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Two Basic Methodological Choices in Wildland Vegetation Inventories: Their Consequences and Implications

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TWO BASIC METHODOLOGICAL CHOICES IN WILDLAND VEGETATION INVENTORIES: THEIR CONSEQUENCES AND IMPLICATIONS

by

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ABSTRACT

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In designing inventories of wildland vegetation, two of the many basic methodological choices are: 1) whether data are collected, reduced, and stored in discrete classes or as continuous variables, and 2) whether data are gathered as general purpose variables to bear upon many questions, or as specific purpose variables optimized for only one type of prediction. The effects of these two choices on accuracy of vegetation inventories to predict plant community production were examined by comparing regression models built upon differing sets of independent variables "inventoried" from a common data base. Contrary to expectations, discrete variables of classified community types were better predictors of plant community production than the same vegetation data reduced as continuous variables by three ordination techniques. Substitution of specific purpose soil and vegetation variables thought to be especially relevant to production did not improve correlations from those of

analogous general purpose variables. These results do not show the anticipated accuracy loss of general purpose inventory variables, but such findings cannot yet be generalized to other situations. Implications for the design of practical, extensive survey methods for wildland vegetation are briefly discussed.

(38 pages)

INTRODUCTION

Many decisions in wildland management require vegetation information. Because of this, the question of how wildland vegetation is best inventoried and described is important. Since there are many possible ways to reduce and store data, one makes certain choices (knowingly or not) in the design or application of any wildland vegetation inventory (West and Shute 1978). While the relative merits of different approaches to vegetation inventory or description have been argued extensively at a qualitative level with little reference to exactly what information is desired (Dale 1978, Daubenmire 1966, Kessell 1976, Whittaker 1962, Whittaker 1973), this paper quantitatively compares different vegetation inventory approaches in terms of their ability to predict plant community production.

All U.S. government agencies managing wildlands presently inventory vegetation by mapping discrete classified units. How much vegetation information is lost by reducing continuous plant community variables into discrete classes, such as habitat types or community types? It is tautalogically true that some information is lost by recording an observation as the value of its nearest class midpoint or mean, be it a simple artificial classification (such as the real numbers into integers) or an agglomerative polythetic, "natural" classification such as plant systematics. This is the essence of Kessell's (1976) assertion that vegetation

ordination techniques (more generally, continuous multivariate reduction techniques) by definition lose less information than reduction into larger, discontinuous units (classes or types). But, to my knowledge, the only study testing this hypothesis on a specific information need with real vegetation data is that of Grigal and Grizzard (1975). They compared the grouping of their deciduous forest study plots in two different classifications defining an equal number of groups. One classification was by cover type (based on unstated rules of canopy dominance), and the other was by concensus of four objective multivariate methods. Their results showed that phenology and nutrient cycling data were more efficiently classified by newer mathematical techniques than by older dominance-based methods. Mao (1975) examined the effects of discrete classification upon correlations among dairy production-breeding records. Both genetic correlations and phenotypic correlations were weakened by reducing continuous data to classified form.

At this point, I cannot conclude that reduction and storage of data in continuous form is more accurate (in predicting needed information) than discrete data, because so much depends on the inventoried variables (X's), predicted variables (Y's), and location of the specific inventory. In comparing the merits of classification versus ordination of vegetation for practical purposes, Greig-Smith (1971) noted two weaknesses of existing ordination techniques. Plot clustering from the landscape or sampling procedures can confound existing ordination methods. Secondly, modern algorithms

for reduction of vegetation data can handle a relatively narrow range of variation compared to older classification methods. Thus, it seems classified data may be best in some situations, and continuous data in others.

One main goal of this paper is to compare discrete and continuous reductions of the same vegetal data set by their accuracy in predicting community production. My effort differs from that of Grigal and Grizzard (1975) in the following aspects: the choice of X's and Y's, ecosystem type, and my level of greater floristic detail.

A second important question in wildland vegetation inventory is whether the X's inventoried were chosen to predict only one Y (special purpose X's) or whether they are a compromise data set to predict many different Y's (general purpose X's). Historically, the first vegetation inventories on U.S. public wildlands were special purposes inventories of the "single use" product (timber or forage) (Poulton 1959). If standing crop or growth increment were not measured directly, chosing the best available predictor was a simple univariate (single purpose) problem. The subsequent growth of competing uses on these lands requires vegetation information for many management objectives. In response to these growing information needs, designers of wildland inventory systems have increasingly chosen to inventory a broad set of general purpose X's to predict many, varied Y's at hopefully reasonable costs (Francis 1978). The following series of wildland inventory systems (presented in chronological order of development)

illustrate this trend: Range Site (Dyksterhuis 1949), Habitat Type (Daubenmire 1952), Land Systems Inventory (Wertz and Arnold 1972), Ecoregions (Bailey 1976), ECOSYM (Davis and Henderson 1977). Intuitively, I expect a set of compromise (general purpose) X's to predict any Y less accurately than a special purpose set of X's chosen in light of mechanisms presumed to control Y. But the existence or magnitude of this predictive loss has not been measured in any case I know of. Testing this intuitive hypothesis is a second goal of this paper.

