Large, climate-sensitive soil carbon stocks mapped with pedology-informed machine learning in the North Pacific coastal temperate rainforest

1 **Title Page**

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28 **Abstract**

29   Accurate soil organic carbon (SOC) maps are needed to predict the terrestrial SOC feedback to

30 climate change, one of the largest remaining uncertainties in Earth system modeling. Over the last decade,

31 global scale models have produced varied predictions of the size and distribution of SOC stocks, ranging

32 from 1,000 to > 3,000 Pg of C within the top 1 m. Regional assessments may help validate or improve

33 global maps because they can examine landscape controls on SOC stocks and offer a tractable means to

34 retain regionally-specific information, such as soil taxonomy, during database creation and modeling. We

35 compile a new transboundary SOC stock database for coastal watersheds of the North Pacific coastal

36 temperate rainforest, using soil classification data to guide gap-filling and machine learning approaches

37 used to explore spatial controls on SOC and predict regional stocks. Precipitation and topographic

38 attributes controlling soil wetness were found to be the dominant controls of SOC, underscoring the

39 dependence of C accumulation on high soil moisture. The random forest model predicted stocks of 4.5 Pg

40 C (to 1 m) for the study region, 22% of which was stored in organic soil layers. Calculated stocks of 228

41 $\pm$ 111 Mg C ha^{-1} fell within ranges of several past regional studies and indicate 11-33 Pg C may be stored

42 across temperate rainforest soils globally. Predictions compared very favorably to regionalized estimates

43 from two spatially-explicit global products (Pearson's correlation: ρ = 0.73 vs. 0.34). Notably,

44 SoilGrids250m was an outlier for estimates of total SOC, predicting 4-fold higher stocks (18 Pg C) and

45 indicating bias in this global product for the soils of the temperate rainforest. In sum our study

46 demonstrates that CTR ecosystems represent a moisture-dependent hotspot for SOC storage at mid-

47 latitudes.

48

49 **Social Media Abstract:** Large soil carbon stocks track climate gradients in the N. Pacific coastal

50 temperate rainforest

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52

53   **1. Introduction**

54   Accurate global soil organic carbon (SOC) maps are necessary to validate terrestrial carbon (C)

55   cycle predictions in Earth System Models (ESMs; Todd-Brown *et al* 2013) however current SOC models

56   drawing on international pedon (soil profile) databases (SoilGRIDs, HWSD, ISCN, etc.) display

57   considerable differences (Köchy *et al* 2015; Sanderman *et al* 2017, 2018). Database construction,

58   including filling data gaps, account for some of these discrepancies (Tifafi *et al* 2018) while other sources

59   of uncertainty are associated with scaling up spatially from relatively sparse pedon observations (~1 m^2)

60   to globally gridded products (Todd-Brown *et al* 2013) and the loss of information relevant to SOC storage

61   at intermediate scales (10 m^2 – 1 km^2) such as topography (Mishra and Riley 2015; Siewert *et al* 2017).

62   Regional digital soil mapping may help bridge these scale discontinuities and produce finer resolution (<

63   100 m) predictions that retain information on the spatial drivers of SOC storage (Minasny *et al* 2013). For

64   example, Sanderman *et al* (2018) compiled mangrove SOC stock measurements and used them in

65   conjunction with a global SOC map (Hengl *et al* 2017) and maps of environmental covariates to estimate

66   global mangrove SOC at 30 m resolution. The integration of detailed pedological information with

67   machine learning approaches for large-scale spatial predictions may also enable improvements in SOC

68   mapping (Ramcharan *et al* 2017) and regional SOC assessments may help diagnose errors in global

69   products by providing higher resolution information on SOC controls and its distribution.

70

71   Regional SOC assessments at high-latitudes have, to date, focused on Arctic and boreal

72   permafrost soils (Hugelius *et al* 2013, 2014), while coastal temperate rainforests (CTR) have not received

73   similar attention despite their similarly high SOC storage (Carpenter *et al* 2014). Globally, temperate

74   rainforests contain the highest density aboveground forest C stocks (up to 1500 Mg ha^{-1}; Keith *et al*

75   2009), and can be found along the coastal margins of North and South America, Japan and Korea,

76   Australasia, and Scandinavia (Alaback 1991). The N. Pacific coastal temperate rainforest (NPCTR)

77   biome is the largest example, and spans 4,000 km of the N. American coast from the Russian River in

78   California, to Kodiak Island in the Gulf of Alaska (DellaSala 2011). Although several studies have

79   produced regional estimates of SOC stocks in Alaska (Leighty *et al* 2006; Johnson *et al* 2011; Mishra *et*

80   *al* 2012), no studies to date have produced spatially-explicit SOC stock estimates across the

81   transboundary domain of southeast Alaska (SEAK) and coastal British Columbia (BC).

