London, 15th August 2020

Dear Fortunat Joos (editor),

Please find our revised manuscript including tracked changes below. We also included a revised version of the supplementary information as we added two additional figures discussed in the response to referee #3 and updated supplementary information describing the field data, which we modified during the reviewing process.

Following the revised documents, we included our responses to the three reviewers and highlighted the suggested relevant changes. The photos added to the response to referee #3 are excluded in this document to reduce the file size.

Kind regards,

Tony Carr on behalf of the authors

Uncertainties, sensitivities and robustness of simulated water erosion in an EPIC-based global-gridded crop model

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Abstract. Water erosion ~~in agricultural fields~~on arable land can reduce soil fertility and agricultural productivity. Despite the impact of water erosion on crops, it is typically neglected in global crop yield projections. Furthermore, previous efforts to quantify global water erosion have paid little attention to the effects of field management on the magnitude of water erosion. In this study, we analyse the robustness of simulated water erosion estimates in ~~wheat~~ maize and ~~maize~~ wheat fields between the years 1980 to 2010 based on daily model outputs from a global gridded version of the Environmental Policy Integrated Climate (EPIC) crop model. Using the MUSS water erosion equation and country-specific and environmental indicators determining different intensities in tillage, residue handling and cover crops, we obtained the ~~simulate~~ global ~~annual~~ median ~~and average~~ water erosion rates of ~~6~~ 7 t ha^{-1} ~~-~~a^{-1} in maize fields and ~~19~~ 5 t ha^{-1} a^{-1}~~t ha^{-1}~~ in wheat fields~~and an annual soil removal of 7 Gt in global wheat and maize fields~~. A comparison of our simulation results with field data demonstrates an overlap of simulated and measured water erosion values for the majority of global cropland. Slope inclination and daily precipitation are key factors in determining the agreement between simulated and measured erosion values and are the most critical input parameters controlling all water erosion equations included in EPIC. The many differences between field management methods worldwide, ~~and~~ the varying water erosion estimates from different equations and the complex distribution of cropland in mountainous regions add uncertainty to the simulation results. To reduce the uncertainties ~~addressed here and to improve~~in global water erosion estimates ~~generally~~, it is necessary to gather more data on ~~more data on~~ global ~~field management~~farming techniques,~~-~~ to reduce the uncertainty in global land use maps and to collect more data on soil erosion rates ~~more field data from study sites~~ representing the diversity of environmental conditions where crops are grown~~ are necessary~~.

1 Introduction

Water erosion is widely recognized as a threat to global agriculture (den Biggelaar et al., 2004; Kaiser, 2004; Panagos et al., 2018; Pimentel, 2006). The removal of topsoil by surface runoff reduces soil fertility and crop yields due to loss of nutrients, degradation of the soil structure, and decreasing plant-available water capacity (Våje et al., 2005). Water erosion is a natural process, but the impact of agricultural field management on surface cover and roughness is decisive for the magnitude of water erosion. High energy precipitation, steep slopes and lack of vegetation cover intensify water erosion. The most vulnerable areas are mountainous regions, due to steep slopes, the tropics and subtropics, due to abundant high energy precipitation, and arid regions, where precipitation events are rare but often intense and the vegetation cover is sparse. ~~Since agricultural cultivation of mountains and arid regions is limited, the most widespread degradation of agricultural land by water erosion occurs in tropical areas.~~ This global distribution of water erosion is indicated by suspended sediment in rivers (Walling and Webb, 1996). South America, Sub-Saharan Africa, South and East Asia have been identified as the most vulnerable regions to erosion on agricultural land by several prior studies (Borrelli et al., 2017; Pimentel et al., 1995).

Despite its importance for global agriculture, water erosion is usually not considered in global gridded crop model (GGCM) studies. Throughout the past decade, GGCMs - typically combinations of agronomic or ecosystem~~s~~ models and global gridded input data infrastructures - have become essential tools for climate change impact assessments, evaluations of agricultural externalities, and as input data providers for agro-economic models (Mueller et al., 2017). Few assessments have considered land degradation processes and found their inclusion and understanding crucial for evaluating climate change mitigation and adaptation strategies (Balkovič et al., 2018; Chappell et al., 2016). Beyond crop models, there is a need to improve the representation of agricultural management and soil-related processes in earth system models to better reflect carbon sinks and sources (Luo et al., 2016; McDermid et al., 2017; Pongratz et al., 2018). Moreover, improving the representation of water erosion in large-scale models is urgently needed to inform major environmental and agricultural policy programs such as the European Union's Common Agricultural Policy (CAP), the United Nations Sustainable Development Goals (SDGs), the United Nations Convention to Combat Desertification (UNCCD) and the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES) (Alewell et al., 2019). Yet, the necessary algorithms to simulate water erosion are often not incorporated in such models. Exceptions among field-scale crop models, which are frequently used in GGCM ensemble studies, are the Environmental Policy Integrated Climate model (EPIC) and Agricultural Production Systems Simulator (APSIM)~~, which are frequently used in GGCM ensemble studies~~. Compared to other commonly used crop models in GGCMs, EPIC stands out in its detailed representation of soil processes including water erosion and the impacts of tillage on soil properties (Folberth et al., 2019).

Recently, water erosion models such as the Universal Soil Loss Equation (USLE) and the Revised Universal Soil Loss Equation (RUSLE) have been used to estimate global water erosion. Annual global soil removal estimates and water erosion rates on cropland of recent studies range between 13 – 22 Gt and 11 - 13 t ha^{-1} (Borrelli et al., 2017; Doetterl et al., 2012; van Oost et al., 2007). USLE and its modifications were developed in the Midwestern United States and should ideally be evaluated against soil erosion measurements when used for other agro-environmental zones (Evans and Boardman, 2016). However, the uneven distribution ~~and limited availability~~ of field data around the world, the lack of long-term soil measurements in most global regions, and the great variability of the designs of erosion rate measurements hamper the evaluation of global soil loss estimates derived from models (Auerswald et al., 2004; Borrelli et al., 2017; García-Ruiz et al., 2015). In addition, model input data on topography, soil properties and land use are often aggregated over large areas and thus simulation results cannot be directly compared to single field measurements at specific locations.

Most global soil removal estimates using water erosion models are based on static observation approaches or on very coarse timescales that do not fall below annual time steps (Borrelli et al., 2017). Therefore, seasonal patterns of soil cover and precipitation intensities are neglected ~~despite the fact that~~even though they are crucial factors for water erosion. The state of the soil and its cover is influenced by land management, such as the choice of crops, planting and harvest dates, tillage and plant residue management. Accordingly, neglecting the impact of seasonal changes in vegetation cover and field management practices constitutes large uncertainty in global water erosion estimates. Crop models usually simulate crop growth on a daily timescale, which allows attached water erosion models to account for daily changes in weather, soil properties and vegetation cover. However, uncertainty remains due to the increasing requirement of input data for daily simulations, which is especially challenging at a global scale.

The overall aim of this study is (i) to analyse the robustness of water erosion estimates in all global agro-environmental regions simulated with an EPIC-based global-gridded crop model and (ii) to discuss the main drivers affecting the robustness and the uncertainty of simulated water erosion rates on a global scale.~~we examine the uncertainties and sensitivities of water erosion estimates in an EPIC-based global-gridded crop model, and evaluate the robustness of large-scale simulation results against field-scale water erosion measurements aggregated from different world environments.~~ We simulate global water erosion rates in ~~wheat~~ maize and ~~maize~~ wheat fields using different empirical erosion equations in EPIC while accounting for the daily crop growth and development under different field management scenarios. Here, ~~wheat~~ maize and ~~maize~~ wheat are used as representative crops of global agriculture, as they are grown under most environmental conditions and represent contrasting soil cover patterns. Our global simulations ~~were~~ are carried out for a baseline crop management scenario based on a set of environmental and country-specific assumptions and indicators, which is a common practice in global gridded crop modelling. In addition~~ to the baseline scenario~~, we quantify the uncertainties of simulated water erosion values ~~-~~stemming from (i) uncertain field management inputs, and (ii) water erosion calculation methods. We also evaluate the model's sensitivity to all inputs involved in the water erosion calculation to interpret the variability and uncertainties of the simulation results, and to discuss the differences between water erosion equations. Finally, we use field measurements from various locations world-wide to evaluate the robustness of estimated water erosion rates under different environmental conditions.

2 Methods

The simplified framework in Figure 1 illustrates the particular stages of the methodological procedure applied by this study and their relationships to input data and model outputs. Both, input and output data are used twofold. We use input data (i) to simulate daily ~~wheat~~ maize and ~~maize~~ wheat growth and water erosion with EPIC, and (ii) to analyse the sensitivity of relevant model parameters to simulate global water erosion with all equations in EPIC. We use model outputs (i) to calculate a baseline global water erosion scenario, and (ii) to address the uncertainty of simulation results. The final step of this study consists of the robustness check of the model outputs using field data. A detailed description of each element of this study is described in the following sections.

2.1 Modelling water erosion and crop growth with EPIC

2.1.1 Global gridded crop model and input data

We use a global gridded version of the Environmental Policy Integrated Climate (EPIC) crop model, EPIC-IIASA (Balkovič et al., 2014), to simulate soil sediment loss with runoff from 1980 to 2010 while accounting for the daily growth of maize and wheat under different field management scenarios. EPIC can simulate the growth of a wide range of crops and has a sophisticated representation of carbon, nutrient and water dynamics as well as a wide variety of possible field management options, including tillage operations and crop rotations (Izaurralde et al., 2006; Sharpley and Williams, 1990). Originally EPIC was named Erosion-Productivity Impact Calculator and was developed to determine the relationship between erosion and soil productivity. Due to its origin, EPIC has several options to calculate water erosion caused by precipitation, runoff and irrigation (Williams, 1990).

EPIC-IIASA requires global soil and topography data and daily weather data. The basic spatial resolution of the model is 5' x 5' at which soil and topographic data are provided. These are aggregated to homogenous response units and further intersected with a 30' x 30' climate grid, the resolution at which global gridded climate data are available. This results in a total of 131,326 ~~simulation unit~~grid cells with a spatial resolution ranging between~~of~~ 5' to 30' (about 9 km to 56 km near the equator) (Skalský et al., 2008). We use global daily weather data from the AgMERRA dataset for the years 1980-2010 (Ruane et al., 2015), soil information from the Harmonized World Soil Database (FAO/IIASA/ISRIC/ISSCAS/JRC, 2009), and topography from USGS GTOPO30 (USGS, 1997). Each grid cell is represented by a single field characterized by the combination of topography and soil conditions prevailing in this landscape unit. Each representative field has a defined slope length (20 – 200 m) and field size (1 - 10 ha) based on a set of rules for different slope classes (Table S1). The slope of each representative field is determined by the slope class covering the largest area in each grid cell (Table S1). Slope classes are taken from a global terrain slope database (IIASA/FAO, 2012) and are based on a high-resolution 90 m SRTM digital elevation model. ~~We run EPIC in each simulation unit upon a representative field with a defined slope length and field size based on a set of rules for different slope classes (Table S1). The slope class for each simulation unit is defined as the most common slope per simulation unit derived from a global terrain slope database . We use global daily weather data from the AgMERRA dataset for the years 1980-2010 (Ruane et al., 2015), soil information from the Harmonized World Soil Database (FAO/IIASA/ISRIC/ISSCAS/JRC, 2009), and topography from USGS GTOPO30 (USGS, 1997).~~ In each ~~simulation unit~~grid cell, we consider reported growing seasons for maize and wheat (Sacks et al., 2010), and spatially explicit nitrogen and phosphorus fertilizer application rates (Mueller et al., 2012).

2.1.2 Water erosion equations

EPIC includes seven empirical equations to calculate water erosion (Wischmeier and Smith, 1978). The basic equation is:

$$Y = R * K * LS * C * P \qquad (1)$$

where Y is soil erosion in ~~Mg~~ t ha^{-1} (mass/area), R is the erosivity factor (erosivity unit/area), K is the soil erodibility factor in ~~Mg~~ t MJ^{-1} (mass/erosivity unit), LS is the slope length and steepness factor (dimensionless), C is the soil cover and management factor (dimensionless) and P is the conservation practices factor (dimensionless).

The main difference between the water erosion equations available in EPIC is their energy components used to calculate the erosivity factor. The USLE, RUSLE and RUSLE2 equations use precipitation intensity as an erosive energy to calculate the detachment of soil particles. The Modified Universal Soil Loss Equation (MUSLE) equation and its variations MUST and MUSS use runoff variables to simulate water erosion and sediment yield. The Onstad-Foster equation (AOF) combines energy through rainfall and runoff (Table 1).

The erosion energy component is calculated as a function of either runoff volume Q (mm), peak runoff rate q_p (mm h^{-1}) and watershed area WSA (ha), or via the rainfall erosivity index EI (MJ ha^{-1}). The latter determines the detachment of soil particles through the energy of daily precipitation and a statistical estimate of the daily maximum intensity of precipitation falling within 30 minutes. RUSLE2 is the only equation calculating soil deposition. If the sediment load exceeds the transport capacity, determined by a function of flow rate and slope steepness, soil is deposited, which is calculated by a function of flow rate and particle size (USDA-ARC, 2013).

The soil cover and management factor is updated for every day where runoff occurs using a function of crop residues, biomass cover and surface roughness. The impact of soil erodibility on simulated water erosion is calculated for the top-soil layer at the start of each simulation year as a function of sand, silt, clay and organic carbon content. The topographic factor is calculated as a function of slope length and slope steepness. A detailed description of the cover and management, soil erodibility and topographic factor is provided in the supporting information (Text S1). The conservation practice factor is included in all equations as a static coefficient ranging between 0 and 1, where 0 represents conservation practices that prevent any erosion and 1 represents no conservation practices. Typical conservation practice factors can be derived from tables, which include values ranging from 0.01 to 0.35 for terracing strategies and from 0.25 to 0.9 for different contouring practices (Morgan, 2005; Wischmeier and Smith, 1978). Alternatively, values can be derived from local field studies and remote sensing (Karydas et al., 2009; Panagos et al., 2015), from equations using topographical data (Fu et al., 2005; Terranova et al., 2009), or from economic indicators (Scherer and Pfister, 2015).

2.1.3 Field management scenarios

Field management techniques influencing soil properties and soil cover have a significant impact on the amount of water erosion. However, these methods are very heterogenous around the world and data on different field management techniques are sparse. Therefore, three tillage management scenarios – conventional tillage, reduced tillage and no-tillage – were designed by altering parameters related to water erosion to analyse the impact of field management on simulated water erosion and to draw conclusions on its impact on the quality of simulation results.

In the reduced and no-tillage scenarios, we decrease soil disturbance by reducing cultivation operations, tillage depth and surface roughness, and we increase plant residues left in the field after harvest. In addition, we reduce the runoff curve numbers, which indicate the runoff potential of a hydrological soil group, land use and treatment class, with decreasing tillage intensification by using pre-defined values for the cover treatment classes presented in Table 2 (Sharpley and Williams, 1990). By lowering the runoff curve numbers, the impact of reduced tillage practices on the hydrologic balance can be taken into account (Chung et al., 1999). We simulate each tillage scenario with and without green fallow ~~(grass)~~ cover in between growing seasons, leading to a total of six field management scenarios.

2.2 Baseline scenario for estimating global water erosion in wheat and maize fields

We estimate the rate of water erosion globally by combining these six tillage and cover crop scenarios in different regions of the world, using climatic and country-specific assumptions and indicators (Table 3). We chose maize and wheat as two contrasting crop types for analysing water erosion in different cultivation systems. Maize is a row crop with relatively large areas of bare and unprotected soil between the crop rows. The plant density in wheat fields is much higher, which improves the protection of soils against water erosion.

We consider conventional and reduced tillage systems globally while considering no-tillage only for countries in which the share of conservation agriculture is at least 5 %. In tropical regions, we simulate water erosion with a ~~grass~~ green cover in between maize and wheat seasons to account for soil cover from a year-round growing season. In temperate and snow regions, we simulate water erosion affected by both soil cover throughout the year and bare soil in winter seasons. In arid regions, we do not simulate ~~grass~~ green cover in between growing seasons due to the limited water supply.

On slopes steeper than 5 %, we consider only rainfed agriculture, as hilly cropland is irrigated predominantly on terraces that prevent water runoff. To account for erosion control measures on steep slopes, we use a conservation P-factor of 0.5 on slopes steeper than 16 % ~~to simulate contouring~~, and a P-factor of 0.15 on slopes steeper than 30 % to simulate contouring and terracing based on the range of P-values presented by ~~(~~Morgan~~,~~ (2005). The threshold for slopes that are cultivated with conservation practices is based on the slope classes used for the underlying structure of slope information of EPIC-IIASA, from which the three highest slope classes (16–30 %, 30–45 %, >45 %) mark slopes that are less likely to be cultivated without ~~provisions~~ measures to prevent erosion. We choose the MUSS equation for the baseline scenario as it generates the lowest deviation between simulated and measured water erosion as discussed below. Table 3 summarises the field management assumptions ~~used in~~of the baseline scenario used to aggregate erosion rates in each grid cell and region.

2.3 Uncertainty analysis of field management scenarios and water erosion equations

Given the global scale of the analysis and the aggregated nature of available field management information, there is much uncertainty about crop management strategies, which introduces uncertainty in the water erosion estimates. In addition, each water erosion equation gives a different overall erosion estimate. To discuss the uncertainty of simulation results, we evaluate the variance in simulated water erosion rates at grid level due to: (i) different management assumptions, and (ii) the choice of water erosion equation. The variance of simulation outputs is defined as the range between minimum and maximum simulated water erosion rates with all combinations of tillage and cover crop scenarios and with each water erosion equation.

2.4 Sensitivity analysis of model parameters

We use a sensitivity analysis to identify the most essential input parameters to the factors in the seven water erosion equations. We use the Sobol method (Sobol, 1990), which is a variance-based sensitivity analysis that is popular in environmental modelling (Nossent et al., 2011). With this method, it is possible to quantify the amount of variance that each parameter contributes to the total variance of the model output. These amounts are expressed as sensitivity indices, which rank the importance of each input parameter for simulated water erosion. In addition, the sensitivity indices can be used to determine the impact of parameter interactions on the model output.

We test 30 parameters directly connected to the water erosion equations in EPIC. In total, we assign 126,976 random values to all input parameters along a pre-defined triangular distribution or a range of discrete values (Table S2). Water erosion is simulated with EPIC using the seven available equations for each random input combination at 40 locations where wheat and maize are cultivated. To represent a heterogenous distribution of global precipitation regimes, we use the natural break optimisation method to choose locations based on average annual precipitation amounts from 1980 to 2010 (Jenks, 1967). For each location and equation, the most sensitive parameters are ranked. To analyse the impact of precipitation regimes on the sensitivity of each parameter, we use Spearman coefficients (ρ) to determine if positive or negative relationships exist between each parameter's sensitivity and annual precipitation.

2.4 Evaluation of simulated erosion against reported field measurements

We compare~~d~~ our simulated water erosion rates with ~~473~~ 606 soil erosion measurements on arable land ~~-~~from 36 countries representing plot and field scale. Most of the selected erosion rates are based on the ^{137}Cs method. In addition, data from erosion plots and volumetric measurements of rills collected by Auerswald et al. (2009), Benaud et al. (2020) and García-Ruiz et al. (2015) are used. In total, ~~; 314~~ 315 records ~~were~~ are derived by the ^{137}Cs method~~ and,~~ ~~159~~ 188 records from ~~erosion plots~~runoff plots, and 103 records from volumetric measurements of rills. An overview of the field data is presented in Fig. ~~S5~~S4-~~S8~~S7, and the full dataset is available in Table S5.

Guidance on the ^{137}Cs method is provided by Fulajtar et al. (2017); Mabit et al. (2014) and Zapata (2002). The ^{137}Cs radionuclide was released by nuclear weapon tests and from the accident of the Chernobyl Nuclear Power Plant to the atmosphere and subsequently deposited in the uppermost soil layer by atmospheric fallout. After its deposition it was bind to soil colloids and can be moved only together with soil particles by mechanical processes such as soil erosion. Its chemical mobility and uptake by plants is negligible (Mabit et al., 2014; Zapata, 2002). If part of the topsoil contaminated by ^{137}Cs is removed by erosion, the ^{137}Cs concentrations in soil profiles can be used to trace soil movements using mass balance equation (Walling et al., 2014). A major advantage of the ^{137}Cs method is that it provides long term mean erosion rates (representing the period since ^{137}Cs fallout in the 1960s until the time of sampling) and overcomes the problem of high temporal variability of erosion. ~~Further advantages are that the obtained values are retrospective and that the erosion rates are determined for a grid of ^{137}Cs sampling points, which can provide valuable information on the spatial distribution of erosion.~~

Bounded plots are the most commonly used method of erosion measurements. They were introduced in the USA in the 1920s (Hudson, 1993) and were used for the development of USLE and WEPP models (Brazier, 2004). Eroded soil material can be quantified with erosion plots in different ways (total collection of sediment, fractioned collection of sediments using multislott divisors, measurement of discharge and sediment concentration by tipping buckets and Coshocton wheels). The overview of this method is provided by ~~(~~Cerdan et al~~.,~~. (2010); Hudson~~,~~ (1993); Mutchler et al~~.,~~. (1994); De Ploey and Gabriels~~,~~ (1980~~;~~) and Zachar~~,~~ (1982).

The volumetric measurements of rill erosion are used since approximately the 1940s in the USA (Kaiser, 1978 in Evans, 2013) and the 1950s in Europe (Lobotka, 1955), usually at field scale (Boardman, 1990, 2003; Boardman and Evans, 2020; Brazier, 2004; Evans, 2002, 2013; Herweg, 1988; Zachar, 1982). The volume of erosion rills is derived from their lengths and profile cross-section areas, which are measured in field or from terrestrial and aerial photos (Evans, 1986, 1988; Watson and Evans, 1991).

~~To expand the field data records for evaluation, we use also erosion rate measurements from erosion plots collected by . In contrast to the measurements using ^{137}Cs tracer, most plot measurements represent short-term erosion rates. Measurement periods span between 1 and 60 years with an average of 10 years.~~

The overwhelming effect of the experimental methodology on measured erosion rates, the lack of sufficient metadata accompanying erosion measurements and ~~in addition to~~ the granular spatial resolution of our simulation setup hinders a direct comparison between simulated and observed water erosion rates. Instead we compare aggregated simulated and observed erosion values for different slope and precipitation classes to analyse the robustness of simulated water erosion rates under different environmental conditions. Therefore, only ~~field~~ measurements with recorded slope steepness and annual precipitation are used. Where annual precipitation ~~amounts are~~ is not recorded, ~~they are~~it is taken from the WorldClim2 dataset (Fick and Hijmans, 2017). Due to the non-normal distribution of the simulated and measured data, the median deviation (MD) is used as a measure to compare the agreement between simulated and measured water erosion values.

3 Results

We estimate global ~~annual average and~~ median water erosion rates ~~in wheat and maize fields~~ of ~~19~~ 7 t ha^{-1} and ~~6~~ 5 t ha^{-1} in maize and wheat fields, respectively. ~~(Fig. S3).~~ ~~The difference between these values indicates that the global average is influenced by extreme values.~~ The total removal of soil in global ~~wheat~~ maize and ~~maize~~ wheat fields is estimated to be ~~7~~ 5.3 Gt a^{-1}~~.~~ and 1.9 Gt a^{-1}~~.~~, respectively. The map in Figure 2 illustrates the global distribution of simulated water erosion rates. Highest water erosion is simulated in mountainous regions and regions with strong precipitation, especially in tropical climate zones. In Asia, those regions are widespread in the east, south-east and the Himalaya region. In Africa, similar areas with high water erosion values are spread around the continent and are most common at the west coast and in East Africa including broad areas in Guinea, Sierra Leone, Liberia, Ethiopia and Madagascar. In South America, highest water erosion is simulated in the south of Brazil and regions around the Andes mountain range and the Amazon river basin. The highest water erosion values on the American continent ~~were~~ are simulated in tropical Central America and the Caribbean. In North America, highest water erosion occurs along the west coast and in the east. Water erosion in Europe is highest in Mediterranean areas and around the Alps.

Median annual water erosion values for the five largest wheat and maize producing countries demonstrate the strong impact of climate and topography on simulated water erosion. In Brazil, China and India, where a large proportion of cropland is in tropical areas, water erosion is relatively high with annual median values of 10 t ha^{-1}, 6 t ha^{-1}, and 37 t ha^{-1}, respectively. In Russia and the United States annual median values are much lower with 1 t ha^{-1}, and 2 t ha^{-1}, respectively. Overall, Figure 2 illustrates the large variation in simulated water erosion between tropical climate regions and regions with a large proportion of flat and dry land.

