

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

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10

11 **Abstract**

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

32

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

35

36 **Introduction**

37 Peat and peaty soils provide vital ecosystem services, including carbon storage,
38 retention and regulation of sub-surface water, and support of biodiversity (Bonn et al.,
39 2009; Minasny et al., 2019). Baseline information that describes this resource is
40 required to better evaluate the benefits of these functions, and inform land management
41 decisions so these soils are protected (e.g. Chapman et al., 2009). An important
42 parameter to quantify in this process is the depth of the organic layer, which forms the
43 peat or peaty soil. However, in upland landscapes this layer is highly variable and
44 mapping its three-dimensional geometry over extensive areas is extremely challenging
45 due to the unknown and irregular nature of the subsoil topography.

46

47 The Soil Survey of Scotland define peat as an organic soil, which contains more than
48 60% organic matter and exceeds 50 cm in depth (Soil Survey of Scotland, 1984). Peaty
49 soils (also known as organo-mineral soils) are distinguished from peat if the organic
50 horizon is shallower than 50 cm (Soil Survey of Scotland, 1984; Smith et al., 2007).
51 They include soils such as peaty rankers, peaty gleys and peaty podzols. These
52 shallower peaty soils extend over large areas, covering 43% of Scotland's land surface
53 (Bruneau & Johnson, 2014), which is almost double the 22% covered by peat (Chapman
54 et al., 2009). With this extensive cover, peaty soils in Scotland have been estimated to
55 represent a carbon store of 754 Mt (Bradley et al., 2005), contributing significantly to
56 national soil carbon stocks. It is therefore important that approaches to understand the
57 variation in organic layer depth include peaty soil types as well as peat, in order to help
58 inform land management decisions.

59

60 Manual methods (e.g. closely-spaced depth probing and ground penetrating radar) are
61 often used to measure organic layer depth, but are not practical over large areas (Gatis
62 et al., 2019). Recent work has therefore focused on utilising information from digital
63 elevation models (DEMs). Organic soils form under waterlogged conditions, where
64 decomposition of organic material is slower than accumulation. Such conditions are
65 influenced by spatial variations in drainage and moisture input, which are dependent
66 upon topography. This is because slope influences surface and subsurface hydrological
67 pathways and elevation influences factors such as temperature and rainfall.
68 Relationships between slope, elevation and organic layer depth have been used
69 successfully to estimate blanket peat thickness in the Wicklow Mountains, Ireland
70 (Holden & Connolly, 2011) and across land units with different soil and vegetation
71 classifications in Dartmoor, south-west England (Parry et al., 2012; Young et al., 2018).
72 Aspect has also been linked to blanket peat location and peat erosion (Graniero & Price,
73 1999; Foulds & Warburton, 2007), and has been suggested as a potential factor which
74 could influence local precipitation received over blanket peat (Parry et al., 2012).

75

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

84

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

101

102 **Setting**

103 The study was undertaken in the 9.2 km² Gleann a’ Chlachain catchment, which forms
104 part of Scotland's Rural College's (SRUC) Hill and Mountain Research Farm, in the
105 western central Scottish Highlands, UK (Fig. 1, S1A). Gleann a’ Chlachain ranges in
106 elevation from 265 m above sea level (a.s.l.) at the outlet in the south, to 1025 m a.s.l.
107 at the highest point, on the summit of Beinn Challuim.

108

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

119

120 *Superficial Geology Classes*

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

126

- 127 • **Bedrock:** areas where unconsolidated sediment cover is interpreted to be thin
128 (<1 m) or absent.
- 129 • **Till and colluvium:** generally comprises poorly-sorted, dense clayey or silty
130 sand with gravel and rare boulders, mantling mid- and lower-valley slopes.
- 131 • **Moraines:** areas of broad mounds comprising poorly-sorted clayey or silty sand
132 with gravel and frequent boulders, and intervening basins with finer grained
133 sediments.

- 134 • **Talus slopes and solifluction lobes:** an openwork accumulation of gravel, with
135 a sandy matrix at depth, occupying the upper slopes of Ben Challuim.
- 136 • **Alluvium:** sorted cobbles, gravel, and sand adjacent to the river.
- 137 • **Peat:** BGS maps include peat as an organic deposit where it is interpreted to be
138 1 m or more in thickness.

