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Cold-Weather Crop Suitability Modelling

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Abstract

This article presents ArcGIS Pro workflow results aimed at rating and mapping cold-weather crop suitability from 0% to 100% at 1-m elevation resolution for the Province of New Brunswick (NB). This rating accounts for variations by soil conditions (texture, coarse fragments, depth, calcareousness, drainage, slope), growing degree days (GDD) and frost-free days (FFD) from within fields to across regions. The ratings so produced reflect a significant part of farm and farm/woodlot property assessment values as these also vary by area and building footprint. While the soil properties for texture, coarse fragments, depth, and calcareousness vary by NB soil association mapping units, within-field suitabilities also vary by slope from flat to steep and by drainage as it correlates across the terrain by depth-to-water (DTW) from very poor to poor, imperfect, moderate, well and excessive. Areas marked by 1.5 < DTW < 10 m away from permanent flow channels, wetlands and open water bodies are generally not too wet and not too dry. Areas with slopes > 10% have low to no suitability because of slope-increased soil erosion and trafficability risks. The number of growing-degree and frost-free days across NB were rated to be sufficient for cold weather cropping, except marginally so at the high-elevation locations.

Keywords

Crop Suitability Rating, Topography, Climate, Soil Properties, Property Values, Regression Analysis

1. Introduction

The increasing availability of high-resolution LiDAR-generated digital elevation models (DEMs) now enables detailed refinements of crop-specific land capability ratings as affected by soil, climate, and topography. The objective of this article is to illustrate how a 1-m resolution DEM enhances this rating across New

Brunswick (NB), with focus on cold-weather cropping (**Figure 1**). The advantages that accrue refer to an improved lay-of-the-land presentation to assess cropping potentials from poor (0%) to fair (50%) and best (100%) by soil substrate, drainage, slope, and climate conditions. The map-generating workflow is based on the Traditional Crop Rating Methodology (TCRM) [1] and its further developments [2] [3] [4]. For example, the Land Suitability Rating System (LRSL) at [5] rates each parcel of land by:

1) climate conditions (mean annual/seasonal temperatures, precipitation amounts, and frost conditions),

2) soil properties (water holding capacity, texture, structure, soil organic matter (SOM), uncompacted soil depth, pH, salinity, sodicity, temperature, parent material, drainage),

3) surface expressions (slope, surface deposits, waterbodies, wetlands, bedrock formations), and

4) vegetation cover (forests, grasslands, deserts).

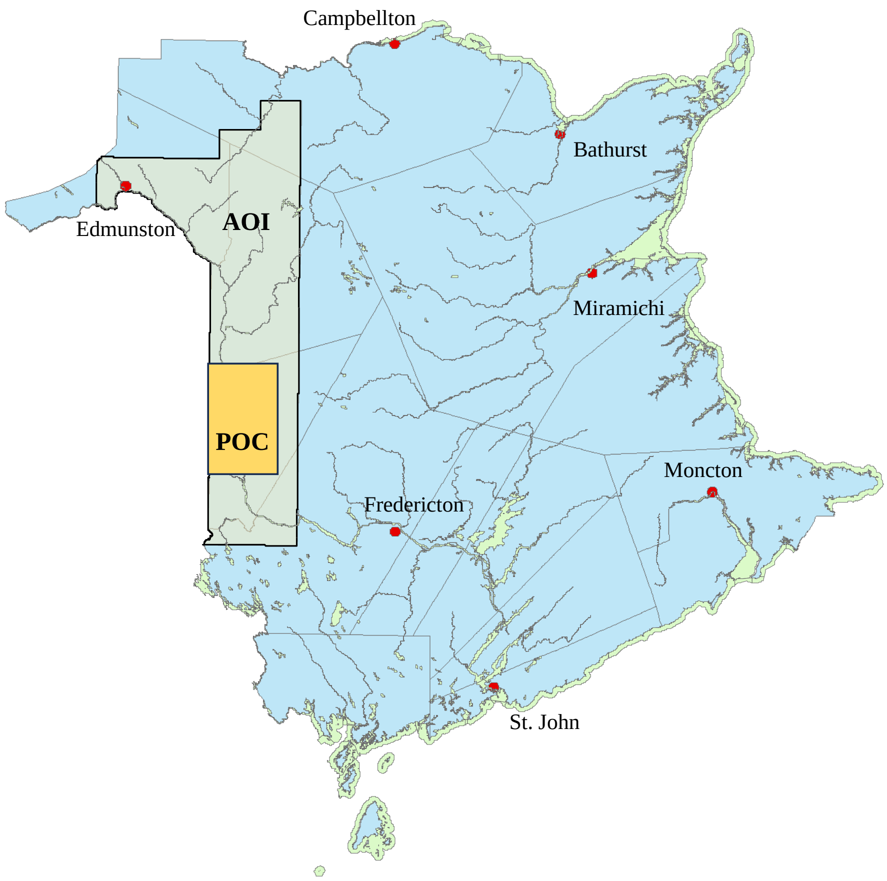

Figure 1. Locator map for the DEM-based cold-weather crop rating initiate across New Brunswick, done at 1-m resolution, followed by examining how the mean suitability ratings for individual farm and woodlot properties relate to the corresponding property tax assessment values. This was done for a proof-of-concept evaluation (POC, yellow area; 142,839 ha), and extending this analysis to the area of interest (AOI, black outline; 971,665 ha) along the "Potato Belt" of the Upper Saint John River Valley. Background shows counties and major lakes and rivers.

This rating scheme involves matching basic crop-growing requirements by some and all of the above items, involving additions, subtractions, multiplications, divisions, and variable transformations. In so doing, several techniques have emerged which may also include applying Analytical Hierarchy Processes (AHP), Fuzzy Logic Methods (FLM), Machine Learning and Crop Simulation (MLCS) [6]. Listed in **Table 1** are examples by location, rating criteria and methods. These efforts also differ by region, areal extent, digital resolution, and choice of soil, climate, and socio-economic factors [7].

The objective of this article refers to producing a cold-weather crop suitability map across NB at 1-m spatial resolution by soil type, drainage, slope, and climate, with socio-economic factors addressed in reference to listed property taxation values. Doing so exceeds NB's current coarse-resolution cold-crop suitability coverage [8], and focuses on potato cropping, which involves managing 21,500 ha each year, with an annual production value of about 1.3 billion dollars [9].

Table 1. Recent land suitability rating methods and criteria, for potato crops.

Author and Location	Potato Crop Rating Criteria	Land Capability Rating Technique
[10]	Mean annual temperature, precipitation	
	Elevation, slope, aspect	
Amazonas, Peru	Land use, distance to rivers, roads	AHP, with remote sensing and GIS-DEM evaluation
	Soil Texture, pH, organic Matter, N, P, K	
	Cation exchange capacity, electrical conductivity	
[11]	Mean annual temperature, precipitation	
	Elevation, slope, aspect	TMRC, using multi-criteria decision making with GIS-DEM evaluations
Amhara Region, Ethiopia	Soil type, crop management	
[12]	Soil root depth, texture, organic matter, stoniness	TMRC using pedo-climatic functions and
	Rainfall, temperature, evapotranspiration	GIS-DEM evaluations; FLM: Fuzzy Logic
England, Wales	Growing season	Methods
[13]	Rainfall, temperature	
Wonosobo,	Elevation, slope	TMRC, with GIS-DEM evalations
Indonesia	Soil texture	
[14]	Annual precipitation	
	Annual average minimal temperature	MLCS with GIS-interpolated weather station data
Across China	Average temperature in the coldest month	
	Sunshine duration	
[15]	Average, max. and min. air temperature	
	Precipitation	
Across	Relative humidity	FM with GIS-based weather station interpolations
Northern China	Solar radiation	
	Wind speed	

AHP: Analytical Hierarchy Processes; TRCM: Traditional Crop Rating Methods; FLM: Fuzzy Logic Methods; MLCS: Machine Learning and Crop Simulation.

This article proceeds by 1) describing the rating process as applied, 2) illustrating and interpreting the results so obtained with local examples, and 3) demonstrating how the officially registered property tax-assessment values are in part influenced by crop-supporting soil quality as rated. Research along this line started by selecting a proof-of-concept area (POC) within the south-central portion of New Brunswick's "Potato Belt". This effort was subsequently expanded to a five times larger area of interest (AOI, **Figure 1**) and then to the entire province.

2. Methods

2.1. Data Layers and Workflow

Available from GeoNB for 1-m resolution crop suitability mapping across NB are:

1) The province-wide 1-m spatial resolution LiDAR-DEM coverage [16] to portray flow channels, slope, cartographic depth-to-water (DTW), and soil drainage.

2) The forest soils map for NB [17] to characterize the overall soil conditions within and across field and forest properties.

3) Province-wide data layers for water bodies, wetlands, farmland, forested and non-forested areas, paved and non-paved roads, and building footprints [18].

4) Province-wide Property Assessment Map [19].

The workflow that tracks, evaluates, combines, and maps the rating factors, criteria, and evaluations is outlined in **Table 2**. The 1-m resolution LiDAR-generated DEM was used to generate province-wide raster layers for Slope (%) and cartographic DTW, as described by [20] [21]. The existing shapefile for forest soils [22] was modified to account for all GeoNB-registered wetland and waterbody locations. The resulting shapefile was 1-m rasterized to allow for pixel-by-pixel texture (topsoil and subsoil), depth-to-compaction, CF content, and degree of calcareousness crop rating. Also retrieved from GeoNB were NB's property, road, crownland, and non-forested area shapefiles. Non-forested areas refer to agricultural fields, other fields, roads, and built-up areas for residential, institutional, and industrial use. Weather station records for air temperature were used to produce province-wide DEM-adjusted rasters for growing degree days (GDD > 5˚C) and frost-free days (FFDs). The results so produced generally correspond with the maps in [23] [24] [25] [26] for GDD and FFD.

2.2. Rating by Soil Texture, Depth to Compaction, and Coarse Fragment Content

The summarized variations in soil texture, depth, coarse fragment content and calcareousness by soil association [22] were rated poor to best as outlined below and in **Table 3**.

Table 2. Workflow for the crop rating factors, criteria, and evaluations.

Rating Factors	Rating Criteria	Rating: mapping, combining, evaluating
Topogrphy →	Slope, DTW →	Using 1-m DEM for slope, flow channel and DTW derivation
NB Forest Soil Association →	Topsoil texture Subsoil texture Depth to compaction → Coarse fragments Calcareousness	Updating the NB Forest Soil Association layer ↓ Using GeoNB's wetland and waterbody delineations
Climate →	Annual growing-degree days Annual frost-free days →	Combining the crop-rated climate, soil and slope rasters
Socioeconomics	→	Evaluating property taxation values in terms of property attributes: size, farm/woodlot combination, building footprint

Table 3. Potato crop suitability rating by topsoil texture, subsoil texture, depth-to compaction of soil, CF content, and calcareousness. **Texture code**: C = coarse; C-M = coarse-medium; M-C = medium-coarse; M = medium; M-F = medium-fine; F = fine. **Depth-to-compaction code**: 1 ≤ 30 cm; 2 = 31 - 65 cm; 3 = 66 - 100 cm; 4 ≥ 100 cm; R = rock. **Coarse fragment code:** H = high; M-H = medium high; M = medium; L-H = low-high; L-M = low-medium; L = low.

