DEVELOPMENT OF A SOIL WATER BALANCE-BASED MODEL FOR PREDICTING ECOSYSTEM OCCURRENCE ON POST-CLOSURE LANDFORMS

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ABSTRACT

Soil moisture regime (SMR) is a fundamental factor determining ecosystem occurrence in B.C.'s Biogeoclimatic Ecosystem Classification system. Applying the SMR concept to mine reclamation is often challenging during early reclamation stages because standard indicators used in undisturbed ecosystems are lacking. Using a provincial ecological survey database of 5789 co-located soil and vegetation plots, a system based on volumetric soil-water supply was developed to predict SMR classifications for reclaimed upland sites, which is more accurate than currently available approaches. The system is based on a small number of parameters that can be easily measured or estimated for reclamation landforms, which are input into a regression model that is adjusted for slope position. An advantage of this system over standard approaches is the use of quantitative measures (e.g. particle-size distribution) rather than categorical variables (e.g. soil classed as 'fine' or 'coarse'), which enables better evaluation of key reclamation questions regarding soil-cover depths and quality of soil-salvage sources. Peer-reviewed climate models have been integrated to make water-balance estimates for both historic normal conditions and future climate-change scenarios. An online tool has been developed to allow reclamation managers to explore the ecohydrological implications of management decisions and select appropriate ecosystem targets.

KEYWORDS

Reclamation, ecology, edaphology, soil moisture regime, ecohydrology

INTRODUCTION

The Biogeoclimatic Ecosystem Classification (BEC) system has been developed in B.C. over the last 50-plus years (Krajina, 1970; Klinka et al., 1984) for classification of ecosystems using a combination of climate, soil, and vegetation characteristics (Pojar et al., 1987; MacKenzie and Meidinger, 2018). Similar systems exist in other provinces and territories (e.g. Bowling and Zelazny, 1992; Beckingham and Archibald, 1996; Keys et al., 2010) and jurisdictions around the world (e.g. Pyatt, 1995). Within a particular BEC subzone or variant (i.e. a local area as defined by climate parameters and climax plant species), it is recognized that soil characteristics dictate the expression of ecosystems, as represented in the edatopic grid concept, which organizes site series (i.e. plant communities) by their characteristic soil moisture regimes (SMR) and soil nutrient regimes (SNR) (Figure 1). SMR is defined as the "capacity of a soil to hold, lose, or receive water ... determined from soils' properties and landscape positions, regardless of climate" (Luttmerding et al., 1990, p. 34), and SNR "indicates, on a relative scale, the availability of nutrient supply for plant growth" (Luttmerding et al., 1990, p. 37). Both of these classification scales lack quantitative definitions, and are typically assessed using classification keys, indicator plant species, and surveyor judgment. Since SNR is largely related to organic matter (OM) inputs, and productivity in most B.C. ecosystems is governed by growing-season soil water deficits, SMR is usually the fundamental edaphic factor driving site series expression (Krajina, 1970; Giles, 1983). This is illustrated in Figure 1, which exhibits a common pattern of site series progressing diagonally from dry and nutrient-poor to wet and nutrient-rich. While all SMR-defining parameters (e.g. soil depth and texture, coarse-fragment content, slope gradient, slope position) lend themselves to quantitative analysis using principles of soil physics (Luttmerding et al., 1990), there is currently no quantitative soil-water-based system for classifying SMR.

