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Combining plot measurements and a calibrated RUSLE model to investigate recent changes in soil erosion in upland areas in Southern Italy

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(Article begins on next page)

| 1 | Combining plot measurements and a calibrated RUSLE model to investigate recent changes |
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| 2 | in soil erosion in upland areas in Southern Italy |
| 3 | |
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| 9 | |
| 10 | Abstract |
| 11 | Purpose In recent decades, soil erosion has been recognized as a serious environmental problem in many countries of the |
| 12 | world and the impacts of climate change have focused attention on potential changes in erosion rates that could further |
| 13 | increase such problem. These impacts are documented by a general decrease of annual precipitation and a corresponding |
| 14 | increase in the number of heavy rainfall events, intensity and frequency that accelerate the loss of fertile soil material. |
| 15 | Materials and methods Direct observations of soil loss obtained during the period 2006-2016 on five experimental plots |
| 16 | in Southern Italy were preliminarily presented and discussed. These measurements, using a calibratedwere used to |
| 17 | calibrate the RUSLE model that, coupled with independent long-term measurements of rainfall erosivity, allowed |
| 18 | calculation of soil erosion from 1954 to date. |
| 19 | Results and discussion The plot measurements showed annual values of soil erosion generally higher than the long-term |
| 20 | estimates provided by the RUSLE (1954-2019) suggesting an increasing trend of soil erosion rates during the last 20-25 |
| 21 | years. On the contrary, a decreasing trend of the annual rainfall measurements can be observed for the same period. |
| 22 | Conclusions The overall results demonstrated that models like the RUSLE can be considered a useful tool to individuate |
| 23 | changes of erosion rates and to isolate the effect of climate change on soil loss. Also, the opposite trend obtained for the |
| 24 | annual rainfall measurements suggests that these should not be used to explore the effects of climate change in |
| 25 | Mediterranean areas but measurements of rainfall at shorter time intervals (\leq 30 minutes) are necessary. |
| 26 | Keywords Soil erosion • Experimental plots • RUSLE • Climate change • Southern Italy. |

<u>±</u>

28 1 INTRODUCTION

29 In the last decades, the impact of climate change on human activities and world economy has attracted increasing interest 30 from the scientific community. According to IPCC (2018), a general increase of temperature and a change in precipitation 31 trends have been documented by many studies over the world (Dore 2005; Alexander 2016). Specific examples are 32 provided in USA by Karl and Knight (1998) that, analysing secular trends of rainfall, established that a general increase 33 in precipitation, reflected primarily in the heavy and extreme daily precipitation events, can be observed. Similar results, 34 related to the intensity distribution of daily precipitation amounts, were observed by Osborne et al. (2000) in UK, Suppiah 35 and Hennessy (1998) in Australia, and Mason et al. (1999) in South Africa. In central and western Europe, Moberg and 36 Jones (2005) documented a significant increase of precipitation trends over the 20th century for both average precipitation 37 intensity and moderately strong events. Recent studies carried out in southern Italy indicated a general increase in the 38 number of heavy precipitation events, intensity and frequency since about 1950 (Capra et al. 2017).

39 These effects have important consequences for environmental risks such as floods, landslides, and land degradation. The 40 latter includes both rates of soil erosion in upland cultivated areas and sediment delivered downstream. The effects of soil 41 erosion in cultivated areas consist mainly of reducing soil productivity and food security (on-site effects) by loss of 42 organic matter and crop yield depression that increases the risk of land abandonment (Kolouri and Giourga 2007; Romero-43 Díaz et al. 2017) and the decline of rural community (Bakker et al. 2005). The effects caused by the amount of sediment 44 generated in the upland areas and delivered downstream (off-site effects) are even morealso dangerous as they can 45 increase pollution of rivers (Boardman and Poesen 2006; Yi et al. 2008; Wen et al. 2017), reduce water resources in the 46 reservoirs (Pimentel et al. 1995; De Araújo et al. 2006), and affect the stability of aquatic ecosystems (Palmer et al. 2009). 47 However, problems of land degradation are also affected by other drivers such as urban sprawl, changes in land use, land 48 abandonment, and other social factors (Shao et al. 2021). For these reasons, in the absence of specific experimental sites 49 able to produce field measurements, it is difficult to establish the precise causes of land degradation. In this context, 50 documenting rates of soil erosion in representative specific experimental sites that are representative of contexts of similar

<u>characteristics</u> can be an important tool to understand better the consequences of climate change on <u>larger areaslarger</u>
 <u>areas</u> and on long-term temporal scale.

Experimental plots, equipped specifically for monitoring rainfall, runoff and soil loss, proved to be an important means
to obtain information on <u>the impacts of soil properties</u>, land use, crop management etc. on erosion rates erosion rates
because external factors are under control (Loughran 1989). However, despite their utility, some difficulties to extrapolate

56 the results for larger spatial scales or different time windows for which no direct measurements are available must be 57 recognized (see Evwans 1995; Boardman 2006). In recent years, the attempt to compile an extensive database of short to medium-term erosion rates as measured on erosion plots in Europe and Mediterranean regions under natural rainfall was 58 59 made by several authors (see Cerdan et al. 2010; Maetens et al. 2012). Even if this effort produced the largest (227 plot-60 measuring sites) database of plot runoff and soil loss data in Europe (Maetens et al. 2012), these measurements are frequently limited to the period of the experiments (normally, a few years) and it is difficult to extend their temporal trend 61 62 in the absence of retrospective information. In other words, this large dataset is very useful to investigate the effects of 63 land use, soil type and topography but insufficient data about climate precludes any statistical analysis aimed at identifying 64 possible trends in soil erosion rates (see Cerdan et al. 2010). In such situations, the use of calibrated models, in which the 65 climate component is taken into account, can be very useful.

66 In this respect, numerical models of different generations have been employed to predict soil loss in the absence of direct 67 measurements during the last decades. These models can be based on empirical approaches, such as the Universal Soil 68 Loss Equation (Wischmeier and Smith 1978) and its derived version (Renard et al. 1994), on simple correlation analyses 69 between soil erosion and topography (Bagarello et al. 2011; 2018), or on more complex algorithms of calculation that 70 interpret physical processes related to detachment and transport of soil particles (Nearing et al. 1989). However, even if 71 their use proved to be very effective for a short-time scale, it is important to note that such models should be calibrated 72 and validated to provide reliable results for larger time windows in which possible effects due to climate change can be 73 expected. Results in this direction were obtained by several authors. Chaplot (2007) and Ficklin et al. (2009), for example, 74 explored the performance of the SWAT model to predict long-term soil loss in cultivated areas of the USA. Pandey et al. 75 (2017), in India, tested the hydrological component of the SWAT model in areas affected by climate change. Pruski and 76 Nearing (2002a,b) provided long-term simulations of soil loss using WEPP coupled with historical rainfall datasets 77 available in three different locations of the USA. Pal and Chakrabortty (2019) made a long-term application of the RUSLE 78 model to evaluate the impact of climate change on soil erosion in sub-tropical monsoon areas in the West Bengal state of 79 eastern India. Favis-Mortlock and Boardman (1995) used the EPIC model to evaluate changes on erosion rate in the UK. 80 However, it must be recognized that most of these contributions, even if USLE derived, are based on simulation exercises 81 in which the rainfall erosivity is not calculated using the basic approach proposed by Wischmeier and Smith (1978) that 82 requires the knowledge of rainfall energy at event scale, but it is derived from indirect relationships with daily or monthly 83 rainfall, using simplified approaches like Arnoldus index (Pal and Chakrabortty 2019) or applying more sophisticated 84 climate generators like CLIGEN (Pruski and Nearing 2002a,b). The importance of direct observations of rainfall erosivity 85 was emphasized by Wischmeier and Smith (1978) that suggested a period of at least 22 years of measurements for

