Estimating organic layer depth for peat and peaty soils in an upland Scottish catchment using linear mixed models with topographic and geological covariates

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Running Title: [Estimating organic layer depth from topography and geology]

Abstract

In order to evaluate and protect ecosystem services provided by peat and peaty soils, accurate estimations for the depth of the surface organic layer are required. This study uses linear mixed models (LMMs) to test how topographic (elevation, slope, aspect) and superficial geology parameters can contribute to improved depth estimates across a Scottish upland catchment. Mean (n=5) depth data from 284 sites (representing full covariate ranges) were used to calibrate LMMs, which were tested against a validation dataset. Models were estimated using maximum likelihood, and the Akaike Information Criterion was used to test whether the iterative addition of covariates to a model with constant fixed effects was beneficial. Elevation, slope, and certain geology classes were all identified as useful covariates. Upon addition of the random effects (i.e. spatial modelling of residuals), the RMSE for the model with constant-only fixed effects reduced by 24%. Addition of random effects to a model with topographic covariates (fixed effects = constant, slope, elevation) reduced the RMSE by 13%, whereas the addition of random effects to a model with topographic and geological covariates (fixed effects = constant, slope, elevation, certain geology classes) reduced the RMSE by only 3%. Therefore much of the spatial pattern in depth was explained by the fixed effects in the latter model. The study contributes to a growing research base demonstrating that widely available topographic (and also here geological) datsets, which have national coverage, can be included in spatial models to improve organic layer depth estimations.

Keywords: **[Organic layer depth, topography, superficial geology, linear mixed model, Scotland]**

Introduction

Peat and peaty soils provide vital ecosystem services, including carbon storage, retention and regulation of sub-surface water, and support of biodiversity (Bonn et al., 2009; Minasny et al., 2019). Baseline information that describes this resource is required to better evaluate the benefits of these functions, and inform land management decisions so these soils are protected (e.g. Chapman et al., 2009). An important parameter to quantify in this process is the depth of the organic layer, which forms the peat or peaty soil. However, in upland landscapes this layer is highly variable and mapping its three-dimensional geometry over extensive areas is extremely challenging due to the unknown and irregular nature of the subsoil topography.

The Soil Survey of Scotland define peat as an organic soil, which contains more than 60% organic matter and exceeds 50 cm in depth (Soil Survey of Scotland, 1984). Peaty soils (also known as organo-mineral soils) are distinguished from peat if the organic horizon is shallower than 50 cm (Soil Survey of scotland, 1984; Smith et al., 2007). They include soils such as peaty rankers, peaty gleys and peaty podzols. These shallower peaty soils extend over large areas, covering 43% of Scotland's land surface (Bruneau & Johnson, 2014), which is almost double the 22% covered by peat (Chapman et al., 2009). With this extensive cover, peaty soils in Scotland have been estimated to represent a carbon store of 754 Mt (Bradley et al., 2005), contributing significantly to national soil carbon stocks. It is therefore important that approaches to understand the variation in organic layer depth include peaty soil types as well as peat, in order to help inform land management decisions.

Manual methods (e.g. closely-spaced depth probing and ground penetrating radar) are often used to measure organic layer depth, but are not practical over large areas (Gatis et al., 2019). Recent work has therefore focused on utilising information from digital elevation models (DEMs). Organic soils form under waterlogged conditions, where decomposition of organic material is slower than accumulation. Such conditions are influenced by spatial variations in drainage and moisture input, which are dependent upon topography. This is because slope influences surface and subsurface hydrological pathways and elevation influences factors such as temperature and rainfall. Relationships between slope, elevation and organic layer depth have been used successfully to estimate blanket peat thickness in the Wicklow Mountains, Ireland (Holden & Connolly, 2011) and across land units with different soil and vegetation classifications in Dartmoor, south-west England (Parry et al., 2012; Young et al., 2018). Aspect has also been linked to blanket peat location and peat erosion (Graniero & Price, 1999; Foulds & Warburton, 2007), and has been suggested as a potential factor which could influence local precipitation received over blanket peat (Parry et al., 2012).

