



1 **Deriving a country-wide soils dataset from the Soil Landscapes of Canada (SLC) database**
2 **for use in Soil and Water Assessment Tool (SWAT) Simulations**

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13 **Abstract**

14 The Soil and Water Assessment Tool (SWAT) model has been commonly used in Canada for
15 hydrological and water quality simulations. However, pre-processing of critical data such as soils
16 information can be laborious and time-consuming. The objective of this work was to pre-process
17 the Soil Landscapes of Canada (SLC) database to offer a country-level soils dataset in a format
18 ready to be used in SWAT simulations. A two-level screening process was used to identify
19 critical information required by SWAT and to remove records with information that could not be
20 calculated or estimated. Out of the 14,063 unique soils in the SLC, 11,838 soils with complete
21 information were included in the dataset presented here. Important variables for SWAT
22 simulations that are not reported in the SLC database [e.g. hydrologic soils groups (HSGs) and
23 erodibility factor (K)] were calculated from information contained within the SLC database.
24 These calculations, in fact, represent a major contribution to enabling the present dataset to be



25 used for hydrological simulations in Canada using SWAT and other comparable models.
26 Analysis of those variables indicated that 21.3 %, 24.6 %, 39.0 %, and 15.1 % of the soils in
27 Canada belong to HSGs 1, 2, 3, and 4, respectively. This suggests that almost two-thirds of the
28 soils have a high (i.e., HSG 4) or relatively high (i.e., HSG 3) runoff generation potential. A
29 spatial analysis indicated that 20.0, 26.8, 36.7 and 16.5 % of soil belonged to HSG 1, HSG 2,
30 HSG 3, and HSG 4, respectively. Erosion potential, which is inherently linked to the erodibility
31 factor (K), was associated with runoff potential in important agricultural areas such as southern
32 Ontario and Nova Scotia. However, contrary to initial expectations, low or moderate erosion
33 potential was found in areas with high runoff potential, such as regions in southern Manitoba
34 (e.g. Red River Valley) and British Columbia (e.g. Peace River watershed). This dataset will be a
35 unique resource to a variety of research communities including hydrological, agricultural and
36 water quality modellers and are publicly available at [doi:10.1594/PANGAEA.877298](https://doi.org/10.1594/PANGAEA.877298).

37 **KEY WORDS:** Modelling, SWAT, input datasets, soils, Canada.

38 **1. Introduction**

39 Integrated environmental modeling is inspired by modern environmental problems and
40 enabled by transdisciplinary science and computer capabilities that allow the environment to be
41 considered in a holistic way (Laniak et al., 2013). In an agricultural context, synthesis and
42 quantification of multi-disciplinary knowledge via process-based modeling are essential to
43 manage systems that can be adapted to continual change (Ahuja et al., 2007). The Soil and Water
44 Assessment Tool (SWAT) (Arnold et al., 1998) is an example of such a process-based model. It
45 has been developed over the past 30-years to evaluate the effects of alternative management
46 decisions on water resources and nonpoint-source pollution in large river basins through the
47 simulation of major processes including hydrology, soil temperature and properties, plant



48 growth, nutrient and pesticides dynamics, bacteria and pathogens transport, and land
49 management (Arnold et al., 2012; Douglas-Mankin et al., 2010). Furthermore, a weather
50 generator is included in the model to fill gaps that may exist in meteorological records.

51 The SWAT model has been extensively tested around the world for a wide range of hydro-
52 climatic conditions, water and land management practices, and time scales (Douglas-Mankin et
53 al., 2010). The wide adoption of the SWAT model has been prompted by pre- and post-
54 processing software tools such as a GIS interface, extensive user documentation (Arnold et al.,
55 2012), as well as several linked databases for crops, soils, fertilizers, tillage, and pesticides
56 (Santhi et al., 2005). Among these, soil properties are especially important as they are needed for
57 the simulation of influential processes such as evapotranspiration, soil water balance, nutrient
58 dynamics, and sediment transport (Neitsch et al., 2005). However, the existing built-in database
59 is only valid for SWAT applications in the USA. Accordingly, studies outside the USA require
60 the development of a soils dataset by pre-processing available soils data into a format readable
61 by SWAT, a time consuming process as not all data required by SWAT is readily available for
62 countries outside of the USA.

63 In Canada, the SWAT model has been used for hydrological simulations in most provinces,
64 including Prince Edward Island (Edwards et al., 2000), New Brunswick (Chambers et al., 2011;
65 Yang et al., 2009), Nova Scotia (Ahmad et al., 2011), Ontario (Asadzadeh et al., 2015; Rahman
66 et al., 2012), Quebec (Lévsque et al., 2008), Manitoba (Yang et al., 2014), Saskatchewan
67 (Mekonnen et al., 2016), Alberta (Mapfumo et al., 2004; Watson and Putz, 2014; Faramarzi et
68 al., 2015), and British Columbia (Zhu et al., 2012). However, preparation of Canadian soils
69 information in a consistent and usable format for SWAT is time consuming (Rahman et al.,
70 2012), as information has to be collected from soil reports, cross-checked against GIS datasets,



71 missing soil variables have to be calculated from other physical and hydraulic properties, and all
72 parameters have to be attributed to specific soil grids or polygons.

73 Some of this pre-processing work can be alleviated by using publically available databases
74 that contain most of the information required by SWAT. The Soil Landscapes of Canada (SLC)
75 database published by Agriculture and Agri-Food Canada (Soil Landscapes of Canada Working
76 Group, 2010) is an example, and has been used in SWAT applications in Ontario (Asadzadeh et
77 al., 2015; Rahman et al., 2012), Saskatchewan (Mekonnen et al., 2016), Alberta (Faramarzi et al.,
78 2015), and British Columbia (Zhu et al., 2012). The SLC contains a series of GIS dataset that
79 provides information about the country's agricultural soils at the provincial and national levels. It
80 was compiled at a scale of 1:1 million, and the information is organized according to a uniform
81 national set of soil and landscape criteria based on permanent natural attributes (Soil Landscapes
82 of Canada Working Group, 2010). The SLC encompasses the southern portions of the Provinces
83 of Ontario and Quebec and a larger portion of the Prairies Provinces of Manitoba, Saskatchewan,
84 and Alberta as far north as to the boreal shield. Coverage in the maritime provinces of New
85 Brunswick, Nova Scotia, and Prince Edward Island is nearly complete (Fig. 1).

