, areas where a small standard error is calculated (mostly corresponding to the croplands of Europe) give predictions of OC content that more accurately approximate the measured values.

4.1.7 Quality check for Soil Organic Carbon in agricultural land

The Soil Organic Carbon obtained using the CENTURY in agricultural land map (fig. 9) was validated against two independent data sets:

LUCAS (Land Use/Cover statistical Area frame Survey) direct field observations gathering fully harmonized data on land use/cover and their changes over time in the EU, that included a soil survey in 2009. Top-soil samples were collected from 10% of the general survey points, thus providing approximately 20000 soil samples. LUCAS soil samples were taken from all land use/land cover types, but mainly on agricultural areas (EUROSTAT, 2011). The samples were analysed in a single ISO-certified laboratory, providing the top-soil SOC expressed in g kg^{-1}. To convert this concentration to a stock, an empirically derived pedotransfer function, developed by Hollis et al. (2012), was used to predict bulk density in European soils. A comparison was made using the LUCAS points and the simulated value of the intersected Soil-Climate-Land unit, for the matching land use category (arable, pasture and permanent crops). However, to avoid the comparison between one point vs. a polygon, data were aggregated at higher hierarchical level corresponding to administrative regions (NUTS2). The same level of aggregation (NUTS2) was adopted as the most suitable for the comparison of LUCAS data with OCTOP map (Panagos et al., 2013b).

The EIONET-SOIL database containing SOC concentration (g kg^{-1}) and SOC stocks (t ha^{-1}) for 1 km cells for the depth range of 0–30 cm (Panagos et al., 2013a). Six countries provided measurements or a best 'estimate' (e.g. based on models) which represents an official standpoint of the country. The model uncertainty was quantified at NUTS2 scale, since these territorial units are considered basic regions for the application of regional policies by EU. Precisely, the absolute errors (AE) were calculated in each NUTS2 region.

5 RECARE JRC datasets consistency check and metadata

5.1 Soil erosion by water

Title: Soil Loss by Water Erosion in Europe

Dataset description: Dataset (GIS map) (2015) that shows the Soil Loss by Water Erosion in Europe and is the result of applying a modified version of the Revised Universal Soil Loss Equation (RUSLE) model, RUSLE 2015; resolution 100m.

Methodology used to develop the dataset: Modified version of Revised Universal Soil Loss Equation (RUSLE) model (Renard et al., 1997). The proposed modified version is named RUSLE2015 and improves the quality of estimation by introducing updated (2010), high-resolution (100 m) peer-reviewed input layers. A major advancement in RUSLE2015 is the modelling of management (reduced/no till, plant residues, cover crops) and support practices (contour farming, maintenance of stone walls and grass margins).

Consistency Check: The soil loss by water erosion rates have been verified with the data received from the Member States through the European Environment Information and Observation Network for soil (EIONET-SOIL) in 2009. The result of this data collection exercise was the EIONET-SOIL database which includes data at 1-km pixel size for ten countries: Austria, Belgium, Bulgaria, Estonia, Germany, Italy, the Netherlands, Poland, and Slovakia (Denmark was included in a later phase). There is a good correspondence both in spatial patterns and in erosion rates with the data received from 7 countries while there are some differences with the national datasets in Slovakia, Wallonia forests (Belgium) and forestlands in Austria.

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 (bad-lands) and northern Europe (mixed vegetation with rocks). The use of remote sensing data on vegetation density has proven to be useful for fine-tuning the erosion-factor values. The soil loss predictions in steep and arid areas can be further improved by separating the effects of erodible soil from the effects of rock and gravel surfaces.

The major benefit of RUSLE2015 is its high-quality input layers (RUSLE2015 input layers have been also directly or indirectly validated with national or regional datasets) due to:

a) the assessment of soil erodibility based on the sampling of topsoils in the field and laboratory analysis of soil properties, plus the K-factor data verification with local and regional published studies,
b) the participation of the Member States in the extensive data collection of high-resolution precipitation data,
c) the use of the first ever high-resolution Digital Elevation Model at 25 m,
d) the combination of the CORINE Land Cover database with remote sensing vegetation density data, plus the use of crop and management practices statistical data, and
e) the first ever assessment of good management practices using LUCAS survey observations and the GAEC database

A sensitivity analysis of RUSLE2015 model has been also performed. More information in Estrada-Carmona et al. (2017).

