Implementation and evaluation of a GIS-based model for estimating risk of soil erosion.

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1. Abstract

Soil erosion through natural factors or poor land management can lead to steep drops in soil nutrient levels, which leads to impactful damage on the natural environment and crop yields. Determining what levels of soil erosion are occurring and where they are occurring is a global issue so that appropriate conservation practices can be put into place. This study used a Geographical Information System (GIS) powered by ArcGIS pro using secondary data sources from the Met Office, Ordnance Survey Northern Ireland (OSNI), the Natural Environment Research Council (NERC) and the European Soil Data Centre (ESDAC) to estimate the risk of soil erosion in Northern Ireland using the Revised Universal Soil Loss Equation (RUSLE). Intolerable erosion levels were defined as locations where erosion exceeds formation rates. This was calculated as the case in 73,233 ha and the amount of soil eroded per year was estimated at 158,501 t ha^{-1} yr^{-1} (gross) and six areas of concern have been highlighted. The RUSLE data inputs were statistically compared to erosion levels to understand how each variable influenced erosion, then the suitability of the model was discussed. Finally, sources of erosion not considered by the model were discussed along with the recommendation that erosion studies should use the most comprehensive approaches possible.

2. Introduction

Agriculture is what makes civilisation possible and poor agricultural practices have ended more civilizations than invading armies (Savory, 1994). Though seemingly overdramatic, it is becoming more pertinent yearly as it is estimated that as much as 40% of the world's topsoil is degraded and this could rise to 90% by 2050 (UNCCD, 2022) with the world's population expected to increase to 10bn in that time (UNDESA, 2023).

The main cause of that degradation, soil erosion is multifaceted. Natural factors including texture, slope, vegetation content, ground cover and rainfall intensity are mediated by human activities on the landscape like farming. Soil erosion above the replenishment rate leads to environmental damage and decreased agricultural potential (Montgomery, 2007) and the estimated economic impact of soil degradation in the UK alone is around £1.2bn yearly (Graves et al., 2015).

Intolerable soil erosion rates occur on a wide range of soils and land uses across the UK (Brazier, 2004). With the population estimated to rise by 2.1 million over the next decade (Office for National Statistics, 2021) it is essential that effective laws and regulations are enacted to ensure food security meaning the provision of accurate data is crucial.

Soil erosion modelling dates to at least the 1930s (Middleton, Byers and Slater, 1934) and many of the parameters used today were established as far back as the 19th century (Warington & Peake, 1880). In recent years GIS and remote sensing have made it possible to estimate soil erosion across larger areas in a more accurate and cost-effective manner than ever before (Chen et al., 2011).

Soil erosion models can be categorized into three types. 1) Physics based, 2) Conceptual and 3) Empirical models. Physics approaches replicate physical processes involved (de Roo et al., 1998). Conceptual models use simplified versions of what are employed in the physics-based models, using knowledge of the key relationships involved (Alewell et al., 2019). Finally Empirical models like the Universal Soil Loss Equation (USLE) and its derivatives (RUSLE) measure variables of soil erosion and use algorithms to predict the outcome, without simulating the actual process of erosion (Wischmeier and Mannering, 1969; Renard & Ferreira, 1993).

The most used approaches today are USLE-type algorithms. Despite their relative simplicity, they have been shown to have no higher uncertainty than other approaches, although this may change with improving computational and data collection techniques (Alewell et al., 2019). This paper outlines a GIS implementation of the RUSLE using ArcGIS Pro to quantify areas of intolerable soil erosion in Northern Ireland.

3. Methodology

The RUSLE is based on the formula:

$$A = R \times K \times LS \times C \times P$$

Where:

- A = soil loss (in tonnes per hectare per year)
- R = rainfall erosivity factor (R-Factor)
- K = soil erodibility factor (K-Factor)
- LS = slope length and steepness factor (LS-Factor)
- C = cover factor (C-Factor)
- P = soil conservation measures (P-Factor)

Table 1 details the datasets used.

Table 1: Datasets used in study.

Name	Type	Description	Analysis performed
Norther Ireland Outline	Vector	**Source:** Ordnance Survey Northern Ireland (OSNI)	Clipping of datasets to study area
Contour data 1:50,000 scale	Vector	**Source**: Ordnance Survey Northern Ireland (OSNI)	Calculation of LS-Factor
Rainfall Sampling Points	Point	**Source:** Met Office	Calculation of R-Factor
Annual Rainfall in mm	Raster	**Source:** Met Office	Used as a comparison for the Interpolated of R-Factor
Landcover	Raster	**Source:** NERC EDS Environmental Information Data Centre	Calculation of C-Factor
P-Factor	Raster	**Source:** European Soil Data Centre (ESDAC)	P-Factor Data
United States Department of Agriculture (USDA) Soil Classification	Raster	**Source:** European Soil Data Centre (ESDAC)	Calculation of K-Factor
Soil Clay Percentage	Raster	**Source:** European Soil Data Centre (ESDAC)	Calculation of K-Factor
Soil Sand Percentage	Raster	**Source:** European Soil Data Centre (ESDAC)	Calculation of K-Factor
Soil Silt Percentage	Raster	**Source:** European Soil Data Centre (ESDAC)	Calculation of K-Factor
Soil Organic Carbon Percentage	Raster	**Source:** European Soil Data Centre (ESDAC)	Calculation of K-Factor

3.1 Rainfall Erosivity (R-Factor)

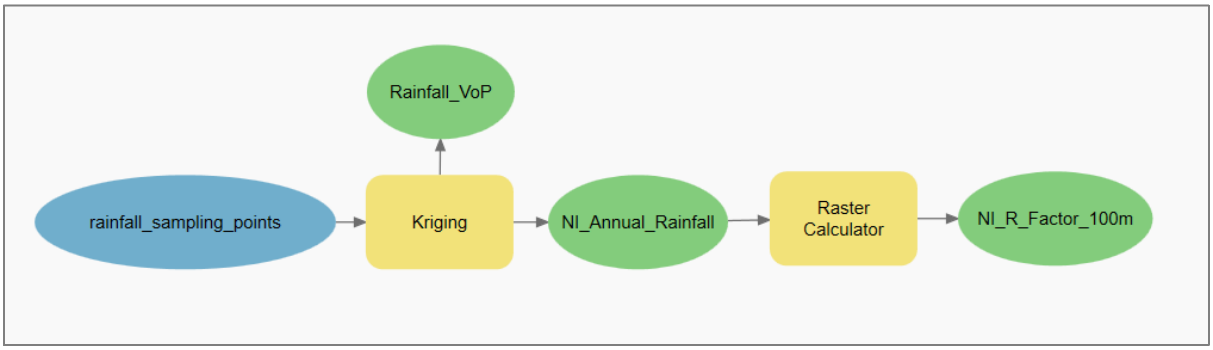
R-factor was calculated using a Met office dataset of 700 rainfall sampling points distributed across Northern Ireland for annual rainfall totals in mm. The data was interpolated using kriging instead of IDW as Rainfall does not dissipate the further one is from a rain gauge (Figure 1).

