Incorporating Soil Parent Material into Prognosis

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Abstract—The Prognosis large-tree basal area increment model is being adapted to include soil parent material (lithology) as a new predictor variable. In this paper, the critical issue of how to aggregate diverse geologic units into a set that is meaningful for growth model prediction is examined. We fit the model in a pilot study to compare subjective (concept-based) and objective (data-based) approaches to aggregation. When compared using Akaike's Information Criterion, the best models were those using data-based approaches. Concept-based approaches produced groupings that are least useful for modelling, and data-based approaches produced groupings that were least meaningful biologically and geologically. Poor data distribution and a narrow data set are likely causes of the discouraging result.

Soil properties have an important and well-recognized influence on tree and forest dynamics. Soils are reservoirs of both water and the mineral nutrients that are required by plants. The properties of soil are substantially defined by the properties of the parent material – usually bedrock – from which soils are derived. Over the past decade a number of studies have revealed empirical evidence of a cause/effect relationship between soil parent rock, soil properties, and forest dynamics. The Intermountain Forest Tree Nutrition Cooperative (IFTNC) has identified a number of interactions between fertilizer type, soil parent rock, forest growth, and mortality using an extensive set of forest fertilization trials (for example, Hayek and others 1999; Garrison and Moore 1998; Mika and Moore 1990). Soil parent rock has also been related to mortality and basal area increment (Shen and others 2001, 2000) in models closely related to those used in the Prognosis Model (Wykoff and others 1982). These studies suggest inclusion of soil parent rock may be a useful operational revision to Prognosis.

Lithology is the branch of geology concerned with the study of the properties of rock. This paper presents an overview of issues involved in using the lithology of soil parent rock as a predictor, and a pilot study that involved incorporating lithology into the Prognosis large-tree basal area increment model.

In: Crookston, Nicholas L.; Havis, Robert N., comps. 2002. Second Forest Vegetation Simulator Conference; 2002 February 12–14; Fort Collins, CO. Proc. RMRS-P-25. Ogden, UT: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station.

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Link Between Lithology and Tree Growth

Five factors define soil attributes: time, climate, biota, topography, and parent material (see for example Buol and others 1989). Parent material is important because the mineralogy of parent rock defines the potential supply of most mineral nutrients used by plants, with nitrogen being the most notable of several exceptions (Garrison and Moore 1998). The physical properties of parent material are also important because they define rock weatherability. In turn, weatherability affects the rate of nutrient release as well as physical properties of soil particles that affect nutrient and moisture holding capacity.

Classification systems are used to categorize the expected particle size and nutrient status of a soil derived from a given parent material. Results for a relatively simple classification developed by the Intermountain Forest Tree Nutrition Cooperative (IFTNC) are presented in table 1. Though granites have moderate mineral nutrient contents, they weather to sandy soils, which have poor moisture and nutrient holding capacity, and thus produce soils of medium to low fertility. In contrast, basalts weather to soils that are richer in clay minerals and produce soils with high nutrient holding capacity (Buol and others 1989). Metamorphosed sedimentary rocks (metasediments) weather to soils with low nutrient holding capacity and low nutrient content, producing soils of generally poor fertility (Garrison and Moore 1998). Thus, soil parent material may be a useful general predictor of the inherent fertility of soils.

Unfortunately, precisely identifying soil parent material at a given location is problematic. Parent material may be field sampled, but this is inefficient at operational scales and is perhaps impossible where soils are developed from complex mixtures of parent material, such as glacial till, fluvial deposits, or loess. Imputing parent material using geologic maps of bedrock lithology is a practical solution, though again, where soils are not developed *in situ* but rather from transported materials, underlying bedrock is obviously not representative of soil parent material. For these and other reasons, the use of bedrock lithology map data is not straightforward.

Using Lithology

Technical difficulties complicate geological mapping. For example, vegetation, water, surficial deposits, and soil development complicate the identification of underlying lithology. Surficial deposits, such as loess, glacial till, or alluvium, may be deep, making identification of underlying rock diffi-

Table 1—Expected soil nutrient status with respect to characteristics of different parent rock types and subclasses common to the Inland Empire. After Garrison and Moore (1998). Used with permission.

