Article

A High-Resolution, Random Forest Approach to Mapping Depth-to-Bedrock across Shallow Overburden and Post-Glacial Terrain

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Abstract: Regolith, or unconsolidated materials overlying bedrock, exists as an active zone for many geological, geomorphological, hydrological and ecological processes. This zone and its processes are foundational to wide-ranging human needs and activities such as water supply, mineral exploration, forest harvesting, agriculture, and engineered structures. Regolith thickness, or depth-to-bedrock (DTB), is typically unavailable or restricted to finer scale assessments because of the technical and cost limitations of traditional drilling, seismic, and ground-penetrating radar surveys. The objective of this study was to derive a high-resolution (10 m²) DTB model for the province of New Brunswick, Canada as a case study. This was accomplished by developing a DTB database from publicly available soil profiles, boreholes, drill holes, well logs, and outcrop transects ($n = 203,238$). A Random Forest model was produced by modeling the relationships between DTB measurements in the database to gridded datasets derived from both a LiDAR-derived digital elevation model and photo-interpreted surficial geology delineations. In developing the Random Forest model, DTB measurements were split 70:30 for model development and validation, respectively. The DTB model produced an $R^2 = 92.8\%$, $MAE = 0.18$ m, and $RMSE = 0.61$ m for the training, and an $R^2 = 80.3\%$, $MAE = 0.18$ m, and $RMSE = 0.66$ m for the validation data. This model provides an unprecedented resolution of DTB variance at a landscape scale. Additionally, the presented framework provides a fundamental understanding of regolith thickness across a post-glacial terrain, with potential application at the global scale.

Keywords: bedrock; regolith; geomorphology; Random Forest; LiDAR; modeling; topography; covariates

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1. Introduction

Bedrock is the consolidated rock that comprises the Earth's surface. It is overlain by an amalgamation of unconsolidated materials, or regolith, including fractured bedrock, deposited (glacial, water, wind) and weathering minerals, and soil or organic residues at various stages of decomposition [1,2]. The composition of regolith can have varying heterogeneity depending on a combination of geology (mineralogy and age), topography, and past depositional processes [3,4]. The depth of the regolith, i.e., depth to bedrock (DTB) similarly varies significantly from fully exposed (outcrops) to depths exceeding 1 km beneath the surface in some locations [3,5]. Regolith composition and depth, in combination with bedrock fracturing and transmissivity, are fundamental regulators of surface (on-ground) and near-surface (below-ground) landscape forming processes [6,7]. Weathering combined with past restructuring in post-glacial landscapes and ongoing hydrological processes dictate the types of landforms including slopes and surface/sub-surface water pathways, and the types of soils [8,9]. These physical features in turn regulate the biota

which occur within the regolith, on its surface, and in the surface waters that follow topography, and feedback within [10,11]. As a consequence, the regolith composition and depth are critical characteristics that influence many human needs and activities, including water supplies, agriculture, mineral extraction, forest harvesting, and most physical constructions on which humans depend, e.g., roads and buildings [12]. Despite its importance, DTB is often misunderstood and ignored because describing and modelling it at broad scales across the landscape is technologically challenging and costly [3–5].

Estimating the DTB shows promise with emerging geospatial technologies and the inclusion of various kinds of remote sensing information, such as digital elevation models (DEMs), associated topo-hydrological derivatives (e.g., slope, aspect, flow accumulation) and orthophotography. Table 1 outlines previous studies that predicted DTB for varying study extents, spatial resolutions, and statistical methods. Of the global DTB models, Shangguan et al. [5] explained 59% of DTB variability at 250 m² using Random Forest (RF) and gradient boosting (GB), whereas Pelletier et al. [13] explained 34% on upland hillslopes at 1 km² using algebraic equations applied to topographic derivatives based on conceptual models. Of the regional models, Yan et al. [2] followed a similar statistical approach to [5] and explained 57% of the DTB variability at 100 m² resolution while [4] compared linear regression and ordinary kriging (OK) for predicting DTB and captured 68% of the variability at 20 m². Metelka et al. [14] used artificial neural networks (ANN) capturing 94.2% of DTB variability at 30 m². Additionally, Wilford et al. [15] and Wilford et al. [16] applied the cubist model to predict 38% and 64% of DTB variability at 90 m² and 10 m², respectively. Gomes et al. [3] achieved an *RMSE* of 1.4 m via Bayesian modeling for their predictions at 4 m² whilst also utilizing linear regression, predicting DTB at 2 m² with an average *RMSE* of 2 m. Finally, Shafique et al. [17] applied stepwise regression to account for 91.7% of the variability at 30 m², while Kuriakose [18] tested regression kriging (RK) for their DTB model at 20 m², explaining 59% of the variability.

Varying interpolation techniques have also been applied for DTB predictions. Karlsson et al. [19] utilized Inverse Distance Weighting (IDW), while Kuriakose [18] applied RK for predicting DTB. Alternatively, other studies have developed models for predicting soil depth, but these typically do not specify whether it is soil depth to parent material or bedrock [20]. Typically, bedrock has been represented in the form of broad-scale, tessellated vector datasets outlining the bedrock formation, age, permeability, etc., but lacks information pertaining to DTB [21,22]. Alternatively, DTB has been measured at specific locations via soil profiles (capturing shallow DTB), drill holes and boreholes for mineral exploration, well logs for water-well development, and transects for locating areas of rock outcrops, with these data represented in point vector format. These data types are commonly used in spatial modeling for predicting DTB across the landscape [2,19]. In some locations, spatial predictions of soil depth can be, and have been, used as surrogates for DTB [4,16].