86 calculating the R-factor (Renard et al. 1997). However, as pointed out by Verstraeten et al. (2006), this period of 22 years 87 is recommended because very few detailed rainfall data records exist for a longer time period in areas outside the USA 88 where the USLE was developed. Verstraeten et al. (2006), provided an example of long-term dataset of rainfall erosivity 89 analysing a record of 10-min rainfall (105 years) in Belgium. These authors established that average 10-year erosion rates 80 calculated with the RUSLE have increased by 24–34% from the first decade (1903–1912) to the last one (1993–2002) of 91 the study period, as a consequence of changing rain erosivity through time and encouraged the use of long-term records 92 of short time-interval rainfall in simulation exercises.

93 Recent studies carried out at a plot scale in Southern Italy documented high rates of soil erosion both on cultivated lands 94 (Bagarello et al. 2010) and in areas subject to afforestation that support discontinuous forest cover (Khodadadi et al. 95 2020). In these areas, several attempts to calibrate and validate numerical models like RUSLE (Di Stefano et al. 1999), MUSLE (Cinnirella et al. 1998), USLE-M (Bagarello et al. 2018), and SEDD (Porto and Callegari 2021) have been 96 97 successful in their ability to reproduce soil erosion rates or sediment yield both at plot and at catchment scale for short 98 time windows. However, the absence of long-term measurements and the general difficulty of obtaining equivalent 99 records of model input parameters like rainfall erosivity or crop factors precluded specific studies aimed at investigating 100 long-term soil erosion rates in Italy. A few exceptions are related to the combined use of radiotracers ¹³⁷Cs and ²¹⁰Pbex 101 that in view of their ability to obtain retrospective information on soil erosion for different time windows provided 102 important results in this direction (see Porto et al. 2016; 2018).

In this contribution, direct observations of soil erosion obtained in 5 experimental plots during 11 years of investigation were combined with a long-term record of rainfall erosivity to reconstruct a trend of soil loss in a typical upland area of Southern Italy. More specifically, the measurements of soil loss served to calibrate the RUSLE model for cultivated soils supporting typical Mediterranean crops and the rainfall erosivity data were used to derive estimates of erosion rates during the last 6-7 decades. This experiment provided evidence of a change of erosion rates during the last 2-3 decades emphasizing the effect of climate change on soil erosion in cultivated lands in Mediterranean areas.

109

110 2 MATERIAL AND METHODS

The study area (38°16' N, 15°49' E) is located in Calabria, Southern Italy at an elevation of 585 m a.s.l. (Fig. 1). The climate is typically Mediterranean, characterized by a rainy season extending from October to March and a dry summer during which occasional thunderstorms may occur. The annual precipitation (*Pa*), measured at the rainfall station of Santa Cristina d'Aspromonte, is approximately 1470 mm (Arpacal datasets 1939-2019). Mean annual temperatures range from

14 °C to 15 °C, based on local reports (Arpacal datasets 1988-2020). The land use is characterized by cultivated soils
where traditional arable and vegetable crops are grown. In 2005, the Department of Agraria of the University
'Mediterranea' of Reggio Calabria established five (5m x 25m) experimental plots (Fig. 1) to explore the effect of different
cropping systems on runoff and soil loss (Preiti et al. 2017).

- 119
- 120

Fig. 1 – The study area and the experimental plots

121 The plots were built on a 10% slope and support Typic Hapludands soils characterised by a silty loam texture (20% sand, 122 76% silt, and 4% clay). The plots were established, with minimum soil disturbance, over an area subject to traditional 123 cultivation in order to make the measurements representative for the local area. In this respect, plot 1 has been maintained 124 bare since the beginning of the experiment, by up and down slope tillage operations according to Wischmeier and Smith 125 (1978). Three plots (plot 2, 3, and 4) have supported different crops typical of the area that include rye, lupin, wheat, oat, 126 cauliflower, sorghum, potatoes, tall fescue, horseradish, aubergines, trifolium. These were cultivated using similar 127 management systems but with different inter-annual rotations. Plot 5 was covered mainly by natural vegetation, tall fescue 128 and lupin and was subjected to minimal tillage and crop operations during the last six years of measurements. Also, crop 129 residues were left on soil surface after each tillage operation. This choice was made to explore the effect of conservative 130 techniques on soil loss (for soil and crop management details see Preiti et al. 2017).

Runoff and soil loss were measured for each plot, at event scale, for the period 2006-2016. More specifically, the runoff and soil loss were collected by gutters installed along the lower ends of each plot and diverted into a sized tank located at the base of the plot (see Fig. 1). Sampling of water and sediment stored in the tanks was undertaken two-three days after the end of each rainfall event. The sediment deposited on the bottom of the tank was collected and transported to the laboratory of the Department of Agraria where it was oven dried at 60 °C and weighed to determine its mass. The measurements of soil loss used in this experiment are related to 135 events that have occurred during the period from January 2006 to December 2016.

138

139 3 RESULTS

140 3.1 The measured values of soil loss obtained for the study period

The empirical frequency of the total annual soil losses obtained for the period 2006-2016 is illustrated in Fig. 2 for eachexperimental plot.

Fig. 2 – Values of soil loss obtained from each plot for the study period 2006-2016. The graph in (a) shows the
 frequency distribution of the annual values. The box plot in (b) indicates the data distribution. Total annual (a) and mean
 (b) soil losses obtained from each plot for the study period 2006-2016. The vertical bars in (b) indicate the standard
 error for each plot

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143

In Fig. 2, summary data <u>distribution for the mean soil loss</u> from each plot during the study period <u>are is</u> also reported.
These results point out both the inter-annual variability of soil loss that reflects changes in erosivity during the study
period and the inter-plot variability related to the impact of different cropping practices on soil loss.