3.1 Sources of model uncertainty related to management assumptions and method selection

The uncertainty of the simulation results due to management scenarios and the choice of water erosion equations is highest in regions most vulnerable to water erosion (Figure 3). The annual median uncertainty range at each grid cell due to management is 30 t ha^{-1}. For 97 % of grid cells, the lowest erosion rates are simulated with management scenarios including no-tillage and cover crops. For 86 % of grid cells, maximum erosion rates are simulated under conventional tillage without cover crops. The annual median uncertainty range at each grid cell due to the choice of erosion equation is 23 t ha^{-1}. In 74 % of grid cells, the lowest erosion rates ~~were~~ are simulated with the MUSS equation. The highest erosion values ~~were~~ are simulated with the RUSLE equation (46 %), followed by the USLE equation (25%).

In most locations, the uncertainty due to field management exceeds the uncertainty caused by choice of erosion equation. For 46 % of grid cells, management scenarios cause the prevailing uncertainty, which we defined as the higher uncertainty range by at least 5 t ha^{-1}. The selected erosion equation causes higher uncertainty by at least 5 t ha^{-1} in 14 % of grid cells. The map in Figure 4 illustrates the global distribution of prevailing uncertainty sources.

3.2 Main drivers of the global erosion model

We designed the sensitivity study to explain the large variability of simulated water erosion rates in different regions and to discuss the main differences between water erosion equations. Water erosion is highly sensitive to slope steepness (SLP) for all equations. The first-order sensitivity index of the slope parameter indicates that 46–54 % of the variance in the model output is attributable to the slope, without considering interactions between the input parameters (Table 4). Daily precipitation (PRCP) is the second most important parameter for calculating water erosion, with an individual contribution of around 9–20 % to the variance of the output. The remaining parameters contribute together 4–13 % to the output variance.

The first-order sensitivity indices do not include interactions between input parameters, which leads to the sum of all first-order sensitivity indices being lower than 1. The total-order sensitivity indices sum all first-order effects and interactions between parameters, which leads to overlaps in case of interactions and a sum greater than 1. The differences between the first-order and the total-order indices can be used as a measure to determine the impact of the interactions between a specific parameter with other parameters. The total-order sensitivity indices show that slope steepness, including interactions to other parameters, contributes 63–75 % of the output variance from which 18–21 % are due to interactive effects with other parameters (Table 5). The total-order sensitivity indices from precipitation range from 21–36 %, from which 10–18 % is due to interactions with other parameters.

The high sensitivity of slope and precipitation is similar for all equations, but the most sensitive parameters after these can be different for each equation. Equations estimating erosion energy by surface runoff and the RUSLE2 equation are very sensitive to the hydrological soil group (HSG), which determines the soils infiltration ability. This parameter is used in the calculation of the curve number, which defines the partition of precipitation into runoff and infiltration. Also, the land use number (LUN), which is ranked among the most sensitive input parameters, is used for the calculation of the curve number. The most sensitive parameters of the USLE and RUSLE equation, following slope inclination and daily precipitation, are soil texture classes (SAND & SILT) followed by daily temperature changes (TMX). Crop residues (ORHI) are relatively important for all equations but especially important for equations based on rainfall-energy. Other parameters relevant for field management, such as surface roughness and mixing efficiency of the topsoil, have little influence on water erosion.

The sensitivity of slope steepness has a strong positive correlation with the amount of annual precipitation at each location ($\rho = 0.69$, $p<0.01$). The increase in the sensitivity of slope steepness with increasing annual precipitation is demonstrated in Figure 5, which illustrates substantially lower sensitivity indices at dry locations compared to wet locations. In contrast, the sensitivity indices of daily precipitation are negatively correlated to annual precipitation with a moderate strength ($\rho = 0.45$, $p<0.05$). Depending on the equation, strong positive or negative correlations between SIs and annual precipitation also exist for other parameters such as slope length, soil texture, soil organic carbon, channel length, channel slope and watershed area (Table S4).

3.3 Evaluation of simulation results against field data

The most recent estimated global water erosion rates on cropland of 11 - 13 t ha^{-1} derived from a comparable method (Borrelli et al., 2017; Doetterl et al., 2012; van Oost et al., 2007) lie above ~~between~~ our simulated median water erosion rates of 7 t ha^{-1} and 5 t ha^{-1} for maize and wheat fields, respectively. Similarly, our global water erosion estimates in maize and wheat fields are lower than the median value of 9 t ha^{-1} from 606 water erosion measurements from cropland around the world.

~~value of 6 t ha^{-1} and our global average value of 19 t ha^{-1}. In comparison to the median and average values of 473 water erosion measurements of 15 t ha^{-1} and 23 t ha^{-1}, respectively, the global median and average values simulated with our baseline scenario are lower.~~

To evaluate the agreement between simulated and observed data, we compare median values between simulated and measured erosion rates grouped by precipitation and slope classes, which are defined along the whole range of recorded slope inclinations and annual precipitation amounts of the field data (Figure 6a). Although slope and precipitation classes from the field are spread unevenly, they cover most climatic and topographic characteristics relevant to global agriculture. The comparison illustrates that the deviation between simulated and field data is highest for locations with steep slopes and high annual precipitation. Where slopes are steeper than 8 % and annual precipitation is higher than 1000 mm, the median of simulated water erosion exceeds the median of measured water erosion in most cases by at least 50 t ha^{-1}. With decreasing slope steepness and annual precipitation, the median deviation between simulated and measured data is decreasing. Where both slope steepness is below 8 % and annual precipitation is below 1000 mm, the median deviation is lower than 5 t ha^{1} in most cases. ~~Higher deviations at those locations are caused by simulated water erosion values being lower than measured values.~~ A comparison of measured and simulated water erosion using other equations with the baseline scenario can be found in Fig. ~~S9~~S8.

The boxplots in Figure 6b illustrate the range of water erosion values measured in the field and simulated with the baseline scenario. The high ~~median~~ deviation between observed and simulated values for grouped locations with slopes steeper than 8 % and annual precipitation higher than 1000 mm can also be observed between the range of simulated and measured water erosion values. Outside locations combining steep slopes and strong precipitation, median deviation between simulated and measured data is lower than the variability within the field data. The range of values at locations with lower precipitation and slope steepness demonstrates that simulated values are mostly below measured values in those environments.

The uncertainty in the choice of management scenarios and water erosion equations included in our baseline scenario leads to an uncertainty of the deviation between simulated and measured erosion values. This uncertainty is demonstrated in Figure 6b by additional three bars illustrating the range of simulated medians ~~defined by minimum and maximum medians stemming from~~due to contrasting tillage management scenarios, cover crop scenarios and different water erosion equations. ~~The uncertainty ranges indicate which management scenario and water erosion equation lead to simulation results that agree best with field data for the evaluated slope and precipitation classes.~~

At locations with low to moderate slope steepness and annual precipitation, the measured water erosion values agree best with the simulation values generated under scenarios implying larger water erosion, such as high intensity tillage and low soil cover. On the other hand, at locations with steep slopes and intensive precipitation, the measured values are closer to the simulated values under scenarios with less intensive tillage and more soil cover. In addition, the varying sensitivities of each water erosion equation lead to a different magnitude of water erosion values in different environments. On low to moderate slopes, water erosion simulated with the MUSS equation is lowest, whereas RUSLE generates the highest values. On steep slopes, the RUSLE equation generates the lowest water erosion values, which agree best with the measured values. The options to increase and decrease simulated water erosion with different field management scenarios and water erosion equations creates both uncertainty in the model results, but also the possibility to closely match field data.

At locations combining steep slopes and intense precipitation, most management scenarios and equations generate water erosion values that are higher than the measured values. However, those environmental conditions cover only a small share of global cropland. Cultivation areas with slopes steeper than 8 % and annual precipitation higher than 1000 mm represent only 7 % of global maize and wheat cropland in our ~~simulation unit~~grid cells. The map in Figure 7 illustrates that the highest concentration of these areas is in East and South-East Asia, followed by Central and South America, and Sub-Saharan Africa.

4 Discussion

4.1 Varying robustness of simulated water erosion in different global regions

Global water erosion estimates generated with an EPIC-based GGCM and our baseline scenario overlap with observed water erosion values under most of the climatic and topographic environments where ~~wheat~~ maize and ~~maize~~ wheat are grown. However, global ~~wheat~~ maize and ~~maize~~ wheat land include locations where environmental characteristics differ significantly from the Midwestern United States, where the data was collected to develop the water erosion equations embedded in EPIC. The USLE model and its modification were developed with data for slopes of up to 20 %, which makes model application for steeper slopes uncertain (McCool et al., 1989; Meyer, 1984). Furthermore, the relations between kinetic energy and rainfall energy in the American Great Plains differ from other regions in the world (Roose, 1996). Similarly, the runoff curve number method, which is the key methodology for the calculation of surface runoff, is based on an empirical analysis in watersheds located in the United States and might be less reliable in different regions of the world (Rallison, 1980). Due to the high sensitivity of slope steepness and daily precipitation for the calculation of water erosion, the reliability of the tested equations decreases in regions where typical slope and precipitation patterns differ from the Midwestern

US. Although some studies have successfully used USLE and its modification under a different environmental context (e.g. Alewell et al., 2019; Almas and Jamal, 2009; Fischer et al., 2018; Sadeghi and Mizuyama, 2007), many studies have concluded that the accuracy of these models may be reduced outside the environments they were created without calibration and model adaptation (e.g. Cohen et al., 2005; Labrière et al., 2015).

The skewed distribution of simulated water erosion values influenced by extreme soil loss rates in few fields highly sensitive to water erosion results in a large difference between the global ~~global~~ median value of 6 t ha^{-1} a^{-1} and the global average value of 19 t ha^{-1} a^{-1} (Fig. S~~3~~9)~~.~~. Due to the strong influence of outliers on average values, ~~the~~ we used ~~simulated~~ median values to ~~is a better representation of~~represent global and regional water erosion rates in wheat and maize fields. The high sensitivity of the simulation results to slope inclinations and precipitation suggests that a significant share of the estimated soil removal of 7.2 Gt a^{-1} originates from small wheat and maize ~~fields~~ cultivation areas on steep slopes with strong annual precipitation.

4.2 Sources of uncertainties in global water erosion estimates

4.2.1 Uncertain land use in mountainous regions

Changing climatic conditions with increasing elevation and the variable soils in mountainous regions can favour crop cultivation in higher elevations over lower elevations (Romeo et al., 2015). However, upland farming without soil conservation measures can lead to exhaustive soil erosion and can become a critical problem for agriculture (Montgomery, 2007). Large areas of land have been abandoned due to high erosion rates as soils were no longer able to support crops (Figure *8*) (Romeo et al., 2015). As mountain agriculture is determined by various environmental and socio-economic factors, the cultivation of steep slopes can be very variable between regions. Regional erosion assessments in mountainous cropland suggested that areas with extreme water erosion rates are mainly limited to marginal steep land cultivated by smallholders (Haile and Fetene, 2012; Long et al., 2006; Nyssen et al., 2019). In some mountainous regions efforts to remove marginal farmlands from agricultural production, and programs to improve land management on steep slopes have reduced high water erosion rates (Deng et al., 2012; Nyssen et al., 2015). On the contrary, recent pressure through increasing population and crop production demands has resulted in re-cultivation of hillslopes and a reduction of fallow periods, which limits the recovery of eroded soil (Turkelboom et al., 2008; Valentin et al., 2008).

To analyse the sustainability of simulated maize and wheat cultivation systems exposed to high erosion rates, we compare simulated annual eroded soil depth with a global dataset on modelled sedimentary deposit thickness (Pelletier et al., 2016). The comparison shows that at 4 % of grid cells permanent maize and wheat cultivation would not be sustainable as the whole soil profile would be eroded at the end of the simulation period (Fig. S10). Most of the unsustainable agriculture is simulated on steep slopes. Although we account for conservation techniques and cover crops, we do not imitate the highly complex farming practices involving intercropping techniques and fallow periods, which are common on hillslopes typically managed by smallholders (Turkelboom et al., 2008). Moreover, we assume that the slope class representing the largest area in each grid cell most likely represents the largest share of arable land. This builds on the idea that a spatially extensive and diverse landscape can be represented by a single “representative field” characterized by the prevailing topography and soil conditions found in the landscape. On hilly terrain this setup simulates maize and wheat cultivation on steep slopes and thus mainly represents unsustainable agriculture. Although unsustainable maize and wheat cultivation can be observed in several mountain regions, cropland is very heterogeneously distributed in mountains and thus erosion rates from one representative field are highly uncertain.

The uncertainty in cropland distribution can partly be reduced by developing a higher resolution global gridded data infrastructure, which is currently not available for EPIC-IIASA. However, due to the large uncertainty in global land cover maps (Fritz et al., 2015; Lesiv et al., 2019), an explicit spatial link between cropland distribution and the corresponding slope category cannot be established without on-site observations. We test the impact of this uncertainty for erosion estimates in Italy, where large maize and wheat cultivation areas are distributed on both flat terrain in the north and mountainous regions in the south. In an ideal scenario where cropland is limited to flattest land available per grid cell, median simulated water erosion in Italy would be reduced to tolerable levels below 1 t ha^{-1}. However, in a scenario, where the most common slopes per grid cell are cultivated, median simulated water erosion increases to 14 t ha^{-1} due to high water erosion simulated in Italy's mountainous regions (Fig. S11). This suggests a high uncertainty in global water erosion estimates due to uncertain spatial links between maize and wheat cultivation areas and different slope categories.

4.2.2 Uncertain field management

Simulated water erosion values are highly variable depending on the ~~choice of water erosion equation and~~ field management scenario. ~~The water erosion equation chosen for the baseline scenario generates the lowest global soil removal estimate. Different water erosion equations embedded in EPIC estimate a higher global soil removal of up to 11 Gt a^{-1} as well as higher median and average water erosion rates of up to 19 t ha^{-1} a^{-1} and 29 t ha^{-1} a^{-1}.~~ Simulating cover crop and no-tillage worldwide results in the lowest global soil removal of 2 Gt a^{-1} with median ~~and average~~ water erosion rates of 1 t ha^{-1} a^{-1} ~~and 7 t ha^{-1} a^{-1}~~ and simulating no cover crops and conventional tillage worldwide results in the highest global soil removal of 13 Gt a^{-1} with median ~~and average~~ water erosion rates of ~~19~~ 17 ~~and 37~~ t ha^{-1} a^{-1}. These variations cause further uncertainties in the simulation results.

Indeed, a proper reconstruction of a business-as-usual field management is important to further narrow down the uncertainty in global crop modelling (Folberth et al., 2019). In this study we allocated ~~a~~ prevailing field management using a set of environmental- and country-specific indicators, similarly to ~~(~~Porwollik et al.~~,~~ (2019). For example, we accounted for conservation agriculture only in countries where this management strategy is likely according to AQUASTAT (FAO, 2016). Furthermore, by assuming cover crops in b~~e~~etween wheat and maize seasons we simulated more complex cropping systems in the tropics, where long and year-round growing seasons and frequent multi-cropping farm practices barely leave the soil uncovered. Hence, we did not simulate bare fallow in the tropics as erroneously high water erosion values would have been simulated at locations with heavy precipitation falling on bare soil. In addition, conservation practices such as contouring and terracing are crucial to reduce the simulation of high water erosion values on steep slopes. We simulated these practices for specific slope classes under the assumption that farmers around the world uniformly use conservation practices when cultivating on steep slopes. The most relevant parameters used for tillage scenarios are related to crop residues left in the field. In addition, equations directly connected to surface runoff are strongly influenced by the land use number used to determine the impact of cover type and treatment on soil permeability. While both crop residues and green fallow decrease water erosion significantly, especially in the tropics, their use varies widely between regions and even farms, based on a complex web of factors such as institutional factors, farm sizes, risk attitudes, interest rates, access to markets, farming systems, resource endowments, and farm management skills (Pannell et al., 2014). Also, soil conservation measures such as terraces or contour farming significantly influence water erosion but are very heterogeneously used between regions, farming systems and farmers. Our baseline scenario is a very rough depiction of the complex patterns of field management around the world but attempts to represent these highly influential practices with the limited available data.

4.2.3 Variable estimates from different water erosion equations

The water erosion equation chosen for the baseline scenario generates the lowest global soil removal estimate. Different water erosion equations embedded in EPIC estimate a higher global soil removal of up to 11 Gt a^{-1} as well as higher median water erosion rates up to 19 t ha^{-1} a^{-1}. The MUSS water erosion equation chosen for the baseline scenario generates water erosion rates closest to the field data. The focus of equations on either rainfall energy or runoff energy is relevant for the different simulation results under specific environmental conditions. Equations based on rainfall-energy such as RUSLE and USLE simulate higher water erosion values than the other equations at most locations. However, on steep slopes they generate the lowest water erosion values as runoff becomes a greater source of energy than rain with increasing slope steepness (Roose, 1996). Also, the varying sensitivities of other parameters to the equations such as soil properties and management parameters lead to a varying agreement between simulated data and field data depending on the equation selection. Detailed field data would facilitate the choice of an appropriate equation to simulate water erosion worldwide or for a specific region.

4.3 The difficulty of evaluating large-scale erosion estimates with field data

The selection of field data for evaluating simulated water erosion was limited by the low availability of suitable water erosion observations covering the entire globe. The lack of reliable data on water erosion rates is a severe obstacle for understanding erosion, developing and validating models and implementing soil conservation (Boardman, 2006; Nearing et al., 2000; Poesen et al., 2003; Trimble and Crosson, 2000). The main reasons for the low availability of suitable data to evaluate simulated water erosion rates are twofold: (i) erosion monitoring is expensive, time consuming and labour demanding; and, (ii) primary data and metadata of measurement sites accompanying final results are often not available and many older measurements are poorly accessible as they are not available online (Benaud et al., 2020). A variety of factors influencing water erosion such as climate, field topography, soil properties and field management need to be considered when modelling water erosion but are often not reported in available field measurements (García-Ruiz et al., 2015). This hampers a direct comparison between simulated and observed water erosion values. We demonstrated the varying match between measured and simulated water erosion using different tillage and cover crop scenarios. Metadata on field management often only provides the crop cultivated and therefore the conditions under which erosion was measured in the field are not known sufficiently to evaluate erosion values simulated under different field management scenarios. Similarly, information on field topography and soil properties is often not provided with recorded field measurements and thus their use is limited in an evaluation of water erosion estimates simulated in different global environments. Moreover, ~~Moreover, the geographical distribution of erosion data is unbalanced. M~~most data are concentrated in the United States, West Europe and the West Mediterranean (García-Ruiz et al., 2015). In summary, there is a lack of field data representing all needed regions, situations and scenarios (Alewell et al., 2019).

The appropriate selection of field data to evaluate model outputs needs to be considered as well. At different spatial scales different erosion processes are dominant and consequently different erosion measurement methods are suitable (Boix-Fayos et al., 2006; Stroosnijder, 2005). ~~An overview of erosion methods is provided~~

~~by Hudson, (1993) and Lal et al. (1994). Recently, most erosion methods are subject of significant criticism (García-Ruiz et al., 2015) and recent development of methodology is in crisis (Stroosnijder, 2005).~~ Most authors use very heterogeneous data sets to evaluate their models, involving data generated by different methods at variable time and spatial scales and variable quality. For example, Doetterl et al. (2012) used plot data, suspended sediments from rivers, and data from RUSLE modelling. Borrelli et al. (2017) used soil erosion rates (measurement methods are not specified), remote sensing, vegetation index (NDVI) and results of RUSLE modelling. In his review on erosion rates under different land use, Montgomery (2007) used field data derived from erosion plots, field-scale measurements, catchment-scale measurements using hydrological methods, ^{137}Cs-method, soil profile truncation and elevated cemetery plots.

Whilst all erosion measurement methods are open to criticism, ~~W~~we decided to use only data obtained by field measurements from ~~erosion~~ runoff plots, ~~and~~ by ^{137}Cs method and volumetric surveys as ~~both~~ these methods are most suitable at plot, slope and field ~~and slope~~ scale. Geodetic methods such as erosion pins and laser scanner are also used at ~~these~~ plot to field scales, but their accuracy is much lower than the accuracy of plot measurements and ^{137}Cs method. Furthermore, erosion pins are mainly suitable for areas with extreme erosion rates (Hsieh et al., 2009; Hudson, 1993), and laser scanners have difficulties to recognize vegetation (Hsieh et al., 2009). Other commonly used methods such as ~~volumetric method,~~ hydrological method (measurements of discharge and suspended sediment load) and bathymetric method are more suitable for larger scales and ~~the latter two methods~~ involve a significant portion of channel erosion, which is not related with agricultural land (García-Ruiz et al., 2015). We did not consider plot experiments using rainfall simulators as they are usually performed on small plots with ~~use~~ artificially generated rainfalls, which mostly have very low energies and thus generate low erosion rates (Boix-Fayos et al., 2006; García-Ruiz et al., 2015) ~~(Boix-Fayos et al., 2006), and usually only small plots are used for rain simulation experiments (García-Ruiz et al., 2015)~~.

The ^{137}Cs method was criticised by ~~(~~Parsons and Foster~~,~~ (2013), who questioned assumptions about the ^{137}Cs behaviour in the environment (variability of the ^{137}Cs input by wet fallout, its microspatial variability at reference sites, its possible mobility in certain soils, the ^{137}Cs uptake by plants and other aspects of ^{137}Cs behaviour in soil). To confront the criticism against the ^{137}Cs method, ~~(~~Mabit et al~~.,~~. (2013) discussed all objections raised by Parsons and Foster (2013) and confirmed its accuracy by listing several studies, in which ^{137}Cs based erosion rates are compared with erosion rates derived from direct measurements. The ^{137}Cs method is based on a set of presumptions which should be met to produce useful results and thus careful interpretation of the obtained results is needed (Fulajtar et al., 2017; Mabit et al., 2014; Zapata, 2002).

Similarly, erosion rates obtained by volumetric measurements require careful interpretation as they are exposed to various potential sources of errors and do not account for interill erosion. Although the latter can be neglected under certain circumstances, studies from Europe and semiarid areas of the USA have reported that interill erosion contributed significantly to the amount of soil eroded in fields (Boardman and Evans, 2020; Parsons, 2019). Further, measuring the lengths and cross-sections of rills during field surveys or on terrestrial and aerial photos can be very subjective (Panagos et al., 2016). Different approaches used to detect and measure rills in fields can cause variability in calculated erosion volumes up to a factor of two (Boardman and Evans, 2020; Casali et al., 2006; Watson and Evans, 1991). In order to obtain soil erosion rates in weight units, soil volumes need to be converted using the soil bulk density, which is often based on estimates (Evans and Brazier, 2005).

The shortcomings of erosion plot measurements were discussed by several authors (Auerswald et al., 2009; Brazier, 2004; Evans, 1995, 2002; Loughran et al., 1988). Erosion plots have various sizes and shapes (few meters to few hundreds of meters) and various approaches of sediment recording are used (total collection, multislot divisors, tipping buckets, Coshocton wheels), which all involve significant uncertainties. Although some long-term plot experiments exist, many plot measurements fail to cover the whole year erosion cycle (Auerswald et al., 2009). Often, they have to be removed during land management operations such as seeding, ploughing, or they are too expensive and labour demanding.

Despite all the shortcomings of available soil erosion data, most data provide valuable information (Benaud et al., 2020).

The evaluation against field measurements in this study provided a first indication of the robustness of results under specific topographic and climatic conditions. In most environments relevant for maize and wheat cultivation the deviation between simulated and measured water erosion values is lower than the variability within the field data. ~~However, t~~The reported data does not enable us to further narrow down the uncertainties addressed. Although the metadata accompanying the field measurements includes information on slope steepness and annual precipitation (or geographic coordinates allowing for overlay with climatic data), information on soil types or texture classes, crop type and tillage system implemented over time are provided only for few points. Also, the various methods used to measure erosion rates, their complex implementation and the bias of field studies towards locations sensitive to erosion lead to an uncertain representation of large-scale erosion rates based on field measurements. To facilitate in-depth evaluation of erosion models across different scales, it is crucial to provide detailed information on site characteristics and to harmonise approaches to measure erosion in the field.

