Journal of Soils and Sediments
https://doi.org/10.1007/s11368-024-03850-6

SEDIMENTS, SEC 3 • HILLSLOPE AND RIVER BASIN SEDIMENT DYNAMICS • RESEARCH ARTICLE

Evaluating erosion risk models in a Scottish catchment using organic carbon fingerprinting

C. Wiltshire[1] · J. Meersmans[3] · T. W. Waine[1] · R. C. Grabowski[1] · B. Thornton[2] · S. Addy[2] · M. Glendell[2]

Received: 6 February 2024 / Accepted: 24 June 2024

Abstract

Purpose Identification of hotspots of accelerated erosion of soil and organic carbon (OC) is critical to the targeting of soil conservation and sediment management measures. The erosion risk map (ERM) developed by Lilly and Baggaley (Soil erosion risk map of Scotland, 2018) for Scotland estimates erosion risk for the specific soil conditions in the region. However, the ERM provides no soil erosion rates. Erosion rates can be estimated by empirical models such as the Revised Universal Soil Loss Equation (RUSLE). Yet, RUSLE was not developed specifically for the soil conditions in Scotland. Therefore, we evaluated the performance of these two erosion models to determine whether RUSLE erosion rate estimates could be used to quantify the amount of soil eroded from high-risk areas identified in the ERM.

Methods The study was conducted in the catchment of Loch Davan, Aberdeenshire, Scotland. Organic carbon loss models were constructed to compare land use specific OC yields based on RUSLE and ERM using OC fingerprinting as a benchmark. The estimated soil erosion rates in this study were also compared with recently published estimates in Scotland (Rickson et al. in Developing a method to estimate the costs of soil erosion in high-risk Scottish catchments, 2019).

Results The region-specific ERM most closely approximated the relative land use OC yields in streambed sediment however, the results of RUSLE were very similar, suggesting that, in this catchment, RUSLE erosion rate estimates could be used to quantify the amount of soil eroded from the high-risk areas identified by ERM. The RUSLE estimates of soil erosion for this catchment were comparable to the soil erosion rates per land use estimated by Rickson et al. (Developing a method to estimate the costs of soil erosion in high-risk Scottish catchments, 2019) in Scottish soils except in the case of pasture/grassland likely due to the pastures in this catchment being grass ley where periods of surface vegetation cover/root network absence are likely to have generated higher rates of erosion.

Conclusion Selection of suitable erosion risk models can be improved by the combined use of two sediment origin techniques—erosion risk modelling and OC sediment fingerprinting. These methods could, ultimately, support the development of targeted sediment management strategies to maintain healthy soils within the EU and beyond.

Keywords Erosion risk · Organic carbon loss modelling · RUSLE factor calibration · Sediment fingerprinting · Terrestrial-to-aquatic fluxes

1 Introduction

Soils provide a range of benefits for society including growing crops and timber and regulating water flow. The ability to store carbon and absorb water (reducing the risk of flooding and drought) makes soil an indispensable part of climate change mitigation and adaptation (European Commission 2021). This has led to healthy soil being a key part of many policies and strategies to further climate, biodiversity and economic objectives within the EU; such as the Green Deal for Europe (Bieroza et al. 2021; European Commission 2022a), EU Soil Observatory (European Commission 2022b) and the Scottish Soil Framework (Scottish Government 2009). Although soil erosion is a natural process, modern land management techniques can lead to increased rates which impact crop yields, cause a loss of soil carbon from

Responsible editor: Olivier Evrard

Dr. Barry Thornton has sadly passed away before the publication of this paper.

Extended author information available on the last page of the article

the land, and pollute waterbodies (Lilly and Baggaley 2014). Tackling rural diffuse pollution, including surface runoff and soil erosion, is a key factor in river basin management to improve the status of waterbodies.

One method of assessing sources of sediment in a catchment is sediment source fingerprinting (Mukundan et al. 2012). The sediment fingerprinting approach involves the collection of catchment source (soil) samples and comparison of their physical and/or biogeochemical features or "fingerprints" to estimate the relative contribution of the sources to a "sink" sediment (e.g., stream). With a suitable set of biomarkers, statistical unmixing models can be used to identify both the sediment sources and the amount of sediment contributed by each source. The biomarkers must be i) characteristic of the sources (able to both identify and differentiate between them), and ii) be conservative (stable) between "source" and "sink" (Collins et al. 2020). Fingerprinting methods using taxonomic / plant-specific tracers (*n*-alkanes, fatty acids) in the soil have been successfully applied to distinguish sediment sources originating from different land uses (Zhang et al. 2017; Glendell et al. 2018; Galoski et al. 2019; Liu et al. 2021a) and are an essential tool to quantify the relative contribution of different land use sources to organic matter load in waterways (Walling et al. 1999; Hancock and Revill 2013; Alewell et al. 2016; Chen et al. 2017; Glendell et al. 2018; Liu et al. 2021b). Wiltshire et al. (2023) used a unique combination of *n*-alkanes and short-chain neutral lipid fatty acids to estimate the proportion of streambed OC originating from different land uses in the catchment of Loch Davan, Aberdeenshire, NE Scotland. It was found that streambed sediment was dominated by input from pasture soils (39–47%), followed by arable soils (23–25%) with smaller contributions from forest and moorland (13–20%). Although the sediment fingerprinting identified the broad land use origin of stream OC in the Loch Davan catchment, these broad source classifications did not enable to identify specific locations (fields or landscape features) where management strategies should be targeted. Building on this previous research, in this manuscript we compare different erosion risk models to identify more precise sediment source locations using sediment fingerprinting for model evaluation.

Pathways of pollution from agriculture to freshwater are complex, but the identification of hotspots though modelling can be a practical simplification. Hotspots are locations in the catchment that contribute greater than average pollutant loads due to the combined effect of land management intensity, connectivity and soil properties (Cloy et al. 2021). Identification of these hotspots, where a high risk of soil degradation could increase the risk of diffuse water pollution, are a key step in the implementation of Good Management Practices (GMP) so that land can be cultivated to maintain a healthy soil and environment and minimize the risk to watercourses (Baggaley et al. 2020). Hotspots can be identified by modelling catchment soil erosion risk. Erosion models include readily available empirical models such as the Revised Universal Soil Loss Equation (RUSLE) (Wischmeier and Smith 1978; Desmet and Govers 1996; Renard et al. 1997) whose extensive application based on accessible data means that it can be easily applied in a wide variety of catchments (Alewell et al. 2019; European Soil Data Centre (ESDAC) 2014, 2015a; Panagos et al. 2014, 2015a). Such models can be a valuable tool for stakeholders to reduce erosion risks and manage their soils sustainably. In addition, use of widely available, Europe scale RUSLE parameterisation allows to compare the relative levels of erosion across the continent. However, these larger scale estimates may not be accurate enough at a regional or catchment level and RUSLE, originally formulated for use on primarily mineral soils and moderately sloped agricultural land, may not be the best option for estimating soil erosion in catchments with steeper slopes and more organic soils. Region- or soil-specific erosion models can predict how soils respond to land use and management pressures, and in Scotland improved erosion risk models have been developed for the specific soil conditions in this region (Lilly and Baggaley 2018; Baggaley et al. 2020). This Erosion Risk Map (ERM) developed by Lilly and Baggaley (2018) covers a large proportion of the Scottish mainland and shows the inherent risk of bare soil being eroded under intense or prolonged rainfall. The ERM considers local soil conditions and topography at a much higher resolution than that allowed by the Europe scale RUSLE parameters and is, therefore, the better choice to identify erosion hotspots and targets for local management strategies. However, the ERM provides no soil erosion rates and results cannot be compared at a country or continental scale. If both the ERM and RUSLE could be shown to provide comparable estimates of OC sediment yields, then the ERM could be used to identify specific erosion hotspots, while RUSLE could provide erosion rates that can be compared with those across the continent. Batista et al. (2019) refute the notion that soil erosion models can be validated and instead emphasize the necessity of defining "fit-for-purpose tests" that allow for a broad investigation of model usefulness. There is, therefore, a need to evaluate the output of erosion models not only to assess their accuracy in identifying hotspots, but to assess their suitability for use in a particular environment and the comparability of their results with other models and other studies.

The output of erosion models such as RUSLE have previously been assessed using sediment discharge data (Marques et al. 2019), outlet bed sediments (Odhiambo et al. 2021), and suspended sediment yield data (Borrelli et al. 2014). However, sediment yield at the outlet of a catchment reflects a complex suite of geomorphic processes. Individual models estimate erosion risk based on a specific process or processes (e.g., RUSLE-based models estimate soil loss due to inter-rill and rill erosion) whereas sediment yield will reflect all geomorphological processes active in the catchment (e.g., gullying, sediment deposition/remobilisation, tillage erosion, bank and channel erosion) (Borrelli et al. 2018). Both RUSLE and the ERM are concerned with the process of surface soil erosion under intense or prolonged rainfall (in contrast to gully or bank/channel erosion in which a higher proportion of deeper, subsoil erosion occurs). Therefore, ideally, the output of these model should be assessed relative to a benchmark characteristic of the upper rather than deeper layers of the soil. The OC fingerprinting proportions estimated using *n*-alkanes and short-chain neutral lipid fatty acid biomarkers by Wiltshire et al. (2023) could be considered as a "land use -specific" relative OC yield (Blake et al. 2012) which could be compared with the estimates derived from erosion risk models in the Loch Davan catchment. Although Wiltshire et al. (2023) identified the land use origin of stream OC in the Loch Davan catchment using OC fingerprinting, the land use source classifications were too broad to enable erosion hotspots (e.g., specific fields or landscape features) to be identified. This study aimed to identify more precise locations by modelling and evaluating catchment soil erosion risk using a comparison of two sediment source techniques – carbon loss modelling and OC sediment fingerprinting. The study had the following objectives:

1. To construct organic carbon loss models to compare land use specific OC yields based on RUSLE and ERM using the OC fingerprinting of Wiltshire et al. (2023) as a benchmark to determine if RUSLE erosion rate estimates could be used to quantify the amount of soil eroded from high-risk areas identified by the ERM.
2. To compare the estimated soil erosion rates with recently published estimates in Scotland (Rickson et al. 2019). These published rates are uncertain, based on data from England, and hence this study is contributing new data to the verification of those rates.