Airborne gamma radiometrics are another data source that have been used to infer peat thickness, because peat attenuates naturally occurring radiation emitted from underlying bedrock (Gatis et al., 2019). However, such surveys have limited ability to infer peat thicknesses that are >50 cm (the required depth for classification of peat in Scotland), and the radiometric signal can vary with bedrock type (Minasny et al., 2019). Additionally, while national radiometric surveys have been carried out in some countries (e.g. Airo et al., 2014), more limited data coverage elsewhere currently prevents wider application of the approach.

This study explores the use of linear mixed models (LMMs), with topographic (elevation, slope, aspect) and superficial geology covariates, derived from datasets with UK-wide coverage, to estimate organic layer depth across a catchment in upland western Scotland. LMMs are often used in model-based geostatistical studies (e.g. Lark et al., 2006; Rawlins et al., 2009) and divide the variation of calibration data into fixed and random effects. The fixed effects are a linear function of environmental covariates, and the random effects describe spatially correlated fluctuations in the soil property that cannot be explained by the fixed effects. Superficial geology (formerly known as 'drift') maps describe the nature of the near-surface geology (usually formed by unconsolidated sediments). Superficial geology classes are included in this study as a potential fixed effect because they are characterised by materials or depositional processes that may influence peat forming conditions (e.g. susceptibility to waterlogging). A further motivation for testing the use of superficial geology data is that 1:50,000 scale British Geological Survey (BGS) DiGMapGB-50 data (BGS, 2016) has national coverage and could therefore be used more widely to contribute to organic layer depth estimates.

Setting

The study was undertaken in the 9.2 km^2 Gleann a' Chlachain catchment, which forms part of Scotland's Rural College's (SRUC) Hill and Mountain Research Farm, in the western central Scottish Highlands, UK (Fig. 1, S1A). Gleann a' Chlachain ranges in elevation from 265 m above sea level (a.s.l.) at the outlet in the south, to 1025 m a.s.l. at the highest point, on the summit of Beinn Challuim.

The geology and geomorphology of the catchment is representative of larger expanses of the western central Scottish highlands. The bedrock belongs to the Ben Lui and Ben Lawers Schist formations, which generally consist of pelites and semipelites with minor amounts of psammite (BGS, 2004). The surface geomorphology is a mix of exposed bedrock on ridges and some upper slopes, with glacial, fluvial and slope deposits mantling the mid and lower slopes and the valley floor (BGS, 2012). The national soil map of Scotland (Soil Survey of Scotland Staff, 1981) indicates the catchment is predominantly covered by peaty gleyed podzols and peaty gleys, with the upper slopes of Ben Challuim and Beinn Chaorach being covered by dystrophic blanket peat and subalpine podzols.

Superficial Geology Classes

In this study the superficial geology classes within the catchment are used as categorical variables in the modelling (Fig. 2A). These classes are adapted from published superficial geology map data (BGS, 2012), and are defined by surface morphology and subsurface materials. The classes are listed below (further descriptions are given in Table S1 of the Supporting Information, and McMillan et al., 1999).

- **Bedrock**: areas where unconsolidated sediment cover is interpreted to be thin (<1 m) or absent.
- **Till and colluvium**: generally comprises poorly-sorted, dense clayey or silty sand with gravel and rare boulders, mantling mid- and lower-valley slopes.
- **Moraines**: areas of broad mounds comprising poorly-sorted clayey or silty sand with gravel and frequent boulders, and intervening basins with finer grained sediments.

- **Talus slopes and solifluction lobes**: an openwork accumulation of gravel, with a sandy matrix at depth, occupying the upper slopes of Ben Challuim.
- **Alluvium**: sorted cobbles, gravel, and sand adjacent to the river.
- **Peat**: BGS maps include peat as an organic deposit where it is interpreted to be 1 m or more in thickness.

