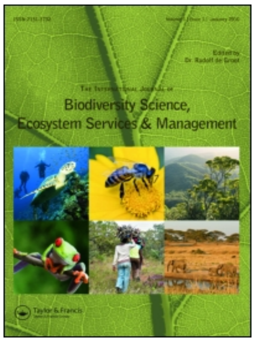

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Natalia Estrada-Carmona, Elizabeth B. Harper, Fabrice DeClerck & Alexander K. Fremier

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Quantifying model uncertainty to improve watershed-level ecosystem service quantification: a global sensitivity analysis of the RUSLE

Natalia Estrada-Carmona [a,b,c], Elizabeth B. Harper[d], Fabrice DeClerck [c] and Alexander K. Fremier[e]

[a]College of Natural Resources, University of Idaho, Moscow, ID, USA; [b]Division of Research and Development, CATIE, Turrialba, Costa Rica; [c]Landscape Management and Restoration, Bioversity International, Montpellier, France; [d]Division of Natural and Social Sciences, New England College, Henniker, NH, USA; [e]School of the Environment, Washington State University, Pullman, WA, USA

ABSTRACT

Ecosystem service-support tools are commonly used to guide natural resource management. Often, empirically based models are preferred due to low data requirements, simplicity and clarity. Yet, uncertainty produced by local context or parameter estimation remains poorly quantified and documented. We assessed model uncertainty of the Revised Universal Soil Loss Equation – RUSLE developed mainly from US data. RUSLE is the most commonly applied model to assess watershed-level soil loss. We performed a global sensitivity analysis (GSA) on RUSLE with four dissimilar datasets to understand uncertainty and to provide recommendations for data collection and model parameterization. The datasets cover varying spatial levels (plot, watershed and continental) and environmental conditions (temperate and tropical). We found cover management and topography create the most uncertainty regardless of environmental conditions or data parameterization techniques. The importance of other RUSLE factors varies across contexts. We argue that model uncertainty could be reduced through better parameterization of cover management and topography factors while avoiding severe soil losses by targeting soil conservation practices in areas where both factors interact and enhance soil loss. We recommend incorporating GSA to assess empirical models' uncertainty, to guide model parameterization and to target soil conservation efforts.

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Introduction

Ecosystem service-support tools simulate biophysical processes (e.g. soil loss, hydrology, pest control, pollination) to quantify relationships between management decisions, ecosystem processes and ecosystem services. Increasingly, researchers use decision-focused ecosystem service-support tools (e.g. Co$ting Nature, InVEST, ARIES) to simplify data collection and analysis, and to simultaneously quantify trade-offs among ecosystem services (Bagstad et al. 2013). Understanding the accuracy of models simulating biophysical processes should play a key role in tool development and decision-making, yet for most tools, model uncertainty produced by local context or parameter estimation, remains poorly quantified and documented.

Knowledge of the uncertainty produced from parameter estimation is important to improve model parameterization procedures during individual ecosystem service quantification (Falk et al. 2009). This is particularly true for empirically formulated models of biophysical processes, for example, the Revised Universal Soil Loss Equation (RUSLE). Because it is simple, robust (Gao et al. 2002; Lu et al. 2004; Bewket & Teferi 2009) and inclusive of universally recognized factors affecting erosion by water (Wischmeier & Smith 1978; Panagos, Borrelli, Poesen et al. 2015), RUSLE is the most commonly used model to estimate average long-term soil loss in agricultural lands (Yu et al. 2001; Naipal et al. 2015; Panagos, Borrelli, Poesen et al. 2015). Empirical models, such as RUSLE, typically evaluate long-term trends rather than specific small spatial-level estimations (Yang et al. 2003; Lu et al. 2004; Wang et al. 2007; Nelson et al. 2009; Schuler & Sattler 2010; Galdino et al. 2015). RUSLE is a deterministic and empirical-based model built with parameter estimates from mostly the US-based erosion studies, which might not be appropriate if applied outside the range of original estimates or using non-plot-level data (e.g. remotely sensed data) (Wischmeier & Smith 1978; Renard et al. 1997; Nearing et al. 2000).

Despite these limitations, practitioners and researchers increasingly apply RUSLE at larger spatial scales and under different environmental conditions than its original intent (e.g. Biesemans et al. 2000; Lu et al. 2004; Bewket & Teferi 2009; Falk et al. 2009; Ligonja & Shrestha 2013; Galdino et al. 2015; Naipal et al. 2015; Panagos, Borrelli, Poesen et al. 2015) and it has been incorporated into ecosystem services

CONTACT Natalia Estrada-Carmona n.e.carmona@cgiar.org
The supplemental data for this article can be accessed here.

decision-support tools, such as InVEST (Sharp et al. 2012). Some skepticism exists in the scientific community on applying empirical models over physically based models because they lack a representation of processes which might lead to erroneous results; however, in many developing countries, easy-to-use models are often the only science-based option.

Studies on model accuracy are typically required to assess uncertainty in our scientific understanding of how decision-making might influence ecosystem service provisioning. Model accuracy assessments are particularly challenging in data-poor regions and developing countries. However, a sensitivity analysis can efficiently provide data to reduce uncertainty in model predictions and decision-making (Harper et al. 2011). Sensitivity analyses assess both the parameters' influence on prediction uncertainty and the influence of parameter estimation (input data) on uncertainty (Saltelli et al. 1999; Harper et al. 2011).