During the last glacial maximum (18,000 years (18 kyr)) ~30% of the Earth's land surface was covered in ice [23]. As the climate warmed, this extent receded to ~10% of the Earth's land surface, limiting ice to high latitudes and altitudes [24–26]. Post-glacial landscapes comprise a cacophony of features such as eskers, kames, kettles, moraines, outwash plains, terraces, deltas, etc., and the depth-to-bedrock in post-glacial landscapes can vary from >100 m, e.g., Northern Alberta, Canada, to <5 m, e.g., New Brunswick, Canada. Understanding the DTB at a landscape scale could significantly advance geological and hydrological sciences and applications in natural resource management and development, e.g., water supplies, mineral exploration, road building, and forest management. The objective of this study was to develop a high-resolution spatial map of DTB in a post-glacial landscape characterized by shallow overburden, covering 72,000 km² region of New Brunswick, Eastern Canada as a case study. This was attempted by building an RF model utilizing field-acquired DTB measurements, high-resolution—LiDAR-derived—topographic and hydrographic derivatives, and geomorphological parameters. New Brunswick was selected for this analysis due to the variability in landforms, elevation, and geological features.

Table 1. Comparison of reviewed literature for predicting overburden depth-to-bedrock, DTB, where RF = Random Forest, GB = gradient boosting, ANN = artificial neural network, OK = ordinary kriging, and RK = regression kriging.

References	Location	Spatial Coverage (km ²)	Resolution (m ²)	Ratio of Resolution/Area Covered	Recently Glaciated (Y/N)	Statistical Procedure
Shangguan et al. (2017) [5]	Global	510,100,000	250	1.2×10^{-10}	Partial	RF and GB
Pelletier et al. (2016) [13]	Global	510,100,000	1000	2.0×10^{-3}	Partial	Algebraic Equations
Yan et al. (2018) [2]	China	9,579,000	100	1.0×10^{-9}	Y	RF and GB
Wilford et al. (2016) [15]	Australian continent	7,692,000	90	2.3×10^{-10}	N	Cubist
Wilford and Thomas (2013) [16]	Mt. Lofty range, South Australia	1280	10	8.0×10^{-8}	N	Cubist
Karlsson et al. (2014) [19]	Three municipalities, Stockholm, Sweden	986	2	2.0×10^{-9}	Y	Linear Regression
Metelka et al. (2018) [14]	Burkina Faso, West Africa	686	30	1.3×10^{-6}	N	ANN
Shafique et al. (2011) [17]	Three cities, Kashmir, India	470	30	1.9×10^{-6}	N	Stepwise Regression
Devkota et al. (2018) [4]	Phewa watershed, Central-Western Hills, Nepal	111	20	3.6×10^{-6}	N	Linear Regression and OK
Kuriakose et al. (2009) [18]	Western Ghats of Kerala, India	9.5	20	4.2×10^{-5}	N	RK
Gomes et al. (2016) [3]	Papagaio river basin, Rio de Janeiro, Brazil	5	4	3.2×10^{-6}	N	Bayesian Modeling

2. Methods

2.1. Study Region

The province of New Brunswick (NB), situated in the Atlantic zone of Eastern Canada, spans an area of ~72,000 km². NB houses an array of diverse geomorphologies resulting from a total glacial coverage during the Pleistocene 40,000 years before the present (ybp), as well as ongoing erosional and depositional processes, resulting in numerous, continuously varying physiographic regions, topographies, landforms, and landscapes which are faced with ongoing erosional and depositional processes (Figure 1A) [12]. Deposits across NB are represented by a combination of sedimentary, igneous, and metamorphic lithological bedrock types ranging from Early Neoprotozoic (850 Ma—1 Ga) to Early Cretaceous (99–145 Ma) with an average DTB of 1.3 m (range of 0–184 m) [27] (Figure 1B). Physiographic regions within the province range from highlands in the southeast (Caledonia Highlands) and northwest (Chaleur Uplands, Miramichi Highlands, and Edmundston Highlands) to lowlands in the east (New Brunswick lowlands), and lowlands/foothills in the southwest (Saint John River Valley/Highland Foothills) [28]. The variability in bedrock type and geomorphological features across the landscape has resulted in a heterogeneous DTB with exposed bedrock occurring within the highlands, uplands, and foothills, to deep post-glacial deposits and glacial landforms [29].

Figure 1. Visualization of the geographic location of New Brunswick, Canada (46.5653° N, 66.4619° W) outlining elevation change and physiographic regions (A) and an overview of bedrock lithology (B), overlain on World Ocean Basemap [30] in ArcGIS 10.3 software [31]. Bedrock geology was acquired from [28] (Scale 1:2,500,000).

2.2. Regolith and DTB Data Sources

Spatially explicit DTB measurements were acquired and amalgamated from publicly available datasets retrieved from governmental sources as outlined in Table 2 and Figures 2 and 3, including:

1. **Boreholes:** A borehole database was accessed from NB Department of Energy and Resource Development (NBERD) via a national topographic system (NTS) index [32]. These data represent the results of petroleum, potash, and coal production/exploration ($n = 332$).
2. **Drillholes:** This database is an amalgamation of drill holes collected as part of diamond drilling mineral exploration within the province. DTB was recorded in exploration reports. These data were accessed from Service New Brunswick's GeoNB data catalogue [21] ($n = 9,828$).
3. **Pedons:** Soil samples collected as part of multiple research projects, including the development of county-based soil surveys by the Canadian Soil Information Service [33] and a permanent sample plot database from NBERD [34]. From the databases, samples were queried and selected for those with DTB recorded ($n = 199$).
4. **Site Cards:** A set of till geochemistry site cards exist that represent till geochemistry surveys conducted throughout NB. Site cards were retrieved from the geoscience publication search query [35] and limiting search results to open file reports. These data were amalgamated and only samples with DTB measurements were selected for analyses ($n = 324$).
5. **Well Logs:** This dataset represents the recorded data for all new and deepened drinking water wells in NB since 1994, amalgamated by the New Brunswick Department of Environment and Local Government (NBELG). The depth at which bedrock was contacted was also recorded in the dataset. This information was retrieved from GeoNB data catalogue [21] ($n = 33,187$).

6. Rock Outcrops: the rock outcrops represent the results of on-ground transects conducted throughout the province to locate areas in which bedrock was exposed at the surface (NBERD) ($n = 126,849$).

