Soil Erosion modelling at European scale by using high resolution input layers

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9.1 Proof of submission in CATENA journal (Chapter 5)

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Summary - Introduction

Soil erosion by water is one of the most widespread forms of soil degradation. 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. The RUSLE is the simple multiplication of 5 soil erosion risk factors:

- Soil erodibility (K-factor)
- Rainfall erosivity (R-factor)
- Cover and management (C-factor)
- Support practices (P-factor)
- Slope length and Steepness (LS-factor)

The PhD study proposes a new soil erosion map of Europe (RUSLE2015) which has the following characteristics:

- It is based on peer review and high quality input factors
- The factors are composite layers: K-factor includes stoniness, C-factor includes Management Practices (tillage practices, cover crops, plant residues) and Vegetation fraction through remote sensing, R-factor includes high temporal resolution precipitation measurements of 1541 stations, P-factor includes support practices (contouring, stone walls, grass margins) and LS-factor is based on 25m Digital Elevation Model.
- has a very fine resolution of 100m
- allows land use and management scenarios and can be used by policy makers
- makes the data available in European Soil Data Centre (ESDAC)
- it is proposed in a transparent way and follows the literature principles

The first chapter makes a comparison of the pan-European soil erosion data collection (named EIONET-SOIL) with the modelled data from PESERA. This data collection concluded that almost all member states of the European Union are using (R)USLE models for the estimation of soil erosion. The paper identified the areas with high discrepancies between the two different soil erosion estimation approaches. By concluding this study, I have decided to use a RUSLE approach at European scale due to limitations of PESERA and data availability from Member states using RUSLE.

The second chapter includes the key parameter for modelling soil erosion which is the soil erodibility, expressed as the K-factor. The soil erodibility 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.

The third chapter proposes a new soil erosion model named G2 which uses the empirical formulas of the Universal Soil Loss Equation (USLE). The difference is that G2 makes allows for the integrated spatio-temporal monitoring of soil erosion as the Rainfall erosivity (R-factor) and Vegetation retention (V-factor; known as C-factor in USLE) are proposed on a monthly temporal resolution. This study in Crete (Greece) allowed to deep the knowledge of each erosion factors which are to be modelled at European scale.

The fourth chapter assesses rainfall erosivity in Europe in the form of the RUSLE R-factor, based on the best available datasets. Data have been collected from 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.

The fifth chapter assesses rainfall erosivity in Greece on a monthly basis in the form of the RUSLE R-factor, based on 30-minutes data from 80 precipitation stations covering an average period of almost 30 years. The proposed R-factor spatio-temporal analysis shows a high intra-annual variability of rainfall erosivity which should also be investigated in whole Europe.

The sixth chapter presents the cover-management factor (C-factor) which is considered to be the most important because policy makers and farmers can intervene and, as a consequence, may reduce soil erosion rates. In arable lands, the C-factor was estimated using crop statistics (% of land per crop) and management practices data such as conservation tillage, plant residues and winter crops. The C-factor in non-arable lands was estimated by weighting the range of literature values found by fractional vegetation cover, which was estimated based on the remote sensing datasets.

The seventh chapter assesses support practice factor (P-factor) which is rarely taken into account in soil erosion risk modelling. The P-factor model considers the latest policy developments in the Common Agricultural Policy (contour farming) and the impact of stone walls and grass margins in reducing soil loss. The P-factor modelling tool can potentially be used by policy makers to run soil-erosion risk scenarios.

The eight chapter proposes an overview of the RUSLE2015 model and presents the final soil erosion map of Europe based on the input layers discussed in previous chapters. This concluding chapter makes an assessment of the soil erosion map per land use, region and per class of soil erosion. The verification of the map with other data sources has been satisfactory. Finally, this chapter proposes the use of soil erosion map for policy making in European Union and predicts the soil erosion trends based on land management and land use changes.

The first 4 chapters are published in peer review journals. The 5th chapter is under revision after initial acceptance, the 6th and 7th chapters have initially been accepted (under second revision) and editors have requested some changes. The concluding chapter (9th) has been submitted in February in a high impact factor peer review journal.

CHAPTER 1

Assessing soil erosion in Europe based on data collected through a European network

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ORIGINAL ARTICLE

Assessing soil erosion in Europe based on data collected through a European network

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Abstract

The European Commission Directorate-General for the Environment (DG Environment) and the European Environmental Agency (EEA) have identified soil organic matter conservation and mitigation of soil loss by erosion as priorities for the collection of policy-relevant soil data at the European scale. In order to support European Union (EU) soil management policies, soil quality indicators are required that can be applied using harmonized data for the EU Member States. In 2010, the European Soil Data Centre (ESDAC) of the European Commission conducted a project to collect data on soil erosion from national institutions in Europe, using the European Environment Information and Observation Network for soil (EIONET-SOIL). The aim of this paper is to present a selection of the results obtained for soil erosion from the participating countries. The data collected were compared with estimates of soil loss using the Pan-European Soil Erosion Risk Assessment (PESERA) model, and aggregated soil erosion data from pan-European experimental plot studies. The comparison focuses on eight countries for which complete soil erosion data have been received. Overall, the mean values of soil loss reported by the national institutes (EIONET-SOIL) are larger than the PESERA estimates, with the main differences being for sloping land (> 2°) and for the land cover type forest and heterogeneous agricultural [land cover types according to CORINE ("coordination of information on the environment") Land Cover 2006].

Key words: soil erosion, EIONET, data collection, PESERA, USLE, RUSLE.

INTRODUCTION

Many national and international environmental protection agencies have already recognized soil degradation, e.g., decline in soil carbon and biodiversity, as a serious problem, and launched programmes (e.g., the 6th Environmental Action Programme, United Nations Sustainable Development (UNCED) Agenda 21) to monitor progress towards achieving sustainable management of land in the foreseeable future. In this context, reporting systems based on environmental indicators have been established to measure environmental problems, compare differences between geographical areas and monitor changes over time (Gobin *et al.* 2004). Soil erosion is a major process of degradation that has been identified as a key priority for action within the Soil Thematic Strategy of the European Commission (2006a, 2006b).

Soil erosion is a natural process that has been largely responsible for shaping the physical landscape of today through distribution of the weathered materials produced by geomorphic processes. When the term "soil erosion" is used in the context of being a threat to soil, it refers to "accelerated soil erosion", i.e., "Soil erosion, as a result of anthropogenic activity, in excess of accepted rates of natural soil formation, causing a deterioration or loss of one or more soil functions" (Jones *et al.* 2008).

Soil erosion has many causes and involves several mechanisms. Soil erosion by water occurs through rills, inter-rills and gullies, as a result of rainfall, snowmelt and slumping of banks alongside rivers and lakes.

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Disturbance or translocation erosion results from tillage, land levelling, harvesting of root crops and trampling or burrowing by animals. Wind erosion is caused by strong air movements displacing bare soil particles, and wave action erodes the coast. Landslides and debris flows are other significant erosion processes, and a hidden form is dissolution erosion by underground water flows, dissolving mainly carbonate soil minerals (Jones *et al.* 2004). The Environmental Assessment of Soil for Monitoring (ENVASSO) Project has identified and examined the performance of a number of soil erosion indicators, concluding that to be useful for environmental protection, an indicator must be quantitative, objectively calculated, validated against measurements and evaluated by experts (Huber *et al.* 2008).

However, policy makers call for an overall assessment of the soil erosion in geographical areas of interest and urge that risk areas for soil erosion, under present land use and climate, should be mapped, such that appropriate measures to control erosion, within the legal and social context of natural resource management, can be taken (Jetten *et al.* 1999). Based on such information, and depending on data availability and reliability, local/national/European authorities should be able to respond to the questions "where, how much, by what means, and when, erosion occurs" (Boardman 2006).

The consequences of soil erosion for society are relatively severe, estimated by Pimentel *et al.* (1995) to cost $44 billion each year in the USA. In Europe, erosion has been estimated to affect 115 million ha (SOER 2010; Kibblewhite *et al.* 2012). In response to the recent developments in soil policy at the European level, the European Soil Data Centre (ESDAC) has been established at the Joint Research Centre, Ispra (I) (Panagos *et al.* 2012), to provide a mechanism for reporting critical information on soil in the European Union (EU) Member States.

ESDAC has made use of the European Environment Information and Observation Network for Soil (EIONET-SOIL), requesting participating institutes (the National Reference Centres for Soil) to provide their best data on actual soil erosion. Soil erosion by water is a widespread problem throughout Europe and accounts for the largest soil losses. Therefore, although coming from different sources, the EIONET-SOIL erosion data can be assumed to be mainly soil loss by water erosion. Because actual soil erosion is particularly difficult to measure directly, it is necessary to use models that predict soil loss from causal parameters that exist for areas where no measurements of soil loss have been made or are feasible. A number of such models to estimate soil erosion risk exist but the data most commonly reported by EIONET-SOIL come from application of the Universal Soil Loss Equation (USLE) (Wischmeier and Smith 1978), and its more recent version, the Revised Universal Soil Loss Equation (RUSLE) revised by Renard *et al.* (1997).

The objective of this paper is to evaluate soil erosion data collected from Member States through EIONET-SOIL by comparing to estimates of soil loss by the Pan-European Soil Erosion Risk Assessment (PESERA). The comparison will allow for the identification of areas with high discrepancies between the different soil erosion estimation approaches and, thus, will help to define regions where validation or further model development is most needed. Available erosion rates measured on plots have also been used for further verification of the comparison.

MATERIALS AND METHODS

The study first describes the data collected through EIONET-SOIL and then the comparison of these data with soil losses modelled by PESERA. The assessment and the comparison are restricted to the geographic cover of the data received: Austria, Belgium, Bulgaria, Germany, Italy, Netherlands, Poland and Slovakia. The current findings could have had greater value if large countries (Romania, Sweden, Finland, United Kingdom) or countries with potentially large soil loss (Spain, Greece, Portugal) had contributed to the data collection. The main reason for the limited participation was that national institutes were requested to submit data on a voluntary basis.

The soil erosion indicator adopted for this paper is the estimated soil loss expressed in tonnes per hectare per year (t ha^{-1} y^{-1}) as described in detail by Huber *et al.* (2008).

EIONET-SOIL data

The EIONET-SOIL erosion data evaluated in this study were collected and managed by ESDAC. The data were collected in 2010 through the EIONET network, which consists of representative organizations from 38 European countries (27 Member States of the European Union plus other Associated European countries). In 2010, ESDAC invited the EIONET members to contribute to a data collection campaign to develop European datasets for soil erosion and soil organic carbon (SOC).

ESDAC adopted a "light" data collection protocol that summarised SOC and soil erosion data on a grid of 1 km × 1 km assigned to each country according to the Directive for an Infrastructure for Spatial Information in the European Community (INSPIRE) (INSPIRE 2007). For soil erosion, the grid values were expressed in tonnes per hectare per year (t ha^{-1} y^{-1}). The data collection protocol defined by ESDAC requested the soil erosion data to include only erosion caused by water (rill and interrill, sheet) and not other types of erosion such as wind, tillage or mass movement/landslides. The EIONET data providers were also requested to include explicit metadata that would allow the correct interpretation of the submitted data. The information requested in the metadata includes the method used for soil erosion estimation and the land use types covered (Table 1). The data provided are estimated based on either the USLE or the RUSLE model. The main input layers for those models are rainfall erosivity (R-factor), soil erodibility (K-factor), vegetation cover (C-factor), slope length and slope angle (LS-factors) and the support practice (P-factor) (Table 1).

Pan-European Soil Erosion Risk Assessment (PESERA)

PESERA was an EU-funded project running in the 5th Framework Programme (FP5) for research aimed at developing a pan-European soil erosion model. PESERA is a process-based model designed to estimate long-term average soil erosion rates at a 1-km resolution (Kirkby *et al.* 2008) and has been applied to most of the European territory. PESERA erosion rates are considered

Table 1 Metadata (soil erosion estimation) reported per country in the European Environment Information and Observation Network for soil (EIONET-SOIL) dataset

Country	Number of 1 km cells	Area coverage with erosion value	Method and land use covered	Input layers (factors)
	No.	%		
Austria	83,338	97.6	Method: Combination of USLE and RUSLE Coverage: all land-cover types	R: Mean annual rainfall 1961–90 (Strauss *et al.* 1995) K: 1: 25,000 (Strauss 2003) C: CLC 2000 (Aubrecht 1998) LS: DEM 10 m
Belgium	17,534	87.3	Method: RUSLE Coverage: all land-cover types (except for urban areas)	R: (not reported) K: Nearing (1997) C: (not reported) LS: Desmet and Govers (1996).
Bulgaria	102,443	91.2	Method: USLE Coverage: all land-cover types	R: Rouseva *et al.* (2006) K: 1: 400,000 soil map of Bulgaria C: CLC 2006 LS: DEM 20 m
Germany	168,359	46.6	Method: USLE Coverage: agricultural land	R: Mean annual precipitation (1 km cells) for the period 1971–2000 K: Soil Map of Germany 1:1,000,000 (BÜK 1000) C: Phenological monitoring data and agricultural statistical census LS: Digital terrain model (DTM) at 25 m
Italy	151,008	49.2	Method: RUSLE Coverage: 9 regions provided data using different rainfall erosivity estimation	See Table 5.
Netherlands	36,560	94.7	Method: RUSLE Coverage: all land-cover types (except for urban areas)	R: erosivity factor of 595 for the whole country K: Dutch Soil map 1: 50,000 (Kempen *et al.* 2009) C: Land use map HGN 2004 at 1:10,000 scale LS: DEM based on Actual Height Model (AHN-25 m)(Scholten 2006)
Poland	220,090	70.1	Method: USLE Coverage: agricultural land	R: DEM and use of relationship between altitude and precipitation (Licznar 2006) K, C: Soil map of Poland 1:250,000 (IUNG) LS: DEM 40 m
Slovakia	49,705	99.5	Method: USLE Coverage: all land-cover types	R: Interpolation of 86 stations (Styk and Pálka 2007) K: Interpolation of 17,000 soil profiles (Styk *et al.* 2008). C: Average of main crops (2010) LS: Digital terrain model (DTM) at 20 m

USLE, Universal Soil Loss Equation; RUSLE, Revised Universal Soil Loss Equation.

Table 2 European Environment Information and Observation Network for soil (EIONET-SOIL), Pan-European Soil Erosion Risk Assessment (PESERA) (Kirkby *et al.* 2008) soil erosion estimates and aggregated soil erosion plot measurements (Cerdan *et al.* 2010) for the entire dataset provided and the intersecting areas

	Soil erosion per dataset			Soil erosion for intersecting areas (common pixels)		Erosion ratio	Coefficient of variation (CV) for intersecting areas	
Country	EIONET [(a)]	Pesera [(b)]	Plot[(c)]	EIONET [(d)]	Pesera [(e)]	F_{common}* [(d/e)]	EIONET [(f)]	Pesera [(g)]
Austria	0.66	0.45	1.6	0.70	0.45	1.6	2.8	4.2
Belgium	3.65	1.07	1.4	3.70	1.10	3.4	1.1	2.1
Bulgaria	1.88	0.56	1.9	1.92	0.61	3.2	1.4	2.7
Germany	1.40	0.89	1.9	1.40	1.30	1.1	1.5	2.3
Italy	6.60	2.70	2.3	6.95	2.69	2.6	2.0	3.3
Netherlands	0.25	0.08	0.4	0.26	0.08	3.2	4.0	3.4
Poland	1.46	0.67	1.5	1.47	0.83	1.8	1.9	1.8
Slovakia	1.04	1.29	3.2	1.06	1.29	0.8	1.5	2.7

*F_{common} = Ratio between national average values for EIONET-SOIL and PESERA.

to be the total amount of sediment delivered to the base of hill slope within each pixel.

The PESERA model combines the effects of topography, climate, vegetation (land cover) and soil into a single integrated calculation of soil erosion. The climate input layers include mean monthly data (temperature, rainfall, evaporation) interpolated at a 1-km grid cell (Jones *et al.* 2003) from Monitoring Agriculture with Remote Sensing (MARS) meteorological database of a 50-km grid cell. The input land use layers are based on CORINE ("coordination of information on the environment") 1990 (land cover types, dominant arable crop, etc.) resampled at a 1-km grid cell. The soil input data are based on the European Soil Database (ESDB) at 1:1,000,000 resolution (King *et al.* 1994; King and Jamagne 1995). The input ESDB attributes such as texture, erodibility and crusting have qualitative class values that were interpreted to numerical values. The topographic input data are based on GTOPO30 which is a global digital elevation model (DEM) with a horizontal grid spacing of 30 arc seconds.

The PESERA dataset and the detailed technical description of the model are freely available from ESDAC (Panagos *et al.* 2012).

European soil erosion estimates based on plot data

In 2010, an extensive database of erosion rates measured on plots in Europe under natural rainfall was compiled (Cerdan *et al.* 2010). The authors gathered plot data from the literature and through personal communication. They used correction factors for topography and soil properties to extrapolate the plot results to the European territory.The aggregated statistics at national level from the database of plot measured erosion rates in Europe (Cerdan *et al.* 2010) were used in this study (Table 2, column c).

Other datasets

CORINE Land Cover 2006 (CLC 2006) is a map of the European environmental landscape based on interpretation of satellite images. CORINE means "coordination of information on the environment" and provides comparable digital maps of land cover for much of Europe at resolution of 100 m. The standard CORINE nomenclature includes 44 land cover classes.

The Shuttle Radar Topography Mission (SRTM) DEM resampled at a 100-m resolution was used to generate a slope dataset with continuous values from 0° to 90°.

Data harmonization and comparison

The PESERA dataset has a significant number of no-data areas as can be noticed in Fig. 2 and 3. The dataset used to compute the PESERA estimates ignores sealed areas (towns, cities, roads, etc), water bodies (lakes, rivers), glaciers (e.g., the Alpine areas in Austria), rocks and areas where rice fields are grown (e.g., Lombardy and Piedmont in Italy). For most EIONET countries, data were provided for all land-cover types. Thus, the EIONET-SOIL erosion dataset covers more pixels than the PESERA dataset. In order to harmonize the spatial extent allowing for reliable comparative analysis, an EIONET-SOIL/PESERA intersection mask (on a pixel basis) was derived and applied for the comparison. The comparison between PESERA and EIONET-SOIL takes into account only those cells for which both datasets have a value. The output of the comparison was a difference dataset expressing the mathematical function: EIONET-SOIL minus PESERA (on a pixel basis).

Stratification per land cover type for both EIONET-SOIL and PESERA was applied by using CORINE Land Cover 2006 at resolution of 100 m. Stratification per slope was applied using the slope dataset derived from SRTM at resolution of 100 m. For each pixel where both an EIONET-SOIL and a PESERA value existed (intersection areas), the difference (EIONET-SOIL minus PESERA), the land cover type and the slope were obtained.

Moreover, the aggregated EIONET-SOIL and PESERA erosion rates were also compared with the available erosion rates as measured plots in Europe (Cerdan *et al.* 2010).

RESULTS

Erosion estimates after EIONET-SOIL

Soil erosion data were received from only 14 out of 38 EIONET countries. Eight EIONET countries provided complete or almost complete (covering more than 50% of the country) data according to the specifications set in the data request. Table 1 gives an overview of the metadata received. The other six countries provided data that could not serve in a nationwide comparison. France and Denmark provided only classes of soil erosion risk; the former Yugoslav Republic of Macedonia (FYROM) provided a complete dataset in non-comparable measuring units; Ireland provided PESERA estimates; Norway and Estonia provided data for a limited spatial coverage. All the data received resulted from modelling.

The metadata analysis shows that most data providers are using USLE (Wischmeier and Smith 1978) or RUSLE (Renard *et al.* 1997) modelling approaches, with the exception of France, which uses the Modèle d'Evaluation Spatiale de l'ALéa Erosion des Sols (MESALES) model, and Ireland, which cropped the coverage from the PESERA map of Europe. In the majority of the cases, the dataset covers all the different land cover types with the exception of urban/sealed areas. Germany and Poland provided the data for agricultural land only. The soil erosion map derived from the EIONET-SOIL erosion data received is shown in Fig. 1, the PESERA data for Ireland being included. National borders are not distinguishable on the EIONET-SOIL erosion map (Fig. 1). The average erosion rate is 2.32 t ha^{-1} y^{-1} for the whole area of the eight countries which submitted data. The highest average erosion rates were reported for Italy (6.60 t ha^{-1} y^{-1}) and the lowest rates by the Netherlands (0.25 t ha^{-1} y^{-1}) (Table 2). This is because of the prevalence of strongly sloping land in Italy whereas the Netherlands is a flat country with almost full vegetation coverage.

Comparison of EIONET-SOIL with PESERA data

Both USLE/RUSLE models, used by the EIONET-SOIL data contributors, and PESERA take into account the

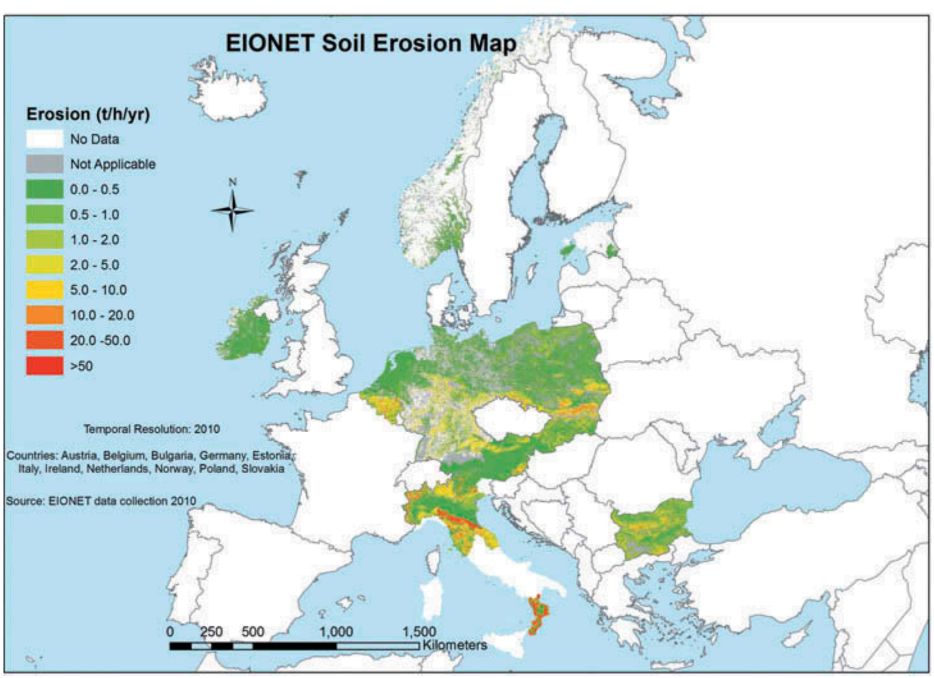

Figure 1 Estimates of soil erosion according to the European Environment Information and Observation Network for soil (EIONET-SOIL) data collection.

soil loss by water and exclude other types of erosion (e.g., by wind and tillage). However, the USLE is an empirical model originally applied at the field/slope scale, while PESERA is a mechanistic (based on physical laws) model mainly applied at the watershed/landscape scale (Karydas *et al.* 2012). The PESERA dataset is used as a reference in Europe because it is publicly available. PESERA data were considered the most appropriate for the comparison with the EIONET-SOIL data.

For each country, an average value of the rate of soil erosion for all provided cells was calculated for EIONET-SOIL (Table 2, column a) and for PESERA (Table 2, column b). For each country an average was computed of EIONET values for the intersection (Table 2, column d) and similarly an average value was computed for PESERA values for the intersection (Table 2, column e).

To compare national average values for EIONET-SOIL and PESERA, the ratio values in columns d and e was calculated (F_{common}). For each country the coefficient of variation (CV) was computed both for the EIONET (Table 2, column f) and PESERA values (Table 2, column g).

For the eight countries with more than 50% of coverage of EIONET-SOIL data, the results of the national comparison are presented in Fig. 2 and 3. The difference (EIONET-SOIL minus PESERA), on a pixel by pixel basis, is mapped in Fig. 4.

Austria

The "Federal Agency for Water Management, Institute for Land & Water Management Research" provided soil erosion data for all country cells. The values are based on the application of USLE and RUSLE models (Strauss 2007). The rainfall erosivity (R-factor) was estimated based on mean annual rainfall data for the period 1961–1990 using the regression of Strauss *et al.* (1995). The soil erodibility (K-factor) was obtained using texture data (silt content) at a 1:25,000 scale published by the Austrian Soil Survey (Strauss 2003). Corine Land Cover 2000 was used as input for the estimation of C-factor (Aubrecht 1998) and a digital elevation model of Austria with grid size of 10 m was used for the calculation of slope angle and length (LS-factor).

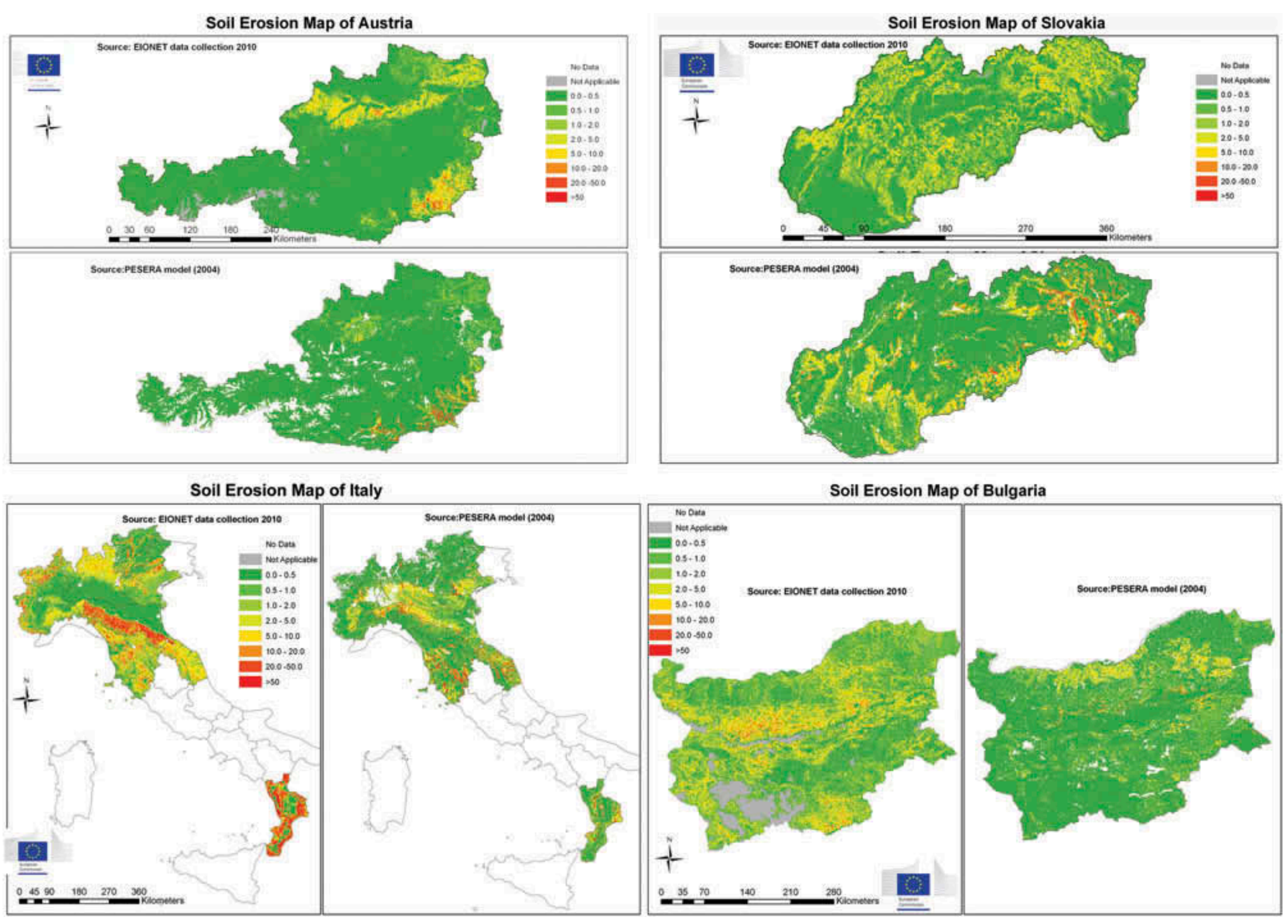

Figure 2 Soil erosion maps for Austria, Slovakia, Italy and Bulgaria.

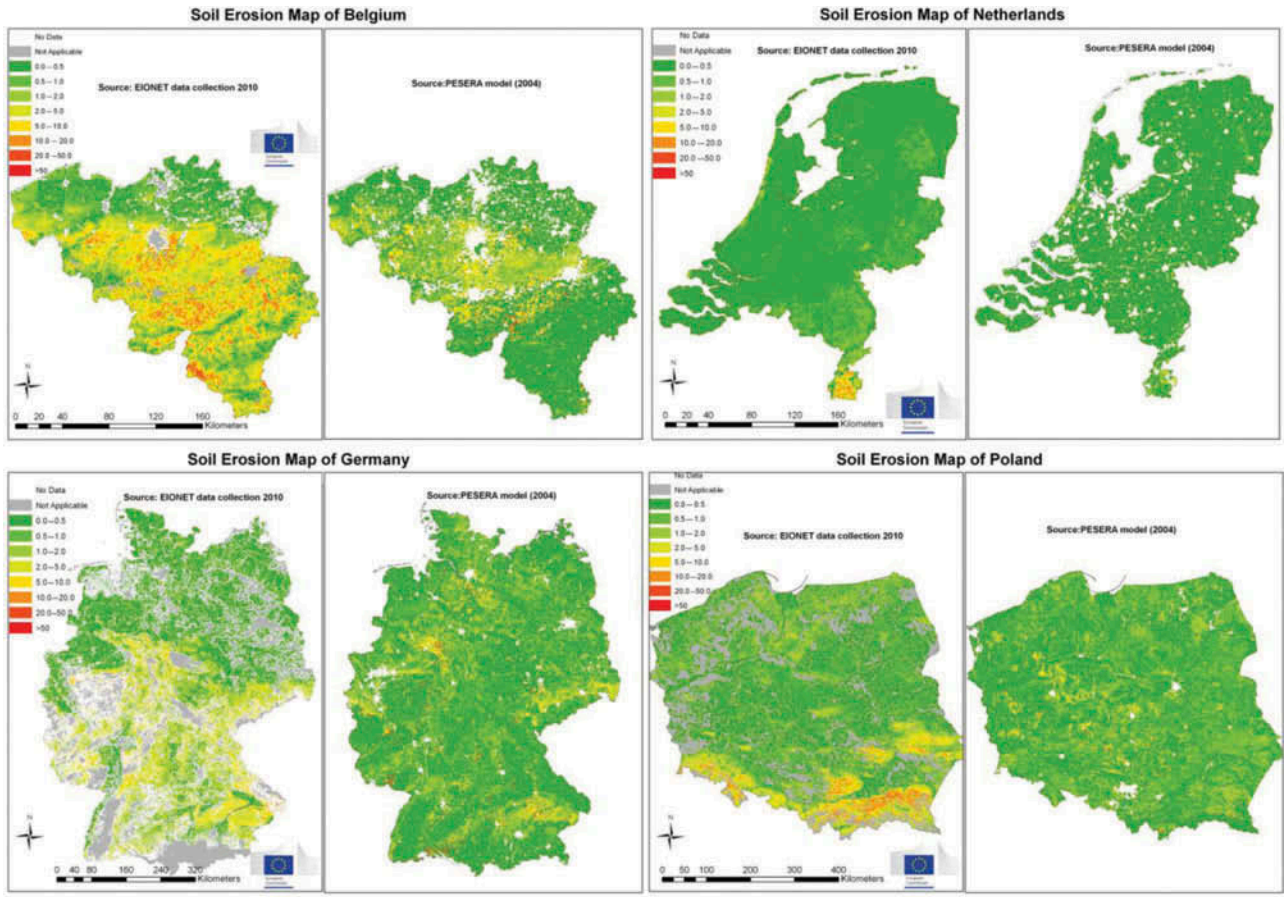

Figure 3 Soil erosion maps for Belgium, Netherlands, Germany and Poland.

For Austria the erosion pattern of EIONET-SOIL and PESERA data is similar except for the CORINE categories "arable land" and "heterogeneous agricultural areas" (Table 3). The aggregated results are very similar for forests, scrublands and pastures. In the flat areas, where the dominant land cover type is arable land, PESERA predicts higher values than EIONET-SOIL. The EIONET-SOIL erosion data have lower variability than does PESERA (Table 2; Fig. 2). The highest soil erosion rates in the PESERA dataset are estimated in Burgenland, Kärnten and Steiermark with a pattern characterized by sudden peaks. Visual interpretation reveals neighboring pixels with very different values (up to 25 t ha^{-1} y^{-1}). Such differences are mainly associated with delineation of the soil mapping units of the European Soil Database (ESDB) (King *et al.* 1994), upon which the soil erodibility input map for PESERA is based.

Belgium

The EIONET-SOIL erosion data were submitted separately by the governmental authorities of Flanders (LNE 2010) and Wallonia (Demarcin *et al.* 2009) using the same RUSLE model. A harmonization procedure consisting of border-fitting and merging has been applied to the two datasets. The soil erodibility (K-factor) is estimated according to Nearing (1997). The LS-factor estimation is based on the approach introduced by Desmet and Govers (1996).

The difference between EIONET-SOIL and PESERA data is very large in Wallonia and especially in the south-western part of the region (see Fig. 3). The regions with the highest rates of soil erosion, according to the EIONET-SOIL dataset, are the provinces of Namur, Liège and Brabant Wallon. The difference is large for all land cover types (2.6 t ha^{-1} y^{-1}) and even larger for forests (3.37 t ha^{-1} y^{-1}) (Table 3). In flat areas (0° slope), the difference is very small (0.10 t ha^{-1} y^{-1}) but increases as the slope increases.

Bulgaria

The "Executive Environment Agency" provided the soil erosion data for almost the entire country, with few exceptions for some forest and semi-natural areas in the south-west part. The USLE model was applied using detailed national datasets as input. The rainfall erosivity map for Bulgaria (Rousseva *et al.* 2006) was used for the estimation

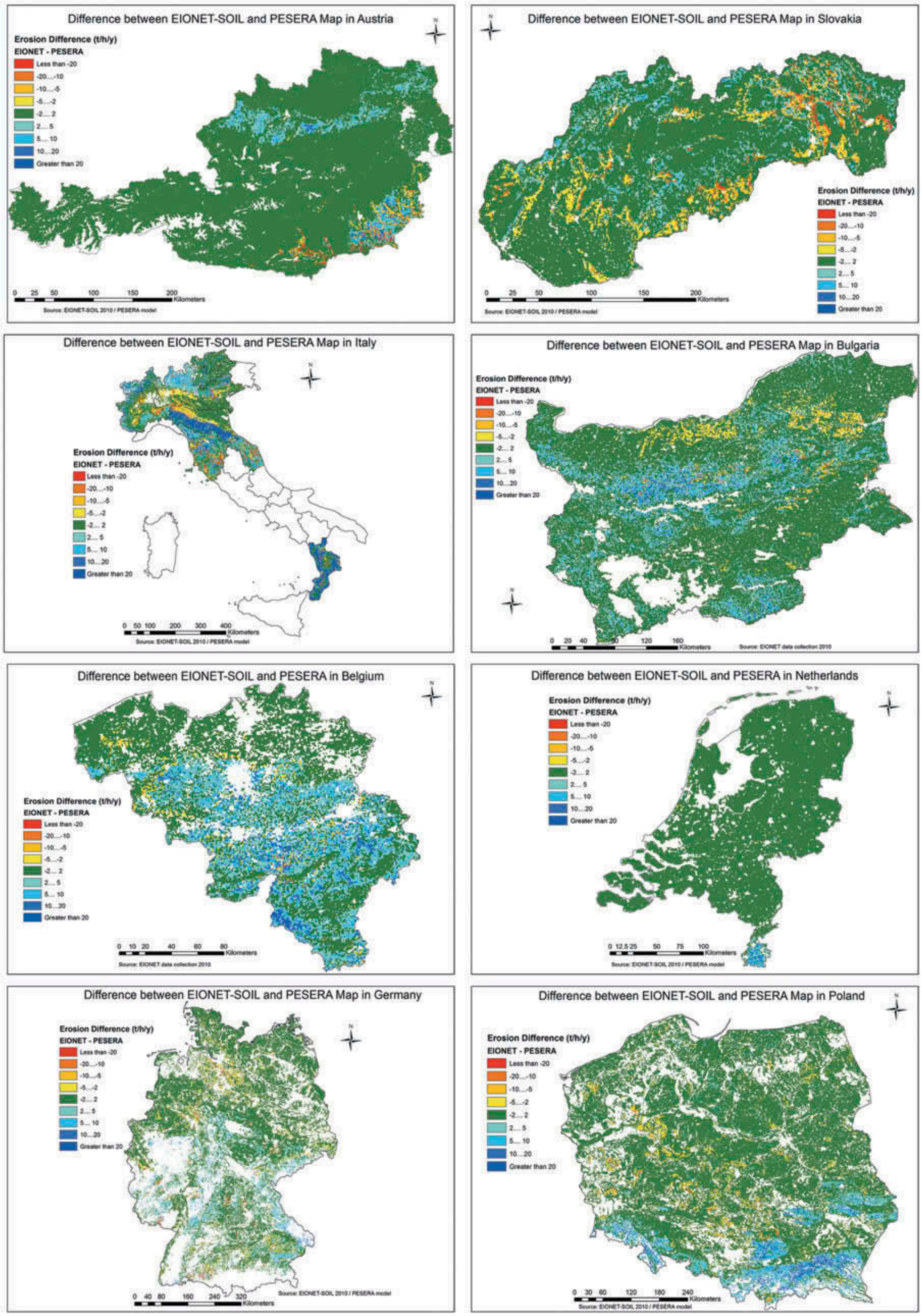

Figure 4 Difference maps yielded by subtracting Pan-European Soil Erosion Risk Assessment (PESERA) soil erosion estimates form European Environment Information and Observation Network for soil (EIONET-SOIL) erosion estimates.

Table 3 Difference (t ha^{-1} y^{-1}) between European Environment Information and Observation Network for soil (EIONET-SOIL) and Pan-European Soil Erosion Risk Assessment (PESERA) soil erosion estimates (EIONET-SOIL minus PESERA) presented per CORINE ("coordination of information on the environment") land cover type

		CORINE Land Cover (CLC) types									
Country	CLC classes	Arable land 12–14	Permanent crops 15–17	Pastures 18	Heterogeneous agr. areas 19–22	Forests 23–25	Scrublands 26–29	Open spaces with little or no vegetation 30–34	Artificial surfaces 1–11	Wetlands-water bodies 35–44	Total area
Austria	Difference (t ha^{-1} y^{-1})	0.34	0.98	0.02	0.57	0.01	0.00	0.00	−0.34	0.02	0.25
	% Total area	*14.9*	*0.9*	*9.5*	*9.4*	*47.6*	*10.2*	*2.8*	*4.2*	*0.5*	
Belgium	Difference (t ha^{-1} y^{-1})	1.94	2.00	1.90	1.93	3.37	1.28		1.94	0.78	2.6
	% Total area	*25.3*	*0.3*	*13.3*	*26.0*	*22.3*	*0.8*		*11.5*	*0.3*	
Bulgaria	Difference (t ha^{-1} y^{-1})	0.33	2.02	1.14	1.65	1.35	1.90	2.02	0.63	0.28	1.31
	% Total area	*38.5*	*2.1*	*3.9*	*11.6*	*29.9*	*9.9*	*0.3*	*3.3*	*0.4*	
Germany	Difference (t ha^{-1} y^{-1})	−0.15	0.06	0.47	1.03	0.77	0.38		−0.14	−0.26	0.1
	% Total area	*67.4*	*0.3*	*8.0*	*9.6*	*10.3*	*0.2*		*3.9*	*0.4*	
Italy	Difference (t ha^{-1} y^{-1})	−1.29	14.39	2.05	9.44	4.60	7.53	6.87	−1.01	−1.44	4.26
	% Total area	*28.8*	*3.9*	*2.2*	*15.4*	*33.3*	*9.9*	*2.4*	*3.7*	*0.4*	
Netherlands	Difference (t ha^{-1} y^{-1})	0.08	0.07	0.03	0.28	0.11	0.09	0.08	0.08	0.02	0.18
	% Total area	*23.4*	*0.2*	*32.7*	*21.2*	*9.6*	*2.1*	*0.1*	*8.5*	*2.1*	
Poland	Difference (t ha^{-1} y^{-1})	0.34	0.33	0.27	1.47	0.97	0.20		0.65	0.60	0.64
	% Total area	*60.1*	*0.6*	*10.8*	*11.6*	*12.4*	*0.5*		*3.3*	*0.7*	
Slovakia	Difference (t ha^{-1} y^{-1})	−1.16	1.41	0.26	0.67	0.11	0.14	0.05	−1.10	−0.24	−0.23
	% Total area	*34.5*	*0.7*	*5.7*	*7.8*	*41.7*	*5.3*	*0.1*	*4.0*	*0.3*	

of the R-factor, a DEM at 20 m resolution for the estimation of LS-factor, the soil map of Bulgaria at a scale of 1:400,000 for the K-factor and Corine Land Cover 2006 (CLC 2006) for the estimation of the C-factor.

The difference (EIONET-SOIL minus PESERA) is very large, especially for the forest and scrubland land cover types (Table 3), which are dominant in the southern parts of the country. Also, as slope increases, the difference shows an increasing trend (Table 4). Again, the variation in the PESERA estimates is higher than for the EIONET-SOIL data (CV of 2.1 and 1.1 for PESERA and EIONET, respectively).

Germany

The Federal Environment Agency ("Umweltbundesamt") has provided soil erosion data for almost 47% of the total territory. The data provided cover only cells where the percentage of arable land is more than 35%. The estimation of actual soil erosion rate is based on a modified USLE (German Allgemeine Bodenabtragsgleichung). The R-factor was calculated based on average total annual precipitation (1-km cells) for the period 1971–2000. A digital terrain model (DTM) at 25 m resolution is used for deriving the LS-factor, and the Soil Map of Germany at 1:1,000,000 (BÜK 1000) was used to derive the K-factor. Phenological monitoring data and agricultural statistical census data were used to derive the C-factor.

The difference (EIONET-SOIL minus PESERA) is very small in Germany. PESERA shows higher mean values in the arable lands and in the flat areas (0–1° of slope). The EIONET-SOIL presents higher values in pastures, heterogeneous agricultural areas and forests with slopes higher than 2°. The distribution in EIONET-SOIL has a lower variability (CV = 1.5) compared to the PESERA dataset (CV = 2.3).

Italy

The "Istituto Superiore per la Protezione e la Ricerca Ambientale (ISPRA)" provided the soil erosion data for Italy. The national coverage is almost 50%, covering eight regions and two autonomous provinces (Trentino and Alto Adige), which form a region. ISPRA has collected the data from each of the regional data providers who have followed the same modelling approach with different input data. Thus, a more in-depth comparison between the EIONET-SOIL and PESERA data on a regional/provincial basis is provided in Table 5. The general procedure applied by all regions was that first soil erosion datasets were calculated at scales between 100 m and 250 m grid resolution, after which an aggregation to 1-km grid cells was performed in order to meet the data collection protocol requirements.

Table 4 Difference (t ha^{-1} y^{-1}) between European Environment Information and Observation Network for soil (EIONET-SOIL) and Pan-European Soil Erosion Risk Assessment (PESERA) soil erosion estimates (EIONET-SOIL minus PESERA) presented per slope classes (in degrees)

Country	Degrees	Slope classes (in degrees) 0	1	2	3	4	5	6–7	8–10	11–15	16–22	23–30	>30	Total area
Austria	Difference (t ha^{-1} y^{-1})	−0.15	0.25	0.48	0.58	0.56	0.35	0.33	0.07	−0.05	−0.08	−0.05	−0.01	0.25
	% Total area	9.6	7.5	6.2	5.1	4.5	4.1	6.6	7.9	11.4	14.8	13.3	8.8	
Belgium	Difference (t ha^{-1} y^{-1})	0.71	2.11	2.81	3.19	3.32	3.95	4.56	5.46	7.67	11.52			2.6
	% Total area	36.6	23.4	13.2	8.3	5.9	3.7	4.2	2.7	1.5	0.4			
Bulgaria	Difference (t ha^{-1} y^{-1})	0.10	0.24	0.45	0.70	1.02	1.31	1.58	1.96	2.08	2.04	1.68	1.62	1.31
	% Total area	15.4	13.7	11.1	8.9	7.4	6.0	9.1	9.4	9.7	6.9	2.3	0.3	
Germany	Difference (t ha^{-1} y^{-1})	−0.37	−0.24	0.24	0.76	1.21	1.44	1.81	1.99	2.17	2.41			0.1
	% Total area	43.0	22.3	12.6	7.5	4.7	3.0	3.5	2.3	1.0	0.2			
Italy	Difference (t ha^{-1} y^{-1})	−2.57	−1.62	2.12	4.03	5.61	6.20	7.51	8.78	9.83	7.41	5.17	5.11	4.26
	% Total area	25.1	5.7	3.2	2.9	3.0	3.0	6.3	9.5	12.5	11.7	9.8	7.3	
Netherlands	Difference (t ha^{-1} y^{-1})	0.04	0.30	0.59	2.52	3.11	2.87	7.41						0.18
	% Total area	86.8	10.1	2.2	0.5	0.2	0.1	0.1						
Poland	Difference (t ha^{-1} y^{-1})	−0.06	0.28	1.07	2.25	3.68	4.72	6.01	6.59	7.53	8.21			0.64
	% Total area	55.6	24.9	9.4	3.9	1.9	1.2	1.3	1.0	0.6	0.2			
Slovakia	Difference (t ha^{-1} y^{-1})	−0.62	−1.21	−1.38	−1.11	−0.67	−0.42	−0.08	0.21	0.43	0.33	0.18	0.17	−0.23
	% Total area	19.3	8.6	6.5	5.7	5.5	5.1	9.1	11.5	14.3	10.2	3.6	0.6	

Table 5 European Environment Information and Observation Network for soil (EIONET-SOIL) vs. Pan-European Soil Erosion Risk Assessment (PESERA) soil erosion estimates for intersecting areas at regional/provincial scale for Italy

REGION-Province	EIONET-SOIL t ha^{-1} y^{-1}	PESERA t ha^{-1} y^{-1}	Erosion Ratio	Metadata
Piemonte (ITC1)	3.3	1.6	2.1	R-Factor (Bazzoffi 2007), DEM 20 m, Regional Land Cover 1:25,000
Valle d'Aosta (ITC2)	11.1	0.1	92.3	R-Factor (Bazzoffi 2007), DEM 20 m, CORINE Land Cover 1:100,000
Lombardy (ITC4)	2.5	2.4	1.0	R-Factor (Renard and Freimund 1994) DEM 20 m, Land Cover 1:25,000
Province of Bolzano (ITH1)	2.0	0.0	68.0	R-factor (Renard and Freimund 1994) DEM 20 m, Land Cover 1:25,000
Province of Trento (ITH2)	2.9	0.1	23.8	R-Factor (Renard and Freimund 1994) DEM 20 m, Land Cover 1:25,000
Veneto (ITH3)	2.7	2.2	1.3	R-Factor (Brown and Foster 1987), DEM 30 m, Land Cover 1:10,000
Emilia Romagna (ITH5)	12.0	2.4	5.0	R-Factor with empirical formula, DEM 10 m, Land Cover 1:25,000
Toscana(ITI1)	5.6	5.0	1.1	Rainfall data 1960–90. DEM 20 m, CORINE Land Cover 1:100,000
Marche (ITI3)	5.3	5.2	1.0	Rainfall data from 230 stations, DEM 20 m, CORINE Land Cover 1:100,000
Calabria (ITF6)	21.7	3.1	6.9	R-Factor (Renard and Freimund 1994), DEM 40 m, CORINE Land Cover 1:100,000

DEM, Digital Elevation Model.

Compared to the EIONET-SOIL data, PESERA modelled very low values in the mountain regions of northern Italy and the Apennines. The differences in these areas can be explained by the fact that the sediment loss module in PESERA predicts low erosion rates under complete vegetation cover. In Tuscany and Lombardy, PESERA assesses very low erosion rates in the hilly/mountain areas and higher values in the flat areas (0°–1° of slope) and in the arable lands, whereas the EIONET-SOIL values are much higher in forests and scrublands.

The Netherlands

The "Alterra Research Institute" provided soil erosion data for almost the entire country. The calculation is based on the RUSLE model using the Dutch Soil map at 1:50,000 scale (Kempen *et al.* 2009), for the K-factor estimation, the land use map HGN 2004 at 1:10,000 scale for the C-factor estimation, the DEM based on the Actual Height Model (Actueel Hoogtebestand Nederland AHN-25 m) (Scholten 2006) for the LS-factor calculation and a fixed rainfall erosivity factor of 595 MJ mm ha^{-1} h^{-1} y^{-1} for the whole country.

Soil erosion rates in the Netherlands are very low and similar patterns have been identified between the EIONET-SOIL and the PESERA datasets except in the southeastern part of the country (see Fig. 3 and 4). Notable are the relatively high soil erosion rates reported for EIONET-SOIL in the Limburg region. In this region, the mean value of EIONET-SOIL data is 2.07 t ha^{-1} y^{-1} compared to the 0.3 t ha^{-1} y^{-1} of the PESERA data. The high values of EIONET-SOIL in this region follow the same data pattern as in the neighbouring province of Liège in Belgium. The Netherlands is a flat country and the difference (EIONET-SOIL minus PESERA) is very small at 0° slope, while it is increasing in the areas where slope ranges from 1° to 2° (Table 4). Regarding the land cover influence, the heterogeneous agricultural area is the type for which the major difference is observed.