Local sensitivity analysis (LSA) is a common statistical method used to assess model behavior and the effect of each factor on model predictions (e.g. Renard & Ferreira 1993; Risse et al. 1993; Ferreira et al. 1995). LSA estimates the contribution of each model factor (or parameter, hereafter just mention factor) to model predictions by varying each model factor singly while holding other factors constant (Saltelli et al. 1999). LSA is a constructive analysis, but it does not capture interactions among factors and interaction effects on model predictions (Wagner 1995; Harper et al. 2011). Global sensitivity analysis (GSA) is considered a more robust approach because it considers higher order interactions among factors to assess model behavior and to estimate factor importance (Harper et al. 2011). GSA simultaneously varies all factors to account for all factor uncertainty and evaluate the combined impact of each factor on model predictions (Wagner 1995).

Sensitivity analysis assessments of RUSLE factors at the plot level have found that the cover-management factor (C factor) is the most important in determining soil loss under different agricultural systems, with the second most important factor being topography (Risse et al. 1993; Benkobi et al. 1994; Ferreira et al. 1995). At the watershed level, discrepancies exist regarding which factor has more effect on model predictions, with some studies highlighting the topography factor (Biesemans et al. 2000; Galdino et al. 2015), slope steepness (Falk et al. 2009), rainfall-runoff erosivity (Zhang et al. 2013) and both slope steepness and rainfall-runoff erosivity (Doetterl et al. 2012). In all cases, local sensitivity analyses were applied.

Here, we focused on the influence of factor estimation on prediction uncertainty rather than model accuracy. We recognize that model formulations will continue to be redesigned and improved, but the importance of our work is to better understand model sensitivity to factor and parameter estimation for the application of particular biophysical models in ecosystem service models, such as RUSLE. We conducted a GSA of RUSLE using four distinct datasets that cover different spatial levels and environmental conditions, and using different parameterization methods. The results of this study provide a description of model sensitivity within and among factor estimates across different environmental conditions and can be used to focus parameterization efforts for future applications. The results are particularly important in data-poor areas where parameterization of physically based models is near impossible and where empirically based models are the most accessible tool to improve efforts to curb soil loss (e.g. applications of the InVEST model).

Materials and methods

Dataset description

To understand model uncertainty, we conducted a GSA on three datasets that cover different spatial levels (plot–watershed–continental), used different methods (ground-collected data versus geographical information system (GIS) proxies) and covered different environmental conditions (climatic, topographic, vegetation and location). Particularly, the purpose of Costa Rica (CR) and European Union (EU) datasets was to understand how factor parameterization methods and factor range (i.e. GIS proxies) influenced uncertainty. To explore uncertainty in the largest possible parameter space, we created a fourth synthetic dataset with the widest possible RUSLE range of factor and parameter estimates. We compared ranks of factor importance in predicting soil loss and identified specific factor interactions predicting greater and lower soil losses.

United States dataset

The US dataset is plot-level data of the original calibration dataset (Risse et al. 1993). It includes 1,704 plot years of data from natural runoff in 198 plots at 21 sites with annual measurements of soil loss and estimates of each RUSLE factor (C, R, LS, P, K), (see also Rapp (1994) and Tiwari et al. (2000)). The US dataset was primarily collected and measured prior to 1960, and therefore it does not represent modern agricultural practices or instrumentation to measure each factor (Risse et al. 1993). Tiwari et al. (2000) estimated a Nash and Sutcliffe model efficiency of R^2 = 0.72. The Nash and Sutcliffe Efficiency is a standard statistic for quantifying prediction accuracy, particularly of soil loss.

The range of estimates for L and S factors in the US dataset was relatively narrow because data were obtained from agricultural plots where 80% of the data had a slope length (L factor) less than 25 m and where 70% of the plots had a slope steepness (S factor) less than 10°. The cover management factor (C factor) included the average crop life cycle values for 21 crops, mostly annual crops with large mean C values (more erosive). This dataset covers a wide range of rainfall-runoff erosivity factor (R factor) and soil erodibility (K factor) (Figure 1).

To perform the GSA, we averaged annual measurements of both soil loss and RUSLE factor estimates per plot. We used mean values since RUSLE is better at predicting long-term average values than annual values or isolated events (Wischmeier & Smith 1978; Renard et al. 1997).

Costa Rica dataset

We estimated RUSLE factors for a set of two CR watersheds using a common approach to apply RUSLE at a watershed level (Yang et al. 2003; Hoyos 2005). We performed the analysis on data from the Pacuare (64,919 ha) and Reventazón (175,915 ha) watersheds located on the Caribbean slopes of CR's central mountain range. We estimated L and S factors from a digital elevation model with 10-m resolution and with the ArcInfoTM Arc Macro Language program developed by Van Remortel et al. (2004). We collected C values for local crops from previous regional studies (Gómez Delgado 2002; Marchamalo & Romero 2007), whereas the land