2 Material and methods

2.1 Study site

Loch Davan is a shallow (mean depth 1.2 m) lake located within the Muir of Dinnet National Nature Reserve (NNR) in north-east Scotland. The catchment (*ca.* 34 km^2) has a mean annual precipitation of 780 mm and average temperature between 3.5 °C and 12.17 °C (Met Office 2021). The lake area of Loch Davan has been significantly reduced over the last century, likely due to inputs of nutrient rich sediment resulting from land use intensification (Addy et al. 2012). Between 2007 and 2018, the loch and its main feeder stream, Logie Burn, were classified as having poor to moderate ecological status (Scottish Environment Protection Agency (SEPA) 2021). The catchment drains a variety of land uses (moorland (29%), forest (22%), arable (10%) and pasture (31%) (Fig. 1b) and soil types (Mineral podzols (49%), Brown soils (22%), Alluvial soils (11%), Peat or Peaty gleys/podzols (5%) (Fig. 1d). There is likely to be a greater protection from sediment erosion afforded by the permanent vegetation and ground cover found in the woodland and moorland areas of this catchment compared to arable land which has more variable vegetation cover due to human-induced processes (tillage, crop planting and establishment). Steep slopes are likely to increase both the speed, and the erosive potential of water runoff and increase the probability of eroded sediment reaching the streams (Renard et al. 1997). In the Loch Davan catchment, areas of steepest slope (13–37 degrees: Fig. 1c) are found under moorland and forest land cover to the west and north-west of the catchment with arable and pasture dominating the relatively flat (typically < 3 degree slope) lowlands.

Logie Burn originates in two main headwaters (Fig. 1) with the northern most sub-catchment (Site 1 -Fig. 1b) supporting similar cover of pasture (30%), forest (29%) and moorland (28%) with around 10% arable land. The western sub-catchment (Site 2) predominantly passes though moorland (78%) with around 14% of the land use being pasture and less than 5% forest. No arable land was present on the land cover map for the Site 2 sub-catchment (Cole et al. 2015) however, some areas of land were identified as being regularly ploughed and/or used for game crops (Game & Wildlife Conservation Trust 2022). As a result of the uncertainty in the land use for Site 2 no results for this sub-catchment are presented in this study. The third site (Site 3) was located close to the outlet of Logie Burn to Loch Davan integrating input from the whole catchment.

2.2 Soil OC content (%OC)

Here, we summarise the soil sample collection described in Wiltshire et al. (2023). Replicate soil samples were taken in June 2019 to characterise each of the four land uses arable (n = 16), forest (n = 16), moorland (n = 18) and pasture (n = 19) at sites shown with a cross (+) in Fig. 1b. Sampling sites were chosen on the basis of likely hydrological connectivity and were stratified by land use and soil type. For each sampling point, three replicates were chosen at random within a 2 m radius. All soil samples were taken with a steel cylinder (6 cm depth and 6 cm diameter) and, if required, litter was removed before taking the sample. All samples were

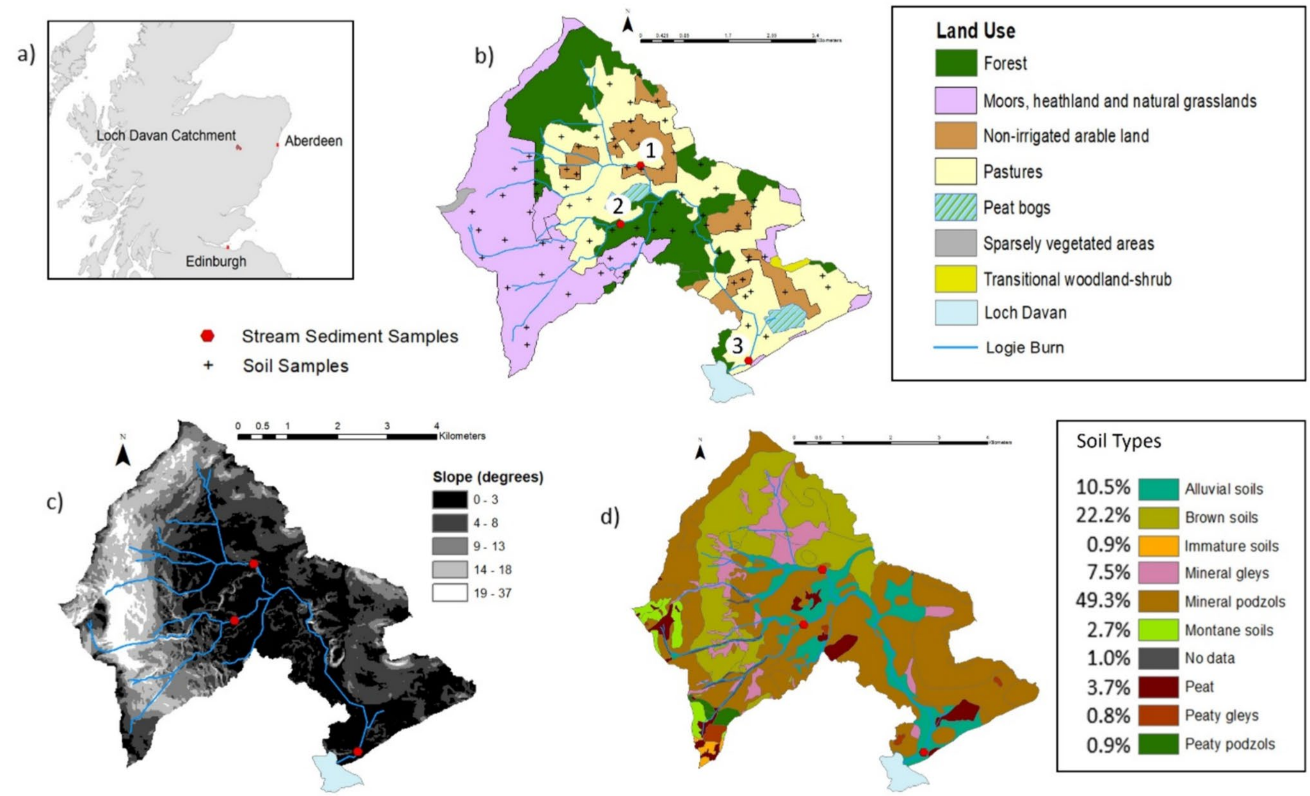

Fig. 1 Loch Davan study catchment. **a** Study catchment location, **b** Land use of the Loch Davan catchment (34 km.^{2}), stream sediment sampling locations (red dots: Sites 1, 2 and 3) and terrestrial soil sampling locations (black crosses), based upon Corine land cover 2012 for the UK, Jersey and Guernsey (Cole et al. 2015), **c** catchment slope (degrees) derived from OS Terrain 5© Crown copyright and database rights 2021 Ordnance Survey (100,025,252)(Ordnance Survey 2021), **d** Catchment soils based on "1:25,000 Hutton Soils Data" copyright and database right The James Hutton Institute (2018). Used with the permission of The James Hutton Institute. All rights reserved. From (Wiltshire et al. 2023)

georeferenced by using a GPS device (horizontal accuracy sub-meter real-time), stored in plastic bags and freeze-dried on return to the laboratory. All samples were passed through a 2 mm sieve to remove stones and larger organic material before being ground. A composite sample was formed for each soil site by adding an equal weight of each of the three finely ground samples. Samples were stored in sealed containers at room temperature until required for analysis.

For this study all soil samples were analysed for carbon concentration (%, w/w) using a Flash EA 1112 Series Elemental Analyser connected via a Conflo III to a Delta^{Plus} XP isotope ratio mass spectrometer (all Thermo Finnigan, Bremen, Germany). USGS40 was used as a reference material for C concentrations, measured using the area output of the mass spectrometer. Long term precision for a quality control standard (dried milled topsoil) was total C 3.80 ± 0.15% (mean ± SD). Data processing was performed using Isodat 2.0 (Thermo Fisher Scientific, Bremen, Germany).

The OC% of each soil sample was interpolated using universal kriging (i.e., external drift kriging) implemented in R (version 3.6.3) (R Core Team 2020) using packages "raster" (Hijmans 2020), "sp" (Pebesma and Bivand 2005) and "gstat" (Pebesma 2004). Seven land use and topographic environmental predictors were considered as covariates: land use (pasture, woodland, arable and moorland), slope, curvature, accumulated flow, aspect, Topographic Wetness Index (TWI) (Mayer et al. 2019) and soil type. Climate data were not considered as predictors as they were not expected to vary significantly across the catchment. The OC% values and covariates were first checked for normality using Kolmogorov–Smirnov (K–S) test before being log-transformed to improve normal distribution for regression modelling. A back-transformation of OC% was carried out following prediction. The best model was selected based on the lowest Akaike Information Criterion (AIC) and highest adjusted R^2 (Meersmans et al. 2012). Covariates that were significantly ($p < 0.05$) associated with OC% were retained and the best model was selected in a forward stepwise regression. A leave-one-out cross-validation routine was implemented, and the root mean square error (RMSE) and R^2 of the model performance calculated using the differences between the observed values and model predictions.

2.3 Connectivity between areas of upslope erosion and streams

To define the connectivity between upslope sediment sources and streams Connectivity Index (CI) was calculated using ESRI ArcMap (V10.6) (ESRI 2017) using the method of (Cavalli et al. 2013) and the catchment DEM (20 × 20 m resolution). The CI uses the distribution of land use and topographic features (DEM) that can produce or store sediment and water (Borselli et al. 2008). A surface roughness index is also calculated from the DEM and used as a weighting for sediment transport impedance (Cavalli et al. 2013). This approach was selected as it requires a minimal number of parameters, uses globally available data, and is spatially explicit. For use as a weighting with RUSLE, CI was re-scaled from 0 to 1. The CI was classified into “high”, “medium” and “low” connectivity (Hooke et al. 2021) using a quantile classification in ESRI ArcMap (V10.6).

2.4 Carbon loss models (CLM)

To predict land use specific OC yields carbon loss models requires estimates of:

- erosion risk (RUSLE and ERM)
- susceptible to erosion due to differences in vegetation cover and land management (cover-management factor (C) already incorporated as an input factor in RUSLE)
- potential connectivity between areas of upslope erosion and streams (Connectivity Index (CI))
- OC content (%) of the soil

Three CLM were constructed in this study which will be referred to as CLM RUSLE, CLM ERM (H) and ERM(HM) (Fig. 2).