86 Although there are more detailed soil datasets available at provincial levels (e.g. AGRASID
87 dataset in Alberta), selection of SLC for integration with SWAT was based on the fact that i) it
88 covers all of Canada's agricultural soils in a single dataset; ii) it has been used in regional studies
89 in Canada, as described above; and iii) it is more easily applicable to large-scale national studies
90 as broad-scale datasets require reduced resources to prepare and process data (Moriassi and
91 Starks, 2010). Modelling studies comparing the performance of a single model (calibrated and
92 un-calibrated) but using soil datasets with varying spatial resolution in the USA [i.e., the State
93 Soil Geographic database (STATSGO) compiled at 1:250,000 scale, and the Soil Survey



94 Geographic database (SSURGO) with scales ranging from 1:12,000 to 1:63,360] also revealed
95 that using either dataset produced comparable results (Mednick, 2008).

96 Due to the importance of the SWAT model for integrated environmental modeling in
97 Canada, and the prominence of the SLC database as a potential input dataset for this model at a
98 national level, the objective of this work was to offer a country-level soils dataset in a format
99 ready to be used in SWAT simulations. The dataset was derived to provide over 20 parameter
100 values for different soil types that are varied for each soil layer. It was prepared in a format
101 suitable for use in the ArcSWAT version of the model, which is attributed to a grid or polygon-
102 based soil map. Such a laborious pre-processing exercise is widely, but inconsistently adopted in
103 SWAT simulations reported in the literature. Finally, deficiencies in the dataset are also
104 presented and discussed.

105 **2. SLC data structure**

106 The SLC database (<http://sis.agr.gc.ca/cansis/nsdb/slc/v3.2/index.html>) is structured as a
107 component-based GIS layer, where a single polygon may contain several soil series. This
108 structure is similar to that of the State Soil Geographic (STATSGO) database in the United
109 States (Srinivasan et al., 2010). Such structure creates a one-to-many relationship where the
110 multiple soil components of a polygon are not spatially defined. The actual soil information in
111 the SLC database is stored in a number of tables linked together through intricate relationships
112 (Soil Landscapes of Canada Working Group, 2010). Among these, four tables are relevant for
113 developing a dataset for SWAT applications:

- 114 • the Polygon Attribute Table (PAT) provides the linkage between geographic locations
115 (polygons in the SLC GIS coverage) and soil landscape attributes in the associated



116 database tables (e.g. unique soil ID in the SNT and respective number of layers in the
117 SLT);

- 118 • the Component Table (CMP) describes each of the individual soil and landscape
119 features comprising the polygons. That is, it describes which soil(s) are present in
120 each spatial unit (i.e., polygon) in the GIS layer;
- 121 • the Soil Name Table (SNT) describes the general physical and chemical
122 characteristics for all of the soils identified in a geographic region;
- 123 • the Soil Layer Table (SLT) contains soil information that varies in the vertical
124 direction (i.e., layered attributes).

125 The CMP table describes the proportion of each non-spatially defined soil component in a
126 polygon if more than a soil component exists [the soil component(s) refer to the soil(s)
127 element(s) that comprise each polygon]. The component numbering follows a sequence of
128 decreasing proportion in a polygon (i.e., first component has the highest proportion; last
129 component has the smallest proportion). This component-based structure of the SLC database
130 does not affect the analysis since all the soils listed in the SNT table were processed to generate
131 the present dataset. However, it has implications for the SWAT model user, who has to make a
132 decision on how to handle the relationship between the polygon (spatially defined) and each non-
133 spatially defined soil component in multi-component polygons (e.g. selecting the larger
134 component in a polygon or generating a hybrid soil incorporating properties of each soil
135 component).

136 **3. SWAT soils data structure**

137 The SWAT soils information is stored in the ‘usersoil’ table, located within the SWAT 2012
138 database in Microsoft Access format (i.e., SWAT2012.mdb). Each soil is stored as a new record



139 (i.e., row) in the table. Specific soil variables (Table 1) comprise the 152 columns of the user soil
140 table. The first column is an OBJECTID field assigning an unique identifier for each record.
141 Columns two through six pertain to soil classification. The second column is the map unit
142 identifier (MUID), which is used for mapping a collection of areas grouped by the same soil
143 characteristics. A single MUID may describe different soil types, which are stored with a record
144 counter in the third column (SEQN), while a soil identifying name (SNAM), a soil interpretation
145 record (S5ID), and the percent of each soil component (CMPPCT) are recorded in the fourth,
146 fifth, and sixth columns, respectively (Sheshukov et al., 2009). Columns seven through twelve
147 describe major soil properties pertaining to the soil type, namely, the number of layers
148 (NLAYERS), the hydrological soil group to which that soil belongs (HYDGRP), the maximum
149 rooting depth of the soil profile (SOL_ZMX), the fraction of soil porosity from which anions are
150 excluded (ANION_EXCL), the potential of maximum crack volume of the soil profile expressed
151 as a fraction of the total soil volume (SOL_CRK), and the texture of the soil layer (TEXTURE).

152 The next 120 columns starting from column 13 (i.e., columns 13 to 132) describe the
153 information for each layer of the soil profile. These columns are arranged in sets of 12 variables
154 each for 10 possible soil layers. The variable NLAYERS indicates how many of these sets
155 should be populated. Variables for any sets beyond NLAYERS should be assigned a value of
156 zero. The variables included in each set of soil layers are the depth from soil surface to bottom of
157 layer (SOL_Z), moist bulk density (SOL_BD), available water capacity of the soil layer
158 (SOL_AWC), saturated hydraulic conductivity (SOL_K), organic carbon (SOL_CBN), clay
159 (CLAY), silt (SILT), sand (SAND), and rock fragment (ROCK) contents, moist soil albedo
160 (SOL_ALB), erodibility factor (USLE_K), and electrical conductivity (SOL_EC). Beyond the
161 columns describing layered soil information, there are 20 columns (i.e., columns 133 to 152)



162 describing two variables [i.e., soil CaCO_3 (SOL_CA) and soil pH (SOL_PH)] for 10 soil layers.