Poland

The "Institute of Soil Science and Plant Cultivation – State Research" has provided soil erosion data for 70% of the country, covering mainly the agricultural areas. The USLE model was used to estimate soil erosion. The rainfall erosivity for Poland was calculated based on DEM using the relationship between altitude and precipitation developed by Licznar (2006). The soil erodibility was estimated from the soil map of Poland at a 1: 250,000 scale (Institute of Soil Science and Plant Cultivation (IUNG). The DEM at 40 m resolution was used for the estimation of the LS-factor.

The overall correspondence between the PESERA and the EIONET-SOIL datasets is relatively good with the exception of the southern part of the country (see Fig. 3 and 4), where EIONET-SOIL values are much higher than those of PESERA in the regions Podkarpackie, Małopolskie, Lubelskie and Dolnośląskie. The higher values of EIONET-SOIL are observed mainly in areas where the dominant land cover type is forest and in heterogeneous agricultural areas. The difference with

PESERA is relatively small in the arable lands (Table 3). In flat areas with 0° slope the EIONET-SOIL and PESERA mean values are close while the difference (higher EIONET-SOIL estimates compared to PESERA estimates) increases as the slope rises (Table 4).

Slovakia

The "Slovakian Soil Science and Conservation Research Institute (SSCRI)" applied the USLE model for the estimation of soil erosion in Slovakia. A rainfall-runoff erosivity (R-factor) map was generated from interpolating measurements of 86 individual rainfall stations (Styk and Pálka 2007). Soil erodibility (K-factor) was calculated from 17,000 soil profiles interpolated with ordinary kriging (Styk *et al.* 2008). Land cover (C-factor) was derived as a weighted average of main crops, which were grown in 72 Slovak districts in the year 2010. A DTM (digital terrain model) at 20 m resolution was used for the calculation of the LS-factor.

The patterns of the EIONET-SOIL and PESERA data match well with the exception of the Východné-Slovensko region in eastern Slovakia, where PESERA estimates erosion rates higher in the arable areas (Fig. 2). Slovakia is the only country for which the mean erosion values for PESERA are higher than EIONET-SOIL. This appears to be due to the large difference between the two datasets in arable lands (Table 3). Moreover, Slovakia is the only country among the eight, where PESERA has higher mean values in the slope classes between 2 and 7°. This is probably associated with the large proportion of arable land on such slopes. For PESERA, the pattern of the soil erodibility map (based on the European Soil Database) is distinguishable.

Summary of the comparison per slope and land use

The comparison between the EIONET-SOIL and the PESERA datasets per slope class (in degrees) (Table 4) is summarized as follows:

- The (EIONET-SOIL minus PESERA) value has an escalating trend as the slope increases for all the countries (except in Austria for land > 5°).
- The mean EIONET-SOIL erosion values are higher than mean PESERA values in all slope classes between 2 and 10° (except in Slovakia where arable land was dominant also on those slopes).
- In flat areas (0–1° of slope) the difference (EIONET-SOIL minus PESERA) is lower than the overall difference in the country.

The comparison between the EIONET-SOIL and PESERA data, based on the stratification per land cover (Table 3), focuses mainly on five land cover types – arable lands, heterogeneous agricultural areas, pastures, forests and scrublands – as they are the most representative ones based on their proportions.

- In all countries (except Austria), the difference (EIONET-SOIL minus PESERA) is higher in forests than in arable lands. The difference in arable lands is lower than the total difference at the country level.
- For each of the five land cover types discussed here, the mean EIONET-SOIL erosion values are larger than the mean PESERA estimates except for arable land in three out of eight countries.
- For pastures, the difference is relatively small, especially in the Netherlands where pastures are the dominant land cover type. In all countries (except Belgium), the heterogeneous agricultural areas show a larger difference than the overall difference within the country. The difference (EIONET-SOIL minus PESERA) in the forest land cover type is quite close to the overall difference within the country.

Comparison of model-based soil erosion estimates to plot data

The comparison between the EIONET-SOIL data and the soil erosion rates based on plot measurements (Cerdan *et al.* 2010) is summarized as follows (Table 2):

- EIONET-SOIL mean rates of soil erosion are much lower in Slovakia and Austria and slightly lower in the Netherlands and Germany compared to the mean values based on plots.
- There is a very close correspondence of EIONET-SOIL mean rates of soil erosion with the mean values based on plots in Bulgaria and Poland.
- EIONET-SOIL mean values are much higher in Belgium and Italy compared to the mean erosion rates based on plot measurements.

In all countries (except Italy) the PESERA mean values are lower compared to the mean erosion rates based on plot measurements (Cerdan *et al.* 2010). A recent comparison of measured catchment sediment yields (SY) estimated with PESERA data and the erosion rates based on plots proved that PESERA values are considerably lower than the SY values (Vanmaercke *et al.* 2012). In the past, Van Rompay *et al.* (2003, 2005) modelled sediment delivery ratios (SDR) and compared the SY to USLE estimated and PESERA modelled erosion rates. Both models underestimated the soil erosion rates compared to SY in Spain, Italy, Belgium and the Czech Republic.

DISCUSSION AND CONCLUSIONS

The EIONET-SOIL data collection was the first attempt by ESDAC to compile comprehensive soil erosion data from the countries in Europe. In 2006, a review of the existing soil erosion datasets in Europe showed that the representation of soil loss varied according to classification schemes and spatial scales (Baade and Rekolainen 2006). National borders are not visible in the EIONET-SOIL map. Thus, in terms of harmonization, the EIONET-SOIL data collection exercise was successful and showed that the approach taken (provision of soil erosion data in the same unit through a standard grid) was a step forward compared to work of the past decade. The experience gained in this exercise can be useful to create a framework for reporting soil data from Member States to EU services, e.g., in the context of data reporting for a future Soil Framework Directive (EC 2012).

The metadata submitted are essential for the correct interpretation of the data received from EIONET-SOIL data, and for the comparison of datasets, which is not always straightforward. In the future, an investigation of the input layers to erosion models (climate, land cover, soil and topography) and closer collaboration with data providers is necessary to allow for a better interpretation of the national soil erosion datasets. The input model layers are mostly nationwide datasets (different from one country to another) but always at better scale than the European input layers used, for example, in PESERA.

Even though large parts of Europe (Nordic countries, the Mediterranean) are not represented in the EIONET-SOIL erosion map (Fig. 1), the data represents the best, albeit still fragmented, picture that can be drawn based on national data with a satisfactory number of countries. The picture could certainly be improved by including soil erosion data at a national scale that have not yet been submitted to ESDAC. This study has shown the potential of the EIONET-SOIL erosion data for the application and, in a later phase, verification of the USLE model at the European scale. The data collection exercise should be repeated by ESDAC to better contribute to the State of Environment Report (SOER) in the year 2015. The future data collection exercise will improve the data received from countries such as France, Denmark and FYROM and will involve the countries that were not represented in the 2009 data collection. Moreover, the metadata request is most important for the interpretation of the erosion data.

The differences between PESERA and EIONET-SOIL erosion data could be due to:

- **Difference in mapping procedures**. The EIONET-SOIL data have a smoother distribution compared to the PESERA data for almost all countries (except the Netherlands and Poland where the CVs are similar); the variation is almost double for PESERA compared to EIONET-SOIL. PESERA data has certain peak values that are mainly driven by the delineation of Soil Mapping Units in the European Soil Database.
- **Influence of slope and vegetation**. PESERA estimates of rates of soil loss are lower than EIONET-SOIL erosion rates in areas with slopes steeper than 2° and in forest land. This is particularly true in the Apennines (Italy), Ardennes (Belgium) and the mountain regions in Bulgaria. For other mountain areas, PESERA soil loss estimates are lower than USLE erosion rates in case of reduced percentage of vegetation cover (Meusburger *et al.* 2010). In all countries (except Belgium), the PESERA mean erosion values are higher than those of EIONET-SOIL for arable land and flat areas (0°). Moreover, PESERA shows relatively high erosion rates in some flat areas where actually deposition is expected, e. g., the Po-valley (Italy) and valleys in the Východné-Slovensko region (Slovakia).
- **The climatic data are crucially important** for PESERA soil loss estimates (Jones *et al.* 2003), USLE and other soil erosion models. Assessing the true influence of climate is hampered by the lack of a pan-European rainfall erosivity dataset at good resolution.
- **The sediment module in PESERA** results in lower erosion values for mountain areas compared to EIONET-SOIL erosion data because CORINE shows these areas to have significant vegetation cover.
- **Different input datasets and scale**. A DEM of finer spatial resolution results in more sharp changes in slopes. According to the metadata, in Bulgaria the data provider used a 20 m DEM and most of the Italian Regions have used DEMs ranging from 20 m to 40 m. These datasets are of much finer resolution than the GTOPO30 used in PESERA, which resulted in much smoother reliefs. The better identification of changes in slopes results in higher soil erosion estimates. Regarding land cover, most of the countries have used CORINE 2000/2006 or national/regional land cover data of the last decade, which are more recent than the CORINE 1990 used as input for PESERA.

The cross-comparison of the different approaches PESERA and EIONET-SOIL could identify regions where there is still a considerable uncertainty related to rates of soil erosion. The exercise of the EIONET data collection highlights the need to validate the soil erosion estimates derived by different methods with local/regional assessments. The present evaluation takes into account two important factors: (1) The national and regional (in the case of Italy) data providers have a better understanding of the national/regional soil erosion situation compared to modelling approaches at a pan-European level, and (2) their model estimates are based on more detailed input datasets in most cases.

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CHAPTER 2

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

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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;

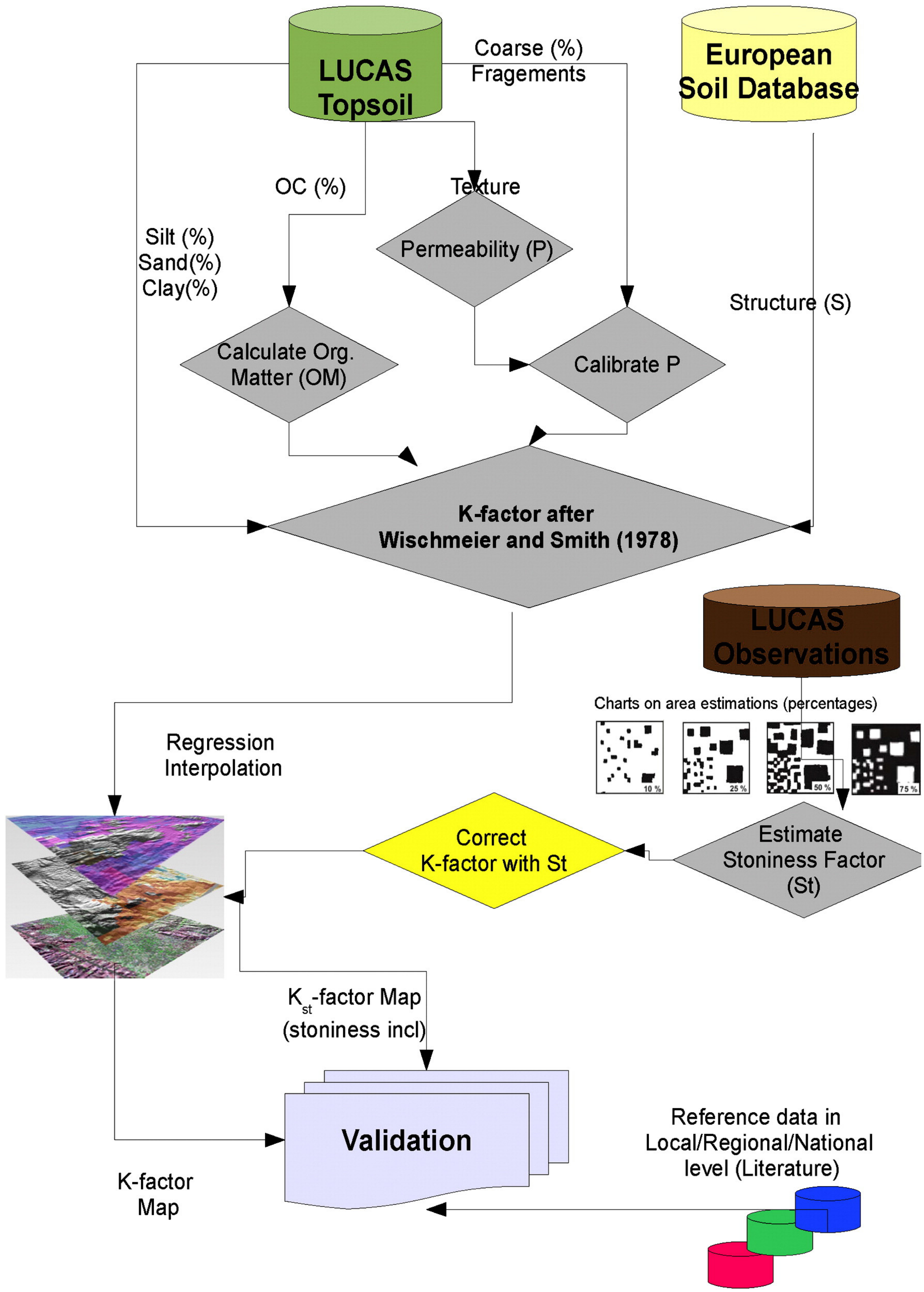

Fig. 1. Methodology applied for the generation of a European K-factor (soil erodibility) map.

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):

$$K_b/K_f = (1 - R_w) \quad (2)$$

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:

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

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.

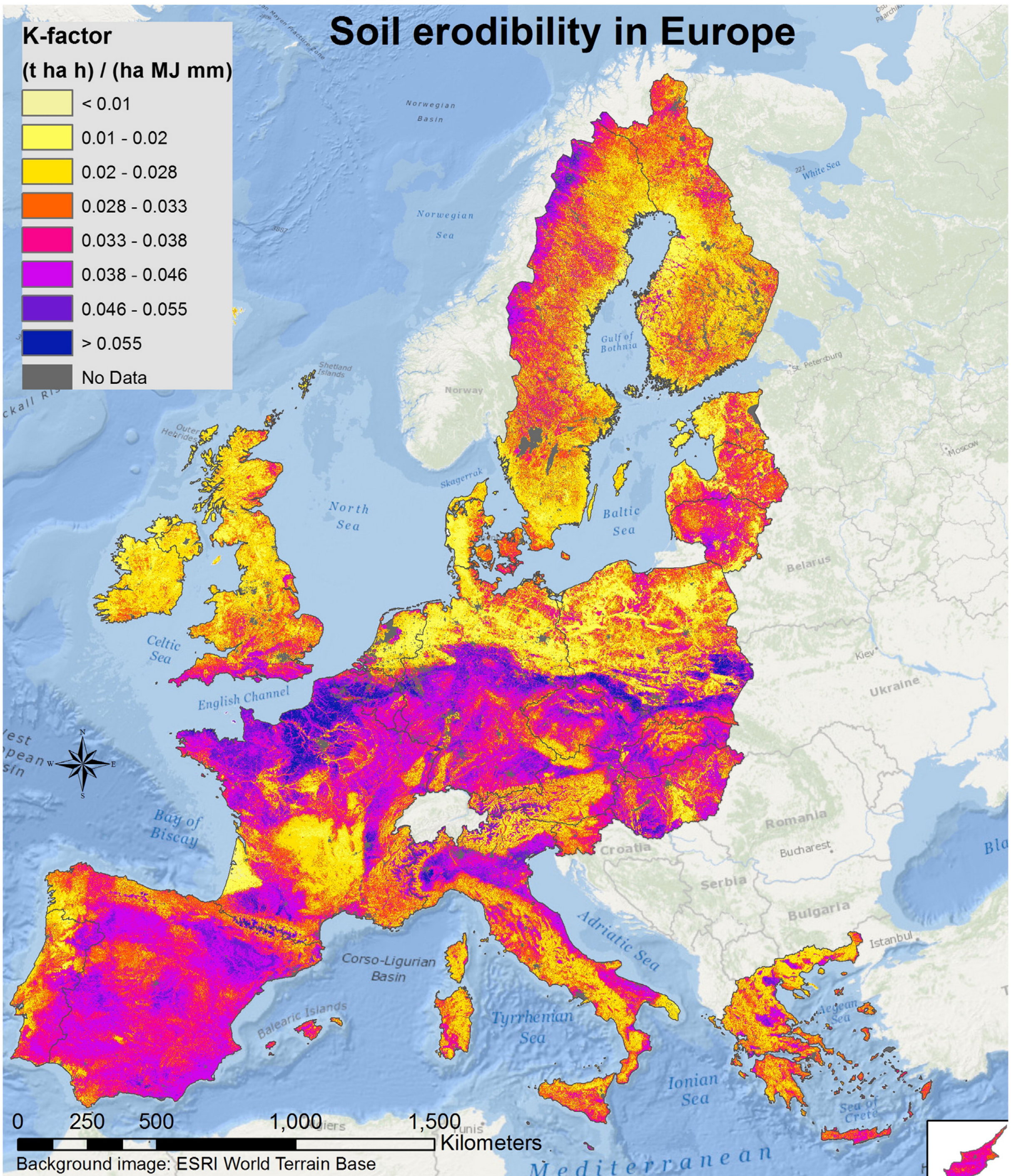

Fig. 2. High-resolution (500 m grid cell size) map of Soil Erodibility estimated as K-factor in the European Union.

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.

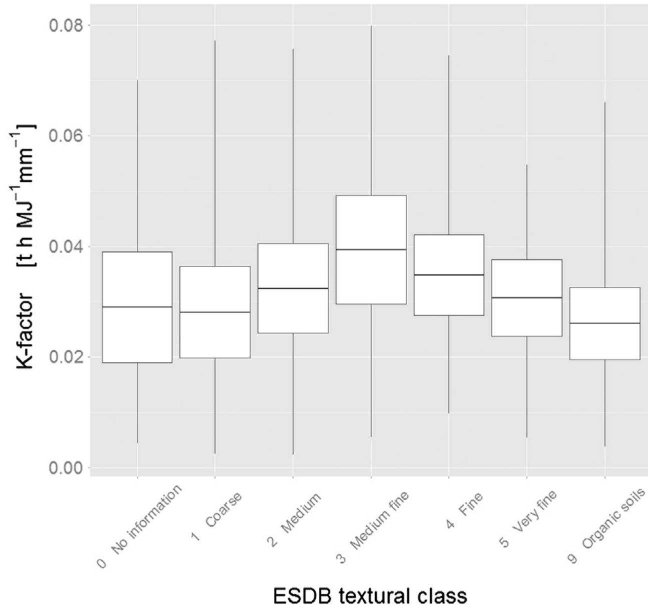

Fig. 3. K-factor compared to the European Soil Database (ESDB) soil surface texture classes.

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 ($\leq$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)

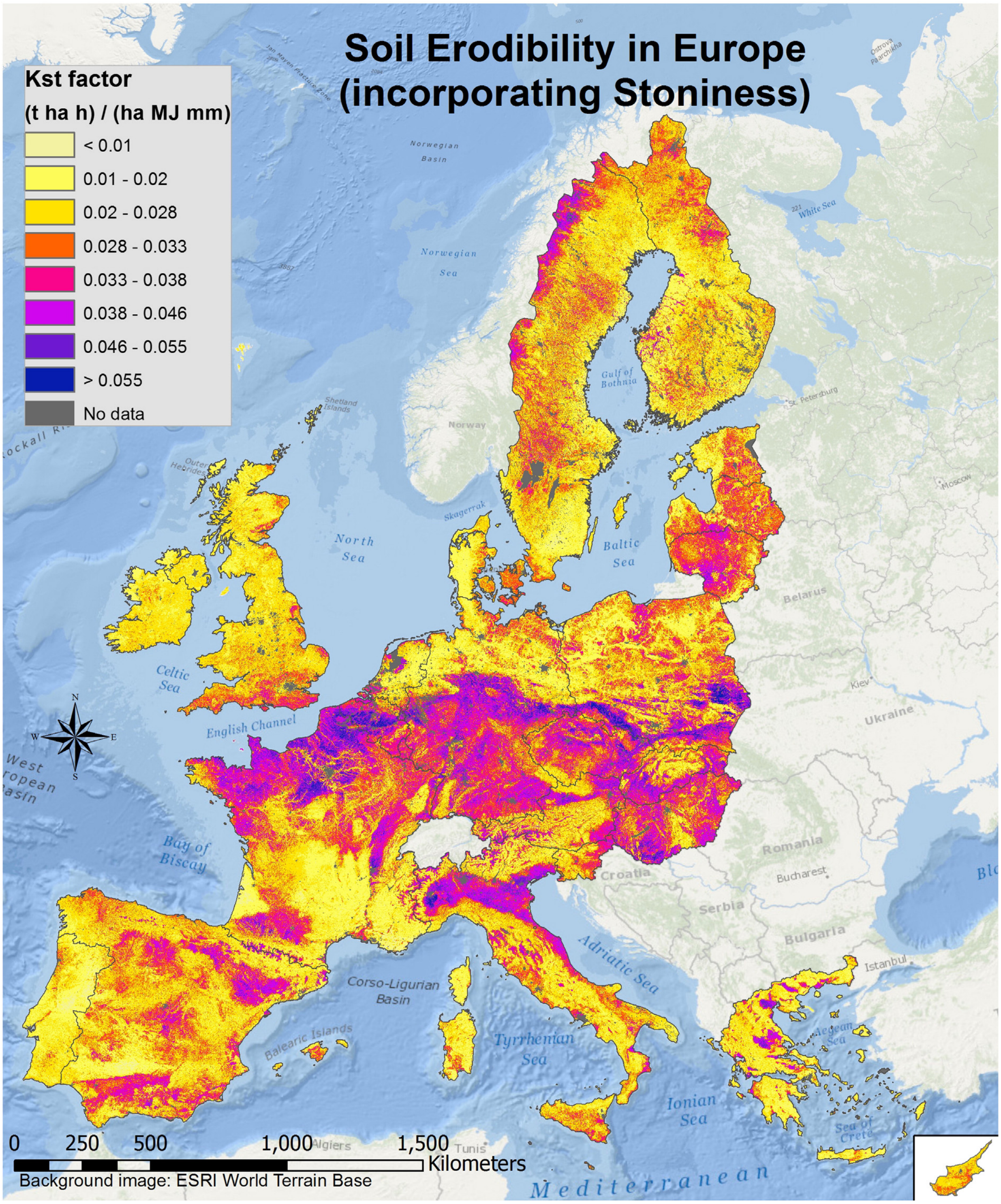

Fig. 4. High-resolution (500 m grid cell size) map of Soil Erodibility estimated as K-factor in the European Union, incorporating stoniness.

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%.

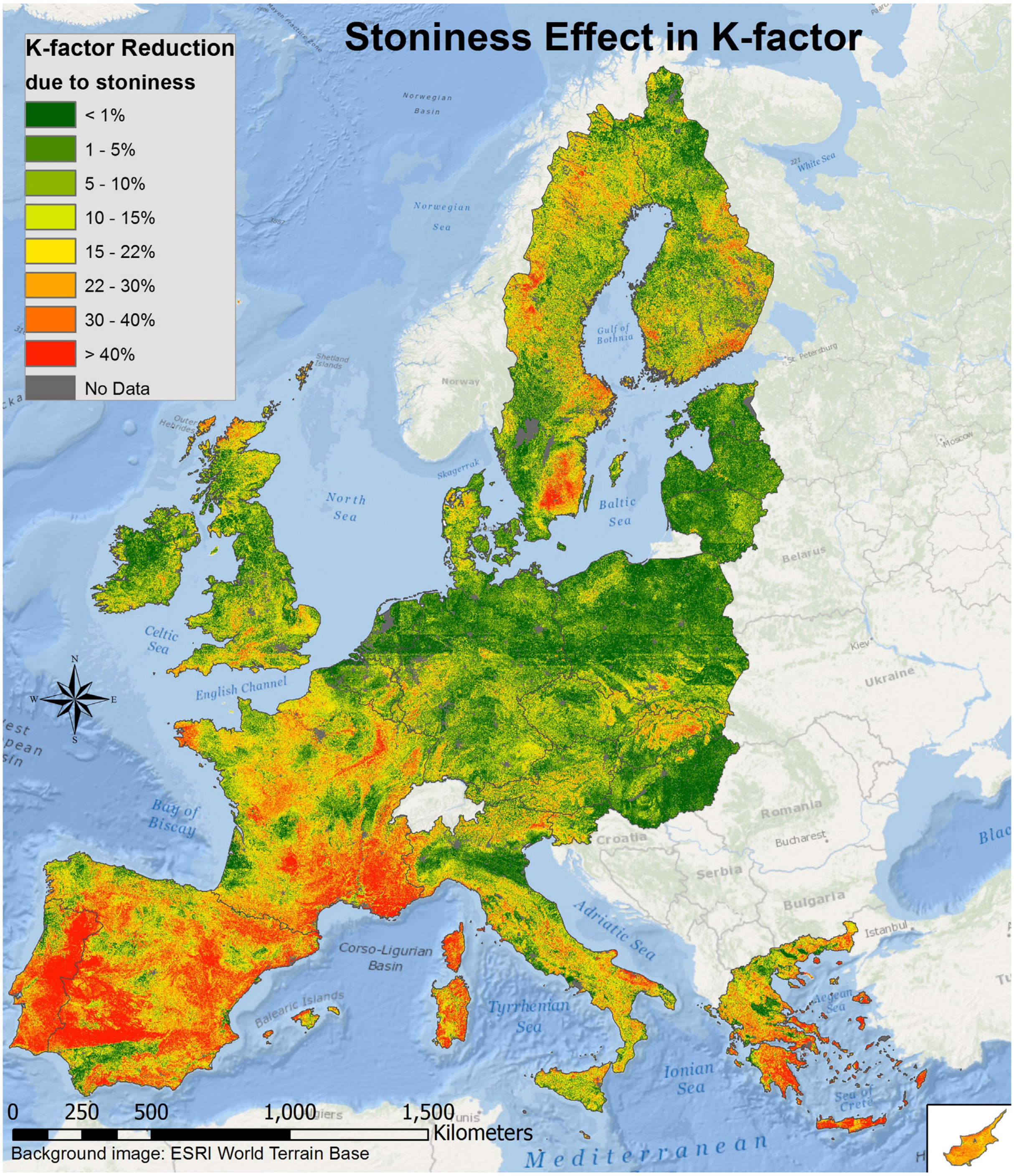

Fig. 5. Reduction in soil erodibility due to the protective effect of stones covering the soil surface (stoniness).

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 (%)

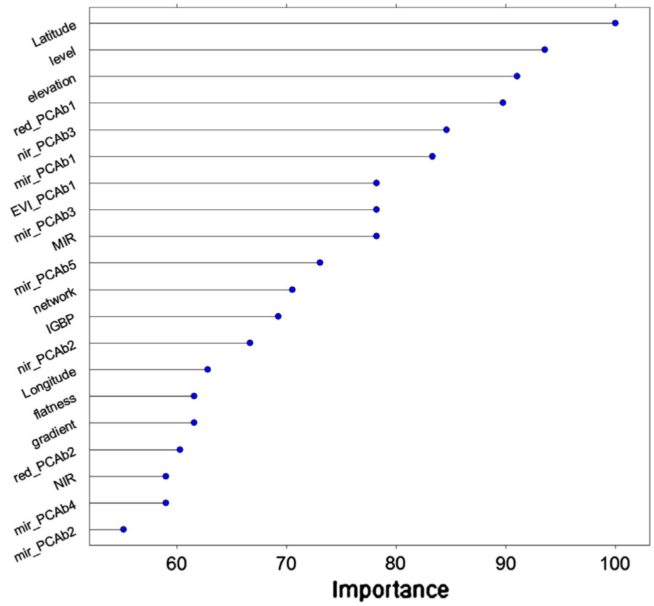

Fig. 6. The twenty most important covariates and their relative importance in the application of Cubist/MBS model for K-factor interpolation.

(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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CHAPTER 3

Seasonal monitoring of soil erosion at regional scale: An application of the G2 model in Crete focusing on agricultural land uses

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Seasonal monitoring of soil erosion at regional scale: An application of the G2 model in Crete focusing on agricultural land uses

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ABSTRACT

A new soil erosion model, namely G2, was applied in the island of Crete with a focus on agricultural land uses, including potential grazing lands. The G2 model was developed within the Geoland2 project as an agro-environmental service in the framework of the Global Monitoring for Environment and Security (GMES, now Copernicus) initiative. The G2 model takes advantage of the empirical background of the Universal Soil Loss Equation (USLE) and the Gavrilovic model, together with readily available time series of vegetation layers and 10-min rainfall intensity data to produce monthly time-step erosion risk maps at 300 m cell size. The innovations of the G2 model include the implementation of land-use influence parameters based on empirical data and the introduction of a corrective term in the estimation of the topographic influence factor. The mean annual erosion rate in Crete was found to be 8.123 t ha^{-1}. The season from October to January (the rainy season in Crete) was found to be the most critical, accounting for 80% of the annual erosion in the island. Seasonal erosion figures proved to be crucial for the identification of erosion hotspots and of risky land uses. In Crete, high annual erosion figures were detected in natural grasslands and shrublands (14.023 t ha^{-1}), mainly due to the intensification of livestock grazing during the past decades. The G2 model allows for the integrated spatio-temporal monitoring of soil erosion per land-use type based on moderate data input requirements and existing datasets.

1. Introduction

Soil erosion caused by water has been addressed globally as one of the most critical soil degradation hazards. It has been found that almost 12% of the European territory (115×10^6 ha) is subject to erosion. The European Union has identified soil erosion as a key priority for the protection of soils (EC, 2006) and has estimated its financial cost as being several billion Euros per year. The risk of erosion is particularly high in Mediterranean areas, especially in areas that are subject to inappropriate agricultural management, land abandonment, intense road construction, or wild fires (Cerdà et al., 2010). Any of the above drivers, alone or in combination, assisted by a dry climate, can trigger or seriously accelerate soil erosion.

Of all the factors influencing erosion, rainfall erosivity and vegetation cover are considered to be the most dynamic. Therefore, capturing detailed temporal rainfall and vegetation characteristics could prove crucial to making realistic and accurate erosion assessments. Based on experience gained in the previous decades, the new G2 model attempts to provide the necessary temporal detail for soil loss assessments at local to regional scales (Karydas et al., 2012). The G2 model uses the empirical formulas of the Universal Soil Loss Equation (USLE), while using rainfall erosivity data and time series of biophysical parameters derived from satellite data on a monthly basis (Panagos et al., 2012a). The importance of monthly rainfall erosivity maps for soil erosion risk assessments has been also suggested by Renard et al. (1997). In addition to rainfall erosivity and vegetation cover, inputs to the G2 model include soil erodibility, topographic influence and slope intercept. The G2 model was developed within the Geoland2 project as an agro-environmental tool in the framework of Global Monitoring for Environment and Security (GMES, now Copernicus) initiative. To date, the G2 model has been applied to the Strymonas (or Struma) river basin (Panagos et al., 2012a) and the Ishmi-Erzeni watershed in Albania, with encouraging results. The G2 model has been further developed in the current study.

The objective of this research study was to make seasonal erosion assessments in Mediterranean agricultural areas using the G2 model. More specifically, the study aimed to:

- Improve the G2 model taking into account land-use data.
- Identify hotspots (spatial dimension) and seasons at high risk of soil erosion (temporal dimension).
- Identify critical land uses and the impact of vegetation cover in agricultural land uses.

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2. Materials and methods

2.1. Study area

The Greek National Committee for Combating Desertification considers Crete to be a high-risk area for desertification due to large-scale deforestation of sloping lands, intensive cultivation and overgrazing, which results in accelerated soil erosion and the formation of badlands. Croke et al. (2000) also consider Crete to be a high-risk area for desertification due to a combination of inappropriate land uses and high spatio-temporal variation of climatic factors.

Crete is located in the Eastern Mediterranean basin (35:20:27 N, 25:07:46 E). With a population of 623,065, it is the largest island of Greece (8336 km^2) (Fig. 1). According to the Nomenclature of Territorial Units for Statistics (NUTS) used for administrative purposes in the European Union, Crete is one of the 13 Greek NUTS2 regions and has four regional units at NUTS3 level (Panagos et al., 2013): Chania, Rethymnon, Heracleion, and Lassithi (from west to east). It is mostly a mountainous area with a mean elevation of 482 m and the highest peak at 2456 m (Mount Psiloritis). The topography of the island is quite undulating due to its carstic geology, with an average slope of 28% (or 15°). Crete has a dry sub-humid Mediterranean climate (humid mild winters; dry warm summers). The mean annual precipitation is 730 mm with a standard deviation of 230 mm. Significant rainfall differences are recorded between the western (wetter) and eastern (drier) parts of the island during the autumn and winter seasons. Rainfall during the spring season is very low, and is negligible during the summer season. The mean annual temperature ranges between 15 and 20 °C.

Soils in Crete are generally poorly developed and shallow. According to the European Soil Database, Leptosols occupy about 56% of the island surface, while Regosols cover another 25% (European Soil Portal, 2013). The presence of these soils is generally attributed to historical human activity, in particular to deforestation and overgrazing. Some Luvisols (about 10%) can be also found in the upper parts of some small fluvial plains.

Crete is mostly covered by natural grasslands and shrubs (46%) and permanent crops (olives 23%, vines 2.6%, and citrus 0.7%). A significant part of the land is covered by heterogeneous agricultural areas or fields mixed with natural vegetation (15.2%), whereas a small share (0.5%) is covered by greenhouses, arable land (irrigated or not) and pastures. Forest coverage is less than 4% of the total area (CLC, 2000). The main land uses in Crete have not changed significantly over the past 50 years, but in some cases the intensity of land use has changed. A large share of vineyards was replaced by new olive plantations, especially during the 1990s and 2000s (Karydas et al., 2008). Moreover, the number of livestock units (LSU) (goats and sheep) grazing the island has increased more than five times (from 1.4 to 6.8 LSU ha^{-1} in the period 1960–2010) due to agricultural policy incentives (Nikolaidis et al., 2013).

2.2. Data

A time series of precipitation data for 11 years (1969–1979) with 10-min resolution was available for four weather stations in Crete (Emprosneros, Nithafri, Archanes, Kalamavka) (Hydroscope, 2012). In addition, a set of 24 weather stations was used from SoilTrEC project (Banwart et al., 2011) with average monthly precipitation records for the same time period (1969–1979). Rainfall data is the main input to the G2 model for estimating rainfall erosivity.

A set of 31 soil samples from the pan-European LUCAS topsoil dataset (Toth et al., 2013; Panagos et al., 2013) and an additional set of 60 soil samples of the SoilTrEC project (Banwart et al., 2011), mainly from the western part of the island, were made available for the study. The samples included soil organic carbon and texture data used in the soil erodibility equation of the USLE, which is adopted by the G2 model.

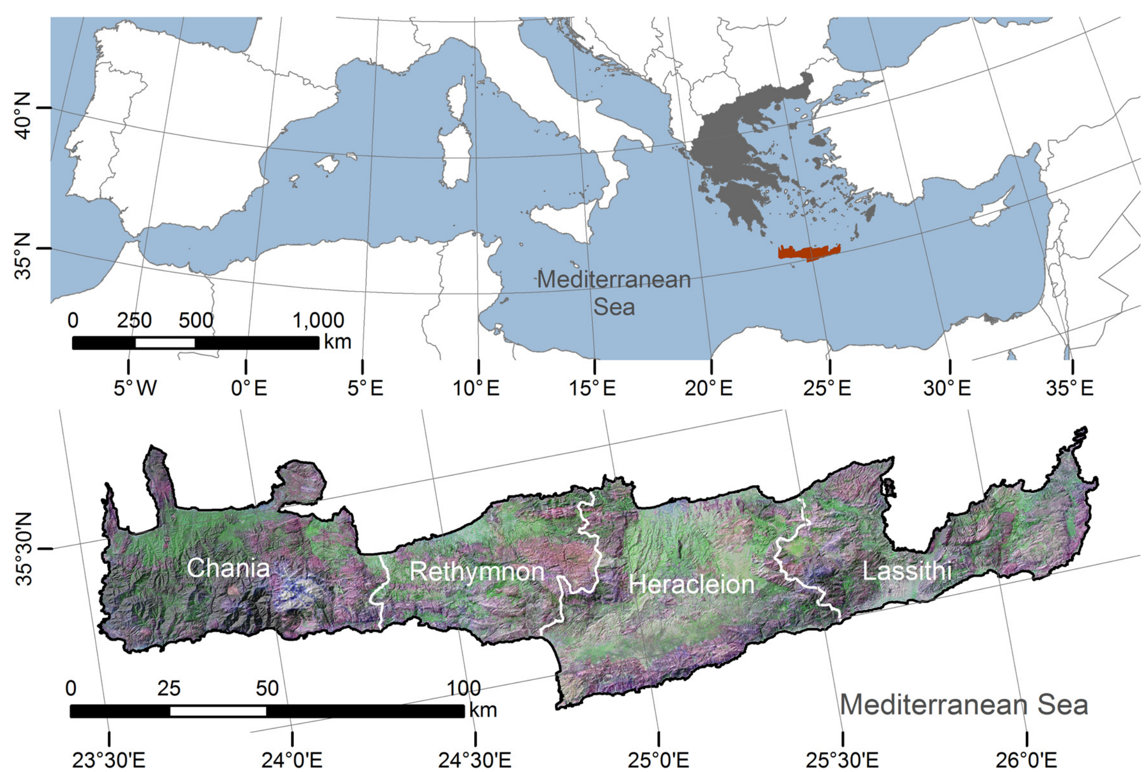

Fig. 1. The Island of Crete. Upper panel: location of Greece (grey) and Crete island (red). Lower panel: false-colour composite of high resolution satellite image mosaic (source: JRC). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)

A time series of 'BioPar' (biophysical parameter) data derived from MEdium Resolution Imaging Spectrometer (MERIS) observations (300 m cell size) from April 2011 to March 2012 was downloaded from the Global Monitoring for Environment and Security (GMES, now Copernicus) geo-portal (Geoland2, 2012). The G2 model uses Fcover spatial layer that expresses the percentage of the surface covered by any kind of vegetation at a specific date. This is estimated using the SAIL and PROSPECT radiative transfer models (Verhoef, 1985). The Fcover spatial layer was combined with CORINE land cover/use data (CLC, 2000) as input to the estimation of the vegetation retention parameter.

A Digital Elevation Model (DEM) derived from the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) satellite sensor at 30 m spatial resolution was used to calculate the topographic influence parameter of the G2 model. A high resolution satellite image mosaic (Soille, 2006) was used to capture features such as roads, paths between parcels, hedges, terrace steeps, crisp cultivation changes and land use alterations. Those features intercept the slope length and runoff and as a result protect soil from erosion.

2.3. Model description

The G2 model is a methodology for producing seasonal maps of sheet and interrill erosion caused by raindrop detachment and runoff at 300 m cell size. It has moderate data requirements and follows the same principles as the Universal Soil Loss Equation (USLE) (Wischmeier and Smith, 1978). The G2 model uses the following formula:

$$E = \left(\frac{R}{V}\right) \times S \times \left(\frac{T}{I}\right) \tag{1}$$

where E is the predicted soil amount removed from an area during a specific time period (t ha^{-1}); R is the rainfall-runoff erosivity factor for a specific time period (MJ mm ha^{-1} h^{-1}), which quantifies the impact of raindrop and runoff energy; S is the soil erodibility factor (t ha h MJ^{-1} ha^{-1} mm^{-1}), identical to the USLE's K-factor, which reflects the ease of soil detachment by raindrop splash or surface flow; T is the topography factor (dimensionless and analogous to the LS-factor of the USLE), which expresses the effect of slope length and slope gradient (Wischmeier and Smith, 1978); V is the vegetation retention factor (dimensionless, and analogous to the USLE's C-factor), which represents the effects of all interrelated cover and management variables (Renard et al., 1997); and I is slope-intercept factor (dimensionless and partially analogous to the USLE's P-factor), which is corrective of T.

Eq. (1) is a redefined version of the original formula ($E = R \times V \times S \times T \times I$) implemented in the Strymonas application (Panagos et al., 2012a). In the revised formula of G2, the V and I factors have been moved to the denominator in order to reflect their protective role in the erosion process. Appropriate modifications have also taken place for each equation factor. The parentheses in Eq. (1) emphasise the (methodological) categorisation of input factors into groups of counteracting actions, i.e. rain on vegetation (R vs. V) and the slope intercept of the terrain (T vs. I).

2.4. Erosion factors

2.4.1. Rainfall erosivity (R)

The relationship between rainfall and sediment yield is given by rainfall erosivity. In most soil erosion studies, the calculation of rainfall erosivity is limited due to lack of time-series rainfall data. Only a few studies in Europe have determined the R-factor directly from high temporal-resolution data (Loureiro and Coutinho, 2001; Mikos et al., 2006; Angulo-Martinez et al., 2009).

Here, the original RUSLE (Revised-USLE) R-factor equation has been used to create a database of the erosive events. The R-factor is the product of the kinetic energy of a rainfall event and its maximum 30-min intensity (Brown and Foster, 1987):

$$R = \frac{1}{n}\sum_{j=1}^{n}\sum_{k=1}^{mj}(\mathrm{EI}_{30})_k \tag{2}$$

where R is the average monthly rainfall erosivity (MJ mm ha^{-1} h^{-1} (y/12)$^{-1}$); n is the number of years recorded; m_j is the number of erosive events during a given month j; and EI_{30} is the rainfall erosivity index of a single event k. The event erosivity EI_{30} (MJ mm ha^{-1} h^{-1}) is defined as:

$$\mathrm{EI} = \mathrm{EI}_{30} = \left(\sum_{r=1}^{0} e_r v_r\right) I_{30} \tag{3}$$

where e_r is the unit of rainfall energy (MJ ha^{-1} mm^{-1}); v_r is the rainfall volume (mm) during a time period r; and I_{30} is the maximum rainfall intensity of the event during a period of 30 min (mm h^{-1}). The unit of rainfall energy (e_r) is calculated for each time interval as follows:

$$e_r = 0.29[1 - 0.72\exp(-0.05 i_r)] \tag{4}$$

where i_r is the rainfall intensity during the time interval (mm h^{-1}).

In practice, the monthly sums of EI_{30} and the average R-factor were calculated for each month. Even though many rainfall datasets are available for Crete (Vrochidou and Tsanis, 2012), they refer to the annual precipitation records which is of little value in the G2 model. Based on the abovementioned Eqs. (2)–(4), Meusburger et al. (2012) developed an algorithm for the calculation of monthly rainfall erosivity in Switzerland using 10-min resolution data. Using this software module, the monthly R-factor was calculated for four weather stations in Crete (Emprosneros, Nithafri, Archanes, Kalamavka), for which precipitation time series of 11 years (1969–1979) with 10-min resolution data were available.

Next, a set of 24 weather stations from the SoilTrEC project was used, giving average monthly precipitation records for the same time period (1969–1979). Monthly R-values were estimated for the 24 stations (Fig. 2) based on their total precipitation and their proximity to the four stations with calculated R-values. The spatial distribution of rainfall erosivity to the island surface used the calculated R-factor of the four stations and the estimated R-factor of the additional 24 (total: 28 stations). A non-linear regression approach was adopted using covariate data from the WorldClim database (Hijmans et al., 2005). The approach established a relationship between the precipitation measured by the 28 weather stations and that predicted by the WorldClim model for each month; this was carried out using Generalised Additive Models (GAM) (Hastie and Tibshirani, 1990). Once this relationship was established, the rainfall erosivity for each month was predicted for the whole of Crete. This approach was highly effective, resulting in a model fit (R^2) of between 0.86 and 0.98 in 'leave-one-out' cross validation.

The mean annual R-factor for Crete was estimated to be 777 MJ mm ha^{-1} h^{-1}, which is in accordance with the proposed pattern maps for Mediterranean areas (Diodato and Bellocchi, 2010). The estimated R-factor values are characterised by a strong seasonality, with highest regime coefficients occurring during the period from October to March (e.g. January: 194 MJ mm ha^{-1} h^{-1}, December: 153 MJ mm ha^{-1} h^{-1} and November: 121 MJ mm ha^{-1} h^{-1}) and lowest (almost zero) occurring during the period from April to September. Similar seasonal patterns have been reported by Koutroulis et al. (2010). The rainfall erosivity has a strong East to West gradient (Fig. 2).

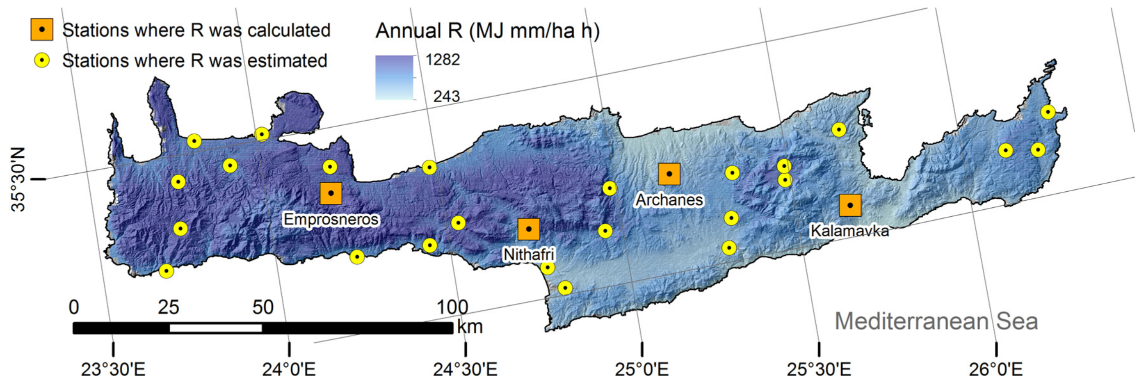

Fig. 2. Rainfall erosivity (*R*-factor) map of Crete.

The mean annual *R*-factor is 67% higher in the western part of Crete (931 MJ mm ha^{-1} h^{-1}) compared to that in the eastern part (559 MJ mm ha^{-1} h^{-1}).

2.4.2. Vegetation retention (V)

The vegetation retention factor (analogous to the USLE's *C*-factor) is the degree to which vegetation cover and management is expected to protect soil from erosion (Wischmeier and Smith, 1978). *C*-factor values can be found in empirical tables or alternatively can be estimated from land use maps or satellite images when details of land-use management are not available (Vrieling, 2006). In the G2 model, *V* is a dynamic factor which combines input from time series of vegetation layers and a constant empirical land-use parameter, and is defined as follows:

$$V = e^{(\mathrm{LU} * \mathrm{Fcover})} \quad (5)$$

where *V* is the vegetation retention (normalised; dimensionless), with $V = 1$ for bare, heavily managed agricultural land and $V > 1$ for land under better management conditions; Fcover is a vegetation layer normalised in the range [0–1]; LU is an empirical land-use parameter (constant for a specific location) ranging from 1 to 10, that corresponds to different management and treatments of land cover.

As derived from the empirical tables of the USLE, the *C*-factor is reduced non-linearly against plant cover and to different degrees for a variety of tillage practices (Wischmeier and Smith, 1978). Similarly, the *V*-factor should be differentiated for intermediate values of Fcover, thus emphasising the influence of different land uses for the same vegetation coverage, while higher LU values would be expected to reduce values of 1 V^{-1}. Therefore, an exponential function of the *V*-factor against Fcover was introduced to satisfy the abovementioned behaviour. In addition, the requirement for a management parameter in the erosion equation was satisfied by the introduction of the LU parameter.

Here, the LU values were derived from the CORINE Land Cover database. The Gavrilovic model (or Erosion Potential Method, EPM) (Gavrilovic, 1988) was used to quantify the nominal values of CORINE as numerical LU values. First, the CORINE classes were associated with corresponding Gavrilovic land-use categories; second, the values of the Xa parameter (analogous to the *C*-factor), taken from the Gavrilovic empirical tables, were assigned to the CORINE classes; and third, the Xa values (ranging from 0 to 1) were linked to LU values (ranging from 1 to 10), i.e. Xa = 1 → LU = 1, Xa = 0.9 → LU = 2, Xa = 0.8 → LU = 3, . . ., Xa = 0.1 → LU = 10.

In Crete, agricultural land is generally treated carefully, given that an adequate number of terraces are preserved in hilly sites (Karydas et al., 2008), manure application is rich, and land abandonment is limited. On the other hand, natural lands are subjected to overgrazing due to the traditional animal breeding activities followed in the area (Lyrintzis and Papanastasis, 1995). As a result, the agricultural land cover (class 2 of CORINE 1st classification level) was associated with the Gavrilovic categories B4, B5 and B6, which correspond to areas under conservation measures. Therefore, they were assigned the highest possible LU values corresponding to the Gavrilovic table (here referred as 'best-case scenario'). On the other hand, natural grasslands and low shrublands (classes 321 and 322/324 of the CORINE 3rd classification level, respectively) were associated with categories A4 and A5 of the Gavrilovic table and thus were assigned the lowest values due to their extensive use for grazing (here referred as 'worst case scenario') (Table 1). Further, class 244 (agro-forestry areas) was given LU = 8.5; class 243 (agricultural land with large portions of natural vegetation) was given LU = 8.0; classes 241 and 242 (associations of annual and permanent crops and complex cultivation patterns, respectively) were given LU = 7.5; class 333 (sparsely vegetated areas) was given LU = 4.0; and class 334 (burnt areas) was given LU = 3.0.

Expert knowledge was used to assign LU values for those CORINE classes that were not considered in the Gavrilovic tables. Most artificial surfaces (class 1 of CORINE's 1st classification level) were assigned the maximum LU value (10.0) as they are considered to be 'non-erosive'. However, mines, dumps, and construction sites (classes 131, 132, and 133) were given LU = 1.0, as these are areas with highly disturbed soils. The maximum value (LU = 10.0) was also assigned to beaches, dunes, sands, bare rocks, and perpetual snow (classes 331, 332, and 335). Wetlands and water bodies (classes 4, 5 of the CORINE 1st classification level) were assigned the maximum LU value of 10.0 as they are 'non-erosive'.