82

83   Soils of the NPCTR can store large quantities of SOC, especially in the wet seasonal and

84   perhumid zones (Carpenter *et al* 2014), with stocks > 300 Mg ha^{-1} (to 1 m mineral soil depth) frequently

85   observed in SEAK (Johnson *et al* 2011) and stocks of > 200 Mg ha^{-1} common in coastal BC (Shaw *et al*

86   2018). These large SOC stocks have accumulated in distinctive soil conditions across the NPCTR's

87   mosaic of three hydropedologic landscape units (Lin et al., 2006): (1) upland forest soils on well-drained

88   slopes, (2) forested wetlands, and (3) poor (lowland) fens (D'Amore *et al* 2015). Despite their relatively

89   young age (12-14 cal ka BP; Eamer *et al* 2017), elevated C concentrations are observed in mineral soils

90   that often exceed 1 m in depth (Chandler, 1943; Michaelson et al., 2013) due to a combination of rapid

91   mineral weathering, high primary production and litter inputs, and the translocation of soluble C into

92   deeper horizons (Alaback 1991). In addition to mineral soils, the perhumid NPCTR also exhibits a variety

93   of vertically-accreting organic soils, including deep (3-5 m) peat-forming bogs and fens (Heusser 1952,

94   1954; Hansen 1955; Ugolini and Mann 1979), and thick (> 40 cm) forest floor organic horizons that

95   accumulate due to slow decomposition under ubiquitous hydric soil conditions and the rarity of fire

96   (Alaback 1991). In places, organic horizons overlay C-rich mineral soils (known as Folisols, or folistic

97   horizons) and contribute to the highest pedon C stocks in the NPCTR (D'Amore and Lynn 2002; Fox and

98   Tarnocai 2011; Johnson *et al* 2011; Michaelson *et al* 2013).

99

100   Quantifying total SOC storage across the NPCTR and understanding its environmental controls is

101   necessary to predict the region's response to global change, including climate feedbacks. Observational

102   data (Buma and Barrett 2015) and ecosystem C models (Genet *et al* 2018) indicate that the NPCTR is

103   sequestering C. However, changes in the amount and form of precipitation and higher annual

104 temperatures may increase growing season length and productivity (Buma *et al* 2016) while soil warming

105 may lead to more rapid decomposition of soil organic matter (Davidson *et al* 2006; Fellman *et al* 2017).

106 In the present study we address the need for a unified SOC model for the NPCTR by compiling a new

107 transboundary pedon database across SEAK and coastal British Columbia that retains relevant

108 pedological details. With this database we train a predictive model to estimate total SOC stocks spatially

109 across the region, to enable meaningful comparisons with other regional and global SOC products, and to

110 explore the environmental controls on SOC in the NPCTR.

111

112 **2. Methods**

113 *2.1 Study Extent and Characteristics*

114   The largest climatic zones within the NPCTR are the seasonal and perhumid forests that form a

115 transboundary extent across SEAK and coastal BC (Alaback 1991). The SOC assessment encompassed

116 all of the perhumid and part of the seasonal zone, spanning 10° of latitude (Figure 1). The study perimeter

117 was defined by the outer boundary of rainforest dominated watersheds mapped using a harmonized

118 transboundary dataset (Gonzalez Arriola *et al* 2018) between the Fraser River in Vancouver, British

119 Columbia (BC) and Lituya Bay south of Yakutat, Alaska, excluding the four major river basins (Taku,

120 Stikine, Nass, Skeena) which extend into interior boreal forest and a more continental climate.

121

122   Mean annual precipitation across the study domain ranges from 1,800 to >3,000 mm and mean

123 annual temperatures range from 6-9 °C, with monthly means of -5 °C in winter in the north (Farr and

124 Hard 1987) and ~15 °C in summer in the south (Alaback 1991). Forest species diversity is relatively low,

125 reflecting a consistent climate and disturbance regime across the study area, and generally dominated by

126 *Picea sitchensis* (Sitka spruce) and *Tsuga heterophylla* (western hemlock) in SEAK (van Hees 2003). In

127 BC, *Tsuga heterophylla* and *Thuja plicata* (western redcedar) become the dominant conifers. *Callitropsis*

128 *nootkatensis* (yellow cedar) and *Tsuga mertensiana* (mountain hemlock) are found from sea level in the

129 north to high elevations in the south and *Pinus contorta var. contorta* (shore pine) is a significant

130   component of bog locations throughout. Geology is varied consisting of granitic, basaltic, and limestone

131   bedrock, the latter of which supports some of the most productive forest, however, much of the surficial

132   geology is dominated by glacial drift including ablation and compact till, alluvial outwash, and

133   glaciomarine sediments (Nowacki *et al* 2003).

134

135   2.2 *Transboundary SOC Database*

136   We compiled a transboundary database of soil profile descriptions (pedons) across SEAK and BC

137   from published and archive data sources. For each pedon we calculated SOC stocks for the top 1 m of

138   mineral soil plus surface organic horizons using data harmonization and gap-filling procedures that are

139   detailed in the Supplementary Information (Sup. Table 1-5). In brief, US soil classification was converted

140   to Canadian where necessary and gaps filled by published or modeled estimates grouped by soil class,

141   horizon, and lithology. In contrast to some other regional and global C assessments, this approach

142   avoided use of generalized empirical relationships between soil properties and missing variables, such as

143   between soil C and soil bulk density, or soil C and depth.

144

145   *2.3 Environmental Covariates*

146   Environmental covariates were selected (Sup. Table 6) to predict SOC stock due to their

147   relationship with soil forming factors (climate, organisms, relief, parent material, and time; Jenny 1994).

148   Covariate data were extracted from the rasters at the pedon coordinates and appended to the final SOC

149   stocks (in Supplemental data) to use in all further analyses. Further details of the 12 selected

150   environmental covariates along with justification for inclusion and pre-processing steps are listed in Sup.