152 It is clear from Fig. 2 that the annual values of soil loss obtained from plot 1, in which vegetation cover was absent for 153 most of the study period, are greater than those from the other plots. This result is expected because it emphasizes the 154 importance of vegetation cover in the other plots that must be seen as a key factor in soil erosion studies. The mean value 155 of soil loss related to plot 1 accounts for ca. 69.0 t ha⁻¹ yr⁻¹ (SE = 13.5 t ha⁻¹ yr⁻¹). Even if this value is in line with the 156 results obtained in areas where similar experiments were conducted (see Bagarello et al. 2018), it cannot be considered 157 representative of a long-term pattern of land use in the area because it reflects the bare conditions maintained in this plot 158 for the duration of the experiment (11 years). The mean values of soil loss obtained from the other plots range from 14.4 159 t ha⁻¹ yr⁻¹ (SE = 7.0 t ha⁻¹ yr⁻¹), obtained from plot 5, to 39.2 t ha⁻¹ yr⁻¹ (SE = 11.7 t ha⁻¹ yr⁻¹) obtained from plot 3. These 160 values, reported in Table 1, reflect the different crop rotations adopted in the plots and indicate the crop system related to 161 plot 5, which was subjected to minimal tillage and crop operations, as the most conservative in the area.

162

163 3.2 The calibration of the RUSLE model using the experimental data

As reported above, the study period extended for 11 years and these measurements, considering the number of events (135) occurred during the experiment, offer an important tool to calibrate soil erosion models in order to obtain soil loss estimates for a longer period. The available datasets and the size of the plots suggested the use of the RUSLE model to make such attempt. This calibration exercise was based on the following version of the USLE as originally proposed by Wischmeier and Smith (1978):

$$A_i = R_i K LS C_i P$$

169 170 (1)

| 175 | In this contribution, the Eq. (1) was calibrated at annual scale and the subscript <i>i</i> represents the i-th year for which soil |
|-----|---|
| 176 | loss observations are available. It is worth noticing that, because of the absence of support practices, the P-factor was set |
| 177 | equal to 1. |
| 178 | The model calibration was carried out in three steps: the first step is related to the calculation of the factors R_i and LS that |
| 179 | required rainfall and topographic measurements, respectively; the second step aimed at calculating the soil erodibility |
| 180 | factor K; the third step allowed the calculation of the <u>C</u> values for each plot the calculation of the <u>C</u> factor for each plot. |
| 181 | These factors were determined as follows. |
| 182 | |
| 183 | 3.2.1 The rainfall erosivity factor and the topographic factor |
| 184 | The rainfall erosivity factor <i>R</i> , as defined by Wischmeier and Smith (1978), represents the mean annual value of the |
| 185 | rainfall erosion index, EIR, calculated by summing the values of the rainfall erosion index, EI-, values-obtained for each |
| 186 | erosive event. The calculation of EI (MJ mm ha ⁻¹ h ⁻¹) for each individual storm required a continuous record of rainfall |
| 187 | intensity and it was determined by the product of total storm energy E (MJ ha ⁻¹) and maximum 30-min intensity i_{30} (mm |
| 188 | h ⁻¹): |
| 189 | $EI = E i_{30} = \left(\sum_{j=1}^{m} e_j \Delta V_j\right) i_{30} \tag{2}$ |
| 190 | |
| 191 | with e_j indicating the rainfall energy per unit depth of rainfall per unit area, and ΔV_j the rainfall depth for the j-th interval |
| 192 | of the storm hyetograph which is divided into m parts with essentially constant intensity. The equations proposed by |
| 193 | Foster et al. (1981) were used to calculate the rainfall energy e_j : |
| 194 | |
| 195 | $e_j = 0.119 + 0.0873 \log_{10}(i_j)$ if $i_j \le 76 \ mmh^{-1}$ (3a) |

if $i_j > 76 \ mmh^{-1}$

in which, the soil loss, A_i , is expressed in t ha⁻¹ yr⁻¹; the rainfall erosivity factor, R_i , is expressed in MJ mm ha⁻¹ h⁻¹ yr⁻¹;

the soil erodibility factor, K, is expressed in t ha h ha⁻¹ MJ⁻¹ mm⁻¹; LS represents the topographic factor (dimensionless);

 C_i represents the cover and management factor (dimensionless), and P indicates the support practice factor

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(dimensionless).

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198 where i_j (mm h⁻¹) is the rainfall intensity calculated as follows **199**

 $e_{j} = 0.283$

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(3b)

$$\dot{i}_{j} = \frac{\Delta V_{j}}{\Delta t_{j}} \tag{4}$$

200

in which Δt_j indicates the interval duration over which intensity is assumed to be constant (Porto 2016). The rainfall record used in this contribution was obtained from the local station of Santa Cristina d'Aspromonte (Arpacal datasets), for which data with a temporal resolution $\Delta t = 5$ min were available. The mean value of the rainfall erosivity factor *R* calculated from this station for the study period 2006-2016 is reported in Table 1.

The topographic factor, *LS* (dimensionless), was calculated using the equation proposed by McCool et al. (1987), (Renard
et al. 1994):

 $LS = (\lambda_i/22.13)^{m_i} \times (16.8 \sin \alpha_i - 0.5)$

208

209

210

211 considering that, for the study plots, $tan \alpha_i > 0.09$, with α_i representing the slope angle.

212 In eq. (5), λ_i indicates the slope length of the plot and the exponent m_i is given by the equation proposed by McCool et al. **213** (1989):

214
$$m_i = \frac{f_i}{1+f_i}$$

215

216 where f_i represents the ratio of rill to interrill erosion and can be expressed by the following formula:

217

$$f_{i} = \frac{\sin \alpha_{i}}{0.0896 \left(3 \sin^{0.8} \alpha_{i} + 0.56\right)}$$
(7)

219

218

220 The value of *LS*, that is assumed constant in each plot for the study period, is reported in Table 1.

221

222 Table 1 – The values of the RUSLE parameters obtained for each plot for the study period (2006-2016). In the last two-

columns are also reported the mean values of soil loss (Ai) measured during the study period (2006-2016) and those

related to the long-term simulation (1954-2019).

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(6)