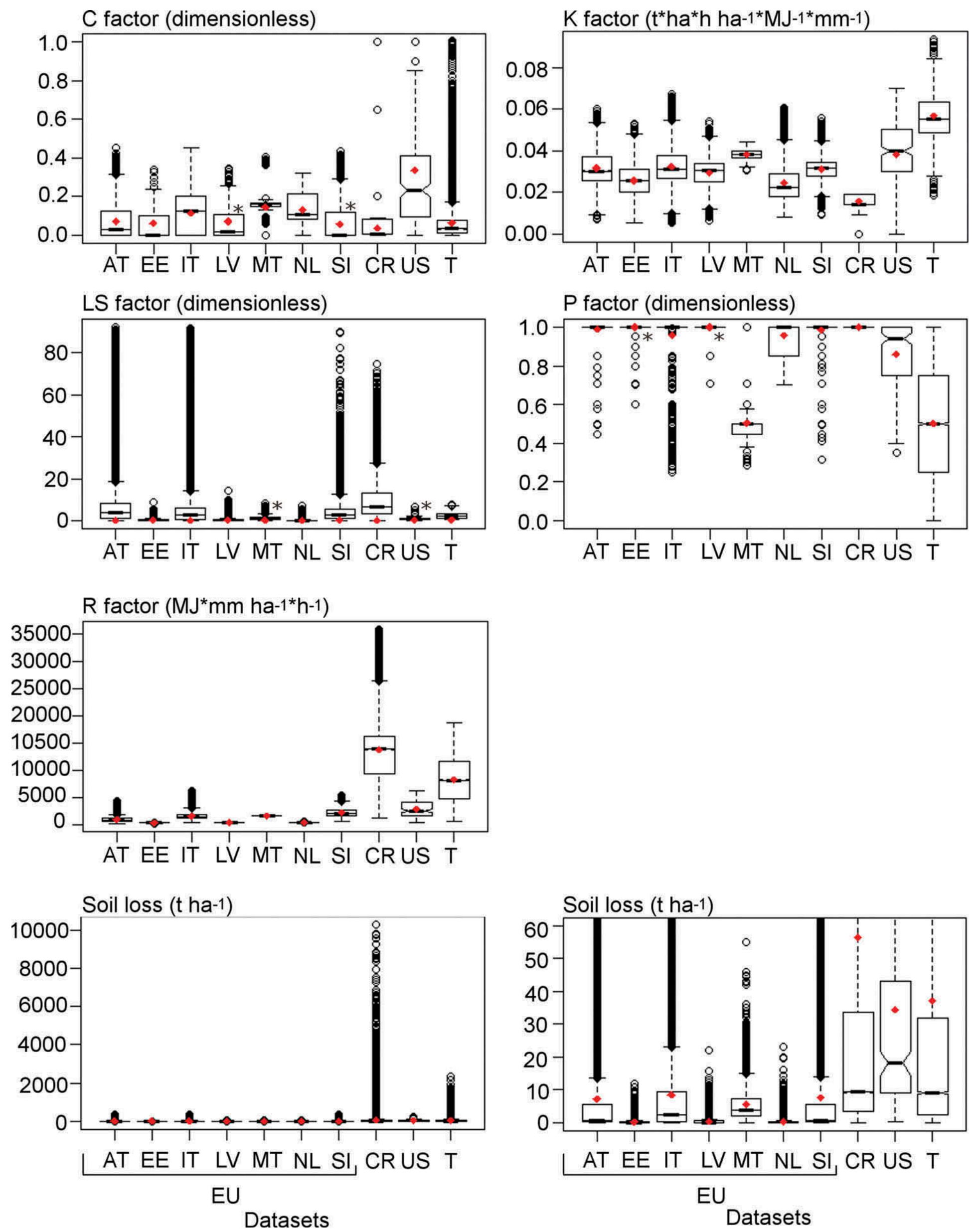

Figure 1. Factor distribution and estimates for the EU (seven countries), the US, CR and T (theoretical) datasets (Box-plot). Mean values are represented by the red diamonds. Factors with statistically similar (significant level p-value ≥0.05) mean and distributions are indicated with an asterisk (*). Soil loss left figure indicate the maximum estimated values and soil loss right figure is the same but limited to a maximum estimated soil loss of 60 t ha^{-1}.

uses were defined by a 1996 LandSat image classification (Pedroni 2003). We obtained K values from national-level Food and Agriculture Organization (FAO) surveys and a 1:200,000 resolution soil-type classification (FAO 1989). We estimated the R factor using the total storm energy (E) at a maximum 30 min intensity (I30) for each erosive storm (i.e. storms with total accumulated rainfall greater than 13 mm and separated by at least 6 h) for 148 station years of measurements from 54 meteorological stations managed by the CR Institute of Electricity – (ICE; Gómez Delgado 2002). We used 1.0 as our P factor value due to the lack of detailed information about support practices in the watersheds. We sampled each layer by generating randomly distributed points at a minimum distance of 60 m with ArcGIS 10.4 (ESRI 2016). We conducted the GSA on the sample (~4.5% of the total pixels) to overcome computational limitations.

