Post-stratified Estimation of Coarse Woody Debris Volume using the Down Woody Materials Sample of Forest Inventory and Analysis

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Abstract

The Forest Inventory and Analysis (FIA) program of the USDA Forest Service conducts a nation wide survey of America's forests. FIA field crews collect data on tree size, condition, and species, as well as data on the conditions in which they grow from a network of permanent ground plots known as Phase two plots (P2). FIA crews also collect more detailed forest health indicators, including data on Coarse Woody Materials (CWD), on a $\frac{1}{16}$ subset of the P2 sample. This subset is known as the Phase 3 (P3) sample.

FIA regularly publishes reports on the quantity and quality of America's forests using data from the P2 sample. A post-stratified estimation technique is used increase the precision of the estimates without increasing the sample size. Currently, research on how to best apply the post-stratified estimator to produce estimates of the P3 forest health indicators has been lacking. This thesis will address this gap by testing 18 candidate geospatial layers (both categorical and continuous) as stratification layers to produce estimates of CWD volume in the Lake-states region of Minnesota, Wisconsin, and Michigan. Continuous geospatial layers will be broken into two to five strata using an optimization algorithm. A simulation experiment is used estimate the long term effectiveness of successful geospatial layers. The simulation experiment is performed to compare the conditional and unconditional variance estimators of the post-stratified estimators. Successful geospatial layers are then applied to sub-populations of varying sizes to determine the effect of spatial extent on the post-stratification method. Stratification layers derived from remote sensing products provided the best results. Using two or three strata is recommended because further partition of the population simply produces ineffective sliver strata. No difference was detected between the two competing variance estimators. The effect of spatial extent of the stratification was volatile. The use of large spatial extents is recommended. The conclusion of this thesis summarizes the lessons learned throughout as well as ideas for future research on the topic.

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Chapter 1

Introduction

The Forest Inventory and Analysis (FIA) program of the U.S. Department of Agriculture, Forest Service conducts a nation-wide survey of all lands. The survey is conducted using a three phase strategy. The first phase (P1) consists of remote sensing of the landscape. In the second phase (P2), permanent plots are installed on the landscape at a sampling intensity of approximately one plot per 6,000 acres. Field crews collect a suite of site and tree measurements on each P2 plot including tree species, diameters, and heights, as well as data on the conditions in which they grow. The third phase (P3) is a $\frac{1}{16}$ subset of the P2 sample where more detailed data about forest health are collected. Forest health indicators include forest soils, understory vegetation, lichens, and down woody material (DWM). The DWM indicator is further divided into measurements of fine woody debris (FWD), duff and litter, shrub and herbs, residue piles, and coarse woody debris (CWD). This study is only concerned with the CWD component of the DWM indicator.

FIA regularly publishes reports on the condition and quantity of forest resources including population estimates of forest area and volume. These reports are based upon data from the P2 and P3 samples. FIA employs a post-stratified estimation technique that incorporates ancillary data to reduce sampling error of the estimates. Geospatial data layers consisting of remote sensing data, political boundaries, ownership maps, and other data are combined to create the required ancillary data. The application of the post-stratified estimator for estimates using the P2 sample is well researched. But, research on the application of this technique to estimates using the P3 sample is lacking.

Currently, FIA has produced plot-level estimates of P3 indicators or estimates under the assumption of simple random sampling (SRS). There is potential for the post-stratified estimation technique to reduce the sampling error of estimates of forest health variables, but the magnitude of the reduction is unknown. Production of population estimates of forest health indicators is a major priority of FIA.

There are two major motivations behind this work. The first motivation is a general one. Carbon (C) cycle science is an increasingly important subject as concern over global climate change continues to increase. DWM is an important component of the C cycle. It has been estimated that approximately 14% of the total C pool of forests occurs in dead organic materials, such as DWM (Woodall and Liknes, 2008). It is one of five pools of environmental carbon defined by the Intergovernmental Panel on Climate Change (Penman et al., 2003). There have been no long-term/large-scale studies of DWM C in the United States available to track changes over time (Woodall et al., 2008). Developing a method for providing the best estimates possible for FIA's DWM indicator will provide a good start to filling this need. Over time these estimates could become increasingly valuable and aid in the understanding of this component of the C cycle.

The second motivation is more specific. There is an internal need in FIA for research on producing population estimates for P3 indicators. Only within the last few years have complete inventories of P3 indicators become available for estimation using a consistent national data collection protocol. The DWM indicator has received theoretical attention meaning that the models for calculating volume per acre values per plot and estimators for combining plots to calculate post-stratified estimates of population parameters are complete (Woodall and Monleon, 2008). Thus, the preliminary work on DWM has been done. However, specific research on how to apply these estimators in terms of the most effective ancillary data and optimal number of strata is lacking. Guidelines for what spatial extent is appropriate for calculating population estimates of CWD have not been worked out. Possible levels of spatial extent include state level, ecological province, or county level. There is also no research available on the magnitude of variance reduction possible using a post-stratified estimator for CWD population estimates. In addition, a review of the literature on post-stratified estimation reveals there are two common estimators for variance; conditional and unconditional. FIA currently uses the unconditional estimator. However, there is no research available that compares the two estimators for use with FIA samples. This thesis will address all of these gaps.

This thesis will optimize the existing post-stratified estimator used by FIA to produce population level estimates of CWD volume. Specifically, it will address the following questions:

1. What geospatial layer or combination of geospatial layers provides the greatest increase in precision when used for post-stratified estimation of the CWD sample of FIA?

2. What is the best estimator (conditional or unconditional) to use for computing the variance of the population mean?

3. What is the appropriate spatial extent to apply the post-stratified estimator for CWD estimates?

1.1 Overview

This project consists of three main components. The first component is the Geospatial Layer Analysis. In this analysis a set of candidate geospatial layers is tested to see which can provide the most precise estimate of the CWD volume population mean. Second, a simulation experiment is conducted on the best performing geospatial layers from the first component. The main objective of the simulation experiment is to examine how the best stratification schemes identified in the Geospatial Layer Analysis perform over many different samples. Information from the simulation experiment will also be used to examine the properties of the two variance estimators over many samples. The third component, Estimation Unit Analysis, will apply the best stratification schemes identified by the first two study components to sub-populations (called estimation units) defined at various levels of spatial extent.

The remainder of chapter one provides a review of several topics relevant to this thesis. First, an overview on the post-stratified estimation technique will be provided. Then, an overview of the FIA sample design will be provided with a discussion of both phase two and DWM sampling protocols. Details on the standard FIA estimation technique are also provided. Chapter one will conclude with a very brief overview of CWD ecology as it pertains to sampling and estimation. The ecology of CWD in northern forests is a large and complex topic. This paper is mainly concerned with the statistical question of how to produce the best estimate possible with a given sample. One cannot ignore the biological component involved, but it was deemed that a full discussion of CWD ecology would distract from the main objectives of this paper. However, there are a few broad statements that should be made concerning the current knowledge of CWD ecology that will aid in the understanding in the results. Chapter two will describe the study area, the FIA field data, and the candidate geospatial layers. Descriptions of the geospatial layers will include the motivation for including them in the study. A detailed description of the analysis methods used will be discussed in chapter three. Chapter four will summarize the results of all three study components. Chapter five will provide a discussion of the results and offer concluding remarks. This project produced a large number of supporting figures and tables. These are included in the appendix.

1.2 Post-Stratified Estimation

Post-stratified estimation is a method of data analysis which is intended to increase the precision of an estimate by partitioning the population into homogeneous subgroups called strata after the sample has been drawn (Smith, 1991; Cochran, 1977; Gregoire and Valentine, 2008; Holt and Smith, 1979). The idea is that the weighted sum of the variances of homogeneous strata will be smaller than the variance computed from an unstratified estimator, e.g., estimates made under the assumption of simple random sampling. The weights can either be estimated or assumed known, depending on the auxiliary information available to the statistician.

Post-stratification is distinct from stratified sampling, in which the population is first divided into strata, and then a sample is independently drawn from each stratum by some method according to an allocation rule (Cochran, 1977; Gregoire and Valentine, 2008;

Särndal et al., 1992; Thompson, 1992). Zhang (2000) points out a difference between the terms *Post Stratification* and *Post Stratified Estimation*. According to Zhang (2000) Post stratification refers to the act of partitioning a population in two or more non-overlaping strata, which imposes a structure on the population. Post-stratified estimation refers to the specific use of the stratification information for producing an estimate. This technique is used by several, large scale surveys such as the current population study and the National Health Interview Study (Valliant, 1993).

There is some inconsistency on the exact definition of *post-stratification* among major sampling texts. The disagreement is over exactly when or how a sample unit is assigned to a stratum. According to Cochran (1977), "*the units can be classified into the strata only after the sample data are known*" This implies that the *post* in post-stratification refers to post-measurement as opposed to post-sampling. Särndal et al. (1992) provides several scenarios that would be referred to as post-stratification. One scenario is when the strata membership is known for all elements in the population, but this information is not used during the sampling phase. After the sample is selected, this information is used to allocate each unit of the sample into a stratum, which Särndal et al. (1992) refer to as "groups". Särndal et al. (1992) states, "*In this case, the group membership information is thus utilized at the estimations stage, not at the design stage.*" In another scenario offered by Särndal et al. (1992) membership of population elements to strata cannot be known beforehand. In this case, strata membership must be observed during measurement, as Cochran (1977) says. Thus, Särndal et al. (1992) provides examples of post-stratification that are both post-measurement and post-sampling. Thompson (1992) only provides a short discussion of post-stratification in which he states, "*In some situations it may be desired to classify the units of a sample into strata and to use a stratified estimate, even though the sample was selected by simple random, rather than stratified, sampling.*" This definition suggests that post-stratification may be used at any time after a sample is drawn. Finally, Gregoire and Valentine (2008) defines post-stratification as, "*The strategy of stratifying the sample after it has been selected and then estimating strata and population parameters in the usual stratified fashion is known as poststratification.*" The above discussion is included in order to provide a more complete discussion of the topic. This thesis is only concerned with estimation process and restrict the terminology used to *post-stratified estimation*. The use of this term is supported by the definition provided by Gregoire and Valentine (2008).

Post-stratified estimation is usually employed for two main reasons. Post-stratified estimation allows the statistician to develop a separate stratification scheme for separate study variables. This can occur frequently in multi-resource samples (Gregoire and Valentine, 2008; Särndal et al., 1992; Holt and Smith, 1979). Second, the auxiliary information required for post-stratified estimation may not be available at the time the sample is taken (Gregoire and Valentine, 2008; Särndal et al., 1992; Cochran, 1977). Post-stratified estimation allows these data to be incorporated in the estimation process whenever it becomes available.

As an aside, the current design of the FIA sample is not conducive to stratified sampling. The current design, commonly referred to as *annual*, calls for the establishment of permanent field plot locations that will be remeasured at regular intervals over time. It is not likely that any stratification used to draw the initial sample would remain an optimal stratification over many remeasurements of the plots. In addition, FIA is a multi-purpose inventory which is used to generate estimates of various forest parameters. Any stratification used to draw the initial sample could not optimize all the possible estimates produced from the FIA sample. As a result, FIA would be forced to choose which variables should be optimized and which should not.

In mathematical terms, a finite population P consisting of $N = \sum_{h=1}^{L} N_h$ elements is divided into $h = 1, \ldots, L$ strata. Every element $i = 1, \ldots, N$ in population P is assigned to one and only one stratum. $Y = \sum_{i=1}^{N} y_i$ is the attribute of interest on each element of the population. A random sample of size n is drawn from population P without regard for the strata. Following the sample, each element of the sample is assigned to one and only one stratum such that $n = \sum_{h=1}^{L} n_h$. One important distinction between a stratified sample and a sample that is post-stratified is that the n_h's are known for stratified samples but random variables for the post-stratified sample (Cochran, 1977; Gregoire and Valentine, 2008; Thompson, 1992). The population mean is defined as

$$\bar{Y} = \sum_{h=1}^{L} \sum_{i=1}^{N_h} \frac{Y_{hi}}{N} \tag{1.1}$$

with variance

$$\bar{Y} = \sum_{h=1}^{L} \sum_{i=1}^{N_h} \frac{(Y_{hi} - \bar{Y})}{N - 1} \tag{1.2}$$

The population mean is estimated by

$$\bar{y} = \sum_{h=1}^{L} \frac{N_h}{N} \bar{y}_h = \sum_{h=1}^{L} W_h \bar{y}_h \tag{1.3}$$

where the estimated stratum mean is computed as

$$\bar{y}_h = \sum_{i=1}^{n_h} \frac{y_i}{n_h} \tag{1.4}$$

and

W_h is the stratum weight defined by $\frac{N_h}{N}$

Notice the post-stratified estimate of the mean is a weighted average of the estimated strata means. It is an unbiased estimator of the population mean as long as the $\bar{y}_h$ are unbiased and none of the n_h's are zero (Cochran, 1977; Gregoire and Valentine, 2008). Gregoire and Valentine (2008) point out that a bias can occur when the strata weights are incorrectly specified. They define this bias in the estimation of the population total as the sum of differences between the true stratum weight and the incorrect stratum weight multiplied by the stratum mean (Equation 1.5).

$$Bias(\bar{Y}_{post}) = \sum_{h=1}^{L} (W'_h - W_h)\mu_{yh} \tag{1.5}$$

Where

W'_h is the incorrectly specified stratum weight of stratum h

W_h is the true stratum weight of stratum h

μ_{yh} is the true mean of stratum h

Estimation of the variance of the population mean is more complex. There are two candidate estimators available to the statistician. The first is the unconditional variance estimator, which ignores the actual observed allocation of the sample across the strata, $\vec{n} = (n_1, \ldots, n_L)$. Rather, it averages across all possible allocations of $\vec{n}$ from a sample of fixed size n (Gregoire and Valentine, 2008; Holt and Smith, 1979; Smith, 1991). The second is the conditional variance estimator which takes the actual sample allocation into account. The terms 'unconditional' and 'conditional' refer to the two possible sampling distributions of $\bar{y}_{post}$. The unconditional estimator is given by

$$V(\bar{y}_{post}) = \left(\frac{1}{n} - \frac{1}{N}\right) \sum_{h=1}^{L} \left(\frac{N_h}{N}\right) s_h^2 + \frac{1}{n^2} \sum_{h=1}^{L} \left(1 - \frac{N_h}{N}\right) s_h^2 \tag{1.6}$$

and the conditional is given by

$$V(\bar{y}_{post}|\vec{n}) = \sum_{h=1}^{L} \left(\frac{N_h}{N}\right)^2 \left(1 - \frac{n_h}{N_h}\right) \frac{s_h^2}{n_h} \tag{1.7}$$

where the unit to unit variability in stratum h (s_h^2) is given by

$$s_h^2 = \frac{\sum_{i=1}^{n_h} (y_{h,i} - \bar{y}_h)^2}{(n_h - 1)} \tag{1.8}$$

There is not general consensus as to which is the better estimator of the variance of the mean, however several authors recommend using the unconditional variance estimator for survey planning purposes and the conditional for inference purposes (Gregoire and Valentine, 2008; Holt and Smith, 1979; Smith, 1991). Holt and Smith (1979) report that the unconditional variance estimator is valid when the sample is approximately proportionally allocated to the strata, which they refer to as a *balanced* sample. They conclude that unconditional variance estimators are valid prior to the sample being taken, but since the configuration of $\vec{n}$ is known once the sample is collected, the variance should be estimated conditioned on this information.

The statistician performing the study must determine which sampling distribution they will employ for the purposes of inference. There are some advantages to the conditional distribution framework in that it may offer better confidence interval coverage than the unconditional distribution when a sample is out of balance, which affects the inference one might draw from the estimate. As the sample becomes out of balance, the conditional variance estimator tends to also increase, which means the confidence interval will more often contain the true population parameter value being estimated. Holt and Smith (1979) provide a numerical example of this phenomenon. Little (1986) points out the difference between the conditional and unconditional estimators is of order $\frac{1}{n^2}$, which is small when the sample size is large.

FIA uses an unconditional estimator for variance computations (see section 1.3.5). Experience has shown that, when post-stratified, the FIA sample is very close to being proportional. This is a result of the hybrid FIA sample design, which can be described as systematic with a random component. When sampling intensities are held constant, the resulting sample tends to be approximately proportionately allocated to strata.

In addition to reduction of variance, post-stratified estimation can also provide a reduction of bias caused from non-response (Zhang, 2000; Smith, 1991; Jagers, 1986; Thomsen and Holmøy, 1998), and consistency with estimates from other sources (Zhang, 2000; Thomsen and Holmøy, 1998). Neither of these two properties of the post-stratified estimator are considered in this paper, but they are reported here for completeness.

Many authors have covered the bias reducing benefits of post stratification (Smith, 1991; Jagers, 1986; Little, 1986; Zhang, 2000; Thomsen and Holmøy, 1998). Anganuzzi and Buckland (1993) describe a technique for reducing bias when the sample is not a probability sample. Little (1986) provides a discussion of post-stratification in a model-based framework, as opposed to the design-based framework used in FIA. He makes the important point that, given different non-response rates, collapsing strata may decrease bias at the expense of precision (page 1005).

Non-response occurs when an element in the population is selected to be part of the sample but due to some unanticipated circumstance it is never sampled. Non-response in a sample survey can cause a bias when the sample elements that are not sampled are different from the elements that were sampled. Failure to account for this possibility can lead to estimates that are either higher or lower than they would be in the absence of non-response. There are two common ways of adjusting for bias caused by non-response in a sample survey; weighting and imputation (Little, 1986). Weighting involves using the known non-response rates to adjust the estimates. This method ignores the non-sampled elements and expands the remaining sample elements. Imputation replaces the missing values with a modeled value. This can become very cumbersome when the data set is large or complex. Imputation models can range from simply applying the stratum mean to elegant non-linear models. Little (1986) points out that using mean imputation can result in a distortion of the distribution of values in a given cell. McRoberts (2003) provides a detailed comparison of nine different non-response compensation techniques, including both weighting and imputation techniques, using FIA samples and estimation procedures.

Consistency with estimates from other sources comes about when the total size of the population is provided by an auxiliary data source. The use of this value forces the estimate of the total size of a population to agree with the auxiliary source. For example, if the U.S. Census geospatial layer is used to post-stratify a state, then the post-stratified estimate of total area will match the area of the Census layer. If simple random sampling is used, then the estimate of total area likely would not match because it lacks this calibration information.

1.2.1 Number of Strata

Cochran (1977) provides a discussion on the relationship between the number of strata used and the corresponding reduction in variance. The general conclusion is that variance of the population parameter of interest will be reduced at roughly a $\frac{1}{L^2}$ rate when strata of roughly equal size are used. In this context, size is interpreted as the number of samples per stratum. This result holds when a sample is stratified using some allocation rule, such as Neyman optimal allocation rule, which may not produce equal strata sizes. The result is more complex when ancillary data are used to stratify a sample. In this situation, the rate of variance reduction of the population parameter of interest depends in part on the correlation between the random variable of interest and the ancillary data. Cochran (1977) illustrates this in terms of the following hypothetical regression model. His discussion is paraphrased below.

Let

$$\phi(x) = E(y|x) \tag{1.9}$$

be the regression of y on x, where y is the variable of interest and x is an ancillary variable. This model can be rewritten as

$$y = \phi(x) + \epsilon \tag{1.10}$$

It is assumed that $\phi(x)$ and ϵ are not correlated. Thus, $S_y^2 = S_\phi^2 + S_\epsilon^2$. In this model S_ϕ^2 can be reduced by stratification but S_ϵ^2 can not. So as the number of strata (L) is increased there will come a point where the constant S_ϵ^2 will overwhelm any gains in precision. The rate at which this point is reached is partially determined by the relative sizes of S_ϕ^2 and S_ϵ^2 and the strength of the unstratified correlation between y and x. If the regression model is linear, then it can be written as

$$y = \alpha + \beta x + \epsilon \tag{1.11}$$

Under this model the variance of $\bar{y}_{strat}$ using stratified estimation is

$$V(\bar{y}_{strat}) = \frac{S_y^2}{n}\left[\frac{\rho^2}{L^2} + \left(1 - \rho^2\right)\right] \tag{1.12}$$

where

ρ is the linear correlation between y and x in an unstratified setting

L is the number of strata

An additional assumption that the strata are of equal size ($\frac{N}{L}$) is also applied. Under these conditions, as ρ approaches 1 the term within the square brackets approaches $\frac{1}{L^2}$. As ρ approaches 0, the term within the square brackets approaches 1, meaning that $Var(\bar{y}_{strat})$ is equal to $Var(\bar{y})$, the population variance estimated under simple random samling. In other words, the stratification offers no reduction in variance. He draws the general conclusion that unless the correlation between y and x is very high, there is little gain beyond 6 strata.

1.2.2 Existing Research on Post-Stratified Estimation in FIA

Many authors have addressed aspects of post-stratified estimation for producing estimates of forest attributes, typically forest area and volume, using FIA data and remote sensing products. All the work summarized here involves the use of the P2 sample. The following section provides a review of the most important work on the topic.

Hansen and Wendt (2000) provided some of the first work in applying digital remote sensing products to post-stratified estimation of FIA data. This work demonstrated that precision improvements comparable to those achieved through double-sampling for stratification can be achieved using digital remote sensing in post-stratified estimation. Hansen and Wendt (2000) compared 1986 population estimates to 1998 population estimates in Illinois and Indiana. The 1986 estimates were produced using traditional double-sampling for stratification where the stratum weights are estimated. The 1998 estimates used remote sensing data and stratum weights were considered known. Landsat Thematic Mapper (TM) data compiled by the National GAP Analysis Program were used to form four strata: Forest, Non-forest, Forest Edge, Non-forest Edge. The width of the two edge strata was two pixels (28.5 meter by 28.5 meter resolution). In general double-sampling for stratification produced lower sample errors for forest area and growing stock volume whereas post-stratified estimates using remote sensing produced lower sampling errors for growing stock growth and sawtimber growth. The authors point out that the differences in sampling error are confounded by changes to field protocol and plot design between 1986 and 1999. However, the operational efficiency incurred through the use of remote sensing products make it preferable to double-sampling which requires manual interpretation of imagery.

McRoberts et al. (2002b) expanded upon the work of Hansen and Wendt (2000). The authors tested a different large-scale land classification product than Hansen and Wendt (2000) known as the National Land Cover Data (NLCD) to measure its effectiveness as a stratification layer. NLCD is a digital map product developed by the Multi-Resolution Land Characterization Consortium (MRLC). It consists of 21 different land cover classes. NLCD data for Indiana, Iowa, Minnesota, and Missouri were acquired and combined with FIA data for those states collected in 1999. Three different investigations were conducted.

First, an assessment of the correspondence between the NLCD forest or non-forest classification based on the pixel and classification based on the FIA plot. Second, the effectiveness of using two different groupings of the the NLCD land cover classes to form forest and non-forest strata. In addition to the these two strata, two edge class strata of varying widths were also tested. Third, the effects of image registration and plot location errors on the precision of forest land area estimates were investigated. McRoberts et al. (2002b) provide four conclusions from this study. First, the high level of correspondence between pixel and plot classifications of forest and non-forest demonstrate a real relationship as opposed to a spurious one. Second, aggregations of NLCD classes are effective when used as a stratification layer for forest area estimates. Third, the use of the two edge class strata enhance the effectiveness of the stratification. Fourth, the effects of image registration error and plot location error are detrimental to the precision of the estimate, but the magnitude of the effect is nearly negligible compared to the overall gains in precision from stratification.

Gormanson et al. (2005) also explored the use of NLCD in stratified estimation. They examined the use of single-date verses multi-date derived stratifications. The study area was defined by the Minnesota portion of Multi-Resolution Land Characteristics Consortium (MRLC) mapping zone 41 which covers about 60 percent of the total land area of Minnesota and 90 percent of its forest land. Classified land cover maps were provided by the National Land Cover Data set (NLCD) from 1992 and the draft of the NLCD 2001 product. These data were used to test 15 distinct stratifications for producing estimates of forest area, volume, growth, mortality and removals. The stratification ranged from simple forest/non-forest methods, to forest/non-forest with a transition strata of varying widths, to the four strata scheme used in Hansen and Wendt (2000) and McRoberts et al. (2002b) with varying widths in the edge strata. Stratifications for the growth, mortality and removals estimates were built from a combination of both the NLCD 1992 and 2001 data sets. As is typical in these studies, the greatest gains in efficiency were seen in the estimates of forest area. It has been hypothesized that this is due to the fact that passive remote sensing products, which are primarily detecting canopy reflectance, classify the presence of forests very well, but do not provide much information about the characteristics of the forest beneath the canopy. There was relatively little difference between the number and width of edge class strata in terms of gained efficiency. For forest area, the observed relative efficiencies (RE) (Equation 1.13) ranged from 2.20 to 2.93. RE is a metric used to measure the increase in precision relative to another estimation method, typically simple random sampling (SRS), and is defined as the variance computed under SRS divided by the variance under post-stratified estimation. A RE of 1.0 indicates no gain in precision and values greater than 1.0 represent a relative gain in precision. RE's for volume, growth, removals and mortality had a range of 1.07 to 1.37. The authors confirmed the previous conclusions of Hansen and Wendt (2000) and McRoberts et al. (2002b) that aggregated land classification maps are effective when used for stratified estimation of forest attributes, and that edge strata increase the effectiveness of the stratification. In addition, the offer three additional conclusions. First, change based stratifications (i.e. those using multiple dates of imagery) do provide an increase in precision over single date stratification, but the increase is small. Second, differences in precision estimates between the usual two edge strata and the one transition strata were minimal. Third, stratifications were much more effective in increasing the precision of forest area estimates than for current volume, growth, mortality, or removals.

$$RE = \frac{V\hat{a}r(\bar{Y}_{SRS})}{V\hat{a}r(\bar{Y}_{Post})} \tag{1.13}$$

Hoppus and Lister (2003) used FIA plots as training data to classify LandSat TM imagery in southern West Virginia. The classified map was then used to stratify the plots and produce estimates of timberland area. Due to a concern that using the same plots to classify the TM imagery as were stratified by the classified map might cause a bias, they divided the counties in the study area into two groups and used one to train the classification for the other. Classification was performed using a method called Iterative Guided Spectral Class Rejection (IGSCR). The end product was two independent forest/non-forest maps. Using these maps, they tested three different stratification schemes: 1) forest/non-forest (2 strata), 2) forest/non-forest and two edge classes of a two pixel width (4 strata), 3) a computed number of forested pixels in a 5X5 pixel window with strata based upon the count of forested pixels. The third method was used to obtain four strata defined as 0 to 6, 7 to 17, 18 to 22 and 23 to 25 forested pixels. This third method was based on results of an earlier study (Hoppus et al., 2000). Each of the three stratification schemes produced a decrease in sampling error of the estimate of total timberland acres, with the third method (5X5 window) produced the best results. Sampling errors (given in percent per million acres of timberland) ranged from 1.10 to 1.23. For comparison, the simple random sampling error was 1.60. It is important to note that this study was done on an area that was 80% forested, which will tend to produce good results for area of timberland.

Nelson (2005) provided discussions of several topics related to post-stratified estimation of FIA attributes. Nelson (2005) conducted a study of the effect of seven NLCD derived stratifications on estimates of forest land area using four approaches to classification: 1) maximum likelihood supervised classification 2) maximum likelihood fuzzy convolution 3) classification via a logistic regression model and 4) classification via a non-parametric k-Nearest Neighbors (k-NN) method. The study was conducted in NLCD 2001 mapping zone 41, which encompasses portions of northern Minnesota, Wisconsin, and Michigan. Results showed a decrease in standard error of the mean proportion forest land relative to simple random sampling. There were no clear winners among the four classification approaches. Nelson et al. (2009) also examined the effects of spatial resolution on estimates of forest area using Landsat Enhanced Thematic Mapper Plus (ETM+), 30m resolution data. 30m pixels were spatially aggregated to coarser spatial resolutions of 90,150,210,270,510,and 990m. Two approaches to spatial aggregation were used, spatial averaging and majority block filtering. Forestland area estimates were derived using design-based and model-based methods for comparison. In particular, a logistic regression model was used to produce per-pixel estimates of proportion forest. The pixel based estimates were then summed to produce a model-based population estimate of forest area. The results showed that spatial resolutions of 90-150m produced the smallest standard errors when used to post-stratify for forestland area. The author hypothesized that this is because the 90-150m resolution is closer in size to a patch of forest land (as defined by FIA) than a 30m pixel is. The author also confirmed that coarse resolution spatial layers are prone to bias in model-based estimates when a majority-based spatial aggregation technique is used, especially in fragmented landscapes. This is caused by the increasing frequency of multiple land cover classes being present with each pixel as pixel size increases. Thus, in landscapes that are heavily forested, the pixel-based estimates will tend to overestimate forest land. Conversely, pixel-based estimates will underestimate forest area in predominantly non-forested landscapes and the pixel spatial resolution increases.

McRoberts et al. (2006) provided a both a good review of recent research into post-stratified estimation from an FIA viewpoint as well as new approach to post-stratified estimation using satellite imagery. This new approach is described in two separate but related studies which seek to increase the precision of estimates of both forest area and volume. The first compared three methods of post-stratified estimation in Wisconsin. The three approaches were designated the North Central (NC), Northeast (NE), and fragmentation (FRAG) approaches. The NC approach applied the method developed by Hansen and Wendt (2000) which uses a forest, non-forest, and two edge classes for a total of four strata. The NE approach was developed by Hoppus and Lister (2003) and uses a forest/nonforest classified map as a starting point. It then examines a 5X5 pixel window around each plot and computes the number of forested pixels in the window. Then, each pixel is assigned to one of 26 possible strata. Adjacent strata were collapsed into a smaller number of strata. Ultimately, four strata were used in the study. The third approach used similar methods, but was based on the 14 fragmentation classes developed by Riiters et al. (2002). Again, similar strata were collapsed to form five final strata. Results were compared on the basis of RE (Equation 1.13). Generally, the NE approach produced the best results with RE's ranging from 1.94 to 3.05 for forest area and 1.31 to 1.71 for volume.

The second study from McRoberts et al. (2006) compared four approaches to stratification in two study areas:TM scene P21R33 in southern Indiana and TM scene P27R27 in northern Minnesota. The NC and NE approaches described above as well as a k-NN model and logistic model constituted the four approaches. For the k-NN and logistic regression model based methods, FIA plot data were used to train models which were used in turn to predict either proportion forest or relative volume (RV) for all pixels in the study area. RV is defined as the ratio of observed volume and the maximum volume observed resulting in a number between 0 and 1. A thorough review of the k-NN technique, including caveats is provided by McRoberts et al. (2002a). These resulting prediction maps were then collapsed into four strata based on several different optimality criteria. The logistic model-derived strata produced the best results in terms of RE with a range of 5.70 to 5.87 in Indiana and 2.26 to 2.33 in Minnesota for area, and 2.47 to 2.71 in Indiana and 1.26 to 1.37 in Minnesota for volume. Note that all four of these methods are design-based methods. Even though the k-NN and logistic models were used, their role was to compute strata which were then used by the standard stratified estimation technique.

In addition to the above results, McRoberts et al. (2006) provided several key observations. First, the footprint of the current plot design used by FIA exceeds the area of the typical 30 meter pixel common to many Lansat-based remote sensing products. When plots are assigned to strata only the location of the center subplot is used. This results in a situation where the plot may sample multiple pixels, and therefore multiple strata, but only be assigned to a single stratum. This phenomenon highlights the utility of defining edge strata described in the NC approach. Second, they also provide a list of conditions that determine when post-stratified estimation will be efficient as a variance reduction tool: when the variables used to stratify the population are closely related to the estimation variable, when sampling units are accurately assigned to strata, when the temporal period of the variables used for stratification is close in time to the sample. They also note that post-stratified estimation may be ineffective when strata have similar means and variances, and in extreme cases could even cause a loss in precision compared to simple random sampling.

Breidt and Opsomer (2008) addressed important questions that arise when using classified land cover maps created from remote sensing data. Frequently, field data (such as FIA phase two data) are used to train models that produce the classified land cover map, and these maps are in turn used to post-stratify the sample data. The authors term this scenario endogenous post-stratification. Endogenous post-stratification appears to violate the assumption that stratum weights are known without error since they were produced from a model which has error. The question is, what effect will this uncertainty have on the post-stratified estimator? To answer this question the authors perform a series of simulation studies. They concluded the effect of using sample data to build a classification model which is in turn used to post-stratify the sample data is very small for moderate to large samples. Further, they show that the endogenous post-stratified estimator is consistent and has very good empirical confidence interval coverage. This is a very important contribution because much of the previous work discussed falls under the endogenous scenario.

1.3 Forest Inventory and Analysis Sample Design

FIA's sampling strategy is composed of three phases designated P1, P2, and P3. This should not be confused with a traditional 3-phase sampling design where the first phase is sample and the subsequent phases are sub-samples of the previous phase. P1 consists of gathering information about the landscape from which the sample will be drawn. It enumerates the population, but does not include any sampling. P2 consists of measurement of permanent ground plots randomly located across the landscape. P3 consists of a sub set of P2 plots on which a broader suite of forest health measurements are made. The FIA sample design and estimation procedures are described in detail in Bechtold and Patterson (2005) and are summarized below for completeness.

1.3.1 Phase One

In P1, the landscape is stratified in order to reduce the variance of population estimates. Historically, FIA's stratification was accomplished through the use of double sampling for stratification using aerial imagery (Bechtold and Patterson, 2005). The result of P1 with double sampling was an estimate of stratum weights. Currently, remotely sensed data combined with other ancillary geospatial layers are used as the basis for stratification. A major benefit of using these data is that both the total population area and the stratum weights can be considered known, rather than estimated. The population total and stratum weights are required by the post-stratified estimators. These estimators will be reviewed in 1.3.5. Each pixel is considered an individual unit of the population. Thus, phase two field plots can be viewed as a subset of the phase one pixels (Hansen and Wendt, 2000). It is important to emphasize that even though the information derived from P1 is used in producing post-stratified estimates, the sample itself is *not* a stratified sample because the P2 sample is drawn independent of the P1 data.

1.3.2 Phase Two

FIA uses a hexagonal sampling frame which covers the United States to select the sample. The hexagons are approximately 6,000 acres (5,947 acres) in size (Brand et al., 1999). FIA plots are established at the national base intensity of one plot per hexagon. Plots chosen to represent each hexagon can either be existing plots selected from a previous (periodic) FIA inventory, or an entirely new annual plot selected at random from a given hexagon. The use of the hexagonal system provides the benefit of forcing the sample to be well distributed across the population, as opposed to a clumped distribution. This method of selecting the sample is a quasi-systematic sample, but for the purposes of estimation it is treated as a simple random sample (Bechtold and Patterson, 2005; McRoberts et al., 2006; McRoberts, 2003). States, National Forests, or other entities may choose to contribute resources to increase the sampling intensity for a population or subpopulation of interest to something greater than one plot per hexagon. The intensification of subpopulations must be accounted for during estimation (see 1.3.5).

FIA field crews visit permanent ground plots (called P2 plots) to collect measurements on trees occurring on forested conditions as well as information on the conditions in which they grow. FIA defines forest as an area of at least one acre in size, at least 120 feet wide, at least 10% stocked by trees or was at least 10% stocked in the past, and not developed for a use other than forest land (USDA Forest Service, 2005). Note that this definition incorporates aspects of both land cover and landuse. Also note that it also includes lands that do not currently have tree cover, such as a clearcut. Field crews collect a suite of National core measurements, which are detailed in a National field manual. Current and previous field guides are available on the National FIA website (http://www.fia.fs.fed.us/library/field-guides-methods-proc/). Each FIA region (see section 1.3.5) has the option to add additional field variables as they choose. Plots are remeasured at regular intervals (generally 5 years in the eastern United States and 10 years in the western United States), which provides estimates of change.

As a cost saving strategy, most FIA units perform some form of pre-field procedure on the sample to determine if a selected plot has any chance of having a forested condition. Plots that obviously have no chance of being forested, such as plots within open water bodies or occurring in major metropolitan or industrial areas, are coded as such and are not sampled in the field. These plots are commonly referred to as *office plots*, and are considered remotely sampled. If there is any doubt about a plot occurring on forest land, it is sent to the field where the final determination is made. Non-forest plots, whether determined in the field or in the office, are coded with a non-forest land use of non-forest, non-census water, or census water. These plots are included in estimates of forest land, although they all represent an observation of zero acres of forest land as defined by FIA.

FIA National Phase 2 Plot Design

The national FIA program uses a four subplot, fixed radius cluster plot design consisting of a center subplot (1) and three satellite subplots. Each circular subplot has a radius of 24 feet. Subplots two through four are spaced at distancess of 120 feet (center to center) from subplot one at azimuths of 0, 120, and 240 respectively. Each subplot also contains a 6.8 foot microplot, which is located 12 feet and 90 degrees from subplot center. The four subplots combined constitute a $\frac{1}{6}$ acre cluster plot. The area sampled is considered to be representative of the area encompassed by a circle drawn around all four subplots, which is about 1.5 acres. Some FIA units operate in areas dominated by more open forests. In these cases there is an optional macroplot with a diameter of 58.9 feet which centers on each subplot which is used to sample larger trees that occur at greater spacing than can be efficiently sampled on the normal subplot. Macroplots are not used in all states. They are included in the description for completeness. A detailed diagram can be seen in figure 1.1.

1.3.3 Phase Three

In addition to the normal core variables collected on all P2 plots, FIA also collects a suite of additional forest health measurements on a $\frac{1}{16}$th subsample of base P2 plots referred to as Phase 3 (P3) plots. This equates to an intensity of approximately one P3 plot

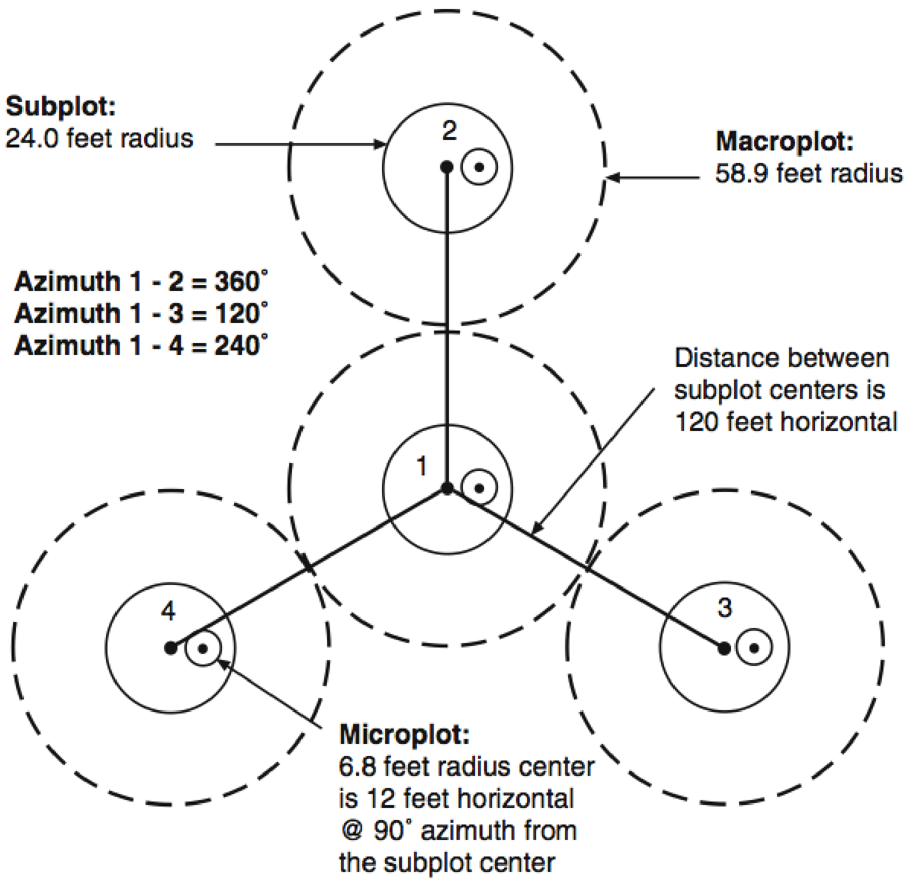

Figure 1.1: National FIA Plot Design

per every 96,000 acres. The P3 sample was created when the Forest Health Monitoring program (FHM) was integrated with FIA. As it was originally conceived, it was intended to produce estimates at a regional level, which is why a lower sampling intensity was used. The lower sampling intensity also allows for two constraints that must be accounted for when sampling for forest health variables. First, an individual P3 plot requires more time, and possibly additional personnel, making it more expensive to sample in terms of time and money. Second, many of the forest health indicators measured on P3 plots are seasonal, which reduces the window of time available to collect data on P3 plots. For example, understory vegetation cannot be accurately sampled in winter throughout much of the United States due to snow cover and/or senescence. The number of P3 plots must be such that they can all be sampled within a defined window of opportunity each year, which is usually the months of the summer growing season.