139

140 **Methods**

141 *Sampling design and field measurements*

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

149

150 Depth was measured by pushing probes into the organic layer until they met resistance
151 at the surface of the underlying mineral layer or rock. Exposed sections in the field
152 revealed that the base of the organic layer was characterised by a sharp boundary, which
153 was easily detected by the probes (Fig. S1B). At each of the sample locations, five depth
154 measurements were taken: one at a central point and four at corners 2.5 m from the
155 centre. This was carried out to account for the local (sampling site scale) variability
156 caused by undulations at the surface of the bedrock or mineral layer (e.g. Fig. S1B),
157 and to reduce any potential impact of obstructions causing measurements to under
158 represent the true depth (Parry et al., 2012; 2014). The average of the five points was

159 used in the statistical modelling. Data were recorded into an attribute table in ARCGIS
160 in the field using a rugged tablet computer with an inbuilt GPS, which with an accuracy
161 of approximately 3 m, was considered to be suitable for making predictions with 10 m
162 resolution (differential GPS would have allowed investigation with a higher resolution
163 DEM).

164

165 *Statistical Analyses*

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

175

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

$$177 \quad \mathbf{z}(\mathbf{x}) = \mathbf{M}\boldsymbol{\beta} + \boldsymbol{\epsilon}, \quad (1)$$

178 where \mathbf{z} is a length n vector of observations, \mathbf{x} is a length n vector of locations where
179 the observations were made, \mathbf{M} is a $n \times p$ matrix containing the values of p spatially
180 varying covariates (elevation, slope, aspect, superficial geology) at each of the
181 observation locations, $\boldsymbol{\beta}$ is a length p vector of regression coefficients and $\boldsymbol{\epsilon}$ is a length
182 n vector containing the spatially correlated residuals at each sampling location. The
183 $\mathbf{M}\boldsymbol{\beta}$ are referred to as fixed effects and the $\boldsymbol{\epsilon}$ as random effects. The fixed effects are a

184 linear function of the covariates. The random effects are assumed to be realized from a
185 multivariate Normal distribution with zero mean and covariance matrix \mathbf{C} . The elements
186 of \mathbf{C} are calculated from a covariance function that relates the covariance between the
187 residual term for a pair of observations to the distance between the observation
188 locations. Here, the Matérn function was used (Minasny & McBratney, 2005) because
189 of the flexibility in how it behaves for small distances.

190

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

196

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

204

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

$$208 \quad \mathbf{AIC} = 2\mathbf{k} - 2\mathbf{L}, \quad (2)$$

209 where k is the number of parameters in the model and L is the logarithm of the
210 maximised likelihood. The preferred model is the one with the smallest AIC value. This
211 model is thought to be the best compromise between quality of fit (likelihood) and
212 complexity (number of parameters).

213

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

226

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

232

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

240

241 **Results**

242 *Peat depth observations*

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

249

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

256

257 *Statistical modelling*

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

266

267 The LMM with constant fixed effects led to an AIC value of 737.85. When an elevation
268 term was added, the AIC reduced to 734.02 and the fixed effects suggested that organic
269 layer depth decreased with elevation (Figs. 5A,6A). Addition of a slope term to the
270 constant model led to a larger reduction in AIC than for the constant plus elevation
271 model, and suggested that peat depth decreases with slope (Figs. 5B,6B). The fixed
272 effects of the LMM with the constant plus aspect term suggested a small increase in
273 organic layer depth on north-facing slopes (Fig. 6C); however, this model had a higher
274 AIC than the constant-only model indicating that aspect was not a beneficial parameter.
275 Overall, when only the topographic covariates were considered, the lowest AIC
276 (709.18) was achieved when the fixed effects included a constant, an elevation and a
277 slope term (Fig. 7A).

278

279 The AIC values reduced further when adjustments for locations within individual
280 superficial geology classes were combined with the topographic covariates. Separate
281 LMMs where the fixed effects included an adjustment for the peat, alluvium, and talus
282 and solifluction classes all produced lower AICs than models based solely on

283 topographic covariates. However, addition of adjustments for the moraine, till and
284 colluvium, and bedrock classes, each resulted in a higher AIC than the topographic
285 covariates alone. A final model was therefore produced with fixed effects including a
286 constant, an elevation and slope term, and adjustments for locations in the peat,
287 alluvium, and talus and solifluction classes. This model achieved the lowest AIC value
288 (678.61) and the fixed effects suggested that organic layer depths decreased with slope
289 and elevation, increased in the peat geology class, and decreased in the alluvium and
290 talus and solifluction classes (Figure 7B).