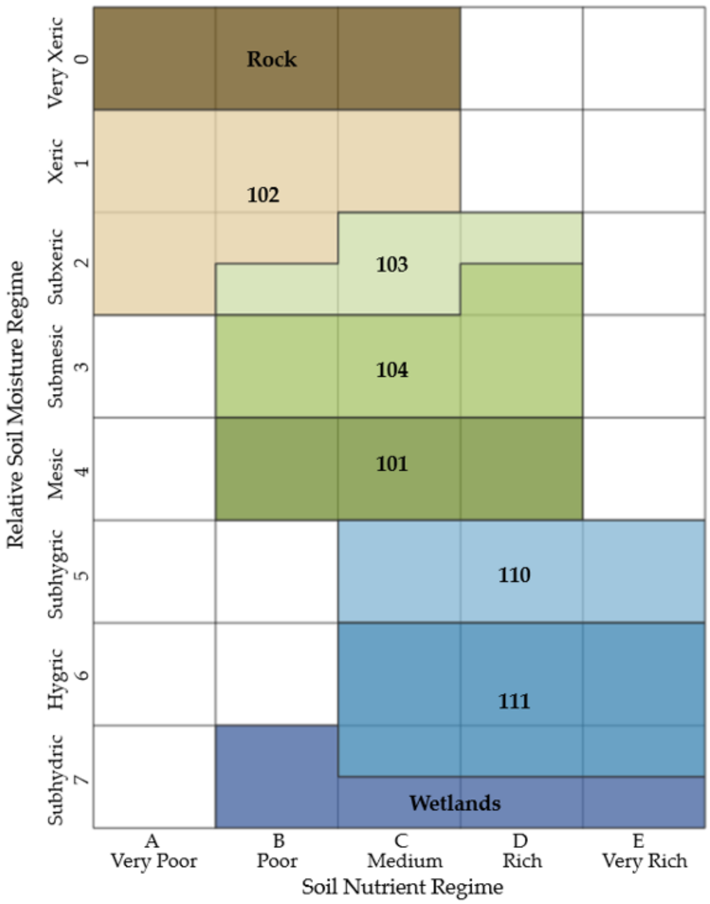

Figure 1. Edatopic grid for the ESSFdk1 variant showing the relationship between site series (coloured boxes), soil moisture regime, and soil nutrient regime.

The standard approaches for classifying SMR in the field are difficult to apply in mine reclamation. The use of field observations and vegetation indicators for SMR classifications is challenging given that reclamation plans are being developed for landscapes that are often many years away from construction. Furthermore, surface soils on reclaimed landforms are often not analogous to natural soil systems, particularly in the lack of impeding soil horizons or bedrock to force downslope conveyance of water within rooting zones. For

SMR classifications on unbuilt or young landforms, the only objective tools available are dichotomous and score-based keys (BCMOE, 2015). A shortcoming of these approaches is their reliance on categorical assessments of soil and site properties (e.g. whether a soil is fine or coarse, deep or shallow, or on a southerly aspect), which do not correspond well to the continuous nature of these variables and ecological intergrades found in the natural world. These categories are also not well-suited for answering key reclamation questions regarding, for example, the relative benefits of potential soil salvage sources, or the depth of soil cover needed to support a target ecosystem, nor can they be integrated with assessments of soil-water balances on a site and landscape level.

In this work, a provincial database of 5789 co-located soil and vegetation survey plots has been used to develop a system to predict SMR classifications based on volumetric soil-water supply. The basis of this model is a small number of site and soil properties that can be easily obtained for reclamation landforms, even those unbuilt. This will enable it to be widely applied to improve objectivity and accuracy in reclamation-design decisions, in keeping with the principles of the forthcoming B.C. Reclamation Guide from the B.C. Ministry of Energy, Mines and Petroleum Resources (EMPR) (Straker and McConnachie, in press).

To the authors' knowledge, no similar attempts at SMR classification have been made in B.C. or other jurisdictions. In Nova Scotia, drainage-related topographical properties have been used to classify SMRs, but these parameters performed poorly for prediction of upland ecosystems (i.e. those not influenced by receipt of seepage and run-on water) (Yang et al., 2017). The proposed system is aimed specifically at upland ecosystems, which predominate on reclaimed mine sites. This paper is a continuation of previous work by the authors (e.g. Straker et al., 2015a; Straker et al., 2015b), and is the subject of ongoing MSc research at UBC by the lead author under Drs. Andy Black and Les Lavkulich.

METHODS

Data preparation

The original database provided by Will Mackenzie of the B.C. Ministry of Forest, Lands, and Natural Resource Operations contains over 15000 plots, consisting of both wetland and upland plots with varying survey detail. Wetland plots (hygric SMR or wetter), plots with seepage as the primary water source, and those with organic soils were removed due to the focus of the current work on upland reclamation. Additionally, plots with incomplete soil surveys or without discernible SMR calls, slope positions, geospatial coordinates, soil depths, soil textures, and coarse fragment contents were discarded.

Data cleaning was done in R (R Core Team, 2019) using field comments from surveyors where possible, and automated rules for other gap-filling (e.g. unrecorded aspects were set to 120˚, which is neither cool or warm) to maximize consistency and repeatability. Ultimately, this left 5789 plots as the basis for this work. A summary of plots by SMR class is presented in Table 1 below.

Table 1. Summary of plots by SMR class.

0. Very xeric	1. Xeric	2. Subxeric	3. Submesic	4. Mesic	5. Subhygric	Total
64	336	841	1620	2239	689	5789
1.1%	5.8%	14.5%	28.0%	38.7%	11.9%	

Soil OM contents, which are not included in the survey data but are required for soil-water modelling, were assigned based on horizon designations using four classes: high (estimated 8% OM) for topsoil horizons (e.g. Ah, Bhf), moderate (4% OM) for upper subsoil horizons (e.g. most B horizons), low (2% OM) for lower subsoil and poorly developed B horizons (e.g. Bfj, Btj, BC), and zero for C, D, and R horizons.