Each P3 plot is also a complete P2 plot, which includes all the associated P2 field variables. The P3 forest health indicators include soils, lichens, down woody material (DWM), tree crowns and damages, understory vegetation, and ozone bioindicators. Most of these indicators were adopted from the Forest Health Monitoring program (FHM) at the same time that the P3 sample was integrated into FIA. Recent field guides for P3 measurements can be found on the FIA webpage (http://www.fia.fs.fed.us/library/field-guides-methods-proc/). A detailed description of the FIA DWM sample is included in section 1.3.4.

1.3.4 Down Woody Material Sample of FIA

The FIA DWM sample includes measurements of coarse woody debris (CWD), fine woody debris (FWD), litter, duff and fuelbed depth, cover and height of herbs and shrubs, and slash/residue piles using various sampling protocol. Several different sampling techniques are used to collect data on the various components of DWM. CWD and FWD are sampled using line intersect sampling (LIS). Litter, duff, and fuelbed depth measurements are taken using systematic point sampling. The percent cover of live and dead shrubs and herbs are estimated on the fixed radius microplot of each subplot of the national plot design (See figure 1.1). Piles of slash or other woody material that are too cumbersome or hazardous to sample normally are sampled on the 24 foot radius subplot of the national plot design. DWM measurements are only taken on accessible forested conditions as defined by FIA. The following is a description of the CWD protocol. A complete description of the field protocol for the remaining DWM components can be found in USDA Forest Service (2003).

CWD consists downed dead wood such as boles, limbs on the ground, or dead trees leaning at least 45 degrees from vertical. Note that leaning trees less than 45 degrees from vertical are tallied as part of the normal P2 sample, and are coded as standing dead trees. There are three CWD transects on each subplot of the national FIA plot design and a total of 12 possible transects. Transects begin at the subplot center and radiate outwards at azimuths of 30, 150 and 270 degrees to a maximum length of 24 feet horizontal distance (See figure 1.2). CWD must be at least 3 inches in diameter where it intersects the transect line and at least 3 feet in length for decay classes 1 - 4, or at least 5 inches above the litter layer and 5 feet long for decay class 5 to qualify. Decay class is determined using a five class scale described by Maser et al. (1979) (see Table 1.1). For pieces tallied in decay classes 1 through 4, large end diameter, transect diameter, small end diameter (or point at which the diameter is 3 inches), length between large and small end diameters, species, decay class, presence/absence of butt end cavity, and a history code are collected. For pieces in decay class 5, only the transect diameter, length, and decay class are recorded.

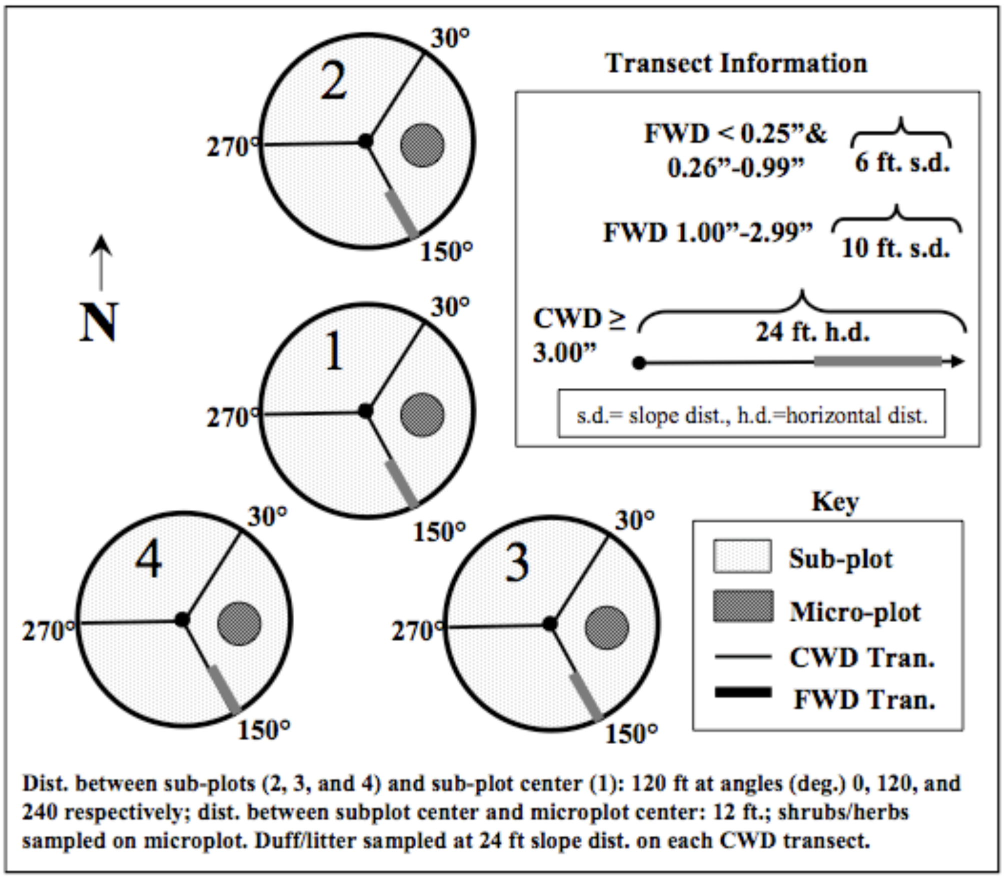

Figure 1.2: Phase 3 Plot Design

Table 1.1: Decay Class Descriptions

Decay Class	Structural Integrity	Texture of Rotten Portions	Color of Wood	Invading Roots	Branches and Twigs
1	Sound, freshly fallen, intact logs	Intact, no rot; conks of stem decay absent	Original color	Absent	If branches are present, fine twigs are still attached and have tight bark
2	sound	Mostly intact; sapwood partly soft (starting to decay) can't be pulled apart by hand	Original color	Absent	If branches are present, many fine twigs are gone and remaining fine twigs have peeling park
3	Heartwood sound; piece supports its own weight	Hard, large pieces; sapwood can be pulled apart by hand or sapwood absent	Reddish-brown or original color	Sapwood only	Branch stubs will not pull out
4	Heartwood rotten; piece does not support its own weight, but maintains its shape	Soft, small blocky pieces; a metal pin can be pushed into heartwood	Reddish or light brown	Throughout	Branch stubs pull out
5	None, piece no longer maintains its shape, it spreads out on ground	Soft; powdery when dry	Red-brown to dark brown	Throughout	Branch stubs and pitch pockets have usually rotted down

1.3.5 Estimation Methods

FIA is organized into four regional units. Each unit is responsible for a defined area of the United States and its territories. The four FIA units are the Northern Research Station (NRS), Southern Research Station (SRS), Interior West Research Station (IWRS) and the Pacific Northwest Research Station (PNWRS). Each FIA unit follows a National protocol for selection of the FIA sample, collection of field data, and estimation. However, the National protocol does allow for some regional variability, especially in the estimation phase. The purpose of this variability is to allow each unit to develop techniques optimized for their area of the country given large differences in landform, forest types, and other ecological variables. This is an important fact because this paper includes details about estimation procedures that may apply only to the NRS unit and should not be considered true for all of FIA units.

FIA surveys are conducted by dividing the United States into subpopulations defined by individual states. States are further subdivided into subpopulations called *estimation units* that can be defined as counties, groups of counties, or other logical groupings such as National Forests. Estimation units are considered to be independent entities and thus the estimates of totals and variances can be summed over subpopulations to arrive at a population estimate (Bechtold and Patterson, 2005). This method of dividing the population into independent estimation units also allows the estimation procedures to account for differences in sampling intensity or non-response rates. It also permits post-stratified estimates to be generated for any of these subpopulations. For example, if a National Forest within a state increases the sampling intensity within its boundaries, then by creating an estimation unit for the National Forest the additional precision gained by additional plots is applied only to the target population, rather than being averaged across all lands.

Once the estimation units are determined for a state, the total area (A_T) of each can be computed using information from P1. The area within each estimation unit is divided into L strata. The weights assigned to each stratum, $W_h (h = 1, ..., L)$ are computed from the P1 data by dividing the number of P1 points (pixels) into the total for the estimation unit, $\frac{N_h}{N}$. Plots are assigned to strata via an overlay procedure using GIS software. In most cases, the plot coordinate used in the overlay is the latest GPS (Global Positioning System) coordinate collected during the most recent plot visit. Occasionally, these coordinates are found to be in error during a post-field coordinate checking procedure, and replaced with the most recent valid coordinate available. Due to errors in the geo-registration of remote sensing products and errors in GPS coordinates, some plots will be assigned to an incorrect stratum. This type of error contributes to the overall sampling error. It does not, however cause a bias in the estimate (Hansen and Wendt, 2000; McRoberts et al., 2006).

Following the overlay procedure, checks are run to assure that a minimum number sampled plots are contained in each stratum. If there are fewer than the minimum number of plots, then either strata are combined, or estimation units are combined until the minimum count it achieved. A minimum of four plots is recommended by Bechtold and Patterson (2005), based upon experience with the P2 sample while McRoberts et al. (2006) recommends a five plot minimum.

Some FIA plots or portions of plots sent to the field are not sampled. This can happen for several reasons including a landowner denying access to a plot (denied access), a plot falling in a hazardous area or situation, or skipping the plot due to limited resources (e.g. budget reductions). The most common reason is denying access. These plots must be accounted for during the estimation process. FIA removes plots that are entirely non-sampled from the pool of plots available for estimation of population means and totals. For plots that are partially non-sampled, FIA increases the weight of the remaining portions of plots in the stratum to account for the area that would have been represented by the non-sampled proportions of plots (Bechtold and Patterson, 2005). This is equivalent to assigning the value of the stratum mean to the non-sampled areas. The stratum variance will go up when totally non-sampled plots are excluded due to the smaller number of observations. There is a risk of bias in this procedure if the non-sampled areas are in some way different than the remaining plots in the stratum, and the stratum mean is not a good representation of the non-sampled plots. FIA's use of estimation units is designed to minimize this risk by defining estimation units that are most likely homogeneous. NRS typically defines estimation units using ownership layers to minimize the risk of bias as described in McRoberts (2003).

Bechtold and Patterson (2005) and Woodall and Monleon (2008) provide estimators for producing estimates of population totals. These estimators were derived from Cochran (1977). The estimators described in Bechtold and Patterson (2005) are used to estimate any attribute of interest on the P2 plot design which uses fixed area plots. However, slightly different estimators are required for CWD attributes because they were sampled using a different plot design; line-intersect sampling (LIS). Woodall and Monleon (2008) provide estimators to compute plot level summaries of the attribute of interest for the various sampling methods used on DWM plots. This thesis is only concerned with the CWD sample, and will only review estimators used for this attribute.

The first step is to sum the attribute of interest within the domain of interest (d) to the plot level in per-unit-area units (1.14). Note that the domain is commonly the entire population, and is thus trivial. However, estimates could be constrained to particular domains such as forest types of interest.

$$y_{yid} = \frac{c\left(\frac{\pi}{2}\right)}{12L\bar{p}_h} \sum_{j=1}^{4} \sum_{m=1}^{3} \sum_{t} \frac{y_{hijmt}\delta_{hijmtd}}{l_{hijmt}} \tag{1.14}$$

where

y_{hijmt} is the attribute of interest measured on CWD piece t intersected by transect m on subplot j of plot i assigned to stratum h

l_{hijmt} the length of CWD piece t intersected by transect m on subplot j of plot i assigned to stratum h

δ_{hijmtd} is an indicator function set equal to 1 if CWD piece t intersected by transect m on subplot j of plot i assigned to stratum h is in domain d, and 0 if not

L is the length of the transect (24 ft.). Note, there are 12 transects per plot, thus the computation is $12L$

c as a constant used to convert the plot level summary to the proper units

$\bar{p}_h$ is the proportion of all transects in stratum h that fell within the population and were sampled and $\bar{p}_h$ computed as:

$$\bar{p}_h = \frac{1}{12Ln_h}\sum_{i=1}^{n_h}\sum_{j=1}^{4}\sum_{m=1}^{3}\sum_{k=1}^{K_{hijm}} L_{hijmk}\delta_{hijmk} \tag{1.15}$$

where

L_{hijmk} is the horizontal length of the transect segment within condition class k on transect m of subplot j on plot i assigned to stratum h

δ_{hijmk} is an indicator function set equal to 1 if condition k on transect m of subplot j on plot i assigned to stratum h is within the population and 0 if not

n_h is the number of plots in stratum h.

K_{hijm} is the number of conditions intersected by transect m of subplot j on plot i assigned to stratum h

Once the attribute of interest is summed to the plot level, the stratum means and variances of the domain of interest (d) are computed as:

$$\bar{Y}_{hd} = \frac{\sum_{i=1}^{n_h} y_{hid}}{n_h} \tag{1.16}$$

with variance estimated by:

$$V(\bar{Y}_{hd}) = \frac{\sum_{i=1}^{n_h} y_{hid}^2 - n_h\bar{Y}_{hd}^2}{n_h\,(n_h - 1)} \tag{1.17}$$

The population total is computed by averaging the stratum means using the stratum weights and multiplying by the total area. The stratum weights and total area were computed from the P1 data.

$$\hat{Y}_d = A_T\sum_{h=1}^{L} W_h\bar{Y}_{hd} = A_T\bar{Y}_d \tag{1.18}$$

The variance of the total is approximated using the unconditional variance estimator:

$$V(\hat{Y}_d) = \frac{A_T^2}{n}\left[\sum_h^L W_h n_h v(\bar{Y}_{hd}) + \sum_h^L (1 - W_h)\frac{n_h}{n} v\left(\bar{Y}_{hd}\right)\right] \tag{1.19}$$

There are three main differences between the estimators presented in Bechtold and Patterson (2005) and Woodall and Monleon (2008) and those presented in Cochran (1977). First, Bechtold and Patterson (2005) and Woodall and Monleon (2008) add the concept of the domain of interest using indicator functions (δ). Second, they use variance notation ($v(\bar{Y}_d)$) where Cochran (1977) uses s^2. Note that these notations are equivalent because $v(\bar{Y}) = \frac{s^2}{n}$ under simple random sampling. Third, Bechtold and Patterson (2005) ignore the finite population correction factors. This is because FIA estimates population parameters under an infinite population framework. The value $\frac{1}{N}$ is very close to 0, and would not make a substantial difference to the estimation of population total. Even under the assumption of a finite population the ratio of n to N would still be negligible.

1.4 Coarse Woody Debris Ecology Overview

The ecology of CWD is a large and complex topic. A complete review of it would detract from the objective of this thesis. Rather, this review will be limited to aspects of CWD ecology that strongly influence the sampling and estimation of CWD attributes. There are two broad points that are relevant to this objective. First, the quantity of CWD is highly variable across multiple temporal and spatial scales. Second, many factors may combine to influence the observed quantity of CWD at a given location. An understanding of these two points will be useful in interpreting the methods and results of this thesis.

Several authors have commented on the high variability of CWD (Harmon et al., 1986; Densmore et al., 2005; Stevens, 1997). This observation is most relevant to the sampling aspect of CWD estimation. Woldendorp et al. (2004) provides a quantitative analysis of sampling methods for CWD. They conclude that high sampling intensities are required to produce an estimate with a coefficient of variation ($\frac{\sigma}{\mu}$) less than 50%. FIA's CWD sample is implemented at the base intensity of 1 plot per $96,000$ acres, which is a very low sampling intensity. Therefore, large sampling errors must be expected when computing estimates of CWD attributes from this sample. The application of post-stratified estimation is intended to reduce sampling errors to highest degree possible.

Before proceeding to a discussion of the variability of CWD quantities over space and time a brief discussion of process of CWD accumulation is useful. The general concept is that the amount of CWD on a given site is determined by the balance of additions to the site and subtractions from the site (Harmon et al., 1986; Stevens, 1997). Additions include various sources by which CWD come to a particular site including tree mortality, disturbances such as windstorms or insect outbreaks, or migration of CWD, such as logs rolling down hill to collect at the bottom. Subtractions include the natural decay of CWD through invertebrates and microorganisms, fragmentation, and transportation, such as a flood removing a piece from a site. Microsite conditions, temperature, moisture, and substrate quality all contribute to the rate of CWD decomposition through their influence on the ecology of the organisms responsible for CWD decay (Harmon et al., 1986; Stevens, 1997). These include both invertebrates and microorganisms.

Harmon et al. (1986) provides a simple, but flexible conceptual model that describes the accumulation of CWD over time. The model depicts the quantity of CWD over successional time under various scenarios of inputs and decay rates. The model assumes some disturbance event at the initial time and depicts the hypothetical successional pathway of the forest following the event. The quantity of CWD observed at a given point in time under this model is a function of the amount present from the previous stand, the amount produced by the disturbance event, and the amount produced by the new stand as a function of normal stand succession (Figure 1.3). The type of disturbance determines the shape of the disturbance curve. An insect outbreak, for example, might incur a delay before the full mortality is expressed in the form of CWD. The speed with which the post-disturbance stand begins to produce CWD through natural stem exclusion is a function of the forest type, site productivity, and climate (Harmon et al., 1986; Stevens, 1997). Many different scenarios can be illustrated using this model, though only two are shown in Figure 1.3. This model demonstrates that the quantity of CWD observed in a given stand is a function of when the stand is sampled and can vary dramatically over time.

Harmon et al. (1986) provides a very good description of the temporal and spatial scales at which CWD varies. According to Harmon et al. (1986), CWD varies differently

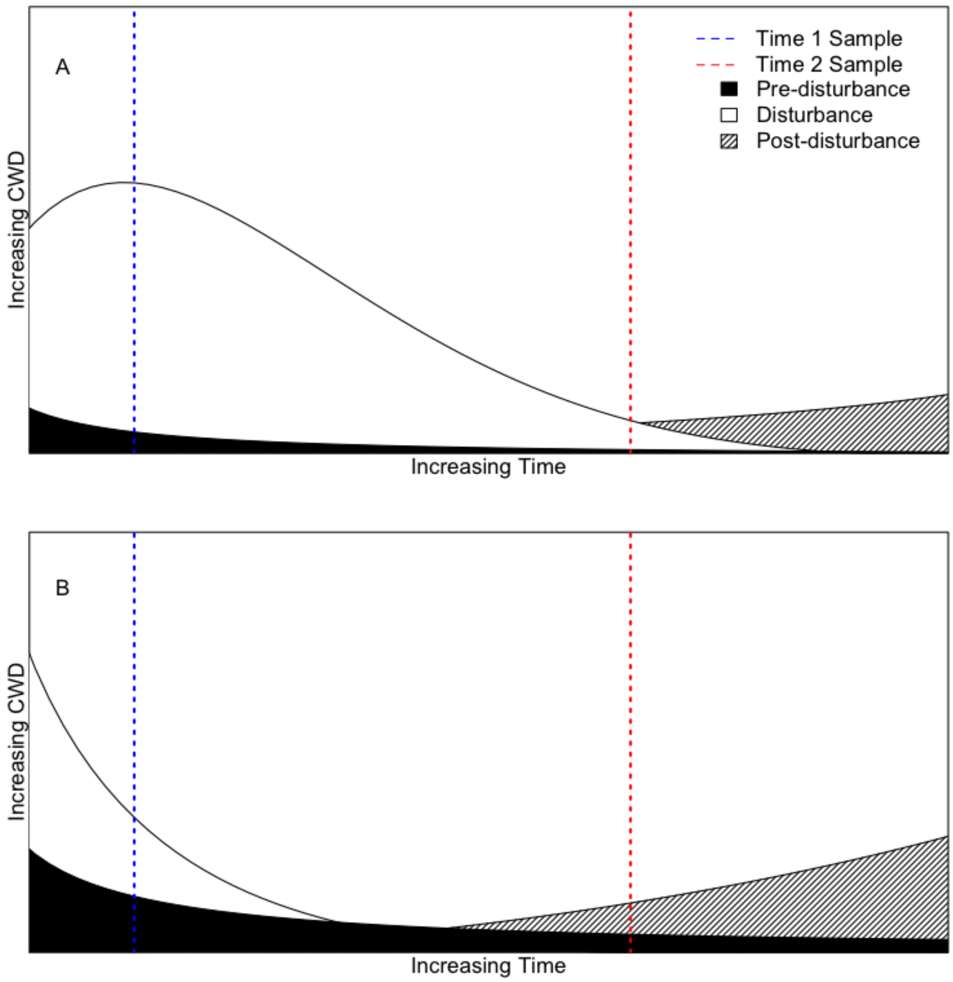

Figure 1.3: Conceptual model of Coarse Woody Debris Quantity Over Time:
This model is based on a model proposed by Harmon et al. (1986). Pre-disturbance CWD is the quantity present prior to the disturbance event. Disturbance is the quantity caused by the disturbance event. Post-disturbance is the quantity produced by the new post-disturbance stand. (A) Depicts a scenario where there is a delay before the full quantity of CWD is produced following a disturbance and the material decays slowly over time. (B) depicts a scenario where the disturbance produces a spike in CWD which decays quicky over time. Time 1 and Time 2 sample show two hypothetical samples in time where the observed quantity of CWD differs in either quantity or type.

at the stand, watershed, and region spatial scales. Spatial patterns at the stand level can be clumped due to the nature of some disturbance events. Windthrow and insect/disease outbreaks tend to kill trees in clumps, rather than a random spatial pattern. Inputs of CWD from natural suppression mortality tends to be more evenly spatially distributed. Watershed patterns tend to be driven by topography (steep slopes) or mass movement events such as avalanches or land slides. Regional patterns are driven partially by the relative influence of disturbance events. Across regions, different forest types tend to have different driving agents producing CWD. Some forest types produce CWD mainly through wind events, while others are driven more by insect and disease. Similar to spatial variability, temporal variability occurs at different scales. CWD input can vary by seasonal, annual, or successional time scales. Harmon et al. (1986) suspect large variability within each time scale, though a lack of comprehensive studies make the variability difficult to quantify. According to Harmon et al. (1986), seasonal variability is mainly due to seasonal weather patterns, such as hurricanes in the late summer to early fall in the Southeastern United States. Annual variability can be quite large due to catastrophic events that can destroy entire stands. A given stand can have a relatively low annual input rate of CWD, then experience an insect outbreak which causes a few years of high mortality. Both type and quantity of CWD inputs can change along the successional pathway of a given stand. Young stands tend to produce most of their CWD through competition caused mortality. Thus, CWD is composed of mainly smaller trees that die and fall over. Mature stands tend to produce CWD through events such as wind storms or ice. Here, CWD is mainly large branches and broken tops with occasional whole trees. The particular successional pathway can also influence the input of CWD. Some forests are composed of short-lived pioneer species early in the stand's life. These species tend to die off within 10 years, resulting in a spike of CWD input of a particular species. The discussion of the spatial and temporal variability of CWD highlights an important source of the unit to unit variability of a sample of CWD attributes.

The second main point to make about CWD ecology concerns the large number of factors related to the presence and quantity of CWD. These factors are numerous and interrelated. They can be divided into the two broad categories of natural and human caused

(Harmon et al., 1986; Stevens, 1997). Under the category of natural factors Stevens (1997) lists the following disturbance agents for CWD: wind, fire, insect, disease, suppression, slope failure, senescence. Other natural factors that have received study include climate variables (Woodall and Liknes, 2008), age and composition (Wehr, 2006; Spies et al., 1988; Guby and Dobbertin, 1996; McMinn and Hardt, 1996; Sturtevant et al., 1997), site variables such as slope and moisture levels (Spies et al., 1988; Rubino and McCarthy, 2003), and forest type (Chojnacky and Heath, 2002; McMinn and Hardt, 1996). Human factors include forest management (Pedlar et al., 2002; Guby and Dobbertin, 1996; McMinn and Hardt, 1996) and development (Christensen et al., 1996). Most authors deal with several of the above factors at once. The interaction of the various factors can strongly affect the quantity of CWD. For example, the expected amount of CWD by age class and forest type may be overwhelmed by forest management or large scale natural disturbance. The above list is not exhaustive, but instead serves to illustrate the complexity of the topic.

The above discussion suggests that many factors are required to explain the quantity of CWD observed during sampling. However, in order for such information to be used in the post-stratified estimation procedure described in section 1.3.5, it must be available to the statistician in a format that can be use to assign plots to strata and compute stratum weights. Many of the factors listed are not widely available across the population of interest; particularly the ones related to human activities. Thus, faced with this limitation, the statistician must choose the best factor or combination of factors that are available across the population of interest. The combination of high spatial and temporal variability, sparse data, and complex factor interactions make estimation of CWD population parameters challenging.

Chapter 2

Study Area and Data

2.1 Study Area

A three State area composed of Minnesota, Wisconsin, and Michigan was chosen as the study area for this project. These three states are commonly referred to as the Lake-states. Each State includes major urban areas, agricultural areas, as well as forested areas. Each State also includes diverse ownership including private forest owners, State and County ownership, and National Forests. This blend of land cover and ownerships offer a good testing ground for the estimation of CWD volume.

The most striking feature about Minnesota's forest land is its spatial distribution across the State (Miles et al., 2007). Minnesota is divided into three distinct ecological provinces (Figure 2.1). Ecological province 212 (Laurentian Mixed Forest) is a transition zone between the central broadleaf forests of ecological province 222 (Eastern Broadleaf Forest) and the boreal forests of Canada. As the name implies, the forests are a mix of coniferous and deciduous species. Most of Minnesota's forests are concentrated in province 212. Province 251 (Prairie Parkland) is predominately prairie land with little forest land. At approximately 54 million acres, Minnesota is the largest State in the study. It is about 32% forested with aspen, pine, and spruce/fir forests in the north and oak/hickory and elm/ash/cottonwood forests in the central and western parts of the State (Miles et al., 2007). In the western areas of the State the forests become more savannah like, with very open stands. Forests in these areas can also concentrate around flood plains and open water bodies forming linear forests features. Minnesota has a very large amount of publicly owned forest land with 40% owned by State or local government and a further 17% owned by federal government entities. The federal lands are divided among the Voyageurs National Park, Chippewa National Forest, Superior National Forest which includes the Boundary Waters Canoe Area Wilderness (BWCAW), National Wildlife Refuges, and smaller holdings of other federal agencies. The remaining 43% are owned privately with the largest component (36%) owned by nonindustrial private forest owners. Like most eastern States, Minnesota's natural history includes heavy forest harvesting around the late 1800 and early 1900's followed by large scale landuse conversion from forest to agriculture. This history explains a large part of the current distribution of forest across Minnesota.

The BWCAW experienced a severe disturbance event on July 4, 1999 in the form of a severe summer storm. The storm was reported to have average wind speeds of 60 mph and gusts up to 100 mph. It caused massive tree blowdowns along a swath 30 miles in length and up to 12 miles wide (Moser et al., 2007). This event was significant enough to warrant an intensification of the P3 sample within the BWCAW boundary and its own discussion here. Moser et al. (2007) reported that the estimated fuel loading within the event boundary increased from approximately 4 to 20 tons per acre to 45 to 100 tons per acre. However, a closer inspection of the data revealed that much of the additional fuel loading occurred in the 100 hour fuel class which corresponds to FIA's large FWD sample and somewhat less in the $1,000$ hour fuel class, which corresponds to FIA's CWD sample. This indicates that many tree limbs and tops were broken as opposed to entire trees coming down (Moser et al., 2007). A large proportion of the CWD occurred in the 3 to 8 inch diameter class which is expected to decay relatively quickly. On disturbed plots overstory species diversity declined and understory species diversity increased, which has the potential to alter the successional pathway of affected stands (Moser et al., 2007). The implications of these changes will be seen for a long time. The main point of this very brief overview of the BWCAW blowdown is that significant disturbance events can significantly affect subpopulations and create a skew in the data. The analyst applying post-stratification needs to be aware of such events to properly account for them in the definition of estimation units (see section 1.3.5).

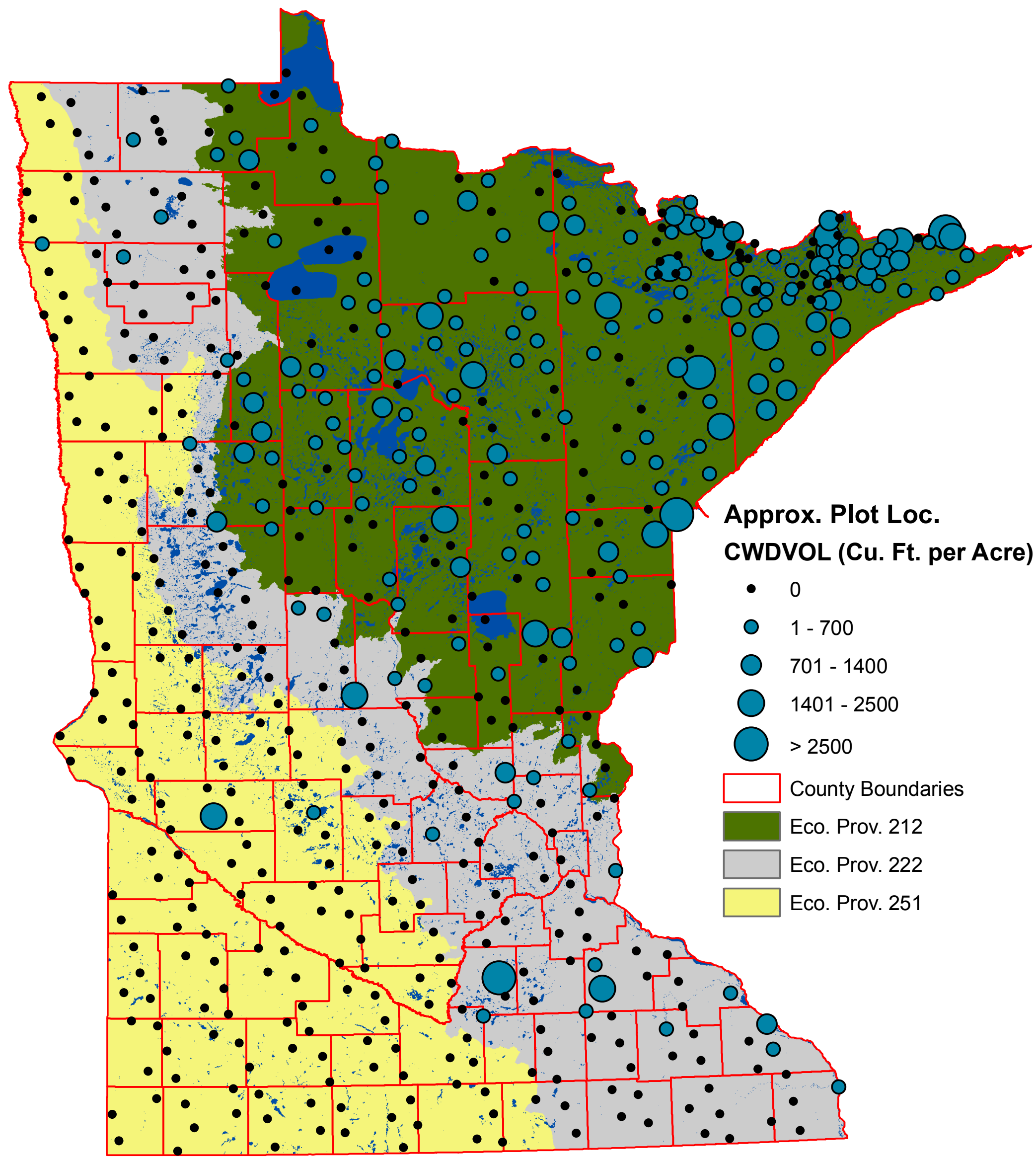

Figure 2.1: Minnesota P3 Sample on Ecological Province

Wisconsin has a more uniform spatial distribution of forest cover than Minnesota, but the highest density of forest cover still occurs in the northern counties. Overall, Wisconsin is 46% forested (Perry et al., 2007). The south-eastern quarter of the State has very low forest cover and accounts for most of the urban and agricultural areas. As with Minnesota, this pattern is heavily influenced by a natural history of forest harvesting and agricultural landuse change. The State is evenly divided between the Laurentian Mixed Forest ecological province and the Midwest Broadleaf Forest province. The mixed forest region is similar to the mixed forest region in Minnesota with maple, beech, and birch species mixing with conifer species like pine, tamarack and spruce. The degree of species mixing is influenced by the quality of the site with hardwoods more prevalent on high quality sites and conifers on low quality sites. The Midwest Broadleaf forests are composed of oaks and hickories on drier sites and elms, ashes, and cottonwoods on lowland sites. Most of Wisconsin's forests are privately owned (68%) with the largest component being nonindustrial private owners (56%). 22% of forest lands are owned by State or local government agencies and 10% are owned federally. Most of the federal lands occur in the Chequamegon-Nicolet National Forest. The largest public land owner is county/local which accounts for 15% of all forest land (Perry et al., 2007). Wisconsin is unique with significant forest land area (2%) owned by the Menominee Tribal Enterprise (Perry et al., 2007).

Michigan is very unique in that it is composed of two peninsulas surrounded by Great Lakes. They are commonly referred to as the upper and lower peninsulas. The lower half of the lower peninsula is dominated by urban and agricultural land uses and has the lowest forest cover and largest human population in the State. As with Minnesota and Wisconsin, history has had a strong influence on this spatial pattern of forest cover. Michigan experienced heavy harvesting and catastrophic fires in the late 1800's followed by wetland draining and landuse conversion in the southern areas. The northern lower peninsula is much more forested than the lower half with aspen/birch, oak, and pine forests dominating. This region also tends to have sandier soils than the lower half. The eastern half of the upper peninsula is heavily forested with maple/beech/birch and spruce/fir forests. This area also contains boggy areas with large acreage of norther white-cedar.

The western upper peninsula continues with heavy forest cover with northern hardwoods dominating. Aspen/birch forest types are also common across the entire upper peninsula and more common in the northern lower peninsula. Overall, Michigan is 53% forested making it one of the most forested States in the country, and the most forested in this study. Across the State, maple/beech/birch is the dominant forest type followed by aspen forests. About 61% of all forest land is privately owned in Michigan, with the largest component owned by nonindustrial private owners (44%). Michigan has the highest private corporate ownership of the three States with 14%. State and local ownership accounts for 23% of forest area and federal accounts for 16%. The eastern and western upper peninsula regions have a high concentration of public lands at 49 and 39% respectively. The northern lower peninsula also has a high proportion of public lands at 41%, but the lower half has very little (15%). The federal ownership is divided up mainly between the Ottowa National Forest and Hiawatha National Forest in the upper peninsula and the Huron-Manistee National Forest in the northern lower peninsula (Pugh et al., 2008).

2.2 Data

2.2.1 FIA Data

Coarse woody debris data were collected on FIA plots during the summer months of 2002 though 2006 as described in 1.3.4. The Minnesota sample includes 58 intensified P3 plots that were collected in 2002 as part of a study on a major blowdown event in the Boundary Water Canoe Area Wilderness (BWCAW). The Minnesota sample including the intensified plots will be referred to as the *intensified* sample. The Minnesota sample excluding the intensified plots will be termed the *base* sample. The other two states have no intensification and will be assumed to use the base sample. Plots that were entirely non-sampled were excluded from the study.

Equations 2.1 and 2.2 were used to compute volume in cubic feet for decay classes 1 though 4 and 5 respectively (Woodall and Monleon, 2008).

$$Vol_{DecayClasses1-4} = \frac{\left(\frac{\pi}{8}\right)\left(DS^2_{jmt} + DL^2_{jmt}\right) l_{jmt}}{144} \tag{2.1}$$

$$Vol_{DecayClass5} = \frac{\left(\frac{\pi}{4}\right)\left(DI^2_{jmt} l_{jmt}\right)}{144} \tag{2.2}$$

$$\tag{2.3}$$

where

DS_{jmt} is the small end diameter of CWD piece t intersected by transect m of subplot j

DL_{jmt} is the large end diameter of CWD piece t intersected by transect m of subplot j

l_{jmt} is the length of the piece of CWD piece t intersected by transect m of subplot j

DI_{jmt} is the diameter at the transect of CWD piece t intersected by transect m of subplot j

Equation 2.4 taken from from Woodall and Monleon (2008) was used to convert individual CWD volumes into a volume per acre value for each plot. Note that no domain restrictions were used in this study, so the domain indicator (δ) is always 1. Equation 2.4 averages CWD volume across all transects on the plot.

$$CWD_{Vol} = c\frac{\frac{\pi}{2}\sum_{j=1}^{4}\sum_{m=1}^{3}\sum_{t}\frac{y_{jmt}\delta_{jmt}}{l_{jmt}}}{\sum_{j=1}^{4}\sum_{m=1}^{3} L_{jmd}} \tag{2.4}$$

where

y_{jmt} is the volume of piece t intersected by transect m of subplot j computed by either equation 2.1 or 2.2

δ_{jmt} is the domain indicator function which takes the value of 1 if piece t intersected by transect m of subplot j falls in domain d and 0 otherwise

l_{jmt} is the length of the piece of CWD piece t intersected by transect m of subplot j

L_{jmd} is the length of transect segment m of subplot j falling in domain d

c is a conversion constant to convert the volume into cubic feet per acre

The distribution of the plot CWD values is dominated by zero values with a long tail of non-zero values that diminish as the volume increases (figures 2.2, 2.3, 2.4, and 2.5). The zero values can theoretically broken down into two types. The first type occurs on plots that fall on non-forest land. FIA only samples CWD on land meeting the FIA definition of forest land. The second type occurs on plots that fall on forest land, but did not have any CWD.

The Michigan sample produced the highest sample mean and the second highest sample variance (Table 2.1). The intensified Minnesota sample had the second highest mean and the highest sample variance. The base sample in Minnesota was very different with a much lower sample mean and variance compared to the intensified sample. The Wisconsin sample produced the lowest sample mean and a sample variance less than half the size of the other two samples. When the sample is summarized using only plots with a forested condition (using FIA's forest definition) the Minnesota intensified sample produces the highest sample mean and variance (Table 2.2). The Michigan sample has the second highest, followed by the Minnesota base sample. Wisconsin has the lowest sample mean and variance across forested plots.

In each State in the study area, there are a small number of very large observations. They can exert a large influence on estimates of population means, total, and associated variances. The term *extreme observation* is preferred over *outlier* because the later term implies that an error has been made. CWD is known be be highly variable and very high levels can occur naturally or in response to human caused disturbance. A good example of an extreme observation comes from the Michigan dataset, where the maximum value is 2,694 cubic feet per acre. For this particular plot, two of the four subplots were non-forest. One subplot recorded wind damage and had several large pieces of CWD, including some that appear to be full trees judging by the diameters and lengths. The other subplot was forested and also had several pieces of CWD. According to equation 2.4, these three different condition are averaged across the plot producing an extremely large value for the plot.