Topsoil Texture		Subsoil Texture		Depth-to-Compaction		Coarse Fragments		Calcareousness			
C	0.6	C	0.6	1	0.1	H	0.1	Cornhill	0.1	Carleton	0.75
C-M	0.8	C-M	0.8	1 - 2	0.2	M-H	0.25	Kennebecasis	0.1	Muniac	0.75
M-C	1	M-C	1	1 - 2/R	0.2	M	0.5	Parleeville/Tobique	0.1	Thibault	0.75
M	0.6	M	0.6	1 - 3	0.3	L-H	0.75	Parry	0.1	Caribou	1
M-F	0.3	M-F	0.3	1 - 3/R	0.3	L-M	0.75	Salisbury	0.1	Siegas	1
F	0.1	F-M	0.2	2	0.5	L	1	Tracadie	0.1	Kedgwick	1
		F	0.1	2-3	0.6			Erb Settlement	0.5	Undine	1
				3	0.8			Saltsprings	0.5	Others	0
				3 - 4	0.9						
				3 - 4/R	0.9						
				4 or 2 - 3/R	0.9						
				4	1						

C: coarse; M: medium; F: fine; L: low; H: high; R: residual layer below compacted soil; 1, 2, 3, 4: increasing depth to compaction.

2.2.1. Soil Texture

While potato crops can be grown in differently textured soil, they grow best in well drained medium-coarse soils such as sandy loams [27] [28]. Hence, medium-coarse soil textures are symbolized as M-C in Table 3 and are rated 1 (*i.e.*, M-C = 1). In contrast, soils with dominant clay content (*i.e.*, sandy clay loam, clay loam, and clay, symbolized by "F = 0.1" in Table 3) are rated low because fine-textured soils are easily compacted, which leads to poor soil aeration followed by potato rot when moist to wet. Across NB, soil textures vary primarily by geological surface deposition. Basal tills as well as lacustrine to marine deposits tend to be fine-textured soil whereas ablation till, riparian and glacio-fluvial deposits tend to be coarse-textured. Among these, ablation tills and basal tills are prevalent.

2.2.2. Coarse Fragments

CF refers to gravel, cobbles, stones, and boulders from smallest (≥2 mm) to largest when present. Low CF content is rated best (L = 1), while high CF content is rated worst (H = 0.1). Large CFs need to be removed from fields to facilitate seedbed preparations and potato harvesting [29].

2.2.3. Soil Depth

Potatoes will not root well in shallow and/or firm to very firm soils. These are symbolized as "1" in Table 3 and are given a "0.1" rating. Restrictions in soil-related rooting depth are encountered on traffic compacted and/or naturally compacted soils, such as fine-textured lacustrine and marine deposits and basal tills. Moderate rooting restrictions occur on basal tills overlain by ablation till. Low to no depth restrictions as found on deep ablation tills, outwash plains, and sandy deposits along riverbanks and well-drained floodplains are symbolized by "4" in Table 3 and are rated as "1".

2.2.4. Calcareousness

Soil parent materials containing limestone and/or calcareous siltstones, sandstones, mudstones, and slates generally improve and maintain good soil qualities in terms of elevated pH (reduced soil acidity), increased exchangeable calcium (Ca) and magnesium (Mg) contents, and enhanced soil aggregation on medium- to fine-textured soils. By soil association, the calcareousness rating varies from 0 (100% siliceous) to 1 (100% calcareous) based on evaluating calcareous content from absent, minor, half-and-half, dominant, and complete.

2.2.5. Overall Rating by Soil Association

Assuming that the coded rate entries in Table 3 capture the soil-affected variations in potato cropping responses, it was necessary to determine how these rates combine into a single potato-crop suitability factor by soil association. To do this, it was decided:

1) to multiply the ratings for topsoil and subsoil texture, rooting depth, and CF, *i.e.*, similar to calculating the probability occurrences of random factor combinations;

2) to add the calcareousness rating to the resulting multiplication product, assuming that calcareousness is one third as important as the best combination of the other four variables;

3) to normalize the results so obtained by dividing this result with its maximum value across all the soil associations;

4) to transform the normalized values so generated to a linear 0 to 1 suitability progression across the soil associations; this was accomplished through 0.33 exponentiation; the result of so doing generated Equation (1), *i.e.*:

$$R_{\text{Soil}} = \left[\frac{R_{\text{Top}} R_{\text{Sub}} R_{\text{Depth}} R_{\text{CF}} + 0.33 R_{\text{Calc}}}{\max\left(R_{\text{Top}} R_{\text{Sub}} R_{\text{Depth}} R_{\text{CF}} + 0.33 R_{\text{Calc}} \right)} \right]^{0.33} \leq 1 \tag{1}$$

with R_{Top} and R_{Sub} referring to texture by topsoil and subsoil, R_{Depth} referring to soil compaction rating, R_{CF} referring to coarse fragment rating, and R_{Calc} referring to calcareousness rating. The results so obtained are listed in **Table 4**.

2.2.6. Soil Suitability Mapping

Applying the soil suitability ratings in **Table 4** province-wide required updating of GeoNB's catalogued forest soil shapefile to conform to GeoNB's waterbody and wetland layers. This was done using ArcGIS Pro procedures dealing with:

1) Erasing all waterbody and organic soil features in the forest soil shapefile for NB.

2) Converting the resulting shapefile into a 1-m resolution raster with "no data" pixels for the GeoNB registered waterbody and wetland locations.

3) Systematically extending all existing soil-association identified pixels into their adjacent "no data" spaces.

4) Once completed, the resulting pixels for the GeoNB's identified waterbody or wetland pixels were set to DTW = 0 via conditional raster calculations.

5) Converting the resulting raster into the updated soil association shapefile followed by feature smoothing to reduce pixelated appearances.

2.2.7. Crop Suitability Rating by Soil Drainage

The crop suitability mapping parts by soil drainage and slope was done using the 1-m DEM for New Brunswick. For this, the slope was derived using the Slope tool in ArcGIS Pro, which determines the percent rise or descent over distance among the eight-cardinal directions adjacent to each DEM pixel. The soil drainage layer was derived using the ArcGIS Pro Cost Distance tool, with the delineated flow channels and waterbodies marking DTW = 0 reference cells, and with the slope percent raster used as cost raster. The resulting DTW > 0 cm pixels refer to the distance between the soil surface and the water table associated with the nearest waterbody and flow channel locations. The flow channels were developed using the D8 algorithm [30] that derives the flow accumulation raster from the depression-filled DEM according to the pixel-determined flow directions.

The resulting flow-channel raster was classified to have no-data pixels with < 4 ha upslope flow accumulation. This threshold refers to mapping the extent of permanent streams consistent with end-of-summer water flow. The end-of-summer conditions for soil drainage, ranging from very poor to poor, imperfect, moderate, well, and excessive generally corresponds to DTW ≤ 0.1, 0.1 to ≤0.25 m, 0.25 to ≤0.5 m, 0.5 ≤ 1 m, 1 to, e.g., ≤20 m and >20 m, respectively. In turn, the 0 to 1 crop suitability rating function for DTW was formulated such that:

Table 4. Potato crop suitability rating by soil association across New Brunswick based on Equation (1), with area and lithology specifications.

Forest soil units	Code	Rating	Area, ha	Primary Lithology of Parent Materials	Forest soil units	Code	Rating	Area, ha	Primary Lithology of Parent Materials
Siegas	SE	0.77	45,698	Argillaceous limestones, minor limestones	**Reece**	RE	0.5	522,674	Grey lithic-feldspathic sandstone, minor quartzose sandstones, Polymictic conglomerates, quartz pebble conglomerates, and/or red mudstones
Caribou	CA	0.83	198,213		**Sunbury**	SN	0.54	281,388	
Undine	UN	0.78	17,416		**Fair Isle**	FA	0.39	63,650	
Kedgwick	KE	0.8	94,304	Calcareous siltstones, calcareous sandstones and/or calcareous slates	**Riverbank**	RI	0.7	148,791	
Carleton	CR	0.86	242,574		**Tetagouche**	TT	0.34	43,445	Mafic volcanic rocks, gabbros and/or diorites
Thibault	TH	0.83	214,897		**Kingston**	KI	0.64	63,546	
Muniac	MU	0.81	26,441		**Mafic Volcanic**	MV	0.34	106,595	
Saltspings	SS	0.63	9282	Grey calcareous mudstones and/or feldspathic to lithic sandstones; minor polymictic conglomerates	**Tuadook**	TU	0.74	142,527	Gneiss, granites, alkali granites, granodiorites and/or quartz diorites
Erb Settlement	EB	0.68	8904		**Juniper**	JU	0.79	245,307	
Salisbury	SA	0.72	167,047	Red polymictic conglomerates, feldspathic to lithic sandstones and/or mudstones; calcium carbonates present as cementing material	**Big Bald Mountain**	BD	0.35	48,283	
Parry	PR	0.82	155,879		**Popple Depot**	PD	0.72	200,003	Felsic volcanic or mixed igneous rocks and/or felsic pebble conglomerates
Cornhill	CH	0.45	23,771		**Jacquet River**	JR	0.81	100,974	
Parleeville Tobique	PT	0.65	1,743,501		**Lomond**	LO	0.46	168,872	
Kennebecasis	KN	0.65	20,616		**Gagetown**	GG	0.62	85,311	
Tracadie	TD	0.52	33,923		**Long Lake**	LL	0.84	336,934	Metasedimentary rocks mixed with igneous rocks; igneous clasts 20% - 50%
Holmesville	HM	0.79	325,472	Metaquartzites, slates, metasiltstones, metaconglomerates and/or metawackes	**Britt Brook**	BR	0.92	233,494	
Victoria	VI	0.71	145,859		**Serpentine**	SP	0.44	41,033	
McGee	MG	0.66	335,809		**Catamaran**	CT	0.79	117,735	Igneous rocks mixed with metasedimentary rocks; sedimentary clasts 20% - 50%
Glassville	GE	0.3	193,900		**Irving**	IR	0.66	121,426	
Grand Falls	GF	0.79	71,227		**Pinder**	PI	0.43	38,828	
Stony Brook	SB	0.33	466,591	Red mudstone (weathered), minor greyed lithic-feldspathic sandstones, quartzose; sandstones and/or polymictic conglomerates	**Rogersville**	RG	0.61	39,529	Greyed sandstones or mudstones mixed with igneous rocks; igneous clasts 20% - 50%
Tracy	TR	0.85	53,942		**Interval**	IN	1	45,185	Undifferentiated.
Harcourt	HT	0.38	531,746		**Acadia**	AC	0.44	15,299	
Becaguimec	BE	0.92	13,078		**Mining Debris**	MD	0	5901	
Barrieau-Buctouche	BB	0.7	95.444		**Organic Soil**	OS	0	235,644	Organic

$$R_{\mathrm{DTW}} = a\left[1-\exp\left(-b\mathrm{DTW}\right)\right]^{c}\left[\exp\left(-d\,\mathrm{DTW}\right)\right] \leq 1 \qquad (2)$$

with $a = 1.065$, $b = 2.5$, $d = 0.03$, $c = 4.8$. As illustrated in Figure 2, R_{DTW} starts from 0 when DTW = 0 (too wet), reaches 1 at 2 m (sufficiently moist most of the time), and trails downward from there to about 0.6 and further as DTW approaches 20 m and beyond due to decreasing uphill soil and subsoil water availability.