2.4.1 RUSLE

RUSLE calculates the long-term average annual soil loss (SL) according to the equation:

$$SL = R.K.L.S.C.P$$

R is the rainfall erosivity factor (MJ mm ha^{-1} h^{-1} yr^{-1}) the spatial distribution of which is shaped principally by precipitation and elevation (Panagos et al. 2015a; Jiang et al. 2021). The K factor is the soil erodibility (t ha h ha^{-1} MJ^{-1} mm^{-1}) representing the susceptibility of a soil to erosion. The K factor is related to soil properties such as texture and structure, organic matter content and permeability (Panagos et al. 2014). S and L are the slope and slope-length factors and P is the dimensionless conservation support practice factor. The RUSLE factors were calculated as follows: The R and K factors were derived respectively from maps generated and described by ESDAC (2015b) and Panagos et al. (2015a), and ESDAC (2014) and Panagos et al. (2014). The R and K factor maps were generated in ESRI ArcMap (V10.6) (ESRI 2017) by interpolating a raster surface using kriging from points defined by the centroid of each cell of the original 500 × 500 m resolution R and K maps. The conservation support practice factor (P) was not considered in this study and was set to 1. The RUSLE LS factors were generated from the DEM in R (version 3.6.3) (R Core Team 2020) using packages “raster” (Hijmans 2020)

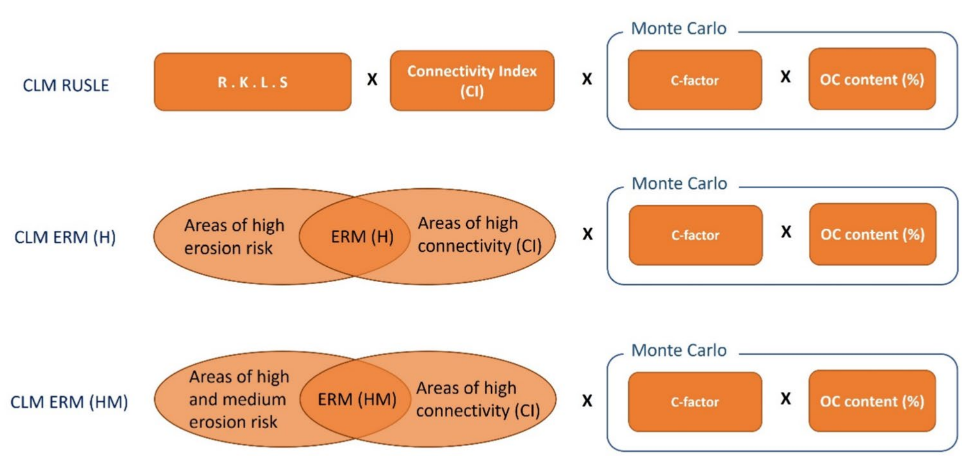

Fig. 2 Structure of Carbon Loss Models (CLM) "RUSLE", “ERM (H) and “ERM (HM)”. RUSLE is the Revised Universal Soil Loss Equation (Wischmeier and Smith 1978; Desmet and Govers 1996; Renard et al. 1997), C factor is a dimensionless cover-management factor, R is the rainfall erosivity factor, K is the soil erodibility and S and L are the slope and slope-length factors. ERM is the erosion risk map developed by Lilly and Baggaley (2018). Monte Carlo analysis (3,000 iterations) to evaluate the magnitude of the errors associated with the C factor and modelling of OC%

and “RSAGA” (Brenning et al. 2018) using the method described by Desmet and Govers (1996).

Cover-management factor (C) RUSLE utilises a dimensionless cover-management factor (C), defined by the land use and management, when calculating the long-term average annual soil loss. A C factor map with a single C factor for each land use was created from the Corine land cover 2012 for the UK, Jersey and Guernsey (Cole et al. 2015) and the C factor data of Europe described by (ESDAC 2015a; Panagos et al. 2015b) in ESRI ArcMap (V10.6) (ESRI 2017). However, the RUSLE C-factor reported by Panagos et al. (2015b) was around 35 times greater for moorland land use than it was for forest; implying less soil cover and/or greater erosional impact from land management/grazing on moorland compared to forest land. In a neighbouring mixed land use sub-catchment, Hirave et al. (2020) found that both forest and moorland contributed marginally to suspended stream sediments (< 2%) which they attributed to well vegetated ground cover leading to reduced soil erodibility. In addition, in their study to identify soil erosion rates in Scotland, Rickson et al. (2019) defined erosion rates for forest/woodland to be equal to those of wildscape (semi-natural landscape). In this study, we hypothesised that the level of soil cover and impact of land management/grazing in moorland could be similar to forest land, and therefore, the C factor for moorland was set equal to forest (Table 1). The values of C factor per land-cover type (Table 1) were assigned to the respective land use areas in the Corine land cover map. The likely variation in these land use values (Table 1: “Range”) were based on the most cited studies covering different countries in Europe reported by (Panagos et al. 2015b).

2.4.2 ERM

The ERM considers local soil conditions and topography at a much higher resolution than that allowed by the Europe scale RUSLE parameters and is, therefore, the better choice to identify erosion hotspots in the Loch Davan catchment. The ERM developed by Lilly and Baggaley (2018) estimates soil erosion risk under intense or prolonged rainfall. Organic and mineral soils are considered separately, and the level of soil erosion risk depends on i) the soil texture and its capacity to absorb rainfall and ii) the slope of the land (steeper slopes lead to faster runoff and consequently more erosive overland flow). The ERM categories of erosion risk and their distribution in the Loch Davan catchment are shown in Fig. 3. There are three main classes (High, Medium/Moderate or Low) for mineral topsoils. Erosion risk is greatest on soils which are i) coarse textured, ii) have a low water adsorption capacity and, iii) are located on steep slopes. There are also three main risk classes (High, Medium/Moderate or Low) for soils with organic (peaty) surfaces. For organic soils, increases in slope and/or the soils having a lesser ability to absorb rainfall increases the risk class.

ERM(H) Areas with both high erosion risk and high connectivity to the streams were identified in ESRI ArcMap (V10.6) (ESRI 2017) by the overlap of areas designated “high” risk in the ERM (Lilly and Baggaley 2018) and areas classified as “high” connectivity in the CI map. The proportion of these areas within each of the four land uses (arable, forest, moorland and pasture) was then calculated. The ERM predictions are based on the inherent soil erosion risk from bare soil, and do not take into account the vegetation cover and the likelihood that soil will be left bare. Hence, the land use proportions were multiplied by the C factor (Fig. 2, Table 1) to account for the likelihood that soil will be left bare due to differences in vegetation cover and land management practices.

ERM (HM) ERM(H) described above was applied to areas with high connectivity to the streams and high erosion risk only—i.e., areas identified as medium or low risk in the ERM were excluded. To assess if the SOC land use proportion calculated from the sediment fingerprinting benchmark would be more closely matched by erosion rates from areas defined as high or medium erosion risk, a second CLM ERM (HM) was constructed as described above except only those areas identified as low risk were excluded.

2.4.3 Monte Carlo analysis

The value of C factor can be used to account for the differences in erosion potential between land uses however, it can be highly variable due to differences in both land use management and season (Schmidt et al. 2018). Therefore, it was important to evaluate the magnitude of the errors associated with this factor, as well as that introduced by the modelling of OC%, using a Monte Carlo analysis with 3,000 iterations. The C factor was sampled from a uniform distribution

Table 1 Range and mean of RUSLE C-factors used for calculation of average annual soil loss within the Loch Davan catchment (adapted from Panagos et al. (2015b*:* Table 2)

Land Use	C-factor	
	Range	Mean
Arable	0.07–0.35	0.21
Pasture	0.05–0.15	0.1
Forest	0.0001–0.003	0.0016
Moorland*	0.0001–0.003	0.0016

* Panagos et al. (2015b: Table 2) values for moorland were range = 0.01 = 0.1 with a mean of 0.055

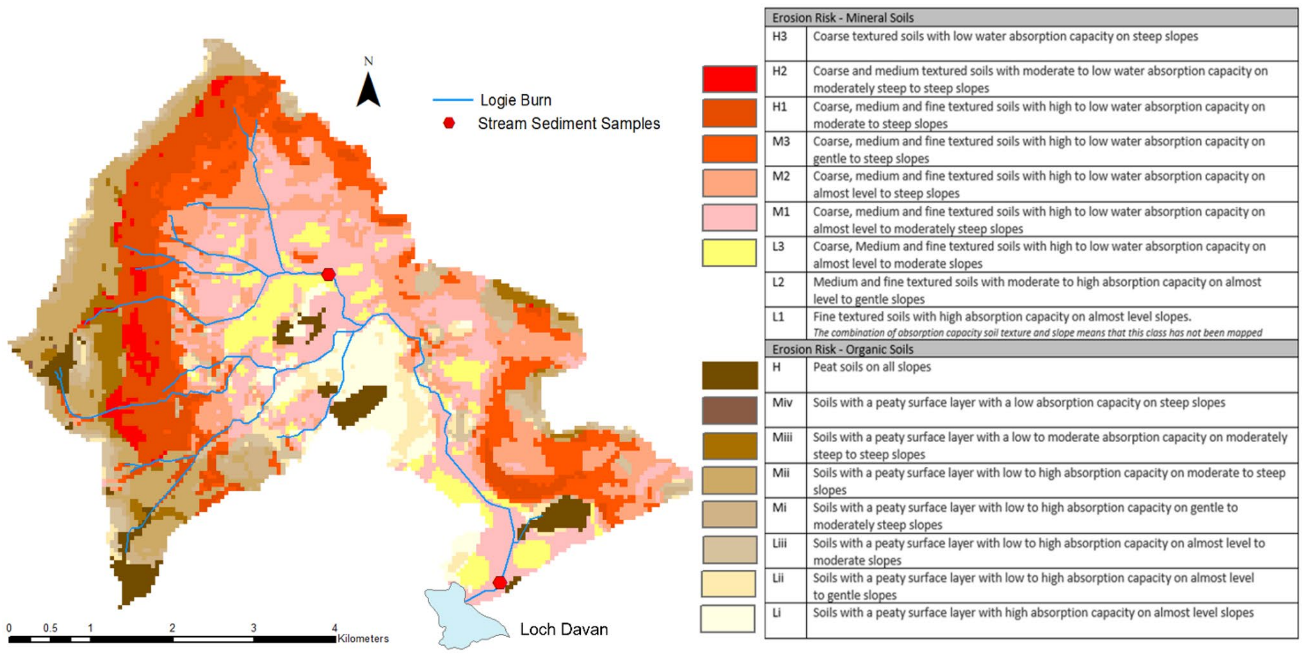

Fig. 3 Erosion Risk Map of Loch Davan catchment adapted from Lilly and Baggaley (2018). Soil erosion risk map of Scotland (partial cover). James Hutton Institute, Aberdeen

defined by the maximum and minimum values found in the literature (Table 1). The OC% content was sampled from a uniform distribution defined using ± RMSE (Section 2.2). At each iteration the proportions of soil OC loss from arable, forest, moorland and pasture land uses were calculated, generating a probability distribution from which mean land use proportions were derived.