Terms and Conditions used (copyright): Data can be downloaded from European Soil Data Centre (ESDAC). No particular copyright is applied.

Metadata

<u>Spatial Coverage</u>: European Union 28 Member States

Resolution: 100m cell cize

Measurement Unit: t ha^{-1} yr^{-1}

Format: Raster (Grid)

Projection: ETRS89 Lambert Azimuthal Equal Area

Input datasets: LUCAS Topsoil, European Soil Database, Lucas Earth Observations, Rainfall Erosivity Database at European Scale (REDES), CORINE Land Cover 2006, COPERNICUS Remote Sensing, EUROSTAT (statistics on Crops, Tillage, Plant residues, cover crops), Digital Elevation Model (DEM) at 25m, Good Agricultural Environmental Condition (GAEC).

Date Release: Semptember 2015

Link: https://esdac.jrc.ec.europa.eu/content/soil-erosion-water-rusle2015

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

Title: **Rainfall erosivity in Europe**

Dataset description: Dataset (GIS map) (2015) and associated products for the "Rainfall erosivity" (R-factor), one of the input layers when calculating the Universal Soil Loss Equation (USLE) model, which is the most frequently used model for soil erosion risk estimation; for EU28+Switzerland; R-factor map at resolutions of 500m.

Methodology used to develop the dataset: Rainfall erosivity equations for calculating the erosive power of rain. The equations are based on amount, intensity and duration of rainfall. The erosivity (R-factor) is the product of kinetic energy of a rainfall event (E) and its maximum 30-min intensity (I_{30}) (Brown and Foster, 1987).

Consistency Check: Rainfall erosivity in Europe is calculated using the best available datasets. We have developed the Rainfall Erosivity Database on the European Scale(REDES) which contains 1,541 precipitation stations in all European Union(EU) Member States and Switzerland, with temporal resolutions of 5 to 60 minutes. The R-factor values calculated from precipitation data of different temporal resolutions were normalised to R-factor values with temporal resolutions of 30 minutes using linear regression functions. Precipitation time series ranged from a minimum of 5 years to maximum of 40 years. The average time series per precipitation station is around 17.1 years, the most datasets including the first decade of the 21st century.

Terms and Conditions used (copyright): Data can be downloaded from European Soil Data Centre (ESDAC). No particular copyright is applied.

Metadata

Spatial Coverage: European Union (28 Countries) & Switzerland

Resolution: 500m cell size

Measurement Unit: MJ mm ha^{-1} h^{-1} yr^{-1}

Format : Raster (Grid)

Projection: ETRS89 Lambert Azimuthal Equal Area

Input datasets: REDES (Rainfall Erosivity Database at European Scale)

Date Release: January 2015

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

Publication Reference: Panagos, P., Ballabio, C., Borrelli, P., Meusburger, K., Klik, A., Rousseva, S., Tadic, M.P., Michaelides, S., Hrabalíková, M., Olsen, P., Aalto, J., Lakatos, M., Rymszewicz, A., Dumitrescu, A., Beguería, S., Alewell, C. 2015. Rainfall erosivity in Europe. Sci Total Environ. 511: 801-814.

Title: **Pan European Soil Erosion Risk Assessment - PESERA**

Dataset description: A 2003 GIS map of Soil erosion estimates (t/ha/yr) by applying the PESERA GRID (physical) model at 1km, using the European Soil Database, CORINE land cover, climate data from the MARS Project and a Digital Elevation Model. The resulting estimates of sediment loss are from erosion by water.

Methodology used to develop the dataset: The Pan-European Soil Erosion Risk Assessment - PESERA - uses a process-based and spatially distributed model to quantify soil erosion by water and assess its risk across Europe. The conceptual basis of the PESERA model can also be extended to include estimates of tillage and wind erosion.

