# Considering lacustrine erosion records and the De Ploey erosion model in an examination of mountain catchment erosion susceptibility and precipitation reconstruction.

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**Abstract**

Reconstruction of paleo-precipitation can provide an insight into past climate and precipitation. De Ploey et al. (1995) presents a highly simplified erosion equation to consider precipitation and erosion susceptibility. This empirical model allows estimation of total precipitation and erosion susceptibility across a range of catchment characteristics (including catchment area, slope, elevation, vegetation cover) and when limited catchment or meteorological data is available. The presented study tests the De Ploey equation using dated lacustrine records of catchment soil deposition both spatially and temporally. The objective is to examine the De Ploey equation's ability and efficiency in reconstructing past long-term precipitation using sedimentological parameters. The erosion susceptibility factor is described as a 'black box' value by De Ploey et al. (1995). This research unravels the erosion susceptibility variable, identifying it to change spatially and temporally according to precipitation, vegetation cover and composition (the extent of tree establishment across the catchment), total lacustrine deposition and geochemical signatures in the archive. Calculation of the erosion sustainability variable and it's use within the De Ploey erosion equation illustrate a reconstruction of an indicative mean annual precipitation and erosion susceptibility change over the recent period (~ 100 years).

Key Words (4 – 6): De Ploey, erosion, lacustrine sediment, precipitation modelling, paleo-precipitation

# 1 Introduction

In the global warming context, finding new proxies for the estimation of paleo-temperatures and paleo-precipitation are essential to assess the resilience of terrestrial ecosystems to abrupt changes. However, paleo-precipitation reconstructions that contain long-term trends and extend prior to medieval times are difficult to find and interpret, and depend not only on the time resolution of natural archives but also on the pertinence and the sensibility of both the proxy used and the chosen archive (Seddon et al., 2014). Past precipitation reconstructions can, for example, be based on tree ring records (Büntgen et al., 2011), pedogenetic magnetic susceptibility variations (Maher and Thompson, 1995), cave records (Hu et al. 2008), pollen assemblages (Peyron et al., 1998), glacial dynamics (Holzhauser et al., 2005), lake-levels records (Magny et al., 2011) or flood events deposits (Wilhelm et al., 2012). Precipitation reconstruction is also often completed directly from lacustrine proxy analysis (such as $^{10}$Be and $\delta^{18}$O, goethite/hematite ratio, granulometry, $^{10}$Be, Sr, Pb, $^{137}$Cs, Ti), with short gauged precipitation records available for validation of empirical or numerical precipitation calculations (Cross, 2001; Hyland et al., 2015; Rozanski et al., 1997; Zhou et al., 2014). This constrains the analysis to discussion of 'more' or 'less' humid periods rather than quantifying the amount of past precipitation (Arnaud et al., 2012; Bjune et al., 2005; Magny et al., 2011; Peyron et al., 1998; Simonneau et al., 2013a). Because precipitation, in conjunction with vegetation cover, is a significant driver in erosion processes, soil erosion fluxes stored in lacustrine archives can potentially provide an insightful indication of past trends and overall precipitation (Simonneau, 2012). Past trends in catchment erosion susceptibility reflect both the land use and climatic changes influencing a specific catchment and the sensitivity of that catchment to precipitation driven erosion.

Numerous organic or inorganic parameters can be measured within lacustrine sediments and interpreted as representative of erosion dynamics of the catchment (Arnaud et al., 2016). However, if these sedimentological erosion proxies provide an indication of terrestrial fluxes over time, they do not always assess the nuances of soil-to-sediment differentiation (Arata et al., 2016; Bajard et al., 2017; Charreau et al., 2011; Davies et al., 2015; Ritchie and McHenry, 1990).

The red Amorphous Particles content in a lacustrine archive (rAP, (Chassiot et al., 2018; Foucher et al., 2014; Graz et al., 2010; Simonneau et al., 2014, 2013a)) is one organic sedimentological proxy indicating soil erosion from catchment surfaces to sinks, such as lakes. rAPs are indicators of allochthonous organic catchment soils, e.g.

Histosol or Leptosol in a high altitude context (Di-Giovanni et al., 1998; Graz et al., 2010). Lacustrine rAP records provide a quantitative representation of allochthonous soil deposition (Chassiot et al., 2018; Guillemot et al., 2015; Simonneau et al., 2013c, 2013a, 2013b). These organic particles are approximately 100 µm in diameter and are the result of lingo-cellulosic fragment degradation in soil profiles (Di-Giovanni et al., 1998; Simonneau, 2012).

Minerogenic or inorganic soil representation can be considered through analysis of rubidium (Rb). Rb has classically been used as a tracer of soil erosion in lacustrine archive studies and adopted as a lithogenic soil tracer (Davies et al., 2015; Hosek et al., 2017; Jin et al., 2001; Sabatier et al., 2014; Schmidt et al., 2006; Simonneau et al., 2013a). Combining rAP and lithogenic soil traces can present a more complete and detailed overview of soil erosion dynamics and soil weathering over time (Chassiot et al., 2018; Oliva et al., 2004). The long-term organic and minerogenic fluxes may therefore be used to estimate the amount of precipitation relative to erosion processes.