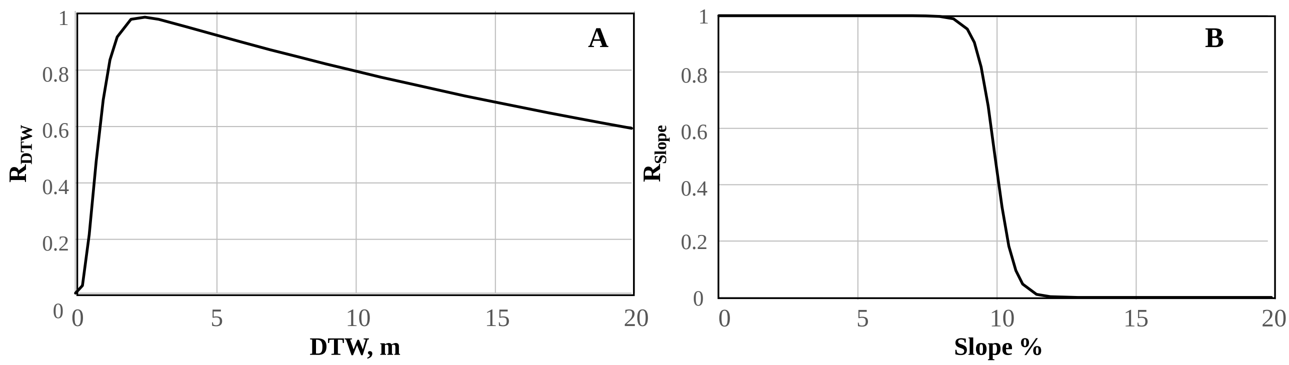

Figure 2. Potato crop rating specific to variations in DEM-derived DTW (A) and Slope % (B).

2.2.8. Crop Suitability by Slope

The 0 to 1 crop suitability rating function for slope (%) was estimated by setting:

$$R_{\text{Slope}} = 1 - 1 \Big/ \left\{1 + \exp\left[-3\left(\text{Slope} - 10\right)\right]\right\} \leq 1 \tag{3}$$

This equation uses Slope = 10% as the DEM-derived slope threshold for ensuring that if Slope < 10%, then 1) field operations pertaining to, e.g., seedbed preparation, seeding, and harvesting remain safe and 2) soil erosion remains minimal. This threshold was modified by gradually approaching the slope = 10% threshold from 8% upwards, and by gradually moving away from this threshold towards 12% (**Figure 2**).

2.2.9. Crop Suitability Rating by Frost-Free Days

Potatoes require about nine weeks (63 days) for full canopy development, and 18 weeks (126 days) to initiate senescence and thereby completing tuber growth (**Figure 3**, [31]). Late frost in spring delays crop preparations and foliage development. Early frost in fall affects tuber quality by tissue damaging (black spots). Formally, the FFD-related potato cropping restriction was formulated and represented in **Figure 4(A)** as follows:

$$R_{\text{FFD}} = 1 \Big/ \left[1 + \exp\left(-0.06\left(\text{FFD} - 100\right)\right)\right] \leq 1. \tag{4}$$

Since FFD exceeds 100 days across NB except for the elevated areas in the northwest (**Figure 5**), the FFD rating can be set at 1 for most of NB, but 0 where FFD << 100 days.

2.2.10. Crop Suitability Rating by Growing Degree Days > 5˚C

Potatoes require about 1000 and 1500 GDDs from emergence to tuber initiation and harvesting (**Figure 6**). Across NB, GDDs range from 1300 to 1800 (**Figure 5**), therefore potato cropping across NB is not GDD restricted except for the high elevation location in the northwest. Where conditions are suitable, GDDs > 1500 lead to additional tuber growth, particular for Russet potatoes (**Figure 6**). The effect of increasing GDD on tuber numbers and tuber length is represented in **Figure 4(B)** by setting:

$$R_{\text{GDD}}\left(\text{tuber numbers}\right) = 1 - 1 \Big/ \left[1 + \exp\left(-0.006\left(\text{GDD} - 800\right)\right)\right] \leq 1, \tag{5}$$

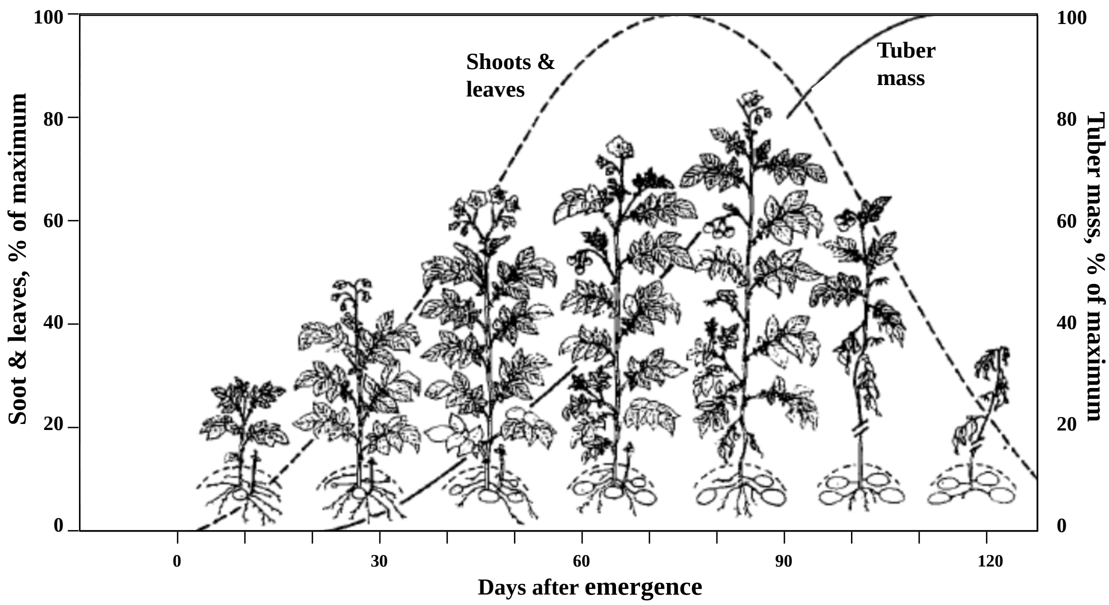

Figure 3. Percent extent of potato shoot, foliage, and tuber developments by days after emergence. Source: [31].

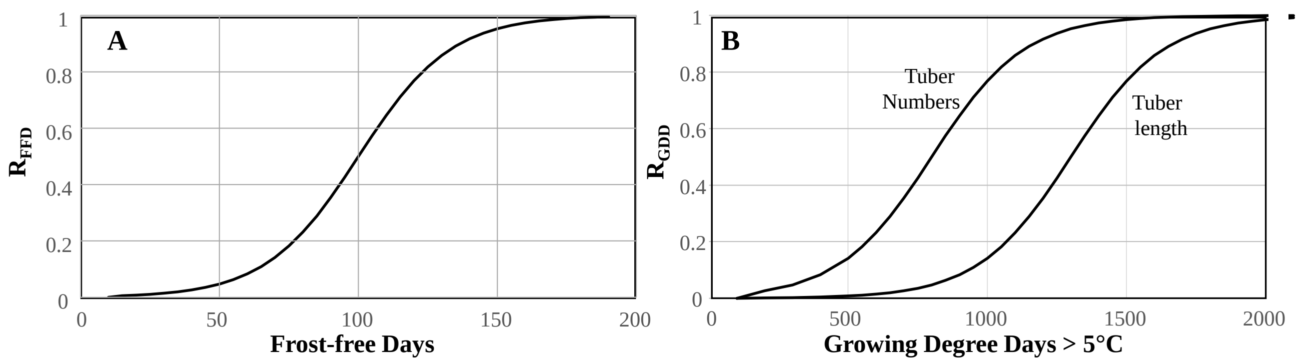

Figure 4. R_{FFD} (A) and R_{GDD} (B) versus FFD and GDD (for tuber numbers and length) as generated with Equations (5)-(7).

and

$$R_{\text{GDD}}\left(\text{tuber length}\right)=1-1/\left[1+\exp\left(-0.006\left(\text{GDD}-1300\right)\right)\right]\leq 1. \quad (6)$$

2.2.11. Crop Suitability Equation, all Factors Combined

The combined equation for crop suitability rating is therefore given by

$$R_{\text{CS}}=R_{\text{Soil}}\times R_{\text{DTW}}\times R_{\text{Slope}}\times R_{\text{FFD}}\times R_{\text{GDD}}\leq 1. \quad (7)$$

Note that R_{Soil} is set to 0 for waterbodies and wetlands. Otherwise, R_{Soil} varies from 0.3 to 1. In contrast, R_{DTW}, R_{Slope}, R_{FFD} and R_{GDD} are set to vary from 0 to 1 because of crop curtailing conditions where too wet (DTW = 0), too steep (Slope > 12%), and insufficient frost-free days (R_{FFD} < 100 days) and/or growing degree day (R_{GDD} < 500).

2.2.12. Crop Suitability Rating by Property

The data layers used to evaluate the extent to which the above crop suitability process for R_{CS} reflects the GeoNB-registered property taxation values per Property

Account Number (PAN) and building footprint layers (PAN data file [19]). This property-by-property evaluation was limited to partially farmed POC and AOI areas in Figure 1. PAN areas not associated with farming, farms < 5 ha, and forestry properties (assessed at $100/ha, [33]) were removed from this analysis.

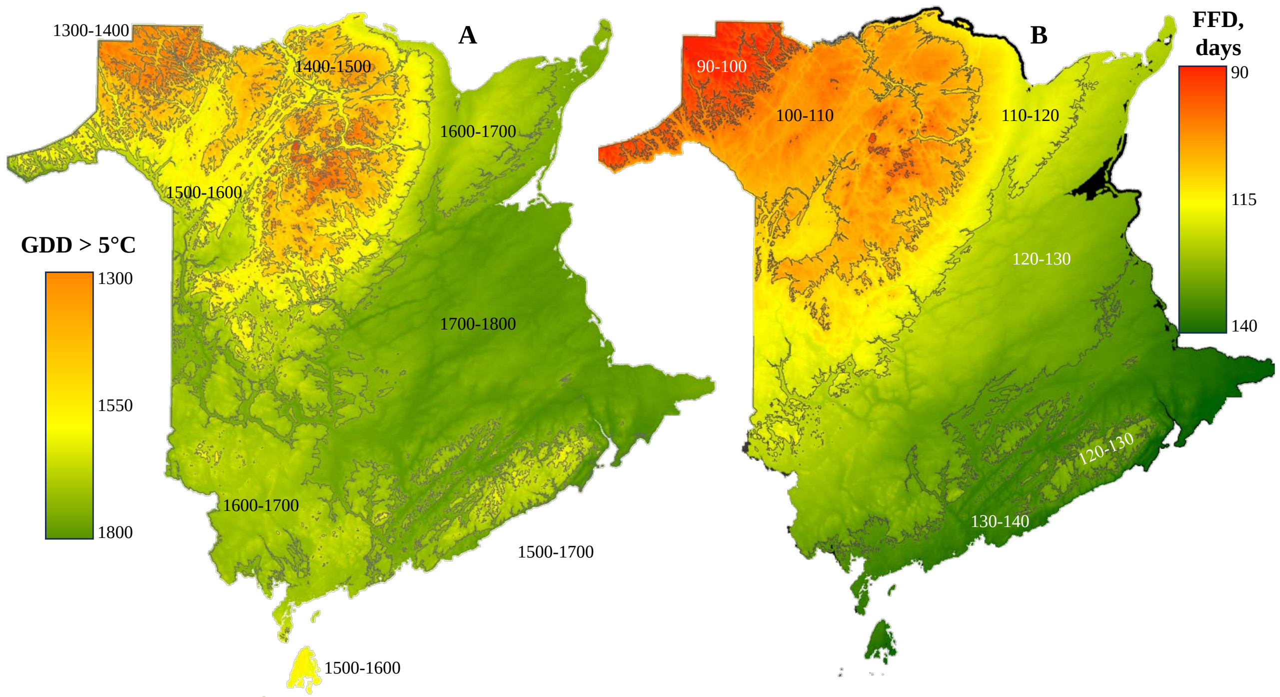

Figure 5. Topographically adjusted growing degree days (GDD > 5˚C, (A) and frost-free days (FFD, B) maps for New Brunswick.