Consistency Check: Local studies in regions of Italy, Netherlands and United Kingdom.

Terms and Conditions used (copyright): Data can be downloaded from European Soil Data Centre (ESDAC). Aknowledgements to PESERA project should be provided.

Metadata

Spatial Coverage: 23 EU Member states (Excluding Croatia, Sweden, Finland, Cyprus and Malta)

Resolution: 1km cell size

Measurement Unit: t ha^{-1} yr^{-1}

Format: raster

Projection: : ETRS89 Lambert Azimuthal Equal Area

Input datasets: 128 layers

Date Release: 2004

Link: https://esdac.jrc.ec.europa.eu/content/pan-european-soil-erosion-risk-assessment-pesera

Publication Reference: M. J. Kirkby, B. J. Irvine, R. J. A. Jones, G. Govers, and PESERA team, 2008. The PESERA coarse scale erosion model for Europe. Model rationale and implementation. European Journal of Soil Science 59 (6) , pp. 1293-1306.

Title: **Topsoil physical properties for Europe (based on LUCAS topsoil data)**

Dataset description: This dataset (GIS maps)(2016) contains 7 soil property maps that have been derived using soil point data from the LUCAS 2009 soil survey (around 20,000 points) for EU-25, using hybrid approaches like regression kriging. Properties: clay, silt and salt content; coarse fragments; bulk density; USDA soil textural class; available water capacity. Resolution 500m.

Methodology used to develop the dataset: Multivariate Additive Regression Splines (MARS). The LUCAS topsoil database was used to map soil properties at continental scale over the geographical extent of Europe. Several soil properties were predicted using hybrid approaches like regression kriging. For those datasets, we predicted topsoil texture and related derived physical properties. Regression models were fitted using, along other variables, remotely sensed data coming from the MODIS sensor. The high temporal resolution of MODIS allowed detecting changes in the vegetative response due to soil properties, which can then be used to map soil features distribution.

Consistency Check: Cross validation of the fittedmodels proved that the LUCAS dataset constitutes a good sample for mapping purposes leading to cross-validation R^2 between 0.47 and 0.50 for soil texture and normalized errors between 4 and 10%. The spatial interpolation model showed a good performance (cross validation R2 = 0.65, 0.62, and 0.60 corresponding to the clay, silt and sand prediction), and high prediction uncertainty was limited to relatively few areas.

Terms and Conditions used (copyright): Data can be downloaded from European Soil Data Centre (ESDAC). No particular copyright is applied.

Metadata

Spatial Coverage: European Union (EU-25) as Coratia, Bulgaria and Romania are not inclued. An extrapolation version exists covering EU-28 plus Balkan countries, Switzerland and Norway.

Resolution: 500m

Measurement Unit: clay(%), Sand(%), Silt (%), Coarse fragments (%)

Format: Raster

Projection: ETRS89 Lambert Azimuthal Equal Area

Input datasets: UCAS 2009 Topsoil 20,000 sample point data

Date Release: September 2015

Link: https://esdac.jrc.ec.europa.eu/content/topsoil-physical-properties-europe-based-lucas-topsoil-data

Publication Reference: Ballabio C., Panagos P., Montanarella L. Mapping topsoil physical properties at European scale using the LUCAS database (2016) *Geoderma*, 261: 110-123.

5.2 Soil erosion by wind

Title: Soil loss by wind erosion in European agricultural soils

Dataset description: This dataset consists of various elements related to Soil loss by wind erosion in European agricultural soils (2016);

Methodology used to develop the dataset: a modified version of Revised Wind Erosion Equation Model (RWEQ) for GIS named GIS-RWEQ. The new version is a simplified GIS-based application of the RWEQ model developed by ARS-USDA (USA). It follows a spatially distributed approach based on a grid structure, running in R and Python scripts. The model scheme is designed to describe the daily soil loss potential at regional or larger scale.