291

292 All the models had small mean errors upon validation and were approximately
293 unbiased. The RMSE generally decreased in line with the improvements in AIC. For
294 the models with solely topographic fixed effects, there was an 11-30% reduction in
295 RMSE when the random effects were included in predictions. This indicates that a
296 substantial proportion of the spatial pattern in the data was still not explained by the
297 covariates. When random effects were included in the model with the lowest AIC (Fig.
298 9C), which included topography terms and adjustments for certain geology classes, the
299 improvement in RMSE in the predictions was reduced to 3%. Therefore more of the
300 spatial pattern was explained by the fixed effects. The output of this model, with depths
301 shown in cm, is shown in Figure 8.

302

303 Similar results are seen upon 10-fold cross-validation (Table S2). The errors for the
304 entire dataset are slightly larger than those for the validation dataset reflecting that
305 depths in the validation set have relatively low variability. The same pattern of
306 improvements in errors upon the addition of covariates is observed, with the largest
307 decrease in errors occurring upon the addition of the slope information. Again, the most

308 accurate fixed effects model results from including slope, elevation and three geological
309 classes, and the addition of random effects only leads to a small further improvement.

310

311 **Discussion**

312 Previous studies have demonstrated that slope and elevation can be used as explanatory
313 variables to inform peat depth estimates (Holden & Connolly, 2011; Parry et al., 2012).

314 The LMMs in this study also indicate that slope and elevation are beneficial parameters
315 for explaining spatial variations in organic layer depth. The LMMs suggest that

316 organic layer depth decreases with altitude in Glean a' Chlachain. This pattern is
317 consistent with the relationship observed by Holden & Connolly (2011) in the Wicklow

318 Mountains, but is opposite to the positive depth-elevation relationship observed over
319 Dartmoor (Parry et al., 2012). This could be due to two reasons. First, the Wicklow

320 Mountains and Glean a' Chlachain rise to higher elevations than Dartmoor; therefore
321 the associated lower temperatures at these sites may play a more important role in

322 limiting growth of peat forming vegetation. At some elevated locations freeze-thaw
323 processes will also loosen the soil and any underlying sediment, influencing drainage.

324 Second, the hypsometry (proportion of surface area at different elevations) of sites
325 could be important. The flatter summits at higher elevations in Dartmoor contrast with

326 narrower, steep-sided summits and ridges which dominate the higher elevations in the
327 Wicklow Mountains and Glean a' Chlachain, (where glacial erosion has played a

328 greater role in shaping the landscape). These contrasts may affect the nature of organic
329 layer depth and elevation relationships and would need to be considered in up-scaled

330 estimates.

331

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

340

341 The inclusion of certain superficial geology classes to the topography-only model
342 reduced the RMSE of the fixed effects and lowered the proportion of spatial variation
343 that needed to be explained by the random effects. These models suggested that
344 organic layer depth decreased over the alluvium and the talus and solifluction classes.
345 This could be because the sediments in these deposits (cobbles, gravel and sand) are
346 characterized by intergranular water flow with high permeability indices (Lewis et al.,
347 2006). Such conditions would reduce waterlogging, promoting less favorable
348 conditions for peat formation. The remaining superficial geology classes comprise
349 materials that are characterised by mixed (intergranular and fracture) flow with low
350 permeability indices (Lewis et al., 2006). The LMMs also suggested that depths
351 increased over the peat category (which is expected since these areas had been
352 interpreted to contain peat >1 m in depth). As the superficial geology underneath peat
353 is not shown on geological maps, this is more difficult to explain in terms of the
354 geological properties. In places (e.g. where peat basins are surrounded by moraines)
355 very low permeability silts and clays may be present below the peat.

356

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

365

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

382

383 Figure 8 shows the modelled organic surface layer depths with contours indicating the
384 10 cm, 40 cm, and 50 cm intervals. This information enables identification of areas
385 that would be classified as peat under different schemes. For example, in England and
386 Wales, soils are classified as peat where the organic layer is >40 cm deep (Avery, 1980),
387 and the World Soil Reference Base for Soil Resources (WRB) and USDA taxonomy
388 also use >40 cm as a condition for classification of histosols. Interestingly, using the
389 40 cm criteria would triple the area classified as peat in Gleann a' Chlachain (from
390 0.245 sq km to 0.721 sq km). The future development of up-scaled maps that can be
391 readily transferred between different classification schemes may therefore be useful,
392 for example in developing coherent international estimates relating to peat deposits (e.g.
393 Tanneberger et al., 2017).