Lithology	Potassium status	Expected soil particle size	Expected soil nutrient status
Igneous			
Plutonic (granites)	medium	coarse – sandy	medium to low
Volcanic (basalts)	good	fine – clayey	high
Metamorphic			
Schists	medium	fine – silty	medium to low
Gneisses	poor	coarse – sandy	medium to low
Metasediments	poor	variable	low
Mixed			
Glacial till	medium	variable	variable
Loess	medium to poor	fine – silty	medium to high
Sedimentary			
Shales	medium to poor	fine – clayey	medium to low
Sandstones	medium to poor	variable	variable
Carbonates	poor	variable	poor

cult. In some situations, bedrock lithology maps show surficial deposits themselves as the lithologic unit. Objective and absolute standards for classification are difficult even when bedrock is visible, because the composition, age, and process of formation of rocks may be extremely variable.

Geologic maps, and specifically maps of bedrock lithology, can be based on different classification schemes that reflect the biases of the mapping geologist or differences in emphasis that relate to intended use of the resulting data. For example, rocks may be classified based on their geochemistry, their petrography, resistance to weathering, or on the process that formed the rock; the latter are the familiar "igneous," "sedimentary," and "metamorphic" processes. Thus, geologists commonly provide detailed descriptions that include various degrees of all these characteristics. The objective, perspective, and bias of the mapmaker are not necessarily clear but have a significant impact on the maps produced.

Systems of classification that are meaningful to geologists are likely suboptimal for modelling forest growth. Interpreting and redefining a geological system to make it useful is challenging for geologists, who are unfamiliar with the language and science of forest growth, and conversely for modellers and physiologists who are unfamiliar with the language and science of geology. For example, how is a "metamorphosed, siliciclastic sedimentary rock" related to potassium available to trees at a given forest plot? Descriptive geological classifications need to be reduced to a set of lithologic classes that are simple enough that they can be understood and analysed by modellers but retain as much information as possible so the effect of the information can be explored. Merging geology and forestry is a challenge in interdisciplinary science.

Research on the effects of lithology on forest dynamics has employed inconsistent approaches, as little precedent exists. Results have nonetheless demonstrated clear and statistically significant influences of parent material on forest dynamics that appear to be the consequence of nutrient supply (for example Shen and others 2000; Garrison and Moore 1998; Hamilton 1998). These results were achieved using relatively simple systems of lithologic classification, suggesting that further study may reveal opportunities for improvement. Possibilities may be to reduce:

1. Inconsistency – geologic units were aggregated into types sometimes defined by parent material attributes, and sometimes by soil properties (for example Hamilton 1998).
2. Generality – two to five qualitative classes were used to define lithology (for example Shen and others 2000) or soil nutrient status (for example Garrison and Moore 1998).
3. Uncertainty – hypotheses about causal factors may be tested by examination against a more extensive data set.

A greater understanding of functional relationships between stand dynamics and lithology would guide efficient classification schemes, bolster the credibility of model products, and guide extrapolation to conditions outside of the range of the data used in model development (for example Hamilton 1990) by increasing biological and physical credibility (Rykiel 1996).

Why Not Use Soils?

Soil properties associated with lithology would ideally be obtained directly from soil maps. Unfortunately, high-quality soils data for Northern Rocky Mountain forestlands are inconsistently available. The Natural Resources Conservation Service Soil Survey Geographic Database (SSURGO) at present covers little of the National Forest area in northern Idaho and north-western Montana. Because most data suitable for fitting Prognosis growth equations in the Northern Rocky Mountains are obtained from National Forests, using SSURGO data would be impossible. Using soil maps would also involve many of the same difficulties that apply to lithology, including the need to aggregate to a manageable set of classes and the possibility that a classification scheme

deemed optimal for soil scientists is substantially suboptimal for modelling tree growth. Indeed, studies of the relationship between soils and forest productivity are not rare in the literature, and despite extensive analytical effort generally produce weak or poorly generalizable results (see Monserud and others 1990 or Kayahara 1989 for an extensive review).

Pilot Study

The objectives were to fit the Prognosis large tree basal area increment model, using lithology as a new predictor, and explore ways to aggregate the large set of lithology units present in the preliminary map into a smaller set that would be appropriate for applying the model in management. We hypothesized that aggregation would improve model fit and reveal patterns in the data that were geologically and biologically meaningful. This hypothesis was tested in two ways. Aggregated units were compared for consistency across species and against *a priori* hierarchies of geologic similarity suggested by first principles expectation of soil properties. Final models fit using different aggregation methodologies were also tested for quality of fit using Akaike Information Criterion (AIC), which is a model-independent metric of quality fit. This exercise used a digital lithology map generated by the U.S. Geological Survey (USGS), which was merged with the database of forest plots.