Modelling such fluxes over long timescales continues to be a challenge as the majority of soil erosion models only function at short timescales (event or pluriannual) and require significant data, such as soil infiltration, roughness or hydraulic conductivity, rainfall event intensity and soil composition. It is acknowledged that the erosive effect of precipitation is dependent on precipitation intensity (especially rainfall intensity) (Lana-Renault et al., 2007; Ziadat and Taimeh, 2013) and, within mountainous catchments, the delineation between snow and rainfall in the precipitation record. However, this level of detail is difficult to establish when using larger timesteps (e.g. 10 years) and lacustrine or paleo archive records. The De Ploey's empirical model of erosion and precipitation is a purposefully simplified method to consider catchment soil erosion across extended time periods (long term) up to and in excess of 100 years (De Ploey et al., 1995). It was designed to approach erosion analysis at a regional or local scale and to consider sediment budgets within a chosen catchment. The De Ploey equation focuses on mean total precipitation as one, quantifiable, driving force behind catchment erosion, without consideration of intensity or snow/rain influence. The second key parameter is the catchment erosion susceptibility (Es), a value selected (but not specifically calculated) by catchment characteristics (location, climate and vegetation, catchment parameters such as slope length and gradient). This model is not well known or frequently used for actual erosion-precipitation modelling due to its lack of complexity regarding soil structure or soil humidity. However, its simplicity may provide a useful method to examine past long-term precipitation, erosion and catchment erosion susceptibility at a decadal time step and over millennia. Es values have been published for of over 60 catchments located globally, using samples that presented time steps of 2 years for some locations (with high deposition rates) to samples with time steps of >500 years. The published range of Es values, relative to generalised catchment conditions for long term erosion susceptibility analysis, generally range from $10^{-3} – 10^{-6}$ $s^2/m^2$, (De Ploey et al. 1995 and

*Figure 1*).

*Figure 1. Long-term erosion susceptibility values ($ES_L$) from published De Ploey Es equation implementation (reconstruction of catchment characteristics from De Ploey et al. 1995 Figures 2-4, 6).*

To date, the calculation of Es in temporal datasets using multiple samples has not been tested (e.g. lacustrine record). Es could be utilised in one of two ways: firstly, as a coefficient (static value) selected for the catchment due to the general catchment characteristics (e.g. high altitude, temperate climate, general open vegetation); secondly, as a variable that changes over time due to one or a combination of changing meteorological and catchment characteristics and more particularly the vegetation cover.

Identification of catchment soils, through use of quantitative palynofacies soil proxies (Chassiot et al., 2018; Foucher et al., 2014; Graz et al., 2010; Simonneau et al., 2013c, 2013b, 2013a), within lacustrine records provides a temporal erosion record for the study catchments. Using this quantified soil erosion record, this research aims to identify a method to calculate the Es value(s) and present a reconstruction of recent precipitation (~1960-present). To undertake this assessment there are two key assumptions made. First, that the soil proxies used within the lacustrine archives are directly representative of the soil eroded from the contributing catchment and deposited in the lake. Second, that there is negligible loss of eroded material from the lake, that the lacustrine deposition presents a strong catchment soil erosion record (Ouahabi et al., 2016).

# 2 Materials and Methods

## 2.1 Spatial and temporal lacustrine dataset

Lacustrine records provide dated archives of soil deposition within a lake catchment (Arnaud et al., 2016). For catchments located at the most upstream extent of a larger watershed or basin, these lakes can be the first or primary deposition point for eroded soil. A spatial dataset was created to evaluate the functionality and variability of the De Ploey equation and Es variable across the French Pyrenees and in the French Alps. This dataset is comprised of lacustrine sediment cores from lakes located in the upstream extent of mountain watersheds of varying size, elevation, contributing catchment area, meteorological conditions and vegetation cover. These lacustrine records were used to identify the quantity of eroded soil deposited into the lake: (1) over the last few years (top-core samples, spatial dataset, Figure 2 and Table 1); and (2) over the last 100 years (looking at the highest resolved lacustrine archive, temporal dataset, Table 2). The spatial dataset was comprised of the most recent 10 mm of sediment deposition from each lacustrine core. The top-core samples present an archive spanning from 7 years in sediment and soil deposition record (e.g. Lake Arbu) to more than 50 years (e.g. Lakes Sigriou, Port Bielh and Gentau). Lake Arbu, a small alpine catchment in the Mid-Pyrenees with a high lacustrine deposition rate, was adopted for the temporal analysis (analysis of the last 100 years using a 1.15m high-resolution core; the recent 100yrs is represented by ~70mm).

*Figure 2. Study lakes and catchments used in the temporal and spatial analysis of erosion susceptibility. The temporal site, Arbu, is noted on blue.*

Lake cores were collected generally from the central most section of the lake. Cores were recovered from beneath the lake floor using a UWITEC coring device operated from a floating platform or similar (Arnaud et al., 2016; Doyen et al., 2016; Simonneau et al., 2013a).

One core was used from each lake, a common and accepted analytical method in paleorecord analysis (Baddouh et al., 2016; Mügler et al., 2010; Wischnewski et al., 2011), with two cores sampled from Lakes Majeur and Paladru as a methodology check. This spatial dataset encompasses catchments with a range of lake sizes (0.02 $km^2$-3.60$km^2$), contributing catchment areas (0.37$mm^2$-66.62$km^2$), altitudes (1168-2658m a.s.l.), and indicative catchment slopes (0.01m/m to 1.1m/m). The vegetation composition, extent and land use also vary across these catchments, with areas such as Barroude, Gentau, Medecourbe and Sigriou dominated by bare rock, Arbu, Arratille, Picot dominated by scrubby alpine vegetation and urban development found in the catchment of Lake Paladru.

