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Soil erodibility in Europe: A high-resolution dataset based on LUCAS

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HIGHLIGHTS

- Soil erodibility in Europe is estimated at 0.032 t ha h ha^{-1} MJ^{-1} mm^{-1}.
- Stoniness has an important impact in Mediterranean countries.
- High resolution (500 m grid cell) dataset of K-factor is available for modelling.
- Coarse fragments, permeability and soil structure were considered in K-factor.
- K-factor map has very good correspondence with regional data in literature studies.

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ABSTRACT

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 the K-factor in the widely used soil erosion model, the Universal Soil Loss Equation (USLE) and its revised version (RUSLE). The K-factor, which expresses the susceptibility of a soil to erode, is related to soil properties such as organic matter content, soil texture, soil structure and permeability. With the Land Use/Cover Area frame Survey (LUCAS) soil survey in 2009 a pan-European soil dataset is available for the first time, consisting of around 20,000 points across 25 Member States of the European Union. The aim of this study is the generation of a harmonised high-resolution soil erodibility map (with a grid cell size of 500 m) for the 25 EU Member States. Soil erodibility was calculated for the LUCAS survey points using the nomograph of Wischmeier and Smith (1978). A Cubist regression model was applied to correlate spatial data such as latitude, longitude, remotely sensed and terrain features in order to develop a high-resolution soil erodibility map. The mean K-factor 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 yielded soil erodibility dataset compared well with the published local and regional soil erodibility data. However, the incorporation of the protective effect of surface stone cover, which is usually not considered for the soil erodibility calculations, resulted in an average 15% decrease of the K-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 highest percentages of surface stone cover were observed.

1. Introduction

Soil erosion is the most widespread form of soil degradation worldwide (Bridges and Oldeman, 1999). Since soil erosion is difficult to measure at large scales, soil erosion models are a crucial estimation tool at regional, national and European levels. The high heterogeneity of soil erosion causal factors, combined with often poor data availability is an obstacle for the application of complex soil erosion models. Thus, the empirical Revised Universal Soil Loss Equation (RUSLE) (Renard et al., 1997), which predicts the average annual soil loss resulting from raindrop splash and runoff from field slopes, is still most frequently used at large spatial scales (Renschler and Harbor, 2002; Panagos et al., in press). The RUSLE is the simple multiplication of 5 soil erosion risk factors, of which one is the soil erodibility also called K-factor. The K-factor is a lumped parameter that represents an integrated annual value of the soil profile reaction to the process of soil detachment and transport by raindrops and surface flow (Renard et al., 1997). As such soil erodibility is best estimated by carrying out direct measurements on field plots (Kinnell, 2010). However, since field measurements are expensive and often not easily transferable in space, researchers investigated the relation between "classical" soil properties and soil erodibility.

A number of equations have been designed to predict soil erodibility, most famous is the soil erodibility nomograph of Wischmeier et al., 1971. Dangler and El-Swaify (1976) developed an equation for

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Hawaiian soils. Other equations, such as that of Young and Mutcher (1977), require attributes that are not widely available to predict soil erodibility (e.g. bulk density). During the 1990s, Römkens et al. (1997), Williams (1995) and Torri et al. (1997) developed simpler equations mainly based on soil texture.

At European level, Panagos et al. (2012a) estimated soil erodibility based on attributes (texture, organic carbon) which were available from the Land Use/Cover Area frame Survey (LUCAS) topsoil data (Toth et al., 2013) using the original nomograph of Wischmeier et al. (1971). Inverse distance weighting (IDW) was used to interpolate erodibility to a map with a grid-cell resolution of 10 km. The dataset attracts great interest and it is available for download from the European Soil Data Centre (ESDAC); approximately 200 users have registered and downloaded the data within two years. The great majority of these used the K-factor as an input for their USLE/RUSLE models, or for validation and comparison to their modelled or measured K-factor estimates. Past experience with the coarse-resolution soil erodibility dataset showed that it is fairly difficult for soil erosion modellers to access soil profile data in their area of interest.

However, a dataset with a resolution of 10-km grid cell can be considered too rough for most applications especially as the vast majority of users downloaded the K-factor for regional and local applications. Thus, the main objective of this paper is to produce a soil erodibility dataset with a higher spatial resolution (500-m grid cell size). In order to enable a better interpolation of the LUCAS point estimates Cubist regression-interpolation is applied. Besides the higher spatial resolution achieved through the abovementioned interpolation technique, this new soil erodibility assessment will consider soil structure and the effect of stones both on the soil permeability and the shielding of rain splash. Moreover, Malta and Cyprus have been included in the analysis. Another major improvement is that the estimated soil erodibility dataset will be verified against local, regional and national data found in the literature.

2. Materials and methods

2.1. Input data

The geographical extent of this study includes 25 Member States of the European Union (EU). Bulgaria, Romania and Croatia were not included as the main input dataset (LUCAS survey 2009) does not include data for those countries.

2.1.1. LUCAS topsoil data

LUCAS (Land Use/Cover Area frame Survey) is an in-situ assessment, which means that the data is gathered through direct field observations. The aim of the LUCAS survey is to establish a fully harmonised database within the EU on land use/cover and to document changes over time. A soil module was included in the LUCAS dataset for the first time in 2009. Topsoil samples (0–30 cm, approximate weight of 0.5 kg) were collected from 10% of the survey points, providing 19,969 soil samples across the 25 Member States. 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 (Panagos et al., 2013).

The objective of the soil module in the LUCAS dataset was to improve the availability of harmonised data on soil parameters in Europe. During the period 2010–2011, the 19,969 LUCAS soil samples were analysed in a single ISO-certified laboratory to obtain a coherent pan-European dataset. The significant advantage of this method is that discrepancies arising from inter-laboratory differences (Cools et al., 2004) have been avoided. The results of the analysis are stored in the LUCAS topsoil database (Toth et al., 2013), which includes (among others) the particle size distribution expressed as percentages of clay (<0.002 mm), silt (0.002–0.05 mm), sand (0.05–2.0 mm) as well as organic carbon (%) and percentage coarse material (>2.0 mm). Analysis of the soil parameters followed standard procedures (LUCAS, 2009a; ISO, 2013).

2.1.2. Stone cover percentage

During the 2009 LUCAS data collection exercise, the surveyors estimated the percentage of the surface that is covered with stones. Surveyors were given a chart (LUCAS, 2009b) to help them estimate the percentage of stones present above the ground (Fig. 1). According to the instruction guide (LUCAS, 2009b), the surveyors removed the vegetation coverage and litters around the sampling point. The surveyors were trained to assign their estimation to one of the five classes (LUCAS, 2009b) based on their visual assessment and the charts provided in the instruction guide (Fig. 1). As surveyors in Cyprus and Malta did not assess the percentage of stones, class = 2 was assigned to their data as this is the predominant stone cover class in LUCAS for the southern parts of the Mediterranean countries.