Consistency Check: The outcomes of the proposed modelling approach were subjected to a validation procedure to assess the model performance. A subset of the literature locations suffering from wind erosion reported by Borrelli et al. (2016) was employed. Out of 156 locations accurately georeferenced in GIS, 90 were found to be located within EU-28 arable land. In the European arable land, 85 of the 90 locations reported in literature (94.4%) were classified by the GIS-RWEQ model as being susceptible to erosion.

Terms and Conditions used (copyright): Data can be downloaded from European Soil Data Centre (ESDAC). No particular copyright is applied.

Metadata

Spatial Coverage: EU-28

Resolution: 1km cell size

Measurement Unit: t ha^{-1} yr^{-1}

Format: Raster (Grid)

Projection: ETRS89 Lambert Azimuthal Equal Area

Input datasets: Erodible Fraction, Soil crust factor, soil roughness factor, combined crop factors, Wind velocity data

Date Release: December 2016

Link: https://esdac.jrc.ec.europa.eu/content/Soil_erosion_by_wind

Publication Reference: Borrelli, P., Lugato, E., Montanarella, L., & Panagos, P. (2017). A New Assessment of Soil Loss Due to Wind Erosion in European Agricultural Soils Using a Quantitative Spatially Distributed Modelling Approach. Land Degradation & Development, 28: 335–344

Title: **Wind erosion susceptibility of European soils**

Dataset description: The wind-erodible fraction of soil (EF) is one of the key parameters for estimating the susceptibility of soil to wind erosion.The predication of the spatial distribution of the EF and a soil surface crust index drew on a series of related but independent covariates, using a digital soil mapping approa

Methodology used to develop the dataset: The wind-erodible fraction of soil (EF) is one of the key parameters for estimating the susceptibility of soil to wind erosion. It was computed for 18,730 geo-referenced topsoil samples (from the Land Use /Land Cover Area frame statistical Survey (LUCAS) dataset).

Consistency Check: Our predication of the spatial distribution of the EF and a soil surface crust index drew on a series of related but independent covariates, using a digital soil mapping approach (Cubist-rule-based model to calculate the regression, and Multilevel B-Splines to spatially interpolate the Cubist residuals). The spatial interpolation showed a good performance with an overall R^2 of 0.89 (in fitting).

Terms and Conditions used (copyright): Data can be downloaded from European Soil Data Centre (ESDAC). No particular copyright is applied.

Metadata

Spatial Coverage: 25 Member States of the European Union where data available (All EU member states except Bulgaria, Romania and Croatia).

Resolution: 500m

Measurement Unit: % of erodible fraction

Format: Raster (Grid)

Projection: ETRS89 Lambert Azimuthal Equal Area

Input datasets: LUCAS point data, European Soil Database.

Date Release: October 2014

Link: https://esdac.jrc.ec.europa.eu/themes/wind-erosion-susceptibility-soils

Publication Reference: Borrelli, P., Ballabio, C., Panagos, P., Montanarella, L. (2014). Wind erosion susceptibility of European soils. Geoderma, 232, 471-478.

5.3 Decline in Soil organic matter

Title: Topsoil Soil Organic Carbon (LUCAS)

Dataset description: This dataset (2015) provides maps for Topsoil Soil Organic Carbon in EU-25 that are based on LUCAS 2009 soil point data through a generalized additive model. Map of predicted topsoil organic carbon content (g C kg-1) : The map of predicted topsoil organic carbon content (g C kg-1) was produced by fitting a generalised additive model between organic carbon measurements from the LUCAS survey (dependent variable) and a set of selected environmental covariates; namely slope, land cover, annual accumulated temperature, net primary productivity, latitude and longitude. It also includes a Map of standard error of the OC model predictions (g C kg^{-1}).

Methodology used to develop the dataset: Generalized additive model (GAM). GAMs are a generalization of linear regression models in which the coeficients can be expanded as s mooth functions of covariates (Hastie & Tibshirani, 1986).