Table 2. Overview of DTB datasets acquired for analysis including source, sample size, and overall representation of each dataset including the overall dataset used for modelling. Note: Sample size represents all samples in the original datasets prior to data filtering.

Data Set	Source	Sample Size	% of Total
Boreholes	NBERD	332	0.17
Drillholes	NBERD	9828	5.15
Pedons	NBERD, CANSIS	199	0.10
Site Cards	NBERD	324	0.17
Well Logs	NBELG	33,187	17.4
Outcrops	NBERD	126,849	76.99

Figure 2. Overview of sample locations for each DTB source: boreholes (A); drillholes (B); pedons (C); site cards (D); well logs (E); and bedrock outcrops (F). Total sample size = 170,719 (see also Table 2).

Figure 3. Histogram and continuous density distribution (red line) of bedrock depth for boreholes (A), drillholes (B), pedons (C), site cards (D), and well logs (E), and all data combined (F), including sample size, minimum, maximum, and mean DTB values for each source. Note: Depth intervals are (i) 0.25 m for pedons and site cards, and 5 m for the remaining sources, and (ii) the total sample size with minimum, maximum, and mean exclude the rock outcrop samples since all of these samples have a DTB of 0.

2.3. Data Quality Assessment

Prior to statistical analyses, a procedure was developed to locate potential outliers within each DTB dataset. First, each dataset was assessed to determine if any point locations had multiple DTB values (two measurements for the same geographic location). This was completed by searching the database for rows that shared identical latitude and longitude. If identical, both samples were removed from the dataset, resulting in the removal of 2 samples from rock outcrops, 12 samples from site cards, 4 samples from boreholes, 1099 samples from drill holes, and 5346 samples from well logs. Second, points that occurred within open quarries and mines were excluded from the analysis. These features were located using the GeoNB non-forest inventory dataset (SLU = Mi and SLU = QU) [36]. This resulted in the removal of 877 drill holes, 4 boreholes, 347 rock outcrops, 1 site card, and 5568 well logs. Next, the aggregate vector data set, acquired from NBERD granular aggregate database [37] was used to identify DTB samples occurring on deep alluvial and glaciofluvial deposits. From this, bedrock outcrop points occurring within the delineated granular aggregates were removed due to the contradictory nature of each source ($n = 347$). At this time, the well logs were removed from the spatial database due to inconsistencies arising throughout the samples. These data were collected as a by-product, with the focus being the depth-to-ground water for each well. As a result, what was believed to be the surface of bedrock may have been a clay belt, hardpan, large coarse fragment deposit,

or fractured bedrock. Thus, the actual DTB may not be adequately captured within this dataset. In addition, some well log recordings had multiple DTB values for any single location, raising caution when incorporating this dataset.

2.4. Modelling Framework

The digital elevation model (DEM) utilized in this study is a seamless dataset at 10 m resolution derived from the amalgamation of light detection and ranging (LiDAR) acquisitions at 1 m resolution. The LiDAR digital elevation models (DEM) were combined, ensuring correct projections, datums, and spatial extents, and re-sampled to 10 m using the mean statistic [31]. The original airborne LiDAR acquisitions for NB were collected between 2015 to 2018 at a point density of 6 points·m⁻². The individual LiDAR datasets are provided in .laz format with a tile size of 1 km². This open-sourced data was retrieved from the GeoNB LiDAR Download web app (<https://www.arcgis.com/apps/webappviewer/index.html?id=a6d24f0cc5f149dfb8b569c4ab8aa9f4> (accessed on 4 June 2017)). This form of elevation data collection results in DEMs at higher quality and resolution than counterparts derived from other forms of remote sensing (i.e., satellites, photogrammetry, or contours).

A framework was developed using several DEMs in combinations of increasing cell size (resolution) and localized averaging of neighboring cells (focal smoothing) of the original LiDAR-derived 10 m DEM to produce myriad topographic datasets via algorithms within ArcGIS and SAGA GIS software (Figure 4, Appendix A). In addition, each DEM was hydro-conditioned to fill depressions and ensure correct hydrological flow patterns and used to develop the hydrological datasets [38–73]. All gridded datasets (topo-hydrological and geological), hereafter referred to as the ‘covariates’ ($n = 398$), were resampled to 10 m resolution so that they shared: (i) spatial projection (NAD 1983 CSRS New Brunswick Stereographic); (ii) resolution (10 m); and (iii) spatial extent (number of columns and rows). Similarly, the point vector dataset (field-based DTB measurements) shared the same spatial projection as covariates. Within the modeling framework, the covariates created were annotated with their DEM resolution, e.g., 10 m resolution DEM abbreviated as ‘dem10’, whereas the 10 m DEM averaged using a 5-cell search window was abbreviated as ‘dem105’. The result was eight variant models for each of the DEM scales, e.g., 10 m (‘dem10’), 10 m smoothed (‘dem105’), 30 m (‘dem30’), 30 m smoothed (‘dem305’), 60 m (‘dem60’), 60 m smoothed (‘dem605’), 100 m (‘dem100’), and 100 m smoothed (‘dem1005’).

2.5. Model Parameters

2.5.1. Geological Data

The available tessellated vector dataset representing bedrock geology [28] at a scale of 1:500,000 was converted to a gridded format to represent bedrock age at 10 m resolution. In addition, available tessellated surficial geology delineations [29], also at a 1:500,000 scale, were utilized to develop gridded datasets (at 10 m resolution), representing the mode of deposition and primary lithology, and from these, mineral hardness (derived from Moh’s hardness scale), dominant rock type, and dominant grain size of the surficial geology. Additionally, the vector dataset representing aggregate deposits, at a 1:50,000 scale, was converted to a 10 m gridded dataset in binary form, where 1 was assigned if within an aggregate and 0 assigned elsewhere. In addition, aggregate locations were used as reference for calculating Euclidean distances from the aggregate deposits as an attempt to highlight possible un-delineated aggregate deposits. This technique was also applied to the rock outcrop locations, delineated waterbodies, and wetlands [21].