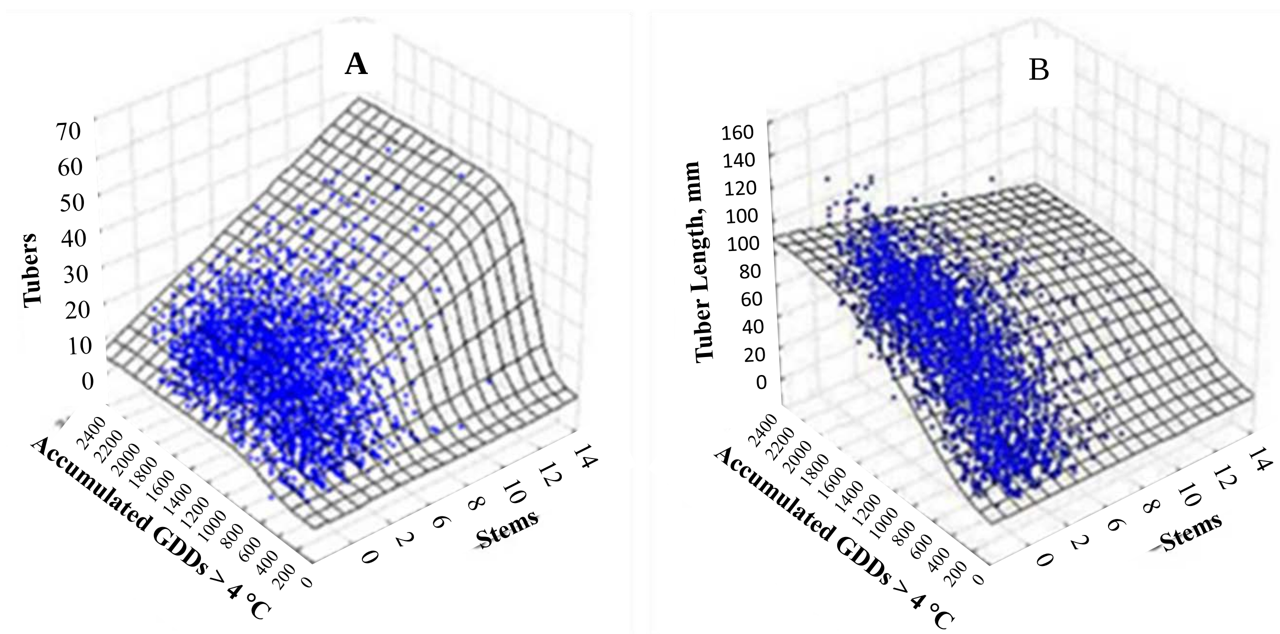

Figure 6. Russet potato tuber numbers (A) and length (B) in relation to number of stems and increasing GDDs > 5˚C. Source: [32].

Also removed were all PAN areas intersected by the POC and AOI borders. The information for the remaining properties compiled included 1) mean PAN taxation value per property and per hectare, 2) mean PAN R_{CS} value, 3) PAN area, 4) PAN building footprint, and 5) a PAN binary "0" code for Farm and "1" for a Farm/Woodlot combination. The resulting PAN values were:

1) summarized by property type and AOI and POC area, and

2) regression analyzed with taxation values per property and per hectare as dependent variables, and PAN area, building footprint, property type and mean R_{CS} value as independent variables.

For best results, it was necessary to log-transform the PAN taxation, area and building footprint numbers. In addition, building footprint numbers needed to be transformed to (Building footprint, m^2)$^{0.33}$ for the best-fitted PAN \$/ha assessment evaluations.

3. Results

3.1. Crop Suitability Map

Figure 7 shows the Equation (1) and Equation (7) rated crop-suitability maps across New Brunswick (R_{Soil}, R_{CS}). The R_{Soil} to R_{CS} modifying R_{DTW} and R_{Slope} components are also shown in **Figure 7**. Close-ups used for illustrating R_{CS} details and related field-level interpretations are provided in **Figure 8** and **Figure 9**, with and without R_{CS} and DEM-generated flow channels overlaying the hill-shaded DEM and surface images. At the local level, R_{CS} generally tracks the layout of cropped fields as traditionally limited by steep slopes and poor soil drainage next to permanent streams and water bodies and wetlands across forest-covered lands. To some extent, there is also partial R_{CS}-to-image alignment along non-permanent flow channels with >1 ha upslope flow accumulation. This occurs where the channels run along image-located ditches and dark-coloured areas. Exceptions also occur where the DEM-based flow-channel delineations: 1) are blocked by roads; 2) are blocked by elevated ground due to ditch excavation; 3) do not follow image-recognizable ditch lines where bare-earth recognition is blocked by overgrown vegetation; 4) cannot be surface recognized because of subsoil drainage-tile installations [33].

3.2. PAN Property Summary by POC and AOI Areas

Numbers, sums and means for PAN areas (ha), building footprints (m^2), mean assessment values (\$), building footprints and crop suitability ratings (R_{CS} %) are listed in **Table 5** and plotted in **Figure 10** by POC and AOI study areas and by PAN type. In terms of PAN property numbers, AOI ≈ 3.3 POI. In terms of PAN property areas, AOI ≈ 7 POI. This is mainly due to increasing woodland properties from south to north. Apart from this, the mean POC and AOI per property PAN evaluations (R_{CS}, areas, \$s, \$/ha, building footprints) for farms, farm/woodlot combinations and forests are similar to one another while covering a wide range of GDD and FFD values from 1200˚C to 2100˚C days, and from 90 to 150 days,

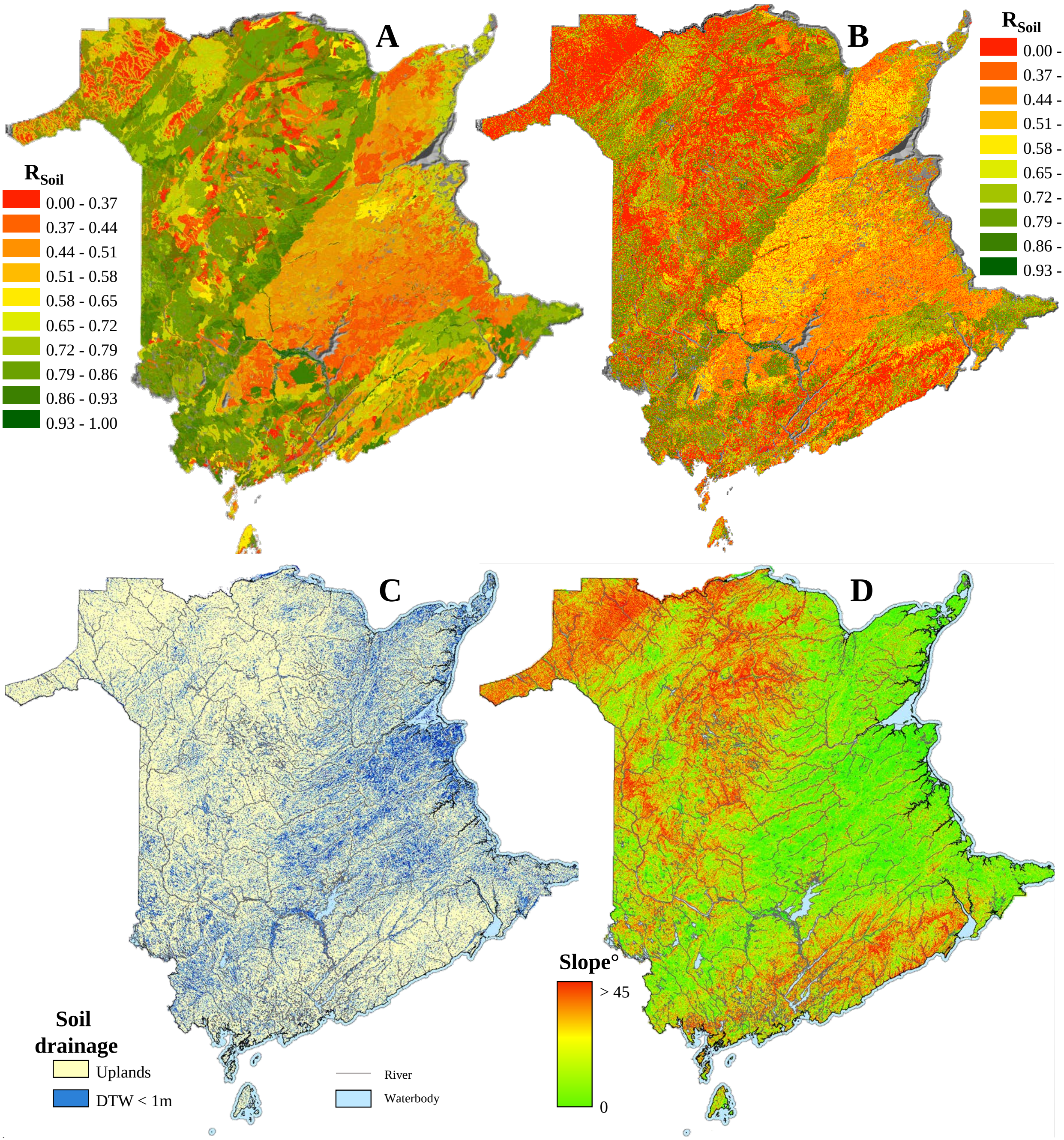

Figure 7. Cold-weather crop suitability maps for New Brunswick. A: R_{Soil}; B: R_{CS}; C: DTW < 1 m; D: Slope.

respectively. There are, however, large variations in PAN suitability and taxation values such that farms > farm/woodlots > forests, as shown by the POC and AOI boxplots in Figure 10.

3.3. Best-Fitted Regression Results: POC versus AOI-POC

The best-fitted regression results for the POC and AOI – POC (POC excluded from AOI) areas and corresponding scatterplots shown in Table 6 and Figure 11 for the log-transformed \$ and \$/ha PAN assessment values as dependent variables, and with PAN $\log_{10}$(Area), $\log_{10}$(Building Footprint), mean R_{CS} and property type (farms 0, farm woodlot combinations 1) as the independent variables.