2.1.3. European Soil Database

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

2.1.4. Covariates used for the Cubist regression model

Cubist (Quinlan, 1992) is a rule based model tree where the terminal leaves contain linear regression models. Prediction is obtained using the linear regression model at the terminal node of the tree and smoothed by taking into account the prediction from the linear model in the previous node of the tree. Various covariates were considered for the Cubist model, but three main types were considered to be significant:

1. Remotely sensed data derived from the Moderate Resolution Imaging Spectro-radiometer (MODIS), including vegetation indices (Normalized Difference Vegetation Index — NDVI, Enhanced Vegetation Index — EVI) and raw band data which have been re-projected using Principal Component Analysis;
2. Terrain features, derived from the Shuttle Radar Topography Mission (SRTM) Digital Elevation Model, including common geo-morphometric descriptors (elevation, slope, base level of streams, altitude above channel base level and multi-resolution index of valley bottom flatness);
3. Latitude and longitude.

The MODIS data was acquired in 2009 during the same period as the LUCAS data, while the SRTM data refer to the year 2000.

2.2. Soil erodibility estimates for the LUCAS point dataset

As direct measurements of K-factor on field plots are not financially sustainable at the regional or national levels, the soil erodibility nomograph (Wischmeier et al., 1971) is most commonly used and cited for soil erodibility calculation. An algebraic approximation of the nomograph that includes five soil parameters (texture, organic matter, coarse fragments, structure, and permeability) is proposed by Wischmeier and Smith (1978) and Renard et al. (1997) in Eq. (1):

$$K = \left[\left(2.1 \times 10^{-4}\ M^{1.14}(12\text{–}OM) + 3.25(s-2) + 2.5(p-3)\right)/100\right] * 0.1317 \quad (1)$$

where:

M	the textural factor with $M = (m_{silt} + m_{vfs}) * (100 - m_c)$;
m_c [%]	clay fraction content (<0.002 mm);
m_{silt} [%]	silt fraction content (0.002–0.05 mm);
m_{vfs} [%]	very fine sand fraction content (0.05–0.1 mm);
OM [%]	the organic matter content;

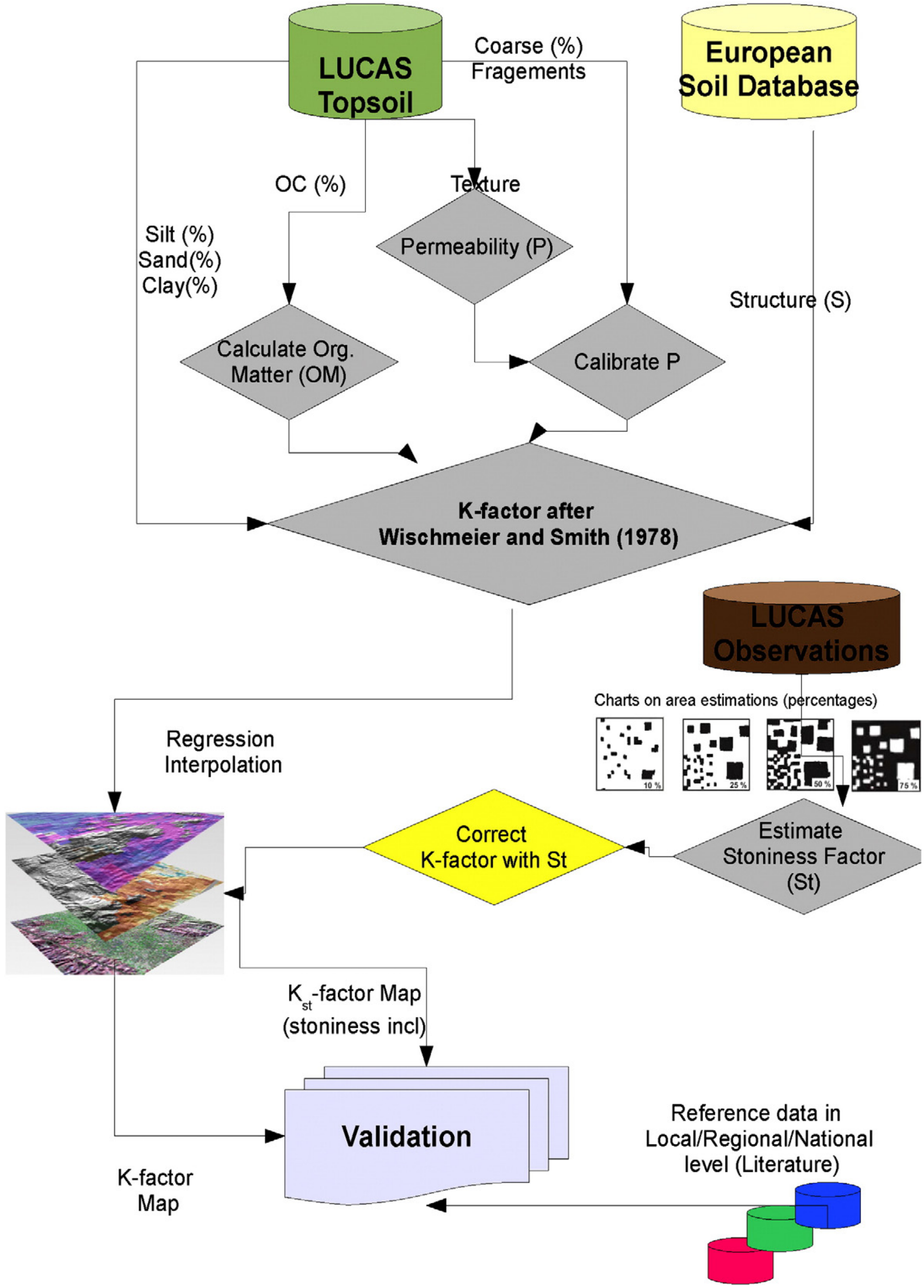

Fig. 1. Methodology applied for the generation of a European K-factor (soil erodibility) map.

s the soil structure class (s = 1: very fine granular, s = 2: fine granular, s = 3, medium or coarse granular, s = 4: blocky, platy or massive; Table 1);

p the permeability class (p = 1: very rapid, ..., p = 6: very slow; Table 2).

The K-factor is expressed in the International System of units as t ha h ha^{-1} MJ^{-1} mm^{-1}. The proposed erodibility equation (Eq. (1)) can only be recommended if organic matter content is known and silt content is below 70%. If these criteria are met, this equation is more precise than alternative equations (Declercq and Poesen, 1992). The

Table 1
Classes of soil structure derived the European Soil Database.

Structure class (s)	European Soil Database
1 (very fine granular: 1–2 mm)	G (good)
2 (fine granular: 2–5 mm)	N (normal)
3 (medium or coarse granular: 5–10 mm)	P (poor)
4 (blocky, platy or massive: >10 mm)	H (humic or peaty top soil)

methodology applied in this study (depicted in Fig. 1) was selected based on the availability of data to calculate input attributes at the European level.

The combined application of the K-factor nomograph with the LUCAS dataset required three adaptions:

- According to Wischmeier and Smith (1978), Eq. (1) is restricted to samples for which the silt fraction does not exceed 70%. A subset of 718 soil samples collected in LUCAS 2009 had silt fractions in the range of 70%–80%. As these were mainly taken from northern France, southern Belgium and central Germany, it was considered essential to be included in the calculation of the K-factor. An upper limit value of 70% silt fraction was assigned to those samples. The 212 soil samples that exceeded the 80% silt fraction were excluded from the calculation.
- In literature the sand fraction is categorised into five classes of sand: very fine, fine, medium, coarse, very coarse (Gee and Bauder, 1986; Gee and Or, 2002). The very fine sand structure (0.05–0.1 mm) as sub-factor (m_{vfs}) in Eq. (1) is usually not subject of standard soil analysis and was therefore estimated as 20% of the sand fraction (0.05–2.0 mm) which is available in the LUCAS topsoil database.
- For soil samples with organic matter content above 4%, the upper limit of 4% has been applied (Wischmeier and Smith, 1978). The application of a 4% limit to soil organic matter intends to prohibit an underestimation of soil erodibility for soils that are rich in organic matter.