European dataset

This dataset includes the peer-reviewed modeling of five RUSLE factors at high resolution (100 m) for 28 countries and 90.3% of the area prone to soil erosion in Europe (Panagos, Borrelli, Poesen et al. 2015). Topography factor (LS) accounts for a precise estimation of flow accumulation through the System for Automated Geoscientific analysis (SAGA), original LS equations (Desmet & Govers 1996) and a digital elevation model with 25-m resolution. C factor novel calculation includes data from remote sensing information (land cover and surface cover) and statistical data on agriculture and practices such as reduced/no tillage, cover crops and plant residues (Panagos, Borrelli, Meusburger, Alewell, et al. 2015). K factor values were calculated from 19,969 soil samples surveyed across 25 EU countries, the Wischmeier and Smith (1978) nomograph and then interpolated using a cubist regression model with remote sensing data (MODIS and SRTM) as covariates (Panagos et al. 2014). R factor was calculated as the total storm energy (E) at a maximum 30-min intensity (I30) for each erosive storm (i.e. storms with total accumulated rainfall greater than 6.35 mm or 12.7 mm in a period of 15 min or 30 min, respectively) for 1,541 precipitation stations across Europe (Panagos, Ballabio, et al. 2015). P factor includes practices such as stone walls, grass margins and contour farming obtained from 226,653 observation points across 27 EU member states (Panagos, Borrelli, Meusburger, van der Zanden, et al. 2015). We conducted the GSA on a subset of European countries covering less erosive (Latvia, the Netherlands and Estonia which altogether contribute 0.37% of the total soil loss in the EU) and more erosive areas (Italy, Slovenia, Austria and Malta which contribute 31.28% of the total soil loss in the EU). As with the CR dataset, we conducted the GSA using a randomly selected sample of 4.5% of the total pixels per country (minimum distance between random samples 200 m).

Theoretical dataset

To create the theoretical dataset, we used the reported maximum and minimum values for each parameter and estimated each RUSLE factor according to Agriculture Handbooks 537 and 703 equations (Wischmeier & Smith 1978; Renard et al. 1997 respectively; Table A.1). The purpose of the theoretical dataset was to evaluate model behavior given the largest possible range of factor and parameter estimates. The ranges of the parameters in this dataset are based on maximum and minimum values corresponding to a physical process or plot measurements (Table A.1). This is the only dataset that provided us with information at the parameter level (C factor estimated with parameters such as percentage of land area covered by surface cover (Sp), canopy height (H), among others) (Tables 1 and A.1). We used parameter-level estimates to evaluate factor-level importance (Table A.1).

We created 30,000 Monte Carlo simulations of randomly chosen parameter estimates in MatLab (Sobol' 2001). Each parameter set was created by randomly drawing from a uniform distribution within the documented parameter ranges, and each factor value was estimated using the reported equations (Renard et al. 1997, Table A.1). Random interactions between parameters were constrained (when required) to represent real interactions; for example, to estimate the K factor, the percentage of sand, silt and clay must add up to 100%. We used the simulations at each factor (6 factors) and at parameter level (18 independent parameters, Tables 1 and A.1) in the GSA. This randomization process breaks potential correlations between parameters and factors, allowing exploration of a parameter space that is larger than what might be expected to occur naturally (Harper et al. 2011).

We conducted two statistical analyses. First, we tested if there were significant differences in factor distribution and factor mean values across datasets. Second, we performed a GSA on the US, EU, CR and theoretical datasets to assess factor importance and factor interactions determining soil loss.

Factor comparisons among datasets

We assessed significant differences among datasets and sampled data (EU and CR dataset), and among mean factor values across datasets using the Kruskal–Wallis test since factors do not follow a normal distribution. We then performed Conover post hoc pairwise comparisons to determine which factor differences were statistically significant (PMCMR package, Pohlert 2014). All analyses were performed in the R statistics software (R Core Team 2016).

Table 1. RUSLE factors description, units and reference. Parameters used to construct the theoretical dataset.

Factor (description)	Independent parameters	Source
Long-term average soil loss – A (t ha^{-1} year^{-1}) A = C·K·L·S·R·P		(Renard et al. 1997)
R: rainfall-runoff erosivity: The effect of raindrop impact and rate of runoff associated with rain of moderately sized storms with occasional large storms. (MJ mm ha^{-1} h^{-1} year^{-1}).	j: No events per year; I: Erosive rain Intensity (mm hour^{-1})	Chapter 2
K: Soil erodibility: Soil profile reaction to hydrologic processes (e.g. raindrop impact, surface flow, roughness (topographic or induced) and rain water infiltration). K is affected by physical, chemical and mineralogical soil properties and their interactions and is calculated as an average annual value (ton ha h ha^{-1} MJ^{-1} mm^{-1})	s: Soil Structure; p: Soil Permeability; OM: Organic matter (%); M: (%Silt +%Very fine sand)(100-%Clay)	Chapter 3
LS: Topography: Slope length (L) which is the horizontal distance from the starting point of the overland flow until deposition or channel formation and slope steepness (S), the slope gradient effect on soil erosion (Dimensionless)	Θ: slope angle (degrees); λ: Slope length (mm)	Chapter 4
C: cover management: Crop type and management practices such as the impacts of previous cropping and management, the protection offered to the soil surface by vegetative canopy, erosion reduction due to surface cover, and surface roughness (dimensionless, but less erosive crops or land cover have smaller values)	Sp: Percentage of land area covered by surface cover; Bur: Mass density of live and dead roots found in the upper 2.54 cm of soil (kg ha^{-1}mm^{-1}); b: effectiveness of surface cover; Bus: mass density of incorporated surface residue in the upper inch of soil (kg ha^{-1}mm^{-1}); Cf: surface soil consolidation factor; Ru: surface roughness; H: Canopy height (mm); Ru: Surface roughness; Fc: Fraction of land surface covered by canopy (%); Cur: Impacts of the subsurface residues (ha mm kg^{-1})	Chapter 5
P: Support practice: The runoff reduction rate by implementing practices such as contouring, strip-cropping, terracing and subsurface drainage (dimensionless)		Chapter 6