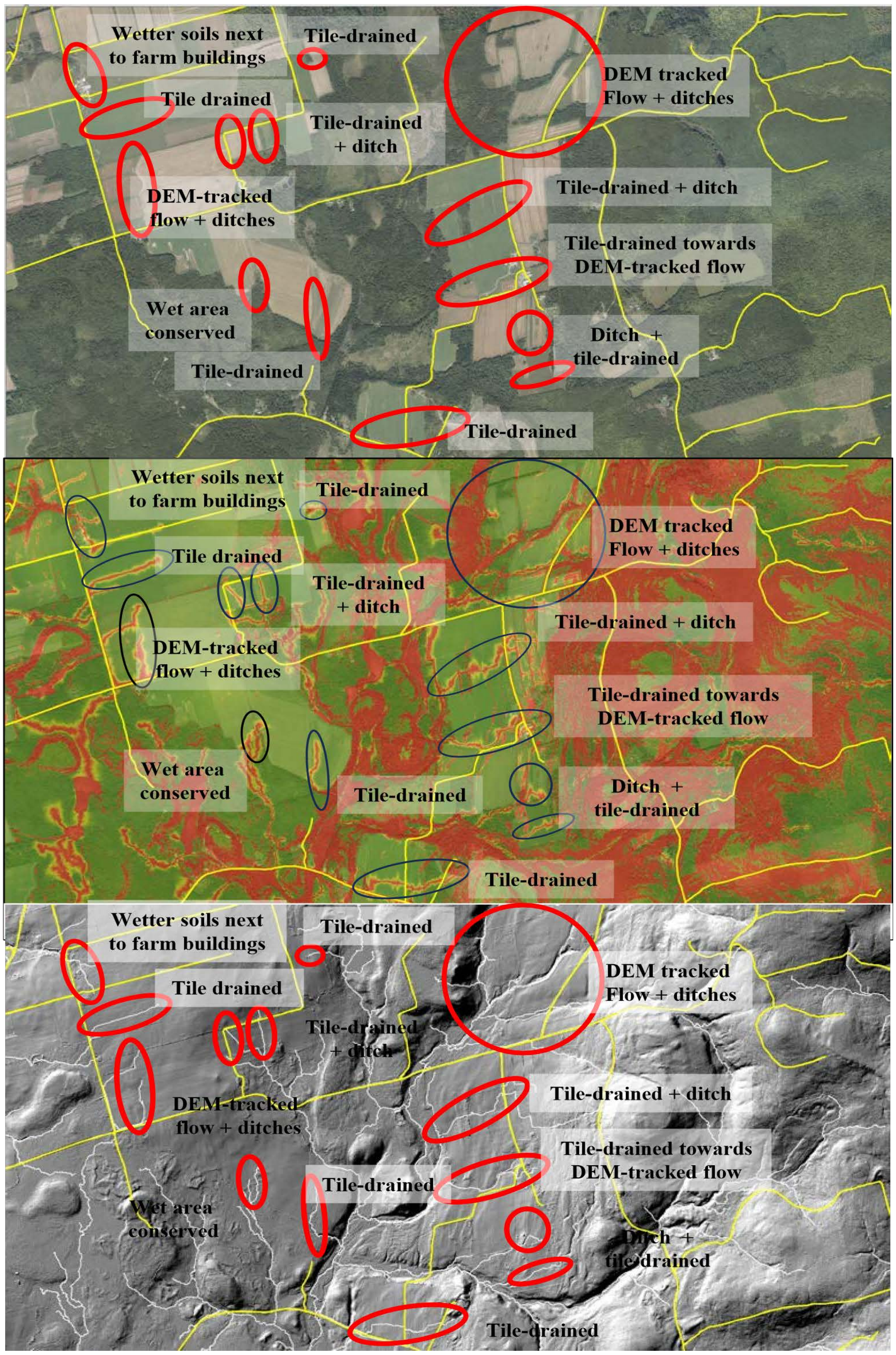

Figure 8. Middle: Cop suitability close-up, showing continuous R_{CS} variations from red (0%) to yellow (50%) and green (100%). Bottom: Corresponding hillshaded 1-m DEM with >1 ha up-slope flow-accumulation channels overlaid (white lines). Top: ESRI surface image. Also shown: 1) PAN property borders (yellow lines); 2) red/black outlines detailing where DEM-tracked wet areas and flow channels coincide with conservation efforts, ditch lines, and/or subsoil drainage.

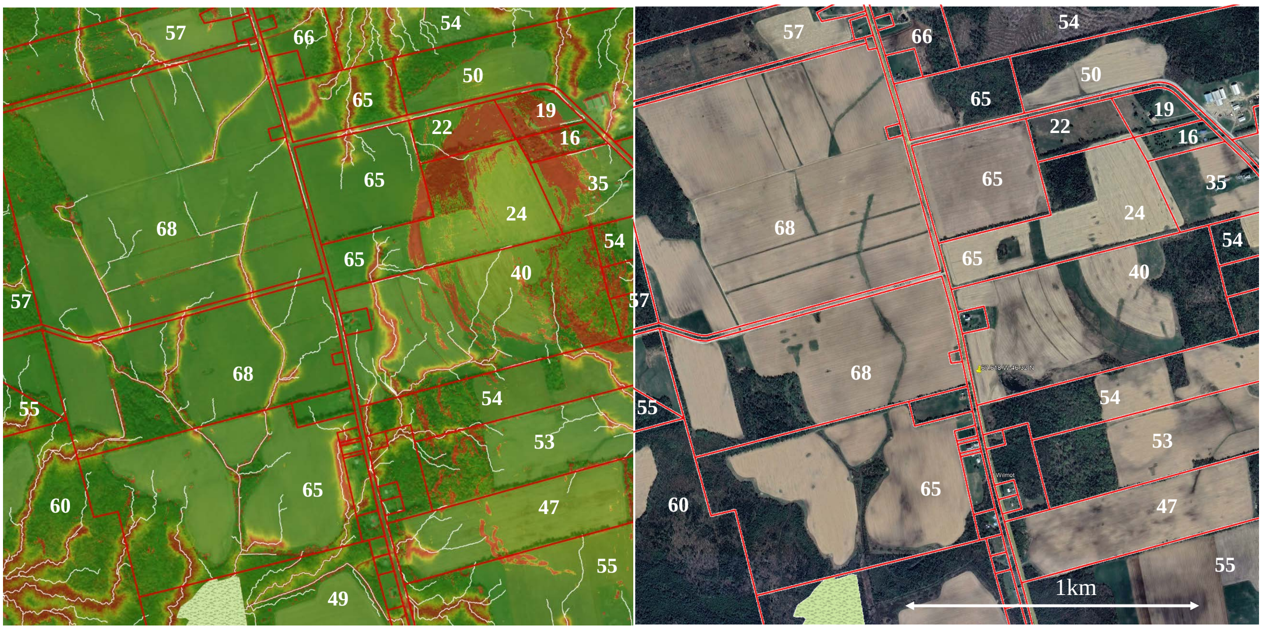

Figure 9. Crop suitability close-up with ESRI surface image focussed on DEM and PAN property assessed values. Red line: PAN properties. Left: continuous R_{CS} % map (red to yellow to green) overlaid on hillshaded full-feature DEM to contrast forest areas (darker green) from fields (lighter green). Right: ESRI surface image. White numbers: mean PAN R_{CS} % values. White lines: DEM-derived flow channels with >1 ha upslope flow accumulation. Pale-green feature on bottom, left and right: a wetland.

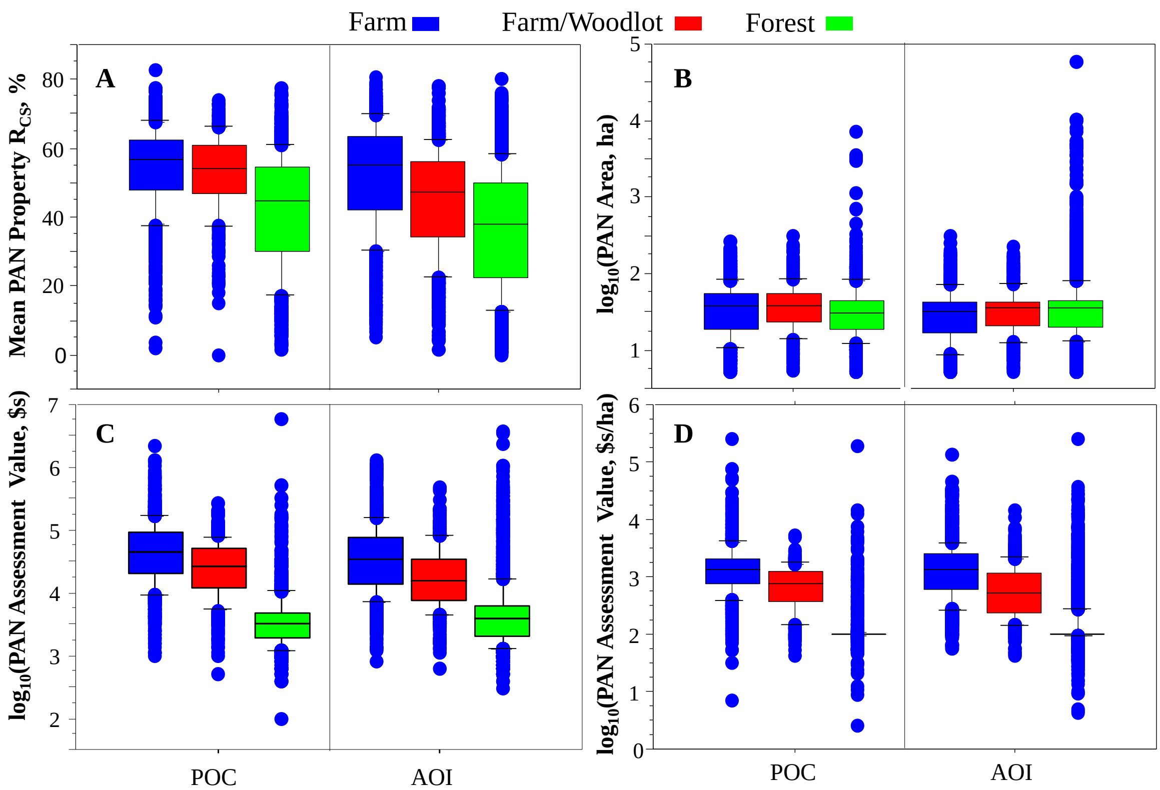

Figure 10. Boxplots of mean PAN property crop suitability ratings (R_{CS} %, A), mean PAN $\log_{10}$ property areas (B, in $\log_{10}$ha), and mean PAN property assessment values ($s per property: C; $s per ha: D), split by land class (farm, forest, and farm/woodlot combination). The boxplots display the 25th, 50th and 75th percentiles of the data and associated assessment values (dots) below and above the 10th and 90th percentiles.