The surficial geology datasets were included since the study extent was heavily influenced by past glaciation. The surficial aggregate data sets (“agg_dist” and “agg_10”) were included because they represent the deep deposits with highest DTBs. The lithological data sets (“geo_class”, “grain_class”, “lith_class”, and “hardness”) were selected because they represent the parent materials’ resistance to weathering. Finally, the landform datasets (“land_class” and “wetland”) were included since they represent the different parent

material modes of deposition, with these also influencing DTB. Definitions for abbreviations are provide in the supplementary data (see Appendix A).

Figure 4. The framework for developing the DTB model covariates. The multi-scale generation of covariates beginning with the 10 m DEM is shown as an example (blue frame) and the correlation analyses that followed to reduce the number of covariates (red frame).

2.5.2. Topo-Hydrological Data

Bedrock plays a large role in influencing current landform patterns and complex changes in topography. As such, topographic datasets are typically used in predicting DTB [3]. These, in combination with delineations of surficial geology, provide the necessary information required to make predictions on DTB across a landscape. With that said, topographic change is not adequately captured via a single spatial resolution, e.g., 10 m DEM. At this resolution, there are trade-offs between improved vertical accuracy of elevation and inability to visualize large-scale changes in topography. At 10 m resolution, it is difficult to interpret the entire hillslope from ridge to valley; instead, small-scale variability in topography is captured with such high-resolution DEMs. Thus, a multi-scale approach was used on a LiDAR-derived 1 m DEM resampled to 10 m in which the same topographic derivatives are produced at multiple DEM resolutions and scales (Figure 4). Recreating the same topographic derivatives at larger resolutions, while applying focal smoothing, better captures the change in topography from ridge to valley. This study created the topo-hydrological derivatives at 10, 30, 60, and 100 m² resolution with each set smoothed using a 5-cell focal search window. The topo-hydrological datasets utilized in this study were chosen due to their ability to represent landscape evolution.

2.5.3. Covariate Reduction

The output covariates from each DEM-scaled model and all geological covariates were matched to the field-measured DTB observations. Null values, locations where the corresponding covariate value for any observation = −9999, were excluded from the analyses. The result was 398 covariates for 176,658 DTB observations. Principal Components Analysis (PCA) was conducted on the covariates using the ‘prcomp’ function

in the ‘stats’ package in R statistical software [74]. Predictor variables were standardized (value/1 standard deviation) and centered (value—average). A Scree plot was then used to determine the suitable number of principal components (PCs) which capture 90% of the variability ($n = 11$) (Figure 5). Variance of 90% was selected for two reasons: (i) it captures adequate variability while keeping the number of PCs low and (ii) adding additional PCs has very few improvements in variability captured. Adversely, adding additional PCs slows down computational efficiency.

Figure 5. Scree plot used to select the number of PCs to capture a minimum of 90% variability ($n = 11$).

From here, the loading values for each covariate were retained for the first 11 PCs, while the others were excluded. Pearson correlation analysis was conducted on the remaining loading values to assess the degree of multicollinearity (absolute correlation values $\geq 70\%$ were considered significant). Counts were conducted to determine how many covariates met this condition. The covariate with the highest count was retained while the correlated covariates were removed. This counting and removal procedure was implemented iteratively until no correlated covariates remained. This covariate reduction technique was chosen for two reasons: (i) the inherent multicollinearity between topo-hydrological datasets produced from the same DEM (although derived at different resolutions and scales), (ii) potential model overfitting, and (iii) the computational limitations arising from the management of 398 covariates, each at 10 m resolution and each covering $\sim 72,000 \text{ km}^2$.

Of the topographic datasets, slope and curvature datasets help represent zones of accumulation and loss with steep convex slopes representing zones of loss, while relatively flat concave slopes represent zones of accumulation. In addition, longer and flatter slopes will have fewer erosional forces over time in comparison to shorter, steeper slopes. Datasets representing surface exposure to the atmosphere (how exposed a position is) (i.e., ‘diu’ [45], ‘aspect’ [38,39], ‘sky’, ‘trn’, ‘view’, ‘vis’ [58–60], ‘tpo’, and ‘tno’ [67,68]) represent areas which may be exposed to prolonged periods of weathering or increased biological activity, which will increase DTB. For example, south-facing slopes receive more direct sunlight and warmer temperatures than north-facing slopes, while areas of exposed ridges may receive more direct temperature fluctuations and precipitation increasing the rate of rock and mineral weathering. Datasets representing overall change in topography (‘mrrtf’, ‘mrvbf’ [57], ‘tpi’ [39,66], ‘rsa’ [57], ‘tri’ [64], ‘tsf’ [65], and ‘vrm’ [70]) represent the change in slope, curvature, and landforms to broader extents, which helps quantify zones of additions and losses. The hydrological datasets are important for understanding the power of water in carving landscapes. For example, ‘ca’ [40,41], ‘cs’ [42,43], ‘sca’ [40], and ‘scs’ [42,43] represent how much water is flowing into any given location and how

fast that water is flowing through the landscape. These, in combination with ‘st_hdist’, ‘st_vdist’, ‘swi’ [71], ‘val’ [69], and ‘mrvbf’, show where steeply incised stream channels have developed, as well as where the eroded sediments have likely deposited, hence representing shallow and thicker DTB, respectively.

2.6. Statistical Modeling

Random Forest (RF) is a machine learning algorithm with which multiple decision trees are produced with each decision tree developed using a random subset (bootstrap sampling) of the original dataset [75,76]. Prior to model development, the dataset was split so that 30% of the data was set aside for validation. Of this 30%, an equal number of samples from each source were selected. The remaining 70% of the dataset was used for model development. The RF model was developed and applied utilizing the ‘caret’ and ‘raster’ packages in R statistical software [75–77]. This model was set up using a tuning grid, k-fold cross validation, and controlling the number of trees to be developed. The tuning grid tested a matrix of covariates at each node within each regression tree, ranging from 3 to 15 at iterations of three. The maximum of 15 variables was selected to ensure that it remained under the ‘p/3’ rule [75]. K-fold cross validation was set at 10 folds with 20 repeats [78]. The 10 folds were selected due to the large population size of the training subset ($n = 94,385$) and as an attempt to limit bias during model development. In addition, 50 trees were selected for RF model development to avoid computational delays. The resulting RF model was applied to the spatial covariates using the ‘write raster’ function, within the ‘raster’ package in R statistical software [76], yielding a spatial prediction for DTB at 10 m resolution for NB. Model performance was assessed using a coefficient of determination (R^2), mean absolute error (MAE), and root mean squared error (RMSE).