Methods

Sampling design and field measurements

The NEXTMap Britain (Intermap Technologies) digital elevation data were subsampled at 10 m resolution and used to derive slope and aspect values. Organic layer depth sampling was undertaken at 323 locations; measurements from 283 of these sites were used to calibrate the LMMs and the remaining locations were used for validation (Fig. 1B). A stratified sampling approach ensured that covariates were represented across their full ranges within the calibration and validation datasets (Fig. 2), in line with recent recommendations (Young et al., 2018).

Depth was measured by pushing probes into the organic layer until they met resistance at the surface of the underlying mineral layer or rock. Exposed sections in the field revealed that the base of the organic layer was characterised by a sharp boundary, which was easily detected by the probes (Fig. S1B). At each of the sample locations, five depth measurements were taken: one at a central point and four at corners 2.5 m from the centre. This was carried out to account for the local (sampling site scale) variability caused by undulations at the surface of the bedrock or mineral layer (e.g. Fig. S1B), and to reduce any potential impact of obstructions causing measurements to under represent the true depth (Parry et al., 2012; 2014). The average of the five points was used in the statistical modelling. Data were recorded into an attribute table in ARCGIS in the field using a rugged tablet computer with an inbuilt GPS, which with an accuracy of approximately 3 m, was considered to be suitable for making predictions with 10 m resolution (differential GPS would have allowed investigation with a higher resolution DEM).

Statistical Analyses

A model-based geostatistical approach consisting of LMMs was used to both model the relationship between the organic layer depth measurements and the covariate information, and to map organic layer depth across the catchment. The model-based approach was required when calibrating relationships with covariates because the data were not collected according to a simple random design and therefore it was necessary to account for spatial correlation amongst the data (Brus & de Gruijter, 1997). Many authors have recently adopted a machine learning approach when utilising covariate information to map soil properties (Hengl et al, 2018). However, such approaches can lead to complex models which are not easily interpretable.

Instead this study represents the variation of organic layer depth by the LMM:

$$\mathbf{z}(\mathbf{x}) = \mathbf{M}\boldsymbol{\beta} + \boldsymbol{\epsilon}, \quad (1)$$

where $\mathbf{z}$ is a length $\boldsymbol{n}$ vector of observations, $\mathbf{x}$ is a length $\boldsymbol{n}$ vector of locations where the observations were made, $\mathbf{M}$ is a $\boldsymbol{n} \times \boldsymbol{p}$ matrix containing the values of $\boldsymbol{p}$ spatially varying covariates (elevation, slope, aspect, superficial geology) at each of the observation locations, $\boldsymbol{\beta}$ is a length $\boldsymbol{p}$ vector of regression coefficients and $\boldsymbol{\epsilon}$ is a length $\boldsymbol{n}$ vector containing the spatially correlated residuals at each sampling location. The $\mathbf{M}\boldsymbol{\beta}$ are referred to as fixed effects and the $\boldsymbol{\epsilon}$ as random effects. The fixed effects are a linear function of the covariates. The random effects are assumed to be realized from a multivariate Normal distribution with zero mean and covariance matrix $\mathbf{C}$. The elements of $\mathbf{C}$ are calculated from a covariance function that relates the covariance between the residual term for a pair of observations to the distance between the observation locations. Here, the Matérn function was used (Minasny & McBratney, 2005) because of the flexibility in how it behaves for small distances.

Marchant (2018) described how regression coefficients and parameters of the covariance function can be estimated by maximum likelihood. This approach uses a numerical optimization procedure to determine parameter values that maximize the probability that observed data would have arisen from the proposed model. This probability is referred to as the likelihood.

Some caution is needed when deciding which covariates to include as fixed effects. If too many covariates are included there is a danger of the model being over fitted. If an additional covariate is added to an existing LMM then the resultant maximised likelihood will be at least as large as that from the existing linear model since this likelihood could be achieved by setting the new regression coefficient to zero. Thus increased likelihood is not sufficient evidence to indicate that an additional covariate should be included.