*Table 1. Dataset of study area lakes and the catchment characteristics*

### 2.1.1 Study area meteorology and catchment characteristics data

Meteorology and vegetation data for all catchments was gathered from the Météo France® precipitation gauging stations and the CORINE land cover dataset. Météo France® provide both gauged precipitation records from field monitoring sites across France and a gridded network of precipitation records (SAFRAN). Wherever possible a local precipitation gauge was used to quantify the precipitation occurring for each study catchment relative to the sample period (e.g. precipitation for Lake Arbu using the Bernadouze meteorology monitoring station for the top sample (7 year time step) (Gascoin and Fanise, 2018; Meteo France, 2019), with confirmation and gap filling using the SAFRAN dataset (Birman et al., 2017; Quintana-Seguí et al., 2017; Vidal et al., 2010). The total precipitation for each year represented by the sample (e.g. for 2006-2013) was identified from these datasets and summed to provide the De Ploey variable $P$ (P is the total precipitation (m per $m^2$) for the corresponding period of erosion activity (De Ploey et al., 1995)). Precipitation is presented in Table 1 as an annual average representative of the sample duration (e.g. 2006-2013 for the top Lake Arbu sample) to allow a visual comparison and overview of relative precipitation of the study area catchments.

Land cover was identified using the European Union CORINE program database. CORINE is an EU open source database of environmental information. It includes a database of land cover (using 44 land classifications) at a cartographic scale of 1:100,000 (Bossard et al., 2000; De Roo et al., 2003; Feranec et al., 2007). Using the gridded CORINE dataset and catchment areas, the composition of each catchment was defined (Table 1). Where possible, this land cover characterisation was confirmed using pollen reconstruction analysis (available for the temporal dataset for Lake Arbu and spatially for Lakes Paladru, Majeur and Sigriou (Doyen et al., 2016; Marquer et al., *in press*)).

The temporal dataset was created using historically recorded precipitation for the Vicdessos catchment of Lake Arbu and the pollen reconstruction of this catchment's vegetation over the past 100 years. Meteo France precipitation datasets from local monitoring sites (Bernadouze, Foix, Vicdessos, and St Girons) in conjunction with the SAFRAN database were used to define the total precipitation for each sample. Pollen reconstruction of past land cover and vegetation type was completed following the techniques presented in Marquer et al. (*in press*), and follow the Landscape Reconstruction Algorithm (Sugita, 2007) modelling approach using the full length of lacustrine core. This provided an age dated record of land cover and vegetation occurrence for this catchment. The most recent period was also defined using the CORINE database and compared to the pollen reconstruction results to ensure compatibility between the datasets (pollen reconstruction provided equivalent but more detailed information compared to CORINE database details).

### 2.1.2 Lacustrine age-dating and elemental analysis

All cores were age-dated following the radiocarbon and $^{210}$Pb dating techniques described in (Doyen et al., 2016; Simonneau, 2012; Simonneau et al., 2013b). A minimum of three $^{14}$C dates were obtained for each core (bottom, mid and upper core samples) and $^{210}$Pb was analysed at ~10mm intervals along the core. Combining the $^{14}$C and $^{210}$Pb results an age-date model (CLAM and/or CRS) (Blaauw, 2010; Pawełczyk et al., 2017; Sikorski, 2019) was created for each core from which top sample (for the spatial dataset) and total core samples (for the temporal dataset) ages and time steps were derived (Table 2).

The element composition within each core was quantified using an ITRAX core scanner core scanner (XRF) (or equivalent) at ~1mm intervals. XRF core scanning is a non-destructive spectrometry method of elemental analysis (Arnaud et al., 2016; Boës et al., 2011; Melquiades and Appoloni, 2004) that can provide high resolution element concentration data for sediment samples. Due to the high sampling resolution along a lacustrine core, detailed trend and concentration analysis for the period of lacustrine archive can be achieved. For the study area cores, multi-elemental XRF analysis was undertaken, specifically to define the content of Titanium (Ti) and Rubidium (Rb) in each sample (results in parts per million (ppm) or % weight). Values were corrected relative to known soil content. Rb was specifically selected as a minerogenic soil proxy and Ti as a commonly used geochemical soil reference (Boës et al., 2011) to provide an indication of the minerogenic (Rb) and general (Ti) soil content in the lacustrine core. It is acknowledged that the conversion of XRF data into concentration is a crucial step and difficult to achieve with XRF data alone and the available data used in this study may therefore incorporate errors and uncertainties.

*Table 2. Sample age (top of sample) and time step durations, element content, deposition of eroded soil (Ve) and erosion susceptibility ($Es_C$, Eqn.1) (calculated from the original De Ploey Es equation (De Ploey et al., 1995)). * indicates lakes located in the Alps. Indicative deposition volume (M) is calculated following the methods published in* (Simonneau, 2012).

## 2.2 Organic and minerogenic soil proxies

The rAP proxy was selected to represent an organosoil. It predominates the upper horizons of the catchment soil, is often larger in size and less dense compared to Rb, which is a constituent of predominantly clay-silt sized soil minerals (Wang et al., 2008). To quantify rAP, ~10mm slices of the lacustrine core were prepared and manually analysed using microscopy following published methods (Simonneau, 2012). rAP is highly sensitive to catchment vegetation composition and cover (decreasing as vegetation occurrence decreases), may move easily in minor precipitation events but may also be easily detained within the catchment due to its size and angular shape. This rAP analysis resulted in a count (quantity) of rAP per sample (% organic soil in the sediment; g/g).