Using Eq. (5), with input from monthly time-step Fcover layers and the LU parameter with values taken from Table 1, twelve monthly V-layers were produced for a complete year (April 2011–March 2012). Areas covered by clouds in Fcover layers (usually bare rocky areas on high mountains) were missing from V-layers. The western part of the island shows a mean *V*-factor value of 62.08, whereas the eastern part shows a mean value of 36.88, i.e. the mean value of the western part was higher by 68% than that of the eastern part (Fig. 3).

2.4.3. Soil erodibility (S)

Soil erodibility is a lumped parameter that represents an integrated annual value of the soil profile's reaction to the process of soil detachment and transport by raindrop and surface flow (Renard et al., 1997). Soil erodibility (denoted as the *K*-factor in the USLE and the *S*-factor in the G2 model) is best estimated from direct measurements of natural plots (Kinnell, 2010). As this is not financially sustainable at the regional/national level, the

Table 1
Assignment of the LU parameter values for natural and agricultural land uses based on correspondence with Gavrilovic (EPM) and CORINE classes.

Gavrilovic land use categories		Xa parameter	CORINE class codes	LU parameter	Worst or best case scenario
A1	Barren untilled soil	1.000	–	–	–
A2	Ploughed field up and down the slope	0.900	–	–	–
A3	Orchards and vineyards without low vegetation	0.700	–	–	–
A4	Degraded woods and under bush with eroded soil	0.600	322/324	5.00	Worst
A5	Mountain pastures	0.600	321	5.00	Worst
A6	Meadows and similar perennial crops	0.400	–	–	–
A7	Good woods on slopes	0.200	311/312/313	9.00	Best
A8	Good woods on flat land	0.050	–	–	–
B1	Contour farming	0.630	–	–	–
B2	Contour farming with mulching	0.540	–	–	–
B3	Contour – strip cultivation with crop rotation	0.450	211/212/213	6.50	Best
B4	Contour orchards and vineyards	0.315	221/222/223	7.85	Best
B5	Terracing of ploughed fields, terraces, graded terraces	0.360	211/212/213	7.50	Best
B6	Grazing, meadow amelioration	0.300	231	8.00	Best
B7	Contour trenches of medium density	0.240	–	–	–
B8	Forestation (holes and strips)	0.200	323	9.00	Best
B9	Forestation and grading	0.100	–	–	–

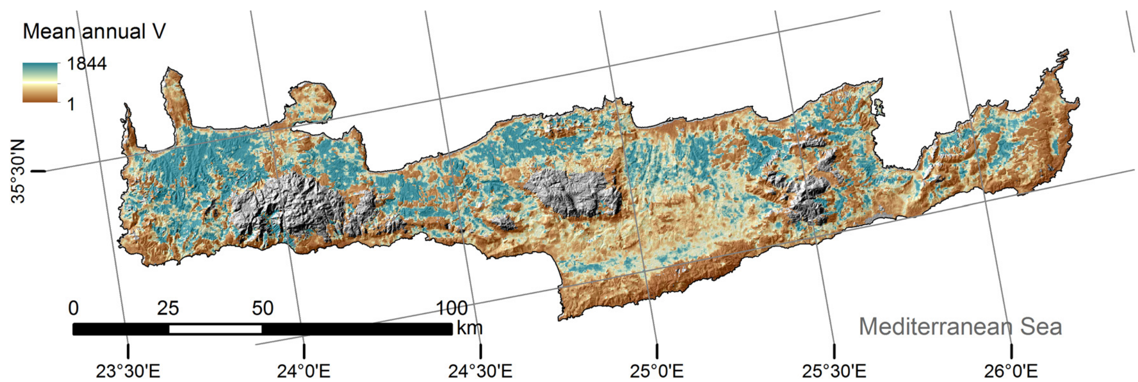

Fig. 3. Annual *V*-factor derived from monthly time-step layers over the period April 2011–March 2012.

S-factor relates to soil properties as proposed for the USLE model by Renard et al. (1997):

$$S = K = \left[\frac{2.1\times 10^{-4}M^{1.14}(12-\mathrm{OM}) + 3.25(s-2) + 2.5(p-3)}{100}\right] \times 0.1317 \qquad (6)$$

where *M* is the textural factor defined as percentage silt + fine sand fraction content multiplied by (100 − clay fraction); OM is the organic matter content (%); *s* is 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); and *p* is the permeability class (*p* = 1: very rapid, . . ., *p* = 6: very slow). *S* (or *K*) is expressed in SI units of t ha h ha^{-1} MJ^{-1} mm^{-1}. Eq. (6) has been used to estimate soil erodibility at the European scale based on the LUCAS topsoil dataset (Panagos et al., 2012b).

By using 31 soil samples from the pan-European LUCAS topsoil dataset and an additional set of 60 soil samples of the SoilTrEC project, the soil organic matter and textural (silt, sand, clay) layers were calculated using regression Kriging techniques (Odeh et al., 1995). The S-layer was then calculated based on Eq. (6). The average *S*-factor for the whole island was found to be 0.040 t ha h ha^{-1} MJ^{-1} mm^{-1}. The mean *S*-factor is 22% higher in the eastern part of Crete (0.043 t ha h ha^{-1} MJ^{-1} mm^{-1}) compared to the western part (0.035 t ha h ha^{-1} MJ^{-1} mm^{-1}).

2.4.4. Topographic influence (T) and slope intercept (I)

To estimate the influence of topography on erosion risk (*T*; or LS as denoted by the USLE), the G2 model uses an equation developed by Moore and Burch (1986) and proposed by Desmet and Govers (1997), that is used by most of the USLE-family models:

$$T = \left(\frac{A_s}{22.13}\right)^{0.4} \times \left(\frac{\sin\beta}{0.0896}\right)^{1.3} \qquad (7)$$

where *T* is the topographic influence (≥0; dimensionless), A_s is the flow accumulation (m) and β is the slope (rad).

Flow accumulation is defined as the accumulated flow to a cell from all upslope cells. It is calculated using a Digital Elevation Model (DEM). The original calculated values are given as the numbers of cells flowing into the specific cell.

When a DEM is used as input for calculating A_s and β, accuracy errors inherent in the DEM are propagated to the erosion outputs (Abd Aziz et al., 2012). In order to compensate for this kind of uncertainty, the G2 model:

- Pays particular attention in the strict implementation of the terms under which the Moore–Burch equation (and the USLE-plot conditions in general) should be applied, i.e. slope gradients less than 14°, slope length up to 100 m (Moore and Wilson, 1992) and elevation raster cell size less than 30 m (obviously, these terms are also affected by the character of the terrain).
- Has developed a corrective parameter for slope length, namely the *I*-factor, which accounts for land use alterations (on a local basis), thus resulting in the proportional reduction of influence of the *T*-factor on erosion risk (Panagos et al., 2012a).

The *T*-factor values are in accordance with the complex topography of the Cretan terrain, as can be verified by the experimental

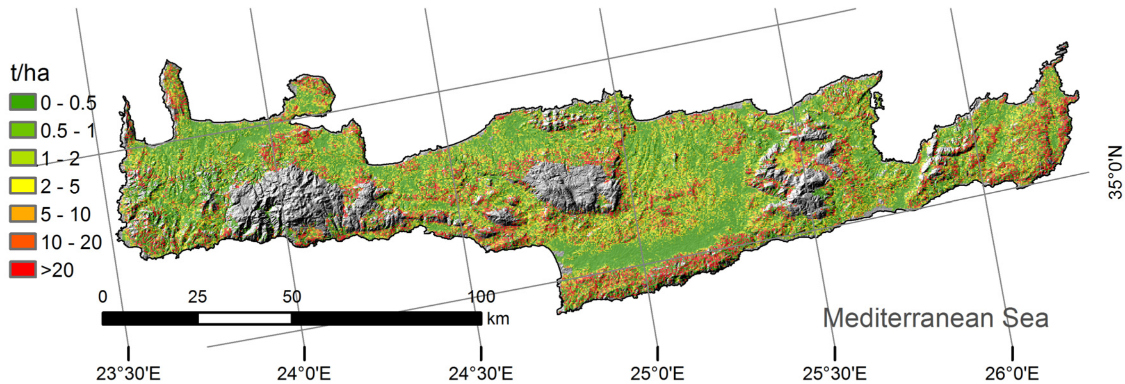

Fig. 4. The mean annual erosion risk map of Crete.

results of the USLE model for irregular slopes (i.e. convex or concave terrain continuums). According to those experiments, for a concave terrain continuum up to 15% of slope gradient, a value of LS (T-factor in G2) = 3.5 is expected (Wischmeier and Smith, 1978). On average, the west of the island is found to be slightly more hilly (by 9%) than the east.

The I-layer was estimated by applying a Sobel filter (a non-directional edge-detection filter) on the high resolution satellite image mosaic (Image 2006) (Soille, 2006). The equation for the computation of I-factor was revised (compared to previous formulation in G2 model, Panagos et al., 2012a) in order to include the I-factor in the denominator of Eq. (1):

$$I = 1 + \sqrt{\frac{S_f}{255}} \quad (8)$$

where S_f is the Sobel filter value of the image in a range [0,255] (8-bit systems). The mean value of I-factor was found to be 1.122, resulting in a reduction of the T-values (and consequently of the erosion risk) by 11% on average. The two parts of the island (western and eastern) were found to have almost equal mean I values.

3. Results

The cartographic product of the G2 model implementation in Crete was a set of maps with a 300 m cell size projected in the ETRS 1989 LAEA system. Some areas are excluded from the maps:

- Areas covered by clouds during winter months (missing Fcover data required for the V-factor estimation), accounting for 15% of the total area.
- Areas with slopes of more than 14° (according to the conditions for T calculation), accounting for 8% of the total area.
- Non-erosive land cover such as bare rocky areas (mountain peaks), accounting for 0.5% of the total area.

As a result, an area of 6417 km^2, accounting for 77% of the total area of Crete, was mapped for erosion risk on a monthly time-step basis. The mean annual soil loss rate was found to be 8.123 t ha^{-1}. This rate was found to be slightly higher (by 8%) in the west than in the east, at 8.479 t ha^{-1} and 7.862 t ha^{-1} respectively (Fig. 4).

The monthly rates range between 0 and 1.746 t ha^{-1}, with December and January being the most erosive and July and August the least erosive (practically non-erosive) (Fig. 5). The distribution of the erosion rates over the year can be grouped into three risk seasons:

- A high-risk season (October to January), with monthly erosion rates over 1 t ha^{-1}, which accounts for 80% of annual erosion.
- A medium-risk season (February to April plus September), with monthly erosion rates between 0.1 and 1 t ha^{-1}, which accounts for 18% of annual erosion.
- A low-risk season (May to August), with monthly erosion rates lower than 0.1 t ha^{-1}, which accounts for only 2% of annual erosion.

A similar temporal trend can be detected for land subject to agricultural use (class 2 of CORINE 1st classification level), except for the fact that the months of October and November show the highest annual erosion rates (as opposed to the general trend of December and January).

The spatial distribution of soil erosion rates per land cover/use class was based on the CORINE Land Cover dataset. Olive plantations (CORINE class 223), which are predominant in Crete and spread throughout the entire island, show a mean annual erosion rate of 2.4 t ha^{-1}. Vineyards (class 221), mainly located in the central and eastern parts of the island (Heracleion and Lassithi regional units), show a mean annual erosion rate of 1.9 t ha^{-1}. Citrus plantations (class 222), located in the west (around Chania city), show a mean annual erosion rate of 0.8 t ha^{-1}. The arable land (classes 211, 212), mainly located in the Lassithi Plateau, show a mean annual erosion rate of 5.5 t ha^{-1}. The heterogeneous agricultural lands (classes 241, 242, 243, 244), spread over the entire island, show a mean annual erosion rate of 4.3 t ha^{-1}.

The limited forest areas (classes 311, 312, 313), mainly located in the southern part of the Chania regional unit and the western part of Lassithi, show an annual rate of 3.7 t ha^{-1}. Pastures (class 231) are very limited in Crete as the livestock of the island is mostly supported by natural grasslands (class 321), which are distributed over the entire island. The mean annual erosion rate of natural grassland areas was estimated at 23.1 t ha^{-1}. Shrublands (classes 322, 323, 324), which could also potentially be used for grazing, show a mean annual erosion rate of 7.1 t ha^{-1}. Sparsely vegetated areas (class 333) show a mean annual erosion rate of about 41 t ha^{-1}. In summary, the mean annual erosion rate is estimated to be 3.065 t ha^{-1} for agricultural land use and 14.023 t ha^{-1} for shrubland and grassland classes used for grazing. Most erosion factors (R, V, T and I) are in favour of higher erosion rates in natural grasslands and shrublands compared to agricultural land use. Natural grasslands are located in steeper and longer slopes with higher rainfall intensity compared to the agricultural land use. Moreover, they have lower vegetation density (Fcover) and they are grazed heavily by an increasing number of livestock (low LU). Even if the same LU value were introduced to the V formula for agricultural land use and natural grasslands, erosion rates would be again higher for the latter by 4 times.

As for the temporal dimension, generally 80% of the soil loss is expected from October to January (high-risk season), which is the

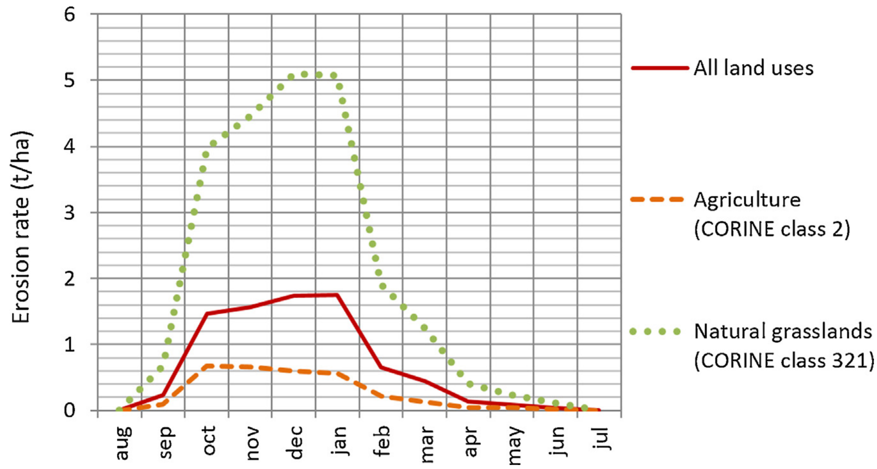

Fig. 5. Temporal distribution of erosion rates for all land uses, agricultural land use and natural grasslands.

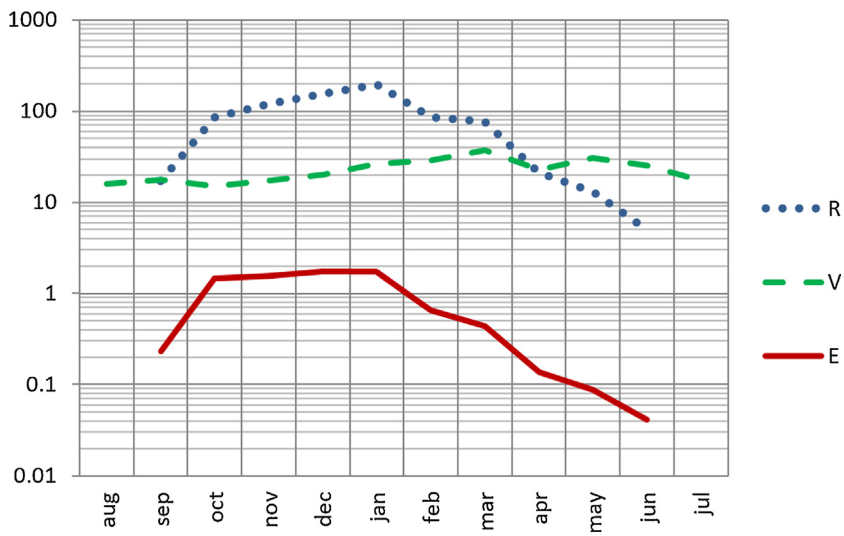

Fig. 6. Monthly time-step distribution of mean rainfall erosivity (R), mean vegetation retention (V) and mean erosion (E) for Crete (logarithmic scale).

rainy season in Crete. It was also shown that vegetation retention is quite constant throughout the year (Fig. 6). Moreover, the relative contribution of every month to the annual erosion figures can be assessed in the spatial domain in terms of a spatio-temporal erosion relative index (STERI), which is the ratio of the monthly erosion rate over the annual erosion rate. In a STERI map, cells of high value indicate the locations of hotspots for a specific time of the year. As an example, Fig. 7 shows the STERI index for the month of December.

The erosion rates measured in an olive field in the Avgeniki village (Kosmas, personal communication) were reported to be less than 0.4 t ha^{-1} y^{-1} and are in accordance with results of this study. As other measurements of soil erosion rates are not available in the study area to perform a systematic validation, authors checked the

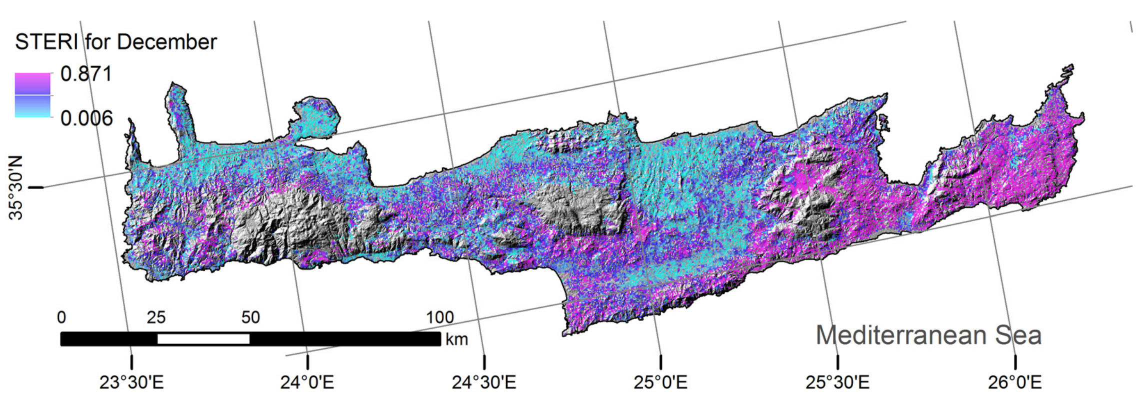

Fig. 7. Spatio-temporal erosion relative index (STERI) for the month of December.

consistency of the study results with other sources found in the literature.

In the context of the EU's 6th Framework Programme DESIRE project (DESIRE, 2012), the application of the PESERA model (Kirkby et al., 2008) to an area of about 70,000 ha in the south-west of Chania city and an area of 37,000 ha in the Messara valley estimated an average soil loss of more than 6 t ha^{-1} y^{-1}.

Kouli et al. (2009) estimated mean erosion values to be around 120 t ha^{-1} y^{-1} in a study conducted in western Crete using the RUSLE model. This extreme difference compared to the current study results is attributed to the significantly higher values of rainfall erosivity and the cover management factor (analogous to 1/V) adopted by Kouli et al. (2009). Karydas et al. (2008) also calculated very high erosion figures, with an average of 106 t ha^{-1} y^{-1} in an area of 6800 ha in the municipality of Kolymvari, west of the city of Chania. Their extreme values can be attributed to their rough estimation of soil erodibility, which was derived from experts' opinion based on geological maps and the unconditioned estimation of the topographic parameters in a very undulating relief.

4. Discussion – conclusions

This study mapped detailed spatial patterns of soil erosion on a regional scale, calculated intra-annual erosion trends on a monthly time-step basis, and differentiated erosion figures per land use in the Mediterranean island of Crete. The consistency of the results was checked against the available (though limited) experimental field measurements and other data sources found in the literature.

The spatial patterns of erosion in Crete were generally homogeneous throughout the island, with a difference of only 8% being recorded between the east and the west (higher mean erosion value in the west). The significantly higher rainfall erosivity figures found in the west (by 67%) were compensated by the vegetation retention figures for the same area (higher by 68%). The other parameters favoured one or the other side of the island, to a lesser degree.

The temporal patterns of erosion in Crete follow the rainfall seasonality as vegetation coverage is generally stable. Starting from the estimated monthly soil erosion rates derived from G2 model, authors propose a new index (STERI, spatio-temporal erosion relative index) suitable for the identification of hotspots and erosive periods.

The original G2 approach implemented in the Strymonas river basin (Panagos et al., 2012a) was improved in this study, especially in terms of the *V*-factor, by incorporating land cover/use information in the revised formula. The development of the new equation was based on inputs from the USLE and Gavrilovic (or EPM) empirical models in terms of parameter adjustments for the most common land use and management conditions, which can be quantified by the user according to a land cover/use database (e.g. CORINE) and his/her knowledge of the area.

The higher erosion values found in natural areas can be attributed to the increasing levels of livestock and inappropriate grazing practices, which further aggravate the current degraded soil erosion status in Crete. Decision makers should be made aware of erosion hotspots (natural grasslands and high density of livestock) in order to take appropriate measures.

The G2 model highlights the spatio-temporal variability of soil erosion. It clearly shows the critical seasons, hotspots and land uses which are more susceptible to erosion. This information is required for developing appropriate conservation policies regarding land use and agricultural practices in order to avoid serious consequences of erosive events. The G2 model can potentially be applied within the Copernicus framework in the direction of better management of agricultural land uses for reducing soil erosion risk. The G2 model offers three important advantages to potential users and policy makers. First, it can provide geographically referenced information, which can be easily reproduced using up-to-date input data layers. Second, the model has the potential to be expanded from regional to country level, as it has modest data input requirements and is easy to use. Third, G2 model and its results are disseminated through the European Soil Data Centre (ESDAC) open data platform (Panagos et al., 2012c), which allows researchers to further apply the model and policy makers to consult the available results.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.jag.2013.09.012. These data include Google maps of the most important areas described in this article.

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CHAPTER 4

Rainfall Erosivity in Europe

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Rainfall erosivity in Europe

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HIGHLIGHTS

- Rainfall erosivity in Europe & Switzerland is estimated to 722 MJ mm ha^{-1} h^{-1} yr^{-1}.
- Rainfall Erosivity Database at European Scale (REDES) includes 1541 stations.
- The highest R-factor is in Mediterranean & Alpine regions and lowest in Scandinavia.
- The erosivity density shows high variability of the R-factor per precipitation unit.
- High resolution (1 km grid cell) dataset of R-factor is available for modelling.

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ABSTRACT

Rainfall is one the main drivers of soil erosion. The erosive force of rainfall is expressed as rainfall erosivity. Rainfall erosivity considers the rainfall amount and intensity, and is most commonly expressed as the R-factor in the USLE model and its revised version, RUSLE. At national and continental levels, the scarce availability of data obliges soil erosion modellers to estimate this factor based on rainfall data with only low temporal resolution (daily, monthly, annual averages). The purpose of this study is to assess rainfall erosivity in Europe in the form of the RUSLE R-factor, based on the best available datasets. Data have been collected from 1541 precipitation stations in all European Union (EU) Member States and Switzerland, with temporal resolutions of 5 to 60 min. 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 covariates used for the R-factor interpolation were climatic data (total precipitation, seasonal precipitation, precipitation of driest/wettest months, average temperature), elevation and latitude/longitude. The mean R-factor for the EU plus Switzerland is 722 MJ mm ha^{-1} h^{-1} yr^{-1}, with the highest values (>1000 MJ mm ha^{-1} h^{-1} yr^{-1}) in the Mediterranean and alpine regions and the lowest (<500 MJ mm ha^{-1} h^{-1} yr^{-1}) in the Nordic countries. The

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erosivity density (erosivity normalised to annual precipitation amounts) was also the highest in Mediterranean regions which implies high risk for erosive events and floods.

1. Introduction

Soil erosion by water affects soil quality and productivity by reducing infiltration rates, water-holding capacity, nutrients, organic matter, soil biota and soil depth (Pimentel et al., 1995). Soil erosion also has an impact on ecosystem services such as water quality and quantity, biodiversity, agricultural productivity and recreational activities (Dominati et al., 2010; Dale and Polasky, 2007).

Since soil erosion is difficult to measure at large scales, soil erosion models are crucial estimation tools at regional, national and European levels. The high heterogeneity of soil erosion causal factors, combined with often poor data availability, is an obstacle to the application of complex soil erosion models. 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 (Kinnell, 2010; Panagos et al., 2014a). In RUSLE, soil loss may be estimated by multiplying the rainfall erosivity factor (R-factor) by five other factors: Soil erodibility (K-factor), slope length (L-factor), slope steepness (S-factor), crop type and management (C-factor), and supporting conservation practices (P-factor).

Among the factors used within RUSLE and its earlier version, the Universal Soil Loss Equation (USLE) (Wischmeier and Smith, 1978), rainfall erosivity is of high importance as precipitation is the driving force of erosion and has a direct impact on the detachment of soil particles, the breakdown of aggregates and the transport of eroded particles via runoff. Rainfall erosivity is the kinetic energy of raindrop's impact and the rate of associated runoff (Wischmeier and Smith, 1978). 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.

A precise assessment of rainfall erosivity requires recordings of precipitation at short time intervals (1–60 min) for a period of at least several years. The rainfall erosivity is calculated by multiplying the kinetic energy by the maximum rainfall intensity during a period of 30-minutes for each rainstorm. The R-factor accumulates the rainfall erosivity of individual rainstorm events and averages this value over multiple years.

Field experiments using plot-sized rainfall simulators provide precise results of rainfall erosivity (Marques et al., 2007). However, since field experiments are expensive and often not easily transferable to large scales, researchers develop models for estimating rainfall erosivity. Two approaches are used to model rainfall erosivity: a) calculate the R-factor based on high-temporal-resolution precipitation data, and b) develop functions that correlate the R-factor with more readily available (daily, monthly, annual) rainfall data (Bonilla and Vidal, 2011). Only a few studies in Europe have determined the R-factor directly from high-temporal-resolution data (the first approach), including those carried out in Slovenia (Mikos et al., 2006), the Ebro catchment in Spain (Angulo-Martinez et al., 2009), Switzerland (Meusburger et al., 2012), and one of the federal states of Germany, North Rhine Westphalia (Fiener et al., 2013). At the continental scale, a recent study has accounted for the rainfall erosivity in Africa based on time series of 3-hours precipitation data (Vrieling et al., 2014).

In most soil erosion studies, the calculation of rainfall erosivity is limited due to the lack of long-term time series rainfall data with high temporal resolution (<60 min). Following the second approach (called the empirical approach), equations have been developed to predict R-factor based on rainfall data with lower temporal resolution (Loureiro and Coutinho, 2001; Marker et al., 2007; Diodato and Bellocchi, 2007; Panagos et al., 2012a). In those cases, expert knowledge of local conditions and seasonal characteristics plays an important role in estimating rainfall erosivity. Authors have suggested that rainfall erosivity equations should be used with caution in different applications, as the empirical relationships are location dependent and, in most cases, cannot be applied to larger areas (Oliveira et al., 2013). Moreover, those empirical equations cannot capture the high rainfall intensities which have significant influence on the average rainfall erosivity. R-factor equations developed for a specific region cannot be applied to the whole of Europe.

The main objective of this study is to estimate rainfall erosivity based on high-temporal-resolution precipitation data in Europe. It aims to:

a) present the spatial and temporal extent of high-resolution precipitation data available in Europe,
b) compute rainfall erosivity for 1541 precipitation stations in Europe, and propose a pan-European database of stations with R-factor data,
c) produce a European R-factor map based on a regression approach,
d) identify spatial patterns and map the relationship of the R-factor to precipitation (erosivity density), and
e) identify the possible use of the final R-factor dataset in situations beyond soil erosion monitoring.

2. Data collection

The geographical extent of this study includes the 28 Member States of the European Union (EU) plus Switzerland. High-resolution precipitation data were also available for the Swiss territory, which permitted us to avoid the “white lake” effect in the European rainfall erosivity map.

Given the growing concerns about climate change, climatic data is particularly important for the scientific community and society in general, as decisions of individuals, business and governments are dependent on available meteorological data (Freebairn and Zillman, 2002). More than 15 years ago, Peterson et al. (1998) recognised that data infrastructures hosting climatic data are becoming more important and that their contributions are becoming more valuable to policy making.

The present data collection exercise is based on an initiative to develop a network of high-temporal-resolution precipitation stations, which could also be useful for other research purposes such as climate change studies. Generally, climatic data of high temporal resolution are not easily accessible in Europe, or are only available for a fee.

The data collection exercise began in March 2013 and was concluded in May 2014. Previous attempts to collect soil erosion data from Member States used a top-down approach, and the response from countries was rather limited. In a recent top-down data collection exercise, only 8 Member States from a network of 38 countries provided estimates on soil loss (Panagos et al., 2014a). For the present rainfall erosivity data collection exercise, a participatory approach has been followed in order to collect data from all Member States.

The participatory data collection approach followed the steps listed below. Each step was followed in a sequential manner in case the preceding step was not successful:

a) High-temporal-resolution precipitation data are publicly available for download. This was the case for data from the Royal Netherlands Meteorological Institute (Netherlands) only.
b) The European Soil Data Centre (ESDAC) contacted the national meteorological services calling for precipitation data at high temporal resolution. Meteorological services such as Meteo-France, the Deutscher Wetterdienst — DWD (Germany), the Flemish Environmental Agency and the Service Public de Wallonie (Belgium), the Estonian Environment Agency, the Latvian Meteorology Centre and the Agrarmeteorologisches Messnetz (Luxembourg) responded to this request as some of them have bilateral agreements with the Joint Research Centre, which hosts ESDAC.
c) If the data were not available to ESDAC, recognised scientists of the various meteorological services were invited to participate in this project. Meteorologists from Cyprus, Finland, Croatia, Hungary and Romania participated in estimating the rainfall erosivity of their respective countries, based on their datasets.
d) By means of a literature review, scientists who have developed similar research activities in their countries and have access to or have developed their own R-factor datasets (based on high-temporal-resolution precipitation data) were identified and contacted.
e) High-resolution precipitation datasets were identified in research project databases such as Hydroskopio (Greece) and Sistema National de Recursos Hidricos (Portugal).
f) A review of the 'grey' literature and searches with national language terms led to the discovery of data sources in Lithuania, Slovakia and Poland.

In Italy and Spain, high-resolution precipitation data were collected at the regional level from regional meteorological authorities (Italy) and water agencies (Spain).

The conditions set for the data collection exercise were:

- Continuous records for at least 10 years. If such data were not available, data collected over a period of at least five years were included. Vrieling et al. (2014) also stated that the R-factor may be cumulated for shorter timespans in calculating rainfall erosivity trends.
- Preference was given to datasets that cover the last decade. Where this was not possible, older time series were also included, e.g., for Bulgaria, Greece, the Czech Republic, Poland and Slovakia. As the priority of this study was to capture the spatial trends of rainfall erosivity by averaging erosive events over several years, we consider this time discrepancy to be of minor importance (Table 1).
- Data of up to 60 minute resolution were included.
- In Italy, which has a larger pool of available stations (>500), 251 stations were selected in order not to bias the pan-European results. A stratified random sample of the Italian stations were selected, covering all climatic conditions (Mediterranean, Continental and Alpine) and all elevation levels.

Priority was given to datasets with high temporal resolution, independent of the period covered, because the objective of this data collection exercise was to capture the spatial trends of rainfall erosivity. In the majority (>75%) of countries, the time-series include the first decade of the 21st century, except for Bulgaria, Greece, the Czech Republic, Poland and Slovakia. However, the time-series for those five countries are long enough (>25 years) to capture the average rainfall erosivity.

Table 1
Overview of the precipitation data collected to estimate the R-factor.

Country		No. of stations	(Main) period covered	Years per station (average)	(Main) temporal resolution: 5 min, 10 min, 15 min, 30 min, 60 min	Source of data
AT	Austria	31	1995–2010	21	12 stations: 10 min 19 stations: 15 min	Hydrographic offices of Upper Austria, Lower Austria, Burgenland, Styria, Salzburg
BE	Belgium	20	2004–2013	10	Flanders (20 stations): 30 min	Flemish Environmental Agency (VMM),
		29	2004–2013	10	Wallonia (29 stations): 60 min	Service Public de Wallonie
BG	Bulgaria	84	1951–1976	26	30 min	Rousseva et al. (2010)
CY	Cyprus	35	1974–2013	39	30 min	Cyprus Department of Meteorology
CZ	Czech Republic	32	1961–1999	35	30 min	Research Institute for Soil and Water Conservation (Czech Republic)
CH	Switzerland	71	1988–2010	22	10 min	Meusburger et al. (2012)
DE	Germany	148	1996–2013	18	60 min	Deutscher Wetterdienst (DWD)
DK	Denmark	30	1988–2012 2004–2012	15	60 min	Danish Meteorological Institute (DMI), Aarhus University
EE	Estonia	20	2007–2013	7	60 min	Estonian Environment Agency
ES	Spain	113	2002–2013	12	14 stations: 10 min, 81 stations: 15 min 18 stations: 30 min	Regional water agencies
FI	Finland	64	2007–2013	7	60 min	Finnish Climate Service Centre (FMI)
FR	France	60	2004–2013	10	60 min	Météo-France DP/SERV/FDP
GR	Greece	80	1974–1997	30	30 min	Hydroskopio
HR	Croatia	42	1961–2012	40	10 min	Croatian Meteo & Hydrological Service
HU	Hungary	30	1998–2013	16	10 min	Hungarian Meteorological Service
IE	Ireland	13	1950–2010	56	60 min	Met Éireann — The Irish National Meteorological Service
IT	Italy	251	2002–2011	10	30 min	Regional meteorological services, Regional agencies for environmental protection (ARPA)
LT	Lithuania	3	1992–2007	16	30 min	Mazvila et al. (2010)
LU	Luxembourg	16	2000–2013	11	60 min	Agrarmeteorologisches Messnetz
LV	Latvia	4	2007–2013	7	60 min	Latvian Environment, Geology and Meteorology Centre
NL	Netherlands	32	1981–2010	24	60 min	Royal Netherlands Meteorological Institute
PL	Poland	9	1961–1988	27	30 min	Banasik et al. (2001)
PT	Portugal	41	2001–2012	11	60 min	Agência Portuguesa do Ambiente
RO	Romania	60	2006–2013	8	10 min	Meteorological Administration
SE	Sweden	73	1996–2013	18	60 min	Swedish Meteorological and Hydrological Institute (SMHI)
SI	Slovenia	31	1999–2008	10	5 min	Slovenian Environment Agency, Petan et al. (2010)
SK	Slovakia	81	1971–1990	20	60 min	Malíšek (1992)
UK	United Kingdom	11	1993–2012	20	60 min	NERC & UK Environ. Change Network (ECN)
		27	2001–2013	11	60 min	British Atmospheric Data Centre (BADC)

Data have been collected from all EU Member States except Malta (the smallest EU Member State). In Malta, precipitation data were available only at a daily time step and, as they do not satisfy the criteria requirement of high temporal resolution, could not be used for R-factor estimation. However, Malta is only 80 km distant from the southern Italian island of Sicily, where a very dense network of stations is able to capture the spatial variability of rainfall erosivity. High-temporal-resolution data was available for Poland, but only against payment. In this case, data from literature sources were used.

3. Methods

Besides the high-temporal-resolution precipitation data collection, the estimation of the R-factor in Europe includes three further steps: a) The calculation of the R-factor for each precipitation station, b) the normalisation of R-factor values calculated using rainfall data with different time steps (5 min to 60 min), and c) the spatial interpolation of R-factor point values.

3.1. R-factor calculation

The erosive power of precipitation is accounted for by the rainfall erosivity factor (R-factor), which gives the combined effect of the duration, magnitude and intensity of each rainfall event. In this study, the original RUSLE R-factor equation was used to create an R-factor database of 1541 precipitation stations in Europe.

The 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):

$$R = \frac{1}{n}\sum_{j=1}^{n}\sum_{k=1}^{mj}(EI_{30})_k \qquad (1)$$

where R = average annual rainfall erosivity (MJ mm ha^{-1} h^{-1} yr^{-1}), n is the number of years covered by the data records, m_j is the number of erosive events of a given year j, and EI_{30} is the rainfall erosivity index of a single event k. The event erosivity EI_{30} (MJ mm ha^{-1} h^{-1}) is defined as:

$$EI30 = \left(\sum_{r=1}^{0} e_r v_r\right) I_{30} \qquad (2)$$

where e_r is the unit rainfall energy (MJ ha^{-1} mm^{-1}) and v_r is the rainfall volume (mm) during a time period r. I_{30} is the maximum rainfall intensity during a 30-min period of the rainfall event (mm h^{-1}). The unit rainfall energy (e_r) is calculated for each time interval as follows (Brown and Foster, 1987):

$$e_r = 0.29[1-0.72\exp(-0.05i_r)] \qquad (3)$$

where i_r is the rainfall intensity during the time interval (mm h^{-1}).

The R-factor calculation requires the identification of erosive rainfall events (m_j) for each station. Three criteria for the identification of an erosive event are given by Renard et al. (1997): (i) the cumulative rainfall of an event is greater than 12.7 mm, or (ii) the event has at least one peak that is greater than 6.35 mm during a period of 15 min (or 12.7 mm during a period of 30 min). A rainfall accumulation of less than 1.27 mm during a period of 6 h splits a longer storm period into two storms. The 12.7-mm threshold defines precipitation events that have erosive power. Interestingly, a reduction of the threshold from 12.7 mm to 0 mm leads to an increase in the R-factor of no more than 3.5% (Lu and Yu, 2002).

The Rainfall Intensity Summarisation Tool (RIST) software (USDA, 2014) was used to calculate the R-factor. The RIST can be used for R-factor calculations using precipitation data that have the same temporal resolution (Klik and Konecny, 2013).

3.2. Normalisation procedure for R-factors with different precipitation recording intervals

The precipitation data collected from the 28 countries across Europe have different temporal resolutions: 60-min, 30-min, 15-min, 10-min and 5-min. This variation in temporal resolutions is due to high numbers of data providers (minimum one per country; data from Spain, Italy, Austria, Belgium and the United Kingdom came from more than one data source, see Table 1).

According to the literature, the R-factor is underestimated as time steps increase from 5, 10, 15, 30 to 60 min (Yin et al, 2007; Williams and Sheridan, 1991). In order to homogenise the R-factor results calculated using different time-step data, conversion factors were established in the present study. The conversion of 60-min-resolution data to very fine resolution introduces quite a high level of uncertainty. As a compromise, the 30-min temporal resolution data was used, even though the most abundant time-step is 60 min. In addition, Yin et al. (2007) recommended that it is not needed to move towards time intervals of less than 30-min to obtain reliable erosivity estimations.

The data at very fine resolution were aggregated to coarse resolutions, and the R-factor was estimated for different temporal resolutions. For example, data of 30-min resolution were aggregated to 60-min resolution, and the R-factor was calculated both at 30-min and 60-min resolutions. Data of 10-min resolution were aggregated to 30-min resolution, and the R-factor was calculated using both 10-min and 30-min resolutions. Regression functions between R-factors based on high and low resolution data were established to normalise the R-factor values to 30-min resolution.

3.3. Spatial prediction of the R-factor

Given the relatively low observation density for the European continent and the huge climatic variability of the study area, interpolation by kriging was not expected to produce realistic results. Instead, given the likely correlation between the R-factor and climatic data, a regression approach was used to infer the distribution of rainfall erosivity from a series of related, but independent, climatic 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, here the R-factor, can be estimated for the area of interest. Various covariates were considered for the regression model, but three main types were identified as being significant:

1. Climatic data: average monthly precipitation, average minimum & maximum monthly precipitation, average monthly temperature, precipitation of the wettest month, precipitation of the driest month and precipitation seasonality (variation of precipitation over seasons). The climatic data are derived from the WorldClim database (Hijmans et al., 2005), which reports monthly averages of precipitation and temperature for the period 1950–2000 at 1-km resolution.
2. Elevation derived from the Digital Elevation Model of the Shuttle Radar Topography Mission (SRTM).
3. Latitude and longitude spatial coordinates, derived from the measuring stations' location, were added explicitly to the regression model in order to model spatial correlation.

In the late 1990's, Goovaerts (1999) introduced the geostatistical interpolation method for calculating rainfall erosivity based on regionalised variables such as elevation. This linear model for spatial R-factor prediction has been widely used because it allows for non-biased estimation at non-sampled points with minimum variance. The high dimensionality (number of degrees of freedom) of the data used and the likely non-linear relation between the target variable and the covariates, discouraged the use of linear regression. Instead, this study adopted Gaussian Process Regression (GPR) (Rasmussen and Williams, 2006; Stein, 1999), a non-linear regression approach.

Compared to linear regression, GPR can model non-linear processes by projecting the inputs into some high dimensional space using basis functions and applying linear model in the said space. In this study the Radial Basis Function (RBF) Gaussian kernel has been used; this is a kernel commonly applied in machine learning (Hofmann et al., 2008). The kernel function is equivalent to a covariance function in kriging and its value is considered as a measure of similarity between the two feature vectors. In this respect, GPR is mathematically equivalent to kriging (Stein, 1999); however, while kriging is usually performed on two- or three-dimension geographical space, GPR can be performed over an arbitrary number of covariates, including terrain features and geographical coordinates. The main advantages of GPR are that it can model complex non-linear relations between covariates and the target variable, and directly model both average and variance estimations, thus providing information about prediction uncertainty.

Gaussian Process Regression was selected as the best performing model in terms of cross validation among a series of candidate models (including OLS, GLM, GAM, and Regression Kriging). The criteria chosen for the selection were the minimization of the root-mean squared error and the maximization of the R^2. The GPR model performance was tested for both a fitting and a cross-validation dataset. The cross-validation is carried out by random sampling with 10% replacement of the original dataset used for validation.

4. Results and discussion

4.1. Rainfall Erosivity Database on the European Scale (REDES)

In preparing the Rainfall Erosivity Database on the European Scale (REDES), high temporal resolution precipitation data were collected from 1541 precipitation stations within the European Union (EU) and Switzerland, covering a territory of 4,422,661 km^2. The average density of the precipitation stations is one in every 53.5 km × 53.5 km (or 2869 km^2). The variability is quite high, with a dense network of stations in Cyprus and Luxembourg, and a sparse network in Poland and some regions of Spain (Fig. 1).

Since erosivity varies significantly from year to year, at least 15 years of data are required to obtain representative estimates of annual erosivity (Foster et al., 2003). Oliveira et al. (2013) carried out an extensive literature review (ISI Web of Science, Scopus, SciELO, and Google Scholar databases) of rainfall erosivity studies using different time series. They identified 35 studies, but only 15% of these used data covering more than 20 years. The Rainfall Erosivity Database on the European Scale (REDES) of precipitation stations is the result of calculating the R-factor for a total of 26,394 years with a mean value of 17.1 years per station (Table 1). In almost all countries, the average time-series per station is more than 10 years, except in Estonia, Finland, Latvia and Romania, where the average recorded period was 7 years.

REDES, with its 1541 precipitation stations, covers all elevation levels. 106 of the stations are at an altitude of more than 1000 m above sea level (asl), in order to reflect the fact that around 6.5% of the total study area has an elevation greater than 1000 m asl. The majority of the stations at high elevations are located in the Alps (Switzerland, Italy, France, Slovenia and Croatia), the Apennines (Italy), Troodos (Cyprus) and Spain.

In terms of the time resolution of precipitation data, 42.3% of the stations (in 13 countries) make hourly recordings, 34.4% make recordings every 30 min (in 8 countries), 6.5% record their data at 15-minute intervals (major part of Spain and Austria), 14.9% make recordings every 10 min (4 countries) and only 2% (in Slovenia) of the data records are at a 5-minute time step.

The availability of data is not scarce in the domain of rainfall intensity. During the past decade (2004–2013), the development of automatic weather stations in many European countries (Belgium, Germany, France, Denmark, Estonia, Finland, Hungary, Italy, Luxembourg, Latvia, Portugal and Romania) led to the generation of more high resolution precipitation data. Besides the data availability, the data quality is considered sufficient for this study as the main source of the high resolution precipitation datasets were the official meteorological services or environmental agencies of the Member States (Table 1). The main limitation was the non-availability of high resolution precipitation data from some Meteorological services (Poland, Slovakia and UK). This limitation will be bypassed by the INSPIRE directive which foresees the data sharing between public authorities. Following the experience of REDES, this data collection can potentially be extended to Norway, Turkey and Balkan states in a later phase.

4.2. Conversion factors for different temporal resolutions

Using a very representative pool of stations (in terms of geographical coverage, R-factor values), regression functions have been developed to convert the R-factor from different temporal resolutions to 30-min resolutions (Table 2). According to the conversion factors (Table 2), there is a strong underestimation of the R-factor (circa 56%) whenever 60-min data are used. The results are in accordance with previous literature findings (Yin et al., 2007; Williams and Sheridan, 1991). However, the R^2 values for the regression between R-factors calculated using precipitation data with different temporal resolutions show that 60-min data in combination with a conversion factor can be successfully used to estimate the R-factor where fine-resolution data are not available (Table 2). The conversion factors for recording time-steps of <30 min are less than 1, which implies that the homogenised 30-min-based R-factor dataset slightly underestimates the "real" rainfall erosivity.

Unfortunately, in Ireland, UK and Scandinavian countries, no data were available at both resolutions (30-min and 60-min) necessary to contribute to the calibration of temporal resolutions.

4.3. Rainfall erosivity in Europe

The mean R-factor of the 1541 precipitation stations included in REDES is 911.3 MJ mm ha^{-1} h^{-1} yr^{-1} with a high standard deviation of 844.9 MJ mm ha^{-1} h^{-1} yr^{-1} as expected due to the high climate variability in Europe. The smallest R-factors were calculated for two stations of the Ebro catchment (Spain), two stations in Slovakia (Gabcikovo, Komarno), and the stations in Tain Range (UK) and Inari Kaamanen (Finland) with values less than 100 MJ mm ha^{-1} h^{-1} yr^{-1}. The maximum values were calculated for five stations in Slovenia (Kneške Ravne, Vogel, Kal Nad Kanalom, Log Pod Mangartom and Lokvein) and one station in north-eastern Italy (Tramonti di Sotto, close to Slovenia) with values greater than 5000 MJ mm ha^{-1} h^{-1} yr^{-1}.

The map of rainfall erosivity in Europe (Fig. 2) gives a spatial overview of the erosive energy of rain. The Gaussian Process Regression (GPR) model used to interpolate the R-factor point values to a map showed a good performance for both the cross-validation dataset ($R^2 = 0.63$) and the fitting dataset ($R^2 = 0.72$). From the large pool of parameters used in calculating the R-factor, the precipitation seasonality (coefficient of the variation of seasonal precipitation), latitude and elevation were found to have the strongest influence.

The R-factor map (Fig. 2) of the 28 European Union Member States and Switzerland has an average value of 722 MJ mm ha^{-1} h^{-1} yr^{-1} and a standard deviation of 478.6 MJ mm ha^{-1} h^{-1} yr^{-1}. The range of R-factor in Europe is 51.4–6228.7 MJ mm ha^{-1} h^{-1} yr^{-1}. The distribution of R-factor values is skewed to the right, with 610 MJ mm ha^{-1} h^{-1} yr^{-1} in the 50th percentile, which implies that a few extremely high values increase the overall mean. The 25% of the study area with the lowest R-factor values (<410 MJ mm ha^{-1} h^{-1} yr^{-1}) is located in Scandinavia, western UK and eastern Germany (Fig. 2). As the definition of high rainfall erosivity depends on the study location, we adopt a statistical approach to define the values in the 4th quartile as high R-factors. The 25% of the study area shows high R-factor values exceeding 900 MJ mm ha^{-1} h^{-1} yr^{-1}. In a quantitative comparison, the rainfall erosivity spatial pattern (Fig. 2) is similar to the results produced by Diodato and

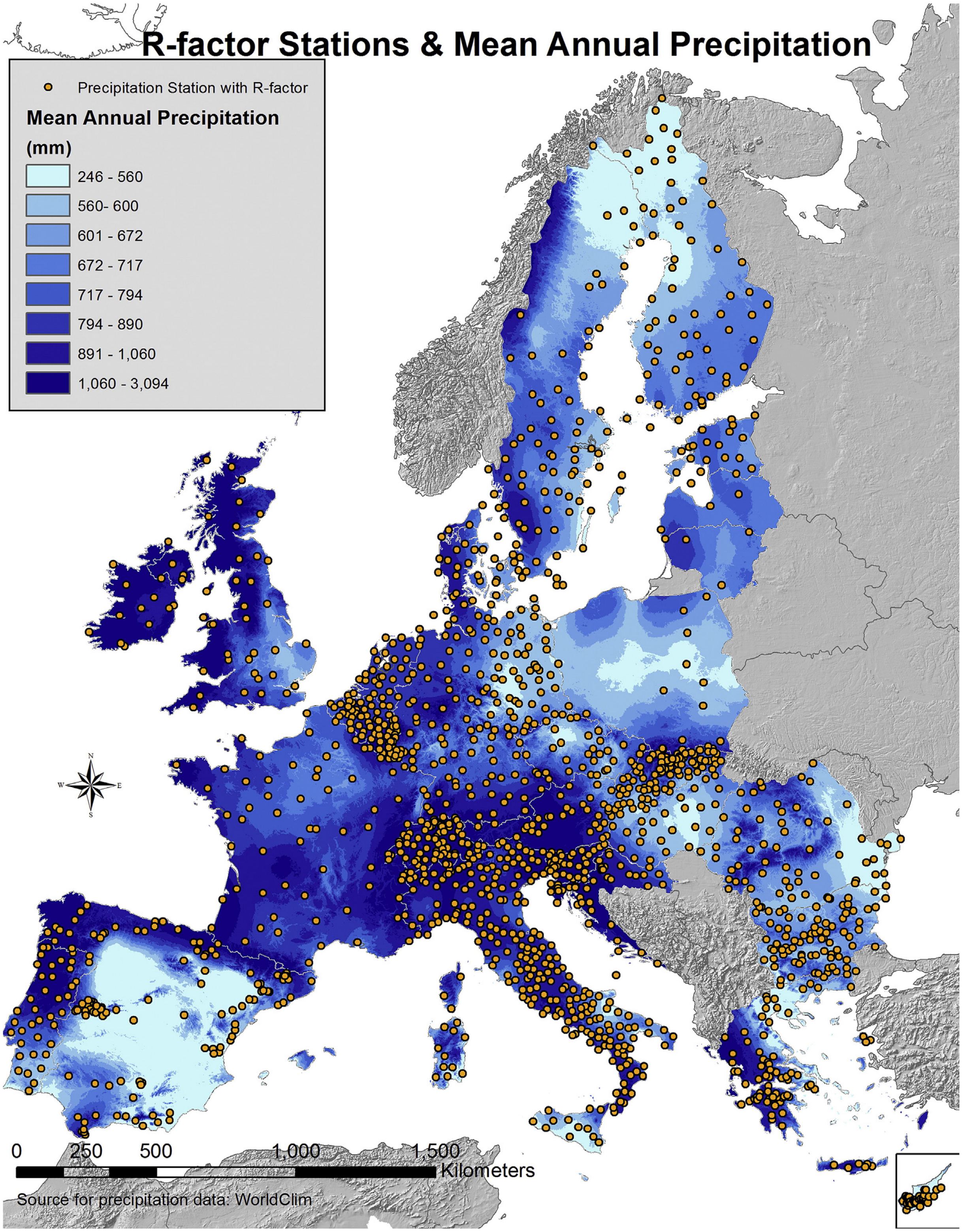

Fig. 1. Spatial distribution of precipitation stations used for the R-factor calculation.