5 Conclusion

The simulation of water erosion with GGCMs is largely influenced by the resolution of global datasets providing topographic, soil, climate, land use and field management data, which is currently not available at the field scale. Yet, considering water erosion in global crop yield projections can provide useful outputs to inform assessments of the potential impacts of erosion on global food production and to identify soil erosion hotspots on cropland for management and policy interventions. To improve the quality of the estimates and to further develop these models, it is crucial to identify, communicate and address the existing uncertainties. Increasing the resolution of global soil, topographic and precipitation data is central for improving global water erosion estimates. In addition, this study provides an insight into the importance of considering field management. The numerous options to simulate the cultivation of fields result in a large range of possible water erosion values, which can only partly be narrowed down at a global scale. Further improvement of global water erosion estimates requires detailed and harmonized field measurements across all environmental conditions to validate and calibrate simulation outputs. Using existing field data, we were able to identify specific environmental characteristics ~~under~~ for which we have lower confidence in the modelled erosion rates~~the model's performance was not sufficient enough~~. These are mainly found in the tropics and mountainous regions due to the high sensitivity of simulated water erosion to slope steepness and precipitation strength, and the complexity of mountain agriculture. -However, these areas represent only a small fraction of global cropland for ~~wheat~~ maize and ~~maize~~wheat. ~~The overlap of simulated and measured water erosion values for most of the global wheat and maize fields underlines the robustness~~The overlap of simulated and measured water erosion values in most environments used to produce maize and wheat underlines the robustness of an EPIC-based GGCM to simulate the differences in water erosion rates of major global crop production regions. ~~of simulated water erosion values generated with an EPIC-based GGCM.~~

Data availability. Additional information on model outputs, methods, ~~the~~ study design and ~~the~~ field data are available in the supporting information file: TWCarr-si.zip.

Author contributions. TC, JB, CF and RS designed the study. TC, JB, CF, EF and RS collected and analysed the data. TC prepared the manuscript with contributions from all co-authors.

Competing interests. The authors declare that they have no conflict of interest.

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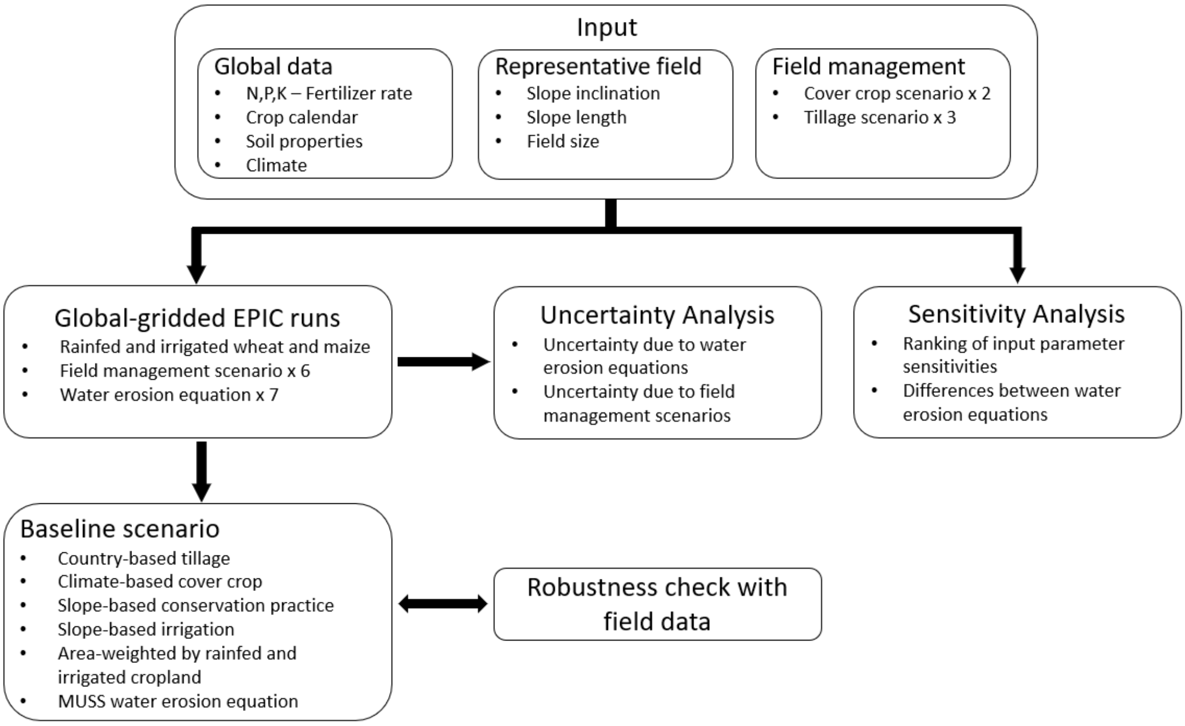
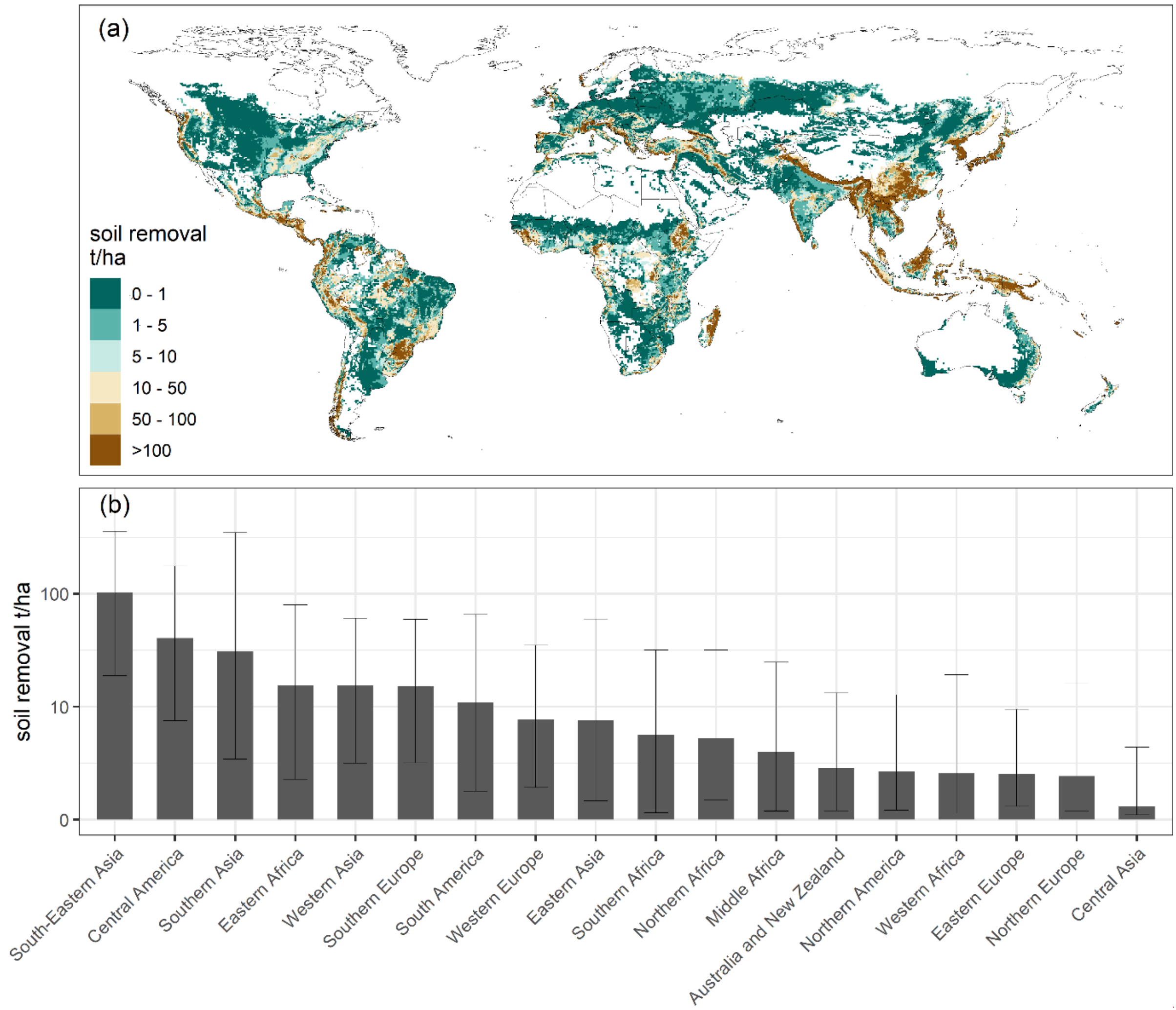


Figure 1: Scheme of procedure used for simulating global water erosion with EPIC-IIASA and for analysing the uncertainty, sensitivity and robustness of our simulation setup.


(a)
soil removal
t/ha
0 - 1
1 - 5
5 - 10
10 - 50
50 - 100
>100
(b)
soil removal t/ha
100
10
0
South-Eastern Asia
Central America
Southern Asia
Eastern Africa
Western Asia
Southern Europe
South America
Western Europe
Eastern Asia
Southern Africa
Northern Africa
Middle Africa
Australia and New Zealand
Northern America
Western Africa
Eastern Europe
Northern Europe
Central Asia

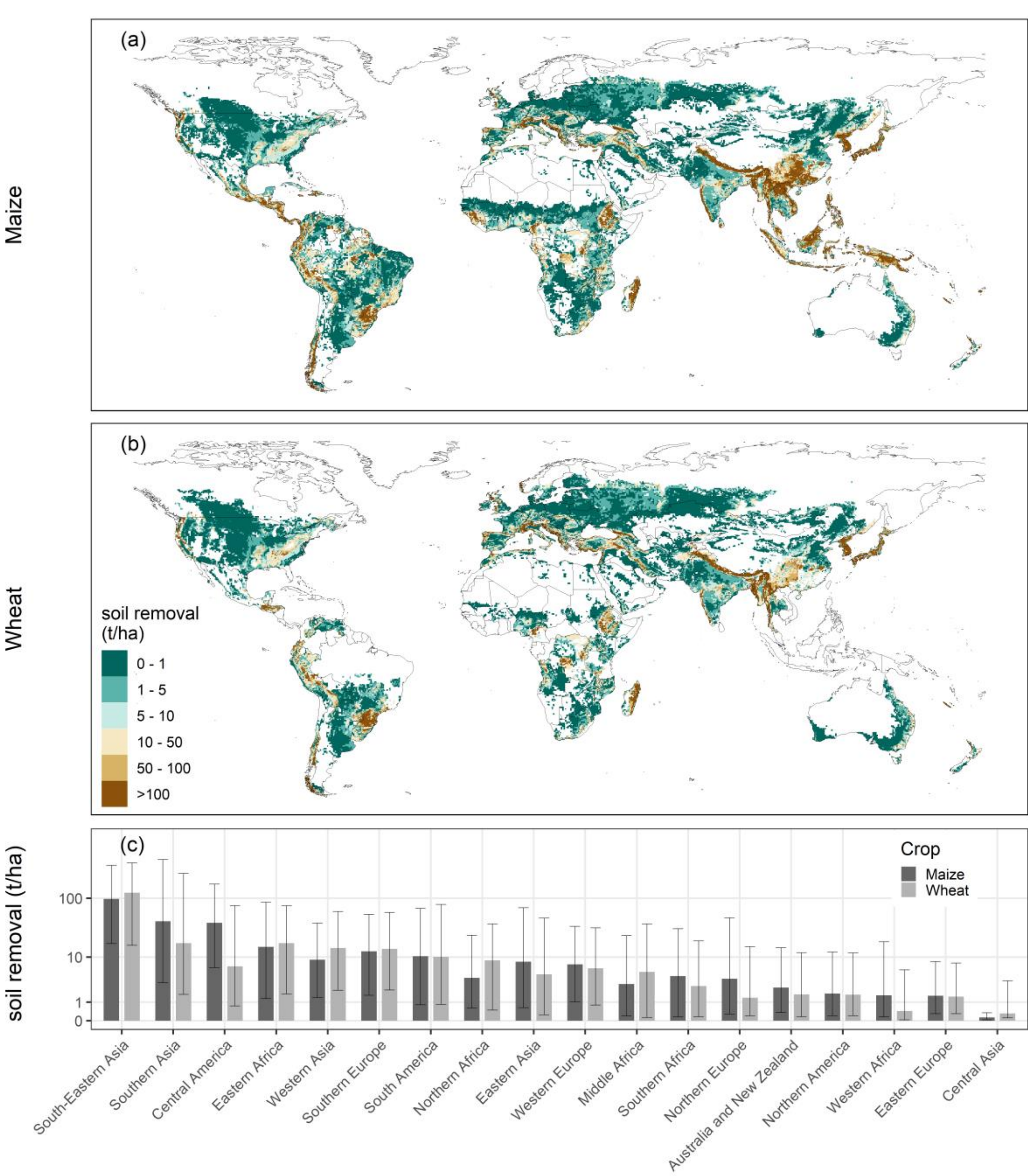


Figure 2: ~~(a)~~ Soil loss due to water erosion in maize (a) and wheat (b) fields simulated with the baseline scenario. Each pixel cell illustrates the median relative water erosion of one representative field. The extent of cropland areas is not considered in pixel cell size. The bars in the bottom plot (c) illustrate median soil removal for major world regions simulated under maize and wheat cultivation. The lines and whiskers illustrate 25th and 75th percentile values. The classification of world regions is illustrated in Fig. S3. Due to the large gap between aggregated values, all values in the bottom plot have been log-transformed to facilitate the visual comparison.~~Soil loss due to water erosion in maize and wheat fields simulated with the baseline scenario. (b) The bars in the bottom plot illustrate the median, the lines and whiskers 25th and 75th percentile of simulated soil loss for major world regions. The classification of world regions is illustrated in Fig. S4. Due to the large gap between aggregated values, all values in the bottom plot have been log-transformed to facilitate the visual comparison.~~

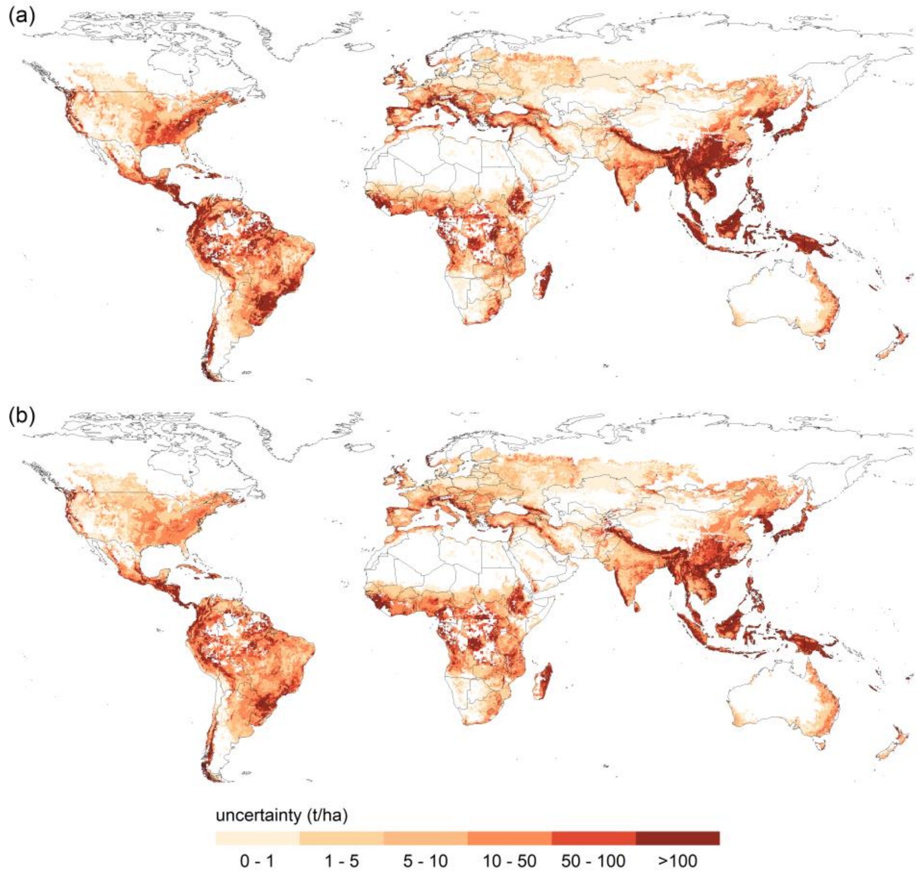


Figure 3: Water erosion uncertainty due to (a) field management assumptions and (b) water erosion equations.

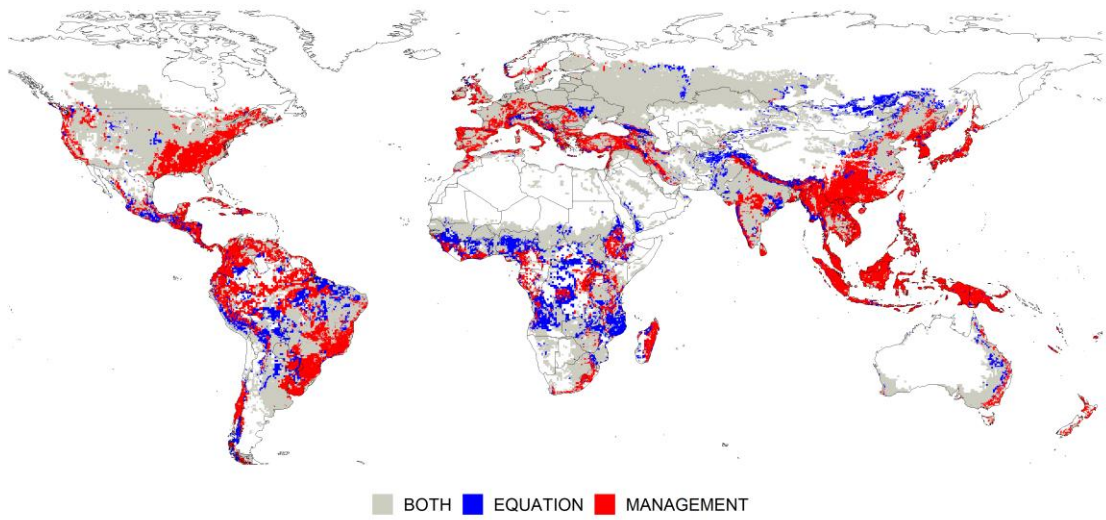


Figure 4: Prevailing uncertainty, defined as the higher uncertainty range by at least 5 t ha^{-1}.

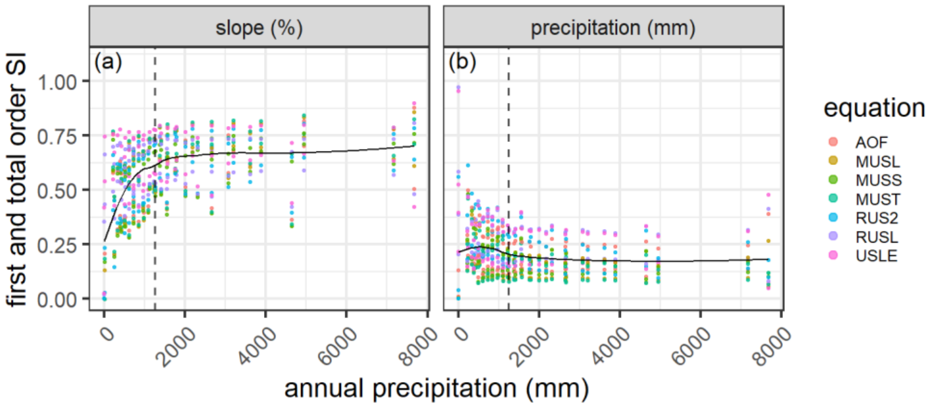
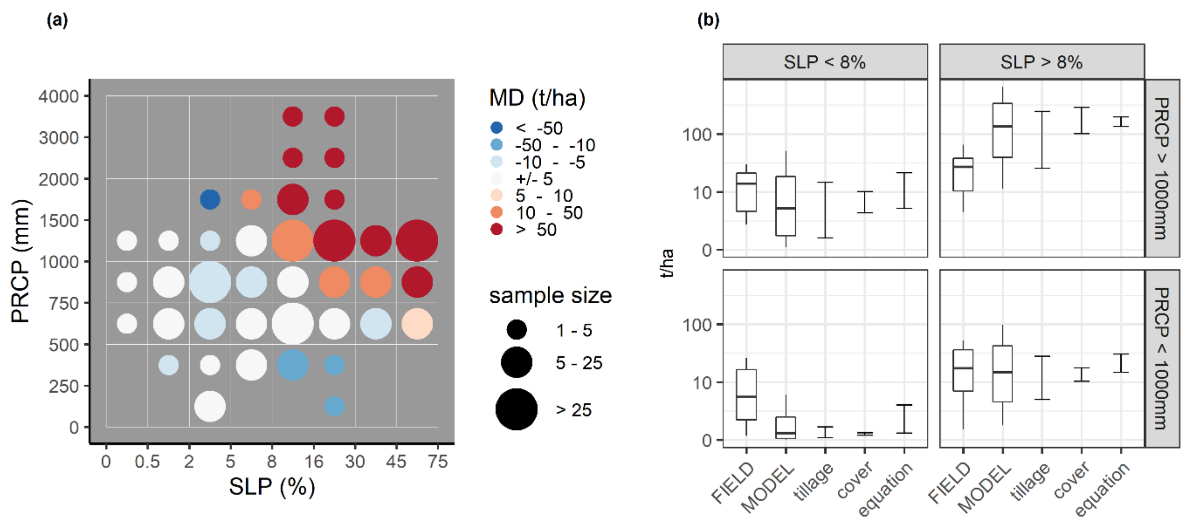


Figure 5: First-order and total-order sensitivity indices (SI) for (a) slope steepness (%) and (b) precipitation [mm]. The dashed vertical line illustrates median annual precipitation at all tested locations (1248 mm).



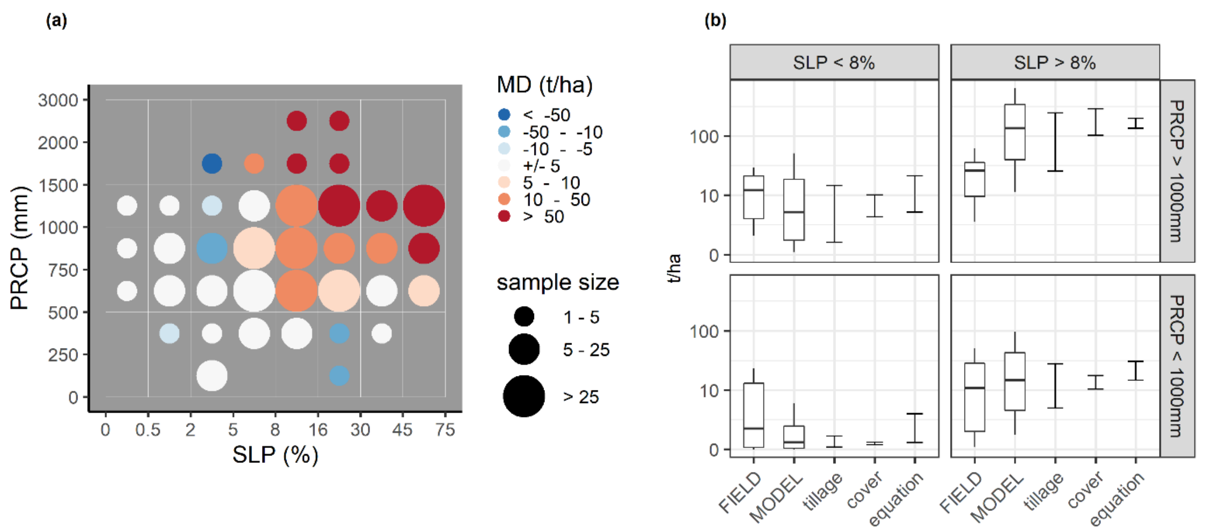


Figure 6: Comparison of simulated erosion with measured erosion. (~~A~~a) Median deviation (MD) in t ha^{1} between simulated erosion using the baseline scenario and measured erosion. Simulated and measured data is grouped into precipitation classes and slope classes used for the simulation setup. (~~B~~b) Distributions of ~~Measured~~ measured erosion rates, erosion rates simulated with the baseline scenario and uncertainty ranges for management assumptions and erosion equations. The boxplots are defined by the median, the 25th and the 75th

percentile of simulated and measured erosion rates. Whiskers illustrate the 10th and 90th percentile. The three bars next to the boxplots illustrate minimum and maximum median erosion rates calculated with all tillage and cover crop scenarios and with all water erosion equations. The values have been log-transformed for better visualization.