Rb was selected to represented lithogenic, mineral soils. Rb may conversely be less easily released (eroded) in minor precipitation events (being retained in the root zones of vegetated areas, potentially buried under or mixed within the organic soil horizons) but be more easily conveyed once entrained in the catchment runoff. There is also a potential, in major precipitation events, for the localised, easily erodible organic soil (rAP) source to be quickly depleted, resulting in major and prolonged precipitation periods presenting a comparably greater Rb representative soil deposition. Similarly, during major precipitation events the Rb content may also become limited as, especially in mountainous catchments where top soil layers such as that represented by Rb may not be infinite.

The differences in composition and transport of these two soil proxies result in the study catchments presenting differing erosion susceptibility values specific to the soil types (organic (rAP) and lithogenic (Rb)). The two complementary proxies have therefore been used as representations of the organic and inorganic catchment soils eroded and transported into the lacustrine records and have been considered (in the De Ploey Es analysis) separately to provide a more detailed analysis of soil erosion in the study catchments.

## 2.3 Application of the De Ploey model to lacustrine records

### 2.3.1 Calculation of Es from the precipitation and erosion dataset ($Es_C$)

The long term De Ploey equation is defined as (De Ploey et al. (1995), equation (3)):

$$E_s = \frac{V_e}{A.P.g.h} \qquad \text{Eqn. 1}$$

Where Es is the contributing catchments erosion susceptibility ($s^2/m^2$), Ve is the total soil volume eroded from the contributing catchment ($m^3$), A is the contributing catchment area ($m^2$), P is the total precipitation (m per $m^2$) for the corresponding period of erosion activity, h is the affected soil thickness (m, accepted as 0.001m for long term erosion analysis (De Ploey et al., 1995; Simonneau, 2012)) and g is acceleration due to gravity (~10 $m.s^{-2}$) (De Ploey et al., 1995; Summer and Walling, 2002).

The De Ploey equation is effective for catchments where derivation of the erosivity measure is difficult (Renard and Freimund, 1994; Wang et al., 2002). It focuses on catchment erosion yield calculated from recorded total precipitation and contributing catchment area, in conjunction with an Es coefficient. The Es coefficient is described by De Ploey et al. (1995) as a 'black box' value due to the limited statistical derivation currently available. Es can simplistically be regarded as a function of the total quantity of eroded soil relative to the total quantity of precipitation on the catchment over a selected period of time.

The De Ploey erosion susceptibility equation (Eqn 1) was employed across the spatial and temporal datasets in several steps (Figure 3). First, the erosion susceptibility parameter was calculated using the known precipitation record, soil deposition quantities and catchment area (P, Ve and A in Eqn. 1). These Es values were defined as the De Ploey calculated Es values, $Es_C$. Using Eqn. 1 $Es_c$ specific to the study catchment and time period were derived. To calculate the volume of rAP and Rb soil represented in the lacustrine sample the De Ploey definition of soil volume was used, as described in (Simonneau, 2012) and presented in Equation 2:

$$Ve_t = S_t \, x \, (Ac_t \, x \, LA) \qquad \text{Eqn. 2}$$

Where t = the period represented by the sample (years), S = the percentage of eroded soil relative to the total amount of sediment deposited in the lake, Ac = the accumulation (depth) of total soil and sediment deposition in the lake (m) for respective period (t), and LA = the lake area equivalent to the lake deposition extent ($m^2$) (Simonneau, 2012). $Ac_t \, x \, LA$ result in the total autochthonous and allochthonous deposition volume in the lake, as published in (Simonneau, 2012) and is further represented as M ($m^3$).

$Es_c$ can be computed if the volume of eroded soil is known (rAP or Rb proxy for the calculations of Ve; Ve(rAP) or Ve(Rb)), the precipitation for the catchment over the period of analysis is known, the assumption of erosion depth (h) for long term erosion calculations is accepted as 0.001m and the catchment and lake sizes are defined.

### 2.3.2 Derivation and calibration of Es from lacustrine archive ($Es_D$)

The calculated $Es_C$ values were correlated to catchment characteristics within the temporal and spatial dataset. Correlation analysis was used to highlight which catchment parameters fluctuated in a similar pattern to the changing erosion susceptibility (and lacustrine erosion record). This analysis was used to identify key parameters that may be effective in calculating $Es_C$. Strongly correlated, significant parameters were incorporated into linear regression to find a function that effectively described $Es_C$ and supported P estimation (Figure 3).

Using regression analysis, the lacustrine archive datasets (presenting vegetation change, metal, mineral and total deposition over specific time periods) were used to derive a function to reproduce $Es_C$. These regression $Es_C$ values, defined through archive data, were defined as derived Es values ($Es_D$). Figure 3 presents a schematic methodology for the derivation of $Es_D$.

No single parameter effectively derived $Es_C$ values, necessitating the use of multiple regression analysis. A separate function was defined for $Es_D$(rAP) and $Es_D$(Rb) due to the differences in the soil typology and correlation results. The regression analysis was created using the catchment parameters that supported the most effective (strongest coefficient of determination and Nash-Sutcliffe efficiency (NSE)) results.