2.5 Sediment fingerprinting data

The sediment fingerprinting benchmark (the source proportions of arable, pasture, forest and moorland sediment at each streambed sample site) used in this study is taken from the sediment fingerprinting study of Wiltshire et al. (2023) which is summerised in this section. It is important to note that, although the study of Wiltshire et al. (2023) provides sediment fingerprinting data for Sites 1, 2 and 3 (Fig. 1), only the data for Sites 1 and 3 are used in this study (see Section 2.1). Here, we summarise the methodology described in Wiltshire et al. (2023).

The sediment fingerprinting approach involves the collection of catchment source (soil) samples and comparison of their physical and/or biogeochemical features or "fingerprints" to estimate the relative contribution of the sources to a "sink" sediment (e.g., stream). The biomarkers must be i) characteristic of the sources (able to both identify and differentiate between them), and ii) be conservative (stable) between "source" and "sink" (Collins et al. 2020). With a suitable set of biomarkers, statistical unmixing models can be used to identify both the sediment sources and the amount of sediment contributed by each source. In the fingerprinting study by Wiltshire et al. (2023) a combination of soil biomarkers of plant, fungal and bacterial origin (*n*-alkanes and short chain (shorter than C22) neutral lipid fatty acids (SC-NLFA)) were used to distinguish sediment sources originating from different land uses in the Loch Davan catchment. The aim of Wiltshire et al. (2023) was to obtain greater discrimination between land use sources as an increased number of sources within sediment fingerprinting can increase the resolution with which erosion hotspots can be identified. The biomarker concentrations and their compound specific stable isotope signatures (CSSI) in four land cover classes (arable land, pasture, forest, and moorland) were determined and their contribution to six virtual sediment mixture samples was modelled. Using a Bayesian un-mixing model, MixSIAR (Stock and Semmens 2016; Stock et al. 2018), the *n*-alkane and SC-NLFA biomarkers performance in distinguishing sediment sources was assessed.

Wiltshire et al. (2023) found that land use could be distinguished more accurately when using only SC-NLFA and their CSSI and these biomarkers were then used with MixSIAR to estimate the source proportions of arable, pasture, forest and moorland sediment at each streambed sample site.

2.5.1 Sample collection and analysis

Soil and sediment samples within the Loch Davan catchment and Logie Burn stream network were collected in June 2019.

Soil samples from four land uses (arable, pasture, forest and moorland) were collected to characterise potential sediment sources for fingerprinting as described in Section 2.2. Streambed samples were collected at three locations to estimate the proportional contribution of each of the land use source to the streambed sediments in two tributaries and a joint outlet (Sites 1, 2 and 3 in Fig. 1b). The Sites 1 and 2 were carefully chosen above their joint junction in the stream network so the contributions from each tributary could be assessed. The third site was located close to the outlet of Logie Burn to Loch Davan integrating input from the whole catchment. At each site three samples of bed sediments were taken at the streambed surface with a steel cylinder (6 cm depth and 6 cm diameter) along a transect across the streambed and composited. All samples were passed through a 2 mm sieve to remove stones and larger organic material before being ground. Samples were stored in sealed containers at room temperature until required for analysis.

The *n*-alkanes and SC-NLFA were extracted from the samples (Wiltshire et al. 2023) and individual *n*-alkane and FAMEs were quantified and their $\delta^{13}C$ values determined by GC-C-IRMS using a Trace GC Ultra gas chromatograph (Thermo Finnigan, Bremen, Germany) equipped with a GC PAL autosampler (CTC Analytics AG, Zwingen, Switzerland) following the method described in (Thornton et al. 2011).

2.5.2 Biomarker selection and source proportion estimation

Here, we summarise the biomarker selection and source proportion estimation described in Wiltshire et al. (2023). Biomarker values of all source (land use) groups were first checked for normal distribution (Kolmogorov–Smirnov test). A Kruskal- Wallis (KW) and posthoc Dunn's test was then carried out to select biomarkers which showed significant differences between land use sources. Those biomarkers that passed the KW test were then assessed (Excel box plots) to ensure values from all "sink" (streambed) mixtures were within the range of the land use sources. The full range (excluding outliers) was used for this "range" test as Bayesian inference best practice suggests comparison of full distributions for hypothesis testing (Fenton and Neil 2018). Land use discrimination was assessed using "virtual" mixtures with 50/50 contributions from each of the four sources (arable, pasture, forest and moorland) by taking the mean of two sources to represent a 50% contribution from each (Collins et al. 2020). Bayesian modelling techniques were commonly employed (Cooper et al. 2015; Mabit et al. 2018; Kelsey et al. 2020) due to their ability to account for variability in both source and mixture (Stock and Semmens 2016). Running MixSIAR (Stock and Semmens 2016; Stock et al. 2018) using the selected biomarkers provided the proportional contribution of the sources to the streambed mixtures. Full details of the biomarker selection and MixSIAR implementation are described in Wiltshire et al. (2023).

2.6 Comparison of two sediment origin techniques—erosion risk models and OC fingerprinting

Both RUSLE and the ERM estimate erosion in the upper layers of soil due to intense or prolonged rainfall. Finer, lighter soil particles are more likely to be mobilised by rainfall and runoff and, therefore, stream sediments may have a finer particle size distribution than terrestrial sediments (Karambiri et al. 2003; Sirjani et al. 2022). It is generally accepted that OC, *n*-alkanes and fatty acids are preferentially associated with the finer particle size fractions (< 63 µm) (Quénéa et al. 2004, 2006; Yu et al. 2019; De Mastro et al. 2020). This finer fraction was present in both soil and sediment samples from the Loch Davan catchment. The amount of OC in soils generally decreases with depth (Wiesmeier et al. 2013) and, in addition, the concentration of *n*-alkanes and fatty acids relative to soil OC also decreases with depth (Angst et al. 2016). Therefore, it is assumed that the *n*-alkane and fatty acid signature of stream sediments will be dominated by soil eroded from the upper layers of the soil modelled by RUSLE and the ERM rather than lower, subsoil layers eroded from gullies or stream banks). In addition, it is assumed that, although the lighter fraction of the eroded material entering the stream will remain in suspension, coarser fractions of the eroded sediment will accumulate over time on the streambed. Streambed sediment was used in this study as i) accumulated sediment (rather than the shorter-term suspended sediment) was required for comparison with the longer-term estimates of a carbon loss model, and ii) the coarser fraction of the eroded sediment may show an OC and biomarker signature closer to that of the original soil than the lighter fraction remaining in suspension (Griepentrog et al. 2016).

2.6.1 Comparing CLM and OC fingerprinting land use specific OC yield

For each CLM the proportions of soil OC yield (loss) from arable, forest, moorland and pasture land uses were calculated. The absolute difference between these proportions and those estimated using OC fingerprinting were then calculated to evaluate the accuracy of the CLM models with respect to the sediment fingerprinting benchmark. The CLM that approximated the relative OC yield in streambed sediments identified by OC sediment fingerprinting most closely was defined to be that which showed the lowest mean absolute difference across all land uses.

3 Results

3.1 Soil OC content (%OC)

Interpolation of OC% using regression kriging found land use to be the best predictor of the quantity and spatial variability of soil OC% with a linear regression relationship OC% = exp(1.3010 + 1.0513 (forest) + 1.5317 (moorland) – 0.0451 (pasture). In the context of the linear regression relationship, the variables"forest", "moorland" and "pasture" are dummy variables which are equal to one when that land use is present and zero otherwise (R^2 = 0.46, RMSE = 7.86). The relationships between soil OC% and other covariates were much weaker (slope (R^2 = 0.19), aspect (R^2 = 0.1) and TWI (R^2 = 0.09)) and these covariates were not significant when modelled together with land use. No significant relationships with soil OC% were found for the other covariates (soil type, curvature and accumulated flow). These results support the assertion of Wiesmeier et al. (2019) that terrain attributes such as slope, aspect and curvature, although influential for soil OC content at small spatial scales (< 100 m), are less relevant across larger landscapes, where soil OC is averaged across soil properties so that other factors (such as land use) become dominant.

Soils under moorland supported the largest soil OC% (21.4 ± 13.9% (± 1 SD)) and OC% of forest soil was also relatively high (12.3 ± 8.0%). The similarity between the OC% in pasture (3.7 ± 0.9%) and arable soils (3.8 ± 1.1%) suggests that these land uses have similar levels of OC inputs and outputs and that pastures in this catchment may be temporary (in agricultural rotation) rather than permanent (Meersmans et al. 2008; Martin et al. 2011).

3.2 Carbon loss models (CLM)

In this study catchment, both RUSLE and ERM models identified areas at highest risk of erosion on steeply sloping (> 8 degrees: Fig. 1c) land in the north and west of the catchment dominated by moorland, in line with the assumptions inherent in these modelling approaches (Wischmeier and Smith 1978; Desmet and Govers 1996; Renard et al. 1997; Lilly and Baggaley 2018). In the absence of significant variation in rainfall and soil erodibility (as is the case for this catchment) differences in soil loss between land uses were dominated by differences in slope, elevation and cover-management. As moorland had the highest mean elevation and slope it was therefore unsurprising that CLM RUSLE and CLM ERM (H) attributed the majority of eroded soil OC reaching the streams to moorland (Site 1 36–48% and Site 3 34–36% Fig. 4c-d), which contrasts with the OC fingerprinting benchmark that estimated pasture as the dominant source of OC (Site 1 39%; Site 3 47%) with only 20% (Site 1) and 13% (Site 3) from moorland soils (SF benchmark Fig. 4a). Conversely, similar to the OC fingerprinting benchmark, CLM ERM (HM)

