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Prediction of topsoil stoniness using soil type information and airborne gamma-ray data

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Manuscripts

1 **PREDICTION OF TOPSOIL STONINESS USING SOIL TYPE**
2 **INFORMATION AND AIRBORNE GAMMA-RAY DATA**

3 **Authors:** Ville Karjalainen¹ Timo Tokola¹, Jukka Malinen². (2020)

4 **Corresponding author:** Ville Karjalainen

5 **E-mail:** ville.karjalainen@uef.fi

Draft

6 Abstract

7 The stoniness of topsoil can have a significant impact on the cost-effectiveness and quality of work
8 in mechanized forest operations. The operations and their models should be selected on a stand-
9 specific basis, considering the physical properties of the soil, including stoniness, in order to achieve
10 maximum efficiency and to minimize the damage caused by heavy forest machinery. The aim of this
11 study was to examine whether the stoniness of the topsoil can be predicted using the gamma-ray
12 values available from low-flying geophysical data and soil type information. Stoniness was measured
13 at several sites with varying soil types, which were then divided into stoniness index classes (SIC)
14 for further analysis by ordinal regression analysis using gamma-ray and soil type data. The SIC
15 classification resulted in 52% accurate prediction performance and 79% acceptable prediction
16 performance (-/+ 1 class from the correct class), with Kappa values of 0.55 and 0.72, respectively.
17 The SIC prediction results were promising and showed the potential of gamma-ray and soil type data
18 for the estimation of topsoil stoniness.

19
20 **Keywords:** Forest trafficability; Gamma-ray radiation; Stoniness index; Ordinal regression; Kappa

21 **Addresses:** ¹University of Eastern Finland, Joensuu School of Forest Sciences, Yliopistokatu 7, FI-
22 80100 Joensuu, Finland; ²Metsäteho Oy, Vernissakatu 1, FI-01300 Vantaa, Finland.

23 1 Introduction

24 The interest towards small-scale variations in soil characteristics and terrain topography has increased
25 in recent times due to the challenges posed by varying weather conditions during rainy spring and
26 autumn periods and the unfrozen state of the soil in some places during the winter. A major challenge
27 for Nordic forestry is to maintain constant but high-quality harvesting with capital-intensive
28 harvesting machinery and still finish the operations with acceptable negative impacts on the soil and
29 without any unexpected difficulties (Siren et al., 2019). The number of seasonal factors involved in
30 timber operations reflects concerns about soil erosion and compaction and the prevention of tree
31 diseases and various forms of damage from heavy vehicles (Geisler et al., 2016). Forest certification
32 standards guide loggers towards keeping damage to a minimum. Rut formation is affected by several
33 factors, such as weather conditions during harvesting operations, the bearing capacity of the soil,
34 certain characteristics of the machines used in harvesting and hauling and the experience of the
35 operator (Suvinen et al. 2009).

36 Trafficability and rut formation both depend on the ability of the soil to resist the force exerted on it
37 by a rotating tyre or roller (Saarilahti, 2002b). There are several Nordic studies on rut formation which
38 show that the rut depth depends on such things as soil properties, the mass or wheel load of the tractor
39 and the characteristics of wheels, chains and tracks (Saarilahti & Anttila, 1999; Bygdén et al., 2003;
40 Eliasson L, 2005; Uusitalo et al., 2015; Palander & Kärhä, 2016; Mattila & Tokola, 2018; Siren et
41 al., 2019; Ala-Ilomäki et al., 2020; Uusitalo et al., 2020). Vehicular loading that exceeds the soil
42 strength can cause not only soil damage, but also damage to trees, mostly to their roots but sometimes
43 to the stem as well due to increasing uncontrolled motion of the forwarder (Pohjankukka et al., 2015).
44 The progressive effect of machine passes can differ significantly according to the physical properties
45 and depth of the soil and depends in a strict sense on the soil texture (Cambi et al., 2015).

46 Areas where soil has low bearing capacity, fuel and time consumption will tend to increase, thus
47 reducing the efficiency and overall profitability of forest operations. A terrain of low bearing capacity
48 can also lead to serious operational problems such as machine down time, relocation of the operation
49 and a reduction in the quality of the end products (Akay et al., 2007).

50 Venäläinen et al. (2018) estimated that the seasonal variation in timber procurement causes costs
51 amounting to approximately 70M € every year in Finland alone, largely on account of frost heave and
52 other bearing capacity constraints, restrictions on the trafficability of stands and fluctuations in plant
53 demand. The costs caused by challenging trafficability conditions could be reduced by obtaining
54 additional information on soil conditions, especially bearing capacity (Pohjankukka et al., 2015).

55 In our constantly changing climate, winter harvesting conditions can vary greatly from year to year,
56 making it difficult to plan harvesting sites in advance. The operation of forest machines is avoided
57 during the period of high soil failure risk and harvesting is postponed to the winter, when the soil is
58 normally frozen (Pohjankukka et al., 2015). In fact, throughout Scandinavia trees growing on such
59 sites are normally harvested in winter, when the soil is frozen and covered by snow. During the early
60 and late winter, the soil is only partly frozen, and the terrain is very sensitive with respect to harvesting
61 vehicle trafficability. Detailed on-site inspections are costly, and weather conditions are constantly
62 changing in those times of year. Mechanized wood harvesting requires adequate trafficability
63 conditions for forest tractors.

64 The incidence of stones and boulders is an important forest soil property, affecting the hydrology of
65 a site, the soil temperature, the amount of available nutrients, and hence the potential for timber
66 production (Viro, 1947; Ashby et al., 1984; Eriksson & Holmgren, 1996). The stoniness of the topsoil
67 also has a major impact on several forest operations, such as harvesting, forwarding and soil
68 preparation.

69 The basic precondition for reforestation is well-planned and executed soil preparation, so that, when
70 successful, the effects will be reflected in the forest yield over the entire rotation period (Immonen et
71 al., 2000). In the context of forest regeneration, the most relevant measure is the stoniness of the soil
72 at depths of 20–30 centimetres (Melander et al. 2019). The stone content of the topsoil is particularly
73 important when planning forest regeneration, since it can often render soil preparation challenging
74 and detract from the overall quality of the work. A high stone content can cause difficulties for both
75 soil preparation and planting, and in some areas proper soil preparation may become impossible or be
76 only partially successful (Saarinen, 2006; Luoranen et al., 2007; Rantala et al., 2010; Lideskog et al.,
77 2014; Saksa et al., 2018; Melander et al., 2019).

78 The choice of soil preparation method depends on the thickness of the soil layer, the soil type, the
79 stoniness of the soil, the current conditions of the forest site and the tree species being planted
80 (Luoranen et al., 2007; Löf et al., 2012; Äijälä et al., 2014). The main soil preparation methods,
81 including harrowing (disc trenching), patch scarification and mounding (Löf et al., 2012), all involve
82 tilling the forest soil in some manner, but at different depths and in different patterns. Mounding is
83 an example of a forest regeneration process that would benefit from knowing the prevailing stoniness
84 of the target site, at least when the continuous mounding method is considered (Rantala et al., 2010;
85 Saksa et al., 2018).

86 Most Finnish forest soils are tills of various types, and stoniness is one of their peculiarities. It has
87 been reported that the volume of coarse fragments in forest soils, i.e. their stoniness (Viro, 1947), is
88 substantial, e.g. averaging 42.3% by volume in Finland (depths of 0 – 30 cm) (Viro, 1958) and 49.5%
89 in Sweden (depths of 0 – 40 cm) (Eriksson & Holmgren, 1996), whereas a large proportion of the rut
90 formation or trafficability studies carried out elsewhere concern homogeneous deep soils such as
91 peatlands and very few of them focus on predicting the vital characteristics of a soil that are used to
92 determine its bearing capacity.

93 GIS-based modelling has been proposed for predicting terrain mobility conditions in support of the
94 planning of forest operations (Suvinen et al., 2009). The operator needs precise information on the
95 soil and site conditions in order to avoid soil damage. The ability to identify individual soil and terrain
96 properties (e.g. stoniness & peat layer thickness) reliably would hugely assist in the estimation of
97 terrain trafficability and help to further develop the existing terrain trafficability maps (Metsäkeskus,
98 2020; Ilmatieteenlaitos, 2020). By observing the geomorphological properties of the soil such as
99 wetness, soil type and stoniness at a small-scale level one could plan routes for heavy harvesting
100 machinery to pass through areas where these soil properties are the most favourable in terms of high
101 bearing capacity. In general, the bearing capacity decreases as the grain-size of the soil becomes finer
102 and the number of boulders and stones diminishes, but high stoniness may also reduce machine
103 mobility. Data on topsoil stoniness are not available in any existing map databases, however, and
104 traditional measurements of the stoniness of soils have always necessitated laborious soil penetration
105 methods. The approach adopted here is to use gamma-ray spectrometry measurements to see whether
106 there is any relation between gamma values and topsoil stoniness.