151   Table 6. Briefly, only high quality and spatially continuous data products were used. Curating covariates

152   based upon knowledge of regional soil development facilitates clearer interpretation and reduces the risk

153   of autocorrelation between variables.

154

155   *2.4 Random Forest Model*

156   A random forest model was trained to predict stocks of SOC across the NPCTR in R (v. 3.4; R

157   Core Team 2018) using the R-package randomForest (4.6; Liaw and Wiener 2002). Random forests grow

158   a large number of regression trees (Breiman 1984) from different random subsets of training data and

159   predictor variables, thereby reducing variance relative to single trees, and greatly reducing the risk of

160   over-fitting model predictions and non-optimal solutions – though at the cost of interpretability (Breiman

161   2001). The transboundary database SOC stocks and associated covariates were first split into training

162   (80%) and testing (20%) data and the model was parameterized to grow 5,000 trees. For each tree, a

163   subsample equivalent to ¼ of the total sample size was utilized (with replacement). Node size was set at 4

164   to minimize the out-of-bag (OOB) error based on preliminary testing. Model performance was measured

165   from goodness-of-fit, distributions of residuals, and predictions of test SOC stocks. Confidence intervals

166   were computed using an infinitesimal jack-knife procedure (Wager *et al* 2013). Predictive performance

167   was measured from test data goodness-of-fit as well as the distribution of the root mean squared error

168   (RMSE). Predictions were made across the NPCTR study extent using R-package *raster* (v2.6; Hijmans

169   2017) which produced a SOC map at 90.5 m resolution. All lakes > 10 ha were clipped from the final

170   map (HydroLakes; Messager *et al* 2016) and glacier area was clipped using the Randolph Glacier

171   Inventory 5.0 (GLIMS; Raup *et al* 2007) database. Final SOC stocks were adjusted for topography by

172   scaling the SOC map with actual land surface area calculated from cell slope values. The random forest

173   model was re-run for the three gap-filling sensitivity analyses (see SI).

174

175   *2.5 Comparison to Regional and Global Maps*

176   Stocks of SOC were compared with two previous Alaskan studies, two regional/national models,

177   and two global models (Table 1). Published summary statistics for NPCTR regions were either referred to

178   directly (Johnson *et al* 2011) or estimated from published data (Michaelson *et al* 2013). The Canadian

179   SOC map produced by Tarnocai and Lacelle (1996) was regionalized, rasterized, and resampled to extract

180   pixels that overlapped with the study boundary and methods to calculate mean and total SOC stocks were

181   replicated. Two global SOC maps, SoilGrids250m (Hengl *et al* 2017) and the Global Soil Organic Carbon

182   map (GSOC; FAO and ITPS 2018), were downloaded as rasters and resampled from 250 m and 1 km

183   resolutions, respectively. SoilGrids250m was built from a database of ca. 150,000 soil profiles and a stack

184   of 158 covariates to produce a continuous global surface of SOC stock to 1 m, whereas the FAO GSOC

185   map is a composite of national SOC stock assessments and covers a depth of 0-30 cm. Genet *et al* (2018)

186   estimated SOC across the N. Pacific Landscape Conservation Cooperative using pedons from relevant

187   forest cover types in SEAK. Differences in SOC stocks are explored quantitatively in the context of

188   different extents, gap-filling procedures, and data sources. Finally, the predictive capacity of the random

189   forest model, measured by the Pearson's correlation coefficient and RMSE of observations versus

190   predictions, is compared to two global SOC products: SoilGrids250m and the FAO GSCO map.

191

192   *2.6 Spatial Controls of SOC*

193   To explore interactions between controls on SOC stocks across the NPCTR, classification and

194   regression trees (CART) was applied to the transboundary SOC database using R-package *rpart* (v4.1;

195   Therneau and Atkinson 2011). Unlike weak learner regression trees grown in random forests, CART

196   analyses fit to entire datasets provide readily interpretable outputs. CART is also well suited to

197   interpretation of complex data with many interacting variables, non-normally distributed data, and can

198   identify key covariate interactions and thresholds.

199

200   **3. Results**

201   *3.1 Summary of PCTR Observations*

202   Pedon SOC stocks and depths were log-normally distributed (Sup. Fig 2 a-d). Median soil depth

203   across all the samples was 66 cm and median calculated SOC density was 168.4 Mg ha^{-1}. Other database

204   summary statistics are provided in Sup. Table 7. Soil classes in the pedon database were mostly

205   Spodosols (426), Inceptisols (214), and Entisols (84), with fewer Histosols (70) and Folists (9).

206

207   Sample locations were generally well distributed across the study extent with some clustering

208   around S Vancouver Is., N BC, and central SEAK (Figure 1; Sup. Fig. 2 e-f). The distributions of the

209   environmental covariate data extracted at pedons were generally very similar to the distributions of

210   covariates across the region (Sup. Fig 2 e-n). Samples were slightly biased to lower and less steep areas,

211   and the presence of large icefields and high alpine (not sampled) explained discrepancies in percent forest

212   cover and land cover classes.