Calculation of plant-available water-storage capacity

A standardized method of estimating plant-available water-storage capacity (AWSC; the volumetric water-content between field capacity and wilting point) from soil-sample data has been employed using adaptations of peer-reviewed models. The input parameters of this approach are soil particle-size distribution (PSD), organic-matter content, soil depth, and topographical data, as well as layering arrangements within the soil profile. Two AWSC models are central to this approach: Arya and Paris (1981; Arya et al., 1999) and Saxton and Rawls (2006; Saxton, 2005).

The Arya and Paris (A&P) approach is a physical model based on the capillary equation and uses only PSD and bulk density as inputs. Its PSD-centric approach ignores the benefit of OM and soil structure on AWSC, and thus appears better suited to poorly developed low-OM soils. To account for this omission, the A&P AWSC value was adjusted by the percent increase in AWSC attributable to OM according to the Saxton and Rawls (S&R) model. The tension at field capacity (T_{fc}) used for calculating AWSC with the A&P model was estimated between 5 and 33 kPa for each sample based on fine-fraction sand content, with coarser samples receiving a lower T_{fc}. This T_{fc} value is used in the profile layering corrections described below.

The S&R approach is an empirical model built on regressions of soil survey data (PSD, OM content, and bulk density) against pressure-plate AWSC results to determine a best-fit prediction of AWSC. Since it is based on agricultural soil samples, this model is likely better-suited to higher-OM, better-aggregated soils.

Fine-fraction (< 2 mm) bulk density was estimated based on texture classes (Saxton, 2005), with increases applied to any layers where compaction was observed during sampling. Whole-soil bulk density was calculated inclusive of coarse fragments (> 2 mm) using an assumed particle-density value of 2700 kg/m^3 for all mineral materials, with packing voids around coarse fragments estimated per Zhang et al. (2011).

In recognition of the different applicability of the two models (A&P for unstructured soils vs. S&R for structured soils), the final AWSC value for each horizon was calculated as a weighted mean between the A&P and S&R results, with weighting derived from total-soil (as opposed to fine-fraction) OM and clay contents, which are used as proxies for soil structural development.

The material AWSC values for each layer in a soil pit are depth-weighted and summed across the upper metre, or to the depth of any root-restricting layer (e.g. bedrock, basal till) found by surveyors, to give a profile AWSC. As layers are compiled, the effects of layering on AWSC are estimated using Clothier et al.'s (1977) model, which is based on the capillary equation. This model does not account for AWSC effects of coarse-over-fine layering situations, which is a shortcoming of the current approach. However, the most common layering arrangement in reclamation is the fine-over-coarse type (e.g. topsoil over waste rock), so layering at most target sites is accounted for.

The final step to calculating a profile's AWSC is to add the estimated AWSC of any accumulated organic material above the soil surface (Table 2).

Table 2. Estimated AWSC values for organic materials and data sources.

Horizon designation	**Material description**	**AWSC value (mm/m)**	**References**
L	Undecomposed litter	35	Sato et al., 2004; Ewell, 2006
F	Partially decomposed fibric material	80	Heineman, 1998
H	Substantially decomposed humic material	170	Heineman, 1998
LFH	Litter layers not differentiated in survey	80	Weighted average assuming 50% of layer depth is L, 25% is F, 25% is H.

Classifying sites by soil moisture regime

Calculated profile AWSC values, mineral-soil depth (depth to root-restricting layers, or 100 cm if none existing), slope gradient (in degrees), and coarse-fragment contents in the upper 50 cm of soil (CF50) were used to estimate SMR using linear regression models. One linear regression model covers slope positions that are typically do not receive significant volumes of upslope water on reclamation landforms (crest, upper, mid, and lower slopes) (SMR = a*log(AWSC) + b*log(depth) + c*slope + d*CF50 + e), while another covers water-receiving toe, depression, and gully slope positions (SMR = a*log(AWSC) + b*slope + c). Regression models were trained over 200 iterations with 80% of points selected at random for model training and 20% used for testing. The mean coefficients over those 200 runs were taken. All terms in the models are significant to the 95% level or better.