107 Gamma-ray spectrometry measures the gamma radiation emitted from the natural decay of
108 radioactive elements present in soil material (Cook, 2002). Although there are many naturally
109 occurring radioisotopes, only three elements, potassium (%K), uranium (ppm eU) and thorium (ppm
110 eTh), have isotopes that emit gamma radiation with sufficient intensity to be measured at airborne
111 heights (Minty, 1997). The energy intensity of these elements ranges 1.37–1.57 MeV for potassium,
112 1.66–1.86 MeV for uranium and 2.41–2.81 MeV for thorium. Each rock and sediment typology has
113 a typical amount of these radionuclides, which results the gamma-ray spectra and allows us to detect
114 different soil and rock types (Priori et.al., 2014).

115 Gamma rays can penetrate up to 30 cm of rock, and 50cm of soil, and several hundred metres of air,
116 and therefore these are the only choice available for the remote sensing of terrestrial radioactivity
117 (Grasty, 1997; Minty, 1997). The technique has been used for soil survey for over 30 years. It has

118 been stated by several authors (Grasty, 1997; Hyvönen et al., 2003) that gamma radiation decreases
119 in intensity with increasing soil moisture and that the soil moisture content is one of the most
120 important factors that can be utilized for the classification of soil material and soil types (Schwarzer,
121 1973; Lundien, 1976; Pohjankukka et al., 2014). Gamma-ray spectrometry data has also been used in
122 several studies to detect different soil attributes e.g., clay, silt, and organic carbon (Heiskanen et.al.,
123 2020; Taylor et.al., 2002; Wong & Harper 1999), soil pH (Dierke & Werban, 2013; Wong & Harper
124 1999), and soil stoniness (Priori et.al., 2014; Heiskanen et.al., 2020).

125 Vegetation not only attenuates the gamma radiation but also acts as a competing source of it, although
126 the concentration of radioactive elements in vegetation is only a fraction of that in the bedrock and
127 soil. In boreal forests, consisting mostly of pine and/or spruce-dominated stands, the concentration of
128 radioactive elements in the forest biomass is marginal compared with that in the underlying soil
129 (Kogan et al., 1971).

130 The radiometric fingerprint of a site mainly depends on the parent material, its mineralogy and
131 geochemistry (Dickson and Scott 1997). In general, the radiometric fingerprint of the parent material
132 is inherited to the soils which develop from them. However, soil formation process can also alter the
133 nuclide signature of soils through hydrolysis, protolysis and redistribution of soil material by erosion
134 process (Taylor et al., 2002; Herrmann et al., 2010). The radiometric signal varies across landscapes
135 and it reacts to different patterns in the terrain which indicate variation in soil properties, but the
136 application does have several limitations (Marchuk & Ostendorf, 2009). The use of gamma
137 radiometrics for soil proximal sensing is strongly site specific, because of the influence of parent
138 material mineralogy on the gamma-rays emitted from the soil (Priori et.al., 2014). In addition, the
139 data gathered using airborne gamma-ray acquisition systems often have poor spatial resolution for
140 small-scale applications (Marchuk & Ostendorf, 2009; Wilford & Minty, 2007).

141 The aim of this study was to see whether the stoniness of the topsoil could be predicted using gamma-
142 ray values from low-flying geophysical data combined with soil type information, both of which are

143 available as open-source data in Finland. The gamma-ray values and soil type were studied using
144 regression analysis and compared with measured stoniness index reference data.

145

146 **2 Material & methods**

147 **2.1 Study area and field data**

148 The area studied (Fig. 1) is located in the region of North Karelia and South Savonia in Eastern
149 Finland. The forests of this area are mostly dominated by Scots pine or Norway spruce, with
150 deciduous trees found in minor proportions. The soil type is either peatland or mineral soil (till and
151 moraine embedded mainly with granite and gneiss) since the majority of the fine-grained mineral
152 soils (silt and clay mixtures) have been put to agricultural use.

153 **(Fig. 1)**

154 The field data were collected in the summer of 2017 from 69 clear-cut sites which varied in size from
155 0.15 hectares to 6.3 hectares. The sample plots were arranged in an even grid and both the distance
156 between sample plots and the number of such plots were proportional to the size of the clear-cut area,
157 so that each site was measured evenly. A total of 1221 sample plots in these clear-cut areas, 828 with
158 mineral soils and 393 with peatland soils, were assessed with respect to the stoniness of the topsoil,
159 topsoil type and soil depth, all measured using a ground spike. On the mineral soils the soil type was
160 assessed by eye from a sample taken from the top 30 cm of the sample plot. The location of each plot
161 was determined using a high precision GPS device. Site attributes such as the above-ground boulder
162 index and the colour of the soil enrichment layer (illuvial horizon) were also determined visually for
163 each plot.

164

165 **2.2 The stoniness Index and resulting classification**

166 The stoniness of the topsoil is expressed here in terms of the Stoniness Index (SI), which describes
167 the stone content at depths of 20–30 centimetres (Melander et al., 2019) as determined by a surface
168 penetration method (Viro’s method) in which a steel bar or spike is inserted into the soil up to a certain
169 depth and the number of contacts with stones are recorded (Viro, 1952). In the present case the SI
170 was measured by making 10 insertions 1 meter apart along the line of sample plots and increasing the
171 index for that plot by 10% for each contact with a stone (zero contacts = 0%, one contact = 10%, two
172 contacts = 20% etc.). No attempt was made to avoid stones visible on the surface.

173 The SI values were then classified into Stoniness Index Classes (SIC) from 1 to 5 (SI 0+1 → SIC 1;
174 SI 2+3 → SIC 2; SI 4+5+6 → SIC 3; SI 7+8 → SIC 4; SI 9+10 → SIC 5). This was carried out after
175 it had been decided that a small variation in the SI values would not be significant as far as forest
176 operations or the bearing capacity of the forest soil were concerned. The distributions of the SI and
177 SIC values is shown in Table 1. It is the SIC values that will be used as the key criteria here when
178 assessing the models and analyses.

179 **2.3 Airborne gamma-ray spectrometry data**

180 The airborne radiometric data were acquired from the national low-flying geophysical database
181 maintained by the Geological Survey of Finland (GSF). The low-altitude surveys concerned were
182 performed from 1972 to 2007, by which time the data covered the whole of Finland. The data applying
183 to the area studied here were acquired in 1981 and 1991 (Geological Survey of Finland [GSF], 2020).

184 The geophysical parameters measured were the earth's magnetic field, the electromagnetic field of
185 the Earth’s crust and natural gamma radiation (radiometric), but only the gamma radiation data are
186 used in this study. These comprise measurements of natural gamma-ray radiation, potassium (%K),
187 uranium (ppm eU), and thorium (ppm eTh), emitted from the ground (Hyvönen et al., 2005).

188 The ground speed of the aircraft during the measurements was approximately 50m/s and the flight
189 altitude 30 - 40 m. The radiometric measurements were performed for positions approximately 40

metres apart along flight lines usually located at 200-metre intervals. The radiometric components measured were interpolated into pixels 50 metres in size.

2.4 Data selected for the study

After the field measurements had been acquired the coordinates of the sample plots were checked and the corrected locations saved as a point-type shape file, while the gamma radiation data comprised four raster-format files each containing the values of one gamma radiation component, i.e., potassium (K), uranium (U), thorium (Th), or total (Tot), and consisting of pixels of size 50 m.

Two sets of data were selected from the total of 1221 sample plots: dataset 1 (n=255) consisted of both mineral soil and peatland plots and dataset 2 (n=215) of only mineral soil plots. This was done in order to see how a model would work solely on mineral soils and to compare the results of the mineral soil model and the mixed model. Another reason was concern about the plausible high correlation between the gamma values and peatlands, but this matter is dealt with more precisely in the Discussion section. The selection methods for both datasets are described in detail below.