3. Results

3.1. Covariate Reduction

The PCA-PCoA covariate reduction technique was applied to the database resulting in the removal of 354 predictor covariates, from 398 to 44 covariates (see Appendix A). Table 3 highlights the remaining covariates used for model development and the number of correlated covariates of each.

Table 3. The final set of covariates including the number of correlated covariates. Refer to Appendix A for full name.

Covariate	# of Correlated Covariates	Covariate	# of Correlated Covariates	Covariate	# of Correlated Covariates
Ca105	18	Max605	15	tan105	6
Ca1005	1	Max1005	2	Tan305	0
Crs605	1	Mca305	21	Tan60	22
Cs10	1	Min1005	23	Tno10	0
Cur105	9	Min30	20	Tno305	0
Cvgr3100	5	Mrrtf1005	6	Tot10	2
Dem10	17	Mrvbf100	15	Tscv1005	11
Diu60	16	Pln10	20	Tst1005	0
Flw30	8	Prf305	4	Val10	17
Flw100	0	Rsa10	2	Val60	5
Flw1005	0	Sky10	14	View30	15
Grain_size	6	Sky100	6	Vis1005	12
Lng60	2	Sky30	6	Wb_dist	0
Locdn10	1	Swi1005	2	Up30	0
Ls60	3	Swi30	13		

3.2. Model Results

Variable importance for the 20 most significant covariates in the RF model is highlighted in Figure 6, with the full list provided in Appendix A. This shows the explanatory strength of the covariates which explain the highest amount of variability, with scores standardized to equal 100. The DEM at 10 m resolution was the strongest predictor, followed by valley depth (10 m), terrain surface texture ('tst', 100 m smoothed with 5 m search window), flow line curvature ('flw') at 100 m smoothed and at 100 m, then multi-resolution index of ridgetop flatness ('mrrtf') at 100 m smoothed. The RF for the training data produced an $R^2 = 92.8\%$, $MAE = 0.18$ m, and $RMSE = 0.61$ m, and an $R^2 = 80.3\%$, $MAE = 0.18$ m, and $RMSE = 0.66$ m for the validation data. The RF model results are visualized in Figure 7 with the resulting spatial DTB predictions for NB, at 10 m² resolution, displayed in Figure 8. As illustrated in Figure 7, model performance decreases with increasing depth, with all samples having a mean DTB of 1.3 m (Figure 3), and 98.9% of samples (both training and validation) with an absolute error of ± 2 m (Table 4).

Figure 6. The RF variable importance plot highlighting the explanatory strength of the 20 most significant covariates with importance measured as decreasing from 100% (most important) to 40%. Covariate abbreviations are explained in Table 3.

Figure 7. Actual vs. fitted model results for the training and validation subsets ((A,B), respectively) including 95% confidence limits, and histograms displaying densities of residual errors for DTB model on training and validation subsets ((C,D), respectively).

Figure 8. Predicted depth to bedrock (DTB) at 10 m² resolution for the Province of New Brunswick, Canada (A) with an example of the fine-scale resolution showing sediment accumulation across an upland–hillslope–valley bottom transition (B).

Table 4. Frequency distribution comparison of residual errors between training and validation subsets for the DTB model.

Range (m)	Training		Validation	
	Count	%	Count	%
−12--8	2	0.002	0	0.000
−8--4	2	0.002	2	0.005
−4--2	50	0.053	22	0.049
−2--0	69,739	73.888	30,112	74.439
0--2	23,604	25.008	9898	24.469
2--4	692	0.733	288	0.712
4--8	228	0.242	104	0.257
8--12	44	0.047	21	0.052
12--24	18	0.019	4	0.010
24--36	5	0.005	2	0.005
36--72	1	0.001	1	0.001

4. Discussion

4.1. Depth-to-Bedrock Model

Post-glacial landscapes account for ~20% of the Earth's surface landscapes. These landscapes, which occur mostly at high latitudes, are also the most at risk from a changing climate [23,24]. This presents an increasing necessity to develop an understanding of the regional-scale mechanisms driving abiotic and biotic processes across, and in, these landscapes. A foundational control on these processes is DTB [79,80]. This study demonstrates that DTB in a post-glacial landscape with shallow overburden can be accurately mapped using a combination of field measurements, multi-scale, high resolution topo-hydrological derivatives, geologic parameters, and a Random Forest model ($R^2 \sim 0.93$). The data underlying the DTB produced here are typically available from regional and local resources managers, and LiDAR data are becoming more ubiquitous. In contrast to most literature on predicting DTB, this study introduces the concept of incorporating delineations of surficial geology into the modelling procedure due to the extensive impact past glacial events have had on shaping the contemporary bedrock composition and geomorphology. The framework presented here provides a pathway for future studies attempting to better understand how DTB varies across post-glacial and other landscapes with shallow DTB.