Regression model outputs for upland sites are adjusted for their specific slope positions using correction coefficients developed through iterative testing on the plot database. The use of correction coefficients for this purpose rather than slope position-specific regressions is to allow for better application on reclaimed sites, which is discussed further in the results section. Initial results for crest, upper, mid, and lower slope positions are adjusted by -1, -0.55, +0.1, and +0.6 SMR classes, respectively, for application to the natural plot database. Based on preliminary conclusions from slope transects surveyed on three western Canadian mine sites (Endako, Faro, and Highland Valley Copper) (Baker, 2020), which showed that slope position effects are relatively muted on reclaimed landforms, predicted SMR classes for reclaimed sites on crest, upper, mid, and lower slope positions are adjusted by -0.5, -0.3, 0, and +0.3 classes, respectively. Since toe slope positions on reclamation landforms are inconsistently affected by water from upslope (Baker, 2020), SMRs on reclaimed toes are estimated based on the mean result for lower and depression slope positions rather than directly from the regression for water-receiving slope positions. Finally, a set of conditional

SMR classification rules is applied to these results, with their boundaries and magnitudes decided by iterative testing (Table 3).

Table 3. Conditional SMR adjustment rules and the number (percentage) of database plots affected by each.

Condition	**SMR adjustment**	**Plots affected**
Gleyed horizon, or seepage as secondary water source, or drainage class poor or very poor	Add 1.5 SMR classes, and adjusted SMR cannot be drier than 2.5 (subxeric-submesic)	144 (2.4%)
Drainage class imperfect	Add 0.5 SMR classes, and adjusted SMR cannot be drier than 1.5 (xeric-subxeric)	167 (2.8%)
Crest slope position	SMR cannot be wetter than 3 (submesic)	112 (1.9%)
Upper slope position	SMR cannot be wetter than 4 (mesic)	12 (0.21%)
Toe and depression slope positions	SMR cannot be drier than 2 (subxeric)	0
Soil depth less than 10 cm and site not in a lower, toe, depression, or gully position	SMR cannot be wetter than 1 (xeric)	8 (0.14%)
Soil depth less than 20 cm and site not in a lower, toe, depression, or gully position	SMR cannot be wetter than 2 (subxeric)	6 (0.10%)
Soil depth less than 30 cm and site not in a lower, toe, depression, or gully position	SMR cannot be wetter than 3 (submesic)	2 (0.05%)

During the creation of the model and selection of predictors, results were assessed by percent of plots matching their field SMR class exactly, percent of plots within one class of their field SMR, root mean squared error (RMSE) of SMR prediction, and Cohen's kappa statistic. Cohen's kappa statistic assesses the quality of a classification model, by comparing its results against the accuracy of predictions made randomly according to the weighted the proportion of classes in a dataset (Cohen, 1960). Kappa values can range from negative (worse than random) to 1 (perfect assessment), with the values found in this study, including those made using the BCMOE's score-based and dichotomous keys, falling into the slight (0 - 0.2) and fair (0.2 - 0.4) categories of improvement.

This AWSC-based method for SMR determination applies only to upland (very xeric to subhygric) SMRs without seepage, as wetter SMRs require input of seepage water or the presence of a water table within 100 cm of the soil surface, and have limited dependence on soil-water storage (BCMOE, 2015). For application in the online tool, any sites with seepage or shallow groundwater will be classified based on depth to water using pre-existing rules (BCMOE, 2015).

Classifying sites by soil nutrient regime

Since the provincial survey database lacks OM and nutrient data from labs, it was not possible to create SNR classification rules in the same way as for SMR. However, the online tool application for estimating reclamation site series still requires an SNR estimate to be paired with an SMR estimate in order to determine appropriate placement on an edatopic grid, from which site series can be obtained. On reclamation sites, laboratory data for cover soils and mine wastes should be obtained, but missing values will be filled based on material type (e.g. waste rock, tailings, salvaged soil), as derived from Integral Ecology Group's (IEG) internal database. An extensive literature survey was performed in order to determine appropriate threshold values for SNR classifications based on lab results for soil total organic carbon (TOC), total nitrogen (TN), and the resulting C:N ratio[1]. Where TN data is unavailable, the rules for TOC alone are used. The mean SNR classification resulting from all applicable rules is given to each site based on surficial material properties in the upper 30 cm (Table 4). TOC is converted from OM content using an OM:TOC ratio of 2.0 (Pribyl, 2010) if not directly measured.

Table 4. Soil nutrient regime classification rules.

Soil property	**Specific form measured**	**Units**	**Range**				
			Very poor	**Poor**	**Medium**	**Rich**	**Very rich**
Carbon	TOC	% wt.	< 0.5	0.5 - 1.25	1.25 - 4	4 - 10	> 10
Nitrogen	TN	% wt.	< 0.025	0.025 - 0.1	0.1 - 0.25	0.25 - 1	> 1
C:N ratio	-	-	> 100	30 - 100	15 - 30	5 - 15	< 5

Estimation of water-balance parameters

The calculated AWSC values for each site are integrated with publicly available climate data (Wang et al., 2016; Wang et al., 2020) to create water-balance estimates. The online tool allows selection of climate data for 30-year historical normal periods (1961-1990, 1981-2010), as well as future projections from ensemble models for the 2020-2030, 2050-2060, and 2080-2090 periods with three climate change intensity settings.