The selection of plots for dataset 1 was carried out by excluding those plots that were close enough to the GSF's geophysical low-flying data flight lines for which data were available from the GSF (open data site Hakku.fi). The flight line data were buffered with 20-metre zones on either side of the flight line, resulting in buffer zones 40 metres in total width. The plots that were inside the buffer zones were excluded from the original sample plot dataset. This was done because, although the distance between the flight lines was approximately 200 metres, the actual measuring zone was only 40 metres wide, thus leaving a distance of about 160 metres between the flight lines. Having done this, we acquired only measured radiometric values and not interpolated values. The selection process reduced the number of plots from 1221 to 231.

When the soil features of the remaining sample plots were reviewed it was noticed that the fact that the fine-grained mineral soil plots and some of the sandy soil plots had been excluded entirely had

214 too great an impact on the model to be created. It was therefore decided to include all the fine-grained
215 mineral soil plots and the rest of the sandy plots in the final data even though they were not within
216 the flight line buffers. After this the total number of plots in dataset 1 was 255 and their proportion
217 was still small compared with the rest of the data.

218 Dataset 2 was selected manually so that all the SIC classes were evenly represented. The total of 215
219 plots in this dataset were divided into subgroups for both training and testing of the model.

220 The stoniness and soil properties and their corresponding mean gamma-ray values of in dataset 1 are
221 presented in Table 1. Here all the SIC classes were well represented except for class two, of which
222 there were relatively few instances (Table 1). As previously stated, both fine grained mineral soil and
223 sandy plots were quite poorly represented in the data and the largest number of samples fell into the
224 class of sandy till (Table 1).

225 **(Table 1.)**

226

227 **2.5 Statistical methods**

228 The first step was to normalize the gamma component values for both datasets using z-score
229 normalization (Eq. 1), which scales the values in relation to the mean for the population.

230 (1),
$$x_{norm} = \frac{x_i - x_{mean}}{S}$$

231

232 where x_{norm} is the normalized value of the gamma component, x_{mean} is the mean for the population
233 and S is the standard deviation within the population.

234 We next used a box & whiskers plot to determine whether SI and SIC were consistent with respect to
235 their normalized gamma radiation component values (K, U, Th) (Figs. 2 & 3). The statistical analysis
236 included a correlation analysis to find the relations between the variables and drop some variables out

237 during the model construction phase if necessary. A Variance inflation factor test (VIF) was
238 conducted for the variables selected to further detect possible multicollinearity (Kuhn et.al. 2020).
239 All the statistical analyses and model construction stages were performed using the *R* statistical
240 computing environment.

241 **(Fig. 2)**

242 **(Fig. 3)**

243

244 **2.5.1 Regression models**

245 The main goal of this work was to determine whether the stoniness of the topsoil (SI and SIC) can be
246 reliably predicted using gamma radiation data and soil type information, and to construct a model for
247 this that could be based on openly available geographic information. Thus, not all the information
248 available in the field was utilized when constructing the models (e.g., boulder frequency and soil
249 depth were ignored). In practice, gamma radiation data and soil type were the only two openly
250 available data species out of our list of plausible predictors.

251 Ordinal regression analysis was used as the main statistical method, and a total of three ordinal
252 regression models were constructed to predict SI and SIC. Ordinal regression was used to determine
253 the significant independent variables to be used in the final models, and K-fold cross-validation was
254 used when constructing each model by means of 10 folds and three repeats.

255 Ordinal regression was performed first on the SI for dataset 1, taking both gamma radiation values
256 and soil type dummy variables as predictors. Secondly, we constructed a similar model but replacing
257 SI with SIC, and thirdly, we constructed another SIC model using dataset 2 with only gamma-ray
258 values as predictors to see how well they performed with respect to mineral soil stoniness alone. K-
259 fold cross-validation for each model were implemented with caret (Kuhn et.al. 2020) package in the
260 R statistical computing environment (R Core Team 2020).

Ordinal regression was used in the analytical modelling since both SI and SIC were class form variables, i.e., the predicted values were selected through class probability. Ordinal regression is commonly used to predict the behaviour of level-dependent variables, since the dependent variable is assumed to be consecutive, and each level must be interdependent (better or worse). Ordinal regression does not give us a class estimate directly, but instead the result is a plot-specific y-value (Eq. 2), so that a class pair probability can be calculated for each plot by comparing this y-value with a plot-specific z-value (Eq. 3). We can then further calculate the class-specific probabilities (Eq.4-8) and choose the class with the highest probability. An ordinal regression model is relatively laborious to use compared with regular linear regression precisely because of these class probability calculations.

$$(2), \quad y = \beta_i X_i \dots + \varepsilon_i$$

where y is a plot-specific y-value, β is the regression coefficient for the predictor variable X and ε is a random error term.

$$(3), \quad p_x = \frac{1}{1 + e^{-(z_x - y)}}$$

where p is the class pair probability (1:2; 2:3; 3:4; 4:5), z is the class pair-specific z-value provides by the ordinal regression analysis, and y is the y-value acquired from Eq. 2. We were able to derive a class-specific probability value $p_1 - p_5$ (Eq. 4 – 8) from the class pair probability p :

$$(4), \quad p_1 = p_{1 \text{ or } 2}$$

$$(5), \quad p_2 = p_{2 \text{ or } 3} - p_1$$

$$(6), \quad p_3 = p_{3 \text{ or } 4} - p_{2 \text{ or } 3}$$

$$(7), \quad p_4 = p_{4 \text{ or } 5} - p_{3 \text{ or } 4}$$

$$(8), \quad p_5 = 1 - p_{4 \text{ or } 5}$$

where p_1 is the probability of class 1, p_2 is the probability of class 2, p_3 is the probability of class 3, p_4 is the probability of class 4 and p_5 is the probability of class 5.

The key assumption in ordinal regression is called assumption of proportional odds which assumes that the independent variables have the same effect on the odds across all levels of categories/classes (i.e., relationship between each class-pair is the same). Since our models estimate one equation over all levels of SI or SIC, we conducted the test of parallel lines for each of our models to see whether the assumption of proportional odds holds. Test of parallel lines compares our ordinal model which has one set of coefficients for all class-pairs, to a new model with a set of class pair-specific coefficients. If the model with separate coefficients for every class pair gives significantly better fit to the data, we reject the assumption of proportional odds.

2.5.2 Accuracy assessment

The performance of the ordinal regression models was assessed by cross-tabulation of the predicted and observed SI and SIC values. The main key quantities in the accuracy assessments were the percentage of agreement and the Kappa values (Eq. 9 & 10), which were calculated for each model separately. The Kappa value differs from a simple agreement percentage in that it also considers the possibility of the agreement occurring by chance. For every model we calculated two sets of results, first the absolute prediction accuracy, in which only correct predictions were considered, and secondly the acceptable prediction accuracy, in which the predictions were not as strictly limited, so that a small possibility for variation was allowed.

$$(9), \quad ef = \frac{\sum r * \sum s}{n}$$

$$(10), \quad Kappa = \frac{\sum a - \sum ef}{n - \sum ef}$$

309 Where r is the sum of the class-specific row values in the cross-tabulations, s is the sum of the class-
310 specific column values, n is the total number of cases, ef is the expected frequency of each class, and
311 a is the number of congruous cases.

312 Finally, the predictive accuracy of the SIC model was further tested by performing a classification of
313 500 randomly selected sample plots from the initial dataset to which the plots used in making the
314 model also belonged. The same key quantities were used to test the accuracy as have been introduced
315 previously.

316 The accuracy of the second SIC model (only mineral soil) was tested by dividing the mineral soil
317 dataset into training and testing datasets in a ratio of 0.7:0.3 and using the same key quantities to
318 assess the accuracy as with the previous models.

319

320 **3 Results**

321 The Spearman correlations between stoniness information, soil types and gamma values are presented
322 in Table 2. All the soil properties and gamma values apart from sand as a soil type seem to have
323 significant correlations with both SI and SIC, and all the correlations between the gamma values and
324 SI and SIC are relatively high. By contrast, the sandy till and peatland soil types have a high negative
325 correlation (-.731), which can be explained by the fact that they are opposing dummy variables (the
326 soils that are not peatland are likely to be sandy till) and they are both well represented in the data.
327 All the gamma values show high correlations with sandy till and peatland soils (significant at the 0.01
328 level), although the high correlations between the peatland and the gamma values may be more a
329 matter of perception with regard to the reliability of the model, as considered in more detail in the
330 Discussion. The tests of parallel lines proved not to be statistically significant for all our models thus
331 the assumption of proportional odds held which indicates that the relationship between each SI or
332 SIC class pair is the same and our models are valid.