The R-Factor was calculated using the following equation as used by Woldemariam *et al* (2018):

$$R = [\ 38.46 + (\ 3.48 \times P\ )]$$

Where P is the total amount of rainfall in mm per year.

Figure 1: ArcGIS Pro Model for calculating R-Factor.



3.2 Soil Erodibility (K-Factor)

K-Factor was calculated by equations as used by Renard et al. (1996) and datasets from Ballabio et al (2016). The overall equation is:

$$K = [(2.1 \times 10^{-4}\ M^{1.14}\ (12 - OM) + 3.25\ (s - 2) + 2.5\ (p - 3)\ )\ /\ 100\ ]\ /\ 7.59$$

Where M is soil surface texture, OM is organic matter percentage, S is USDA soil structure code and p is USDA permeability code.

3.2.1 Calculating *M*

M was calculated using raster datasets mapped by Ballabio *et al* (2016) that gave percentages for clay, sand, silt and organic carbon inputted into the following formula.

$$M = [(\ 100 - Ac\ ) \times (\ L + Armf\ )]$$

Where Ac is clay percentage, L is silt percentage and $Armf$ is sand percentage.

3.2.2 Calculating *OM*

OM was calculated by taking organic carbon percentages as mapped by Jones *et al* (2005) and multiplying it by 1.724. This assumes that organic material in the soil is composed of 58% carbon (USDANRCS. 2022).

$$OM = OC \times 1.724$$

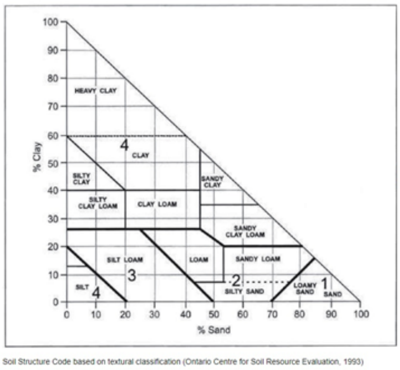
Where OC is soil organic carbon percentage.

The raster was modified to reclassify all OM values higher than 12, as 12, because the K-factor equation produces invalid negative results with higher OM values.

3.2.3 Calculating *S* and *p*

S and p were determined by reclassifying a soil textural classes dataset mapped by Ballabio *et al* (2016) based on a lookup table provided by Alisawi (2016) (figure 2).

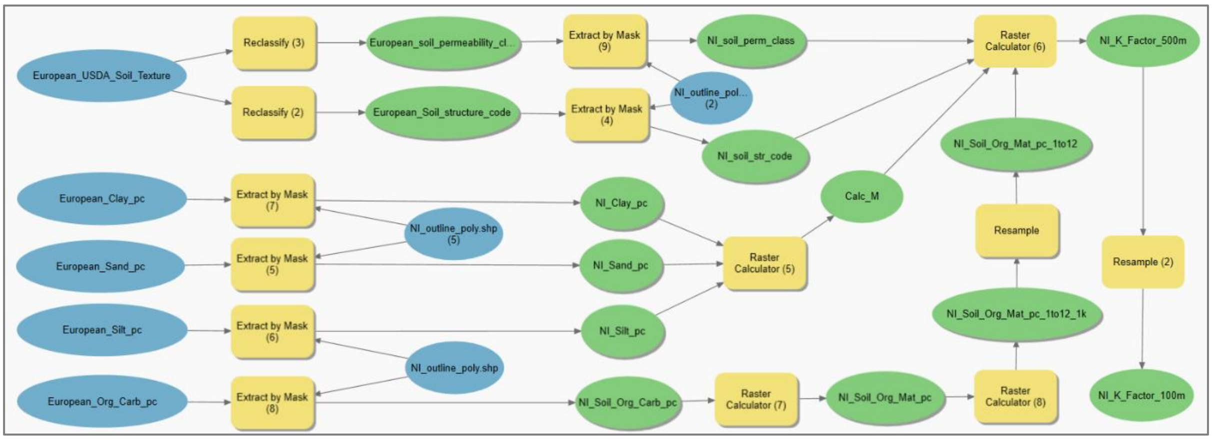
Figure 2: Soil Structure Code and Permeability Code look-up tables as shown in Alisawi (2016)



Soil Texture	Permeability Code[1]	Hydrologic Soil Group[2]
Heavy clay ,Clay	6	D
Silty clay loam, Sandy clay	5	C-D
Silty clay loam, Sandy loam	4	C
Loam, Silt loam	3	B
Loam sand, Sandy loam	2	A
Sand	1	A+
Note: 1-National Soil handbook. 2- National Engineering Handbook (SCS, 1972).		

The processes for determining K-Factor can be seen in figure 3.

Figure 3: ArcGIS Pro Model for calculating K-Factor



3.3 Slope Length and Steepness (LS-Factor)

The LS-Factor was calculated by using a digital terrain model (DTM) built using an ONSI 10m interval contour line dataset, converted into a raster with a 10m horizontal resolution. Fu et al. (2015) illustrated that slope steepness is underestimated with decreasing DTM resolution and slope length is progressively overestimated but a 10m resolution was optimal.

The dataset was processed to determine slope angle in % and slope length (figure 4). After the equation by Stone & Hilborn (2012) was used:

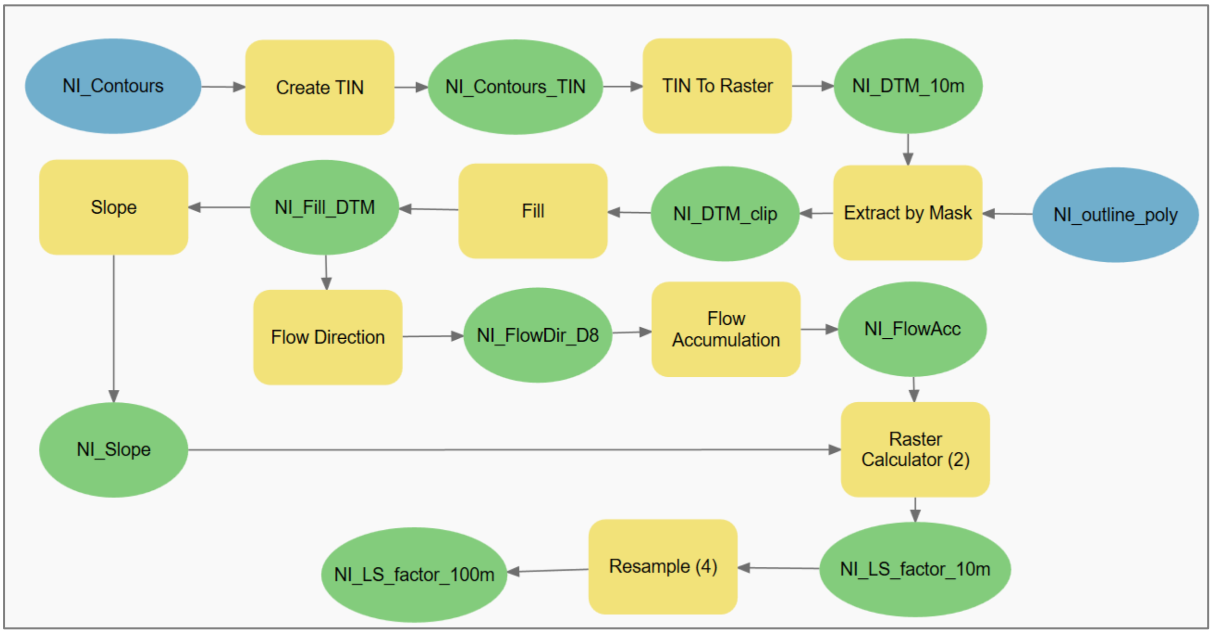
$$LS = [\,0.065 + 0.0456\,(SS) + 0.006541\,(SS)^2]\,(SL / 22.1)^{NN}$$

Where *SS* is slope steepness in percent and *SL* is slope length in metres. A single value for *NN* of 0.5 was chosen because 58% of the slope values measured were above 3% and 49% above 5%

Table 2. NN Values (Stone & Hilborn (2012)

Slope %	<1	1 ≤ Slope < 3	3 ≤ Slope < 5	≥ 5
NN	0.2	0.3	0.4	0.5

Figure 4: ArcGIS Pro Model for calculating LS-Factor



3.4 Cover (C-Factor)

The C-factor raster was produced using a landcover dataset with 21 classes mapped by Marston *et al* (2022) in combination with the C-Factor values for landcover types given by Panagos *et al* (2015) (table 3).

Table 3: C-Factors by Landcover Type (Panagos et al., 2015)

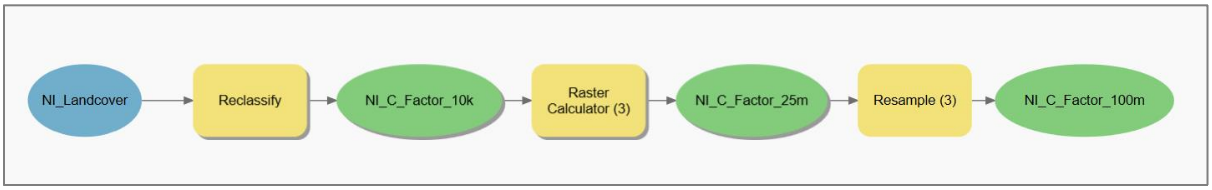
Land Cover	C-Factor
Deciduous woodland	0.0029
Coniferous woodland	0.0029
Arable	0.223
Improve grassland	0.0319
Neutral grassland	0.0319
Calcareous grassland	0.0319
Acid grassland	0.0319
Fen	0.0001
Heather	0.042
Heather grassland	0.042
Bog	0.0001
Inland rock	0.0001
Saltwater	0.0001
Freshwater	0.0001
Supralittoral rock	0.0001
Supralittoral sediment	0.0001
Littoral rock	0.0001
Littoral sediment	0.0001
Saltmarsh	0.0001
Urban / suburban	0.0001

Arable land is often the most erodible and can have wide ranging C-Factor values (Panagos et al, 2015). Data from the Department of Agriculture, Environment and Rural Affairs (DAERA) (2021) was used to estimate the relative landcover ratios of the most common crops in Northern Ireland, from which the C-Factor value of 0.223 was derived (table 4).

Table 4: C-Factor values for most common crops in Northern Ireland. Data from Panagos et al (2015) and DAERA (2021)

Crop type	Relative Landcover %	C-Factor	Weighted C-Factor for Arable Land
Barley	62	0.21	0.223
Wheat	22	0.20	
Potatoes	10	0.34	
Oats	6	0.20	

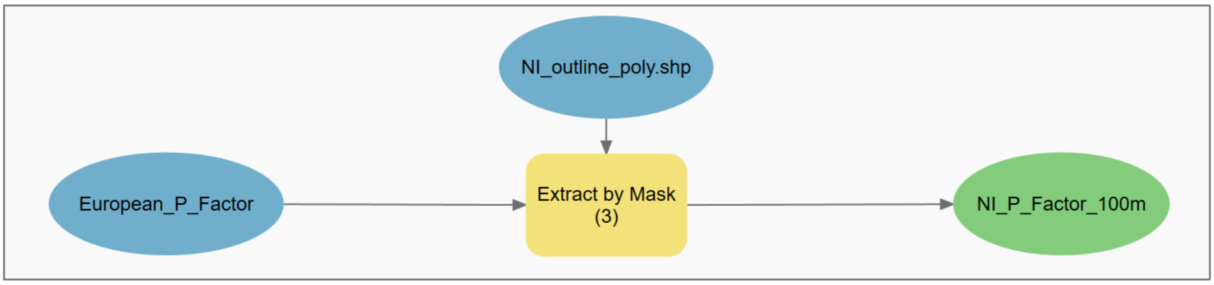
Figure 5: ArcGIS Pro Model for Producing C-Factor Raster



3.5 Soil Conservation Measures (P-Factor)

The P-factor raster of 100m resolution was obtained from the European Soil Data Centre and clipped to the study area (Panagos et al, 2015) (figure 6).