Global sensitivity analyses

We applied the GSA approach designed by Harper et al. (2011). This GSA approach uses Random Forest (RF) to rank factor and parameter importance and classification and regression tree (CART) to analyze and visualize the complex relationships among model factors. RF is an improved version of CART, since it is a forest (a collection of trees) where each tree is created by bootstrap sampling and where the factor and parameter at each node of the tree is randomly selected (Cutler et al. 2007). For every tree, 30% of the data (called the out-of-bag – OOB data) are randomly sampled and used to estimate model efficiency by cross validating results with the other 70% of the data (Cutler et al. 2007). Model efficiency is estimated as one minus the ratio between the mean squared error (MSE) and response variable variance (Pang et al. 2006). We used the R package randomForest 4.6–2 to estimate model efficiency (Breiman & Cutler 2011).

The contribution of each factor to model predictions (or importance) was assessed by the node impurity metric, which measures changes in the residual sum of squared errors by splitting the factor at each node of the tree (Breiman & Cutler 2011). Node impurity values for each factor were normalized by the sum of the total node impurity and reflect the relative importance of each factor estimate using randomForest 4.6–2 R package (Breiman & Cutler 2011). To visualize the higher order interactions between factors, we applied a CART analysis to each dataset. With CART, we were able to identify the specific factor combinations that generated lower and greater estimates of soil loss (R package rpart 4.1–9; Therneau & Atkinson 2011), indicating which factors create the most uncertainty in model predictions.

Results

GSAs across all the datasets showed that the RUSLE predictions are most sensitive (i.e. produce the most uncertain predictions) to the cover management factor (C factor) and topography factor (LS) regardless of factor and parameter estimates (Figures 1 and 2). When C factor distributions are narrow (e.g. in Malta), the LS factor became the most important factor (Figure 2). The relative importance of the C factor was at least 1.4 times higher than LS factor in each dataset except in Malta (Figure 2). At the parameter level, root mass density (Bur) and percent surface cover (Sp) were the most important parameters from the C factor driving uncertainty in model predictions in the theoretical dataset (Table 1, Figure 3). This result was consistent despite significant differences among factor estimates across datasets (p-value <0.05) except for C factor in Slovenia and Latvia