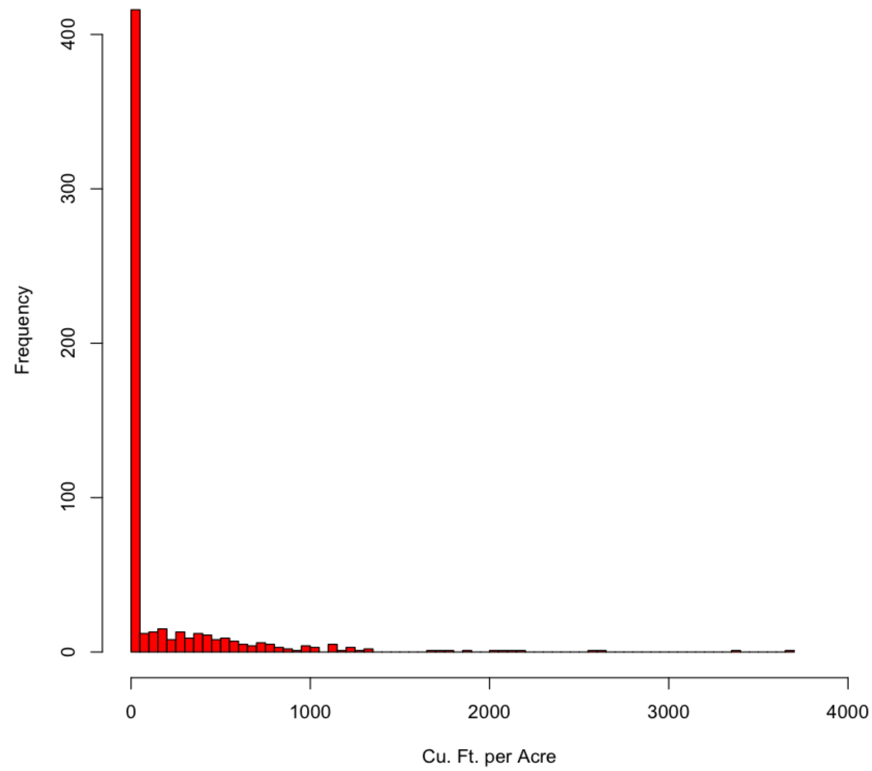

Figure 2.2: Histogram of Per-plot CWD Volume in Minnesota (Intensified Sample, Including BWCAW Intensified Plots)

Table 2.1: Numerical Summary of CWD Volume (Cu. Ft. per Acre) by State

State	Min.	1st Quan.	Median	Mean	3rd Quan.	Max.	Var.
Minnesota (Intensified)	0.0	0.0	0.0	176.3	155.2	3,680.0	173,602
Minnesota (Base)	0.0	0.0	0.0	145.7	90.2	3,369	129,867
Wisconsin	0.0	0.0	0.0	119.0	122.0	2,159.0	63,433
Michigan	0.0	0.0	0.0	217.7	289.6	2,694.0	144,081

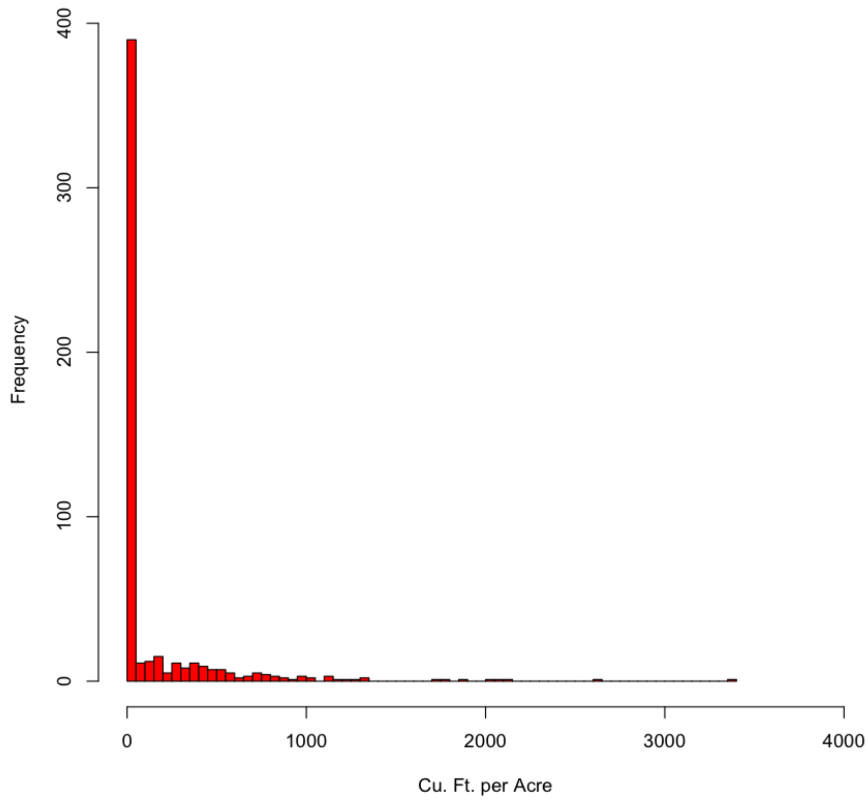

Figure 2.3: Histogram of Per-plot CWD Volume in Minnesota (Base Sample, Excluding BWCAW Intensified Plots)

Table 2.2: Numerical Summary of CWD Volume (Cu. Ft. per Acre) on Forested Plots by State (*Plots are classified as forested if they record at least one condition that meets the FIA definition of forest land*)

State	Min.	1st Quan.	Median	Mean	3rd Quan.	Max.	Var.
Minnesota (Full)	0.0	102.0	360.6	600.6	779.3	4,454.0	539,564
Minnesota (Base)	0.0	92.7	329.1	534.2	705.6	4,454.0	437,422
Wisconsin	0.0	57.5	219.3	360.5	448.8	4,629.0	271,026
Michigan	0.0	79.7	277.3	491.0	670.6	6,854.0	456,386

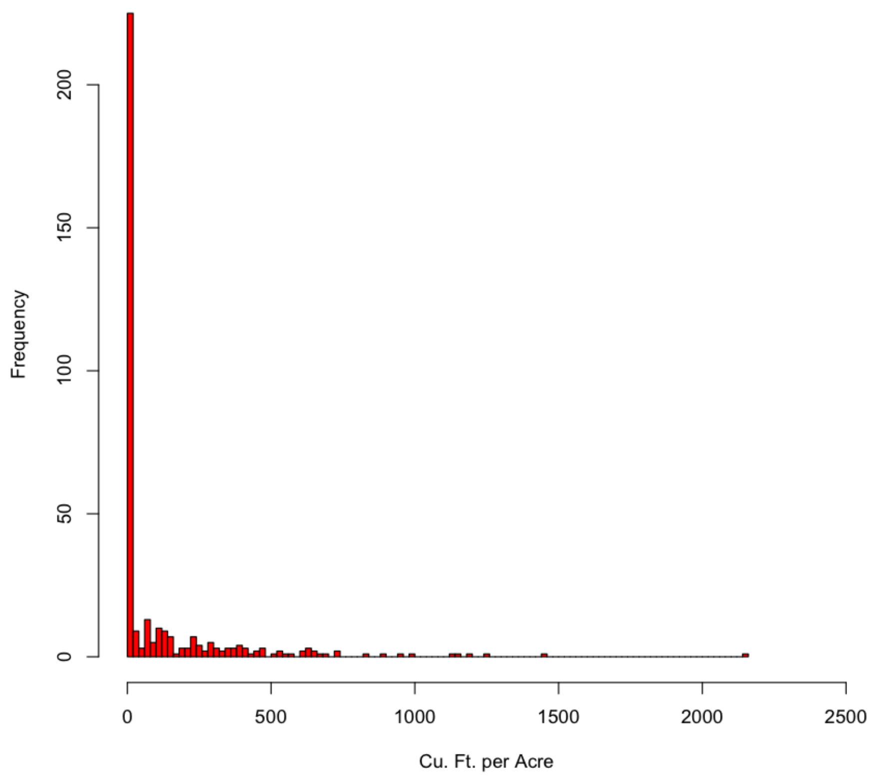

Figure 2.4: Histogram of Per-plot CWD Volume in Wisconsin

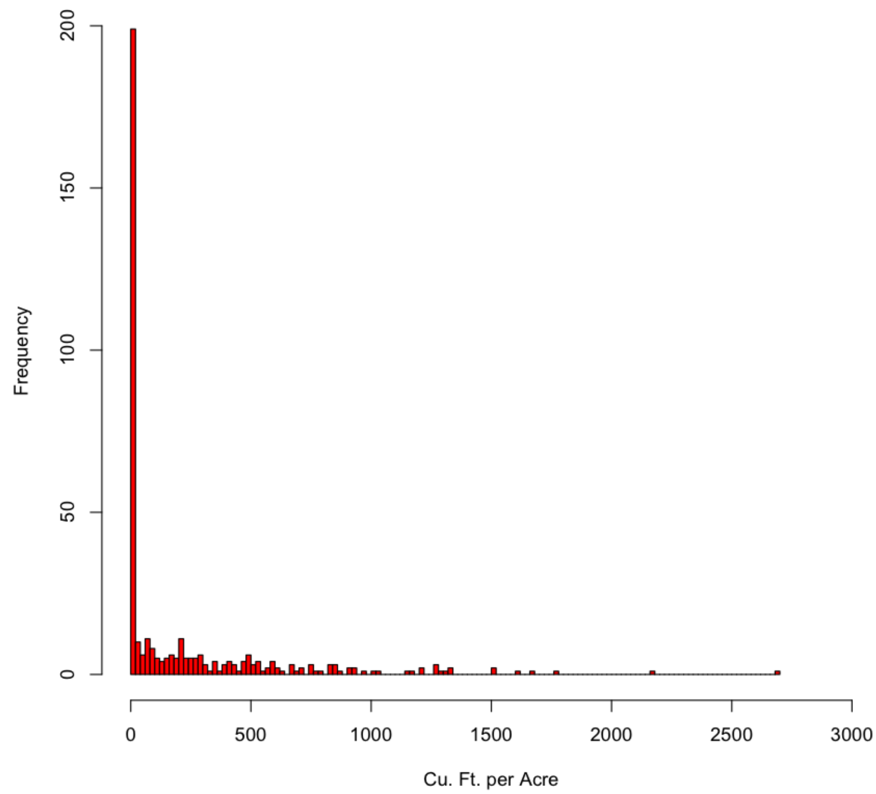

Figure 2.5: Histogram of Per-plot CWD Volume in Michigan

2.2.2 Spatial Data

The first question to be addressed in this study is: what is the best geospatial layer to use when using post-stratified estimation to compute population estimates of CWD volume? To answer this, a collection of candidate layers was compiled from various sources. There were three criteria used to select candidate geospatial layers: 1) broad coverage of the United States, 2) easily acquirable, 3) representation of a logical relationship with CWD volume. One can easily imagine a very large number of possible geospatial layers that might be useful for this purpose. However, not all possible layers will meet the above criteria. In addition, as the number of layers included grows, the study becomes more unwieldy and the analysis becomes diluted. This study includes 18 candidate geospatial layers (Table 2.3). Each candidate layer was assigned a short name (Table 2.3) that will be used through out this paper to make figures and discussion more clear and concise. The sources and processing of each layer is described below along with a brief discussion of the motivation for including the layer in the study.

Table 2.3: Geospatial Layers

Layer	Resolution	Data Type	Short Name
Ownership	30m	Categorical	OWN
Landform	30m	Categorical	LNDFRM
Compound Topographic Index (CTI)	30m	Continuous	CTI
Percent Canopy Cover	30m	Continuous	PC
Percent Canopy Cover (5 Strata)	30m	Categorical	PCSTAND
Bailey's Ecological Province	30m	Categorical	ECOP
Logistic Model	30m	Continuous	LOG
Zhu & Evans Forest Type	1000m	Categorical	Z&E
RSAC Forest Type	250m	Categorical	RSAC
Average Precipitation	1000m	Continuous	AVGPREC
Average Temperature	1000m	Continuous	AVGTEMP
Number of Growing Degree Days	1000m	Continuous	GROW
January Minimum Temperature	1000m	Continuous	JANMIN
July Maximum Temperature	1000m	Continuous	JULMAX
Mean NDVI (MODIS)	250m	Continuous	MNDVI
Standard Deviation of NDVI (MODIS)	250m	Continuous	SNDVI
Mean EVI (MODIS)	250m	Continuous	MEVI
Standard Deviation of EVI (MODIS)	250m	Continuous	SEVI

Ownership

The ownership geospatial layer is a compilation of various spatial layers. It includes boundary files from National Forests, State Forests, as well as the Protected Areas Database (PAD), which is a product of the Conservation Biology Institute (www.consbio.org). These layers are compiled each year as part of the standard stratified estimation process used at NRS-FIA.

The selection of this layer is based on the hypothesis that the quantity of CWD can vary by ownership. Essentially, ownership is used as a proxy for land history and current management strategy. A wilderness area, for example, might be expected to show higher levels of CWD because the management strategy allows the forest to age naturally. The quality of the ownership layer is variable because it is a compilation of many other sources.

Landform

The landform geospatial layer was constructed using a Digital Elevation Model (DEM) from the National Elevation Dataset (NED) produced by the United States Geological Survey (USGS). The spatial model was built in a Geographic Information System (GIS) software package based on the methods described by Tagil and Jenness (2008). The idea is to construct two Topographic Position Index (TPI) values for every pixel in the DEM; one for each neighborhood size. The neighborhood sizes of 2000m and 500m were used in this study. Each TPI can take the value of -1, 0 or 1. The TPI is set to -1 or 1 if the absolute value of the difference between a given pixel's elevation and the mean elevation of the neighborhood is greater than the standard deviation of the neighborhood. The sign of the TPI is taken from the sign of the difference. The TPI is assigned to 0 otherwise. The slope layer is used to determine the difference between an open plain and an open slope. A threshold of 5 degrees slope was selected to differentiate between flat plains and slopes. The unique combination of the two TPI values can be used to describe several landform scenarios (Table 2.4).

There are two hypothetical relationships between landform and the quantity of CWD on a given site. First, areas of dramatic topography might show a tendency for larger CWD quantities to collect in valleys and canyons, and not on slopes. Second, soil and moisture conditions, and light are influenced by landform. These factors in turn influence the forest productivity and forest type of a given site. The review of CWD ecology indicated that both of these variables are related to a sites ability to accumulate CWD.

Table 2.4: Landform Categories

TPI 2000	TPI 500	Slope	Landform
-1	-1	NA	Canyon
-1	0	NA	Valley
-1	1	NA	Ridge in Valley
0	-1	0	Shallow Valley
0	0	0	Plain
0	0	1	Open slope
0	1	0	Hill in Plain
1	-1	NA	Headwaters
1	0	NA	Upper Slope
1	1	NA	Hill Top

Compound Topographic Index

A Compound Topographic Index (CTI) layer is available through the Elevation Derivatives for National Applications (EDNA) database provided by the USGS. CTI is also know as the Steady State Wetness Index. CTI is defined as $\ln \frac{A}{\tan B}$ where A is the catchment area expressed in square meters and B is the slope in degrees. CTI Values tend to be higher in the lower reaches of a watershed, where more hydrologic pathways converge. The EDNA CTI layer excluded some small portions of the study area, such as some of the smaller Apostle Islands in Wisconsin. A spatial model was created in a GIS software package to compute the CTI values for these missing areas. The original EDNA CTI and the computed CTI layers were then combined to create one layer to cover the entire study area.

The CTI layer was included in the study to represent the moisture available to trees, and thus to forest productivity. Harmon et al. (1986) hypothesizes that the variability in CWD input rates is driven primarily by the productivity of the site because more productive sites produce more massive trees. Excessive moisture can also affect decay rates, resulting in net accumulation.

Percent Canopy Cover

The Multi-Resolution Land Characteristics Consortium (MRLC) produces a line of spatial products known as the National Land Cover Database (NLCD). The 2001 edition of the product includes a tree canopy cover layer with values ranging from 0% to 100%. The tree canopy density layer is currently used as a stratification layer for population estimates of forest area and volume at NRS-FIA.

The logic for including this layer is based on the fact that denser canopies tend to have larger, more mature trees and thus the potential for higher levels of CWD. At a minimum, a canopy density layer will be able to separate forested plots into separate strata from non-forest plots. This is important because FIA does not sample CWD on non-forested lands. Grouping non-forest plots into a non-forest strata would theoretically produce a more precise estimate because non-forest plots would all contribute 0 CWD volume to the population total. In reality, there will be a small number of misclassifications due either to error in the NLCD layer, registration error in the image, or GPS error on the plots.

This layer will be tested in two different ways. First, the same five strata used in forest area, volume, and change (growth, removals, and mortality) estimation at NRS-FIA will be tested to see if they perform well for the CWD volume estimate (PCSTAND). This layer will be treated as a categorical layer based on the fact that it will not undergo optimization to identify strata breakpoint as all the continuous layers will. These breakpoints are given as 0-5%, 6-20%, 21-50%, 51-80%, and 80-100% canopy cover. Second, the layer will be examined to see if a different number of strata or different strata breakpoints perform better than the standard five strata.

Bailey's Ecological Province

Bailey's Ecological Province is a spatial layer that depicts broad ecological areas that are similar in climate and vegetative characteristics (Bailey and Hogg, 1986). It is available through the National Atlas (www.nationalatlas.gov). The layer is distributed as a vector (polygon) layer, but it is converted to a 30m x 30m raster (pixel) layer for this study using conversion tools available in ArcMap 9.2. Rasterizing Ecological Provinces makes it easier to combine with other raster layers.

This layer may contribute to the precision of a CWD estimate by grouping similar plots together. A good example occurs in Minnesota where the western portion of the state occurs in the Prairie Parkland Temperate Province. As the name implies, it is largely prairie and contains little forest. Thus plots in this Ecological Province will tend to be non-forest. This layer also defines very large strata that will include many plots. As a result, the strata level statistics should be well estimated due to large sample sizes.

Logistic Regression Models

A logistic regression model was constructed based on the binary response variable presence/absence of CWD. All geospatial layers were included as covariates in the model, though most were dropped during variable selection. The details of the creation of this spatial layer will be discussed in the Methods section (3.2).

The motivation for including a logistic model in this study is twofold. First, previous authors have reported good results when testing a logistic regression model for stratifying other population parameters (McRoberts et al., 2006; Nelson, 2005). Second, the overview of CWD ecology indicates that the many factors that drive CWD amounts on a given site interact with each other. Using a logistic regression model allows for the potential of multiple factors to interact and adjust the probability of CWD accordingly.

Zhu & Evans Forest Type

Zhu and Evans (1994) created a forest type map of the conterminous 48 States using AVHRR (Advanced Very High Resolution Radiometer) data. This was a 1-km x 1-km resolution map composed of 25 different forest types. The map was created in support of the Forest and Rangeland Renewable Resources Planning Act (RPA) of 1974. Regression models were used to identify AVHRR bands that were useful for forest type classification. Then, an iterative process of running an unsupervised classification algorithm, evaluating and masking or recoding pixels was performed. A percent forest cover map was used to mask out areas of non-forest from the classification algorithm. Various other ancillary data were used in various regions to help identify the spectral signatures of local forest types.

This layer was included in the study to represent the hypothetical relationship between CWD and forest type. Different forest types produce variable amounts of CWD and retain their CWD for variable lengths of time (Chojnacky and Heath, 2002; McMinn and Hardt, 1996; Harmon et al., 1986). The coarse spatial resolution (1,000 meters by 1,000 meters) may limit the effectiveness of this layer.

RSAC Forest Type

Researchers at the Remote Sensing Applications Center and FIA scientists used Classification and Regression Tree (CART) models implemented as part of the See5 software package (www.rulequest.com) to create a forest type map of the United States (Ruefenacht et al., 2008). MODIS, topographic data, and other ancillary data were used as prediction variables and FIA plots were used response variables. The output product was a 250-m x 250-m map of FIA forest types. Forest types were defined using the same codes as FIA uses for forest type. This work constitutes a temporal update and spatial enhancement of the previous forest type map constructed by Zhu and Evans (1994).

The motivation for including this layer is the same as for Zhu & Evans. It was included so that the connection between forest type and CWD could be tested twice with two independent layers and at different spatial resolutions.

Climate Data

Climatic variables could be important in understanding the spatial distribution of CWD. Moisture and temperature can influence the decay rates of CWD as well has the productivity of the forest. Areas with generally warmer temperatures and longer growing seasons may accumulate more CWD due to higher productivity. Longer growing seasons might also contribute to faster rates of decay, depending on the site and the species of tree. The level of productivity is determined in part by the moisture levels available to the forest. Some previous work with CWD found some relationship with climate variables (Woodall and Liknes, 2008). Five different climate variables were tested as part of this research. All of them were 18 year averages over the period from 1980 to 1997. They were extracted from the Daymet climate database (Thornton et al., 1997). See table 2.3 for a listing of these and other layers. Climate layers were chosen to describe the regions moisture (precipitation), temperature (both in terms of average value and extremes), and growing season. Each geospatial layer has a coarse spatial resolution of 1,000-m x 1,000-m. However, the phenomenon they describe have low spatial variability meaning that average annual temperature, for example, does not vary very much from one 1,000-m x 1,000-m pixel to the next. These layers are expected to stratify CWD into broad categories of climate.

Vegetation Indices

The Moderate Resolution Imaging Spectroradiometer (MODIS) instrument collects spectral data at a high temporal and radiometric resolution that is useful for many natural resources modeling efforts (modis.gsfc.nasa.gov). As the name implies, the spatial resolution is moderate, meaning 250-m x 250-m pixels. MODIS data are available in the form of product lines. The MOD13Q1 product includes vegetation indices computed over 16 day periods, resulting in 22 values per year. Each pixel will have multiple observations over the 16 period. These observations are sorted by quality based on the observation quality in terms of view angle and atmospheric contamination. The best single observation is selected to represent the pixel for that 16 day period.

Vegetation Indices are numerical values intended to quantify the amount of green vegetative cover at a given point on the ground. They are functions of input spectral data. Two common vegetation index numbers are the Normalized Difference Vegetation Index (NDVI: Equation 2.5) and the Enhanced Vegetation Index (EVI: Equation 2.6). NDVI was defined by J. W. Rouse et al. (1974) and EVI was defined by Liu and Huete (1995).

$$NDVI = \frac{NIR - RED}{NIR + RED} \tag{2.5}$$

$$EVI = G\frac{NIR - RED}{NIR - (C_1RED - C_2BLUE) + L} \tag{2.6}$$

where

NIR is the reflectance value in the near infrared spectral band

RED is the reflectance value in the red spectral band

BLUE is the reflectance value in the blue spectral band

G, L, C_1, and C_2 are model coefficients

The MODIS vegetation indices represent not only the amount of vegetation at a point in time, but also contain phenological information about how constant that vegetation level is throughout the year. This information can be summarized by looking at the mean and variance of all the 16 day index values over the year. MODIS NDVI and EVI data from the 2005 calendar year were acquired for this purpose. Volume of CWD could be related to both the amount of vegetation and the length of time a location is vegetated over a year. The difference between softwood and hardwood forests will become apparent in the phenological information, which may also affect observed CWD volumes.

Chapter 3

Methods

3.1 Study Terminology

Before delving into the details of the methods used in this study it is useful to clarify some terminology used throughout the methods, results, and discussion. The term *scheme* will be use to describe a geospatial layer used in a defined way for post-stratified estimation. The geospatial layer will be identified by its short name given in table 2.3. For continuous geospatial layers, the scheme would specify the short name for the particular layer as well as the number of strata it has been divided into. For example, PC4 would denote a 4 strata scheme using the percent canopy cover geospatial layer. In all cases, the particular set of strata breakpoints that define individual strata will be determined by an optimization algorithm described in section 3.3. In the case of categorical geospatial layers the number of strata is is already determined by the values of the different categories. Thus, the number of strata are not specified for categorical geospatial layers. The term *stratification* will be used to describe the combination of a scheme and a set of estimation units. For example, ECOP PC4 describes a stratification where the estimation units are defined by Bailey's ecological provinces and within each province the subpopulation is stratified by the PC4 scheme. The scheme terminology will be immediately useful for the geospatial layer analysis (section 3.3) while the stratification terminology will only become useful in the final component of the study (section 3.5).

3.2 Logistic Regression Models

A logistic regression model was created for each state using the binary response variable presence/absence of CWD. The presence/absence of CWD variable is defined as:

$$y_i = \begin{cases} 1, & \text{if the volume of CWD} > 0; \\ 0 & \text{otherwise.} \end{cases} \tag{3.1}$$

All modeling was performed in the statistical computing package R (R Development Core Team, 2008). The candidate covariates include all of the available geospatial layers (Table 2.3), plus additional topographical variables including slope in degrees, and the sin and cosine of the aspect. The output of the logistic regression model is the probability of occurrence of CWD. The model is of the form:

$$E(y|x) = \theta(x_i) = M(\beta^T x_i) = \frac{\exp(\beta^T x_i)}{1 + \exp(\beta^T x_i)} \tag{3.2}$$

where

$E(y|x)$ is the mean function of y given x

$\theta(x_i)$ is the probability that CWD is present

$M(\beta^T x_i)$ is a link function between the mean function and the covariates

The β^T is a vector of coefficients estimated from the data

The x_i are the independent variables

The linear predictors are related to the mean function through the logistic link function, which is defined as

$$\log\left(\frac{\theta(x)}{1 - \theta(x)}\right) = \beta^T x \tag{3.3}$$

A variable selection algorithm that uses Bayesian model averaging (bic.glm) was run in each state to select the best set of covariates. The algorithm was run in two ways which differed in the way they processed factor (categorical) variables. First, factors levels were considered independent *dummy* variables and allowed to enter the model independent of the other levels of the factor. Second, factor variables were considered sets that were entirely included or excluded from the candidate models. The output was a short list of the best logistic regression models in each state. The model with the lowest Bayesian Information Criteria (BIC) which had all significant terms was selected. The following three models were developed using the above framework for Minnesota (3.4), Wisconsin (3.5), and Michigan (3.6) respectively:

$$E(y_i|x) = \frac{\exp(3.6 - 4.4W - 0.002CTI + 0.05PC + 2.4R2 - 0.001GR)}{1 + \exp(3.6 - 4.4W - 0.002CTI + 0.05PC + 2.4R2 - 0.001GR)} \tag{3.4}$$

$$E(y_i|x) = \frac{\exp(-3.9 + 0.05PC + 0.002SL + 1.4R1 + 2.6R2 + 2.3R3)}{1 + \exp(-3.9 + 0.05PC + 0.002SL + 1.4R1 + 2.6R2 + 2.3R3)} \tag{3.5}$$

$$E(y_i|x) = \frac{\exp(.05PC - 0.0006AP + 0.0009MEVI)}{1 + \exp(.05PC - 0.0006AP + 0.0009MEVI)} \tag{3.6}$$

where

W is the census water indicator variable from the OWN layer. It takes the value of 1 if the pixel is a census water pixel and 0 otherwise.

CTI is the Compound Topographic Index layer

PC is the NLCD Percent Canopy Cover

GR is the average growing degree days layer

SL is the slope in degrees

AP is the average annual precipitation

$MEVI$ is the mean Enhanced Vegetation Index (EVI)

$R1$ is the softwood forest type indicator variable from the RSAC forest type layer. It takes the value of 1 if the pixel is a softwood and 0 otherwise.

$R2$ is the hardwood forest type excluding aspen/birch indicator variable from the RSAC forest type layer. It takes the value of 1 if the pixel is a hardwood other than aspen/birch and 0 otherwise.

$R3$ is the aspen/birch forest type indicator variable from the RSAC forest type layer. It takes the value of 1 if the pixel is an aspen/birch forest type and 0 otherwise.

The models obtained very good accuracy when tested using a leave-one-out cross-validation with 10 random folds (Table 3.1).

Models 3.4, 3.5, and 3.6 were used to create a geospatial layer depicting the probability of CWD occurrence. All input layers with a spatial resolution greater than 30-m x 30-m were resampled to 30-m x 30-m resolution using the nearest neighbor method.

Table 3.1: Logistic Regression Model Accuracy from Cross-validation

State	Accuracy
Minnesota	0.910
Wisconsin	0.896
Michigan	0.864

3.3 Geospatial Layer Analysis

The purpose of the geospatial layer analysis is to identify geospatial layers that can reduce the variance of the estimates when used in a post-stratified estimation procedure. These analyses were conducted at the state level. Therefore, the state can be considered the estimation unit for all estimates in the geospatial analysis study component. It can be thought of as an initial screening process of the candidate geospatial layers. The output of the geospatial layer analysis is a list of schemes and a RE (Equation 1.13) value. RE is defined as the ratio of the variance computed under the assumption of simple random sampling (SRS) and the variance computed under post-stratified estimation. It can be thought of in more concrete terms as the factor by which n under a simple random sample must be multiplied in order to achieve the precision of the post-stratified estimator. A RE > 1.0 indicates a gain in precision for the post-stratified estimator while a value < 1.0 indicates a loss in precision relative to the simple random sampling estimator. All REs in all three study components were computed using the unconditional variance estimator.

Plot locations were intersected with each candidate geospatial layer using a GIS software package. Each spatial layer was clipped to conform to the same state boundary layers. The clipping procedure insures an upper boundary to the total area of the population. The different spatial layers did produce slightly different estimates of total area of the population. These differences are caused by differences in spatial resolution, by issues related to the conversion of vector layers (such as ecological province) to raster format, and by the accuracy of boundary delineations. These differences in total area are unimportant to the study as they will not affect the effectiveness of a given stratification. The value and frequency (pixel count) for each spatial layer was output to a table. In the terminology of FIA, these data are referred to as the P1 data.

The plot intersection data and the pixel count data for each candidate geospatial layer were input into the statistical computing program R (R Development Core Team, 2008). This was done separately for each state. A post-stratified estimate of the mean CWD volume and the associated variance was computed using the estimators section 1.3.5 (Bechtold and Patterson, 2005; Woodall and Monleon, 2008). Once the variances were computed, a RE was computed for each of the candidate schemes.

For categorical geospatial layers, each category was counted as a separate stratum unless there were too few observations. Strata with too few observations were collapsed into the most logical neighboring stratum. The definitions for categorical codes and the collapsed categorical codes are shown in the section A of the appendix. A minimum of 10 plots per stratum was required. The minimum is more than twice the recommended minimum of 4 plots per stratum recommended in Bechtold and Patterson (2005) and was considered appropriate due to the smaller sample size and greater variability in the CWD sample compared with the normal P2 sample.

Continuous geospatial layers do not naturally form strata the way categorical layers do. Thus, the optimum number of strata and the associated strata break points must be computed. To do this, a program was written in R (R Development Core Team, 2008) that breaks the continuous variable into a given number of discrete bins. Then, every unique combination of contiguous bins for a given number of strata is examined. Each distinct combination of discrete bins was required to have at least 10 observations to be considered valid during the optimization process. An estimate of the mean CWD volume and variance of the mean was computed for each set of bins.

The identification of strata breakpoints is an optimization problem which requires an objective function be defined. Because RE will be used to judge the effectiveness of each scheme it is a natural choice for the objective function. A RE was then computed for each of the possible bin groupings. The combination of bins that produced the highest RE was selected as the best. Once the best set of strata breakpoints was identified, the pixels of the candidate geospatial layer are reclassified into strata. Similarly, each plot is assigned to a strata based on the intersection value. Upon completion of this process a scheme is created and can be used to compute an estimate of the mean or total CWD volume of the state and a RE.

This method of computing optimal strata breakpoints for continuous variables is systematic, meaning it examines every possible combination of contiguous bins. It's limitation is in the granularity determined by the number of bins. Consider the continuous variable of percent canopy cover (PC). Its range is $0-100$. If the number of discrete bins examined was 10, then the estimate of the optimal strata breakpoints would be limited to combinations of 10% bins. However, as the number of bins is increased, the number of distinct combinations of contiguous bins and therefore the computational burden increases geometrically. The number of bins used in this study was 50, which provided a good balance of granularity and breakpoints that were reasonably well spaced. The program was run for all continuous geospatial layers to create schemes of 2, 3, and 4 strata. Schemes consisting of 5 strata were also computed for a small set of geospatial layers that produced the best RE values in each state. In all three states, this included the PC and LOG schemes. A five strata MEVI scheme was computed in Michigan.

Each state recorded a small number of extreme observations (figures 2.2, 2.4, and 2.5). These observations can exert a strong influence on stratum means and variances. They can also influence the computation of the optimal strata break points for continuous geospatial layers as discussed above. In order to examine the sensitivity of the methods used in the geospatial layer analysis to extreme observations some of these observations were dropped from the sample. This new sample is referred to as the NEO (No Extreme Observations) sample. Then, the analysis was rerun using the NEO sample. Estimates and schemes computed using the NEO will include NEO in the label. Note that this is a new sample, and a new SRS estimate will be generated in order to compute the RE's. The cutoff value for extreme observations was selected for each state by examining the histograms of sampled CWD values. A threshold was selected that would eliminate large gaps between observations in the right tail of the distribution (Table 3.2).

Table 3.2: Extreme Observation Threshold Values by State (Cu. Ft. per Acre)

State	CWD Vol. $\geq$	No. Obs. Removed
Minnesota (base sample)	3,000	1
Wisconsin	2,000	1
Michigan	2,000	2

The Minnesota intensified sample was not used for the geospatial layer analysis. Including the intensified plots would confound the comparison of results across states because the sampling intensity would not be constant. Also, including the intensified plots would affect the optimization process used for continuous variables because the additional plots target a subpopulation that is thought to have elevated CWD values. Because the optimization was run over the entire state, inclusion of the additional plots would erroneously inflate the strata means for high volume strata and influence the optimal strata breakpoints. The result would be strata breakpoints that are not optimal for the state population nor the BWCAW subpopulation.

3.4 Simulation

One limitation of the geospatial layer analysis is that there is only one set of data per state that is being examined under many post-stratification schemes, which means there is a sample of size 3 (one for each state) for determining which geospatial layer to use. Thus, the best layer in each state could be a product of the biological relationship between the spatial layer and the variable of interest or a function of the particular sample realized from all possible samples. The difference between the two scenarios is that a true biological relationship would be effective at reducing variance across future samples whereas if the observed RE was simply a function of the observed sample the gains in precision may not occur in future samples. One way the latter situation can arise is due to extreme observations in the sample. In cases where an extreme observation falls in a stratum with a low stratum weight, then the variance caused by such a large value is constrained by the stratum weight. Consequently, the variance of the population estimate is low relative to the simple random sample estimate and an increase in RE occurs. If the extreme observation is removed, then the RE may plummet because the other strata were ineffective at reducing variance. In this example, the apparent RE is a function of one or a small number of extreme observations.

The second purpose of simulation is to inspect the difference between the conditional and unconditional variance estimators. Several authors have argued strongly for the use of the conditional variance estimator versus the unconditional (section 1.2). FIA assumes that the realized sample is approximately proportional, meaning the proportion of plots in each stratum is about the same as the proportion of land area in each stratum. Under these conditions, the two variance estimators are essentially equal. A simulation study will allow a quantitative comparison between the two. With only three observations available in the geospatial layer analysis it is not possible to address this question analytically.

If the sample for each state can be assumed to be a good representation of the true population of CWD, then a simulation experiment can be constructed to estimate the true sampling distribution of the population mean under the SRS and post-stratified assumptions as well as their variances. Once these distributions have been generated, the applicability of the stratification across many samples, and the difference between the two variance estimators can be examined.

A function was written in R (R Development Core Team, 2008) to carry out the simulation experiment. The function requires three inputs: an Empirical Cumulative Density Function (ECDF) for the candidate scheme, stratum weights for the stratification in the form of pixel counts by stratum, and the sample size to draw at each iteration of the simulation. Another R (R Development Core Team, 2008) function was written to compute the ECDF in the form of a table of values and associated cumulative density by stratum.

The simulation function works in three steps. The first step is to iteratively draw a random number between 0 and 1 and assign it to a stratum up to the sample size per iteration. This number represents a simulated plot. Assignment of the simulated plot to strata is done randomly but in approximate proportion to the stratum weights. Thus, over many iterations of the simulation the average number of plots per stratum will be approximately the same as the stratum weights, but there will be variability between iterations. This simulates the observed variability in the actual samples. The second step is to create a smoothed representation of the ECDF in each stratum. The degree of smoothing is a function of the number of unique values in each stratum. The more unique values in the stratum, the less smoothing was required because the shape of the ECDF was already well estimated. Third, for each simulated sample in a given stratum, another random number was generated between 0 and 1. The smoothed ECDF was used to translate the random number into the corresponding value of CWD volume. This second random number represents the simulated observation (CWD per acre) on the simulated plot. The smoothed ECDF is capable of interpolation, so the simulated CWD values are not necessarily the values observed in the original sample, but can theoretically take any value between 0 and the observed maximum.

At the completion of the three steps a simulated sample is achieved. From this sample estimates of the population mean and variance were computed using simple random sampling and post-stratified estimators. Both conditional and unconditional variance estimators were used in the post-stratified estimation procedure. The RE was also computed at each iteration using the unconditional variance estimator. Histograms of RE are the primary output of the simulation study and are used to determine if the stratification was effective across many samples or not. The ECDF's are a secondary output of the simulation experiment. The simulation results were also used to compute estimates of the population mean and variance. As with the geospatial layer analysis, all simulations were run at the state level, which is to say that the estimation unit was the state. Also like the geospatial layer analysis, the Minnesota intensified sample was not used in the simulation study component. Each simulation consists of $5,000$ simulated samples.

Simulation is computationally intensive. Because of this, not every scheme was selected for simulation. In each state, the schemes that produced the highest RE values based on a visual inspection of the geospatial layer analysis results were selected for simulation (Table 3.3). In addition, a small number of schemes that produced moderate RE values (relative to the best schemes) were selected for simulation.

Table 3.3: Summary of Simulations

Scheme	Minnesota (Base)	Wisconsin	Michigan
PCSTAND	✓	✓	✓
PC4	✓	✓	✓
PC5	✓	✓	✓
LOG4	✓	✓	✓
LOG5	✓	✓	✓
JULMAX4	✓		✓
JULMAX3	✓		✓
GROW4	✓		
GROW3	✓		
AVGTEMP4			✓
AVGTEMP3			✓
MEVI5			✓
MEVI4			✓
MEVI3			✓

Further simulations were conducted using the schemes developed using the NEO samples in the geospatial layer analysis (Table 3.4). These simulations were intended to address the effect of extreme observations on the selection of optimal strata. Because only the continuous geospatial layers were optimized, only continuous geospatial layers were included in this set. This is a different strategy than what was used in the geospatial layer analysis. In the geospatial layer analysis, the methods were held fixed and the sample was changed in order to measure the effects of extreme observations on the process of selecting the best scheme. In the simulation study, a comparison of the long term effectiveness of schemes optimized with and without extreme observations is the objective. In order for a meaningful comparison to take place, the sample must be held fixed. Thus, the simulations of the NEO schemes will be run using the base sample in each state.

The simulation study provides an opportunity to evaluate the properties of the conditional and unconditional variance estimators over many samples. For each iteration a

Table 3.4: Summary of Simulations of NEO Schemes

Scheme	Minnesota (Base)	Wisconsin	Michigan
PC4	✓	✓	✓
PC5	✓	✓	✓
LOG4	✓	✓	✓
LOG5	✓	✓	✓
JULMAX4	✓		✓
JULMAX3	✓		✓
GROW4	✓		
GROW3	✓		
AVGTEMP4			✓
AVGTEMP3			✓
MEVI5			✓
MEVI4			✓
MEVI3			✓

50% confidence interval was computed in the standard way ($\bar{Y} \pm 0.674\hat{\sigma}$). It was thought the the use of the 50% interval be more sensitive to differences between the two variance estimators because there should be an equal chance of a particular estimated mean falling within the interval. The mean of the $5,000$ simulated samples was taken as the true population mean. Then, the proportion of the iterations that include this mean in the 50% confidence interval was computed for both variance estimators. The results will indicate if there is any difference between the two estimators for the purposes of inference. This experiment was conducted at the state level on all simulations in all three states.

3.5 Estimation Unit Analysis

The previous two study components have produced candidate schemes that perform well in terms of RE at the state level and simulations that estimate their performance across many samples. The estimation unit analysis will use the best schemes to post-stratify estimation units defined at decreasing spatial extents. Recall that a unique combination of a set of estimation units and a scheme is termed a *stratification*. The objective is to determine the effect of spatial extent on the performance of the best schemes. Once the effect is understood, recommendations on the appropriate spatial extent to use when defining estimation units can be made. The results of this study component will consist of a set of candidate stratifications and associated RE values.

In addition to creating the estimation units within each state, the major difference between this and the geospatial layer analysis is the enforcement of a minimum sample size per stratum and collapsing of strata that don't meet the minimum requirement. This requirement is necessary because when a population is divided into estimation units, the sample size within each may produce small or even 0 sample sizes in individual strata. A minimum sample size per stratum of 5 was used for this study component. The exception to this rule occurs in the census water ownership category from the OWN geospatial layer, in which case a minimum of 3 plots was required. This lower minimum allows these entirely non-forest estimation units to be separated from other estimation units. The minimum plot requirements are simple to implement in practice. These minimum requirements also allow the stratification to function at smaller spatial extents than they were developed for.

There are two opposing concerns to consider when determining the minimum sample size per stratum requirement. First, when enforcing higher minimum plot counts per stratum for estimation units that are defined over smaller geographic extents there are fewer plots available and thus strata are collapsed more frequently. This can result in estimates being reduced to SRS in extreme cases. However, allowing too few plots results in potentially poor estimates of strata means and variances. Note that some stratifications work by constraining small population components with high variance into low weighted strata. There is no need to obtain good estimates of the strata mean or variance in these cases because the objective is to dampen their effect on the overall estimate. An example of such strata are the edge class strata defined in several of the papers covered in section 1.2.2. Overly stringent minimum plot requirements would eliminate all benefits from these types of strata. Experience has shown that the FIA sample design produces an approximately proportional sample. When the sample is approximately proportional, the minimum plot per stratum rules affect only small population components that are relatively unimportant to the overall estimate in a given estimation unit. The defined stratum minimums have a good balance of these opposing concerns and will allow the effects of various estimation units to be examined.

The analysis begins at the state level, which was already computed as part of the geospatial layer analysis. Then, each state was broken down into estimation units of increasingly smaller spatial extents in the following three ways: ecological provinces, ownership categories, ecological provinces and ownership categories combined (Table 3.5). The ownership categories used to define estimation units were restricted to: 1) General Public, 2) Private, 3) Inland Census Water, 4) National Forests, and 5) BWCAW (Minnesota intensified sample only). Minnesota's base and intensified samples were analyzed separately. Because Minnesota's intensified sample was constrained to the BWCAW lands, two addition stratifications were created. The first uses ecological province and BWCAW ownership only, and the second uses simply the BWCAW lands and all other lands to form estimation units. The latter case creates a state level estimate for the Minnesota intensified sample, which was not part of the geospatial analysis. In addition, the ecological province stratification was not computed for the Minnesota intensified sample because it would fail to constrain the intensification to the BWCAW estimation unit. The analysis of the Minnesota base sample was the same as the other two states.

Each estimation unit was stratified using the best schemes identified in the first two study components. Strata with insufficient sample sizes were combined with the neighboring stratum with the lowest plot count to form a new combined stratum. If combined strata had insufficient sample sizes they were collapsed until the minimum requirement was met. In rare cases where the minimum plot counts could not be met across an entire estimation unit, then the estimation unit was collapsed with the most logical estimation unit and the strata plot counts were reassessed. For example, if estimation units are defined by the intersection of ecological province and ownership, there may be cases were there are simply too few publicly owned lands in a particular ecological province to carry out post-stratified estimation. In this case, the public and private estimation units would be collapsed within that ecological province.