Bosco (2014). Both studies predicted rainfall erosivity higher than 1000 MJ mm ha^{-1} h^{-1} yr^{-1} in Italy, southern France, Switzerland, Slovenia, western Croatia, Pyrenees, Andalusia, Galicia (Spain) and North Portugal.

The regions found to have the highest rainfall erosivity levels are in line with the three major regions identified by van Delden (2001) as having the highest frequency of thunderstorms. The first region includes the Southern Alps, the Apennines, Istria and Slovenia. The second region includes the gulf of Liguria and Corsica. In both regions the rainfall erosivity exceeded the 1500 MJ mm ha^{-1} h^{-1} yr^{-1} in agreement also with the findings of Diodato and Bosco (2014). The third region expands (in an arch form) from the higher parts of Bavaria in southern

Table 2
Conversion factors for the calibration of temporal resolutions.

Source data resolution	No. of stations	Countries covered	Regression function	R^2 Coefficient of determination
60-min	82	BE, CZ, CH, CY, DE, EE, FR, IT, LU, RO	$R_{30\ min} = 1.5597 * R_{60\ min}$	0.994
15-min	31	BE, ES	$R_{30\ min} = 0.8716 * R_{15\ min}$	0.998
10-min	31	CZ, CY, CH, DE, EE, HR, HU, LU, RO	$R_{30\ min} = 0.8205 * R_{10\ min}$	0.998
5-min	12	CZ, CY, FR, HR, LU	$R_{30\ min} = 0.7984 * R_{5\ min}$	0.998

Germany, to cross the Swiss plateau and the area close to Dijon, and ends in the Lyon valley. All of those regions have the three characteristics likely to produce thunderstorms: potential instability of atmospheric pressure (indicated by a decrease of the equivalent potential temperature with increasing height), high levels of moisture in the atmospheric boundary layer, and forced lifting (McNulty, 1995). Little thunderstorm activity was found in the Scandinavian countries studied (Finland and Sweden) by van Delden (2001).

At country level, the highest levels of rainfall erosivity (R-factor) are found in Italy and Slovenia, while Croatia and Austria also have mean values that are greater than 1000 MJ mm ha^{-1} h^{-1} yr^{-1} (Table 3). The lowest values were identified in Sweden and Finland followed by Denmark, the Netherlands and the three Baltic states (EE, LT, LV). The mean R-factor values of all of those North European countries are less than 500 MJ mm ha^{-1} h^{-1} yr^{-1} (Table 3).

The coefficient of variation (CV) is used as an indicator to identify the degree of variability of the R-factor inside a country. The Netherlands and Baltic States show a very smooth distribution of the R-factor, with a CV of less than 10% (Table 3). By contrast, the United Kingdom has a very pronounced erosivity gradient with a CV of more than 81%, with extremely high R-factors in Western Wales and Scotland and very low R-factors in the eastern parts of England and Scotland. Medium to high variability is found in Croatia (Adriatic coast–inland), France (north–south gradient) and Greece (west–east gradient). The distribution of the R-factor values in the countries is skewed to the right with the exception of Baltic States, Hungary, Netherlands and Romania (normal).

The rainfall erosivity was further evaluated in the context of climatic zones. The official Biogeographical regions dataset (EEA, 2011) delineates the main climatic zones in Europe, and is independent of political boundaries. The Mediterranean climatic zone, which has hot summers and mild winters, has the highest mean rainfall erosivity, followed by the Alpine zone, which covers the Alps and the Pyrenees (Table 4). The Atlantic zone, which has a humid climate, has a high variability with high erosivity values in northern Spain, western France and western UK, and relatively low R-factor values in the Netherlands, eastern UK and northern France. The highest spatial variability is noticed in Alpine and Continental zones mainly due to orographic effect. The Continental zone, which is characterised by warm summers and cold winters, is the largest climatic zone and also has a high variability of rainfall erosivity. The Boreal zone (which is dominated by forests) includes the greater part of Scandinavia and the Baltic states, and has the lowest R-factor. The Boreal zone has a relatively low variability of rainfall erosivity considering its spatial extent. The mean R-factor of the Pannonian zone, also known as the central Danubian basin, is similar to that of Hungary. Finally, the Black Sea and Steppic zones have a relatively minor spatial extent in the study area, covering the eastern parts of Bulgaria and Romania. The third highest R-factors were mapped for this climatic zone.

The R-factor map (Fig. 2) and the related statistics (Tables 3, 4) can be used for soil erosion modelling at European and national scale. At regional or local scale, it is recommended to modellers to use REDES plus local high resolution data for making their interpolations. Combining the relatively high R-factor values with the relatively high K-factor values (> 0.038 t ha h ha^{-1} MJ^{-1} mm^{-1}) of the soil erodibility dataset (Panagos et al., 2014b), the modellers may identify the areas at high risk of soil erosion. The development of the remaining factors (topography, support practices, land use and management practices) will contribute to the perfecting of soil erosion modelling at the European scale. Furthermore, the calculation of monthly R-factor values in REDES will contribute to the seasonal estimation of rainfall erosivity in Europe.

4.4. Erosivity density

In the present study, the erosivity density is used for a post-assessment of rainfall erosivity patterns and type of precipitation involved in erosive events in Europe. Annual erosivity density is the ratio of the mean annual erosivity to the mean annual precipitation (Kinnell, 2010). In practice, erosivity density (ED) measures the erosivity per rainfall unit (mm), and is expressed as MJ ha^{-1} h^{-1}.

$$ED = R/P \tag{4}$$

where R is the average annual rainfall erosivity (MJ mm ha^{-1} h^{-1} yr^{-1}) and P is the average annual rainfall (mm yr^{-1}) according to the WorldClim database (Hijmans et al., 2005).

According to WorldClim statistics, the mean annual precipitation in the study area is 788.4 mm with a range from 246 to 3094 mm and a standard deviation of 253 mm (Fig. 1). High erosivity density areas indicate that the precipitation is characterised by high intensity events of short duration (rainstorms). Particularly high erosivity density is observed in Italy, Slovenia and Spain (Fig. 3), where the R-factor is 2–3 times higher than the amount of precipitation. By contrast, the rain distribution is much smoother in the northern parts of Europe (northern Germany, France, and the Netherlands), where relatively high amounts of precipitation have a smaller erosive effect (Fig. 3).

The erosivity density has a mean value of 0.92 MJ ha^{-1} h^{-1}, with high variability ranging from 0.1 to 4.47 MJ ha^{-1} h^{-1}. This high variability highlights the fact that rainfall erosivity is not solely dependent on the amount of precipitation. Consequently, it is impossible to predict the R-factor in Europe exclusively based on precipitation levels. Regional patterns can be identified, and although regression functions may be developed, they cannot be extrapolated to other regions with different climatic characteristics.

The erosivity density may contribute to the identification of risk areas, taking into account the precipitation volume. The precipitation (Fig. 1) and erosivity density (Fig. 3) datasets have been classified in nine combined categories that represent the four quartiles of each parameter. The highest risk is identified in areas where low annual mean precipitation is accompanied by high erosivity. Thus, highly erosive rainfall hits long-period dry soils which usually causes great damage and is connected to a very high flood risk (Diodato et al., 2011). We define this category as the highest overall risk (1st quartile of precipitation volume which is less than 600 mm annually) with values of erosivity density higher than 1.2 MJ ha^{-1} h^{-1} (4th quartile). The lowest risk is identified in those areas where, even though annual precipitation levels are high, the precipitation is relatively homogenously distributed and therefore has low erosivity (green in Fig. 4). Dry soils, which account for 9.6% of the study area, are identified in central and southern Spain, Sicily, Sardinia and Puglia (IT), the Greek islands, Cyprus, western Romania and central Hungary (Fig. 4). Most of Ireland, the northern

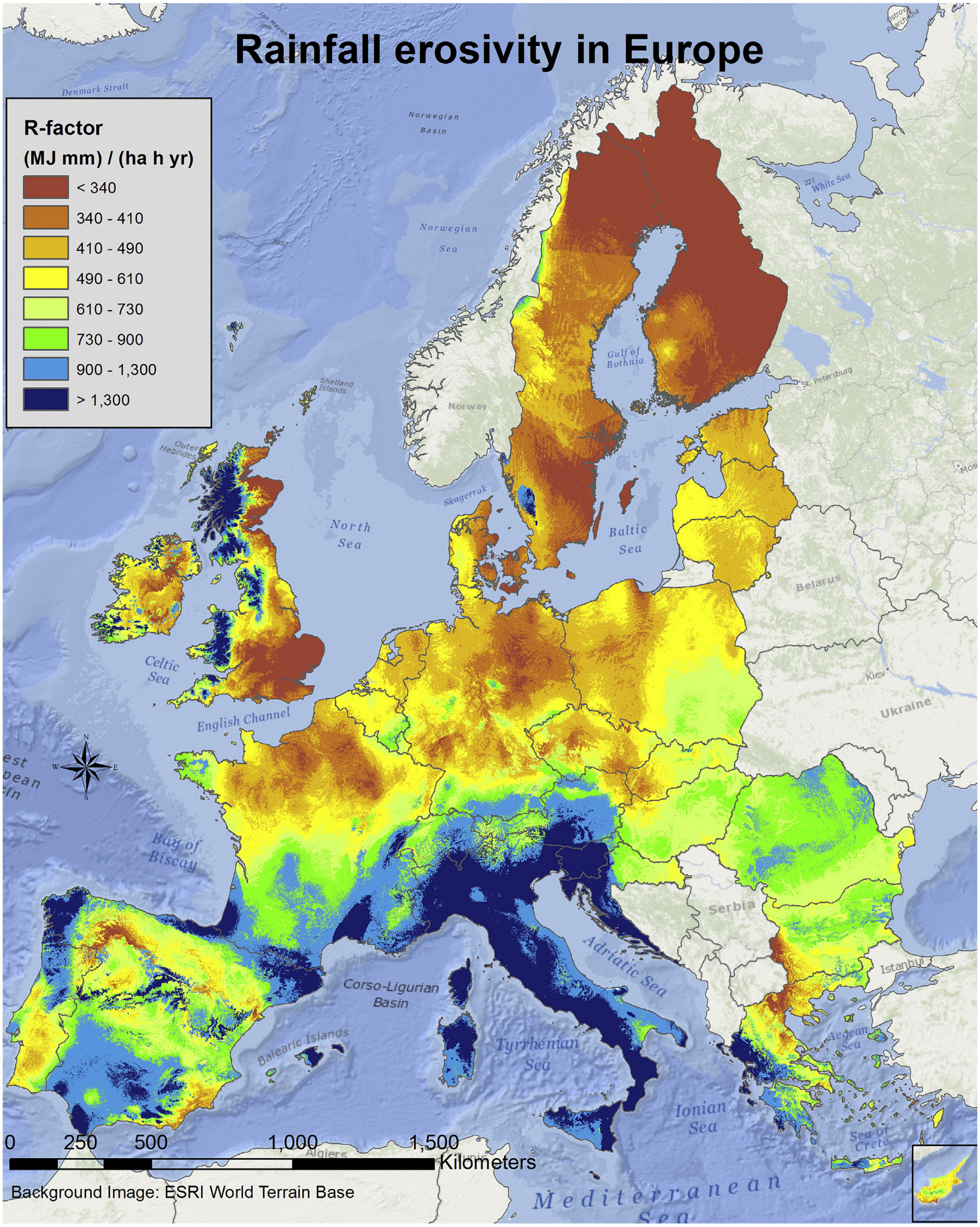

Fig. 2. High-resolution (1-km grid cell) map of rainfall erosivity in Europe.

United Kingdom and small parts of Germany were found to have the lowest risk (4th quartile of precipitation which is higher than 890 mm annually), with erosivity density values that are lower than 0.55 (1st quartile). The combination of high levels of rainfall and high erosivity densities (blue areas in Fig. 4) may also be associated with some risk: high rainfall amounts falling on moist or even saturated soils could trigger landslides or wetland erosion.

4.5. Mapping of rainfall erosivity and related uncertainties

Catari et al. (2011) identified the following main sources of uncertainty in estimating rainfall erosivity:

(1) measurement errors of precipitation stations,
(2) the efficiency of the equation used (methodology) to derive the

Table 3
R-factor descriptive statistics per country.

Country		Mean	Standard deviation	Minimum	Maximum	Coefficient of variation
		$MJ\ mm\ ha^{-1}\ h^{-1}\ yr^{-1}$				
AT	Austria	1075.5	517.1	346.9	4345.7	0.48
BE	Belgium	601.5	106.6	412.7	1253.8	0.18
BG	Bulgaria	695.0	151.8	79.8	1447.1	0.22
CH	Switzerland	1039.6	449.3	367.2	4249.6	0.43
CY	Cyprus	578.1	115.1	223.6	1353.5	0.20
CZ	Czech Republic	524.0	118.5	218.0	1093.5	0.23
DE	Germany	511.6	160.9	262.3	1489.3	0.31
DK	Denmark	433.5	93.6	143.8	800.5	0.22
EE	Estonia	444.3	33.2	330.1	568.3	0.07
ES	Spain	928.5	373.0	164.8	3071.2	0.40
FI	Finland	273.0	67.0	65.5	555.6	0.25
FR	France	751.7	353.5	235.2	2661.1	0.47
GR	Greece	827.7	387.6	152.0	2728.5	0.47
HR	Croatia	1276.2	633.5	523.4	3522.7	0.50
HU	Hungary	683.3	73.1	361.4	1000.8	0.11
IE	Ireland	648.6	389.6	205.1	3403.3	0.60
IT	Italy	1642.0	598.0	477.6	6228.8	0.36
LT	Lithuania	484.2	32.6	371.5	605.3	0.07
LU	Luxembourg	674.5	97.6	436.8	1002.8	0.14
LV	Latvia	480.4	42.1	373.9	602.4	0.09
MT	Malta	1672.4	65.6	1491.4	1869.2	0.04
NL	Netherlands	473.3	46.1	348.3	646.0	0.10
PL	Poland	537.1	100.0	247.7	1055.3	0.19
PT	Portugal	775.1	317.5	226.4	2758.1	0.41
RO	Romania	785.0	95.6	462.2	1150.1	0.12
SE	Sweden	378.1	152.6	51.4	2033.8	0.40
SI	Slovenia	2302.0	954.6	757.0	5655.8	0.41
SK	Slovakia	579.7	93.6	330.8	1111.2	0.16
UK	United Kingdom	746.6	604.9	78.1	4107.4	0.81

kinetic energy of rainfall from its intensity,

(3) the efficiency of regressions obtained between daily precipitation (or even annual precipitation) levels and the R-factor,
(4) the temporal variability of annual rainfall erosive values, and
(5) the spatial variability.

The third point is not addressed here, as the R-factor values were calculated based on high temporal resolution precipitation data. While the calibration of different temporal resolutions could be considered to be a source of uncertainty, this source of uncertainty is minimised by the amount of experimental data and the excellent performance of the regression functions used (Table 4).

With respect to instrumental errors, the participatory approach of involving the major meteorological services in Europe has a high likelihood of yielding high data quality. In addition, the RIST software calculates all the individual erosive events. Possible outliers (single events of >1000 $MJ\ mm\ ha^{-1}\ h^{-1}$) were verified with the source data. The RUSLE R-factor equation used to derive rainfall kinetic energy from intensity (see Eq. (3)) is empirical and was derived from long-term experiments (Brown and Foster, 1987). It is applied in the majority of studies worldwide.

Table 4
R-factor descriptive statistics per biogeographical region.

Climatic zone	Proportion of the study area	Mean	Standard deviation	Coefficient of variation
	%	$MJ\ mm\ ha^{-1}\ h^{-1}\ yr^{-1}$		
Alpine	9.2	932.3	666.9	0.72
Atlantic	17.7	678.2	446.7	0.66
Black Sea	0.2	702.1	144.8	0.21
Boreal	19.1	359.5	126.6	0.35
Continental	29.7	695.7	394.3	0.57
Mediterranean	20.4	1050.6	502.0	0.48
Pannonian	2.9	660.1	100.5	0.15
Steppic	0.8	729.8	91.0	0.12

In the present study, the uncertainty due to temporal variability is lessened by averaging long-term time-series (average 17.1 years per station). Regarding the spatial uncertainty, the extensive data collection exercise was carried out on a dense network with good geographical coverage. Furthermore, the dataset is representative of all possible elevation and climatic levels covered in the regression analysis.

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. 5) 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 (Fig. 5). 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.

4.6. Potential applications of R-factor dataset

Rainfall erosivity (R-factor) in Europe is a key parameter for estimating soil erosion loss and soil erosion risk, but the use of this dataset can be widely extended to other applications. The R-factor dataset can be used by landslide experts as a predictor to improve landslide susceptibility assessment in Europe (Günther et al., in press). The landslide susceptibility map is the spatial probability of generic landslide occurrence based on topographic and climatic conditions.

Flood risk is of crucial importance for civil protection, due to the large numbers of people affected and the related economic costs. According to Barredo (2007), 40% of the flood-related casualties in Europe during the period 1950–2006 were due to flash floods. Flash floods are associated with short and high-intensity rainfall events, and their likelihood of occurrence increases exponentially when such rainfall events occur on dry and hydrophobic soils (see Fig. 4). Flash flood occurrence is generally more intense in Mediterranean countries than in continental areas (Marchi et al., 2010), in line with the rainfall erosivity pattern. Differences in the spatial and temporal scales of the rainfall events (and rainfall erosivity) should be taken into account in the design of flash flood forecasting and warning systems.

Most forest fires in Europe occur in the south — 75% of the total area burnt every year in the European Union is located in Portugal, Spain, the south of France, Italy, Greece and Cyprus (European Commission, 2009). The post-fire effect in areas that are susceptible to highly erosive events may accelerate the risk of flash floods and soil loss due to lack of vegetative protection. The rapid damage assessment carried out by the European Forest Fire Information System (EFFIS) (San-Miguel-Ayanz et al., 2012) generates burnt area maps at 250-m spatial resolution. In combination with the R-factor dataset, such maps can help identify areas that are at high risk of soil erosion, in order to decide where critical prevention measures should be swiftly applied so as to avoid further disasters.

In the context of the European Common Agricultural Policy (CAP), sustainable agricultural practices should take into account the soil and water resources and specific local or regional conditions such as climate. As an example, Renschler et al. (1999) showed the high impact of rainfall erosivity in evaluating the vulnerability of different crop rotation scenarios in Andalusia. It has been found that extreme rainfall events and high erosivity can reduce or completely destroy yields of permanent crops (olives, vineyards, fruit trees), which are of particular importance in the Mediterranean (Maracchi et al., 2005). The R-factor dataset

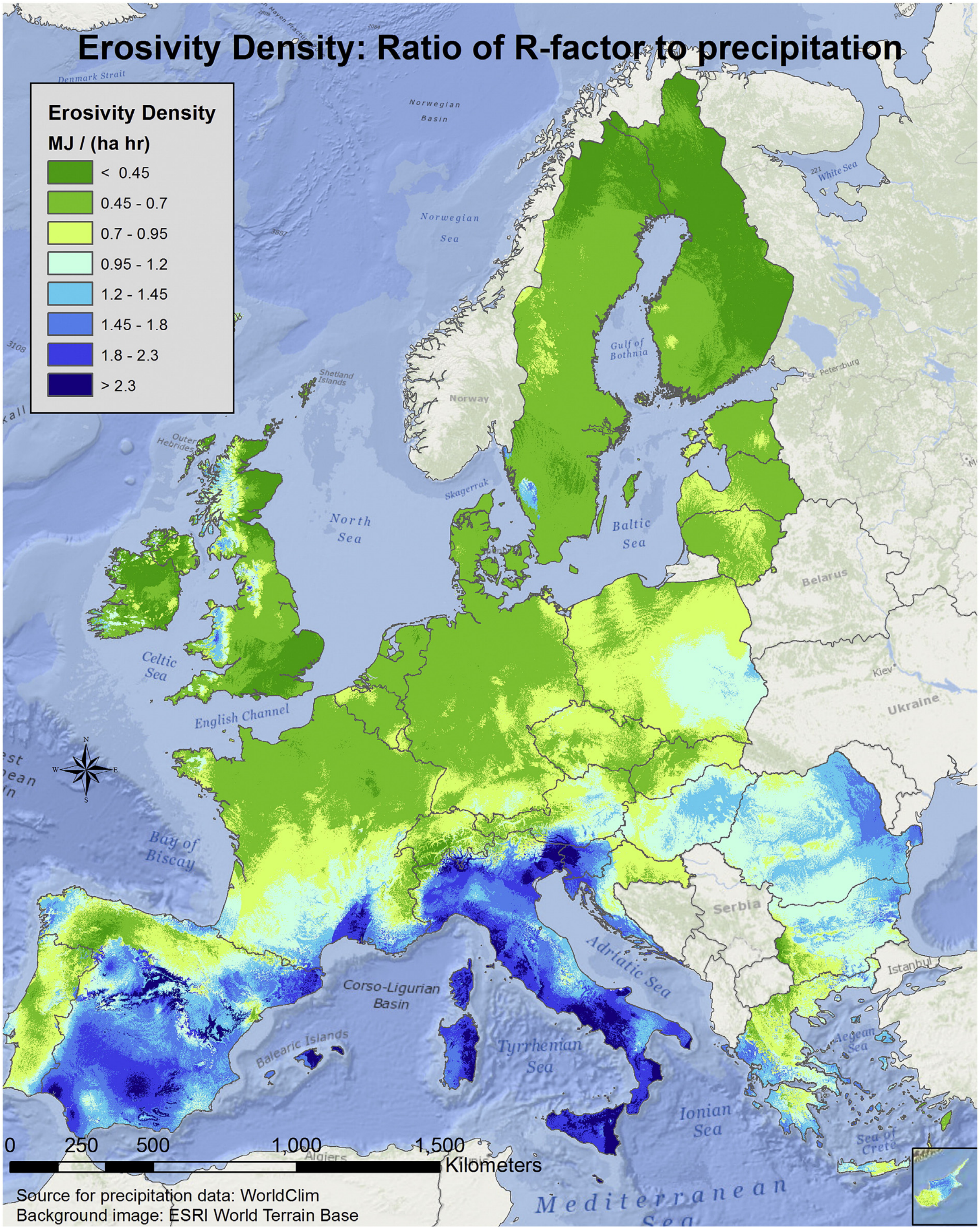

Fig. 3. Erosivity density (rainfall erosivity per mm of precipitation).

should therefore be taken into account in the application of crop-rotation scenarios, agricultural management, and conservation policies.

REDES can also be used to identify the trends and threats of climate change. It was found that the increase of extreme rainfall events between 1960 and 2001 in the Carpathian region (Romania, Slovakia, Czech Republic, Hungary, southern Poland) was coupled with a lower frequency, leading to constant precipitation totals (Bartholy and Pongrácz, 2007). On the other hand, Fiener et al. (2013) and Verstraeten et al. (2006) have reported higher erosivity values in their areas of study (North Rhine Westphalia, Ukkel) after the 1990s. Also, Diodato et al. (2011) have found increased erosive events in low Mediterranean latitudes in the last 50 years. Future research will focus on subset of REDES precipitation stations with high temporal scale (<30 min) and long continuous records (>20 years) well distributed in Europe. The objective

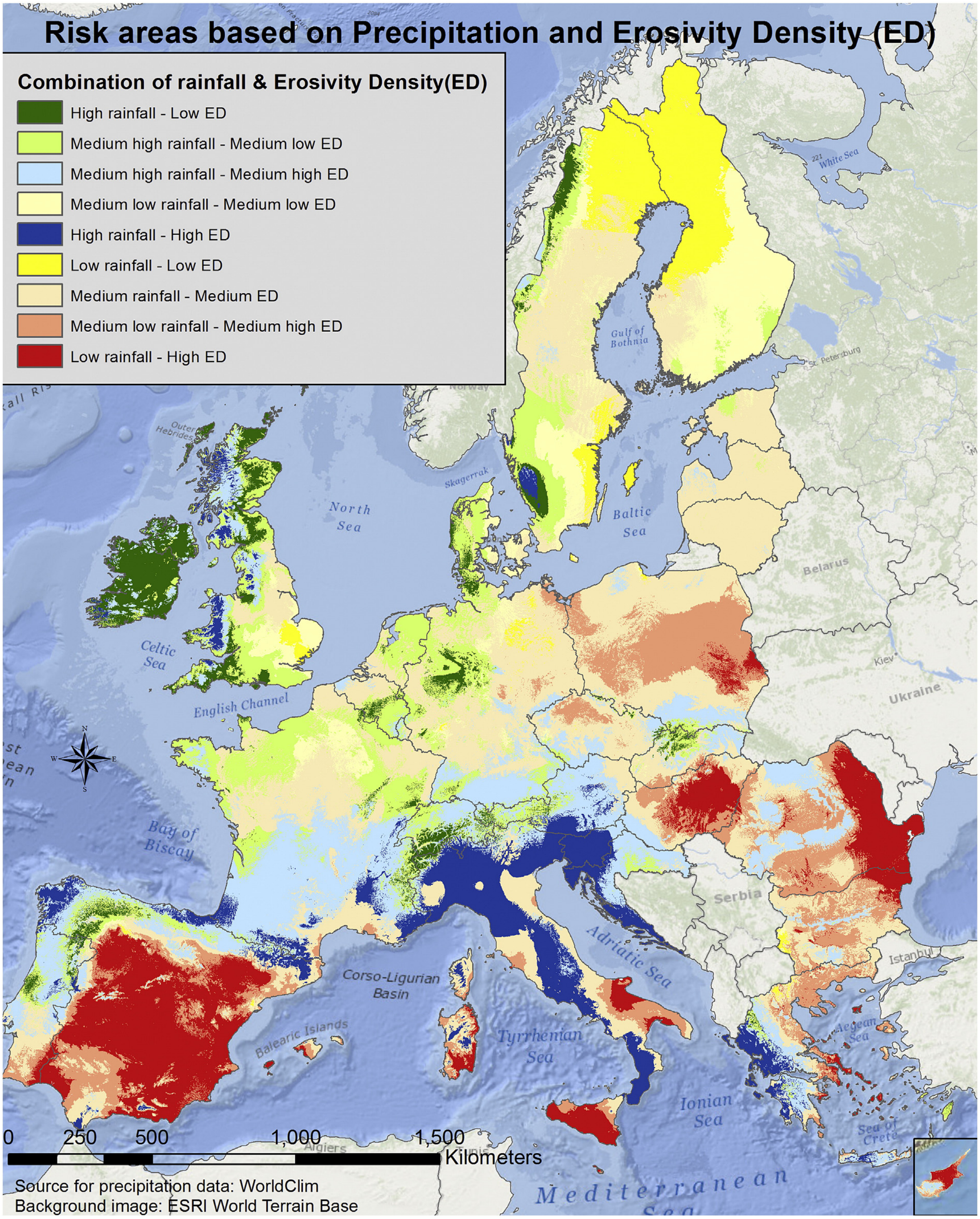

Fig. 4. Risk areas based on precipitation and erosivity density. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

will be to identify trends of rainfall erosivity in Europe and incorporate them in future climatic scenarios for predicting soil loss.

The R-factor data availability is a key issue for modellers who have no access to high temporal resolution data. With the publication of this study, modellers and in general scientists will be able to download the R-factor dataset from the European Soil Data Centre (Panagos et al., 2012b). Besides the application for soil erosion modelling, the European rainfall erosivity dataset can be used in different areas such as landslide risk assessment, flood risk forecasting, post-fire conservation measures, agricultural management and design of crop rotation scenarios.

5. Conclusions

The R-factor was successfully mapped at 1-km grid cell resolution for the European Union and Switzerland, applying the Gaussian Process Regression model. The spatial interpolation model showed a very good

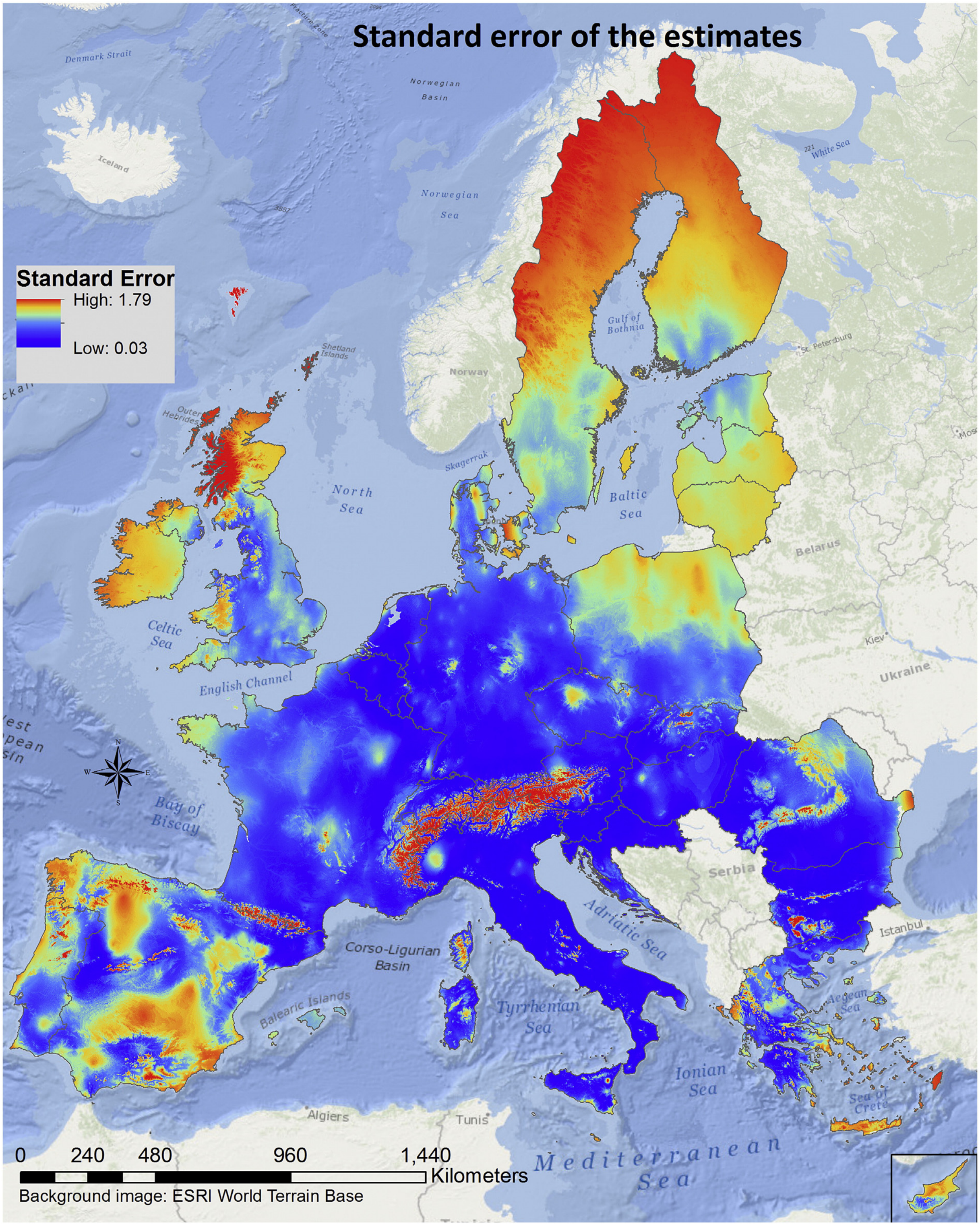

Fig. 5. Uncertainty of the R-factor prediction calculated with the GPR spatial interpolation model.

performance ($R^2 = 0.62$ for the cross validation, $R^2 = 0.73$ for the fitting dataset). The low number of stations and the high diversity of environmental features resulted in high prediction uncertainty in North Scandinavia, West Ireland, Scotland, high Alps and parts of Spain. The high variability of climatic and terrain conditions in an area of more than 4.4 million km^2 resulted in a broad spectrum of rainfall erosivity, ranging from 51.4 to 6228.7 MJ mm ha^{-1} h^{-1} yr^{-1}, with a mean value of 722 MJ mm ha^{-1} h^{-1} yr^{-1}. The Mediterranean and Alpine regions were found to have the highest R-factor values, while Scandinavia countries were found to have the lowest.

There is a large amount of data available regarding rainfall intensity. The inclusive participatory data collection approach applied in this study showed that high temporal precipitation data is available free of charge for the European Union. Even though the selected approach was time-consuming and requested laborious pre-processing, it has resulted in Rainfall Erosivity Database at European Scale (REDES), with R-factor estimations for 1541 stations across Europe.

Due to different temporal resolutions of input data, the proposed conversion to 30-min based R-factor was an important step towards a homogeneous database. Comparisons between different temporal resolutions showed that the use of 60-min precipitation data for the calculation of the R-factor results in a strong underestimation (56%) compared to the use of 30-min data.

Using the large number of R-factor stations available on a large scale (Europe), it was found that R-factor does not solely depend on precipitation. The erosivity density indicator showed that the R-factor per unit of precipitation is highly variable. Therefore, the choice of regression equations should be made with caution and should be based on local climate studies and high temporal resolution data. The Mediterranean countries and the Alpine areas have a relatively high erosivity density and high rainstorm frequency compared to northern Europe, where the erosivity density is much lower. Furthermore, an assessment of the erosivity density and the risk areas which combine low amounts of precipitation with high erosivity density demonstrates that the Mediterranean regions have the highest risk not only of erosive events, but also of floods and/or water scarcity.

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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CHAPTER 5

Spatial and temporal analysis of rainfall erosivity in Greece

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Spatial and temporal analysis of rainfall erosivity in Greece

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Abstract

Rainfall erosivity considers the effects of rainfall amount and intensity on soil detachment. Rainfall erosivity is most commonly expressed as the R-factor in the Universal Soil Loss Equation (USLE) and its revised version, RUSLE. Several studies focus on spatial analysis of rainfall erosivity ignoring the intra-annual variability of this factor. This study assesses rainfall erosivity in Greece on a monthly basis in the form of the RUSLE R-factor, based on 30-minutes data from 80 precipitation stations covering an average period of almost 30 years. The spatial interpolation was done through a Generalized Additive Model (GAM). The observed intra-annual variability of rainfall erosivity proved to be high. The warm season is 3 times less erosive than the cold one. November, December and October are the most erosive months contrary to July, August

and May which are the least erosive. The proportion between rainfall erosivity and precipitation varies throughout the year. Rainfall erosivity is lower than precipitation in the first 5 months (January – May) and higher in the remaining 7 months (June – December) of the year. The R-factor maps reveal also a high spatial variability with elevated values in the western Greece and Peloponnesus and very low values in Western Macedonia, Thessaly, Attica and Cyclades. The East-West gradient of rainfall erosivity differs per month with a smoother distribution in summer and a more pronounced gradient during the winter months. The aggregated data for the 12 months result in an average R-factor of 807 MJ mm ha^{-1} h^{-1} yr^{-1} with a range from 84 to 2825 MJ mm ha^{-1} h^{-1} yr^{-1}. The combination of monthly R-factor maps with vegetation coverage and tillage maps contributes to better monitor soil erosion risk at national level and monthly basis.

Keywords: R-factor, seasonality, rainfall intensity, erosivity density, soil erosion

1 Introduction

Soil erosion is one of the most serious environmental and public health problems that human society is facing, as every year at global scale almost 10 million hectares of cropland are lost due to soil erosion (Pimentel, 2006). To design efficient policies, land use planners and decision makers need, among others, information on the on-site private costs and the offsite consequences (desertification, rural depopulation, siltation of waterways and reductions in biodiversity) plus data on soil erosion (Colombo et al., 2005).

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, has widely been used as a tool for predicting soil erosion at large spatial scales (Kinnell, 2010; Panagos et al., 2014a). In RUSLE, soil loss can be estimated by multiplying the rainfall erosivity factor (R-factor) by five other factors: Soil erodibility (K-factor), slope length (L-factor), slope steepness (S-factor), crop type and management (C-factor), and supporting conservation practices (P-factor).

Among the factors used within RUSLE and its earlier version, the Universal Soil Loss Equation (USLE) (Wischmeier and Smith, 1978), rainfall erosivity is of high importance, as precipitation is the driving force of erosion and has a direct impact on the detachment of soil particles, the breakdown of aggregates and the transport of eroded particles via runoff. Rainfall erosivity is the kinetic energy of raindrop's impact and the rate of associated runoff (Wischmeier and Smith, 1978).

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. Moreover, R-factor and C-factor are both dynamic factors changing over a year time. By capturing the variability of those two factors, it is possible to have a more realistic and precise soil erosion assessment. For instance, a rainstorm may cause severe soil loss in the fallow period but hardly any damage during the growing season. A monthly estimation of precipitation and rainfall intensity has been used for assessing the temporal variability of rainfall erosivity in Ethiopia (Nyssen et al., 2006), Switzerland (Meusburger et al., 2012), and a long-term analysis in one of the federal states of Germany, North Rhine Westphalia (Fiener et al., 2013). Furthermore, the spatial and the temporal variability of the R-factor have been important in risk assessments in Andalusia (Renschler et al., 1999); in the recent developments of G2 soil erosion model in North Greece, South Bulgaria (Panagos et al., 2012), and Crete (Panagos et al., 2014b).

Greece is located in south Eastern Europe extending over 32.5° to 42.5°N and 17.5° to 30°E. As for rainfall erosivity, Greece is a very interesting study area due to the high climate diversity mainly attributed to high relief variability. The main objective of this study is to assess the spatio-temporal variability of rainfall erosivity in Greece based on high-temporal solution precipitation data. Specific aims of this study are to:

a) compute monthly rainfall erosivity on 80 precipitation stations in Greece,
b) produce linear regression functions that can predict monthly R-factor on station basis,
c) interpolate station R-factor values to produce 12 monthly R-factor maps using a Generalized Adaptive Model and spatial covariates which among others can potentially be used for monthly soil erosion modelling, and
d) identify spatial and temporal patterns to map the relationship between the R-factor and the precipitation (monthly erosivity density).

2 Data and Methods

2.1 Study area

Greece is classified as Mediterranean climate type according to Kopper classification (Kopper, 1918): mild and rainy winters, relatively warm and dry summers, and l extended periods of sunshine throughout most of the year. The orographic and topographic influences, along with the influence of the Mediterranean waters (warmer than the adjoining land in winter and cooler in summer) cause an uneven temporal and spatial distribution of precipitation (Hatzianastassiou et al., 2008). In the Eastern Mediterranean basin, seasonal precipitation patterns are generally expected (Kioutsioukis et al., 2010).

WorldClim statistics (Hijmans 2005) reports 698 mm as the mean annual precipitation, 189 mm as the standard deviation, and from 380 to 1,406 mm as the range of annual precipitation values in the study area for the period 1950 - 2000 (Fig. 1). According to Hellenic National Meteorological Service (HNMS, 2014), the weather in Greece varies from the dry climate of Attica (Athens' greater area) and of East Greece, to the wet climate of Northern and Western Greece (Fig. 1).

In Greece, the year can be broadly subdivided into two main seasons: The cold and rainy period lasting from mid-October until the end of March, and the warm and dry season lasting from April until September. The wettest months are January (94.8mm) and December (107.6mm), whereas the driest ones are July (19.6mm) and August (16.3mm) according to the WorldClim data for the 1950-2000 period. The precipitation regime in Greece has been extensively studied in past, further climatic details are provided by Bartzokas et al. 2003; Tolika and Maheras 2005; Pnevmatikos and Katsoulis 2006.

2.2 Precipitation data collection

High-resolution precipitation datasets (30 minutes) have been extracted from 80 stations: 77 precipitation stations from the database of the research project Hydroskope, and 3 stations from the database of the Aegean University. Hydroscope is a Greek nation-wide research programme aiming at developing a database system for meteorological, hydrological and hydrogeological information at national level (Sakellariou et al., 1994). Regarding the spatial distribution of the precipitation stations with high resolution data, the average density is ca. 1 station per 40km x 40km grid cell (Fig. 1).

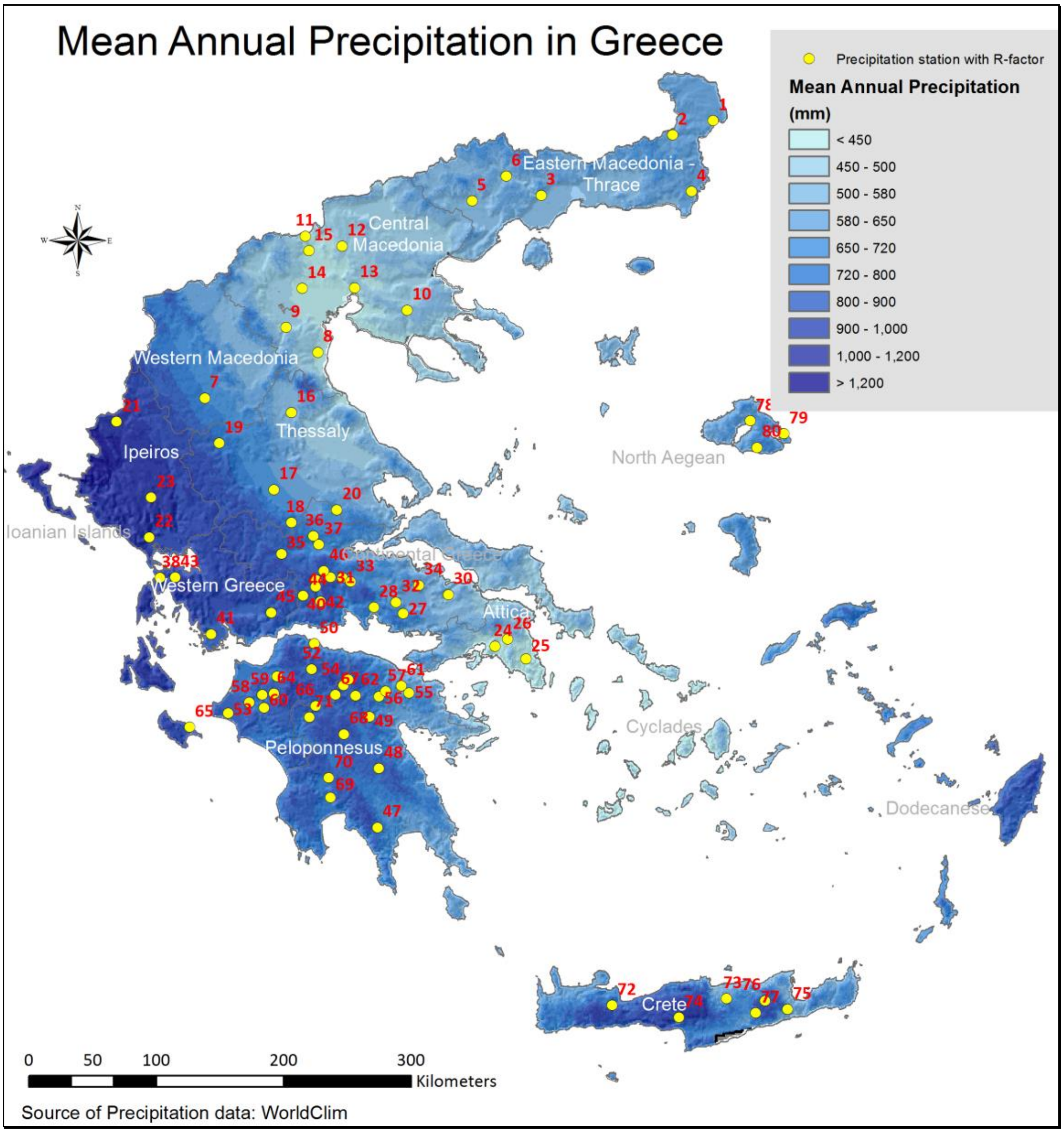

Fig. 1: Spatial distribution of mean annual precipitation and stations used for the R-factor calculation in Greece

There is a quite dense network of precipitation stations in Peloponnesus and in the Continental Greece, whereas there is a lack of stations in Western Macedonia and in the Aegean islands. According to the Nomenclature of Territorial Units for Statistics (NUTS), precipitation stations are located in 33 out of the 51 Greek prefectures (NUTS3 level) (Table 1). The stations are located at different altitudes so as to represent the huge topographic variability in Greece. Regarding the temporal resolution, the data have been collected from 2,373 stations for 29.7 years per station on average. Most of the stations recorded data startting from 1960s up to the year 1997.

Table 1: List of stations recording high resolution precipitation data used to estimate the R-factor.