227 3.2.2 The soil erodibility factor *K*

| 228 | The soil erodibility factor K, as defined by Wischmeier and Smith (1978), represents the mean annual value of the relative |
|---|---|
| 229 | inherent resistance of a soil to the detachment, entrainment and transport actions operated by rainfall and runoff. The K- |
| 230 | factor can be determined according to certain soil characteristics that include texture, presence of organic matter, |
| 231 | permeability. In this respect, Wischmeier et al. (1971) provided a nomograph, supported by an explicit equation, to |
| 232 | determine the value of K based on the above variables. However, if soil loss measurements are available at a plot scale, a |
| 233 | direct evaluation of K is possible. The method is based on a simple regression analysis between soil loss measurements |
| 234 | and rainfall erosivity, as proposed by Wischmeier and Mannering (1969), using the USLE unit plot (22.1 m long with a |
| 235 | uniform 9% slope, continuously maintained in a clean-tilled fallow condition with upslope and downslope tillage). |
| 236 | |
| 227 | |
| 237 | Fig. 3 – Calculation of the soil erodibility factor K |
| 237 | Fig. 3 – Calculation of the soil erodibility factor K |
| 237 238 239 | Fig. 3 – Calculation of the soil erodibility factor K In this contribution, we used the annual measurements of soil loss from the bare plot to obtain a representative value of |
| 237 238 239 240 | Fig. 3 – Calculation of the soil erodibility factor K In this contribution, we used the annual measurements of soil loss from the bare plot to obtain a representative value of K for the soils under investigation. Considering that our bare plot has a length of 25 m and a slope of 10%, an adjustment |
| 237 238 239 240 241 | Fig. 3 – Calculation of the soil erodibility factor K In this contribution, we used the annual measurements of soil loss from the bare plot to obtain a representative value of K for the soils under investigation. Considering that our bare plot has a length of 25 m and a slope of 10%, an adjustment was necessary according to eq. (1). In other words, plotting the annual values of soil loss obtained from the bare plot |
| 237 238 239 240 241 242 | Fig. 3 – Calculation of the soil erodibility factor K In this contribution, we used the annual measurements of soil loss from the bare plot to obtain a representative value of K for the soils under investigation. Considering that our bare plot has a length of 25 m and a slope of 10%, an adjustment was necessary according to eq. (1). In other words, plotting the annual values of soil loss obtained from the bare plot against the corresponding values of the product R_iLS , assuming that the <i>C</i> -factor and the <i>P</i> -factor are equal to 1, it was |
| 237 238 239 240 241 242 243 | Fig. 3 – Calculation of the soil erodibility factor <i>K</i> In this contribution, we used the annual measurements of soil loss from the bare plot to obtain a representative value of <i>K</i> for the soils under investigation. Considering that our bare plot has a length of 25 m and a slope of 10%, an adjustment was necessary according to eq. (1). In other words, plotting the annual values of soil loss obtained from the bare plot against the corresponding values of the product R_iLS , assuming that the <i>C</i> -factor and the <i>P</i> -factor are equal to 1, it was possible to use the slope of the computed least-squares regression line, passing through the origin, to determine <i>K</i> . The |
| 237 238 239 240 241 242 243 243 244 | Fig. 3 – Calculation of the soil erodibility factor <i>K</i> In this contribution, we used the annual measurements of soil loss from the bare plot to obtain a representative value of <i>K</i> for the soils under investigation. Considering that our bare plot has a length of 25 m and a slope of 10%, an adjustment was necessary according to eq. (1). In other words, plotting the annual values of soil loss obtained from the bare plot against the corresponding values of the product R_iLS , assuming that the <i>C</i> -factor and the <i>P</i> -factor are equal to 1, it was possible to use the slope of the computed least-squares regression line, passing through the origin, to determine <i>K</i> . The method is illustrated in Fig. 3 in which the line of equation $y=mx bx$ is superimposed on the experimental pairs. The slope |

247

246

248 3.2.3 The cover and management factor C

representative for our plots.

The availability of soil loss measurements, together with the calculation of $R_{\underline{i}}$ and *LS*, and the direct determination of *K* from the bare plot, made it possible to derive the values of the cover and management factor $C_{\underline{i}}$ for the plots 2, 3, 4, and 5 in which different combinations of cropping systems were adopted during the 11 years of investigation. Again, this calibration exercise was carried out using the annual data of soil loss A_i and the following equation (Cinnirella et al. 1998):

$$C_i = \frac{A_i}{R_i K LS}$$

254

256 in which, for each plot, C_i is the value representing the crop factor for the year *i*.

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(8)

| 257 | The results of eq. (8) are summarized in Fig. 4, where the the frequency distribution of C_i values single values of C_i and | _ | Formatted: Font: Italic | |
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| 258 | their frequency distribution are is reported for each plot. | | Formatted: Font: Italic, S | Subscript |
| 259 | A visual inspection of Fig. 4 suggests that the values of C _i show evidence of an interannual variability for each single plot | | | |
| 260 | and document a significant difference from plot to plot. These findings are expected because the values of C_i depend both | | | |
| 261 | on the cropping system adopted in each period and on the value of the rainfall erosivity factor calculated for that | | | |
| 262 | corresponding period. For this reason, it is difficult to choose a representative value of C for each plot as it assumes the | | | |
| 263 | meaning of a random variable. | | | |
| 264 | It can be seen from Fig. 4 that each frequency distribution follows, approximately, a log-normal distribution (see dotted | | | |
| 265 | line superimposed in each graph) that suggests the presence of a random component. Based on these findings, we decided | | | |
| 266 | to calculate the value of Cm that produced the perfect agreement between measured and calculated soil loss for the study | | | |
| 267 | period and we assumed this value as the C-factor, value representative for each plot. The four values of Cm resulting from | | Formatted: Font: Italic, S | Subscript |
| 268 | this calculation are also reported in Table 1. | | | |
| 269 | | | | |
| 270 | Fig. 4 – The frequency distribution of the C-factor, for each plot. The dashed line represents a log-normal theoretical | | Formatted: Font: Italic, S | Subscript |
| 271 | distribution | | | |
| 272 | | | | |
| 273 | The cropping systems supported by the plots 2, 3, 4, and 5 are typical of the cultivation techniques practiced in the upland | | | |
| 274 | areas of Southern Italy since the early 50s. For these reasons, the values of Cm reported in Table 1 can be considered | | | |
| 275 | representative of a long-term period in these areas. The same considerations can be extended to the mean value of the K- | | | |
| 276 | factor that can be assumed characteristic for this type of soil. Following this logic, in the absence of support practices and | | | |
| 277 | assuming a constant value of LS, only the rainfall erosivity factor R_i would affect the temporal variability of soil loss and | | | |
| 278 | it can be used to reconstruct the trend of soil erosion rates since the early 50s if a long-term dataset of $\underline{R}_{i}R$ is available. | | | |
| 279 | The annual values of R_i were obtained using the rainfall data available at the local station of Santa Cristina d'Aspromonte | | | |
| 280 | since 1954. These measurements were produced by the Italian Hydrographic Service at different temporal resolutions: | | | |
| 281 | the data for the period 1990-2019 are available at a time interval $\Delta t = 5$ min, with some short breakdown (Arpacal | | | |
| 282 | Datasets); the data for the period 1954-1989 were provided in a graphical form that required manual digitization to allow | | | |
| 283 | calculation of R _i at a temporal resolution of 30 minutes (see Wischmeier and Smith 1978). In order to get the values of | | | |
| 284 | precipitation amount and intensity consistent with those derived from the second dataset, the 5-minute data available for | | | |
| 285 | the period 1990-2019 were aggregated at a 30-minute temporal scale and the corresponding values of R_i were calculated | | | |
| 286 | accordingly (Porto 2016). | | | |

| 287 | Calculation of R_i for the missing years (1954-2005 and 2017-2019) and the availability of a calibrated RUSLE model for |
|-----|---|
| 288 | the shorter study period (2006-2016) allowed the reconstruction of soil erosion rates for the period 1954-2019. This |
| 289 | calculation was made by hypothesizing 4 scenarios, one for each plot, in which only the C-factor, was considered different |
| 290 | from plot to plot and assumed equal to the C_m values listed in Table 1. The results of these predictions are illustrated in |
| 291 | Fig. 5, where the values of soil loss A_i (t ha ⁻¹) are reported in graphical form for each year. It is worth noticing that the |
| 292 | predicted values of A_i (t ha ⁻¹) are related to the two periods 1954-2005 and 2017-2019 for which soil erosion measurements |
| 293 | are absent. On the contrary, the values of A_i (t ha ⁻¹) for the study period 2006-2016 are those measured by the experimental |
| 294 | device-and incorporated into the long term record of Fig. 5. The mean values of soil loss for the period 1954-2019, that |
| 295 | include measured and estimated data, are reported in Table 1. |