213

214   *3.2 Random Forest SOC Model Performance*

215   Model performance was strongest for larger scale patterns in SOC. Though predictions on test

216   data by the random forest model was low ($R^2 = 0.32$), the predictive model performance on all

217   observations was high and considerably better than two global SOC products ($\rho = 0.73$; Figure 2). In

218   addition, model covariates were representative of the region (Sup. Fig. 2), the mean of the residuals was

219   zero, and largest errors were under-estimations concentrated in areas otherwise correctly predicted to have

220   higher than typical SOC (Sup. Fig. 3). We therefore have high confidence in model predictions for

221   median values and the regional scale patterns in SOC, with less confidence for extreme values and

222   variation at finer spatial scales. The predictions of the random forest in this study were much more

223   accurate ($R^2 = 0.53$ vs. 0.11) compared to those extracted from two global products SoilGrids250 and the

224   FAO GSOC map at the same locations (Figure 2).

225

226   *3.3 Estimates of SOC Stocks*

227   Total SOC within the NPCTR of SEAK and BC was estimated at 4.5 Pg C (Table 1) with highest

228   stocks (> 500 Mg ha^{-1}) found in the central islands of SE Alaska and westerly locations, and lower stocks

229   (< 200 Mg ha^{-1}) predicted for more southerly and easterly locations. Sensitivity analyses indicated that

230   SOC stock estimates were most sensitive to bulk density gap-filling assumptions as estimates increased

231   by approximately 50% after increasing organic horizon bulk density ca. 3-fold to 0.33 g cm^{-3} (Sup. Table

232   5). From the fractional increase in SOC caused by the tripling of organic horizon bulk density, we

233   computed that 22% of the predicted NPCTR SOC stocks must be stored in organic soil horizons.

234

235   *3.4 Environmental Covariates of SOC Stock*

236   CART analysis (Figure 3) showed that the lowest SOC stocks ranging from 128.5 to 194.8 Mg

237   ha^{-1} were associated with the driest (< 2,147 mm MAP), southeasterly locations. Intermediate stocks

238   (252.7-442.9 Mg ha^{-1}) were assigned to wetter climates at higher topographic positions (upslope). Very

239   high SOC stocks (336.0-523.3 Mg ha^{-1}) were also associated with wet climate areas (2,147 – 2,833 mm)

240   on foot-slope (downslope) landscape positions. Finally, exceptionally high SOC stocks of 446.2 - 708.6

241   Mg ha^{-1} were assigned to the wettest climates (> 2,833 mm) at relatively low elevations (< 189 m).

242

243   **4. Discussion**

244   *4.1 SOC Stocks in the Global Context*

245   The estimated 4.5 Pg C stored within perhumid and the northern seasonal NPCTR watersheds

246   indicates the region contains approximately 2% of North American SOC within less than 1% of its

247   surface area (Köchy *et al* 2015). Using a simple upscaling from study region mean stocks (228 ± 111 Mg

248   ha^{-1}) to global CTR extent (ca. 9.7 x 10^5 km^2; Alaback 1991) we can estimate that 22 ± 11 Pg C may be

249   stored globally in CTR ecosystems. These estimates are likely conservative due to our 1 m depth range,

250   our assumption that the coarse fraction is entirely mineral (Zabowski *et al* 2011), the abundance of deep

251   (3-5 m) peat-forming fens that can form in wet landscape depressions (Sup. Fig. 5, 6) that are smaller than

252   our spatial resolution (Heusser 1952; D'Amore and Lynn 2002), as well as the likely occurrence of

253   cryptic wetlands hidden within forests (Creed *et al* 2003).

254

255   In a review of global SOC, Jackson *et al* (2017) calculated the first biome-specific SOC stocks,

256   estimating that 64 Pg C is stored in ca. 6 M km^2 of non-permafrost soils in temperate conifer forests. Our

257   results disaggregate this result further, suggesting CTRs within the temperate conifer forest biome contain

258   one-third of the total SOC, while representing less than one-sixth of the biome's area. Jackson *et al*

259   (2017) also estimated that 22% (14 Pg) of the SOC was stored in organic peatlands, which, remarkably,

260   matched exactly our estimate of the proportion of SOC in organic soil (peatlands and surface organic

261   accumulations). The exact agreement, while remarkable, is not truly scalable, but it does likely reflect a

262   common suite of C input and stabilization mechanisms in cool, wet temperate conifer forest ecosystems

263   that may lead to consistent partitioning of stocks between mineral and organic soils.

264

265   As has been demonstrated for above-ground biomass (Keith *et al* 2009), SOC densities in the

266   CTR appear to rank among the highest globally. The mean SOC stock estimate from this study (228 ± 111

267   Mg ha^{-1}) positions the NPCTR below estimates for permafrost soils (178-691 Mg ha^{-1}; 5th – 95th

268   percentile), but substantially higher SOC densities than grasslands (56-289 Mg ha^{-1}), evergreen broadleaf

269   forests (83-223 Mg ha^{-1}), and croplands (60-200 Mg ha^{-1}), and within a similar range as permanent

270   wetlands (114-474 Mg ha^{-1}; Sanderman *et al* 2018). Our results also suggest SOC densities to 1 m in

271   temperate rainforests are higher than in tropical rainforests (85-271 Mg ha^{-1}) perhaps in part due to litter

272   accumulations which are typically absent in tropical rainforest floors due to very favorable conditions for

273   decomposition (Parton *et al* 2007).

