

1 Preprint: Downscaling digital soil maps 2 using electromagnetic induction and aerial 3 imagery

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8 **Abstract**

9 Coarse-resolution soil maps at regional to national extents are often inappropriate for mapping
10 intra-field variability. At the same time, sensor data, such as electromagnetic induction
11 measurements and aerial imagery, can be highly useful for mapping soil properties that correlate
12 with electrical conductivity or soil color. However, maps based on these data nearly always require
13 calibration with local samples, as multiple factors can affect the sensor measurements. In this study,
14 we present a method, which combines coarse-resolution, large extent soil maps with sensor data in
15 order to improve predictions of soil properties. We test this method for predicting clay and soil
16 organic matter contents at five agricultural fields located in Denmark. We test the method for one
17 field at a time, using soil samples from the four other fields to predict soil properties. Results show
18 that the method generally improves predictions over the predictions from the coarse-resolution
19 maps, especially for soil organic matter. The method generally overestimates prediction

20 uncertainties, a disadvantage, which will require improvements. Overall, the method is a simple,
21 promising tool for giving a quantitative estimate of soil properties, when no local soil samples are
22 available.

23 *Keywords:* clay, soil organic matter, electrical conductivity, remote sensing, topsoil, Denmark

24 **1 Introduction**

25 Over the last decades, sensor technologies have become widely applied means for mapping soil
26 properties. In many cases, sensors have facilitated the creation of soil maps with unprecedented
27 detail and accuracy. The resulting maps have large benefits for agricultural management practices
28 and planning both at farm and field level (Corwin and Lesch, 2005, Magri et al., 2005). The key to
29 the success of sensors lies in the fact that they can quickly collect large numbers of measurements,
30 which are good proxies for soil properties. The high spatial densities of the measurements enables
31 the creation of soil maps with similar densities.

32 Electromagnetic induction (EMI) is a widely applied proximal sensing technology. EMI instruments
33 consist of a transmitter coil and one or more receiver coils. The transmitter coil induces circular
34 eddy-current loops in the soil, and the receiver coils measure the resulting electromagnetic fields
35 (Everett, 2013). EMI measures apparent electrical conductivity (EC_a) and is therefore useful for
36 mapping soil properties that correlate with the electrical conductivity (EC) of the soil, including
37 salinity, moisture, clay contents and soil organic matter (SOM) (Corwin and Lesch, 2005). Early

38 studies focused on measurements of soil salinity (Corwin and Rhoades, 1982, Williams and Baker,
39 1982, Wollenhaupt et al., 1986), but later studies have proven EMI as a reliable method for
40 mapping clay contents (Williams and Hoey, 1987, Triantafilis and Lesch, 2005, Michael Mertens et
41 al., 2008, Heil and Schmidhalter, 2012, Doolittle and Brevik, 2014). EC_a measurements obtained
42 with EMI are depth-weighted averages (Corwin and Lesch, 2005, Callegary et al., 2007, Heil and
43 Schmidhalter, 2017). However, in recent years, researchers have started inverting EC_a to obtain
44 depth-specific EC estimates. These values make it possible to map soil properties in three
45 dimensions (Koganti et al., 2018, Khongnawang et al., 2019).

46 At the same time, bare soil imagery is useful for mapping SOM, as soils with high amounts of
47 organic matter have a darker color (Ladoni et al., 2009). Some studies have employed multispectral
48 images of soils to predict SOM (Varvel et al., 1999, Fox and Sabbagh, 2002, Roberts et al., 2010),
49 while others have used RGB imagery (Chen et al., 2000, Achasov and Bidolakh, 2011) or even
50 greyscale images (Gelder et al., 2011). A review by Ladoni et al. (2009) showed that infrared
51 spectral bands had a higher correlation with SOM than bands in the visible spectrum. Likewise, Fox
52 and Sabbagh (2002) showed that including near-infrared reflectance improved the accuracy of the
53 predictions. However, in most cases, the red band has a higher correlation to SOM than the other
54 visible spectral bands (Ladoni et al., 2009, Achasov and Bidolakh, 2011, Wu et al., 2018).

55 While EMI and bare soil imagery are useful for mapping, both techniques require local samples for
56 calibration. Maps based on EMI require soil samples for calibration, as the relationships with soil
57 properties are often site-specific, and factors that vary over short time intervals, such as temperature
58 and water contents, can influence the measurements (Corwin and Lesch, 2005, Heil and
59 Schmidhalter, 2017). Likewise, it is difficult to establish universal models linking SOM to soil
60 color, as moisture, vegetation, crop residues and tillage affect colors in the images (Ladoni et al.,
61 2009, Roberts et al., 2010).

62 Unlike EMI and aerial imagery, large-extent soil maps often do not account for intra-field
63 variability of soil properties. In many cases, this is due to their coarse resolution. However, even
64 when the resolution is nominally high, other factors, such as the sampling strategy can limit the
65 ability to map soil properties within fields. For example, Adhikari et al. (2013) and Adhikari et al.
66 (2014) mapped soil texture and SOM, respectively, at 30.4 m resolution for Denmark, using legacy
67 soil observations (Madsen and Jensen, 1985, Madsen et al., 1992, Greve et al., 2014). The majority
68 of the soil samples used by Adhikari et al. (2013) and Adhikari et al. (2014) originated from a large
69 mapping effort carried out in the 1970s (Madsen et al., 1992). In this effort, surveyors used
70 judgment sampling to select representative areas within fields. Furthermore, the samples were all
71 composites of 25 to 30 subsamples from within areas of about 5000 m². Therefore, the samples
72 from this effort have limited use for mapping intra-field variability in soil properties.

73 In short, sensors and large extent soil maps have contrasting capabilities. On the one hand, sensors
74 can account for intra-field variability but need local samples for calibration. On the other hand,
75 coarse-resolution large-extent soil maps may well represent the mean of a soil property within a
76 field, but fail to account for intra-field variability.

77 In this study, we propose an approach that combines sensor data with coarse-resolution large-extent
78 soil maps. The aim is to map clay and SOM contents for agricultural fields without using local soil
79 samples by combining predictions from coarse-resolution soil maps with regression models that
80 relate variation in the soil properties with sensor data. Firstly, we will use median values from the
81 coarse-resolution rasters within the fields. We will then modify these values with models that
82 account for deviations from the median, using deviations from the sensor data medians as
83 explanatory variables.

84 The usefulness of this approach relies on the following assumptions:

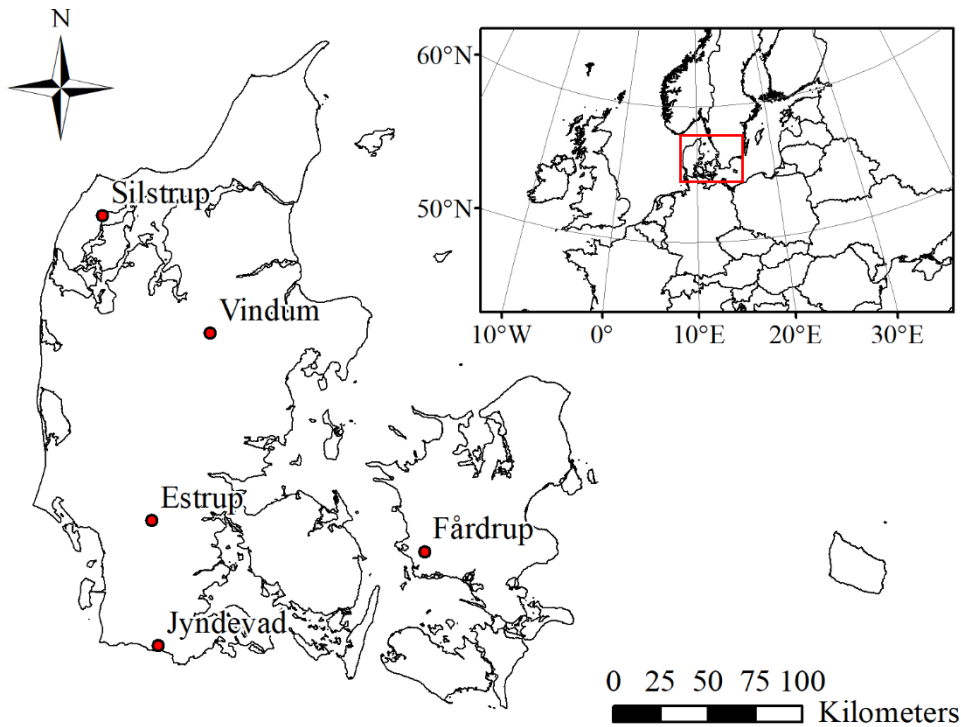
- 85 1. The clay and SOM contents in the coarse-resolution rasters represent accurately the median
86 values within the agricultural fields.
- 87 2. Variations in clay contents within the fields are the main driver for variation in EC.
- 88 3. Variations in SOM contents within the fields are the main driver for variation in soil
89 brightness (SB) in aerial images.