Consistency Check: A generalized additive model (GAM) was fitted on 85% of the dataset (R^2 = 0.29), using OC content as dependent variable; a backward stepwise approach selected slope, land cover, temperature, net primary productivity, latitude and longitude as suitable covariates. The validation of the model (performed on 15% of the data-set) gave an overall R^2 of 0.27 and an R^2 of 0.21 for mineral soils and 0.06 for organic soils. Organic C content in most organic soils was under-predicted, probably because of the imposed unimodal distribution of our model, whose mean is tilted towards the prevalent mineral soils. This was also confirmed by the poor prediction in Scandinavia (where organic soils are more frequent), which gave an R^2 of 0.09, whilst the prediction performance (R^2) in non-Scandinavian countries was 0.28

Terms and Conditions used (copyright): Data can be downloaded from European Soil Data Centre (ESDAC). No particular copyright is applied.

Metadata

Spatial Coverage: EU-25 : All the European Union Member states except Croatia, Romania and Bulgaria

Resolution: 1km cell size

Measurement Unit: g C kg^{-1}

Format: Grid (Raster)

Projection: ETRS89 Lambert Azimuthal Equal Area

Input datasets: LUCAS topsoil database; secondary inputs: CORINE LC, NASA SRTM, WorldClim, Moderate Resolution Imaging Spectroradiometer (MODIS), European Soil Database

Date Release: Nov 2014

Link: https://esdac.jrc.ec.europa.eu/content/topsoil-soil-organic-carbon-lucas-eu25

Publication Reference: de Brogniez, C. Ballabio, A. Stevens, R. J. A. Jones, L. Montanarella and B. van Wesemael (2015). A map of the topsoil organic carbon content of Europe generated by a generalized additive model. European Journal of Soil Science, 66(1): 121-134

Title: **Pan-European SOC stock of agricultural soils**

Dataset description: Data (2014) related to Pan-European SOC stock of agricultural soils, containing GIS maps for a) Pan-European SOC stock of agricultural soils (shapefile), b) Potential carbon sequestration by modelling a comprehensive set of management practices (shapefile), c) Average Eroded SOC in agricultural soils (raster).

Methodology used to develop the dataset: A comprehensive model platform was established at a pan-European scale (EU + Serbia, Bosnia and Herzegovina, Croatia, Montenegro, Albania, Former Yugoslav Republic of Macedonia and Norway) using the agro-ecosystem SOC model CENTURY. The model was implemented with the main management practices (e.g. irrigation, mineral and organic fertilization, tillage, etc.) derived from official statistics. The model results were tested against inventories from the European Environment and Observation Network (EIONET) and approximately 20,000 soil samples from the 2009 LUCAS survey, a monitoring project aiming at producing the first coherent, comprehensive and harmonized top-soil dataset of the EU based on harmonized sampling and analytical methods.

Consistency Check: The simulated values were generally in agreement with measurements for all three aggregated land use (LUVCAS Topsoil 20,000 points) and EIONET data on soil organic carbon (Panagos et al., 2013).

The uncertainty calculated was <40% in half of the NUTS2 regions.

Terms and Conditions used (copyright): Data can be downloaded from European Soil Data Centre (ESDAC). No particular copyright is applied.

Metadata

Spatial Coverage: Pan-European scale (EU + Serbia, Bosnia and Herzegovina, Croatia, Montenegro, Albania, Former Yugoslav Republic of Macedonia and Norway)

Resolution: 1km

Measurement Unit: Soil organic stock (t C ha^{-1}) ; b) ha = hectares under agricultural land use

Format: Raster (Grid) and Shape files

Projection: ETRS_1989_LAEA_L52_M10

Input datasets: European Soil Database; CORINE LC; Monthly temperature and precipitation were taken from East Anglia university; Land use and management crop statistics (EUROSTAT)

Date Release: Nov 2013

Link: https://esdac.jrc.ec.europa.eu/content/pan-european-soc-stock-agricultural-soils

Publication Reference: Lugato E., Panagos P., Bampa, F., Jones A., Montanarella L. (2014). A new baseline of organic carbon stock in European agricultural soils using a modelling approach. Global change biology. 20 (1), pp. 313-326.