274

275   *4.2 Model Comparisons*

276   Estimated SOC stocks agreed with some past estimates of SOC storage in Alaskan coastal

277   rainforests (Johnson *et al* 2011) but were much lower than the SEAK SOC estimates from Michaelson *et*

278   *al* 2013 (Table 1). The two regional/national studies that approximate SEAK (Tongass National Forest;

279   Leighty *et al* 2006) and BC (Tarnocai and Lacelle 1996), when summed, produced an estimate of 5.3 Pg

280   C compared to our estimate of 4.5 Pg C. However, Tarnocai and Lacelle (1996) integrated SOC to the full

281   observed depth of organic soils which was found to be approximately ~1.51 m, or ~50% greater than the

282   reference depth in this study (1 m), which may explain the larger estimate. The GSOC map estimated

283   lower SOC stocks (2.5 Pg C) because it only considers the top 30 cm of soil, but if it is assumed that ca.

284   50% of the SOC stock is stored from 30-100 cm (James *et al* 2014), then the estimates (~ 5 Pg C) align

285   well with the present study.

286

287   For one study and two global SOC products we identified large discrepancies with our SOC

288   predictions. The global model SoilGrids250m and the regional Alaska database produced by Michaelson

289   *et al* (2013) were outliers in our comparison, predicting 4-fold higher total SOC for the region, and 2 or 3-

290   fold higher mean SOC, respectively (Table 1). Our model also more accurately predicted the spatial

291   variation in SOC across the NPCTR relative to the FAO GSOC map and SoilGrids250m (Figure 2). Both

292   global products showed strong bias for the region, with over-estimates where we predict lower stocks and

293   weak correlation with the observed stocks overall. Finally, unrealistic spatial discontinuities are present in

294   the FAO GSOC map at the US-Canada border that did not exist in our transboundary assessment (Figure

295   5). Global SOC maps created from a mosaic of national inventories clearly benefit where nations conduct

296   quality SOC assessments, evidenced by the reasonable summed stock estimates of GSOC for the NPCTR

297   (Table 1). However, we propose that biome-specific assessments are better than national inventories

298   because spatial discontinuities that form within global mosaics will fall along ecologically significant,

299   rather than arbitrary political, boundaries (Ramcharan *et al* 2017).

300

301   The bulk density gap-filling procedure applied by Michaelson *et al* (2013) was not replicated in

302   this study due to the observation that the pedotransfer functions (Van *Looy et al* 2017) relating %C to

303   bulk density over-estimate organic layer (high %C) bulk density by up to 4-fold relative to published

304   values (Sup. Fig. 4; Shaw *et al* 2005). Using these pedotransfer functions would bias the SOC estimates

305   too high in the NPCTR where organic soils are common (D'Amore *et al* 2010) and forest floor organic

306   horizons are often deep (Kranabetter and Banner 2000). Direct comparison of our database with that of

307   Michaelson *et al* (2013) illustrates how gap-filling procedures can lead to very different SOC estimates.

308   Similar issues may underlie discrepancies observed with SoilGrids250m (18 Pg C; Table 1). Models built

309   using the Harmonized World Soil Database and SoilGrids250m have been gap-filled using pedotransfer

310   functions that may overestimate organic soil bulk density and lead to overestimated SOC stocks (Köchy

311   *et al* 2015). A recent global model comparison found much larger SOC stock estimates using the

312   SoilGrids database than from other global databases (Tifafi *et al* 2017). Our study similarly suggests

313   SoilGrids250m overestimates SOC stocks within the NPCTR, and possibly in other organic and/or high-

314   latitude soils (Figure 2c). We cannot explain the differences with organic soil bulk density alone, based

315   upon our sensitivity analysis where bulk density was tripled. We propose that the juxtaposition of highly

316   contrasting soils in the NPCTR (Sup. Fig. 5, 6) may make the region particularly susceptible to SOC

317   errors when aggregating and modeling pedon observations. In the NPCTR, C-rich litter layers and organic

318   soils lie adjacent (vertically and laterally) to mineral soils (Michaelson *et al* 2013; Shaw *et al* 2018) and,

319   without separate representation during gap-filling or modeling steps values may be artificially inflated.

320   Populating the database and calculating SOC on the basis of pedological information, including

321   distinguishing surface from subsurface soil horizons, may have improved SOC variable estimation in this

322   study.

323

324   *4.3 Covariates of NPCTR SOC Stocks*

325   Digital soil mapping assumes properties, such as SOC, can be predicted spatially across

326   landscapes from the distribution of geospatial covariates related to the classical factors of soil formation

327   (Jenny 1994; Minasny 2011). We found that high precipitation is the primary control on SOC storage in

328   the NPCTR; SOC stocks tracked regional gradients in MAP, and longitude, with the highest stocks in the

329   north coast of BC and especially central SEAK (Figure 3; Figure 4). Topographic attributes including

330   elevation, wetness, and slope position, which modulate temperature and soil moisture conditions, also

331   emerged as important controls. Land cover was not a strong predictor, however both the region and pedon

332   database are dominated by conifer forest which did not distinguish between upland and cryptic forested

333   wetland coverage. Though lithology has been shown to be important across Alaska generally as a

334   predictor of SOC stocks (Mishra *et al* 2012), we did not find support for lithology as a broadly important

335 covariate. However, lithology is an imperfect indicator of parent material for soil formation across the

336 region due to the extensive presence of glacial deposits.