90 We will test the proposed approach for five agricultural fields located in Denmark. We hypothesize
91 that (1) the median values modified by sensor-data will predict clay and SOM contents more
92 accurately than the coarse-resolution rasters. We also hypothesize that (2) it is possible to estimate
93 accurately the uncertainties associated with the method. Lastly, we hypothesize that (3) the
94 fulfilment of the three assumptions listed above will be the deciding criterion for the accuracy of the
95 predictions.

96 **2 Materials and methods**

97 2.1 Study areas

98 The five fields used in this study are located in Denmark in northern Europe (Figure 1).



99

100 *Figure 1: Location of Denmark in Europe and the locations of the five fields used in the study.*

101 *2.1.1 Estrup*

102 The field at Estrup (Figure 2A) has an area of 1.3 ha and lies on a hill, 56 to 58 m above sea level in
103 a Saalian moraine landscape. The topography is mildly undulating and slopes slightly (1.1%)
104 towards the northeast. The dominant surface geology within the field is clay till, while some small
105 areas contain glaciofluvial sand. The soils within the field include Abruptic Argiudolls, Aquic
106 Argiudolls and Fragiaquic Glossudalfs (Lindhardt et al., 2001).

107 *2.1.2 Fårdrup*

108 The field at Fårdrup (Figure 2B) has an area of 2.4 ha and lies near the top of a hill, 30 to 33 m
109 above sea level in a Weichselian moraine landscape. The field generally slopes towards the west
110 with a mean gradient of approximately 1.7%. Clay and sand till are the dominant surface geologies,
111 with smaller parties of glaciofluvial sand. The soils within the field include Haplic Vermudolls,
112 Oxyaquic Hapludolls and Oxyaquic Argiudolls (Lindhardt et al., 2001).

113 *2.1.3 Jynde vad*

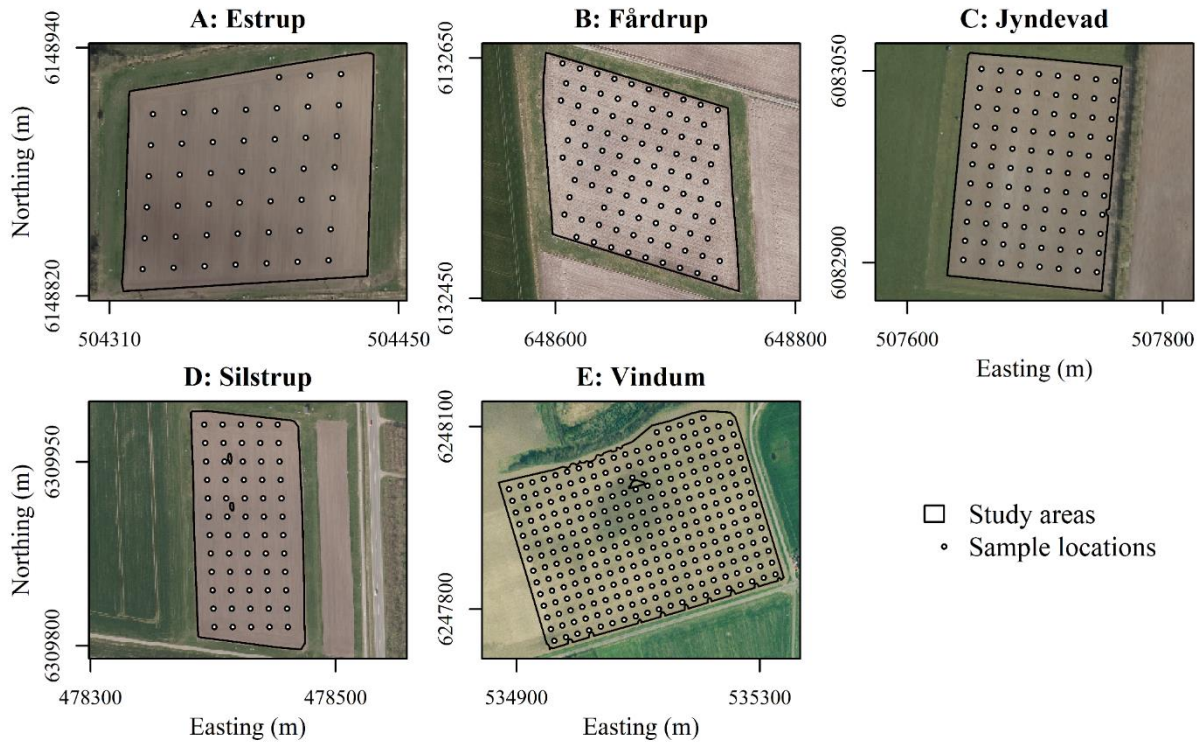
114 The field at Jynde vad (Figure 2C) has an area of 2.4 ha and lies in a glacial outwash plain, 14 to 15
115 m above sea level. The field generally slopes towards the southwest with a mean gradient of 1.3%.
116 Glaciofluvial sand is the dominant surface geology. The soils within the field are Typic Haplorthods
117 (Lindhardt et al., 2001).

118 *2.1.4 Silstrup*

119 The field at Silstrup (Figure 2D) has an area of 1.7 ha and lies at 41 to 45 m above sea level, close
120 to the top of a hill in a terminal moraine formed by a late-Weichselian ice advance from the north.
121 The field slopes towards the north with a mean gradient of 2.2%. The dominant surface geology is
122 clay till. The soils within the field are Alfic Argiudolls and Typic Hapludolls (Lindhardt et al.,
123 2001).

124 *2.1.5 Vindum*

125 The field at Vindum (Figure 2E) has an area of 11.7 ha and lies 55 to 66 m above sea level in a
126 Weichselian kettled moraine landscape. The landscape is undulating with a depression near the
127 center of the field. Surface geologies include clay till, glaciofluvial sand and peat (Olesen and
128 Simmelsgaard, 1995). Based on data from the Danish Soil Profile Database (Madsen and Jensen,
129 1985), soil types within the field include Alfisols, Inceptisols, Mollisols and Histosols. In most
130 cases, they are Arenic Oxyaquic Hapludalfs, Mollic Oxyaquic Hapludalfs or Oxyaquic Humudepts.
131 The depression near the center of the field contains most of the Histosols (Møller et al., 2019,
132 Pouladi et al., 2019). Greve and Greve (2004) showed a high correlation between clay contents and
133 EC_a within the field.



134

135 *Figure 2: Maps of the five fields used in the study, including field boundaries and sampling*
136 *locations. Backgrounds show orthophotos from the spring 2017 (A, B, C, D) and from the spring*
137 *2006 (E) (Agency for Data Supply and Efficiency, 2019). The axes show coordinates for UTM zone*
138 *32N, ETRS 1989.*

139 2.2 Input data

140 2.2.1 *Soil samples*

141 We used soil samples extracted from the depth interval 0 to 25 cm for all five fields. At Estrup, the
142 samples were located in a rhombic grid, while in the other fields a square grid was in use (Figure 2).
143 At Vindum, the grid spacing was 20 m, while the other fields had 15-m grid spacings. Table 1 gives
144 the number of samples extracted from each field, and Figure 2 gives an overview of the grid
145 sampling design of the different fields.