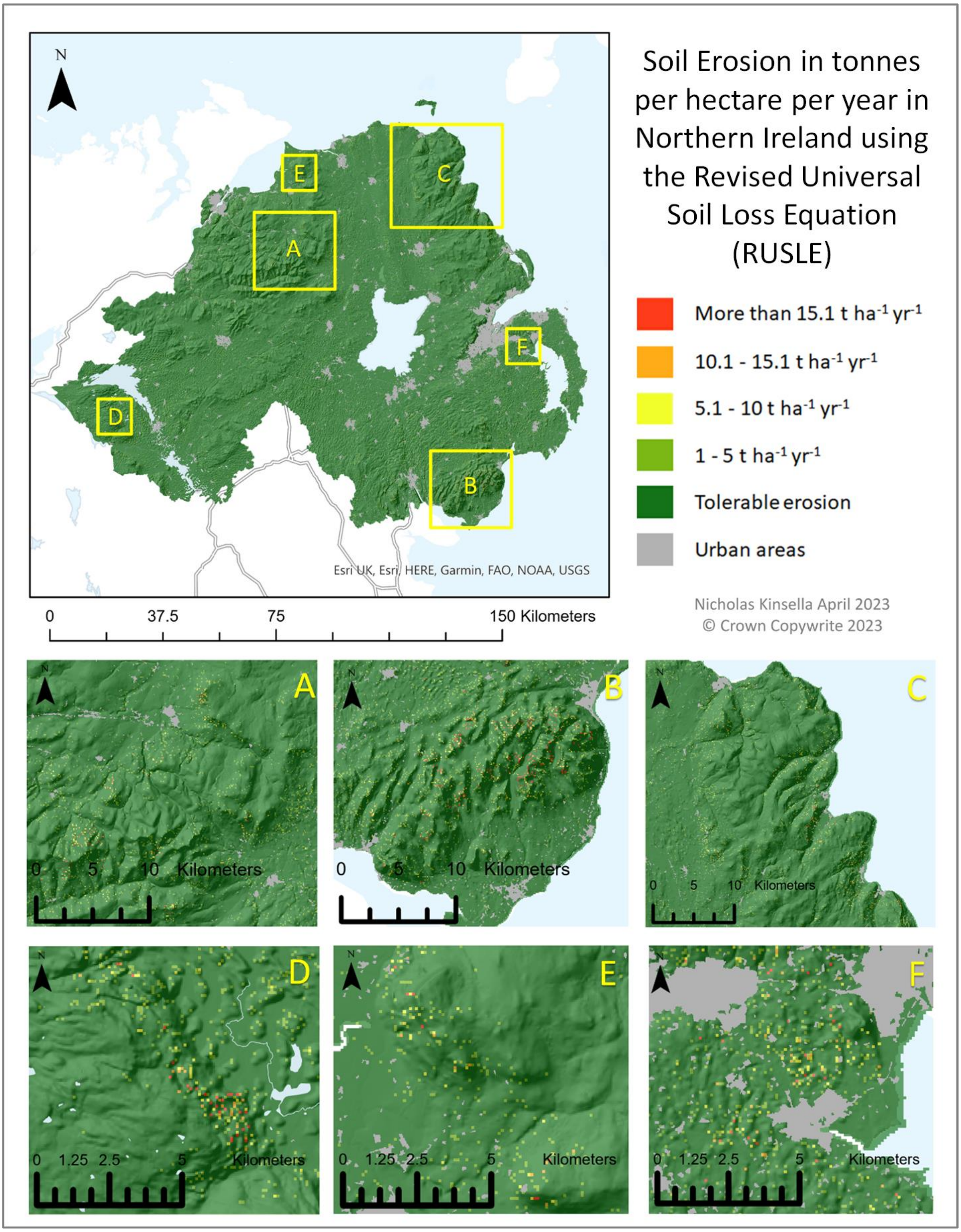
Figure 6: ArcGIS Pro Model for Processing P-Factor Raster



4. Results and discussion

Figure 7 shows the rate of erosion at the hectare resolution for Northern Ireland. The areas of concern were frequently located in the higher mountain ranges of Sperrin (A), Mourne (B) and Antrim (C). Outside of mountain ranges clusters of high erosion levels were found near the east-facing cliffs of Magho to the north-west of Enniskillen (D), the north-western Keenaght Hills (E) and an area to the east of Belfast at the northern end of Strangford Lough (F).

Figure 7: Areas of Intolerable Erosion in Northern Ireland
(Further detail of this map can be access via the web app here: https://tinyurl.com/yv4bpber)



4.1 Total erosion

Verheijen et al. (2009) described lower and upper limits of soil formation in Europe of between 0.3 and 1.4 t ha^{-1} yr^{-1}. 1 t ha^{-1} yr^{-1} was chosen as the breakeven point of soil loss where intolerable erosion begins. This was simplistic and if this analysis is expanded, erosion prone areas should be separated out by landcover type, lithology, and management practices to allow a distinction between areas that replenish quicker than others.

Total affected land areas were calculated and grouped according to erosion rate. The total area affected by intolerable erosion rates was 73,233ha which is half the size of London, England (Britannica. 2023).

Table 5: Soil loss in hectares grouped by rate of erosion.

Soil loss t ha^{-1} yr^{-1}	1-1.9	2-2.9	3-3.9	4-4.9	5-5.9	6-6.9
Area affected in ha	48122	12197	4723	2515	1496	950
Soil loss t ha^{-1} yr^{-1}	**7-7.9**	**8-8.9**	**9-9.9**	**10-14.9**	**≥15**	**Total area affected in ha**
Area affected in ha	639	435	352	933	871	73,233

From this it was estimated that the soil lost per year because of rainfall erosion was 158,501 1 t ha^{-1} yr^{-1}.

To provide a broader perspective on the erosion figures presented in this study, soil formation rates were investigated (as shown in table 6). Unfortunately, this study could not find any country-wide datasets of soil formation rates. Formation rates are highly dependent on local factors such as underlying lithologies, latitude, altitude, and vegetation type and as Verheijen et al. (2009) note, much more work is needed in this area. To estimate the total amount of new soil produced annually, Alexander's (1988) research on topsoil erosion rates and the landcover affecting them was used in conjunction with the study's landcover map. This analysis suggests that the total new soil produced per year is approximately 1,403,200 t yr−1.

Table 6: Soil formation rates by landcover type and estimated formation totals.

Land Cover type	Estimated soil formation rate t ha^{-1} yr^{-1}	Total area ha	Total soil formation t yr^{-1}
Deciduous woodland	0.3425	63,925	21,894
Coniferous woodland	0.7725	234,869	181,436
Arable land and grasslands	0.23	3,989,125	917,498
heather	1.90	98,789	187,699
heather grassland	1.065	88,895	94,673
		Total	1,403,200

The net figure for soil is +1,244,699 t yr^{-1} indicating rainfall erosion alone is not enough to degrade Northern Ireland's soils. However, soil erosion and more broadly soil degradation is affected by multiple factors beyond the scope of this analysis. RUSLE primarily focuses on rainfall erosivity as its mechanism for soil degradation. Some erosive forces not considered in RUSLE include wind erosion, the erosive effect of tilling soil as well as landslides (Alewell et al., 2019). Beyond simple erosive factors soil compaction using heavy machinery leads to a limiting of root growth and the reduction of the amount of water and nutrients available to plants. Loss of organic matter in the soil also impacts fertility and climate change affects weather patterns and temperatures (Huber et al., 2008; Gregory et al., 2015; Alewell et al., 2019)

4.2. RUSLE Analysis.

The USLE model was developed in the United States from decades of research made on small fields and watersheds. It served to evaluate management and cropping systems for mitigating soil erosion on these scales. This was partly because collecting data over wider areas than a few fields was not feasible (Alewell et al., 2019). Today advances in remote sensing and GIS, some of the limitations on acquiring and processing data at scale have been overcome with datasets for the specific R, K, LS, C, and P factors made publicly available for download (Jones et al., 2005; Panagos et al., 2015; Ballabio et al., 2015) and dozens of derivative versions of USLE exist including RUSLE used in this study which have served to make the model a more reliable predictor outside of its original narrower purview.