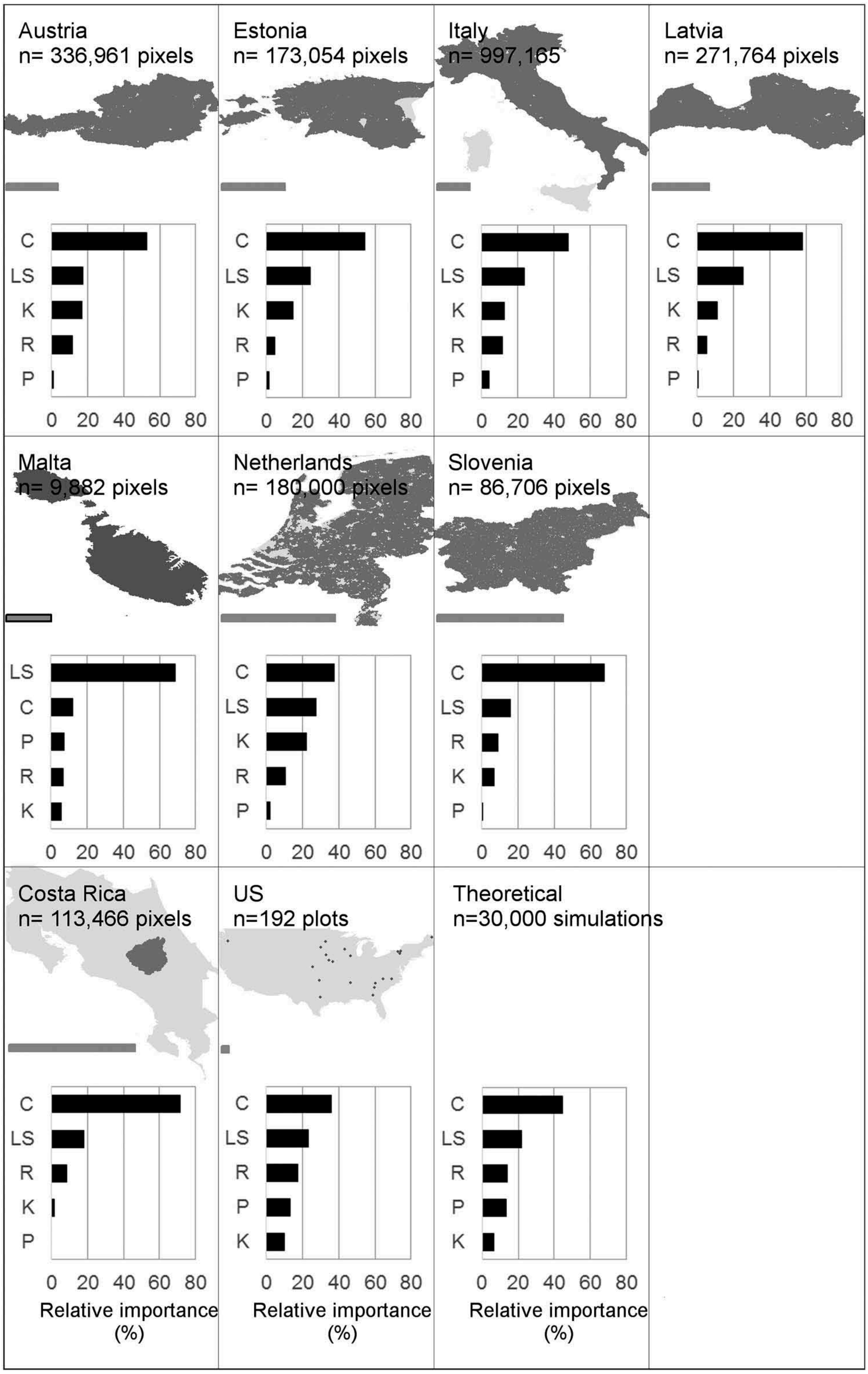

Figure 2. RUSLE factor importance for EU (seven countries), the US, CR and theoretical dataset. Sample size (*n*) and sample distribution are indicated with dark gray points. Country size is indicated with the 200 km gray scale (except for Malta, outlined scale = 10 km). Relative importance is the normalized factor node impurity metric obtained from the Random Forest statistical procedure and indicates the relative importance of each factor in influencing model predictions.

(p-value = 0.13), LS factor in Malta and the US data (p-value = 0.18) and P factor in Latvia and Estonia data (p-value = 0.20) (Figure 1).

Factor distribution and variability may cause differences in the less sensitive factors (Figures 1 and 2). After the C and LS factors, soil erodibility (K factor) was ranked as the third most sensitive factor in both, low (e.g. Estonia, Latvia and the Netherlands) and highly erosive countries (e.g. Austria, Italy) (Figure 2), while R factor was the third most sensitive in only highly erosive countries and datasets (Figure 2). LS factor was the second most sensitive factor in the CR dataset despite the greater rainfall-runoff erosivity (R factor) estimates (Figure 2).

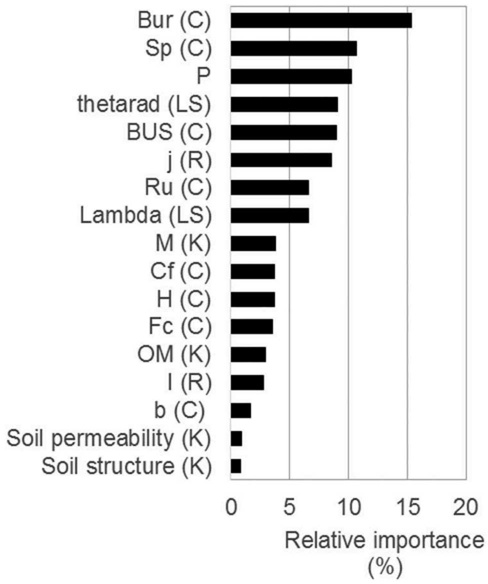

Figure 3. Parameter (factor) importance for the theoretical dataset. See Table 1 for parameter description.

Higher order factor interactions, illustrated by the CART analysis, confirm that the interaction between C and LS factors is the most important in determining greater magnitudes of soil loss across datasets (Figure 4). In the EU dataset, severe soil loss (>10 t ha^{-1} year^{-1}) occurred mostly in the erosive countries and in areas with different C and LS thresholds. For example, in Italy and Malta, croplands with C values above 0.08 located on areas with LS values of 1.2 or 1.6, respectively, produced erosions above 10.8 t ha^{-1} year^{-1} (Figure 4). Severe erosions in Austria and Slovenia occurred in crops with C values above 0.01 located in roughed (LS > 4.39) and level areas (LS > 0.91), respectively (Figure 4). In the assessed-less erosive countries (Estonia, Latvia, the Netherlands) the interactions between C and LS led to very low soil losses (<2.1 t ha^{-1} year^{-1}). Very low soil losses in the most erosive countries mostly occurred on areas with C values <0.01 (Figure 4). In CR and the US datasets, non-severe erosion (2–10 t ha^{-1} year^{-1}) mostly occurred in croplands with C values <0.07 and <0.30 located on areas with LS values of <9.78 and <1.28, respectively (Figure 4). Finally, the most important factor interaction (C and LS factors) threshold was similar C ~ 0.08–0.07 for the theoretical (within original equation factor estimates) and CR datasets (outside original equation factor estimates) despite the differences in factor estimates and parameterization (Figures 1 and 3).

Severe soil losses account for >65% of the total estimated soil loss in Austria, Italy, Malta and Slovenia data; however, only 17–23% of the area in those regions experience severe soil loss (>10 t ha^{-1} year^{-1}) (Figure 4). On the contrary, 53%, 60% and 74% of the data in the CR, US and theoretical datasets produced severe soil loss (Figure 4).