333 **(Table 2)**

334

335 **3.1 SI and SIC models**

336 As previously stated, the models and results will be considered here primarily in terms of SIC which
337 will be taken as a measure of stoniness at a level above that of SI. Having used a stepwise selection
338 method to acquire the significant independent variables, we performed the classification of stoniness
339 using ordinal K-fold cross-validation on these variables. Two models were constructed for SI and
340 SIC using dataset 1, both based on the same variables.

341 From soil type dummy variables sandy till was selected to be used as the reference soil type, since it
342 has the highest case count. As seen in Table 3, fine-grained till and peat soil type dummy variables
343 proved to be significant at the 0.05 level. Sand was included in the final model, so every soil type
344 would be accounted for, even though sand was not a significant variable. Of the gamma values,
345 potassium (K) and uranium (U) had high enough significance levels to be used in the final model for
346 dataset 1. Although high correlations were detected, the conducted VIF-test revealed moderately high
347 VIF score only for variable peat (4.04).

348 **(Table 3)**

349

350 **3.1.1 SI**

351 Ordinal regression managed to classify 36.47% of the SI cases correctly, with a kappa value of 0.199
352 (Table 4) and correctly with an acceptable two-class-off variation in 65.88% of the cases, with a
353 kappa value of 0.587 (Table 4). The resulting cross-validation table showed that the correctly
354 classified cases were divided between the extreme SI classes, in that only classes 0, 7, 8 and 9 had

355 classifications in them, and the rest had none. Classification with acceptable variation caused more
356 classes to have predictions in them, and only classes 3 and 4 were left empty.

357 **(Table 4)**

358

359 When the SI model was tested with 500 randomly selected plots it managed to predict 29.00% of the
360 cases correctly with a Kappa value of 0.000 and correctly with an acceptable two-class-off variation
361 in 60.40% of the cases, with a Kappa value of 0.440. The resulting cross-validation table showed that
362 the correctly classified cases were divided between classes 0, 7 and 8 while the rest of the SI classes
363 had no correct classifications. Classification with an acceptable level of variation caused more classes
364 to have predictions in them, and only classes 3 and 4 were left without any predicted cases.

365 **3.1.2 SIC**

366 Ordinal regression managed to classify 52.16% of the SIC cases correctly in the modelling phase,
367 with a Kappa value of 0.547, and correctly with an acceptable one-class-off variation in 78.82% of
368 cases, with a kappa value of 0.719 (Table 4). The resulting cross-validation table (Table 5) showed
369 that the correctly classified cases were divided among all the SIC classes except for class 2, which
370 had zero correct predictions. Classification with an acceptable level of variation divided the cases
371 more evenly among the classes, including class 2. A total prediction error of three classes or over was
372 observed in 7.45% of cases.

373 **(Table 5)**

374

375 When the ordinal regression model for SIC was tested using the same 500 randomly selected cases
376 as for testing the SI model the proportion of correctly classified cases decreased from 52.16% to
377 49.00% and the level of acceptable variation improved slightly relative to the modelling phase,
378 increasing from 78.82% to 82.00%. The Kappa value for the correctly classified cases decreased

379 slightly from 0.547 in the modelling phase to 0.478 and the Kappa value for the acceptable
380 classifications increased from 0.719 to 0.766, which is an excellent result. The testing phase part of
381 Table 5 shows that the classification again concentrates the sites into classes 1, 3 and 4. A total
382 prediction error of three classes or over was observed in 4.00% of cases.

383 3.1.3 Mineral soil SIC

384 The classification for mineral soil alone was performed only at the SIC level and employed dataset
385 2, which had been manually picked to represent all the SIC classes evenly. This 2 consisted of 215
386 cases and it was divided into modelling and testing data in the ratio 0.7/0.3. We decided to use all the
387 gamma components (K, U and Th) in the mineral soil SIC model even though uranium did not seem
388 to be significant at the 0.05 level (Table 6), as it was decided that it would complement the other
389 gamma values, since it was also significant in the previous models. As can be seen in Fig 3. the
390 gamma values tend to vary consistently with the SIC classes. Further information on the modelling
391 can be seen in Table 6.

392 (Table 6)

393 In modelling phase using dataset 2 and only the gamma component values as predictors, ordinal
394 regression managed to classify 32.24% of the cases correctly with a Kappa value of 0.181 (Table 7).
395 The model classified stoniness correctly with acceptable one-class-off variation in 67.11% of cases
396 with a Kappa value of 0.589 (Table 7). Each SIC class contained some correct classifications, but
397 classes 1 and 4 possessed the highest numbers.

398 (Table 7)

399

400 The percentage of correctly classified cases decreased in the testing phase, from 32.24% to 28.57%
401 and the level of acceptable variation improved slightly relative to the modelling phase, from 67.11%
402 to 74.60%. The Kappa value in the correctly classified cases decreased markedly from 0.181 in the

modelling phase to 0.07, and the Kappa value in the acceptable classifications increased from 0.589 to 0.671, which indicates a good result.

4 DISCUSSION

4.1 Overview of the results

Since forestry operations in Scandinavia are highly affected by seasonality and can vary greatly from year to year, there is urgent need to develop predictors of terrain trafficability. Although contractors try to plan their activities well in advance, they face unpredictable weather conditions during the contractual timber harvesting periods (Rittenhouse & Rissman 2015). We studied a GIS-based method for predicting the stoniness of the topsoil employing airborne gamma-ray measurements and soil maps.

When assessing Table 1 we notice that the SIC and gamma-ray values have clear parallel trend, with larger gamma values in the higher SIC classes, as can be clearly seen in Figure 2. In the SI figures the trend is not as clear and the gamma values do not increase consistently with the SI classes. This is also the case with the gamma values and SIC in the mineral soil samples that make up dataset 2 (Fig. 3).

The results of the SI predictions were better than expected, achieving correct prediction in 36.47% of cases and correct results with an acceptable level of variation in the SI classes in 65.88%. Even though the results seemed good, ordinal regression had major difficulties in creating boundaries between most of the SI classes, as it was able to assign values only to the SI classes 0, 7, 8 and 9. The same variation in the gamma values can also be seen in Table 1, where only the “extremes” in the SI classes are clearly separated from the mid-section.

425 The good performance of the model in the low SI classes can be explained by the fact that a large
426 number of the sample plots with low SI values were on peatlands, where the soil contains large
427 amounts of water, which will have affected the radiation properties of the soil by reducing the
428 intensity of the gamma radiation (Hyvönen et al., 2005). Peatlands are also known for having
429 relatively small quantities of stones as compared with mineral soils. This is also reflected in the high
430 correlations between the predictor variables (Table 2), so that there is presumably some
431 autocorrelation between peatlands, stoniness and gamma values. This is indicated by the increased
432 VIF-score (4.04) for variable peat which causes some uncertainty towards the performance of the
433 model but is not considered being a severe violation in this case.

434 The model also performed moderately well among the high SI classes (7, 8 and 9), in that the high SI
435 values were typically obtained in areas where bedrock or large boulders lay close to the ground
436 surface. It is known that the intensity of gamma radiation is affected by the grain size of the mineral
437 particles in a soil (Hyvönen et al., 2005), the larger the particle, the higher the emitted radiation –
438 which explains the correlation between high gamma-ray values and SI findings. When interpreting
439 the class probabilities acquired from ordinal regression, most of the values were quite evenly
440 distributed among several SI classes, apart, that is, from classes 0, 7 and 8. The results indicate
441 moderate performance at the extremes of the scale but poor overall results of SI prediction, so that
442 the use of SIC is seen to be justified.

443 As seen in Table 4, the results of SIC prediction (based on dataset 1) were good in both the modelling
444 (correct 52.2%, acceptable 78.8%) and testing phase (correct 49.0%, acceptable 82.0%). The Kappa
445 value for correct predictions was 0.547, which is good, and that for acceptable predictions is 0.719,
446 which is excellent (Table 4). When considering how the probabilities for the 17 original SIC 2 cases
447 were divided between the classes, it was noted that none of them even came close to being selected
448 for SIC class 2, but rather they were evenly distributed between classes 1, 3 and 4. This is very likely
449 to be due to the small number of cases in SIC class 2, making it difficult for cases to be assigned to it

450 in ordinal regression. SIC classes 1 and 4, on the other hand, seem to attract predictions from the
451 surrounding classes, possibly as a result of already possessing the highest numbers of cases.