394

395 **Conclusion**

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

405

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512 **TABLES**

513 **Table 1.** Summary statistics for organic layer depth from calibration sites across Gleann

514 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

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517 **Table 2.** Log-likelihood (L), AIC, mean error upon validation of the fixed effects (FE
518 ME), root mean squared error upon validation of the fixed effects (FE RMSE), mean
519 error upon validation of the linear mixed model (LMM ME), root mean squared error
520 upon validation of the linear mixed model (LMM RMSE), and reduction in RMSE upon
521 inclusion of the random effect for each estimated linear mixed model. All units of errors
522 are \log_e (cm) unless otherwise stated. Predictors are: co constant, el elevation, as aspect,
523 pe peat geology class, al alluvium geology class, ta talus and solifluction geology class,
524 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+elxsl	-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

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531 **FIGURE CAPTIONS**

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

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

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

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

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

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

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

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

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

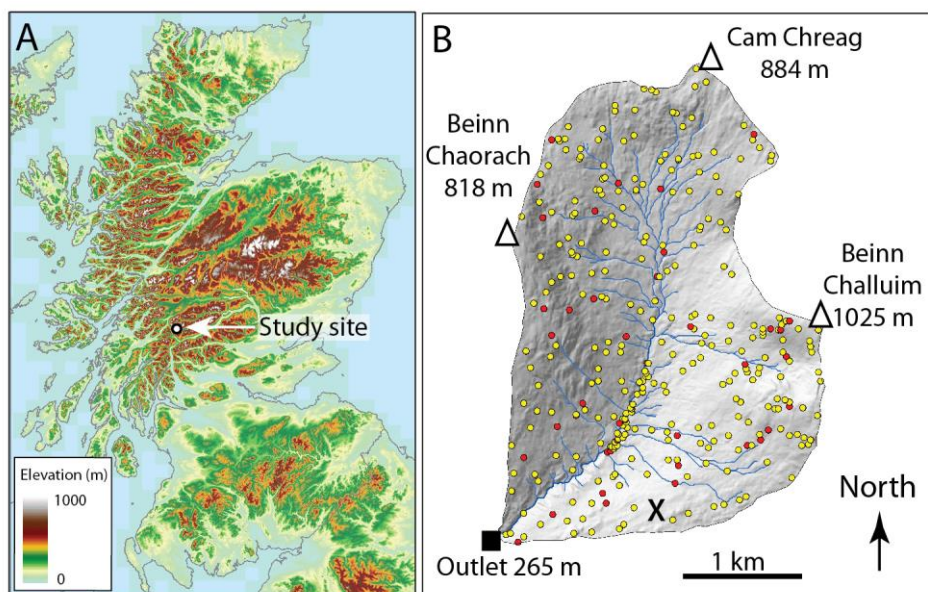


Figure 1. (A) Location of Gleann a Chlachainn catchment in western Scotland. (B) Catchment map together with sampling sites. Yellow circles are the sites used for model calibration and red circles are the sites used for validation. Position 'X' marks the location from where the photograph in Figure S1A (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.