Table 3.5: Summary of Stratifications

Stratification	Minnesota (Intensified)	Minnesota (Base)	Wisconsin	Michigan
STATE & BWCAW PC4	✓			
STATE & BWCAW PC5	✓			
STATE & BWCAW LOG4	✓			
STATE & BWCAW LOG5	✓			
ECOP & BWCAW PC4	✓			
ECOP & BWCAW PC5	✓			
ECOP & BWCAW LOG4	✓			
ECOP & BWCAW LOG5	✓			
STATE & PC4		✓	✓	✓
STATE & PC5		✓	✓	✓
STATE & LOG4		✓	✓	✓
STATE & LOG5		✓	✓	✓
STATE & MEVI4				✓
STATE & MEVI5				✓
OWN PC4	✓	✓	✓	✓
OWN PC5	✓	✓	✓	✓
OWN LOG4	✓	✓	✓	✓
OWN LOG5	✓	✓	✓	✓
OWN MEVI4				✓
OWN MEVI5				✓
ECOP PC4		✓	✓	✓
ECOP PC5		✓	✓	✓
ECOP LOG4		✓	✓	✓
ECOP LOG5		✓	✓	✓
ECOP MEVI4				✓
ECOP MEVI5				✓
ECOP & OWN PC4	✓	✓	✓	✓
ECOP & OWN PC5	✓	✓	✓	✓
ECOP & OWN LOG4	✓	✓	✓	✓
ECOP & OWN LOG5	✓	✓	✓	✓
ECOP & OWN MEVI4				✓
ECOP & OWN MEVI5				✓

After all required strata collapsing was done, population estimates of both mean and total were computed in each estimation unit along with their associated variances. The simple random estimate of mean and total was also computed, with variance estimates. Estimates of the population total and variance of the total were summed across estimation units for both the stratified and simple random estimates. An estimate of the population mean was computed as the sum of the totals divided by the total area (Equation 3.7). The variance of the population mean was computed as the sum of the variances of the totals divided by the total area squared (Equation 3.8). Note that these computations rely on the assumption that the estimation units are independent and thus their variances can be summed without computing the covariance (Bechtold and Patterson, 2005). Finally, RE was computed in the usual way.

$$\bar{Y}_{Pop} = \frac{\sum_{e=1}^{E} \hat{Y}_e}{A_T} \tag{3.7}$$

$$Var(\bar{Y}_{Pop}) = \frac{\sum_{e=1}^{E} Var(\hat{Y}_e)}{A_T^2} \tag{3.8}$$

where

$\bar{Y}_{Pop}$ is the population mean

$\hat{Y}_e$ is the total of estimation unit e

E is the number of estimation units in the population

A_T is the total area of the population

$Var(\bar{Y}_{Pop})$ is the variance of the population mean

Chapter 4

Results

4.1 Geospatial Layer Analysis Results

4.1.1 Minnesota Results

The geospatial layer analysis in Minnesota produced the best observed RE's of any state in the study (Figure 4.1). The highest RE's were achieved by the LOG schemes, which surpassed 1.5. The PC schemes performed nearly as well with RE's above 1.4. The PC-STAND scheme was the next best at 1.28, which was also the highest of all the categorical schemes tested. Of the remaining categorical layers, none surpassed a RE of 1.2. The climate related schemes showed mixed results. The JULMAX4 and GROW4 schemes were the best at 1.2. The remaining three (JANMIN, AVGTEMP, and AVGPREC) produced RE's of less than 1.12. The CTI schemes, which were included to attempt to describe site productivity, only produced a maximum RE of 1.10. However, CTI was included in the Minnesota logistic regression model, which was used to create the LOG schemes. This suggests that CTI does provide useful information, but is not effective on its own. The MODIS derived schemes produced similar results to the climate derived schemes with the mean vegetative index schemes outperforming the standard deviation schemes. The overall range of REs was 1.01 to 1.55. Each of the continuous schemes tested demonstrated the predicted pattern of increasing RE's with increasing number of strata, but at a decreasing rate.

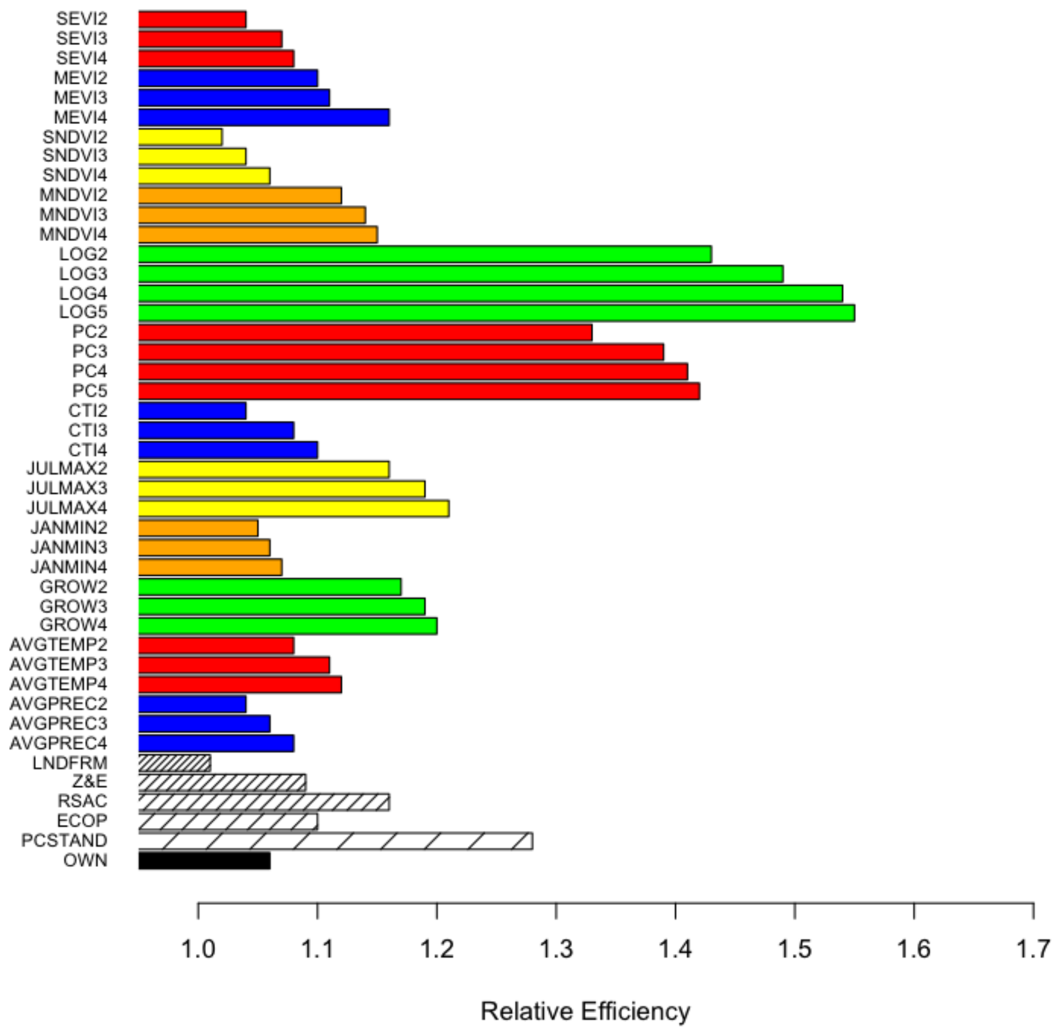

Figure 4.1: Minnesota (Base Sample) Relative Efficiencies by Scheme. *Categorical schemes are shown in hollow bars with diagonal lines of varying density. Optimized continuous schemes are shown in solid color bars.*

The Minnesota geospatial layer analysis using the NEO (No Extreme Observations) sample produced similar results to the base sample (Figure 4.2). The highest RE's were produced by the LOG schemes, followed by the PC schemes. The PCSTAND scheme was again third. Most of the schemes computed under the NEO sample showed a slightly improved RE value (Figure 4.3). The maximum gain occurred in the LOG3 scheme, which improved by 0.086. The magnitude of most of the differences was less than 0.05. The PC3 through PC5 schemes along with the three CTI schemes all performed better using the base sample, which could indicate that they gained efficiency by constraining extreme observations. The pattern of increasing RE with increasing strata for continuous schemes is mostly upheld using the NEO sample. There is an exception to this rule for the PC 5 scheme.

Each candidate scheme also produced an estimate of the population total in millions of cubic feet (Figure 4.4). The actual estimates produced are less important than the pattern shown. The SRS estimate of the total was 7.8 million cubic feet. Each candidate scheme produced a slightly different estimate of the total, but none were more than one standard error (as calculated under SRS) from the SRS estimate. In this analysis, the sample is fixed and is being summarized in many different ways. The range of population totals, which is approximately 1.0 million cubic feet, demonstrates the magnitude of the influence that the choice of post-stratification scheme can have on the ultimate estimate.

The range of population totals computed using Minnesota's NEO sample show a similar pattern (Table 4.5). The total range was about 0.9 million cubic feet, which was slightly less than the range under the base sample. The SRS estimate fell from 7.8 million cubic feet under the base sample to 7.5 under the NEO sample. As with with base sample results, none of the post stratified estimates is more than one SRS standard error from the SRS estimate.

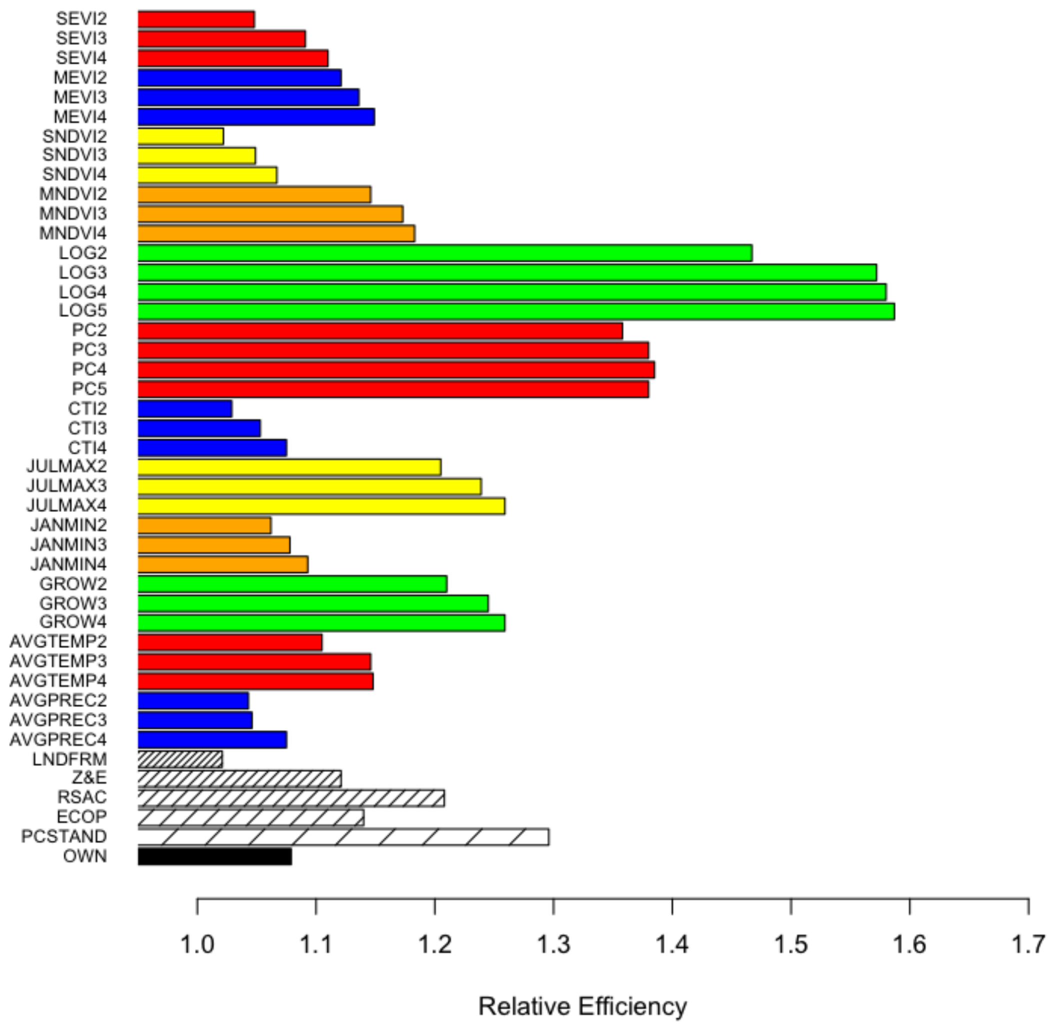

Figure 4.2: Minnesota (NEO Sample) Relative Efficiencies by Scheme. *Categorical schemes are shown in hollow bars with diagonal lines of varying density. Optimized continuous schemes are shown in solid color bars.*

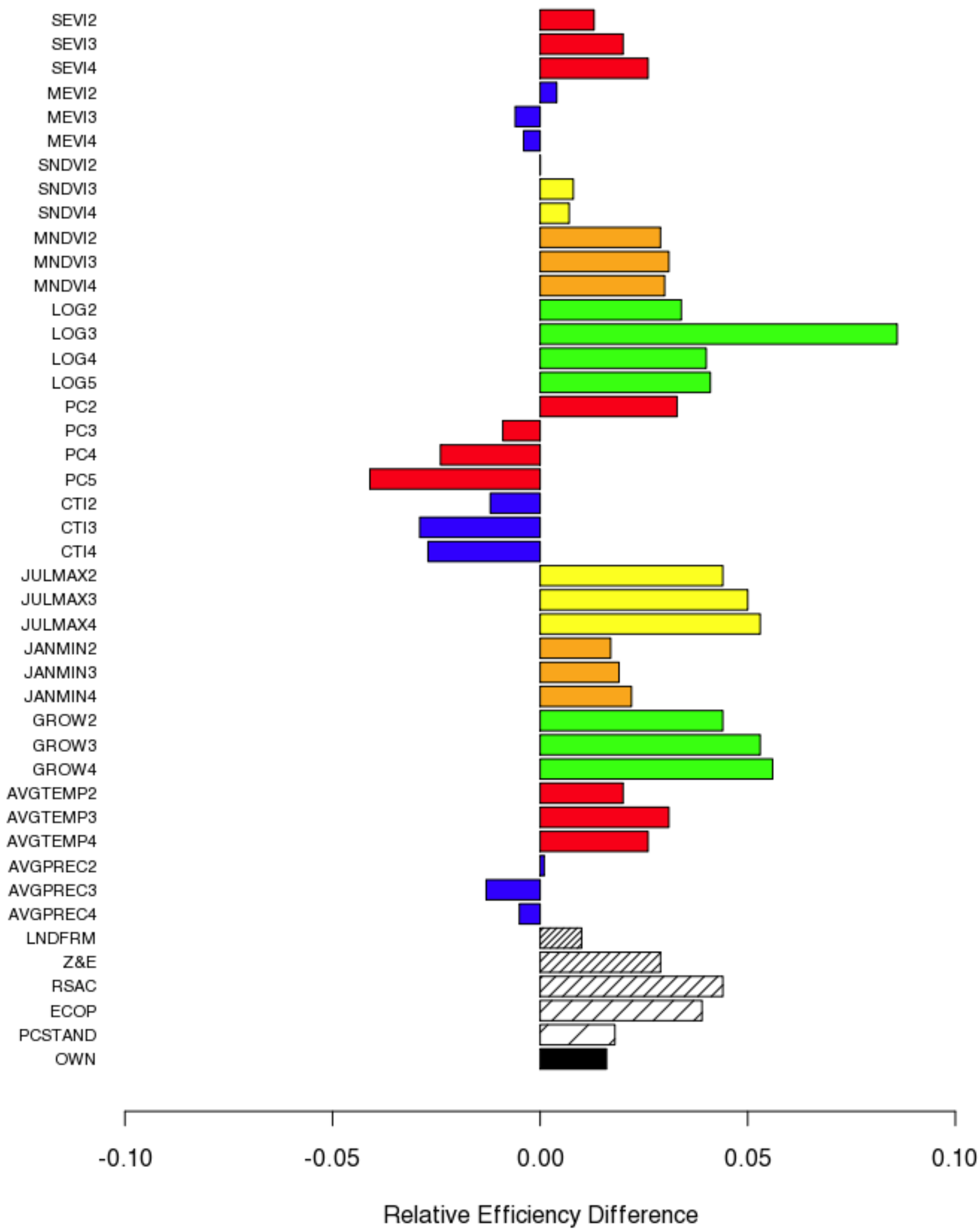

Figure 4.3: Minnesota NEO Sample Relative Efficiencies Minus Base Sample Relative Efficiencies by Scheme. *Categorical schemes are shown in hollow bars with diagonal lines of varying density. Optimized continuous schemes are shown in solid color bars. Positive values indicate an improvement in RE using the NEO sample. Negative values indicate better results under the base sample.*

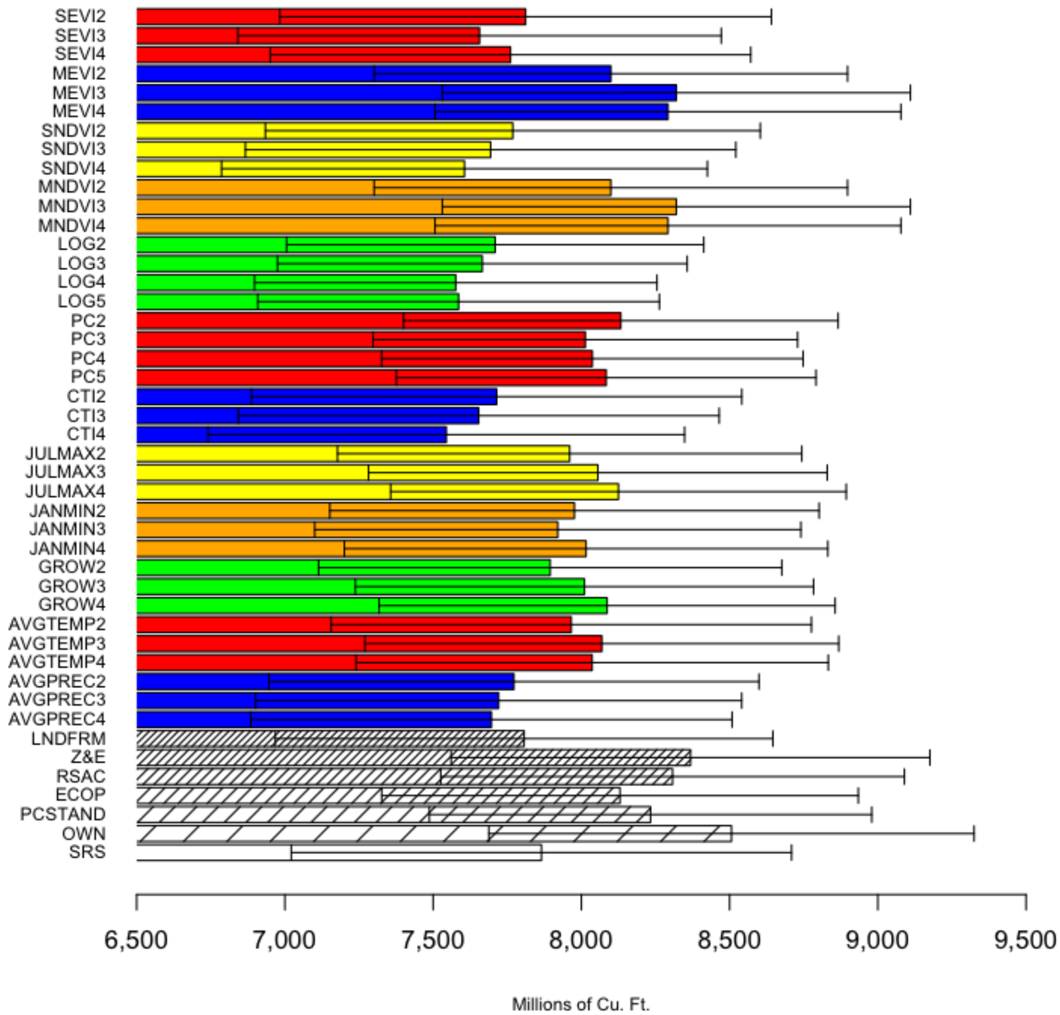

Figure 4.4: Minnesota (Base Sample) Population Totals by Scheme (*Error bars depict one standard error. Categorical schemes are shown in hollow bars with diagonal lines of varying density. Optimized continuous schemes are shown in solid color bars.*)

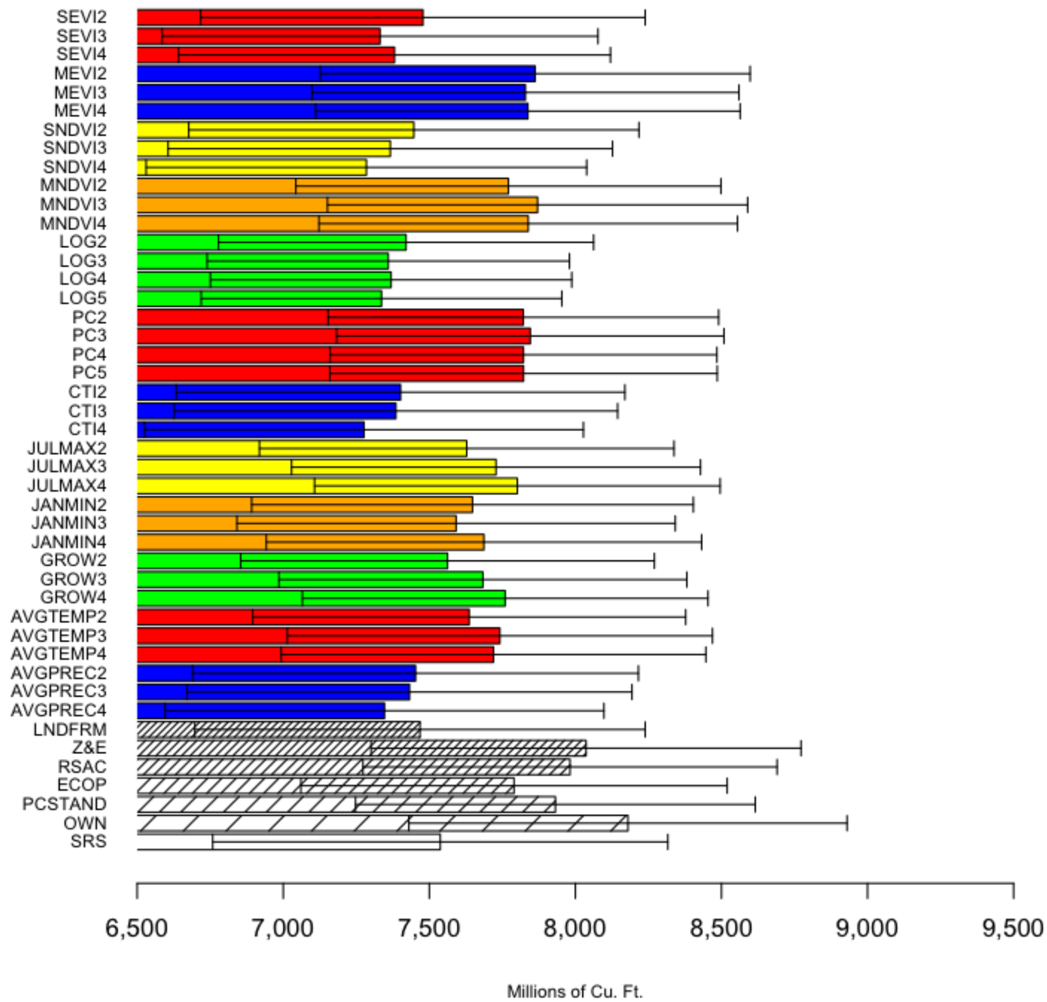

Figure 4.5: Minnesota (NEO Sample) Population Totals by Scheme (*Error bars depict one standard error. Categorical schemes are shown in hollow bars with diagonal lines of varying density. Optimized continuous schemes are shown in solid color bars.*)

4.1.2 Wisconsin Results

The Wisconsin geospatial layer analysis results follow a similar pattern as the Minnesota results (Figure 4.6). The highest RE's were produced under the LOG schemes, with the LOG5 producing the highest at 1.38. The PC schemes produced the next highest results. Interestingly, the PC schemes all clustered at a RE of approximately 1.3 The PC5, PC4 and PC3 schemes produced nearly identical results with RE's of 1.315, 1.316, and 1.314 respectively. The PCSTAND performed nearly as well as the PC schemes at 1.29. The next best performing categorical schemes was RSAC. The RSAC scheme did not perform very well on its own, but was included in the logistic regression model that produced the LOG schemes. None of the climate derived schemes performed better than 1.15. The AVGPREC2 scheme actually performed slightly worse than SRS, with a RE of 0.99. The CTI schemes performed poorly with a maximum RE of 1.03. The MNDVI and MEVI outperformed the SNDVI and SEVI schemes easily. The MNDVI and MEVI schemes produced moderate results at almost 1.20. The total range of RE's was 0.99 to 1.38. With the exception of the PC schemes, the general pattern of of increasing RE associated with increasing strata is maintained.

The use of the NEO sample in Wisconsin produced very similar results to the base sample (Figure 4.7). The LOG schemes continue to be the best with RE's over 1.40. The PC schemes follow a more predictable pattern than under the base sample, however the PC4 and PC5 schemes are still nearly identical with RE's of 1.393 and 1.395 respectively. PCSTAND improved to 1.34. The largest improvements using the NEO sample were seen in the LOG and PC schemes, followed by the PCSTAND and RSAC categorical schemes (Figure 4.8). The maximum improvement was 0.08, but most schemes changed by less than 0.025.

The SRS estimate of the population total was 4.3 million cubic feet. Most of the post-stratified estimates of the population total were very close to the SRS estimate (Figure 4.9). The LOG and PC schemes produced estimates noticeably above the SRS estimate. These were also the best performing schemes in terms of RE. The PCSTAND and RSAC categorical layers also produced estimates that were higher than the rest. None of the differences in population totals exceeded one standard error. When the NEO sample was

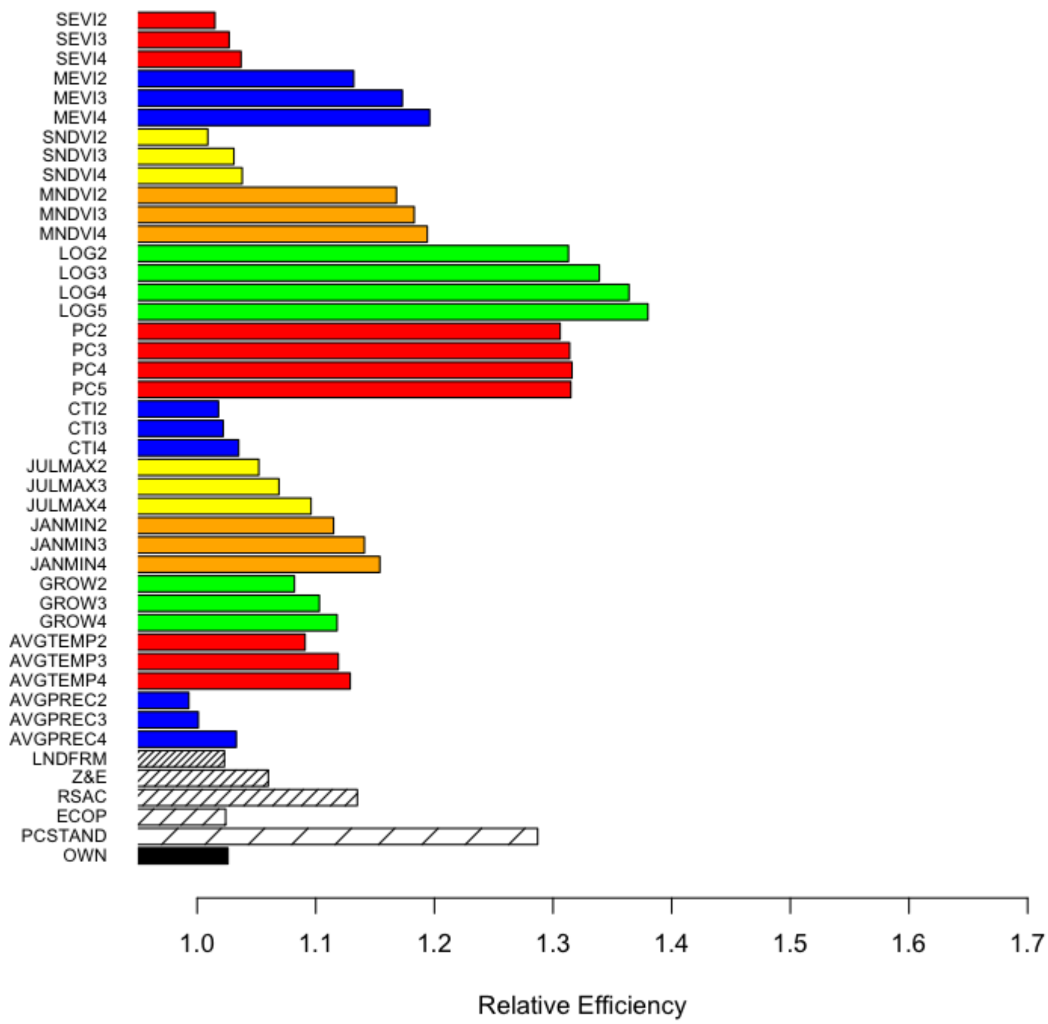

Figure 4.6: Wisconsin Relative Efficiencies by Scheme *Categorical schemes are shown in hollow bars with diagonal lines of varying density. Optimized continuous schemes are shown in solid color bars.*

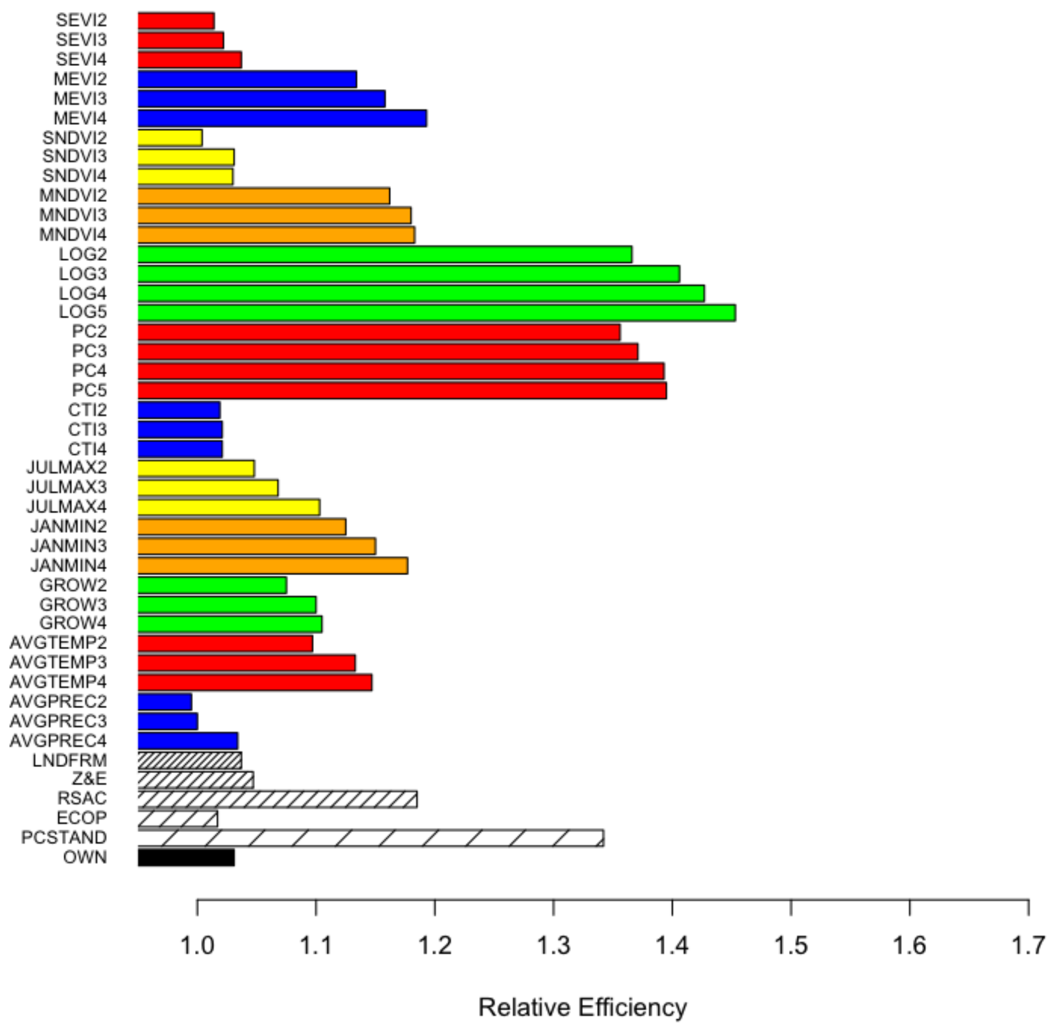

Figure 4.7: Wisconsin (NEO Sample) Relative Efficiencies by Scheme *Categorical schemes are shown in hollow bars with diagonal lines of varying density. Optimized continuous schemes are shown in solid color bars.*

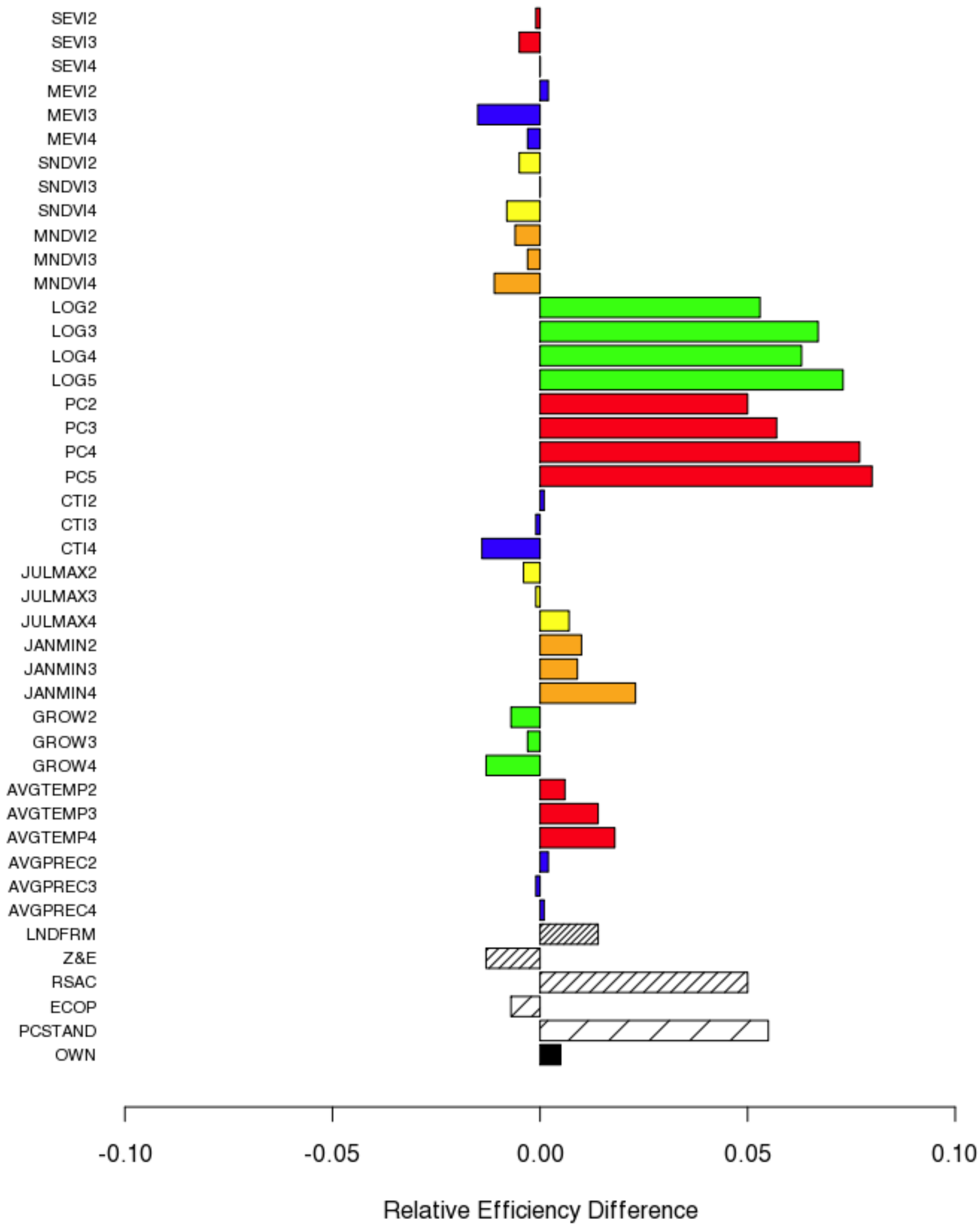

Figure 4.8: Wisconsin NEO Sample Relative Efficiencies Minus Base Sample Relative Efficiencies. *Categorical schemes are shown in hollow bars with diagonal lines of varying density. Optimized continuous schemes are shown in solid color bars. Positive values indicate an improvement in RE using the NEO sample. Negative values indicate better results under the base sample.*

used, the SRS estimate of the population total falls to 4.1 million cubic feet. The pattern of population totals using the NEO sample remains the same (Figure 4.10). The LOG, PC, RSAC, and PCSTAND schemes all produce estimates that are noticeably different from the rest of the estimates.