Discussion

RUSLE sensitivity across datasets

Our results show that cover management (C factor) and topography (LS factor) are the most important factors driving predicted soil loss in RUSLE regardless of parameter estimation technique or range of estimates. Likewise, the C factor produced the greatest degree of variation in model predictions. This agrees with the early sensitivity analyses for the RUSLE when applied at plot level (Risse et al. 1993; Benkobi et al. 1994; Ferreira et al. 1995) but disagrees with previous sensitivity assessments at the watershed level (Biesemans et al. 2000; Falk et al. 2009; Zhang et al. 2013; Galdino et al. 2015). The data from Malta were an exception, where LS is the most important due to the low C factor variability. Consistent importance of C and LS factors across datasets indicates that RUSLE model prediction sensitivity is produced from the original formulation of soil loss process equations, with less uncertainty originating from factor and parameter estimates. RUSLE applications should pay close attention to C and LS factor parameterization regardless of method used or data source spatial level. More generally stated, the greatest model prediction uncertainty is produced from RUSLE C and LS factors formalization. Therefore, focusing on C and LS factors estimation over other factors may greatly reduce model prediction uncertainty.

Topography (LS factor) is affected by digital elevation model spatial resolution (Gertner et al. 2002; Yang et al. 2003; Van Remortel et al. 2004), its quality (Lewis et al. 2005) and by the equations used to calculate the factors, particularly the L factor (Van Remortel et al. 2004; Kinnell 2007). However, LS importance was similar between CR and EU datasets despite the differences in dataset parameterization (Panagos, Borrelli, Meusburger, et al. 2015).

We expected the R factor to be more important, particularly in CR, due to significantly larger R values and previous sensitivity analysis in a subtropical zone (Zhang et al. 2013), yet this was not the case. Nevertheless, the R factor was ranked as third most important in countries and datasets with significantly larger rainfall erosivity and average soil loss values such as CR, Slovenia, the US and the theoretical dataset. The P factor was often ranked as least important despite the novel efforts to quantify it for the EU (Panagos, Borrelli, Meusburger, van der Zanden, et al. 2015). The P factor was only ranked as third most important in Malta due to the average value of 0.5 and the large density of stone walls (Panagos, Borrelli, Meusburger, van der Zanden, et al. 2015).

Our consistent results obtained in the GSA were due to the capacity of the method to capture a

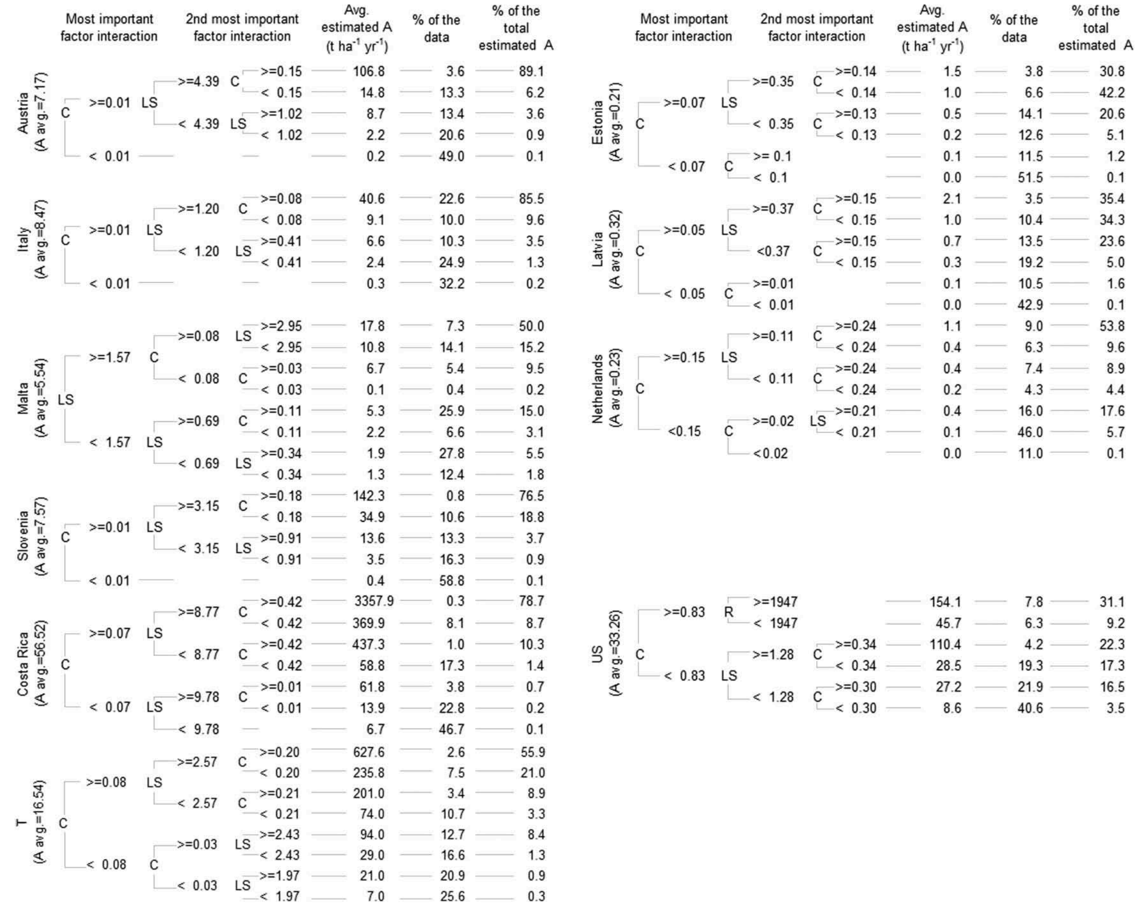

Figure 4. RUSLE factor interactions for EU (seven countries), the US, CR and theoretical datasets obtained from the CART analysis. Each dataset is represented as a tree, the left side of the tree represents factors combinations and the right side represent the end of the tree with the averaged soil loss, the percentage of data that follow each specific factor combination (or tree branch) and the percentage of the total estimated soil loss. Factor interactions importance is from left to right, and the value next to each factor is the factor threshold value at which the data are split and combined with the next factor.