The Akaike Information Criterion (AIC; Akaike, 1973) was used to compare models with different numbers of covariates and to decide which model was the most parsimonious representation of the data. The AIC is defined as:

$$\mathbf{AIC} = \mathbf{2}\boldsymbol{k} - \mathbf{2}\boldsymbol{L}, \qquad (2)$$

where $\boldsymbol{k}$ is the number of parameters in the model and $\boldsymbol{L}$ is the logarithm of the maximised likelihood. The preferred model is the one with the smallest AIC value. This model is thought to be the best compromise between quality of fit (likelihood) and complexity (number of parameters).

Initially LMMs with constant fixed effects were estimated by setting $\mathbf{M}$ as a vector of ones. Covariates were added iteratively and tested for a decrease in AIC and better fit. Models were first tested utilising the topographic covariates. Once the individual covariates that led to the smallest AIC were determined, models with two or more topographic covariates and products of covariates were tested. Finally, adjustments to the fixed effects were made if sampling locations were situated within specified superficial geology classes, and the models were tested for further improvements. Continuous variables (e.g. elevation, slope) were added by including those variables as columns of $\mathbf{M}$. Since the aspect is a cyclic property, the sine and cosine of the aspect were each added as new columns of $\mathbf{M}$. The superficial geology classes were included as categorical variables with a one indicating that the class is present at a location and a zero that it is absent.

Once the optimal model had been identified and calibrated, the empirical best linear unbiased predictor (often referred to as regression kriging) was used to predict organic layer depth across the catchment (Lark et al., 2006). These predictions included the influence of the covariates and the spatial correlation of the organic layer depth measurements.

Each model was fitted using just the calibration data and the expected organic layer depth was predicted at the validation locations using (i) just the fixed effects and (ii) the entire LMM. Since the set of validation data only consists of 40 observations, a 10-fold cross-validation procedure was also conducted. Here, the entire dataset (including both calibration and validation observations) were randomly allocated to 10 groups or folds. Each fold was treated as a validation dataset and the remaining nine folds as calibration data.

Results

Peat depth observations

The observed organic layer depths are summarized in Table 1. The mean depth measured across the catchment was 30.9 cm, with a high standard deviation of 34.7 cm. The maximum depth (303 cm) was measured in the area classified as peat. The mean depth measured in this category was 75.6 cm, which is less than the 1 m that is assumed in BGS geology maps. The shallowest organic layers were measured over the areas classified as solifluction lobes and talus slopes.

Local-scale depth variability was represented by the five measurements taken at each sample site (Fig. S2). The average variation in depth resulting from local irregularities of the mineral-organic interface was 10-15 cm or less for all of the classes except peat, which was slightly higher. However, when considered as a percentage of the local mean depth, the local variation is smallest in the peat class and largest in the solifluction and talus class (Fig. S2B).

Statistical modelling

The overall distribution of depth measurements is highly skewed (skewness=3.48) and inconsistent with the Gaussian assumptions of a LMM (Figure 3A). Therefore the logarithm of organic layer depth plus one was used for modelling the spatial variation in depth (Figure 3B). The skewness of this variable is -0.74. Figure 4 shows a spatial plot of log transformed organic layer depths, and Figure 5 shows these depth values alongside the topographic variables. The results of the LMMs using different combinations of predictors are given in Table 2. Errors upon validation are shown both for the fixed effects only and where random effects are included in the predictions.

The LMM with constant fixed effects led to an AIC value of 737.85. When an elevation term was added, the AIC reduced to 734.02 and the fixed effects suggested that organic layer depth decreased with elevation (Figs. 5A,6A). Addition of a slope term to the constant model led to a larger reduction in AIC than for the constant plus elevation model, and suggested that peat depth decreases with slope (Figs. 5B,6B). The fixed effects of the LMM with the constant plus aspect term suggested a small increase in organic layer depth on north-facing slopes (Fig. 6C); however, this model had a higher AIC than the constant-only model indicating that aspect was not a beneficial parameter. Overall, when only the topographic covariates were considered, the lowest AIC (709.18) was achieved when the fixed effects included a constant, an elevation and a slope term (Fig. 7A).