2.2.1. Estimation of structure classes

Good soil structure and high aggregate stability are important for improving soil fertility, enhancing porosity and decreasing erodibility (Bronick and Lal, 2005). In past studies (Bonilla and Johnson, 2012; Lopez-Vicente et al., 2008; Perez-Rodriguez et al., 2007), soil structure was assigned based on soil types of the Food and Agriculture Organization (FAO). A pedotransfer rule for estimating soil structure when no direct measurements are available has been developed by Van Ranst et al. (1995). In the European Soil Database, this pedotransfer rule classifies the soil structure as humic, poor, normal or good (Table 1), using pedological inputs such as the FAO soil name and soil texture (Jones et al., 2003). The latter dataset was used to derive the structure class values needed for K-factor calculation as given in Table 1.

2.2.2. Soil permeability estimation

For the estimation of the soil permeability, classes described in the US Department of Agriculture's National Soils Handbook No. 430 (USDA, 1983) were assigned according to soil texture classes (Table 2) (Rawls et al., 1982). These soil textural classes have also been employed for the estimation of the range values of saturated hydraulic conductivity, which are explained below (Table 2).

Table 2
Soil permeability classes and saturated hydraulic conductivity ranges estimated from major soil textural classes.

Permeability class (p)	Texture	Saturated hydraulic conductivity, mm h^{-1}
1 (fast and very fast)	Sand	>61.0
2 (moderate fast)	Loamy sand, sandy loam	20.3–61.0
3 (moderate)	Loam, silty loam	5.1–20.3
4 (moderate low)	Sandy clay loam, clay loam	2.0–5.1
5 (slow)	Silty clay loam, sand clay	1.0–2.0
6 (very slow)	Silty clay, clay	<1.0

Soil permeability is affected by the content of stones (>2 mm). The Agriculture Handbook No. 537 (Wischmeier and Smith, 1978) separates the influence of stone fragments into two components: a) surface rock fragments which can further reduce the splash detachment rate in a similar way to how vegetation protects soils from rainfall intensity; b) subsurface rock fragments that lead to increased soil loss due to reduced water infiltration.

The latter effect of coarse fragments is due to a reduction in the empty spaces (voids). As the LUCAS topsoil database includes coarse fragments (>2 mm), their effect on saturated hydraulic conductivity and soil erodibility can be calculated using the following equation (Brakensiek et al., 1986):

$$K_b/K_f = (1 - R_w) \tag{2}$$

where K_b (mm day^{-1}) is the modified saturated hydraulic conductivity after accounting for the effect of rock fragments, and K_f is the saturated hydraulic conductivity of the fine soil fraction (<2 mm). Initial estimates for K_f were also assigned by classification of LUCAS texture information into the corresponding texture classes and associated saturated hydraulic conductivities of the US Department of Agriculture's National Soils Handbook No. 430 (USDA, 1983). R_w is the percentage of coarse fragments greater than 2 mm. R_w reduces the saturated hydraulic conductivity in the soil profile and can likely change the permeability class, as indicated in Table 2.

2.2.3. Adjustment of K-factor by inclusion of surface stone cover

Besides the percentage of coarse fragments for the 0–30 cm soil samples, LUCAS provides also a percentage estimate of the surface stone cover. Surface stone cover may have a negative effect on sediment yield and thus, can be considered as natural soil-surface stabiliser. Rubio and Recatalá (2006) proposed stoniness to be included in the soil erodibility index qualitative estimation. Poesen and Ingelmo-Sanchez (1992) carried out a review of the negative relationship between stone cover and the relative interrill sediment yield. This negative relationship is generally observed where stones are either partly embedded in the top layer or are on the surface of the soil.

Poesen et al. (1994) developed a soil erodibility reduction factor expressed as an exponential decay function based on experimental field data:

$$St = e^{-0.04(R_c - 10)} \tag{3}$$

where:

St is the correction factor for the relative decrease in sediment yield;
R_c is the percentage of stones cover with $10\% < R_c < 100\%$.

The mean rate of decay was calculated as 0.04. Similar equations with different parameters that were proposed by other authors have given different rates of decay: 0.025 (Box, 1981), 0.044 (Simanton et al., 1986), 0.050 (Martin, 1988).

Table 3
Classes of percentage surface stone cover of LUCAS database.

Class	Percentage of stones	Value (%) used for the St calculation	Number of samples and proportion (%)	St (correction factor)
0	0%	0.0%	95 (0.48%)	1
1	Stones ≤ 10%	5.0%	14,585 (73.37%)	1
2	10% < Stones < 25%	17.5%	3114 (15.66%)	0.740
3	25% ≤ Stones < 50%	37.5%	1442 (7.25%)	0.332
4	Stones ≥ 50	75.0%	643 (3.23%)	0.074

Surface stone cover was estimated by the LUCAS surveyor in five classes (Table 3). The majority of the samples were found to have less or equal to 10% of stones and a correction factor cannot be applied according to Eq. (3). For classes 2, 3 and 4 (Table 3), the mean value of the percentage class (Table 3 column 3) was applied in Eq. (3) resulting in three correction factors (St).

The updated soil erodibility value (K_{st}) incorporating surface stone cover was calculated according to Eq. (4):

$$K_{st} = K * St. \tag{4}$$

2.3. Spatial prediction of the K-factor

Given the linearity of Eq. (1), a regression approach was used to predict the K-factor in order to infer the distribution of soil erodibility from a series of related, but independent, covariates (Goovaerts, 1998). Basically, this approach aims to find a statistical relationship between the property to be predicted and a set of spatially exhaustive covariates. Once this relationship is established, the dependent property can be estimated for the area of interest.