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values while white bars report the measured values obtained for the study period

Fig. 5 - The annual soil loss reconstructed for each plot for the period 1954-2019. Grey bars indicate the estimated

In order to confirm this hypothesis The datasets illustrated in Fig. 5 were processed by_z a standard trend analysis test was
 performed using the software TREND (2012). More specifically, the Cumulative Deviation Test and the Student's *t* Test
 were carried out for each scenario in order to see if the means in two parts of each record are different (for an unknown
 time of change). The overall results suggested, at a level of probability P<0.05, that, for each scenario, the mean for the
 period 1954-1995 is significantly lower than the mean related to the period 1995-2019 and confirmed the above
 hypothesis indicated that soil loss has not been stationary over the past 66 years.

307 4 DISCUSSION

308 The histograms illustrated in Fig. 5 and the mean values of soil loss reported in Table 1 provide important information on 309 the magnitude of soil erosion since 1954 and offer a basis to understand the longer-term variability of soil loss in this 310 area. The mean values of soil loss (plot measurements) related to the study period 2006-2016 are systematically higher 311 than the corresponding long-term estimates for the period 1954-2019 (see Table 1). Also, a first visual inspection of the 312 four graphs in Fig. 5 together with the linear trend overlaid on each figure suggests that soil loss shows an increasing 313 trend for the period covered by this study. In order to confirm this hypothesis, a standard trend analysis test was performed 314 using the software TREND (2012). More specifically, the Cumulative Deviation Test and the Student's / Test were carried 315 out for each scenario in order to see if the means in two parts of each record are different (for an unknown time of change). 316 The overall results suggested, at a level of probability P≤0.05, that, for each scenario, the mean for the period 1954-1995 317 is significantly lower than the mean related to the period 1995-2019 and confirmed the above hypothesis that soil loss has

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318 not been stationary over the past 66 years. These results are consistent with the work of Verstraeten et al. (2006) that 319 observed an increase of an average 10-year erosion rate calculated in Belgium with the RUSLE as a consequence of 320 changing rainfall erosivity through time. In fact, these changes reflect the temporal trend of R_i reported in Fig. 6 and are 321 a consequence of a general increase in the magnitude of the rainfall erosivity during this period. In this respect, Verstraeten 322 et al. (2006) observed a significant increase of the R-factor in central Belgium for the period 1991-2002 compared to the 323 period 1898–1990, and suggested that care must be taken when a single, invariant, value of R is adopted for simulating 324 long-term scenarios of soil loss. In our experimental site, a statistical interpretation of R_i , based on the Mann-Kendall test 325 and the linear trend test (Hirsch et al. 1992), established that an increasing trend for this variable can also be recognized 326 at a level of probability P≤0.10 and this provides a further confirm of the above hypothesis. Similar results were obtained 327 in a simulation study conducted by Pruski and Nearing (2002a) that explored the effects on soil erosion in three locations 328 of the USA by combining changes of rainfall intensity and number of rainy days over time. In that case, the simulation 329 scenarios obtained with CLIGEN, even if in line with our findings, were never confirmed by empirical evidence. 330

Fig. 6 – The annual values (R_i) of the R-rainfall erosivity factor obtained for the period 1954-2019 (a) and the annual values of rainfall measured in the same period (b)

However, the results summarized in Fig. 6 pose another important question whether an accurate estimate of R_i requires a proper relationship between rain intensity and rain kinetic energy or whether a simple correlation analysis between rainfall erosivity and rainfall amount can be adopted. In order to answer the above question, the annual rainfall Pa for the corresponding period (1954-2019) is <u>also</u> reported in Fig. 76. Surprisingly, the histograms of Fig. 7-6 show a decreasing trend of Pa in this area and a Cumulative Deviation Test suggested that this hypothesis cannot be rejected at a level of probability P \leq 0.1.

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Fig. 7 - The annual values of rainfall obtained for the period 1954-2019

These findings are really important because they suggest that a) the two variables (R_i and Pa) do not necessarily show the same temporal trends, and b) the *R*-factor cannot be predicted indirectly using rainfall data at annual scale but it is necessary to use the proper time intervals (5 min $\leq \Delta t \leq 30$ min) (Buffoni et al. 1999; Brunetti et al. 2001, 2002, 2004; Porto 2016). In other words, the above results indicate that the use of simplified models like those provided by Fournier (1960) or Arnoldus (1980) that are based on monthly and annual rainfall datasets, even if largely employed in many areas in the world (see, among the others, de Asis and Omasa 2007; Wolka et al. 2015; Cartacuzencu et al. 2016; González-12 Morales et al. 2018; Wang et al. 2018; Pal and Chakrabortty 2019) may not be adequate to predict the rainfall erosivity
in Mediterranean areas (Capra et al. 2017).

351 It is also important to notice that the CUSUM test (Trend, 2012) applied to the R_i dataset in Fig. 6 shows a distinct change 352 point in 2001 and this supports the hypothesis that the measurements of soil loss related to the study period 2006-2016 353 may not be representative of the long-term soil erosion in this area as they clearly overestimate soil loss (see Table 1). 354 Again, this seems to confirm that the length of the observation record has an important impact on soil erosion estimates 355 (Verstraeten et al. 2006) and suggests that care must be taken when a representative value of soil loss is requested for an 356 area with lacks of data. Similar problems occur when calibration and/or validation exercises are necessary to establish the 357 ability of a model to predict reliable values of soil erosion. For example, during the last 2-3 decades, alternative 358 approaches, based on the use of fallout radionuclides (FRN), including mainly cesium-137 (137Cs) and unsupported lead-359 210 (210Pbex), proved to be very effective to assemble information on long-term and spatial patterns of erosion and 360 deposition rates especially if coupled with existing traditional methods (Di Stefano et al. 2005; Porto and Walling 2015). 361 These models need validation and the availability of a long-term representative value of soil erosion to be compared with 362 the model estimate is a key issue. In this respect, Porto and Walling (2012) carried out a sampling campaign for ¹³⁷Cs and 363 ²¹⁰Pbex analyses to estimate long-term soil erosion in the five plots used in this study. The overall results, updated to 2009, 364 indicated that the estimates provided by ¹³⁷Cs, related to the period 1954-2006, were systematically lower that the 365 measurements provided by the plots for the four-year period 2006-2009. The authors recognized that the four-year 366 measurements of soil loss may have overestimated soil erosion and emphasized the need to consider a longer dataset to 367 obtain a more reliable measured value. Also, a higher estimate of soil erosion obtained with the use of $^{210}Pb_{ex}$ suggested 368 a possible increase of soil erosion rates during the previous 15-20 years. These results are well in agreement with our 369 findings and suggest that the RUSLE model can be very effective for reconstructing long-term records of soil loss if 370 reliable input datasets are available.