The AIC values reduced further when adjustments for locations within individual superficial geology classes were combined with the topographic covariates. Separate LMMs where the fixed effects included an adjustment for the peat, alluvium, and talus and solifluction classes all produced lower AICs than models based solely on topographic covariates. However, addition of adjustments for the moraine, till and colluvium, and bedrock classes, each resulted in a higher AIC than the topographic covariates alone. A final model was therefore produced with fixed effects including a constant, an elevation and slope term, and adjustments for locations in the peat, alluvium, and talus and solifluction classes. This model achieved the lowest AIC value (678.61) and the fixed effects suggested that organic layer depths decreased with slope and elevation, increased in the peat geology class, and decreased in the alluvium and talus and solifluction classes (Figure 7B).

All the models had small mean errors upon validation and were approximately unbiased. The RMSE generally decreased in line with the improvements in AIC. For the models with solely topographic fixed effects, there was an 11-30% reduction in RMSE when the random effects were included in predictions. This indicates that a substantial proportion of the spatial pattern in the data was still not explained by the covariates. When random effects were included in the model with the lowest AIC (Fig. 9C), which included topography terms and adjustments for certain geology classes, the improvement in RMSE in the predictions was reduced to 3%. Therefore more of the spatial pattern was explained by the fixed effects. The output of this model, with depths shown in cm, is shown in Figure 8.

Similar results are seen upon 10-fold cross-validation (Table S2). The errors for the entire dataset are slightly larger than those for the validation dataset reflecting that depths in the validation set have relatively low variability. The same pattern of improvements in errors upon the addition of covariates is observed, with the largest decrease in errors occurring upon the addition of the slope information. Again, the most accurate fixed effects model results from including slope, elevation and three geological classes, and the addition of random effects only leads to a small further improvement.

Discussion

Previous studies have demonstrated that slope and elevation can be used as explanatory variables to inform peat depth estimates (Holden & Connolly, 2011; Parry et al., 2012). The LMMs in this study also indicate that slope and elevation are beneficial parameters for explaining spatial variations in organic layer depth. The LMMs suggest that organic layer depth decreases with altitude in Glean a' Chlachain. This pattern is consistent with the relationship observed by Holden & Connolly (2011) in the Wicklow Mountains, but is opposite to the positive depth-elevation relationship observed over Dartmoor (Parry et al., 2012). This could be due to two reasons. First, the Wicklow Mountains and Glean a' Chlachain rise to higher elevations than Dartmoor; therefore the associated lower temperatures at these sites may play a more important role in limiting growth of peat forming vegetation. At some elevated locations freeze-thaw processes will also loosen the soil and any underlying sediment, influencing drainage. Second, the hypsometry (proportion of surface area at different elevations) of sites could be important. The flatter summits at higher elevations in Dartmoor contrast with narrower, steep-sided summits and ridges which dominate the higher elevations in the Wicklow Mountains and Glean a' Chlachain, (where glacial erosion has played a greater role in shaping the landscape). These contrasts may affect the nature of organic layer depth and elevation relationships and would need to be considered in up-scaled estimates.

This work only considered basic topographic variables (elevation, slope, aspect). Additional topographic derivatives may also be beneficial in estimation of organic layer depth. Aitkenhead (2017) identified slope curvature as an input variable that has an effect on the predicted presence of peat in Scotland. In British Columbia, Scarpone et al. (2017) found that topographic roughness, valley bottom flatness, and ridge top flatness were all important variables in predicting exposed bedrock. These types of variables could therefore be associated with the presence or absence, and potential thickness of an organic layer.

The inclusion of certain superficial geology classes to the topography-only model reduced the RMSE of the fixed effects and lowered the proportion of spatial variation that needed to be explained by the random effects. These models suggested that organic layer depth decreased over the alluvium and the talus and solifluction classes. This could be because the sediments in these deposits (cobbles, gravel and sand) are characterized by intergranular water flow with high permeability indices (Lewis et al., 2006). Such conditions would reduce waterlogging, promoting less favorable conditions for peat formation. The remaining superficial geology classes comprise materials that are characterised by mixed (intergranular and fracture) flow with low permeability indices (Lewis et al., 2006). The LMMs also suggested that depths increased over the peat category (which is expected since these areas had been interpreted to contain peat >1 m in depth). As the superficial geology underneath peat is not shown on geological maps, this is more difficult to explain in terms of the geological properties. In places (e.g. where peat basins are surrounded by moraines) very low permeability silts and clays may be present below the peat.