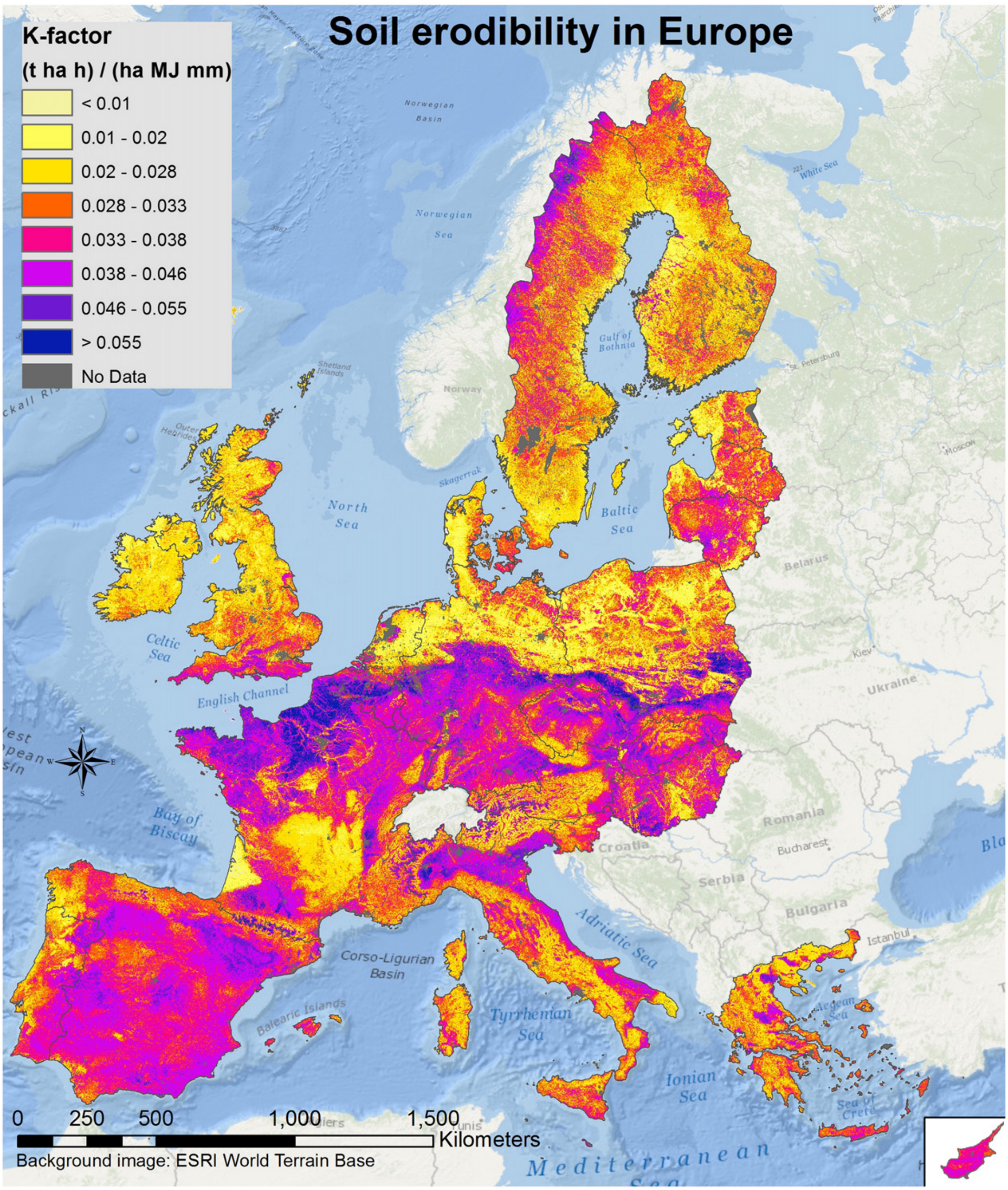

Fig. 2. High-resolution (500 m grid cell size) map of Soil Erodibility estimated as K-factor in the European Union.

2.3.1. Spatial analysis

In this study, the K-factor value of each LUCAS point sample was interpolated using a series of spatially exhaustive environmental descriptors (covariates) in order to derive a continuous map for Europe. An alternative approach would have been to apply the equation to interpolated maps of all the soil properties needed in Eq. (1). However, the latter approach has some critical drawbacks; first of all, every predicted property has its own error and (possibly) bias. This could lead to a misestimation of the K-factor which is not constant in the geographical space. Moreover, it is inherently simpler to evaluate the effect of covariates on the value of K-factor if this is directly modelled as such, and not as the combination of the mapped variables upon which the K-factor is calculated.

The approach followed in this study made the calculation in two stages. Firstly, the regression model based on the Cubist rule (Quinlan, 1992) was used to predict the value of the K-factor using a series of covariates. Cubist is a tree model where each terminal leaf contains a linear regression model. The prediction is made using the linear regression model at the terminal nodes of the tree smoothed by taking into account the predictions from previous nodes of the tree. Cubist makes an average of the sample value over a given neighbour (Quinlan, 1993). Once the first model is fitted, the nearest neighbours of a given instance can be averaged and used as the proxy value for that instance. This procedure avoids overfitting and makes the model more robust to outliers.

In the next stage, the residuals from the Cubist model were interpolated using Multilevel B-Splines (MBS) (Lee et al., 1997). In terms of accuracy and unbiasedness, MBS performs as well as kriging but it is computationally faster and allows an easy estimation of the interpolated field (K-factor).

Model performance was tested for both the fitting and a cross-validation dataset. In the bootstrapped cross-validation the random sampling with replacement 1/10 of the original dataset (mutually exclusive with the training set) was used as a validation sample. The bootstrap procedure was repeated 100 times to produce reliable estimates of the model predictive performance over LUCAS samples.

2.3.2. Verification

The proposed high-resolution dataset was validated against local and regional studies. An extensive review of published studies that use Eq. (1) was carried out. More than 100 soil erodibility assessments were found in the literature at local, regional or even national level (Hungary, Lithuania, Czech Republic and Slovakia). The authors contacted the scientists who developed those assessments and received replies and aggregated data of 21 published studies. The authors attempted to ensure the maximum representativeness for the whole study area (with at least one study for each country).

3. Results and discussion

3.1. Soil erodibility in Europe

The mean K-factor for the 25 Member States was calculated as 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} (Fig. 2). The range of values is 0.004–0.076 t ha h ha^{-1} MJ^{-1} mm^{-1}. The map (Fig. 2) does not include lakes, bare rocks, glaciers and urban areas.

The Cubist regression model predicted the pan-European distribution of the K-factor with a good performance as $R^2 = 0.4$ and RMSE = 0.0102 t ha h ha^{-1} MJ^{-1} mm^{-1} in k-fold cross validation. The interpolation using MBS further increased the prediction performance of the K-factor to an R^2 of 0.94 for the fitting dataset. Cross-validation gives a less good performance (R^2 of 0.74), given that part of the original LUCAS points are left out for the prediction.

The spatial pattern of areas with high soil erodibility (Fig. 2) largely follows the Loess map of Europe 1:2,500,000 according to Haase et al. (2007). The mean K-factor value for the Loess areas of Europe was estimated at 0.0419 t ha h ha^{-1} MJ^{-1} mm^{-1}. A comparison between the resulting K-factors and the textural classes of the European Soil Database shows that the highest mean values of the K-factor are in the medium–fine textural class (3), followed by the fine (4) and medium (2) classes, while the lowest mean values are recorded for coarse (1) and very fine (5) classes (Fig. 3). This follows the main rules of soil science that coarse particles are relatively heavy and fine particles have, due to their relatively large surface areas, high cohesion strength and thus are less susceptible to soil detachment. Thus, the medium sized texture classes are more prone to soil erosion. The organic soils (no mineral texture) have the lowest mean K-factor value.