146 The soil samples were dried and crushed to pass through a 2 mm sieve. Particle size distribution
147 was determined by sieving and hydrometric methods (Gee and Bauder, 1986), while soil organic
148 carbon content was determined by combustion in a LECO induction furnace and converted to SOM
149 by multiplication with 1.72 (Tabatabai and Bremner, 1970).

150 Adhikari et al. (2013) and Adhikari et al. (2014) did not use the soil observations from the five
151 fields when producing the coarse-resolution maps of clay and SOM contents.

152 2.2.2 *EMI surveys*

153 We used EC_a measurements from EMI surveys conducted with a DUALEM-21S sensor (Dualem
154 Inc., Milton, ON, Canada) in the years 2010 to 2012 at the five fields. Table 1 lists the dates of the
155 surveys for each field.

156 The DUALEM-21S is a single-transmitter multi-receiver electromagnetic induction (EMI)
157 instrument operating at a frequency of 9 kHz. It has a transmitter coil located at one end. Two pairs
158 of receiver coils in horizontal coplanar (HCP) and perpendicular (PRP) orientations share the
159 transmitter coil. For the HCP configurations, the transmitter-receiver separation distances are 1 and
160 2 m, and for the PRP configurations, they are 1.1 and 2.1 m respectively. The quadrature-phase and
161 in-phase signal responses of the EMI sensor are representative of the EC_a and the magnetic
162 susceptibility of the soil (McNeill, 1980). At low induction numbers, the depth sensitivity of EC_a
163 measurements is approximately a function of coil spacing (S) and array orientation. Furthermore,
164 the depth of exploration can be defined as the depth at which the signal accumulates 70% of its total
165 sensitivity (McNeill, 1980). Hence, the depth of exploration for HCP and PRP arrays are $1.6 S$ and
166 $0.5 S$, respectively when the instrument is placed on the ground (DuaLEM Inc, 2007). As such, the
167 1.1 m and 2.1 m PRP configurations provide measures of EC_a for soil volumes reaching depths of
168 0.5 and 1.0 m, whereas the 1 m and 2 m HCP configurations provide EC_a to depths of 1.6 and 3.2
169 m, respectively. The actual depth of investigation can vary significantly depending on the true EC.
170 This is because the low induction number approximation is no longer valid in highly conductive ($>$
171 100 mS m^{-1}) conditions, and the corresponding measurement depth will be smaller (Christiansen et
172 al., 2016).

173 The instrument was mounted on a sled (at a height of 0.3 m above the ground) attached to an ATV,
 174 with real-time data georeferencing using an RTK GPS. Dedicated data processing was performed
 175 using Aarhus Workbench software (Auken et al., 2009) by removing the negative EC_a values and
 176 noise due to anthropogenic coupling (metal cables, field monitoring installations etc.). Afterwards,
 177 the data were corrected for the offset between GPS and the individual channels. We further
 178 improved the signal-to-noise ratio (SNR) by averaging the data, choosing an appropriate sounding
 179 distance and running mean width. We inverted EC_a with a quasi-3D spatially constrained inversion
 180 algorithm (Viezzoli et al., 2008, Auken et al., 2015) using a ten-layer model to estimate the average
 181 EC of the topsoil (0 – 30 cm). Afterwards, we interpolated point values of topsoil EC to a 1.6 m
 182 raster using ordinary kriging with an exponential variogram.

183 *Table 1: Overview of the fields used in the study, including their area, number of samples, the date*
 184 *of the EMI survey and the dates of the orthophotos, with the number of orthophotos for each field in*
 185 *parentheses.*

Field	Area (ha)	Samples (n)	EMI survey (date)	Orthophotos [dates (n)]
Estrup	1.3	45	2011-09-05	Spring 2016, spring 2017, spring 2018 (3)
Fårdrup	2.4	95	2011-07-28	Spring 2012, spring 2016, spring 2017, spring 2018 (4)
Jynde vad	2.4	88	2012-05-02	Summer 2010, summer 2012, spring 2017 (3)
Silstrup	1.7	65	2011-05-16	Spring 2015, spring 2016, spring 2017 (3)
Vindum	11.7	307	2010-04-17	Spring 2006, spring 2018 (2)

186 *2.2.3 Aerial images*

187 We obtained two to four bare-soil orthophotos for each field from the years 2006 to 2018. We used
188 orthophotos from the GeoDanmark webservice (Agency for Data Supply and Efficiency, 2019).
189 Table 1 lists the dates of the images obtained for each field. Some of the images contained an
190 infrared band in addition to RGB data. However, we omitted the infrared data, as this allowed us to
191 use more images. Furthermore, aerial images often only contain RGB data, and by omitting the
192 infrared band, we aimed to make our results more generally applicable. We stored the images as
193 RGB rasters and manually cropped out shadows and non-soil features. The resolutions of the
194 images ranged from 10 to 50 cm. We extracted SB in the red band for each image and then
195 aggregated the rasters to a common 1.6 m resolution. We then averaged SB across the images for
196 each field in order to reduce effects from individual images.

197 *2.2.4 Coarse resolution maps*

198 We used coarse-resolution maps of clay and SOM contents produced by Adhikari et al. (2013) and
199 Adhikari et al. (2014), respectively. The authors of these studies produced these maps at 30.4 m-
200 resolution for all of Denmark, using Cubist regression models with kriged residuals. The authors
201 produced predictions for several depth intervals, but we used only the predictions for the depth
202 interval 0 to 30 cm.

203 2.3 Centered measurements

204 A preliminary analysis showed a correlation between the standard deviation (SD) of EC within each
 205 field and their median ($R^2 = 0.85$, $n = 5$, $p < 0.05$). However, there was no correlation between
 206 median EC and median clay contents from the coarse-resolution map ($\widetilde{clay}_{CR,i}$, $p > 0.05$, $n = 5$).
 207 This suggested to us that EC variation within each field was proportional to the median EC, but not
 208 proportional to variation in clay contents. We therefore scaled EC for each field using the median
 209 clay contents from the coarse-resolution map in order to make variation proportional to the
 210 predicted clay contents:

$$211 \quad EC_{SC} = EC * \frac{\widetilde{clay}_{CR,i}}{\widetilde{EC}_i} \quad [1]$$

212 where EC_{SC} is scaled EC, $\widetilde{clay}_{CR,i}$ is the median clay content from the coarse-resolution map for
 213 field i , and \widetilde{EC}_i is median EC for field i .

214 Furthermore, our approach relies on the assumption that intra field variations in EC and SB reflect
 215 variation in clay contents and SOM, respectively. We therefore centered clay and SOM contents,
 216 EC_{SC} and SB for each field using the median of each variable. We used the median, as it is robust
 217 towards outliers. Furthermore, we transformed SOM contents by natural logarithm:

$$218 \quad clay_c = clay_o - \widetilde{clay}_{o,i} \quad [2]$$

$$219 \quad \ln(SOM)_c = \ln(SOM)_o - \ln(\widetilde{SOM})_{o,i} \quad [3]$$

$$220 \quad EC_c = EC_{SC} - \widetilde{EC_{SC,i}} \quad [4]$$

$$221 \quad SB_c = SB - \widetilde{SB_i} \quad [5]$$

222 where c signifies centered values, o signified observed values.

223 2.4 Prediction of clay and SOM contents

224 We trained regression models to account for the relationship between $clay_c$ and EC_c and between
 225 $\ln(SOM_c)$ and SB_c . We used two forms of regression: linear regression (LR) and local regression
 226 (LOESS) (Cleveland et al., 1992). On the one hand, we included LR for its relative robustness and
 227 mathematical simplicity. On the other hand, we included LOESS for its ability to account for non-
 228 linear relationships between variables. In our study, each LOESS model combined several locally
 229 fitted LR models, each spanning 67% of the data.