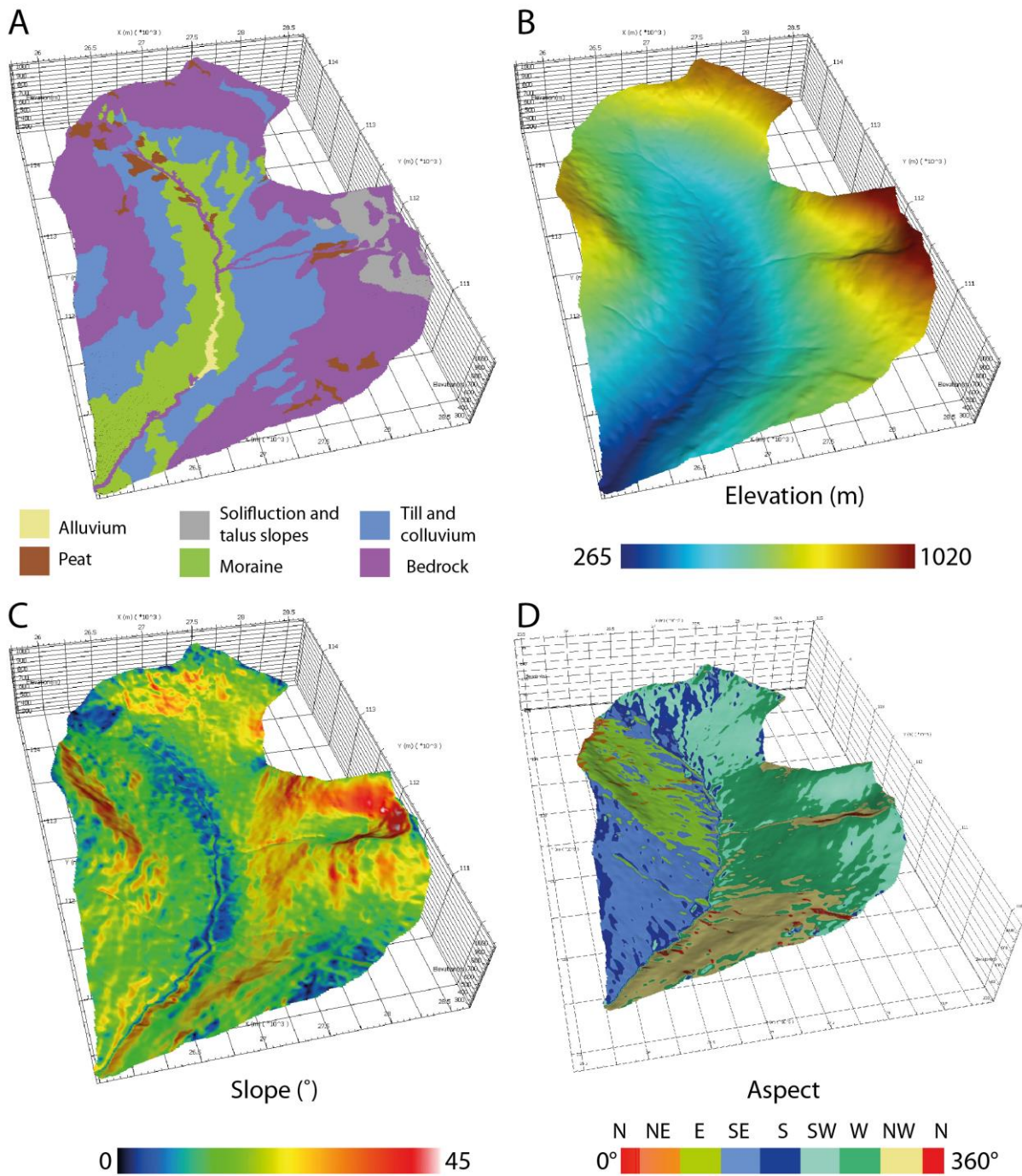


Figure 2. Plots of (A) superficial geology classes, (B) elevation, (C) slope angle, and (D) aspect in the Gleann a' Chlachain catchment. Representative organic soil depth sampling was carried out across each superficial geology class and across the topographic variables. The topographic variables were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

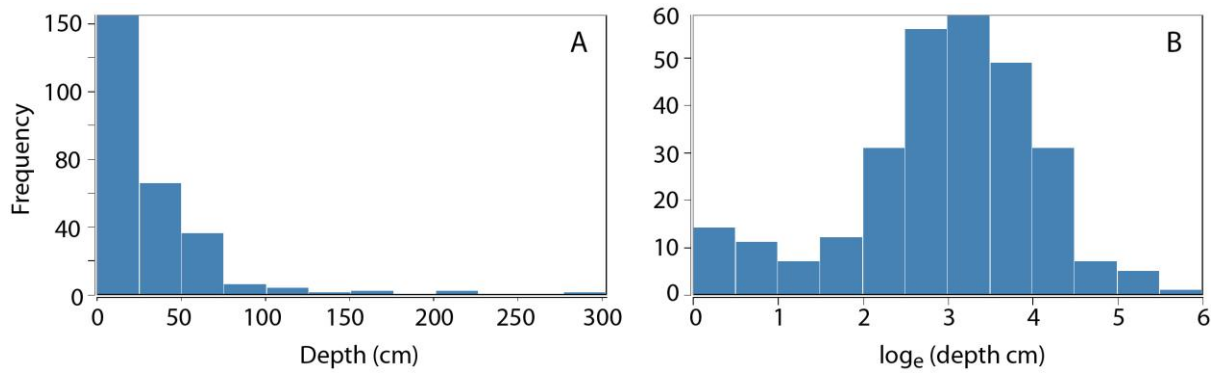


Figure 3. Histograms showing (A) observed organic layer depth measurements and (B) observed $\log_e(\text{organic layer depth} + 1)$.