Without ground truthing surveys it is impossible to know how effective the RUSLE model was at predicting soil loss on the scale that this study attempted. What can be done is to assess each of the variables in the equation and see if their effect broadly conforms with what we know about the process of erosion.

12,907 random samples were taken from the data of cells with intolerable erosion. These were then statistically compared to the total erosion amount (table 7).

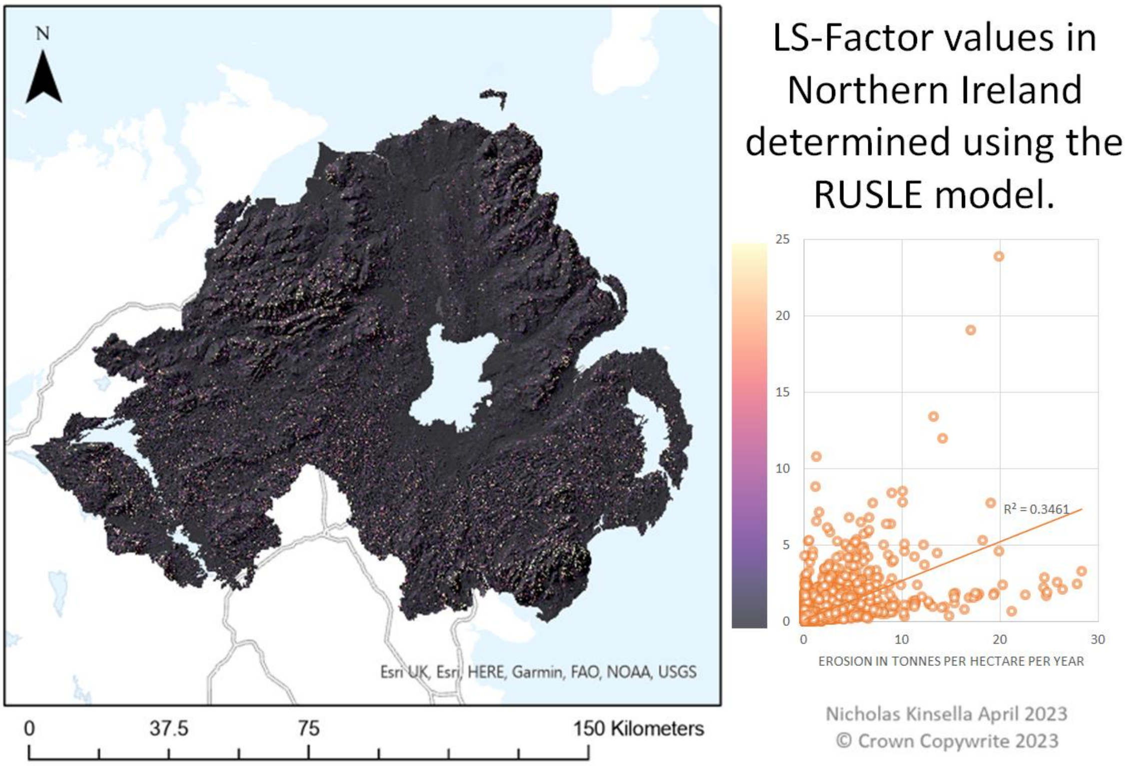
Table 7: RUSLE factors ranked by influence with the most influential to the left and least to the right.

Erosion level vs:	LS	K	C	R	P
R	0.588295	0.245872	0.179034	0.043145	-0.02406
R^2	0.346091	0.060453	0.032053	0.001862	0.000579

4.2.1 LS Factor Analysis

The most dominant factor is LS indicating that according to the RUSLE, soil erosion is most strongly affected by slope length and gradient. Figure 8 below shows high values clustered near mountainous terrain and a clear positive trend indicating that as slope length and steepness increases, so does erosivity as expected.

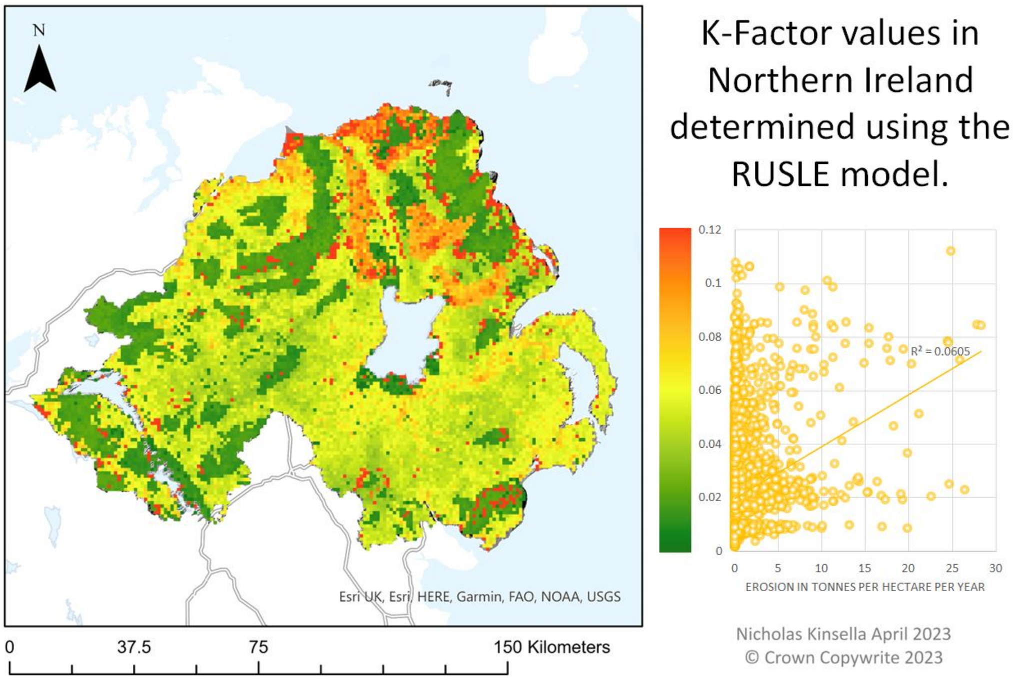
Figure 8: Slope Length and Steepness (LS factor) for Northern Ireland



4.2.2 K Factor Analysis

The second most dominant factor is K indicating that soil composition is an important ULSE element. Figure 9 shows a positive association between K and erosion levels although it is clear from the map that many areas with high K values in northern areas such as the Bann Valley were not flagged by RUSLE as areas of high erosion.