230 We tested the approach for one field at a time, using leave-site-out (LSO) cross validation. For each
 231 field, we trained models from the centered values of the four other fields. We then used these
 232 models to predict $clay_c$ and $\ln(SOM_c)$ for the field that was left out and added the medians from the
 233 coarse-resolution maps. We also transformed SOM estimates from logarithmic to a linear scale.

$$234 \quad \widehat{clay} = \widehat{clay}_c + \widehat{clay}_{CR,i} \quad [6]$$

$$235 \quad \widehat{SOM} = e^{\ln(\widehat{SOM})_c + \ln(\widehat{SOM}_{CR,i})} \quad [7]$$

236 where \wedge indicates predicted values, and CR indicates values from the coarse-resolution maps.

237 We calculated uncertainties for the predictions as 95% prediction intervals. First, we calculated the
 238 standard error of the predictions by adding the standard error of the median values in the coarse
 239 map to the prediction standard error of the model:

$$240 \quad SE_p = \sqrt{SE_{fit}^2 + SE_{res}^2 + SE_{CR,i}} \quad [8]$$

241 where SE_p is the standard error of the predictions, SE_{fit} is the standard error of the model fit, SE_{res} is
 242 the standard error of the model residuals, and $SE_{CR,i}$ is the standard error of the median values in the
 243 coarse-resolution map for the fields used in the model.

244 We then calculated the boundaries of the prediction interval by adding and subtracting standard
 245 error multiplied by the quantile of Student's t-distribution from the predicted value.

$$246 \quad PI_{0.95} = \hat{y} \pm SE_p * Q(p = 0.975, v = n) \quad [9]$$

247 where \hat{y} the predicted soil property (clay (%) or $\ln[\text{SOM} (\%)]$), Q is the quantile of Student's t-
 248 distribution, p is the probability, and v is the degrees of freedom n . For LR, n is a constant, but for
 249 LOESS, n varies for prediction points.

250 As we produced predictions for each field without using local samples, we assessed the accuracies
 251 of the predictions using all samples for each field. We calculated accuracies as Pearson's R^2 and
 252 root mean square error (RMSE). We also calculated the proportion of soil observations that were
 253 within the 95% prediction interval.

254 Furthermore, for comparison, we calculated accuracies for the coarse-resolution maps and for
255 regression using local samples. We assessed the accuracies of regression with local samples by
256 leave-one(-sample)-out (LOO) cross validation.

257 To compare the RMSE of the LSO predictions with the RMSEs of predictions with local samples
258 and of the coarse-resolution maps, we also calculated for each field the relative improvements (RI)
259 for clay and SOM predictions, respectively:

$$260 \quad RI_i = \frac{RMSE_{LSO,i} - RMSE_{CR,i}}{RMSE_{LOO,i} - RMSE_{CR,i}} \quad [10]$$

261 where RI_i is the relative improvement for field i (%), $RMSE_{LSO,i}$ is the RMSE of LSO predictions for
262 field i , $RMSE_{CR,i}$ is RMSE for the coarse-resolution map for field i , and $RMSE_{LOO,i}$ is the lowest
263 RMSE for predictions with local samples (LR or LOESS), calculated using leave-one(-sample)-out
264 (LOO) cross-validation for field i .

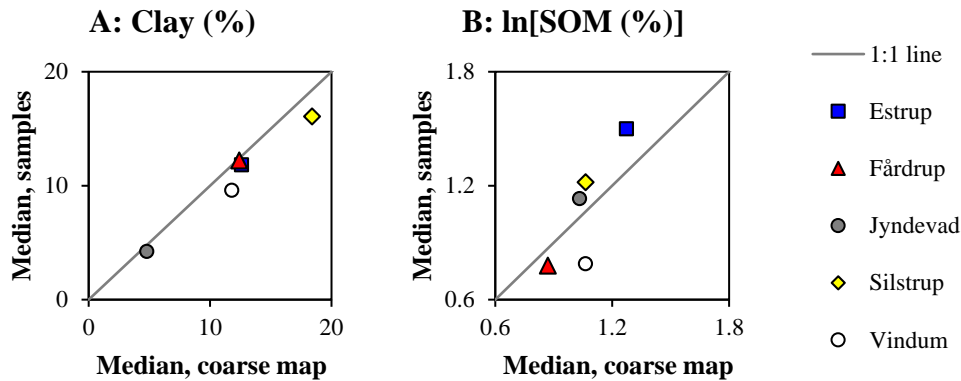
265 $RI = 0\%$ indicates RMSE on par with the coarse-resolution map, while $RI = 100\%$ indicates RMSE
266 on par with regression using local samples.

267 **3 Results and discussion**

268 **3.1 Comparison with coarse-resolution maps**

269 The observed medians for clay and $\ln[\text{SOM}]$ generally showed linear relationships with the medians
270 in the coarse-resolution maps (Figure 3). However, the observed median clay contents at Silstrup

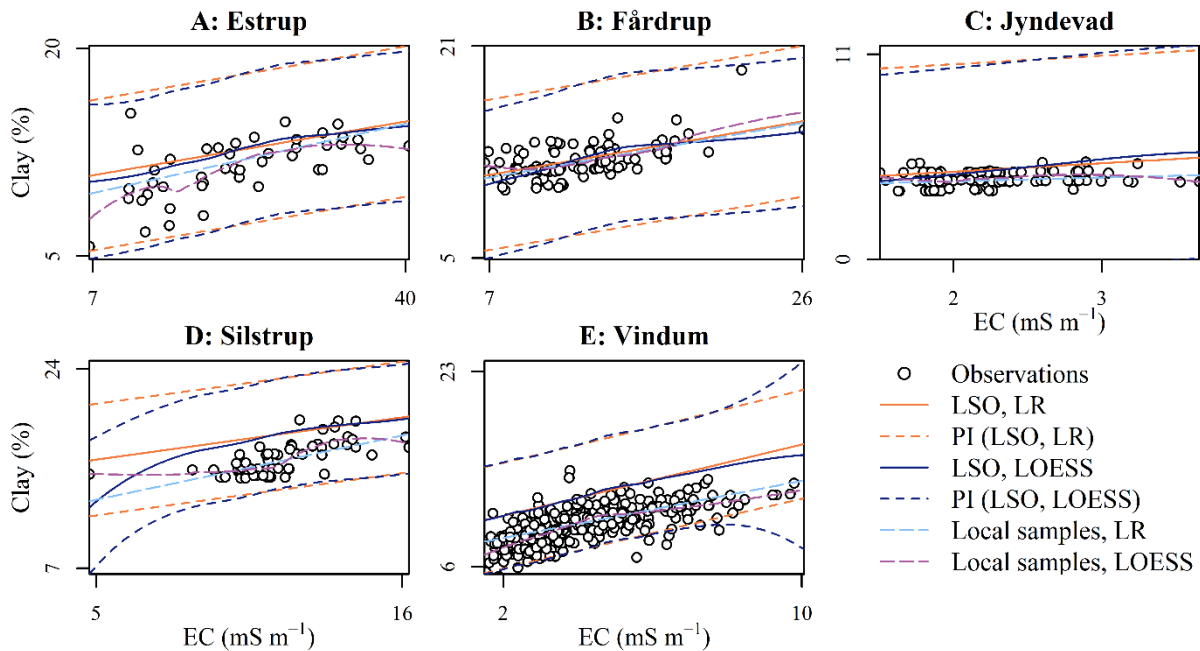
271 and Vindum were visibly lower than the medians in the coarse-resolution map (2.3 and 2.2% lower,
 272 respectively). Meanwhile, the coarse-resolution SOM map overstated values for fields with low
 273 SOM contents and understated values for fields with high SOM contents. In the extremes, the
 274 mapped median SOM content was 1.3 times higher than the observed median at Vindum, and the
 275 mapped median was 1.3 times lower than the observed median at Estrup. One should expect these
 276 deviations to cause biases in the predictions.