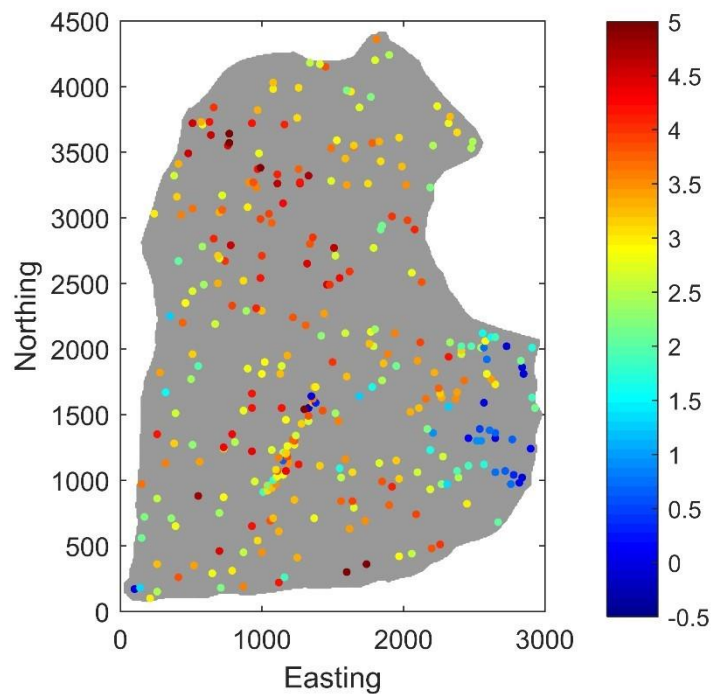


Figure 4. Spatial pattern of observed $\log_e(\text{organic layer depth} + 1)$. Coordinates are relative to (235787, 730277).