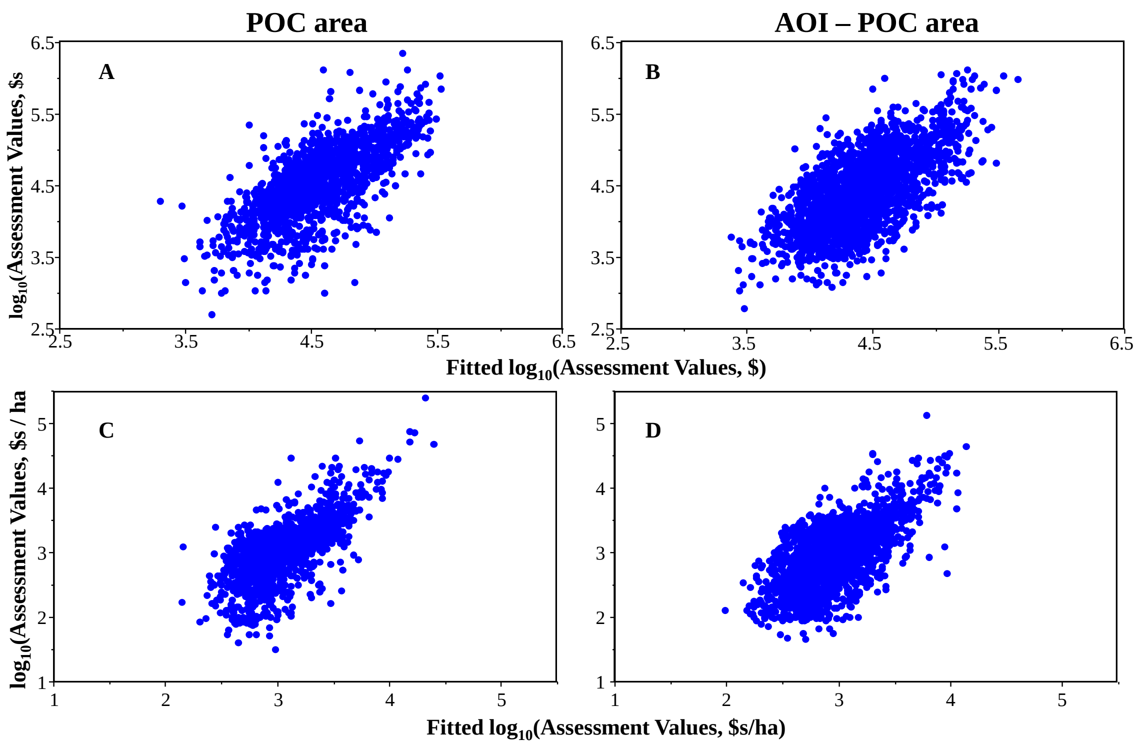

Figure 11. Actual versus best-fitted tax assessment scatterplots for the POC and AOI PAN Property assessment values in values $s (A, B) and $s/ha (C, D), with PAN area, building footprint, and property type (farm versus farm/woodlot combination) as PAN-specific predictor variables.

Table 5. Statistics (numbers, means, sums) for PAN areas, building footprints, R_{CS}, assessment values ($) by study area (POC, AOI) and PAN type.

	Property Type	POC	AOI
Number of PAN Properties	Farm	1154	2471
	Forest	1024	5031
	Farms & woodlots	444	1120
	Total	**2622**	**8622**
Combined PAN Areas, ha	Farm	49,633	97,053
	Forest	61,783	490,812
	Farms & woodlots	20,166	46,583
	Total	**131,582**	**634,447**
Combined PAN Building Footprints, m^2	Farm	421,822	797,189
	Forest	17,374	163,502
	Farms & woodlots	15,845	59,236
	Total	**455,040**	**1,019,927**
Mean PAN Area, ha	Farm	43	39.3
	Forest	60.3	97.6
	Farms & woodlots	45.4	41.6
	Total	**50.2**	**73.6**

Continued

Mean PAN Building Footprint, m^2	Farm	365.5	322.6
	Forest	17	32.5
	Farms & woodlots	35.7	52.9
	Total	**173.5**	**118.3**
Mean PAN R_{CS}, %	Farm	54.2	52.9
	Forest	42.1	37.7
	Farms & woodlots	52.7	47.9
	Total	**49.2**	**43.4**
Mean PAN Assessment Value, $	Farm	80,353	75,564
	Forest	13,074	14,649
	Farms & woodlots	37,006	33,785
	Total	**46,738**	**34,592**

Table 6. Best-fitted regression results using POC and AOI PAN-based $ and $/ha tax assessment values as dependent variables and PAN area, mean PAN R_{SC}, PAN building footprint and PAN property type (Farm "0", Farm/Woodlot "1") as independent variables.

Tax assessment variable	**PAN numbers**		**R^2**		**RMSE**	
	POC	AOI-POC	POC	AOI-POC	POC	**AOI-POC**
$\log_{10}$(PAN assessment value, $)	1585	3561	0.5	0.474	0.353	0.375
$\log_{10}$(PAN assessment value, $/ha)			0.424	0.425	0.337	0.36

Dependent variable	**Regression variables**	**Regression coefficient**		**Std. Error**		**t-Value**		**p-Value**	
		POC	**AOI-POC**	**POC**	**AOI-POC**	**POC**	**AOI-POC**	**POC**	**AOI-POC**
$\log_{10}$(PAN assessment value, $)	Intercept	2.87	2.9	0.06	0.04	48.5	75.9	<0.0001	<0.0001
	$\log_{10}$(PAN Area, ha)	0.64	0.61	0.03	0.02	22.8	30.5	<0.0001	<0.0001
	R_{CS}, %	0.0111	0.0113	0.0008	0.0005	22.0	29.1	<0.0001	<0.0001
	$\log_{10}$(Building Footprint, m^2)	0.164	0.158	0.008	0.005	14.7	25	<0.0001	<0.0001
	Farm 0, Farm/Woodlot 1	−0.143	−0.165	0.021	0.014	−6.8	−12.0	<0.0001	<0.0001
$\log_{10}$(PAN assessment value, $/ha)	Intercept	2.85	2.88	0.06	0.004	50.6	78.5	<0.0001	<0.0001
	$\log_{10}$(PAN Area, ha)	−0.38	−0.412	0.027	0.019	−14.0	−21.0	<0.0001	<0.0001
	R_{CS}, %	0.0107	0.0110	0.0007	0.0004	14.9	25.4	<0.0001	<0.0001
	(Building footprint, m^2)$^{0.33}$	0.064	0.064	0.002	0.002	26.4	35.1	<0.0001	<0.0001
	Farm 0, Farm/woodlot 1	−0.12	−0.142	0.02	0.014	−6.0	−10	<0.0001	<0.0001

The equations that can be derived from the Table 6 for the AOI-POC entries are as follows:

$$\begin{aligned}&\log_{10}(\text{PAN assessment value},\$)\\&=2.90+0.61\log_{10}(\text{PAN area, ha})+0.158\left(\text{PAN building footprint, m}^2\right)\\&\quad+0.0113\log_{10}(\text{PAN } R_{CS},\%)-0.165(\text{PAN farm/woodlot})\end{aligned} \tag{8}$$

$$\begin{aligned}&\log_{10}(\text{PAN assessment value},\$/\text{ha})\\&=2.88+0.064\left(\text{PAN building footprint, m}^2\right)^{1/3}+0.0110(\text{PAN } R_{CS},\%)\\&\quad-0.412\log_{10}(\text{PAN area, ha})-0.142(\text{PAN farm/woodlot})\end{aligned} \tag{9}$$

Together, Equations (8) and (9) imply that:

1) The negative farm/woodland coefficient indicates that combined farm/woodland properties are assessed lower than farm properties without woodlots.

2) The PAN $ assessment values correlate positively while the PAN $/ha assessment values correlate negatively with PAN area.

3) The suitability rating coefficients for the POC and AOI PAN $ and PAN $/ha values effectively remain the same, *i.e.*, 0.0113 versus 0.0110, respectively. This indicates that the above analysis is not much affected by the POC versus AOI extent, or analysing the property assessment values by $s or $s/ha per PAN area.

4) The building footprint coefficient is positive which indicates that taxation by property increases with increasing building footprint.

5) The t-values indicate that the mean R_{CS} ratings per property appear to be as influential as PAN area and building footprint on the $ and $/ha property assessments; this means that properties not encumbered by steep slope, poor soil drainage and poor soil type ratings are seen to have higher farm-related assessment values.

6) Table 7 shows how the PAN $ and $/ha assessment values change from an $\underline{R_{CS}}$ of 100% to 33% for a 100-ha farm with a 100 m^2 building footprint. For R_{CS} = 100%, the numbers are $368,129 for the farm, with 2809 $/ha. For R_{CS} = 33%, the numbers drop to $64,402 ha and 515 $/ha. Dropping the R_{CS} rating from 100 to 33 therefore lowers the PAN assessment values by a factor of 6. For a similar farm/woodlot combination the PAN assessment values for R_{CS} = 100% and 33% drop from $251,768 and $44,045, and from 2025 and 371 $/ha, respectively.

7) Note that the best fitted R^2 in Table 6 values fall between 0.4 and 0.5. Hence, Equations (8) and (9) should only be used to emulate likely property assessment values. Still, the PAN assessment value for a wetland with an assigned R_{CS} = 0 value and no building footprint leads to $/ha = $114 (Table 6), *i.e.*, similar to the NB-set 100 $/ha value for forested lands [34].

4. Discussion

The approach taken above differs from the literature on potato crop suitability mapping as follows:

Table 7. PAN property assessment values including \$/ha estimates via Equations (8) and (9) for farm, farm/woodlot and wetland crop suitability ratings set at R_{CS} = 100%, 33% and 0%.