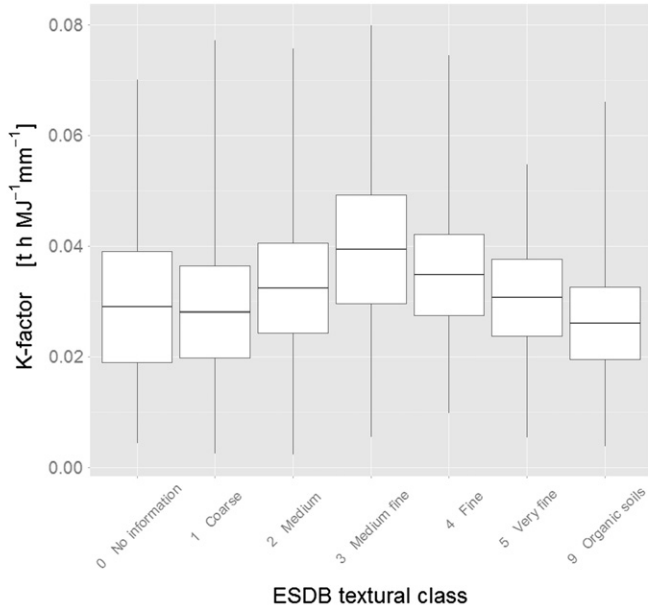

Fig. 3. K-factor compared to the European Soil Database (ESDB) soil surface texture classes.

Most of the soil samples belong to the Normal (N) soil structure class of the ESDB corresponding to the fine granular (class: 2). The majority of the samples had a moderate permeability class (3) which was corrected to moderate low (class: 4) with the incorporation of coarse fragments. A soil sample having as attributes the mean values (Table 4) of the input parameters of Eq. (1) will result in a K-factor equal to 0.032 t ha h ha^{-1} MJ^{-1} mm^{-1}.

The aggregated country-level statistics present an overview of the soil erodibility in Europe (Table 5). Organic matter has an important impact on the soil erodibility pattern as countries with high concentrations of organic matter have the lowest soil erodibility. Ireland, Estonia, Denmark, the Netherlands, the United Kingdom, Finland, Sweden and Latvia with high mean organic matter values (Jones et al., 2005) have mean soil erodibility values of less than 0.030 t ha h ha^{-1} MJ^{-1} mm^{-1}. On the other hand, the highest mean values (higher than 0.035 t ha h ha^{-1} MJ^{-1} mm^{-1}) are observed in

Table 4
Summary of input soil property values used for the estimation of the K-factor.

Eq. (1) attributes	Range	Mean value	Standard deviation
Organic matter (OM)	0–4%	3.08%	1.05%
Structure (S)	0, 1, 2, 3, 4	2[a]	
Permeability incorporating coarse fragments (P)	1, 2, 3, 4, 5, 6	4[a]	
Clay (m_c)	0–100%	18.5%	13.4%
Silt corrected (<70%) (m_{silt})	0–70%	35.5%	19.0%
Very fine sand (m_{vfs})	0–20%	8.1%	5.5%
K-factor (t ha h ha^{-1} MJ^{-1} mm^{-1})	0.004–0.076	0.0320	0.009

[a] Dominant value.

Table 5
Comparison of soil erodibility with and without considering surface stone content (K-factor and K_{st}-factor, respectively) per country.

Country		K-factor equation (Eq. (1))		K_{st}-factor stoniness	Reduction due to stoniness (%)
ISO	Name	Mean value (t ha h ha^{-1} MJ^{-1} mm^{-1})	Standard deviation (t ha h ha^{-1} MJ^{-1} mm^{-1})	Mean value (t ha h ha^{-1} MJ^{-1} mm^{-1})	
AT	Austria	0.0321	0.0080	0.0291	9.5%
BE	Belgium	0.0422	0.0092	0.0387	8.2%
CY	Cyprus	0.0362	0.0028	0.0265	26.8%
CZ	Czech Republic	0.0373	0.0076	0.0342	8.3%
DE	Germany	0.0334	0.0102	0.0311	7.0%
DK	Denmark	0.0246	0.0065	0.0225	8.7%
EE	Estonia	0.0254	0.0074	0.0242	4.5%
EL	Greece	0.0298	0.0057	0.0229	23.3%
ES	Spain	0.0368	0.0058	0.0265	27.9%
FI	Finland	0.0273	0.0058	0.0242	11.2%
FR	France	0.0356	0.0101	0.0284	20.1%
HU	Hungary	0.0349	0.0078	0.0337	3.3%
IE	Ireland	0.0234	0.0047	0.0216	7.4%
IT	Italy	0.0322	0.0077	0.0276	14.5%
LT	Lithuania	0.0321	0.0067	0.0309	3.8%
LU	Luxembourg	0.0392	0.0036	0.0345	11.9%
LV	Latvia	0.0290	0.0067	0.0281	3.2%
MT	Malta	0.0381	0.0022	0.0284	25.5%
NL	Netherlands	0.0246	0.0084	0.0236	3.9%
PL	Poland	0.0299	0.0106	0.0285	4.8%
PT	Portugal	0.0333	0.0069	0.0194	41.8%
SE	Sweden	0.0293	0.0068	0.0252	13.9%
SI	Slovenia	0.0313	0.0052	0.0282	9.6%
SK	Slovakia	0.0362	0.0074	0.0321	11.3%
UK	United Kingdom	0.0271	0.0063	0.0241	11.1%

Belgium, Luxembourg, central European countries (Slovakia, Czech Republic, and Hungary), Spain and France. Those relatively high values can be attributed partly to the Loess belt and partly to relatively lower organic matter content compared to the northern countries. The smallest variations were noticed in small countries (Cyprus, Malta and Luxembourg) with more homogenous regions, while higher variations were noticed in the Loess regions (Poland, Germany and Netherlands).

3.2. The effect of surface stone cover (stoniness)

The K_{st} values of the LUCAS points were interpolated using the same methods and covariates as for the K-factor. The Cubist model for the K_{st}-factor prediction performed with $R^2 = 0.31$ and an RMSE = 0.0081 t ha h ha^{-1} MJ^{-1} mm^{-1} for the k-fold cross validation. The MBS was used to model the spatial distribution of the residuals. The resulting K_{st}-factor map (Fig. 4) is slightly different compared to the K-factor map (Fig. 2). The mean K_{st}-factor value is 0.0271 t ha h ha^{-1} MJ^{-1} mm^{-1} with a standard deviation of 0.0087 t ha h ha^{-1} MJ^{-1} mm^{-1}. The range is 0.001–0.0737 t ha h ha^{-1} MJ^{-1} mm^{-1}. The application of the stoniness correction factor (St) reduces the K-factor on average by 15%. The stoniness effect is much stronger in the Mediterranean Basin, as also confirmed by past studies (Danalatos et al., 1995; Poesen et al., 1998).

The considerable effect of surface stone cover (named stoniness in the following) on soil erodibility in the Mediterranean Basin has also been presented in recent studies (Zavala et al., 2010). The effect of high stoniness can be greater than the protection of vegetation in limiting soil loss. The protective effect of stoniness is strongest in Portugal, Spain, Greece and France (Table 5) where it reduces the K-factor by 20–42%. In contrast, stoniness reduces soil erodibility by less than 5% in the Baltic States, Poland, Hungary and the Netherlands (Table 5). The regional effect of stoniness, visualised as percentage reduction map (Fig. 5) is most pronounced in eastern Portugal, western Spain, southern France, the Italian islands and southern Greece (Fig. 5).