The multiple linear regression modelling of $Es_D$ was completed using R studio standard functions (lm). Variable selection was made by correlation strength (variables with the strongest and most significant correlation values were selected). The selection of variables used to create the $Es_D$ model were not meteorological parameters, all variables were lacustrine proxy or XRF sampled metal values. This ensured the $Es_D$ model was created from a dataset distinct from the precipitation record, independent from all meteorological data, therefore allowing later validation using recorded precipitation. It was important to define a function with the fewest parameters to support statistical validity in regression function modelling. The number of variables used in the $Es_D$ regression models were kept to a minimum (4) to ensure the number of variables in the equation were less than the number of data points (e.g. recorded precipitation data points).

A spatially diverse dataset was necessary to effectively derive the $Es_D$ linear regression function. The temporal analysis was undertaken on Lake Arbu's lacustrine archive. The temporal and spatial datasets were used to help examine the temporal and spatial robustness of the Es function defined through the regression analysis. To test the efficiency of the correlation, statistical model calculation of $Es_D$ was compared to the De Ploey back-calculated $Es_C$ values.

*Figure 3. Schematic of Es and P calculations and analysis*

The linear regression function provides coefficient values (a weighting and scaling factor for each variable) for the model and an intersect value, if an intersect ≠ to zero is requested. The selection of variables incorporated into the $Es_D$ regression model were varied until the regression analysis provided $Es_D$ values as close to $Es_C$ as possible.

### 2.3.3 Validation of the method

The effectiveness of the regression to calculate $Es_C$ has been considered using the coefficient of determination of the $Es_D$ function ($r^2$), root mean square error (RMSE), and Nash-Sutcliffe efficiency (NSE). Relative error, the difference between recorded and modelled precipitation (m, %) was used to assess the accuracy of the $Es_D$ regression function in replicating the recorded total precipitation dataset alongside RMSE and MAE. NSE is a method to quantitatively assess the efficiency and accuracy of a model ($Es_D$), mean absolute error (MAE) and RMSE are comparisons on the modelled versus observed datasets to define the error in model results. MAE considers the individual differences (for each lacustrine sample), weighted equally. RMSE functions is a similar way but weights the individual errors relative to their size. RMSE results can therefore illustrate outlier or isolated extreme error result occurrence while MAE provides an average magnitude of error.

The uncertainty in $Es_D$ calculation of P using lacustrine archive data was considered in a similar way. The dataset is comprised of physical sample results (lacustrine records) which hold uncertainty due to analytical quantification methodology (Liu and Gupta, 2007). The lacustrine dataset is dated using $^{14}C$ and $^{210}Pb$ and this sample analysis incorporates a temporal uncertainty. Consideration of both sampling (e.g. Ve quantification) and age dating uncertainty has been considered in the $Es_D$ calculation of P.

# 3 Results

## 3.1 Es variability and potential drivers

Four $Es_C$ datasets have been created, temporal and spatial $Es_C$ from the rAP soil erosion records (resulting in $Es_C$(rAP)) and temporal and spatial $Es_C$ from the Rb soil erosion records (resulting in $Es_C$(Rb)), and these values have been compared with literature reported $Es_L$ values (Figure 4). The $Es_C$ values calculated using recorded precipitation and lacustrine erosion records generally fall within the literature recommended range ($Es_L$) (Figure 4). The temporal $Es_C$ values illustrate a range almost as great as the spatial dataset, approximately an order of magnitude in range. The calculated $Es_C$ values for the temporal dataset are not static.

*Figure 4. $Es_L$ value range for long term erosion analysis published in literature (dark grey bar). $Es_C$ values were calculated using the De Ploey equation (Eqn 1), recorded precipitation and lacustrine erosion records (light grey and blue bars). Dark points within the $Es_C$ ranges illustrate the individual temporal and spatial calculated $Es_C$ values specific to catchment and sample period.*

$Es_D$(rAP) illustrated a range between $2.5 \times 10^{-7}$ – $7.5 \times 10^{-5}$ (mean = $2.4 \times 10^{-5}$) while $Es_D$(Rb) values range between $4.3 \times 10^{-5}$ to $1.4 \times 10^{-3}$ (mean = $3.2 \times 10^{-4}$) (Figure 4). There is an order of magnitude difference in the erosion susceptibility, with rAP illustrating a lower erosion potential than Rb, driven by the recorded lacustrine deposition.

## 3.2 Correlation Analysis

Correlation analysis of catchment characteristics was completed to define key $Es_C$ parameters. Table 3 lists the catchment characteristics considered, the respective correlation values with $Es_C$ and correlation significance. Spatial dataset $Es_C$ illustrated minor correlations with catchment area, elevation, slope, total deposition and Ti. Catchment parameters showing moderate correlation with $Es_C$ included average flow path length, soil type and vegetation coverage.

The temporal $Es_C$ datasets show moderate and generally significant correlation to vegetation composition and coverage. Ti, the geochemical catchment characteristic included in this analysis, illustrated a moderate and significant correlation with and temporal $Es_C$ values. Rb was found to correlate to temporal $Es_C$(rAP) suggesting a possible link or similar trend in rAP and Rb erosion and deposition in the Arbu catchment.

*Table 3. $Es_C$ correlation to geochemical and physical catchment characteristics*

The representation of vegetation cover, described in Table 3 (and Table 1) as ‘indicative small tree % vegetation cover’, is derived from the corrected pollen vegetation reconstruction in the temporal datasets. This catchment characteristic correlated with $Es_C$ values, suggesting that the erosion susceptibility in the temporal dataset may follow similar trends and illustrating the known driving influence of vegetation cover and change on erosion (Noël et al., 2001; Rosenmeier et al., 2002).