163 These variables are not currently active in SWAT and are assigned a value of zero.

164 **4. Merging the two datasets**

165 Despite its usefulness as a source of soil information for hydrological simulations, the SLC
166 dataset is not assembled in a format readable by SWAT or other similar models. For example,
167 SWAT stores all the properties for a specific soil in a single row in the the ‘*usersoil*’ table, while
168 this information is stored in the SLC as multiple rows in two different tables (i.e., SNT and
169 SLT). Thus, the information contained in the SLT database has to be processed to satisfy
170 SWAT’s format requirements. In addition, all properties in the *usersoil* are spatially defined
171 while those of SLC are often stored in a multi-polygon structure with no unique spatial
172 identification. Variables required by SWAT and contained in the dataset presented here were
173 either extracted from SNT and SLT, or calculated from the information therein. Some other
174 variables were estimated from published values. Extraction or calculation of variables was done
175 through an R code that imported both SNT and SLT, screened the data for missing records and
176 missing SWAT-required information (data screening is described in section 5), and sequentially
177 populated unique soil records in the database. This section describes how these variables were
178 defined.

179 **5. Data screening**

180 *5.1 Screening out incomplete soil information in the SNT*

181 The use of the SNT is necessary as it links the soils information to the GIS coverage
182 containing the PAT. However, a first screening was required to remove soils from the SNT that
183 are not present in the SLT, as soil layer information is required by SWAT. The mismatch among



184 soils in both tables can occur for a number of reasons. For example, there are soils in both tables
185 that pedologists have identified but their properties have not yet been characterized. Also, soils
186 listed in one table may be absent from another table due to changes in soil classification. Finally,
187 soils listed as unclassified in the SNT (i.e., variable KIND=U) do not have any data associated
188 with them in the SLT and do not occur on any published map.

189 Out of the 14,063 unique soils in the SNT, 489 soils were missing in the SLT and, therefore,
190 removed from the analysis. These 489 soils correspond to around 3.5 % of the soils listed in the
191 SNT. Most of the missing soils were reported as “unclassified” (305 soils; 62.2 %), suggesting
192 that these soils have been identified, but their properties have not yet been characterized. Mineral
193 soils corresponded to 29.4 % (144 soils) of the total, likely a reflection of changes in
194 classification. The other two classes comprised non-true soils (e.g. mine tailings, urban land; 33
195 soils; 6.7 %) and organic soils (8 soils; 1.6 %). Also, only 58 of the 489 missing soils (11.0 %)
196 could be mapped through linking with the CMP table, making it impossible to do any spatial
197 analysis on the distribution of these soils across the country. However, since the SNT assigns a
198 province for each soil, it is possible to identify where these missing records occur. Most of the
199 missing soils were in British Columbia (167 soils; 34.2 %), Manitoba (151 soils; 30.9 %), and
200 Saskatchewan (133 soils; 27.2 %), with smaller proportions in Yukon (13 soils; 2.7 %), Ontario
201 (11 soils; 2.3 %), Nova Scotia (9 soils; 1.8 %) and Newfoundland (5 soils; 1.0 %).

202 *5.2 SWAT requirements*

203 The SWAT data requirements were used as a second level of screening to build the present
204 dataset. The soil input variables in SWAT can be either required or optional (Table 2; Arnold et
205 al., 2013). Required variables that could not be calculated or estimated (e.g., SOL_BD, SOL_K,
206 SOL_CBN, CLAY, SILT, and SAND) were used to separate complete from incomplete records.



207 Soils in the SLT containing or allowing derivation of all the variables required by SWAT were
208 compiled in a dataset comprising 11,838 unique soils that were importable into the model. Soils
209 in the SLT with missing records (i.e., variables entered as -9 in the database) for the required
210 SWAT variables (gray rows in Table 2) were removed from the analysis. These soils were
211 compiled into a soils list provided as a reference.

212 As for the non-matching soils in the SNT and SLT, only 547 out of 1736 (i.e., 31.5 %) soils
213 with missing information could be mapped through linking with the CMP table, which renders
214 any spatial representation of these soils unmeaningful. However, the provinces where these soils
215 occur could also be identified. The highest proportions of soils with incomplete information were
216 in British Columbia (490 soils; 28.2 %), Manitoba (391 soils; 22.54 %). Ontario (182 soils;
217 10.5 %) and Alberta (180 soils; 10.4 %) had intermediate values, while Newfoundland (123
218 soils; 7.1 %), Saskatchewan (102 soils; 5.9 %), New Brunswick (93 soils; 5.4 %), the Northwest
219 Territories (80 soils; 4.6 %), Nova Scotia (47 soils; 2.7 %), Quebec (30 soils; 1.7 %), and Yukon
220 (17 soils; 1.0 %) had less than 10 % of the soils missing information.

221 **6. Populating the user soil table in SWAT**

222 The variables in SWAT's 'usersoil' table refer to record indexing and soil classification, as
223 well as soil properties pertaining to the entire profile or specific layers. The variables in each of
224 these groups are described in the following sub-sections. The 'usersoil' table starts with a
225 number of columns that define the database and soil classification variables, followed by soil
226 profile and layer information, and inactive soil properties (Table 2).