Geomorphic features that characterize post-glacial landscapes can dilute the relationship between DTB and surface topographic derivatives [81,82]. Terminal moraines, for example, are formed by glaciers, pushing eroded material downslope and depositing upon glacier retreat [78,83]. Sub-glacial tunnel melt waters that deposit glaciofluvial material become eskers as glaciers retreat [9,84], while a low gradient valley bottom set in a paleo-valley may comprise of deposits >40 m [8,85]. Such geomorphic features are driven by erosion and deposition processes, and undoubtedly confound the relationship between topographic controls on DTB [86]. We sought to capture some of this variance by utilizing multi-resolution topographic derivatives, geological parameters such as bedrock, surficial geology, and aggregate deposition in valleys by applying a non-linear machine learning model (RF). Unsurprisingly, the model's capacity to capture DTB diminished with increasing depth (Figure 7); however, the model illustrated some ability to delineate zones of deposition, and their deeper DTB, in valley bottoms (Figure 8). The results outlined in this study are similar to those of [14] and [17] in terms of model performance, while outperforming the others. Of the models which utilized RF, the model produced in this study outperformed those ([5] and [2]) by 21 and 23%, respectively. The performance of this model is likely due to the high resolution of the input predictor data sets as well as the distribution of the DTB, with most measurements being <2 m.

Some insights into controls on DTB in this post-glacial landscape are also evident. In NB, DTB is shallowest (0–1 m) in the Highlands and deepens moving eastward towards the NB Lowlands (100+ m) (Figures 1 and 8). The variable importance results from the

RF model show that elevation was the strongest covariate for predicting DTB. Areas of higher elevation in NB represent dense igneous bedrock within the upland and highland physiographic regions (Figure 1). Additionally, highland areas in NB also have tors, which have been attributed to the presence of cold-based glaciers [87]. Cold-based glaciers are characterized by basal temperatures below 0 °C, and can be fused to the bedrock, limiting deposition of eroded materials relative to warm-based glaciers, and potentially leading to shallow DTB in these areas [88,89]. Contrastingly, areas with prolonged, subtle changes in elevation (such as the New Brunswick Lowlands—Figure 1) may represent regions which have been more eroded and/or more influenced by glacial activity. These areas also represent locations with sedimentary bedrock, which is more susceptible to weathering [90,91]. Valley depth was the second most important predictor, followed by the real surface area ('rsa') and terrain surface texture ('tst'). Areas with steeply incised stream channels tend to have shallower DTB (Figure 8). The geomechanical characteristics of the glacial deposits in NB can be broadly classified as having low angles of repose, excluding basal tills and clays [28,92]. Weathering, and fluxes in effective stresses underpinned by pore water pressure in this northern temperate region likely lead to recurrent slope failures; thus, shallow DTB across steep slopes in NB.

Flowline curvature ('flw', at three resolutions and scales) and topographic negative openness ('tno') represented four of the strongest covariates. Flowline curvature is a function of elevation, slope, and rate of change of the slope. We suggest that these areas result in shallow DTB due the eroding capacity of water. Conversely, areas defined as 'open' have lower slopes, are mostly delimited by wetlands and glaciofluvial outwash areas, and result in deep DTB [28,93]. This is clearly illustrated in the depositional zone in Figure 8, where a large open valley, comprising outwash, is demarcated by deep DTB. This runs congruent to the open, upland areas which are also characterized by deeper DTB (see Figure 1). The final hydrological covariate identified as a strong predictor is modified catchment area ('mca'), representing the upriver catchment contributing area. The largest upriver catchment-contributing areas occur at the lowest elevations. A decrease in potential energy in these lowland areas leads to deposition in these river reaches [93]. The New Brunswick Lowlands are populated with paleo-terraces that defined the hydrography of the ancient Northumbrian Valleys (see [94]). Hence, deeper DTB is to be expected in this physiographic setting (Figures 1 and 8).

The exposure of ridge tops and upper portions of hills is represented by a multi-resolution index of valley bottom flatness ('mrrtf'), sky view factor ('sky', at three resolutions and scales), real surface area ('rsa'), and diurnal anisotropic heating ('diu'). Exposed ridge tops and upper hillslopes tend to have shallower DTB than lower lying areas (e.g., [95,96]). This is likely caused by glaciers removing material from exposed areas and compacting the remaining material as basal tills [97,98]. The curvature covariates: tangential curvature ('tan'), longitudinal curvature ('lng'), local downslope curvature ('locdn'), maximum curvature ('max'), and upslope curvature ('up'), all represent the rate of change in elevation. Concave landscapes accumulate material, whereas their upslope, convex counterparts tend to lose material as weathering, gravity, glaciers, and runoff erode materials [99,100]. Finally, the grain size ('grain_size') of the lithology of the parent material was a dominant predictor. While this may be pointing towards weathering rates associated with differing lithological units, it is possible that this is also a function of geographic position. Most of the sedimentary parent material occurs in the NB Lowlands (Figure 1). This area is characterized by low relief and wetlands [101,102]. Low potential energy in this environment facilitates deposition, hence the identification of deeper DTB along with grain size (Figures 1 and 8).

4.2. Limitations & Uncertainties

Using multi-sourced data always requires an emphasis on the quality assessment of each dataset, i.e., (i) the source of each dataset, (ii) methods of measurement, (iii) units of measurement, and (iv) assessing the spatial location of point observations. This study

has highlighted techniques to develop a homogenous database from different sources of data, but inconsistencies still occur which cannot be addressed. For example, drill hole information does not provide the angle in which the drill pierced the regolith to reach the bedrock. It is assumed that this occurred at 90° through the regolith, and if not, then the DTB was corrected for the drilling angle. Additionally, when drilling, it is difficult to distinguish the contact zone between consolidated bedrock and overlying regolith. The regolith can be composed of fractured bedrock, dense basal till, or even physically or chemically induced compacted or cemented mineral soil horizons, such as hardpans and orstein horizons, respectively. Additionally, contradictions arose when comparing delineations of surficial geology to the spatial locations for field-based measurements, e.g., rock outcrops occurring within or adjacent to aggregate delineations. These points were excluded, but emphasize the critical importance of quality the assessment for each data set.