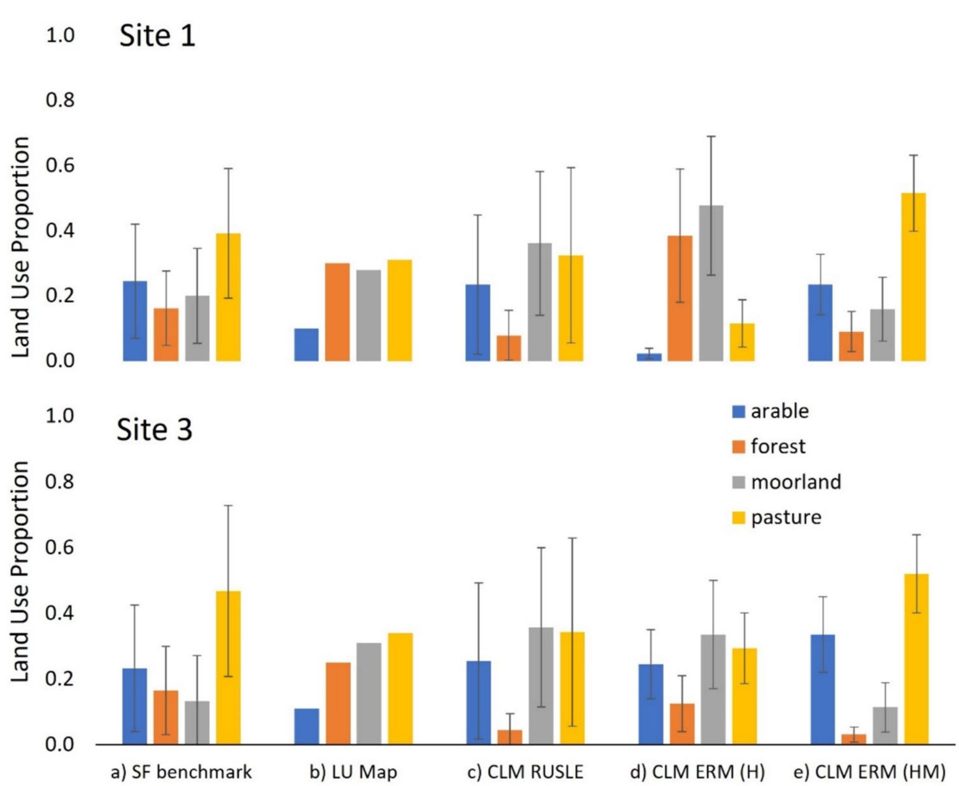

Fig. 4 Proportions of OC contribution from different land uses estimated at Site 1 and Site 3 by **a** Sediment fingerprinting of streambed sediments (SF benchmark), **b** Land Cover Map, **c** CLM RUSLE **d** CLM ERM (H) and **e** CLM ERM (HM)

estimated pasture to be the dominant OC source (52% at each site; Fig. 4e).

3.2.1 Site 1 – Headwater sub-catchment

The headwater sub-catchment (Site 1) has almost equal extents of pasture (30%), forest (29%) and moorland (28%) with around 10% arable land (Fig. 4b). In this sub-catchment both moorland and forest are found on areas of steepest slope (13–37 degrees: Fig. 1c). This is reflected in the high contributions from both moorland (48%) and forest (39%) modelled by CLM ERM (H) (Fig. 4d). However, although CLM RUSLE attributed the majority of stream OC to moorland (36%) the forest land provided the smallest contribution (8%) (Fig. 4c). This difference in forest contribution from CLM RUSLE and CLM ERM is likely due to the higher resolution soil characteristics used by the ERM which characterises most of the more organic soils under the moorland in this sub-catchment to be of "medium" rather than "high" risk.

Arable and pasture dominate the relatively flat (typically < 3 degree slope) lowlands. The CLM ERM (H) considers only a very small amount of this land to be at high risk of erosion so even with the elevated risk of bare soil (reflected in a significantly larger C-factor for these land uses) the contributions from pasture and arable land were estimated to be small (pasture 12%: arable land 2%). Unlike the CLM ERM (H) the soil erosion estimates of CLM RUSLE were not restricted to areas considered at "high" risk and estimated that the contributions from pasture and arable land would be relatively higher at 33% and 24% respectively. In contrast when considering land at both medium and high risk of erosion CLM ERM (HM) estimated pasture to be the dominant OC source (52%) with smaller amounts attributed to arable (24%), moorland (16%) and forest (9%) (Fig. 4e). The results of CLM ERM (HM) correspond well to the OC fingerprinting benchmark that also estimated pasture as the dominant source of OC (39%) followed by arable land (25%) with lesser amounts from moorland (20%) and forest (16%) (SF benchmark Fig. 4a). These results would suggest that considering areas defined by the ERM as either high or medium risk (rather than exclusively concentrating on areas of high risk) gives the closest match to the land use specific OC yields measured in the streams using sediment fingerprinting.

3.2.2 Site 3 – Catchment outlet near Loch Davan

Site 3 was located close to the outlet to Loch Davan integrating input from the whole catchment which has a land use composition of arable (10%), pasture (34%), forest (25%) and moorland (31%) (Fig. 4b). There is relatively more lowland forest at the catchment scale and this is reflected in smaller contributions of forest land to stream OC for Site 3 relative to Site 1: CLM RUSLE only estimated 4% (Fig. 4c), CLM ERM (H) 13% (Fig. 4d) and CLM ERM (HM) only 3% (Fig. 4e) from forest land. Both CLM RUSLE and CLM ERM (H) attributed similar amounts of stream OC to moorland (36 and 34% respectively), pasture (34 and 29% respectively) and slightly smaller amounts to arable land (26 and 25% respectively) (Fig. 4c, d respectively). At Site 3 CLM ERM (HM) again estimated pasture to be the dominant OC source (52%) with smaller amounts attributed to arable (34%), with little to moorland (11%) and forest (3%) (Fig. 4e). The results of CLM ERM (HM) again correspond best to the OC fingerprinting benchmark that also estimated pasture as the dominant source of OC (47%) followed by arable land (23%) with lesser amounts from moorland (13%) and forest (17%) (SF benchmark Fig. 4a). These results would also suggest that considering areas defined by the ERM as either high or medium risk gives the closest match to the land use specific OC yields measured in the streams using sediment fingerprinting. However, the amount of OC from forest land measured in the streams using sediment fingerprinting is higher than that modelled by CLM ERM (HM). In this study it has been assumed that using *n*-alkanes as biomarkers should be representative of the surface erosion processes modelled by RUSLE and ERM as they primarily derive from land-based plant material which is transferred to the soil and are more abundant in topsoil than subsoil. However, forest organic matter can be directly transferred to the streams via leaves and litter in riparian forest (Wiltshire et al. 2022). It is, therefore, important to note that the stream OC reflects a complex suite of processes and an exact correspondence between the processes inputting OC to streams and the processes modelled by an erosion risk model is unlikely.

For each CLM the proportions of soil OC yield (loss) from arable, forest, moorland and pasture land uses were calculated. The absolute difference between these proportions and those estimated using OC fingerprinting were then calculated to evaluate the accuracy of the CLM models with respect to the sediment fingerprinting benchmark. The CLM that approximated the relative OC yield in streambed sediments identified by OC sediment fingerprinting most closely showed the lowest mean absolute difference across all land uses.

At Site 1 the mean absolute difference across all land uses for CLM RUSLE was 8%, CLM ERM (H) was 25%, and CLM ERM (HM) was 6% (Fig. 5a). At Site 3 the mean absolute difference across all land uses for CLM RUSLE was 12%, CLM ERM (H) was 11%, and CLM ERM (HM) was 8% (Fig. 5a). At both Sites CLM ERM (HM) showed the lowest mean absolute difference across all land uses and therefore the closest approximation to the relative OC yield in streambed sediments identified by OC sediment fingerprinting. Therefore, the ERM, which takes into account local soil textures as well as land use, was found to be the better

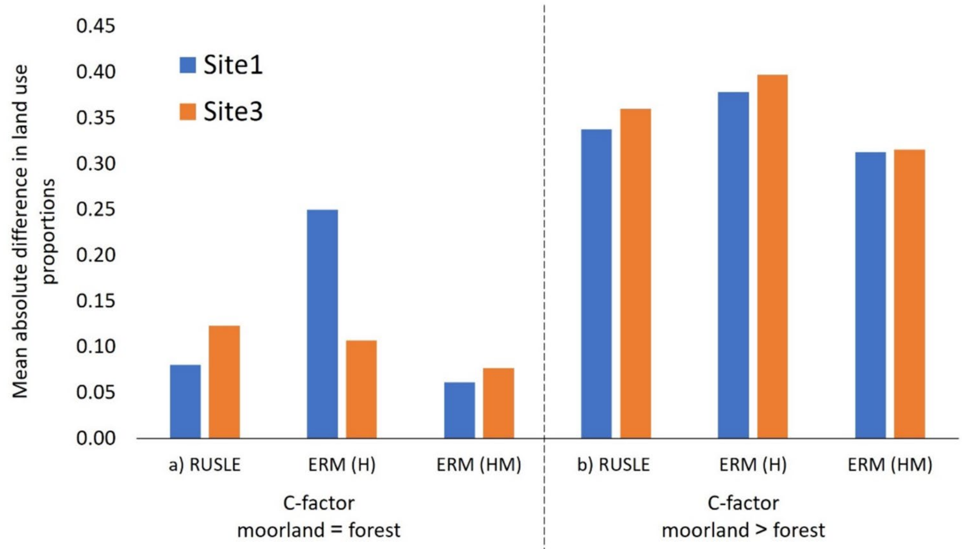

Fig. 5 For Sites 1 and 3 the mean difference between land use proportions estimated by the SF benchmark and **a** CLM RUSLE, CLM (H) and CLM ERM(HM) with the C-factor for moorland = forest, **b** CLM RUSLE. CLM (H) and CLM ERM(HM) with the C-factor for moorland > forest

model for the Loch Davan catchment. However, at both sites the mean absolute difference for the CLM RUSLE was similar to those of CLM ERM (HM): 8% vs 6% at Site 1 and 12% vs 8% at Site 2 (Fig. 5a)). Therefore, although it was not originally formulated for use on steep slopes and more organic soils such as those found in this Scottish catchment, RUSLE performed almost as well as ERM. This suggests that, for this catchment, RUSLE erosion rate estimates could be used to quantify the amount of soil eroded from the high or medium risk areas characterised by the ERM.

3.3 Hotspots and erosion rates

Although Wiltshire et al. (2023) identified the land use origin of stream OC in the Loch Davan catchment using OC fingerprinting, the land use source classifications were too broad to enable precise sources or hotspots (e.g., specific fields or landscape features) to be determined. The OC fingerprinting estimated pasture as the dominant source of OC followed by arable land with lesser amounts from moorland and forest. In this study, more precise sources were identified by modelling catchment soil erosion risk. The closest approximation to the relative OC yield in streambed sediments identified by OC sediment fingerprinting was obtained by considering areas defined by the ERM as high or medium erosion risk, with high connectivity to the streams (CLM ERM (HM)). Areas of Loch Davan catchment defined by CLM ERM (HM) were therefore mapped to characterise locations most likely to contribute OC to the feeder streams and, consequently, be targeted for soil management strategies (Fig. 6a, b).

Erosion risk maps such as the ERM can identify areas where a high risk of soil degradation could increase the risk of diffuse water pollution (Baggaley et al. 2020), however they do not provide quantitative estimates of soil or OC erosion rates. In this catchment, RUSLE performed almost as well as ERM suggesting RUSLE erosion rate estimates (t ha^{-1} yr^{-1}) could be used to estimate the amount of soil eroded from areas defined as "high" and "medium" risk by the ERM.