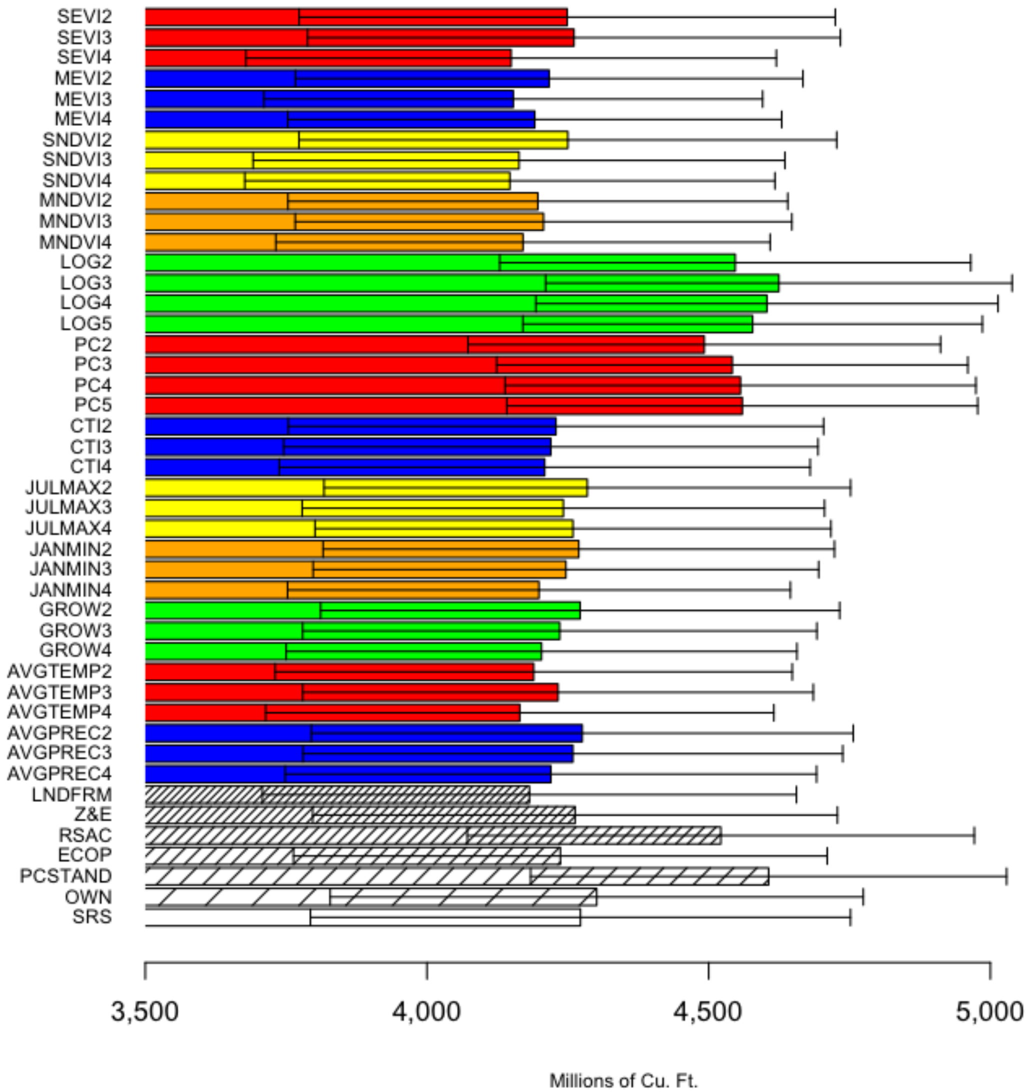

Figure 4.9: Wisconsin Population Totals by Scheme (*Error bars depict one standard error. Categorical schemes are shown in hollow bars with diagonal lines of varying density. Optimized continuous schemes are shown in solid color bars.*)

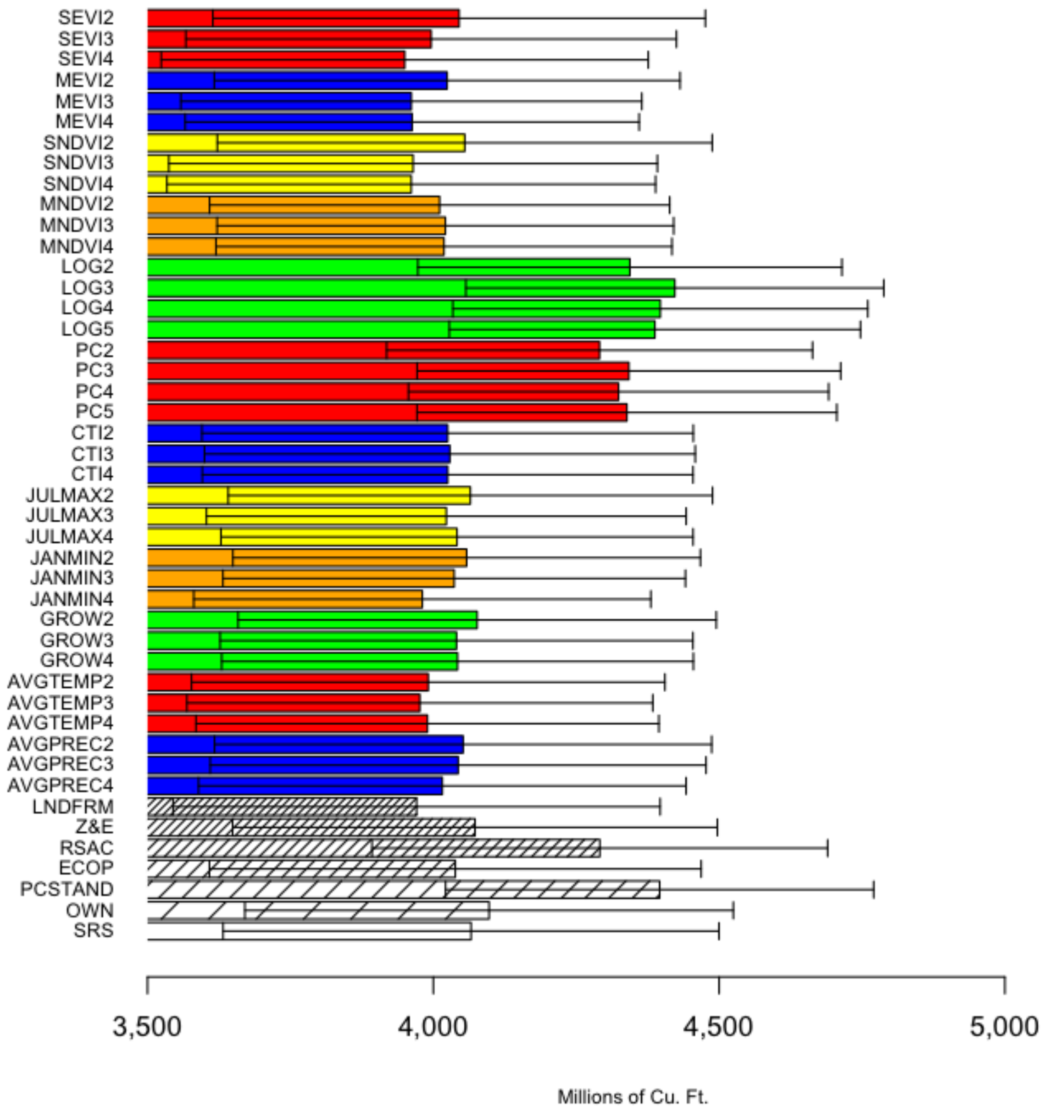

Figure 4.10: Wisconsin (NEO Sample) Population Totals by Scheme Excluding Extreme Observations (*Error bars depict one standard error. Categorical schemes are shown in hollow bars with diagonal lines of varying density. Optimized continuous schemes are shown in solid color bars.*)

4.1.3 Michigan Results

The results of the geospatial layer analysis in Michigan differ from the other states in several interesting ways (Figure 4.11). First, the LOG schemes are not the best, although they are competitive with the best. The best layer is actually the PC5 scheme, with a RE of 1.34. The PCSTAND layer performed moderately well at 1.25, which was again the best of the categorical layers. The RSAC scheme was the second best categorical layer at 1.16. The CTI schemes showed similar performance to the other two states, with RE's much less than 1.10. Many of the climate derived schemes performed moderately well with RE's in the range of 1.20 to 1.24. The exception was the AVGPREC set of schemes, which only achieved a maximum RE of 1.03. In contrast to the other two states, the MEVI schemes produced good results, with a maximum RE of 1.32, which is very competitive with the PC schemes. A 5 strata optimization was run on the MEVI geospatial layer in order to examine how it compared with the 5 strata LOG and PC schemes. The MEVI5 produced the second highest RE in the state. The MEVI3, MEVI4, and MEVI5 schemes out performed their LOG scheme counterparts. The MNDVI schemes produced noticeably lower results with a maximum of 1.15. The SNDVI and SEVI results were much less. All of the continuous schemes followed the pattern of increasing RE associated with increasing strata, but at a decreasing rate.

The results under the NEO sample were again very similar to the base sample (Figure 4.12). The PC5 scheme was the best with a RE of 1.40. PC5 is closely followed by LOG5 at 1.38. In fact, under the NEO sample. the LOG schemes perform slightly better than the MEVI schemes. The PCSTAND improved slightly to 1.31. The climate derived schemes showed the same pattern as under the base sample, with all schemes showing a slight improvement. The performance of the CTI schemes remained poor, and in fact performed less well under the NEO sample. The largest improvement was shown by the MEVI2 scheme, which improved its RE by a margin of 0.09. In fact, most schemes improved under the NEO sample (Figure 4.13), with many improving by margin of over 0.05. This shows the highest sensitivity to extreme observations of the three states in the study.

The population total computed under SRS for Michigan is 8.1 million cubic feet. The population totals computed under the various candidate schemes produced very similar

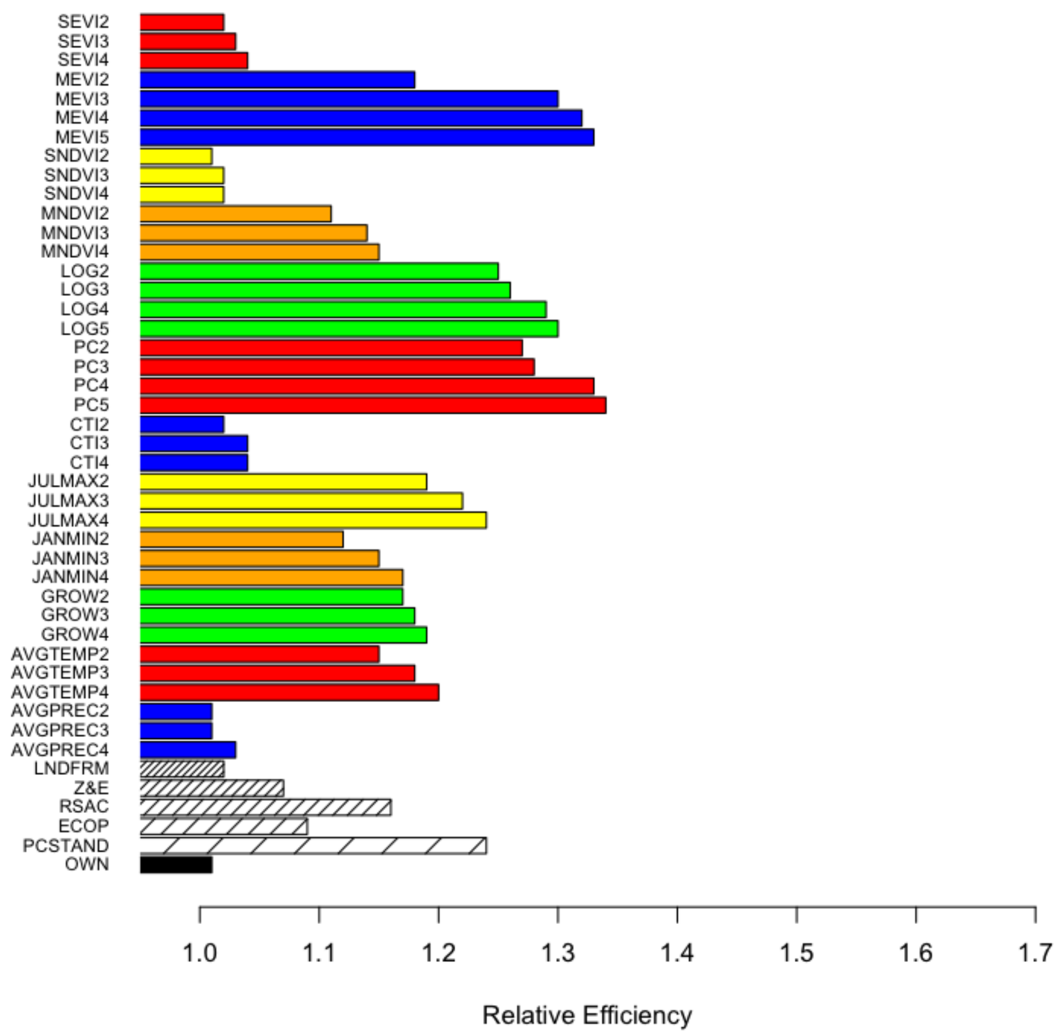

Figure 4.11: Michigan Relative Efficiencies by Scheme *Categorical schemes are shown in hollow bars with diagonal lines of varying density. Optimized continuous schemes are shown in solid color bars.*

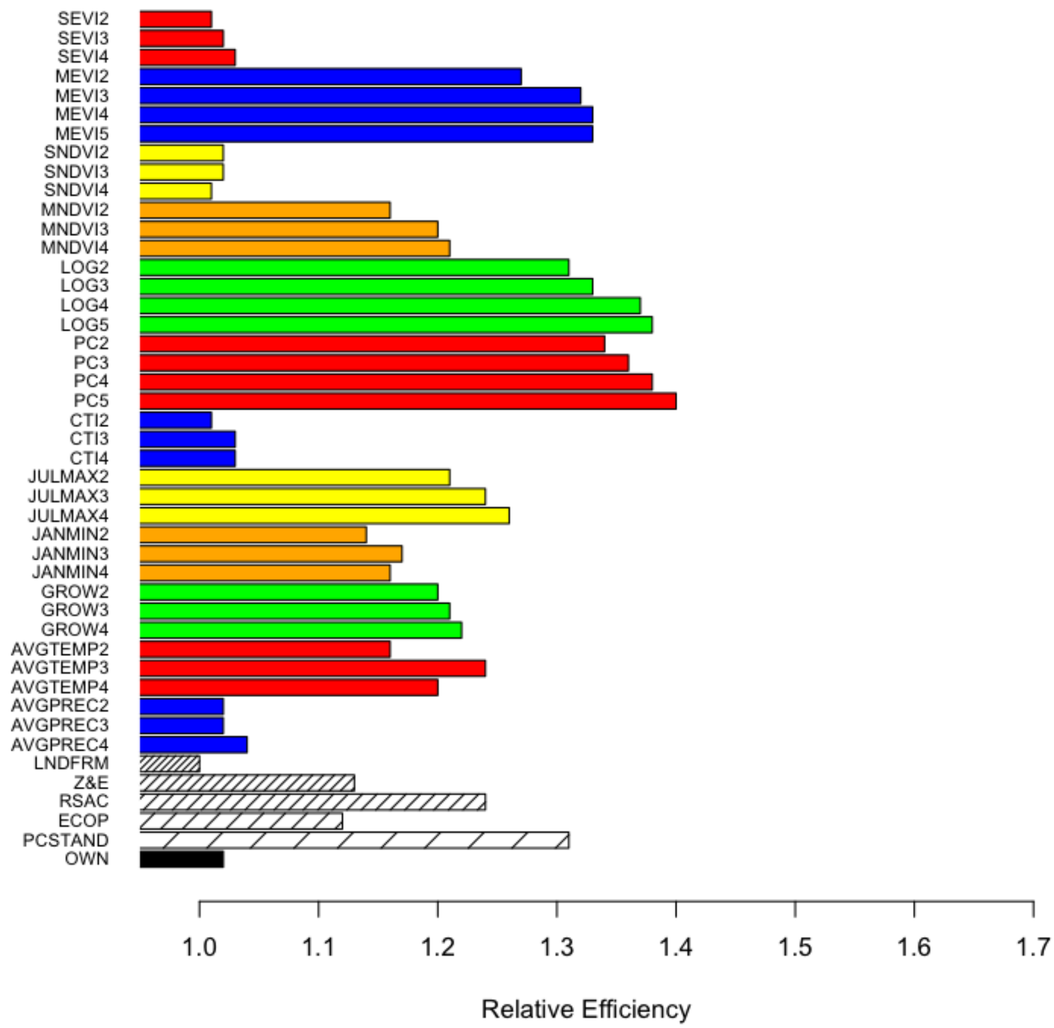

Figure 4.12: Michigan (NEO Sample) Relative Efficiencies by Scheme *Categorical schemes are shown in hollow bars with diagonal lines of varying density. Optimized continuous schemes are shown in solid color bars.*

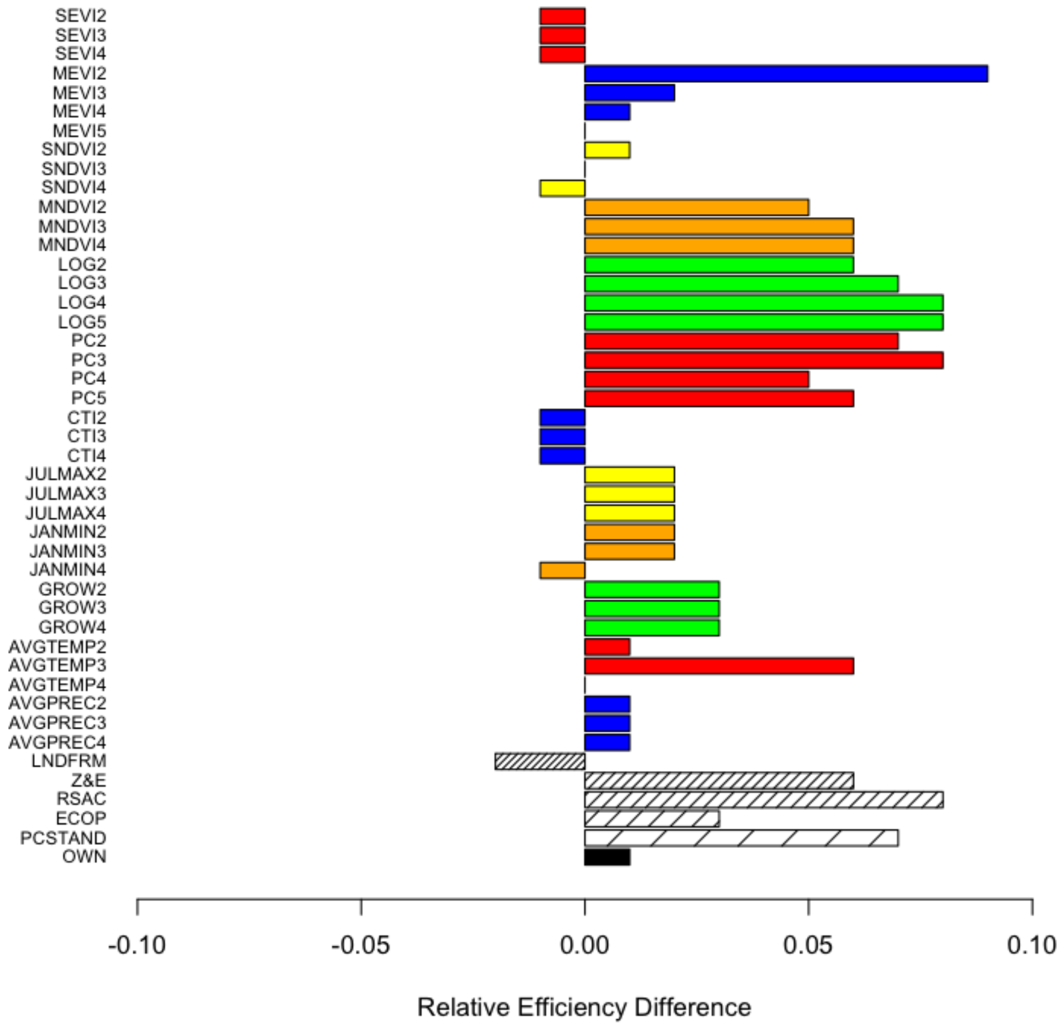

Figure 4.13: Michigan NEO Sample Relative Efficiencies Minus Base Sample Relative Efficiencies. *Categorical schemes are shown in hollow bars with diagonal lines of varying density. Optimized continuous schemes are shown in solid color bars. Positive values indicate an improvement in RE using the NEO sample. Negative values indicate better results under the base sample.*

estimates of the total (Figure 4.14). The range of the estimates was approximately 0.6 million cubic feet, which was the narrowest of the three states. The SRS estimate of the population total using the NEO sample was 7.7 million cubic feet. The use of the NEO sample did not alter the pattern of population estimates (Figure 4.15). The range of population estimates was approximately the same.

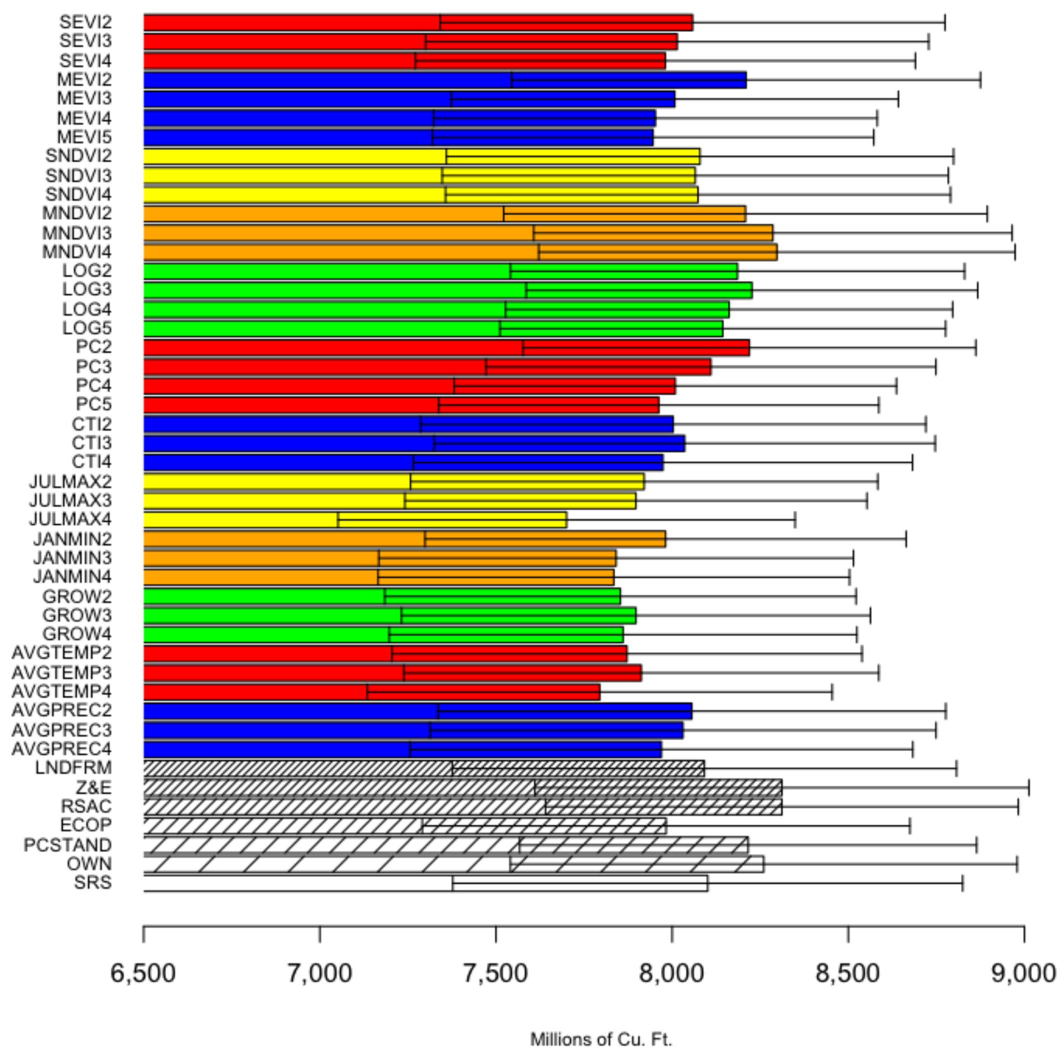

Figure 4.14: Michigan Base Sample Population Totals by Scheme (*Error bars depict one standard error. Categorical schemes are shown in hollow bars with diagonal lines of varying density. Optimized continuous schemes are shown in solid color bars.*)

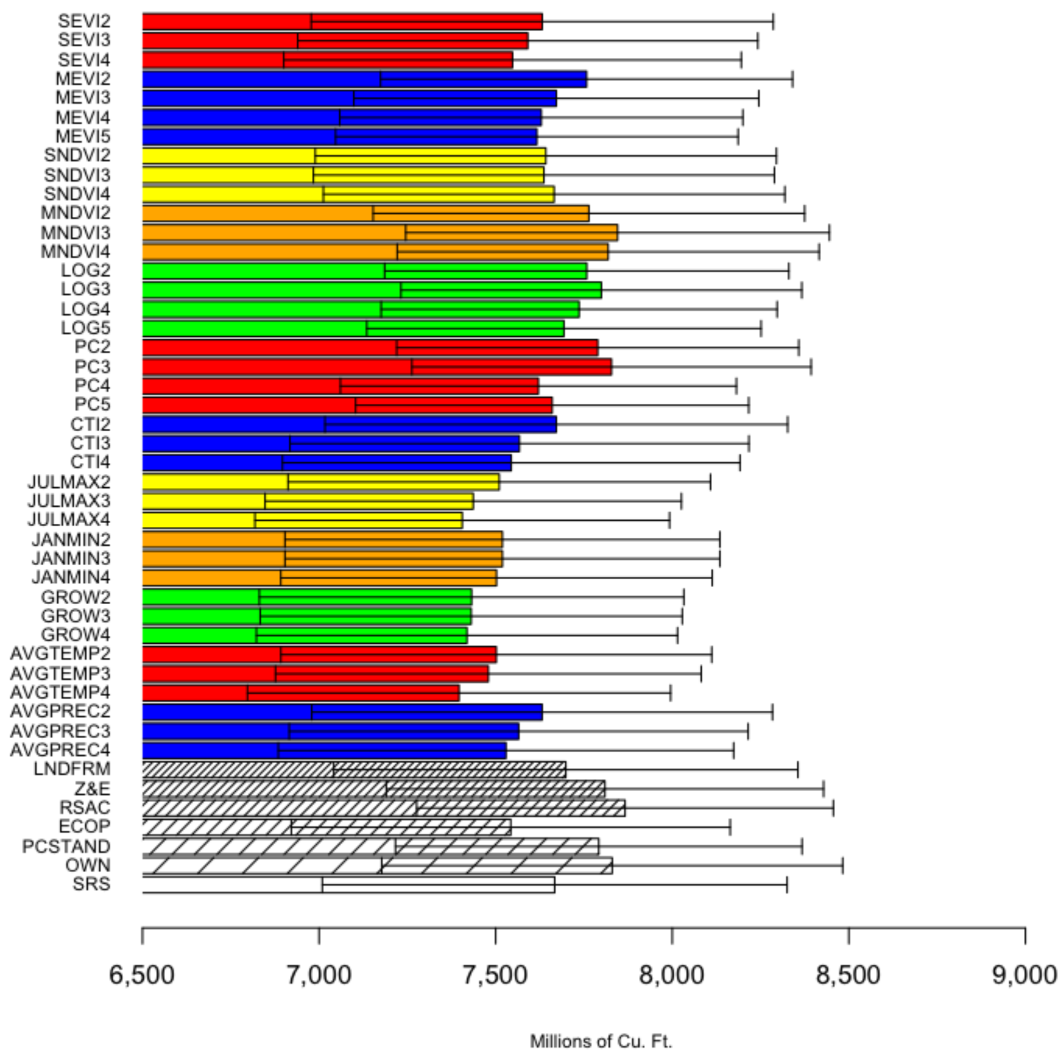

Figure 4.15: Michigan Base Sample Population Totals by Scheme Excluding Extreme Observations (*Error bars depict one standard error. Categorical schemes are shown in hollow bars with diagonal lines of varying density. Optimized continuous schemes are shown in solid color bars.*)

4.2 Simulation Results

The simulation study produced histograms of RE for each of the simulated schemes. Only a subset of representative histograms will be presented in this section to avoid unnecessary clutter. The complete of collection histograms can be found in the Appendix (Section C).

4.2.1 Minnesota Results

The Minnesota LOG simulations support the geospatial layer analysis results, which show that the LOG schemes produce the highest RE's. The simulation of the LOG5 scheme (constructed using the base sample) and the LOG5 NEO scheme (constructed using the sample excluding extreme observations) show mean RE's very close to the observed RE from the geospatial analysis (Figure 4.16). The LOG5 histogram shows a small number of samples with RE's near 1.0, indicating that this scheme can perform poorly for very rare samples. The LOG5 simulation also shows that rare samples can achieve a RE of 2.0 or higher. The PC schemes showed similar results to the LOG schemes, except that the observed RE's fell further to the left of the mean than in the LOG simulations and the shape tends to be more tightly clustered around the mean, with fewer extreme samples. The PC simulations suggest that these schemes will perform slightly better over the long run than what was observed in the geospatial layer analysis. The GROW and JULMAX simulations confirmed the results of the geospatial layer analysis that the RE's are well below those of the LOG and PC schemes. The simulation of the PCSTAND scheme showed an interesting result. Although the observed RE from the geospatial layer analysis was less than 1.30, the mean RE from the simulation was 1.44, which is only slightly less than the optimized PC schemes.

The histograms show very little effect of removing the extreme observations on the optimization process. The Minnesota simulations show very similar shape and mean values of each of the NEO simulations compared to their base sample counterparts. These data demonstrate that the optimization method is robust in terms of insulating the optimized strata from the effects of extreme observations in Minnesota.

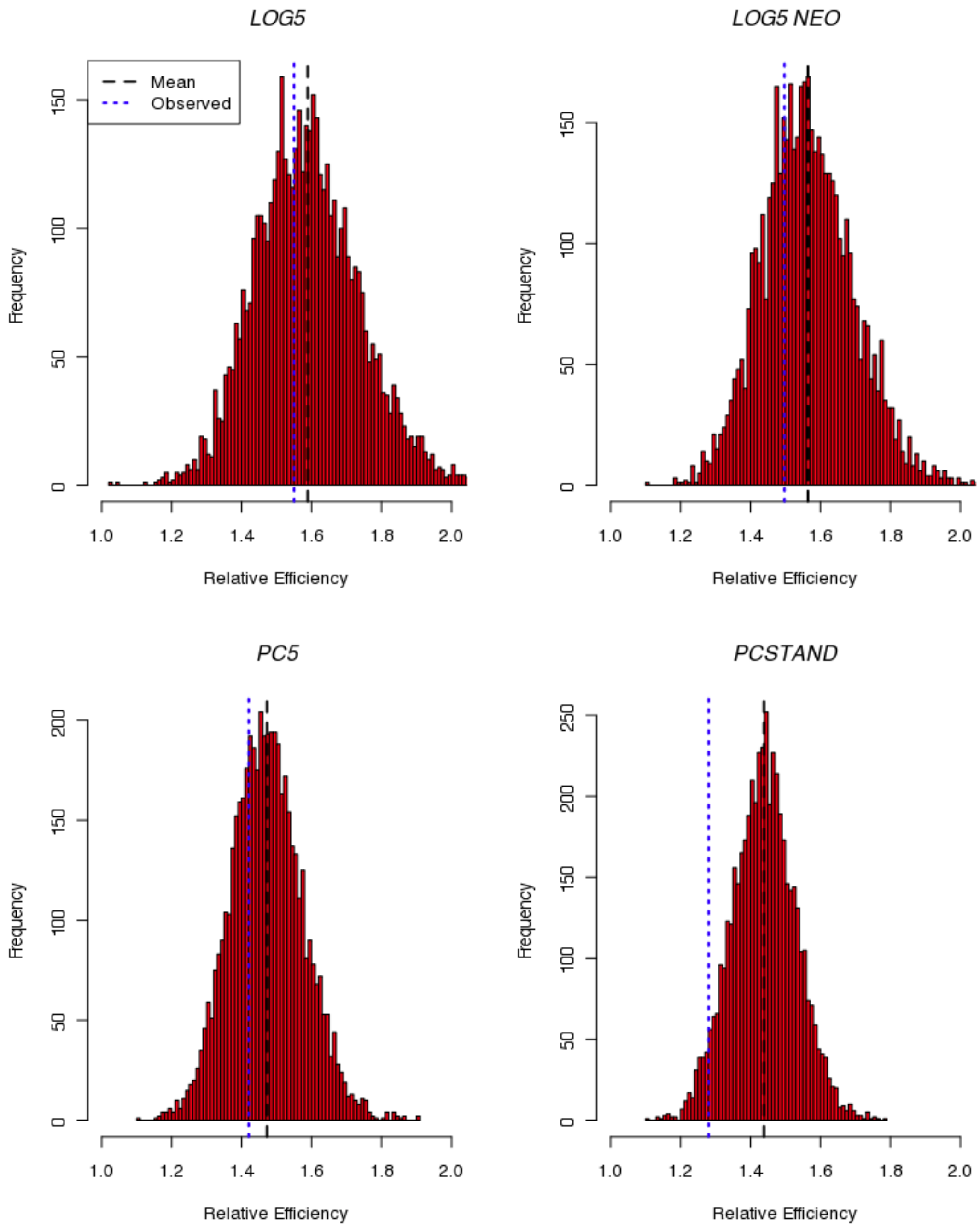

Figure 4.16: Histograms of Simulated Relative Efficiency for the LOG5, LOG5 NEO, PC5, and PCSTAND schemes in Minnesota

4.2.2 Wisconsin Results

The Wisconsin LOG simulations show the observed RE from the geospatial layer analysis are well below the mean RE over many samples (Figure 4.17). This result will be discussed in section 5.4. The observed RE for the LOG5 scheme was 1.38 in the geospatial layer analysis and the mean of the LOG5 simulation was 1.56. This pattern is indicative of all the simulations in Wisconsin, however the LOG5 example is one of the most extreme cases. The PC5 scheme is another example where the observed RE was 1.32 and the mean simulated RE was 1.47. The mean RE's for the LOG and PC schemes are very similar to the means computed in the Minnesota simulation, suggesting that their long term effectiveness should be about equal. As in Minnesota, the PCSTAND scheme showed that the mean RE over many samples is competitive with the optimized PC schemes with a mean RE of 1.47, which was higher than the Minnesota result.

The effect of removing the extreme observations on the optimization method was weak. Neither the shape nor the mean of each of the simulated schemes was significantly changed. Note that a direct comparison to the NEO results in the geospatial layer analysis cannot be made here because the samples are different. The simulations show that the effect on the quality of the scheme over the long run is minimal.

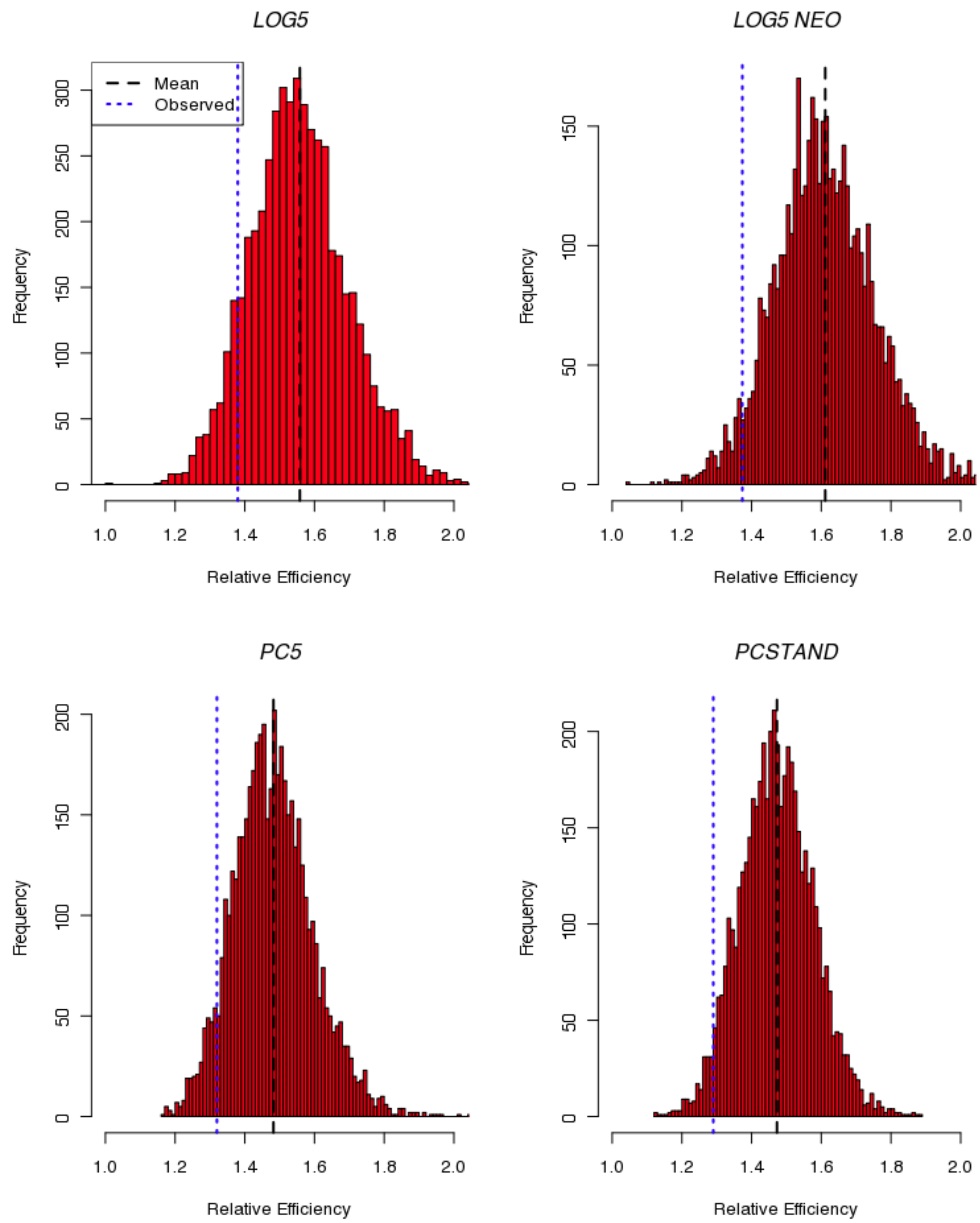

Figure 4.17: Histograms of Simulated Relative Efficiency for the LOG5, LOG5 NEO, PC5, and PCSTAND schemes in Wisconsin

4.2.3 Michigan Results

The Michigan simulation results for the LOG and PC schemes support a different conclusion than the geospatial layer analysis. The geospatial layer analysis of the base sample shows that the PC schemes are superior to the LOG schemes. The simulations show that the mean RE of the LOG schemes are higher than those from the PC schemes (Figure 4.18). The mean simulated RE from the LOG5 scheme was 1.38 while the simulated mean RE from the PC5 scheme was 1.33. The observed RE's from the geospatial layer analysis fall in different location relative to the means of each distribution. Thus, the PC schemes might be better for the current sample, but the LOG schemes will perform better over the long run. The JULMAX and AVGTEMP simulations confirm the geospatial results that those schemes will perform less well compared to the PC and LOG schemes, even though the observed RE's appear competitive. The simulation of the MEVI schemes supports the same conclusion as the JULMAX and AVGTEMP simulations. The observed RE's appear to be very competitive, but the long run average is below the PC and LOG schemes. Even the MEVI5 scheme, which was the second highest RE in the geospatial layer analysis, will be inferior to the LOG5 and PC5 schemes over the long run with a mean RE of 1.29. The simulation results for the PCSTAND scheme continue a trend started in the other two states, which is the PCSTAND will perform better over the long run than what is indicate by the geospatial layer analysis alone. However the long run average is not quite as high at 1.32.

Removing the extreme observations had a similar effect on simulations as it did in Wisconsin. The effect is seen as only minor adjustments to both the shape and mean of the simulated distribution of RE's. These results are consistent with the other two states.

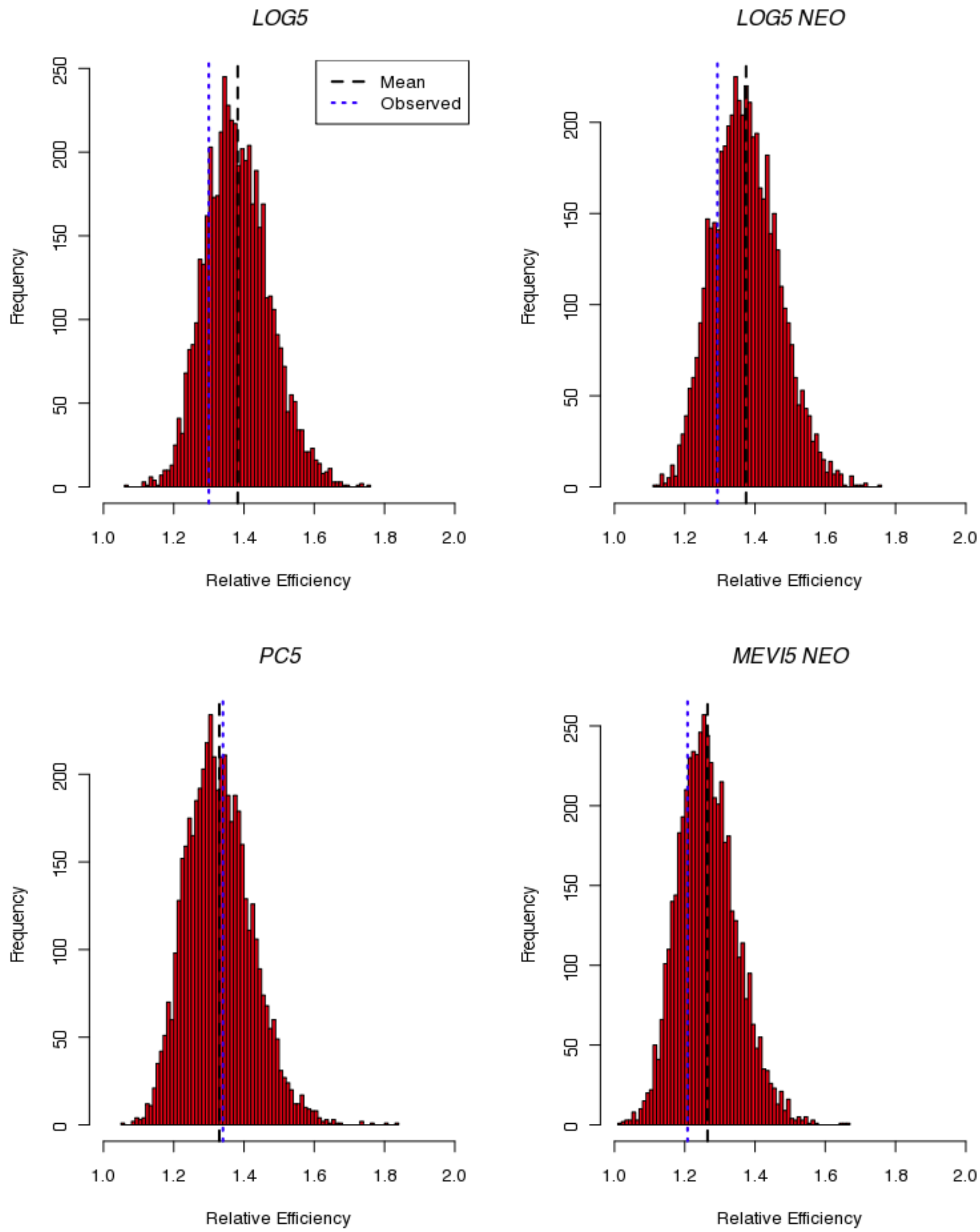

Figure 4.18: Histograms of Simulated Relative Efficiency for the LOG5, LOG5 NEO, PC5, and MEVI5 NEO schemes in Michigan

4.2.4 Comparison of Variance Estimators

Results for the comparison of the conditional and unconditional variance estimators show that the two variance estimators have not only the same empirical confidence interval coverage of the mean, but both are almost exactly the prescribed 0.50 (Tables 4.1, 4.2, 4.3). The slight fluctuations about 0.50 are insignificant and will not affect inference derived from the estimates. Not only do the estimators produce the same overall coverage, but they also tend to accept or reject the same simulated samples. For example, for the Minnesota JULMAX3 simulation, both estimators found the mean outside the 50% confidence interval for 2,566 simulated samples and both found the mean within the interval on 2,402 samples (Table 4.4). There were only a total of 32 simulated samples where the two estimators disagreed. The figures presented for the Minnesota JULMAX3 simulation are representative of all the simulations examined.