	Variable specifications		Regression coefficients	$\log_{10}$(PAN assessment value contributions per ha)	Variable specifications		Regression coefficients	$\log_{10}$(PAN assessment value contributions per property)
Farm property with R_{CS} = 100%	Intercept		2.880	2.880	Intercept		2.900	2.90
	PAN area, ha	100	−0.412	−0.82	PAN Area, ha	100	0.610	1.22
	Building footprint, m^2	100	0.064	0.29	Building Footprint, m^2	100	0.158	0.32
	Property type	0	−0.142	0.00	Property Type	0	−0.165	0.00
	R_{CS} %	100	0.0110	1.10	R_{CS}, %	100	0.0113	1.13
	Estimated PAN assessment value, \$/ha			**2809**	**Estimated PAN assessment value, \$**			**368,129**
Farm property with R_{CS} = 33%	Intercept		2.880	2.880	Intercept		2.900	2.90
	PAN area, ha	100	−0.412	−0.82	PAN Area, ha	100	0.610	1.22
	Building footprint, m^2	100	0.064	0.29	Building Footprint, m^2	100	0.158	0.32
	Property type	0	−0.142	0.00	Property Type	0	−0.165	0.00
	R_{CS} %	33	0.0110	0.36	R_{CS}, %	33	0.0113	0.37
	Estimated PAN assessment value, \$/ha			**515**	**Estimated PAN assessment value, \$**			**64,402**
Farm/Woodlot property R_{CS} =100%	Intercept		2.880	2.880	Intercept		2.900	2.90
	PAN Area, ha	100	−0.412	−0.82	PAN Area, ha	100	0.610	1.22
	Building Footprint, m^2	100	0.064	0.29	Building Footprint, m^2	100	0.158	0.32
	Property Type	1	−0.142	−0.14	Property Type	1	−0.165	−0.17
	R_{CS} %	100	0.0110	1.10	R_{CS}, %	100	0.0113	1.13
	Estimated PAN assessment value, \$/ha			**2026**	**Estimated PAN assessment value, \$**			**251,768**
Farm/Woodlot property R_{CS} = 33%	Intercept		2.880	2.880	Intercept		2.900	2.90
	PAN Area, ha	100	−0.412	−0.82	PAN Area, ha	100	0.610	1.22
	Building Footprint, m^2	100	0.064	0.29	Building Footprint, m^2	100	0.158	0.32
	Property Type	1	−0.142	−0.14	Property Type	1	−0.165	−0.17
	R_{CS} %	33	0.0110	0.36	R_{CS}, %	33	0.011	0.37
	Estimated PAN assessment value, \$/ha			**371**	**Estimated PAN assessment value, \$**			**44,045**
Wetland	Intercept		2.880	2.880	Intercept		2.900	2.90
	PAN Area, ha	100	−0.412	−0.82	PAN Area, ha	100	0.610	1.22
	Building Footprint, m^2	0	0.064	0.00	Building Footprint, m^2	0	0.158	0.00
	Property Type	0	−0.142	0.00	Property Type	1	−0.165	−0.17
	R_{CS} %	0	0.0110	0.00	R_{CS}, %	0	0.0113	0.00
	Estimated PAN assessment value, \$/ha			**114**	**Estimated PAN assessment value, \$**			**9016**

1) The approach makes use of high-resolution airborne 1-m LiDAR data. The articles quoted in Table 1 do this at significantly coarser resolution.

2) The province-wide GDD and FFD data layers in **Figure 5** account for elevation-induced temperature variations at 10 m resolution. A similar pattern for the coarser-resolution GDD contours in [23] augmented by ArcGIS Pro topo-to-raster interpolation is shown in **Figure 12** (top left). In contrast, the corresponding pattern for critical alfalfa harvesting in **Figure 12** (top right, [35]) is similar to the NB-wide FFD pattern in **Figure 5**. This is to allow for sufficient growing time for alfalfa to regain over-wintering dormancy before frost reoccurrence.

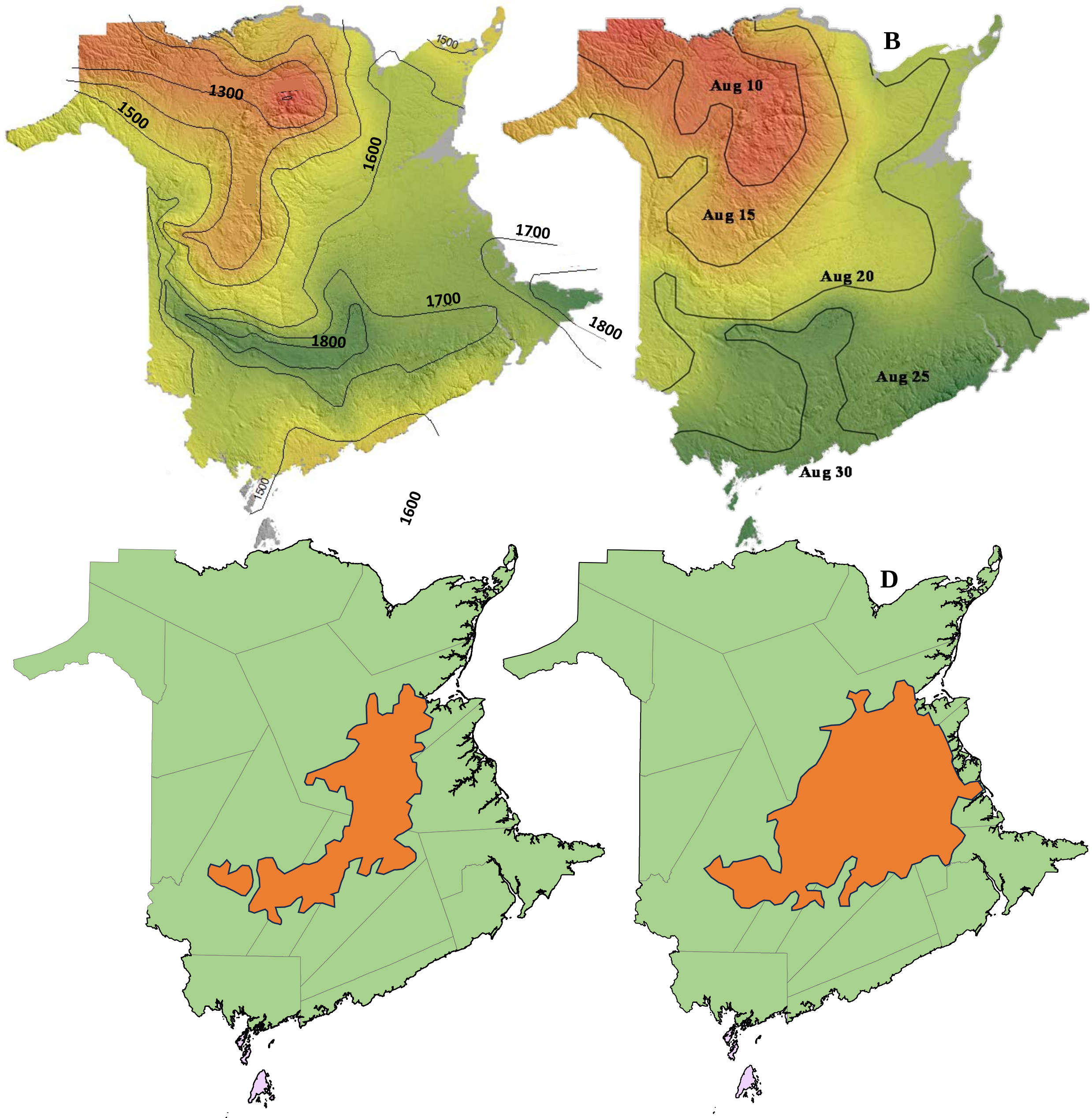

Figure 12. Growing degree days (GDD, A) according to [23] and critical alfalfa harvest periods (B) according to [35] centered on New Brunswick (top). Also: area outlines for mean maximum July temperature > 25˚C, from 1951 to 1980 (C) and from 1981 to 2010 (D) across Atlantic Canada (bottom) according to [3].

3) Also shown in **Figure 12** (bottom) is the regional expansion of the mean 1951-1980 to 1981 to 2010 maximum July temperatures > 25˚C as compiled in [3]. These projections imply an elevated GDD trend along the central to eastern NB lowlands, thereby gradually favouring warm-weather crops when also supported by sufficient rainfall and irrigation across this region.

4) While GDDs and FFDs tend to decrease with increasingly northern latitudes and elevation, their variations across NB remain within the feasible GDD and FFD ranges for potato cropping (**Figure 4**, **Figure 5**), but becoming marginal in the northwest at high elevations.

5) The above potato crop suitability analysis explicitly accounts topsoil and subsoil texture, CF content, depth-to-compaction, calcareousness, slope, and soil drainage. Similarly, crop suitability was rated by slope, drainage, texture, calcareousness, and erosion risk in [36], and by soil texture, organic matter (SOM), and structure in [12]. The articles in [13] and [14] respectively dealt with soil texture and climate only. In contrast, the articles in [10] [11] and [37] referred to soil pH, organic matter (SOM), total nitrogen (N), phosphorus (P), potassium (K), cation exchange capacity (CEC), and electrical conductivity (EC), thereby addressing field-specific management actions on overall crop performances.

6) Further advances could be made by replacing the above R_{Soil} results by soil association with results generated by mapping topographically affected variations in topsoil and subsoil texture, CF content, depth-to-compaction, and calcareousness ([38] at 1-m resolution [39]). Doing so, however, requires undertaking detailed field and forest-specific transect surveys coupled with 1-m DEM modelling to ensure proper digital soil modelling calibrations.

7) Since there the best-fitted POC versus AOI – POC regression coefficients do not differ by much, it is reasonable to expect that the above methodology would work equally well for all other PAN-identified farmlands and farm/woodland combinations across NB [40].

8) Besides property-based suitability evaluations, socioeconomic factors require further considerations. For NB, this would entail assessing a) the transportation costs from fields and farms to nearby processing facilities, b) the costs needed for upgrading existing fields or adjacent forested areas to enable potato cropping, and c) the costs required to establish new fields and nearby processing facilities.

5. Conclusions

To conclude, the above rating process at 1-m elevation resolution accounts for 40% to 50% of the province-wide property assessment variations by property area, building footprint, farm versus farm/woodlot combination, soil type, drainage, and slope. The related cold-weather crop suitability map generally reflects how the crop suitability conditions vary across and within fields and their mostly forested surroundings. Applying the above approach to locations other than New Brunswick would also require accessing and adjusting readily available data layers for elevation, climate (e.g., [41]) and soil associations (e.g., [42]) for general field-specific crop-suitability rating and evaluation purposes. As such, the maps so generated would provide a means to ascertain and to explore/survey further field and forest-specific details. This could be done in terms of, e.g.,

1) setting field borders;

2) evaluating already emplaced drainage structures;

3) notching the LiDAR DEM to correctly reflect where streams and drainage channels are crossing roads or enter ditches;

4) accounting for erosion-induced soil texture, coarse fragment, and soil depth variations.

More details would yet be required for rating of field-targeted crop management actions pertaining to, e.g., pH adjustments, fertilization ([10] [11]), crop rotations ([43]), and access to markets ([44] [45]).

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

References

[1] Storie, R. (1932) An Index for Rating the Agricultural Values of Soils. California Agricultural Experiment Station, Berkeley, Bulletin 556.

[2] O'Geen, A.T., Southard, S.B. and Southard, R.J. (2008) Revised Storie Index for Use with Digital Soils Information. Publication 8335. University of California, Division of Agriculture and Natural Resource, Berkeley. https://doi.org/10.3733/ucanr.8335

[3] Bock, M., Gasser, P.-Y., Pettapiece, W.W., Brierley, A.J., Bootsma, A., Schut, P., Neilsen, D. and Smith, C.A.S. (2018) The Land Suitability Rating System Is a Spatial Planning Tool to Assess Crop Suitability in Canada. *Frontiers in Environmental Science*, **6**, Article No. 77. https://doi.org/10.3389/fenvs.2018.00077

[4] Van Vliet, L.J., Mackintosh, E.E. and Hoffman, D.W. (1979) Effects of Land Capability on Apple Production in Southern Ontario. *The Canadian Journal of Soil Science*, **59**, 163-175. https://doi.org/10.4141/cjss79-016

[5] Agronomic Interpretations Working Group (1995) Land Suitability Rating System for Agricultural Crops: 1. Spring-Seeded Small Grains. Edited by W.W. Pettapiece. Tech. Bull. 1995-6E. Centre for Land and Biological Resources Research, Agriculture and Agri-Food Canada, Ottawa, 90 pages, 2 maps.