METHODS

Scope of study

Annual aboveground plant community production was chosen as the Y on which to compare the predictive value of different inventory data sets in order to utilize a pre-existing data base. From a previous project to develop a new, comprehensive wildland inventory system (Davis and Henderson 1977) I was familiar with a detailed local classification of existing vegetation (Shute and West 1978), observed and modelled environmental data for the area, and a regression model predicting rangeland herbage production from this data base (Roberts 1978). By returning to these known study sites and collecting additional information (continuous measures of the vegetation, and environmental X's thought to be especially relevant to community production) I was able to compare data bases representing different inventory strategies applied to the same set of vegetation samples.

Study area

The study area was a 5 x 29 km east-west strip crossing the Wasatch Plateau in central Utah, between the towns of Fairview and Price. The vegetation of the study area varies from a sub-alpine meadow-forest mosaic to sagebrush-grass and pinyon-juniper-woodland vegetation types. I limited my samples to only one wide-ranging sagebrush-grass dominance type, the Artemisia tridentata[1]-

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1. Nomenclature follows Welsh and Moore (1973) for dicots and Cronquist et al. (1977) for monocots.

Chrysothamnus viscidiflorus (Artr-Chvi) cover type (Shute and West 1978). This was done because a certain density of data is necessary to interpret or compare multiple regression models, and the number and distribution of recoverable sites were predetermined. Examining a wider variety of vegetation would have 1) confounded ordination techniques used, 2) resulted in an unacceptably small number of observations within some vegetation classification units, and 3) caused greater differences in degrees of freedom among some models, complicating comparison and interpretation. The final 45 plots remeasured in the Artr-Chvi cover type ranged from 3025 m elevation (123 cm estimated 1976 precipitation) to a low of 2131 m (44 cm precipitation).

Study design

This study involves two sets of comparisons. The first compares regression models predicting production from vegetation data alone. This addresses the question of how type (continuous versus discrete) and degree of data reduction affect vegetation information. The second set compares regression models using both vegetal and environmental X's. This allows comparison of specific purpose versus general purpose environmental X's in predicting community production. Table 1 lists the X's included in each of the combined vegetation-environment regression models. Model 1 uses only general purpose X's (relative to production), with soil and vegetation data in discrete classes. Models 2 and 3 differ from Model 1 in that vegetation data are reduced into a general purpose, continuous form. Model 2 includes the original continuous canopy cover measures for the five best predictor species, while Model 3 reduces canopy

Table 1. Subsets of variables used in vegetation-environment regression models to predict plant community production.

	Subset Description	Subset Degrees of Freedom
Model 1	Vegetation: 6 community types (classified)	5
(total	Soils: 9 great groups (classified)	8
d.f. = 15)	Elevation	1
	% Slope	1
Model 2	Vegetation: canopy cover of 5 species	5
(total	Soils: 9 great groups (classified)	8
d.f. = 15)	Elevation	1
	% Slope	1
Model 3	Vegetation: 3 principal component	3
(total	Coordinates reduced from 24 species	
d.f. = 13)	Soils: 9 great groups (classified)	8
	Elevation	1
	% Slope	1
Model 4	Vegetation: canopy cover of 5 species	5
(total	% cover taller than exclosure height	1
d.f. = 12)	Soils: available water capacity top 1 m	1
	Relative infiltration	1
	Drainage position (3 classes)	2
	Elevation	1
	% Slope	1
Model 5	Best X's from Models 1-4	

cover data from 24 major species into three continous synthetic X's by principal components analysis. Model 4 has both general purpose continuous and specific purpose vegetation data. Soil information is specific purpose continuous data and elevation and slope are as before.

The goal in both sets of comparisons is to compare curves of r^2 of different models across increasing degrees of freedom as less important X's or subsets of X's are added in a stepwise upward mode. The relative shapes and locations of these curves compare the predictive value of different subsets of X's, and the assumptions about plant communities that encourage their collection.

Data collection, reduction, and analysis

In 1976 60 wire mesh exclosures were placed by Roberts (1978) within the sagebrush-grass portions of the study area in a modified systematic pattern. Each exclosure protected a .88 m^2 area from grazing by larger mammals during the growing season. Roberts clipped, dried, and weighed the 1976 plant production (above-ground biomass produced that season) in his effort to develop an extensive, rangeland productivity model for the area. Soil at each plot location was classified to the Great Group level.