5.4 Soil compaction

Title: **Relative normalized density (RND) for European subsoil horizons**

Dataset description: Relative normalized density (RND) for European subsoil horizons covering the depth 0.25 – 0.7 m as calculated by pedo-transfer rules based on the SPADE8 database (Koue et al., 2008). RND>1 may be considered a dense soil

Methodology used to develop the dataset: The dataset hosted on the DMS is the SPADE8 soil database (Koue *et al.*, 2008). This is a further development of the SPADE1 database initiated in 1992 (Breuning-Madsen and Jones, 1995). The SPADE database was constructed to support the EU-soil map at scale 1:1,000,000 with soil analytical data for modelling purposes. The SPADE8 database includes a range of soil properties for a total of approximately 900 soil profiles (~3500 soil horizons) across 28 countries in Europe.

Consistency Check: Not Avalable

Terms and Conditions used (copyright): Data are not available.

Metadata: Not Available

Title: **Soil bulk density**

Dataset description: Bulk density map at 500m rersolution derived from LUCAS clay and pedotransfer rules.

Methodology used to develop the dataset: The bulk density was obtained from the packing density and the mapped clay content (Ballabio et al., 2016) following the equation of Jones et al. (2003). USDA classificaton was followed for the pedotransfer rules.

Consistency Check: Derived from Pedotrasfer rules which have tested Jones et al. (2003). Range of values between limits reccomended inEuropean Soils

Terms and Conditions used (copyright): Data can be downloaded from European Soil Data Centre (ESDAC). No particular copyright is applied.

Metadata

Spatial Coverage: European Union (EU-25) as Coratia, Bulgaria and Romania are not inclued. An extrapolation version exists covering EU-28 plus Balkan countries, Switzerland and Norway.

Resolution: 500m

Measurement Unit: Mg (Tonnes) m^{-3}

Format: Raster

Projection: ETRS89 Lambert Azimuthal Equal Area

Input datasets: LUCAS 2009 Topsoil 20,000 sample point data

Date Release: September 2015

Link: https://esdac.jrc.ec.europa.eu/content/topsoil-physical-properties-europe-based-lucas-topsoil-data

Publication Reference: Ballabio C., Panagos P., Montanarella L. Mapping topsoil physical properties at European scale using the LUCAS database (2016) *Geoderma*, 261: 110-123.

5.5 Soil Sealing

Title: **Percentage of soil sealing according to EAA soil sealing layer, year 2006**

Dataset description: Raster data set of built-up and non built-up areas including continuous degree of soil sealing ranging from 0 - 100% in aggregated spatial resolution (100 x 100 m and 20 x 20m).

Methodology used to develop the dataset: Comparing the artificial surfaces of different version of CORINE Land Cover. The term "artificial surfaces" is used in the CORINE Land Cover nomenclature and refers to "continuous and discontinuous urban fabric (housing areas), industrial, commercial and transport units, road and rail networks, dump sites and extraction sites, but also green urban areas (Prokop *et al.*, 2011).

Consistency Check: CORINE Land Cover

Terms and Conditions used (copyright): Data can be downloaded from European Soil Data Centre (ESDAC). No particular copyright is applied.

Metadata

Spatial Coverage: EU

Resolution: 20m

Measurement Unit: sealed area (ha, %)

Format: Raster Dataset

Projection:

Input datasets: CORINE Land Cover

Date Release: 2011

Link: https://www.eea.europa.eu/data-and-maps/data/eea-fast-track-service-precursor-on-land-monitoring-degree-of-soil-sealing

Publication Reference:

Title: **Soil Sealing & food security (Loss of Potential Agricultural Production Capability)**

Dataset description: This dataset (2015), an Excel file, contains the data associated to the peer-reveiwed paper: Gardi, C., Panagos, P., Van Liedekerke, M., Bosco, C., de Brogniez, D. 2015. Land take and food security: assessment of land take on the agricultural production in Europe.

Methodology used to develop the dataset: As a first step, two land-take maps were generated by applying a number of GIS operations to CORINE datasets, one for the period 1990–2000 and another for the period 2000–2006. In a second step, each land-take map was overlaid with NUTS2 polygons, in order to compute the extent of agricultural land taken in each NUTS2 administrative unit. Then the Potential Agricultural Production Capability (PAPC) for a certain area is defined as the potential agricultural production in this area. The output of winter wheat production activities is taken as a proxy for PAPC, expressed in tonnes (t).