Aggregation Methodologies

Developing objective criteria for aggregating across classification variables is not a new problem in forestry. Most literature concerns growth modelling in tropical forests, where an often-overwhelming number of tree species necessitates the reduction into fewer groups for purely technical reasons (for example, Alder and others 2000; Kohler and Huth 1998; Leech and others 1991; Vanclay 1991). Aggregation methodologies generally follow one of two approaches: subjective (concept-based) or objective (data-based). Concept-based grouping may be either based entirely on *a priori* beliefs about function or combined with statistical techniques that suggest initial groupings (Alder and others 2000; Kohler and Huth 1998; Leech and others 1991). A common theme to each of these three examples is that they allow or require a predetermined number of classes to be set as an initial step in the methodology.

Data-based grouping emphasizes the use of statistical techniques to objectively elucidate structure in the classification variable (for example, Vanclay 1991; Meldahl and others 1985; Wykoff and others 1982). Wykoff and others (1982) aggregated diverse ecosystem units into similar sets based on "statistical similarity," defined as groups where none of the estimated coefficients that are grouped into a class differs from any other at the 50 percent level of significance. Wykoff's technique attempts to aggregate only intercept effects, fit uniquely by group, rather than the entire model. Vanclay (1991) introduced arguably the most objective methodology. Classes were sorted by decreasing order of data set size, and whole model F-tests conducted recursively *sensu* Leech and others (1991) to identify "founding classes" that were statistically different from all others. Then remaining classes were grouped with the most similar founding members, based on minimizing the increase in residual sums of squares.

Data and Methodology

Forest Plots

Data from the USDA Forest Service Region 1 permanent plot program were available at the time of the pilot study. This program is a network of plot clusters installed in treated stands across National Forests in Region 1, which includes central and northern Idaho as well as Montana portions of the overall study area. Plot establishment began in the early 1980s, with a target measurement cycle of 5 years; thus, up to three remeasurements were available on some plots. Measurements in a given stand comprise three or more plot clusters installed in treated areas, paired with a single control cluster in an untreated area. Three measurement plots are included in each cluster. Region 1 is in the process of cleaning and certifying the permanent plot database, and clean data were only available for the Idaho Panhandle and Flathead National Forests, which restricted the geographic extent of the exercise. Only data for the four species most abundant in the database were used in the analysis: Douglas-fir (*Pseudotsuga menziesii*), grand fir (*Abies grandis*), western larch (*Larix occidentalis*), and lodgepole pine (*Pinus contorta*).

Lithology

The USGS preliminary lithology map covered the northern Idaho portions of the Bonners Ferry, Sandpoint, Coeur d'Alene, St. Maries, Thompson Falls, and Wallace 1-by-2 degree quadrangles. The total coverage was approximately 60 percent of the entire study area. Lithologic diversity within the map was extensive, including 784 unique lithologic units and nearly 37,000 individual polygons. Permanent plot locations were intersected with the USGS digital lithology map to impute lithology at plot locations.

Model

The Prognosis large tree basal area model formulation described by Wykoff (1990, 1986) was the base model used in the analysis. This model already uses the Wykoff t-test matrix algorithm to aggregate habitat type and location effects on the model intercept and as interactions with some predictors. Because the objectives of this study were to explore aggregation techniques themselves and reveal patterns in the dataset related to lithology, a modified version of the model was specified to focus on these questions. This version, in which mean annual precipitation was substituted for habitat and location, was used principally in the analysis. The Wykoff (1990) formulation was subsequently fit, applying aggregation techniques to lithology only, to examine whether using the modified version affected the results. In the modified model, mean annual precipitation is a continuous variable and was imputed at each plot from 2 km digital precipitation grids. Precipitation and lithology

were introduced simply as linear terms and not as interactions with any other variables.

Aggregation Schemes

Six aggregation schemes were tested:

1. Null — the model is fit without separate intercepts, effectively combining the effect of all lithology classes in the intercept.
2. Full — the model is fit with separate intercepts for all lithology classes.
3. Shen — set of five classes (granite, basalt, metasediment, sediment, mixed) from Shen and others (2000).
4. IFTNC — the USGS classes are interpreted following table 1 and placed into classes "good," "medium," and "poor."
5. Wykoff and others (1982) t-test matrix.
6. Vanclay (1991) paired F-test method.

Schemes 1 through 4 were implemented by introducing a class variable in standard linear regression functions in S-Plus, Version 6. The effect is to estimate parallel functions with separate intercepts for the class variables. The final two schemes were implemented by writing S-Plus scripts that coded their respective algorithms.