Figure 9: Soil Erosivity (K factor) for Northern Ireland:



Soil texture is an essential element of K. An analysis of the relative predictivity of sand, silt, clay, and organic matter to erosion suggests that erosion levels tend to decrease as the percentage of silt, clay, and organic matter increase, whereas the inverse is true for sand content, indicating the model considers sand to have a lower cohesive force compared to the other soil types, which it does (Wischmeier and Smith, 1978; Renard et al., 1996).

Table 8: Relative impact of soil texture and organic matter content on soil erosion.

	Silt %	Sand %	Clay %	Organic matter %
R	-0.08207061	0.094872721	-0.10242462	-0.037190674
R^2	0.006735585	0.009000833	0.010490804	0.001383146

A limitation of applying the RUSLE to Northern Ireland is its incompatibility with highly organic soils like peatlands (figure 10). The input raster had to be modified to remove this data. Even if RUSLE could accommodate these figures, it wouldn't have correctly modelled peatland erosion as the dominant factors in those environments are more related to freezing thawing actions (Li et al., 2018) which are not modelled by RUSLE.

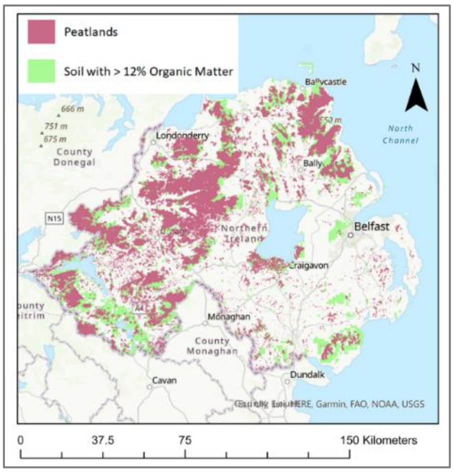
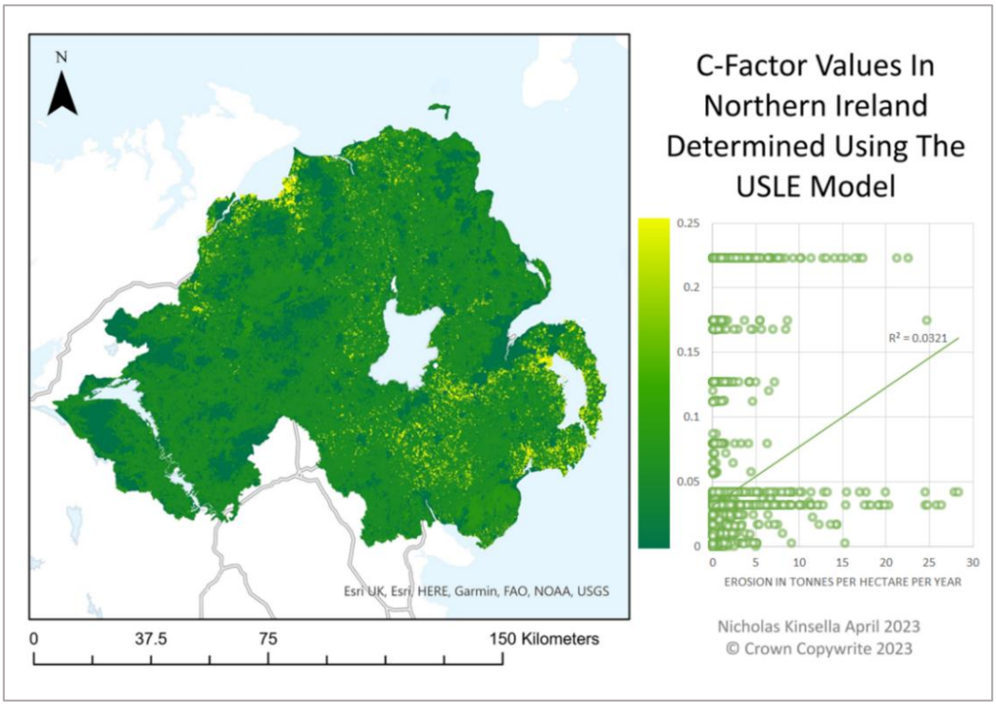


Figure 10: Peatlands of Northern Ireland Evans et al (2017) superimposed on soils with > 12% organic matter.

4.2.2 C Factor Analysis

The third most dominant factor is C. C is higher with less vegetation cover and Figure 11 shows a positive correlation indicating that less cover allows more erosion by rainfall, which makes sense (Zhou et al., 2008), although many areas with high erosion levels do not have correspondingly high C values.

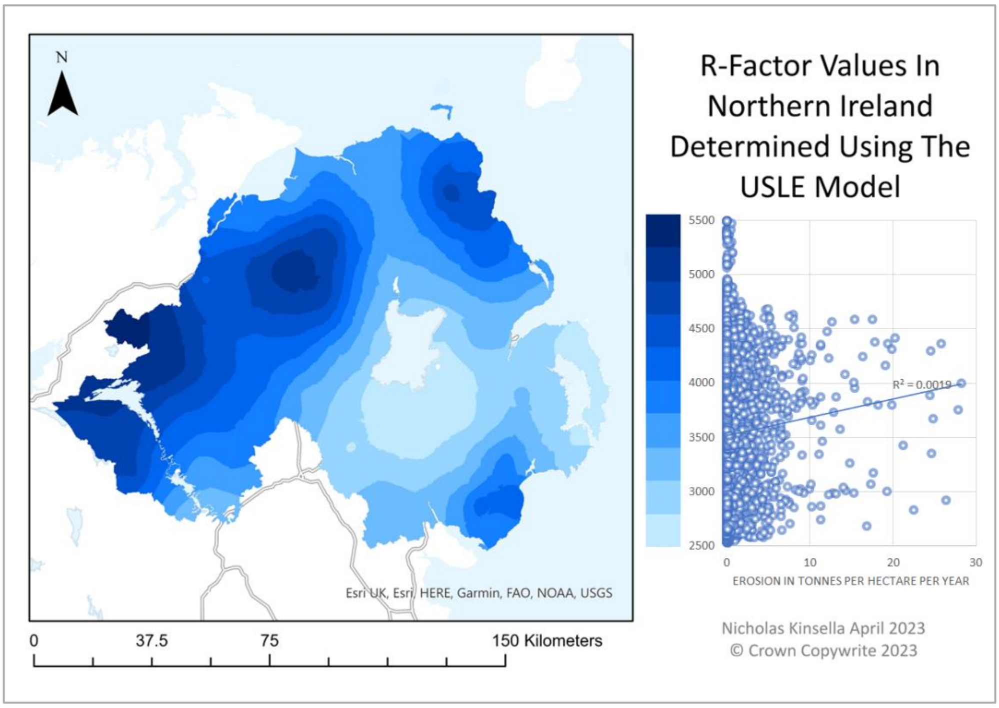
Figure 11: Cover (C factor) for Northern Ireland.