Consistency Check: Input datasets have been validated and verified.

Terms and Conditions used (copyright): Data can be downloaded from European Soil Data Centre (ESDAC). No particular copyright is applied.

Metadata

Spatial Coverage: 21 Member States of the European Union (Data were not available for Finland, Sweden, UK, Greece, Cyprus, Bulgaria, Latvia)

Resolution: NUTS2 units

Measurement Unit: tonnes

Format: Shape files

Projection: ETRS89 Lambert Azimuthal Equal Area

Input datasets: CORINE Land Cover; NUTS dataset; MARS input data on crop production

Date Release: December 2014

Link: https://esdac.jrc.ec.europa.eu/content/soil-sealing-food-security-loss-potential-agricultural-production-capability

Publication Reference: Gardi, C., Panagos, P., Van Liedekerke, M., Bosco, C., de Brogniez, D. 2015. Land take and food security: assessment of land take on the agricultural production in Europe. Journal of Environmental Planning and Management, 58 (5) , pp. 898-912.

5.6 Soil Contamination

Title: Heavy Metals in topsoils (version 2008)

Dataset description: GIS Maps (2008) produced by mapping the concentrations of eight critical heavy metals (arsenic, cadmium, chromium, copper, mercury, nickel, lead and zinc) using the 1588 georeferenced topsoil samples from the FOREGS Geochemical database. The concentrations were interpolated using block regression-kriging over the 26 European countries that contributed to the database

Methodology used to develop the dataset: Geostatistical analysis with Block kriging.

Consistency Check: The success of the technique was evaluated using the leave-one out cross validation method, as implemented in the krige.cv method of gstat.

Terms and Conditions used (copyright): Data can be downloaded from European Soil Data Centre (ESDAC). No particular copyright is applied.

Metadata

Spatial Coverage: EU-28 without Romania, Bulgaria and Cyprus (plus Switzerland, Albania)

Resolution: 5km

Measurement Unit: Various units depending on the method

Format: Grid

Projection: European Terrestrial Reference System (ETRS) .

Input datasets: 1588 analysed points of Forum of European Geological Surveys (FOREGS)

Date Release: 2008

Link: https://esdac.jrc.ec.europa.eu/content/heavy-metals-topsoils

Publication Reference: Rodriguez Lado, L., Hengl, T., Reuter, H.I., (2008) Heavy metals in European soils: a geostatistical analysis of the FOREGS Geochemical database. Geoderma 148, 189-199.

5.7 Soil Salinization

Title: Saline and Sodic Soils in European Union

Dataset description: The Saline and Sodic Soils Map shows the area distribution of saline, sodic and potentially salt affected areas within the European Union.

Methodology used to develop the dataset: The accuracy of input input data only allows the designation of salt affected areas with a limited level of reliability (e.g. < 50 or > 50% of the area); therefore the results represented in the map should only be used for orientating purposes.

Consistency Check: High uncertainty as the results fo this map have not been verified or validated.

Terms and Conditions used (copyright): Data can be downloaded from European Soil Data Centre (ESDAC). No particular copyright is applied.

Metadata

Spatial Coverage: 27 Member States of the European Union

Resolution: 1km

Measurement Unit: Qualitative classes

Format: Raster

Projection: ETRS89 Lambert Azimuthal Equal Area

Input datasets: Soil data - European Soil Database v2 , 1:1.000.000 scale Map of Salt Affected Soils in Europe (Szabolcs 1974)

Date Release: 2008

Link: https://esdac.jrc.ec.europa.eu/content/saline-and-sodic-soils-european-union

Publication Reference: Tóth et al. (2008) Updated Map of Salt Affected Soils in the European Union. In: Tóth, G., Montanarella, L. and Rusco, E. (Eds.) Threats to Soil Quality in Europe. EUR23438 – Scientific and Technical Research series Luxembourg: Office for Official Publications of the European Communities p.61-74