In 1977 60 exclosures were revisited. An exclosure was rejected for further study if the vegetation or environment did not appear homogeneous within the 500 m^2 circular plot size used, or if the plot was not in the Artr-Chvi cover type. These criteria left 45 exclosures as acceptable study sites.

The following continuous measures of plant community and environment were taken directly or calculated for each plot: percent canopy cover of each species (by visual estimation), percent plant cover taller than exclosure height (1.4 m), slope, aspect, available water capacity (AWC) of the top 1 m of soil, and relative infiltration rate. Drainage position was recorded as a discrete variable.

The soil samples used to approximate AWC and infiltration rate were recovered from three arbitrary depths by soil auger: 0-20 cm, 40-60 cm, and 80-100 cm. "Horizons" too stony to be recovered in three auger attempts were assumed to have AWC=0. Calcic horizons were penetrated by the auger. Soil samples were lightly ground to reduce structure, oven dried, and sifted to remove gravel and rock fragments greater than 2 mm. Care was taken to grind up and include calcium cemented lumps of fines, yet exclude shale or sandstone fragments which did not slake overnight in water. Fines were analyzed for soil texture by hydrometer method (Bouyoucos 1962), with the sand fraction of sandy loam and coarser textures screened into USDA sand classes by weight (Soil Conservation Service 1975). AWC of each sample (-.5 to -15 bars) was estimated from texture, percent volume greater than 2 mm, and sand size distribution by the table of Erickson and Searle (1974). AWC of the 0-30 cm, 30-70 cm, and 70-100 cm depth intervals were summed for each plot to approximate maximum water storage in the top meter of soil.

The percent volume of particles greater than 2 mm plus percentage sand weight was used as a rough index of relative infiltration.

Each plot was classified into one of three qualitative drainage classes: run-on, flat, or run-off. Elevation was used as a single, integrated climatic variable because it is the predominant variable in the temperature and precipitation models of this area (Zsiray and Wooldridge 1978).

Using 1977 species cover records, the 45 plots were classified into six community types using a combined key developed by Shute and West (1978) and Kerr and Henderson (1979) from 1975 and 1976 data. The 24 species which individually reached at least 10 percent cover on one of the 45 plots were reduced by principal components analysis (PCA) "PRINCO" (Dunn 1969) into three synthetic variables. Only major species were used in order to minimize missing data problems described by Swan (1970). The three principal component variables were used as vegetation X's in Model 3. Of the 24 species selected above as potential dominants, the canopy cover of the 17 more important (constancy greater than 20 percent, or first or second highest correlate of a principal component axis) species were evaluated individually as X's in stepwise multiple regression. A subset of the five best predictor species were used as X's in Models 2 and 4.

Graphing of all X's against measured production showed quadratic and higher order regressions could be ignored. Models were built by stepwise upward, multiple linear regression on subsets of X's. Classified (discrete) information (i.e., n levels of soil and vegetation units) were handled as subsets of n-1 dummy variables. Vegetation data alone were also built into regression models by stepwise upward routines. Results were expressed as graphs of r^2 versus

degrees of freedom in the model, and also as graphs of standard error of regression (here $\sqrt{SSE/45}$ for all models) versus degrees of freedom.