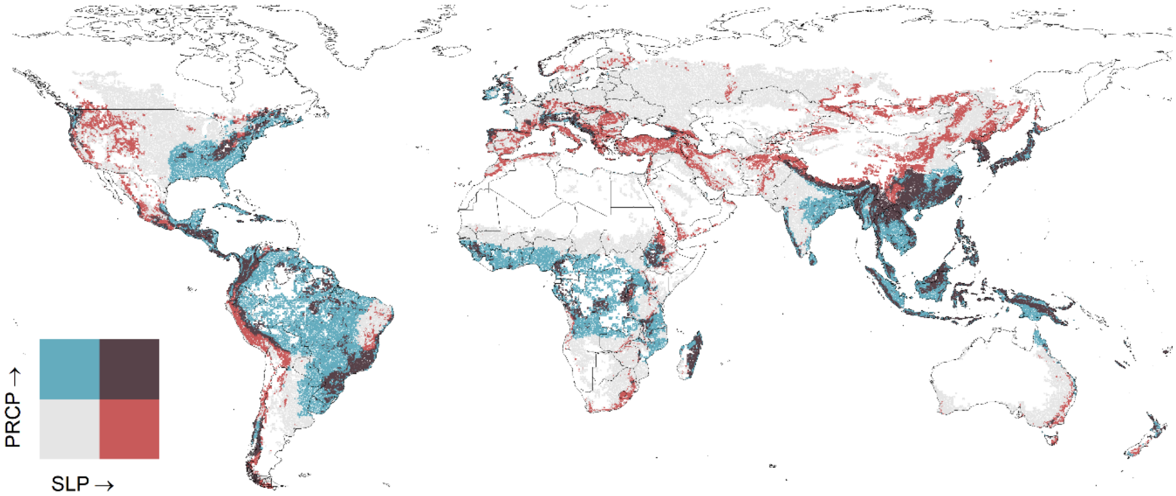


Figure 7: Distribution of low to high slope steepness (SLP) and annual precipitation (PRCP) in maize and wheat fields. Dark areas illustrate grid cells where dominant slopes are steeper than 8 % and annual precipitation is above 1000 mm. Correspondingly, blue, red, and grey pixels are below one or both thresholds.

(a)

(b)

(c)

(d)

Figure 8: (a) Sugar cane cultivation on steep slopes in South China (the steepest slopes are already abandoned and reforested by eucalyptus trees). (b) Maize cultivation on strongly eroded slopes in South West Uganda. (c) Abandoned fields and maize cultivation on a slope in South West Uganda. (d) Degraded and abandoned maize fields in Northern El Salvador.

Table 1: Equations for calculating the erosivity factor in each water erosion equation available in EPIC.

Erosivity factor	Equation
$R = EI \quad (2)$	USLE, RUSLE, RUSLE2 (Renard et al., 1997; USDA-ARC, 2013; Wischmeier and Smith, 1978)
$R = 0.646 * EI + 0.45 * (Q * q_p)^{0.33} \quad (3)$	AOF (Onstad and Foster, 1975)
$R = 1.586 * \left(Q * q_p\right)^{0.56} * WSA^{0.12} \quad (4)$	MUSLE (Williams 1975)
$R = 2.5 * Q * {q_p}^{0.5} \quad (5)$	MUST (Williams, 1995)
$R = 0.79 * (Q * q_p)^{0.65} * WSA^{0.009} \quad (6)$	MUSS (Williams, 1995)

Table 2: Tillage management scenarios for maize and wheat cultivation

	Conventional tillage	**Reduced tillage**	**No-tillage**
total cultivation operations	6 – 7	4 – 5	3
max. surface roughness	30 – 50 mm	20 mm	10 mm
max. tillage depth	150 mm	150 mm	40 – 60 mm
plant residues left	25 %	50 %	75 %
cover treatment class	straight	contoured	contoured & terraced

Table 3: Management assumptions and erosion equation selected for the baseline scenario

<table>
<tr><th>Option</th><th colspan="4">Baseline</th></tr>
<tr><td>TILLAGE</td><td colspan="4">• Mix of conventional, reduced and no-tillage in regions where the national share of conservation agriculture is > 5 % according to the latest reported data in ~~FAO~~ AQUASTAT (2007-2014) (FAO, 2016): Argentina, Australia, Bolivia, Brazil, Canada, Chile, China, Colombia, Finland, Italy, Kazakhstan, New Zealand, Paraguay, Spain, USA, Uruguay, Venezuela, Zambia and Zimbabwe.
• Mix of conventional and reduced tillage in the rest of the world.</td></tr>
<tr><td>OFF-SEASON COVER</td><td colspan="4">• Cultivation only with cover crops in tropics according to Koeppen-Geiger regions (Fig. S1) (Kottek et al., 2006).
• Mix of off-season cover with and without cover crops in temperate and cold zones.
• No cover crops in arid regions.</td></tr>
<tr><td rowspan="2">CONSERVATION PRACTICE FACTOR</td><td>Slope</td><td>0 – 16 %</td><td>16 – 30 %</td><td>> 30 %</td></tr>
<tr><td>P-Factor</td><td>1.0</td><td>0.5</td><td>0.15</td></tr>
</table>

~~CROP~~	~~Water erosion is simulated in wheat and maize fields based on the global crop distribution by MIRCA2000 (Fig. S2) (Portmann et al., 2010).~~ ~~Weighted average of water erosion under wheat and maize cultivation where both crops are grown.~~
CROP	Water erosion is simulated in wheat and maize fields based on the global crop distribution by MIRCA2000 (Fig. S2) (Portmann et al., 2010).
IRRIGATION	• Only on slopes ≤ 5 %. • Weighted average of irrigated and rainfed cropland based on MIRCA2000 (Portmann et al., 2010).~~.~~
METHOD	MUSS water erosion equation.
AGGREGATION	Median of all management scenarios per grid cell and region

Table 4: First-order sensitivity indices (SI) ranking for the five most sensitive input parameters (PARM) for each water erosion equation including slope steepness (SLP), daily precipitation (PRCP), soil hydrologic group (HSG), land use number (LUN), soil silt content (SILT), soil sand content (SAND), curve number parameter (S301), maximum air temperature (TMX) and crop residues left after harvest (ORHI). The sensitivity indices of the remaining parameters are presented in Table S3.

	AOF		**MUSL**		**MUSS**		**MUST**		**RUSLE2**		**RUSLE**		**USLE**	
rank	**PARM**	**SI**	**PARM**	**SI**	**PARM**	**SI**	**PARM**	**SI**	**PARM**	**SI**	**PARM**	**SI**	**PARM**	**SI**
1	SLP	0.47	SLP	0.47	SLP	0.46	SLP	0.48	SLP	0.46	SLP	0.50	SLP	0.54
2	PRCP	0.13	PRCP	0.10	PRCP	0.12	PRCP	0.09	PRCP	0.16	PRCP	0.20	PRCP	0.18
3	HSG	0.03	HSG	0.04	HSG	0.05	HSG	0.04	HSG	0.03	SAND	0.05	SILT	0.02
4	SILT	0.02	LUN	0.02	LUN	0.02	LUN	0.02	SAND	0.01	TMX	0.01	TMX	0.01
5	LUN	0.01	SILT	0.02	S301	0.01	SILT	0.02	LUN	0.01	ORHI	0.01	ORHI	0.01
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
sum		0.69		0.68		0.71		0.69		0.71		0.78		0.77

Table 5: Total-order sensitivity indices (SI) ranking for the five most sensitive input parameters (PARM) for each water erosion equation including slope steepness (SLP), daily precipitation (PRCP), soil hydrologic group (HSG), land use number (LUN), soil silt content (SILT), soil sand content (SAND), maximum air temperature (TMX) and crop residues left after harvest (ORHI). The sensitivity indices of the remaining parameters are presented in Table S3.

	AOF		**MUSL**		**MUSS**		**MUST**		**RUSLE2**		**RUSLE**		**USLE**	
rank	**PARM**	**SI**	**PARM**	**SI**	**PARM**	**SI**	**PARM**	**SI**	**PARM**	**SI**	**PARM**	**SI**	**PARM**	**SI**
1	SLP	0.68	SLP	0.68	SLP	0.63	SLP	0.68	SLP	0.66	SLP	0.69	SLP	0.75
2	PRCP	0.28	PRCP	0.23	PRCP	0.22	PRCP	0.21	PRCP	0.32	PRCP	0.36	PRCP	0.36
3	HSG	0.09	HSG	0.12	HSG	0.13	HSG	0.12	HSG	0.08	SAND	0.12	SILT	0.05
4	SILT	0.07	LUN	0.07	LUN	0.07	LUN	0.07	LUN	0.05	TMX	0.02	TMX	0.02
5	LUN	0.05	SILT	0.07	SILT	0.05	SILT	0.07	SAND	0.04	ORHI	0.01	SAND	0.01
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
sum		1.29		1.30		1.25		1.27		1.34		1.27		1.27

Text S1.

The following equations describe the calculation of the cover and management factor, the soil erodibility factor and the topographic factor of each water erosion equation:

The **cover and management factor** is calculated the same way for each equation:

$$C = FRSD * FBIO * FRUF \qquad (1)$$

where FRSD is the crop residue factor, FBIO is the growing biomass factor and FRUF is the soil random roughness factor, which are calculated with the following equations (Wang et al., 2011; Williams et al., 2012):

$$FRSD = exp(-P23 * CVRS) \qquad (2)$$

$$FBIO = 1 - \frac{STL}{(STL + exp(SCRP1(23) - SCRP2(23) * STL))} * exp\,(-P26 * CPHT) \qquad (3)$$

$$FRUF = exp\,(-0.026 * (RR - 6.1)) \qquad (4)$$

where P23 is an exponential coefficient ranging from 0.01-0.5, CVRS is the amount of above ground crop residue [t ha^{-1}], STL is the amount of standing live biomass of the crop [t ha^{-1}], SCRP1(23) and SCRP2(23) are coefficients defining an S-shaped growth curve used to estimate the fraction of the ground covered by the plant as a function of the Leaf Area Index, P26 is an exponential coefficient ranging from 0.01-0.2, CPHT is the crop height [m] and RR is the soil surface random roughness [mm].

The **soil erodibility factor** is calculated the same way for the USLE, AOF, MUSLE, MUST and MUSS equation using a function of sand, silt, clay and organic carbon contents in the soil:

$$K = X1 * X2 * X3 * X4 \qquad (5)$$

$$X1 = 0.2 + 0.3 * exp\,(-0.0256 * SAND * (1 - 0.01 * SILT)) \quad 6)$$

$$X2 = \left(\frac{SILT}{CLAY + SILT}\right)^{0.3} \qquad (7)$$

$$X3 = \frac{1 - 0.25 * OC}{OC + exp\,(3.718 - 2.947 * OC)}, IF\ OC \leq 5 \qquad (8)$$

$$X3 = 0.75, IF\ OC > 5 \qquad (9)$$

$$X4 = \frac{1 - 0.7 * SN1}{SN1 + exp(-5.509 + 22.899 * SN1)} \qquad (10)$$

$$SN1 = 1 - 0.01 * SAND \qquad (11)$$

Where SAND, SILT, CLAY, and OC are the sand, silt, clay, and organic carbon contents of the soil in %. For the RUSLE and RUSLE2 method soil erodibility is calculated without the organic carbon contents of the soil using the following equation:

$$KR = 9.811 * \left(0.0034 + 0.0405 * exp\left(-0.5 * \left(\frac{Log10(DG) + 1.659}{0.7101}\right)^2\right)\right) \qquad (12)$$

$$DG = exp\ (SUM) \qquad (13)$$

$$SUM = \frac{SAND*0.0247 - SILT*3.65 - CLAY*6.908}{100} \qquad (14)$$

The **topographic factor** is calculated the same way for the USLE, AOF, MUSLE, MUST and MUSS equation using a function of slope length and slope steepness:

$$\mathrm{LS} = \left(\frac{\mathrm{SLPL}}{22.127}\right)^{\mathrm{XM}} * (\mathrm{SLP} * (65.41 * \mathrm{SLP} + 4.56) + 0.065) \qquad (15)$$

$$\mathrm{XM} = 0.3 * \frac{\mathrm{SLP}}{\mathrm{SLP} + \exp\ (-1.47 - 61.09 * \mathrm{SLP})} + 0.2 \qquad (16)$$

Where SLPL is the slope length in m, SLP is the land surface slope in m/m and XM is an exponent dependent upon slope. The topographic factor for the RUSLE method is calculated using a function of slope length and slope steepness as well:

$$\mathrm{LSR} = \mathrm{RSF} * \mathrm{RLF} \qquad (17)$$

$$\mathrm{RSF} = 10.8 * \mathrm{SLP} + 0.03, \mathrm{IF\ SLPL} > 4.57\ \&\ \mathrm{SLP} < 0.09 \qquad (18)$$

$$\mathrm{RSF} = 16.8 * \mathrm{SLP} - 0.5, \mathrm{IF\ SLPL} > 4.57\ \&\ \mathrm{SLP} > 0.09 \quad (19)$$

$$\mathrm{RSF} = \mathrm{X1}, \mathrm{IF\ SLPL} < 4.57 \qquad (20)$$

$$\mathrm{X1} = 3 * \mathrm{SLP}^{0.8} + 0.56 \qquad (21)$$

$$\mathrm{RLF} = \frac{\mathrm{SLPL}}{22.127}^{\mathrm{RXM}} \qquad (22)$$

$$\mathrm{RXM} = \frac{\mathrm{B}}{1+\mathrm{B}} \qquad (23)$$

$$\mathrm{B} = \frac{\mathrm{SLP}}{0.0896 * \mathrm{X1}} \qquad (24)$$

Where SLPL is slope length in m and SLP is land surface slope in m/m. The slope steepness factor RSF is adjusted for different slope steepness and slope length thresholds based on experimental data (Renard et al., 1997). The slope length factor RLF includes an exponent RXM, which is a function of the ratio B of rill erosion caused by flow and interill erosion caused by raindrop impact (USDA-ARC, 2013). B reflects how steepness affects rill erosion differently than it does interrill erosion. Rill erosion is assumed to vary linearly with steepness. The topographic factor for the RUSLE2 method is calculated the same way than for the RUSLE equation if the transport capacity determined by a function of flow rate and slope steepness exceeds sediment load. When sediment load exceeds transport capacity RUSLE2 computes deposition. Interrill erosion is assumed to occur even when RUSLE2 computes deposition, which can be calculated without a distance term as detachment is solely caused by impacting raindrops (USDA-ARC, 2013). Therefore, the slope length factor is not considered in the RUSLE2 equation when deposition occurs.

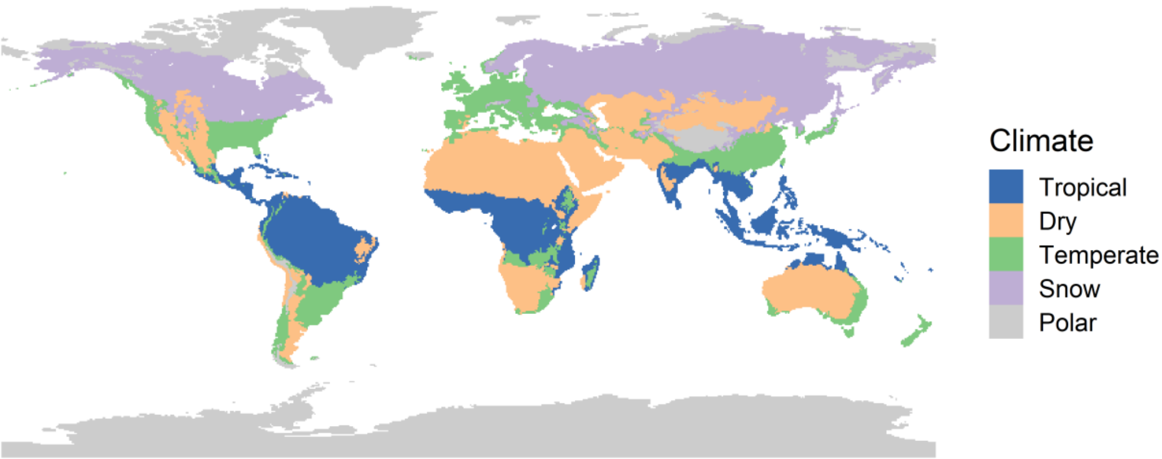


Figure S1. Main climate zones using the updated Koeppen-Geiger climate classification (Peel et al., 2007).

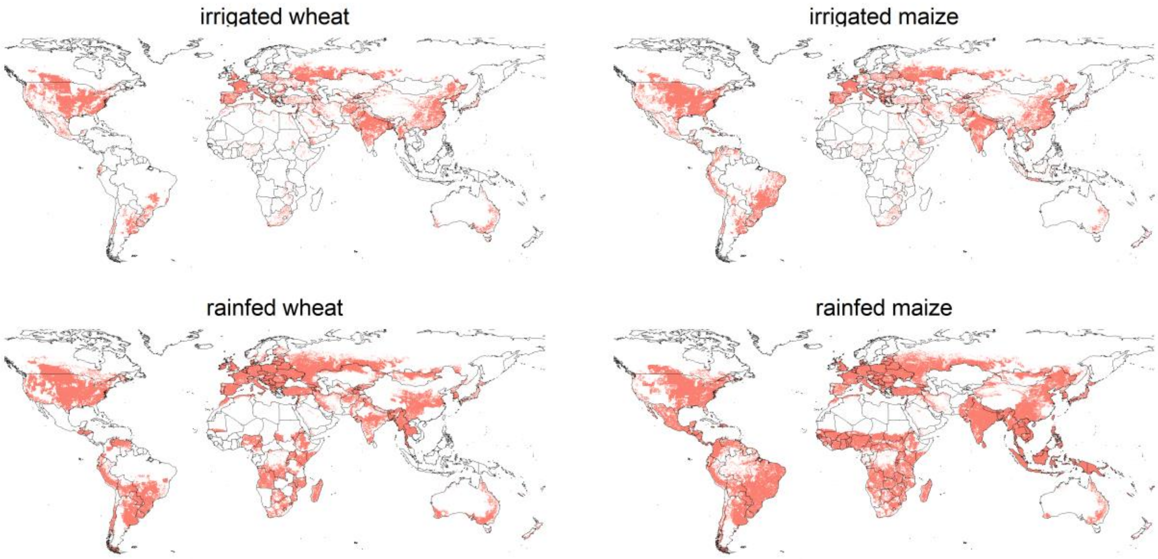
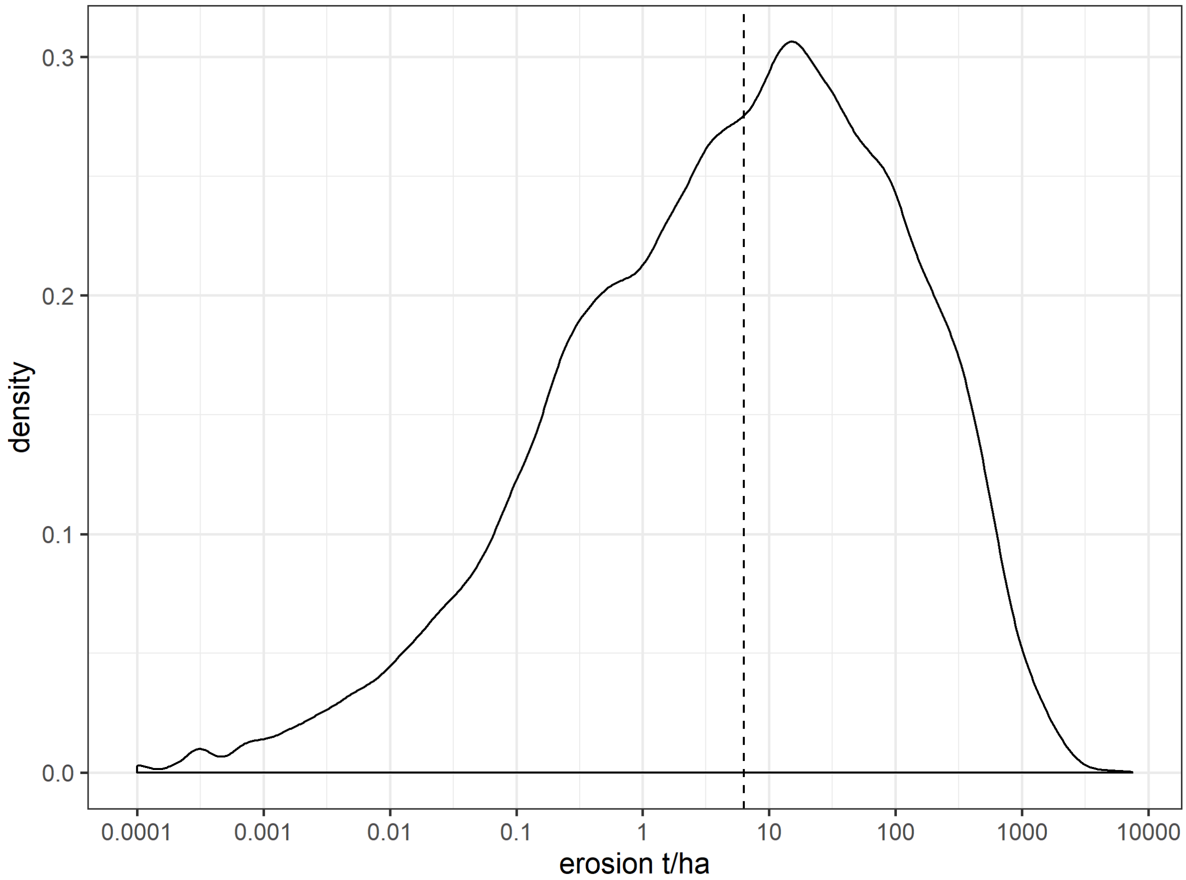


Figure S2. Grid cells with irrigated and rainfed wheat and maize cultivation around the year 2000 (Portmann et al., 2010).



~~**Figure S3**. Distribution of average water erosion values from 1980 – 2010 simulated with the baseline scenario and weighted for each simulation grid. The dashed vertical line illustrates the median of the distribution, which represents global median water erosion of 6 t ha^{-1} a^{-1}. Average water erosion at each grid and the global average water erosion of 19 t ha^{-1} a^{-1} has been calculated as a weighted average based on the distribution of irrigated and rainfed maize and wheat acreage (Portmann et al., 2010).~~

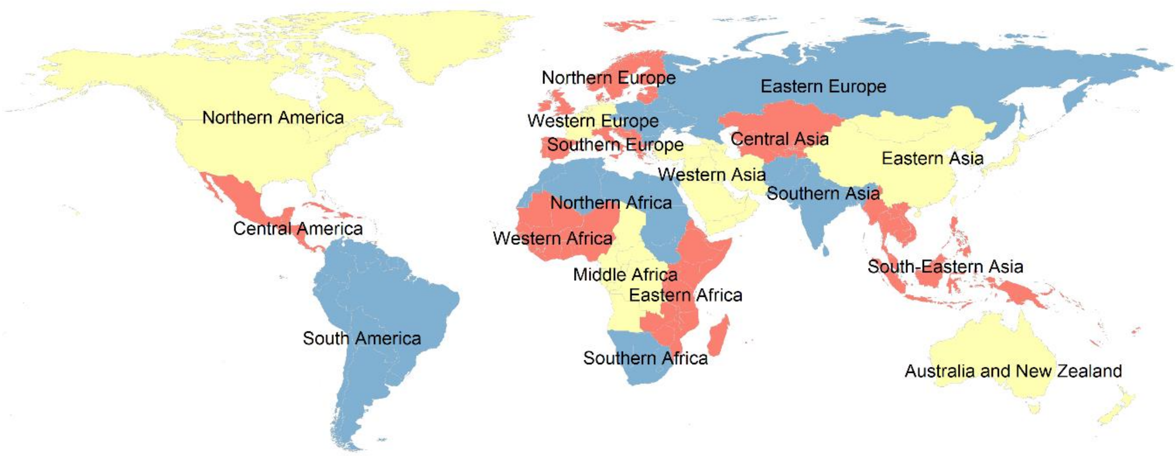


Figure ~~S4~~S3. World regions classified using the United Nations geoscheme (UN, 1999) with minor modifications ~~(UN, 1999)~~: Melanesia has been added to South-~~E~~eastern Asia and the Caribbean has been added to Central America.