227 *6.1 Database and soil classification variables*

228 The SWAT soil classification variables include the OBJECTID (general listing number),
229 MUID (map unit identifier), SEQN (sequence number), SNAM (soil name), S5ID (Soils5-ID
230 number for USDA soil series data) and CMPPCT (percentage of the soil component in the
231 MUID). A numbering system used for the OBJECTID variable was chosen to avoid conflicts
232 with existing soils in the user soil table. The SWAT model comes with more than 200 soils in a
233 built-in database that cannot be easily overwritten, and any soils imported into the database with
234 the same OBJECTID as existing soils will not be imported. Thus, the OBJECTID field was
235 populated sequentially from 1001 to the number of unique soils in the SLC database plus 1000
236 (i.e., OBJECTID ends in 12,838 in the case of the COMPLETE dataset, which has 11,838 unique
237 soils). The map unit ID (MUID) was assigned the SOIL_ID code in the SLC dataset, which is a
238 concatenation of the province code (two digits), a soil code (three digits), a modifier code (five
239 digits), and a profile code (one digit). The sequence number (SEQN) variable was assigned the
240 same value as the OBJECTID variable. This process created a unique SEQN for each recurrence
241 in the SLC dataset.

242 Similar to the MUID variable, the soil name variable (SNAM) was also assigned the
243 SOIL_ID code in the SLC, despite the soil name being in the database, so as to link the soil
244 information to the GIS layer. The S5ID variable was created as a concatenation between the
245 acronym “SLC” and the province two-digit abbreviation code. For example, all the soils in the
246 province of Alberta have S5ID equal to “SLCAB”. The CMPPCT variable was assigned a value
247 of 100, meaning that the soil comprises 100 % of this component. As stated in section 2, the user
248 has to make a decision on how to handle multipart polygons in the pre-processing of the SLC
249 GIS dataset since the soils in multi-component polygons are not spatially defined.



250 *6.2 Soil profile information*

251 The following six variables in the dataset (i.e., columns 7 to 12) pertain to soil profile
252 information. The number of layer variables (NLAYERS) was defined according to the soil layers
253 in the SLT below the soil surface. The SLT table also contains information for layers above the
254 soil surface as is the case of litter, which have negative values for upper and lower depths (i.e.,
255 the ground surface corresponded to the zero depth, while above surface and below surface layers
256 have negative and positive values, respectively). Above-surface layers were removed from the
257 dataset prior to analysis through filtering layers with lower depth above the soil surface (i.e.,
258 lower depth less than or equal to zero).

259 The hydrologic soil group (HSG) variable (HYDGRP) is an influential parameter for
260 estimation of runoff using the SCS-Curve Number method and, consequently, for hydrological
261 simulations in SWAT (Gao et al., 2012; Neitsch et al., 2005). The HSGs were calculated
262 according to the method outlined by USDA-NRCS (1993), which is based on depth to the
263 impermeable layer (e.g., bedrock), depth from soil surface to shallowest water table during the
264 year, hydraulic conductivity of the least conductive layer of the soil profile, and depth range of
265 the hydraulic conductivity. The specific criteria used are provided in tabular form as
266 supplementary material. Soils in the dual HSG classes were assigned to the less restrictive class
267 since most agricultural soils in Canada exhibit some degree of drainage (e.g., municipal drainage
268 network, surface drains, or tile drainage). SWAT translates HSG alphabetical classification into a
269 numeric system, where HSGs A, B, C, and D, are interpreted as 1, 2, 3, and 4, respectively. The
270 runoff potential increases with increasing numeric designations.

271 The depth to the impermeable layer is not reported in the SLC database and was estimated
272 based on the soil layers available in the SLT. When a bedrock layer or specific soil horizons



273 were present [i.e., fragipan; duripan; petrocalcic; orstein; petrogypsic; cemented horizon; densic
274 material; placic; bedrock, paralithic; bedrock, lithic; bedrock, densic; or permafrost; USDA-
275 NRCS (1993)], its upper depth was used as the depth to impermeable layer. When a bedrock
276 layer was absent, the lower depth of the deepest mineral soil layer was used as an alternative.
277 The shallowest annual depth to water table is also not reported and was estimated based on
278 drainage class reported in the SNT. Very poorly drained, poorly drained, imperfectly drained,
279 moderately well drained, and well drained (or better) soils were assigned water table depths of 0 ,
280 25 , 75, 100, and 125 cm, respectively. The variables pertaining to hydraulic conductivity of the
281 least conductive layer of the soil profile and depth range of the hydraulic conductivity were both
282 calculated using information from the SLT.

283 Out of the 11,838 soils in the generated dataset, 21.3, 24.6, 39.0, and 15.1 % belonged to
284 HSGs 1, 2, 3 and 4, respectively. These results suggest that more than half of the soils in Canada
285 have a relatively high or high runoff generation potential (i.e., HSGs 3 and 4, respectively). A
286 spatial analysis indicated that 20.0, 26.8, 36.7, and 16.5% of the areal extend of the soils
287 belonged to HSGs 1, 2, 3, and 4, respectively. Much of the soils with higher potential for runoff
288 generation are in the humid regions of Ontario, Quebec, and the Maritimes (Fig. 2). Not
289 surprisingly, this region has extensively adopted measures to address excess moisture in
290 agricultural soils, such as tile drainage (Stonehouse, 1995; Rasouli et al., 2014). Excess moisture
291 is also a problem in areas of Canadian Prairies, such as the Red River Valley in Manitoba, where
292 surface drainage (Bower, 2007) and a growing use of tile drainage (Cordeiro and Sri Ranjan,
293 2012, 2015) have been used to address this problem. Conversely, soils with low potential for
294 runoff generation are located in Saskatchewan and Southeastern Alberta (along the
295 Saskatchewan border), which are among the most arid regions in Canada (Wolfe, 1997).



296 The maximum rooting depth of the soil profile (SOL_ZMX) was assumed to be the lower
297 depth of the deepest layer in the SLC soil profile. The fraction of soil porosity from which anions
298 are excluded (ANION_EXCL) was not available in the SLC database and was set to the default
299 value of 0.5 in SWAT (Arnold et al., 2013). This variable affects the concentration of nitrate in
300 the mobile water fraction, which is directly related to nitrate leaching. The potential of maximum
301 crack volume of the soil profile expressed as a fraction of the total soil volume (SOL_CRK) can
302 be calculated by the FLOCR model using 30-yr weather data (Bronswijk, 1989). However, due
303 to the fact that the model is not readily available for download and the unreasonable time
304 required to run the model for such a large number of soil types, as well as the fact that
305 SOL_CRK is optional in SWAT, its value was set of 0.5. In large scale studies this value is
306 further adjusted through a spatially explicit calibration scheme (Whittaker et al., 2010). The
307 SOL_CRK variable controls the potential crack volume for the soil profile. This value was
308 selected based on the fact that all of the built-in soils in the SWAT soils database have the
309 SOL_CRK variable set to 0.5. The TEXTURE variable, although not required for simulations
310 with the SWAT model, was estimated for reference using the ‘TT.points.in.classes’ function
311 from the ‘soiltexture’ R package (Moeys, 2016). The Canadian soil texture classification system
312 was used as a reference.