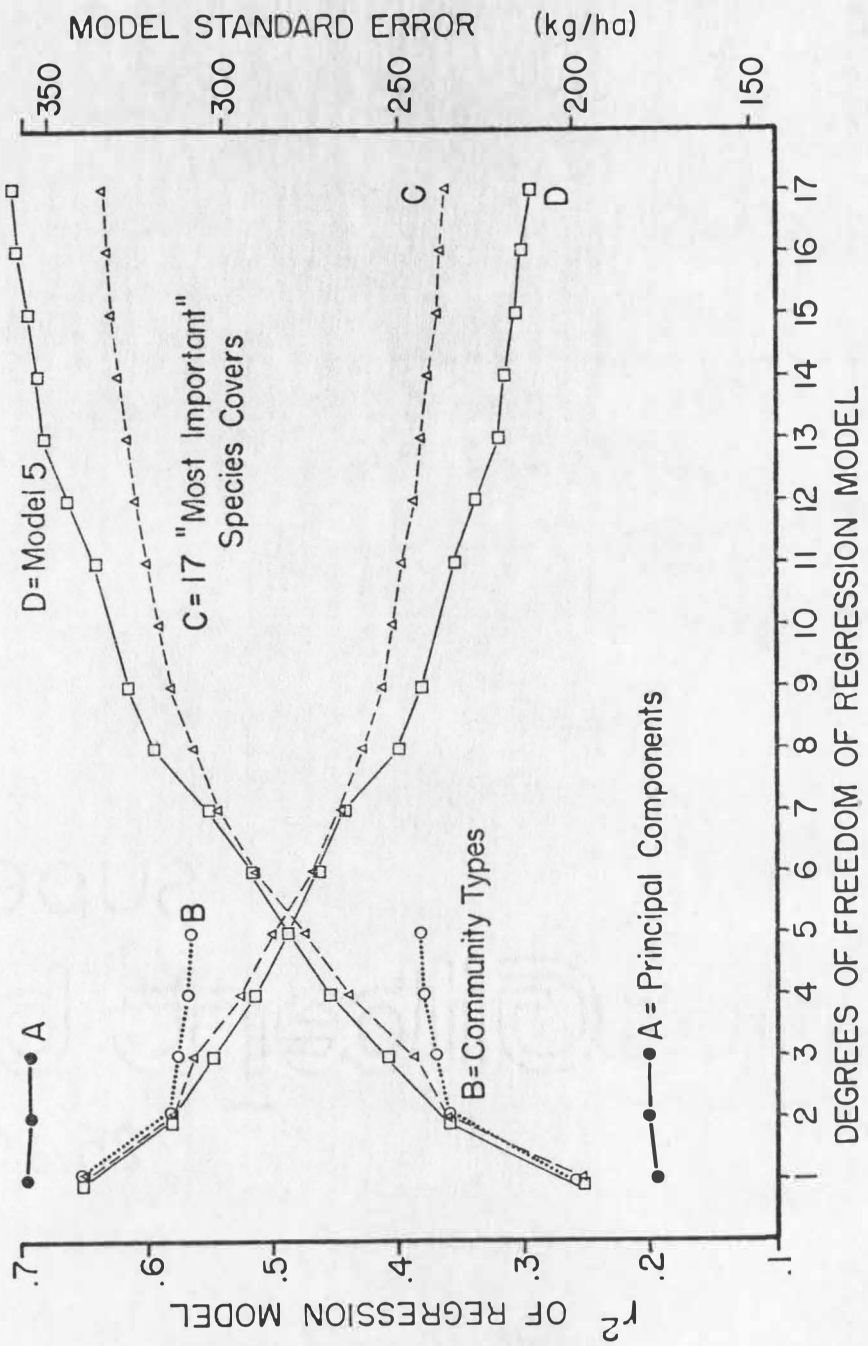
RESULTS

Using vegetation X's alone to predict production

Figure 1 shows the results of three stepwise addition regression models built from vegetation data alone (curves A, B, C), and one "best possible" regression curve (D) differing from C only in the inclusion of several environmental X's. The data sets A, B, C are different reductions of the original data set of 115 species over 45 plots. Model C uses the canopy cover of the 17 species described above as independent variables. Model C thus uses as continuous X's a subset of the original data matrix of all species over all plots. Model B uses five dummy variables to cover the six community types found over the 45 plots. Model A uses the three principal component coordinates of each plot as three independent variables.

Each curve is drawn twice. Ascending curves are read against the left ordinate showing r^2 of the model corresponding to the number of independent variables shown on the abcissa. Descending curves are read against the right ordinate of model standard error of prediction in kg per hectare. Both curves are given since standard error expresses model accuracy in practical units, and r^2 states what percentage of the total variance is explained. Note in comparing curves A, B, C that on a per degree of freedom (or number of X's inventoried) basis, species covers give production correlations equal to or better than those from community type classification of the study plots or principal components descriptions. This is reasonable in that species abundances are individually adjusted to observed production in Model C,

Figure 1. Regression model degrees of freedom versus r^2 and standard error comparing three different reductions of the original species cover data set (A, B, C), and one "best possible" regression curve for comparison (D). Curve A represents reduction of species cover data set into three principal component axes, Curve B into six community types, C a truncation of original data set into 17 species suspected "most important" in predicting production. Regression Model D is similar to C, with addition of environmental variables (see text).


MODEL STANDARD ERROR (kg/ha)
350
300
250
200
150
D=Model 5
C=17 "Most Important" Species Covers
B=Community Types
A=Principal Components
A
B
C
D
.7
.6
.5
.4
.3
.2
.1
r^2 OF REGRESSION MODEL
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17
DEGREES OF FREEDOM OF REGRESSION MODEL

but adjusted in groups in Models B and A. The high final r^2 (df=17) of Model C is still surprising considering the many zeros in the 17x45 matrix. This high frequency of zeros resulted in poor regression coefficients for some species.