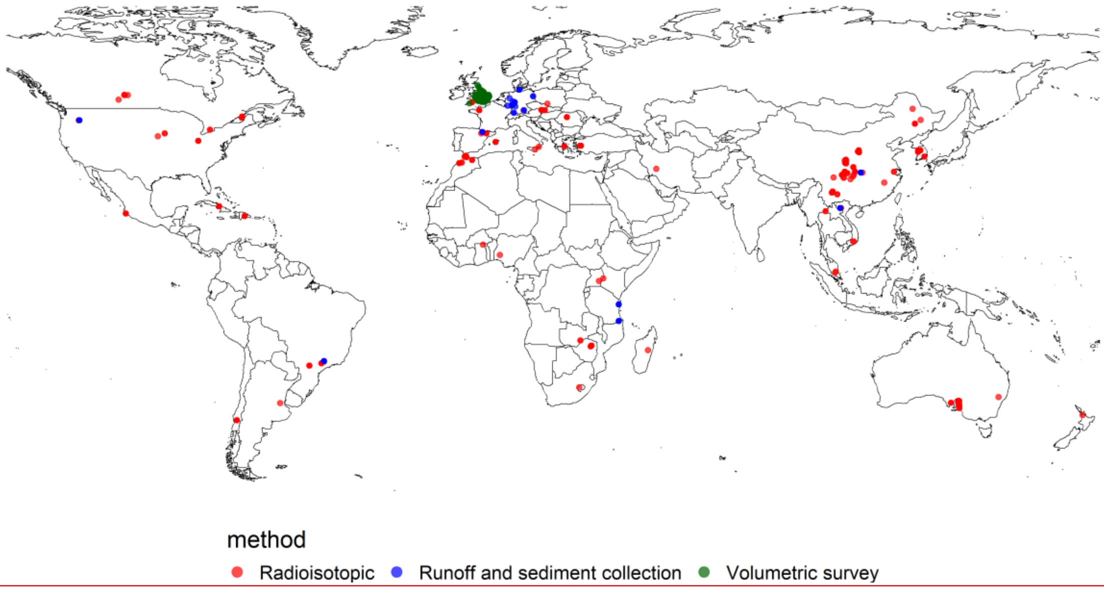
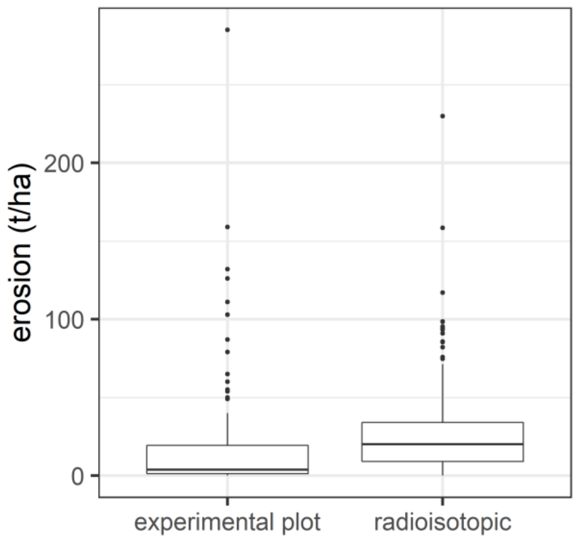


Figure S4. Locations of water erosion field data from cropland where coordinates were recorded (n=554).



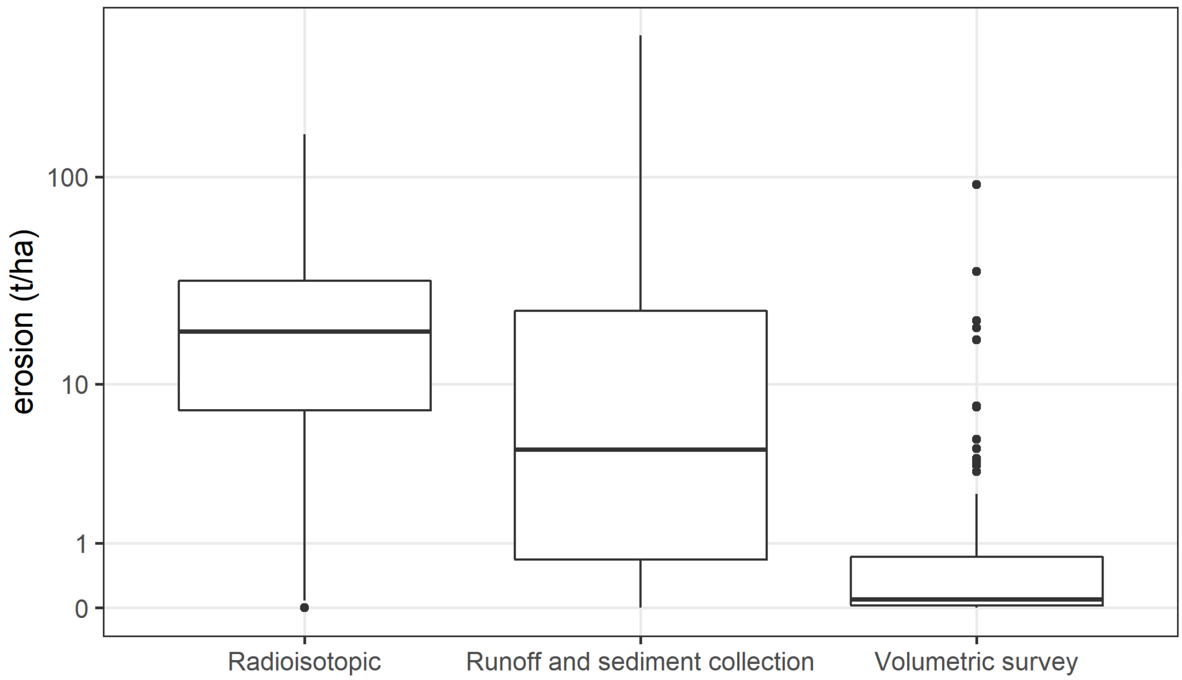
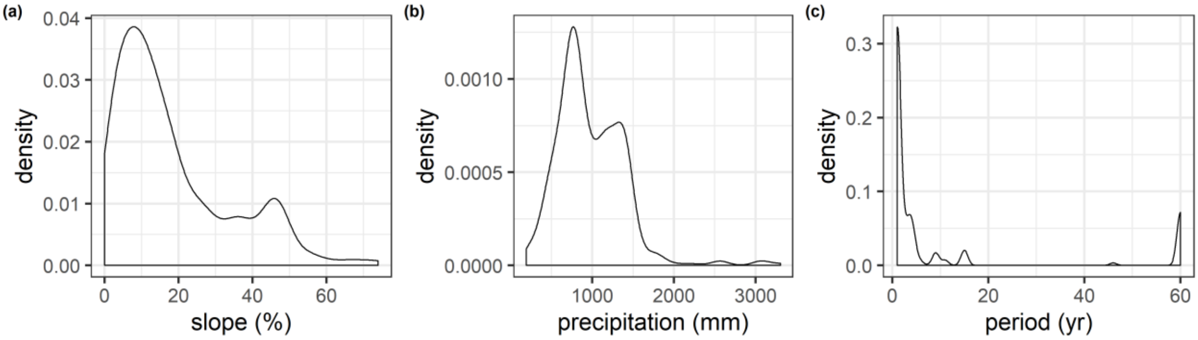


Figure ~~S5~~S5. Distribution of erosion (t ha^{-1}) values measured in agricultural fields using runoff and sediment collection ~~plot experiments~~ (n = ~~159~~188, Mean = ~~17~~ 21 t ha^{-1}; Median = 4 t ha^{-1}), ~~and the~~ ^{137}Cs method (n = ~~314~~315, Mean = ~~26~~ 24 t ha^{-1}; Median = ~~20~~ 18 t ha^{-1}) and volumetric surveys (n = 103, Mean = 2 t ha^{-1}; Median = 0.1 t ha^{-1}).



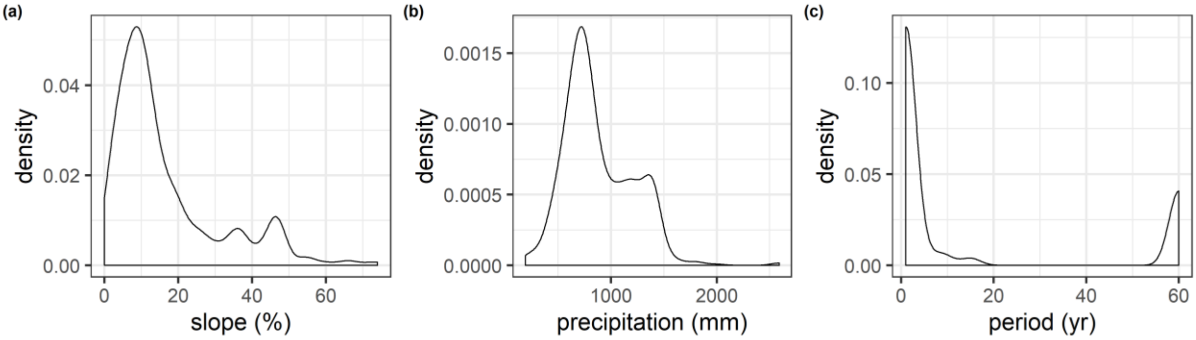
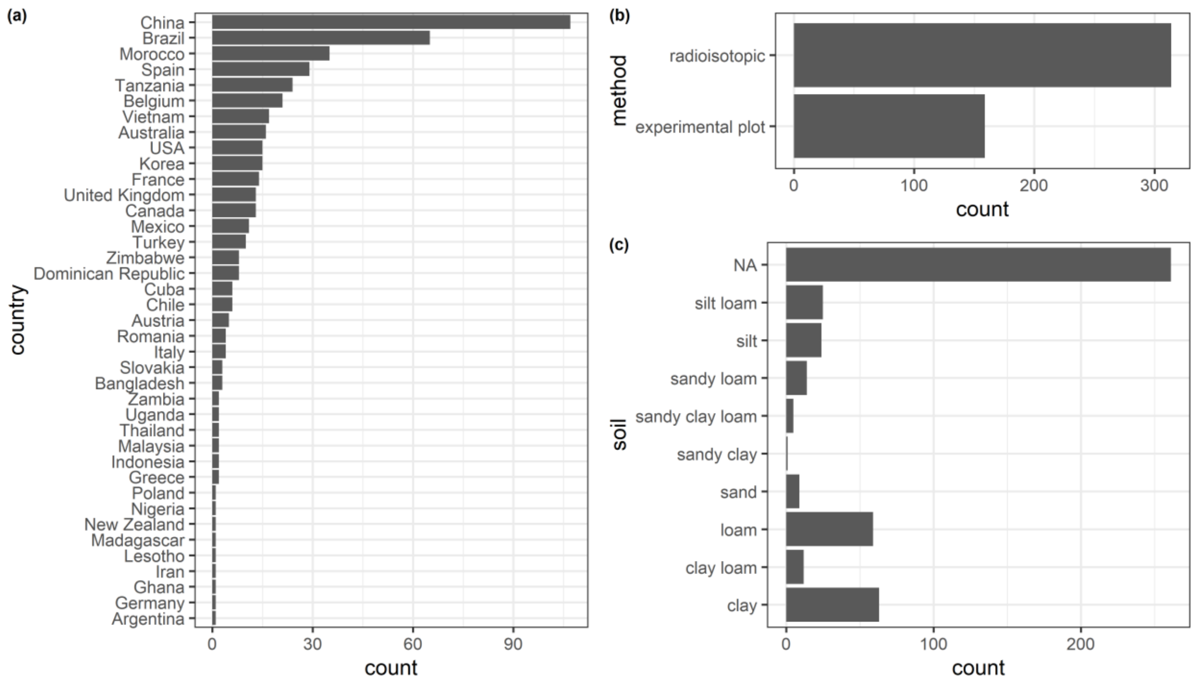


Figure S~~6~~6. (a) Distribution of slope steepness (%) records for measured erosion values (n = ~~473~~606; Mean = ~~18.3~~16 %; Median = ~~13~~ 11 %). (b) Distribution of annual precipitation (mm) records for measured erosion values (n = ~~473~~606; Mean = ~~974~~ 879 mm; Median = ~~872~~ 774 mm). (c) Distribution of recorded measurement periods for soil loss experiments excluding radioisotopic methods (n = ~~159~~95; Mean = ~~10~~ 15 a; Median = 1 a).


(a)
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Vietnam
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Korea
France
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Mexico
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Zimbabwe
Dominican Republic
Cuba
Chile
Austria
Romania
Italy
Slovakia
Bangladesh
Zambia
Uganda
Thailand
Malaysia
Indonesia
Greece
Poland
Nigeria
New Zealand
Madagascar
Lesotho
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Ghana
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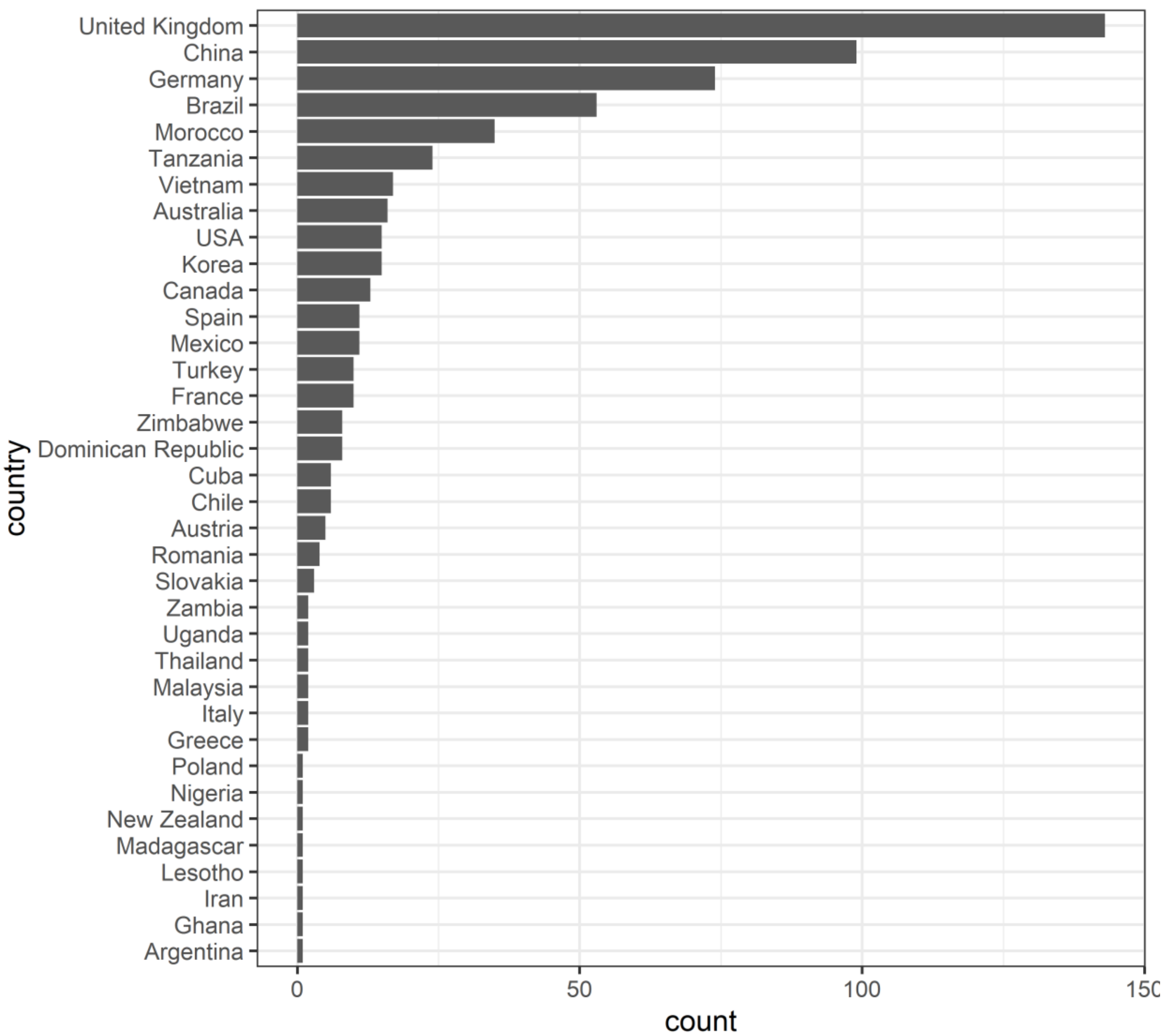
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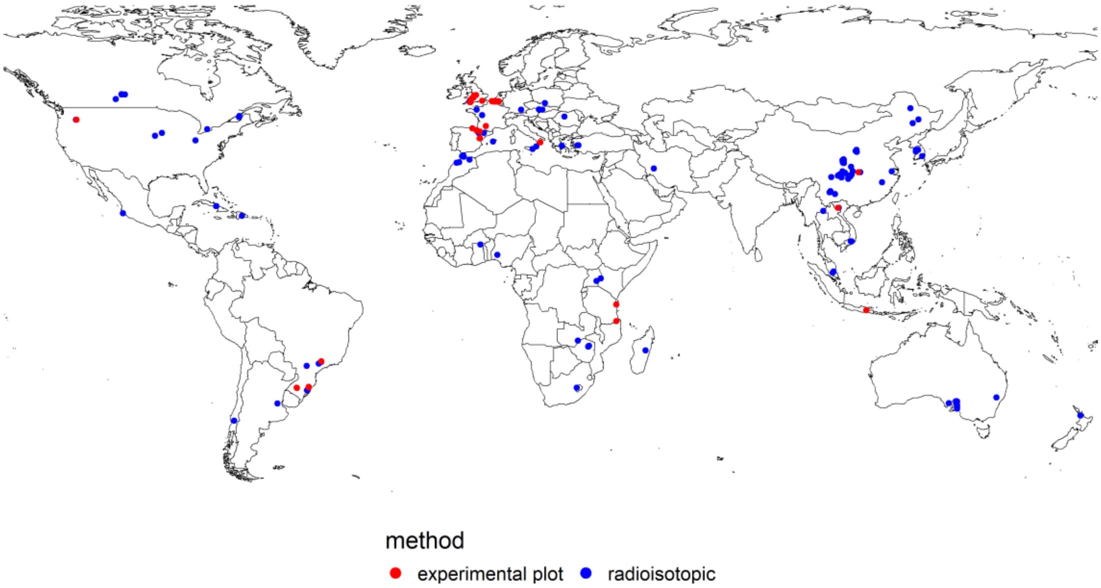
Chile
Austria
Romania
Slovakia
Zambia
Uganda
Thailand
Malaysia
Italy
Greece
Poland
Nigeria
New Zealand
Madagascar
Lesotho
Iran
Ghana
Argentina
0
50
100
150
count

Figure ~~S7~~S7. ~~(a)~~ Number of measured water erosion records (n=~~473~~606) per country (n=~~39~~3~~7~~6). ~~(b) Methods used to measure water erosion in agricultural fields (n=473). (c) Soil texture recorded at sites of water erosion measurement (n = 473).~~



~~**Figure S8.** Locations of water erosion field data from cropland where coordinates were recorded (n=468).~~

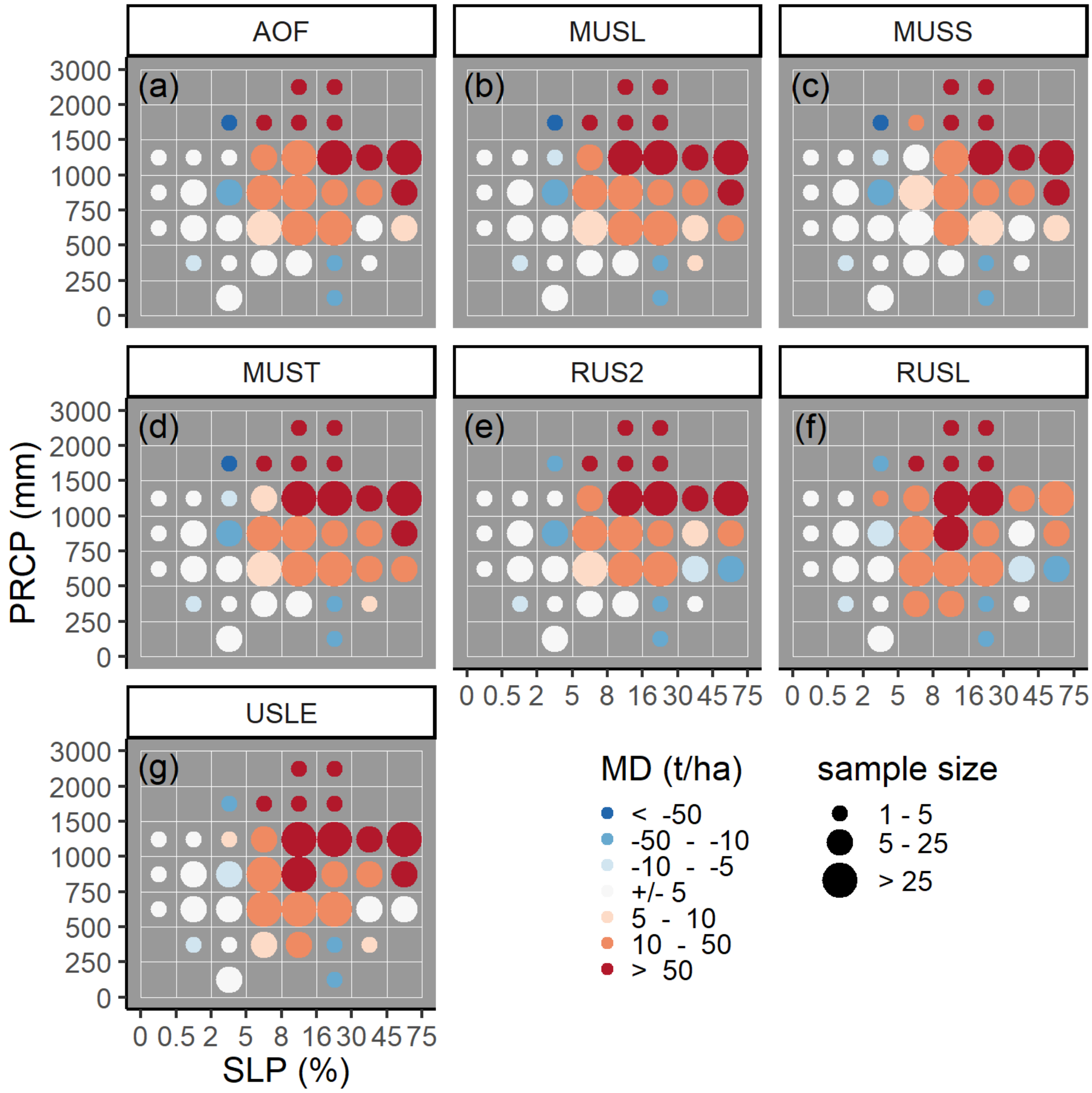


Figure ~~S9~~S8. Median deviation (MD) in t ha^{-1} between measured and simulated water erosion using the baseline scenario with different water erosion equations. Measured and simulated medians were calculated for different slope and precipitation classes.