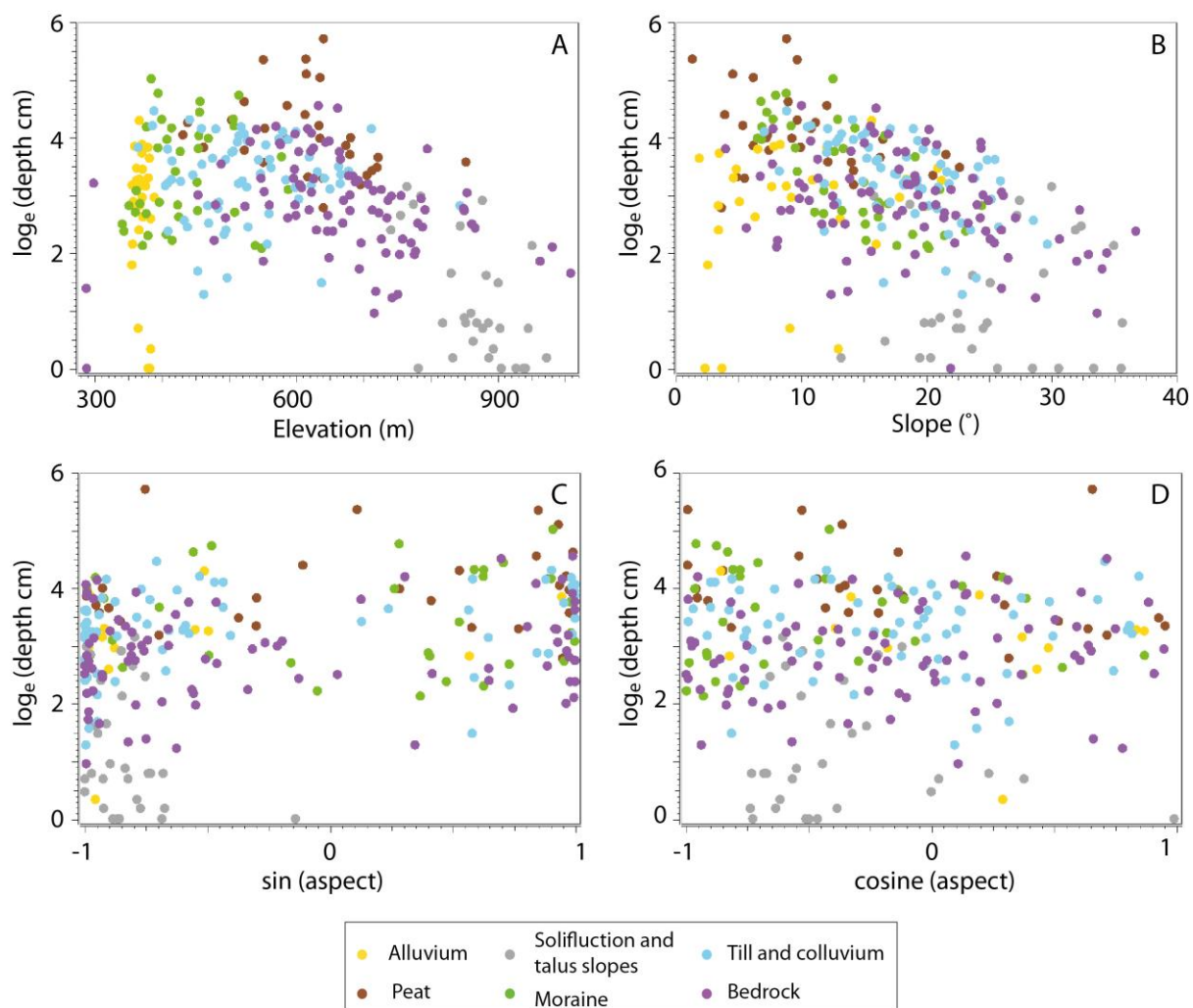


Figure 5. The relationship between organic layer depth and (A) elevation, (B) slope, (C) the sine of aspect, and (D) the cosine of aspect.

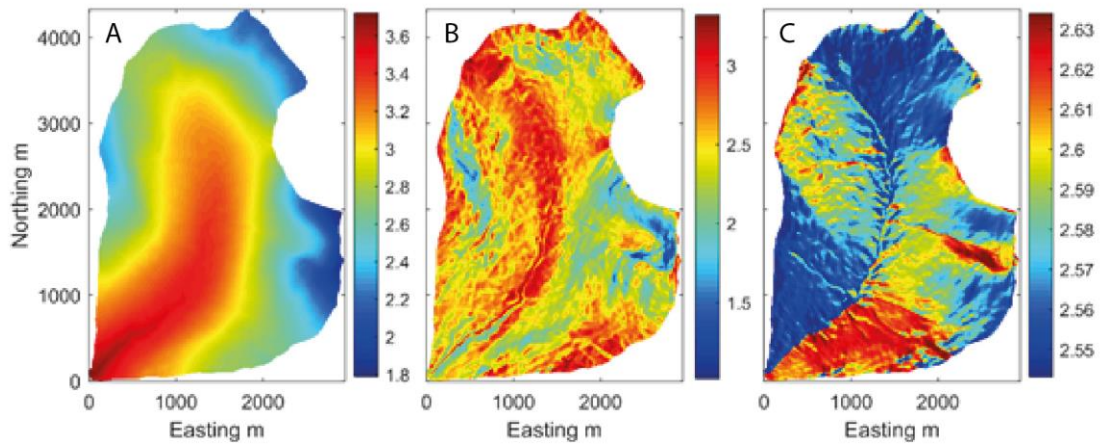


Figure 6. Predicted \log_e (organic layer depth+1) according to fixed effects consisting of: (A) a constant and elevation, (B) a constant and slope, and (C) constant and aspect. Units are \log_e (cm). Coordinates are relative to (235787, 730277).