371 Another important indication can be inferred from Fig. 5 that shows the trend of soil loss reconstructed for plot 5. A-The 372 comparison with the equivalent estimates obtained from the other plots in Fig. 5 indicates that the amount of soil loss 373 related to plot 5 is much lower. This result reflects the lower value of Cm calculated for this plot and suggests that the 374 adoption of a proper strategy that includes the use of rotations with natural vegetation and conservative practices 375 (mulching, no-tillage etc.) can be effective in reducing soil loss. This assumption is confirmed by several studies in the 376 world that explored the effect of land use changes on soil loss (see, among the others, Maetens et al. 2012). In our case, 377 the mean value of A_i for plot 5, related to the long-term period 1954-2019, is equal to 12.0 (t ha⁻¹ yr⁻¹). This value is still 378 a little higher than that (ca. 11.5 t ha⁻¹ yr⁻¹) assumed by Bagarello et al. (2015) as tolerable soil loss for similar geographic 379 contexts. However, it indicates that the adoption of the conservative practices described above allowed to reduce it-soil 13

| 380 | loss significantly considering that the equivalent value obtained for plot 3 is ca. three times higher (31.9 t ha ⁻¹ yr ⁻¹). This |
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| 381 | result is encouraging and suggests that an appropriate crop rotation is a key factor to minimize land degradation in these |
| 382 | areas. In this respect, models like the RUSLE, based on empirical parameters of simple calculation, offer a good |
| 383 | opportunity to predict soil loss for different scenarios and to evaluate possible countermeasures for long-term planning |
| 384 | DUIDOSES. |

386 <u>5</u>CONCLUSIONS

387 The experimental plots used in this study provided important information on soil erosion rates obtained in an upland area 388 of the Mediterranean environment. The first, important, result is related to the direct observations of soil loss obtained 389 during the period of the experiment from 2006 to 2016. In this respect, the study demonstrated that direct measurements 390 of soil loss can be misleading if the dataset cannot be extended for longer period. In order to avoid such problems, it is 391 strongly suggested to account for long-term rainfall erosivity measurements in the absence of soil loss data. In the study 392 area, the availability of rainfall data at short-time interval (5-30 minutes) from a local station allowed the calculation of 393 the rainfall erosivity factor from 1954 to date. Based on this information, a RUSLE model was calibrated using the 11 394 years of soil loss measurements and it was applied to the extended period 1954-2019 to reconstruct the longer-term trend 395 of soil erosion in the area. The overall results revealed that soil erosion has increased during this long-time window and 396 showed a changing point at the beginning of the last two decades. These findings, in line with the results obtained from 397 other authors, suggest that care must be taken when direct observations of soil loss are used for planning purpose as they 398 could not be representative for the area under investigation for long-term periods. A second, important, result is related 399 to the use of empirical models like RUSLE to predict soil loss for long periods. In this respect, the RUSLE model proved 400 a good performance in its ability to reproduce soil loss rates in Mediterranean areas. However, the adoption of proper 401 datasets of rainfall erosivity, derived from specific relationships between rainfall intensity and the R-factor, are strongly 402 suggested and should be considered an essential tool to extend the representativeness of measurements.

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410 <u>Declarations</u>

| 411 | Consent to participate. All authors consented to participate in the study. |
|-----|---|
| 412 | Consent for publication. All authors consented to the publication of the article. |
| 413 | Conflict of interest. The authors declare no competing interests. |
| 414 | |
| 415 | References |
| 416 | Alexander LV (2016) Global observed long-term changes in temperature and precipitation extremes: A review of progress |
| 417 | and limitations in IPCC assessments and beyond. Weather Clim Extremes 11:4-16 |
| 418 | Arnoldus HMJ (1980) An approximation of the rainfall factor in the USLE. In: Assessment of Erosion. England: Wiley |
| 419 | Chichester: 127–132 |
| 420 | Bagarello V, Di Stefano C, Ferro V, Pampalone V (2010) Statistical distribution of soil loss and sediment yield at Sparacia |
| 421 | experimental area, Sicily. Catena 82:45-52 |
| 422 | Bagarello V, Di Stefano C, Ferro V, Pampalone V (2015) Establishing a soil loss threshold for limiting rilling. J Hydrol |
| 423 | Eng 20(6):C5014001-1-C5014001-12 |
| 424 | Bagarello V, Di Stefano C, Ferro V, Kinnel PIA, Pampalone V, Porto P, Todisco F (2011) Predicting soil loss on moderate |
| 425 | slopes using an empirical model for sediment concentration. J Hydrol 400:267-273 |
| 426 | Bagarello V, Ferro V, Pampalone V, Porto P, Todisco F, Vergni L (2018) Predicting soil loss in central and south Italy |
| 427 | with a single USLE-MM model. J Soils Sediments 18(12):3365-3377 |
| 428 | Bakker MM, Govers G, Kosmas C, Vanacker V, Van Oost K, Rounsevell M (2005) Soil erosion as a driver of land-use |
| 429 | change. Agr Ecosyst Environ 105:467–481 |
| 430 | Boardman J (2006) Soil erosion science: Reflections on the limitations of current approaches. Catena 68:73-86 |
| 431 | Boardman J, Poesen J (2006) Soil Erosion in Europe. Wiley, Chichester. 878 pp |
| 432 | Brunetti M, Colacino M, Nanni T (2001) Trend in the daily intensity of precipitation in Italy from 1951 to 1996. Int J |
| 433 | Climatol 21:299–316 |
| 434 | Brunetti M, Maugeri M, Nanni T, Navarra A (2002) Droughts and extreme events in regional daily Italian precipitation |
| 435 | series. Int J Climatol 22:1455–1471 |
| 436 | Brunetti M, Buffoni L, Mangianti F, Maugeri M, Nanni T (2004) Temperature, precipitation and extreme events during |
| 437 | the last century in Italy. Global Planet Change 40:141-149 |
| 438 | Buffoni L, Maugeri M, Nanni T (1999) Precipitation in Italy from 1833 to 1996. Theor Appl Climatol 63:33-40 |
| 439 | Capra A, Porto P, La Spada C (2017) Long-term variation of rainfall erosivity in Calabria (Southern Italy). Theor Appl |