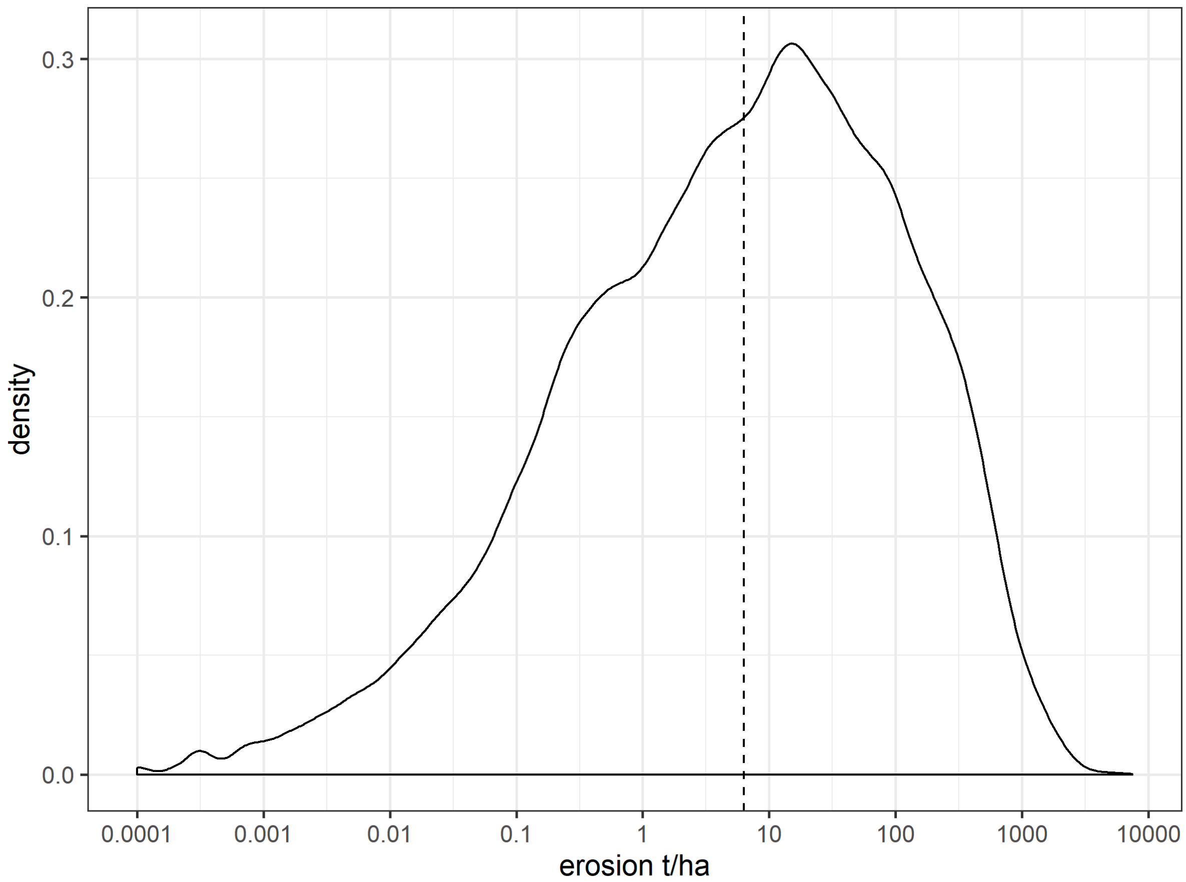


Figure S~~3~~9. Distribution of average water erosion values from 1980 – 2010 simulated with the baseline scenario and weighted for each simulation grid. The dashed vertical line illustrates the median of the distribution, which represents global median water erosion of 6 t ha^{-1} a^{-1}. Average water erosion at each grid and the global average water erosion of 19 t ha^{-1} a^{-1} has been calculated as a weighted average based on the distribution of irrigated and rainfed maize and wheat acreage (Portmann et al., 2010).

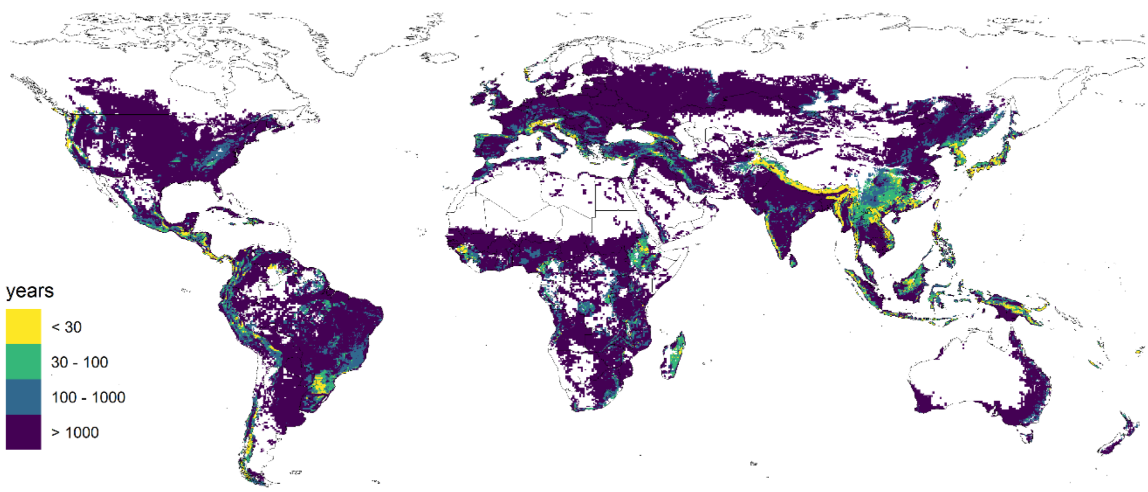


Figure S10. Simulated years left until the whole soil profile is eroded under permanent maize and wheat cultivation. Calculated as a ratio of the sedimentary deposit thickness [m] (Pelletier et al., 2016) and the eroded soil depth per year (water erosion [t ha^{-1} a^{-1}] x bulk density [g m^{-3}]).

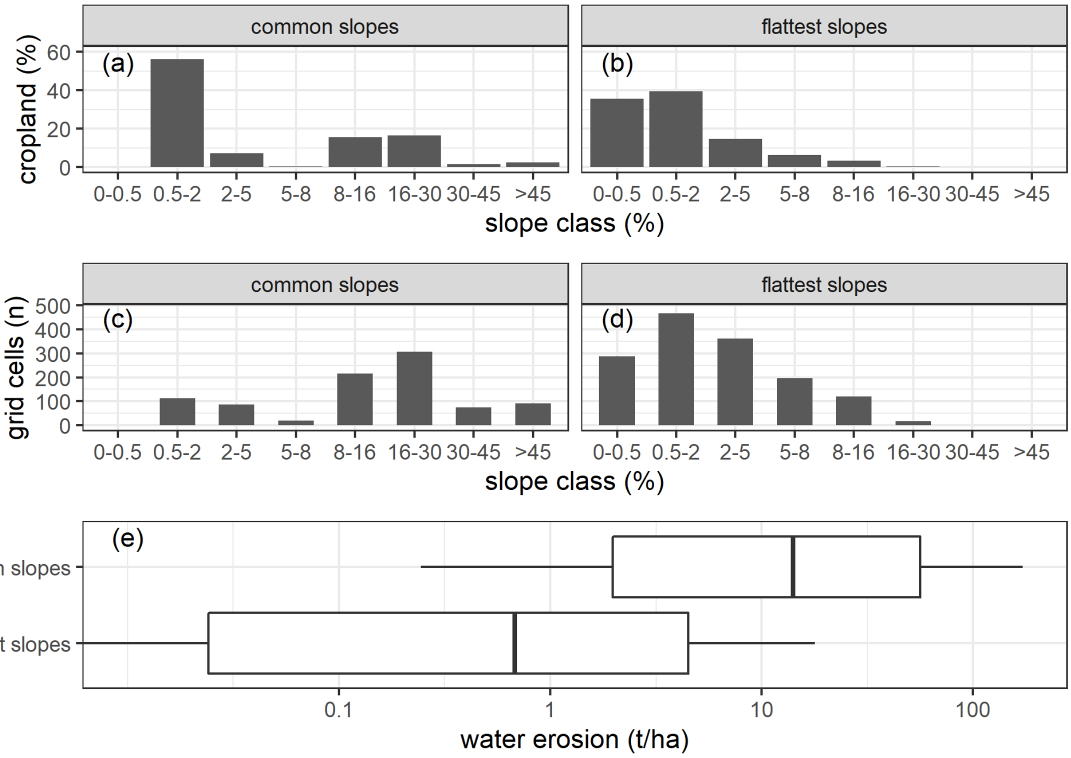


Figure S11. Comparison of slope inputs and simulated water erosion outputs between the cropland distribution scenario using the most common slopes and the cropland distribution scenario using the flattest terrain available in Italy. (a, b) distribution of the cropland share (Portmann et al., 2010) per slope class. (c, d) distribution of grid cells per slope class. (e) Simulated water erosion for Italy using both cropland distribution scenarios. Midlines visualise median values, boxes include values from the 25th to the 75th percentiles and whiskers bracket values between the 10th and the 90th percentiles.

Dominant slope class	Lower value (%)	Upper value (%)	Mid value (%)	Slope length (m)	Field size (ha)
1	0	0.5	0.25	200	10
2	0.5	2	1.25	200	10
3	2	5	3.5	200	10
4	5	8	6.5	200	10
5	8	16	12	100	5
6	16	30	18	75	5
7	30	45	35.5	50	1
8	45	100	60	20	1

Table S1. A set of rules for field size and slope length estimation for each dominant slope class. The area/dominant slope class was assigned to each grid cell from a global slope and terrain dataset (Fisher et al., 2007) providing 3 arc-sec spatial resolution distributions of nine slope gradient classes: 0–0.5%, 0.5–2%, 2–5%, 5–8%, 8–16%, 16–30%, 30–45%, and > 45% interpreted from SRTM elevation data (CGIAR-CSI, 2006). Mid-interval value of the dominant slope class was used as an input for EPIC.

Table S2. Input parameters for the sensitivity analysis of the water erosion equations. Random values assigned to each input parameter in the sensitivity analysis are defined by a range of discrete values or a triangular distribution defined by the values given in the table.

Table S3. First- and total-order sensitivity indices (SI) ranking for 30 input parameters for each water erosion equation.

Table S4. Spearman coefficients explaining the positive or negative correlation between the first- and total-order sensitivity indices of the input parameters from each equation and the amount of annual rainfall at a location.

Table S5. Measured water erosion values collected from 1~~0~~13 studies. The reference list of each study is available at TWCarr-si02.docx.

Uncertainties, sensitivities and robustness of simulated water erosion in an EPIC based global-gridded crop model
By T. W. Carr et al.

Reply to Anonymous Referee #1

Referee comment is printed in purple and is addressed below

Despite the decades of research, modelling spatially distributed phenomena such as soil water erosion, still represents very challenging job. The biggest challenge lies in comparing modelled and measured soil erosion rates, especially in case of global scaled models such EPIC. The main added values of presented paper are: 1. Evaluation of simulation results against field data and uncertainty assessment. Uncertainty assessment represents a crucial factor, when communicating the results of simulation and further incorporation of such models into for instance global circulation models. 2. The authors pointed out several obstacles, which prevent further development of soil erosion modelling research such as lack of uniform and reliable data on water erosion rates, lack of datasets providing distributed data on topography, soil, climate, land use and field management at the field scale. Supplementary TableS5 contains the list of soil erosion measurement records, it would be good to add an information about the scale of measurement (plot, field, : : :) The article is of high scientific value and I recommend it for the publication without any substantial revision.

Thank you for your positive comment. We added a column to the supplementary TableS5 specifying the scale of the erosion measurement as “Hillslope”, “Plot” and “Field”. A more detailed discussion about the field data scale can be found in the reply to referee #2.

Uncertainties, sensitivities and robustness of simulated water erosion in an EPIC based global-gridded crop model
By T. W. Carr et al.

Reply to Anonymous Referee #2

Dear reviewer,

Before we address each of your comments, we briefly clarify the main incentive of this study. Large-scale indicators about global-scale phenomena are needed to inform all major environmental and agricultural policies such as the European Union's Common Agricultural Policy (CAP), the United Nations Sustainable Development Goals (SDGs), the United Nations Convention to Combat Desertification (UNCCD) and the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES). Water erosion will not be considered in any of these major environmental and agricultural policy programs without large-scale assessments (Alewell et al., 2019). Global-gridded crop models have the capacity to develop large-scale indicators and to inform about agricultural productivity in a transparent and consistent way across large areas (Mueller et al., 2017). This paper aims to address the gaps in the literature of the links between water erosion and crop cultivation in various large-scale and global impact assessments, as accurately as is currently feasible given data availability. Studies on large-scale and global climate change impacts in the agricultural sector lack representation of water erosion impacts on crops (Balkovič et al., 2018), studies on global terrestrial carbon fluxes do not account for carbon runoff from cropland through soil erosion (Chappell et al., 2016), and studies assessing large-scale and global market impacts of soil erosion rely on simple linear estimates of water erosion impacts on crop production (Panagos et al., 2018; Sartori et al., 2019). It is important, though, to understand the limitations of such assessments so that they can be improved in the future, and that is why we systematically test a number of approaches in our paper.

The model used in this study has been confirmed as a reliable tool for global crop yield projections and stands out against comparable global models due to its detailed representation of soil processes including water erosion and the impacts of tillage on soil properties. Therefore, a global-gridded EPIC model has the potential to deliver much needed indicators about relationships between erosion and crop productivity on large and global scales. This paper has the objective to support the ongoing development of large-scale and global model applications by analysing the robustness of average long-term water erosion estimates generated with global-gridded crop models. In other words, we do not attempt to reproduce soil loss rates measured in single fields but to analyse the robustness of large-scale water erosion estimates based on global-gridded crop model outputs. Moreover, we focus on the necessary improvements needed to account for water erosion in global models by analysing and discussing its robustness across global agro-environmental conditions, the importance of global input data on field management and the uncertainty resulting from different erosion equations.

Most of the criticism by the referee is directed against the lack of field data, model calibration, and general criticism on RUSLE-based erosion models and the ^{137}Cs-method used for erosion measurements. Each point of criticism is addressed in the following (Referee comments are printed in purple and our replies are listed below):

The EPIC model has been used to look at climate change impacts on crop yields and erosion rates e.g. Favis-Mortlock et al. (1991) and to model 7000 years of erosion under changing climates and land uses for a single field (Favis-Mortlock et al., 1997). It is stressed that EPIC needs calibration in order *to give reasonable results. This is the very firm conclusion of the GCTE erosion model testing exercise (Favis-Mortlock, 1998; Boardman and Favis-Mortlock, 1998).*

The first point of criticism is on the need to calibrate the EPIC model for reasonable results. The EPIC-IIASA model uses state-of-the-art global crop management and agro-environmental input data and has been positively evaluated for representing national average yields and inter-annual yield variability globally (Balkovič et al., 2014). It was used in several studies and its outputs have been compared to regional yield statistics and other global crop and land use models as a part of ISI-MIP and GGCMI model inter-comparison initiatives (Mueller et al., 2017). Global crop models are not calibrated to reproduce crop yields at field scale but rather to represent the crop yield patterns across regions and countries to address research questions that cannot be addressed through field scale studies. Following the same paradigm, we aim to analyse the robustness of EPIC to represent regional differences and regional spatial patterns in water erosion estimates rather than accurately reproduce erosion events occurring in the past in response to individual rain events of rainy seasons. We are aware that our approach would be inappropriate for the latter case. We are also aware that a proper model calibration is always needed to meet experimental data obtained from the field, foremost for a complex process like soil loss due to water erosion. At the same time, sound calibration for a wide range of global environments and crop management practices would require enormous capacity and work force while still facing a high degree of subjectivity in experimental data (e.g. Panagos et al. 2016). Given the current lack of consistent field measurements representing all global environments, it is not possible to produce plausible global erosion estimates using only bottom-up, field-scale modelling.

To further clarify the intention of this study, we add a reference clarifying the usefulness of large-scale models to line 59: "*Moreover, improving the representation of water erosion in large-scale models is urgently needed to inform major environmental and agricultural policy programs such as the European Union's Common Agricultural Policy (CAP), the United Nations Sustainable Development Goals (SDGs), the United Nations Convention to Combat Desertification (UNCCD) and the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES) (Alewell et al., 2019).*"

We will further clarify the focus of this paper in the introduction, line 91: "*The overall aim of this study is: (i) to analyse the robustness of water erosion estimates in all global agro-environmental regions simulated with an EPIC-based global-gridded crop model; and, (ii) to discuss the main drivers affecting the robustness and the uncertainty of simulated water erosion rates on a global scale.*"

We will modify the last conclusion on line 606: "*The overlap of simulated and measured water erosion values in most environments used to produce wheat and maize underlines the robustness of an EPIC-based GGCM to simulate the differences in water erosion rates of major global crop production regions"*

The authors claim that they are evaluating their results against field-scale measures (lines 84 and 95). This is not the case: they use 137Cs and erosion plot data (line 219). Erosion plot data cannot be up-scaled to field scale: it is useful for relative assessments e.g Cerdan et al. (2010). Extrapolation from12 plots in central Belgium to give an average rate of erosion for Europe is a well-known (?) example of misuse of experimental plot data (Boardman, 1998): the current paper is heading in that direction!

The referee criticises the use of our erosion plot data. We do not extrapolate plot data to represent water erosion on continental scales as in the Belgium-example mentioned by the referee. As explained on line 235-239, we aggregate field data into groups with similar slope classes and precipitation classes and compare the values to model outputs with the same slope and precipitation classes. Thereby, we analyse the robustness of model outputs for different environments characterised by the most important parameters affecting water erosion on a global scale. Slope and precipitation are the most sensitive parameters influencing model outputs and are the parameters found previously to be most critical for the robustness of RUSLE-based models. We chose this method to illustrate the varying robustness of our model outputs around the globe and we identified regions where the model performance is not sufficient, which is communicated in the discussion (line 367-370) and the conclusion (line 472 – 473).

More generally, plot and field scale are not exactly defined. These two categories can be overlapping as large plots can have similar slope length as fields. Plots of 20 m are most common, and if they are equipped by multislot divisors, typing buckets they can be up to 100 m long, or even several hundred meters if equipped by Coshocton wheels. We know about 100 m erosion plots from Slovakia and Austria or 30 m plots in Zimbabwe. Fields can also have slope length about 20-100 meters, especially if they are on slopes, contour oriented or when they belong to small family farms in developing countries. We have seen 30-50 m long slopes in Uganda, Madagascar, or Slovakia.

Regarding the real scale of our data, most of them (both 137Cs and erosion plots) represent slopes of 10-100 m so they are at the margin of plot and field scale. Therefore, in the paper, we will name the range of spatial scales of the field data on line 239 (we increased the field data sample as explained below). "*We compared our simulated water erosion rates with 606 soil erosion measurements on arable land from 36 countries representing plot and field scale. Most of the selected erosion rates are based on the ^{137}Cs method. In addition, data from erosion plots and volumetric measurements of rills collected by Auerswald et al. (2009), Benaud et al. (2020) and García-Ruiz et al. (2015) were used. In total, 315 records were derived by the 137Cs method, 188 records from runoff plots, and 103 records from volumetric measurements of rills.* "

The term "*field-scale measurements*" on line 95 will be deleted as this sentence will be replaced with the sentence stating the overall aim of this study presented above.

The term "*field measurements*" on line 106 is not related to scale.

RUSLE is an unvalidated model and its problems and poor performance are reviewed in Evans and Boardman (2016a and b). For a review of the general problems of using erosion models see Favis-Mortlock et al. (2001): in Harmon and Doe (ed) book.

Further criticism is focused on the validity of the RUSLE method in general, which is one out of seven similar erosion models included in our EPIC study. The RUSLE methodology is based on more than 10,000 plot-years of experiments and has been applied in more than 100 countries with varying robustness (Alewell et al., 2019; Renard et al., 1997; Wischmeier & Smith, 1978). As already disputed above, the limited availability of global input and experimental data requires simple erosion models for global studies. Therefore, RUSLE has been chosen by most studies focusing on global erosion (Borrelli et al., 2017; Doetterl et al., 2012; van Oost et al., 2007) and it is unfortunate that the referee disagrees with the approach adopted by most of the scientific community. We agree that the varying robustness of RUSLE-based methods around the world need to be considered, which is one of the main foci of this paper and has been addressed in the introduction and in the discussion. Furthermore, we present the varying estimates of different water erosion equations and thereby demonstrate the uncertainty of relying on erosion estimates from a single model. The references used for criticising the RUSLE method by the referee promote field studies as alternatives to erosion models. However, this is not feasible for a range of research applications focusing on analysing scenarios at large and global scales (Alewell et al., 2019; Panagos et al., 2016), which is also a major purpose of global gridded crop models. Instead, focusing on the improvement of the application of simple erosion models such as RUSLE-based models as intended with this paper supports the ongoing development of global erosion impact assessments (Naipal et al., 2015).

137Cs has been seriously criticised recently (Parsons and Foster, 2011). The technique should not be used without dealing with these limitations. This problem is ignored in the paper.

The objections of Parsons and Foster (2011) were discussed by Mabit et al. (2013) published as a direct answer to Parsons and Foster in the same journal. One of the most important confirmation of the usefulness of the 137Cs method given by Mabit et al (2013) are the positive results of a comparison between erosion values obtained with various measurement methods and erosion values obtained by 137Cs method: "*Several studies at various scales (from plot to watershed scales) have been conducted to compare the 137Cs based erosion rates obtained with direct erosion measurement approaches such as erosion plots and catchment sediment yields (e.g. Schuller et al., 2003; Porto et al., 2003; Porto et al., 2004; Stankoviansky et al., 2006;Mabit et al., 2009; Parsons et al., 2010; Ceaglio et al., 2012; Porto and Walling, 2012a, 2012b). In northern California, rates of erosion from accumulated pond sediment and soil lost from hillsides assessed through 137Cs agreed well (i.e. O'Farrell et al., 2007). In Italy, the reliability of the mass balance model at slope and catchment scale was verified and confirmed by comparing the basin net soil erosion value obtained by 137Cs measurements against the mean annual value of sediment yield measured at the basin outlet (i.e. Di Stefano et al., 2005). For three small catchments located in Southern Italy, measurements of sediment output validated 137Cs theoretical conversion models to estimate soil redistribution rates (i.e. Porto et al., 2004)*".

Another paper by Parsons (2019) also criticises erosion plots, modelling (several models) and volumetric measurements of rills. As our paper is focused on global erosion modelling, we did not include the extensive literature on the advantages and disadvantages of each erosion measurement method. A comprehensive discussion of the objections against the 137Cs method and other measurement methods would but too extensive for our paper. However, we will address Parsons and Fosters objections in this response:

a. Regional and local heterogeneity of 137Cs fallout and its local redistribution by vegetation, infiltration, bioturbation, etc.: this is well known fact but it is considered in the methodology and the solution is the selection of reference sites in immediate vicinity of study sites and using statistical criteria (variation coefficient) criteria for microvariability of 137Cs. The microvariability of 137Cs is similar to most other soil properties and the potential error is similar or smaller than for other erosion measuring methods (as it will be demonstrated further). There is set a limit for variation coefficient which reference site should not exceed.
b. Mobility of 137Cs: the references presented by Mabit et al. (2013) clearly demonstrate that 137Cs is strongly bind to colloids (with details on particular clay minerals and organic matter) and its mobility (washing by runoff during the deposition, leaching and plant uptake are negligible (representing less than one percentage to very few percentages of 137Cs fallout). The ideas about mobility, leaching and plant uptake of 137Cs presented by Parsons and Foster are based mainly on laboratory experiments with Caesium which do not represent its real behaviour in nature because the laboratory conditions are artificial, and the used doses of Caesium are too high. Parsons and Foster admit that in their paper. If these ideas would be correct, we would frequently see leached Caesium in deeper part of soil profile or the whole inventories at sites undisturbed by erosion would be depleted by plant uptake. But this is never the case in natural soil.

c. Selective removal and sorting of the particles: This is well known by all authors using the 137Cs method and it is mentioned in all handbooks and conversion procedure has a parameter for that. But it is true that this factor is difficult to quantify. But similar weak points are common in most methods of erosion measurements as will be demonstrated below.
d. Conversion models: Indeed, procedures to calculate soil loss require some parameters which are not always available. The accuracy of calculation depends on quality of input data and is different in individual studies. But this is the case for all erosion measurements and all methods as it will be demonstrated below.
e. Sample preparation: the problems with coarse fraction, dry or wet sieving can occur in specific soils, especially when having porous coarse fraction and concretions containing clay or organic matter so that the coarse fraction has electrical charges. This of course should be understood by staff who is expected to have basic pedological education. It is true that not all these details are mentioned in every methodological guidance, but they are discussed by some authors.
f. Gammaspectroscopy: Criticism of gammaspectroscopy is not relevant at all. Indeed, there are possible different geometries of detectors and detectors have to be calibrated. But this is task for laboratory staff. Cs-method obviously require staff having background in nuclear physics. Each laboratory method whether physical or chemical require staff with appropriate qualification.

Finally, we accept that we could have mentioned the limitations of the field data we collected and referred to some of the existing literature. We will mention the main limitations of the field data we collected on line 552:

"The 137Cs method was criticised by Parsons and Foster (2013), who questioned assumptions about the 137Cs behaviour in the environment (variability of the 137Cs input by wet fallout, its microspatial variability at reference sites, its possible mobility in certain soils, the 137Cs uptake by plants and other aspects of 137Cs behaviour in soil). To confront the criticism against the 137Cs method, Mabit et al. (2013) discussed all objections raised by Parsons and Foster (2013) and confirmed its accuracy by listing several studies, in which 137Cs based erosion rates are compared with erosion rates derived from direct measurements. The 137Cs method is based on a set of presumptions which should be met to produce useful results and thus careful interpretation of the obtained results is needed (Fulajtar et al., 2017; Mabit et al., 2014; Zapata, 2002).