[6] Mugiyo, H., Chimonyo, V.G.P., Sibanda, M., Kunz, R., Masemola, C.R., Modi, A.T. and Mabhaudhi, T. (2021) Evaluation of Land Suitability Methods with Reference to Neglected and Underutilised Crop Species: A Scoping Review. *Land*, **10**, Article No. 125. https://doi.org/10.3390/land10020125

[7] Akpoti, K., Kabo-bah, A.T. and Zwart, S.J. (2019) Agricultural Land Suitability Analysis: State-of-the-Art and Outlooks for Integration of Climate Change Analysis. *Agricultural Systems*, **173**, 172-208. https://doi.org/10.1016/j.agsy.2019.02.013

[8] Government of New Brunswick (2022) Agriculture Site Suitability. https://www2.gnb.ca/content/gnb/en/departments/10/agriculture/content/agriculture-suitability.html

[9] Government of Canada (2023) Potato Market Information Review 2021-2022. https://agriculture.canada.ca/en/sector/horticulture/reports/potato-market-information-review-2021-22

[10] Trigoso, D.I., López, R.S., Briceño, N.B.R., López, J.O.S., Fernández, D.G., Oliva, M., Huatangari, L.Q., Murga, R.E.T., Castillo, E.B. and Gurbillón, M.Á.B. (2020) Land Suitability Analysis for Potato Crop in the Jucusbamba and Tincas Micro Watersheds (Amazonas, NW Peru): AHP and RS-GIS Approach. *Agronomie*, **10**, Article No. 1898. https://doi.org/10.3390/agronomy10121898

[11] Asfaw, M. (2017) Agricultural Land Suitability Analysis for Potato Crop by Using GIS and Remote Sensing Technology, in the Case of Amhara Region, Ethiopia. *Journal of Biology*, *Agriculture and Healthcare*, **7**, 5-16.

[12] Daccache, A., Keay, C., Jones, R.J.A., Weatherhead, E.K., Stalham, M.A. and Knox, J.W. (2012) Climate Change and Land Suitability for Potato Production in England and Wales: Impacts and Adaptation. *The Journal of Agricultural Science*, **150**, 161-177. https://doi.org/10.1017/S0021859611000839

[13] Yusianto, R., Dian, U., Semarang, N., Marimin, M., Suprihatin, S. and Hardjomidjojo, H.H. (2020) Spatial Analysis for Crop Land Suitability Evaluation: A Case Study of Potatoes Cultivation in Wonosobo, Indonesia. 2020 *International Seminar on Application for Technology of Information and Communication* (*iSemantic*), Semarang, 19-20 September 2020, 313-319. https://doi.org/10.1109/iSemantic50169.2020.9234284

[14] Wang, C., Shi, X., Liu, J., Zhao, J., Bo, X., Chen, F. and Chu, Q. (2021) Interdecadal Variation of Potato Climate Suitability in China. *Agriculture*, *Ecosystems & Environment*, **310**, Article ID: 107293. https://doi.org/10.1016/j.agee.2020.107293

[15] Zhao, J., Zhan, X., Jiang, Y. and Xu, J. (2018) Variations in Climatic Suitability and Planting Regionalization for Potato in Northern China under Climate Change. *PLOS ONE*, **13**, e0203538. https://doi.org/10.1371/journal.pone.0203538

[16] New Brunswick Digital Elevation Model (NB DEM) (2022). https://open.canada.ca/data/en/dataset/213fbdff-93dd-b7df-7bcd-8239fca8fce8

[17] Forest Soils of New Brunswick (2013) CANSIS. https://sis.agr.gc.ca/cansis/publications/surveys/nb/nb9538/index.html

[18] GeoNB Data Catalogue (2022). http://www.snb.ca/geonb1/e/dc/catalogue-E.asp

[19] SNB Property Assessment Online (2022). https://paol-efel.snb.ca

[20] Murphy, P.N.C., Ogilvie, J. and Arp, P.A. (2009) Topographic Modelling of Soil Moisture Conditions: A Comparison and Verification of Two Models. *European Journal of Soil Science*, **60**, 94-109. https://doi.org/10.1111/j.1365-2389.2008.01094.x

[21] Murphy, P.N.C., Ogilvie, J., Connor, K. and Arp, P.A. (2007) Mapping Wetlands: A Comparison of Two Different Approaches for New Brunswick, Canada. *Wetlands*, **27**, 846-854. https://doi.org/10.1672/0277-5212(2007)27[846:MWACOT]2.0.CO;2

[22] Colpitts, M.C., Fahmy, S.H., MacDougall, J.E., Ng, T.T.M, McInnis, B.G. and Zelazny, V.F. (1995) Forest Soils of New Brunswick. https://www2.gnb.ca/content/dam/gnb/Departments/nr-rn/pdf/en/Publications/forest_soils_of_NB-e.pdf

[23] Gordon, R. and Bootsma, A. (1993) Analyses of Growing Degree-Days for Agriculture in Atlantic Canada. *Climate Research*, **3**, 169-176. https://doi.org/10.3354/cr003169

[24] Hassan, Q.A., Bourque, C.P.-A., Meng, F.R. and Richards, W. (2007) Spatial Mapping of Growing Degree Days: An Application of MODIS-Based Surface Temperatures and Enhanced Vegetation Index. *Journal of Applied Remote Sensing*, **1**, Article ID: 013511. https://doi.org/10.1117/1.2740040

[25] Jong, Q.B., Gameda, R., Huffman, S., Neilsen, T., Desjardins, D., Wang, R. and McConkey, H.B.G. (2013) Impact of Climate Change Scenarios on Canadian Agroclimatic Indices. *The Canadian Journal of Soil Science*, **93**, 243-259. https://doi.org/10.4141/cjss2012-053

[26] Pedlar, J.H., McKenney, D.W., Lawrence, K., Papadopol, P., Hutchinson, M.F. and Price, D. (2015) A Comparison of Two Approaches for Generating Spatial Models of Growing Season Variables for Canada. *Journal of Applied Meteorology and Climatology*, **54**, 506-518. https://doi.org/10.1175/JAMC-D-14-0045.1

[27] Rees, H.W., Chow, T.L., Zebarth, B.J., Xing, Z., Toner, P., Lavoie, J. and Daigle, J.L. (2011) Effects of Supplemental Poultry Manure Applications on Soil Erosion and Runoff Water Quality from a Loam Soil under Potato Production in Northwestern New Brunswick. *The Canadian Journal of Soil Science*, **91**, 595-613. https://doi.org/10.4141/cjss10093

[28] Redulla, C.A., Davenport, J.R., Evans, R.G., Hattendorf, M.J., Alva, A.K. and Boydston, R.A. (2002) Relating Potato Yield and Quality to Field Scale Variability in Soil Characteristics. *American Journal of Potato Research*, **79**, 317-323. https://doi.org/10.1007/BF02870168

[29] Chow, T.L., Rees, H.W., Monteith, J.O., Toner, P. and Lavoie, J. (2007) Effects of Coarse Fragment Content on Soil Physical Properties, Soil Erosion and Potato Production. *The Canadian Journal of Soil Science*, **87**, 565-577. https://doi.org/10.4141/CJSS07006

[30] Tarboton, D.G. (1997) A New Method for the Determination of Flow Directions and Upslope Areas in Grid Digital Elevation Models. *Water Resources Research*, **33**, 309-319. https://doi.org/10.1029/96WR03137

[31] Ekelöf, J. (2008) Potato Yield and Tuber Set as Affected by Phosphorus Fertilization. Master Thesis, Swedish University of Agricultural Sciences, Uppsala, 38 p. https://stud.epsilon.slu.se/12491/1/ekelof_j_171027.pdf

[32] Goeser, N.J., Mitchell, P.D., Esker, P.D., Curwen, D., Weis, G. and Bussan, A.J. (2012) Modeling Long-Term Trends in Russet Burbank Potato Growth and Development in Wisconsin. *Agronomy*, **2**, 14-27. https://doi.org/10.3390/agronomy2010014

[33] Milburn, P. and Gartley, C. (1987) Subsurface Drainage and Land Use in New Brunswick. *Canadian Agricultural Engineering*, **30**, 13-17.

[34] Cook, B.A. (1992) Forest Property Taxation in New Brunswick: A Comment. *Forestry Chronicle*, **68**, 335-338. https://doi.org/10.5558/tfc68335-3

[35] Bootsma, A. and Suzuki, M. (1985) Critical Autumn Harvest Period for Alfalfa in the Atlantic Region Based on Growing Degree-Days. *Canadian Journal of Plant Science*, **65**, 573-580. https://doi.org/10.4141/cjps85-079

[36] Vassiliki, J., Kollias, D. and Kalivas, P. (1999) Land Evaluation Methodology and GIS for Soil Resource Management. Example with Cotton Crop in Greece. *Agronomie*, **19**, 107-118. https://doi.org/10.1051/agro:19990203

[37] Selassie, Y.G., Ayalew, G., Elias, E. and Getahun, M. (2014) Soil Characterization

and Land Suitability Evaluation to Cereal Crops in Yigossa Watershed, Northwestern Ethiopia. *The Journal of Agricultural Science*, **6**, 199-206. https://doi.org/10.5539/jas.v6n5p199

[38] Perron, I., Cambouris, A.N., Chokmani, K., Gutierrez, M.F.V., Zebarth, B.J., Moreau, G., Biswas, A. and Adamchuk, V. (2018) Delineating Soil Management Zones Using a Proximal Soil Sensing System in Two Commercial Potato Fields in New Brunswick, Canada. *The Canadian Journal of Soil Science*, **98**, 724-737. https://doi.org/10.1139/cjss-2018-0063

[39] Lemieux, K. and Arp, P.A. (2023) Re-Examining Field-Surveyed Variations in Elevation and Soil Properties with a 1-m Resolution LiDAR-Generated DEM. *Open Journal of Soil Science*, **13**, 371-390. https://doi.org/10.4236/ojss.2023.139017

[40] Faber, J. and Fonseca, L.M. (2014) How Sample Size Influences Research Outcomes. *Dental Press Journal of Orthodontics*, **19**, 27-29. https://doi.org/10.1590/2176-9451.19.4.027-029.ebo

[41] Gridded Historical Climate Data (CanGRD) (2022). https://www.canada.ca/en/environment-climate-change/services/climate-change/canadian-centre-climate-services/basics.html

[42] Canadian Soil Information Service (2022). https://sis.agr.gc.ca/cansis/

[43] Fenz, S., Neubauer, T., Heurix, J., Friedel, J.K. and Wohlmuth, M.-L. (2023) AI- and Data-Driven Pre-Crop Values and Crop Rotation Matrices. *European Journal of Agronomy*, **150**, Article ID: 126949. https://doi.org/10.1016/j.eja.2023.126949

[44] Bahadur, K.K.C., Green, A.G., Wassmansdorf, D., Gandhi, V., Nadeem, K. and Fraser, E.D.G. (2021) Opportunities and Trade-Offs for Expanding Agriculture in Canada's North: An Ecosystem Service Perspective. *Facets*, **6**, 1728-1752. https://doi.org/10.1139/facets-2020-0097

[45] Bhullar, A., Nadeem, K. and Ali, R.A. (2023) Simultaneous Multi-Crop Land Suitability Prediction from Remote Sensing Data Using Semi-Supervised Learning. *Scientific Reports*, **13**, Article No. 6823. https://doi.org/10.1038/s41598-023-33840-6