Areas identified as "high" or "medium" risk in ERM had mean RUSLE soil erosion estimates of 1.51 and 0.88 t ha^{-1} yr^{-1} for arable land, 1.26 and 0.64 t ha^{-1} yr^{-1} for pasture land, 0.04 and 0.03 t ha^{-1} yr^{-1} for forest land and 0.04 and 0.04 t ha^{-1} yr^{-1} for moorland, respectively (Table 2). The areas defined as high risk by the ERM showed a higher mean erosion rate than those defined as medium risk, except moorland which supported the same erosion rate in both areas. The predicted values of mean soil erosion rates show that moorland (and forest) have lowest soil erosion rates which appears to contrast with the high percentage of stream sediment apportioned to moorland by both CLM RUSLE and CLM ERM(HM). However, it is important to note that the CLM are OC loss models. The CLM include not just the soil erosion rate (Table 2) but also the catchment area classified as medium and high risk and the average amount of carbon contained in the eroded soil.

In a recent report to the Scottish Government, Rickson et al. (2019) assessed annual erosion cost in Scotland by adopting the approach that soil erosion rates should be driven by land use, and the probability of erosion occurring should be driven by erosion risk class (as defined by the ERM). As RUSLE does not make a distinction between mineral and organic soils, RUSLE results are compared with the full range of values (irrespective of soil type) estimated by Rickson et al. (2019) for each land use. The RUSLE estimates of soil erosion for this catchment are comparable to the soil erosion rates per land use estimated

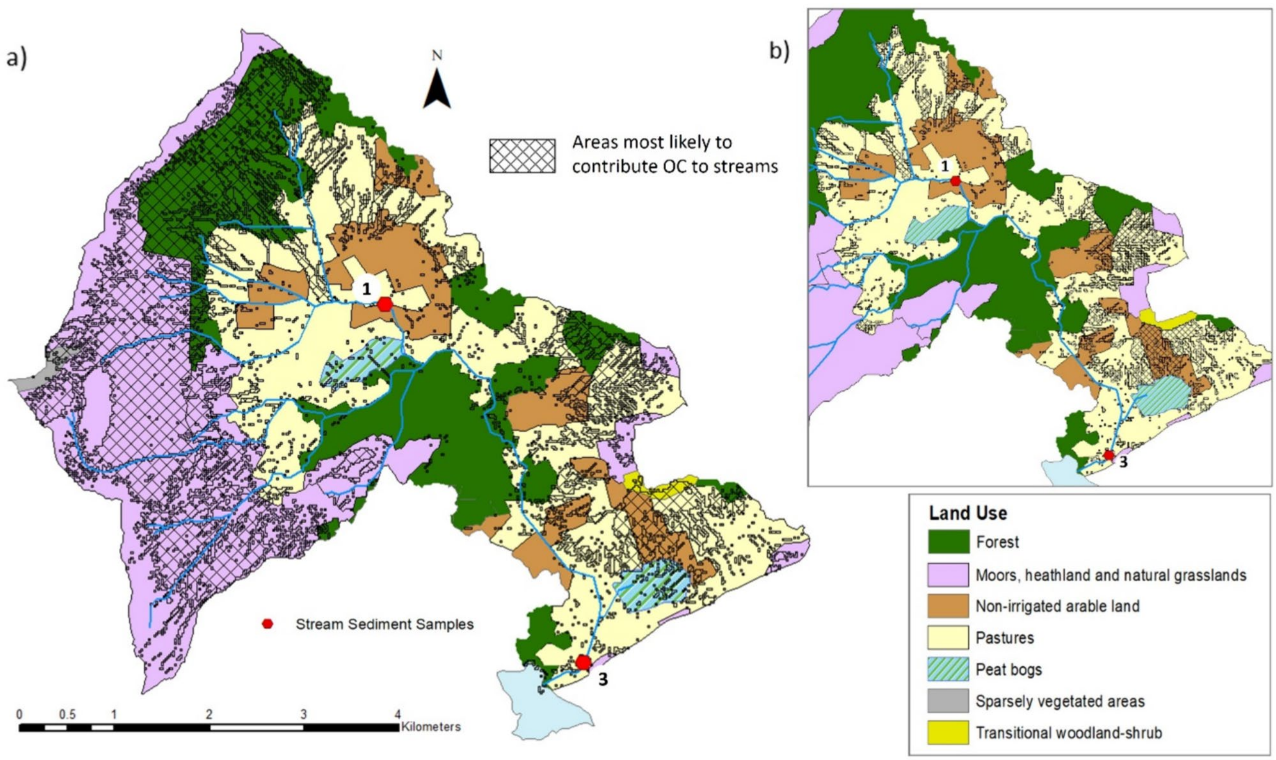

Fig. 6 Areas most likely to contribute OC to the catchment streams across **a** the entire Loch Davan catchment, **b** for arable and pasture land use only. These are areas of "High" or "Medium" erosion risk (Lilly and Baggaley 2018) and high connectivity to streams defined in CLM ERM(HM)

by Rickson et al. (2019) (Table 2) except in the case of pasture/grassland where the erosion rates for pasture soils in this catchment are greater than those quoted for grassland by Rickson et al. (2019). It is possible the RUSLE C factor for grassland (Table 1; Panagos et al. 2015b) could have been set too high for this catchment, however, the pasture source proportion identified by the OC fingerprinting benchmark is similar to that modelled by both CLM ERM(HM) and CLM RUSLE using this C factor. Alternatively, it has already been suggested (Section 3.1) that pastures in this catchment may be temporary (grass leys) rather than permanent due to the similarity between the OC% in pasture and arable soils. Rickson et al. (2019) found that the land preparation (reduced vegetation cover) and reseeding of grass leys increased the rate of soil erosion. In addition, Hirave et al. (2020) found a higher than expected contribution of permanent grasslands to suspended sediments in a nearby catchment in Scotland.

Table 2 RUSLE mean rates of soil erosion (t ha^{-1} yr^{-1}) for areas characterised as “High” or “Medium” risk in CLM ERM(HM) and comparison with soil erosion rates from Rickson et al. (2019) for arable, grassland, forest and moorland (wildscape/semi-natural landscape)

	Mean soil erosion (t ha^{-1} yr^{-1})						
	This study			(Rickson et al. 2019)			
	Catchment	ERM high risk areas	ERM medium risk areas	High Risk		Medium risk	
				Mineral	Organic	Mineral	Organic
Arable	0.83	1.51	0.88	0.58 – 1.03	1.55 – 3.10	0.31 – 0.56	0.60 – 1.20
Pasture/grassland	0.63	1.26	0.64	0.50 – 0.72	0.12 – 0.31	0.27 – 0.39	0.05 – 0.12
Forest	0.02	0.04	0.03	0.14	0.04	0.08	0.02
Moorland/wildscape	0.04	0.04	0.04	0.14	0.04	0.08	0.02

3.4 Comparison of two sediment origin techniques—erosion risk models and OC fingerprinting

The comparison of two sediment origin techniques in this study—erosion risk modelling and OC sediment fingerprinting was used to determine that RUSLE erosion rate estimates could be used to quantify the amount of soil eroded from high-risk areas identified by the ERM.

Comparison of these two sediment origin techniques could be carried out in many catchments and has a number of advantages. Firstly, as demonstrated in this study, the most suitable model for use in a particular environment can be evaluated by determining which model most closely matched an OC fingerprinting benchmark.

Secondly, large discrepancies between the results of OC sediment fingerprinting and an erosion model such as RUSLE could indicate that the assumed process of OC input to streams in a catchment (in the case of RUSLE rill and inter-rill erosion of soil) is incorrect and other processes such as bank or gully erosion (Liu et al. 2021a) or direct input (e.g., organic litter or leaf debris) (Wiltshire et al. 2022) may be dominant.

Finally, previous sensitivity analysis assessments of RUSLE factors at the plot level have found that the C factor is the most important in determining soil loss under different agricultural systems (Estrada-Carmona et al. 2017). In this study a Monte Carlo analysis was carried out to estimate uncertainties due to the C factor and the OC content modelling as described in Section 2.4.3. It should be noted that uncertainties due to the connectivity index were not included. The CI was classified into "high", "medium" and "low" connectivity (Hooke et al. 2021) using a quantile classification in ESRI ArcMap (V10.6). The same CI was used for each CLM so uncertainties introduced by this factor should not have affected the comparison between the two CLM. However, using a different classification method for CI would have affected the area defined as "high" connectivity and therefore, potentially, the comparison between the CLM and the sediment fingerprinting benchmark. In any future work, using a number of different classification methods could be used to estimate the uncertainty connected with CI. Our hypothesis that the level of soil cover and impact of land management/grazing in moorland in the study catchment was similar to forest land, led to the C factor for moorland being set equal to forest. To assess the magnitude of the difference in relative OC yield due to this change in the moorland C factor the CLM RUSLE and CLM ERM(HM) were recreated using the original moorland C factor of Panagos et al. (2015b) (as noted in Table 1). The mean absolute difference between the CLM's and the OC fingerprinting benchmark increased markedly as shown in Fig. 5b (e.g., for Site 1 CLM RUSLE 8% to 34% and CLM ERM(HM) 6% to 31%). Changing the moorland C factor to be equal to that of forest, therefore, led to OC yield estimates much closer to the sediment fingerprinting benchmark. It is possible that RUSLE C factors for the other land uses in this study could also be adjusted to bring the estimates of CLM RUSLE closer to those of the OC fingerprinting benchmark. This process of C factor modification could provide insights into the level of cover and management for the arable, pasture, forest and moorland land uses in this catchment relative to those in the wider UK and Europe. However, it has already been highlighted that the stream OC reflects a complex suite of processes and an exact correspondence between the processes inputting OC to streams and the processes modelled by an erosion risk model is unlikely. Therefore, modifying RUSLE C factors to closely match a sediment fingerprinting benchmark requires i) knowledge of a catchment rendering other stream OC input processes unlikely and ii) having confidence that the OC sediment fingerprinting can equated to the "land use -specific" relative OC yield. Detailed knowledge of a catchment is always important to facilitate the best choice of erosion model (e.g., whether stream OC most likely to originate from bank/gully/rill soil erosion) but also to improve confidence in the selection of sources for OC fingerprinting. Confidence in OC sediment fingerprinting can be further improved by combining different types of OC biomarkers to improve land use discrimination (Wiltshire et al. 2023) but will also require further research on assessing catchment processes that may affect biomarker conservative behaviour (stability between "source" and "sink") on which OC fingerprinting relies.