Map Id	**Station name**	**NUTS3 (Province)**	**Latitude (Y)**	**Longitude (X)**	**Elevation (m)**	**Period Covered** (month/year)	**Precipitation (mm)**
1	Didimoticho	Evros	41.35405	26.49872	24	02/55 - 12/96	382.2
2	Mikro Dereio	Evros	41.31599	26.10254	116	10/73 - 12/96	487.7
3	Toxotes	Xanthi	41.08741	24.78914	74	05/56 - 12/96	455.0
4	Ferres	Evros	40.89620	26.17231	43	07/62 - 12/96	438.0
5	Drama	Drama	41.14207	24.14637	100	12/53 - 11/96	416.4
6	Paranesti	Drama	41.26727	24.49992	122	06/60 - 12/96	463.5
7	Grevena	Grevena	40.08452	21.4223	544	08/72 - 12/96	318.5
8	Katerini	Pieria	40.27724	22.51264	30	06/57 - 12/96	413.2
9	Fragma Aliakmona	Imathia	40.48957	22.25492	44	11/72 - 10/89	384.8
10	Agios Prodromos	Chalkidiki	40.46565	23.38273	420	07/66 - 10/95	359.3
11	Euzonoi	Kilkis	41.10406	22.55803	72	01/67 - 01/97	345.4
12	Kilkis	Kilkis	40.99158	22.88417	261	01/67 - 12/96	429.7

13	Oraiokastro	Thessaloniki	40.68622	22.93811	71	03/76 - 12/96	341.5
14	Paralimni Giannitsa	Pella	40.74280	22.45596	4	11/59 - 12/90	300.6
15	Polikastro	Kilkis	40.99829	22.57279	55	01/67 - 08/97	502.2
16	Elassona	Larisa	39.88816	22.19085	276	08/60 - 12/96	379.0
17	Karditsa	Karditsa	39.3669	21.93047	106	08/60 - 12/96	418.3
18	Loutropigi	Karditsa	39.11708	22.04425	722	01/71 - 07/97	599.6
19	Megali Kerasia	Trikala	39.75185	21.4977	509	01/71 - 12/96	336.3
20	Skopia	Larisa	39.15481	22.4684	444	12/70 - 06/97	345.0
21	Basiliko	Ioannina	40.00916	20.59495	764	10/53 - 01/97	687.8
22	Louros	Preveza	39.16478	20.75262	10	10/57 - 07/66	1256.9
23	Pentolakos	Preveza	39.44194	20.81775	890	11/74 - 01/97	1376.6
24	Nikaia-Egaleo	Attiki	38.00632	23.68099	67	01/62 - 12/96	282.6
25	Markopoulo	Attiki	37.87894	23.93447	83	12/61 - 12/96	300.9
26	Chalandri	Attiki	38.04167	23.79903	189	02/65 - 05/92	259.2
27	Agia Triada	Viotia	38.34894	22.91608	400	12/62 - 01/97	679.8
28	Distomo	Viotia	38.42879	22.66645	457	12/62 - 12/96	499.0
29	Gravia	Fokida	38.67258	22.43033	380	11/62 - 12/96	823.0
30	Limni Ilikis	Viotia	38.42698	23.34401	85	02/58 - 12/96	319.6
31	Kaloskopi	Fokida	38.68932	22.32333	1050	04/72 - 01/97	703.7
32	Livadia	Viotia	38.43819	22.8701	175	11/62 - 01/97	465.1
33	Lilaia	Fokida	38.63432	22.49465	339	03/86 - 12/96	795.6
34	Pavlos	Viotia	38.52984	23.09265	212	11/62 - 05/97	379.7
35	Timfristos	Ftiotida	38.90961	21.91575	847	12/54 - 01/97	938.2
36	Trilofo	Ftiotida	38.99834	22.22209	575	12/54 - 01/97	413.7
37	Zilefto	Ftiotida	38.93192	22.25904	97	12/54 - 01/97	409.6
38	Agios Nikolaos	Aitoloakarnan	38.86975	20.80366	10	10/65 - 01/97	670.3

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39	Athan. Diakos	Fokida	38.68742	22.19244	846	08/63 - 01/97	949.2
40	Koniakos	Fokida	38.64219	22.17676	875	10/89 - 01/97	781.4
41	Lesinio	Aitoloakarnania	38.42059	21.19437	2	11/57 - 12/96	515.6
42	Lidoriki	Fokida	38.53099	22.20285	547	08/63 - 12/96	783.4
43	Monastiraki	Aitoloakarnania	38.85628	20.94071	245	08/75 - 12/95	509.6
44	Pentagioi	Fokida	38.59218	22.05453	921	08/63 - 01/97	868.1
45	Poros Rigani	Aitoloakarnania	38.50779	21.74962	181	11/60 - 01/97	1087.7
46	Pyra	Fokida	38.74262	22.27196	1137	08/63 - 12/96	853.9
47	Arna	Lakonia	36.88002	22.41292	779	06/56 - 12/96	1007.6
48	Karyes	Lakonia	37.29266	22.50099	917	06/56 - 12/96	410.7
49	Neochori	Argolida	37.66605	22.48392	703	11/59 - 01/97	659.8
50	Aigio	Achaia	38.2412	22.09343	37	03/78 - 12/96	618.4
51	Asteri	Achaia	38.05388	21.72425	214	10/73 - 08/97	431.7
52	Drossato	Achaia	38.06748	22.03728	888	11/76 - 12/96	733.5
53	Gastouni	Ilia	37.84893	21.24938	10	10/57 - 12/95	679.5
54	Kalivia -Feneos	Korinthia	37.91782	22.29722	821	11/64 - 12/96	721.4
55	Klenia	Korinthia	37.78613	22.86304	379	09/78 - 12/96	528.8
56	Leontio	Korinthia	37.79900	22.59210	379	11/91 - 12/96	491.1
57	Nemea	Korinthia	37.82641	22.65780	305	12/64 - 12/96	577.7
58	Fragma Pinios	Ilia	37.90026	21.44676	59	06/53 - 01/97	423.4
59	Portes	Achaia	37.93958	21.57198	395	12/75 - 10/96	763.1
60	Simopoulo	Ilia	37.84754	21.57144	201	11/55 - 01/97	387.9
61	Spathovouni	Korinthia	37.84771	22.80302	149	05/64 - 01/97	353.2

62	Lafka Stimfalaia	Korinthia	37.83186	22.39007	722	04/53 - 12/96	486.1
63	Tarsos	Korinthia	37.95307	22.34878	867	04/53 - 12/96	590.6
64	Ksirochorio	Achaia	37.93711	21.67702	290	11/88 - 01/97	501.1
65	Zakinthos	Zakinthos	37.78789	20.89648	11	05/57 - 12/96	577.6
66	Dafni	Achaia	37.80488	22.02614	582	09/84 - 10/96	655.7
67	Lykouria	Achaia	37.86074	22.21243	758	05/85 - 12/96	329.3
68	Piana	Arkadia	37.57345	22.24073	997	12/71 - 12/96	783.6
69	Pidima	Mesinia	37.14474	22.04472	36	11/64 - 12/96	717.5
70	Souli	Arkadia	37.28467	22.05182	592	11/64 - 05/95	800.0
71	Tropaia	Arkadia	37.73155	21.95937	727	03/53 - 12/96	440.9
72	Ebrosneros	Chania	35.34493	24.18705	271	10/62 - 12/96	811.0
73	Ano Archanes	Heraclio	35.23747	25.1608	392	09/62 - 12/96	544.4
74	Nithafri	Rethimno	35.17029	24.73157	460	06/68 - 03/80	597.6
75	Kalamafka	Lasithi	35.07620	25.65611	502	10/68 - 12/80	326.7
76	Agios Georgios	Lasithi	35.16758	25.48357	836	08/54 - 03/58	489.4
77	Ebaros-Anapodiaris	Heraclio	35.09526	25.38611	438	01/68 - 03/74	349.3
78	Agia Paraskevi	Lesvos	39.24478	26.28084	94	01/4 - 04/9	407.8
79	Panepistimio Aegean	Lesvos	39.07597	26.53969	71	06/3 - 10/13	575.5
80	Akrasi	Lesvos	39.04221	26.32586	362	06/3 - 10/13	615.4

2.3 R-factor calculation

The erosive power of precipitation is accounted by the rainfall erosivity factor (R-factor), which gives the combined effect of the duration, magnitude and intensity of each rainfall event. In this study, the original RUSLE R-factor equation was used to create an R-factor database of 12 monthly values per

80 precipitation stations (960 records) in Greece. The Rainfall Intensity Summarisation Tool (RIST) software developed by United States Department of Agriculture (USDA) was used to calculate the monthly R-factor.

The 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):

$$R = \frac{1}{n}\sum_{j=1}^{n}\sum_{k=1}^{mj}(EI_{30})_k \qquad (1)$$

where: R is the average monthly rainfall erosivity (MJ mm ha^{-1} h^{-1} month^{-1}); n is the number of years recorded; m_j is the number of erosive events during a given month j; and EI_{30} is the rainfall erosivity index of a single event k. The event erosivity EI_{30} (MJ mm ha^{-1} h^{-1}) is defined as:

$$EI_{30} = \left(\sum_{r=1}^{0} e_r v_r\right) I_{30} \qquad (2)$$

Where e_r is the unit rainfall energy (MJ ha^{-1} mm^{-1}) and v_r the rainfall volume (mm) during a time period r. I_{30} is the maximum rainfall intensity during a 30-min period of the rainfall event (mm h^{-1}). The unit rainfall energy (e_r) is calculated for each time interval as follows (Brown and Foster, 1987):

$$e_r = 1099[1-0.72\exp(-1.27 i_r)] \qquad (3)$$

where i_r is the rainfall intensity during the time interval (mm h^{-1}).

The sums of EI_{30} and the average R-factor have been calculated on a monthly basis. To compute the R-factor, the erosive rainfall events (m_j) for each station has to be defined. Renard et al. (1997) provide three criteria for the identification of an erosive event: (i) the cumulative rainfall of an event is greater than 12.7 mm, or (ii) the event has at least one peak that is greater than 6.35 mm during a period of 15 min (or 12.7 mm during a period of 30 min), and iii) a rainfall accumulation of less than 1.27 mm during a period of six hours splits a longer storm period into two storms.

2.4 *Spatial interpolation of the R-factor*

In the late 1990's Goovaerts (1999) introduced a geo-statistical interpolation method to calculate rainfall erosivity based on regionalised variables such as elevation. Rainfall erosivity is mainly correlated with climatic data and, especially, with the amount of precipitation, the elevation and the geographical position (x, y coordinates).

A series of twelve Generalized Additive Models (GAM) have been used to predict the corresponding monthly R-factor datasets. As a non-linear approach, GAMs are a generalization of linear regression models in which the coefficients can be expanded as link functions, typically splines, of covariates (Hastie & Tibshirani, 1986). GAMs are semi-parametric and can account for some non-linear relationships between dependent variable and covariates (Equation 4),

$$E\,(Y\,|\,X_1, X_2, \ldots, X_p) = a + f_1\,(X_1) + f_2\,(X_2) + \ldots f_p\,(X_p), \qquad (4)$$

where X_1, X_2, …, X_p are the covariates, Y is the dependent variable and f_j's are the link functions.

Like generalized linear models, GAMs specify a distribution for the response variable Y and use a link function g relating the conditional mean μ (Y) of the response variable to an additive function of the predictors as follows:

$$g\,[\mu\,(Y)] = a + f_1\,(X_1) + f_2\,(X_2) + \ldots f_p\,(X_p) \qquad (5)$$

In this study, thin plate regression splines served as link functions and were fitted by maximum penalized likelihood (Wood, 2006). Subsequently a stepwise backward approach was used to select the best set of covariates and to determine the relative influence of each of the covariates on the overall model performance.

2.5 Covariates for spatial interpolation

Three main covariates were considered for the GAM regression model as being significant:

1. **Average monthly precipitation** derived from the WorldClim database (Hijmans, 2005), which reports monthly averages of precipitation and temperature for the period 1950-2000 at 100m resolution.
2. **Elevation** derived from the Digital Elevation Model of the Shuttle Radar Topography Mission (SRTM) at 100m resolution.
3. **Latitude and longitude**.

3 Results and discussion

This section will address two issues: a) the seasonal rainfall erosivity per station and how this can contribute by extrapolating regression functions to stations with low resolution (e.g. monthly) data and b) the mapping of monthly rainfall erosivity using spatial interpolation and its further application in estimating soil erosion risk.

3.1 *Seasonal rainfall erosivity per station*

The mean R-factor of the 80 precipitation stations is 849.6 MJ mm ha^{-1} h^{-1} yr^{-1} (Table 2) with a high standard deviation of 564.2 MJ mm ha^{-1} h^{-1} yr^{-1} as expected due to the high climate variability and high topographic diversity. The smallest R-factors (< 300 MJ mm ha^{-1} h^{-1} yr^{-1}) were calculated in two stations in Central and Western Macedonia (Grevena, Evzonoi) and in Viotia (Lake Iliki). The maximum values was calculated in Western Ipeiros (Pentolakos) with a value higher than 3,500 MJ mm ha^{-1} h^{-1} yr^{-1} followed by 2 stations having values over 2,000 MJ mm ha^{-1} h^{-1} yr^{-1} (Pentagioi Fokidas in continental Greece, Arna in western Peloponnesus).

Table 2: Seasonal and annual R-factor per precipitation station.

Map Id	Station name	Winter (Dec-Jan-Feb)	Spring (Mar-Apr-May)	Summer (Jun-Jul-Aug)	Autumn (Sep-Oct-Nov)	Annual R-factor
		(MJ mm ha^{-1} h^{-1} yr^{-1})				
1	Didimoticho	111.2	138.9	112.7	197.3	560.0
2	Mikro Dereio	116.4	97.3	204.4	334.1	752.2

3	Toxotes	321.4	102.3	102.1	235.9	761.7
4	Ferres	282.3	177.4	190.6	429.8	1080.1
5	Drama	69.7	89.3	107.6	111.0	377.6
6	Paranesti	140.9	101.6	151.7	173.4	567.6
7	Grevena	64.5	60.4	57.5	94.5	276.8
8	Katerini	68.0	100.4	80.8	239.6	488.8
9	Fragma Aliakmona	67.1	125.2	40.2	142.1	374.5
10	Agios Prodromos	40.8	72.1	92.8	96.8	302.5
11	Euzonoi	41.6	77.4	87.0	84.8	290.8
12	Kilkis	54.4	80.4	183.5	105.7	424.0
13	Oraiokastro	46.4	80.1	236.4	114.3	477.3
14	Paralimni Giannitsa	35.5	66.4	76.5	156.1	334.5
15	Polikastro	75.2	91.8	174.7	137.7	479.4
16	Elassona	35.2	109.4	114.6	151.2	410.4
17	Karditsa	68.3	76.4	99.3	114.5	358.4
18	Loutropigi	132.5	123.5	123.7	296.8	676.5
19	Megali Kerasia	102.3	69.7	59.6	131.3	362.9
20	Skopia	64.2	66.1	83.2	140.8	354.3
21	Basiliko	193.2	113.1	75.0	380.9	762.2
22	Louros	890.0	292.3	48.8	723.2	1954.3
23	Pentolakos	1319.3	537.6	403.2	1349.2	3609.2
24	Nikaia-Egaleo	160.5	71.0	20.3	85.5	337.2

25	Markopoulo	167.1	69.7	12.5	103.1	352.3
26	Chalandri	149.6	45.2	10.8	124.8	330.5
27	Agia Triada	310.1	187.1	51.7	270.6	819.5
28	Distomo	179.2	79.9	51.3	200.4	510.8
29	Gravia	278.7	119.1	98.0	367.8	863.5
30	Limni Ilikis	93.0	41.1	14.0	123.8	271.9
31	Kaloskopi	504.8	120.4	198.3	531.8	1355.2
32	Livadia	229.1	115.0	120.2	314.8	779.1
33	Lilaia	309.9	162.4	197.3	397.4	1067.1
34	Pavlos	129.2	65.6	42.9	147.8	385.5
35	Timfristos	520.6	297.0	84.6	464.2	1366.4
36	Trilofo	89.0	54.6	40.7	121.5	305.7
37	Zilefto	75.9	56.9	71.3	171.7	375.7
38	Agios Nikolaos	304.1	173.9	76.3	871.4	1425.7
39	Athan. Diakos	748.0	295.0	185.8	639.8	1868.7
40	Koniakos	665.7	150.4	24.7	326.3	1167.1
41	Lesinio	209.5	68.3	22.4	430.5	730.5
42	Lidoriki	385.1	146.4	69.1	384.5	985.1
43	Monastiraki	226.1	127.4	37.9	421.2	812.6
44	Pentagioi	983.0	357.2	149.3	554.3	2043.8
45	Poros Rigani	856.3	326.1	90.6	707.1	1980.0
46	Pyra	336.7	155.9	200.0	361.7	1054.3
47	Arna	986.5	260.2	63.7	691.8	2002.3
48	Karyes	170.7	98.5	39.4	129.5	438.1
49	Neochori	284.5	124.5	201.1	451.9	1062.0

50	Aigio	253.8	102.2	23.0	332.6	711.7
51	Asteri	119.4	105.8	75.9	254.9	555.9
52	Drossato	254.2	124.5	115.8	344.6	839.0
53	Gastouni	474.8	174.2	45.1	750.3	1444.3
54	Kalivia -Feneos	524.4	145.0	194.6	432.4	1296.4
55	Klenia	266.0	147.4	151.8	315.5	880.7
56	Leontio	201.5	153.4	104.9	83.5	543.3
57	Nemea	372.3	155.5	75.2	236.1	839.1
58	Fragma Pinios	233.5	70.9	44.5	277.4	626.4
59	Portes	478.5	228.6	76.9	880.5	1664.4
60	Simopoulo	200.9	99.1	64.5	261.3	625.8
61	Spathovouni	192.8	68.8	100.5	131.4	493.4
62	Lafka Stimfalaia	152.2	83.0	56.2	147.3	438.7
63	Tarsos	257.8	152.3	128.5	305.3	844.0
64	Ksirochorio	222.6	290.0	119.3	504.0	1135.9
65	Zakinthos	425.0	144.9	38.9	677.7	1286.5
66	Dafni	398.0	109.8	27.2	203.3	738.2
67	Lykouria	90.1	64.7	36.9	112.3	304.0
68	Piana	606.9	229.0	214.8	578.9	1629.5
69	Pidima	577.1	166.1	62.5	663.0	1468.6
70	Souli	562.8	177.4	76.7	719.4	1536.4
71	Tropaia	169.2	85.6	77.5	235.0	567.4
72	Ebrosneros	555.7	360.5	14.4	312.1	1242.6
73	Ano Archanes	341.2	113.6	8.2	205.3	668.3

74	Nithafri	539.1	63.1	5.9	349.0	957.1
75	Kalamafka	318.1	34.3	0.0	111.2	463.6
76	Agios Georgios	217.4	84.8	0.0	305.3	607.4
77	Ebaros-Anapodiaris	330.7	54.8	0.0	147.4	533.0
78	Agia Paraskevi	165.7	69.8	232.5	66.1	534.0
79	Panepistimio Aegean	498.4	137.4	16.3	208.7	860.7
80	Akrasi	564.5	185.8	7.0	146.2	903.5
Average		**303.2**	**135.1**	**90.9**	**320.4**	**849.6**

According to the individual stations' R-factor, autumn is the most erosive period with an average of 320.4 MJ mm ha^{-1} h^{-1} $yr^{-1,}$ followed by winter with 303.2 MJ mm ha^{-1} h^{-1} yr^{-1}, spring with an average of 135.1 MJ mm ha^{-1} h^{-1} yr^{-1} and summer with 90.9 MJ mm ha^{-1} h^{-1} yr^{-1}. In practice 73% of the rainfall erosivity takes place in autumn and winter.

R-factor values can potentially be extrapolated to additional precipitation stations (Bonila & Vidal, 2011). The relatively high number of stations with R-factor data allow to develop regression functions (Table 3) which are potentially applicable in Greece for stations with available time-series monthly precipitation data. Monthly precipitation ($Prec_{Month}$), latitude(y), longitude(x) and elevation (Elev) are the attributes used for getting the regression functions at a p value < 0.05.

Table 3: Regression functions for monthly R-factor estimation of individual stations

Period	**Regression functions from individual stations**	**R^2**
January	$-39.1 + 1.8*Prec_{January}$	0.84
February	$-37.5 + 1.65*Prec_{February}$	0.81
March	$-34.4 + 1.65*Prec_{March}$	0.64
April	$-22.5 + 1.5*Prec_{April}$	0.76
May	$259 + 2.2*Prec_{May} -0.026*Elev - 7.3*Y$	0.58
June	$-6.6 + 2.1*Prec_{June}$	0.71
July	$243 + 3.2*Prec_{July} – 6.7*Y$	0.71
August	$242 + 3.1*Prec_{August} – 6.5*Y$	0.51
September	$228 + 3.5*Prec_{September} – 0.015*Elev – 6.65*Y$	0.7
October	$275 + 3.3*Prec_{October} – 0.08*Elev – 8.2*Y$	0.84
November	$-78.9 + 2.96*Prec_{November} – 0.04*Elev$	0.81
December	$-79 + 2.45*Prec_{December}$	0.78

Precipitation is always significant in the monthly regression functions while the longitude(X) has not been significant (Table 3). The effect of elevation is inter-correlated to precipitation. For the summer period the latitude is significant as southern areas have higher R-factor values. The equations may also be useful for predictions of R-factor based on future climate change scenarios. For example, to estimate the effect to rainfall erosivity of 1 mm increase of precipitation during June. The coefficients of precipitation in those regression functions show that R-factor during the period May to December is more 'sensitive' to precipitation compared to the period January-April. However, those extrapolation functions are not recommended for spatial interpolation.

3.2 *Monthly maps of rainfall erosivity in Greece*

The 12 maps of monthly rainfall erosivity in Greece (Fig. 2) give a spatial and temporal overview of the erosive energy of rain. In all maps, a gradient of high erosivity in Western Greece, Ionian Islands, Peloponnesus and western Crete to lower erosivity in Northern Greece, Thessaly, Attica and the Cyclades islands is obvious.

The spatial resolution of the maps is at 100m as all selected covariates (WorldClim, DEM) were available at this resolution. Using the covariates at high resolution, the generation of artefacts by downscaling was avoided (Ballabio et al., 2014). The Generalised Adaptive Model (GAM) used for the interpolation of the monthly erosivity point data showed a good performance in most of the months with the exception of May, July, August and September (Table 4). This confirms the difficulty to predict rainfall erosivity based on few rainstorms in summer.

Since the spatial interpolation was performed with GAM, the spline functions may be presented only in a graphical way. In addition, a linear regression was applied, however, the Linear Model (LM) performed worse than GAM according to the coefficient of determination R^2 (Table 4). Precipitation is the slope (β_1) and β_0 is the intercept of the Linear Model (LM).

Table 4: Performance of the spatial interpolation for each month

Period	R^2 GAM	R^2 Linear Model (LM)	LM β_1	LM β_0
January	0.56	0.40	1.47	-59.16
February	0.43	0.30	1.21	-30.57
March	0.72	0.23	1.35	-39.85
April	0.51	0.27	1.34	-25.53
May	0.18	0.11	0.83	5.15
June	0.71	0.38	1.52	-7.58
July	0.12	0.11	1.23	9.83
August	0.14	0.05	1.05	17.34
September	0.28	0.22	1.78	-15.19
October	0.54	0.40	2.49	-65.58
November	0.65	0.47	3.22	-160.31
December	0.66	0.25	1.91	-84.60

The monthly rainfall erosivity maps are displayed in Fig. 2. The highest mean R-factor is noticed in November (144.6 MJ mm ha^{-1} h^{-1} $month^{-1}$), December (136.2 MJ mm ha^{-1} h^{-1} $month^{-1}$) and October (111.8 MJ mm ha^{-1} h^{-1} $month^{-1}$) while the lowest values are found in August(32.3 MJ mm ha^{-1} h^{-1} $month^{-1}$), July(33.3 MJ mm ha^{-1} h^{-1} $month^{-1}$), May (36.3 MJ mm ha^{-1} h^{-1} $month^{-1}$) and June (37.1 MJ mm ha^{-1} h^{-1} $month^{-1}$). The rainfall erosivity is almost 3 times higher during the cold and wet season (October – March) compared to the warm and dry season (April – September). However, there are regions such as Western Macedonia and Thessaly where mean summer rainfall erosivity is almost equal to mean winter rainfall erosivity. On the contrary, western part of Greece, Ionian Islands, Western Crete and Dodecanese show a pronounced seasonal variability with mean winter R-factor 4-5 higher than the summer one.

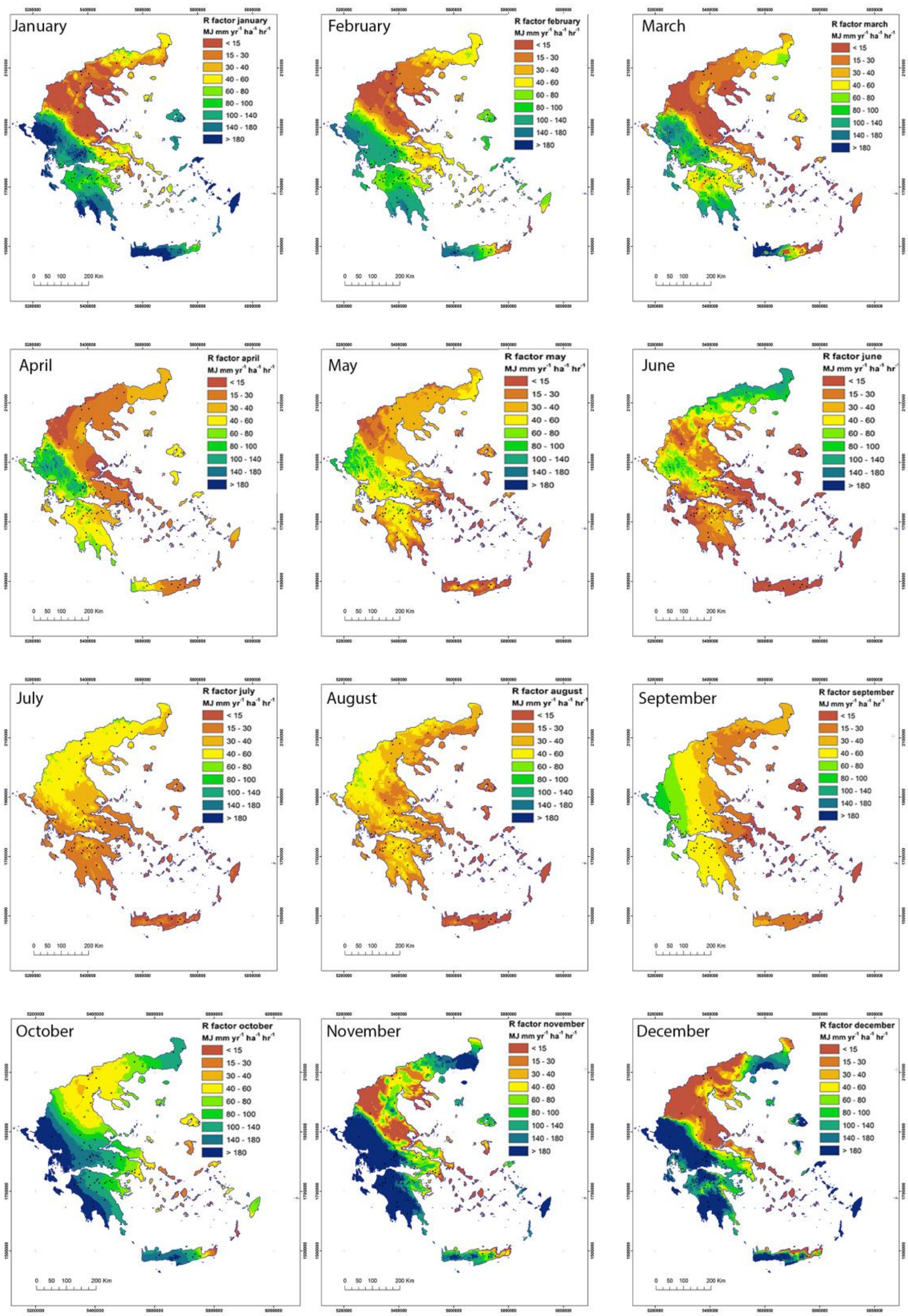

Fig. 2: High-resolution (100m grid cell) monthly maps of rainfall erosivity (MJ mm ha^{-1} h^{-1} $month^{-1}$) in Greece.

The aggregated annual R-factor map of Greece has an average value of 807.4 MJ mm ha^{-1} h^{-1} yr^{-1} and a standard deviation of 527.7 MJ mm ha^{-1} h^{-1} yr^{-1}. The range of R-factor in Greece is 84.2 – 2,825 MJ mm ha^{-1} h^{-1} yr^{-1}. The R-factor distribution is skewed to the right, with 686 MJ mm ha^{-1} h^{-1} yr^{-1} in the 50th percentile which implies that there are few high values over 2,000 MJ mm ha^{-1} h^{-1} yr^{-1} (in western Greece) which increase the overall mean.

The general pattern of the R-factor in Greece (Fig. 3) is also in accordance with spatial variability rain intensity in Greece (Kambezidis et al., 2010). Authors of this publication calculated the mean rainfall intensity (RI) as mm of rain per hour and depicted the western regions as the ones with highest RI (4 mm/h) and eastern costal zones with lowest (1.1 mm/h).

The mean annual R-factor in Crete Island is 846 MJ mm ha^{-1} h^{-1} yr^{-1} (Fig. 3) which is ca. 10% higher than the one calculated in the application of G2 erosion model in Crete (Panagos et al., 2014b). However, the current spatial pattern is similar to the previous application with high erosive part in the Western Crete and much lower value sin eastern part. The current application has 2 more stations in Crete compared to the past one.

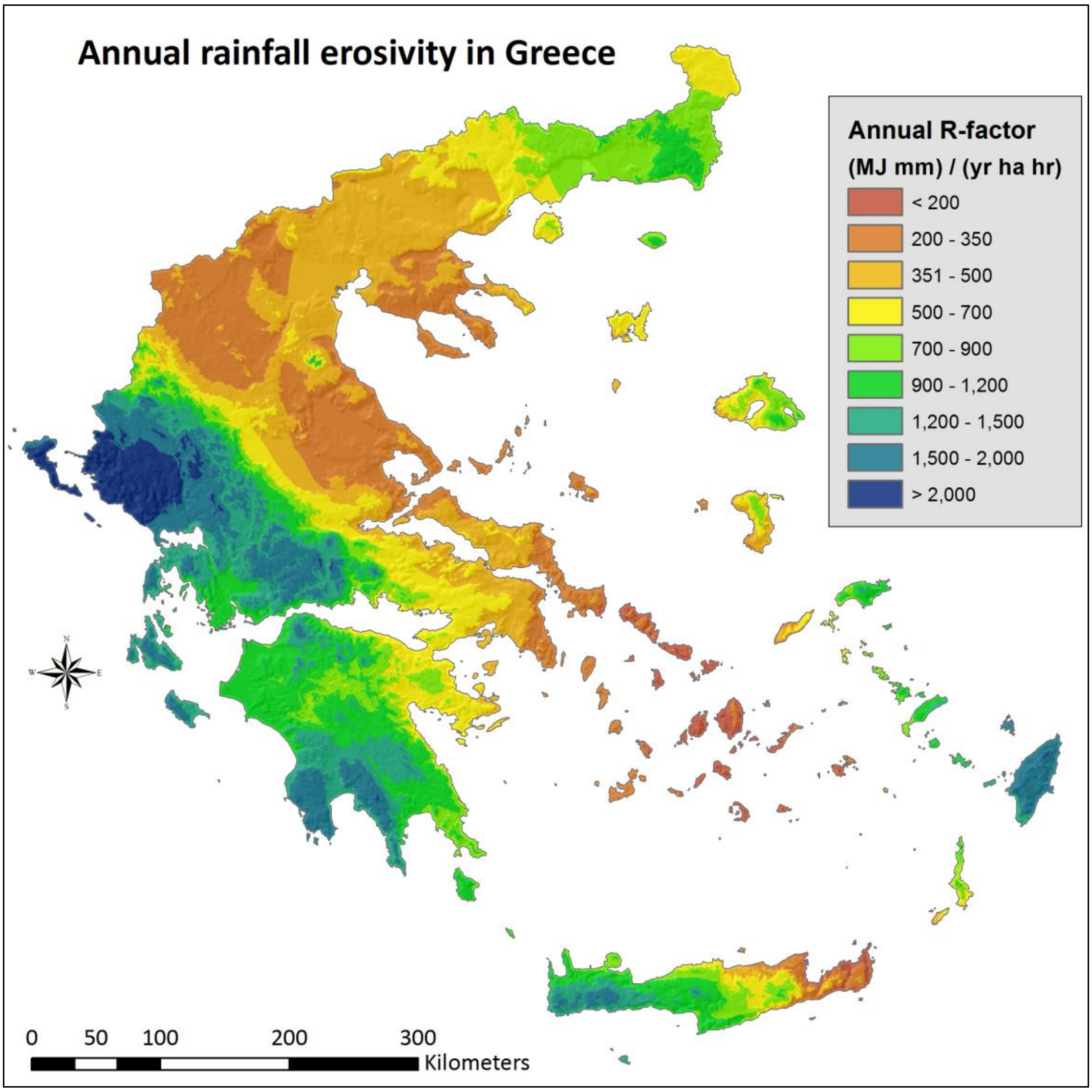

Fig. 3: High-resolution (100m grid cell) annual map of rainfall erosivity (MJ mm ha^{-1} h^{-1} yr^{-1}) in Greece.

The model prediction was generally satisfactory for the large part of the study area (Fig. 4). The standard deviation is used to access the precision of the predictions. The standard deviation (Fig. 4) in combination with the mean values (Fig. 3) can be used for estimating the prediction intervals at a given confidence level. The prediction was found to have increased uncertainty levels in the Dodecanese islands, Cyclades, Corfu and Western Macedonia due to lack of stations with rainfall erosivity data.

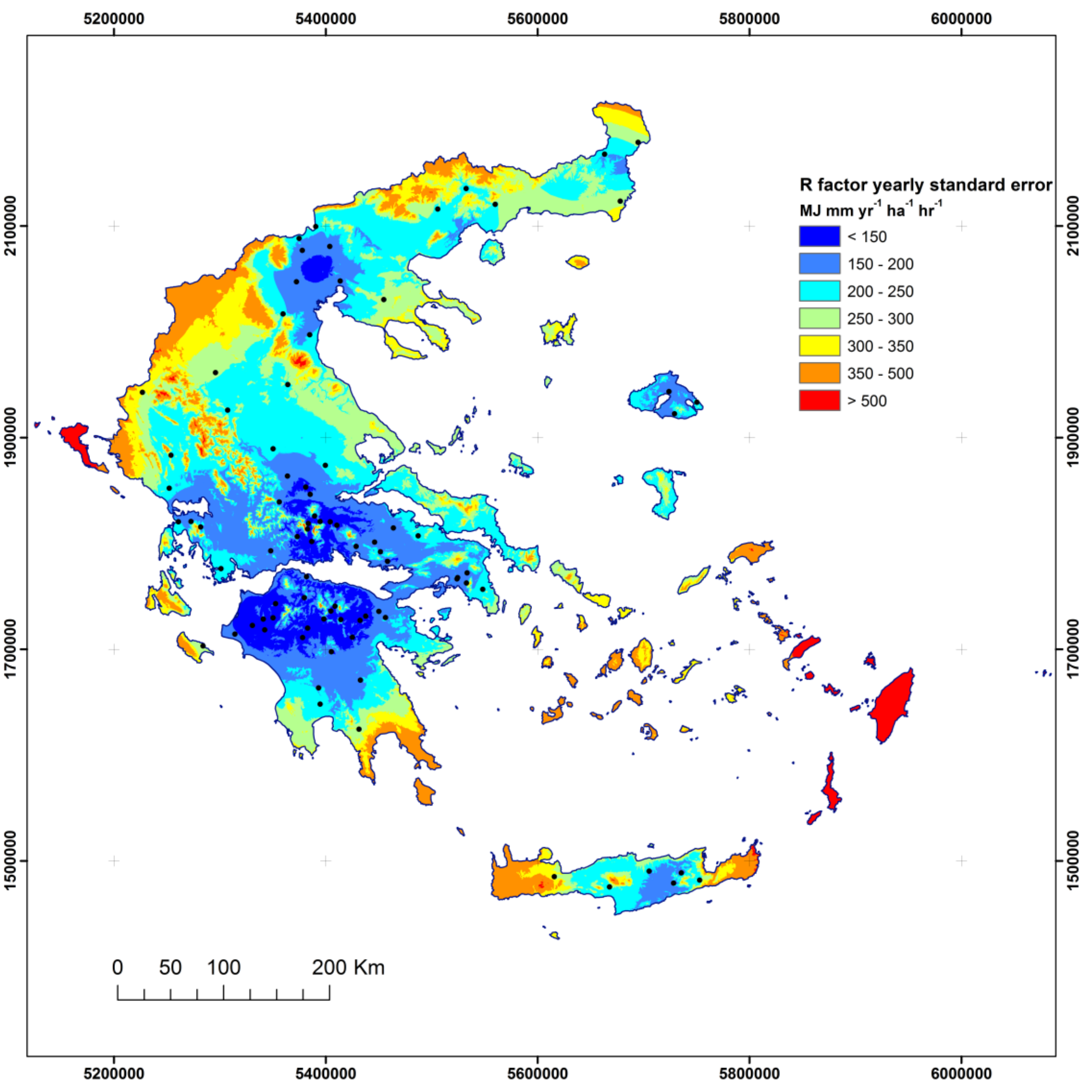

Fig. 4: Uncertainty of the R-factor prediction calculated with the GAM spatial interpolation model

3.3 *Monthly erosivity density*

The erosivity density is the ratio of R-factor to precipitation (Kinnell, 2010) and in practice measures the erosivity per rainfall unit (mm), and is expressed as MJ ha^{-1} h^{-1}. Monthly precipitation data have been extracted from the WorldClim database (Hijmans 2005). In practice, each monthly erosivity dataset (Fig. 2) is divided by the corresponding monthly precipitation dataset resulting in monthly erosivity density datasets.

Erosivity density values higher than 1 mean that a certain precipitation amount may cause relatively higher rainfall erosivity. For the first five months of the year (January to May), erosivity density (ED) is lower than 1 (Fig. 5) ranging from 0.76 to 0.87 due to the predominance of low intensity rainfall events. Starting from June the ED has an increasing trend during the summer months. Especially in August the average rainfall erosivity per precipitation amount is almost double. High erosivity density months indicate that the precipitation is characterised by high intensity events of short duration (rainstorms). For example, January and November are the wettest months after December with similar mean rainfall amount (ca. 92 – 95 mm). However, mean R-factor in November is 50% higher compared to January which indicates that November has a higher number of rainstorms.

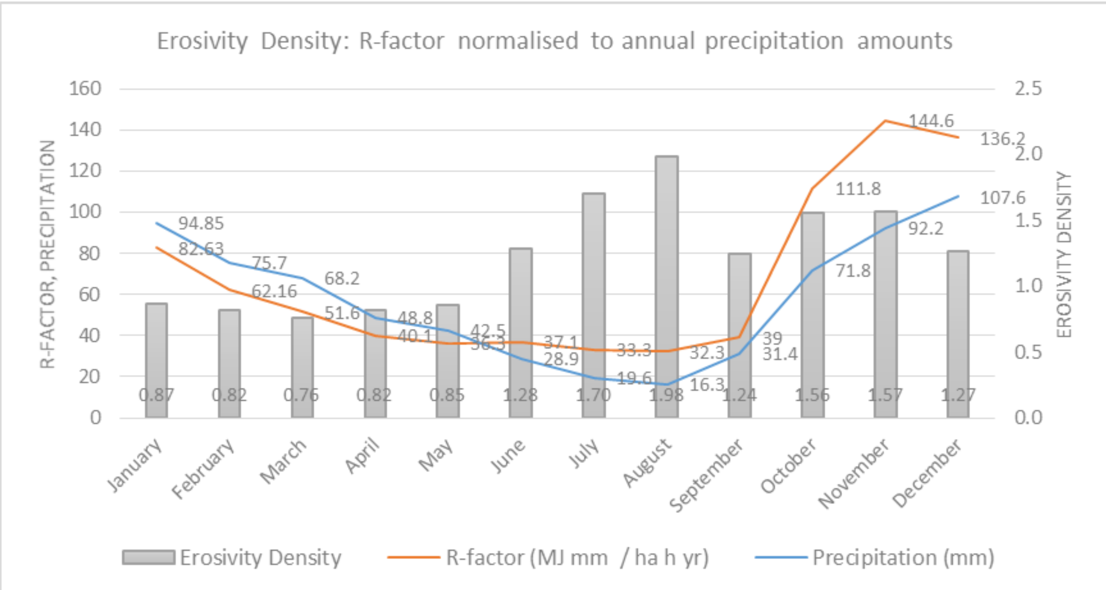

Fig. 5: Monthly R-factor, precipitation and erosivity density

The annual erosivity density has a mean value of 1.22 MJ ha^{-1} h^{-1}, with high variability ranging from 0.15 to 2.14 MJ ha^{-1} h^{-1}. The seasonal variability of erosivity density is also very high as the summer has the highest mean erosivity density with 1.89 MJ ha^{-1} h^{-1} followed by autumn with 1.36 MJ ha^{-1} h^{-1}, winter with 0.85 MJ ha^{-1} h^{-1} and spring with 0.78 MJ ha^{-1} h^{-1} (Fig. 6) . Different spatial patterns of erosivity density are noticed during the four seasons. For example in Peloponnesus, the southern part has much higher values than northern for winter and spring while the west-east gradient is more visible in autumn and overall high values are noticed during summer. Moreover, the winter and spring have similar erosivity density but very different spatial patterns with lower variability in spring. This high spatial and temporal variability of ED highlights the fact that rainfall erosivity is not solely dependent on the amount of precipitation. Consequently, it is impossible to predict spatially the monthly R-factor in Greece exclusively based on precipitation levels.

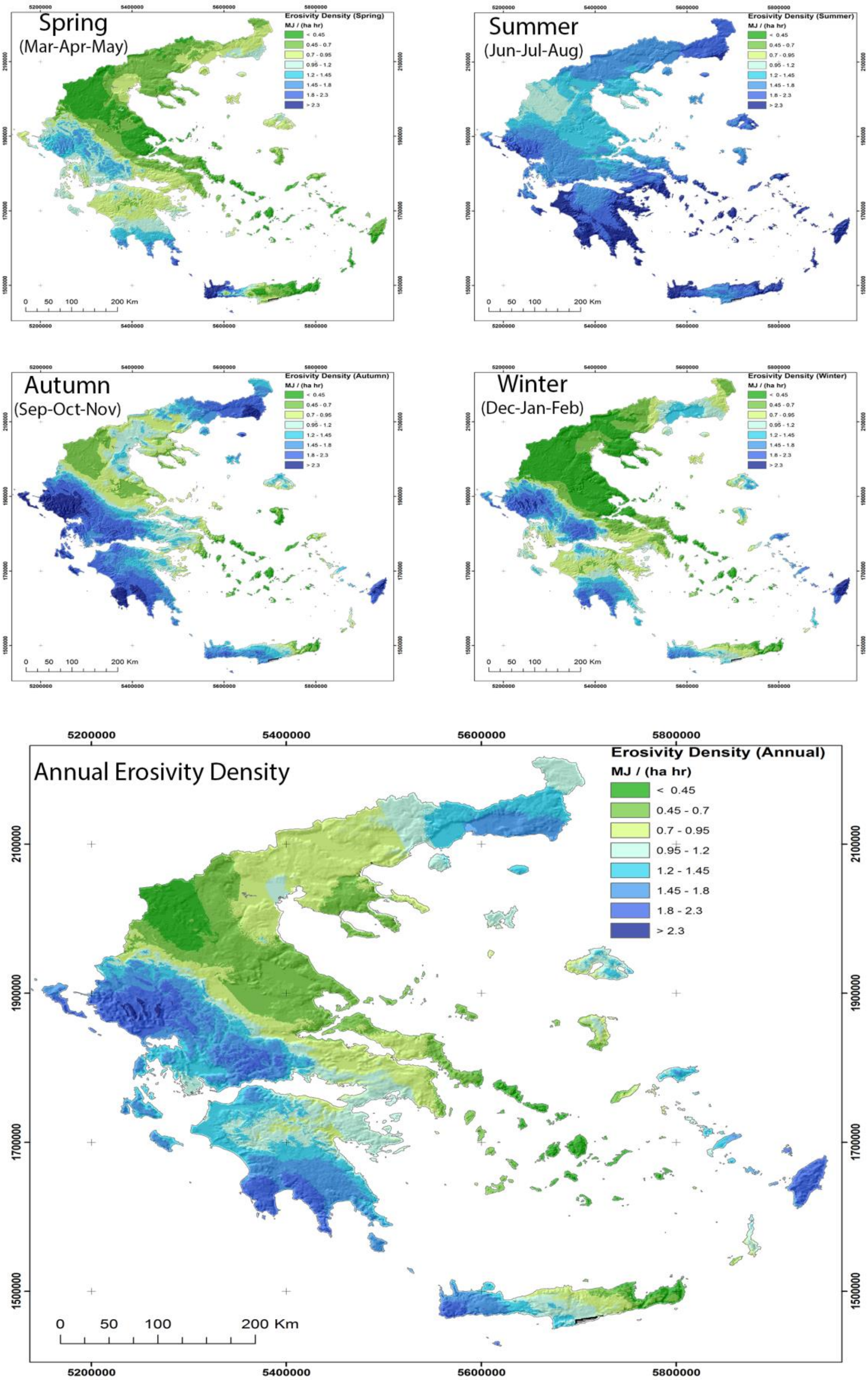

Fig. 6: Seasonal erosivity density (rainfall erosivity per mm of precipitation).

3.4 Monthly rainfall erosivity and soil erosion risk

Seasonal rainfall erosivity (R-factor) maps may be used in many environmental sectors, e.g. landslides mapping, post fire erosion risk assessment, crop productivity, crop growth modelling and flash flood risk assessment. Most important R-factor maps may contribute to more accurate soil erosion risk predictions. For the latter purpose the monthly R-factor maps need to be combined with soil erodibility (K-factor), which is proposed at a high resolution (Panagos et al., 2014c) and slope length and steepness (LS factor), which is due to new geo-information software not a major obstacle. Most important and probably most challenging is the combination of rainfall erosivity (R-factor) with the crop and management factor (C-factor), which is the second factor in the RUSLE model with pronounced intra-annual variability. This combination of dynamic layers will result in seasonal erosion datasets using RUSLE based models such as the G2 soil erosion model.

Greece is characterised by a high proportion (26.5%) of bare soil (Eurostat, 2014a). At regional level, Ipeiros has even a proportion of 57% of bare soil in agricultural lands (Eurostat, 2014a). The combination of high R-factor in Ipeiros and western Greece with bare soil coverage may cause severe soil loss and have detrimental impacts on the resource soil. In light of the high erosivity in the winter season also the habit of farmers in Greece to burn the crop residues during summer (Barbayiannis et al., 2010) may be judged negative with respect to soil conservation. A positive land use statistic is that the proportion of permanent grasslands is by 50% higher in the regions with the highest rainfall erosivity (Western Greece, Peloponnesus and Western Crete) compared to the average percentage of grasslands cover. However, a negative aspect of grassland management in Greece is that around 71% of the grasslands are grazed for a period longer than 10 months, which is one of the highest in European Union both in terms of duration and proportion.

Tillage practice is another soil erosion risk factor with high spatio-temporal variability. It may be incorporated in the RUSLE model via the P-factor, which accounts for soil conservation practices or proposed as a new management factor. According to the tillage practices agro-environmental indicator (Eurostat, 2014b), only 2% of agricultural land in Greece is under zero tillage and conservation tillage is applied for around 20% of the area. Both values are lower than the European Union averages. However, the conventional tillage has quite low shares in high erosive regions such as Peloponnesus (44%), Crete (55%) and Western Greece (66%).

4 Conclusions

This study presented a spatio-temporal analysis of rainfall erosivity expressed as monthly R-factor maps for Greece. Monthly rainfall erosivity in Greece has a high intra-annual variability with the highest value in November of 144.6 MJ mm ha^{-1} h^{-1} $month^{-1}$ and lowest in July with 37.1 MJ mm ha^{-1} h^{-1} $month^{-1}$. In Greece, the wet period especially October, November and December are the most erosive months. The wet period (October – March) contribution to the total annual rainfall erosivity is around 73%.

The spatial interpolation model performed well during the high erosive months while it had relatively 'poor' performance during summer months due to few and unpredictable rainstorms events. The monthly erosivity density as a ratio of R-factor to rainfall amount is useful to identify months with more rainstorms and moreover quantify which will be the impact of precipitation change (climate change) to erosivity. The erosivity density analysis and the monthly R-factor regression functions based on station data indicates that rainfall erosivity per precipitation amount is higher during the period June-December.

The average annual R-factor in Greece is 807 MJ mm ha^{-1} h^{-1} yr^{-1}. The spatial variability of rainfall erosivity is high in Greece with the Western part and Peloponnesus having the highest values while the eastern coast, Macedonia region, Thessaly and Cyclades have relatively low R-factor. The East-West gradient of rainfall erosivity has different patterns per month with smoother distribution during summer and high variability during winter months. Moreover, the spatio-temporal analysis of erosivity density demonstrates that it is impossible to spatially predict the R-factor per month exclusively based on precipitation levels.

To conclude, the spatio-temporal maps of R-factor are useful for agronomists to identify the locations and periods when highest erosivity risk meets susceptible crops and may allow for timely soil conservation measures such as zero tillage and crop residues.

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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CHAPTER 6

Estimating the soil erosion cover-management factor at European scale

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Estimating the soil erosion cover-management factor at European scale

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Abstract

Land use and management influences the magnitude of soil loss. Among the different soil erosion risk factors, the cover-management factor (C-factor) is considered to be the most important because policy makers and farmers can intervene and, as a consequence, may reduce soil erosion rates. The present study proposes a methodology for estimating the C-factor in the European Union (EU), using pan-European datasets such as CORINE Land Cover, biophysical attributes derived from remote sensing and agricultural statistical data on crops and practices. In arable lands, the C-factor was estimated using crop statistics (% of land per crop) and management practices data such as conservation tillage, plant residues and winter crops. The C-factor in non-arable lands was estimated by weighting the range of literature values found by fractional vegetation cover, which was estimated based on the remote sensing dataset F_{cover}. The mean C-factor in the EU is estimated to be 0.1043, with an extremely high variability; forests have the lowest mean C-factor (0.00116) and arable lands and sparsely vegetated areas the highest means (0.233 and 0.2651 respectively). The conservation management practices (reduced/no tillage, use of cover crops and plant residues) reduce the C-factor by on average 19.1% in arable lands.

The methodology is reproducible with past land cover datasets and statistical data, and is designed to be a tool for policy makers to assess the effect of future land use and crop rotation scenarios on soil erosion. The impact of land use changes (deforestation, arable land expansion of shrub lands) and the effect of policies (such as the Common Agricultural Policy and the push to grow more renewable energy crops) can potentially be quantified with the proposed model. The C-factor data and the statistical input data used are available on the European Soil Data Centre.

Keywords: C-factor; tillage; crop residues; cover crop; RUSLE; soil conservation;

1 Introduction

Agriculture and management practices play an important role in soil erosion control. For instance the decrease of water erosion rates with increase of vegetation cover is exponential (Gyssels et al., 2005). Besides vegetation cover, several other land use and management related factors affect soil loss, such as type of crop, tillage practice etc. The influence of land use and management is often parameterized in the cover-management factor (C-factor). The C-factor is among the 6 factors which are multiplied for the estimation of soil erosion risk with the most commonly used Universal Soil Loss Equation (USLE) and its revised version, the RUSLE. The C-factor is perhaps the most important factor in regards to policy and land use decisions as it represents conditions that can be managed most easily to reduce erosion (Renard et al., 1991). The bare plot (no vegetation) with till up and down the slope is considered as a reference condition and has a C-factor value equal to 1. The soil loss for different land cover types is compared to the loss of reference plot and results to a ratio. The C-factor value for a land cover type is the weighted average of those Soil Loss Ratios (SLRs) and ranges between 0 and 1. Following the RUSLE handbook (Renard et al., 1997), SLRs are computed based on 5 sub-factors: prior land-use, canopy cover, surface cover, surface roughness and soil moisture. This approach is feasible on plot to field scale.

For larger spatial scales simplified approaches are adopted: i) assigning uniform literature C-factor values to a land cover map (De Vente et al., 2009;

Borrelli et al., 2014) and ii) mapping vegetation parameters using techniques like image classification and Normalized Difference Vegetation Index (NDVI). NDVI was not considered in the present study as this is proved to correlate poorly with vegetation attributes due to the effect of soil reflectance and vitality of vegetation (De Jong, 1994). For this study at European scale, covering an area of 4,381,376 Km^2 of the 28 Member states of the European Union (EU-28) a hybrid C-factor Land Use and Management (LANDUM) model has been developed. LANDUM model is based on literature review, remote sensing data at high spatial resolution and statistical data on agriculture and management practices.

The main objective of this study is to estimate the land cover and management factor (C-factor) based on the best available data in combination with a literature review at European scale (EU-28). The proposed C-factor incorporates management practices such as reduced tillage or no till, cover crops and plant residues (Reeves, 1994; Wall et al., 2002). Please note that other management related practices such as contour farming, terracing, strip cropping and hedge rows are, by definition, considered in the support practice factor (P-factor). More specifically, this study aims to:

a) propose weighted average C-factor values for arable lands based on the crop composition of an area;
b) calibrate the C-factors found in the literature for the non-arable lands based on biophysical attributes derived from remote sensing data;
c) estimate the effect of management practices such as reduced tillage, cover crops and plant residues to reduce soil erosion rates;
d) quantify the impact of land use and conservation management scenarios.