Although high-resolution datasets pertaining to topo-hydrology from a LiDAR-derived DEM were utilized in this analysis, it is difficult to fully capture the DTB variability across the landscape. This is due to the influence of past glacial events and the ongoing erosional and depositional processes, which have been acting on the soil and parent material for the past centuries since the Pleistocene glaciation. Varying surficial geological deposits have resulted in DTB values ranging from 0 m (exposed bedrock) on ridges and steep banks, to 80+ m in sediment-filled valleys. As such, existing delineations of surficial geology are unable to capture the full variability in changing surficial deposits and more information is required in the form of specific glacial deposit types (e.g., drumlins, kames, and eskers) and lithology of different deposits (the type of rock and grain size), since this will influence how easily weathered the material will be. These are reflected in the model results in Figure 8 with the maximum DTB prediction error reaching 30 m. Although lacking information, existing surficial geology datasets have importance in the DTB predictions since water-deposited materials (i.e., alluvial floodplains and glaciofluvial outwash plains) have more accumulated sediments on top of bedrock than some glacial and residual deposits (e.g., basal till and residual material). In any case, the ability to predict DTB at increasing depths will become more difficult since there are no single attributes explaining these depths. For example, the aggregate deposits do not specify the depth of the aggregates; thus, the bedrock could be 10 m from the surface or 80+ m. This is reflected in Figure 6 in which model performance decreases with DTB exceeding 5 to 10 m.

Applying such a model to other geographic locations poses additional difficulties. This model was developed for a post-glacial landscape in which topography is largely a replicate of shallow DTB. The transferability of this model is likely limited to regions that have witnessed similar landscape and climatic evolution, e.g., the eastern United States and Scotland. Inversely, this modelling exercise would most likely perform poorly in areas with deep overburden, where topography is not a replicate of topography, e.g., north-central United States and Alberta, Canada [5]. Additionally, the database used for model development is biased to shallow DTB measurements (Figure 3), with 94.6% of the samples recording a DTB of ≤ 1 m. Hence, model results and spatial prediction are biased toward shallow DTB. A more homogenous sample distribution would likely lead to poorer performance results due to the inherent difficulty in predicting deeper DTB.

5. Conclusions

This study aimed to model DTB at 10 m² resolution for the Province of New Brunswick, Canada, by way of RF modeling on open-sourced data. New Brunswick was selected due to its variability in both bedrock and geomorphological features, as well as the availability of open-sourced data. Using this information, the model captured 80.3% of the variability on a randomly selected validation subset of the DTB measurements with an MAE and RMSE of 0.18 and 0.66 m, respectively. At 10 m resolution, the DTB model derived in this study can directly aid in spatial analyses which attempt to quantify natural processes across the landscape. These predictions were derived by comparing LiDAR-derived topo-

hydrological, and geology-derived gridded datasets (from tessellated vector delineations) to an amalgamated, spatially explicit dataset of DTB measurements. The final model was then applied to the covariates, yielding a spatial prediction of DTB for NB at 10 m resolution (Figure 8).

The DTB model developed in this study provides two main benefits to further spatial analyses: (i) a 10m DTB spatial dataset and (ii) a framework for similar analyses to be conducted in other geographic settings, or with updated data and statistical techniques as these come to light. This analysis highlights the applicability and limitations of utilizing multiple open-sourced datasets in spatial statistical modeling studies. We continue to work on improving datasets, defining covariates, and testing alternative statistical approaches, and we look forward to testing the framework on other glaciated and non-glaciated landscapes. The framework we present for building landscape scale maps of regolith depth is a promising step to advance science and resource management in post-glacial terrains with shallow overburden.

Understanding DTB at a landscape scale is certain to advance earth science studies, such as those investigating regolith structure, soils, hydrogeology, and hydrology. Mapping DTB and defining its characteristics at landscape scales will also advance applications in mineral exploration, e.g., aggregates, hydrogeology of water supplies, and engineering human structures. These DTB maps are also consequential to ecological studies, for instance, examining the spatial variability of habitats and biota, e.g., forest type and productivity; thus, they are also useful for regional natural resource management and conservation which rely heavily on landscape scale data. Unfortunately, it is often too difficult and costly to obtain detailed depictions of DTB. This study addressed this limitation by developing an RF model to derive a high-resolution depiction of DTB utilizing publicly available data.

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Appendix A

Table A1. Covariates assessed for use in bedrock modeling with description, reference, and software utilized for development.

Covariate	Abbreviation	Definition	Reference	Software Used
Aggregate	Agg1_0	Binary representing if a cell falls within a delineated aggregate deposit or not.	This study	ArcGIS
Distance to Aggregate	Agg_Dist	Euclidean (horizontal) distance to aggregate deposit	This Study	ArcGIS
Aspect	Asp	Cardinal direction of slope (measured in degrees)	[38,39]	SAGA GIS
Bedrock Age	Bed_age	Average age of bedrock geology types across New Brunswick	This Study	ArcGIS
Catchment Area	Ca	Upslope area contributing discharge into any given cell, calculated from flow accumulation	[40,41]	ArcGIS
Catchment Slope	Cs	Slope of catchment, derived as intermediate with SAGA Wetness Index	[42,43]	SAGA GIS
Convergence Index (gradient)	Cvgr	Determines the convergence or divergence based on neighboring cells (calculated using gradient)	[44]	SAGA GIS
Convergence Index (aspect)	Cvas	Determines the convergence or divergence based on neighboring cells (calculated using aspect)	[44]	SAGA GIS
Cross-sectional Curvature	Crs	Like planar curvature	[38]	SAGA GIS
Distance to Waterbody	Wb_Dist	Euclidean (horizontal) distance to delineated waterbody	This study	ArcGIS
Distance to Wetland	Wetland	Euclidean (horizontal) distance to delineated wetland	This study	
Diurnal Anisotropic Heating	Diu	Influence of topography on diurnal heat balance	[45]	SAGA GIS
Curvature Classification	Cur	Representation of surface curvature/ 9 geometric forms of hillslopes	[46,47]	SAGA GIS
Downslope Curvature	Dwn	Like profile curvature	[40]	SAGA GIS
Downward Distance Gradient	Dwd	Measures impact of local slope on hydraulic gradient	[49]	SAGA GIS
Digital Elevation Model	Dem	Representation of elevation change across landscape, height above sea level	[50,51]	ArcGIS
Filled DEM	Fi	Depression-filled version of the DEM	[52]	SAGA GIS
Flowline Curvature	Flw	Like profile curvature	[40]	SAGA GIS
General Curvature	Gen	Combination of planar and profile curvature	[39]	SAGA GIS
Dominant Geology Type	Geo_class	Gridded representation of changing geological types (sedimentary, igneous, metamorphic) of parent material	This study	ArcGIS
Dominant Grain Size	Grain_class	Gridded representation of changing mineral sizes from very fine to coarse based on lithology of parent material	This study	ArcGIS
Horizontal Distance to Stream	St_hdist	Euclidean distance to nearest stream	This study	ArcGIS

Table A1. Cont.