4 Conclusions

Although Wiltshire et al. (2023) identified the land use origin of stream OC in the catchment of Loch Davan catchment using OC fingerprinting, the land use source classifications were too broad to enable erosion hotspots (e.g., specific fields or landscape features) to be determined and provided no estimate of soil erosion rates. This study aimed to identify more precise sources by modelling and evaluating catchment soil erosion risk using a comparison of two sediment origin techniques – carbon loss modelling and OC sediment fingerprinting.

Although the region-specific ERM most closely approximated the relative land use OC yields in streambed sediment, the results of RUSLE were very similar, suggesting that, in this catchment, RUSLE erosion rate estimates could be used to quantify the amount of soil eroded from the high-risk areas identified by ERM. The RUSLE estimates of soil erosion for this catchment were comparable to the soil erosion rates per land use estimated by Rickson et al. (2019) in Scottish soils except in the case of pasture/grassland likely due to the pastures in this catchment being grass ley where periods of surface vegetation cover/root network absence are likely to have generated higher rates of erosion.

This study highlighted that a combination of two sediment origin techniques – carbon loss modelling and OC sediment fingerprinting can enable a more precise identification and quantification of catchment sediment sources. These methods could, ultimately, support the development of targeted sediment management strategies to maintain healthy soils within the EU and beyond.

Acknowledgements This work was supported by the Natural Environment Research Council and the Biotechnology and Biological Sciences Research Council (Grant number NE/ M009106/1) through a studentship award to CW by STARS (Soils Training And Research Studentships) Centre for Doctoral Training and Research Programme. The authors thank the CASE funder for this work Scottish Environment Protection Agency (SEPA). We thank Nikki Baggaley from The James Hutton Institute, Aberdeen, UK for providing access to the soil erosion risk maps. We also thank the reviewers whose comments helped focus and strengthen the manuscript.

Funding Natural Environment Research Council, NE/ M009106/1, Catherine Wiltshire

Data availability Data supporting this study are openly available from Cranfield Online Research Data (CORD) at https://doi.org/10.17862/cranfield.rd.19397651.v1.

Declarations

Competing interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Addy S, Ghimire S, Cooksley S (2012) Assessment of the multiple benefits of river restoration: the Logie Burn meander reconnection project. BHS Eleventh National Symposium, Hydrology for a Changing World, Dundee 2012:01–05. https://doi.org/10.7558/bhs.2012.ns01

Alewell C, Birkholz A, Meusburger K et al (2016) Quantitative sediment source attribution with compound-specific isotope analysis in a C3 plant-dominated catchment (central Switzerland). Biogeosci 13:1587–1596. https://doi.org/10.5194/bg-13-1587-2016

Alewell C, Borrelli P, Meusburger K, Panagos P (2019) Using the USLE: Chances, challenges and limitations of soil erosion modelling. Int Soil Water Conserv Res 7:203–225. https://doi.org/10.1016/j.iswcr.2019.05.004

Angst G, John S, Mueller CW et al (2016) Tracing the sources and spatial distribution of organic carbon in subsoils using a multibiomarker approach. Sci Rep 6:1–12. https://doi.org/10.1038/srep29478

Baggaley N, Lilly A, Blackstock K et al (2020) Soil risk maps – Interpreting soils data for policy makers, agencies and industry. Soil Use Manag 36:19–26. https://doi.org/10.1111/sum.12541

Batista PVG, Davies J, Silva MLN, Quinton JN (2019) On the evaluation of soil erosion models: Are we doing enough? Earth Sci Rev 197:102898. https://doi.org/10.1016/j.earscirev.2019.102898

Bieroza MZ, Bol R, Glendell M (2021) What is the deal with the Green Deal: Will the new strategy help to improve European freshwater quality beyond the Water Framework Directive? Sci Total Environ 791. https://doi.org/10.1016/j.scitotenv.2021.148080

Blake WH, Ficken KJ, Taylor P et al (2012) Tracing crop-specific sediment sources in agricultural catchments. Geomorphol 139–140:322–329. https://doi.org/10.1016/j.geomorph.2011.10.036

Borrelli P, Märker M, Panagos P, Schütt B (2014) Modeling soil erosion and river sediment yield for an intermountain drainage basin of the Central Apennines, Italy. CATENA 114:45–58. https://doi.org/10.1016/j.catena.2013.10.007

Borrelli P, Van Oost K, Meusburger K et al (2018) A step towards a holistic assessment of soil degradation in Europe: Coupling on-site erosion with sediment transfer and carbon fluxes. Environ Res 161:291–298. https://doi.org/10.1016/j.envres.2017.11.009

Borselli L, Cassi P, Torri D (2008) Prolegomena to sediment and flow connectivity in the landscape: A GIS and field numerical assessment. CATENA 75:268–277. https://doi.org/10.1016/j.catena.2008.07.006

Brenning A, Becker M, Bangs D (2018) RSAGA: SAGA Geoprocessing and Terrain Analysis. R package. https://cran.r-project.org/package=RSAGA

Cavalli M, Trevisani S, Comiti F, Marchi L (2013) Geomorphometric assessment of spatial sediment connectivity in small Alpine catchments. Geomorphol 188:31–41. https://doi.org/10.1016/j.geomorph.2012.05.007

Chen FX, Fang NF, Wang YX et al (2017) Biomarkers in sedimentary sequences: Indicators to track sediment sources over decadal timescales. Geomorphol 278:1–11. https://doi.org/10.1016/j.geomorph.2016.10.027

Cloy JM, Lilly A, Hargreaves PR et al (2021) A state of knowledge overview of identified pathways of diffuse pollutants to the water environment. CRW2018_18. https://www.crew.ac.uk/publications

Cole B, King S, Ogutu B et al (2015) Corine land cover 2012 for the UK, Jersey and Guernsey. In: NERC Environmental Information Data Centre. https://doi.org/10.5285/32533dd6-7c1b-43e1-b892-e80d61a5ea1d. Accessed 18 Jan 2021

Collins AL, Blackwell M, Boeckx P et al (2020) Sediment source fingerprinting: benchmarking recent outputs, remaining challenges and emerging themes. J Soils Sediments 20:1460–1493. https://doi.org/10.1007/s11368-020-02755-4

Cooper RJ, Pedentchouk N, Hiscock KM et al (2015) Apportioning sources of organic matter in streambed sediments: An integrated molecular and compound-specific stable isotope approach. Sci Total Environ 520:187–197. https://doi.org/10.1016/j.scitotenv.2015.03.058

De Mastro F, Cocozza C, Brunetti G, Traversa A (2020) Chemical and spectroscopic investigation of different soil fractions as affected by soil management. Appl Sci 10. https://doi.org/10.3390/app10072571