One surprise was the superiority of discrete vegetation reduction (B) to continuous reduction by PCA (A), contrary to the assertions of Kessell (1976). Nichols (1977) and Gauch, Whittaker and Wentworth (1977) have pointed out shortcomings of PCA in vegetation ordination. Although some of their arguments do not apply to my data set because of its relatively narrow floristic range (common overstory dominants by design), I tried two other continuous reduction (ordination) techniques suggested as improvements over PCA. Phillips (1978) developed Polynomial Ordination as a modification of PCA to correct for nonlinearity and condense results into fewer axes. Although his testing showed polynomial ordination superior to PCA and Bray-Curtis ordination, combination of my first and second PCA axes into a single X did not improve the correlation with production (r^2 = .20). PCA axis three was not significantly correlated with axis one and was thus ignored. Contrary to the findings of Gauch et al. (1977) reciprocal averaging ordination (using Cornell Ecology Program 25A), did not give a better reduction of the 24 species cover data set than PCA (r^2 = .19, for df = 3).

Are curves A, B, and C meaningfully different? Models B, C, D all chose Stipa lettermannii, Bouteloua gracilis, and Elymus salina in the same order between X_1 and X_4 (as single species or community type labels), indicating these species covers are the most important

vegetal predictors of production. Curve B flattens before C or D because the last two community types do not organize the information contained in the species chosen as X_5 and above in curve C. Stipa lettermannii is again X_1 in Curve A, as the highest species correlate of principal component one, but components two and three do not organize the subsequent species described above, nor contain other information relevant to production. Thus distances between curves A, B, C at lower degrees of freedom show real differences in how efficiently different techniques (and their underlying assumptions) reduce the same vegetation data set.

Comparing the final "plateau" r^2 of curves A, B, C is more difficult because of the different degrees of freedom of the "final" models. Even at a constant df=3 (three X's), a regression model built from a longer list of random X's would be expected to have a higher r^2. The higher r^2 of curve C over most of its length seems not to be an artifact of more X's to chose from because of its rate of increase; an increase of .03 r^2 from adding X_n may not be practically useful, but it is too large for X_n to be random. Thus it seems that real production information is lost by condensing the vegetation data set into discrete community types, and more is lost by any of the continuous ordination techniques tested. Curve D (Model 5 of next section) is a "best fit" curve using both vegetal and environment X's. All X's in it are species covers (as in C) except: df 9=AWC top 1 m of soil, df 10, 11=surface drainage, df 14=infiltration rate. While addition of environmental X's does improve correlations, it is interesting how late these environmental X's

were chosen by the regression routine, and their relatively small effect. At this level of resolution, the environmental X's used here are either redundant with vegetation information (see next section), or of low predictive value.

Comparing the descending family of curves on the ordinate of standard error of regression (in kg per ha), we see that the magnitude of information lost by the inferior reduction/inventory techniques (especially PCA) is large enough to be of practical value.

Comparison of regression models including vegetation, soils, and environmental data

Figures 2 and 3 show that vegetation, data treatment, and relative curve positions in Models 3, 1, and 2-4 are identical to Curves A, B, C (Fig. 1), respectively. Not only can continuous species covers (original data form) be the most powerful X's (Models 2, 4, 5), but some predictive information appears to be unique to vegetation data and not contained in the environmental data. Otherwise, Models 1, 2, 3 would reach similar final accuracy. Specifically, the difference between PCA and community type classification are not masked or lessened by addition of other data. But vegetation X's are to some degree redundant with the soil or environmental X's studied (especially elevation); loss of species cover information by either classification or PCA causes preferential selection of partly redundant, previously less efficient environmental X's ahead of subsets of vegetation X's (compare Models 2, 1, 3). Thus, relative to other data, optimization of vegetation data reduction is important.

Figure 2. Degrees of freedom versus r^2 for five regression models using vegetation and environmental data to predict plant community production. Subsets of X's added to stepwise upward fashion are: V = vegetation data, S = soils data, EL = elevation, SL = % slope. Models 1-5 represent different strategies in data collection and reduction (see text).