Given that national coverage of superficial geology maps exist at scales of 1:50,000 or higher, the identification of superficial geology as a beneficial variable is valuable, as data could be used to aid depth predictions elsewhere. Information from soil or land cover maps has not been used in this work; however, these datasets have been incorporated in recent models that successfully map the occurrence of peat in Scotland (Aitkenhead, 2017). Soil and land cover maps are available at a national scale in Scotland (Soil Survey of Scotland Staff, 1981; MLURI, 1988), and future investigations could also test these parameters as covariates for estimating organic layer depth.

The study provides an example where the depth of the organic surface layer across the entire catchment has been modelled at high spatial resolution, and includes areas of both peat and peaty soil. The complex mix of peat and shallow peaty soil types in the landscape is considered a challenge for the assessment of carbon stocks (Chapman et al., 2009). Presenting continuous depth estimations for the organic layer offer a way to visualize this mix (Fig. 8), potentially enabling more detailed mapping of carbon stocks, which could inform how ecosystem services across different parts of a landscape are valued. Recent analyses from environmental impact assessments in Scotland have identified limitations in the existing practices of peat depth reporting (Wawrzyczek et al., 2018). The approach adopted here could contribute to improvements, particularly where decisions are made at a catchment scale. This information is also relevant for land management where knowledge of peat depth informs decisions, such as forest establishment or siting upland infrastructure (Scottish Government, 2013; Forestry Commission 2017). Presenting peat depth in this way could also be of benefit for assessing peat landslide hazards, where depth is an important parameter (Scottish Government, 2017).

Figure 8 shows the modelled organic surface layer depths with contours indicating the 10 cm, 40 cm, and 50 cm intervals. This information enables identification of areas that would be classified as peat under different schemes. For example, in England and Wales, soils are classified as peat where the organic layer is >40 cm deep (Avery, 1980), and the World Soil Reference Base for Soil Resources (WRB) and USDA taxonomy also use >40 cm as a condition for classification of histosols. Interestingly, using the 40 cm criteria would triple the area classified as peat in Gleann a' Chlachain (from 0.245 sq km to 0.721 sq km). The future development of up-scaled maps that can be readily transferred between different classification schemes may therefore be useful, for example in developing coherent international estimates relating to peat deposits (e.g. Tanneberger et al., 2017).

Conclusion

There is a growing body of work that demonstrates topographic parameters can be used to help estimate blanket peat depth. The LMMs in this study provides one of the first examples demonstrating that these covariates are beneficial for estimating organic layer depth for peat and peaty soils in upland Scotland – a country with > 60 % cover of these soil types, and which contains the largest proportion of UK soil carbon stocks (Bradley et al., 2005; Bruneau & Johnson, 2014). This work has also shown that widely available superficial geology map data has potential to be included as covariate data. The model outputs could help inform land management decisions, particularly where detailed depth estimates are required over large upland sites or catchment scales.

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TABLES

Table 1. Summary statistics for organic layer depth from calibration sites across Gleann a' Chlachain.

Class	n	Mean (cm)	Median (cm)	Standard deviation (cm)	Minimum (cm)	Maximum (cm)
All	283	30.9	22.1	34.7	0	303
Peat	30	75.6	52.3	67.5	15.2	303
Alluvium	30	23.3	22.4	17.9	0	72.6
Talus slopes and solifluction lobes	30	4.7	1.2	6.6	0	22.4
Moraines	38	40.5	21.2	36.3	7	151
Till and colluvium	66	32	27.6	19.5	2.7	86
Bedrock	89	22.4	16	19.1	0	94.4

Table 2. Log-likelihood (L), AIC, mean error upon validation of the fixed effects (FE ME), root mean squared error upon validation of the fixed effects (FE RMSE), mean error upon validation of the linear mixed model (LMM ME), root mean squared error upon validation of the linear mixed model (LMM RMSE), and reduction in RMSE upon inclusion of the random effect for each estimated linear mixed model. All units of errors are $\log_e$ (cm) unless otherwise stated. Predictors are: co constant, el elevation, as aspect, pe peat geology class, al alluvium geology class, ta talus and solifluction geology class, mo moraine geology class, ti till and colluvium geology class, br bedrock geology class.