Table 4.1: Empirical 50% Confidence Interval Coverage for the Conditional and Unconditional Variance Estimators by Scheme for Minnesota Simulations

Simulation	Unconditional	Conditional
PCSTAND	0.499	0.498
PC4	0.491	0.493
PC5	0.507	0.505
LOG4	0.488	0.488
LOG5	0.496	0.496
JULMAX3	0.484	0.483
JULMAX4	0.500	0.501
GROW3	0.500	0.497
GROW4	0.500	0.501

Table 4.2: Empirical 50% Confidence Interval Coverage for the Conditional and Unconditional Variance Estimators by Scheme for Wisconsin Simulations

Simulation	Unconditional	Conditional
PCSTAND	0.501	0.502
PC4	0.499	0.499
PC5	0.504	0.504
LOG4	0.500	0.489
LOG5	0.507	0.504

Table 4.3: Empirical 50% Confidence Interval Coverage for the Conditional and Unconditional Variance Estimators by Scheme for Michigan Simulations

Simulation	Unconditional	Conditional
PCSTAND	0.496	0.497
PC4	0.508	0.507
PC5	0.498	0.500
LOG4	0.508	0.509
LOG5	0.500	0.500
JULMAX3	0.500	0.499
JULMAX4	0.497	0.498
AVGTEMP3	0.501	0.502
AVGTEMP4	0.502	0.505
MEVI3	0.494	0.496
MEVI4	0.506	0.505
MEVI5	0.504	0.506

Table 4.4: Summary of the Number of Simulated Samples that Exclude or Include the Mean Within the 50% Confidence Interval for the Minnesota JULMAX3 Simulation

	Uncond. Excludes Mean	Uncond. Includes Mean
Cond. Excludes Mean	2,566	15
Cond. Includes Mean	17	2,402

4.3 Estimation Unit Analysis Results

4.3.1 Minnesota Results

The results for the Minnesota estimation unit analysis are the first to use the intensified sample. The results of this analysis show a very distinct pattern. The smaller the spatial extent of the estimation units, the poorer the performance of the stratification relative to SRS (Figure 4.19). This result will be explored in the Chapter 5. In Minnesota, there were three different ecological provinces and three to five ownerships within each. This produced 10 distinct estimation units for the ECOP OWN stratifications. Across the state, there were five distinct estimation units for the OWN stratification. There were four estimation units for the ECOP BWCAW stratifications, and two for the STATE BWCAW stratification. The best RE's for the intensified sample were noticeably lower than for the base sample. The range of RE's for a given scheme over the various stratifications was 0.22 to 0.32.

The results for the Minnesota base sample showed the same general pattern as the intensified sample (Figure 4.20). The ECOP OWN stratifications did not perform as differently from the OWN stratifications as they did for the intensified sample, but the pattern was the same. For each scheme, the largest jump in RE occurred between the ECOP and STATE level stratifications. For the base sample, the ECOP OWN stratification included 9 distinct estimation units. This was less than for the intensified sample because the BWCAW estimation unit was collapsed with other National Forest lands due to insufficient plots. The OWN stratification included four estimation units and the ECOP included three. The LOG based stratification outperformed the PC stratifications for the same number of strata. This was true of both the intensified and base samples.

4.3.2 Wisconsin Results

The Wisconsin results for the estimation unit analysis showed two distinct patterns for the PC and LOG stratifications (Figure 4.21). The PC stratifcations produced slightly higher RE's for the ECOP OWN stratification than for the OWN stratifications. This pattern was not observed in the other two states. The LOG stratifications performed

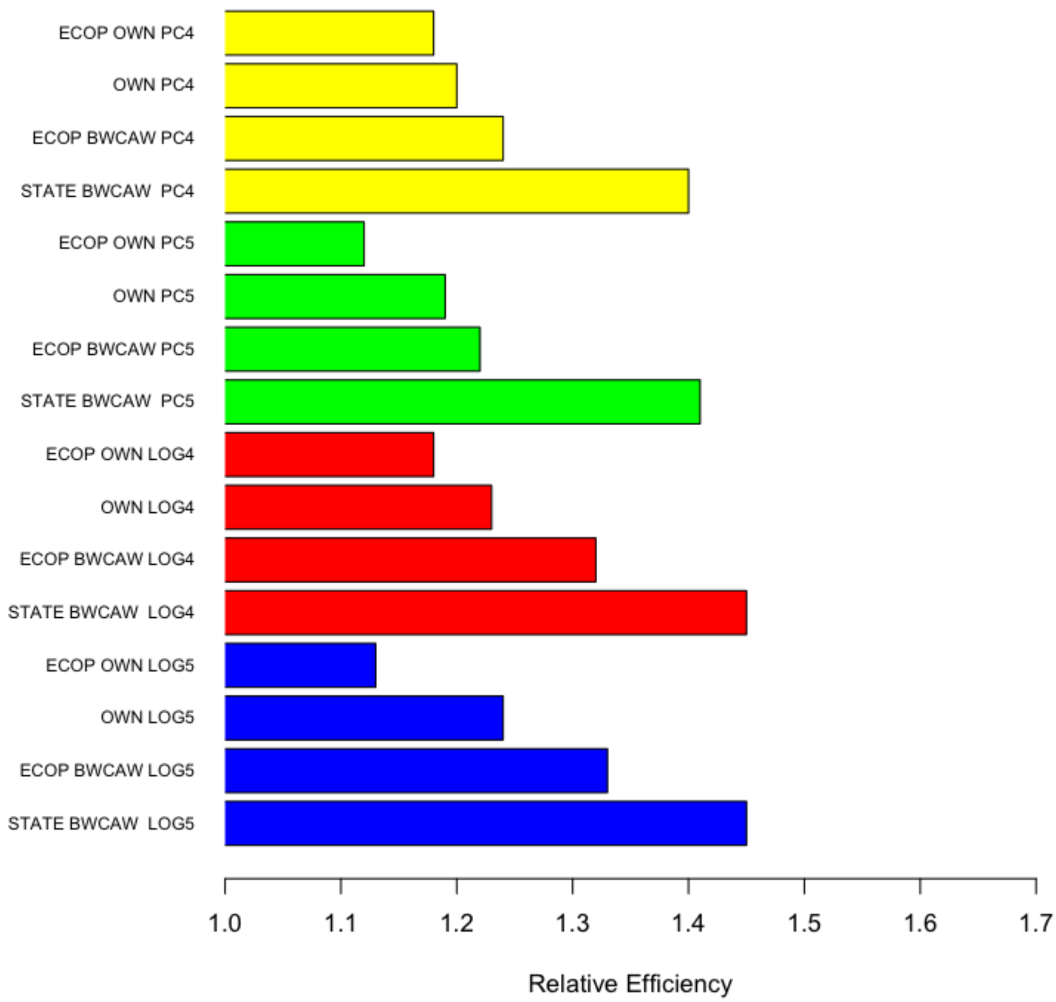

Figure 4.19: Minnesota Intensified Sample Relative Efficiencies by Stratification

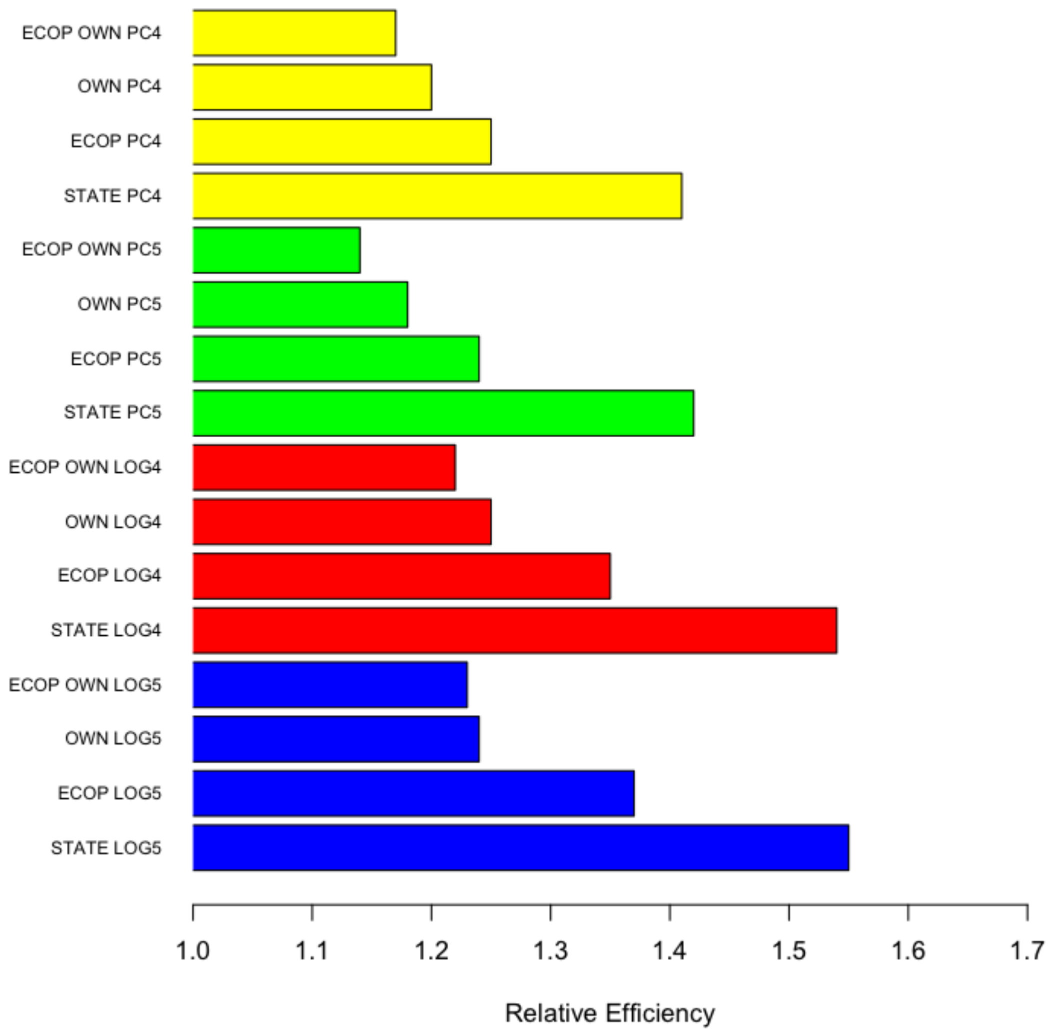

Figure 4.20: Minnesota Base Sample Relative Efficiencies by Stratification

much more poorly when ECOP was used. The ECOP OWN stratifications for both the LOG4 and LOG5 schemes were around 1.1. The RE's for the ECOP stratification were only slightly better. The results for the OWN stratifications were much better for the LOG schemes. For each scheme, the STATE stratification was the best, followed by the OWN stratification. There were seven distinct estimation units for the ECOP OWN stratifications in Wisconsin. There were four estimation units for the OWN stratifications and only two for the ECOP stratifications. The general pattern of decreasing RE with increasing estimation units does not hold in Wisconsin as it did in Minnesota. This phenomenon will be covered in section 5.6.

4.3.3 Michigan Results

The Michigan estimation unit analysis was unique because it included the MEVI4 and MEVI5 schemes as well as the PC and LOG schemes. The MEVI, PC, and LOG stratifications each produced distinct patterns. The OWN stratifications of the MEVI4 and MEVI5 schemes produced the highest RE, even surpassing the state level result. This was the only such result in all three states. The ECOP produced the lowest RE's for the MEVI schemes. The MEVI4 and MEVI5 results were very similar with the MEVI5 only slightly higher in terms of RE. Results for the MEVI schemes were also more consistent than other schemes with a narrow range of RE's. The PC schemes produced a pattern similar to the Minnesota results, with the RE's decreasing with increasing numbers of estimation units. The ECOP OWN PC5 stratification produced the lowest RE of all the PC stratifications. It produced a RE well below the ECOP OWN PC4 stratification. The LOG stratifications produced lower RE's for stratifications involving ECOP. This was similar to the Wisconsin results. The state level stratifications produced the best results for the LOG schemes, followed by the OWN stratifications. In Michigan, the ECOP OWN stratifications included 7 distinct estimation units. The ECOP and OWN included two and four respectively.

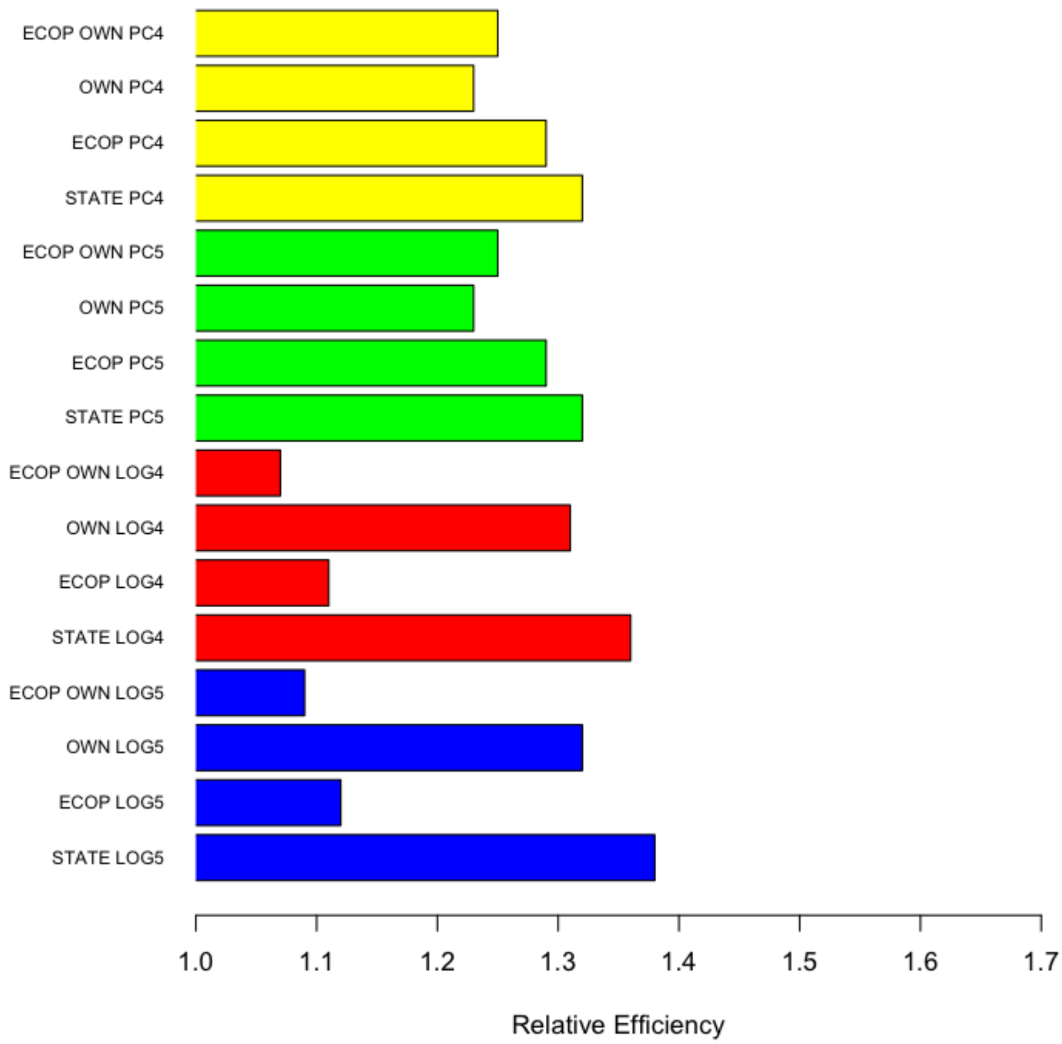

Figure 4.21: Wisconsin Relative Efficiencies by Stratification

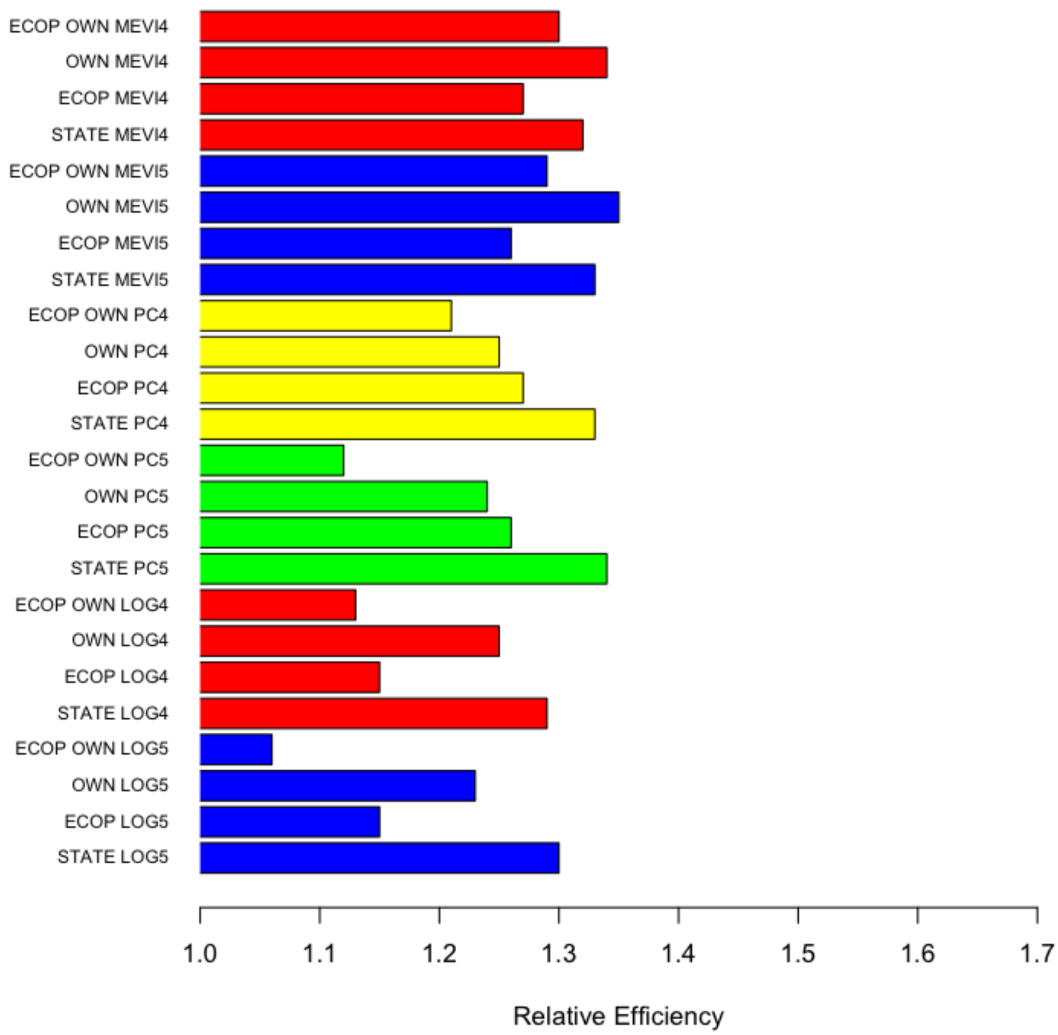

Figure 4.22: Michigan Relative Efficiencies by Stratification

Chapter 5

Discussion

5.1 Variability of Population Totals

Each candidate scheme of the geospatial layer analysis produced an estimate of the population total. These estimates varied from one another. Minnesota showed the largest range of estimates at 962 million cubic feet and Wisconsin showed the least at 477 (Table 5.1). The differences in population totals can be traced to differences in population means because $\hat{Y} = N\bar{Y}$, where N is the total size of the population provided by the geospatial layers. The population means computed under post-stratification will naturally be different from a mean computed under the assumption of SRS. The primary cause of this difference is the allocation of plots to strata. If the proportion of plots per stratum exactly matches the stratum weight, then the estimate of the mean will equal the SRS estimate. This scenario is called proportional allocation. However, the allocation of plots to stratum (n_h) is random under post-stratification, and therefore variability in plot allocation should be expected. The variability in population totals does *not* indicate a bias in the post-stratified estimator. It is worth restating that in the geospatial layer analysis, the same sample is being summarized in many different ways producing many different estimates. The magnitude of the range illustrates how much influence the estimation procedure has on the estimate. The following discussion will provide an explanation for these observed ranges in population totals by explaining the differences in the population means.

Table 5.1: Range of Population Estimates of CWD Volume by State (Millions of Cu. Ft.)

State	Minimum	Maximum	Range
Minnesota	7,544	8,506	962
Wisconsin	4,147	4,624	477
Michigan	7,710	8,311	601

To demonstrate how the variability in plot allocation to strata affects the population total, the LOG3 scheme from Wisconsin will be used as an example. This scheme produced an estimate of 4,624, which was a moderate distance from the SRS estimate of 4,272. The first comparison to make is between the proportion of plots allocated to each of the three strata versus the stratum weights as determined by the geospatial layers (Table 5.2). The post-stratified estimator weights each stratum mean by the stratum weights. Table 5.3 shows the difference between the stratum weighted mean and the plot weighted mean. Even though the differences are not great, they do account for a moderate difference in the weighted stratum means. As expected, the plot weighted mean is equal to the SRS estimate of 118.98. The post-stratified estimate of the mean is greater. When the population means are multiplied by the total area of the population (approximately 35,891,000 acres), the difference between the two means (128.87 - 118.98 = 9.89) equals approximately 352 million cubic feet. Even though the SRS and post-stratified estimates differ, there is no bias involved. The differences are simply due to the random allocation of plots to strata.

Table 5.2: Comparison of the Proportion of Plots per Stratum Versus the Stratum Weights for the LOG3 Scheme in Wisconsin

	Stratum 1	Stratum 2	Stratum 3
Prop. Plots	0.65	0.32	0.03
Stratum Weight	0.63	0.34	0.04

Table 5.3: Comparison of the Plot Weighted Mean Versus the Stratum Weighted Mean for the LOG3 Scheme in Wisconsin

	Stratum 1	Stratum 2	Stratum 3	Sum
Unweighted Stratum Mean	20.55	279.87	594.46	
Plot Weighted Mean	13.45	88.83	16.70	118.98
Stratum Weighted Mean	12.89	93.89	22.09	128.87

5.2 RE as the Objective Function for Optimal Strata Breakpoints

Relative Efficiency (RE) is defined as the ratio $\frac{Var(\bar{y})_{SRS}}{Var(\bar{y})_{Post}}$. When the algorithm for computing the optimal strata breakpoints for continuous variables is run, the sample remains the same for each candidate set of breakpoints. Therefore the Var_{SRS} is a constant. This means that the algorithm that maximizes the RE also seeks to identify any stratification that produces the lowest variance. However, in general smaller variances are associated with smaller means. So, even though the post-stratified estimator is known to be unbiased, using RE as the objective function for optimizing strata breakpoints can prejudice the stratification towards smaller means.

An alternative objective function for optimization could be minimizing the coefficient of variation (CV), which is defined as $\frac{\hat{\sigma}}{\hat{\mu}}$. This method was not used anywhere in this study. It is presented for comparison purposes only. Notice that CV is the ratio of two estimates, as opposed to the ratio of a constant and an estimate. Each time a set of strata breakpoints is applied to the sample, both the numerator and denominator of the CV are computed. When CV is minimized, the stratification produces the smallest standard error relative to the estimated mean possible. In a sense, the CV method optimizes the stratification scheme whereas using RE optimizes the observed sample.

Graphing the stratified mean versus the stratified variance (using the unconditional estimator) for the Minnesota LOG5 scheme produces a linear relationship with a positive slope (Figure 5.1). Therefore, smaller variances are associated with smaller means. However, graphing the stratified mean on the CV produces a more of a column of data.

The relationship is not as clear, but as the CV moves towards the minimum, the mean tends to increase. The Minnesota LOG5 scheme is the best performing scheme tested. Selecting a scheme that did not perform as well in terms of RE produces the same results. For example, the Michigan AVGPREC4 scheme produced a RE of only 1.03. However, the pattern remains the same. In fact, the pattern of the mean versus CV is very clear and suggests that optimizing using minimum CV would prejudice the estimates toward slightly larger estimates.

It is important to note that these relationships are confounded by the issues raised in section 5.1, which is that slight differences between the proportion of plots assigned to a stratum (plot weight) and the stratum weight will also affect the estimate of the mean. The optimization algorithm used in this study reassigns plots to stratum for every combination of contiguous bins and thus some variability in these weights does occur. The main point of this discussion is to demonstrate how much influence the optimization method has on the ultimate estimate produced. There are many ways to apply the post-stratified estimator to the given sample. The objective is to apply it in the best way possible as defined by some objective criteria. In this case, the objective criteria was maximum RE, which is the same thing as minimized $Var(\bar{Y}_{post})$. It would be possible to augment the optimization algorithm with constraints to minimize the difference between plot and stratum weights, or to specify a minimum stratum weight. Such augmentations would reduce the range of possible stratified means at the expense of precision.

5.3 Geospatial Layer Performance

A geospatial layer's performance is judged in terms of increasing an estimate's precision as measured by RE. In theory, the post-stratified estimator accomplishes this by separating the sample into homogeneous sub-groupings (strata). Because each stratum is homogeneous, they should have small within stratum variance, and the weighted sum of the stratum variance should be small relative to the unstratified sample. If the stratification is effective, then the homogeneous strata should also be unique, meaning they should have distinct means. However, the distribution of sample values in the CWD sample, which

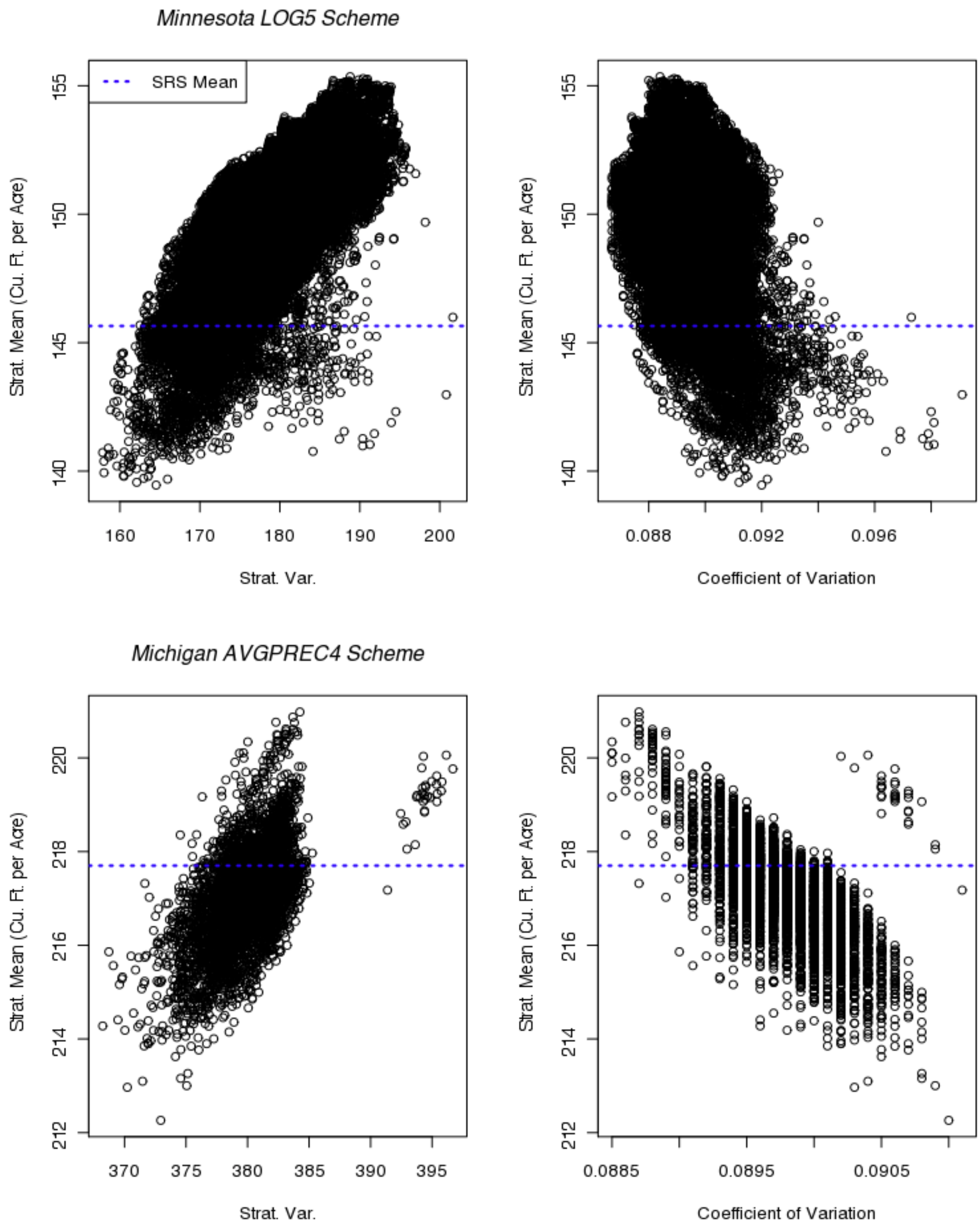

Figure 5.1: Stratified Means Versus Stratified Variance or CV for the Minnesota LOG5 and Michigan AVGTEMP4 Schemes

is dominated by zero observations, makes these theoretical conditions more difficult to achieve.

None of the categorical schemes tested, with the exception of the PCSTAND scheme, were competitive with the continuous schemes. Note that the PCSTAND scheme is being treated as a categorical scheme in the sense that the five strata are taken as categories. But, PCSTAND is really based on a PC scheme designed to optimize estimates of forest area. Therefore, it should be excluded from general discussion about the properties of categorical schemes. It is not surprising that the categorical schemes failed to achieve high RE's because each one attempts to depict one factor that determines the quantity of CWD on a given site. However, there are many inter-related factors which determine this (see section 1.4). One factor alone simply doesn't provide enough information on its own. They can provide valuable information when used in the logistic regression models. For the purposes of understanding why schemes were effective this discussion will focus on the continuous schemes because they produced the best results in all states.

In this study, most of the continuous schemes that were effective tended to form a stratum that was mostly zero observations and one or two strata of non-zero observations. The mostly zero stratum typically had large stratum weights and low stratum variances. The non-zero strata tended to have moderate stratum weights, on the order of 0.20 to 0.40, and moderate variance. In this setting *moderate* variance is less than 2,000, though this is a rough guideline. The remaining strata, if there were any, tended to form *sliver* strata characterized by high variance and low stratum weight. For the purposes of this discussion, *High* variance is anything above 2,000; much higher in some cases. There will be more to say about these sliver strata later in section 5.5.

5.3.1 Zeros and Non-zeros

To illustrate the separation of zero from non-zero observations, the LOG4 and PC4 schemes for each state will be used as examples. In addition, Michigan's MEVI4 scheme will be included in order to point out some important differences. These schemes produced the highest observed RE's in the geospatial analysis and the highest mean RE's in the simulation study and are therefore the best examples of effective schemes.

For both the PC and LOG schemes, the zero observation stratum is stratum 1, which represents areas of low canopy cover or low probability of CWD respectively. The landscapes of the Minnesota, Wisconsin, and Michigan are 32%, 46%, and 53% forested respectively (see section 2.1). When the state is used as the estimation unit (as in the geospatial layer analysis) one would expect the stratum weights for stratum one to be approximately 68%, 54%, and 47% respectively, which is approximately what these schemes show (Tables 5.4, 5.5, and 5.6). These heavily weighted and low variance strata are the primary reason why the post-stratified estimator produces RE's above 1.0. The larger non-forest percentage and corresponding stratum weights partially explain why the Minnesota and Wisconsin results showed higher RE's than the Michigan results.

In Minnesota and Wisconsin, the LOG4 scheme tends to over weight stratum 1 while the PC stratum is much closer to the expected weight. This trend is not followed in Michigan, and this point will be addressed later. This phenomenon is explained by the different units of the LOG and PC schemes. The PC scheme, which uses units of percent canopy cover, is attempting to separate zero from non-zero observations using a forest/non-forest approach. The LOG scheme, which uses units of probability of CWD, incorporates more information than just the percent canopy cover. Thus, some pixels with moderate canopy cover might have a low probability of CWD due to other factors included in the logistic regression models. This allows more of the population to be included in stratum one and a greater reduction in variance in these two states.

The stratum 1 variances for the Minnesota and Wisconsin schemes are less than 100, which is consistent with the theoretical purpose of stratum 1. The Michigan schemes do not follow this trend as well as the other two states, with stratum 1 variances over 200. The high variance in the Michigan schemes will be addressed below. For Minnesota and Wisconsin, the stratum weight for stratum 1 accounts for more than half the total weight in the state and is responsible for most of the gain in precision.

The anomalous results in Michigan are a function of its landscape. Michigan has fewer large areas dominated by non-forest. Consequently, Michigan has fewer zero observations and a correspondingly higher variance. This presents the Michigan schemes with less opportunity to reduce variance through the partitioning of zeros and non-zeros and is the primary reason for the lower observed RE's. In addition to a lower number of zero observations, Michigan's sample also intersected more intermediate PC pixels with values between 5 and 40. This is a result of the more fragmented landscape in Michigan's lower peninsula. The greater number of intermediate PC values affected the optimization of both the LOG4 and PC4 schemes, but the PC4 scheme was affected more strongly. Specifically, the first breakpoint which defines stratum 1 was pushed further from 0 than in the other states which resulted in the higher stratum weight for PC4 and the greater stratum variance (see section 5.5).

The relative success of the MEVI schemes was unique to Michigan. The stratum level statistics (Table 5.6) show a different pattern than the PC and LOG schemes. MEVI4 formed three nearly equal-weighted strata with distinct means, plus a low weighted sliver stratum. The effectiveness of the MEVI4 scheme is dependent on the landscape pattern, but in a different way than the PC and LOG schemes (See section 5.5). It does not form a heavily weighted stratum 1 with low variance. Rather, it divides the population into low, moderate, and high CWD strata with increasing means and variances. The success of MEVI4 in Michigan indicate that MODIS vegetation indexes might be more effective in more heavily forested landscapes.

Table 5.4: Stratum Statistics for the Minnesota LOG4 and PC4 Schemes

LOG4	Stratum 1	Stratum 2	Stratum 3	Stratum 4
Stratum Mean	28.48	563.22	323.87	631.34
Stratum Variance	58.40	40751.98	2210.68	5175.67
Stratum Weight	0.74	0.02	0.13	0.10
Acres	40,039,253	1,342,542	7,243,266	5,280,567
Prop. Plots	0.74	0.03	0.13	0.10
PC4	Stratum 1	Stratum 2	Stratum 3	Stratum 4
Stratum Mean	8.31	205.10	424.97	534.48
Stratum Variance	9.23	5013.02	1828.77	18042.77
Stratum Weight	0.64	0.07	0.26	0.03
Acres	34,319,158	3 714 829	14 100 270	1,867,086
Prop. Plots	0.65	0.07	0.23	0.05

Table 5.5: Stratum Statistics for the Wisconsin LOG4 and PC4 Schemes

LOG4	Stratum 1	Stratum 2	Stratum 3	Stratum 4
Stratum Mean	20.55	284.77	242.17	594.46
Stratum Variance	38.67	1085.01	2484.79	20388.06
Stratum Weight	0.63	0.28	0.05	0.04
Acres	22,514,687	10,156,664	1,882,072	1,333,318
Prop. Plots	0.65	0.28	0.04	0.03
PC4	Stratum 1	Stratum 2	Stratum 3	Stratum 4
Stratum Mean	16.11	37.87	267.26	449.94
Stratum Variance	43.61	252.06	884.88	8637.10
Stratum Weight	0.54	0.07	0.33	0.06
Acres	19,275,274	2,617,977	11,817,022	2,197,318
Prop. Plots	0.58	0.06	0.32	0.05

Table 5.6: Stratum Statistics for the Michigan LOG4, PC4, and MEVI4 Schemes

LOG4	Stratum 1	Stratum 2	Stratum 3	Stratum 4
Stratum Mean	42.68	362.50	139.26	427.34
Stratum Variance	319.57	26496.24	1031.27	1162.72
Stratum Weight	0.45	0.02	0.11	0.42
Acres	16,700,582	660,488	4,185,505	15,506,676
Prop. Plots	0.47	0.03	0.09	0.41
PC4	Stratum 1	Stratum 2	Stratum 3	Stratum 4
Stratum Mean	62.43	435.50	258.96	493.29
Stratum Variance	240.86	2837.16	1909.20	3702.74
Stratum Weight	0.56	0.20	0.10	0.13
Acres	20,970,547	7,532,076	3,749,064	4,964,006
Prop. Plots	0.57	0.19	0.08	0.16
MEVI4	Stratum 1	Stratum 2	Stratum 3	Stratum 4
Stratum Mean	357.64	25.81	107.85	413.22
Stratum Variance	38441.14	179.06	478.53	1173.95
Stratum Weight	0.02	0.24	0.35	0.39
Acres	818892	8834589	12961990	14601441
Prop. Plots	0.04	0.22	0.36	0.38

5.3.2 Separation of Stratum Means

Once the zero observations have been separated from the non-zero observations, the remaining strata should form homogeneous groupings of observations, with a distinct mean computed for each stratum. The LOG4 and PC4 schemes had mixed success doing this. One objective way to evaluate the effectiveness of a scheme at producing distinct means is the R statistic as defined by Holt and Smith (1979). The R statistic computes the proportion of the total variability accounted for by the within stratum component (Equation 5.1).

$$R = \frac{\sum N_h S_h^2}{\sum N_h S_h^2 + \sum N_h (\mu_h - \bar{\mu})^2} = \frac{Within}{Within + Between} \tag{5.1}$$

Where

N_h is the size in acres of stratum h

S_h^2 is the unit to unit variability of stratum h computed as $n_h v(\bar{Y}_h)$

$\bar{\mu} = \frac{\sum N_h \mu_h}{N}$

A value close to 1 indicates that almost all of the total variability in the sample is contained in the within stratum component, and only a small proportion remains in the between stratum component. This occurs when the stratum means are similar to each other, or when the within strata variances are so large that they overwhelm the between stratum component. Holding the within strata component fixed, as the strata means separate the between strata component increases and the value of R goes down. If the strata are composed of homogeneous observations then the within strata component will be small and a smaller between strata component will be required to produce a low value of R. However, if the within strata variances are large, then a larger between stratum component will be required. Thus, a lower value of R represents a stratification that works well from the perspective of forming unique and well estimated strata. It takes both the homogeneity of strata and separation of means into account. It also takes account of stratum weights through the N_h's, so strata with extreme variances but low weights will not dominate the R statistic.

When R statistics are graphed on RE's for each scheme, a linear pattern with a negative slope emerges (Figures 5.2, 5.3, and 5.4). Those schemes that were able to separate stratum means also produced the highest RE values. In the case of Minnesota, the LOG schemes have the clear advantage over the PC schemes. It was mentioned in section 5.3.1 that the PC and LOG schemes did not separate stratum means for non-zero strata very well. And yet they produced the lowest R values. This is because of the extreme low weighting of the sliver strata which makes them unimportant to the overall R statistic. For example, stratum two of Minnesota's LOG4 scheme has a very low weight and does not contribute meaningfully to the R statistic. The Minnesota PC4 scheme has only one stratum with a weight of at least 0.10 (other than stratum 1). The pattern in Wisconsin seems to have a steeper slope, but the same conclusion. The LOG schemes perform better in terms of both R and RE than the PC schemes. For Michigan, the pattern is noticeably stunted. The LOG and PC schemes achieved very similar R statistics, but the PC scheme was able to produce slightly higher RE's. The between stratum component is clearly smaller for the PC4 scheme in Michigan because of the similarity of the stratum 2 and 4 means and stratum weights. The reason for the LOG4 R value being similar to the PC4 R value is not as obvious. In fact, it is due to a larger within stratum component of variance overwhelming the between stratum component. Michigan's MEVI schemes produced the highest RE's and lowest R's of the MEVI schemes in the three states. The observed R values are consistent with the stratum level statistics for MEVI4, which indicate good separation of stratum means.