277
 278 *Figure 3: Median measured contents of (A) clay (<2 μm, % weight of mineral fraction) and (B)*
 279 *natural logarithmic soil organic matter (ln[SOM]) in the five fields included in the study relative to*
 280 *the median values of the fields in the coarse-resolution maps (Adhikari et al., 2013, Adhikari et al.,*
 281 *2014). Grey lines represent the 1:1 line.*

282 3.2 Clay predictions

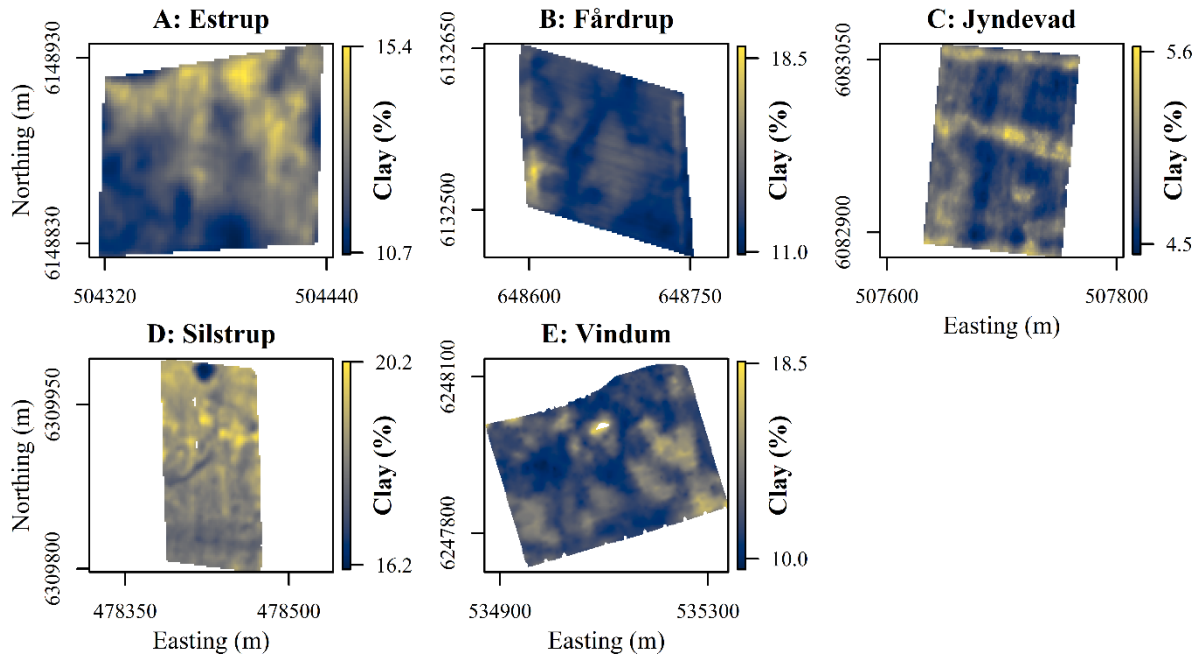
283 LR and LOESS generally predicted similar relationships between clay contents and EC (Figure 4).
284 A notable difference is that LOESS predicted lower clay contents at low EC for Silstrup. Another
285 difference is the wider prediction interval of LOESS at high EC at Vindum.
286 The predicted relationships between clay contents and EC also generally matched the observed
287 relationships. The main difference is the positive bias of the predictions at Silstrup and Vindum.
288 The bias in the coarse-resolution map for these fields is the most likely cause of this prediction bias.
289 Furthermore, the observed clay contents at Jyndevad show no trend in their relationship with EC.
290 This is attributable to the low clay contents of the soil, compared to the other fields, but both LR
291 and LOESS still predicted a slight positive trend.
292 Moreover, in all fields except Vindum, all observations were within the 95% prediction interval, for
293 LR as well as LOESS.



294

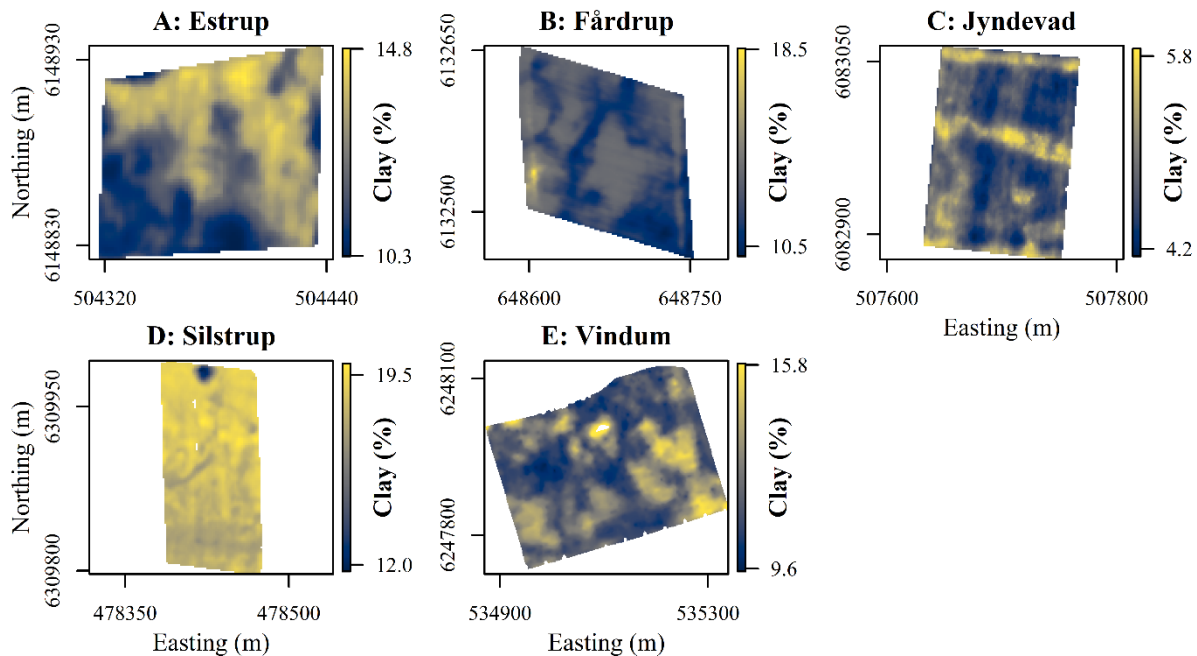
295 *Figure 4: Predicted and observed relationships between clay contents and EC (0 – 30 cm) for the*
 296 *five fields. Each plot shows the relationship predicted with linear regression (LR) and local*
 297 *regression (LOESS). For both regression types, the plots show predictions using local samples as*
 298 *well as leave-site-out (LSO) predictions. Furthermore, the plots show the 95% prediction intervals*
 299 *(PI) for LSO predictions. Figure 10 shows the accuracies of the predictions.*

300 The maps of clay contents produced with LR (Figure 5) and LOESS (Figure 6) are also very
 301 similar. At Silstrup, LOESS predicted lower clay contents than LR for a small area in the northern
 302 part of the field. In addition, LOESS predicted lower maximum clay contents than LR at Estrup,
 303 Silstrup and Vindum. However, the differences are generally small.



304

305 *Figure 5: Maps of leave-site-out (LSO) predictions of clay contents for each field with linear*
306 *regression (LR). The axes show coordinates for UTM zone 32N, ETRS 1989.*



307

308 *Figure 6: Maps of leave-site-out (LSO) predictions of clay contents for each field with local*
309 *regression (LOESS). The axes show coordinates for UTM zone 32N, ETRS 1989.*