452 It is significant that prediction errors of three classes or over amount to only 7.45% of the total number
453 of cases, and only 4.00% in the testing data. This shows that the number of major prediction errors is
454 low. SIC class 1 stands out with its relatively high correct prediction percentage of 89% in modelling
455 phase and 91% in testing phase, probably due to the high number of SIC class 1 cases and the
456 correlation between peatlands and gamma values described earlier.

457 The results of the SIC predictions with only mineral soil, using dataset 2 (Table 7), were poorer than
458 with dataset 1 (Table 4), as was expected, since there were no peatland plots to lay weight on the low
459 SIC values. The results were nevertheless promising, for although correct predictions were noticeably
460 less frequent with dataset 2 (modelling 32.2%, testing 28.6%) than with dataset 1 (modelling 52.2%,
461 testing 49.0%), acceptable predictions were relatively similar in both datasets (dataset 1: modelling
462 78.8%, testing 82.0%; dataset 2: modelling 67.1%, testing 74.6%), which indicates that it is more
463 difficult to get correct predictions but the prediction error is mainly restricted to within one SIC class.

464 Similar results were reported by Melander et al. (2019) who acquired 70 % accuracy in their study of
465 topsoil stoniness prediction (with three stoniness classes) using excavator boom vibration data. In the
466 method used by Melander et al. (2019) the results/information is gathered during mounding
467 operations and therefor the information for stoniness of particular site is available only in the next
468 operation or to be used as reference data.

469 In contrast to our results, some studies (eg. Heiskanen et.al., 2019; Priori et.al., 2014) reported poor
470 results in prediction of soil stoniness using gamma-ray data. In study Heiskanen et.al. (2019), they
471 managed to predict the volumetric proportion (%) of stones at the level of $R^2 = 17\%$ when using
472 cover of bare rock, height of dominant trees and Gamma-ray values (%K) as predictors. We acquired
473 the absolute prediction result (for mineral soil) of 29 – 31 % (Table 7.) which is slightly higher, but

we used stoniness index classification (SIC) where Heiskanen et.al. (2019) used volumetric proportion (%) of stones. Heiskanen et.al. (2019) study area covered the whole of Finland resulting high variation in parent material which might have resulted the poor predictability of stoniness, where our study area was located in a relatively homogenous area in respect to parent material.

4.2 Potential of the method

There are already terrain trafficability maps available, as described in the Introduction (Metsäkeskus, 2020; Ilmatieteenlaitos, 2020), but it would be beneficial to focus more on soil sub-properties that have an impact on trafficability. Information on a number of sub-properties would provide us with the necessary data for estimating trafficability more precisely. Similarly, information on internal variations in site trafficability is in any case needed for both economic and ecological reasons, e.g. to avoid undesirable soil damage (Mattila & Tokola, 2018).

When measuring the stoniness data the size of the stones was not considered at all, because the measuring tool could be stopped even by a small stone. On the other hand, small stones do not affect terrain trafficability or the cost of forest operations as much as do large stones. Also, the existing soil class data are based on a set of sparse observation samples and are not very accurate, so that they may need to be replaced with a predicted measure (Ala-Ilomäki et al., 2015). In this respect it would be important to focus the prediction of stoniness on mineral soils, as the bearing capacity of peatlands is affected more by organic matter and the high moisture content of the soil than by stoniness.

The bedrock in the geographic region of the study area shows little variation consisting mainly of migmatite. Previous studies state the parent mineralogy having greater weight of the parent material mineralogy, respect to the soil features (Dierke & Werban, 2013; Rawlins et al., 2007, Priori et.al., 2014) and in result, soil mapping using gamma-ray is strongly site-specific. Priori et.al. (2014) stated in their study that general regression model is not useful when predicting soil texture and stoniness in different parent material. This greatly limits the usage of our constructed model, but it could be

498 applicable on some areas where the parent material is similar to our study area. To tackle this issue,
499 we could consider a petrologic adjustment factor which could improve the usage of models between
500 different parent materials.

501 The present results show that gamma radiation measurements can be used to some extent as a tool for
502 predicting topsoil stoniness in the case of mineral soils (Table 7). Problem is that soils do not have
503 unique radioelement signatures which means that similar responses can relate to different soils
504 (Wilford & Minty, 2007). Also, the resolution of the existing gamma-ray data is too coarse to be used
505 in accurate stand-wise predictions. As Väänänen et al. (2007) stated when studying the classification
506 of radiometric data, the largest errors usually occur in small-scale terrain with marked variations in
507 topography.

508 In addition to gamma values, we could consider using information on above-ground boulders to assist
509 in the prediction of topsoil stoniness. Stendahl et al. (2009), for example, found a relationship between
510 surface boulder frequency and stone and boulder content, but the strength of the relationship varied
511 regionally, and each result might only be valid within a geologically homogenous area. Similar results
512 were reported by Knuttsen (1973). We could also introduce complementary use of other geo-
513 electrical sensors along with gamma-ray spectrometry, e.g., electromagnetic induction (EMI) sensor
514 (Castrignanò et.al., 2012). Another approach to the prediction of stoniness and soil type would be
515 machine learning (Priori et.al., 2014). After gathering more stoniness and soil information we could
516 study how well they correlate with different landforms and topographies using artificial intelligence.
517 Most of the soils and soil types in Finland were formed during the Ice Age as a result of glacial
518 meltwater activity, and therefore similar landforms and topographies would presumably correlate
519 with similar soil types. Gamma-ray data could be a significant source of supporting data in this case.

520

521 **5 Conclusions**

522 The acquisition of stoniness data using the Viro method is very useful, as some previous studies have
523 stated, but it does not reveal the true stoniness of the soil, since the steel rod might stop at a relatively
524 small stone. In addition, an increased risk of correlation between peatlands and low gamma values
525 was detected when both are used as predictors. The potential for using SIC models to predict topsoil
526 stoniness is limited and the results should be viewed with caution. It is therefore necessary to make a
527 separate model for use solely with mineral soil data, for which the results were promising when using
528 only gamma values as predictors on geologically homogenous area. In general, however, the results
529 obtained from our SIC models indicate that there is a considerable degree of correlation between
530 gamma values and topsoil stoniness. The formation of separate stoniness models for peatlands and
531 mineral soils would require a broader scope in the stoniness data, especially with respect to different
532 types of mineral soil and varying peat depths. It is important to notice that the used method is
533 appropriate when variation of parent material is small. A petrologic adjustment factor could be
534 introduced in future studies to improve applicability of results. More accurate gamma-ray data would
535 also be needed to make precise predictions, for which purpose a handheld or drone operated gamma-
536 ray spectrometer could be considered a useful tool.

537

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541

542 **References**

543 Äijälä et al. 2014. Metsänhoidon suositukset. Metsätalouden kehittämiskeskus Tapion
544 julkaisuja. Available: <http://www.metsanhoitosuosituksset.fi/suosituksset/metsanhoidonsuosituksset/>
545 (In Finnish)