The water-balance routine is a filling-bucket model run on a daily timestep over a water-year from October 1 to September 30, following from Spittlehouse and Black (1981). Monthly data from Wang et al. (2020) are split into daily totals using multi-year weather patterns derived from Environment Canada data from 3 stations: Highland Valley Lornex, B.C. (2000-2011), Sparwood, B.C. (2000-2018), and Faro Airport, Yukon (2000-2015). For each day with a mean temperature below 0˚ C, incoming precipitation is added to the snowpack. Sublimation losses from the snowpack are estimated conservatively at 16% of the annual accumulation (Reba et al., 2012). As temperatures warm, snowpack is released as meltwater in accordance with Moussav et al. (1989) and is added to any incoming rain for the day. The maximum storage volume of a soil is defined by the AWSC calculations described above. At the beginning of each day, the available volume of soil-water storage is replenished as possible by any added melt or precipitation. The soil pore volume between field capacity (FC) and saturation is also available for storage of incoming melt or precipitation and extraction by evapotranspiration, but this water is drained at a rate of 50% of the original volume per day and is depleted by the end of the second day. Any melt or precipitation accrued after the soil pore volume is full, plus water drained after temporary storage in the FC-saturation pores, is counted as excess water and lost from the system. Excess water is not specified further as either net percolation or run-off, but field observations indicate that most growing-season excess water will report as net percolation,

[1] Klinka et al., 1984; Courtin et al., 1988; Kabzems and Klinka, 1987; Klinka et al., 1994; Chen et al., 1998; CEMA, 2006; Amacher et al., 2007; Kranabetter et al., 2007

particularly on waste rock and level tailings areas. Water is removed via evapotranspiration (ET) at a rate that does not exceed potential ET (PET) for the day[2] and is scaled by the proportion of available water in the system (Spittlehouse and Black, 1981; Giles et al., 1985). The soil moisture storage at the end of the day after addition of meltwater and precipitation and subtraction of ET water carries over to the following day where the model repeats. Over the course of the year, the daily totals are summed into annual estimates which are displayed in the online tool.

RESULTS AND DISCUSSION

The proposed model for SMR classification matches field survey results for 46% of plots and is within one SMR class for 93% of plots. Its kappa value of 0.23 falls into the slight improvement category (Table 5). While these results are modest, particularly the kappa value, they still represent better results compared to BCMOE's score-based and dichotomous key methods, except for the kappa value for the dichotomous key result. It is significant to note that, unlike the proposed system, the key-based methods of SMR prediction are not independent of the data they are being tested on. Plots in the database are the basis of the keys' ongoing development and most plots surveyed in recent decades have been assessed using various iterations of the keys (e.g. Lloyd et al., 1990). It is therefore surprising that the keys do not perform better than the proposed model.

Table 5. Summary of SMR classification model accuracies.

	SMR accuracy		**RMSE**	**kappa**
	Exact	**+/- 1 class**		
Proposed model	46%	93%	0.84	0.23
Score-based key	39%	89%	0.99	0.17
Dichotomous key	42%	88%	0.97	0.24
Best-fit model	54%	97%	0.68	0.34

The accuracy of the model varies by field SMR class (Table 6, Figure 2). While the most abundant classes in the dataset, submesic and mesic, are classified quite well, the model struggles with drier SMR classes in particular. One possible reason for this that was observed during data review is that soil pits in drier SMRs are typically dug in areas with above-average soil depth, particularly where bedrock exposures are frequent, which creates unrepresentative data. A more fundamental source of error causing low accuracy in drier SMRs, as well as the model's tendency to overpredict submesic and mesic SMRs (Figure 2), comes from the use of an unbalanced dataset to train the model, wherein almost 70% of plots are submesic and mesic. Work is underway to use data-balancing algorithms (e.g. Chawla et al., 2002) to counteract this problem and will be incorporated into future iterations of the system. Since mine reclamation soils are rarely shallow to restricting layers and, therefore, most likely to mostly produce subxeric to mesic SMRs, lower accuracies for drier SMR classes are of reduced importance in the intended application.

[2] PET from Wang et al. (2020) is adjusted for the effects of slope and aspect using the R package EcoHydRology (Fuka et al., 2018), with aspect-based temperature adjustments based on Fu and Rich (2002) and McCune (2007).