5.8 Flooding and Landslides

Title: **European Landslide Susceptibility Map (ELSUS1000) v1**

Dataset description: The map shows landslide susceptibility levels at continental scale, derived from heuristic-statistical modelling of main landslide conditioning factors using also landslide location data

Methodology used to develop the dataset: ELSUS1000 version 1 shows levels of spatial probability of generic landslide occurrence at continental scale. Basically, the map has been produced by regionalizing the study area based on elevation and climatic conditions, followed by *spatial multi-criteria evaluation* modelling using pan-European slope gradient, soil parent material and land cover spatial datasets as the main landslide conditioning factors. In addition, the location of over 100,000 landslides across Europe, provided by various national organizations or collected by the authors, has been used for model calibration and validation.

Consistency Check: Landslides inventories in European countries are used to check the map

Terms and Conditions used (copyright): Data can be downloaded from European Soil Data Centre (ESDAC). No particular copyright is applied.

Metadata

Spatial Coverage: EU-28 Member States (except Cyprus) and Albania, Bosnia and Herzegovina, Croatia, Kosovo, FYR Macedonia, Montenegro, Norway, Serbia and Switzerland.

Resolution: 1 km

Measurement Unit: 5 classes (qualitative assessment|

Format: Raster (ESRI GRID)

Projection: ETRS89 Lambert Azimuthal Equal Area

Input datasets: Climato-Physiographic Regions, Classified Slope Gradient, Classified Soil Parent Material and Classified Land Cover maps

Date Release: February 2013

Link: https://esdac.jrc.ec.europa.eu/content/european-landslide-susceptibility-map-elsus1000-v1

Publication Reference: Günther, A., Van Den Eeckhaut, M., Malet, J.-P., Reichenbach, P., Hervás, J., 2014. Climate-physiographically differentiated Pan-European landslide susceptibility assessment using spatial multi-criteria evaluation and transnational landslide information. Geomorphology, 224: 69-85

5.9 Decline in biodiversity

Title: Potential threats to soil biodiversity in Europe

Dataset description: Three major components of soil biodiversity are assesed: a) soil microorganisms, b) fauna, and c) biological functions. The maps were developed based on 13 potential threats to soil biodiversity which were proposed to experts with different backgrounds in order to assess biodiversity threat.

Methodology used to develop the dataset: use of 13 proxy datasets and the expert knowledge to create formulas of soil biodiversity risk.

Consistency Check: The expert knowlegde is based on large pool of experts in the field. High uncertainty in spatializing the results of expert knoweldge based on the proxies.

Terms and Conditions used (copyright): Data can be downloaded from European Soil Data Centre (ESDAC). No particular copyright is applied.

Metadata

Spatial Coverage: European Union (27 Countries - Croatia was not included)

Resolution: 500m

Measurement Unit: 5 classes describing the level of risk

Format: Raster

Projection: ETRS89 Lambert Azimuthal Equal Area

Input datasets: habitat fragmentation use of GMOs in agriculture, introduction of invasive species, climate change, soil compaction, soil sealing, soil erosion, soil salinization, land use change, nuclear pollution, soil pollution from industry, organic matter decline, intensive human exploitation

Date Release: September 2015

Link: https://esdac.jrc.ec.europa.eu/content/potential-threats-soil-biodiversity-europe

Publication Reference: Orgiazzi, A., Panagos, P., Yigini, Y., Dunbar, M.B., Gardi, C., Montanarella, L., Ballabio, C. 2016. A knowledge-based approach to estimating the magnitude and spatial patterns of potential threats to soil biodiversity. Science of the Total Environment, 545-546: 11-20.

5.10 Template used for the Metadata description (including quality check, copyrights and info about the dataset).

Title:

Dataset description:

Methodology used to develop the dataset:

Consistency Check:

Terms and Conditions used (copyright): Data can be downloaded from European Soil Data Centre (ESDAC). No particular copyright is applied.

Metadata

Spatial Coverage:

Resolution:

Measurement Unit:

Format:

Projection:

Input datasets:

Date Release:

Link:

Publication Reference:

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