313 *6.3 Soil layer information*

314 The soil profile variables are followed by 10 sets of 12 variables (i.e., columns 13 to 132)
315 pertaining to layered soil information. The lower depth of each soil layer in the SLT was used as
316 the depth from soil surface to the bottom layer (SOL_Z). The soil bulk density (SOL_BD) was
317 extracted directly from the SLT. The available water capacity of the soil layer (SOL_AWC) was
318 calculated from the water retention of the soil reported in the SLT at different matric potentials.



319 The water moisture content at -33 and -1500 kPa were assumed to represent the soil moisture at
320 field capacity (FC) and permanent wilting point (PWP), respectively (Givi et al., 2004). The
321 SOL_AWC was calculated as the difference between FC and PWP (Hillel, 1998). Soil moisture
322 content at -33 kPa was not available for 2,658 layer records (i.e., 4.3% of the 61905 original
323 records in the SLT table), which would result in the variable SOL_AWC not being calculated
324 and the loss of more soils from the dataset. To avoid this, the moisture content at -10 kPa was
325 used to replace that at -33 kPa. On average, the soil moisture content in the soil profile was
326 around 6 mm larger at -10 kPa than that at -33 kPa (Table 3), indicating an overestimation of
327 SOL_AWC in these soils. Larger differences between soil moisture content at -10 kPa and -33
328 kPa in the top soil layers were likely driven by lower bulk densities, which increase the water
329 holding capacity of the soil (Table 3).

330 The variables saturated hydraulic conductivity (SOL_K) and soil organic carbon content
331 (SOL_CBN), as well as the clay (CLAY), silt (SILT), sand (SAND), and rock fragment (ROCK)
332 contents, were extracted directly from the SLT. The moist soil albedo (SOL_ALB) variable was
333 only required for the top layer as subsequent layers were assigned a value of zero. Since this
334 variable is not reported in the SLC database, it was estimated as the average (i.e., 0.10) of the
335 range reported by Maidment (1993) for moist, dark, plowed fields (i.e., 0.05-0.15). Again, this
336 value was selected since the SLC version 3.2 focuses on agricultural areas, which is also the
337 major domain simulated by SWAT.

338 Another important variable for SWAT is the erodibility factor (USLE_K), used as an input to
339 the Universal Soil Loss Equation (USLE). This equation is used to calculate soil erosion, which
340 is inherently linked to sediment and nutrient transport (Sharpley et al., 1992; He et al., 1995;
341 Sharpley et al., 2002; Aksoy and Kavvas, 2005; Koiter et al., 2013) and therefore, critical for



342 simulations of non-point sources of pollution. The erodibility factor was calculated using the
 343 method presented by Sharpley and Williams (1990), which is based on the sand, silt, clay, and
 344 organic carbon content of the soil (Eq. 1):

$$K = \left(0.2 + 0.3 \cdot \exp \left[-0.256 \cdot m_s \cdot \left(1 - \frac{m_{silt}}{100} \right) \right] \right) \cdot \left(\frac{m_{silt}}{m_c + m_{silt}} \right)^{0.3} \cdot \left(1 - \frac{0.25 \cdot orgC}{orgC + \exp [3.72 - 2.95 \cdot orgC]} \right) \cdot \left(1 - \frac{0.7 \cdot \left(1 - \frac{m_s}{100} \right)}{\left(1 - \frac{m_s}{100} \right) + \exp \left[-5.51 - 22.9 \cdot \left(1 - \frac{m_s}{100} \right) \right]} \right) \quad (1)$$

346 where K is the erodibility factor [0.01 (ton·acre·hr)/(acre ft·ton in)], m_s is the sand content
 347 (percent), m_{silt} is the silt content (percent), m_c is the clay content (percent), and $orgC$ is the
 348 organic carbon content (%) of the respective soil layer.

349 As for SOL_ALB, USLE_K is only required for the top layer and subsequent layers were
 350 also assigned a value of zero. When converted from Imperial to SI units (Foster et al., 1981), the
 351 range of calculated values (Table 4) generally agrees with the ranges reported for Canada (Wall
 352 et al., 2002), taking into consideration that K values may vary, depending on particle size
 353 distribution, organic matter, structure and permeability of individual soils (Wall et al., 2002).
 354 However, the units in the dataset presented here were kept in Imperial units for consistency with
 355 the SWAT input format. The spatial distribution of the erodibility factor (Fig. 3) was anticipated
 356 to align with HSG, which was the case in areas of low erosion potential in Saskatchewan where
 357 sandy soils prevail and in areas where runoff potential is high such as in southern Ontario.
 358 However, the spatial distribution of USLE_K somewhat contrasted to that of HSG in some areas
 359 of Manitoba and British Columbia, where low sediment transport potential was predicted in areas
 360 with high runoff potential. This contrast was likely due to other factors reducing the potential for



361 sediment transport, such as soils with high clay to silt ratios or high organic carbon contents
362 (Sharpley and Williams, 1990).

363 The soil electrical conductivity (SOL_EC) information was extracted directly from the SLT.
364 The last twenty columns of the dataset (i.e., columns 133 to 152), which correspond to
365 SOL_CAL for the 10 soil layers followed by SOL_PH for the same layers, were all populated
366 with zeros since these variables are not currently active in SWAT. These variables also had
367 values of zero for all the pre-existing soils in the built-in database in the model.