- 546 Akay, A.E., Session J., Aruga K., 2007. Designing a forwarder operation considering tolerable
547 soil disturbance and minimum total cost. J. Terramech. 44(2):187–195.
548 <https://doi.org/10.1016/j.jterra.2006.10.001>.
- 549 Ala-Ilomäki J., Salmivaara A., Launiainen S., Lindeman H., Kulju S., Finér L., Heikkonen J.,
550 Uusitalo J., (2020) Assessing extraction trail trafficability using harvester CAN-bus data,
551 International Journal of Forest Engineering, 31:2, 138-145.
552 <https://doi.org/10.1080/14942119.2020.1748958>.
- 553 Ashby, W.C., Vogel, W.G., Kolar, C.A., Philo, G.R. (1984). Productivity of Stony Soils on
554 Strip Mines. In Erosion and Productivity of Soils Containing Rock Fragments (eds J.D. Nichols, P.L.
555 Brown & W.J. Grant). <https://doi.org/10.2136/sssaspecpub13.c4>.
- 556 Bygdén G, Eliasson L, Wästerlund I (2003) Rut depth, soil compaction and rolling resistance
557 when using bogie tracks. J Terramech 40:179– 190. <https://doi.org/10.1016/j.jterra.2003.12.001>.
- 558 Cambi M, Certini G, Fabiano F et.al., (2016) Impact of wheeled and tracked tractors on soil
559 physical properties in a mixed conifer stand. IForest:9. <https://doi.org/10.3832/ifor1382-008>.
- 560 Cambi, M., Certini, G., Neri, F., Marchi, E., 2015. The impact of heavy traffic on forest soils:
561 a review. The impact of heavy traffic on forest soils: a review. For. Ecol. Manag. 338, 124–138.
562 <https://doi.org/10.1016/j.foreco.2014.11.022>.
- 563 Castrignanò, A., Wong, M.T.F., Stelluti, M., De Benedetto, D., Sollitto, D., 2012. Use of EMI,
564 gamma-ray emission and GPS height as multi-sensor data for soil characterization. Geoderma 175–
565 176, 78–89 <https://doi.org/10.1016/j.geoderma.2012.01.013>
- 566 Cook S., Corner R., Groves P., Grealish G., Use of airborne gamma radiometric data for soil
567 mapping. Soil Research 34 (1996): 183-194. <https://doi.org/10.1071/SR9960183>.
- 568 Dierke, C., Werban, U., 2013. Relationships between gamma-ray data and soil properties at
569 an agricultural test site. Geoderma 199, 90–98. <https://doi.org/10.1016/j.geoderma.2012.10.017>

- 570 Eliasson L (2005) Effects of forwarder tyre pressure on rut formation and soil compaction.
571 Silva Fenn Monogr 39:549–557. <https://doi.org/10.14214/sf.366>.
- 572 Eliasson, L., Wästerlund, I., 2007. Effects of slash reinforcement of strip roads on rutting and
573 soil compaction on a moist fine-grained soil. For. Ecol. Manage. 252, 118–123.
574 <https://doi.org/10.1016/j.foreco.2007.06.037>.
- 575 Eriksson, C.-P., Holmgren, P., 1996. Estimating the stone and boulder content in forest soils—
576 evaluating the potential of surface penetration methods. Catena 28, 121–134.
577 [https://doi.org/10.1016/S0341-8162\(96\)00031-8](https://doi.org/10.1016/S0341-8162(96)00031-8).
- 578 ESRI Inc., 2016. ArcGIS Desktop, version 10.5. Esri Inc. Available from:
579 <https://desktop.arcgis.com/en/>
- 580 Geisler, E., Rittenhouse, C.D., Rissman, A.R., 2016. Logger perceptions of seasonal
581 environmental challenges facing timber operations in the upper midwest, USA. Soc. Nat. Resour. 29
582 (5). DOI: [10.1080/08941920.2015.1107789](https://doi.org/10.1080/08941920.2015.1107789).
- 583 Geological Survey of Finland (GSF), 2020. File Service of Open Data. <https://hakku.gtk.fi/en>,
584 Accessed date: 6 May 2020.
- 585 Grasty, R.L., 1997. Radon emanation and soil moisture effects on airborne gamma-ray
586 measurements. Geophysics 62, 1379–1385. <https://doi.org/10.1190/1.1444242>.
- 587 Heiskanen J., Hallikainen V., Salmivaara A., Uusitalo J., Ilvesniemi H., 2019. Predictive
588 models to determine fine soil fractions and organic matter from readily available soil and terrain data
589 of soils under boreal forest, Geoderma Regional, Volume 20, 2020,
590 <https://doi.org/10.1016/j.geodrs.2019.e00251>.
- 591 Herrmann, L., Schuler, U., Rangubpit, W., Erbe, P., Surinkum, A., Zarei, M., Stahr, K., 2010.
592 The potential of gamma-ray spectrometry for soil mapping. Proceedings of 19th World Congress of
593 Soil Science.

- 594 Hyvönen E., Turunen P., Vanhanen E., Arkimaa H., Sutinen R., 2005. Airborne gamma-ray
595 surveys in Finland. In: Airo M-L (ed.), *Aerogeophysics in Finland 1972-2004: Methods, System*
596 *Characteristics and Applications*. Geological Survey of Finland, Special Paper 39: 119–134.
- 597 Hyvönen, E., Päänttjä, M., Sutinen, M.-L., Sutinen, R., 2003. Assessing site suitability for
598 Scots pine using airborne and terrestrial gamma-ray measurements in Finnish Lapland. *Can. J. For.*
599 *Res.* 33 (5), 796–806. <https://doi.org/10.1139/x03-005>.
- 600 Ilmatieteenlaitos, 2020. Finnish meteorological institute, Harvester Seasons.
601 <https://harvesterseasons.com/> Accessed date 23 November 2020.
- 602 Immonen K., Kauppinen A., Kuru K., Tamminiemi M., Kallonen J., Strandström, M.. 2000.
603 *Metsäteho: Maanmuokkauksen koulutusaineisto*. (In Finnish)
- 604 Knutsson, G., 1973. Block- och stenhalt i morän. Arkiv- och fältstudier. Statens väg- och
605 trafikinstitut, Stockholm. Internrapport 144.
- 606 Kogan, R.M., Nazarov, I.M., Fridman, S.D., 1971. Gamma spectrometry of Natural
607 Environments and Formations: theory of the method applications to geology and geophysics.
- 608 Kuhn M., Wing J., Weston S., Williams A., Keefer C., Engelhardt A., Cooper T., Mayer Z.,
609 Kenkel B., R Core Team, Benesty M., Lescarbeau R., Ziem A., Scrucca L., Tang Y., Candan C., Hunt
610 T., 2020. caret: Classification and Regression Training. R package version 6.0-86. Available from:
611 <https://CRAN.R-project.org/package=caret>
- 612 Lideskog H., Ersson B.T., Bergsten U., Karlberg M. (2014). Determining boreal clearcut
613 object properties and characteristics for identification purposes. *Silva Fennica* 48(3) article 1136.
614 <https://doi.org/10.14214/sf.1136>.
- 615 Löf M., Dey D.C., Navarro R.M., Jacobs D.F. (2012). Mechanical site preparation for forest
616 restoration. *New Forests* 43(5–6): 825–48. <https://doi.org/10.1007/s11056-012-9332-x>.
- 617 Lundien, J. R. 1967. Terrain analysis by electromagnetic means: Laboratory investigations in
618 the 0- to 2.82 –MeV gamma-ray spectral region. Technical report 3-693, U.S. Army Engineers

- 619 Waterways Experiment Station, Vicksburg, Mississippi, U.S.A, 41 p.
 620 <https://hdl.handle.net/11681/32386>.
- 621 Luoranan J., Rikala R., Smolander H. (2011). Machine planting of Norway spruce by Bracke
 622 and Ecoplanter: an evaluation of soil preparation, planting method and seedling performance. *Silva*
 623 *Fennica* 45: 341–357. <http://dx.doi.org/10.14214/sf.107>.
- 624 Luoranan, J., Saksa, T., Finêr, L., Tamminen, P. 2007. Metsämaan Muokkausopas. Jyväskylä:
 625 Gummerus Kirjapaino Oy. (In Finnish). <http://urn.fi/URN:ISBN:978-951-40-2059-9>.
- 626 Marchuk S., & Ostendorf B. 2009. Relationship between soil properties and airborne
 627 GAMMA-radiometric data. In: Ostendorf, B., Baldock, P., Bruce, D., Burdett, M. and P. Corcoran
 628 (eds.), *Proceedings of the Surveying & Spatial Sciences Institute Biennial International Conference*,
 629 Adelaide 2009, Surveying & Spatial Sciences Institute, pp. 1041-1051. ISBN: 978-0-9581366-8-6.
- 630 Mattila U. & Tokola T., 2018. Terrain mobility estimation using TWI and airborne gamma-
 631 ray data. *Journal of Environmental Management*, Volume 232, 531-536.
 632 <https://doi.org/10.1016/j.jenvman.2018.11.081>.
- 633 Melander L., Ritala R., Strandström M. (2019). Classifying soil stoniness based on the
 634 excavator boom vibration data in mounding operations. *Silva Fennica* vol. 53 no. 2 article id 10068.
 635 <https://doi.org/10.14214/sf.10068>.
- 636 Metsäkeskus, 2020. Maanmittauslaitos korjuukelpoisuus powered by
 637 esri. [https://metsakeskus.maps.arcgis.com/apps/webappviewer/index.html?id=ede3c15b78da423bb1](https://metsakeskus.maps.arcgis.com/apps/webappviewer/index.html?id=ede3c15b78da423bb15e3b62af5ce85f)
 638 [5e3b62af5ce85f](https://metsakeskus.maps.arcgis.com/apps/webappviewer/index.html?id=ede3c15b78da423bb15e3b62af5ce85f) Accessed date: 23 November 2020.
- 639 Minty, B. R. S. 1997. Fundamentals of airborne gamma-ray spectrometry. *AGSO Journal of*
 640 *Australian Geology & Geophysics*, 17 (2), 39–50.
- 641 National land survey of Finland (NLS), 2020. File Service of Open Data.
 642 <https://www.avoindata.fi/data/fi/dataset/suomen-maakunnat-2021-vuoden-2018-maakuntakoodeilla>
 643 Accessed: 6/2021.