Climatol 128(1-2):141-158

| 441 | Cartacuzencu S, Coman A, Rosu G, Tincu R, Lazar G (2016) Analysis of hydric erosion produced by the Siret River, | |
|-----|--|--|
| 442 | Romania during 1989-2008. Environ Eng Manag J 15:537-544 | |
| 443 | Cerdan O, Govers G, Le Bissonnais Y, Van Oost K, Poesen J, Saby N, Gobin A, Vacca A, Quinton J, Auerswald K, Klik | |
| 444 | A, Kwaad F J P M, Raclot D, Ionita I, Rejman J, Rousseva S, Muxart T, Roxo M J, Dostal T (2010) Rates and | |
| 445 | spatial variations of soil erosion in Europe: A study based on erosion plot data. Geomorphology 122:167-177 | |
| 446 | Chaplot V (2007) Water and soil resources response to rising levels of atmospheric CO ₂ concentration and to changes in | |
| 447 | precipitation and air temperature. J Hydrol 337:159-171 | |
| 448 | Cinnirella S, Iovino F, Porto P, Ferro V (1998) Anti-erosive effectiveness of Eucalyptus coppices through the cover | |
| 449 | management factor estimate. Hydrol Process 12(4):635-649 | |
| 450 | De Araújo JC, Güntner A, Bronstert A (2006) Loss of reservoir volume by sediment deposition and its impact on water | |
| 451 | availability in semiarid Brazil. Hydrolog Sci J 51(1):157-170 | |
| 452 | de Asis A M, Omasa K (2007) Estimation of vegetation parameter for modeling soil erosion using linear Spectral Mixture | |
| 453 | Analysis of Landsat ETM data. ISPRS J Photogramm Remote Sens 62:309-324 | |
| 454 | Di Stefano C, Ferro V, Porto P. (1999) Linking sediment yield and caesium-137 spatial distribution at basin scale. J Agric | |
| 455 | Eng Res 74:41–62 | |
| 456 | Di Stefano C, Ferro V, Porto P, Rizzo S (2005) Testing a spatially distributed sediment delivery model (SEDD) in a | |
| 457 | forested basin by caesium-137 technique. J Soil Water Conserv 60(3):148-157 | |
| 458 | Du D, Zhao X, Huang R (2017) The impact of climate change on developed economiesEcon Lett 153:43-46 | |
| 459 | Evans R (1995) Some methods of directly assessing water erosion of cultivated land - a comparison of measurements | |
| 460 | made on plots and in fields. Prog Phys Geog 19(1):115-129 | |
| 461 | Favis-Mortlock D, Boardman J (1995) Nonlinear responses of soil erosion to climate change: A modeling study on the | |
| 462 | UK South Downs. Catena 25:365-387 | |
| 463 | Ficklin D L, Luo Y, Luedeling E, Zhang M (2009) Climate change sensitivity assessment of a highly agricultural | |
| 464 | watershed using SWAT. J Hydrol 374(1):16-29 | |
| 465 | Foster GR, McCool DK, Renard KG, Moldenhauer WC (1981) Conversion of the universal soil loss equation to SI metric | |
| 466 | units. J Soil Water Conserv 36(6):355-359 | |
| 467 | Fournier F (1960) Climat et erosion. Presses Universitaries de France, Paris | |
| 468 | González-Morales SB, Mayer A, Ramírez-Marcial N (2018) Assessment of soil erosion vulnerability in the heavily | |
| 469 | populated and ecologically fragile communities in Motozintla de Mendoza, Chiapas, Mexico. Solid Earth 9:745- | |
| 470 | 757 | |

| 471 | Hirsch RM, Helsel DR, Cohn TA, Gilroy EJ (1992) Statistical analysis of hydrologic data. In: Maidment DR (ed) | |
|-----|--|--------------------|
| 472 | Handbook of Hydrology, McGraw-Hill, pp. 1711-1730 | |
| 473 | IPCC (2018) Special Report on Global Warming of 1.5°C, <u>https://www.ipcc.ch/reports/</u> October 2018 | Field Code Changed |
| 474 | Karl TR, Knight RW (1998) Secular Trends of Precipitation Amount, Frequency, and Intensity in the United States. Bull | |
| 475 | Am Meteorol Soc 79:231-241 | |
| 476 | Khodadadi M, Zaman M, Mabit L, Blake WH, Gorji M, Bahrami AS, Meftahi M, Porto P (2020) Exploring the potential | |
| 477 | of using 7Be measurements to estimate soil redistribution rates in semi-arid areas: results from Western Iran and | |
| 478 | Southern Italy. J Soils Sediments 20(9):3524-3536 | |
| 479 | Loughran RJ (1989) The measurement of soil erosion. Prog Phys Geogr 13:216-233 | |
| 480 | Maetens W, Poesen J, Vanmaercke M (2012) How effective are soil conservation techniques in reducing plot runoff and | |
| 481 | soil loss in Europe and the Mediterranean? Earth-Sci Rev 115:21-36 | |
| 482 | Mason SJ, Waylen PR, Mimmack GM, Rajaratnam B, Harrison JM (1999) Changes in extreme rainfall events in South | |
| 483 | Africa. Clim Change 41:249–257 | |
| 484 | McCool DK, Brown LC, Foster GR, Mutchler CK, Meyer LD (1987) Revised slope steepness factor for the universal soil | |
| 485 | loss equation. Trans ASAE 30(5):1387-1396 | |
| 486 | McCool DK, Foster GR, Mutchler CK, Meyer LD (1989) Revised slope length factor for the Universal Soil Loss | |
| 487 | Equation. Trans ASAE 32(5):1571-1576 | |
| 488 | Miyan MA (2015) Droughts in Asian Least Developed Countries: Vulnerability and sustainability. Weather Clim | |
| 489 | Extremes 7:8-23 | |
| 490 | Moberg A, Jones PD (2005) Trends in indices for extremes in daily temperature and precipitation in central and western | |
| 491 | Europe. Int J Climatol 25:1149–1171 | |
| 492 | Nearing MA, Foster GR, Lane LJ, Finkner SC (1989) A process-based soil erosion model for USDA- water erosion | |
| 493 | prediction project technology. Trans ASAE 32:1587-1593 | |
| 494 | Osborn TJ, Hulme M, Jones PD, Basnett TA (2000) Observed trends in the daily intensity of United Kingdom | |
| 495 | precipitation. Int J Climatol 20:347–364 | |
| 496 | Pal SC, Chakrabortty R (2019) Simulating the impact of climate change on soil erosion in sub-tropical monsoon | |
| 497 | dominated watershed based on RUSLE, SCS runoff and MIROC5 climatic model. Adv Space Res 64:352-377 | |
| 498 | Palmer MA, Lettenmaier DP, Poff NL, Postel SL, Richter B, Warner R (2009) Climate Change and River Ecosystems: | |
| 499 | Protection and Adaptation Options. Environ Manage 44:1053-1068 | |
| 500 | Pandey BK, Gosain AK, Paul G, Khare D (2017) Climate change impact assessment on hydrology of a small watershed | |