337

338 *4.4 Vulnerabilities of NPCTR SOC Stocks*

339   Stocks of SOC in the NPCTR may be sensitive to several climate-related changes in the coming

340 century, but the overall direction of effects is uncertain. Wolken *et al* (2011) highlighted loss of winter

341 snow and ice as the most important biophysical change in the coastal temperate rainforests of Alaska,

342 driven by projected average temperature increases of 3.5 ± 1.5 °C by 2100. Based upon the primacy of

343 MAP and topographic wetness in our analyses, both higher predicted MAP and a reduction in the

344 percentage as snow (Shanley et al. 2015) may expand the spatial and temporal domain for high SOC

345 accumulations in the NPCTR. However, this may be balanced by increases in lateral exports of terrestrial

346 DOC, which is already a distinctively large component of NPCTR ecosystem C budgets (Oliver *et al*

347 2017). Similarly, effects of temperature may also be bi-directional. Elevated temperatures lead to rapid

348 decomposition of NPCTR soil organic matter under laboratory conditions (Fellman *et al* 2017) however it

349 is unclear to what degree this effect will be limited by the saturated soil conditions *in situ*, which

350 constrain decomposition rates (Freeman *et al* 2008), or offset by concurrent increases in SOC inputs via

351 enhanced primary productivity and litterfall (Buma *et al* 2016; Genet *et al* 2018).

352

353 *4.5 SOC Modeling Considerations*

354   Our study shows that digital soil mapping can be valuable across the NPCTR where soil survey

355 and conventional soil mapping is challenging (Carpenter *et al* 2014), however a baseline of high quality

356 pedon data is still essential for accurate predictions. Vitharana *et al* (2017) found that existing data for SE

357 Alaska well represented environmental variability and our covariate data distributions (Sup. Fig. 2) agree

358 with this conclusion, however, much of the central and northern BC coastline is less well sampled (Figure

359 1) and those data we did obtain required extensive gap-filling. Our model also under-predicted the largest

360 SOC stocks which, as random forests subset data to grow each tree, may be due to relatively few

361 observations of very high SOC.

362

363   Model improvements may also be possible if input covariate datasets and the final map are

364 obtained at finer spatial resolution. For example, the NPCTR displays complex topography that may not

365 be fully resolved at 90 m. Mishra and Riley (2015) found that soil wetness (derived from landform) and

366 aspect were lost as significant predictors of Alaskan C stocks when moving from a 50 m to a 100 m

367 resolution. Similarly, Siewert (2017) compared a wide range of resolutions (2 – 1,000 m) for random

368 forest predictions of a sub-Arctic peatland SOC stocks in Sweden and found resolutions > 30 m led to

369 underestimates. Building models using more accurately georeferenced pedon data and more finely

370 resolved (< 50 m) covariate surfaces may improve spatial predictions of SOC.

371   .

372 **5. Conclusions**

373   Regional SOC stock assessments can validate and improve global maps by considering drivers,

374 and compiling datasets, in greater detail. We compiled a SOC database for the NPCTR, using pedology

375 data to guide gap-filling and predictive modeling. Regression tree models predicted high SOC stocks in

376 wet coastal watersheds, indicating that the coastal temperate rainforest represents a moisture-dependent

377 hotspot for SOC at mid-latitudes.

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380 **References**

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Contributions

570   BB, DB, and AB conceived of the project. PS, CB, SS, and DD provided data for, and supervised

571 GM during the compilation, and gap-filling of, the transboundary NPCTR SOC database. BB supervised

572 GM on random forest and CART analyses. IG, SA, and PS created NPCTR digital surface products and

573 provided unpublished data from digital soil mapping efforts by the Hakai Institute in 2014 and 2016. CB

574 and SS provided BEC and BCSIS datasets and CB supervised GM in gap-filling of BEC pedon data. GM

575 and BB authored the first draft of the manuscript and CB, DD, PS, IG, AB, and DB contributed to later

576 drafts.

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588 **Figure Captions**

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590 **Figure 1:** The extent of the NPCTR displaying the distribution of soil profile descriptions (light green

591 circles) and the study extent (dark green pixels) used in the SOC stock assessment. Inset maps show

592 global (small) and continental (large) extent of the full NPCTR along with the boundaries of climatic sub-

593 regions.

594

595 **Figure 2:** Predicted vs. observed SOC stocks (Mg ha^{-1}) for individual database profile locations

596 compared for (a) this study's spatial predictions, (b) the FAO GSOC map, and (c) SoilGrids250m, with

597 smooth spline fits (solid line) and 1:1 line (dashed). Pearson's correlation coefficients (ρ) and root mean

598 squared error (RMSE) between predicted and observed values are reported for each model. Note FAO

599 predictions (for 0-30 cm) are doubled assuming approximately 50% of SOC stocks are stored from 30-
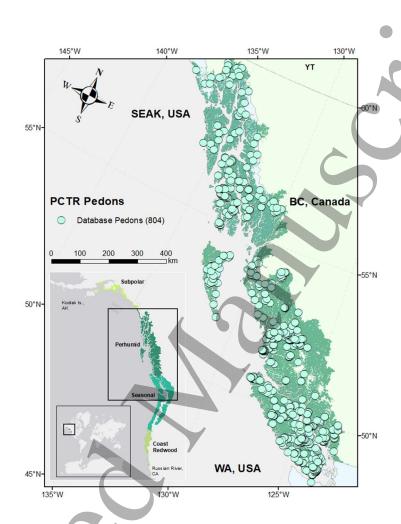
600 100 cm depth (James *et al* 2014).