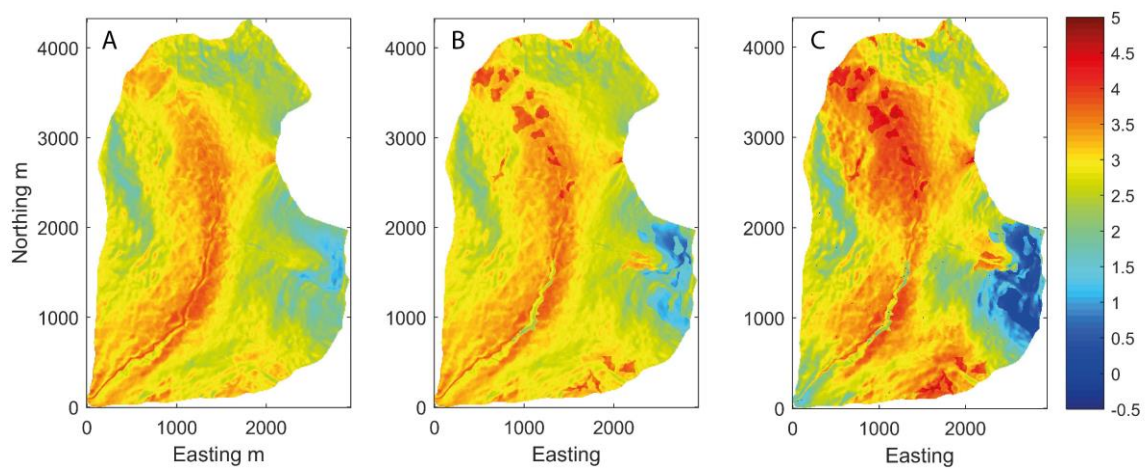


Figure 7. Predicted \log_e (organic layer depth+1) according to fixed effects consisting of: (A) a constant, slope and elevation; and (B) a constant, slope, elevation, and of peat, alluvium and talus and solifluction geology classes. (C) Predicted \log_e (organic layer depth+1) according to a linear 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).

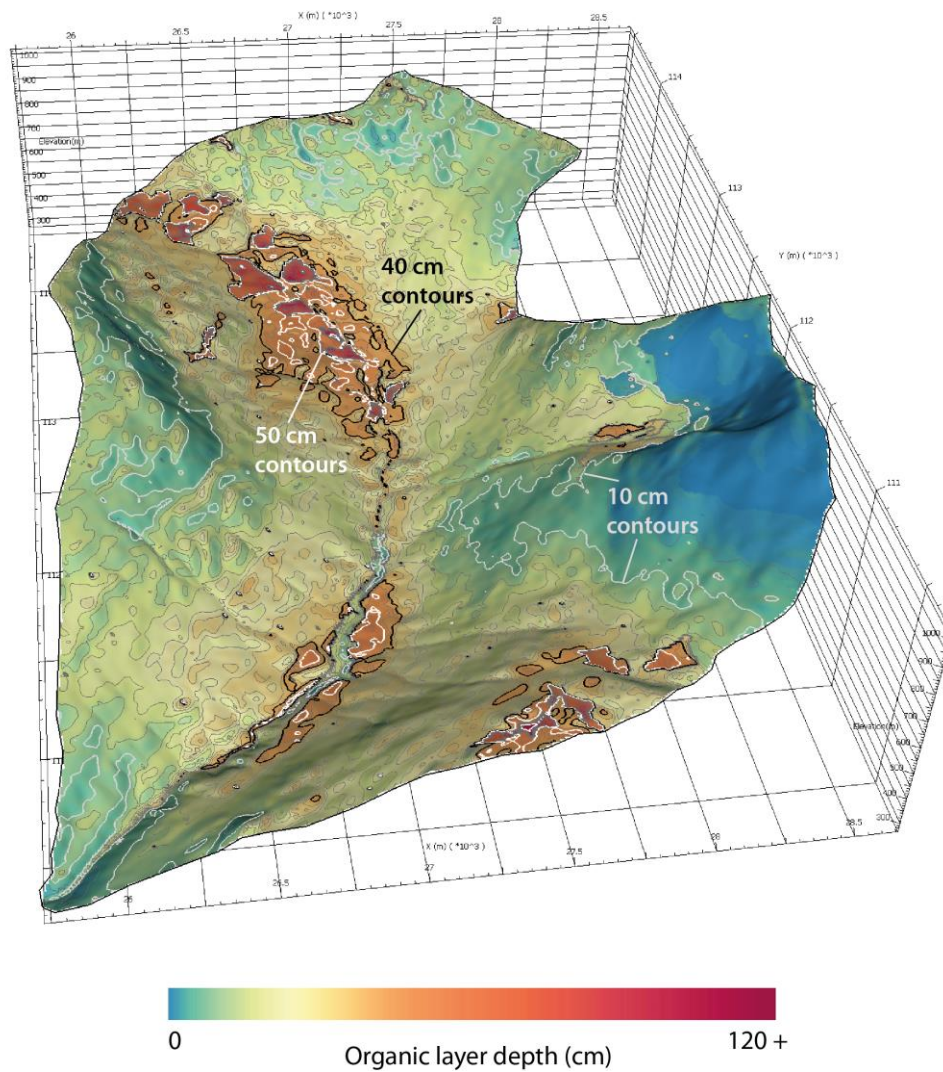


Figure 8. Predicted organic layer depth (in cm) across the catchment. Thick contour lines are shown at 50 cm (white), 40 cm (black), and 10 cm (light grey).