Table 6. Accuracy of model SMR predictions by field-observed SMR class.

Accuracy of model	Field-observed SMR class					
	0. Very xeric	**1. Xeric**	**2. Subxeric**	**3. Submesic**	**4. Mesic**	**5. Subhygric**
Exact	17%	16%	21%	59%	57%	26%
+/- 1 class	63%	62%	91%	99%	98%	79%

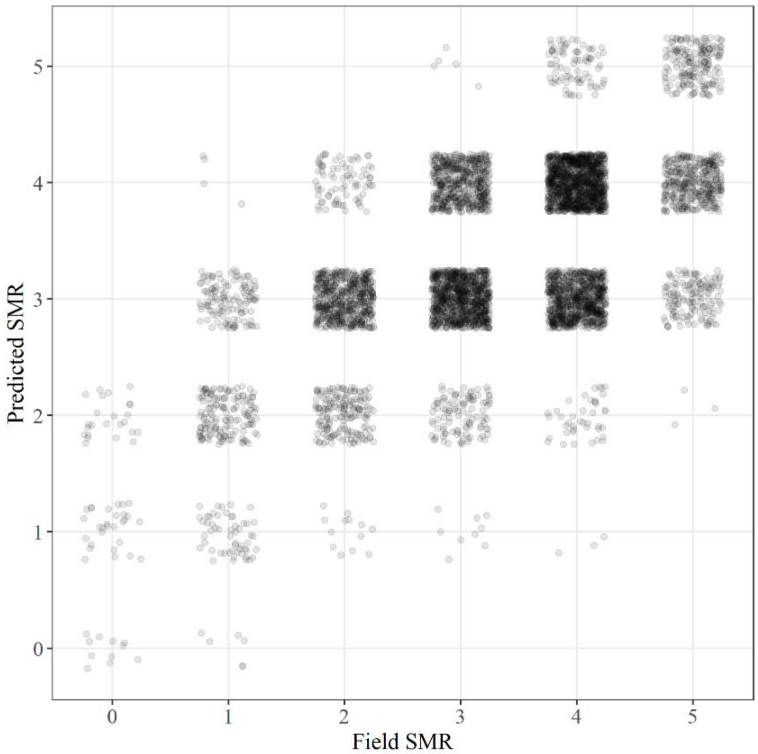

Figure 2. Comparison of predicted and field-observed SMRs. All SMR classes have been rounded to integers, and staggering among points in each group are only for display purposes.

As a proof of concept, and to illustrate the upper limit of accuracy that could be expected from such an approach, Table 5 provides results for a best-fit model, which uses separate regression equations for each slope position. The best-fit model performs well relative to the other approaches, but results, particularly in regards to kappa indicating only a “fair” improvement on random SMR assignments, are not outstanding. Possible sources of error in both the proposed model and the best-fit model are the preference for using vegetation indicators by field ecologists rather than relying on soil-based approaches to SMR classifications[3], evolution of SMR classification keys and concepts over time, variable interpretation of the qualitative SMR classes by surveyors, and errors in surveys and data entry.

While the results from the best-fit model are significantly better than the proposed model, this approach has not been chosen because of field observations showing that ecosystems on reclaimed landforms do not vary

[3] This is not to say that use of vegetation indicators are faulty. Indeed, plants could be argued to act as more reliable indicators of long-term site conditions that may not be seen in a one-time survey (Wang, 2000), particularly with respect to the sampling error inherent in using a single soil pit to characterize a larger ecosystem.

by slope position as much as on natural landforms (Baker, 2020). This is almost certainly related to the lack of impeding soil or bedrock features on reclaimed landforms that typically force downslope transfer of water through rooting zones on natural landforms. On most reclaimed landforms, soil water tends to be lost vertically through cover soils, if present, and downwards through underlying waste materials that usually have high permeability and hydraulic conductivity. The best-fit model, while improving results for natural plots, would likely produce worse results on reclaimed landforms (Baker, 2020). For example, toes of waste-rock landforms without soil covers are unlikely to receive significant, or any, seepage and run-on water from upslope. The best-fit model implicitly assumes such sites are water-receiving like most natural toes and assigns a mesic SMR, rather than the subxeric to submesic SMR assigned by the proposed model, which conforms much better to field observations. Further work on this subject is being conducted, including more rigorous incorporation of findings from recent fieldwork and integration of models to estimate water transfer along reclaimed slopes.