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602 **Figure 3:** Regression tree results for environmental covariates controlling NPCTR SOC stocks.
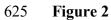
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604 **Figure 4:** Soil organic carbon stock predictions to 1 m (Mg C ha^{-1}) at 90.5 m resolution for small

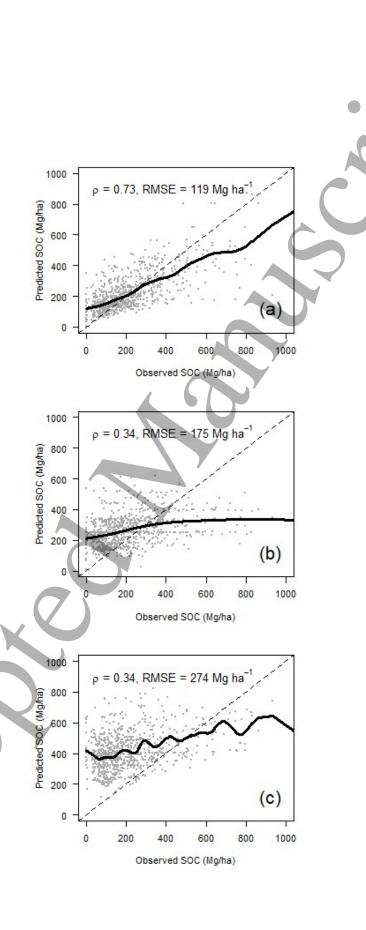605 NPCTR watersheds across BC and SE Alaska.

606

607 **Figure 5:** (a) Sharp spatial discontinuities at the border of Alaska (USA) and BC (Canada) in the FAO

608 Global Soil Organic Carbon (GSOC) map are, in the current study (b), smooth landscape-to-regional

609 gradients, due to harmonized data compilation, gap-filling, and modeling approaches across the

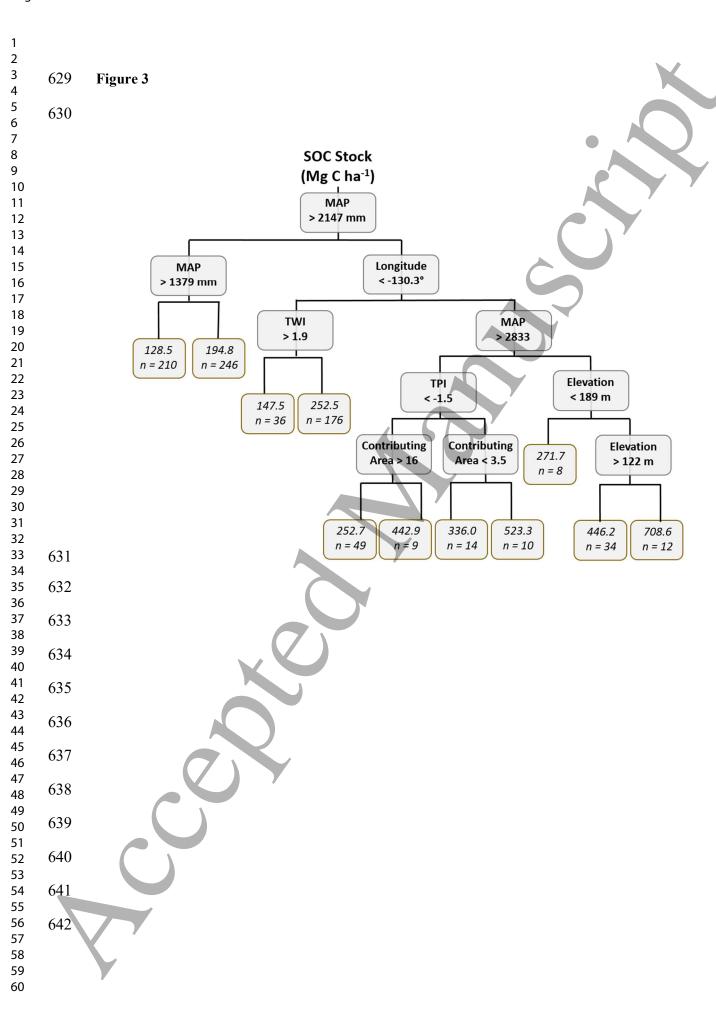610 transboundary extent. Note the FAO GSOC map stock estimates are lower due to a shallower depth range

611 (0-30 cm).