The impact of stoniness on the K-factor was included for the first time at European scale. This is a major improvement of the former K-factor map. As a future development for the next LUCAS 2015 soil survey, a larger number of stoniness classes (more than the 5 classes in Table 3) could be made available to the surveyors and targeted training could be given on how to estimate this attribute. As past research (Poesen et al., 1994) proved that the presence of surface-level stones can lead to an exponential decrease in soil erosion, soil erosion modellers should also take the K_{st}-factor into account.

3.3. Mapping of soil erodibility and related uncertainties

The application of Cubist regression interpolation for the development of the high-resolution soil erodibility map facilitates the identification of the dependencies of the K-factor on other covariates such as geo-morphometric indices, hydrology, topography, elevation and land cover. As the covariates are available in high resolution (≤500 m), the values can be interpolated to the pixels between the sampled points with much better accuracy than with the inverse weighted distance method and the spatial variability can be modelled.

The variable importance is defined as the relevant proportion (%) of K-factor variance which is explained by a given variable (Fig. 6). The selection of variables for the Cubist model and the variable importance was performed using Recursive Feature Elimination (RFE) (Iguyon and Elisseeff, 2003). The variables were ranked in relation to their influence on the overall performance of the model (Cross validation — RMSE) and model complexity (number of rules in the Cubist model). Variables whose removal significantly increases the RMSE of the model are retained while variables with little influence are not taken into account in the model. Latitude is the most important variable and the significance of the remaining 19 variables is relative to the latitude.

MODIS derived products (Fig. 6) are indicated by a prefix such as "red", "nir" (Near Infrared), "mir" (Medium Infrared) and "EVI" (Enhanced Vegetation Index). The suffixes "_PCAb1", "_PCAb2", etc. correspond to the 1st, 2nd, etc. axes of the Principal Component Analysis (PCA) performed on said MODIS products over a time frame of 1 year (2009). Regarding the rest of the variables (Fig. 6), 'level' is the channel network base level (Böhner and Antonić, 2009), 'network' represents the altitude above channel network (Böhner and Antonić, 2009), 'IGBP' is the MODIS global land cover (Friedl et al., 2010), 'gradient' is the downslope distance gradient (Hjerdt et al., 2004)

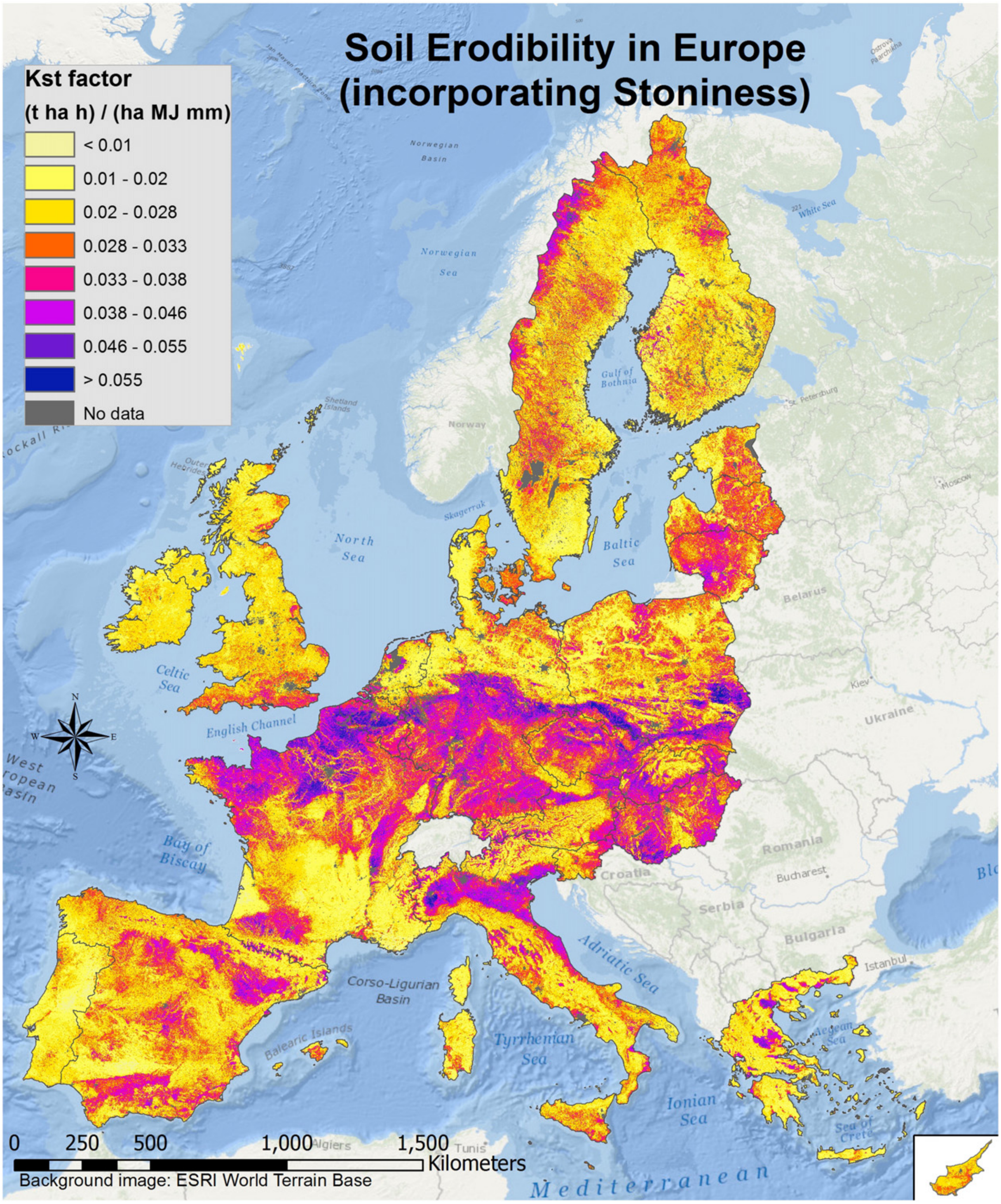

Fig. 4. High-resolution (500 m grid cell size) map of Soil Erodibility estimated as K-factor in the European Union, incorporating stoniness.

and 'flatness' is the multi-resolution index of valley bottom flatness (Gallant and Dowling, 2003). The remaining variable names are self-explanatory.

Since soil erodibility is a result of complex relationships between soil properties, the authors attempted to identify the impact of a change in one input parameter on soil erodibility, keeping all the other attributes constant. The uncertainty analysis is also related to the three adaptions of the methodology (mentioned above). For example, high soil organic carbon values contribute to low K-factor values. If the input attributes are considered to be representative of the whole dataset (Table 4), then an increase in organic matter to 4% (from 3.08%) will lead to a 9% decrease in the soil erodibility (K-factor = 0.0294). The application of a 4% limit to soil organic matter (as required by the nomograph of Wishmeier and Smith) is not taken into account in many regional assessments, which results in lower K-factor values. A possible solution would be a correction with an experimental mathematical curve of the effect of organic matter in those cases where organic matter levels are higher than 4%.