Results

Over 45,000 individual tree observations were available for model fitting after processing to generate the variables used in the model. However, since up to three successive measurements were made in some cases, only 124 unique stands were represented in the data (table 2). The sample of stands was distributed unevenly across the 14 lithology classes. In terms of the three broad geologic types: eight were granitic (6 percent), 78 were metamorphic (63 percent), and the remaining 38 were fluvial (31 percent). Nine of the 14 classes (64 percent) were represented by seven or fewer stands; three classes were represented by a single stand. The four species most prevalent in the data set were used for analysis (table 2).

Of the six aggregation methods, all but the Vanclay and Wykoff methods were completely determined *a priori* and were by definition constant across species. The Shen and IFTNC systems show some correspondence (table 3), mostly because of their simplicity. For example, metasedimentary types are all rated "poor" in the IFTNC system. However, the data contained only two IFTNC types; no units classified as "good" were present. The Wykoff approach, which tended to produce groups with only two or rarely three members, produced more classes than Vanclay method (tables 3, 4). Aggregated groups of up to five members were produced with the Vanclay method. Results from both the Wykoff and Vanclay algorithms were inconsistent across species, especially in comparison to the other aggregation methods. Consider the metasedimentary types, which are grouped together in both the Shen and IFTNC systems. In the Wykoff approach, none of the five metasedimentary types were grouped for any species, with the exception of two classes aggregated for grand fir. Results were only marginally more consistent using the Vanclay method. The same two classes were aggregated for grand fir, and three of five classes aggregated for lodgepole pine. Otherwise, few patterns are apparent. Notably, every set aggregated under the Wykoff system was also aggregated under the Vanclay system with one exception, though not *vice versa*.

Comparing models by AIC showed that generally a greater the number of classes resulted in a better fit (table 5). Only a minor improvement resulted from using any of the aggregation schemes compared to using all classes. The lowest AIC, and therefore presumably best model, was that developed with the Vanclay approach for Douglas-fir and grand fir, and the Wykoff approach for lodgepole pine and western larch.

Table 2—Summary of parent material classes from USGS lithology map by stand and tree species in the fitting data.

USGS mapped dominant lithology	Domlith code	No. stands	No. trees DF[1]	GF	L	LP
glacial sediments[2]	glac1	7	325	84	923	1531
glaciofluvial	glac2	21	436	10	1588	4104
granitoid	gran2	6	365	231	180	497
granodiorite	gran3	2	329	0	46	7
meta-claystone	meta1	1	28	4	22	2
metamorphosed siliciclastic sedimentary rocks	meta11	14	772	695	470	180
meta-mudrock or "shale" (>50% silt and clay)	meta3	17	1146	599	687	1125
metamorphosed carbonate/siliciclastic sedimentary	meta7	4	191	24	396	150
metamorphosed siliciclastic/carbonate sedimentary	meta8	29	2774	1703	963	1144
mixed metamorphic/igneous plutonic	mixe3	1	12	0	286	181
natural unconsolidated sediments	natu	14	857	545	1328	130
older alluvium	olde	1	14	237	0	0
semi-pelitic rocks	semi	3	83	116	41	43
unconsolidated sediments	unco	4	22	164	0	518
	totals	124	7354	4412	6930	9612

[1] DF = Douglas-fir; GF = grand fir; L = western larch; LP = lodgepole pine.
[2] Though the class "glacial sediments" and some others here are strictly geomorphologic and not lithologic descriptors, they are the descriptive terms assigned to the bedrock lithology polygon by the USGS and are used accordingly.

Table 3—Results of aggregating classes using the Shen, IFTNC and Wykoff methods. Units with the same name or number are grouped together.

Domlith code	Shen	IFTNC	DF[1]	GF	L	LP
glac1	mixed	medium	1	1	1	1
glac2	mixed	medium	2	2	2	2
gran2	granite	medium	3	3	3	3
gran3	granite	medium	4		1	4
meta1	metased	poor	1	4	4	5
meta11	metased	poor	5	5	5	6
meta3	metased	poor	2	5	6	3
meta7	metased	poor	6	3	7	2
meta8	metased	poor	7	6	8	7
mixe3	granite	medium	8		9	5
natu	mixed	medium	9	7	10	3
olde	mixed	medium	6	8		
semi	metased	poor	4	8	11	8
unco	mixed	medium	6	5		4

[1]DF = Douglas-fir; GF = grand fir; L = western larch; LP = lodgepole pine.

Table 4—Results of aggregating classes using the Shen, IFTNC, and Vanclay methods. Units with the same name or number are grouped together.