2 Data

2.1 CORINE Land Cover

The CORINE land cover map was developed by image analysis and digitalisation of Landsat photos in a GIS environment. CORINE Land Cover datasets are available for 1990, 2000, and 2006 and have been used to calculate the C-factor at the European level (Panagos et al., 2014a). The datasets contain homogeneous data on land cover areas, which are provided in vector format (as polygons). All CORINE Land Cover datasets (CLC, 2014) were established following harmonized procedures based on a common classification system, and can therefore be easily compared. Data are classified in 44 land-cover classes, which are grouped into three hierarchical levels. The data are also available in a raster format at a pixel size of 100 m and refer to the year 2006.

2.2 Biophysical attributes derived from remote sensing data

Under the Copernicus Programme (Copernicus, 2012) the ENVISAT MERIS sensor produced regular standardised biophysical parameter layers over Europe at 300 m resolution covering the period 2011-2012 and at 1 Km resolution for about 10 continuous years (2002-2012). The biophysical attributes named 'BioPar' are derived from MERIS using the 'SAIL/PROSPECT' baseline vegetation model (Verhoef 1985). Among the nine biophysical parameters available in Geoland2 (2012) portal, the current C-factor development considers that F_{cover} is the most appropriate layer as it represents the percentage(fraction) of the surface covered by any kind of vegetation. The F_{cover} dataset is used with the purpose to weight C-factors of a specific land use type depending on the fractional vegetation cover.

2.3 Agricultural statistical data from Eurostat

NUTS (Nomenclature of Territorial Units for Statistics) is a system used by the administrative authorities of European Union and Member States for classifying the European territory into hierarchical levels according to the population size. NUTS2 level represents regions of 0.8–3 million people at which regional policies are implemented and agricultural data are available. Among the statistics that the European Commission statistical service (Eurostat) provides to the public, three datasets were used in this study at NUTS2 level: a) regional agricultural statistics and land use (named agr_r_landuse) b) tillage methods (named ef_pmtilaa) and c) soil conservation (named ef_pmsoilaa). The first one includes crop statistical data at annual basis. The crop statistical data (land use by NUTS2) provide, for a given crop, the area (hectares) during the crop year at regional (NUTS2) level. The mean values for each crop category of the period 2008-2012 have been taken in order to incorporate the crop variation (rotation) during this period.

The dataset tillage method includes statistics for tillage practices and the soil conservation dataset provides statistics for cover crops and plant residues; both are results from the Farm Structure Survey (FSS). Eurostat collected the data from the Farm Structure Survey on Agricultural Production Methods (SAPM, 2010) which is a once-only survey carried out in 2010 to collect data at farm level on agro-environmental measures. The European Union (EU) member states collected information from individual agricultural holdings and, following rules of confidentiality, data were transmitted to Eurostat. Those data have been aggregated at regional level NUTS2.

In this study, the statistical data of tillage practices, cover crops and plant residues are used as input for the C-factor estimation. Tillage practices data are defined as the share (%) of arable areas under conventional, conservation and zero tillage at NUTS2 level.

3 Methods

The LANDUM model for C-factor estimation is differentiated between a) arable lands and b) all the remaining land uses (non-arable). Wetlands, water bodies and artificial areas are not considered in C-factor evaluation. Finally, a mosaic layer composed of C-factor for arable lands and C-factor for non-arable lands is proposed as annual C-factor in Europe.

3.1 C-factor estimation for arable lands

The arable lands (CORINE Land Cover classes 21x) cover around 25.2% of the total European land. Arable lands are strongly affected by decisions of policy makers (e.g. Common Agricultural Policy). In the past, published studies (De

Vente et al., 2009; Borrelli et al., 2014) assigned constant C-factor values for all agricultural lands without considering the type of crop and management. The C-factor values for croplands are assigned based on field experiments which are very time-consuming, expensive and therefore rare (Gabriels et al., 2003). In the present study, a C-factor has been calculated for the arable lands of each NUTS2 region:

$$C_{arable} = C_{crop} * C_{management} \quad (1)$$

Where C_{crop} is the C-factor based on the crop composition of an agricultural area and $C_{management}$ quantifies the influence of management practices (reduced tillage, cover crop and crop residues) on soil erosion reduction.

3.1.1 Crop factor

The annual soil loss in agricultural lands is dependent on crop type. At NUTS2 level, there are available statistical data for 16 different crops plus fallow land. A literature review has performed to identify C_{crop} factor for each of the 16 crops. C-factor values per crop type (Table 1) are based on experimental data from previous studies (Bolline, 1985; Onchev et al. 1988; NS 2001; Rousseva 200s4; Biesemans et al. 2000; Wischmeier & Smith, 1978; David 1988; Cai 1988; Palmquist & Danielson, 1989; Roose 1977; Nyakatawa et al. 2001; Gabriels et al. 2003; Boellstorff & Benito 2005; Antonino et al. 2005; Vezina et al. 2006; Bazzoffi, 2007; Junakova & Balintova 2012) and applications of the proposed C-factor values (Van Rompay & Govers 2002; Wall et al., 2002; Shi et al., 2004; Morgan 2005; Bakker et al. 2008; Marker et al. 2008; Terranova et al. 2009; de Vente et al., 2009; Borrelli et al., 2014). Eurostat statistics consider as fallow land 3 types of land use: a) bare land bearing no crops at all or b) land with spontaneous natural growth which may be used as animal feed or c) land sown exclusively for the production of green manure. Taking into account this definition and literature values for fallow land which is used in crop rotation systems (Nyakatawa et al. 2007; Shi et al. 2004), the value of 0.5 has been assigned for this land use.

The C_{crop} factor represents the weighted C-factor average of 17 different crops presented in each NUTS2 region.

$$C_{crop} = \boxed{\sum_{n=1}^{17} C_{cropn} * \%NUTS2_{cropn}} \quad (2)$$

Where C_{crop} is the C-factor of the n-crop (Table 1) and $\%NUTS2_{crop}$ is the share of this crop in the agricultural land of a region at NUTS2 level. According to equation (2), each NUTS2 region has a different C_{crop} according to its crop composition and apparently, regions with crops susceptible to erosion will have higher C_{crop} factors.

Table 1: Area covered by differed crop types and assigned C-factor (C_{crop})

n	Crop Type	Share (%) of the total arable land (EU28)	C-factor
1	Common wheat and spelt	28.5	0.20
2	Durum wheat	3.2	0.20
3	Rye	3.0	0.20
4	Barley	14.8	0.21
5	Grain maize – corn	12.9	0.38
6	Rice	0.6	0.15
7	Dried pulses (legumes) and protein crop	1.9	0.32
8	Potatoes	2.4	0.34
9	Sugar beet	3.1	0.34
10	Oilseeds	5.8	0.28
11	Rape and turnip rape	8.1	0.3
12	Sunflower seed	4.8	0.32
13	Linseed	0.1	0.25
14	Soya	0.5	0.28
15	Cotton seed	0.4	0.5
16	Tobacco	0.1	0.49
17	Fallow land	9.8	0.5

Similar to the presented approach Bakker et al. (2008) introduced an average C-factor value based on the most dominant arable crops grown in 4 catchments.

The F_{cover} has not taken into account in C-factor estimation in arable lands as the vegetation growth is volatile during the year. The C-factor per crop (Table

1) is applied in the whole study area. The crop rotation in each agricultural field is an important issue but the overall share of crops at such large scale (NUTS2 region) is generally stable in short term. A 5-years period (2008-2012) was taken into account to assess crop composition. The present methodology allows to estimate C_{crop} factor based also on past arable statistics. It should be also noticed that the C-factor estimation is limited due to non-available geo-referenced data on crop composition and rotation at European scale.

3.1.2 Management factor

The management factor ($C_{management}$) quantifies the effect of management practices on soil loss in agricultural lands. The tillage practices, the cover crops and the impact of crop residues are considered as management practices that influence the C-factor at arable lands (Wischmeier and Smith, 1978; Renard et al. 1997). Support practices such as contour farming, terracing and strip cropping are considered in the support practice factor (P-factor). The combined effect of tillage practice ($C_{tillage}$) and plant residues ($C_{residues}$) or cover crops (C_{cover}) is also taken into account for the estimation of management factor:

$$C_{management} = C_{tillage} * C_{residues} * C_{cover} \quad (3)$$

Reeves (1994) combined those 3 practices in various experimental sites in U.S.A with different crops (cotton, corn, wheat, rye) and estimated that they can reduce soil erosion by 85%.

3.1.2.1 Reduced tillage and no till practices

The potential soil erosion by water is affected by tillage operations, depending on the depth, direction and timing of plowing, the type of tillage equipment and the number of passages. Generally, the less the disturbance of vegetation or residue cover at or near the surface, the more effective is the tillage practice in reducing water erosion. Minimum till or no-till practices are effective in reducing soil erosion by water. Reduced tillage systems and cover cropping can reduce soil erosion and leaching of nutrients into ground water (Nyakatawa et al., 2001).

Tillage practices refer to the tillage operations carried out between the harvest and following sowing/cultivation operation. Conventional tillage is the most wide-spread tillage practice applied in 74.4% of the arable site in the study area. Conservational tillage refers to a practice or system of practices applied in arable lands that leaves plant residues (at least 30%) on the soil surface for erosion control and moisture conservation, normally by not inverting the soil (Eurostat, 2013). Conservation tillage includes the following practices: a) ridge tillage b) tined tillage or vertical tillage and c) strip tillage or zonal tillage. In the EU-28, around 21.6% of the arable land is under conservation tillage.

Zero tillage refers to the arable land on which no tillage is applied between harvest and sowing. Zero tillage is a minimum tillage practice in which the crop is sown directly into soil not tilled since the harvest of the last crop (Eurostat, 2013). Zero tillage is applied only to 4% of the arable land in the EU-28.

In order to predict long-term average soil loss from agriculture, Siegerist et al. (2013) proposed a C-factor which incorporates a tillage sub-factor. Faist Emmenegger et al. (2009) and the USLE factsheet (Stone and Hilborn, 2012) propose different values of this $C_{tillage}$ factor depending on the practices:

- $C_{tillage}$ = 1 for conventional tillage;
- $C_{tillage}$ = 0.35 for conservation/ridge tillage;
- $C_{tillage}$ = 0.25 for no till practices

Nyakatawa et al (2001) also estimated that no tillage reduces soil erosion at the rate of 75% compared to conventional tillage.

The $C_{tillage}$ factor depends on the intensity this region follows the conservation and no till practices. In case that only conventional tillage is applied then $C_{tillage}$ equals to 1.

$$C_{tillage} = (\%_{Conventional} * 1 + \%_{Conservation} * 0.35 + \%_{Notill} * 0.25) \qquad (4)$$

In equation (4), the percentages (%) represent the share of each tillage practice in the region.

3.1.2.2 Crop residues practices

In cropland, leaving adequate residue on the ground after harvest reduces sheet and rill erosion (Santhi et al., 2006). However, farmers often plow the land after harvest, which results in erosion. Maintaining crop residues on soil surfaces not only protects the soils from splash erosion but also increases infiltration rates (Mannering and Meyer, 1963), and reduces surface runoff (Greenland, 1975) resulting in less soil loss. In their experimental field, Campbell et al (1979) found that crop residues decrease water erosion by around 12%.

The implementation of a combined crop management scenario which incorporates cover crops (in order to protect bare soil in winter and spring against storms) and leaving the previous crop residues on the field resulted in 35% soil loss reduction in Belgian loess belt (Verstraeten et al., 2002). The former contributed to this reduction by 22% (reduction of C-factor 0.36 to 0.28) while the latter contributed with 13%. Finally, a residue crop cover of around 10-30% may result in reducing soil loss to around 12% (Andrews, 2006). According to the previous literature findings, the proposed $C_{residues}$ for this study is set to 0.88.

$$C_{residues} = 1 * (1 - \%_{residues}) + (0.88 * \%_{residues}) \quad (5)$$

Where $\%_{residues}$ is the share of agricultural land which has a residues treatment.

3.1.2.3 Cover crop practices

Cover crops reduce erosion by improving soil structure and increasing infiltration, protecting the soil surface, scattering raindrop energy and reducing the velocity of water that moves over the soil surface (Smith et al., 1987). An efficient management practice in reducing soil and nutrient loss is keeping the land covered with crop during the whole year. These crops should not be mistaken for normal winter crops or grassland. Those crops are sown specifically to protect bare soil in winter (and early spring) after the harvest of summer crops like sugar beets, cotton, maize and potatoes. The economic interest of the cover crops is low, and the main goal is soil and nutrient protection.

Niyakatawa et al (2001) found that cover crop (e.g. rye) significantly reduces soil erosion by 15% in cotton fields. Verstraeten et al., (2002) estimated the reduction of soil loss to around 23% due to cover crops. Comparing the C-factor reduction due to application of cover crops, Wall et al. (2002) and Bazzoffi (2007) have estimated to be around 20%.

$$C_{cover} = 1 * (1-\%_{crop\text{-}cover}) + (0.80 * \%_{crop\text{-}cover}) \qquad (6)$$

Where $\%_{crop\text{-}cover}$ is the share of agricultural land where cover crop practice is applied during winter or spring.

3.2 C-factor estimation for non-arable lands

It is feasible and economically affordable to estimate soil erosion at large scales using the latest developments in remote sensing and geographical information system (GIS) techniques (Wang et al., 2003). In the early 2000's, remote-sensing data were used for first time to develop the USLE cover-management factor through land-cover classifications (Millward and Reusing et al., 2000; Ma et al., 2003). Those approaches assume that the same land covers have the same C-factor values throughout the study area. The result greatly depends on the spatial resolution of land-cover maps and their classification accuracy; and the determination of the suitable C-factor value for each land cover class.

However, the same land-cover class may have different C factors due to variations in vegetation density (Lu et al., 2004). In the same context, different land uses with the same vegetation coverage result in different C-factors (Panagos et al., 2014a). C-factor estimation should take into account the combined effects of the above- and below-ground biomass plus the different environmental conditions (Smets et al., 2008).

The C-factor was defined for each CORINE Land Cover class according to literature values (Table 2). However, a range of values ($C_{landuse}$) has been assigned to each class due to the variety of values found in the literature. The range of values (Table 2) has been developed based on studies covering different countries among them in Italy, Belgium, Slovakia, Greece, Bulgaria, France, Switzerland, Portugal and Spain (USDA, 1977; Van Rompay & Govers 2002; Wall et al., 2002; Yang et al., 2003; Angeli, 2004; Santhi et al., 2006; Terranova et al., 2009; de Vente et al., 2009; Pelecani et al. 2009; Bakker et al. 2008; Antronico et al., 2005; Borselli et al. 2009; Konz et al., 2009) . The range of values for grasslands and pastures have been estimated based on exponential equations (Elwell, 1977). The range of values for "Heterogeneous agricultural areas" (Codes: 24x) was calculated using values from arable lands, permanent crops, pastures, grasslands and woodlands and applying the shares (%) of those categories in the worst case scenario (higher value) and best case scenario (lower value).

The influence of vegetation density can be quantified by the use of biophysical parameters derived from MERIS satellite images (Panagos et al., 2014b). In a similar way, de Asis & Osama, (2007) estimated C-factor as a function of the fractional abundance of bare soil and ground cover using Landsat. Using a proxy vegetation layer allows to quantify the impact of vegetation cover in C-factor estimation. F_{cover} is a vegetation layer available in COPERNICUS programme and normalized in the range [0–1] describing the % of soil covered by any type of vegetation.

$$C_{NonArable} = Min(C_{landuse}) + Range(C_{landuse}) * (1 - F_{cover}) \quad (7)$$

Based on this approach, the C-factor reaches its maximum value when the F_{cover} is equal to 0 (no vegetation protection and high risk of erosion) and gets its minimum value when F_{cover} is equal to 1 (soil is fully covered with vegetation). In equation (7), the range per land use is the result of maximum – minimum values (Table 2).

Table 2: C-factor per non-arable land cover type

Group	CLC class	Detailed class	Description	C-factor values ($C_{landuse}$)
Permanent crops	221	Vineyards	Areas planted with vines	0.15-0.45
	222	Fruit trees &berry plantations	Parcels planted with fruit trees or shrubs: single/mixed fruit species, fruit trees associated with permanently grassed surfaces.	0.1-0.3
	223	Olive groves	Areas planted with olive trees	0.1-0.3
Pastures	231	Pastures	Dense, predominantly graminoid grass cover, of floral composition, not under a rotation system. Mainly used for grazings.	0.05-0.15
Heterogeneous agricultural areas	241	Annual crops associated with permanent crops	Non-permanent crops (arable land or pasture) associated with permanent crops on the same parcel (non-associated annual crops represent less than 25%)	0.07-0.35
	242	Complex cultivation patterns	Juxtaposition of small parcels of diverse annual crops, pasture and/or permanent crops (Arable land, pasture and orchards each occupy less than 75% of the total surface area of the unit)	0.07-0.2
	243	Land principally occupied by agriculture, with significant areas of natural vegetation	Areas principally occupied by agriculture, interspersed with significant natural areas (Agricultural land occupies between 25 and 75% of the total surface of the unit)	0.05-0.2
	244	Agro-forestry areas	Annual crops or grazing land under the wooded cover of forestry species	0.03-0.13
Forests	311	Broad-leaved forest	Vegetation formation composed principally of trees, including shrub and bush understories, where broadleaved species predominate.	0.0001-0.003
	312	Coniferous forest	Vegetation formation composed principally of trees, including shrub and bush understories, where coniferous species predominate	0.0001-0.003
	313	Mixed forest	Vegetation formation composed principally of trees, including shrub and bush understories, where broadleaved and coniferous species co-dominate.	0.0001-0.003

Scrub and/or herbaceous vegetation associations	321	Natural grasslands	Low productivity grassland. Often situated in areas of rough uneven ground	0.01-0.08
	322	Moors and heathland	Vegetation with low and closed cover, dominated by bushes, shrubs and herbaceous plants (heath, briars, broom, gorse, laburnum)	0.01-0.1
	323	Sclerophyllous vegetation	Bushy sclerophyllous vegetation. Includes maquis (dense vegetation association composed of numerous shrubs) and garrige (oak, arbutus, lavender, thyme, cistus)	0.01-0.1
	324	Transitional woodland-shrub	Bushy or herbaceous vegetation with scattered trees. Can represent either woodland degradation or forest Regeneration / colonisation.	0.003-0.05
Open spaces with little or no vegetation	331	Beaches, dunes, sands	Beaches, dunes and expanses of sand or pebbles in coastal or continental	0
	332	Bare rocks	Scree, cliffs, rocks and outcrops	0
	333	Sparsely vegetated areas	Includes steppes, tundra and badlands. Scattered high-attitude vegetation	0.1-0.45
	334	Burnt areas	Areas affected by recent fires, still mainly black	0.1-0.55
	335	Glaciers and perpetual snow	Land covered by glaciers or permanent snowfields	0

4 Results and Discussion

4.1 C-factor in arable lands

The mean C-factor (C_{arable}) value in the arable lands of EU-28 is 0.233 taking into account the management practices. The mean C_{crop}-factor without any application of conservation management practice is increasing to 0.287. The mean $C_{management}$ factor is 0.809 which means that combination of all management practices (tillage practices, crop residues, cover crop) reduce the average C-factor by 19.1% overall the arable lands of EU-28. The lowest C-factor values in croplands (< 0.17) have been identified in Germany (Thüringen, Sachsen-Anhalt and Sachsen), United Kingdom (South East, East Midlands) and Bulgaria (Yugoiztochen, Severoiztochen) due to high percentages of conservation tillage. The highest C-factor values in croplands (> 0.39) have been found in Portugal (Algarve), Malta, France (Corse) and Spain (Región de Murcia, Comunidad Valenciana) (Fig. 1) due to high shares of fallow land and lack of conservation practices. Romania, Hungary, Malta, Greece and the Iberian Peninsula (Spain, Portugal) have the highest mean values at national scale with (> 0.27). Instead, the lowest mean values at national scale are found in United Kingdom, Bulgaria, Cyprus, Czech Republic and Germany (< 0.20).

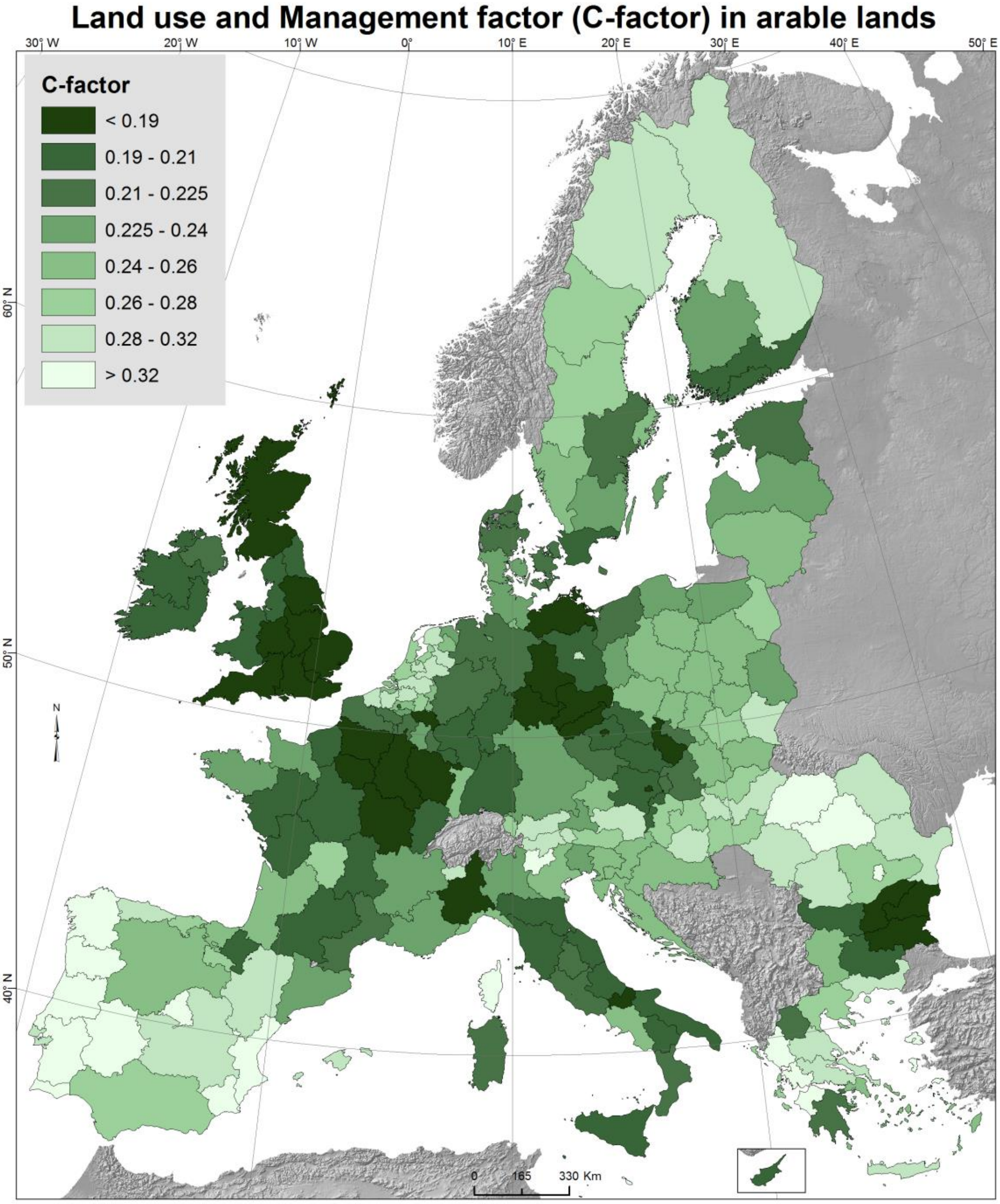

Fig. 1: Land use and management factor (C-factor) in arable lands of the European Union

The conservation tillage practices is reducing the C-factor by 17% ($C_{tillage}$ = 0.83) mainly due to reduced tillage as no till practices have a very small share (4%) in the arable lands of EU-28. The greatest influence of conservation tillage practices is noticed in the regions with the lower C-factor values (Fig. 2a).

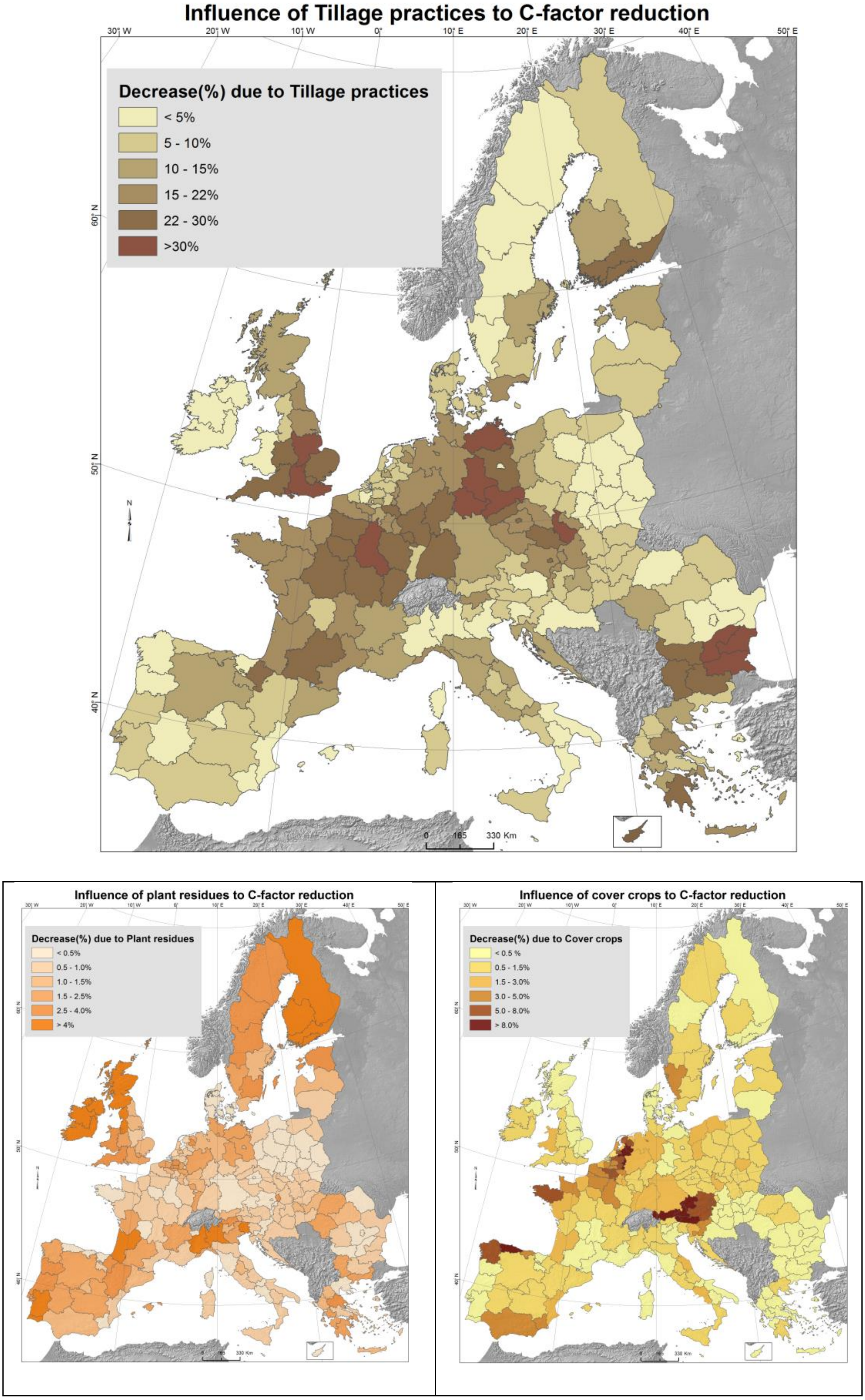

Fig. 2: C-factor reduction due to a) tillage practices (upper frame) b) plant residues (down left) c) cover crops (down right)

The crop residues application reduced C-factor by 1.2% ($C_{residues}$ = 0.988) as this practice is applied to the 10.6% of the arable lands in EU-28. The highest impact of plant residues (>6%) is noticed in the two Irish regions (Border, Midland and Western - Southern and Eastern) and in two Finish regions (Etelä-Suomi, Helsinki-Uusimaa) due to the high share of arable lands with plant residues (>53%) (Fig. 2b).

Cover crops reduced C-factor by another 1.3% (C_{cover} = 0.987) as 6.5% of the EU-28 arable lands have cover crops during winter/spring. The highest impact of cover crops (> 12.3% C-factor reduction) is noticed in three Austrian regions (Vorarlberg, Salzburg and Tirol) due to the high share of cover crops (> 61.5%). The cover crops are a usual practice also in The Netherlands and Belgium while it is hardly applied in the Mediterranean regions (Fig. 2c).

4.2 C-factor in non-arable lands

The mean C-factor value in the non-arable lands of the EU-28 is 0.0539 with a high standard deviation of 0.073 due to the large range of assigned values in the different land cover classes. The mean values per land cover type at European scale (Table 3) are the result of applying the equation (7) at pixel level and then aggregating per land cover. The mean C-factor values (Table 3) demonstrate the influence of vegetation density in the C-factor estimation.

Table 3: Mean C-factor per land cover type after using the remote sensing data

Group	**CLC class**	**Description**	**% of the area**	**C-factor values**
Permanent crops	221	Vineyards	1.3%	0.3527
	222	Fruit trees &berry plantations	0.9%	0.2188
	223	Olive groves	1.4%	0.2273
Pastures	231	Pastures	12.9%	0.0903
Heterogeneous agricultural areas	241	Annual crops associated with permanent crops	0.3%	0.2323
	242	Complex cultivation patterns	8.2%	0.1384
	243	Land principally occupied by agriculture, with significant areas of natural vegetation	6.7%	0.1232
	244	Agro-forestry areas	1.2%	0.0881
	311	Broad-leaved forest	14.7%	0.0013

Forests	312	Coniferous forest	22.1%	0.0011
	313	Mixed forest	10.3%	0.0011
Scrub and/or herbaceous vegetation associations	321	Natural grasslands	3.9%	0.0435
	322	Moors and heathland	2.8%	0.0420
	323	Sclerophyllous vegetation	3.2%	0.0623
	324	Transitional woodland-shrub	8.7%	0.0219
Open spaces with little or no vegetation	333	Sparsely vegetated areas	1.3%	0.2652
	334	Burnt areas	0.04%	0.3427
TOTAL (Non-arable)			100%	0.0539

However, the mean C-factor value per land cover type can be also estimated at national (Table 4) or even at NUTS2 level giving information on different management practices or influence of climate. For instance, the vineyards (class 221) have the highest mean C-factor value in Spain (0.396), followed by Bulgaria (0.375) and Hungary (0.36). On the other hand, the lowest mean C-factor values in vineyards are found in Luxembourg (0.29) followed by Slovenia (0.299) and Germany (0.311). In major parts of vineyards in Spain the soil is bare while in Germany and Slovenia there is an herbaceous protective coverage.

An influence of climate might be seen as the pastures in Ireland are less susceptible to erosion (C-factor = 0.077) than in Cyprus (C-factor = 0.125) as they have denser vegetation coverage. Likewise, the forests in Finland and Sweden are two times denser (C-factor = 0.0009) than in Cyprus (C-factor = 0.0018).

Table 4: C-factor per land cover type and country

Cover Type (class) / *Country*	***Vineyards*** 221	***Olives*** 223	***Pastures*** 231	***Complex cultivation*** 242	***Agriculture& & Natural areas*** 243	***Forests*** 31X	***Grasslands*** 321	***Transitional Woodland &Shrub*** 324	***Sparse Vegetation*** 333
AT	0.3403		0.0853	0.1300	0.1211	0.0012	0.0345	0.0215	0.2308
BE			0.0893	0.1286	0.1153	0.0011	0.0372	0.0216	
BG	0.3750		0.1185	0.1517	0.1449	0.0016	0.0498	0.0302	0.2889
CY		0.2524	0.1256	0.1659	0.1595	0.0019	0.0639	0.0359	0.3780
CZ	0.3546		0.0927	0.1506	0.1253	0.0014	0.0391	0.0235	0.2865
DE	0.3111		0.0920	0.1282	0.1219	0.0012	0.0421	0.0235	0.2810
DK			0.0905	0.1250	0.1152	0.0012	0.0424	0.0216	0.2648
EE			0.0829	0.1171	0.0997	0.0009	0.0342	0.0171	0.2794

ES	0.3963	0.2413	0.0901	0.1585	0.1457	0.0015	0.0516	0.0296	0.3517
FI			0.0971	0.1102	0.0981	0.0009	0.0273	0.0161	0.2052
FR	0.3363	0.2145	0.0906	0.1302	0.1195	0.0012	0.0403	0.0229	0.2581
GR	0.3269	0.2094	0.1132	0.1476	0.1307	0.0014	0.0522	0.0260	0.3062
HR	0.3254	0.1981	0.0975	0.1461	0.1193	0.0011	0.0440	0.0228	0.2752
HU	0.3605		0.1167	0.1583	0.1491	0.0017	0.0564	0.0306	0.3564
IE			0.0770	0.1087	0.0902	0.0010	0.0294	0.0165	0.2171
IT	0.3454	0.2163	0.0988	0.1478	0.1245	0.0013	0.0416	0.0242	0.2509
LT			0.0873	0.1224	0.1021	0.0011	0.0389	0.0190	0.2822
LU	0.2905		0.0907	0.1254	0.1107	0.0011		0.0231	
LV			0.0819	0.1169	0.0944	0.0010	0.0331	0.0171	0.2671
MT					0.1483				
NL			0.0900	0.1317	0.1126	0.0013	0.0489	0.0251	
PL			0.0933	0.1358	0.1214	0.0012	0.0432	0.0231	0.3115
PT	0.3313	0.2216	0.1030	0.1432	0.1342	0.0015	0.0491	0.0270	0.2858
RO	0.3460		0.1026	0.1398	0.1313	0.0013	0.0419	0.0242	0.2449
SE			0.0833	0.1082	0.0947	0.0009	0.0317	0.0162	0.2301
SI	0.2993		0.0965	0.1359	0.1185	0.0013	0.0447	0.0244	0.2864
SK	0.3433		0.0922	0.1465	0.1212	0.0013	0.0395	0.0228	0.2254
UK			0.0867	0.1201	0.1068	0.0011	0.0319	0.0183	0.1825
EU-28	0.3527	0.2273	0.0903	0.1384	0.1232	0.0012	0.0435	0.0219	0.2652

4.3 C-factor map

The land cover and management factor, known as C-factor in RUSLE, was mapped at 100 m resolution. LANDUM model used as input the CORINE Land Cover map, the MERIS remote sensing dataset F_{cover} at 300 m resolution, statistical data on crops and management practices plus literature references to C-factor. The C-factor is estimated in agricultural (arable and permanent crops), grasslands, pastures, forests and semi natural areas (Fig. 3). This area which is potentially erodible accounts for 90% of the total EU-28 surface. The rest 10% of land is covered with non-erodible areas such as artificial areas, wetlands, bare rocks, water bodies, beaches and glaciers which are not taken into account in the study. Obviously the arable lands have the highest C-factor and forests have lowest values. The mean C-factor in EU-28 is 0.1043 with a standard deviation of 0.1046 and values ranging from 0.0001 to 0.526.

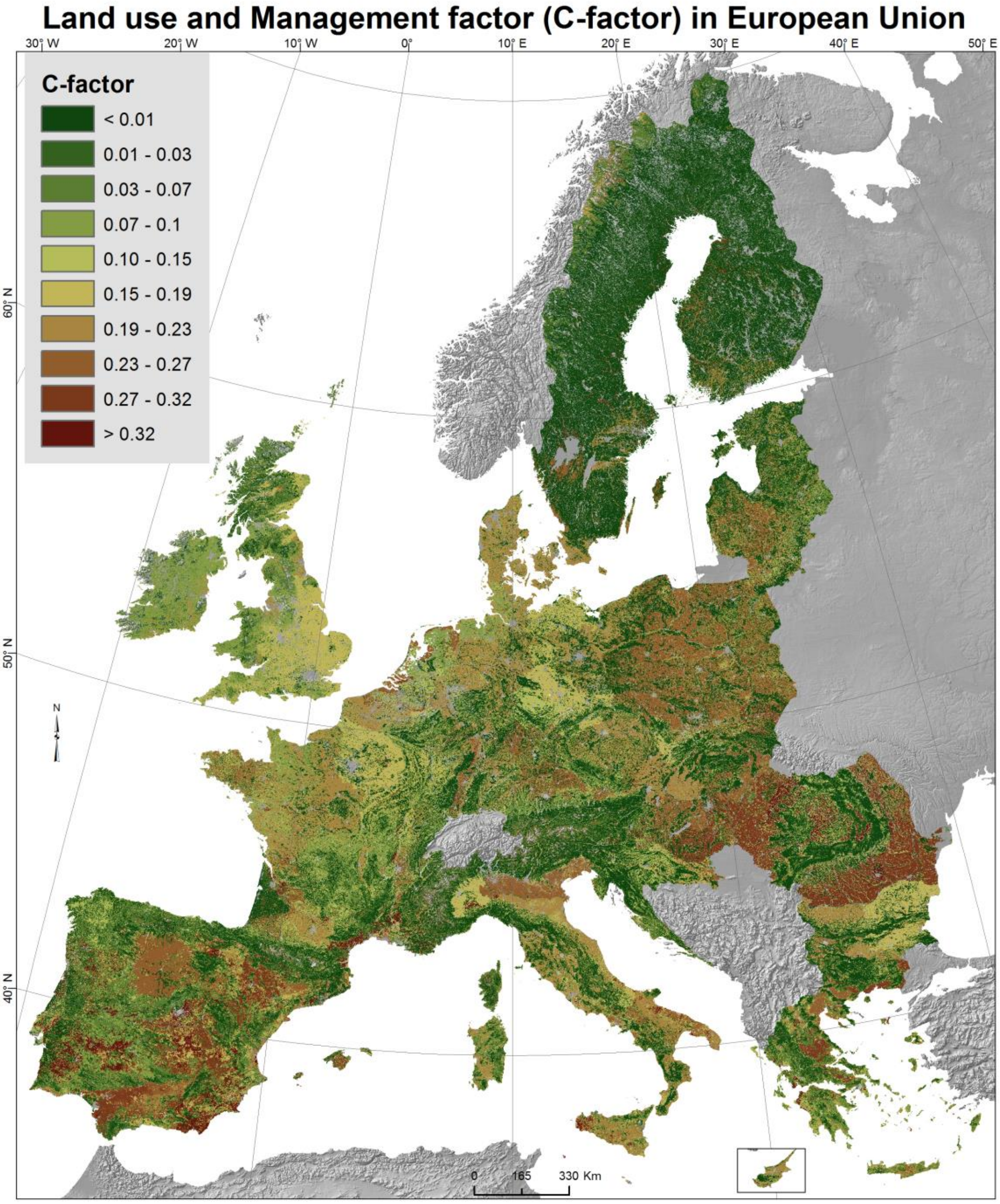

Fig. 3: C-factor map of the European Union

At country level, the highest mean C-factors (> 0.15) are found in Hungary, Denmark, Malta and Romania (Table 5) for different reasons. Denmark and Hungary have the highest shares (%) of arable lands and Romania has the second highest C_{arable} factor due to its crop composition and minimum application of conservation practices. In Malta, the $C_{non\text{-}Arable}$ is high due to dominance of land principally occupied by agriculture, with significant areas of natural vegetation (class 243). The lowest C-factor values (< 0.075) were identified in Finland and Sweden followed by Slovenia, Estonia, Latvia and Austria where forest is the dominant land use.

Table 5: C-factor per country

		Arable lands		Non Arable lands	
Country	**C-factor**	**C-factor**	**% share**	**C-factor**	**% share**
AT	0.071	0.218	15.3%	0.045	84.7%
BE	0.121	0.245	27.9%	0.073	72.1%
BG	0.105	0.188	37.5%	0.055	62.5%
CY	0.129	0.193	30.8%	0.100	69.2%
CZ	0.107	0.199	41.1%	0.042	58.9%
DE	0.112	0.200	42.1%	0.048	57.9%
DK	0.178	0.222	72.4%	0.061	27.6%
EE	0.059	0.217	16.7%	0.027	83.3%
ES	0.140	0.289	24.9%	0.090	75.1%
FI	0.023	0.231	6.2%	0.010	93.8%
FR	0.108	0.202	30.3%	0.068	69.7%
GR	0.111	0.280	17.5%	0.075	82.5%
HR	0.075	0.255	7.5%	0.061	92.5%
HU	0.188	0.275	58.3%	0.066	41.7%
IE	0.082	0.202	9.6%	0.069	90.4%
IT	0.119	0.211	30.4%	0.078	69.6%
LT	0.121	0.242	36.5%	0.051	63.5%
LU	0.082	0.215	13.4%	0.061	86.6%
LV	0.070	0.237	16.4%	0.037	83.6%
MT	0.151	0.434	1.7%	0.148	98.3%
NL	0.133	0.260	26.4%	0.088	73.6%
PL	0.140	0.247	47.3%	0.043	52.7%
PT	0.123	0.352	14.8%	0.083	85.2%
RO	0.150	0.296	38.5%	0.058	61.5%
SE	0.032	0.237	8.1%	0.014	91.9%
SI	0.057	0.248	5.8%	0.046	94.2%
SK	0.106	0.235	36.5%	0.032	63.5%
UK	0.099	0.177	32.2%	0.062	67.8%

The LANDUM model has been dependent on the best available pan-European input datasets (CORINE Land Cover, official agricultural statistical data from Eurostat, MERIS Remote sensing) and the literature values of land uses and management practices.

4.4 *Drivers & policies influence to land use and management factor*

The C-factor and as a consequence the soil erosion rates can potentially be influenced by land use changes, crop rotation and modifying management practices. The highest impact on C-factor is the land use change and especially the deforestation due to cropland expansion. In the past century, demographic, cultural and political changes had a strong impact on deforestation and replacement of forests with croplands increasing soil erosion (Begueria et al., 2006). This land use change may have resulted in a significant increase of C-factor and as a consequence in an increase of soil loss. Other important drivers influencing the land cover change are the expansion of agricultural areas (for wheat production) in shrub land covers. The latter is possible mainly due to technologically advanced irrigation systems and the technical developments (machinery) which allow cultivating land in the hilly areas.

In the early 1980s, the Common Agricultural Policy (CAP) subsidized cereal crops as well as traditional permanent crops, which were extended at the expense of shrublands resulting in higher soil erosion risk (Onate & Peco, 2005). The mean C-factor of cereal crops is at least 5-times higher than the one in shrublands (Table 3). The CAP financial incentives to farmers and market prices for commodities induced land use changes and crop rotation changes. For example in Mediterranean countries, the CAP subsidies for olive and almond trees have transformed parts of semi-natural areas (mainly in hilly slopes) to permanent crops (Garcia-Ruiz, 2010) increasing soil erosion risk. Another example of CAP incentives was the cotton cultivation (high erosive) in Greece which has been increased four time during the period 1980 -1996 (Tzouvelekas et al., 2001).

On the other hand the CAP reform in 2000's included some agro-environmental measures, which had positive effects on runoff and soil erosion. For instance, the creation of buffer strips, the maintenance of terraces, the promotion of hedge planting and the measures to convert arable land to extensively managed grassland are some of the CAP agro-environmental measures. Pastures have a protective effect against erosion as the C-factor is around 2.5 times lower than the one in arable lands. An additional benefit of the conversion to grasslands or their preservation is the high soil organic carbon accumulation (Lugato et al., 2014), which in turn promotes soil aggregation preventing erosion. Germany is an illustrative example of the effectiveness of government subsidies for reduced tillage in erosion risk areas (Lahmar 2010). As a result of the subsidies the reduced tillage is now applied to almost 40% of arable lands. At EU policy level, the Sustainable agriculture and soil conservation (SoCo) project identified the importance of plant residues as a protective measure against soil erosion (Louwagie et al. 2011).

In the context of energy policy, the European Union has set the target to achieve 10% biofuel share by 2020. This target will increase the demand for energy crops such as sugar beets, sunflowers, maize and oil seeds at the expense of wheat which is the less erosive crop. Moreover, this will decrease the plant residues with an overall negative impact on soil conservation, including the potential loss of soil organic carbon (Lugato et al., 2014). In a scenario of transforming 10% of arable land from cereals to energy crops production and reduction of plant residues to 5%, the mean C-factor in arable lands will be 0.242, showing an increase of 3.8% and resulting in 2.2% overall increase in soil erosion risk.

With the proposed LANDUM model, crop rotation and management practices scenarios can be applied. For example, if conservation tillage will be applied to 50% (compared to existing 25%) of the European arable lands combined with an increase of cover crops to a level of 35% (compared to existing 10.6%) and crop residues to 25% (compared to 6.5%), then the C-factor in arable lands will be 0.172 showing a remarkable decrease of 40% (compared to the existing 19.1%) due to conservation management practices. This would result in 16.5% reduction on the overall C-factor and as a consequence to soil erosion risk. In another scenario, if pastures are increased by 15% by replacing arable lands, this will result in a decrease of 2% in soil loss.

5 Conclusions

At European scale, the LANDUM model has been developed for C-factor estimation both in arable land and rest of land uses. Special focus was given in the arable lands and the main model features were the incorporation of crop composition and the conservation management practices for first time at European scale. The conservation management practices (reduced/zero tillage, cover crops and plant residues) reduced the C-factor in arable lands by an average of 19.1%. Conservation tillage has the major impact among the management practices. The LANDUM model can be used by policy makers to run crop rotation, land use and conservation practices scenarios.

Among the soil erosion risk factors, the rainfall erosivity, soil erodibility, slope length and steepness (R, K, LS) are mainly nature dependent and cannot be not easily be altered. The support practices (P-factor) such as contour farming and terracing can reduce soil erosion but they request considerable financial contributions from farmers. Actually, only the land use and management factor (C-factor) can be modified by policy makers and farmers with rational costs, reducing soil erosion in arable hence nutrients loss and preserving the soil organic carbon.

The incorporation of vegetation coverage density from remote sensing data (F_{cover}) in the C-factor estimation is a major advancement compared to constant values assigned to CORINE classes which are quite generic and they differ from country to country. For example, the new C-factor map (Fig. 3) reflects that pastures in Ireland have much higher density and protective function than in Cyprus and Bulgaria.

The C-factor dataset plus the derived products provide the most up-to-date general picture of land cover and management practice at the European Union scale. It is not intended to be a substitute for regional-scale or local maps in case they are based on spatialized crop statistics or higher resolution remote sensing data. Since those C-factor datasets rarely exist even at regional level, the proposed C-factor dataset provides this information to soil erosion modellers. The maps and tools (Excel tables of crops composition & management practices) produced in this study will be freely available for download from the European Soil Data Centre (Panagos et al., 2012).

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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CHAPTER 7

Modelling the effect of support practices (P-factor) on the reduction of soil erosion by water at European Scale

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Modelling the effect of support practices (P-factor) on the reduction of soil erosion by water at European Scale

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Abstract

The USLE/RUSLE support practice factor (P-factor) is rarely taken into account in soil erosion risk modelling at sub-continental scale, as it is difficult to estimate for large areas. This study attempts to model the P-factor in the European Union. For this, it considers the latest policy developments in the Common Agricultural Policy, and applies the rules set by Member States for contour farming over a certain slope. The impact of stone walls and grass margins is also modelled using the more than 226,000 observations from the Land use/cover area frame statistical survey (LUCAS) carried out in 2012 in the European Union.

The mean P-factor considering contour farming, stone walls and grass margins in the European Union is estimated at 0.9702. The support practices accounted for in the P-factor reduce the risk of soil erosion by 3%, with grass margins having the largest impact (57% of the total erosion risk reduction) followed by stone walls (38%). Contour farming contributes very little to the P-factor given its limited application; it is only used as a support practice in eight countries and only on very steep slopes. Support practices have the highest impact in Malta, Portugal, Spain and Belgium where they reduce soil

erosion risk by at least 5%. The P-factor modelling tool can potentially be used by policy makers to run soil-erosion risk scenarios for a wider application of contour farming in areas with slope gradients less than 10%, maintaining stone walls and increasing the number of grass margins under the forthcoming reform of the Common Agricultural Policy.

Keywords: RUSLE; GAEC; stone walls; grass margins; LUCAS; contour farming;

1 Introduction

The Common Agricultural Policy (CAP) is the main EU policy through which farmers are receiving incentives in the European Union (EU). In order to get those incentives, farmers must comply with "best practice" landuse management practices (named cross-compliance). The main component of cross-compliance is the farmer's obligation to keep his land under Good Agricultural and Environmental Condition (GAEC, 2009). This regulation requests the farmers to prevent soil erosion, conserve soil organic carbon and maintain soil structure. An option to assess the effect of GAEC on soil erosion reduction is based on the use of soil erosion risk models. At national scale, models based on the Universal Soil Loss Equation (USLE) are most commonly applied (Panagos et al., 2014a).

Of the six RUSLE/USLE input factors (Renard et al. 1997), values for the support practice P-factor are considered as the most uncertain (Haan et al. 1994; Morgan and Nearing 2011). The P-factor accounts for control practices that reduce the erosion potential of runoff by their influence on drainage patterns, runoff concentration, runoff velocity and hydraulic forces exerted by the runoff on the soil surface (Renard et al., 1997). It is an expression of the overall effects of supporting conservation practices – such as contour farming, strip cropping, terracing, and subsurface drainage – on soil loss at a particular site, as those practices principally affect water erosion by modifying the flow pattern, grade, or direction of surface runoff and by reducing the volume and rate of runoff (Renard et al. 1997). The value of P-factor decreases by adopting these supporting conservation practices as they reduce runoff volume and velocity and encourage the deposition of sediment on the hill slope surface. The lower the P-factor value, the better the practice is for controlling soil erosion. Human influence on soil erosion control is important to include in soil erosion risk assessment, but there is no global reference because erosion control is a very local activity (Yang et al., 2003).