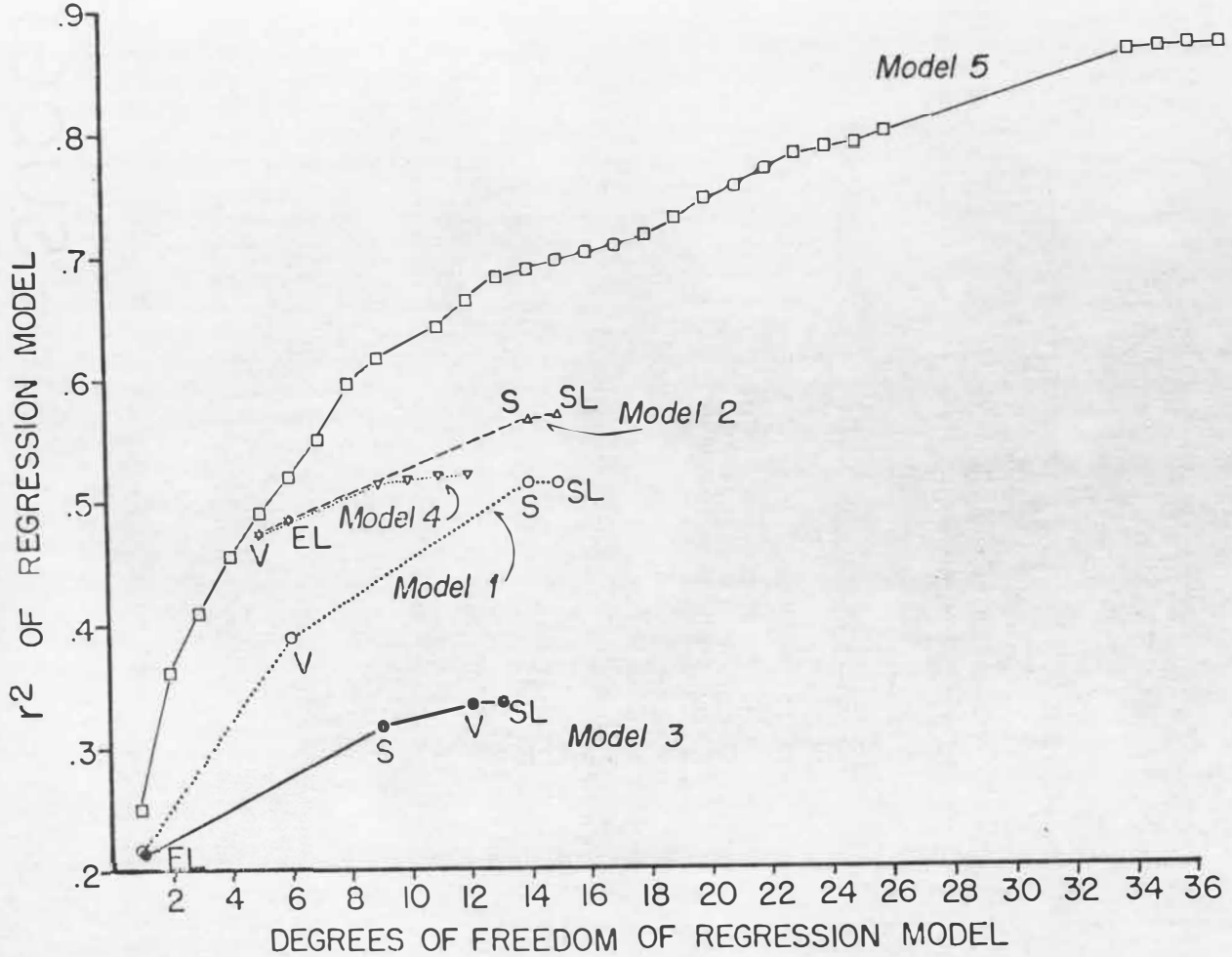
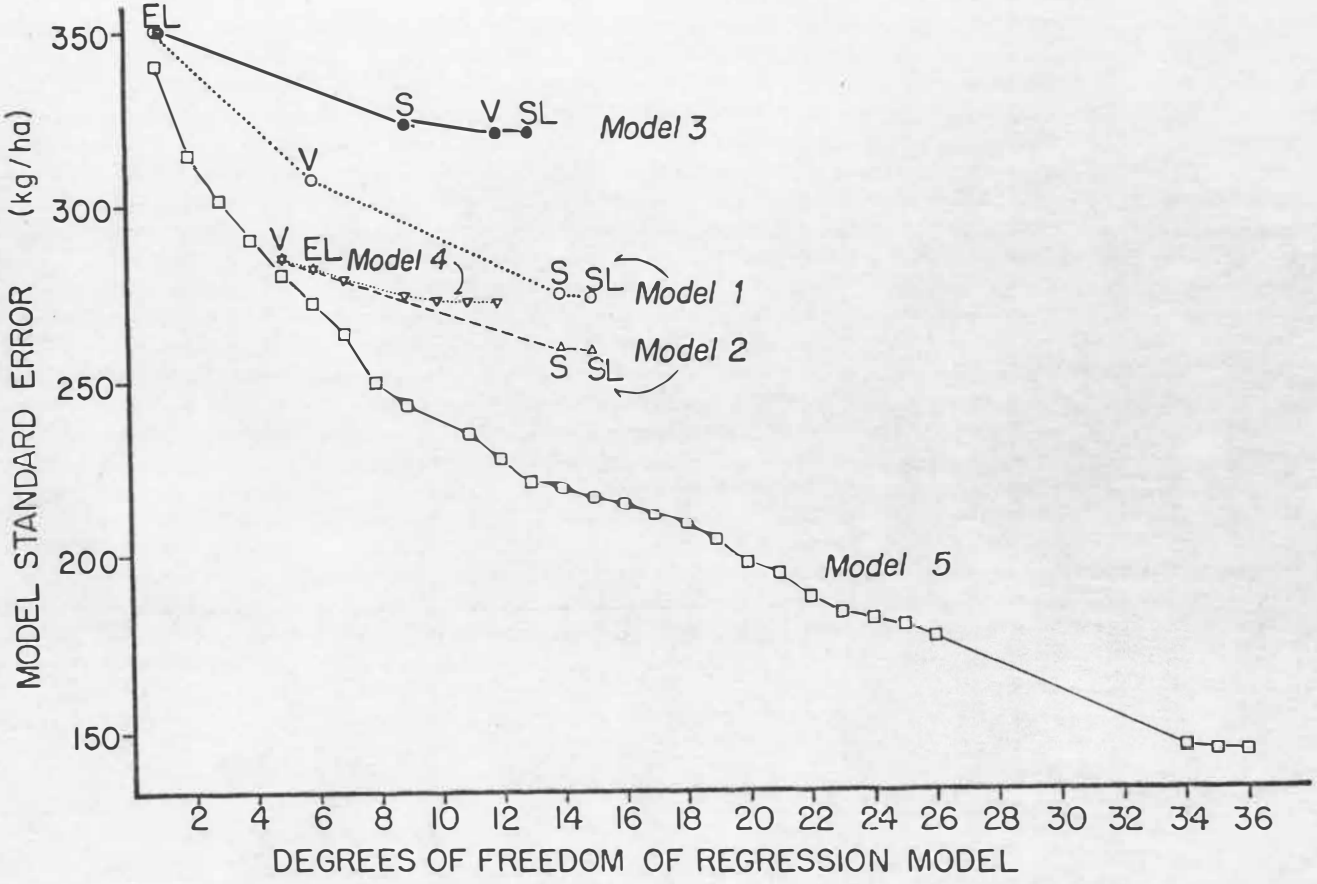