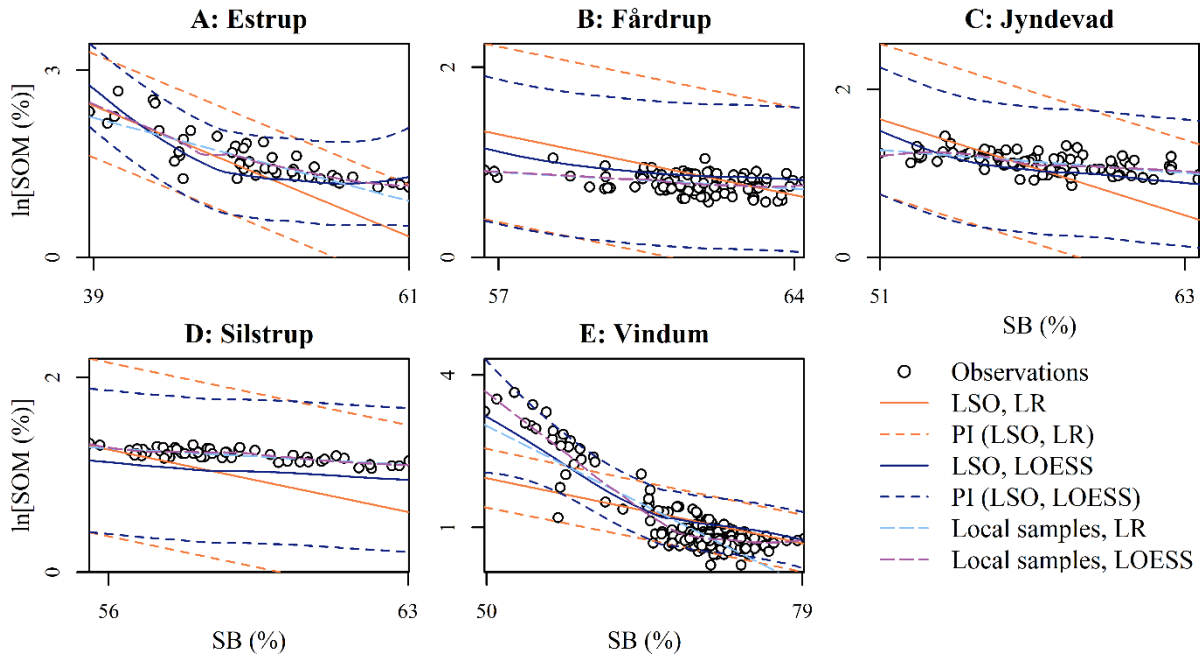
310 3.3 SOM predictions

311 LR and LOESS predicted different relationships between SB and SOM (Figure 7). The observed
312 relationships were non-linear. As a result, at Estrup, Jydevad and Silstrup, LR predicted SOM
313 contents that were lower than observed values for areas with high SB. At Vindum, for areas with
314 low SB, both LR and LOESS predicted SOM contents that were lower than observed values, but the

315 difference was largest for LR. At Fårdrup and Jynde vad, LR predicted SOM contents at low SB that
316 were higher than observed values.

317 LOESS matched observed patterns more closely than LR. The only clear deviation from the
318 observed patterns is the systematically low SOM prediction at Silstrup. The negative bias for
319 Silstrup in the coarse-resolution map is the most likely cause of this deviation (Figure 3). However,
320 Estrup and Vindum also had large biases in the coarse-resolution map without similar effects on the
321 predictions.

322 At Vindum, some observations were outside the 95% prediction interval, but at Estrup, Fårdrup,
323 Jynde vad and Silstrup, all observations were within the prediction intervals of both regression
324 types.

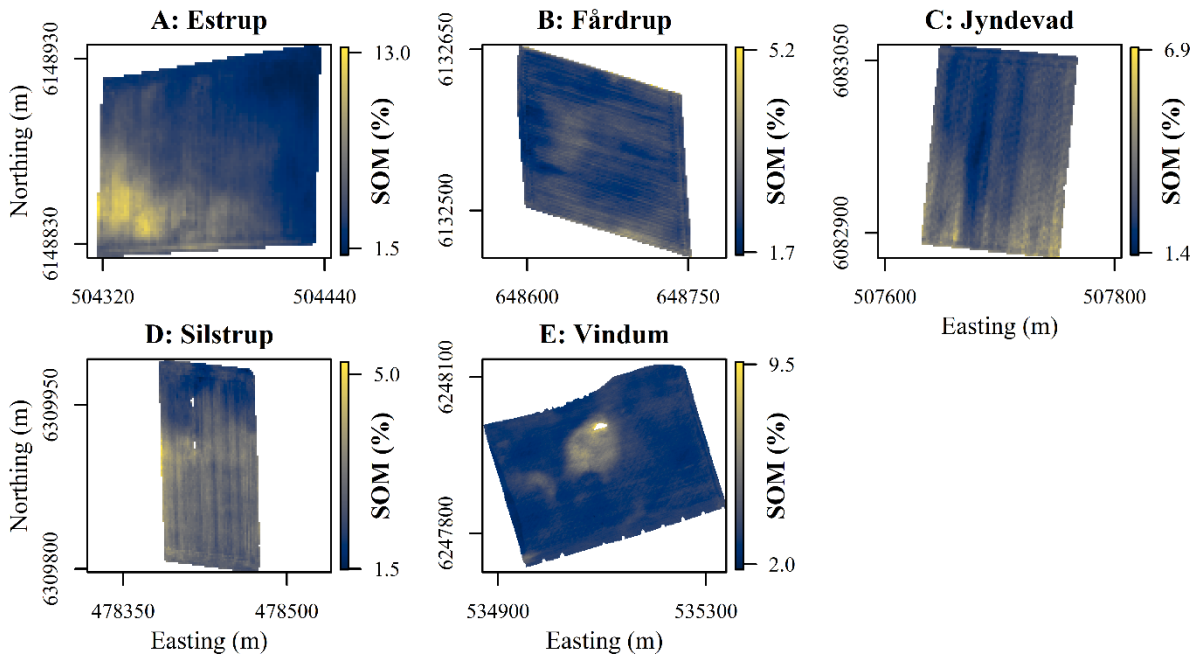


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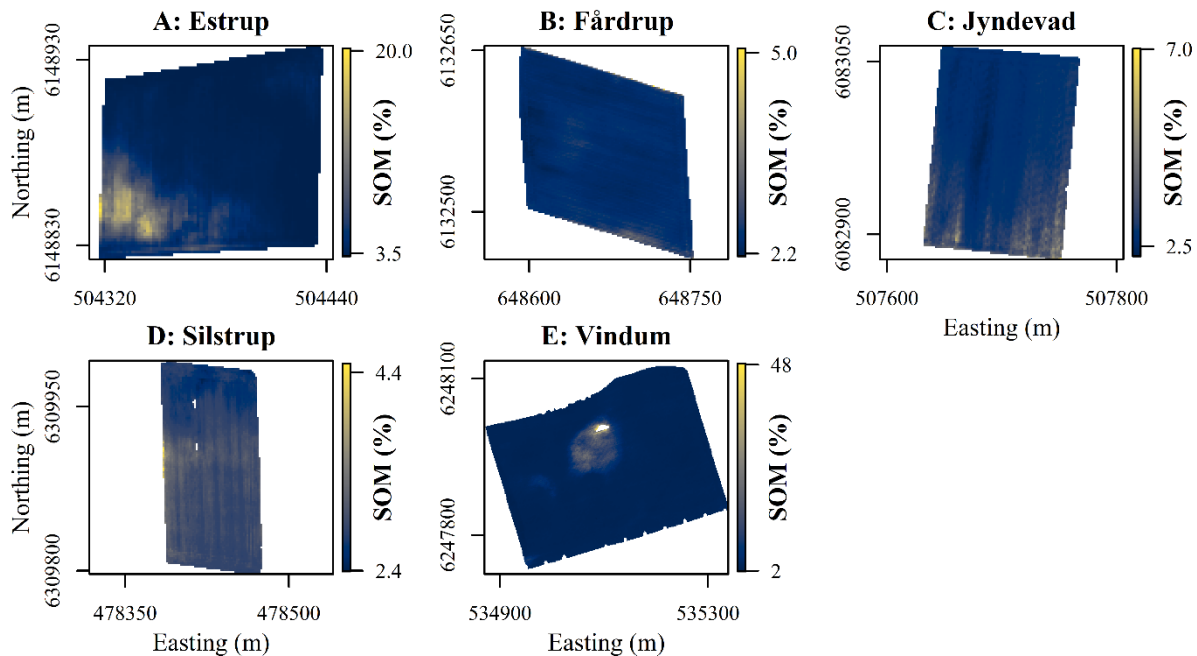
326 *Figure 7: Predicted and observed relationships between natural-logarithmic transformed soil*
 327 *organic matter contents ($\ln[SOM]$) and soil brightness (SB) in the red band for the five fields. Each*
 328 *plot shows the relationship predicted with linear regression (LR) and local regression (LOESS).*
 329 *For both regression types, the plots show predictions using local samples as well as leave-site-out*
 330 *(LSO) predictions. Furthermore, the plots show the 95% prediction intervals (PI) for LSO*
 331 *predictions. Figure 10 shows the accuracies of the predictions.*

332 At Fårdrup, Jyndeved and Silstrup, LR and LOESS generally predicted similar SOM contents, in
 333 terms of patterns and range (Figure 8, Figure 9). However, in all three fields, LOESS generally
 334 concentrated high SOM predictions in smaller areas than LR. Furthermore, the maximum SOM

335 contents predicted with LOESS were higher than the maximum SOM contents predicted with LR at
336 Estrup and Vindum. This is especially clear at Vindum, where the highest SOM contents predicted
337 by LOESS were more than five times larger than the highest SOM contents predicted with LR.
338 Estrup and Vindum had the highest observed and predicted maximum SOM contents.