Similarly, erosion rates obtained by volumetric measurements require careful interpretation as they are exposed to various potential sources of errors and do not account for interill erosion. Although the latter can be neglected under certain circumstances, studies from Europe and semiarid areas of the USA have reported that interill erosion contributed significantly to the amount of soil eroded in fields (Boardman and Evans, 2020; Parsons, 2019). Further, measuring the lengths and cross-sections of rills during field surveys or on terrestrial and aerial photos can be very subjective (Panagos et al., 2016). Different approaches used to detect and measure rills in fields can cause variability in calculated erosion volumes up to a factor of two (Boardman and Evans, 2020; Casali et al., 2006; Watson and Evans, 1991). In order to obtain soil erosion rates in weight units, soil volumes need to be converted using the soil bulk density, which is often based on estimates (Evans and Brazier, 2005).

The shortcomings of erosion plot measurements were discussed by several authors (Auerswald et al., 2009; Brazier, 2004; Evans, 1995, 2002; Loughran et al., 1988). Erosion plots have various sizes and shapes (few meters to few hundreds of meters) and various approaches of sediment recording are used (total collection, multislot divisors, tipping buckets, Coshocton wheels), which all involve significant uncertainties. Although some long-term plot experiments exist, many plot measurements fail to cover the whole year erosion cycle (Auerswald et al., 2009). Often, they have to be removed during land *management operations such as seeding, ploughing, or they are too expensive and labour demanding."*

It is simply not true to claim that there is a limited availability of field data and lack of long term measurements (lines 68-69). There are extensive data sets from Switzerland, north Germany and the UK. These could be used to validate the results of erosion models: see Boardman and Evans (2020: PPG) for a review of these methods of assessment of erosion at a field scale.

The need for slope and precipitation information accompanying erosion measurements in our evaluation method narrows down suitable field datasets, as meta data such as slope steepness is often not available in published datasets. Moreover, when we refer to a lack of field data, we are talking about the global scale and especially the imbalance in data availability among world regions. We have addressed the uneven distribution of global field data in the introduction and the skewed focus of field data on the United States and Europe in the discussion. Also, the difficulty of gathering field data from a very heterogenous mix of measurement methods is comprehensively addressed in the discussion. We attempted to gather field data from as many continents as possible to represent different global environments. Insufficient field data representing all global regions and the lack of sufficient metadata in available datasets to further improve erosion modelling on large and global scale is an important conclusion of this paper.

We will further clarify these issues in the discussion after line 514

"*A variety of factors influencing water erosion such as climate, field topography, soil properties and field management need to be considered when modelling water erosion but are often not reported in available field measurements (García-Ruiz et al., 2015). This hampers a direct comparison between simulated and observed water erosion values. We demonstrated the varying match between measured and simulated water erosion using different tillage and cover crop scenarios. Metadata on field management often only provides the crop cultivated and therefore the conditions under which erosion was measured in the field are not known sufficiently to evaluate erosion values simulated under different field management scenarios. Similarly, information on field topography and soil properties is often not provided with recorded field measurements and thus their use is limited in an evaluation of water erosion estimates simulated in different global environments. Moreover, most data are concentrated in the United States, West Europe and the West Mediterranean (García-Ruiz et al., 2015). In summary, there is a lack of field data representing all needed regions, situations and scenarios (Alewell et al., 2019)."*

We increased the field data sample to 606 records using publicly available datasets from Germany and the UK provided by Auerswald et al. (2009) and Benaud et al. (2020).

We add a description of the additional field data after line 256:

"*Bounded plots are the most commonly used method of erosion measurements. They were introduced in the USA in the 1920s (Hudson, 1993) and were used for the development of USLE and WEPP models (Brazier, 2004). Eroded soil material can be quantified with erosion plots in different ways (total collection of sediment, fractioned collection of sediments using multislott divisors, measurement of discharge and sediment concentration by tipping buckets and Coshocton wheels). The overview of this method is provided by Cerdan et al. (2010); Hudson (1993); Mutchler et al. (1994); De Ploey and Gabriels (1980) and Zachar (1982).*

The volumetric measurements of rill erosion are used since approximately the 1940s in the USA (Kaiser, 1978 in Evans, 2013) and the 1950s in Europe (Lobotka, 1955), usually at field scale (Boardman, 1990, *2003; Boardman and Evans, 2020; Brazier, 2004; Evans, 2002, 2013; Herweg, 1988; Zachar, 1982). The volume of erosion rills is derived from their lengths and profile cross-section areas, which are measured in field or from terrestrial and aerial photos (Evans, 1986, 1988; Watson and Evans, 1991)."*

An attempt to further increase the field data sample using the source provided by the referee (Boardman & Evans (2020)) was not possible as only aggregated values are provided for the large datasets listed in Boardman & Evans (2020).

Some more general remarks: Although huge effort was spent by the erosion community to generate an enormous number of data, there is a serious lack of useful data to evaluate large-scale models. It was very challenging to gather the amount of field data used in this study for the following reasons:

1. As we are working with USLE-derived models, we were looking for data from certain spatial extend only. The USLE was developed at short slopes and represents sheet erosion and initial stages of rill erosion. Therefore, we preferred data from ca 10-100 m long slopes. This is the case for field data derived with the 137Cs method and erosion plots. Initially, we decided against using data from long slopes (several hundred of meters), which is usually the case of volumetric measurements of rill erosion and hydrological measurements in small watersheds.

2. At the beginning of this project we tried to focus only on data derived by 137Cs method as different methods represent different erosion processes and are subject to different systematic errors which are presented in the following:

   Erosion plots with total collection of sediment have problems to collect great volumes of sediment in case of extreme rain events (the sediment may exceed the capacity of containers) and it can be difficult to determine the weight of sediment (when it is wet, the whole volume cannot be carried to the laboratory for drying so the quantity of soil in the collected mud is just estimated by taking a sample of the mud to measure concentration).

   Multislot divisors, tipping buckets and Coshocton wheels have many technical problems (multislot divisors may split the sediment unequally if they are not fixed exactly horizontally, the tipping buckets and Coshocton wheels loose part of the sediment when they are tipping or when the stream is strong water is splashing out, if the stream is weak the soil material is sedimenting immediately in tipping buckets and the sample is not representative, data loggers can break, etc.).

   Studies with replicated plots showed great variability for replicas. Nearing et al. (1999) report from almost 800 replicated plot pairs/year data a coefficient of variation ranging between 14% and 150%. Variability was decreasing with increasing soil loss. The rates of 10 tons/ha had coefficient of variability of ca 40%.

   Geodetical method (erosion pins) has much bigger error than erosion plots because it has poor resolution. If one mm of soil is removed, the change of surface is hardly seen. But this represents already 10 tons of soil per hectare. On arable land the geodetic method has problems to distinguish between erosion and compaction.

   Rill and gully volumetric measurements (<u>preferred method in the reference provided by the referee (Boardman & Evans (2020)</u>) neglects sheet erosion completely. The recalculation of obtained volumetric data to weight is problematic because of the limited information on soil bulk density and its vertical and horizontal variability. This is problematic as we need data in t/ha to compare with models. Usually it is not indicated whether rill measurement represent the whole year or only the vegetation season, whether they involve rills from snow melt or not, etc.

The measurement of rill volumes itself is a source of huge error. Authors who use this method know this (for example Evans, 2013, stated: "Mollenhauer notes (2002: 4) 'The measurement of lengths and cross-section areas of linear forms can be extremely error ridden'; and quotes from Ruttiman and Prasuhn's (1990) work in Switzerland that the 'total error for soil loss volume can amount to between 20 and 40%' (Mollenhauer, 2002: 4)" and further "The level of accuracy of field-based estimates depends on the amount of time spent in measuring/estimating the number, lengths and dimensions of rills and gullies and assessing volumes of depositional features such as fans. The larger an area surveyed inevitably means that cruder estimates of eroded amount will be made, for example, numbers, lengths and cross-sectional areas of channels will all have to be estimated rather than measured").

Measurements have very few traverses (sometimes only 4, Boardman, 2003), which is a huge source of error. Boardman even says that sometimes one traverse is enough (Boardman, 2003: "The number of traverses is clearly subject to the time and resources available and also the purpose of the survey as to how much detail and accuracy is required. In many situations, it is reasonable to undertake one traverse across the mid-point of the eroded slope and estimate total erosion based on the mean rill length."). Measurement based on one traverse compared to measurements based on 4 traverse revealed errors from -18,1% to +48,7%.

The method neglects interrill erosion which is an important portion of the whole erosion process. Estimates of the importance of interrill erosion differ significantly for different conditions (negligible amount of 0.3 m3/ha/y provided by Evans (1990, in Boardman 2003), few % of total erosion: 5-11% (Morgan et al., 1987, in Evans, 2013), up to few tens of %: 25% (Prasuhn, 2011) and 10-30% (Zachar, 1982)).

Parsons (2019) emphasize that the volumetric measurements of rills severely underestimate overall erosion because rills also involve large quantity of material which was delivered by sheet erosion to rills and further transported by rills. These proportions can be 40% for rill erosion and 60% for interrill. Luk et al. (1993, in Parsons, (2019)) determined the portion of rill erosion ranging between 0 (when only sheet erosion develops) and 56%. Our own experience from Central Europe with more heavy rainfalls from own unpublished measurements is that at steep slopes (ca 8-12 degrees) it can be in some years 10-40 tons per ha. Govers and Poesen found that the proportion between rill and interrill erosion can change significantly with time and according to changes in physical properties of top layer and deeper layers either proportion of rill erosion can rise or the proportion of interrill erosion can rise. In their case study the proportion of interrill erosion was decreasing with time from 46 to 22%, but other authors found opposite trends. Therefore, estimating interrill erosion from rill erosion using fixed ratios is wrong. They also find, that interrill erosion has higher proportion on short slopes than on long slopes.

Sometimes the presented rill measurements are not real measurements but just very rough and brief estimation. The rills and their lengths are estimated from photos, where smaller rills might be difficult to detect (for example Boardman, 2003: "Ground-level photographs of rills and gullies may be used as a record of length and size; subsequent analysis shows them to be a reliable means of estimating soil losses (Watson and Evans, 1991)" or Evans, 2013: "In this review paper, 'direct' assessment of water erosion is taken to mean the mapping of erosion and deposition as evident in fields (Figures 1–9) or on ground or aerial photographs and then when possible estimating eroded volumes based on lengths and cross-sections of rills and gullies and areas and depths of deposition (Evans, 1988; Herweg, 1996; Stocking & Murnaghan, 2001)." Watson and Evans (1991) estimate the sizes of rills on photos comparing it with the widths of crop rows and height of crop and thickness of colluvial fans they estimate according to their colour. They compared the results of volumetric measurements in field and on photos (12 photos) and found ratios from 0.67 to 2.12.

Hydrological measurements in elementary watershed do not represent erosion only from agricultural land but also bank erosion and road erosion, and both these can be significant.

Sampling of suspended sediment is not well representative, and samplers or data loggers can break. The range of discharge in small catchments is so huge that it makes instrumentation of hydrological profiles difficult.

For these various possible sources of errors, we did not want to mix up different methods. The optimal case would have been to only use field data derived from one method, but to increase the amount of data we decided to take 137Cs data and some selected erosion plots (to further increase our sample we included suitable data from volumetric surveys).

3. Large amount of existing data is not accessible for various reasons:
    a. Many older publications are in national languages
    b. Many older publications are not on internet
    c. Many measurements were published in grey literature, local conference proceedings, national acta of scientific institutions, unpublished reports, etc.
    d. Many published data are hardly interpretable because metadata are lacking (slope lengths, or inclinations or crop cover, period of measurement is not recorded, geographical position of the sites is not recorded, many measurements were running only during vegetation period of studied crop so they do not represent annual erosion but just few months, etc.).
    e. International journals do not have interest to publish usual case studies which present raw data. To get paper published the authors need to present some special objectives to follow some special goals or developing methodological innovations. Therefore, also many new data sets cannot be found online.
    f. Even if paper is published, journals have usually size limitations. To save space the primary data are not presented, only the results of interpretation, statistical processing, etc. are there. In publications using 137Cs it is more common to find primary data than in studies using other methods.

Please consider that all methods have a lot of weak points, methodological shortcomings and sources of errors, uncertainties and variability and there is lack of reliable comparisons and comprehensive assessment of all methods which would be widely accepted by the whole erosion community. There are different schools and groups of researchers who use predominantly one method. One group uses 137Cs method, other groups prefer erosion plots, the next one focuses on elementary watersheds using hydrological methods based on discharge and sediment concentration sampling (or combination of plots and watersheds) and other group focuses on volumetric measurements of rills and gullies. Some researchers using certain method are very critical about other methods, but they are very tolerant regarding the shortcomings of their favoured method. Although each method has advantages and limitations and each group has success and achievements as well as challenges and failures, it is normal if individual researchers or teams prefer one particular approach. But they should respect also other approaches.

Our collected data set represents a reasonable compromise to achieve the objectives of this study. It is far beyond the capacities of the team and the objectives of this study to collect all existing erosion data. Such task would require years lasting international project with participation of research teams from most countries, so that each team would be able to revise data sources in his country and provide summary of data including those published in national language and unpublished reports. Most existing data have limited accuracy and representativeness, but we cannot wait until dense coverage of perfect data will cover the Globe. Erosion is running, agriculture is in troubles and we should proceed under existing circumstances and using available tools.

The method of deriving a common slope within an area of 9x56 km is not clear and seems rather dubious (line 122). Averaging slope from a large cell (eg. 1km2) is a common failing of erosion modelling exercises (e.g. Evans and Brazier, 2005).

The most common slope is determined by a slope class covering the largest area in each simulation grid. Slope classes are taken from a global terrain slope database (IIASA/FAO, 2012) and are based on a high-resolution 90 m SRTM digital elevation model. We assume that the slope class representing the largest area in each grid cell is most likely covered by the largest area of cropland. This builds on the idea that a spatially extensive and diverse landscape can be represented by a single "representative field" characterized by the prevailing combination of topography and soil condition found in the landscape. This method is designed to represent differences in large-scale global crop production with an emphasis on the most important global crop production regions.

We clarify the concept of the representative field on line 134: "*Each grid cell is represented by a single field characterized by the combination of topography and soil conditions prevailing in this landscape unit. Each representative field has a defined slope length (20 – 200 m) and field size (1 - 10 ha) based on a set of rules for different slope classes (Table S1). The slope of each representative field is determined by the slope class covering the largest area in each grid cell (Table S1). Slope classes are taken from a global terrain slope database (IIASA/FAO, 2012) and are based on a high-resolution 90 m SRTM digital elevation model.*"

A detailed discussion about the uncertainty in slope input data has been added in response to comments by the third referee (see response to referee #3).

One conclusion seems to be that wheat erodes are a greater average rate ((19t/ha) than maize (6t/ha) (line 244): this is contrary to all field evidence that I am aware of.

The criticised conclusion on falsely higher erosion rates in wheat fields compared to maize fields is based on a misunderstanding. The values represent a global average value (19 t/ha) and a median value (6 t/ha) of water erosion rates for both maize and wheat fields combined.

To avoid confusion, we will focus only on median values in the revised version as median values are less influenced by the skewed distribution of erosion values. In the discussion line 418 we mention both mean and median value to illustrate the skewed distribution of erosion rates due to very high values simulated on steep slopes.

We will present global median water erosion for both maize (7 t/ha) and wheat (5 t/ha) fields on lines 26, 280 and 349, and will delete average values.

Global average water erosion values simulated under different management scenarios and different water erosion equations are deleted on line 466 – 468 and 497 to focus only on median values.

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Uncertainties, sensitivities and robustness of simulated water erosion in an EPIC based global-gridded crop model
By T. W. Carr et al.

Reply to Anonymous Referee #3

Dear reviewer, we appreciate your thoughtful comments and have responded to each in the following (Referee comments are printed in purple and are each addressed below).

This manuscript describes a study to characterize global soil erosion rates on cropland using the exploration of a large parameter space of driver data and erosion models. Starting with global information on climate, soils, agricultural practices, and field properties, the authors calculate representative erosion rates. In a series of experiments, they show the sensitivity of the model to driving inputs and parameter assumptions. They evaluate the model results against a large dataset of observed soil erosion data. The authors conclude that the model results are very sensitive to assumptions about management strategy, and the accuracy of the model is limited by a lack of field observations for calibration and evaluation.

In general this manuscript is well written and simple enough to understand. However some key information is lacking in the main text of the manuscript, and some of the results seem rather suspicious, possibly because of artifacts in the input data. In particular, the headline numbers for global soil erosion, and the mapped model output, appear to be strongly influenced by erosion in mountainous areas, where in reality land use for agriculture may be much more limited than the model assumes. These issues need to be addressed in a revision before the manuscript is ready for publication.

Our experience (not only from modelling, but also from field work, excursions and own observations and measurements) shows that in some mountainous areas the erosion rates reaches very high levels. But to some extent you are right and we considered your objection. Below, when answering other comments on this issue we will try to demonstrate in detail the situation in mountains. We will provide also some photos.

Looking at the model results in Figure 2a, what stands out immediately is that very high rates of erosion are plotted in many regions of the world where I would not be sure that there is any significant amount of agriculture, including the central highlands of Borneo, the Himalaya, eastern Madagascar, South Korea, and parts of the Alps. These are indeed high-rainfall/high slope regions and in some of the area agriculture is practiced. But where there is cropland, it almost certainly must be limited to valley bottoms or other low-slope areas, or only performed with substantial investment in erosion mitigation measures, such as terracing.

Digging deep into the manuscript supplementary materials, I discovered that the actual crop distribution data used in this study (5') comes from Portmann et al. (2010). This citation, and explanation for how the crop areas were determined, must be moved to the main body of the text. It appears that Portmann et al. (2010) do not use slope or any other topographic characteristics in determining the spatial allocation of cropland in their crop area maps. Furthermore, 5' resolution is probably too coarse even in the authors' own admission to accurately determine appropriate mean slope classes for their soil erosion calculations.

The reference to Portmann et al. (2010) is listed in Table 3 in the main text, which summarises the field management assumption and aggregation of model outputs.

We extend the reference to table 3 on line 212. "*Table 3 summarises the field management assumptions of the baseline scenario used to aggregate erosion rates in each grid cell and region.*"

We agree, that in some mountainous areas the erosion rates obtained by modelling do not represent typical rates. However, it is not the case for all mountains. The values are overestimated most probably in mountains of temperate areas such as Europe (Alps), Korea and Japan and also in some tropical rice grooving regions on tropical Monsoon Asia (such as Borneo). However, in many mountainous areas in tropics the land is cultivated, and maize and wheat are grown even in very steep slopes and often without any soil conservation practices or conservation practices are used with insufficient efficiency. We attached a collection of photos demonstrating these phenomena (**photos are attached in the pdf-file including the direct response to referee #3**). In the tropics, agriculture is very active in mountains especially for four reasons:

1. While in temperate areas such as Europe the temperature is limiting factor of agriculture and in higher altitudes (several hundred meters above the see level) it is too cold for most crops and if agriculture exist there, it is mainly grazing. In contrary, in tropics the temperature is sufficient also in high mountains.

2. The limiting factor in tropics is drought. Therefore, mountains having more rainfall and less heat are popular agricultural area. Very good example is Uganda, where the whole flat central part of the country is too dry and it is used only for grazing, while steep mountains in west and east peripheries of the country are intensively cultivated. The same is in Madagascar and in whole Latin America where mountains are more agriculturally exploited than lowlands.

3. In tropics the weathering crusts are very thick and so the loose materials constitute thick soils. Tropical soils are poor in organic matter so the difference between topsoil and subsoil is not very big. These soils can be exposed to extreme erosion rates much longer than thin soils of temperate areas, so farmers do not feel the decrease of fertility and production potential. It is decreasing slowly, and they do not realize the impact of erosion.

4. In developing countries, a great portion of land is still under hand management of small family subsistence farming. These farmers can cultivate steep slopes easier than farmers who use heavy machines.

Some examples from our own field work, where the extreme exploitation of steep slopes exists are following:

1. In Latin America, especially in mountains with volcanic rocks are cultivate even in extreme slopes and here maize is dominant crop (see photos from El Salvador).
2. Mountainous area of Sub-Saharan Africa: Extremely steep slopes are cultivated, many crops with low conserving efficiency are grown (such as cassava and other sweet potatoes, beans, maize, etc.), there are terraces, but these are not really horizontal but inclined so they reduce erosion partially but not much (see photos from Uganda and Madagascar)
3. South and East Asia: In this region the major crop is rice which is usually grown on paddy field with flood irrigation. Therefore, the large mountainous areas are well terraced and well protected from erosion. However, there are also very large mountainous areas which are not terraced at all and steep slopes are cultivated. They are growing various crops there such as

dryland rice, tea, fruit trees, sugar cane, etc. For example, in large part of southern China the rice terraces are only in valley bottoms occupying minor areas and all steep slopes occupying majority areas are used to grow sugar cane without any soil conservation.

An explanation and further discussion of the resolution of slope input and cropland distribution data follows below

These limitations mean that the headline numbers for erosion (e.g., lines 25-26 of the abstract), and much of the results are likely to be skewed by calculations that are not realistic, because they are biased by high-slope/high-precipitation areas where in reality, agriculture is not practiced at all, or only in very limited and specialized forms, e.g., agroforestry, and perennial crops such as tea and orchards. This source of uncertainty needs to be addressed more thoroughly and the methods presented more transparently before this manuscript is suitable for publication.

Finally, it would be interesting if the authors performed a "reality check" on their erosion numbers. With some of the extreme values that they calculated, could agriculture be sustainable at all? How long would it take before most soil is completely eroded away?

Unfortunately, in many mountainous areas especially in tropics conventional agriculture with very bad management is practiced and it has huge negative impact on land. We demonstrated it by photos. In many mountainous areas agriculture is not sustainable at all. But unfortunately, despite of that in many areas the destructive land management is going on and poor farmers are destroying the land completely. We even do not know how many cases like this occur. We have examples also from Slovakia, mainly historical but also recent. There are known cases that some slopes were cultivated just 10-20 years and then one extreme storm event removed all soil and the field was abandoned. In tropics frequently happens that when the field is destroyed, it is abandoned for 5-10 years being fallow and then cultivated again, but there are many cases also when slope is cultivated for 5-7 years and destroyed once for ever. See attached photos.

There are indications of this problems also in literature, for example Montgomery (2007) calculated mean erosion rate under conventional agriculture (n= 448) to be over 3.9 mm (what is ca 60 tons per hectare). Of course, such agriculture is not sustainable at all. He concluded: "A direct implication of the imbalance between agricultural soil loss and erosion under both native vegetation and geologic time is that, given time, continued soil loss will become a critical problem for global agricultural production under conventional upland farming practices." Catastrophic effects of agriculture on land discuss Pimentel and Burges (2013). They argue that annually 10 million ha of cropland is abandoned due to deteriorating production potential caused by erosion. Further, they estimate that recently the world cropland covers 1.5 billion ha but since the beginning agriculture people abandoned 2 billion ha of crop land. So, more soil is already destroyed and abandoned then what is still used.

Lines 122-123

What is the justification for choosing the "most common slope"? At the very least, wouldn't it make more sense to choose the lowest slope class in each 5' gridcell? At least until all of the area in the slope class is filled by agricultural land use before moving to the next steeper class? If not, the authors' choice of modal slope class should be justified with citations.

The most common slope is determined by the slope class covering the largest area in each simulation grid. Slope classes are taken from a global terrain slope database (IIASA/FAO, 2012) and are based on a high-resolution 90 m SRTM digital elevation model. We assume that the slope class representing the largest area in each grid cell is most likely covered by the largest area of cropland. This builds on the idea that a spatially extensive and diverse landscape can be represented by a single "representative field" characterized by the prevailing combination of topography and soil condition found in the landscape. This method is designed to represent differences in large-scale global crop production with an emphasis on the most important global crop production regions.