501 using semi-distributed model. Appl Water Sci 7:2029–2041

| 502 | Pimentel D, Harvey C, Resosudarmo P, Sinclair K, Kurz D, McNair M, Crist S, Shpritz L, Fitton L, Saffouri L, Blair R |
|-----|---|
| 503 | (1995) Environmental costs of soil erosion and conservation benefits. Science 267:1117-1123 |
| 504 | Porto P (2016) Exploring the effect of different time resolutions to calculate the rainfall erosivity factor R in Calabria, |
| 505 | southern Italy. Hydrol Process 30:1551-1562 |
| 506 | Porto P, Callegari G (2021) Using 7Be measurements to explore the performance of the SEDD model to predict sediment |
| 507 | yield at event scale. Catena 196: 104904 |
| 508 | Porto P, Walling DE (2012) Validating the use of ${}^{137}Cs$ and ${}^{210}Pb_{ex}$ measurements to estimate rates of soil loss from |
| 509 | cultivated land in southern Italy. J Environ Radioact 106:47-57 |
| 510 | Porto P, Walling DE (2015) Use of caesium-137 Measurements and long-term records of sediment load to calibrate the |
| 511 | sediment delivery component of the SEDD model and explore scale effect: examples from Southern Italy. J Hydrol |
| 512 | Eng 20(6) |
| 513 | Porto P, Walling DE, La Spada C, Callegari G (2016) Validating the use of ¹³⁷ Cs measurements to derive the slope |
| 514 | component of the sediment budget of a small catchment in southern Italy. Land Degrad Dev 27:798-810 |
| 515 | Porto P, Walling DE, Callegari G (2018) Using repeated ¹³⁷ Cs and ²¹⁰ Pbex measurements to establish sediment budgets |
| 516 | for different time windows and explore the effect of connectivity on soil erosion rates in a small experimental |
| 517 | catchment in Southern Italy. Land Degrad Dev 29:1819-1832 |
| 518 | Preiti G, Romeo M, Bacchi M, Monti M (2017) Soil loss measure from Mediterranean arable cropping systems: Effects |
| 519 | of rotation and tillage system on C-factor. Soil Till Res 170:85-93 |
| 520 | Pruski FF, Nearing MA (2002a) Runoff and soil loss changes expected for changes in precipitation patterns under global |
| 521 | climate change. J Soil Water Conserv 57:7-16 |
| 522 | Pruski FF, Nearing MA (2002b) Climate-induced changes in erosion during the 21st century for eight U.S. locations. |
| 523 | Water Resour Res 38(12):1298, doi:10.1029/2001WR000493 |
| 524 | Renard KG, Foster GR, Yoder DC, McCool DK (1994) RUSLE revisited: status, questions, answers, and the future. J |
| 525 | Soil Water Conserv 49:213-220 |
| 526 | Renard KG, Foster GR, Weesies GA, McCool DK, Yoder DC (1997) Predicting Soil Erosion by Water: A Guide to |
| 527 | Conservation Planning with the Revised Universal Soil Loss Equation (RUSLE), Agric. Handbk., vol. 703, U. S. |
| 528 | Dep. of Agric., Washington, D. C. |
| 529 | Romero-Díaz A, Ruiz-Sinoga JD, Robledano-Aymerich F, Brevik EC, Cerdà A (2017) Ecosystem responses to land |
| 530 | abandonment in Western Mediterranean Mountains. Catena 149:824-835 |
| 531 | Shao Z, Sumari NS, Portnov A, Ujoh F, Musakwa W, Mandela PJ (2021) Urban sprawl and its impact on sustainable |
| 532 | urban development: a combination of remote sensing and social media data. Geo Spat Inf Sci 24(2):241-255 |

| 533 | Shiferaw B, Tesfaye K, Kassie M, Abate T, Prasanna BM, Menkir A (2014) Managing vulnerability to drought and |
|-----|---|
| 534 | enhancing livelihood resilience in sub-Saharan Africa: Technological, institutional and policy options. Weather |
| 535 | Clim Extremes 3:67-79 |
| 536 | Suppiah R, Hennessy KJ (1998) Trends in total rainfall, heavy rain events and numbers of dry days in Australia, 1910- |
| 537 | 1990. Int J Climatol 18:1141–1164 |
| 538 | Verstraeten G, Poesen J, Demaree G, Salles C (2006) Long-term (105 years) variability in rain erosivity as derived from |
| 539 | 10- min rainfall depth data for Ukkel (Brussels, Belgium): implications for assessing soil erosion rates. J Geophys |
| 540 | Res 111:D22 |
| 541 | Wang M, Baartman JE, Zhang H, Yang Q, Li S, Yang J, Cai C, Wang M, Ritsema CJ, Geissen V (2018) An integrated |
| 542 | method for calculating DEM-based RUSLE LS. Earth Sci Inform 11:579–590 |
| 543 | Wen Y, Schoups G, van de Giesen N (2017) Organic pollution of rivers: Combined threats of urbanization, livestock |
| 544 | farming and global climate change. Nature Sci Rep 7:43289 |
| 545 | Wischmeier WH, Johnson CB, Cross BV (1971) A soil erodibility nomograph for farmland and construction sites. J Soil |
| 546 | Water Conserv 26:189-193 |
| 547 | Wischmeier WH, Mannering JV (1969) Relation of soil properties to its erodibility. Soil Sci Soc Am Proc 39:131-137 |
| 548 | Wischmeier WH, Smith DD (1978) Predicting Rainfall-erosion Losses. A Guide to Conservation Farming, vol. 537. US |
| 549 | Dept. of Agric., Agr. Handbook, pp. 151 |
| 550 | Wolka K, Tadesse H, Garedew E, Yimer F (2015) Soil erosion risk assessment in the Chaleleka wetland watershed, |
| 551 | Central Rift Valley of Ethiopia. Environ Syst Res 4:1-12 |
| 552 | Yi Y, Wang Z, Zhang K, Yu G, Duan X (2008) Sediment pollution and its effect on fish through food chain in the Yangtze |
| 553 | River. Int J Sediment Res 23(4):338-347 |

| | R | К | Cm | LS | Ai (2006-2016) | Ai (1954-2019) |
|--------|----------------------------------|--|------|------|-----------------------|-----------------------|
| | $(MJ mm ha^{-1} h^{-1} yr^{-1})$ | (t ha h ha ⁻¹ MJ ⁻¹ mm ⁻¹) | | | $(t ha^{-1} yr^{-1})$ | $(t ha^{-1} yr^{-1})$ |
| Plot 1 | 5032 | 0.011 | 1.00 | 1.20 | 69.5 | 56.1 |
| Plot 2 | | | 0.38 | 1.27 | 28.6 | 22.5 |
| Plot 3 | | | 0.50 | 1.36 | 39.2 | 31.9 |
| Plot 4 | | | 0.41 | 1.35 | 32.2 | 25.7 |
| Plot 5 | | | 0.21 | 1.25 | 14.4 | 12.0 |

Figure Captions

Fig. 1 The study area and the experimental plots

Fig. 2 Values of soil loss obtained from each plot for the study period 2006-2016. The graph in (a) shows the frequency distribution of the annual values. The box plot in (b) indicates the data distribution

Fig. 3 Calculation of the soil erodibility factor K

Fig. 4 The frequency distribution of C_i for each plot. The dashed line represents a log-normal theoretical distribution

Fig. 5 The annual soil loss reconstructed for each plot for the period 1954-2019. Grey bars indicate the estimated values while white bars report the measured values obtained for the study period

Fig. 6 The annual values (R_i) of the rainfall erosivity factor obtained for the period 1954-2019 (a) and the annual values of rainfall measured in the same period (b)













annual trend



a)

 R_{i} (MJ mm ha⁻¹ h ⁻¹ yr ⁻¹)