- 644 Nilsson U., Luoranan J., Kolström T., Örlander G., Puttonen P. (2010) Reforestation with
645 planting in northern Europe. *Scandinavian Journal of Forest Research* 25: 283–294.
646 <http://dx.doi.org/10.1080/02827581.2010.498384>.
- 647 Palander, T. & Kärhä, K. (2016). Development of Computational Model to Predict Rut
648 Formation using GIS for Planning of Wood Harvesting on Drained Peat Lands. *International Journal*
649 *of Advanced Engineering, Management and Science*. 2. 2040-2057.
- 650 Pohjankukka, J., Nevalainen, P., Pahikkala, T., Hyvönen, E., Sutinen, R., Hänninen, P.,
651 Heikkonen, J., 2014. Arctic soil hydraulic conductivity and soil type recognition based on aerial
652 gamma-ray spectroscopy and topographical data. In: Borga, M., Heyden, A., Laurendeau, D.,
653 Felsberg, M., Boyer, K. (Eds.), *Proceedings of the 22nd International Conference on Pattern*
654 *Recognition (ICPR 2014)*. IEEE, pp. 1822–1827. DOI: [10.1109/ICPR.2014.319](https://doi.org/10.1109/ICPR.2014.319).
- 655 Priori S., Bianconi N., Costantini E., 2014. Can γ -radiometrics predict soil textural data and
656 stoniness in different parent materials? A comparison of two machine-learning methods, *Geoderma*,
657 Volumes 226–227, 2014, Pages 354-364. <https://doi.org/10.1016/j.geoderma.2014.03.012>
- 658 R Core Team. (2020). R: a language and environment for statistical computing. R Foundation
659 for Statistical Computing, Vienna, Austria. <https://www.R-project.org/>
- 660 Rantala J., Saarinen V.-M., Hallongren H. (2010). Quality, productivity and costs of spot
661 mounding after slash and stump removal. *Scandinavian Journal of Forest Research* 25(6): 507–14.
662 <https://doi.org/10.1080/02827581.2010.522591>.
- 663 Rawlins, B.G., Lark, R.M., Webster, R., 2007. Understanding airborne radiometric survey
664 signals across part of eastern England. *Earth Surface Processes and Landforms*. 32. 1503 - 1515. DOI:
665 10.1002/esp.1468
- 666 Rittenhouse, C.D., Rissman, A.R., 2015. Changes in winter conditions impact forest
667 management in north temperate forests. *J. Environ. Manag.* 149, 157–167.
668 <https://doi.org/10.1016/j.jenvman.2014.10.010>.

- 669 Saarilahti, M. 2002. Soil interaction model. EU 5th Framework Project (Quality of Life and
670 Management of Living Resources) Contract No.QLK5- 1999-00991 (1999-2002).
- 671 Saarilahti, M., & Anttila, T. (1999). Rut Depth Model for Timber Transport of Moraine Soils.
672 In Proceedings of the 9th International Conference of International Society for Terrain-Vehicle
673 Systems (pp. 29-37). <http://hdl.handle.net/1975/8068>.
- 674 Saarinen V.-M. (2006). The effects of slash and stump removal on productivity and quality of
675 forest regeneration operations – preliminary results. Biomass and Bioenergy 30(4): 349–56.
676 <https://doi.org/10.1016/j.biombioe.2005.07.014>.
- 677 Saksa T., Miina J., Haatainen H., Kärkkäinen K. (2018). Quality of spot mounding performed
678 by continuously advancing mounds. Silva Fennica vol. 52 no. 2 article id 9933
679 <https://doi.org/10.14214/sf.9933>.
- 680 Schwarzer, T. F. & Adams J.A.S. 1973. Rock and soil discrimination by low altitude airborne
681 gamma-ray spectrometry in Payne County, Oklahoma. Economic Geology, 68, pp. 1297-
682 1312. <https://doi.org/10.2113/gsecongeo.68.8.1297>.
- 683 Sirén M., Ala-Ilomäki J., Lindeman H., Uusitalo J., Kiilo K.E.K., Salmivaara A., Ryyänen
684 A. (2019). Soil disturbance by cut-to-length machinery on mid-grained soils. Silva Fennica vol. 53
685 no. 2 article id 10134. <https://doi.org/10.14214/sf.10134>.
- 686 Sirén M., Salmivaara A., Ala-Ilomäki J., Launiainen S., Lindeman H., Uusitalo J., Sutinen R.,
687 Hänninen P., (2019) Predicting forwarder rut formation on fine-grained mineral soils, Scandinavian
688 Journal of Forest Research, 34:2, 145-154, <https://doi.org/10.1080/02827581.2018.1562567>
- 689 Stendahl J., Lundin L., Nilsson T., 2009. The stone and boulder content of Swedish forest
690 soils. Catena 77 (3), 285-291. <https://doi.org/10.1016/j.catena.2009.02.011>
- 691 Suvinen, A., Tokola, T., Saarilahti, M., 2009. Terrain trafficability prediction with GIS
692 analysis. For. Sci. 55, 433–442.

- 693 Taylor, M., Smettem, K., Pracilio, G., Verboom., W., 2002. Relationships between soil
694 properties and high-resolution radiometrics, central eastern Wheatbelt, Western Australia.
695 Exploration Geophysics. 33, 95–102. DOI: 10.1071/EG02095
- 696 Uusitalo, J., Ala-Ilomäki, J. (2013). The significance of above-ground biomass, moisture
697 content and mechanical properties of peat layer on the bearing capacity of ditched pine bogs. Silva
698 Fennica vol. 47 no. 3 article id 993. <https://doi.org/10.14214/sf.993>.
- 699 Uusitalo, J., Ala-Ilomäki, J., Lindeman, H. et al. Predicting rut depth induced by an 8-wheeled
700 forwarder in fine-grained boreal forest soils. Annals of Forest Science 77, 42 (2020).
701 <https://doi.org/10.1007/s13595-020-00948-y>.
- 702 Uusitalo, J., Salomäki, M., Ala-Ilomäki, J. (2015). The Effect of Wider Logging Trails on Rut
703 Formations in the Harvesting of Peatland Forests. Croatian Journal of Forest Engineering: Journal for
704 Theory and Application of Forestry Engineering, 36, 125-130.
- 705 Uusitalo, J., Salomäki, M., Ala-Ilomäki, J., 2015. Variation of the factors affecting soil
706 bearing capacity of ditched pine bogs in Southern Finland. Scand. J. For. Res. 30 (5), 429–439.
707 <https://doi.org/10.1080/02827581.2015.1012110>.
- 708 Väänänen T., Hyvönen E., Jakonen M., Kupila J., Lerssi J., Leskinen J., Liwata P., Nevalainen
709 R., Putkinen S., Virkki H., 2007. Maaperän yleiskartan tulkinta- ja kartoitusprosessi. Geological
710 Survey of Finland. (Only in Finnish) Available: http://tupa.gtk.fi/raportti/arkisto/p22_4_2007_58.pdf
- 711 Venäläinen, P., Alanne, H., Ovaskainen, H., Poikela, A., Strandström, M., 2018.
712 Kausivaihtelun kustannukset ja vähentämiskeinot puun toimitusketjussa. Metsätehon tulosalvosarja
713 8/2017. Available in Finnish: [http://www.metsateho.fi/kausivaihtelun-kustannukset-ja-](http://www.metsateho.fi/kausivaihtelun-kustannukset-ja-vahentamiskeinot/)
714 [vahentamiskeinot/](http://www.metsateho.fi/kausivaihtelun-kustannukset-ja-vahentamiskeinot/)
- 715 Viro, P. 1952. Kivisyyden määrittäminen. Communicationes Instituti Forestalis Fenniae 40
716 (3)

Viro, P.J., 1947. The mechanical composition and fertility of forest soil taking into consideration especially the stoniness of the soil. *Communicationes Instituti Forestalis Fenniae* 25 (2).