Predictors	L	AIC	FE ME	FE RMSE	LMM ME	LMM RMSE	LMM RMSE reduction (%)	LMM RMSE (cm)
co	-367.92	737.85	-0.35	0.96	0.01	0.73	23.96	22.12
co+el	-365.01	734.02	0	0.81	0.01	0.72	11.11	22.04
co+sl	-353.73	711.47	-0.45	0.88	-0.03	0.62	29.55	18.39
co+as	-367.86	741.72	-0.35	0.95	0.01	0.73	23.16	22.3
co+el+sl	-351.59	709.18	-0.11	0.72	-0.03	0.61	15.28	18.6
co+el+sl+el×sl	-350.68	709.36	-0.13	0.71	-0.02	0.6	15.49	18.85
co+el+s+as	-350.66	711.32	-0.11	0.69	-0.02	0.6	13.04	17.73
co+el+sl+pe	-346.64	701.27	-0.12	0.66	-0.01	0.59	10.61	16.91
co+el+sl+al	-343.73	695.45	-0.2	0.69	-0.04	0.6	13.04	19.21
co+el+sl+ta	-345.62	699.25	-0.11	0.68	0	0.62	8.82	18.64
co+el+sl+mo	-351.1	710.2	-0.11	0.73	-0.03	0.61	16.44	19.1
co+el+sl+ti	-350.33	708.65	-0.1	0.72	-0.02	0.63	12.50	19.6
co+el+sl+br	-351.15	710.29	-0.1	0.73	-0.02	0.61	16.44	18.96
co+el+sl+pe+al+ta	-333.3	678.61	-0.17	0.6	0	0.58	3.33	16.8

FIGURE CAPTIONS

Figure 1. (A) Location of Gleann a Chlachainn catchment in western Scotland. (B) Catchment map together with sampling sites. Yellow circles are the sites used for model calibration and red circles are the sites used for validation. Position 'X' marks the location from where the photograph in Figure S1A (Supporting Information) was taken. The elevation plot in (A) and the hillshade base map in (B) were built from Intermap Technologies NEXTMap Britain elevation data.

Figure 2. Plots of (A) superficial geology classes, (B) elevation, (C) slope angle, and (D) aspect in the Gleann a' Chlachain catchment. Representative organic soil depth sampling was carried out across each superficial geology class and across the topographic variables. The topographic variables were derived from Intermap Technologies NEXTMap Britain elevation data.

Figure 3. Histograms showing (A) observed organic layer depth measurements and (B) observed $\log_e$ (organic layer depth+1).

Figure 4. Spatial pattern of observed $\log_e$ (organic layer depth+1). Coordinates are relative to (235787, 730277).

Figure 5. The relationship between organic layer depth and (A) elevation, (B) slope, (C) the sine of aspect, and (D) the cosine of aspect.

Figure 6. Predicted $\log_e$ (organic layer depth+1) according to fixed effects consisting of: (A) a constant and elevation, (B) a constant and slope, and (C) constant and aspect. Units are $\log_e$ (cm). Coordinates are relative to (235787, 730277).

Figure 7. Predicted $\log_e$ (organic layer depth+1) according to fixed effects consisting of: (A) a constant, slope and elevation; and (B) a constant, slope, elevation, and of peat,

alluvium and talus and solifluction geology classes. (C) Predicted $\log_e$ (organic layer depth+1) according to a linear mixed model where fixed effects are a constant, slope, elevation, and presence of peat, alluvial deposits and talus and solifluction superficial geology classes. Units are $\log_e$ (cm).

Figure 8. Predicted organic layer depth (in cm) across the catchment. Thick contour lines are shown at 50 cm (white), 40 cm (black), and 10 cm (light grey).