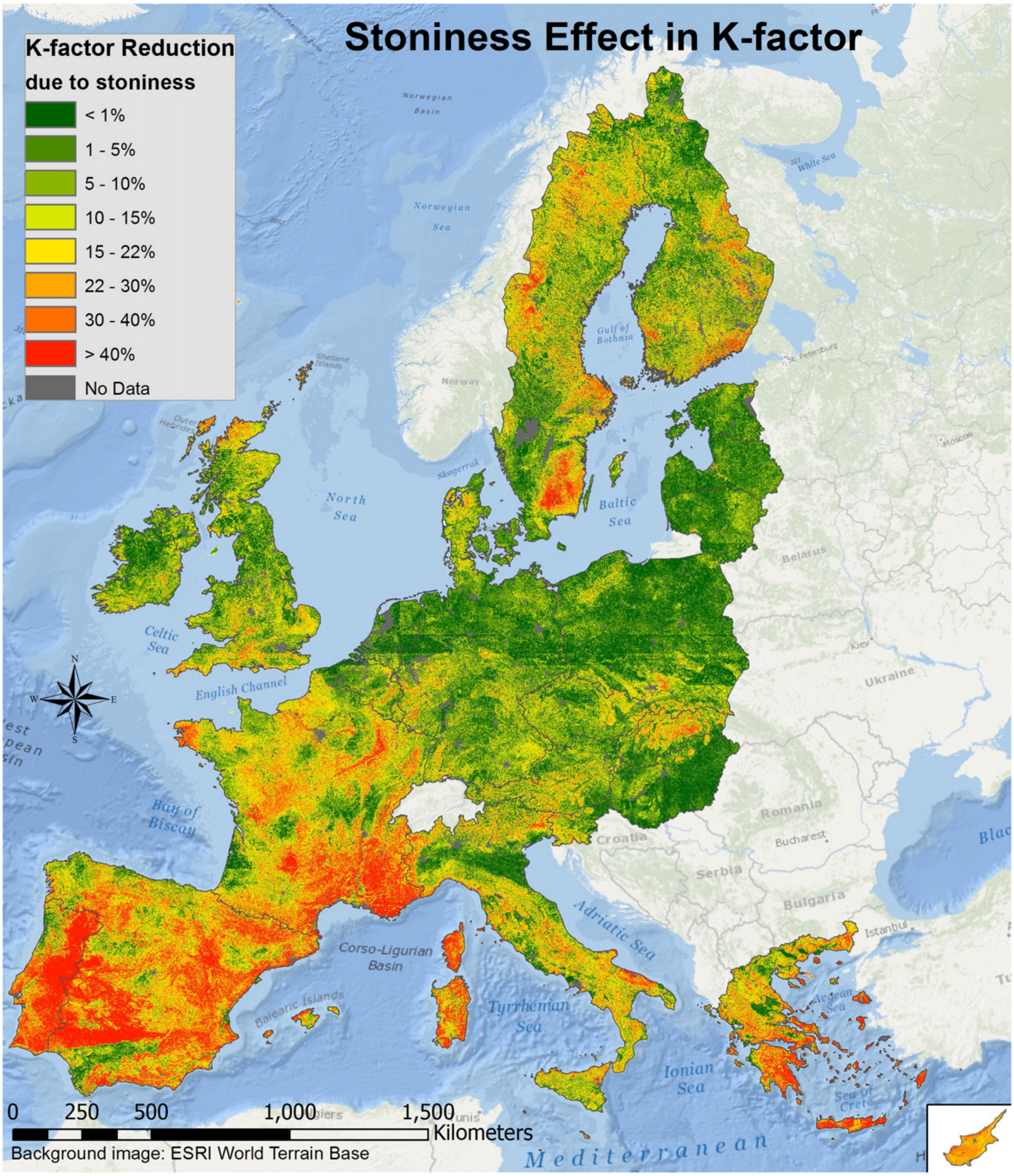

Fig. 5. Reduction in soil erodibility due to the protective effect of stones covering the soil surface (stoniness).

If the belowground coarse fragments were not taken into account, the permeability class would be much lower, with a dominant value of 3 (compared to actual 4), and the average calculated soil erodibility would have been 15% lower (K-factor = 0.0279).

If the soil structure was not considered in Eq. (1), then the soil erodibility would have decreased by an average of 2.5% (K-factor = 0.0313). In most cases, soil erosion modellers ignore both permeability and soil structure due to a lack of data. In these cases, the mean decrease of soil erodibility would be around 16.3% (K-factor = 0.0276).

The very fine sand fraction is estimated to be around 20% of the total sand fraction. If the very fine sand fraction is taken to be 33.3% of the total, then the soil erodibility will increase by 11% (K-factor = 0.0361).

3.4. Comparison of K-factor estimates to local and regional assessments

Scientists of most countries provided datasets or aggregated data of K factors (Table 6: column d). However, no studies with soil erodibility reference data were found for the United Kingdom and Nordic countries, even though our literature review on soil erodibility was extensive.

The findings in the literature are heterogeneous in scale (from plot data to national level), nonetheless all were taken into account for the verification of K-factor dataset. None of these literature studies have included the stoniness effect. The comparison of K-factor/K_{st}-factor with the literature results is performed by the absolute deviation (%)

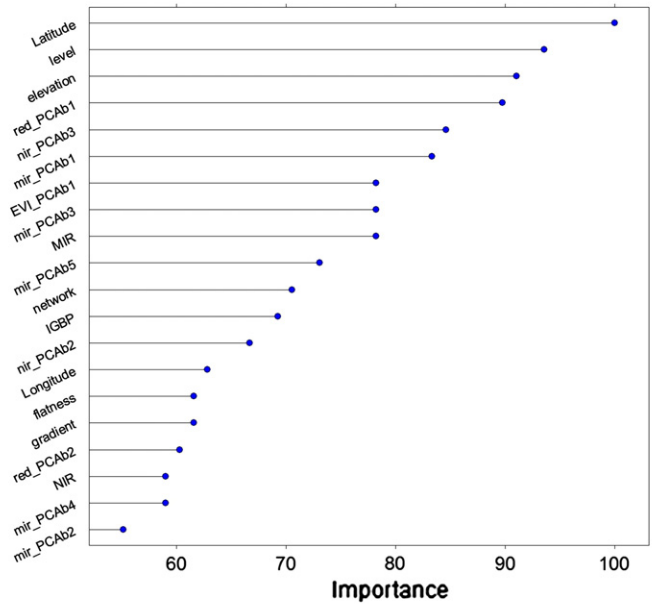

Fig. 6. The twenty most important covariates and their relative importance in the application of Cubist/MBS model for K-factor interpolation.

(Table 6: columns g, h). The sign (−) is applied in case the aggregated K-factor/K_{st}-factor data are lower than the ones found in the literature.

The comparison of our K-factor (Table 6: column e) against the regional studies (Table 6: column d) shows a deviation of about 14.3% in absolute terms (Table 6: column g). In most of the cases, K-factor mean values are higher than those of the regional studies, with the exception of the Lithuanian study, two local Polish studies and French catchment. At national and regional levels, the correspondence of K-factor to the study area aggregated data was very positive with the exception of Brandenburg (Deumlich, 2009) where the permeability had not been taken into consideration. The 14.3% average deviation can be attributed to either the application of the 4% limit in organic matter or to the incorporation of coarse fragments in the calculation of the permeability. However, the very good correspondence of K-factor with literature data at local and regional scales shows how the soil erodibility equation can be successfully applied at the European scale.