broader range of model sensitivities and interactions among model factors and parameters (Wagner 1995), both of which are important in understanding and parameterizing complex models (Harper et al. 2011). LS and C factors interactions indicate ~21% of the area (sampled pixels, plots or simulations) is frequently the source of severe soil losses (>10 t ha^{-1} yr^{-1}) particularly in the erosive countries in EU, indicating that most soil loss occurs in limited landscape areas. These results are consistent with soil loss assessment in Eastern Himalaya (Mandal & Sharda 2013). In contrast, we found that in CR, the US and in the theoretical data, around 62% of the area produced severe soil loss (> 10 t ha^{-1} year^{-1}) which is also consistent with soil loss assessment in Tanzania (Ligonja & Shrestha 2013).

These findings have important implications for ecosystem service management of all RUSLE factors, C is the most easily managed factor (Panagos, Borrelli, Meusburger, Alewell, et al. 2015). Ecosystem service-based interventions (Fremier et al. 2013; Mandal & Sharda 2013) and landscape planning (de Groot et al. 2010) can facilitate and guide targeted soil conservation efforts to greatly reduce extremely high soil loss rates (Cerda et al. 2009; Galdino et al. 2015).

While novel and promising methods are tested to improve factor parameterization and model accuracy, practitioners can target efforts to reduce soil loss through ecosystem services-based interventions (i.e. plant cover). Vegetation influences soil loss through complex processes (Schwilch et al. 2012). For example, incorporating cover crops, grass filters, hedgerows, intercropping or agroforestry systems provide a wide range of ecosystem services (Schipanski et al. 2014; Thorn et al. 2015; Garbach et al. 2016). In particular, increased root density and surface cover reduce and control soil loss (Linse et al. 2001; Gyssels et al. 2005; De Baets et al. 2006, 2011; García-Orenes et al. 2012). Our theoretical dataset indicated similar results in which, the density of live and dead roots found in soil surface and the percentage of surface cover are the most important C factor parameters for determining soil loss.

Incorporating sensitivity analysis into decision-support tools to assess ecosystem services

Our discussion is not intended to support or refute the application of RUSLE or other empirical models. We understand RUSLE's wide use and acceptance (Eslinger et al. 2005; Panagos, Borrelli, Poesen et al. 2015) is due to its relative ease of calibration and lack of data requirements compared with more physically based models (Bewket & Teferi 2009). However, there is a pressing need to guide science-based policy (Daily et al. 2009; Adhikari & Nadella 2011). A range of tools is needed to help untangle relationships between management decisions, ecosystem processes and ecosystem services, particularly at the scale at which ecosystem services are produced and consumed (Bagstad et al. 2013; Fremier et al. 2013).

We find that there is still poor adoption of sensitivity analysis in ecosystem service assessments, despite its importance (Renard & Ferreira 1993; Ferreira et al. 1995) as a basic modeling exercise to support real-world decision-making (Ruckelshaus et al. 2013). We have demonstrated the applicability of GSA to assess model uncertainty to improve science-based decision-making. Our goal is to push the adoption of GSA as a companion tool with empirical models for decision-support of ecosystem services science (see Renard & Ferreira 1993; Ferreira et al. 1995).

Conclusions

Empirical models play a key role as support tools for ecosystem services assessment and decision-making. The applicability of empirical-based models outside the original factor and parameter estimates is a legitimate concern; however, we argue this is better than a total lack of science. Here, we demonstrate the applicability and importance of conducting GSA to assess model uncertainty, which can be a companion analysis for model accuracy. We used a widely used empirical model to assess soil loss, which incorporates universally recognized factors affecting erosion by water. We compared model prediction uncertainty across spatial-level, environmental conditions, and parameterization method to show that cover management and topography factors are the most important factors in RUSLE.

GSA is more robust than LSA since it captures interactions among factors and is less impacted by data variability. We propose the use of GSA, particularly with empirical models, to better understand model sensitivity to parameter estimation (see Harper et al. 2011). GSA can help guide model parameterization efforts on the factors that contribute the greatest uncertainty in model predictions. Similarly, GSA provides rich information for practitioners to target efforts. Coupling sensitivity with accuracy analysis will make the application of empirical models more transparent and effective. This is critical since empirical models will keep playing a key role in decision-making, both in data-poor and data-rich regions of the world; we believe this is a better approach than the alternative of making decisions in the absence of model insights.

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Disclosure statement

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ORCID

Natalia Estrada-Carmona http://orcid.org/0000-0003-4329-5470
Fabrice DeClerck http://orcid.org/0000-0002-3631-8745

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