Wilford, J. & Minty, B., 2006. The use of airborne gamma-ray imagery for mapping soils and understanding landscape processes. *Developments in soil science.*, 31: 207-218. [https://doi.org/10.1016/S0166-2481\(06\)31016-1](https://doi.org/10.1016/S0166-2481(06)31016-1)

Wong, M.T.F. & Harper, R.J., 1999. Use of on-ground gamma-ray spectrometry to measure plant-available potassium and other topsoil attributes. *Australian Journal of Soil Research*, 37 (2). pp. 267-278. <http://dx.doi.org/10.1071/S98038>

In total 65 references.

Figure captions:

Fig. 1. Locations of the 69 sites studied here. The sample plots were located in the immediate proximity of each site. Northwest corner: 28°49'43.057"E. 62°39'12.131"N Southeast corner: 29°36'25.932"E, 62°16'27.702"N (ETRS-TM35FIN). Base map downloaded from avoindata.fi (National land survey of Finland, 2020). Figure created with ArcGIS Desktop, version 10.5 (ESRI Inc., 2016).

Fig. 2. Box plots for SI and SIC and their normalized gamma values in dataset 1. The ends of the box are the upper and lower quartiles, the median is marked by a horizontal line inside the box and the whiskers extend to the highest and lowest observations. Figure created with R statistical computing environment (R Core Team 2020).

741 **Fig.3.** Box plots for SI and SIC and their normalized gamma values in dataset 2 (only mineral soils).

742 Figure created with R statistical computing environment (R Core Team 2020).

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Table 1. Deviation of SI and SIC classes and soil types in the sample plots. Means of normalized gamma values on every SI, SIC and soil type.

		Frequency	Percentage	Mean K	Mean Th	Mean U
SI	0	70	27.45	-0.88	-0.75	-0.59
	1	9	3.53	-1.07	-0.66	-0.28
	2	7	2.75	-0.22	0.09	-0.56
	3	10	3.92	0.37	-0.04	-0.17
	4	16	6.27	-0.04	-0.20	-0.37
	5	18	7.06	0.40	0.30	-0.06
	6	21	8.24	0.20	0.24	0.21
	7	31	12.16	0.36	0.43	0.28
	8	30	11.76	0.48	0.40	0.35
	9	20	7.84	0.71	0.34	0.63
	10	23	9.02	0.72	0.73	0.76
SIC	1	79	30.98	-0.92	-0.74	-0.56
	2	17	6.67	0.11	-0.13	-0.39
	3	55	21.57	0.17	0.14	-0.03
	4	61	23.92	0.47	0.46	0.36
	5	43	16.86	0.76	0.59	0.71
Peatland	0	178	69.80			
	1	77	30.20	-0.77	-0.74	-0.53
Fine-grained till	0	236	92.55			
	1	19	7.45	-0.50	-0.22	-0.11
Sandy till	0	114	44.71			
	1	141	55.29	0.49	0.38	0.29
Sand	0	237	92.94			
	1	18	7.06	0.00	0.40	0.07

Table 2. Spearman correlation coefficients between stoniness information, soil properties and gamma-ray values. SI=stoniness index, SIC=stoniness index classes, Peat=peatland, FT=fine-grained till, ST=sandy till, SND=sand, K=potassium values, TH=thorium values, U=uranium values.

		SI	SIC	Peat	FT	ST	SND	K	TH	U
SI	Spearman Correlation	1	.983**	-.378**	-.314**	.511**	-.006	.622**	.503**	.457**
	Sig. (2-tailed)		.000	.000	.000	.000	.920	.000	.000	.000
SIC	Spearman Correlation		1	-.397**	-.302**	.522**	.009	.634**	.508**	.455**
	Sig. (2-tailed)			.000	.000	.000	.881	.000	.000	.000
Peat	Spearman Correlation			1	-.187**	-.731**	-.181**	-.475**	-.455**	-.344**
	Sig. (2-tailed)				.003	.000	.004	.000	.000	.000
FT	Spearman Correlation				1	-.316**	-.078	-.190*	-.087	-.021
	Sig. (2-tailed)					.000	.213	.002	.166	.740
ST	Spearman Correlation					1	-.306**	.549**	.428**	.339**
	Sig. (2-tailed)						.000	.000	.000	.000
SND	Spearman Correlation						1	-.021	.075	-.021
	Sig. (2-tailed)							.740	.233	.741
K	Spearman Correlation							1	.799**	.640**
	Sig. (2-tailed)								.000	.000
TH	Spearman Correlation								1	.579**
	Sig. (2-tailed)									.000
U	Spearman Correlation									1
	Sig. (2-tailed)									

** Correlation is significant at the 0.01 level (2-tailed)

* Correlation is significant at the 0.05 level (2-tailed)

Table 3. Ordinal regression model predicting SIC classes based on dataset 1 using soil information and gamma values. Peat = Peatland, FT = Fine-grained till, Sand = sand, K = potassium gamma values, U = uranium gamma values. The intercepts in the model are class-pair specific and are used for calculating class-pair probabilities. The model uses a negative loglog link function.

Coefficients	value	std.error	t-value	p-value
Peat	-1.0557	0.232	-4.546	5.48E-06
FT	-2.7356	0.724	-3.780	1.57E-03
SND	-0.4363	0.327	-1.335	1.82E-01
K	0.4672	0.113	4.128	3.67E-05
U	0.3997	0.109	3.658	2.54E-04
Intercepts				
1 2	-0.8041	0.128	-6.277	3.45E-10
2 3	-0.4604	0.121	-3.819	1.34E-04
3 4	0.4380	0.128	3.417	6.34E-04
4 5	1.6645	0.177	9.407	5.11E-21

Table 4. Results of the stoniness ordinal regression models in both the modelling and testing phases using dataset 1. The allowable values have the sum of all cases with acceptable variation within their classification result.

Modelling			Testing	
	Correct	Acceptable	Correct	Acceptable
SIC				
Count	133	201	245	410
%	0.522	0.788	0.490	0.820
Kappa	0.547	0.719	0.478	0.761
SI				
Count	93	168	145	302
%	0.365	0.659	0.290	0.604
Kappa	0.199	0.587	0.000	0.440

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Table 5. Correlation between observed (rows) and predicted SIC classes (columns) in the modelling and testing phases. Correct predictions are indicated with grey shading. The total numbers in the observed SIC classes in the test data (rows) were: SIC 1, n=121; SIC 2, n=44; SIC 3, n=136; SIC 4, n=114; SIC 5, n=85; and those in the testing phase results (columns) were: SIC 1, n=172; SIC 2, n=0; SIC 3, n=160; SIC 4, n=168; SIC 5, n=0.

Modelling phase prediction of SIC						Testing phase prediction of SIC						
SIC		1	2	3	4	5		1	2	3	4	5
	1	70	0	8	1	0	110	0	9	2	0	0
	2	7	0	3	7	0	16	0	17	11	0	0
	3	12	0	22	20	1	21	0	64	51	0	0
	4	14	0	7	33	7	10	0	33	71	0	0
	5	4	0	7	24	8	8	0	29	48	0	0

Table 6. Ordinal regression model predicting the SIC classes of dataset 2 using only gamma values for potassium (K), uranium (U) and thorium(Th). The model uses a cauchit link function.

Coefficients	value	std.error	t-value	p-value
K	3.2352	0.703	4.600	4.22E-06
U	0.0162	0.386	0.042	9.66E-01
Th	-0.8005	0.319	-2.507	1.22E-02
Intercepts				
1 2	-1.3347	0.201	-6.627	3.43E-11
2 3	-0.3205	0.123	-2.608	9.10E-03
3 4	0.5360	0.140	3.838	1.24E-04
4 5	1.7664	0.277	6.372	1.87E-10

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Table 7. SIC classification results for both the modelling and testing phases with dataset 2

SIC	Modelling		Testing	
	Correct	Acceptable	Correct	Acceptable
Count	49	102	18	47
%	0.322	0.671	0.286	0.746
Kappa	0.181	0.589	0.066	0.671

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Potassium

Uranium

Thorium

Potassium

Uranium

Thorium

Potassium

Uranium

Thorium