Domlith code	Shen	IFTNC	DF[1]	GF	L	LP
glac1	mixed	medium	3	5	1	1
glac2	mixed	medium	1	4	1	1
gran2	granite	medium	2	3	5	3
gran3	granite	medium	2		3	4
meta1	metased	poor	3	5	5	3
meta11	metased	poor	2	2	1	3
meta3	metased	poor	1	2	3	3
meta7	metased	poor	4	3	5	1
meta8	metased	poor	1	1	2	2
mixe3	granite	medium	3		4	3
natu	mixed	medium	1	3	1	3
olde	mixed	medium	4	4		
semi	metased	poor	2	4	5	2
unco	mixed	medium	4	2		4

[1]DF = Douglas-fir; GF = grand fir; L = western larch; LP = lodgepole pine.

Table 5—Akaike Information Criterion values, by species, for models fit using different aggregation methodologies.

Model	DF[1]	GF	L	LP
base	16320.1	10039.4	15505.8	22101.4
all	15934.1	9759.7	15084.2	21437.0
Shen	16076.1	9977.7	15378.7	21767.6
IFTNC	16143.4	9975.9	15407.8	21871.0
Vanclay	15920.5	9751.8	15094.8	21431.1
Wykoff	15924.7	9752.4	15082.2	21427.7

[1]DF = Douglas-fir; GF = grand fir; L = western larch; LP = lodgepole pine.

Similar results are produced when the Wykoff (1990) base model is used instead of the modified model, which substitutes precipitation for habitat type and location. Overall, when the Wykoff (1990) base model is used, AIC values are 1 to 3 percent lower than under the modified model, but the relative ranking of aggregation methodologies is nearly identical. In either case, within and across species few patterns are apparent in the grouping of lithology classes by the Vanclay or Wykoff methods, and little correspondence is found between the final result for both methods using either base model.

Discussion

Data-based and concept-based approaches to aggregating classification variables have different strengths. Objective statistical techniques may reduce the potential for bias as well help elucidate the correct interpretation of the functional relationship between class variables and the modelled system. This is most useful when little is known about the relationship in advance. Yet when knowledge about function is available, schemes that incorporate knowledge may be superior to statistical techniques that produce some hierarchies that are an artifact of random data patterns (Vanclay 1991).

Our goal was to test the hypothesis that biologically meaningful patterns could be discerned. The results are not encouraging. This is principally because data-based techniques have suggested groupings that are not biologically sensible, and because groupings that are biologically or geologically sensible were not useful in modelling. If lithology is in fact not related to tree growth, or our interpretation of what is biologically sensible is inappropriate, this result is not surprising. Nonetheless, the analysis was limited by a data set that may not contain a sufficient breadth of information to discern meaningful relationships. A larger data set would include more lithologic diversity, and independent data would permit a more extensive evaluation.

Data structure is a better explanation for the results than causal links between lithology groupings and tree growth for this data set. Any signs of model improvement through the addition of lithology may be due more to overfitting than a true increase in explanatory power. This is evidenced by the chaotic aggregation results from the data-based techniques, which are at odds with even the simplest conceptual expectations, and inconsistent results across species, aggregation method, and underlying base model formulation. Lithology may be acting as a proxy for unmeasured site values, given the poor data distribution across lithology classes, in some cases with a class represented by a single site. Again, model development and testing using a broader data set is necessary.

The results do offer some insights into the tradeoffs between aggregation methodologies. The Wykoff and Vanclay data-based techniques were able to identify similar data patterns, albeit only within single species. AIC comparisons suggest that the two techniques produce models of similar quality. However, the Wykoff technique allows for the final decision to aggregate to be made subjectively, which may be desirable especially where some *a priori* knowledge is available to guide modelling. Vanclay's technique, which was

initially proposed for modelling of tropical species, would have an advantage where the number of groups was overwhelming or where little information is available in advance that could guide subjective decisionmaking.

A key objective of the pilot study was to produce some results that could guide and refine future work, and to this end the study has been useful. Clearly a broader data set with more lithologic diversity is needed. Lithologic units were also simplistic; greater diversity should include descriptions and information that are useful for linking lithology conceptually to soil properties and tree growth.

Acknowledgments

This research was supported in part by a research joint venture agreement (USDA FS RMRS-99541-RJVA) between the USDA Forest Service Rocky Mountain Research Station and the University of Idaho Forest Biometrics Laboratory. We thank Nick Crookston, Bob Havis, Dennis Ferguson, and Bill Wykoff, all of the USDA Forest Service, for helpful review and comments. Our special thanks go to Bill Wykoff for his patient, durable support of Prognosis work at the Forest Biometrics Lab.

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