The patterns shown by the R statistics graphed on RE support the conclusion that the greatest gains in efficiency are from separating zero and non-zero observations for states with less than 50% forest cover. As forest cover increases, the MEVI schemes seem to become more effective. The PC and LOG schemes become less effective as forest cover increases. However, the PC and LOG schemes might not perform as expected in landscapes dominated by non-forest, such as the plains-states. In this case, the sample would include even more zero observations, and much would depend on the PC or LOG scheme's ability to separate zero's from a very small number of non-zeros. It is possible that there would be simply too few non-zero observation to form meaningful strata and

SRS would just as efficient in such extreme conditions.

Examination of each individual continuous scheme shows that there is relatively little gain in R after two strata. This demonstrates that there is little further separation of means after the first two. This suggests that fewer strata are almost as effective as more strata and would be easier to implement.

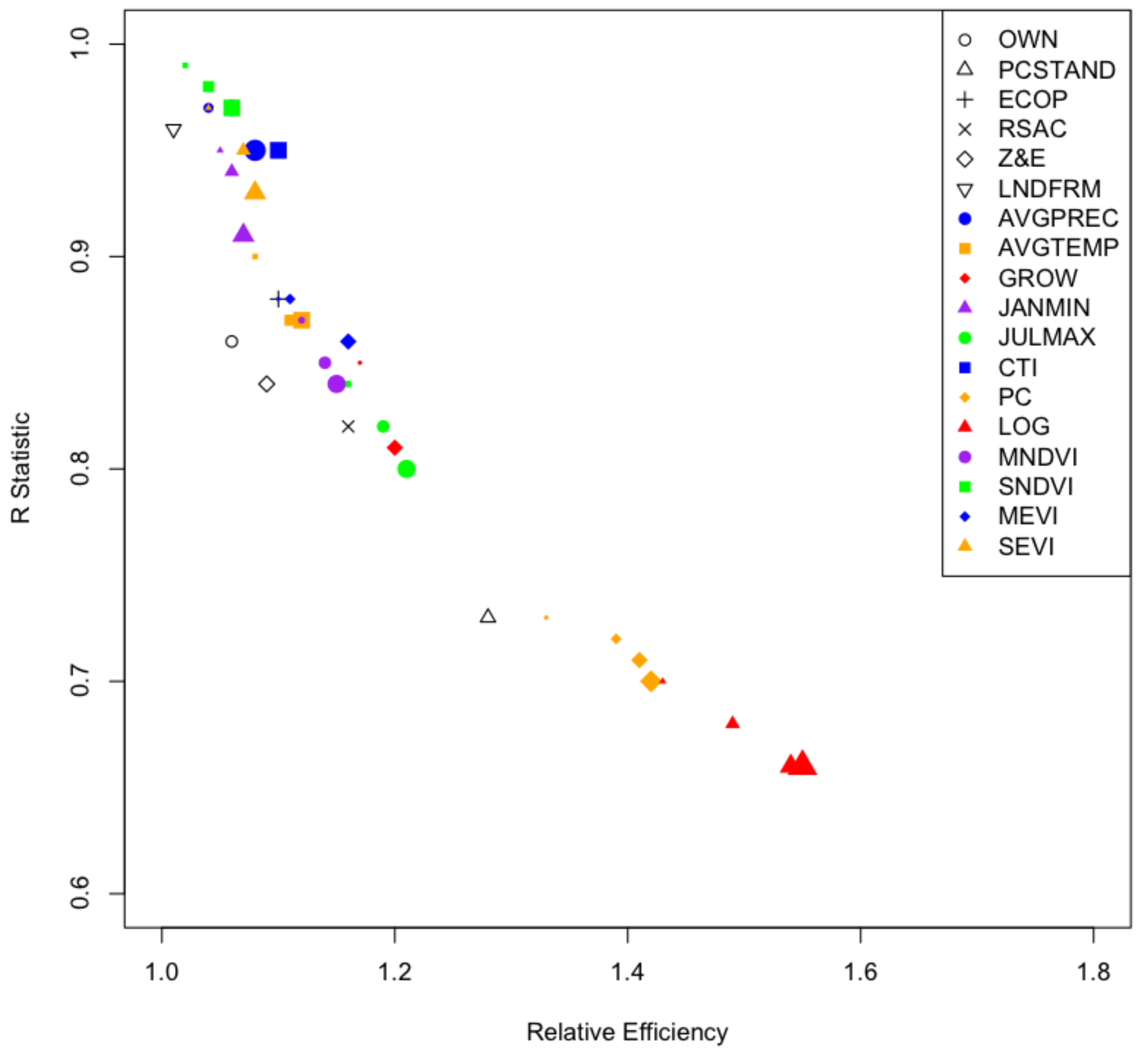

Figure 5.2: Minnesota R Versus Relative Efficiency
Categorical schemes are depicted with simple black symbols and continuous schemes are depicted as shapes with solid colors. Increasing size of the colored shapes indicates increasing number of strata beginning with two.

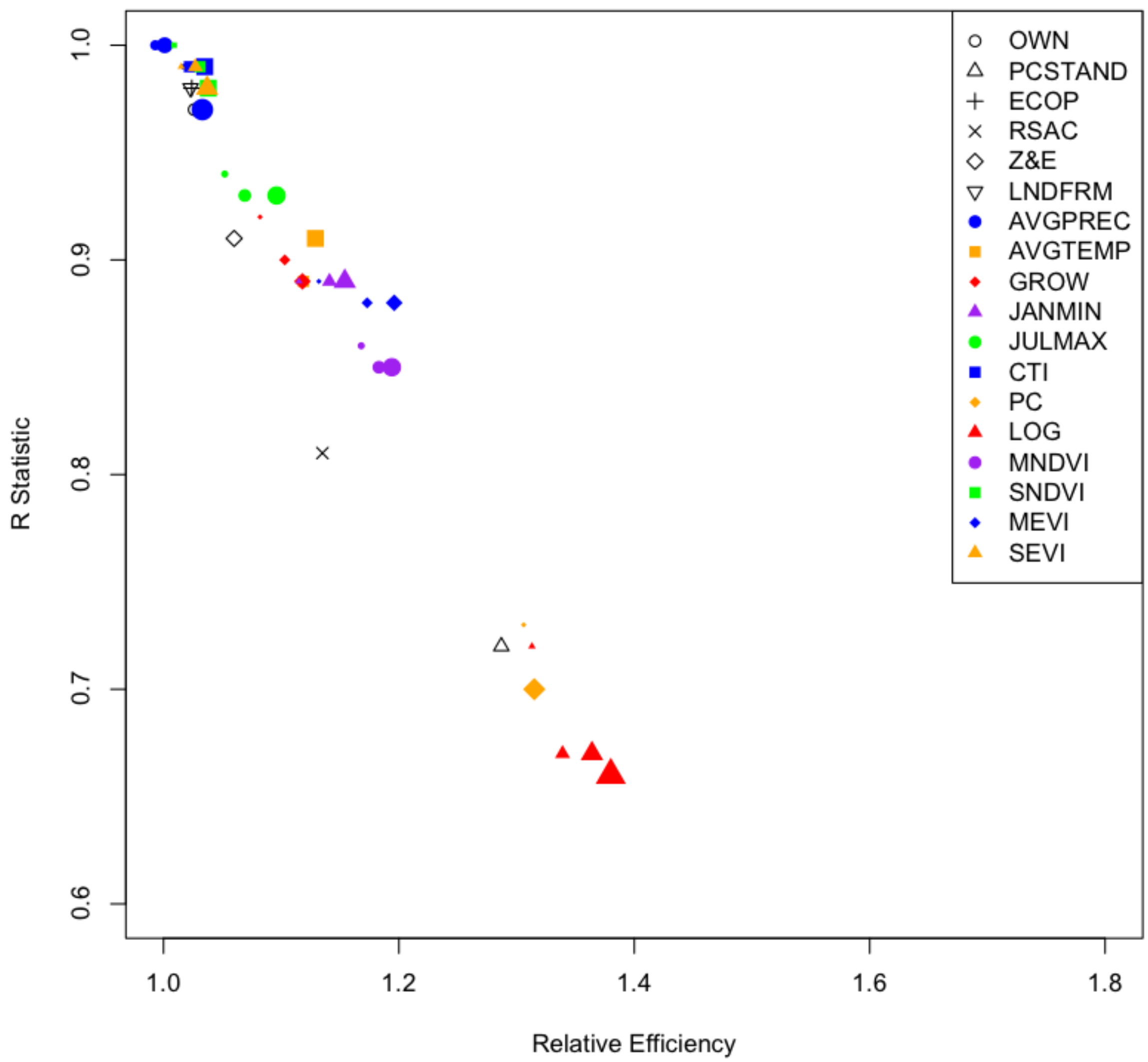

Figure 5.3: Wisconsin R Versus Relative Efficiency
Categorical schemes are depicted with simple black symbols and continuous schemes are depicted as shapes with solid colors. Increasing size of the colored shapes indicates increasing number of strata beginning with two.

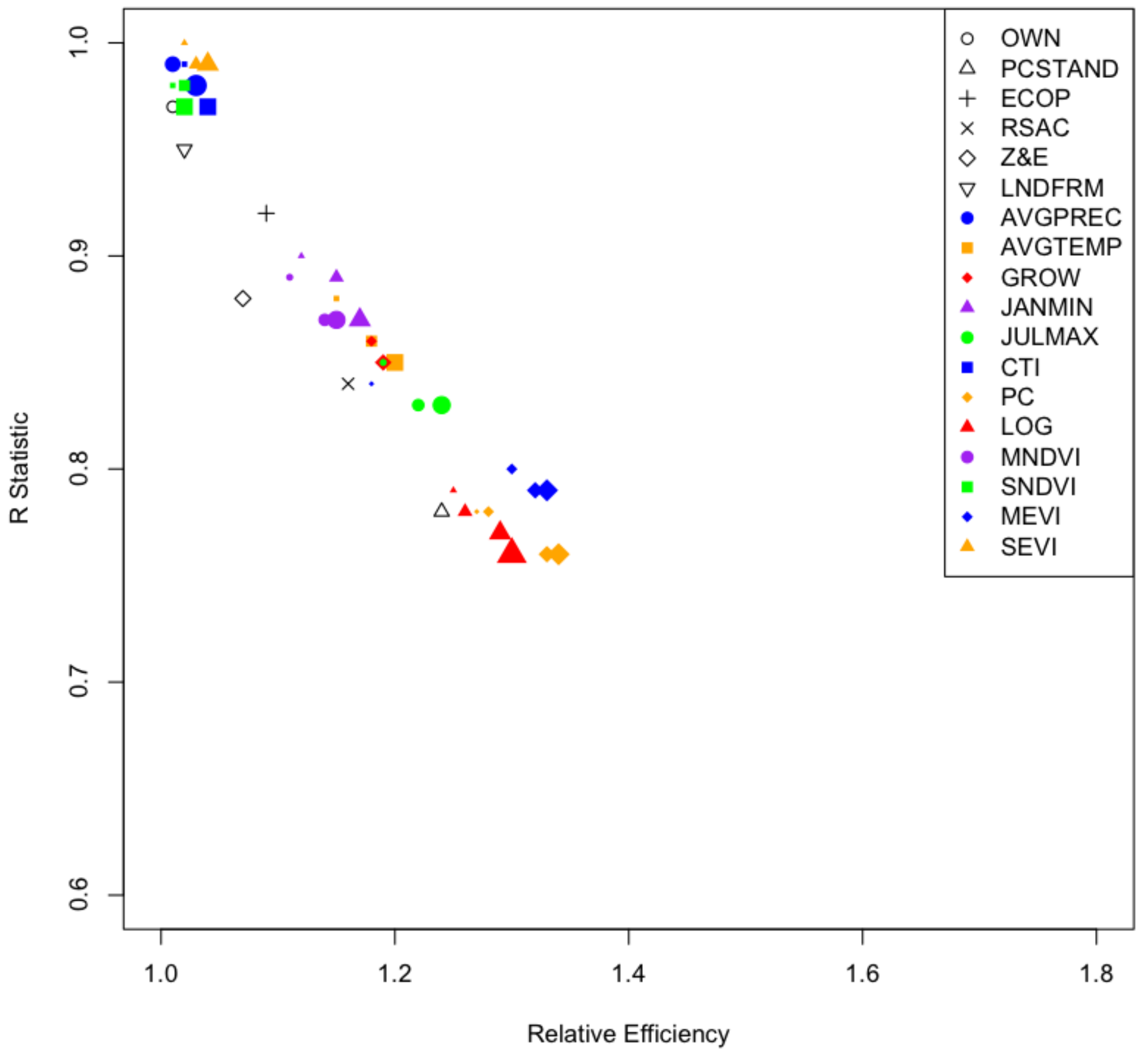

Figure 5.4: Michigan R Versus Relative Efficiency
Categorical schemes are depicted with simple black symbols and continuous schemes are depicted as shapes with solid colors. Increasing size of the colored shapes indicates increasing number of strata beginning with two.

5.4 Observed Versus Mean Relative Efficiencies

The simulation results showed that the observed RE from the geospatial layer analysis can sometimes be quite different from the mean RE generated from the simulation study. This occurred in all three states but was most noticeable in Wisconsin. Because the observed sample was used to generate the empirical cumulative density functions (ECDF) for each simulation, one might intuitively expect that the observed RE should be very close to the mean RE. However, the scheme being simulated can have a strong influence on the random samples generated on each iteration of the simulation. Specifically, the scheme influences the magnitude of the variance for each simulated sample and its allocation among the strata.

To illustrate how the scheme can influence the variance of the simulated sample consider two examples; one with the observed RE far less than the mean RE and one where they are similar. The former will be represented by the Wisconsin LOG4 simulation and the latter by the Michigan MEVI4 simulation. The variances of the simulated samples computed under both SRS and post-stratified estimation can be graphed on each other (Figures 5.5 and 5.6). The pattern shown by both figures 5.5 and 5.6 are similar and illustrate the range of variances possible under each scheme. The intersection of the SRS variance and post-stratified variance computed using the observed sample (depicted by the red lines) provide two interesting insights. First the intersection of the red lines in the Wisconsin LOG4 simulation is below the blue mean line whereas the Michigan MEVI4 simulation shows the intersection above the mean line. All the points that occur above the blue mean line represent RE's above the average while points below the line represent RE's lower than the average. The observed sample is just one of many possible samples computed under this scheme, and its location relative to the average RE is random. Second, the observed SRS and post-stratified variances are larger than the simulated mean values of each (shown by the green lines). Thus, most simulated samples have a lower overall variance than the observed sample. The reasons for this will be discussed below.

To better understand how the simulation process produces these results it is helpful to reference the ECDF for each scheme (Figures 5.7 and 5.8). Recall that the simulation study used a two stage randomization process. The first randomization stage randomly assigns a simulated plot to a stratum in approximate proportion to the stratum weight. The second stage randomly assigns an CWD volume value to each simulated plot according to the ECDF for the stratum. Stratum one of the Wisconsin LOG4 scheme is almost 90% zero observations followed by a moderate increase in CWD volume up to about 500 cubic feet per acre. Following that is a narrow band of much higher observations with a maximum value over 1,000 cubic feet per acre. The last two or three values form a long flat area of the ECDF that will be referred to as a *shelf*. For a simulated plot to sample from the shelf in stratum 1, a second stage random number greater than 0.996 would need to be randomly selected. This is relatively rare event. Therefore, the average simulated sample has a lower stratum variance in stratum one than the observed sample. Stratum one has a weight of 0.63 (refer to table 5.5) and therefore has the strongest influence on the ultimate population variance computed from the simulated sample. Stratum two of Wisconsin's LOG4 scheme has the second largest weight at 0.28. It is approximately 90% non-zero values, with a slow increase in CWD volume up to a value of about 500 cubic feet per acre. This is followed by a more rapid increase in CWD volume up to the maximum value for the state at over 2,000. Again, the highest two values in stratum two form a shelf. For a simulated plot to sample from the stratum two shelf, the second stage random number must be at least 0.98. This number, though not as extreme as the 0.996 from stratum one, represents a small target. The most extreme observation in the state occurred in stratum two for this scheme. Simulated samples that include these extremes would have a correspondingly high SRS variance and a greater opportunity for the stratification to reduce the variance. Simulated samples that do not include these extremes would have a lower SRS variance, and therefore less opportunity for the stratification to dampen the effects of extreme observations.

The MEVI4 scheme in Michigan shows a much different structure with three different strata having a weight of at least 0.20 (refer to table 5.6). Comparing the ECDF for this scheme to the WI LOG4 scheme reveals an important though subtle difference. Only stratum three in the MI MEVI4 scheme has a shelf caused by an extreme observation. The most influential stratum is stratum four with a weight of 0.39. The ECDF for this stratum does not include a shelf. Rather, it forms a relatively smooth distribution to sample from. Note that the increase in CWD volume is more rapid than in stratum two of the Wisconsin LOG4 scheme. This is logical since the Michigan sample was previously observed to be more variable than the Wisconsin sample. The shape of the stratum four ECDF indicates that samples from this stratum are more likely to be similar in variance to the observed sample because it lacks the rare and highly influential value indicated by the presence of a shelf. The most extreme observation in Michigan occurs in stratum one, which has a weight of only 0.02. The slope of the ECDF in stratum one is relatively flat, which means that the more extreme values are more frequently sampled in this stratum. Thus, for many simulated sample, the SRS variance would be high due to these large values but the post-stratified estimate of the variance would dampen this effect due to the low stratum weight. A simulated sample including the very highest value of stratum one would still be relatively rare, however.

In the case of the Wisconsin LOG4 scheme, the observed RE is below the mean RE because of a number of factors. The average simulated sample did not sample from the most extreme CWD volumes because they were located only on narrow shelves in strata one and two. Therefore, the stratum variances in the two most important strata (one and two) were significantly lower for the average sample which produced a post-stratified estimate of variance that was lower relative to the SRS estimate. The Michigan MEVI4 observed RE was slightly higher than the mean RE mainly because of the influence of the extreme observation in stratum one. The stratum weight of 0.02 provides a significant reduction in variance relative to SRS. However, most samples did not sample that extreme and therefore did not experience the corresponding gain in precision. Each scheme that was simulated is different and would require individual interpretation to understand how each one is functioning.

The above discussion illustrates how the structure of the ECDF can influence the magnitude of the variances from simulated sample to simulated sample. In particular, it showed how the location of the extreme observations in each state is important. The specific allocation of simulated sample to strata determines if the RE is above or below the mean RE. If a given simulated sample includes a high or extreme observation in a low weighted stratum, then the post-stratified variance will be reduced relative to the SRS estimate. Alternatively, if a high or extreme observation is included in a heavily weighted stratum, then the variance reduction under post-stratified estimation will be much less relative to SRS. Many mixed scenarios are also possible such as cases where the extreme end of a stratum ECDF is heavily sampled in one stratum but under-sampled in another stratum. The relative magnitudes of the over/under sampling and stratum weights would then determine the ultimate outcome in terms of RE.

5.5 Strata Breakpoints

In this study schemes consisting of two to five strata were created which required one to four strata breakpoints to be identified. The optimized breakpoints can be visualized by graphing them on histograms of the stratification variables (Figures 5.9 and 5.10). The histograms used in this section represent the frequency of plots at each value of the stratification variable, but a similar histogram could be constructed using pixel counts from the P1 data. Given that the FIA sample is approximately proportionally allocated, histograms based on the plots should be very similar in shape to histograms based on the pixels. The relationship between the stratification variable and the response variable can also be visualized by graphing the CWD volume values versus the stratification variable on top of the histogram. Such visualizations can be very useful for understanding how a scheme is working.

The distribution of stratification variables varied widely among geospatial layers. For example, the climate geospatial layers tended to have a well distributed sample of values with no gaps, whereas the PC layer formed a much different distribution with large gaps. These gaps can form natural break points. The Minnesota LOG5, Wisconsin PC4 and LOG5, and the Michigan LOG5 schemes all placed a breakpoint near the zero line which takes advantage of the natural gap between low PC or LOG values and the remaining values. Not every scheme found this to be the optimal location for the first breakpoint. The PC schemes in Minnesota placed the first breakpoint around 40 precent canopy cover. Note that in this case the difference in stratum weight at the state level between a breakpoint a 2 percent canopy cover and a breakpoint at 40 is very small because the PC geospatial layer

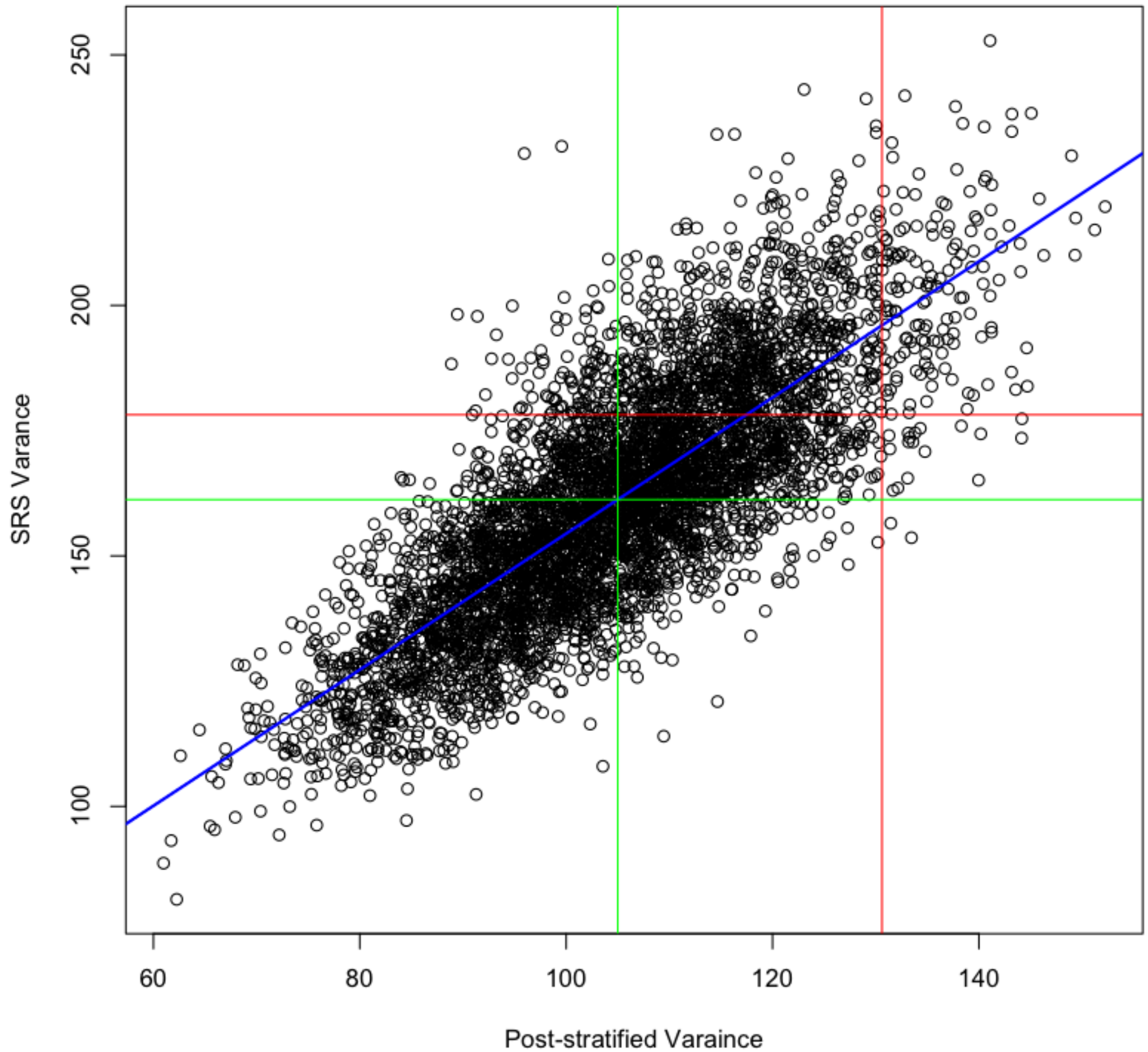

Figure 5.5: Wisconsin LOG4 Simulated Variances: SRS Variance on Post-stratified Variance

Each point shows the variance of the population mean computed under both SRS and post-stratified estimation. The red lines depict the variances computed from the observed sample. The green lines show the mean simulated variances computed under SRS and post-stratified estimation. The blue line depicts a simple linear regression of y on x and represents the average value.

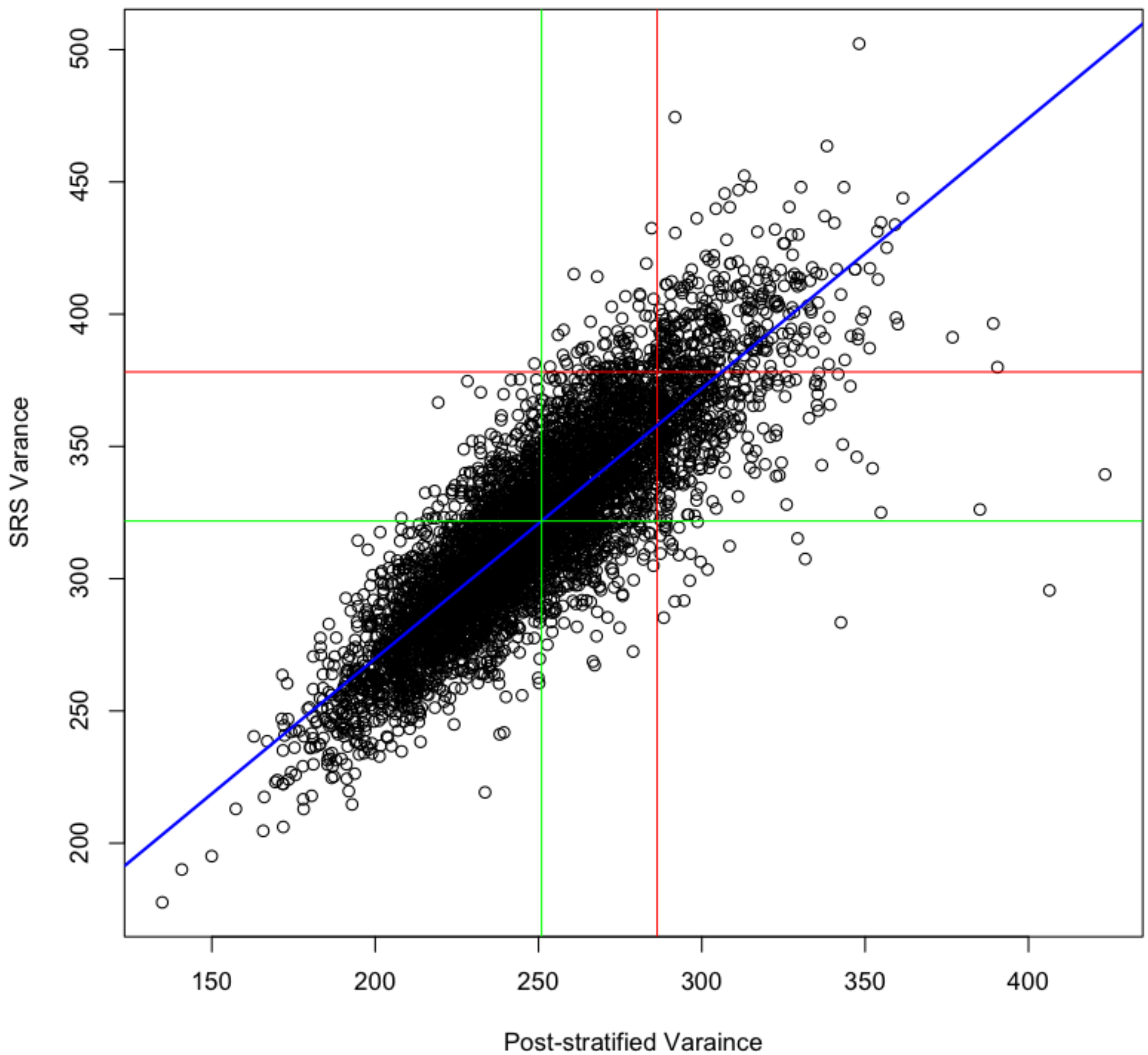

Figure 5.6: Michigan MEVI4 Simulated Variances: SRS Variance on Post-stratified Variance

Each point shows the variance of the population mean computed under both SRS and post-stratified estimation. The red lines depict the variances computed from the observed sample. The green lines show the mean simulated variances computed under SRS and post-stratified estimation. The blue line depicts a simple linear regression of y on x and represents the average value.

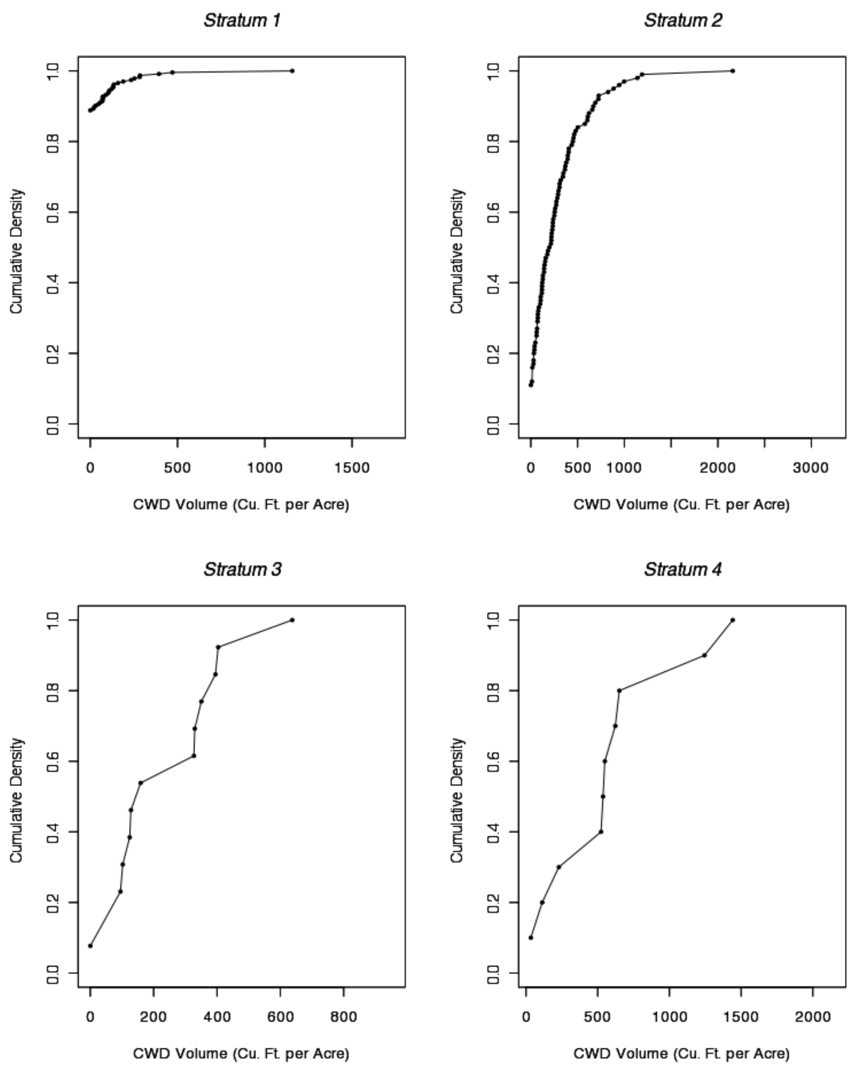

Figure 5.7: Wisconsin Empirical Cumulative Density Function for the LOG4 Scheme

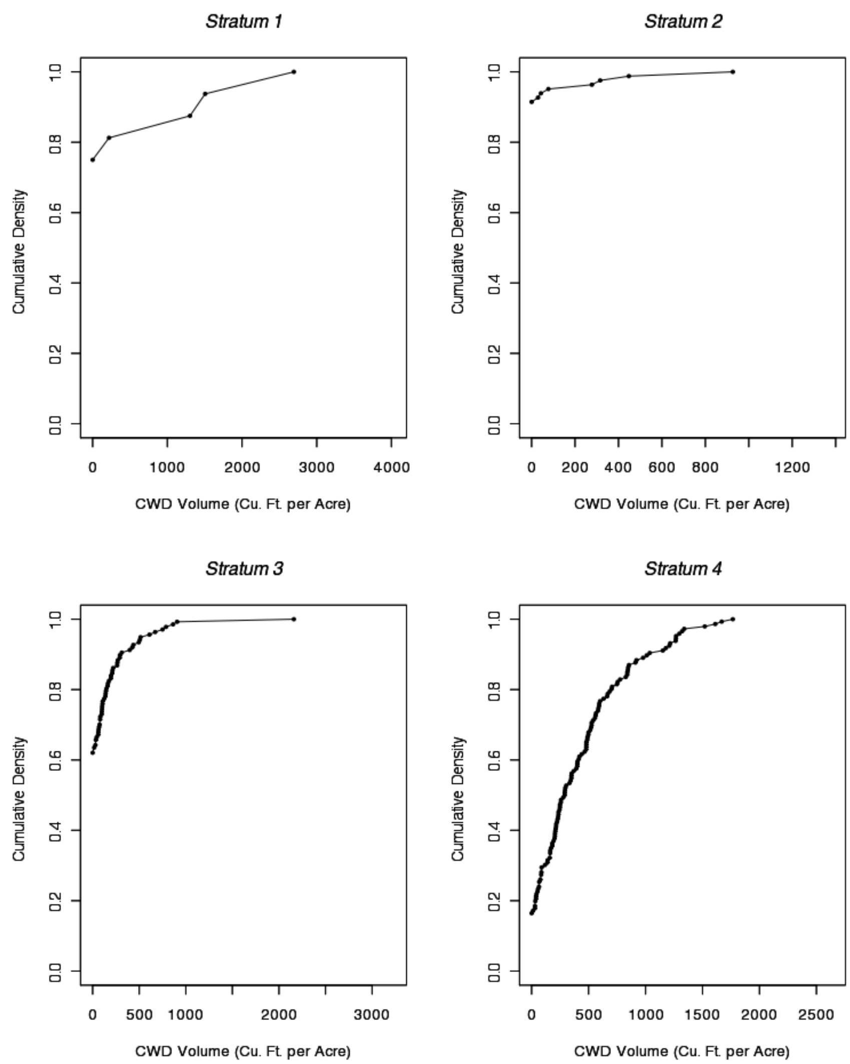

Figure 5.8: Michigan Empirical Cumulative Density Function for the MEVI4 Scheme

simply doesn't have many pixels with PC values between 2 and 40. However, as the PC schemes are applied to different estimation units the difference between the two possible breakpoints (2 and 40) could become much more important because the distribution of PC values will change.

In most cases, the effect of adding additional strata to an existing scheme was to partition an existing stratum into two which is done by adding an additional breakpoint and retaining the others. A different possible outcome would be to define an entirely new set of breakpoints, but this was not observed in any of the schemes. The additional strata might represent a new distinct stratum which would be beneficial, or simply add a new stratum that does the least damage to the RE. An example of the former would be the addition of a third stratum to the LOG2 scheme in Minnesota. The additional stratum of LOG3 split stratum 2 of LOG2, creating a stratum with a distinct mean and increased the RE from 1.43 to 1.49. An example of the latter is the addition of a fifth stratum to the Wisconsin PC4 scheme, which split the existing stratum 2 into two very similar strata (Figure 5.9). The result was no gain in RE. This explains why the pattern in increasing RE with increasing number of strata is not observed for the Wisconsin PC results (Figure 4.6).

The *sliver* strata mentioned in section 5.3 can be seen where there are two breakpoints close together on the x axis (Figures 5.9 and 5.10). In these cases, such as the Minnesota PC5 and Michigan PC5 schemes, the sliver stratum was produced by adding a fifth stratum. In these cases it is likely that there is not enough information to create a meaningful fifth stratum and the location of the new breakpoint is determined to be the one that does the least harm. If the algorithm did not have a minimum plot count per stratum constraint, it is very possible that the breakpoints might be even closer together. Figure 5.9 shows that a sliver stratum exists already in the Minnesota LOG4, Wisconsin LOG4, and Michigan PC4 and LOG4 schemes. These slivers were created when the fourth stratum was added to their three stratum counter parts. The existence of sliver strata likely indicates that the maximum number of strata has already been achieved and that additional strata will probably not be distinct or homogeneous. Such strata are also the first to be collapsed when a scheme is applied to smaller estimation units than the state.

The histograms of stratification variables also provide an easy way to evaluate the difference between the PC and LOG schemes. As previous noted, the PC geospatial layer is included in all three logistic regression models, along with a small number of additional layers. The additional information helps the model adjust the probability of CWD presence or absence. When this is done, the distribution of values becomes more spread out, particularly at the zero end of the range (Figures 5.9 and 5.10). This effect is particularly strong in Michigan where the typical high count of zero values is transformed into several columns of between 0 and about 15% probability. Michigan is the only state where the zero column is not the tallest column in the LOG histograms. This is likely due to the more fragmented landscape of Michigan producing fewer areas where there is a zero probability of CWD.

The distribution of MEVI values across the sample was very different from the PC and LOG distributions. Interestingly, the histograms of MEVI are very similar for the three states. One possible reason why the MEVI is more effective in Michigan is because more of the vegetated areas are forests, as opposed to agricultural crops or other vegetation. The PC scheme is targeted to detecting only tree canopies, which works better in landscapes with low to moderate forest cover, but high vegetation cover. As more of the vegetation becomes trees there is less need to distinguish non-tree vegetation from tree vegetation. In these conditions the MEVI geospatial layer seems to be able to divide the population into distinct and homogeneous strata. A close examination of the MEVI results across all three states shows that it was least effective in Minnesota, slightly more effective in Wisconsin, and most effective in Michigan. This pattern corresponds with increasing forest land across the three states.

The plot CWD values for the MEVI stratification variable in Figure 5.10 seem to suggest a breakpoint around the second black dashed line ($x \approx 2,900$). This break might coincide with a transition from more agricultural areas to more forested areas because the more moderate MEVI values are only green between planting and harvesting. Forests are green over the growing season (or all year depending on the type of forest) which would produce higher MEVI values.

The CWD volume values are much more concentrated in the MEVI histogram than they are in the PC or LOG schemes for Michigan (Figure 5.10). In fact, comparing the pattern of CWD volume values across the PC and LOG stratification variables for the three states reveals that Michigan has the least concentrated pattern. Michigan has more intermediate CWD volumes ($<$ 500 cubic feet per acre) across the 20 - 60 PC or LOG range then Minnesota or Wisconsin. The Michigan sample was the most variable of the three states (excluding the Minnesota intensified sample). The MEVI schemes in Michigan seem to concentrate that variability into a narrower range on the x axis than the PC or LOG schemes do.

This discussion of strata breakpoints suggests that fewer strata should be preferred over more strata for the stratification of CWD, especially for PC and LOG schemes. For the PC and LOG schemes, two to three strata should be used. Additional strata simply split existing strata. Small gains in RE might occur when this happens, but these gains are probably relegated to the current sample only, as demonstrated by the mean RE's from the simulation study. The presence of sliver strata indicates that the optimal number of strata have already been reached. The MEVI schemes might be able to use more strata because they don't appear as dependent on the separation of zero and non-zero observations. The MEVI schemes might also be more effective on more heavily forested landscapes than the PC and LOG schemes.