## 3.3 Es Regression Analysis

The $Es_D$(rAP) regression function is derived from the lacustrine erosion record (Ve(rAP)), the total sediment deposition volume (M, $m^3$) for respective period, the corrected pollen reconstruction model of vegetation pattern (represented as a % of tree cover), and the Ti:Rb ratio (indicator of general erosion and precipitation). It is noted that the Rb:Ti ratio illustrated a stronger correlation to $Es_C$(rAP) however when considered within the multiple regression analysis the inverse ratio (Ti:Rb) presents a model with a more effective coefficient of determination and smaller p-values. The Ti:Rb parameter was therefore included in the regression function.

$$Es_D(rAP) = a.Ve(rAP) + b.M + c.\%tree\ cover + d.Ti{:}Rb \qquad \text{Eqn. 3}$$

The $Es_D$(Rb) regression is derived from the lacustrine erosion record (Ve(Rb)), the deposition volume ($m^3$), pollen reconstruction of vegetation patterns (represented as a % of tree cover), and the Ti trend (indicator of general erosion and precipitation).

$$Es_D(Rb) = a.Ve(Rb) + b.M + c.\%tree\ cover + e.Ti \qquad \text{Eqn. 4}$$

The regression coefficients for Equations 3 and 4 are presented in Table 4. The coefficients for the temporal, spatial and total (cumulative) datasets of rAP and Rb have been calculated.

*Table 4. Regression analysis coefficients. The $r^2$ are relative to the dataset used in the model, not the total dataset.*

The functions presented in Equations 3 and 4 have been calculated for the spatial and temporal datasets separately. A 'total dataset' analysis was completed but while the coefficients defined using the total dataset are relatively effective in modelling $Es_C$, it was noted that separating the temporal and spatial dataset presented greater accuracy in $Es_D$ calculations. For the purposes of this analysis, the spatial and temporal datasets were treated separately to try and define the most effective model possible for the reconstruction of total precipitation for the spatial and temporal datasets. The $Es_C$ values relative to the regression $Es_D$ values are presented in Figure 5.

*Figure 5. Graphical representation of EsD values calculated using Equations 3 and 4 respectively. The spatial dataset $Es_D$ values are illustrated in black outlined points; temporal $Es_D$ values are presented as orange points. The error bars represent the uncertainty range around $Es_D$ calculations when Ve and P values are modified to represent the Ve quantification and sample date uncertainties.*

The $Es_D$(rAP) values from the regression derivation have a coefficient of determination ($r^2$) of 0.93 (RMSE of $4.8x10^{-6}$) and NSE of 0.93 (Figure 5a). The $Es_D$(Rb) values from the regression derivation have a coefficient of determination ($r^2$) of 0.92 (RMSE of $8.3x10^{-5}$) and NSE of 0.91 (Figure 5b). The $Es_D$ regression equations (Eqn 3 and 4) illustrate a strong coefficient of determination ($r^2 > 0.8$) and NSE ($0.7 < NSE > 1$) suggesting model efficiency in synthesising $Es_C$ values from lacustrine data.

## 3.4 Estimation of total P using lacustrine record

The total precipitation calculated using $Es_D$(rAP) and $Es_D$(Rb) were compared to recorded precipitation based on a split sample method. Figure 6 illustrates the modelled P relative to recorded values, and the general trend in P when historic lacustrine data is considered back past recorded P. Both rAP and Rb results illustrate notable uncertainties and errors, however there is some capacity for these $Es_D$ equations to estimate P and provide information on the trends in recent and past P. As a first step towards using a highly simplified, limited data availability model to consider mean annual P, this method could be useful.

*Figure 6. Calculation of P from regression $Es_D$(rAP) (6a) and $Es_D$(Rb) (6b) defined values. The black error bars show the uncertainty in P values due to Ve quantification uncertainty. The grey error bars illustrate the uncertainty in P due to the sample date uncertainty. Spatial P results are presented as black points, Lake Arbu catchments temporal dataset results are presented as orange points. Figure 6(c) shows the temporal estimated P using historic data extending past the recorded records for Lake Arbu.*

The RMSE for the recorded vs modelled P using the rAP dataset and $Es_D$(rAP) equation was 0.29 (total dataset), with the spatial dataset presenting a RSME of 0.32 and temporal dataset RSME of 0.22. The mean absolute error (MSE) for the total dataset was 0.24, 0.22 for the temporal dataset and 0.25 for the spatial dataset. The RMSE and MAE for P estimated using the rAP dataset were <35% of the recorded average annual precipitation. The RSME is higher than MAE for the total dataset and spatial subset, suggesting some extreme results or outliers in the spatial modelled dataset.

The RMSE for the recorded vs modelled P using the Rb dataset and $Es_D$(Rb) equation was 0.34 (total dataset), with the spatial dataset presenting a RSME of 0.40 and temporal dataset RSME of 0.14. The MSE for the total dataset was 0.25, 0.10 for the temporal dataset and 0.32 for the spatial dataset. As with the rAP dataset, the RMSE and MAE (total dataset) are <35% of the recorded average annual precipitation, suggesting no significant difference between the rAP and Rb modelled P results when the total dataset is considered. The RSME is slightly higher than MAE for all Rb estimated P results, suggesting outliers and extreme results across the dataset results. Both modelled P results illustrate a smaller RMSE and MAE for the temporal datasets compared to the spatial datasets, suggesting that using this method is slightly more effective for temporal analysis than when used for the spatial dataset.