4.2.3 R Factor Analysis

Rainfall erosivity (figure 12) has a slight positive correlation and is higher in the mountains where a lot of erosion was predicted but statistical analysis indicates that it was a weak predictor of erosion levels overall, this may be due to these areas having good vegetation coverage as shown in figure 11.

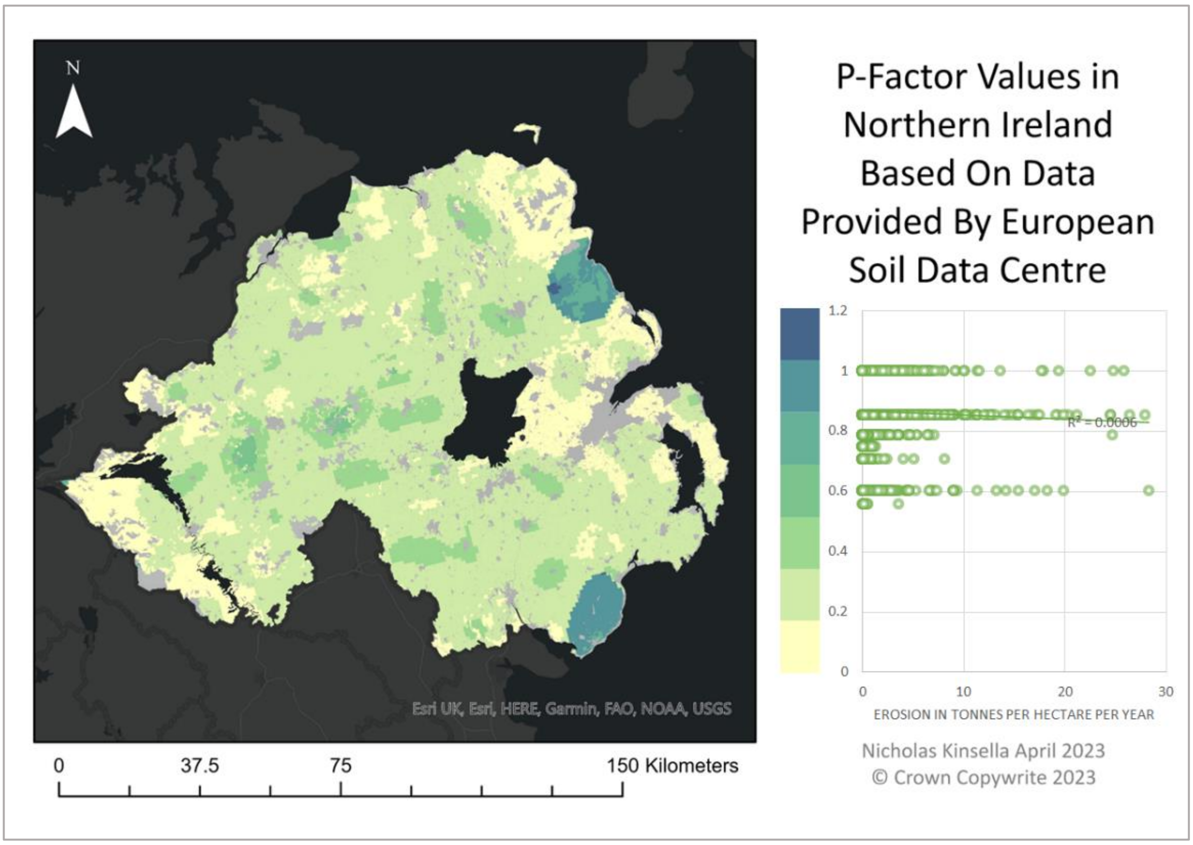
Figure 12: Rainfall (R factor) for Northern Ireland.



4.2.3 P Factor Analysis

P factor had by far the weakest correlation with erosion levels. This may be due to it being implemented where erosion is already a significant issue, its effect being cancelled out.

Figure 13: Soil conservation measures (P factor) for Northern Ireland



5. Conclusions and recommendations

Applying RUSLE to Northern Ireland using a GIS identified intolerable erosion levels in 73,233 hectares of land, with an estimated soil loss rate of 158,501 t ha^{-1} yr^{-1}. Particularly affected areas typically cluster around escarpments like those found in mountainous and hilly areas with soil texture and organic content playing an important secondary role. When compared to the total estimated soil formation rates, rainfall-based erosion as estimated by the RUSLE is not sufficient to degrade Northern Ireland's topsoil alone.

It is important to note that the RUSLE model is designed to estimate soil erosion caused by rainfall and associated factors. As such, it cannot be used in isolation to understand the environmental and economic impacts of soil degradation. Many other factors are at play such as compaction, and the loss of organic matter as well as mass movements. Nevertheless, the RUSLE has shown its ability to identify areas where rain-based soil erosion is expected. Reduction of soil erosion maintains the viability of our agricultural system and so the information that RUSLE can provide is vital for soil resource management in helping environmental managers decide where soil conservation work needs to take place.

Word count: 2,598

6. References

Alewell, C., Borrelli, P., Meusburger, K. and Panagos, P. (2019) 'Using the USLE: Chances, challenges and limitations of soil erosion modelling', International Soil and Water Conservation Research, 7(3), pp.203-225.

Alexander, E.B. (1988) Rates of soil formation: Implications for soil-loss tolerance. *Soil Science*, 145(1), 37-45.

Alisawi, H. A. O. (2016). Modeling Sewer Overflow of a City with a Large Floating Population. LAP LAMBERT Academic Publishing. ISBN: 978-3-659-94596-0, pp. 31-32.

Ballabio, C., Panagos, P., & Montanarella, L. (2016). Mapping topsoil physical properties at European scale using the LUCAS database. *Geoderma*, 261, 110-123. Available at: https://esdac.jrc.ec.europa.eu/content/topsoil-physical-properties-europe-based-lucas-topsoil-data

Brazier, R. (2004) Quantifying soil erosion by water in the UK: a review of monitoring and modelling approaches. *Progress in Physical Geography*, 28(3), pp.340-365.

Britannica. (2023). London. *Britannica Online*. Accessed 08 April 2023. Available at: https://www.britannica.com/place/London

Chen, T., Niu, Rq., Li, Px. et al. (2011). Regional soil erosion risk mapping using RUSLE, GIS, and remote sensing: a case study in Miyun Watershed, North China. Environmental Earth Sciences, 63(3), 533-541.