Covariate	Abbreviation	Definition	Reference	Software Used
Landform	Land_Class	Gridded representation of parent material (surficial geology) mode of deposition	This study	ArcGIS
Latitude	Lat	Gridded representation of changing latitude from north to south (decimal degree format)	This study	ArcGIS
Local Curvature	Loc	Calculates the total gradient to neighboring cells	[40]	SAGA GIS
Local Downslope Curvature	Locdn	Same as local curvature but only looks at downslope cells	[40]	SAGA GIS
Local Upslope Curvature	Locup	Same as local curvature but only looks at upslope contributing cells	[40]	SAGA GIS
Longitude	Long	Gridded representation of changing longitude from west to east (decimal degree format)	This study	ArcGIS
Longitudinal Curvature	Lng	Like profile curvature	[38]	SAGA GIS
Lithology	Lith_class	Gridded representation of parent material (surficial geology lithology)	This study	ArcGIS
Maximum Curvature	Max	Calculates the maximum slope of the slope on a defined search radius (secondary derivative)	[38,53–55]	SAGA GIS
Mineral Hardness	Hardness	Gridded representation of the hardness of lithologic types based on Moh's hardness scale	This study	ArcGIS
Minimum Curvature	Min	Calculates the minimum slope of the slope on a defined search radius (secondary derivative)	[38,53–55]	SAGA GIS
Modified Catchment Area	Mca	Adjustment to catchment area calculation to correct for flow in low-lying flat areas.	[42,43]	SAGA GIS
Modified Specific Catchment Area	MscA	Modified version of Specific Catchment Area	[40]	SAGA GIS
Multi-resolution Index of Valley Bottom Flatness	Mrvbf	Delineation of valley bottom flatness from surrounding hillslopes	[56]	SAGA GIS
Multi-resolution Index of Ridge Top Flatness	Mrrtf	Delineation of ridgetops flatness from surrounding hillslopes, intermediate of MRVBF	[56]	SAGA GIS
Outcrop Distance	Out_Dist	Euclidean (horizontal) distance to rock outcrops	This study	ArcGIS
Planar Curvature	Pln	Curvature perpendicular to slope	[38]	SAGA GIS
Profile Curvature	Prf	Curvature parallel to slope	[38]	SAGA GIS
Real Surface Area	Rsa	Calculation of 'real' cell area	[57]	SAGA GIS
Dominant Rock Type	Rock_class	Gridded representation of changing rock types based on lithology of parent material	This study	ArcGIS
SAGA Wetness Index	Swi	Computes a modified topographic wetness index	[42,43]	SAGA GIS
Sky View Factor	Sky	Amount of sky hemisphere visible from the ground	[58–60]	SAGA GIS

Table A1. Cont.

Covariate	Abbreviation	Definition	Reference	Software Used
Slope (%)	Slp	Rate of elevation change between adjacent cells (as %)	[38,39]	SAGA GIS
Slope Length	Sl	Determine the length of slope	[61]	SAGA GIS
Slope Length and Steepness	Ls	Calculates slope length factor, typically used in Revised Universal Soil Loss Equation (RUSLE)	[43,62,63]	SAGA GIS
Specific Catchment Area	Sca	Catchment area divided by cell width	[40]	SAGA GIS
Specific Catchment Slope	Scs	Catchment area divided by cell width	[42,43]	SAGA GIS
Tangential Curvature	Tan	Determines areas of convex and concave flows, calculated from planar and profile curvature	[39]	SAGA GIS
Terrain Ruggedness Index	Tri	Total change in elevation within a defined radius of any given cell	[64]	SAGA GIS
Terrain Surface Convexity	Tscv	Determines percentage of upward and convex cells within a defined radius	[65]	SAGA GIS
Terrain Surface Concavity	Tscc	Determines percentage of upward and concave cells within a defined radius, same algorithm as terrain surface convexity	[65]	SAGA GIS
Terrain Surface Texture	Tst	Determines the variability in frequency and intensity of pits and peaks within a defined radius	[65]	SAGA GIS
Terrain View Factor	Trn	Output covariate from Sky View Factor	[58–60]	SAGA GIS
Multi-scale Topographic Position Index	Tpi	Position on hillslope in relation to adjacent cells	[39,66]	SAGA GIS
27Topographic Positive Openness	Tpo	Represents landscape exposure to atmosphere (positive)	[67]	SAGA GIS
Topographic Negative Openness	Tno	Represents landscape exposure to atmosphere (negative)	[67,68]	SAGA GIS
Total Curvature	Tot	Curvature of the surface	[39]	SAGA GIS
Upslope Curvature	Up	Average local curvature of upslope contributing area for any given cell	[40]	SAGA GIS
Valley Depth	Val	Like inverse of vertical distance to channel network	[69]	SAGA GIS
Vector Ruggedness Measure	Vrm	Quantifies landscape ruggedness via slope and aspect	[70]	SAGA GIS
Vertical Distance to Stream	St_vdist	Vertical distance from nearest stream based on increasing elevation	[71,72]	ArcGIS
View Distance	View	Average distance to horizon, output from Sky View Factor	[58–60]	SAGA GIS
Visible Sky	Vis	The percentage of unobstructed hemisphere, output from Sky View factor	[58–60]	SAGA GIS

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