We clarify the concept of the representative field on line 134:

"*Each grid cell is represented by a single field characterized by the combination of topography and soil conditions prevailing in this landscape unit. Each representative field has a defined slope length (20 – 200 m) and field size (1 - 10 ha) based on a set of rules for different slope classes (Table S1). The slope of each representative field is determined by the slope class covering the largest area in each grid cell (Table S1). Slope classes are taken from a global terrain slope database (IIASA/FAO, 2012) and are based on a high-resolution 90 m SRTM digital elevation model."*

Slope input data is an important uncertainty for simulating global water erosion estimates as we cannot identify cultivated slopes on a global scale. This will be discussed in the revised paper by addressing: (i) the simulation of extreme values on steep slopes including the proposed 'reality check'; (ii) the consequences of using the most common slope; and, (iii) an ideal scenario, where cultivation is limited to the flattest terrain available. We used Italy as a test case for a comparison between water erosion rates simulated under the proposed ideal slope scenario and the slope scenario based on the most common slope. We chose Italy because it has large maize and wheat cultivation areas, which are located on both flat terrain in the north and in hilly regions in the south, and thus the country represents a diverse landscape with a wide range of possible water erosion rates. We add a comprehensive discussion addressing each slope related issues after line 426:

"Changing climatic conditions with increasing elevation and the variable soils in mountain regions can favour crop cultivation in higher elevations over lower elevations (Romeo et al., 2015). However, upland farming without soil conservation measures can lead to exhaustive soil erosion and can become a critical problem for agriculture (Montgomery, 2007). Large areas of land have been abandoned due to high erosion rates as soils were no longer able to support crops (Figure 8) (Romeo et al., 2015). As mountain agriculture is determined by various environmental and socio-economic factors, the cultivation of steep slopes can be very variable between regions. Regional erosion assessments in mountainous cropland suggested that areas with extreme water erosion rates are mainly limited to marginal steep land cultivated by smallholders (Haile and Fetene, 2012; Long et al., 2006; Nyssen et al., 2019). In some mountainous regions efforts to remove marginal farmlands from agricultural production, and programs to improve land management on steep slopes have reduced high water erosion rates (Deng et al., 2012; Nyssen et al., 2015). On the contrary, recent pressure through increasing population and crop production demands has resulted in re-cultivation of hillslopes and a reduction of fallow periods, which limits the recovery of eroded soil (Turkelboom et al., 2008; Valentin et al., 2008).

To analyse the sustainability of simulated maize and wheat cultivation systems exposed to high erosion rates, we compare simulated annual eroded soil depth with a global dataset on modelled sedimentary deposit thickness (Pelletier et al., 2016). The comparison shows that at 4 % of grid cells permanent maize and wheat cultivation would not be sustainable as the whole soil profile would be eroded at the end of the simulation period (Fig. S10). Most of the unsustainable agriculture is simulated on steep *slopes. Although we account for conservation techniques and cover crops, we do not imitate the highly complex farming practices involving intercropping techniques and fallow periods, which are common on hillslopes typically managed by smallholders (Turkelboom et al., 2008). Moreover, we assume that the slope class representing the largest area in each grid cell most likely represents the largest share of arable land. This builds on the idea that a spatially extensive and diverse landscape can be represented by a single "representative field" characterized by the prevailing topography and soil conditions found in the landscape. On hilly terrain this setup simulates maize and wheat cultivation on steep slopes and thus mainly represents unsustainable agriculture. Although unsustainable maize and wheat cultivation can be observed in several mountain regions, cropland is very heterogeneously distributed in mountains and thus erosion rates from one representative field are highly uncertain.*

The uncertainty in cropland distribution can partly be reduced by developing a higher resolution global gridded data infrastructure, which is currently not available for EPIC-IIASA. However, due to the large uncertainty in global land cover maps (Fritz et al., 2015; Lesiv et al., 2019), an explicit spatial link between cropland distribution and the corresponding slope category cannot be established without on-site observations. We test the impact of this uncertainty for erosion estimates in Italy, where large maize and wheat cultivation areas are distributed on both flat terrain in the north and mountainous regions in the south. In an ideal scenario where cropland is limited to flattest land available per grid cell, median simulated water erosion in Italy would be reduced to tolerable levels below 1 t ha-1. However, in a scenario, where the most common slopes per grid cell are cultivated, median simulated water erosion increases to 14 t ha-1 due to high water erosion simulated in Italy's mountainous regions (Fig. S11). This suggests a high uncertainty in global water erosion estimates due to uncertain spatial links between maize and wheat cultivation areas and different slope categories."

The following photos (taken by Emil Fulajtar) will be added to the discussion

(a)

(b)

(c) (d)

Figure 1: (a) Sugar cane cultivation on steep slopes in South China (the steepest slopes are already abandoned and reforested by eucalyptus trees). (b) Maize cultivation on strongly eroded slopes in South West Uganda. (c) Abandoned fields and maize cultivation on a slope in South West Uganda. (d) Degraded and abandoned maize fields in Northern El Salvador.

The following two figures addressed in the discussion will be added to the supplementary information.

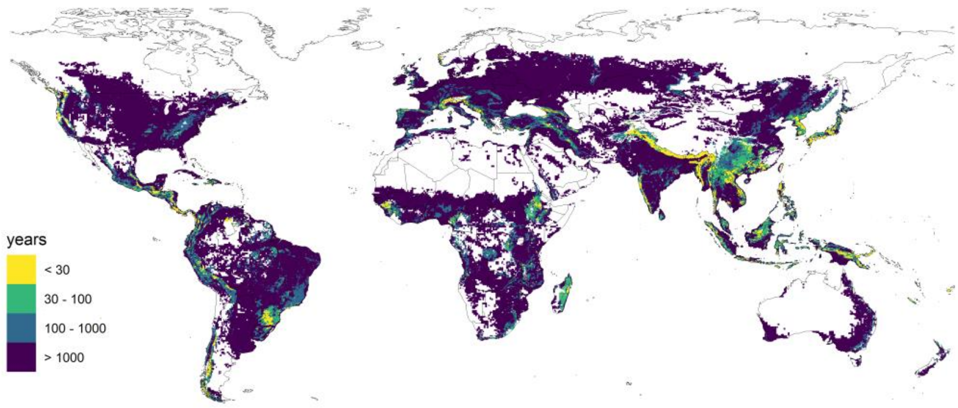

Figure 2:Simulated years left until the whole soil profile is eroded under permanent maize and wheat cultivation. Calculated as a ratio of the sedimentary deposit thickness [m] (Pelletier et al., 2016) *and the eroded soil depth per year (water erosion [t ha^{-1} a^{-1}] x bulk density [g m^{-3}]).*

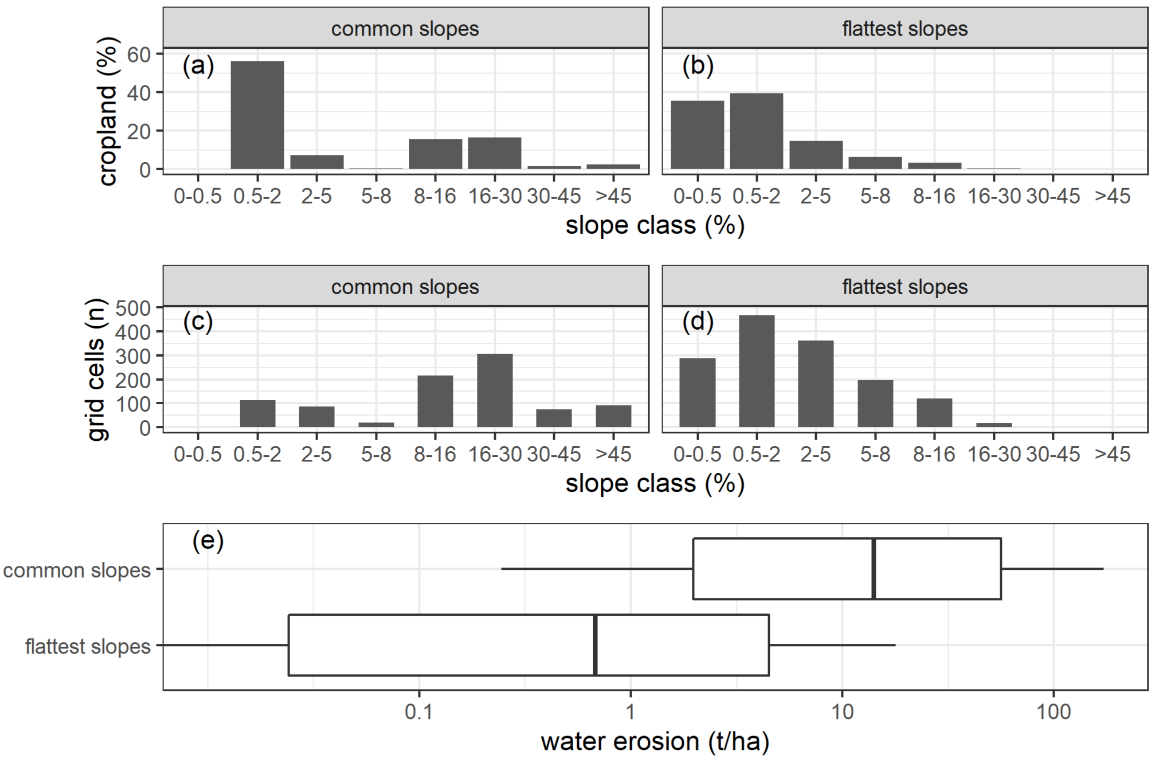

Figure 3: Comparison of slope inputs and simulated water erosion outputs between the cropland distribution scenario using the most common slopes and the cropland distribution scenario using the flattest terrain available in Italy. (a, b) distribution of the cropland share (Portmann et al., 2010) *per slope class. (c, d) distribution of grid cells per slope class. (e) Simulated water erosion for Italy using both cropland distribution scenarios. Midlines visualise median values, boxes include values from the 25th to the 75th percentiles and whiskers bracket values between the 10th and the 90th percentiles.*

Line 184-187

Again, where is the evidence that steeper slopes are actually cultivated, and on what basis are these P-factors selected? Were the parameters selected using empirical evidence, or a citation?

As described above, we cannot be certain that steep slopes are cultivated, but we assume that steep slopes are only cultivated with conservation techniques to reduce high water erosion values. The P-values for contouring and terracing are within the range of the values reported by Morgan (2005).

We modify line 205 accordingly: "*To account for erosion control measures reducing high water erosion on steep slopes, we use a conservation P-factor of 0.5 on slopes steeper than 16 %, and a P-factor of 0.15 on slopes steeper than 30 % to simulate contouring and terracing based on the range of P-factors presented by Morgan (2005).*"

Lines 377-379

"…a significant share of the estimated soil removal of 7 Gt a-1 originates from small wheat and maize fields on steep slopes with strong annual precipitation". So here the authors admit that the global numbers are skewed by extreme levels of simulated erosion. But more evidence that these fields actually exist needs to be provided.

See comments and discussion above about the high uncertainty in cropland distribution on steep slopes.

We delete the total soil loss value from the abstract, line 27, as it is significantly influenced by extreme water erosion rates from mountainous regions. But we will keep the value in the discussion, where we address the uncertainty of the global soil loss value.

Lines 391-392
How were the countries where "conservation agriculture… is likely" selected? What evidence is there for this?

We selected countries where conservation agriculture is most likely based on the share of conservation agriculture reported by AQUASTAT (2005-2014). The criteria is presented on lines 184-185 and table 3.

We will refer to AQUASTAT (FAO, 2016) on line 477.

Lines 423-425
That "…many older measurements are poorly accessible as they are not available online" seems to be a bit of a weak argument for not collecting more measurements on soil erosion. Can the authors elaborate a bit more in what kind of data are out there and precisely what it would take to utilize them for future studies?

Indeed, this is true. There was huge amount of erosion measurements at experimental plots in many countries. For example, in USA first measurements started in 1915 and when Wischmeier and Smith were developing their equation they had about 10000 erosion plot/year data and this was in 1970s. These data are archived by USDA but they are not directly accessible on internet. When in Germany Schwertmann was verifying USLE for Germany he used about 2500 plot/year data, but they are not available on internet and only small part was published and it was in German. We know situation mainly in central Europe. In Slovakia we have about 50 plot/year data published in Slovak language, we know about erosion plot measurements in Hungary, a lot of old data are in Czechia (starting with measurements by Maran in 1950ies, and Poland (starting by Gerlach in 1950ties), significant data set is in Austria, whole book about long term measurements (ca 20 years) was published in Croatia in Croatian language, there was extensive measurement programme in Yugoslavia (Serbia, Gavrilovic, Djorovic,). A lot of data exists in China, Japan, UK and Russia. In Africa we know about data from Uganda and Zimbabwe, most data from Francophone Africa are in French, from Latin America in Spanish, etc. There are five major reasons why most data are not available:

1. Many older publications are in national languages
2. Many older publications are not on internet
3. Many measurements were published in grey literature, local conference proceedings, national acta of scientific institutions, unpublished reports, etc.
4. Many published data are hardly interpretable because metadata are lacking (slope lengths, or inclinations or crop cover, period of measurement is not recorded, geographical position of the sites is not recorded, many measurements were running only during vegetation period of studied crop so they do not represent annual erosion, etc.).
5. International journals do not have interest to publish usual case studies which present raw data. To get paper published the authors need to present some special objectives to follow some special goals or developing methodological innovations. Therefore, also many new data sets cannot be found online.

6. Even if paper is published, journals have usually size limitations. To save space the primary data are not presented, only the results of interpretation, statistical processing, etc. are there.

The collected data set represents a reasonable compromise to achieve the objectives of this study. It is far beyond the capacities of the team and the objectives of this study to collect all existing erosion data. Such task would require 3-5 years lasting international project with participation of research teams from most countries, so that each team would be able to revise data sources in his country and provide summary of data including those published in national language and unpublished reports.

We added a more comprehensive discussion to available field data to the response addressing the second referee.

We increased the field data sample from 473 to 606 following a comment by the second referee. We will change the values and the presentation of the field data accordingly on lines 239-244, 349 – 351.

We will further clarify the field data needs in the discussion line 510:

"*The main reasons for the low availability of suitable data to evaluate simulated water erosion rates are twofold: (i) erosion monitoring is expensive, time consuming and labour demanding; and, (ii) primary data and metadata of measurement sites accompanying final results are often not available and many older measurements are poorly accessible as they are not available online (Benaud et al., 2020). A variety of factors influencing water erosion such as climate, field topography, soil properties and field management need to be considered when modelling water erosion but are often not reported in available field measurements (García-Ruiz et al., 2015). This hampers a direct comparison between simulated and observed water erosion values. We demonstrated the varying match between measured and simulated water erosion using different tillage and cover crop scenarios. Metadata on field management often only provides the crop cultivated and therefore the conditions under which erosion was measured in the field are not known sufficiently to evaluate erosion values simulated under different field management scenarios. Similarly, information on field topography and soil properties is often not provided with recorded field measurements and thus their use is limited in an evaluation of water erosion estimates simulated in different global environments. Moreover, most data are concentrated in the United States, West Europe and the West Mediterranean (García-Ruiz et al., 2015). In summary, there is a lack of field data representing all needed regions, situations and scenarios (Alewell et al., 2019).*"

We additionally mention "*the lack of sufficient metadata accompanying erosion measurements*" on line 270.

We add two sentences comparing the high variability within field data with the deviation between simulated values and measured values based on the evaluation results to Line 371: "*Outside locations combining steep slopes and strong precipitation, median deviation between simulated and measured data is lower than the variability within the field data.*" Line 579: "*In most environments relevant for maize and wheat cultivation the deviation between simulated and measured water erosion values is lower than the variability within the field data.*"

Lines 466-467
Yes, it seems clear that increased resolution would be important. Several datasets are already available however, including 100m agricultural cover fraction data (Buchhorn et al., 2019) and 90m topography from a range of different datasets, such as MERITHydro (Yamazaki et al., 2019). Global climate and soils data are available at at least 1km resolution and could be downscaled (Fick Hijmans, 2017; Hengl et al., 2017). Some more explanation as to why the authors were limited to 5' and more concrete

recommendations for future research would be valuable.

We rely on the existing data infrastructure of the EPIC-IIASA model, which has been constructed and evaluated for large-scale and global crop yield projections. The EPIC-IIASA model uses state-of-the-art global crop management and agro-environmental input data and has been positively evaluated for representing national average yields and inter-annual yield variability globally (Balkovič et al., 2014). It was used in several studies and its outputs have been compared to regional yield statistics and other global crop and land use models as a part of ISI-MIP and GGCMI model inter-comparison initiatives (Mueller et al., 2017). One of the main goals of this study is to analyse if EPIC-IIASA can account for relationships between water erosion and crop cultivation. Therefore, we rely on the existing model setup and data infrastructure of EPIC-IIASA, which has been confirmed as a reliable model to simulate daily crop growth on a global scale. The Input data for EPIC-IIASA originally available at different scales were aggregated at 5' resolution grid. In EPIC-IIASA, each simulation grid is represented by a representative field (1 to 10 hectares, depending on the prevailing slope category) while the field topography was calculated as a "dominant combination" from the high-resolution 90-m SRTM digital elevation model. Given the large uncertainty in land cover maps (Fritz et al., 2015; Lesiv et al., 2019), EPIC-IIASA does not provide an explicit link between land cover category, such as cropland, and the dominant fields. Instead, an area share of each land cover category per simulation grid is provided based on the GLC2000 land cover map with 1x1 km spatial resolution.

As mentioned above a discussion on the uncertainty in cropland distribution and slope input data will be added, as well as an explanation of the concept of the "representative field".

We will further clarify the focus of this paper in the introduction, line 91: "*The overall aim of this study is: (i) to analyse the robustness of water erosion estimates in all global agro-environmental regions simulated with an EPIC-based global-gridded crop model; and, (ii) to discuss the main drivers affecting the robustness and the uncertainty of simulated water erosion rates on a global scale.*"

We further highlight the model's weakness in conclusion line 600: "*Using existing field data, we were able to identify specific environmental characteristics for which we have lower confidence in the modelled erosion rates. These are mainly found in the tropics and mountainous regions due to the high sensitivity of simulated water erosion to slope steepness and precipitation strength, and the complexity of agricultural systems in mountainous regions.*"

Lines 473-474
As the high erosion "areas represent only a small fraction of global cropland for wheat and maize", why not show median values as the headline results instead of means?

We agree that the presentation of both mean and median values can be confusing. In the revised version we will focus only on median values. However, in the discussion, line 391 we mention both mean and median value to demonstrate the skewed distribution of erosion rates due to extreme values simulated on steep slopes.

We present global median water erosion in maize (7 t/ha) and wheat (5 t/ha) fields on line 26, 280, 349 and delete average values.

Global average water erosion values simulated under different management scenarios and different water erosion equations will be deleted on line 470 – 472 and 497 to focus only on median values.

We add a row to Table 3 clarifying that the median is used to aggregate water erosion values simulated under all management scenarios for grid cells and regions.

Lines 684-689; Figure 2
I would like to see the map and statistics separated out into two, one figure set each for maize and wheat. As the growing areas are different and only partially overlapping, it would be very helpful to see these individually in the main body of the manuscript.

We will present two maps for maize and wheat respectively in the revised paper (see figure below).

We will group bars by crop in the revised version (see figure below).

The explanation that water erosion is presented as a weighted average from maize and wheat fields will be deleted in table 3.

We include a note in the figure label explaining that pixel cells in figures do not indicate cropland sizes. "*Each pixel cell illustrates the median relative water erosion of one representative field. The extent of cropland areas is not considered in pixel cell size.* "

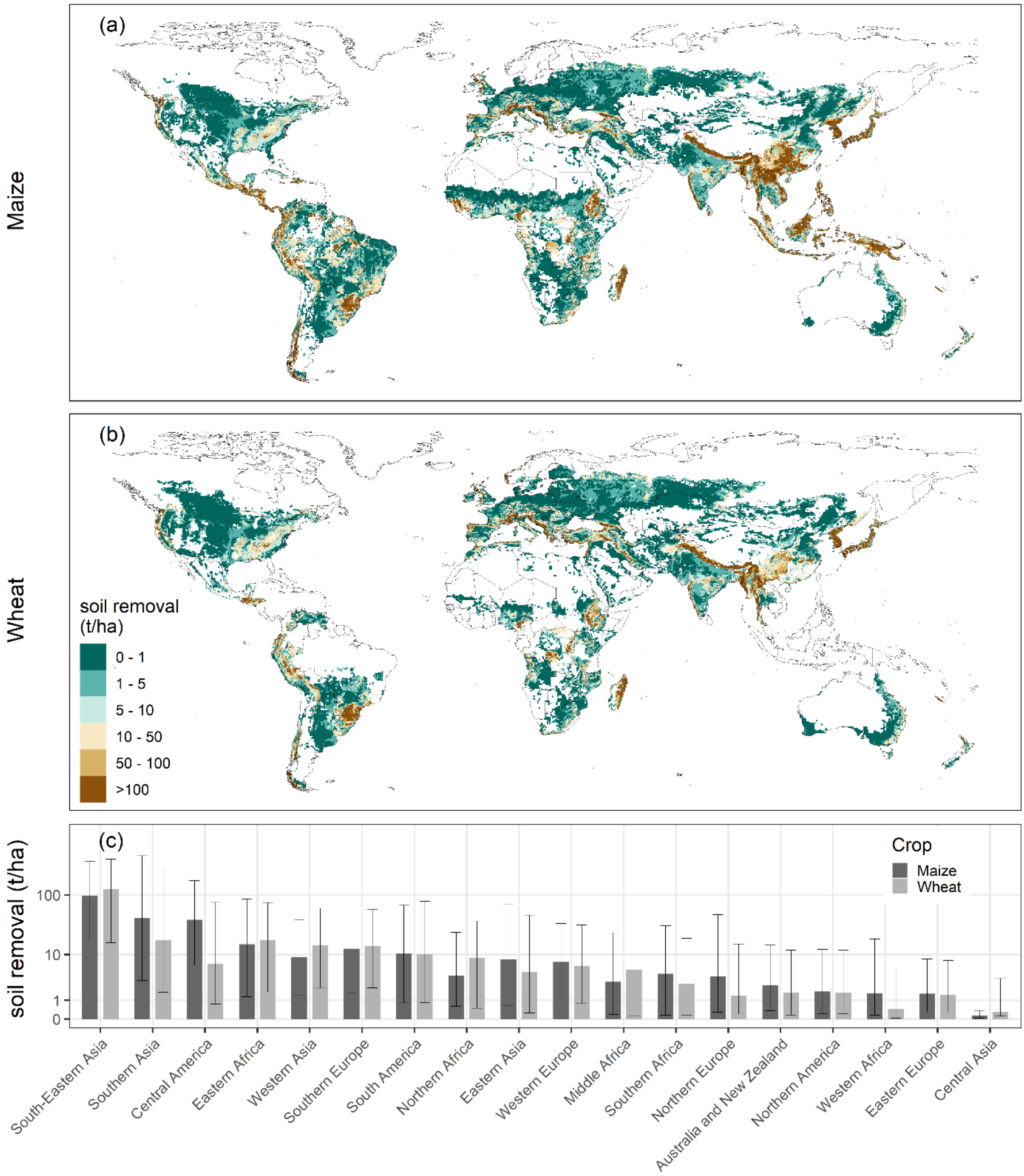

Figure 4: Soil loss due to water erosion in maize (a) and wheat (b) fields simulated with the baseline scenario. Each pixel cell illustrates the median relative water erosion of one representative field. The extent of cropland areas is not considered in pixel cell size. The bars in the bottom plot (c) illustrate median soil removal for major world regions simulated under maize and wheat cultivation. The lines and whiskers illustrate 25th and 75th percentile values. The classification of world regions is illustrated in Fig. S4. Due to the large gap between aggregated values, all values in the bottom plot have been log-transformed to facilitate the visual comparison.

Lines 706-709; Figure 7

I am quite suspicious that there is any substantial amount agriculture at all in the purple areas marked on the map, e.g., Borneo highlands, northern Laos, Himalayan front, western Madagascar, Korea, Japan. If there is, agriculture must be limited to valley *bottoms that are not detected at 5' resolution or done with extreme terracing.*

Each pixel in the maps illustrates the median erosion rate of one representative field. The pixel cells in each map do not indicate total cropland area. In other words, most of the pixel in mountainous regions represent a very small cultivated area. Table 3 lists details on how erosion rates in each pixel are aggregated.

Lines 691-693; Figures 3 and 4
Would also be useful to see how much uncertainty is caused by the assumption of what slopes are being farmed, e.g., always lowest slopes first, mean slope, median slope, etc.

We will address slope uncertainty in an extended discussion (see comments above)

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