The use of a database of undisturbed plots to develop this model for reclaimed ecosystems is recognized as a shortcoming. However, there are not enough reclaimed sites in the province (perhaps none at all) that have undergone sufficient soil and vegetation development to be a reliable basis for SMR and SNR assessment. In particular, the standard practice of estimating ranges of SMR and SNR from site and soil properties then using indicator species and plant communities to decide upon final classifications cannot be applied to sites that often are dominated by agronomic and early seral species, lack indicator species, and/or contain a complement of species that reflects the results of planting programs rather than natural succession and establishment. The approach put forward in this document, including the use of reclamation-specific correction factors, is our best attempt given the data at hand.

AN ONLINE TOOL FOR RECLAMATION DESIGN

The approach to classification of reclaimed ecosystems and estimation of surface water balances described in this paper have been used to develop an online dashboard tool to guide reclamation design, management, and assessment. The tool's intended users include mine personnel, staff at EMPR, and representatives of mine-affected communities. While IEG has an extended toolbox employing these approaches for streamlining landscape- and mine-level applications, the tool is run using the same code and provides the same results on the site level. The code behind the tool will be updated regularly as IEG's system evolves. It is scheduled for initial release online by the end of 2020, and will include an accompanying user guide.

Users are required to enter soil (Figure 3) and site (Figure 4) characteristics, as well as select a climate time-period. The tool returns estimated climate and soil-water balance values as well as an edatopic grid for the study area indicating the estimated site series (Figure 5). A full explanation of returned parameters will be given in the tool's user guide.

Data format: Sand-silt-clay only

	Horizon/layer	Material type	Upper depth (cm)	Lower depth (cm)	Compaction	Coarse fragments, > 2 mm (% wt. total)	Sand, 0.05 - 2 mm (% wt. fine-fraction)	Silt, 0.002 - 0.05 mm (% wt. fine-fraction)	Clay, < 0.002 mm (% wt. fine-fraction)	Organic matter (% wt. fine-fraction)	Total Kjehdahl nitrogen (% wt.)
1	A	Cover soil	0.00	20.00	Normal	40.00	50.00	35.00	15.00	6.00	1.00
2	B	Cover soil	20.00	50.00	Normal	50.00	60.00	35.00	5.00	4.00	0.80
3	C	Waste rock	50.00	100.00	Normal	75.00	70.00	25.00	5.00	1.00	0.10

Figure 3. Entry of soil properties in the online tool.

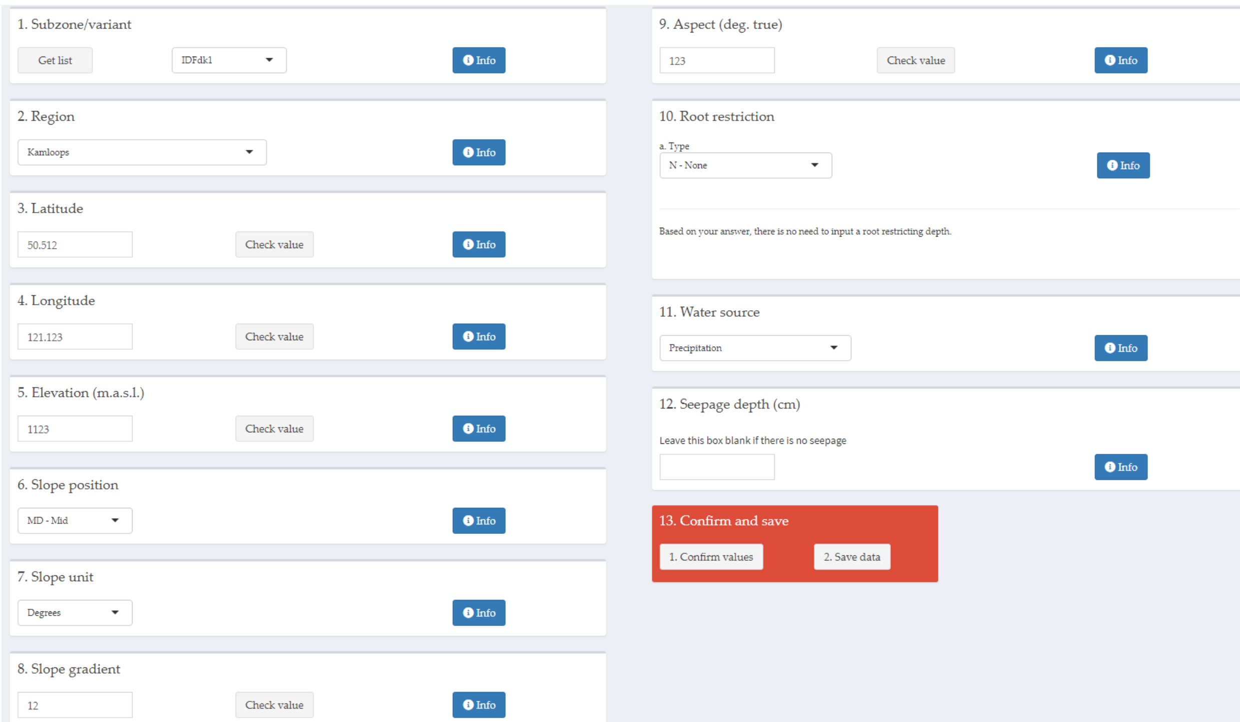

Figure 4. Entry of site properties in the online tool.