The uncertainty in precipitation estimation has been calculated with consideration of the uncertainty in quantifying rAP and Rb (and therefore Ve) in the lacustrine archive and the uncertainty in dating the samples. Uncertainty analysis has been completed considering these uncertainty elements individually and cumulatively. The individual (Ve and sample dating) uncertainties are presented in Figure 5, with the spatial and temporal breakdown of uncertainties is summarised in Table 5.

*Table 5. Summary of uncertainty influence on error*

It is noted that while $Es_D$ was effectively calculated using Equations 3 and 4, the calculation of P is highly sensitive to small inaccuracies in Es values, resulting in sizable relative errors in precipitation estimations. A 1% change in $Es_D$ values (without any further uncertainty considerations) results in a relative error in P of -43% to 59% (Rb) and -16% to 34% (rAP). A 1% error or uncertainty in Es values illustrates a similar precipitation calculation error to the $Es_D$ model relative error or uncertainty in Ve quantity.

# 4 Discussion

## 4.1 Variable erosion susceptibility (Es)

Literature Es values ($Es_L$) for long term erosion analysis fall between $1x10^{-3}$ – $1x10^{-6}$ $s^2/m^2$. $Es_L$ values have previously been considered and used as a constant, with little available information on the derivation of the long-term erosion sustainability values. For the first time, lacustrine records of erosion (rAP and Rb indicators of erosion in mountain catchments) have been coupled with catchment specific precipitation records to calculate $Es_D$ values. The simple $Es_c$ calculation illustrates a range of $Es_c$ values falling within the range of published ($Es_L$)

values, but that the definition of Es is difficult unless precipitation and erosion are quantified for the study catchment and respective time period. This makes section of an Es value for use in the De Ploey erosion equation or as a description of a catchment's erosion susceptibility challenging, with current selection guidance focused on catchment vegetation and soil typology.

The $Es_c$ value is found to range (for the study catchments) from $1x10^{-3} – 1x10^{-6}$ $s^2/m^2$ spatially but also temporally. This illustrates that $Es_c$ is not a coefficient but that to achieve effective erosion, erosion susceptibility and precipitation representation using the De Ploey erosion equation over a time period (with multiple sub-samples) the Es value is a variable (as illustrated in Figure 4 and 5). This is logical, as erosion is driven by vegetation and precipitation, both naturally and anthropically influenced and changing over time. Therefore, given that vegetation and precipitation fluctuate over time, it is important that erosion susceptibility act as a variable which responds to precipitation and vegetation trends, a spatio-temporal variable.

$Es_c$ is noted to correlate most strongly to meteorological conditions. However, if: (1) Es is to be calculated for catchments or time periods where meteorological records are scarce; or (2) the De Ploey equation is to be used to assess historic erosion and precipitation patterns, then Es must be described as a function of non-meteorological parameters. The correlation and simple linear regressions present a description of erosion susceptibility ($Es_D$) specific to the time period and individual catchment characteristics. This function (Eqn. 3 and 4) provides a new method to estimate Es for a catchment beyond the use of generalised vegetation and soil descriptions ($Es_L$). This descriptive $Es_D$ function supports estimation of the temporal and spatial variability in Es based on catchment specific lacustrine erosion and geochemical indicators. The functions are a step towards greater description and understanding of the driving forces and catchment (temporal and spatial) representation of erosion susceptibility.

The difference in lacustrine quantities of rAP and Rb may be due to the relatively thin soil profile in the study (mountain) catchments, organic carbon content in Pyrenees mountain catchments of ~10% (Garcia-Pausas et al., 2007) and correspondingly relatively small quantity of organic soil available for erosion. As a result, there is a smaller quantity of organic soil (rAP) available in the catchment and therefore a correspondingly smaller quantity of rAP in the lacustrine archive. The difference in $Es_C$ values suggests that the erosion susceptibility value may be specific to soil typology and catchment soil availability.

## 4.2 Lacustrine erosion indicators

The two erosion indicators (rAP and Rb) considered in this study represent different soil types (organo-mineral and mineral soils). Both $Es_D$ functions show effective model capability (0.7<NSE>1) however the effectiveness in precipitation representation using these modelled Es values varies (Figure 5, Table 5). This is due to the driving influence of the Es parameter in the De Ploey erosion equation, and the resultant sensitivity in calculated precipitation to small changes in Es. It is also due to the coarse reconstruction of precipitation driven erosion possible using the De Ploey method given the lack of differentiation between rainfall and snow in the dataset and the significantly different erosion impact snow and rainfall have on a catchment or soil.

There is limited diference in the representation of erosion susceptibility and precipitation from the two datasets, rAP and Rb. There is slightly greater error and uncertainty in the Rb dataset results compared to rAP. This may be due to the different physical transport properties of these two erosion indicators. rAP are particles that may be broken but do not dissolve or transform. Rb is a property of the underlying (granite) bedrock and soil. Rb absorbance is strongest to fine (silt-clay size) particles (De Vos et al., 2006; Salminen et al., 2015). The $Es_D$(Rb) function may need an additional parameter (variable) that describes the changing catchment pH, individual precipitation events and soil composition properties (as indicators of the Rb transport mechanisms relative to the time period) to support more effective future $Es_D$(Rb) modelling.