339
340 *Figure 8: Maps of the leave-site-out (LSO) predictions of soil organic matter (SOM) contents for*
341 *each field with linear regression (LR). The axes show coordinates for UTM zone 32N, ETRS 1989.*



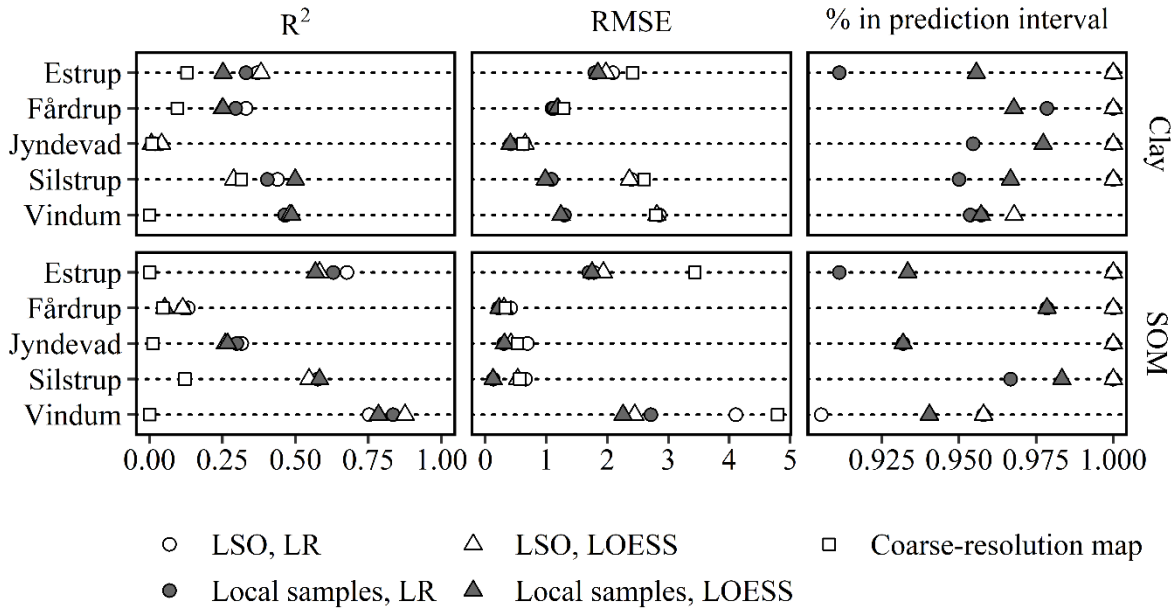
342

343 *Figure 9: Maps of the leave-site-out (LSO) predictions of soil organic matter (SOM) contents for*
344 *each field with local regression (LOESS). The axes show coordinates for UTM zone 32N, ETRS*
345 *1989.*

346 3.4 Predictive accuracy

347 R^2 for the coarse-resolution maps was generally low, with a maximum of 0.31 for clay contents at
348 Silstrup (Figure 10). R^2 for LSO predictions was generally higher, and in most cases, it was on par
349 with the R^2 of predictions with local samples. For clay contents, the R^2 of LSO predictions ranged
350 from 0.04 at Jynde vad (LR) to 0.48 at Vindum (LOESS). For SOM contents, the R^2 of LSO

351 predictions ranged from 0.11 at Fårdrup (LOESS) to 0.88 at Vindum (LOESS). The mean R^2 for
 352 LSO predictions of clay contents was highest for LR (0.33 versus 0.29), but for SOM contents, it
 353 was similar for LR and LOESS (0.49 and 0.48, respectively).



354
 355 *Figure 10: Accuracy of the predictions of clay and soil organic matter (SOM) contents for each*
 356 *field, calculated as Pearson's R^2 and root mean square error (RMSE), as well as the percentage of*
 357 *observations in the 95% prediction interval. The figure shows accuracies of predictions with linear*
 358 *regression (LR) and local regression (LOESS). For both regression types, the figure shows*
 359 *accuracies for leave-site-out (LSO) predictions and predictions with local samples. It also shows*

360 *the accuracies of the coarse-resolution maps. The coarse-resolution maps have no prediction*
361 *intervals.*

362 The RMSE for the coarse-resolution maps was highly variable. For clay contents, the RMSE of the
363 coarse-resolution map varied from 0.6 at Jyndevad to 2.8 at Vindum, and for SOM contents, it
364 varied from 0.3 at Fårdrup to 4.8 at Vindum. The RMSE of the LSO predictions was generally
365 lower than the RMSE of the coarse-resolution maps. For clay contents, it varied from 0.6 at
366 Jyndevad (LR) to 2.9 at Vindum (LR). For SOM contents, it varied from 0.3 at Fårdrup (LOESS) to
367 4.1 at Vindum (LR). The mean RMSE of the LSO predictions of clay contents was similar for LR
368 and LOESS (1.8 for both), but for SOM contents, it was lowest for LOESS (1.1 versus 1.5).
369 As LR yielded a higher R^2 than LOESS for clay contents (0.33 versus 0.29), we decided to use LR
370 for this purpose. Furthermore, the behavior of LR was more robust than the behavior of LOESS.
371 However, for SOM contents, the RMSE of the LSO predictions was lowest for LOESS, and we
372 therefore decided to use LOESS for this purpose. LOESS generally predicted the non-linear
373 behavior of $\ln[\text{SOM}]$ more closely than LR.

374 For clay contents predicted with LR, relative improvement (RI) in RMSE was large at Estrup (70%)
375 and Fårdrup (116%), but low at Jyndevad (-12%), Silstrup (15%) and Vindum (-1%). The mean RI
376 for clay contents was 38%. For SOM contents predicted with LOESS, RI was high at Estrup (95%)
377 and Vindum (92%), moderate at Jyndevad (49%) and low at Fårdrup (19%) and Silstrup (8%). The

378 mean RI for SOM was 53%. Therefore, in the best cases, the RMSE of the LSO predictions was on
379 par with the RMSE of predictions with local samples. However, in the worst cases, the RMSE of
380 LSO predictions was higher than the RMSE of the coarse-resolution maps. The results therefore
381 only partially confirm Hypothesis 1, which stated that the LSO predictions would be more accurate
382 than the coarse-resolution maps.

383 The prediction intervals were generally wider than expected, as the 95% prediction intervals
384 contained 100% of the observations for all fields except Vindum. LR predictions of SOM for
385 Vindum were the only case where the 95% prediction intervals contained less than 95% of the data.
386 The results therefore reject Hypothesis 2, which stated that it was possible to estimate accurately the
387 uncertainties related to the method.

388 3.5 Validity of assumptions

389 The first assumption, that the median values in the coarse-resolution maps represented accurately
390 the observed medians, was generally true (Figure 3). Moreover, the validity of this assumption had
391 a large impact on the accuracy of the predictions. Deviations from the observed median in the
392 coarse-resolution maps created clear biases in the predictions. Such biases were clear in the clay
393 contents predicted at Silstrup and Vindum (Figure 4) and the SOM contents predicted at Silstrup
394 (Figure 7).