368 **7. Importing the SLC dataset into SWAT database**

369 Although the SWAT database is in a proprietary format (i.e., Microsoft Access), the present
370 soils dataset has been published in a non-proprietary format [i.e., comma-separated values (CSV)
371 file] that can be opened in a variety of software packages. However, the dataset can be easily
372 imported into the SWAT soils database using an automated import routine in Microsoft Access.
373 This import process consists of opening the SWAT2012 database and using the ‘Import Text
374 File’ tool under the ‘Import & Link’ section of the ‘External Data’ tab to read the CSV file. This
375 action will prompt a window where the user can select the path to where the present dataset is
376 stored and specify how and where the data is stored in the database. The option ‘Append a copy
377 of the record to the table’ should be selected, which activates a drop-down menu from which the
378 ‘usersoil’ table should be highlighted. Once these options have been processed, an ‘Import Text
379 Wizard’ window will be prompted, where the option ‘Delimited – Characters such as comma or
380 tab separate each field’ should be selected. Processing of this selection will prompt another
381 window where the option ‘comma’ should be automatically selected by the wizard. However, the
382 user should activate the box ‘First Row Contains Field Names’ since the first row of the present



383 dataset contains the variable labels. Confirming the processing of the next windows should
384 finalize the import process, and the data should be ready to be used in SWAT predictions.

385 **8. Data access**

386 PANGAEA, an open access library to archive, publish and distribute georeferenced data,
387 supports database-dependent research. Therefore, the entire dataset is published and archived in
388 the PANGAEA database (<https://doi.pangaea.de/10.1594/PANGAEA.877298>) under Creative
389 Commons Attribution 3.0 Unported, where the user must give appropriate credit, provide a link
390 to the license and indicate if changes are made.

391 **9. Conclusions**

392 The soils dataset presented and discussed in this work represent an effort to facilitate
393 hydrological simulations using the SWAT model in Canada. The dataset consists of a
394 compilation of 11,838 different soils from the SLC database with all the information required by
395 SWAT and is ready to be imported into the model's soils database. A two-level data screening
396 procedure removed 489 soils with missing layered information (i.e., not present in the SLT),
397 while 1,736 soils were removed due to the lack of critical information required by SWAT, such
398 as soil bulk density or saturated hydraulic conductivity. Among the major contributions of this
399 dataset, the calculation and/or estimation of variables not reported in the SLC database are of
400 special importance. The hydrologic soil groups (HSGs) calculated from SLC database suggests
401 that about half of the soils in Canada belong to classes with higher potential to generate runoff
402 (i.e., HSG classes 3 and 4). Occurrence of soils in HSG 3 and 4 agree with management practices
403 aimed at addressing excess moisture conditions in agricultural fields, such as subsurface drainage
404 in southern Ontario and Manitoba. The erodibility factor, which is another important variable for
405 SWAT simulations of non-point source pollution, suggest a relationship with runoff potential in



406 portions of southern Ontario and Nova Scotia. However, low erodibility potential likely driven
407 by high clay to silt ratios or high organic carbon content were found in areas with higher runoff
408 potential in Manitoba and British Columbia.

409 **Author contribution**

410 M.R.C Cordeiro and R. Kroebel developed the concept for development of the dataset. G.
411 Lelyk interpreted the soil information contained in the SLC database. M.R.C Cordeiro and G.
412 Lelyk developed the methodology for deriving the soil variables. M.R.C Cordeiro developed the
413 code using R programming language to process the SLC dataset and performed data analysis. All
414 the authors revised the dataset and participated in manuscript preparation.

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419 2016E017R).

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560 Table 1. Description of variables in SWAT's 'usersoil' table.

Variable Group	Column number in 'usersoil' table	Variables ^a
Database indexing	1	OBJECTID
Soil classification	2 through to 6	MUID; SEQN; SNAM; S5ID; CMPPT
Soil properties		
Profile	7 through to 12	NLAYERS; HYDGRP; SOL_ZMX; ANION_EXCL; SOL_CRK; TEXTURE
Layers	13 through to 132 (12 variables for 10 soil layers)	SOL_Z _x ; SOL_BD _x ; SOL_AWC _x ; SOL_K _x ; SOL_CBN _x ; CLAY _x ; SILT _x ; SAND _x ; ROCK _x ; SOL_ALB _x ; USLE_K _x ; SOL_EC _x
Inactive	133 through to 152	SOL_CAL _x ; SOL_PH _x

561 ^a Subscript x corresponds to soil layer from 1 to 10.



562 Table 2. Variables included in the SWAT user soil table.

Column	Variable ^a	Description	Units	Status
1	OBJECTID	Object identifier	–	Optional
2	MUID	Mapping unit identifier	–	Optional
3	SEQN	Record counter calculated by SWAT	–	Optional
4	SNAM	Soil identifying name	–	Optional
5	S5ID	Soil interpretation record	–	Optional
6	CMPPCT	Soil component percent	–	Optional
7	NLAYERS [†]	Number of layers	–	Required
8	HYDGRP	Hydrologic Soil Group	–	Required
9	SOL_ZMX	Maximum rooting depth of the soil profile	mm	Required
10	ANION_EXCL	Fraction of soil porosity from which anions are excluded	–	Optional
11	SOL_CRK	Potential of maximum crack volume of the soil profile expressed as a fraction of the total soil volume	mm ³ mm ⁻³	Optional
12	TEXTURE	Texture of soil layer	–	Optional
13	SOL_Z _x	Depth from soil surface to bottom of layer	mm	Required
14	SOL_BD _x	Moist bulk density	Mg m ⁻³ or g cm ⁻³	Required
15	SOL_AWC _x	Available water capacity of the soil layer	mm mm ⁻³	Required
16	SOL_K _x	Saturated hydraulic conductivity	mm h ⁻¹	Required
17	SOL_CBN _x	Organic carbon content	% (w/w)	Required
18	CLAY _x	Clay content	% (w/w)	Required
19	SILT _x	Silt content	% (w/w)	Required
20	SAND _x	Sand content	% (w/w)	Required
21	ROCK _x	Rock fragment content	% (w/w)	Required
22	SOL_ALB _x	Moist soil albedo	–	Required
23	USLE_K _x	Erodibility factor (K)	0.01 (ton·acre·hr)/(acre ft·ton in)	Required
24	SOL_EC _x	Electrical conductivity	dS m ⁻¹	Optional