P-values can be derived either from image classifications using remote sensing data or from previous studies or even from expert knowledge. Karydas et al. (2009) have mapped landscape objects (terraces, roads, physical obstacles) with Object-oriented image analysis (OAA) and assigned P-values by expert knowledge in the Kolymbari catchment study in Crete. Another approach is to use IMAGE 2006 and Sobel filters for identifying physical obstacles (Panagos et al., 2014b) that can reduce runoff and soil erosion. The image classifications approach requests very high resolution remote sensing datasets and some experimental results which are currently not available.

The literature reports various tables and formulas proposing P-factor values for the different supporting conservation practices adopted to different environmental contexts (e.g. Wischmeier and Smith 1978; Renard et al. 1997; Foster et al. 2002). Typical values range from about 0.2 for reverse-slope bench terraces, to 1.0 where there are no erosion control practices (Wischmeier and Smith 1978). The effectiveness of the support conservation measures is obtained from plot studies and often applied at small catchments. However, since it is difficult to quantify the impact of different support practices applied in very large areas (e.g. Europe), only a first estimate of the P-factor can be calculated at European scale.

An alternative approach for an approximation of the P-factor is based on empirical equations. For instance, the Wener's method assumes that the P-factor is linked to topographical features. This method is commonly employed to determine P-factor values using as input the slope gradient (%) (Lufafa et al. 2003; Fu et al. 2005; Terranova et al. 2009). Our study does not use such equations as slope gradient is already incorporated in the topographic LS factor.

The main objective of this study is to estimate the support practice factor (P-factor) based on earth observation datasets at European scale (EU-28) following the literature guidelines and taking into account the current agro-environmental policies that are implemented in the individual member states. The proposed P-factor model for Europe takes into consideration contour farming, stone walls and grass margins. Management practices such as reduced tillage, cover crops and plant residues are incorporated in the land cover and management practice factor (C-factor of the RUSLE). More specifically, this study aims to:

a) Estimate the P-factor values for arable lands in Europe based on the Common Agricultural Policy implementation;
b) Assess the impact of conservation practices such as stone walls and grass margins in reducing soil loss at European scale;
c) Discuss the implications of policy scenarios that may affect those support practices.

2 Policy context and materials

2.1 Good Agricultural and Environmental Condition (GAEC) measures applied in the EU Member States

Member States have the flexibility to define the contents of GAEC requirements taking into account the local conditions (Angileri et al., 2009). Regarding protection of soils against soil erosion, GAEC has introduced among others the prevention of erosive farming practices (ploughing and planting up and down the slope) in hilly areas and the maintenance of landscape features such as stone walls (and terraces) and buffer strips. Some Member States have set the requirement for contour ploughing (and ban up- and downslope cultivation) for areas exceeding a certain slope gradient (Table 1).

Table 1: GAEC application (mainly on contour farming) in Member States

Member	Farming practice	Slope (%)	Crop

State			(if specified)
Belgium -Flanders (BE-F)	crop to be sown along contours (if plot extends >100 m in that direction)	Any	winter cereals, spring grain or linen
Cyprus (CY)	cultivation along the contour	> 10	
Estonia (EE)	cultivation along the contour	> 10	
Denmark (DK)	Reduced till	> 21	
Greece (GR)	cultivation along or diagonal to the contour (Cross slope contour farming)	> 10	
Italy (IT)	contouring every 80m of agricultural land (named solco in Italian)		
Malta (MT)	cultivation along the contour	> 10	
Romania (RO)	soil tillage along the contour	> 12	row crops
Slovenia (SI)	ploughing along contour	> 20	
Spain (ES)	no overturn of soil in the direction of the maximum slope no overturn of soil in the direction of the maximum slope	>10 >15	herbaceous crops vineyards, olive groves and nut crops

The maintenance of dry stone walls is among the GAEC standards that Member States have adopted. Stone walls are considered effective for reducing slope length and as a consequence soil erosion (Bazzoffi et al, 2009). Moreover, according to GAEC standards, small landscape elements such as hedges or buffer strips should not be removed as they protect habitats and reduce runoff volumes.

2.2 Land Use/Cover area frame statistical survey (LUCAS)

The study uses the Land Use/Cover area frame statistical survey named LUCAS (LUCAS, 2012) which includes ground observations both on land use/cover and landscape features for over 270,000 observation points visited by surveyors in 2012. The survey has been made in the 27 member states (EU-27) of the European Union covering an area of ca. 4.3 million Km^2 with an average density of 1 observed point every 16 Km^2. Surveyors recorded data on land use/cover plus additional information such as slope gradient, presence of grazing, height of trees and irrigation management. The surveyor also collects multi-directional photographs and walks eastwards along a transect of 250m recording the sequence of land-cover types and linear landscape features. Among the total number of observations, 226,653 records (83.9%) are considered valid for this study because the rest were not completed by a surveyor (van der Zanden et al, 2013). Invalid points were well distributed all over Europe. The data is geo-referenced and is available in the LUCAS database (LUCAS, 2012). Among the landscape features recorded by a surveyor (LUCAS, 2013), we focused in this study on stone walls and grass margins (Fig. 1).

Fig. 1: Examples of dry stone walls (photos above) and grass margins (photos below) reported in LUCAS survey.

2.2.1 Stone walls

Dry stone walls are widespread landscape features in the Mediterranean and especially in the islands (Malta, Sicily, Cyprus, Isle Balearides, Aegean islands). These stone walls were primarily used to delimit parcels being bequeathed by farmers to their children and to clean the land from stones. This also includes stone heaps which were collected by the farmer on the field (Fig. 1a) even though not in a linear form. Stone walls prevent soil erosion; especially in hilly areas. Their predominance in Southern Europe is also linked to the availability of stones in soil (Poesen et al. 1994; Panagos et al., 2014c).

Stone walls should be at least 20m long in order to be recorded by a LUCAS surveyor. According to the LUCAS observations, stone walls have been recorded in 11,141 (4.9%) transects. The largest number of stone walls have been observed in Spain, France, Italy and Portugal (Table 2). In all Mediterranean countries (IT, ES, PT, GR, CY, MT) as well as in Ireland and United Kingdom the density of stone walls (No of stone walls divided by total number of observations) exceeds 8% (Table 2). The highest density is noticed in Malta (72.5%) followed by Portugal (22.6%), Ireland and Spain.

Table 2: Presence of stone walls and grass margins in EU Member States according to the LUCAS survey in 2012

Country		**Stone walls**			**Grass margins**			**Total No of valid observa-tions**
Name	**code**	**No of observa-tions**	**% of grand total**	**Density (%)**	**No of observa-tions**	**% of grand total**	**Density (%)**	
Austria	AT	45	0.4%	0.8%	1593	2.6%	28.9%	5504
Belgium	BE	20	0.2%	0.9%	1014	1.7%	45.6%	2224
Bulgaria	BG	18	0.2%	0.3%	1319	2.2%	22.6%	5838
Cyprus	CY	104	0.9%	8.4%	164	0.3%	13.3%	1235
Czech Rep.	CZ	27	0.2%	0.5%	784	1.3%	14.5%	5400
Germany	DE	54	0.5%	0.2%	7416	12.1%	32.3%	22947
Denmark	DK	10	0.1%	0.3%	995	1.6%	33.0%	3016
Estonia	EE	3	0.0%	0.2%	273	0.4%	15.5%	1765
Spain	ES	4165	37.4%	13.8%	9020	14.7%	29.8%	30287
Finland	FI	78	0.7%	0.7%	2080	3.4%	19.6%	10595
France	FR	1444	13.0%	4.5%	12161	19.9%	37.8%	32182
Greece	GR	565	5.1%	8.9%	1379	2.3%	21.7%	6361
Hungary	HU				1084	1.8%	25.4%	4273
Ireland	IE	346	3.1%	13.9%	419	0.7%	16.8%	2493
Italy	IT	1295	11.6%	8.1%	5256	8.6%	33.0%	15922
Lithuania	LT	2	0.0%	0.1%	619	1.0%	17.2%	3600
Luxembourg	LU	6	0.1%	2.9%	77	0.1%	36.8%	209

Latvia	LV	3	0.0%	0.1%	403	0.7%	12.4%	3253
Malta	MT	50	0.4%	72.5%	20	0.0%	29.0%	69
Netherlands	NL	2	0.0%	0.1%	714	1.2%	38.8%	1841
Poland	PL	14	0.1%	0.1%	5599	9.1%	29.0%	19292
Portugal	PT	1377	12.4%	22.6%	1131	1.8%	18.6%	6091
Romania	RO	7	0.1%	0.1%	1948	3.2%	19.3%	10119
Sweden	SE	542	4.9%	2.8%	1891	3.1%	9.8%	19341
Slovenia	SI	78	0.7%	5.5%	300	0.5%	21.0%	1430
Slovakia	SK	4	0.0%	0.2%	295	0.5%	14.5%	2039
United Kingdom	UK	882	7.9%	9.5%	3270	5.3%	35.1%	9327
Grand Total		11141	100.0%	**4.9%**	61224	100.0%	**27.0%**	226653

The LUCAS earth observations for stone walls were compared with the data from the Farm Structure Survey (FSS) which was also performed by Eurostat in 2010 (SAMP, 2010). According to FSS, 727,830 out of 12,248,040 agricultural holdings (5.9%) have reported stone walls in EU-28. The FSS data could not be used in this study as they are not geo-referenced. The FSS data set report the same trends for stone walls in Mediterranean countries (PT, ES, CY, MT, GR, IT) as the LUCAS survey.

2.2.2 Grass margins

In the LUCAS survey, grass margins are defined as strips of mainly uncultivated land with vegetation dominated by grasses or herbs. Grass margins are recorded in the LUCAS database when their width is between 1 and 3 meters and the length exceeds 20 meters (LUCAS 2013). Grass margins are mainly located at the edge of the fields, between cropped areas (beetle banks) (Fig. 1b) or bordering roads and tracks (roadside verge). The grass margins can be spontaneous or planted and they are managed by farmers.

According to the LUCAS observations, grass margins have been reported for 61,224 (27%) transects (Table 2). Large countries (FR, DE, ES, IT, PL) had the higher absolute numbers of grass margins. The highest density of grass margins compared to the total number of observations is found in Belgium (45.5%), Netherlands (38.8%), France (37.8%), Luxembourg (36.8%) and the United Kingdom (35.1%).

For both, stone walls and grass margins, the surveyors have also recorded their density inside the 250m transect. The vast majority of the observed transects where those features are present, has 1 feature per transect (Table 4).

2.3 CORINE Land Cover

The CORINE Land Cover datasets (CLC, 2014) contain homogeneous data on land cover areas provided as polygons. The datasets are outputs of harmonised procedures based on a common classification system, and can therefore be easily compared. Land cover is classified in 44 classes, which are grouped into three hierarchical levels. The used CLC data are in raster format at pixel size of 100m and refer to the year 2006. The CLC data are used for stratification of support practices.

3 Methods

At European level, the effect of support practices (compulsory for farmers to receive incentives under the CAP-GAEC) on soil loss were assessed by P-factor estimation taking into account a) contour farming b) maintenance of stone walls and c) grass margins. P-factor was proposed as a product of those 3 sub-factors by Blanco and Lal 2008; applied by Lopez-Vicente and Navas, 2009:

$$P = P_c \times P_{sw} \times P_{gm} \qquad (1)$$

Where P_c is the contouring sub-factor for a given slope of a field, and P_{sw} is the stone walls sedimentation sub-factor (known as terrace sub-factor) and P_{gm} is grass margins sub-factor (known as strip cropping sub-factor and buffer strips). In the same context, Angima et al. (2003) computed the P-factor as a product of individual support practices (contour farming, terracing and strips) that are used in combination to reduce soil erosion in Kenya.

3.1 Contour farming sub-factor

Contouring is a specific support practice applied only in croplands (CORINE land cover classes 21x) which account for around 25.2% of the total European Union land area. Contour farming means that farmers apply certain field practices (ploughing, planting) along contours, perpendicular to the normal flow direction of runoff. Contour cultivation reduces runoff velocity by increasing up- and downslope surface roughness. The increased surface roughness reduces water velocity providing more time for infiltration (Stevens et al. 2009). The effectiveness of contour farming in reducing soil erosion depends on the slope gradient (Table 3).

In the Good Agricultural and Environmental Conditions (GAEC), each country has the flexibility to decide the compulsory requirements for farmers to apply contour farming. Among the EU Member States, only 10 have applied contour farming. It was not possible to estimate the contour faming sub-factor in Belgium (Flanders) and Denmark as it was not specified in their GAEC. Using the Digital elevation model at 25 m resolution, the arable lands of 8 countries (Table 1) have been attributed a P-factor based on their topographic feature (slope %) and the P-factors proposed by Morgan (2005) in Table 3:

Table 3: P-factor for contour support practice for different slope gradient

Slope (%)	**Support practice factor for contouring P_c**
9-12	0.6
13-16	0.7
17-20	0.8
21-25	0.9
>25	0.95

3.2 *Stone walls sub-factor*

Stone walls are mainly built on hilly land and reduce the velocity of overland flow and as a consequence reduce soil erosion rates (Morgan 1995). Slope length is reduced due to the presence of stone walls. In the longer term, the hillslope gradient may even be reduced due to progressive terrace formation (Nyssen et al 2007). Finally, stone walls trap sediments within the borders of the field parcels. Stone walls, even if they are partly degraded, continue to provide protection against soil erosion (Bazzoffi & Gandin, 2011).

For 14 plots (representing 21 plot-year data) in Europe and the Mediterranean, Maetens et al. (2012) calculated that stone wall terraces reduced soil loss to 0.75 (mean) and 0.35 (median) of the soil loss values for control plots (i.e. without terraces). Regarding the efficiency of stone walls, field experiments at a plot scale in Ethiopia showed that dry stone walls led to a 68% reduction of soil erosion (Gebremichael et al., 2005). In the Tigray highlands of Ethiopia, Munro et al. (2008) proposed P-factor values depending on the quality of stone walls (remains: 0.8, poor: 0.6, moderate: 0.4, good: 0.2). These values can also be interpolated and applied in non-arable lands. In Kenya, Angima et al. (2003) has calculated the P-factor value between 0.5 and 0.7 depending on the gradient and the density of stone walls. Mediterranean traditional dry stone walls (in Greece) do not protect the soil surface from water erosion completely, because of the existing slope gradient between successive terraces (Koulouri & Giourga, 2007).

A simple model estimates soil loss with or without the presence of stone walls in various land use, rainfall erosivity, soil erodibility and topographic conditions (scenarios). This model assumes that stone walls reduce slope length; thus, the impact of stone walls on soil loss reduction can be predicted. We estimated the impact of stone walls in reducing soil loss for 4 different scenarios:

a) Forest with high R-factor =1500 MJ mm ha^{-1} h^{-1} yr^{-1}, low K-factor =0.02 ha h ha^{-1} MJ^{-1} mm^{-1} and slopes up to 45%
b) Arable land with medium R-factor = 750 MJ mm ha^{-1} h^{-1} yr^{-1}, mean K-factor 0.03 ha h ha^{-1} MJ^{-1} $mm^{-1}$and slopes up to 3%

c) Grassland with R-factor = 1000 MJ mm ha^{-1} h^{-1} yr^{-1}, low K-factor=0.02 ha h ha^{-1} MJ^{-1} $mm^{-1}$and slopes up to 10%

d) Pastures with R-factor = 900 MJ mm ha^{-1} h^{-1} yr^{-1}, low K-factor=0.02 ha h ha^{-1} MJ^{-1} mm^{-1} and slopes up to 5%.

We ran 4 land use scenarios with different stone wall densities and also considered the overall impact of stone walls on soil losses measured at experimental sites (Gebremichael et al., 2005; Angima et al., 2003; Murno et al., 2008; Koulouri & Giourga, 2007; Maetens et al. 2012) in assigning P_{sw} values (Table 4). P_{sw}-factor values range between 0.32 and 0.71 depending on stone walls density.

Table 4: Density of stone walls and grass margins along a transect (LUCAS database) and assigned P-factor (P_{sw} is stone walls sub-factor, P_{gm} is grass margins sub-factor) values for Europe.

No of features (stone walls or grass margins)	**% of total stone walls observations**	**P_{sw}**	**% of total grass margins observations**	**P_{gm}**
0	95.08%	1	72.99%	1
1	2.51%	0.707	11.36%	0.853
2	1.10%	0.577	9.73%	0.789
3	0.53%	0.500	3.06%	0.750
4	0.32%	0.448	1.70%	0.724
5	0.15%	0.408	0.60%	0.704
6	0.10%	0.378	0.30%	0.689
7	0.06%	0.354	0.12%	0.677
8	0.05%	0.334	0.07%	0.667
>8	0.09%	0.317	0.07%	0.660
Total	100.0%		100.0%	

The above-mentioned experimental studies showed the effectiveness of stone walls in all land use types. The analysis of stone walls per CORINE land cover class shows a relatively high number of those features in heterogeneous agricultural areas and scrub lands (Table 5). Thus, the impact of stone walls is taken into account for all CORINE land cover classes except for artificial land and water bodies.

Table 5: Presence of stone walls and grass margins per CORINE Land Cover class in Europe

Land Cover	**CORINE classes**	**% of stones walls**	**% of grass margins**
Arable lands	211-213	12.5%	48.9%
Permanent Crops	221-223	9.2%	4.3%
Pastures	231	11.4%	9.9%
Heterogeneous Agr. Areas	241-244	29.0%	16.7%
Forests	311-313	15.0%	12.5%
Scrub/herbaceous vegetation	321-324	18.4%	3.5%
Open Spaces/little vegetation	331-334	0.9%	0.1%
Artificial land - Water bodies - Other	1x,4x,5x	3.8%	4.1%
Total		100.0%	100.0%

3.3 *Grass margins sub-factor*

Haan et al (1994) considered grass margins as one of the most effective measure for reducing sediment delivery. The grass margins obstruct runoff, induce infiltration, trap sediments and reduce sediment transport. The reduction of sediment yield when applying grass margins is relatively small. (Verstraeten et al., 2002). Experimental results show that grass margins can trap between 10-30% of inflowing sediment (Dillaha et al, 1987; Haan et al., 1994). In USA, Dabney et al. (1999) estimated the P-factor to be 0.81 for hedge rows (1-2 m wide) of dense vegetation. Using GUSED (Griffith University Soil Erosion & Deposition) model, Hussein et al. (2007) estimated a reduction of soil loss between 5.9 and 11.6% (P-factor = 0.88 – 0.94) due to buffer strips in different slope conditions. In two different catchments (Gibuuri, Kianjuki) in Kenya where buffer strips have been applied, two studies (Angima et al 2002; Hessel & Tenge 2003) found P_{gm} sub-factor equal to 0.7. Nyssen (2001) estimated that grass strips can accumulate half of the sediment yield compared to stone walls.

Taking into account the values of P-factor for grass margins reported in the literature (Dillaha et al. 1987; Haan et al. 1994; Dabney et al. 1999; Angima et al. 2002; Hessel and Tenge 2003), we assumed that grass margins trap on average half of the sediments compared to those trapped by stone walls. Thus, depending on the density of grass margins, the P_{gm}-factor will vary from 0.66 to 0.85 (Table 4).

Almost half of the observed grass margins are located in arable lands (Table 5). The impact of grass margins is estimated only for agricultural areas (arable – permanent), pastures and heterogeneous agricultural areas which in total account for 80% of the observation points having grass margins.

3.4 Spatial interpolation of stone walls and grass margins

The LUCAS ground observations have been performed at 270,000 points. The transect findings record the density of stone walls and grass margins. To assess the impact of those features to the whole European Union area, a spatial interpolation should be performed. In the environmental domain, spatial interpolations approaches range from simple interpolation such as Inverse Weighted Distance (IWD) to Ordinary Kriging (OK) and even more complex regression models.

Since the objective of this study is to capture the density of stone walls and grass margins (spatial patterns) and by using the past experience in this field (van den Zanden et al. 2013), the ordinary kriging method was selected for spatial interpolation. This technique assumes a spatial homogeneous surface with constant variance and constant mean. In this study, the ordinary kriging was based on 25 observation points for the radius setting. More complex regression models are recommended for a spatial interpolation at regional scale.

4 Results and Discussion

4.1 P-factor assessment at European level

The contour sub-factor (P_c) was estimated based on a Digital Elevation Model (DEM) at 25m resolution. The mean P_c for the EU-28 was calculated to 0.9985 (0.9942 in arable lands) due to the limited number of countries applying contour farming in GAEC and due to the application of this support practice mostly to slopes over 10%. The largest effect of contour farming is estimated for Cyprus (0.990) followed by Spain and Greece and the lowest mean value is found in Slovenia due to the very limited application of contouring (only on slopes > 20%).

The stone walls sub-factor (P_{sw}) was estimated based on the interpolated stone walls dataset at 1 km resolution. The mean P_{sw} for the EU-28 was calculated to be 0.9884 and the largest effect of stone walls is noticed in Malta (P_{sw} = 0.529) followed by Portugal and the rest of the Mediterranean countries (Table 6). The interpolated stone wall dataset has less uncertainty compared to the grass margins dataset. The Root Mean Square Error (RMSE) for the stone wall interpolation was 0.568 and 1.031 for the grass margins which was in line with previous modelling efforts (van der Zanden et al., 2013).

The grass margins sub-factor (P_{gm}) was estimated based on the interpolated grass margins dataset at 1 km resolution. The mean P_{gm} for the EU-28 was calculated to be 0.9829 with the highest effect in reducing soil loss in Belgium, Netherlands, United Kingdom and France (Table 6). This sub-factor is the most important (compared to contouring and stone walls) in support practices estimation for Europe due to the abundance of grass margins (observed in 27% of the LUCAS transects).

Table 6: Support practice (P-factor) and sub-factors per country

Country	P_c (contouring)	P_{sw} (stone walls)	P_{gm} (grass margins)	P-factor
AT	1	0.9996	0.9887	0.9883
BE	1	0.9998	0.9467	0.9465
BG	1	0.9999	0.9912	0.9911
CY	0.9909	0.9828	0.9991	0.9730
CZ	1	0.9999	0.9983	0.9982
DE	1	0.9998	0.9784	0.9782
DK	1	0.9999	0.9844	0.9843
EE	0.9995	0.9998	0.9996	0.9989
ES	0.9926	0.9580	0.9778	0.9293
FI	1	0.9998	0.9943	0.9942
FR	1	0.9935	0.9691	0.9627
GR	0.9939	0.9676	0.9883	0.9502
HR	1	0.9999	0.9995	0.9994
HU	1	1	0.9840	0.9840
IE	1	0.9738	0.9952	0.9690
IT	0.9992	0.9786	0.9725	0.9519
LT	1	0.9999	0.9980	0.9980
LU	1	0.9991	0.9725	0.9716
LV	1	0.9999	0.9995	0.9995
MT	0.9993	0.5299	0.9915	0.5251
NL	1	0.9999	0.9561	0.9561
PL	1	0.9999	0.9781	0.9781
PT	1	0.9245	0.9921	0.9178
RO	0.9948	0.9999	0.9950	0.9898
SE	1	0.9976	0.9984	0.9961
SI	0.9999	0.9919	0.9940	0.9860
SK	1	0.9999	0.9986	0.9985
UK	1	0.9878	0.9647	0.9528

The mean P-factor in the EU-28, combining the 3 sub-factors, is estimated to be 0.9702 (Fig. 2). Due to the high density and impact of stone walls, Malta has the lowest P-factor (0.525) followed by Portugal, Spain and Belgium which have P-factor values less than 0.95. The implementation of support practices are very limited in the Baltic States, Slovakia and Czech Republic with P-factor values close to 1.0. The support practices have greater influence in agricultural land use as they reduce soil erosion risk by 5% ($P_{agriculture}$ = 0.95)

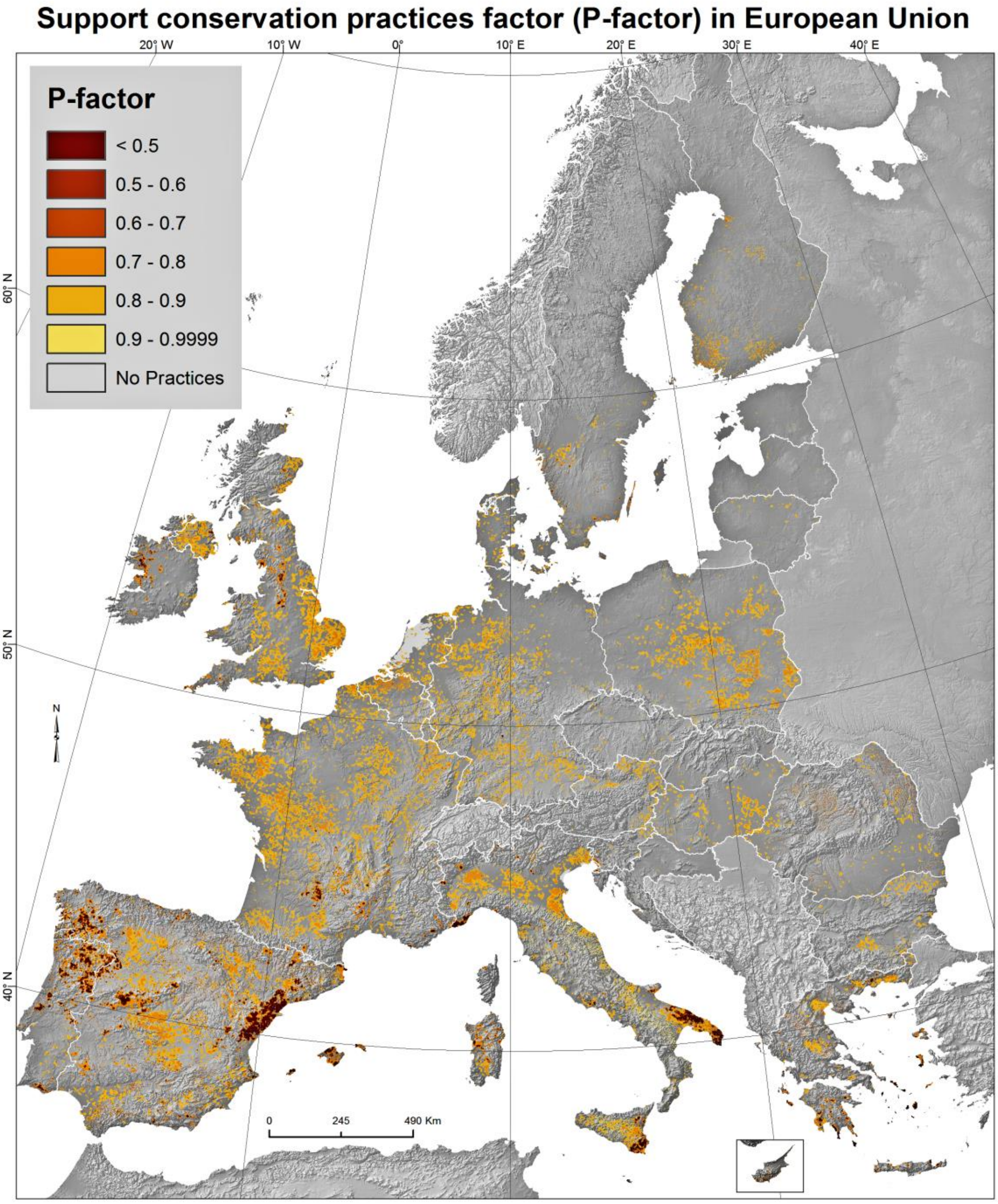

Fig. 2: Support practice factor (P-factor) in the European Union

The P-factor map at 1km resolution (Fig. 2) spots the areas where support conservation practices are mostly applied. At European scale and for policy makers, it is recommended to aggregate the data at regional level. NUTS2 (Nomenclature of territorial units for statistics) level represents regions of 0.8–3 million people at which regional policies are implemented and agricultural data are available. The aggregated P-factor map (Fig. 3) at NUTS2 level classifies the regions according to the application of support practices. The highest concentration of support practices driven mainly by the density of stone walls is found in 3 island regions: Malta, Isle Balearides (ES) and Notio Aigaio (GR). Those are followed by Puglia (IT), Comunidad Valenciana (ES), Norte (PT) and Voreio Aigaio (GR) which all have P-factor values less than 0.85 (Fig. 3). P-factor values in the range of 0.85 - 0.90 are found in regions from Mediterrean countries, United Kingdom, Netherlands and Belgium.

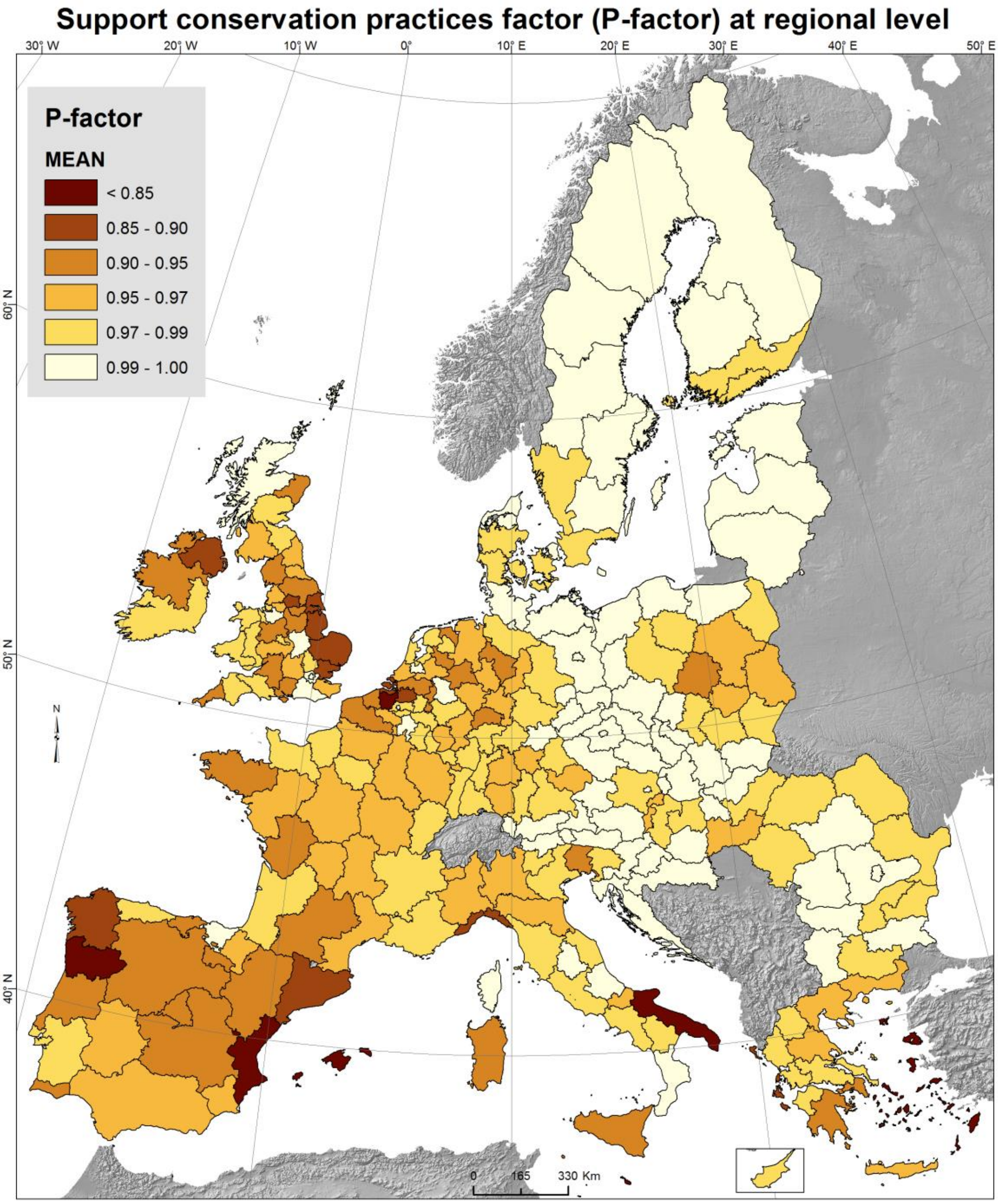

Fig. 3: Mean P-factor at regional (NUTS2) level in the European Union.

The stone walls are usually found in hilly areas while the grass margins are observed in more gently sloping areas. The protective role of stone walls is higher compared to the grass margins as they can reduce soil erosion in erosion-prone hilly areas. Other protective practices such as subsurface drainage or fences were not taken into account due to either a limited number of observations at European scale or the lack of data on their effectiveness in reducing soil loss. The proposed methodology is repeatable as LUCAS survey is performed in Europe every 3 years. This creates an opportunity for future monitoring of changes in the P sub-factors for stone walls and grass margins.

4.2 Limitations of the results

The contour sub-factor estimation is based on the assumption that farmers are following the GAEC guidelines which is true as they receive incentives and they are controlled by authorities. However, contour farming may also be applied in areas which have not been recorded in this study due to lack of observations.

The presence of stone walls and grass margins in this model depends on the surveyed points selected in LUCAS. Due to financial constraints, the number of visited points is limited. The original findings in LUCAS earth observations are also influenced by the transect length. The interpolated datasets (stone walls, grass margins) are also dependent on the selected interpolation technique.

The impact of grass margins is based on certain assumptions as those features have different physical forms (height, density and seasonal effect) from country to country. Moreover, the influence of the practices (stone walls, grass margins) depends much on the slope direction and slope gradient. To overcome these limitations, a conservative model approach has been followed as the impact of grass margins and stone walls has been estimated to a minimum level.

4.3 Policy making and options for maintenance of support practices

The proposed P-factor estimation methodology is a useful tool for policy makers to simulate policy relevant scenarios. For instance, the scenario of applying contour farming in all European arable lands (EU-28) having slopes steeper than 10% will result in a reduction of the contour sub-factor (P_c) to 0.9942 (0.978 in arable lands). As a consequence the mean P-factor in Europe will be reduced by 0.5% (0.966). The countries where the largest erosion-reducing impact of this measure would be achieved are Italy (P_c = 0.9843), Czech Republic (P_c = 0.9872) and Bulgaria (P_c = 0.9893).

A drastic scenario of applying contour farming in all European arable lands having slopes steeper than 5% will result in a P_c = 0.977 and P-factor = 0.949. The preservation of stone walls is very important for soil conservation on steep slopes whereas the increase of grass margins may potentially reduce soil erosion risk in cropland on rolling topography. A scenario of combining contour farming in slopes steeper than 5% with doubling grass margins and preserving stone walls may result in P-factor = 0.92.

In the new EU Common Agricultural Policy (CAP 2014-2020), the regulations state that farmers must ensure that 5% of their land is set aside from farming as an Ecological Focus Area (EFA) to receive their full payment under the Basic Payment Scheme. Buffer strips are listed as one of the options but they must be on or adjacent to arable land, next to a watercourse or parallel to it (CAP Rural Development Plan 2014-2020).

Also, research has to identify the areas and conditions where the support practices are more efficient. For example, perennial grass which is more rigid than grass margins can reduce soil loss by 50% (Dabney et al., 2009). In the future, GAEC can also set maximum livestock rates per region, land use and slope to prevent compaction and overgrazing which leads to erosion.

European policy makers have become aware of the costs of soil erosion during the recent decade (Boardman and Poesen 2006); thus they focus on strengthening both the soil and crop management practices (reduced tillage, plant residues and cover crops) and the support practices (contouring, maintenance of stone walls and grass margins) for reducing soil erosion risk. The present P-factor modelling approach together with the estimation of the C-factor at European scale (Panagos et al., 2015) are evaluation tools for estimating the potential of interventions for soil conservation. Experimental results demonstrated that combined practices (e.g. cover crops and contour farming) have better results in controlling sediment loss (Verstraeten et al. 2002). A cost/benefit analysis of the support practice measurements is also needed. This will allow drawing conclusions if the effectiveness of the conservation measures is financially sustainable to support additional subsidies to farmers in order to apply those support practices.

Another important aspect is increasing awareness and stakeholders' participation. This requests to explain to farmers the GAEC concepts and underlining their important role in protecting their land. Moreover, the Member States should assist farmers to identify soil erosion risk areas through modelling and GIS simulations. Moreover, policy makers should also develop the channels for having the farmer's feedback. In the current world with smartphone developments, each farmer could easily take a photo of soil erosion features or even of applied support practices. Such photos with date and GPS coordinates registered in a database then could potentially be used for several purposes: control of GAEC implementation, validation of soil erosion modelling results, improvement of criteria for incentives, etc.

4.4 Data availability and use

The P-factor dataset plus the 3 sub-factors (contouring, stone walls and grass margins) produced in this study will be freely available for download from the European Soil Data Centre (ESDAC, 2012).

Since those data exist at European scale for the 3 support practices, they cannot be ignored in modelling soil loss at European scale. Based on a large number of field observations, we attempted to model the support practices that reduce soil erosion. The results present the areas in Europe where those practices are implemented. Even if the results are presented at pixel level, it would be better to aggregate these at regional level for demonstrating the concentration and impact of support conservation practices.

5 Conclusions

Support practices have a local effect in reducing soil erosion risk. This is due to the limited application of the support measures, especially contour farming. The stone walls are also limited at European scale and they can contribute more efficiently if they are built on steep slopes. The application of Good Agricultural Environmental Conditions (GAEC) had an impact in reducing soil loss, especially in hilly areas. In the future, policy instruments such as GAEC could apply to all Member States implementing contour farming in slopes of less than 10% (e.g. 5%), preserving the stone walls and increasing the number of grass margins especially in erosion-sensitive areas.

Despite the shortcomings of the model for P-factor prediction at European scale and simplifying assumptions regarding the data, the calculated P-factor is a first estimate of the effects of support practices application on soil loss at European level. At catchment or regional level, scientists may have a larger number of field observations for contour farming, stone walls and grass margins. However, those support practices and their local effectiveness (reported in the literature) cannot be ignored in soil erosion modelling neither at regional not at European scale.

The P-factor for Europe was estimated to be 0.97 and thus the three support practices discussed reduce the overall soil erosion risk by 3%. Even if the average % reduction is relatively small, the effect is considerably larger in erosion-sensitive regions such as the Mediterrean or the loess belt. Support practices are mainly applied in areas susceptible to soil erosion due to their large values of the LS-factor (slope length and gradient) which results in a significant reduction of absolute soil loss. The impact of support practices is mainly observed in agricultural areas where soil erosion risk is reduced by 5%.

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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CHAPTER 8

Overall discussion and conclusions: Soil erosion map of Europe

This chapter is under the final review among authors and it is going to be submitted during February 2015 in a high impact factor peer review journal.

Overall discussion and conclusions: Soil erosion map of Europe

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Abstract

Soil erosion is one of the major threats of soils in the European Union having an impact on ecosystem services decline, crop production, drinking water and carbon stocks. The European Commission Soil Thematic Strategy has identified the soil erosion issue and proposed a soil erosion monitoring approach. In this policy context, a modified RUSLE model (named RUSLE2015) has been applied for the estimation of soil erosion in Europe for the reference year 2010 where the input factors (Rainfall erosivity, Soil erodibility, Cover-Management, Topography, Support practices) are modelled with the most recently available pan-European datasets. RUSLE has been used before in Europe but here we advance the quality of estimation as we introduce up-dated (2010), high resolution (100m), peer-reviewed input layers. The mean soil erosion rate in the European Union erosive lands (agricultural, forests and semi-natural areas) is 2.46 t ha^{-1} yr^{-1} resulting in a total soil loss of 970 Mt annually.

A major advancement of RUSLE2015 is the option to host policy making scenarios based on land-use changes and support practices. The impact of the Good Agricultural and Environmental Condition (GAEC) of the Common Agricultural Policy and the guidelines for soil protection can be grouped in the management practices (reduced/no till, plant residues, cover corps) and support practices (contour farming, maintenance of stone walls and grass margins). The policy interventions (GAEC, Soil Thematic Strategy) during the last decade have reduced soil erosion by 7% on an average rate in Europe but even more in arable lands (20%). Special focus is given in croplands where policy measures should be applied in 14 * 10^6 hectares unsustainable soil erosion rates of more than 5 t ha^{-1} yr^{-1}.

Keywords: RUSLE, erodibility, erosivity, management practices, agricultural sustainability, policy scenarios

1 Why RUSLE?

Soil erosion exceeding soil production is a land degradation process which has been contributed to shaping the physical landscape today (Alewell et al., 2014). As such, soil erosion is among the eight soil threats identified within the Soil Thematic Strategy of the European Commission (EC, 2006). During the last decade, the problem of soil erosion is part of the environmental agenda in the European Union due to the impacts on food production, drinking water quality, decrease of ecosystem services, eutrophication, biodiversity and carbon stock shrinkage (Broadman and Poesen, 2006). Soil erosion by water accounts for largest soil losses in Europe compared to other erosion forms (e.g. wind). The recent policy developments in the European Commission (Soil Thematic Strategy, Common Agricultural Policy, Europe 2020, and 7th Environmental Action Programme) call for quantitative assessment of soil erosion rates at European level. Since actual soil erosion is financially unsustainable to be measured at continental scale(by means of experimental plots, Caesium 137 measurements, sampling of sediment load), soil erosion modelling approaches are used. Besides the policy requests, a continental soil erosion assessment can contribute to a) quantifying the soil erosion impacts at such a large scale, b) assess the main effects of climate, vegetation and land use in erosion processes and c) prioritize effective remediation programmes (Lu et al., 2003).

The main drivers for soil erosion by water are precipitation, soil, topography, land use and management. In a recent inventory, Karydas et al (2014) identified 82 water erosion models classified in different spatial/temporal scales with various levels of complexity. Among them, the most common used erosion model is the Universal Soil Loss Equation (USLE) (Wischmeir and Smith, 1978) and it is revised version (RUSLE) (Renard et al., 1997) which estimate long-term average annual soil loss. Besides the critics of this model, RUSLE is still the most frequently used model at large scales (Renschler and Harbor, 2002; Kinnell, 2010) as it facilitates the data input at large regions and provides a basis for scenario analysis and measures against erosion (Lu et al., 2003). In addition, a recent data collection of erosion data in Europe (Panagos et al., 2014a) under the European Environmental Information and Observation Network (EIONET) has proved that all participating countries have modelled soil erosion by USLE/RUSLE.

The objective of this chapter is to bring chapter 1, 2, 4, 6, 7 Y together into one up-to-date soil erosion map of the European Union using the RUSLE model. The research findings in chapters 3 and 5 were taken into consideration in this map development. This map aims to:

a) use the most updated input layers of precipitation, soil, topography, land use and management,
b) host policy scenarios
c) be replicable, comparable and utilized in a broad scale (other than soil erosion modelling)

2 Methodology

The adopted model approach is a modified RUSLE (named RUSLE2015) which calculates soil erosion risk by sheet and rill erosion according to the following equation:

$E = R * K * C * LS * P$ (1)

Where

E: Annual average of soil loss (t ha^{-1} yr^{-1})

R: Rainfall erosivity factor (MJ mm ha^{-1} h^{-1} yr^{-1})

K: Soil Erodibility factor (t ha h ha^{-1} MJ^{-1} mm^{-1})

C: Cover-Management factor (dimensionless)

LS: Slope length and Slope Steepness factor (dimensionless)

P: Support practices factor (dimensionless)

The RUSLE2015 model introduces certain improvements in each of the soil erosion factors adapting to the current data availability in European scale and respecting the literature. The main difference with past studies which modelled soil erosion with RUSLE in Europe (van der Knijff et al., 2000; Bosco et al., 2014) is the advance quality of input layers. The estimation of each input factors has been done in a transparent way and it has been submitted for revision by the scientific community in the last 2 years. The soil erodibility factor (Panagos et al., 2014) and rainfall erosivity (Panagos et al., 2015) factors have been published in peer review journals and the corresponding datasets are available in the European Soil Data Centre (ESDAC, 2012). The rest of the factors (Cover-management, support practices and topography) are currently under review. For the estimation of input factors, RUSLE 2015 made use of the most updated and freely available datasets at European scale (Fig. 1).

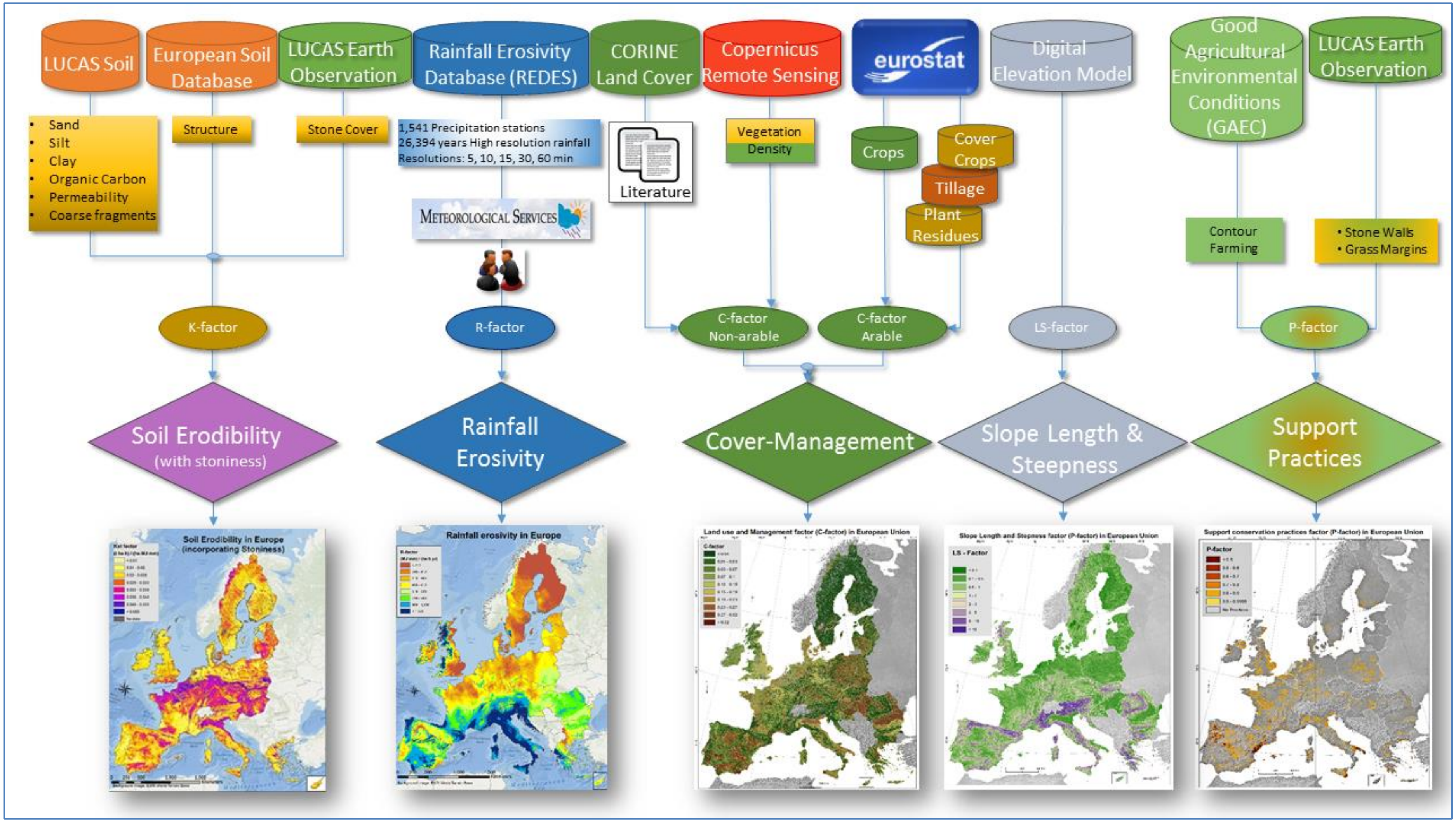

Fig. 1: Input datasets for the estimation of soil erosion factors in RUSLE2015.

2.1 *Rainfall erosivity (R-factor; chapter 4)*

Precipitation his the driving force for soil erosion by water as it affects the detachment of soil particles, the aggregate breakdown and the transport of eroded particles via runoff (Wischmeir and Smith, 1978). The erosive power of precipitation is expressed with rainfall erosivity. The R-factor (rainfall erosivity) is the product of kinetic energy of a rainfall event and its maximum 30-minutes intensity (Brown and Foster, 1987). The erosive events identified by specific criteria set by Renard et al. (1997) are summed up in order to produce the average annual rain fall erosivity (MJ mm ha^{-1} h^{-1} yr^{-1}) (Meusburger et al., 2012).

In RUSLE20015, the R-factor is calculated based on high resolution temporal rainfall data (5, 10, 15, 30 and 60 minutes) collected from 1541 well distributed precipitation stations across Europe (Panagos et al., 2015a). The used precipitation time series ranged between 5 and 40 years with an average of 17.1 years. In most than 75% of the countries, the time-series precipitation data cover the 2000-2010 decade. This first ever Rainfall Erosivity Database on the European Scale (REDES) has been a major advancement in calculating rainfall erosivity in Europe (Fig.1). Regression functions have been used for the normalisation of R-factor at 30 minutes time interval. The participatory approach of involving national meteorological services and scientists from Member states has contributed in the high data quality.

The Gaussian Process Regression (GPR) model (Rasmussen and Williams 2006) has been applied for the spatial interpolation of the 1541 stations of REDES using as covariates the climatic data (precipitation, temperature), the Digital Elevation Model and latitude/longitude. GPR has been selected among other models as it was performing better both in cross validation (R^2=0.63) and in fitting dataset (R^2=0.72). The highest uncertainty has been noticed in North-western Scotland, North Sweden and Finland, Southern Alps and Pyrenees due to limited number of stations in REDES. The highest R-factor are estimated in Mediterrean and Alpine regions and lowest in Scandinavian countries.

2.2 Soil erodibility (K-factor; chapter 2)

The soil erodibility (K-factor) is a lumped parameter accounting for the 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 direct measurement of soil erodibility on all possible field plots of the European Union is not financially sustainable, the K-factor using the relationship between "classical" soil properties and soil erodibility.