395 Correlation between EC and clay contents was moderate ($R^2 = 0.33 - 0.47$) for most fields except
396 Jyndevad, where it was low ($R^2 = 0.04$). The assumption that clay contents were the main driver of
397 variation in EC for each field was therefore moderately true. Moreover, Jyndevad had both the
398 lowest R^2 and the smallest RI, most likely due to its low clay contents, which give a low SNR. This
399 shows that good correlation between EC and clay contents is necessary in order to predict clay
400 contents accurately with this method.

401 Correlation between $\ln[\text{SOM}]$ and SB was low at Fårdrup ($R^2 = 0.13$), but moderate to high for the
402 other fields ($R^2 = 0.31 - 0.75$). The assumption that SOM is the main driver of variation in SB
403 within each field is therefore generally true. In addition, Estrup and Vindum had the highest
404 correlation between $\ln[\text{SOM}]$ and SB ($R^2 = 0.68$ and 0.75 , respectively) and the highest RIs (95%
405 and 92%, respectively), while Fårdrup had the lowest R^2 and a low RI. This shows that a high
406 correlation between SOM and SB was important in order to predict SOM contents accurately.
407 The results therefore confirm Hypothesis 3, which stated the fulfillment of the three assumptions
408 listed in the introduction would be the deciding criterion for the accuracy of the LSO predictions.

409 3.6 Effect of inverting EMI measurements

410 In this study, we used inverted EMI measurements for the depth interval 0 to 30 cm. We did this to
411 obtain the EC only for the topsoil and to remove effects from soil properties at larger depths.

412 Inversion should therefore improve the correlation between EC and clay contents in the topsoil. The

413 results of our study shows that the correlation between clay contents and EC has a large impact on
 414 the accuracy of predicted clay contents. We therefore tested the assumption that inversion improved
 415 correlation by comparing correlation between clay contents and EC, as well as correlation between
 416 clay contents and EC_a of the individual DUALEM channels (Table 2).

417 *Table 2: Pearson's R^2 for the correlation between observed clay contents, EC and EC_a . The table*
 418 *lists R^2 for EC for the depth interval 0 to 30 cm as well as EC_a measured by each of the four*
 419 *DUALEM channels.*

Field	EC	EC_a			
	0 - 30 cm	1mPRP	1mHCP	2mPRP	2mHCP
Estrup	0.37	0.32	0.24	0.26	0.17
Fårdrup	0.33	0.28	0.25	0.23	0.15
Jyndevad	0.04	0.04	0.02	0.00	0.01
Silstrup	0.44	0.31	0.34	0.23	0.03
Vindum	0.47	0.56	0.56	0.53	0.47

420
 421 The comparison shows that R^2 for EC was higher than R^2 for EC_a in any of the individual
 422 DUALEM channels except for Vindum. At Vindum, R^2 for EC was lower than R^2 for EC_a in any of
 423 the individual DUALEM channels. This is partly because of the smoothing of the data using a
 424 larger running mean width to improve the SNR before performing the inversion routine. However,
 425 despite this fact, even for EC, Vindum had a higher R^2 than the four other fields. As inverted data

426 yielded higher correlations for most fields, we recommend that researchers use inverted EMI
427 measurements for the method proposed in this study.

428 3.7 Possible improvements

429 The most obvious need for improvement to the method used in this study is a better way to estimate
430 the uncertainties of the predictions. The prediction intervals were almost universally too wide. It is
431 possible that a non-parametric method of uncertainty estimation, such as bootstrapping, would
432 provide more accurate prediction intervals. The computational simplicity of the method would
433 make it very straightforward to carry out a large number of repetitions from bootstrap samples of
434 the soil observations from each field and use these repetitions to estimate uncertainties. Preferably,
435 each of these repetitions should recalculate the median of the observations, in order to account for
436 uncertainties in the median values, in addition to the uncertainty of the trend.

437 It is also a question if the coarse-resolution maps present systematic biases in the median values for
438 the fields. Figure 3 suggest that this may be the case. It appears that the median clay contents in the
439 coarse-resolution map are systematically higher than the observed medians, especially at higher
440 clay contents. It also appears that the median SOM contents are higher than observed values for
441 fields with low SOM contents and lower than observed values for fields with high SOM contents.
442 However, the number of fields is too low for one to assess if these biases are truly systematic or if it
443 is a spurious relationship.

444 In this study, we used only existing data and therefore selected the five fields based on data
445 availability. The number and representability of the fields therefore constitute limitations.
446 The first limitation is the relatively small number of fields. The current number is adequate for a
447 first test of the method. However, although the improvements in accuracy are in most cases
448 promising, it is still possible that the results constitute a “lucky shot” with the current number of
449 fields. Furthermore, the current approach is relatively simple, and in order to develop a more
450 advanced approach, a larger number of fields would be necessary.

451 The second limitation is the representability of the results for SOM. We only used fields with
452 predominantly mineral topsoils. Estrup and Vindum had small areas with organic topsoils, but
453 mineral topsoils dominated all five fields. It is therefore a question how well the method used in this
454 study will work for fields with predominant organic topsoils. It is likely that the method will need
455 alterations to work for this purpose, and the accuracy of the predictions will likely depend on
456 whether or not the coarse-resolution maps correctly predict the mineral or organic nature of the
457 topsoil.

458 With these limitations in mind, it should also be possible to use the proposed method to map
459 additional soil properties in addition to clay and SOM contents. For example, soil salinity also
460 correlates with EC_a (Corwin and Lesch, 2005), and in arid and semi-arid areas, the purpose of the

461 method could instead be to map soil salinity at field level. In this case, the use of the method would
462 require large extent maps of soil salinity as an input, in order to adjust median salinity.

463 Furthermore, the method for mapping SOM could rely on additional sources of imagery in addition
464 to aerial imagery. If no bare-soil aerial imagery is immediately available, soil mappers could instead
465 use drone imagery or high-resolution satellite imagery, for example from the Sentinel 2 mission
466 (European Space Agency, n.d.).

467 In this study, bias in the median values of the coarse-resolution map generally imposed a clear
468 limitation on the accuracy of the predictions. Therefore, a way to increase the accuracy of the
469 predictions would be to use coarse-resolution maps with higher accuracies. Methods for digital soil
470 mapping constantly develop, and it is likely that future coarse-resolution maps will be more
471 accurate. Even if a new map does not account for intra-field variability more accurately than the
472 previous map, a more accurate median value would increase the accuracy of predictions with the
473 method used in this study.

474 **4 Conclusions**

475 In this study, we present a method to predict clay and SOM contents from EMI and aerial imagery
476 without the use of local samples. We tested the method for five agricultural fields in Denmark and
477 found that the method generally, but not universally, provided more accurate results than national-
478 level, coarse-resolution maps. The improvements were largest and most consistent for SOM

479 predictions, especially for fields with large ranges in SOM contents. Linear regression (LR)
480 generally predicted clay contents most accurately, while local regression (LOESS) generally
481 predicted SOM contents most accurately. Methods for estimating the uncertainties of the method
482 need further refinement, as prediction intervals were generally too wide. However, as it is, the
483 method constitutes a simple and reliable tool for estimating clay and SOM contents within
484 agricultural fields. This can be useful for situations when no local data are available, for example
485 when planning sampling designs, or screening for constraints to agricultural land uses or
486 environmental threats. Although soil surveyors may be skilled at interpreting EMI data and aerial
487 imagery, being able to provide a quantitative estimate, instead of a relative estimate, greatly
488 increases the usefulness of these data.

489 **5 Code and data availability**

490 The data and R code used in the study are available at <https://doi.org/10.5281/zenodo.3699130>.

491 **6 Author contribution**

492 All authors collaborated to the design of the study. Anders Bjørn Møller prepared the data, and
493 Triven Koganti carried out inversion of EMI data. Anders Bjørn Møller carried out the analyses and
494 prepared the manuscript with inputs from all authors.

495 **7 Competing interests**

496 The authors declare that they have no conflict of interest.

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