A shortcoming of the water-balance results provided by the tool is that ET is not scaled according to the vegetation present on a site during early development stages. It represents only the estimated maximum possible ET from the site in a fully vegetated condition, which is still useful as a check on water balances derived from other modelling approaches, particularly in indicating realistic upper bounds on ET. Future versions of the model will incorporate the expected progression of ET over the course of site development.

Development is in progress to integrate the work of Wang et al. (2020) that predicts future BEC subzones for a given location, which is important since currently mapped BEC classifications for the province are expected to change substantially over coming decades (Mahony et al., 2018).

Site Characteristics

P ann. (mm)	P g.s. (mm)	PET (mm)	CWD (mm)	AWSC (mm)	SWD (mm)	AETmax (mm)	AETmax:PET	Dry days
402	238	593	355	59	296	304	0.512	81

ASMR ratio	ASMR days	ASMR	RSMR	Site Series	Site Series (unshifted grid)	P - E ann. (mm)	P - E g.s. (mm)
2. Very Dry 1	4. Moderately Dry	Very Dry 2	3. Submesic	04 03 (01)	01 04	75.00	0.00

Soil Characteristics

Layer	Depth interval (cm)	Material type	Texture class	Coarse fragments (% vol.)	Material AWSC (mm/m)	Layering effect (% incr.)	Layer AWSC (mm)	Profile AWSC (mm)
A	20	COV	L	40	109.4	0	21.9	59.1
B	30	COV	SL	50	80	1.7	24	59.1
C	50	WR	SL	75	26.5	0	13.3	59.1

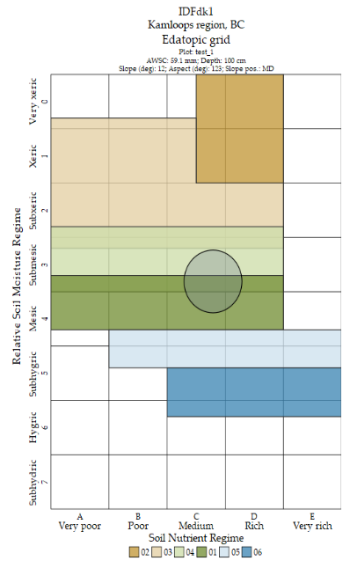

Figure 5. The results provided by the online tool using the inputs given in Figure 3 and 4 and the 1981-2010 climate period.

CONCLUSION

The work outlined in this paper represents an important step towards making objective and repeatable estimates of ecosystems on reclaimed landscapes, and fits the approach of the forthcoming B.C. Reclamation Guide from EMPR. The results of the model are roughly equal to or better than those from the standard SMR classification methods, which are the only other objective SMR-classification methods available to practitioners. While there are issues in applying a model to reclaimed ecosystems that has been developed based on the characteristics of undisturbed ecosystems, the use of reclamation-specific correction factors based on field research on reclaimed sites is expected to make the system a superior approach to the alternatives. Furthermore, the system can be used to answer common reclamation-design questions that cannot be dealt with using existing approaches. For example, to understand marginal returns from increased cover placement depths in order to create soil-cover plans that optimize ecological outcomes within a site’s material-balance constraints. The online version of the tool is scheduled for release by the end of 2020 for use in reclamation design and monitoring by industry, regulators and mine-affected communities.

ACKNOWLEDGEMENTS

The authors would like to acknowledge Will Mackenzie of the B.C. Ministry of Forest, Lands, and Natural Resource Operations for providing the BEC classification database, Jaimie Dickson of Teck Resources Limited’s Highland Valley Copper mine and Elvis Acheampong of Centerra Gold’s Endako mine for enabling site access for field research, Teck Resources Limited for supporting this research in its initial stages, and Drs. Andy Black and Les Lavkulich of UBC for their valuable input. The literature review for SNR classification was an invaluable contribution from Meghan Nickels of IEG. NSERC is supporting this research through the provision of a Canada Graduate Scholarship to Trevor Baker.

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