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3 **Figures**
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613 **Figures**

614 **Figure 1**

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625   **Figure 2**

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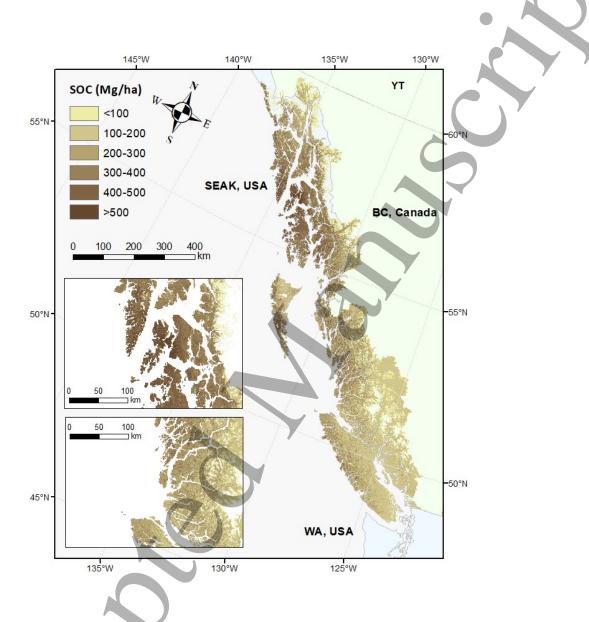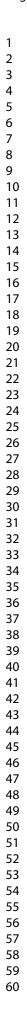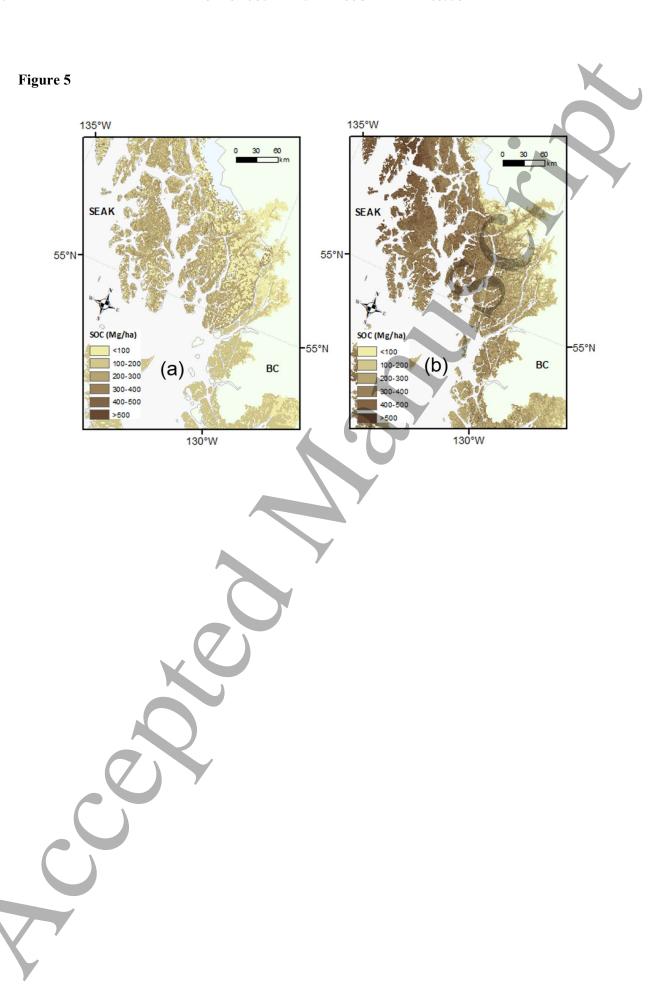660

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668 **Tables**

Table 1: Comparison of methods and results of NPCTR SOC stocks estimated in this study and other regional and global SOC studies

Study	Scale	Region	Method	Mean SOC[1] (Mg ha^{-1})	Total SOC[2] (Pg C)
Present Study	Regional	PCTR Watersheds	Random Forest	228 ± 111	4.5
Present Study – Sens. Test			*+ High Bulk Density*	*329 ± 160*	*6.5*
Present Study – Sens. Test			*+ High Mineral %C*	*249 ± 125*	*4.9*
Present Study – Sens. Test			*+ No Coarse Fra.*	*224 ± 118*	*4.5*
Johnson *et al* (2011)	Regional	Coastal Rainforests (Upland)	Database Summary Stats.	240 ± 132	-
Johnson *et al* (2011)	Regional	Coastal Rainforests (Lowland)	Database Summary Stats.	258 ± 174	-
Michaelson *et al* (2013)	Regional	SE Alaska	Database Summary Stats.	587 ± 379	-
Tarnocai and Lacelle (1996)	National	Regionalized to NPCTR (BC only)	Soil Map Unit Assignment	294 ± 180	3.4[3]
Leighty *et al* (2006)	State	Tongass Nat. Forest (AK)	Econometric Flow Chart	-	1.9[3]
Genet *et al* (2018)	State	North Pacific Coast LLC (AK)	Land Cover Class	-	4.8[3]
SoilGRIDS250m (Hengl *et al* 2017)	Global	Regionalized to NPCTR	Random Forest	486 ± 149	18.0
GSOC (FAO and ITPS 2018)	Global	Regionalized to NPCTR	US: Soil Map Unit BC: Ensemble	136 ± 60	2.5[4]

[1]Map of database mean ± SD; a dash denotes no means reported. [2]SOC stock for overlap extent with present study; a dash denotes no regional prediction. [3]Partially overlap extent with this study. Genet *et al* (2018) extent excludes BC but includes maritime upland and alder forest cover across southeast *and* south central Alaska. [4]The FAO Global SOC map extends only to 30 cm.

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