Department of Agriculture, Environment and Rural Affairs (DAERA). (2021): Crop yield and production estimates. Available at: https://www.daera-ni.gov.uk/publications/crop-yield-and-production-estimates [Accessed 30 March 2023].

de Roo, A., Jetten, V., Wesseling, C., Ritsema, C. (1998). LISEM: A Physically-Based Hydrologic and Soil Erosion Catchment Model. In: Boardman, J., Favis-Mortlock, D. (eds) *Modelling Soil Erosion by Water*. NATO ASI Series, vol 55. Springer, Berlin, Heidelberg.

Evans, C., Artz, R., Moxley, J., Smyth, M-A., Taylor, E., Archer, N., Burden, A., Williamson, J., Donnelly, D., Thomson, A., Buys, G., Malcolm, H., Wilson, D., Renou-Wilson, F. (2017). Implementation of an emission inventory for UK peatlands. Report to the Department for Business, Energy and Industrial Strategy. *Centre for Ecology and Hydrology*, pp88.

Fu, S., Cao, L., Liu, B., Wu, Z. and Savabi, M.R., (2015). Effects of DEM grid size on predicting soil loss from small watersheds in China. *Environmental Earth Sciences*, 73, pp.2141-2151.

Jones, R.J.A., Hiederer, R., Rusco, E., & Montanarella, L. (2005). Estimating organic carbon in the soils of Europe for policy support. *European Journal of Soil Science*, 56(5), 655-671. Available at: https://esdac.jrc.ec.europa.eu/content/octop-topsoil-organic-carbon-content-europe

Graves, A.R., Morris, J., Deeks, L.K., Rickson, R.J., Kibblewhite, M.G., Harris, J.A., Farewell, T.S., & Truckle, I. (2015). The total costs of soil degradation in England and Wales. *Ecological Economics*, 119, 399-413.

Gregory, A. S., Ritz, K., McGrath, S. P., Quinton, J. N., Goulding, K. W., Jones, R. J., Harris, J. A., Bol, R., Wallace, P., Pilgrim, E. S., & Whitmore, A. P. (2015). A review of the impacts of degradation threats on soil properties in the UK. *Soil Use and Management*, 31(Suppl 1), 1-15.

Huber, S., Prokop, G., Arrouays, D., Banko, G., Bispo, A., Jones, R.J.A., Kibblewhite, M.G., Lexer, W., Moller, A., Rickson, R.J., Shishkov, T., Stephens, M., Toth, G., van den Akker, J.J.H., Varallyay, G., Verheijen, F.G.A. & Jones, A.R. (eds) (2008). Environmental Assessment of Soil for Monitoring: volume

I, Indicators & Criteria. EUR 23490 EN/1. Office for the Official Publications of the European Communities, Luxembourg.

Li, C., Grayson, R., Holden, J., & Li, P. (2018). Erosion in peatlands: Recent research progress and future directions. *Earth-Science Reviews*, 185, 870-886.

Marston, C.; Rowland, C.S.; O'Neil, A.W.; Morton, R.D. (2022). Land Cover Map 2021 (25m rasterised land parcels, GB). *NERC EDS Environmental Information Data Centre*. Accessed: 30 March 2023. Available at: https://catalogue.ceh.ac.uk/documents/a1f85307-cad7-4e32-a445-84410efdfa70

Middleton, H.E., Byers, H.G. and Slater, C.S. (1934) 'The physical and chemical characteristics of the soils from the erosion experiment stations: second report', No. 430, *US Department of Agriculture.* Available at: https://pubs.rsc.org/en/content/articlelanding/1880/CT/CT8803700617

Office for National Statistics. (ONS) (2021). National population projections: 2020-based interim. Accessed: 6 April 2023. Available at: https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/populationprojections/bulletins/nationalpopulationprojections/2020basedinterim

Oldeman, L.R. (1992) Global extent of soil degradation. In: Bi-Annual Report 1991-1992, *International Soil Reference and Information Centre*, pp. 26.

Panagos, P., Borrelli, P., Meusburger, K., Alewell, C., Lugato, E., & Montanarella, L. (2015). Estimating the soil erosion cover-management factor at the European scale. *Land Use Policy*, 48, 38-50.

Panagos, P., Borrelli, P., Meusburger, K., van der Zanden, E.H., Poesen, J., & Alewell, C. (2015). Modelling the effect of support practices (P-factor) on the reduction of soil erosion by water at European scale. Environmental Science & Policy, 51, 23-34 Available from: https://esdac.jrc.ec.europa.eu/content/support-practices-factor-p-factor-eu

Renard, K. G., & Ferreira, V. A. (1993). RUSLE model description and database sensitivity. *Journal of environmental quality*, 22(3), 458-466

Renard, K. G., Foster, G. R., Weesies, G. A., McCool, D. K., & Yoder, D. C. (1996). Predicting soil erosion by water: A guide to conservation planning with the Revised Universal Soil Loss Equation (RUSLE). Agriculture Handbook, 703. Available from : https://www.ars.usda.gov/arsuserfiles/64080530/rusle/ah_703.pdf

Savory, A. (1994) 'Will We Be Able to Sustain Civilization?', *Population and Environment*, 16(2), pp. 139-147.

United Nations Convention to Combat Desertification (UNCCD). (2022). Global Land Outlook 2. Available from: https://knowledge.unccd.int/publications/global-land-outlook-2

United Nations Department of Economic and Social Affairs Population Division (UNDESA). (2023). Demographic Profiles: World Population Prospects. Accessed: 6 April 2023. Available from: https://population.un.org/wpp/Graphs/DemographicProfiles/900

Verheijen, F.G.A., Jones, R.J.A., Rickson, R.J., & Smith, C.J. (2009). Tolerable versus actual soil erosion rates in Europe. *Earth-Science Reviews*, 94(1-4), 23-38.

Warington, R. & Peake, W. A. (1880). LIII.—On the determination of carbon in soils. Journal of the Chemical Society, Transactions, 37(0), 617-625. Available from: https://pubs.rsc.org/en/content/articlelanding/1880/ct/ct8803700617

Wischmeier, W.H. and Mannering, J.V. (1969) Soil and Water Management and Conservation. Relation of Soil Properties to Its Erodibility. *Soil Science Society of America, Proceedings*, 33, 131-137.

Wischmeier, W.H. and Smith, D.D. (1978) Predicting rainfall erosion losses: a guide to conservation planning (No. 537). *Department of Agriculture, Science and Education Administration*. pp 8-10

Woldemariam, GW, Iguala, AD, Tekalign, S, and Reddy, RU. (2018). Spatial Modeling of Soil Erosion Risk and Its Implication for Conservation Planning: the Case of the Gobele Watershed, East Hararghe Zone, Ethiopia. *Land*, 7(1), 25.

Zhou, P., Luukkanen, O., Tokola, T., & Nieminen, J. (2008). Effect of vegetation cover on soil erosion in a mountainous watershed. Catena, 75(3), 319-325.

7. Appendices

Appendix 1: Entire Data Processing Workflow In ArcGIS Pro