.9
.8
.7
.6
.5
.4
.3
.2
r2 OF REGRESSION MODEL
Model 5
S
SL
Model 2
V
EL
Model 4
S
SL
Model 1
V
V
SL
S
Model 3
EL
2 4 6 8 10 12 14 16 18 20 22 24 26 28 30 32 34 36
DEGREES OF FREEDOM OF REGRESSION MODEL

Figure 3. Regression model degrees of freedom versus standard error of regression for five different models (see text) using vegetation and environmental data to predict community production. Subsets of X's added in stepwise upward mode are: V = vegetation data, S = soils data, EL = elevation, SL = % slope.


MODEL STANDARD ERROR (kg/ha)
350
300
250
200
150
EL
S
V
SL
Model 3
V
V
EL
Model 4
S
SL
Model 1
S
SL
Model 2
Model 5
2
4
6
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28
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34
36
DEGREES OF FREEDOM OF REGRESSION MODEL

General purpose soils data classified at the Great Group level is partially redundant with vegetation data, as indicated by the relative order of its inclusion and size of contribution relative to vegetation in Models 1, 2, 3. The replacement of classified general purpose soils data with the specific purpose continuous X's (Model 4) of maximum available water storage in the top 1 m, relative infiltration rate, and a qualitative evaluation of surface water drainage did not increase correlations. While AWC and drainage were important enough to be selected as df 9-11 in Model 5, the subset of classified soils data appeared to carry unique information for production as indicated by its inclusion later in Model 5. Percent canopy cover taller than exclosure height (not clipped in measuring site production) was of no predictive value.

Steepness of slope was found consistently useless in all models. The leveling of the four curves due to addition of this final X should not be interpreted as an impossibility of further model improvement. Unlike the vegetation only models illustrated in Fig. 1, the better vegetation-environment models in Figs. 2 and 3 continue to improve correlations as more data are added.

DISCUSSION AND IMPLICATIONS FOR VEGETATION INVENTORY

Vegetation inventory systems can be quantitatively compared; this paper demonstrates one of many possible approaches. I wish to encourage land management agencies to develop and test inventory tools before application.

How widely can the results of specific comparisons, such as this one, be generalized? Conservatively, these findings apply to only the study area and specific reduction methods compared. Year to year variation in species' covers is great, and production values should have ideally been clipped over larger plot areas. But I believe certain perspectives gained from this study can be useful elsewhere.