563 Adapted from Arnold et al. (2013) and Sheshukov et al. (2009). ^a Subscript x corresponds to soil layer from 1 to 10. The variables SOL_CAL_x and SOL_PH_x are
 564 present in the user soil table after all the columns listed above for all the 10 pre-existing layers. These variables refer to soil CaCO₃ and soil pH, respectively, and
 565 are not currently active in the model. Thus, their records are entered zero in the SWAT 2012 database. [†]The number of layers defines how many entries will be
 566 required in the layered information, signalled by the subscript x. For example, a soil with NLAYERS=4 should have subscript x corresponding to soil layer
 567 variables from 1 to 4. As a result, the records extend to column 60 in the user soil table. (i.e., 4 layers×12 variables + 12 preceding variables=60).



568 Table 3. Average soil moisture content at matric potentials -10 kPa and -33kPa and average soil bulk density for
 569 discrete layers of the soil profile. The average was calculated for all soils in the dataset. Each layer could have
 570 different depths for individual soils used in the average.

Layer	$\bar{\theta}_{at-10kPa}$	$\bar{\theta}_{at-33kPa}$	Difference (mm)	Average soil bulk density (g cm ⁻³)
1	36.8	29.67	7.13	1.13
2	33.65	26.72	6.93	1.27
3	31.99	25.36	6.63	1.38
4	29.48	23.32	6.16	1.47
5	28.1	22.17	5.93	1.50
6	27.26	21.53	5.73	1.52
7	27.03	21.42	5.61	1.54
8	26.98	21.17	5.81	1.54
9	25.05	18.86	6.19	1.55
AVERAGE	29.59	23.36	6.24	1.43

571 $\bar{\theta}$ = average soil moisture content (mm).



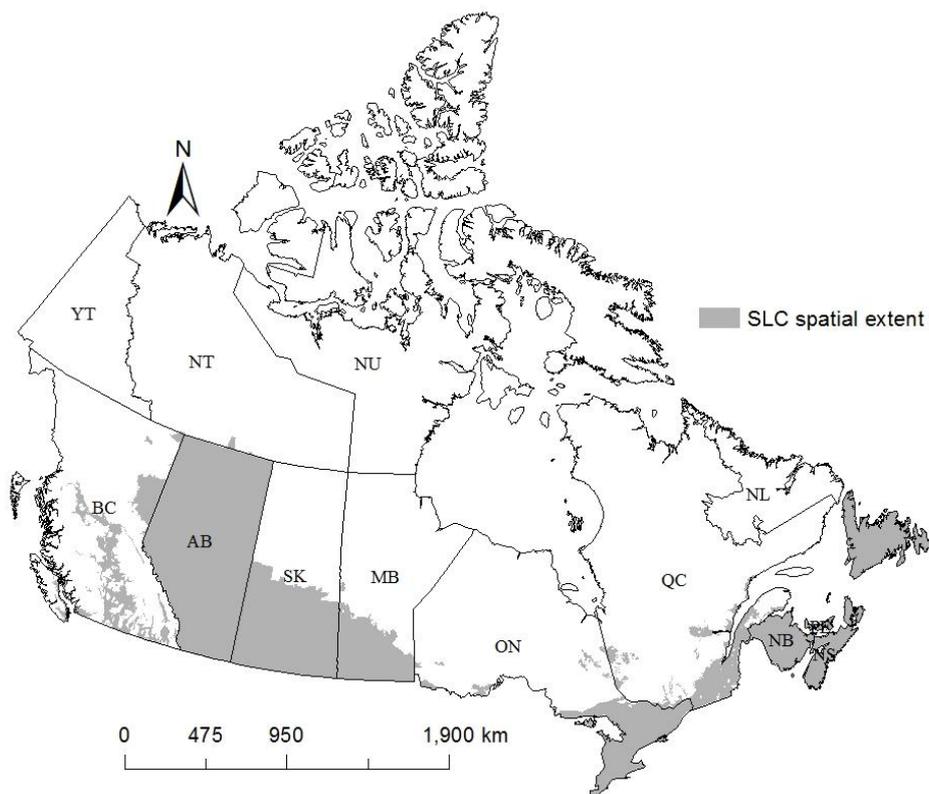
572 Table 4. Comparison between the average erodibility factor (K) calculated for
 573 each soil textural class in the SWAT dataset and values reported in the
 574 literature.

Soil Textural Class	Acronym	Calculated average K	Reported K range [†]
Loam	L	0.14	0.23 – 0.30
Heavy clay	HCl	0.18	0.05 – 0.23
Silty clay loam	SiClLo	0.22	0.30 – 0.38
Clay loam	ClLo	0.14	0.23 – 0.30
Silt loam	SiLo	0.22	0.30 – 0.38
Sand	Sa	0.04	< 0.05
Sandy loam	SaLo	0.11	0.05 – 0.23
Clay	Cl	0.14	0.23 – 0.30
Silty clay	SiCl	0.22	0.23 – 0.30
Loamy sand	LoSa	0.07	< 0.05
Sandy clay loam	SaClLo	0.10	0.23 – 0.30
Silt	Si	0.55	0.30 – 0.38 [‡]
Sandy clay	SaCl	0.09	0.05 – 0.23 [#]

575 [†]Adapted from Wall et al. (2002). [‡]Range not reported; value from SiLo
 576 used. [#] Range not reported; value from SaLo used.