In RUSLE2015, the K-factor is estimated for the 20,000 sampled points within Land Use/Cover Area frame (LUCAS) survey. Following the Wischmeir and Smith (1978) nomograph, K-factor takes as inputs 5 soil parameters: texture (silt, clay, sand), organic matter, coarse fragments, permeability and soil structure. The first four inputs are calculated from LUCAS soil database (Toth et al., 2013) and the soil structure was derived from European Soil Database (King et al., 1994) (Fig.1). The surface stone content which is protective against soil erosion by water (Poesen et al., 1994) was incorporated in the K-factor estimation resulting in an average 15% reduction of soil erodibility (Panagos et al, 2014).

The 20,000 LUCAS point data were interpolated with Cubist regression model using spatial covariates such as remote sensed and terrain features producing a 500 m resolution K-factor map of Europe. The published K-factor dataset was compared well with 21 local/regional and national soil erodibility datasets. The highest soil erodibility areas are noticed in Belgium, Luxembourg, South Germany and central east European countries following the Loess belt (Haase et al., 2007). The lowest K-factor mean values are found in Scandinavian countries and some mediterrean areas (Portugal, Greece and Spain) mainly due to the stoniness effect.

2.3 Cover-Management (C-factor; chapter 6)

The C-factor accounts the influence of land use (mainly due to vegetation cover) and management (mainly in arable lands) in reducing water erosion rates. The C-factor is the ratio of the soil loss in a specific land cover type compared to the soil in a bare plot and ranges between 0 and 1 (Dimensionless) (Renard et al., 1997). The cover management factor (C-factor) is considered as a critical one as human intervention can alter the land use and as a consequence reduce or increase soil erosion.

In RUSLE2015, the C-factor estimation is differentiated between arable lands and the non-arable ones (Fig. 1). For all non-arable lands, C-factor is controlled mainly on vegetation. In non-arable lands accounted for around 75% of the European Union, the CORINE land Cover (CLC, 2012) was used to derive the different land use classes and then for each class a range of C-factor values was assigned based on the literature findings. Then, using biophysical attributes such as vegetation coverage density (derived from remote sensing datasets in Copernicus Programme) allowed to assign the C-factor pixel value based on the combination of land use class and vegetation density (Panagos et al., 2015b).

For the arable lands, the C-factor was estimated using crop statistics from EU Statistical service (EUROSTAT) and assigning the C-factor values per crop type after an extensive literature review (Panagos et al., 2015b). In addition to this, the influence of management practices was quantified for first time at European scale. The C-factor in arable lands included tillage practices, cover crops and plant residuals. Those datasets are made available from Eurostat (2014b) (Fig. 1). The management practices (reduced till/No till, cover crops and plant residuals) decrease C-factor by an average 19.1% in arable lands with reduced tillage having the major impact due to large application extent.

The arable lands have almost the highest mean C-factor (0.233) in the European Union (EU) while only sparse vegetated areas and burnt areas have higher values (0.265 and 0.342). As it was expected, forests have the lowest mean C-factor values (0.012). The mean C-factor in the European Union (EU) has been estimated to 0.1046 with highest mean values (>0.15) in Hungary, Denmark, Malta and Romania mainly due to highest shares of arable lands. The lowest C-factor (<0.075) were found in Finland, Sweden, Slovenia, Baltic states and Austria mainly due to forest dominant land use.

2.4 Slope length and steepness (LS-factor)

The topography influence is accounted in soil erosion modelling within the slope steepness and slope length. The L-factor accounts the impact of slope length and the S-factor the influence of slope angle. The combined LS-factor (dimensionless) describes the potential of surface runoff in accelerating soil erosion and in most cases its spatial resolution determines the cell size of soil erosion model results.

In RUSLE 2015, the LS-calculation is performed using the equations proposed by Desmet and Govers (1996). The greatest advancement is the use of Digital Elevation Model (DEM) at 25m which was recently available from Eurostat (2014). The high resolution DEM allows for an LS-factor dataset at 25m resolution which is a major advantage for mapping soil erosion potentially at this scale. The use of SAGA software incorporates a multiple flow algorithm contributing to a higher precision of flow accumulation. In RUSLE, the 2015 LS-factor calculation does not apply any limitations in slope length as it is done in recent assessments (Bosco et al., 2014; Borrelli et al., 2014) which have put arbitrary limitations of maximum 150/300 meters slope length. The only limitation put in the LS-factor calculation is the 50% maximum value for slope angle after literature review (Wilson, 1986) and testing the hypothesis that exceptionally few cells of land uses (forests, grasslands) exist over this angle. Concluding, the RUSLE 2015 LS-factor with its high spatial resolution attempts to capture the geomorphological changes with high precision and as a consequence to map soil erosion with greater accuracy.

2.5 Support practices (P-factor; chapter 7)

The P-factor takes into account the support practices that reduce erosion potential of runoff by influencing drainage patterns, runoff concentration and velocity (Renard et al., 1997). The better practice applied for controlling soil erosion will result in reducing P-factor. Support practices are rarely taken into account in soil erosion modelling due to lack of input data for support practices.

The RUSLE2015 P-factor takes into account the contour farming implemented in agro-environmental policies in EU plus the protection against soil erosion provided by stone walls and grass margins (Panagos et al., 2015c). The P-factor was estimated using the latest developments in the Common Agricultural Policy (CAP) in Europe and applying the rules set for contour farming over a certain slope derived from Good Agricultural Environmental Conditions (GAEC) (Fig.1). The 270,000 earth observations from Land use/cover area frame statistical survey (LUCAS, 2012) have been used to model the presence and density of stone walls and grass margins (van den Zanden et al., 2013).

The mean P-factor in the European Union was estimated to 0.97 while in agricultural lands it was estimated around 0.95(Panagos et al., 2015c). Even if the average % reduction of soil erosion due to the application of support practices is relatively small, the effect is considerably larger in erosion-sensitive regions such as the Mediterrean or the loess belt. The major impact in support practices is due to the grass margins which have been reported in 27% of the LUCAS transect observations followed by the stone wall which are present in 4.9% of the transects. The contour farming had a very limited impact as it is mainly applied in slopes over 10% and in a limited number of Member States.

3 Results and Discussion

3.1 Soil Erosion map in the European Union

The soil erosion map of the European Union is presented with RUSLE2015 at 100m resolution (Fig. 2). The resolution depends on data availability of input factors. As the C-factor layer (100m) can be altered due to policy interventions and due to low resolution of the P-factor, the 100m pixel size was selected as the most appropriate one. The 100m selected resolution is also between the coarse resolutions of K-factor (500m), R-factor (500m), P-factor(1km) and the very high resolution of LS-factor (25m). Soil erosion potential is estimated for 90.3% of the EU surface (3,941 $*10^3$ Km^2 out of total 4,366 $*10^3$ Km^2) as the rest 9.7% is non-erosive surfaces such as artificial land, bare rocks, glaciers, wetlands, lakes, rivers, inland waters and marine waters.

The reference year of the soil erosion map of the European Union (Fig. 2) is 2010 as most of the input factors are estimated with the most recent input datasets: R-factor is using Rainfall Erosivity Database on the European Scale (REDES) which includes the first decade of 21st century, K-factor major input is the LUCAS 2009 soil survey, C-factor is based on CORINE land cover (2006), Copernicus Remote sensing data (2011-2012) and Eurostat databases (crop statistics, tillage practices, cover crops, plant residuals) having as reference the year 2010, LS-factor is estimated with the recently published (2014) Digital Elevation Model and finally P-factor takes into account the GAEC database (2010) and the LUCAS earth observations (2012).

The mean annual soil erosion by water for the reference year 2010 is 2.46 t ha^{-1} yr^{-1} for the potentially erosive land cover. The total soil loss is 970Mt annually in the European Union. The average rate of soil erosion is reduced to 2.22 t ha^{-1} yr^{-1} if we consider the non-erosive areas in the statistical analysis. The average annual rates of soil erosion in Europe is higher than the 1.4 t ha^{-1} yr^{-1} soil formation rate in Europe (Verheijen et al., 2009).

The variation of soil erosion in the EU is extremely high due to different topographic, climatic, land use, management and soil conditions. Taking into account the maximum soil loss rates in experimental plots, maximum values of 325 t ha^{-1} yr^{-1} has been imposed for very few pixels (< 0.001%). Maertens et al. (2012) has set the maximum soil loss to 325 t/ha annually which was also applied in the current study as the upper limit of soil loss in order to avoid model outliers.

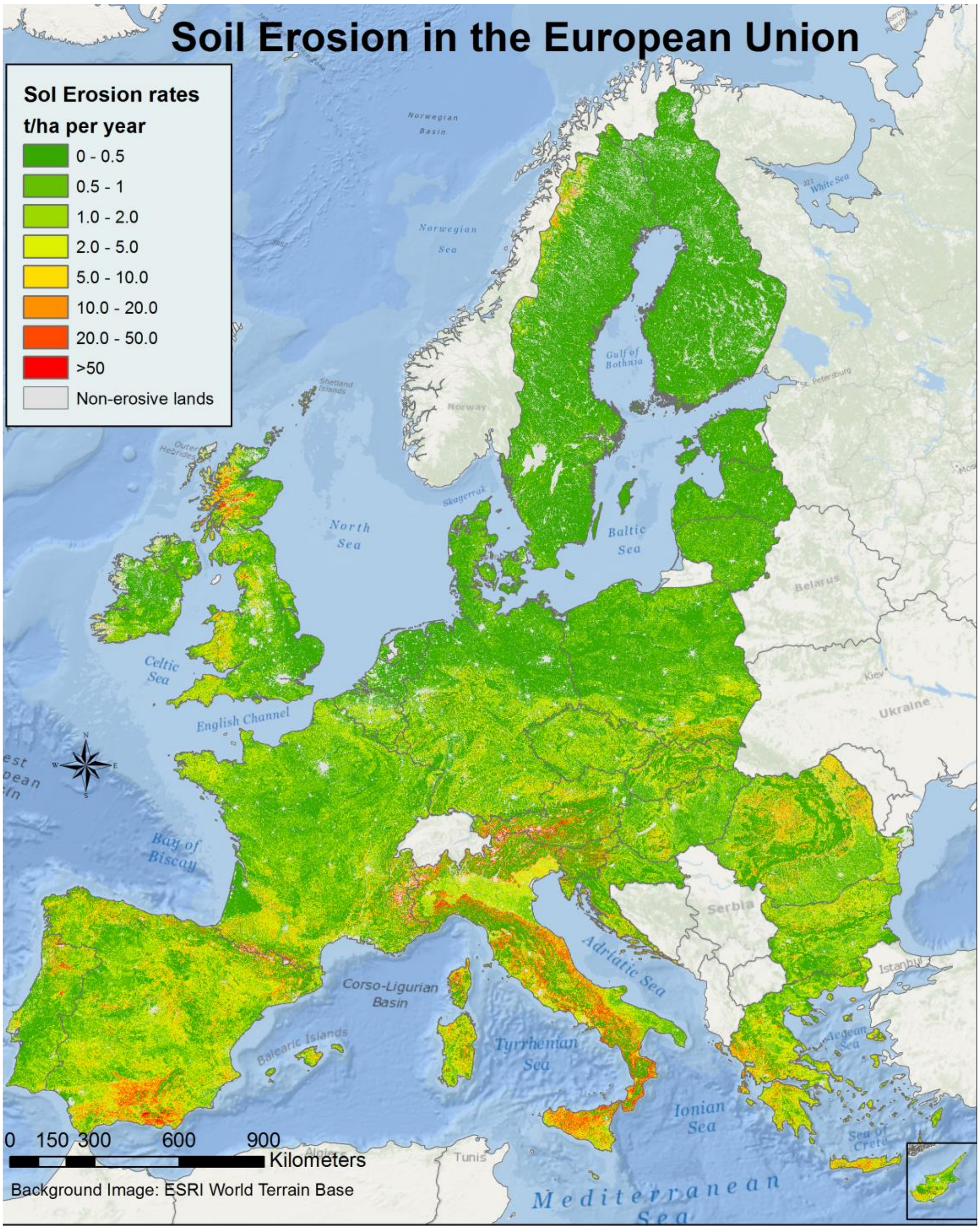

Fig. 2: Soil Erosion map in the European Union (Reference year: 2010)

3.2 *Regional assessments*

The higher soil erosion rates (Fig. 2) are noticed in the Mediterrean areas (low C-factor, high R-factor and LS-factor) while lower ones are determined in the Scandinavian and Baltic States. The combination of high rainfall erosivity (R-factor) as shown in Chapter 3 with relatively steep areas (LS-factor) results also in elevated soil erosion rates (Fig. 2) in the Alpine areas, Apennines (IT), Pyrenees, Sierra Nevada (southern Spain), western Greece and western Wales and Scotland (UK). The effect of low vegetation (C-factor) is mostly visible in Andalusia (ES) and eastern Romania. The impact of soil erodibility (K-factor) is noticed in the Loess belt (Belgium, southern Germany and southern Poland) (chapter 2). The support practices (P-factor) have an effect at local level and it is not visible at this map (Fig. 2). However, the P-factor map (Panagos et al., 2015c) is a useful decision making tool for financing support practices (chapter 7).

The highest mean annual soil erosion rate is noticed In Italy (8.46 t/ha), followed by Slovenia (7.43 t/ha) and Austria (7.19 t/ha) (Table 1) due to a combination of high rainfall erosivity (Panagos et al., 2015a) and extreme topography (steep and long slopes). The rest of the Mediterrean countries (Spain, Greece, Malta and Cyprus) have also rates of mean soil erosion higher than the pan-European average. The lowest mean annual soil erosion rates are noticed in Finland (0.06 t/ha), Estonia (0.21 t/ha) and the Netherlands (0.27 t/ha). All the Scandinavian and Baltic states have mean annual soil erosion rates of less than 0.52 t/ha (Table 1).

Large countries with elevated mean soil erosion rates such as Italy and Spain have the higher share of total soil loss in the European Union. The estimated total soil loss in 8 Mediterrean member states (IT, ES, FR, GR, PT, HR, SI and CY) is 67% of the total soil loss in the European Union 28 countries.

Table 1: Average soil erosion per country (all lands, arable lands) and share of soil loss.

Country		Overall Mean	Mean in arable lands	Mean in arable lands without GAEC	GAEC effect	% of the total soil loss
		t ha-1 yr-1			(%)	
AT	Austria	7.19	3.97	5.23	31.8	5.65%
BE	Belgium	1.22	2.06	2.71	31.8	0.30%
BG	Bulgaria	2.05	2.47	3.77	52.5	2.21%
CY	Cyprus	2.89	1.85	2.82	52.6	0.25%
CZ	Czech Republic	1.65	2.52	3.30	31.0	1.24%
DE	Germany	1.25	1.75	2.51	43.5	4.15%
DK	Denmark	0.50	0.61	0.68	11.4	0.20%
EE	Estonia	0.21	0.70	0.88	25.3	0.09%
ES	Spain	3.94	4.27	5.56	30.3	19.61%
FI	Finland	0.06	0.46	0.64	37.9	0.18%
FR	France	2.25	1.99	2.78	39.5	11.85%
GR	Greece	4.13	2.77	3.63	31.1	5.31%
HR	Croatia	3.16	1.67	1.80	7.5	1.74%
HU	Hungary	1.62	2.10	2.35	12.0	1.42%
IE	Ireland	0.96	1.32	1.52	15.7	0.55%
IT	Italy	8.46	8.38	9.80	16.9	24.13%
LT	Lithuania	0.52	0.95	1.02	7.5	0.32%
LU	Luxembourg	2.07	4.54	6.19	36.3	0.05%
LV	Latvia	0.32	1.01	1.11	10.1	0.20%
MT	Malta	6.02	15.93	18.72	17.5	0.01%
NL	Netherlands	0.27	0.54	0.68	24.7	0.08%
PL	Poland	0.96	1.61	1.79	11.2	2.92%
PT	Portugal	2.31	2.94	3.55	20.6	2.01%
RO	Romania	2.84	3.39	3.88	14.3	6.31%
SE	Sweden	0.41	1.12	1.31	16.6	1.57%
SI	Slovenia	7.43	4.63	5.33	15.0	1.49%
SK	Slovakia	2.18	3.54	4.09	15.6	1.03%
UK	United Kingdom	2.38	1.04	1.49	43.2	5.14%

Soil erosion is further assessed per Biogeographical regions which are classified based on climatic and ecological criteria (EEA, 2011). The highest mean annual soil erosion rate (5.27 t/ha) is noticed in the Alpine climatic zone

(Alps, Pyrenees, and Transylvania Alps) due to the combined effect of rainfall erosivity and topography. The Mediterrean climatic zone has also a high soil erosion rate (4.61 t/ha) due to the highest R-factor in Europe. The largest part of EU covered by the Atlantic and the Continental climatic zone have mean annual erosion rates corresponding to 1.78 and 1.98 t/ha, respectively, which are much lower than the rates for the Alpine and Mediterranean region. Finally, the lowest mean annual erosion rates (0.16 t/ha) are found in the Boreal zone due to very little rainfall erosivity, flat topography and high vegetation density.

3.3 Land cover/use assessment

The soil erosion map (Fig. 2) has been analysed per land cover/use using the major CORINE land cover classes of the 2nd level. The mean annual soil erosion rate in arable lands (2.67 t/ha) is marginally higher than the overall soil erosion rate. Permanent crops have a high mean erosion rate (9.47 t/ha) as most of the vineyards and olive trees are located in Mediterrean hilly areas with high rainfall erosivity. The mean annual soil erosion rate in pastures is 2.02 t/ha mainly due to higher vegetation densities and as a consequence lower C-factors. The heterogeneous agricultural areas have overall a higher mean erosion rate (4.21 t/ha) than the arable land alone even if their C-factor is lower (chapter 6). The latter is due to the difference in topography (influencing the LS factor) as the arable lands are located in flat areas. The agricultural areas including arable, permanent crops, grasslands and heterogeneous agriculture lands and counting for 46.7% of the EU surface area (or 52% of the potentially erosive studied region) have a mean soil erosion rate of 3.24 t ha^{-1} yr^{-1}. The agricultural lands sum up the 68.3% of the total soil losses (Fig. 3).

The forests and semi-natural CORINE land cover/use class have a huge heterogeneity in soil erosion estimates. Forests have by far the lowest soil erosion rate of 0.07 t ha^{-1} yr^{-1} contributing to less than 1% of the total soil loss in Europe even if they occupy more than 30% of the EU land. The shrub and herbaceous vegetation have a mean annual soil erosion rate of 2.69 t/ha. In this land cover group, the natural grasslands have a mean erosion rate of 4.41 t/ha mainly due to their location in steep areas. Severe soil erosion rates (40.16 t/ha) have been accounted in the sparsely vegetated areas (Fig. 3) which mainly are bad-lands in high attitude with scattered vegetation. Those sparsely vegetated areas explain the high erosion rates in Andalusia (ES). However, this land cover group is the most uncertain one due to its original uncertainty in CORINE land cover classification.

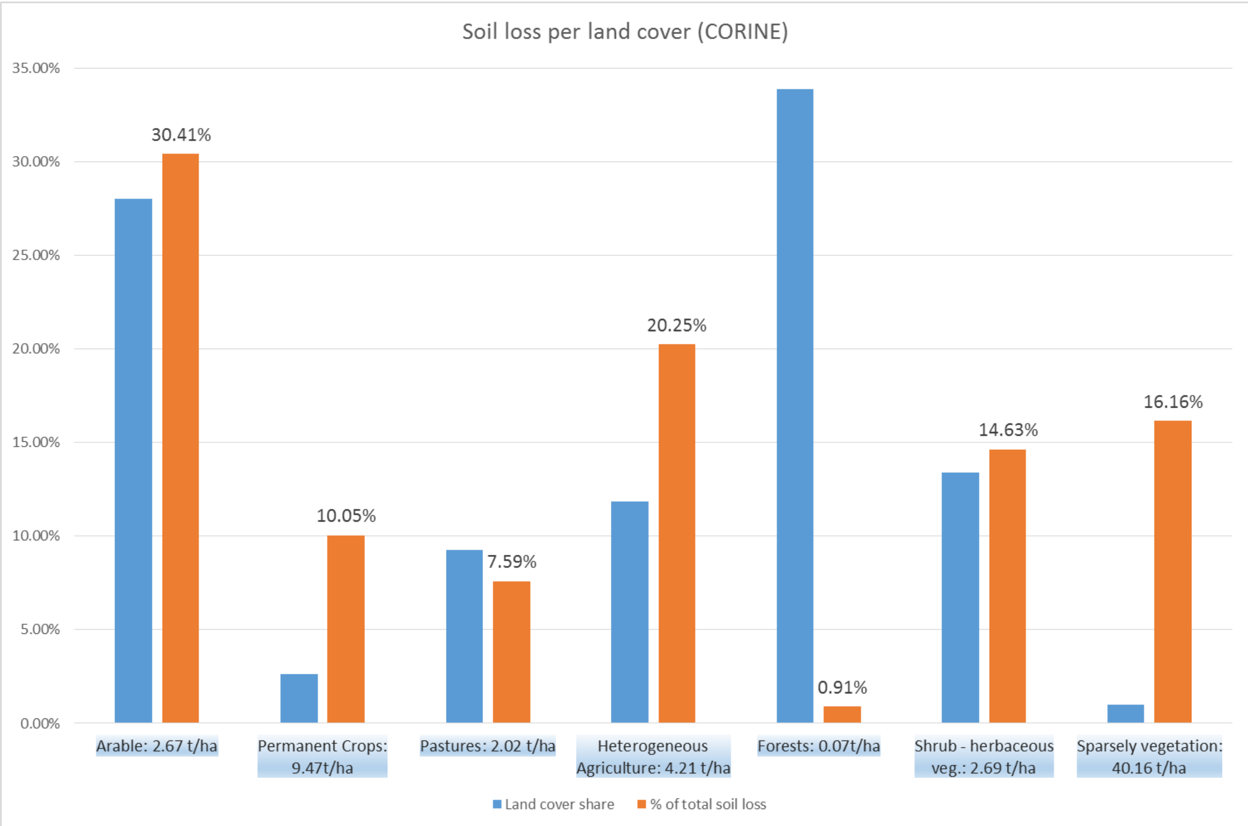

Fig. 3: Rates of soil erosion per land cover group and corresponding shares of soil loss

3.4 *Comparison with other data sources and uncertainties*

In 2010, the European Soil Data Centre (ESDAC) of the European Commission conducted a project for collecting data on soil erosion from national institutions in Europe using the European Environment Information and Observation Network (EIONET). As shown in chapter 1, the result of this data collection was the EIONET-SOIL database which included data at 1km pixel size for 8 countries: Austria, Belgium, Bulgaria, Germany, Italy, Netherlands, Poland, Slovakia (Panagos et al, 2014) plus Denmark which provided data in a latter phase.

The mean soil erosion rates estimated by RUSLE2015 are compared with the mean EIONET soil erosion data for the intersecting pixels. Even if they are different modelling approaches, the Pan-European Soil Erosion Risk Assessment (PESERA) model mean estimates (Kirkby et al., 2008) and the erosion rates from plots in Europe (Cerdan et al., 2010) are also listed (Table 2) in this comparison as both datasets have been used extensively during the previous decade in Europe. The erosion ratio (Table 2) expresses the division of RUSLE2015 results with the EIONET-SOIL data in the common intersecting pixels.

Table 2: Comparison of RUSLE2015, European Environment Information and Observation Network for soil (EIONET-SOIL), Pan-European Soil Erosion Risk Assessment (PESERA) (Kirkby et al. 2008) soil erosion estimates and aggregated soil erosion plot measurements (Plot, Cerdan et al. 2010).

Country		RUSLE2015	EIONET-SOIL	PESERA	Plot	Erosion ratio RUSLE2015 : EIONET-SOIL
		$t\ ha^{-1}\ yr^{-1}$				
AT	Austria *	3.50	2.01	1.24	1.6	1.7
BE	Belgium	1.25	3.70	1.10	1.4	0.3
BG	Bulgaria	2.11	1.92	0.61	1.9	1.1
DE	Germany	1.44	1.41	1.30	1.9	1.0
DK	Denmark **	0.50	0.33-0.61 (0.47)	3.29	2.6	1.1
IT	Italy	8.77	6.95	2.69	2.3	1.3
NL	Netherlands	0.27	0.26	0.08	0.4	1.0
PL	Poland	1.25	1.46	0.83	1.5	0.9
SK	Slovakia	2.15	1.06	1.29	3.2	2.0

*Austria: only the agricultural lands

**Denmark: The EIONET-SOIL data were given in classes and as a result a range has been estimated (Mean value is in parenthesis).

The PESERA model tends to estimate generally lower erosion rates than all other approaches (chapter 1) due to its sediment module (Panagos et al., 2014a) with the exception of overestimating soil erosion in flat areas (Denmark, Po Valley). In the plot database, rainfall intensity is not included in the analysis (Cerdan et al., 2010) and the results are lower estimates for erosion rates in countries with high rainfall erosivity (Italy, Austria). The RUSLE2015 mean erosion rates and spatial patterns are very close to the reported EIONET-SOIL data in Germany, Netherlands, Bulgaria, Poland and Denmark. In Italy, the RUSLE2015 results are slightly higher than the EIONET-SOIL and in Austrian agricultural lands this overestimation is higher. In Belgium, the reported EIONET-SOIL values are much higher than the RUSLE2015, especially in the Wallonia forests while in Slovakia, the reported EIONET-SOIL values are lower than the RUSLE2015. The very good correspondence of RUSLE2015 mean annual soil erosion rates with the country estimates from EIONET-SOIL in six member states is considered to confirm the modelling while the reasons for having differences in two Member States (Slovakia, Belgium) should be further investigated.

The major advancement in RULSE2015 is the high quality input layers due to a) assessment of soil erodibility with ground observations after laboratory analysis plus the data verification with local and regional published studies (chapter 1), b) the Member States participatory approach in the extensive data collection of high-resolution precipitation data (chapter 4), c) the first ever employed high resolution Digital Elevation Model at 25m, d) the combination of CORINE Land Cover with remote sensing vegetation density data plus the use of statistical crop/management practices and (Chapter 6) e) the first ever assessment of support practices using LUCAS survey observations in combination with the GAEC database (Chapter 7). The major source of uncertainty is some highly erosive CORINE land cover classes (e.g. sparsely vegetated areas) which demonstrate high variability between Mediterranean regions (badlands) and northern Europe (mixed vegetation with rocks). The use of vegetation density remote sensing data has been proved useful for fine-tune the cover protection against erosion. The predictions in sloppy and arid areas can further be improved by distinguishing the effects of erodible soil to the effects of rocks and gravels.

3.5 Policy making and future scenario analysis

The European Union with its 2.9% of world land contributes to 1.3% of the total global annual soil erosion estimate of 75 Mt (Pimentel et al. 1995). A Pan-European assessment such as the current study allows to guide investments for soil protection against erosion and prioritise actions for effective remediation. The spatial analysis of the EU soil erosion map per land cover/use, country, climatic zone and soil erosion class allows to identify hot spots where efforts to prevent further soil degradation should be focused. In a cost-benefit analysis, Kuhlman (2010) demonstrated the economic benefit (onsite and offsite) of 1.35 Billion Euros after of taking anti-erosion measures (terracing – stone walls, grass margins, contour farming, reduced tillage cover crop and plant residues) in severe erosive agricultural areas (> 10 t/ha annually).

The distribution of erosion rates is positively skewed with a median value of 1.27 t ha^{-1} yr^{-1}. More than ¾ of the total European land has erosion rates lower than 2 t ha^{-1} yr^{-1} which are considered sustainable according to the general accepted soil formation rates (Verheijen et al., 2009). The rest 24% of the study area with erosion rates higher than 2 t ha^{-1} yr^{-1} contributes to the almost 87% of the total soil loss (Table 3). Soil protection measures should definitely be taken in the 5.2% of the European land suffering of severe erosion (> 10 t ha^{-1} yr^{-1}) and contributing to the 52% of the total soil loss. An example of such measurement is the afforestation or re-vegetation of sparse vegetation areas which have extreme erosion rates.

Focusing on arable lands, the 12.7% of the croplands in the European Union (eq. 14 * 10^6 ha) have erosion rates higher than 5 t ha^{-1} yr^{-1} (Table 3). A layer of at least 0.4 mm is eroded annually (Montgomery, 2007) at those croplands, where emerging management practices should be applied in order to ensure agricultural sustainability in EU.

Table 3: Analysis of erosion rates per classes (in whole study area and focus on croplands)

Erosion Class t ha^{-1} yr^{-1}	**% of total area**	**Mean Erosion rate in the class (t ha^{-1} yr^{-1})**	**% contribution in total soil loss**	**% of cropland**
0 - 1	63.5%	0.24	6.1%	44.4%
1 - 2	12.3%	1.43	7.2%	23.0%
2 - 5	12.8%	3.18	16.8%	19.9%
5 - 10	6.2%	7.00	17.8%	7.6%
10 - 20	3.2%	13.79	18.2%	3.6%
20 - 50	1.6%	29.51	19.0%	1.4%
> 50	0.4%	88.67	14.9%	0.1%
Total	100.0%	2.46	100.0%	100.0%

Soil erosion is among the agro-environmental indicators developed in the European Commission services for monitoring the agricultural and environmental policies. The EU soil erosion map (Fig. 2) supports the statistical service DG-EUROSTAT with aggregated data at various geographic levels (national, regional, provincial). The Directorate General responsible for the implementation of Common Agricultural Policy (CAP) in EU (DG AGRI) focuses on soil erosion in agricultural lands and requests indicators of soil erosion in agricultural lands. An example of such indicators is the annual soil erosion rates in arable lands at NUTS3 (Nomenclature of Territorial Units for Statistics level 3) level (Fig. 4). The percentage of agricultural land affected by erosion is among the Green growth indicators of the Organisation for Economic Co-operation and Development (OECD).

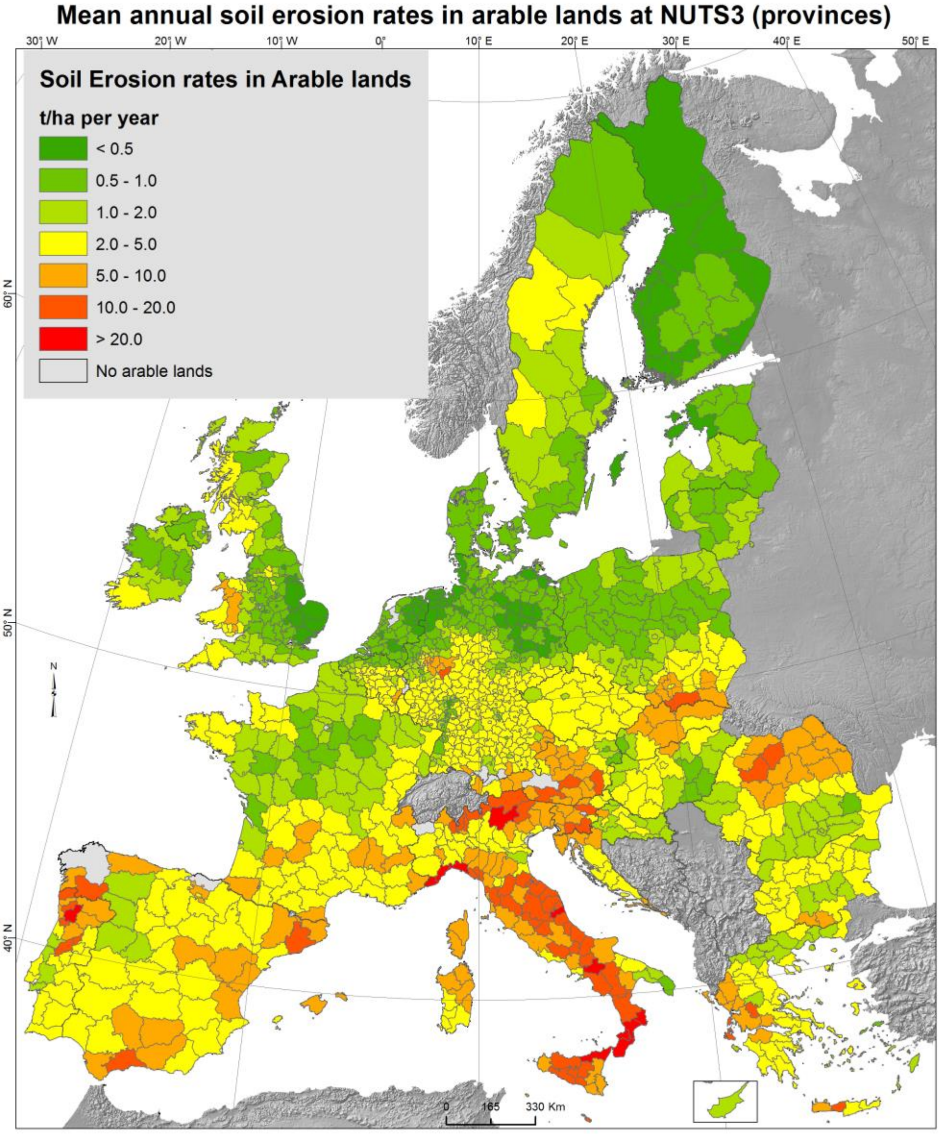

Fig. 4: Mean soil erosion rates at Province level (NUTS3) for arable lands in EU

The RUSLE2015 model structure has the option to host land management and land use change plus climate change scenarios. As such, the model becomes a useful tool for policy makers to make both past assessments and estimate erosion changes based on future scenarios.

In terms of land management, we gave special focus on agricultural lands as C-factor can be changed by farmers' intervention. In the European Union and specifically in the context of Common Agricultural Policy (CAP), farmers are receiving direct payments that requiring them to follow particular management practices beneficial to the environment. Agro-environmental standards are set in the Good Agricultural and Environmental Condition (GAEC) introduced by the CAP reform in 2003 and implemented by the Member States after 2005 (Angileri et al., 2009). The GAEC includes as mandatory the measures for soil protection by erosion and proposes the limitation of bare soils, the promotion of reduced tillage and the minimum soil cover, the contour farming in sloppy areas, the maintenance of terraces and stone walls and the increase of grass margins (Matthews, 2013).

The implementation of GAEC in agricultural lands of Member states has a positive impact in reducing soil erosion rates. Since there are no statistical data about reduced tillage, soil cover, contour farming, terracing and grass margins before the GAEC implementation in 2003, we make the hypothesis that those management practices were not applied before or they were very limited. Their impact during the last decade (2003-2010) was to reduce soil erosion in agricultural lands from 3.35 t ha^{-1} yr^{-1} to 2.67 t ha^{-1} (-20.2%). Under the condition that no GAEC have been applied in EU, the mean soil erosion rate in the study area (agricultural lands, forests and semi-natural areas) would have been 2.65 t ha^{-1} yr^{-1}. Compared to the current estimated mean annual rate of 2.46 t ha^{-1} yr^{-1}, this implies that overall soil erosion in EU was reduced by 7% during the last decade due to policy measurements (GAEC). The highest effect of GAEC has been noticed in Cyprus, Bulgaria, Germany, United Kingdom and France with a reduction of more than 30% in mean erosion rates in agricultural lands. The less impact has been noticed mainly in Eastern European countries (new Member states after the 2004 enlargement) with a decrease of mean erosion rates in agricultural lands of less than 13.5%.

As was shown in chapter 6, the management practice with the greater impact was the reduced and no tillage which is currently applied in more than 25% of the agricultural lands of the European Union (Panagos et al., 2015b). Plant residues and cover crops are the other two management practices incorporated in the RUSLE2015 C-factor which had very limited contribution to soil erosion rate decrease (c.a 1% each), mainly due to their limited extent in agricultural lands of EU. Among the support practices (P-factor) applied in agricultural lands of EU during the last decade (chapter 7), the grass margins had the major effect (>1%) in reducing soil erosion rates while the contour farming impact was insignificant (0.15%) due to very limited application in Europe (Panagos et al, 2015c).

A sensitivity analysis of in the cover-management factor (C-factor) allows to perform future scenarios of land use based on crop rotation changes that may be imposed by EU policies. An evident example is the European Union Biofuels Directive (BFD) which will put a pressure in transforming cereal croplands (C-factor: 0.20) to energy croplands such as sugar beets, sunflowers and maize (C-factor: 0.38) and in addition will result in sreducing crop residues. Taking into account the BFD requests and applying a scenario of 10% crop change from cereals to energy crops (Frondel and Peters, 2007) will result in a C-factor increase by 3.8% in arable lands and as a consequence 2.2% growth of mean soil erosion rates.

In the context of climate change, we selected one of the most applied future scenarios of the Fifth Assessment Intergovernmental Panel on Climate Change (IPCC, 2013) report named HadGEM2 (Martin et al., 2011) and we considered a relatively conservative increase of greenhouse gas concentration and a global temperature increase by 1 degree till 2050 (Representative Concentration Pathways - RCP 2.6). Based on this scenario, the future predictions of precipitation in Europe from the Worldclim (Hijmans et al., 2005) are used in combination with the rainfall erosivity (Panagos et al., 2015a) to develop a future rainfall erosivity prediction. The erosivity density is the ratio of mean annual R-factor to the mean annual precipitation (Kinnel, 2010) and is considered as constant in the future climate change scenario. This conservative scenario allows to estimate a decrease of rainfall erosivity in the EU by 8.2% by 2050 (similar to the precipitation decrease) and as a result a similar decrease in soil erosion rates. The most important outcome of this future scenario is that the Mediterranean climatic zone will have the highest decrease of the R-factor by 10.4% and the boreal will experience the lowest decrease (4.6%) while the rest of the climatic zones will notice decrease of rainfall erosivity around 7%. However, this scenario should be improved by taking into account the possible increase of erosivity density in the next 40 years.

Similar to climate change, we selected the projections of land use change for year 2050 based on pan-European Land Use Modelling Platform (LUMP) (Lavalle et al., 2013). LUMP translates policy scenarios into land-use changes such as afforestation and deforestation, pressure on natural areas, abandonment of productive agricultural areas and urbanization. According to LUMP, all agricultural land uses will be reduced (croplands will decrease by 1.2%, permanent crops by 0.2% and pastures by 0.6%) plus semi-natural areas will also decrease by 1%. The urban areas will increase by 0.7% and the forests by 2.2%. Forestlands are the less erosive with mean annual soil loss of 0.065 t/ha and will replace erosive land uses (permanent crops, arable, pastures and semi-natural). In total soil loss terms, the projected land use changes according to LUMP will result in soil erosion reduction by 5.8%. However, LUMP should take into consideration the imminent threat of peak phosphorous with the only noteworthy P resources left in the Western Sarah and Marocco after 2013 (Elser and Bennett, 2013). Under this threat, the European states will most likely start to increase their area of arable land considerably in the near future.

4 Overall conclusions

The RUSLE2015 application and the produced EU soil erosion map overcome the problems that previous pan-European assessments (Cerdan et al., 2010; Bosco et al., 2014) have outlined: lack of high-resolution pan-European datasets, non-uniform available data and lack of rainfall intensity datasets. The model is presented in a transparent way and the input layers have been peer-reviewed following the literature principles. The transparent model ensures comparability with other regional/national data sources, replicability of the results with future database and usability by policy makers and scientists. An advance option in the RUSLE2015 model is the scenario analysis based on past and future land management and land use changes plus climatic change.

The soil erosion map of Europe at 100m resolution referring to year 2010 is available in the European Soil Data Centre (ESDAC, 2012) together with the input layers. The data availability is an important issue both for decision makers and modellers in various environmental domains such as agricultural production, food security, carbon sequestration, biodiversity, ecosystem services and water management. However, it is recommended not to take decisions at pixel level (100 meters resolution) where it is recommended to use local measurements. It should also be underlined that presented soil erosion rates are long-term averages and should not be compared with event-based observations due to large seasonal variability of R and C factor (demonstrated in chapter 3). Moreover, users should take into account that an additional model component is needed to predict sediment yield from catchments. The temporal distribution of soil erosion (Greece as an example in Chapter 5) and the sedimentation module are the future developments of RUSLE2015.

The RUSLE2015 has been applied using the most updated high resolution input layers at European scale. The soil erosion map of the European Union at 100m resolution for the reference year 2010 has mean annual soil erosion rate 2.46 t/ha excluding non-erosive areas (urban, bare rocks, glaciers, water bodies). The total annual soil loss is estimated to around 970Mt in EU. The results of RUSLE2015 compared with national reported data in EIONET-SOIL database reveal a satisfactory consistency.

The higher soil erosion rates in Mediterrean areas, Slovenia and western Austria are mainly due to combination of high rainfall erosivity and topography. The spatial analysis per land cover demonstrated that croplands have a mean annual soil erosion of 2.67 t/ha similar to the shrublands while pastures show quite lower rates (2 t/ha) and forests are almost non-erosive areas (0.065 t/ha). The highest erosion rates are noticed in sparsely vegetated areas. Special focus was given to the arable lands where management practices and support measures in the context of Common Agricultural Policy reduced the soil erosion rate by 20% in those areas and by 7% in total during the last decade.

The regional assessment of EU soil erosion map showed the highest mean annual rates in the Alpine regions (5.27) and Mediterrean countries (4.61) while the lowest rates (< 0.52 t/ha) are found in the Scandinavian and Baltic States. The combination of topography and rainfall erosivity is mainly the reason for this distribution. The soil erosion map delineates hot spots where protection measures are emerging. In the12.7% of arable lands experiencing non-sustainable erosion rates (> 5 t/ha annually), policy makers can finance anti-erosion measures such as reduced tillage, cover crops, plant residues maintenance of stone walls, increase of grass margins and contour farming.

RUSLE2015 has demonstrated to be the more suitable approach for estimating soil erosion at European scale. The mean soil erosion rate in EU exceeds the average soil formation rate by factor 1.6. The soil protection measures should focus in the 24% of the European lands experiencing mean annual erosion rates greater than 2 t/ha. The mean erosion rates in permanent crops and heterogeneous agricultural areas are much higher than the ones in the croplands. The land management and agricultural practices applied in EU during the last decade are not as bad as their reputation in the longer past (e.g. 20 years ago).

Based on the land-use changes predicted for year 2050 with LUMP model, RUSLE2015 estimated a decrease in soil erosion rates mainly due to increase of forest and in the expense of semi-natural and pastures. On the other side, the arable land extension creates an uncertainty in future erosion estimates. The Common Agricultural Policy foresees the increase of grass margins, maintenance of stone walls and the application of contour farming which can further reduce soil erosion rates in arable lands. On the other side the pressure for cultivation of energy crops (mainly erosive) from other policies (e.g. Biofuels Directive) may increase soil erosion if no additional management practices are applied. RUSLE2015 is the tool for simulating the policy developments, land use changes and impact of land management.

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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Appendix

Appendix

Proof of submission in CATENA journal (Chapter 5)

Proof of submission in Land use policy journal (Chapter 6)

Proof of submission in Environmental Science &Policy journal (chapter 7)

Elsevier Editorial System(tm) for Catena
Manuscript Draft

Manuscript Number: CATENA3669

Title: Spatial and temporal analysis of rainfall erosivity in Greece

Article Type: Research Paper

Keywords: R-factor; seasonality; rainfall intensity; erosivity density; soil erosion; RUSLE

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Order of Authors: Panos Panagos, MBA; Cristiano Ballabio, PhD; Pasquale Borrelli, PhD; Katrin Meusburger, PhD

Abstract: Rainfall erosivity considers the effects of rainfall amount and intensity on soil detachment. Rainfall erosivity is most commonly expressed as the R-factor in the Universal Soil Loss Equation (USLE) and its revised version, RUSLE. Several studies focus on spatial analysis of rainfall erosivity ignoring the intra-annual variability of this factor. This study assesses rainfall erosivity in Greece on a monthly basis in the form of the RUSLE R-factor, based on 30-minutes data from 80 precipitation stations covering an average period of almost 30 years. The spatial interpolation was done through a Generalized Additive Model (GAM). The observed intra-annual variability of rainfall erosivity proved to be high. The warm season is 3 times less erosive than the cold one. November, December and October are the most erosive months contrary to July, August and May which are the least erosive. The proportion between rainfall erosivity and precipitation varies throughout the year. Rainfall erosivity is lower than precipitation in the first 5 months (January - May) and higher in the remaining 7 months (June - December) of the year. The R-factor maps reveal also a high spatial variability with elevated values in the western Greece and Peloponnesus and very low values in Western Macedonia, Thessaly, Attica and Cyclades. The East-West gradient of rainfall erosivity differs per month with a smoother distribution in summer and a more pronounced gradient during the winter months. The aggregated data for the 12 months result in an average R-factor of 807 MJ mm ha-1 h-1 yr-1 with a range from 84 to 2825 MJ mm ha-1 h-1 yr-1 . The combination of monthly R-factor maps with vegetation coverage and tillage maps contributes to better monitor soil erosion risk at national level and monthly basis.

Elsevier Editorial System(tm) for Land Use Policy
Manuscript Draft

Manuscript Number: LUP-D-14-00763

Title: Estimating the soil erosion cover-management factor at European scale

Article Type: Regular Paper

Keywords: C-factor; tillage; crop residues; cover crop; RUSLE; soil conservation

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Abstract: Land use and management influences the magnitude of soil loss. Among the different soil erosion risk factors, the cover-management factor (C-factor) is considered to be the most important because policy makers and farmers can intervene and, as a consequence, may reduce soil erosion rates. The present study proposes a methodology for estimating the C-factor in the European Union (EU), using pan-European datasets such as CORINE Land Cover, biophysical attributes derived from remote sensing and agricultural statistical data on crops and practices. In arable lands, the C-factor was estimated using crop statistics (% of land per crop) and management practices data such as conservation tillage, plant residues and winter crops. The C-factor in non-arable lands was estimated by weighting the range of literature values found by fractional vegetation cover, which was estimated based on the remote sensing dataset Fcover. The mean C-factor in the EU is estimated to be 0.1043, with an extremely high variability; forests have the lowest mean C-factor (0.00116) and arable lands and sparsely vegetated areas the highest means (0.233 and 0.2651 respectively). The conservation management practices (reduced/no tillage, use of cover crops and plant residues) reduce the C-factor by on average 19.1% in arable lands.

The methodology is reproducible with past land cover datasets and statistical data, and is designed to be a tool for policy makers to assess the effect of future land use and crop rotation scenarios on soil erosion. The impact of land use changes (deforestation, arable land expansion of shrub lands) and the effect of policies (such as the Common Agricultural Policy and the push to grow more renewable energy crops) can potentially be quantified with the proposed model. The C-factor data and the statistical input data used are available on the European Soil Data Centre.

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Elsevier Editorial System(tm) for Environmental Science & Policy
Manuscript Draft

Manuscript Number: -D-4146

Title: Modelling the effect of support practices (P-factor) on the reduction of soil erosion by water at European Scale

Article Type: Research Paper

Keywords: RUSLE; GAEC; stone walls; grass margins; LUCAS; contour farming

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Abstract: The USLE/RUSLE support practice factor (P-factor) is rarely taken into account in soil erosion risk modelling at sub-continental scale, as it is difficult to estimate for large areas. This study attempts to model the P-factor in the European Union. For this, it considers the latest policy developments in the Common Agricultural Policy, and applies the rules set by Member States for contour farming over a certain slope. The impact of stone walls and grass margins is also modelled using the more than 226,000 observations from the Land use/cover area frame statistical survey (LUCAS) carried out in 2012 in the European Union.

The mean P-factor considering contour farming, stone walls and grass margins in the European Union is estimated at 0.9702. The support practices accounted for in the P-factor reduce the risk of soil erosion by 3%, with grass margins having the largest impact (57% of the total erosion risk reduction) followed by stone walls (38%). Contour farming contributes very little to the P-factor given its limited application; it is only used as a support practice in eight countries and only on very steep slopes. Support practices have the highest impact in Malta, Portugal, Spain and Belgium where they reduce soil erosion risk by at least 5%. The P-factor modelling tool can potentially be used by policy makers to run soil-erosion risk scenarios for a wider application of contour farming in areas with slope gradients less than 10%, maintaining stone walls and increasing the number of grass margins under the forthcoming reform of the Common Agricultural Policy.

Elsevier Editorial System(tm) for Earth-Science Reviews
Manuscript Draft

Manuscript Number: EARTH2715

Title: The new map of soil loss by water erosion in Europe

Article Type: Review Article

Keywords: RUSLE; soil erodibility; rain erosivity; management practices; agricultural sustainability; policy scenarios

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Abstract: Soil erosion by water is one of the major threats to soils in the European Union, with a negative impact on ecosystem services, crop production, drinking water and carbon stocks. The European Commission's Soil Thematic Strategy has identified soil erosion as a relevant issue for the European Union, and has proposed an approach to monitor soil erosion. This paper presents the application of a modified version of the Revised Universal Soil Loss Equation (RUSLE) model (RUSLE2015) to estimate soil loss in Europe for the reference year 2010, within which the input factors (Rainfall erosivity, Soil erodibility, Cover-Management, Topography, Support practices) are modelled with the most recently available pan-European datasets. While RUSLE has been used before in Europe, RUSLE2015 improves the quality of estimation by introducing updated (2010), high-resolution (100 m), peer-reviewed input layers. The mean soil loss rate in the European Union's erosion-prone lands (agricultural, forests and semi-natural areas) was found to be 2.46 t ha-1 yr-1, resulting in a total soil loss of 970 Mt annually.

A major benefit of RUSLE2015 is that it can incorporate the effects of policy scenarios based on land-use changes and support practices. The impact of the Good Agricultural and Environmental Condition (GAEC) requirements of the Common Agricultural Policy (CAP) and the EU's guidelines for soil protection can be grouped under land management (reduced/no till, plant residues, cover crops) and support practices (contour farming, maintenance of stone walls and grass margins). The policy interventions (GAEC, Soil Thematic Strategy) over the past decade have reduced the soil loss rate by 7% on average in Europe, and by 20% for arable lands. Special attention is given to the 4 * 106 ha of croplands which currently have unsustainable soil loss rates of more than 5 t ha-1 yr-1, and to which policy measures should be targeted.

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