Desmet PJJ, Govers G (1996) A GIS procedure for automatically calculating the USLE LS factor on topographically complex landscape units. J Soil Water Conserv 51:427–433
European Commission (2021) EU Soil Strategy for 2030: Reaping the benefits of healthy soils for people, food, nature and climate. 1–26. https://ec.europa.eu/environment/publications/eu-soil-strategy-2030_en
European Commission (2022a) A European Green Deal: Striving to be the first climate-neutral continent. https://ec.europa.eu/info/strategy/priorities-2019-2024/european-green-deal_en. Accessed 13 Mar 2022
European Commission (2022b) EU Soil Observatory (EUSO). https://joint-research-centre.ec.europa.eu/eu-soil-observatory-euso_en. Accessed 13 Mar 2022
ESDAC (2014) Soil Erodibility (K- Factor) High Resolution dataset for Europe. In: Joint Research Centre of the European Commission. https://esdac.jrc.ec.europa.eu/content/soil-erodibility-k-factor-high-resolution-dataset-europe. Accessed 7 Jun 2019
ESDAC (2015a) Estimating the soil erosion cover-management factor at European scale. In: Joint Research Centre of the European Commission. https://esdac.jrc.ec.europa.eu/content/cover-management-factor-c-factor-eu. Accessed 19 Mar 2012
ESDAC (2015b) Rainfall Erosivity in the EU and Switzerland (R-factor). In: European Commission, Joint Research Centre. https://esdac.jrc.ec.europa.eu/content/rainfall-erosivity-european-union-and-switzerland. Accessed 7 Jun 2019
ESRI (2017) ArcGIS Desktop. https://www.esri.com/
Estrada-Carmona N, Harper EB, DeClerck F, Fremier AK (2017) Quantifying model uncertainty to improve watershed-level ecosystem service quantification: a global sensitivity analysis of the RUSLE. Int J Biodivers Sci Ecosyst Serv Manag 13:40–50. https://doi.org/10.1080/21513732.2016.1237383
Fenton N, Neil M (2018) Risk Assessment and Decision Analysis with Bayesian Networks. CRC Press Taylor & Francis, Boca Raton, Florida USA
Game & Wildlife Conservation Trust (2022) Scottish Demonstration Farm Auchnerran. https://www.gwct.org.uk/auchnerran
Galoski CE, Jiménez Martínez AE, Schultz GB et al (2019) Use of n-alkanes to trace erosion and main sources of sediments in a watershed in southern Brazil. Sci Total Environm 682:447–456. https://doi.org/10.1016/j.scitotenv.2019.05.209
Glendell M, Jones R, Dungait JAJ et al (2018) Tracing of particulate organic C sources across the terrestrial-aquatic continuum, a case study at the catchment scale (Carminowe Creek, southwest England). Sci Total Environ 616:1077–1088. https://doi.org/10.1016/j.scitotenv.2017.10.211
Griepentrog M, Bodé S, Boeckx P, Wiesenberg GLB (2016) The fate of plant wax lipids in a model forest ecosystem under elevated CO2 concentration and increased nitrogen deposition. Org Geochem 98:131–140. https://doi.org/10.1016/j.orggeochem.2016.05.005
Hancock GJ, Revill AT (2013) Erosion source discrimination in a rural Australian catchment using compound-specific isotope analysis (CSIA). Hydrol Process 27:923–932. https://doi.org/10.1002/hyp.9466
Hijmans RJ (2020) Raster: Geographic Data Analysis and Modeling. R package. https://cran.r-project.org/package=raster.
Hirave P, Glendell M, Birkholz A, Alewell C (2020) Compound-specific isotope analysis with nested sampling approach detects spatial and temporal variability in the sources of suspended sediments in a Scottish mesoscale catchment. Sci Total Environ 142916. https://doi.org/10.1016/j.scitotenv.2020.142916
Hooke J, Souza J, Marchamalo M (2021) Evaluation of connectivity indices applied to a Mediterranean agricultural catchment. CATENA 207:105713. https://doi.org/10.1016/j.catena.2021.105713
Jiang Y, Gao J, Yang L et al (2021) The interactive effects of elevation, precipitation and lithology on karst rainfall and runoff erosivity. CATENA 207:105588. https://doi.org/10.1016/j.catena.2021.105588
Karambiri H, Ribolzi O, Delhoume JP et al (2003) Importance of soil surface characteristics on water erosion in a small grazed Sahelian catchment. Hydrol Process 17:1495–1507. https://doi.org/10.1002/hyp.1195
Kelsey SA, Grottoli AG, Bauer JE et al (2020) Effects of agricultural and tillage practices on isotopic signatures and fluxes of organic and inorganic carbon in headwater streams. Aquat Sci 82:1–13. https://doi.org/10.1007/s00027-019-0691-7
Lilly A, Baggaley N (2014) Developing simple indicators to assess the role of soils in determining risks to water quality, CREW project number CD2012_42. https://www.crew.ac.uk/publications
Lilly A, Baggaley NJ (2018) Soil erosion risk map of Scotland. https://soils.environment.gov.scot/maps/risk-maps/map-of-soil-erosion-risk-partial-cover/
Liu C, Hu BX, Li Z et al (2021a) Linking soils and streams: Chemical composition and sources of eroded organic matter during rainfall events in a Loess hilly-gully region of China. J Hydrol 600:126518. https://doi.org/10.1016/j.jhydrol.2021.126518
Liu C, Wu Z, Hu BX, Li Z (2021b) Linking recent changes in sediment yields and aggregate-associated organic matter sources from a typical catchment of the Loess Plateau. China Agric Ecosyst Environ 321:107606. https://doi.org/10.1016/j.agee.2021.107606
Mabit L, Gibbs M, Mbaye M et al (2018) Novel application of Compound Specific Stable Isotope (CSSI) techniques to investigate on-site sediment origins across arable fields. Geoderma 316:19–26. https://doi.org/10.1016/j.geoderma.2017.12.008
Marques VS, Ceddia MB, Antunes MAH et al (2019) USLE K-factor method selection for a tropical catchment. Sustainability 11:1–17. https://doi.org/10.3390/su11071840
Martin MP, Wattenbach M, Smith P et al (2011) Spatial distribution of soil organic carbon stocks in France. Biogeosci 8:1053–1065. https://doi.org/10.5194/bg-8-1053-2011
Mayer S, Kühnel A, Burmeister J et al (2019) Controlling factors of organic carbon stocks in agricultural topsoils and subsoils of Bavaria. Soil Tillage Res 192:22–32. https://doi.org/10.1016/j.still.2019.04.021
Meersmans J, De Ridder F, Canters F et al (2008) A multiple regression approach to assess the spatial distribution of Soil Organic Carbon (SOC) at the regional scale (Flanders, Belgium). Geoderma 143:1–13. https://doi.org/10.1016/j.geoderma.2007.08.025
Meersmans J, Martin MP, De Ridder F et al (2012) A novel soil organic C model using climate, soil type and management data at the national scale in France. Agron Sustain Dev 32:873–888. https://doi.org/10.1007/s13593-012-0085-x
Met Office (2021) UK Climate Average. https://www.metoffice.gov.uk/research/climate/maps-and-data/uk-climate-averages/gfjuxqwcs. Accessed 18 Jan 2021
Mukundan R, Walling DE, Gellis AC et al (2012) Sediment source fingerprinting: transforming from a research tool to a management tool. J Am Water Resour Assoc 48:1241–1257. https://doi.org/10.1111/j.1752-1688.2012.00685.x
Odhiambo BK, Rihl G, Hood-Recant S (2021) Historic land use and sedimentation in two urban reservoirs, Occoquan Reservoir and Lake Manassas, Virginia, USA. Environ Sci Pollut Res. https://doi.org/10.1007/s11356-021-16461-2
Ordnance Survey (2021) OS Terrain 5 [ASC geospatial data], Scale 1:10000, Tiles: nj30ne,nj30nw,nj30se,nj30sw,nj31se,nj31sw,nj40ne,nj40nw,nj40se,nj40sw,nj41se,nj41sw,nj50ne,nj50nw,nj50se,nj50sw,nj51se,nj51sw,no39ne,no39nw,no49ne,no49nw,no59ne,no59nw,. In: EDINA Digimap Ordnance Survey Service. https://digimap.edina.ac.uk. Accessed 14 Dec 2018
Panagos P, Meusburger K, Ballabio C et al (2014) Soil erodibility in Europe: A high-resolution dataset based on LUCAS. Sci Total

Environ 479–480:189–200. https://doi.org/10.1016/j.scitotenv.2014.02.010
Panagos P, Ballabio C, Borrelli P et al (2015a) Rainfall erosivity in Europe. Sci Total Environ 511:801–814. https://doi.org/10.1016/j.scitotenv.2015.01.008
Panagos P, Borrelli P, Meusburger K et al (2015b) Estimating the soil erosion cover-management factor at the European scale. Land Use Policy 48:38–50. https://doi.org/10.1016/j.landusepol.2015.05.021
Pebesma EJ (2004) Multivariable geostatistics in S: the gstat package. Comput Geosci 30:683–691. https://doi.org/10.1016/j.cageo.2004.03.012
Pebesma EJ, Bivand RS (2005) Classes and methods for spatial data in R: The sp package. R News 5 (2). https://rdrr.io/cran/sp/f/inst/doc/intro_sp.pdf
Quenea K, Derenne S, Largeau C et al (2004) Variation in lipid relative abundance and composition among different particle size fractions of a forest soil. Org Geochem 35:1355–1370. https://doi.org/10.1016/j.orggeochem.2004.03.010
Quénéa K, Largeau C, Derenne S et al (2006) Molecular and isotopic study of lipids in particle size fractions of a sandy cultivated soil (Cestas cultivation sequence, southwest France): Sources, degradation, and comparison with Cestas forest soil. Org Geochem 37:20–44. https://doi.org/10.1016/j.orggeochem.2005.08.021
R Core Team (2020) R: A language and environment for statistical computing. https://www.r-project.org/
Renard KG, Foster GR, Weesies GA et al (1997) Predicting soil erosion by water: A guide to conservation planning with the revised universal soil loss equation (RUSLE)., Agricultur. U.S. Dept. of Agriculture, Agricultural Research Service, Washington, D.C
Rickson RJ, Baggaley N, Deeks LK et al (2019) Developing a method to estimate the costs of soil erosion in high-risk Scottish catchments. Report to the Scottish Government. Available online from https://www.gov.scot/ISBN/978-1-83960-754-7
SEPA (2021) Water Classification Hub. In: Scottish Environment Protection Agency. https://www.sepa.org.uk/data-visualisation/water-classification-hub/
Schmidt S, Alewell C, Meusburger K (2018) Mapping spatio-temporal dynamics of the cover and management factor (C-factor) for grasslands in Switzerland. Remote Sens Environ 211:89–104. https://doi.org/10.1016/j.rse.2018.04.008
Sirjani E, Mahmoodabadi M, Cerdà A (2022) Sediment transport mechanisms and selective removal of soil particles under unsteady-state conditions in a sheet erosion system. Inter J Sediment Res 37:151–161. https://doi.org/10.1016/j.ijsrc.2021.09.006
Scottish Government (2009) The Scottish Soil Framework. http://www.gov.scot/Resource/Doc/273170/0081576.pdf
Stock BC, Semmens BX (2016) MixSIAR GUI User Manual. Version 3.1. https://github.com/brianstock/MixSIAR
Stock BC, Jackson AL, Ward EJ et al (2018) MixSIAR model description. 2018. https://peerj.com/articles/5096
The James Hutton Institute (2018) 1:25,000 Soil Map (partial cover). https://www.hutton.ac.uk/soil-maps/
Thornton B, Zhang Z, Mayes RW et al (2011) Can gas chromatography combustion isotope ratio mass spectrometry be used to quantify organic compound abundance? Rapid Commun Mass Spectrom 25:2433–2438. https://doi.org/10.1002/rcm.5148
Walling DE, Owens PN, Leeks GJL (1999) Fingerprinting suspended sediment sources in the catchment of the River Ouse, Yorkshire, UK. Hydrol Process 13:955–975. https://doi.org/10.1002/(SICI)1099-1085(199905)13:7%3c955::AID-HYP784%3e3.0.CO;2-G
Wiesmeier M, Prietzel J, Barthold F et al (2013) Storage and drivers of organic carbon in forest soils of southeast Germany (Bavaria) - Implications for carbon sequestration. For Ecol Manage 295:162–172. https://doi.org/10.1016/j.foreco.2013.01.025
Wiesmeier M, Urbanski L, Hobley E et al (2019) Soil organic carbon storage as a key function of soils - A review of drivers and indicators at various scales. Geoderma 333:149–162. https://doi.org/10.1016/j.geoderma.2018.07.026
Wiltshire C, Glendell M, Waine TW et al (2022) Assessing the source and delivery processes of organic carbon within a mixed land use catchment using a combined n-alkane and carbon loss modelling approach. J Soils Sediments 22:1629–1642. https://doi.org/10.1007/s11368-022-03197-w
Wiltshire C, Waine TW, Grabowski RC et al (2023) Assessing n -alkane and neutral lipid biomarkers as tracers for land-use specific sediment sources. Geoderma 433. https://doi.org/10.1016/j.geoderma.2023.116445
Wischmeier W, Smith D (1978) Predicting rainfall erosion losses: a guide to conservation planning. Agricultural Handbook No. 537.
Yu M, Eglinton TI, Haghipour N et al (2019) Molecular isotopic insights into hydrodynamic controls on fluvial suspended particulate organic matter transport. Geochim Cosmochim Acta 262:78–91. https://doi.org/10.1016/j.gca.2019.07.040
Zhang Y, Collins AL, McMillan S et al (2017) Fingerprinting source contributions to bed sediment-associated organic matter in the headwater subcatchments of the River Itchen SAC, Hampshire, UK. River Res Appl 33:1515–1526. https://doi.org/10.1002/rra.3172

Authors and Affiliations

C. Wiltshire[1] · J. Meersmans[3] · T. W. Waine[1] · R. C. Grabowski[1] · B. Thornton[2] · S. Addy[2] · M. Glendell[2]

✉ C. Wiltshire
katy.wiltshire@cranfield.ac.uk

[1] School of Water, Energy and Environment, Cranfield University, Bedford MK43 0AL, UK

[2] The James Hutton Institute, Craigiebuckler, AB15 8QH Aberdeen, Scotland, UK

[3] TERRA Teaching and Research Centre, Gembloux Agro-Bio Tech, University of Liège, 5030 Gembloux, Belgium