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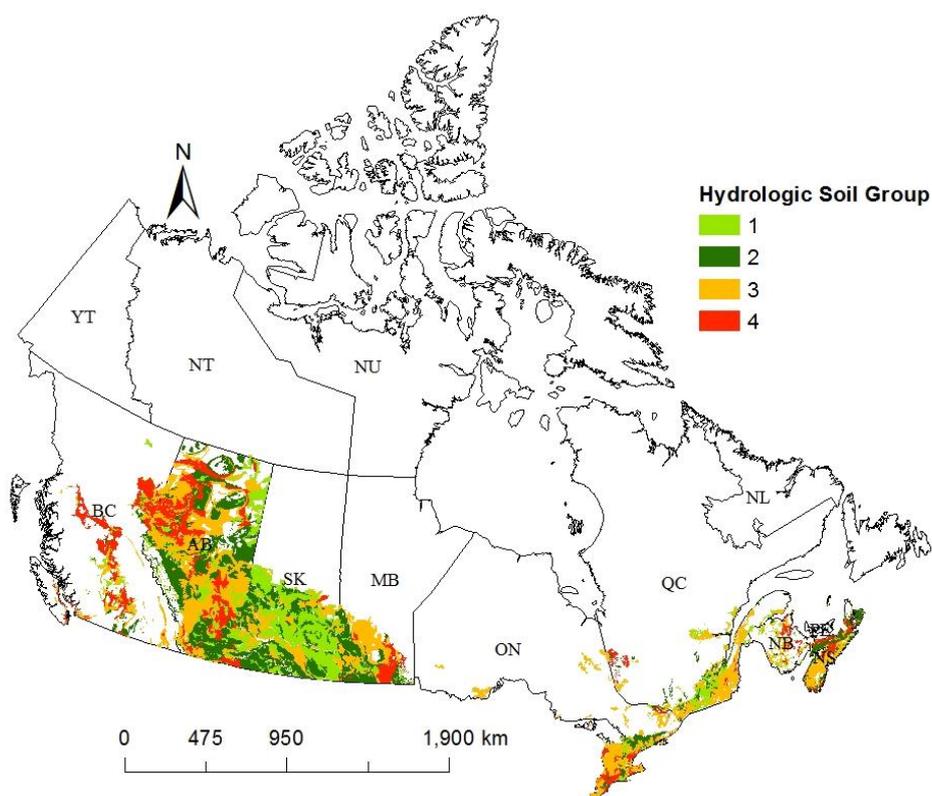


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Figure 1. Spatial extent of the Soil Landscapes of Canada (SLC) database showing coverage in the Provinces of Newfoundland and Labrador (NL), Prince Edward Island (PE), Nova Scotia (NS), New Brunswick (NB), Quebec (QC), Ontario (ON), Manitoba (MB), Saskatchewan (SK), Alberta (AB), and British Columbia (BC), as well as the Northwest Territories (NT).

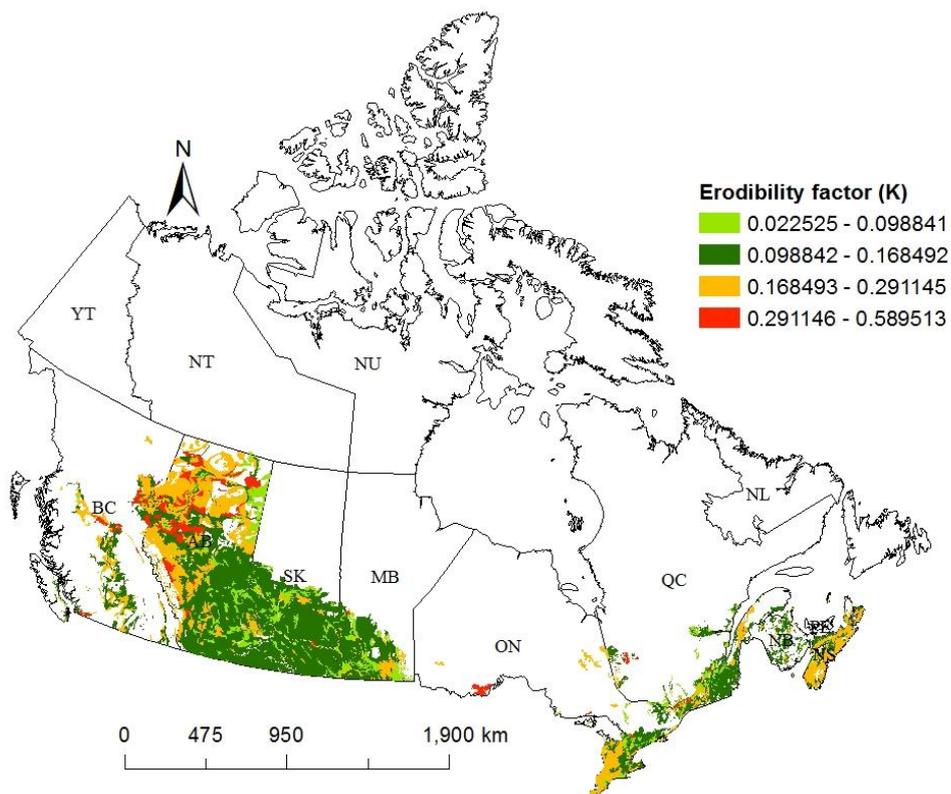


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Figure 2. Spatial distribution of the hydrologic soil groups (HYDGRP) variable calculated for the Soil Landscapes of Canada (SLC) database. HSG A=1, HSG B=2, HSG C=3, and HSG D=4 shown for the Provinces of Prince Edward Island (PE), Nova Scotia (NS), New Brunswick (NB), Quebec (QC), Ontario (ON), Manitoba (MB), Saskatchewan (SK), Alberta (AB), and British Columbia (BC). Some HSG could not be mapped [e.g. Province of Newfoundland and Labrador (NL)] due to missing records in the PAT of the GIS layer or being part of the soils with missing data in the SLT.



592
593 Figure 3. Spatial distribution of the erodibility factor (K) calculated for the Soil Landscapes of Canada (SLC)
594 database (Imperial units). The K factor shown for the Provinces of Prince Edward Island (PE), Nova Scotia (NS),
595 New Brunswick (NB), Quebec (QC), Ontario (ON), Manitoba (MB), Saskatchewan (SK), Alberta (AB), and British
596 Columbia (BC). Some HSG could not be mapped [e.g. Province of Newfoundland and Labrador (NL)] due to
597 missing records in the PAT of the GIS layer or being part of the soils with missing data in the SLT.