The relative agreement between the stoniness-corrected (K_{st}-factor) and the literature data is almost equally good. The K_{st}-factor (Table 6: column f) has an average deviation of 18.0% compared to the literature studies (Table 6: column h) and especially for the Mediterranean countries the change towards smaller K-factor values is considerable. Thus, neglecting surface stone cover will likely result in an overestimation of soil erosion risk in these countries.

4. Conclusions

The presented soil erodibility map (Fig. 2) is an important contribution to the estimation of soil erosion from local to European scales, as the K-factor is very crucial among the input factors used to estimate soil loss according to RUSLE and other models. In addition, the K-factor can usually not easily be determined or calculated by individual soil erosion modellers with no extensive data access. With the publication of this study, modellers and in general scientists will be able to download the high-resolution datasets (K-factor, K_{st}-factor) from the European Soil Data Centre.

Compared with past attempts to predict soil erodibility at the European level (Van der Knijff et al., 2000), the presented K-factor dataset has the advantage of pan-European harmonised soil data. In addition, topsoil data was collected within one year (2009) all across Europe and analysed by the same ISO-certified laboratory. Furthermore, the past approach to map soil erodibility at European scale (Van der Knijff et al., 2000) was based on 5 estimated textural classes of large soil mapping units of the European Soil Database while the new K-factor dataset is based on measured values.

The proposed model provides a framework for the digital soil mapping of the soil erodibility at continental scale. The Cubist regression model successfully established the relation between the K-factor and environmental features with the advantage of explaining the spatial distribution of soil erodibility. This also improves the spatial accuracy of the end product and allows establishing rules upon which the K-factor can be estimated from remotely sensed data.

Table 6
Comparison of K-factor estimates with local/regional/national studies.

Catchment/region (country) (a)	Coverage (no of points) (b)	Reference study (c)	K-factor of reference study (d)	K-factor (Fig. 2) (e)	K_{st} factor (Fig. 4) (f)	Deviation of K-factor vs. study (g)	Deviation of K_{st}-factor vs. study (h)
			Mean value (t ha h ha^{-1} MJ^{-1} mm^{-1})			(%)	
Hungary (HU)	National (2851)	Centeri and Pataki (2000)	0.0293	0.0349	0.0337	16.0%	13.1%
Slovakia (SK)	National	Styk et al. (2008)	0.029	0.0362	0.0321	19.9%	9.7%
Czech Republic (CZ)	National	Dostal et al. (2002)	0.0376	0.0373	0.0342	(−) 0.8%	(−) 9.9%
Lithuania (LT)	National	Mažvila et al. (2010)	0.035	0.0321	0.0309	(−) 9.0%	(−) 13.3%
Hessen federal state (DE)	Regional	Tetzlaff et al. (2013)	0.0400	0.0411	0.0382	2.6%	(−) 4.8%
Bavaria federal state (DE)	Regional (1051)	Auerswald (1992)	0.0331	0.0367	0.0337	9.7%	1.8%
Nordrhein-Westfalen federal state (DE)	Regional	Elhaus (2013)	0.033	0.0370	0.0337	10.7%	2.2%
Brandenburg federal state (DE)	Regional	Deumlich (2009)	0.0163	0.0232	0.0223	29.7%	27.0%
Region of Sicily (IT)	Regional (1813)	Bagarello et al. (2012)	0.0291	0.0300	0.0230	3.2%	(−) 26.7%
Geul catchment (Maastricht, NL)	Regional	de Moor and Verstraeten (2008)	0.0420	0.0449	0.0383	6.5%	(−) 9.6%
Strymonas (GR)	Regional	Panagos et al. (2012b)	0.0241	0.0292	0.0247	17.4%	2.3%
Andalucia (ES)	Regional (8)	Ruiz-Sinoga and Diaz (2010)	0.0303	0.0379	0.0245	20.1%	(−) 23.7%
Sele Catchment, Basilicata (IT)	Regional	Diodato et al. (2011)	0.026	0.0269	0.0230	3.5%	(−) 13.2%
Lautaret, Province Alps-Cote d'Azur (FR)	Local	Bakker et al. (2008)	0.037	0.0344	0.0254	(−) 7.6%	(−) 45.7%
Yialias River Catchment (CY)	Local	Alexakis et al. (2013)	0.0261	0.0378	0.0280	30.9%	6.6%
Gregos (PT)	Local (97)	Ferreira and Panagopoulos (2010)	0.0344	0.0383	0.0215	10.2%	(−) 60.2%
Pico (PT)	Local (25)	Ferreira and Panagopoulos (2010)	0.0290	0.0394	0.0192	26.4%	(−) 50.9%
Roncão (PT)	Local (82)	Ferreira and Panagopoulos (2010)	0.0229	0.0382	0.0201	40.1%	(−) 13.7%
Bogucin, Poznan (PL)	Local	Rejman et al. (2008)	0.0598	0.0623	0.0594	4.1%	(−) 0.7%
Lazy, Carpathian foothill (PL)	Local (7 plots)	Swiechowicz (2010)	0.0738	0.0588	0.0552	(−) 25.6%	(−) 33.8%
Lublin, South Warsaw (PL)	Local	Wawer et al. (2005)	0.0285	0.0267	0.0261	(−) 6.6%	(−) 9.2%
Overall average	21 studies		0.0344	0.0373	0.0308	14.3%	18.0.%

Another advantage is that the remote sensing products are constantly updated giving the possibility for dynamic prediction of the K-factor. On the contrary, the used remote sensing products are not tailed for the prediction of soil properties and this possibly limits the model accuracy.

The high-resolution soil erodibility map (Fig. 2) incorporates certain improvements over the coarse-resolution map (Panagos et al., 2012a):

- Soil structure was for the first time included in the K-factor estimation.
- Coarse fragments were taken into account for the better estimation of soil permeability.
- Surface stone content, which acts as protection against soil erosion was for the first time included in the K-factor estimation. This correction is of great interest for the Mediterranean countries where stoniness is an important regulating parameter of soil erosion.

Soil erodibility, together with management practices (P-factor) and vegetation cover (C-factor) can be influenced by agricultural practices. Therefore, the K-factor dataset can be a guide for applying better conservation practices (e.g., increase or preserve soil organic carbon in areas prone to high levels of soil erosion risk or adaption of soil management at areas of high risk).

The K-factor dataset may also be proposed as an index for the vulnerability of ecosystems. The soil erodibility maps (Figs. 2, 4) delineate areas where soil reaction to erosive rainfall events is considerably high. Areas where the stoniness effect is relatively low (<10%) and soil erodibility is still high ($K_{st} > 0.046$ t ha h ha^{-1} MJ^{-1} mm^{-1}) should be treated with considerable care in terms of agricultural practices and vegetation cover. For example, dependent on the force and timing of erosive rain events, local/regional policies can classify those areas as being ecologically vulnerable and propose the application of permanent crops or permanent grasslands.

The study also identified possible future improvements that can be made in the future LUCAS topsoil 2015 data collection process. Data analysis of the fraction of very fine sand and hydraulic conductivity would certainly improve the textural and permeability calculation factors, and lead to more precise estimations of soil erodibility.

Conflict of interest

The authors confirm and sign that there is no conflict of interests with networks, organisations, and data centres referred in the paper.

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