There is uncertainty in both erosion quantification (sampling) and the age dating model. The rAP and Rb erosion datasets react similarly to these uncertainties. Both datasets illustrate a greater sensitivity to age depth model uncertainty than rAP or Rb sampling uncertainty (Table 5). Both rAP and Rb temporal results show lower sensitivity to sampling and age depth uncertainty than the spatial datasets. This suggests that the $Es_D$ may be more effective for site specific longitudinal (archive) analysis that spatial analysis.

## 4.3 Snow/rain influence on erosion and De Ploey estimation of past precipitation

A significant proportion of precipitation in mountainous catchments occurs as snow rather than rainfall. Snowmelt may or may not mimic erosion events occurring due to rainfall or be represented clearly in annual precipitation records. Within the lacustrine deposition it is difficult to differentiate erosion due to snow versus rain. Correspondingly, the generalised precipitation available and used in this De Ploey analysis provides no distinction between snow and rainfall precipitation but instead presents an overall precipitation value. As such, the influence of snowfall on these catchments is not taken into account in either precipitation estimation or erosion calculations. This is expected to be a key influence in the error in De Ploey Es estimation of precipitation using lacustrine records, resulting in inexact estimation of past precipitation as illustrated in Figure 6.

Furthermore, the influence of rainfall intensity is not taken into account in this De Ploey analysis (total or annual precipitation are the only parameters prescribed, De Ploey et al. 1995). Rainfall intensity is a significant driver of erosion, in conjunction with top soil composition. While the complexities of top soil composition and details of rainfall event intensity are key to erosion, the De Ploey Es model is designed for a gross estimation of precipitation and erosion without provision of intensity or catchment soil complexity. This is therefore a further source or error and uncertainty in the De Ploey estimation of past precipitation.

# 5 Conclusions

Lacustrine erosion records have been used within the De Ploey erosion equation to consider the erosion susceptibility and precipitation of 12 French mountain catchments. Using recorded precipitation and erosion, the $Es_C$ value for each time step and catchment has been calculated, illustrating $Es_C$ values for these catchments to fall within the published literature. $Es_C$ (and $Es_D$) values are only representative of the sampled time period analysed and incorporate consideration of the continuously changing climate (precipitation) and vegetation (type and extent) in the specific study area under review. As climate and vegetation change over time, so $Es_C$ values can be expected to change. Results demonstrate that there is complexity in estimating $Es_C$ and that $Es_C$ is a variable when considered in a spatial and temporal context.

Through analysis of the lacustrine archive, a description of the $Es_C$ variable has been created allowing $Es_D$ to be calculated using lacustrine archive data. This supports erosion susceptibility and precipitation estimation for catchments and time periods where either erosion susceptibility or precipitation records are unavailable. While $Es_D$ is effectively calculated, the simulation of P is indicative but inexact, and this analysis illustrates the need for further development of the Es model to accurately reconstruct P using lacustrine records. This research therefore presents a step towards an effective simplistic approach in precipitation reconstruction using lacustrine records and provides a method to define Es values using non-meteorological parameters commonly available for catchments.

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Acronyms and Abbreviations

| | |
|---|---|
| rAP | Red Amorphous Particles |
| Rb | Rubidium |
| Ti | Titanium |
| Pb | Lead |
| A | Catchment area ($m^2$) |
| P | Precipitation (m) |
| h | Surface erosion depth (m) |
| g | Acceleration due to gravity ($ms^{-2}$) |

| | |
|---|---|
| M | Lacustrine total soil and sediment deposition (autochthonous and allochthonous sediment) (per sample) |
| Ve | soil volume eroded from the contributing catchment ($m^3$) |
| Ve(rAP) | volume of rAP represented eroded soil ($m^3$) |
| Ve(Rb) | volume of Rb represented eroded soil ($m^3$) |
| Es | contributing catchments erosion susceptibility ($s^2/m^2$) |
| $Es_L$ | published literature erosion susceptibility values ($s^2/m^2$) |
| $Es_C$ | catchment calculated erosion susceptibility ($s^2/m^2$) using known erosion, precipitation and catchment area |
| $Es_C$ (rAP) | catchment calculated erosion susceptibility ($s^2/m^2$) for rAP represented soil erosion |
| $Es_C$ (Rb) | catchment calculated erosion susceptibility ($s^2/m^2$) for Rb represented soil erosion |
| $Es_D$ | catchment erosion susceptibility ($s^2/m^2$) derived from regression analysis |
| $Es_D$ (rAP) | catchment erosion susceptibility ($s^2/m^2$) derived from regression analysis for rAP represented soil erosion |
| $Es_D$ (Rb) | catchment erosion susceptibility ($s^2/m^2$) derived from regression analysis for Rb represented soil erosion |
| S | the quantity of eroded soil in the lake sediment deposition (mg/mg) |
| Ac | accumulation of total soil and sediment deposition in the lake (m) for respective period |
| LA | lake area equivalent to the lake deposition extent ($m^2$) |
| t | the period represented by the sample (years) |
| $R^2$ | Coefficient of determination |
| RMSE | Root mean square error |
| NSE | Nash-Sutcliffe efficiency |
| MAE | Mean absolute error |
| $^{10}Be$ | Beryllium isotope 10 |
| Sr | Strontium |
| $^{137}Cs$ | Caesium isotope 137 |
| $\delta^{18}O$ | Oxygen isotope 18 |
| a.s.l. | above sea level |
| Sqrt | Square Root |
| log | Logarithm base 10 |