The three ordination techniques used to reduce the truncated (24 species) data matrix (unstandardized PCA, Polynomial ordination, reciprocal averaging) included the currently better general purpose ordination techniques. I did not include polar ordination (Bray-Curtis) because much of its power is lost when "true" end stands are not known (Phillips 1978). Why did these reduction techniques producing continuous, synthetic S'x perform poorly, contrary to expectations? As mentioned before, much of the production information is contained in the covers of a few common grasses and herbs. Regression upon these X's individually produced the "best fit" Model 5. Apparently much information or resolution of these most

important X's was lost by their submergence into synthetic variables of ordination axes coordinates. Stated another way, regression of variables in groups yields correlations inferior to a multiple regression model which adjusts each X individually. Data loss by reduction into continuous variables can be less or greater than the loss into classified X's. What matters more is how the reduction model handles that subset of observations or X's which best predict the desired Y's. Acknowledging the degree to which these X's are natural (ultimate cause) versus artificial (convenient) predictors will affect your choice of how to weigh, reduce, and apply the data.

Why did community type classification give better correlations per degree of freedom than the ordination techniques? The classification method applied to the data set had the effect of weighting those species named as understory labels. Thus it approached the individual species regression of curve C (Fig. 2) more closely. Information on less important species was confounded or hidden by the species abundance criteria in the identification key, hence the community type curve (curve B, Fig. 2) flattens quickly. The classification of continuous data into discrete units was more accurate (higher r^2 at any df) than ordination not necessarily because of any inherent superiority of classification versus ordination, but because the combination of specific methods and data weighted some of the better predictive X's.

In summary, the form (continuous versus discrete) of the final reduced data is here less important than the effectiveness of the

reduction scheme in preserving the better predictors of the specific data desired. Optimization of any wildland inventory requires: 1) isolation of Y's of interest, 2) hypothesized mechanisms connecting them to readily observable X's, 3) testing of candidate X's and their connecting mechanisms, and finally 4) choice of collection methods, and reduction methods should X's be too numerous or bulky to handle separately. The need for reduction methods is ideally eliminated by sufficient attention to the first three steps!

Returning to the second goal of quantifying data loss from specific purpose to general purpose X's, my candidates for more accurate, specific purpose predictors of community production did not give higher final correlations than their general purpose analogs (compare Models 4 and 2, Fig. 3). The four specific purpose soil and drainage X's of Model 4 were slightly better predictors, as evidenced by their earlier selection in Model 5 than the general purpose Great Group classifications. But these two different sets of soil-environmental measures were different in the information they contained, with the general purpose measures less redundant with vegetal information already in the model. This neither supports nor disproves my suspicion that a general purpose data base is a less accurate compromise for any one data need; it merely emphasizes that the second and third steps of the procedure outlined above can be difficult. A main benefit of these two steps is a greater knowledge of what affects your Y's of interest. For example, the order of selection of the four specific purpose soils variables of Model 4 in

Model 5 show that in my study area, storage of winter precipitation affects production more than summer precipitation.

The procedure described above for developing and testing new wildland inventory schemes applies not only to on-the-ground vegetation inventory, but also to aerial inventory, and remote sensing with climatological or physiological models.

Inventoried variables are usually stored over the landscape in map form, not just isolated points as in this study. This requires a fifth, final step in the procedure proposed above: deciding how best to record the final X's on a map. Because this step is usually assumed, it has been confused with the fourth step of data collection and reduction.

Under many conditions the most information-rich mapping technique for a single continuous variable is to record its closely-spaced contours on the map base. Discrete, qualitatively different classes can only be mapped as polygons, although this approach can be more practical for certain patchy, discontinuous variables on a very large map scale. Many possible intermediate mapping procedures exist for appropriate variables. Unfortunately, gradient vegetation mapping techniques have not been well developed. Kessell's (1976) work is a first effort in this direction. The development of useable techniques for field mapping of continuous vegetation variables would stimulate new approaches to vegetation inventory where this inherently more accurate mapping method is appropriate.

For example, Fig. 3 suggests that above certain minimum accuracies n maps of n continuous species' covers over the landscape would give

better production estimates than one map of n community types. Continuous maps of such a variables might be drawn in the field or from photos by: 1) deciding on an interpolation algorithm, 2) mapping a relatively few cover (or other) values of species X as points or lines subjectively chosen (in value and location) to efficiently describe the landscape, then 3) digitizing the hand-drawn map for computer interpolation of the value of all "empty" map cells. Discontinuities could be indicated as easly as gradual changes. The Y (or Y's) of interest could be anything, not just production.

So far in this paper, I've compared different vegetation inventories only in terms of final accuracy of records or prediction. Efficiency (accuracy per unit cost) is the practical criterion by which the land manager compares inventory systems. Questions of efficiency can best be addressed with field tests. Such tests are of minor cost compared to the combined losses of inferior methods used over large areas for many years. Besides addressing the two basic methodological questions identified, I hope this paper shows that 1) more accurate vegetation inventory methods exist than those in present use, and that 2) questions of accuracy and efficiency can and should be objectively answered in the choice of any vegetation inventory system to be used extensively.

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