5.6 Effects of Spatial Extent on Scheme Performance

There are two main reasons to divide a population into smaller estimation units. First, breaking the population into logical subpopulations can help minimize the risk of bias when compensating for non-response bias. This topic was not included in this study in order to keep the focus on the process of post-stratified estimation. Second, estimation units must be defined to account for differences in the sample, such as an intensification. As the number of estimation units increases, each individual estimation unit becomes smaller along with the number of plots available. The natural consequence of this is that more strata must be collapsed in order to achieve the required minimum plots per stratum. In the extreme case, all strata are collapsed and a SRS estimate is produced with no gain

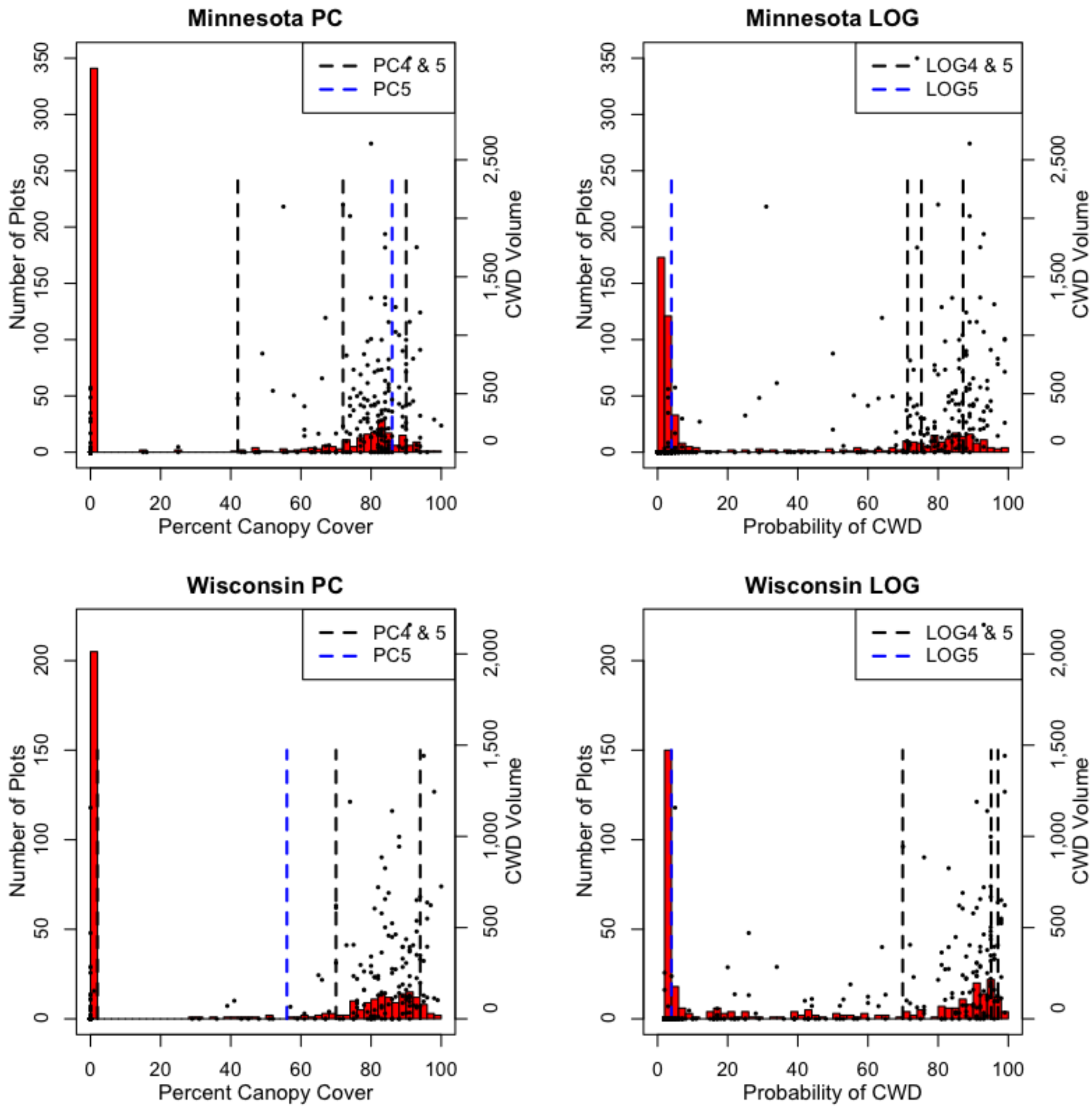

Figure 5.9: Histograms of Stratification Variables for Minnesota and Wisconsin. *The black dashed lines show breakpoints shared by both the 4 and 5 stratum schemes. The blue dashed line indicates a breakpoint belonging only to the 5 stratum scheme. Each dot represents a plot. The right axis shows the volume of CWD associated with each dot.*

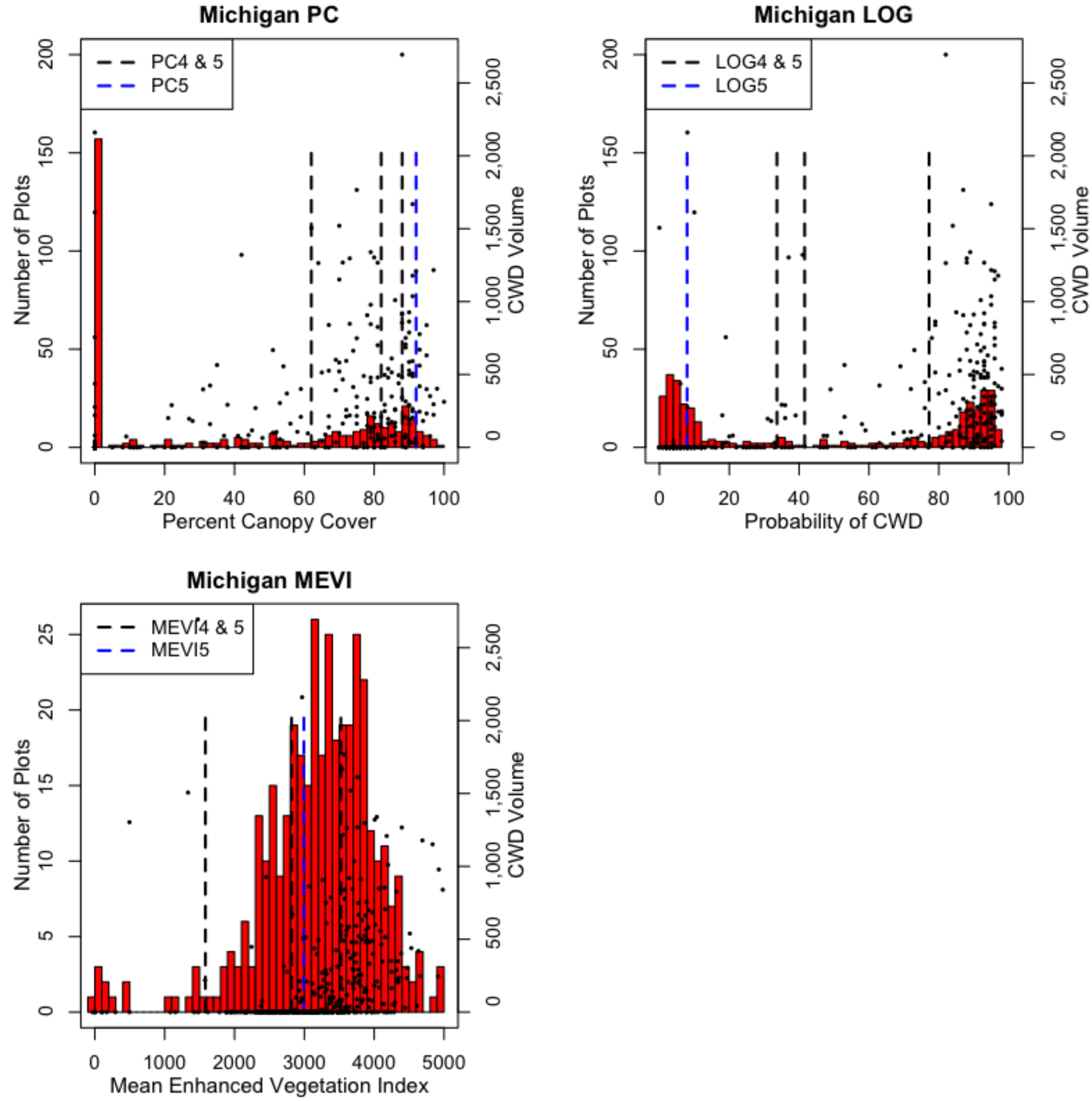

Figure 5.10: Histograms of Stratification Variables for Michigan. *The black dashed lines show breakpoints shared by both the 4 and 5 stratum schemes. The blue dashed line indicates a breakpoint belonging only to the 5 stratum scheme. Each dot represents a plot. The right axis shows the volume of CWD associated with each dot.*

in efficiency. Because of this phenomenon, the expected result of the estimation unit analysis was to show decreasing RE's associated with increasing numbers of estimation units. However, only the Minnesota (base and intensified samples) and the Michigan PC stratifications followed this pattern.

The decreasing number of plots available is not the only reason for collapsing strata when increasingly small estimation units are used. The specific strata breakpoints computed in the geospatial layer analysis used the entire range of the stratification variable available at the state level. Individual estimation units may not have the same range available. Even if there are an adequate number of plots in an estimation unit, they may all be concentrated in one or two strata requiring several strata to be collapsed. Furthermore, this newly collapsed strata might not be optimal for the estimation unit. In some cases, the scheme developed at the state level can perform worse than SRS in extreme estimation units.

The Minnesota LOG5 stratifications using the intensified sample provide an excellent illustration of both of these phenomena. The four stratifications involved follow the theoretical pattern exactly. The ECOP OWN LOG5 and STATE BWCAW LOG5 stratifications produced the minimum and maximum RE's and accounted for the most and fewest estimations units respectively.

The plot counts for the ECOP OWN LOG5 stratification show that three of the 10 estimation units were collapsed to SRS (Table 5.7). A further three were collapsed into two strata. Both the NFS and the BWCAW estimation units had RE's less than 1.0, which was worse than the precision achieved under SRS (Table 5.8). In fact, only the private ownership category in eco-province 212 was able to use all 5 strata without collapsing. The STATE BWCAW stratification had only two strata, but the BWCAW estimation unit is exactly the same as the one from the ECOP OWN stratification.

In these examples, strata are collapsed for both reasons described above. In the case of the ECOP251 PUB estimation unit, there were only 6 plots total, which is far less than the minimum 25 required to use all 5 strata. The ECOP251 PRIV estimation unit had 161 plots total, but almost all of the plots were concentrated in stratum 1 and 2. This resulted in the estimation unit being collapsed into two strata. Eco-province 251 is known as the

Prairie Parkland province. Therefore, a heavily non-forest distribution is to be expected in the ECOP251 PRIV estimation unit, and observed distribution of plots across strata is logical. In spite of collapsing five strata into two, the ECOP251 PRIV estimation unit was still able to produce a RE of 1.27.

The ECOP BWCAW LOG5 stratification is the simplest computed for the Minnesota intensified sample. Even so, the BWCAW estimation unit still required three strata to be collapsed. The total number of plots available was adequate at 44, but they were concentrated in the fifth stratum (Table 5.7). This distribution of plots to strata is logical considering that the estimation unit is a protected wilderness area managed by the USDA Forest Service, and therefore heavily forested.

The results for the BWCAW are unexpected because the intensification was intended to produce more precise estimates of a sub-population. However, the problem is not with the sample. The stratification applied to the BWCAW was optimized to the state level for Minnesota. This optimization leverages heavily off of the separation of zero and non-zero values (see section 5.3). It performs poorly because the landscape pattern with the BWCAW is too different from the larger landscape. The stratum level statistics confirm that the LOG scheme did not form distinct strata ($R = 0.9998$). The strata means for the three strata were 707, 702, and 735. Dividing the BWCAW into these three particular strata simply reduced the number of plots available to compute the variance of essentially the same stratum mean in each stratum. This case perfectly illustrates the caveat provided by McRoberts et al. (2006) (See section 1.2.2).

Even though this particular scheme did not work well in the BWCAW, the intensification was still beneficial. It allowed a high variance sub-population to be separated from the overall population and estimated separately. This is evidenced by the fact that the SRS estimate of the mean and variance changes from 145 and 244 over the entire state to 133 and 214 with the BWCAW removed.

A different scheme could be used within the BWCAW to produce a better RE, and therefore improve the overall performance of the STATE BWCAW stratification. If a scheme cannot be developed to separate strata means effectively, the SRS could be used. Each estimation unit is considered an independent sub-population and therefore a different post-stratification scheme could be used in each one, if necessary. The resulting totals and variances of totals are simply summed over all the estimation units of the population, and this final estimate remains unbiased.

Table 5.7: Plot Counts and Strata Grouping for the Minnesota Intensified ECOP OWN LOG5 and ECOP BWCAW LOG5 Stratifications by Estimation Unit (*The forward slash (/) indicates a separate stratum.*)

ECOP OWN LOG5	1	2	3	4	5	Sum	Strata Group
ECOP212 PUB	3	17	6	28	17	71	12/3/4/5
ECOP212 BWCAW	0	5	3	8	28	44	123/4/5
ECOP212 PRIV	17	41	6	25	20	109	1/2/3/4/5
ECOP212 WATER	32	2	0	0	0	34	12345
ECOP212 NFS	0	1	0	6	12	19	1234/5
ECOP222 PUB&PRIV	69	46	3	9	4	131	1/2/345
ECOP222 WATER	9	3	0	0	0	12	1/2345
ECOP251 PUB	5	1	0	0	0	6	12345
ECOP251 PRIV	129	31	0	1	0	161	1/2345
ECOP251 WATER	2	1	0	0	0	3	12345
SUM	266	148	18	77	81	590	
STATE BWCAW LOG5	1	2	3	4	5	Sum	Strata Group
BWCAW	0	5	3	8	28	44	123/4/5
STATE	266	143	15	69	53	546	1/2/3/4/5
SUM	266	148	18	77	81	590	

There were several stratifications that deviated from the expected pattern. Consider Wisconsin's ECOP OWN stratifications which produced a slightly higher RE than the OWN stratifications using the PC schemes (Figure 4.21). This was unexpected because there were seven estimation units for ECOP OWN and only four for OWN. The reason for this result is that the PC stratifications performed moderately well within each estimation unit of the ECOP OWN stratification, with estimation unit RE's ranging from 1.17 to 1.32. This range excludes the the two water estimation units which both had a mean and variance of zero, and NFS estimation unit which was reduced to SRS. The PC scheme also produced good RE's for the OWN stratification with a minimum of 1.23 and a maximum of 1.29 (excluding the NFS ownership, which used SRS, and water which had a variance of zero). Note that this range is slightly lower than the range under ECOP OWN. The weighted contribution of the variance of each estimation unit was slightly higher for the

Table 5.8: Estimation Unit Summary Statistics for the Minnesota Intensified ECOP OWN LOG5 and ECOP BWCAW LOG5 Stratifications by Estimation Unit

ECOP OWN LOG5	Mean	Var.	Acres	SRS Mean	SRS Var.	RE
ECOP212 PUB	282.85	1,741	7,638,559	307.05	2,152	1.24
ECOP212 BWCAW	706.05	14,894	764,874	709.23	13,223	0.89
ECOP212 PRIV	213.33	937	10,503,520	221.69	1,236	1.32
ECOP212 WATER	19.04	362	2,101,792	19.04	362	1.00
ECOP212 NFS	644.00	24,458	2,104,916	679.89	21,454	0.88
ECOP222 PUB&PRIV	81.20	767	14,035,200	79.90	831	1.08
ECOP222 WATER	6.89	393	621,481	26.13	683	1.74
ECOP251 PUB	56.04	3,141	342,199	56.04	3,141	1.00
ECOP251 PRIV	10.43	134	15,489,100	13.62	170	1.27
ECOP251 WATER	0.00	0	296,488	0.00	0	
ECOP BWCAW LOG5	Mean	Var.	Acres	SRS Mean	SRS Var.	RE
BWCAW	706.05	14,894	764,873.68	709.23	13,223	0.89
STATE	130.14	147	53,133,450.00	133.40	214	1.46

OWN than the ECOP OWN stratification, which accounts for the difference. This result could also be compounded by the approximately proportional allocation of plots to strata (see section 5.1).

A more extreme example of a deviation from the expected pattern was the poor performance of the ECOP stratifcations of the LOG schemes in Wisconsin which produced RE's well below stratifications that did not include ECOP (Figure 4.21). This result contrasts sharply with the Wisconsin ECOP PC stratification results. A detailed comparison of the estimation unit (Table 5.9) and stratum level (Table 5.10) statistics reveals that both the PC4 and LOG4 schemes appear to have produced similar summaries. Note that the LOG4 scheme collapsed strata 3 and 4 in ecological province 222, resulting in only three strata. Within ecological province 222, both the PC4 and LOG4 schemes produced a heavily weighted stratum 1 with a low mean and variance, an intermediate stratum with a mean around 250 and a moderate weight, and an extreme stratum with a high mean and low weight. The PC4 scheme also produced a low weighted stratum with a low mean and moderate variance (Stratum 2). Functionally, they were very similar. However, when the weighted variance was computed for each scheme (Table 5.11) it is clear that the LOG4 strata 3 & 4 produced a much higher variance and ultimately reduced the RE of the entire estimation unit. The difference between the PC4 Stratum 4 and LOG4 Stratum 3&4 statistics are relatively minor considering the low weights of both strata. The PC4 Stratum 4 mean and variance are higher than the LOG4 Stratum 3 & 4 mean and variance, however the PC4 weight is only 0.03 compared to 0.08 for the LOG4. This difference, though not dramatic, was large enough to cause the RE for the estimation unit to drop below 1.0. A similar pattern occurs in the Michigan ECOP OWN LOG and ECOP LOG stratifications.

Table 5.9: Estimation Unit Summary Statistics for the Wisconsin ECOP PC4 and ECOP LOG4 Stratifications by Estimation Unit

ECOP PC4	Mean	Var.	Acres	SRS Mean	SRS Var.	RE
ECO212	164.10	308	18,504,020	155.83	389	1.26
ECO222	85.68	220	17,400,480	77.75	296	1.34
ECOP LOG4	Mean	Var.	Acres	SRS Mean	SRS Var.	RE
ECO212	166.40	315	18,489,880	155.83	389	1.23
ECO222	95.58	306	17,394,820	77.75	296	0.97

Table 5.10: Stratum Statistics for the Wisconsin ECOP222 PC4 AND ECOP222 LOG4 Estimation Units

ECOP222 PC4	Stratum 1	Stratum 2	Stratum 3	Stratum 4
Stratum Mean	16.76	43.80	246.64	724.62
Stratum Variance	93.54	596.00	2628.65	72112.99
Stratum Weight	0.71	0.07	0.19	0.03
Acres	12318071.00	1181426.00	3335109.00	565878.00
No. Obs.	125.00	10.00	28.00	5.00
ECOP222 LOG4	Stratum 1		Stratum 2	Stratum 3&4
Stratum Mean	18.74		266.99	595.21
Stratum Variance	82.78		2810.15	64758.66
Stratum Weight	0.79		0.13	0.08
Acres	13828513.00		2191572.00	1374739.00
No. Obs.	136.00		26.00	6.00

Michigan's MEVI4 and MEVI5 schemes were also used to compute stratifications. These stratifications produced more consistent RE's than either the PC or LOG based stratifications. The most interesting result from the MEVI stratifications was that the

Table 5.11: Weighted Variance of the Mean by Stratum for the Wisconsin ECOP PC4 and ECOP LOG4 Stratifications by Estimation Unit

	Stratum 1	Stratum 2	Stratum 3	Stratum 4	Sum
ECOP222 PC4	49.39	2.61	86.08	82.16	220.24
	Stratum 1		Stratum 2	Stratum 3&4	Sum
ECOP222 LOG4	53.36		57.06	195.46	305.88

OWN stratifications were slightly better than the STATE stratifications. There were four estimation units in the OWN MEVI stratifications. All of them except the water estimation unit produced RE's above 1.0 ranging from 1.17 to 1.42. The best was the PRIV estimation unit at 1.42 for the MEVI5 and 1.40 for the MEVI4 scheme. The success in these estimation units was enough to raise the over-all RE of the stratification above the STATE stratification.

The MEVI stratifications also had difficulties when ECOP was used to define estimation units. Ecological province 222 was was the least forested of the ecological provinces in Michigan. This produced low RE's when the MEVI schemes were used to stratify. However, where the PC and LOG schemes produced RE's less than 1.0, the MEVI schemes produced RE's of 1.07 and 1.10 for MEVI5 and MEVI4 respectively. While these are not impressive, they at least to not damage the overall estimate's precision as the PC and LOG schemes did.

This discussion highlights the volatility of these schemes when applied to estimation units for which they were not optimized. Small differences in strata breakpoints can generate large differences in RE. The schemes that were successfull in this study rely on landscape pattern. This pattern can change dramatically between estimation units, and the consequences of this can be dramatic. This situation is compounded by the low sampling intensity of the FIA P3 sample and naturally large variance of CWD attributes. Caution should be used when applying schemes to estimation units other than the one they were developed for because the results could be unpredictable and possibly worse than SRS. Schemes might be made more robust by using only two or three strata, but this hypothesis requires more research to confirm.

5.7 Conclusions

This study demonstrates that post-stratified estimation can produce moderate increases in the precision of CWD volume estimates relative to SRS. RE's on the order of 1.30 to 1.60 are achievable. More importantly, there are several general lessons that can be learned from this work.

Before summarizing the lessons learned from this study it may be useful to describe the range of RE's (1.30 to 1.60) in more concrete terms. If a RE of 1.30 is achieved, then the sample size would need to be increased by 30% in order to achieve the same precision using SRS. In the case of Minnesota, the sample base sample size was 532. Therefore, the sample would need to be increased by $532 \times 0.30 = 160$ additional plots. Assume a P3 plot costs \$1,000 to collect. However, each P3 plot is also a P2 plot that would be visited anyway. To reduce this cost to only the P3 portion assume an increase of 0.33% on top of the normal P2 cost to account for an additional field crew member. Therefore, the total savings would be $532 \times 0.30 \times \$1,000 \times 0.33 = \$52,800$. Assuming a RE of 1.60 would produce a savings of \$105,600. These figures can be used to make objective decisions on whether or not it is worth using post-stratified estimation versus just SRS.

Categorical geospatial layers are generally less effective as a stratification variable because they are inflexible. Categorical geospatial layers attempt to reduce variance by grouping CWD observations according to a factor known to influence the quantity of CWD observed on a given site, such as forest type. However, the relationship between the observed quantity and driving factors is simply too complicated for a single factor to depict. Categorical layers do have a role in stratification by helping to define estimation units, or as covariates in a logistic regression model.

Consistently, the highest RE's were achieved by remote sensing geospatial layers, or derivatives of them. The PC and LOG schemes performed the best in all three states. The MEVI geospatial layer did produce results that were competitive with PC and LOG in Michigan, but not in the other two states. This is likely caused by the two different ways in which these layers reduce variance. The PC and LOG schemes tend to produce gains in efficiency by separating zero CWD volume observations from non-zero observations at the state level. In fact, the PC and LOG layers achieved the best results in Minnesota followed by Wisconsin then Michigan. This corresponds with the proportion of the landscape that is forested in each state. Minnesota was the least forested, followed by Wisconsin and then Michigan. The MEVI layer appears less dependent on this concept, but rather appears to separate non-zero observations into increasingly larger values. MEVI may be more effective on a more forested landscape, which explains why it was competitive in Michigan. Further research is required on this topic.

The optimization algorithm used to compute the optimal strata breakpoints for continuous geospatial layers was relatively simple in this study. The objective function was simply to find the maximum RE and the only constraint was to have at least 10 observations in each stratum. This worked reasonably well, however it did produce some strata that were very small, even at the state level. This resulted in schemes that did not work well in smaller estimation units within the state, and in some cases performed worse than SRS. A future enhancement to the optimization algorithm might be to constrain the solution to a minimum stratum weight as well as a minimum plot count. Another possible enhancement would be to only add additional strata if the increase in precision surpasses a defined threshold. Such an enhancement would limit the creation of meaningless sliver strata.

Examination of the strata breakpoints also suggests that only two or three strata should be attempted for post-stratification of CWD variables. Additional strata beyond two or three simply split existing strata but do not necessarily define meaningful strata. This is especially true for the PC and LOG schemes, which were not able to produce meaningful strata of non-zero values as evidenced by only small gains (and sometimes no gain) in RE for each additional stratum.

Schemes developed at the state level should be applied to smaller estimation units only with great caution. Their behavior at these smaller spatial scales can be erratic. It is possible to use different schemes within each estimation unit. Doing so would require an analysis of each estimation unit in order to select the appropriate scheme, even if it is SRS. In general, however, it is safer to use the minimum number of estimation units possible. They should only be used to deal with important differences in the sample, such as an intensification of a subpopulation. In almost all cases, efficiency was lost when estimation units smaller than the state were used. The losses in efficiency were sometimes severe. The lone exception to this was the MEVI scheme in Michigan which produced very slightly higher RE's using the OWN estimation units than at the state level. It is still safer to use the state wherever possible.

It was seen that the landscape pattern can influence the effectiveness of the schemes. The states included in the study ranged from approximately 32% forested to 53% forested. The effectiveness of various schemes was observed to correspond with this trend. Future studies should focus on more extreme conditions, such as the plain states for the lower extreme and Maine for the upper extreme. Results from such a study would build on the knowledge gained in this study about the stratification of CWD on various landscape patterns.

This study focused on finding the best methods for using the post-stratified estimator to compute population estimates for CWD volume in three states. It treated each state as a separate population and attempted to optimize the estimate independently in each. No attempt was made to define a scheme that would work the best across all three states. Given the moderate range of RE's observed in this study it is unlikely that a single stratification would perform adequately for each state, but this could be a topic for future research. The immediate recommendation is to create a post-stratification scheme for each state that will be effective over many samples and use this scheme over time. Holding the stratification constant over several estimates removes one component of variability and allow easier interpretation of trends.

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Appendix A

Categorical Geospatial Layer Codes

Table A.1: Ownership Collapsed Codes

Code	Meaning
1	Public
4	Private
9	Inland Census Water
12	All Forest Service Lands

Table A.2: Ownership Codes

Code	Meaning
1	Public
2	Boundary Waters Canoe Area Wilderness
4	Private
9	Inland Census Water
902	Chequamegon National Forest
903	Chippewa National Forest
904	Huron-Manistee National Forest
906	Nicolet National Forest
907	Ottawa National Forest
909	Superior National Forest
910	Hiawatha National Forest

Table A.3: Landform Collapsed Codes

Code	Meaning
1	Canyon/valley
4	Shallow valley
5	Plain
6	Open slope
7	Hill in plain
8	Headwaters
9	Upper slope
10	Hill top

Table A.4: Landform Code

Code	Meaning
1	Canyon
2	Valley
3	Ridge in valley
4	Shallow valley
5	Plain
6	Open slope
7	Hill in plain
8	Headwaters
9	Upper slope
10	Hill top

Table A.5: Bailey's Ecological Province

Code	Meaning
212	Laurentian Mixed Forest
222	Eastern Broadleaf Forest
251	Prairie Parkland (Temperate)

Table A.6: Zhu & Evans Forest Type

Code	Meaning
0	ocean fill
1	Non-U.S. land
2	White-red-jack pine
3	Spruce-fir
7	Oak-hickory
9	Elm-ash-cottonwood
10	Maple-beech-birch
11	Aspen-birch
23	Non-forest
24	Lakes

Table A.7: RSAC Collapsed Forest Type

Code	Meaning
1	Softwoods (> 500)
2	Hardwoods except aspen/birch (≥ 500 and < 900)
3	Aspen/birch (≥ 900)

Table A.8: RSAC Forest Type

Code	Meaning
0	non-forest
101	Jack pine
102	Red pine
103	Eastern white pine
121	Balsam fir
122	White spruce
125	Black spruce
126	Tamarack
127	Northern white-cedar
401	Eastern white pine/ northern red oak/ white ash
409	Other pine/hardwood
501	Post oak/ blackjack oak
503	White oak/red oak/hickory
505	Northern red oak
509	Bur oak
520	Mixed upland hardwoods
701	Black ash/American elm/red maple
707	Silver maple/Americal elm
709	Cottonwood/willow
801	Sugar maple/beech/yellow birch
805	Hard maple/basswood
809	Red maple/upland
901	Aspen
902	Paper birch
904	Balsam poplar

Appendix B

State Maps

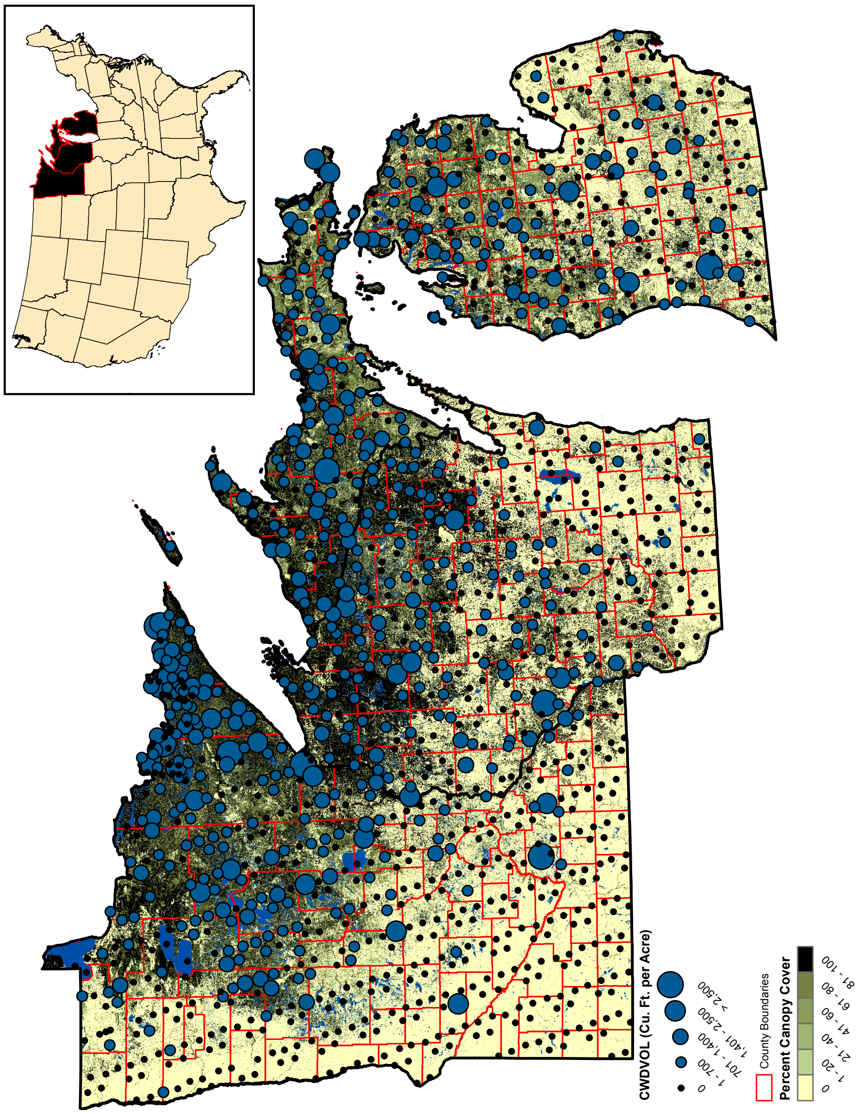

Figure B.1: Lake-States Study Area

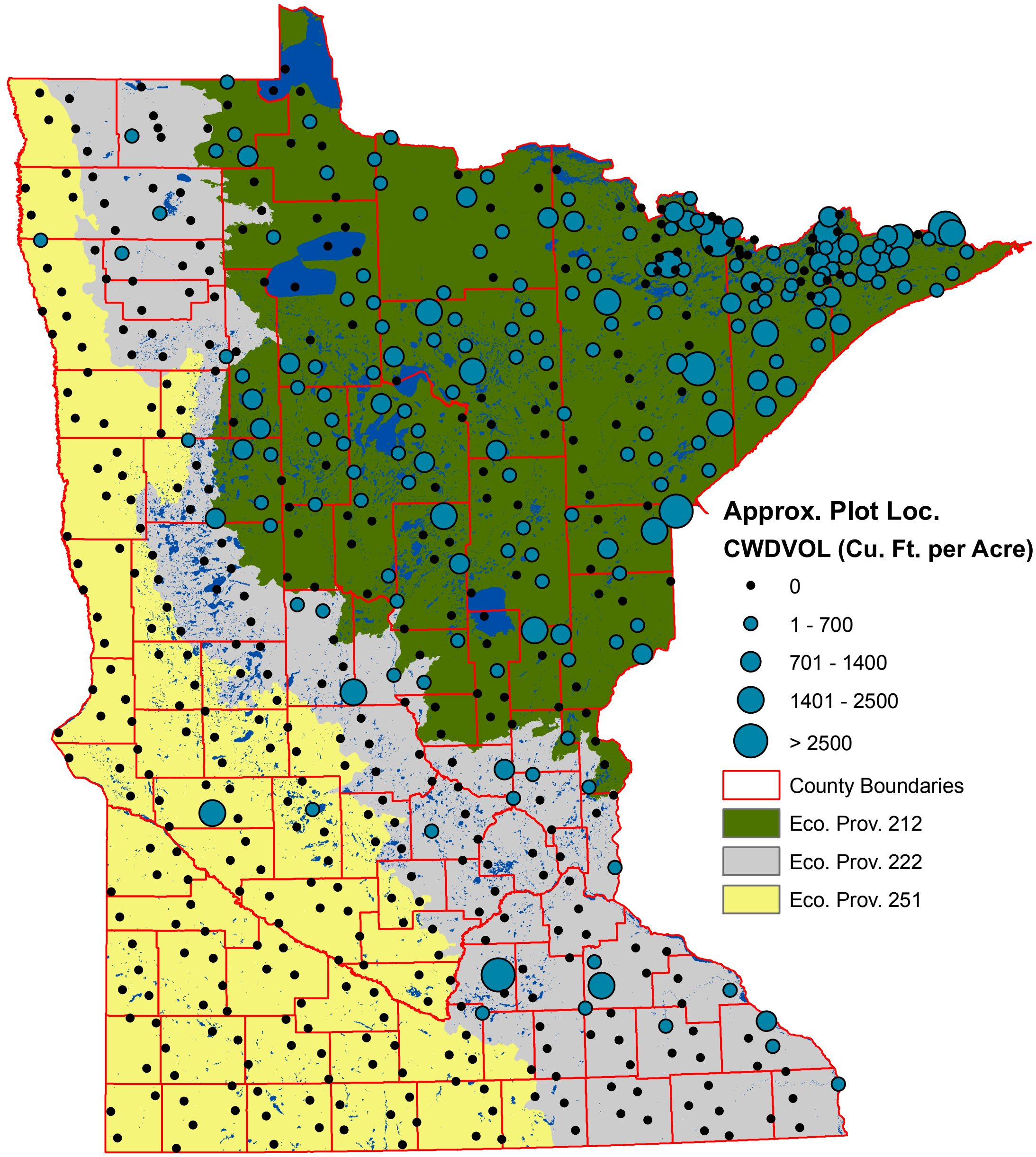

Figure B.2: Minnesota P3 Sample on Ecological Province

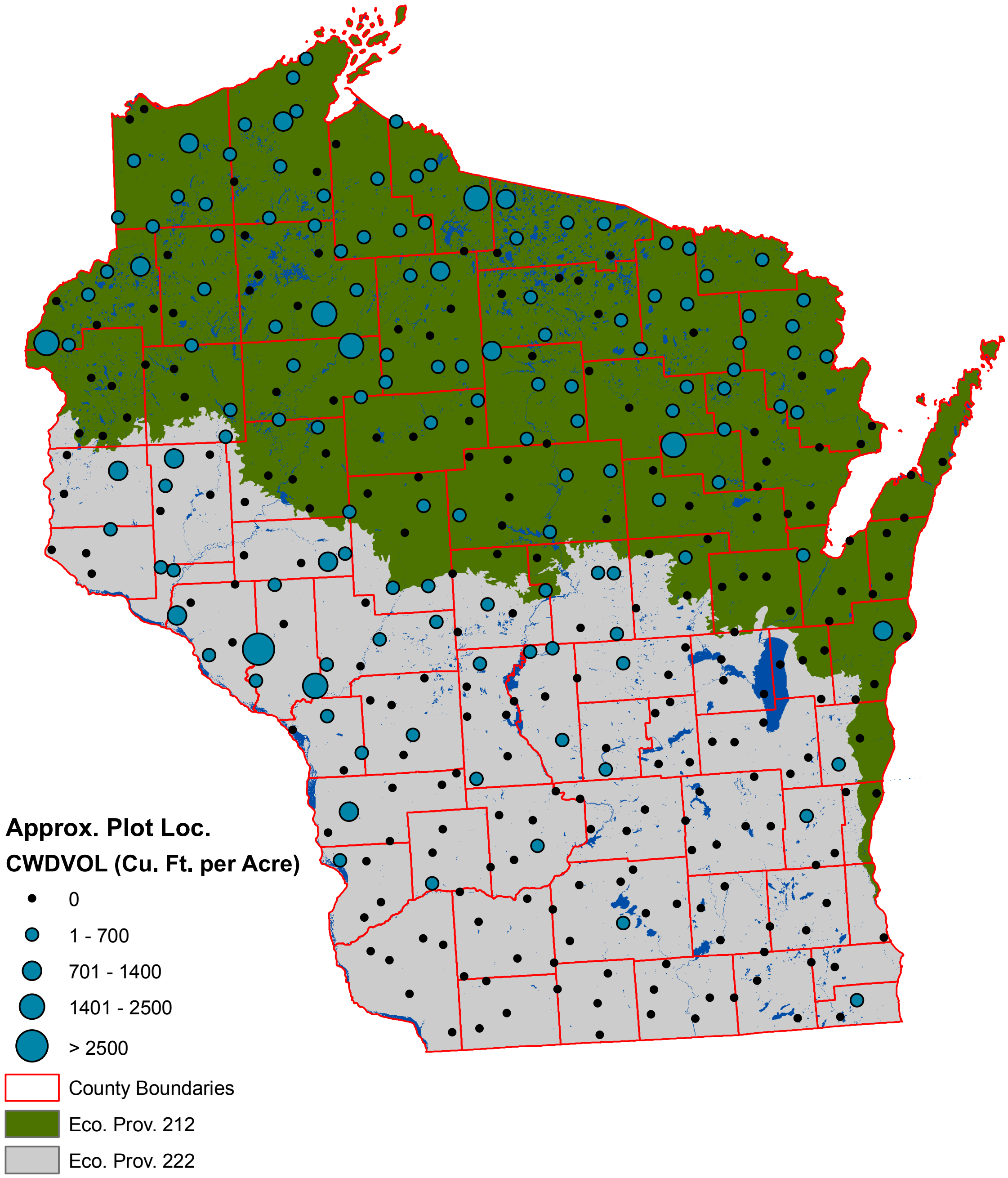

Figure B.3: Wisconsin P3 Sample on Ecological Province

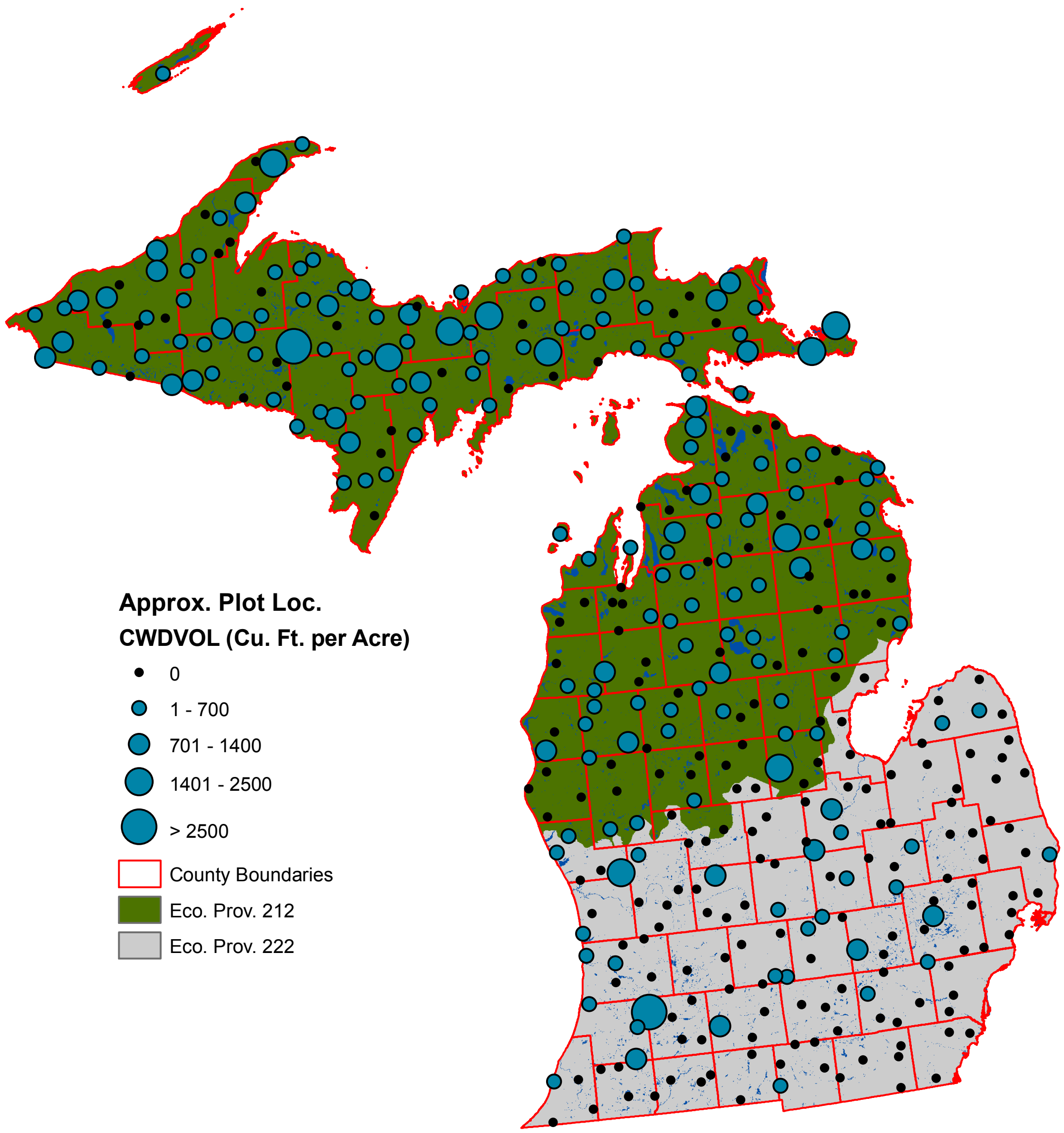

Figure B.4: Michigan P3 Sample on Ecological Province

Appendix C

Simulation Histograms

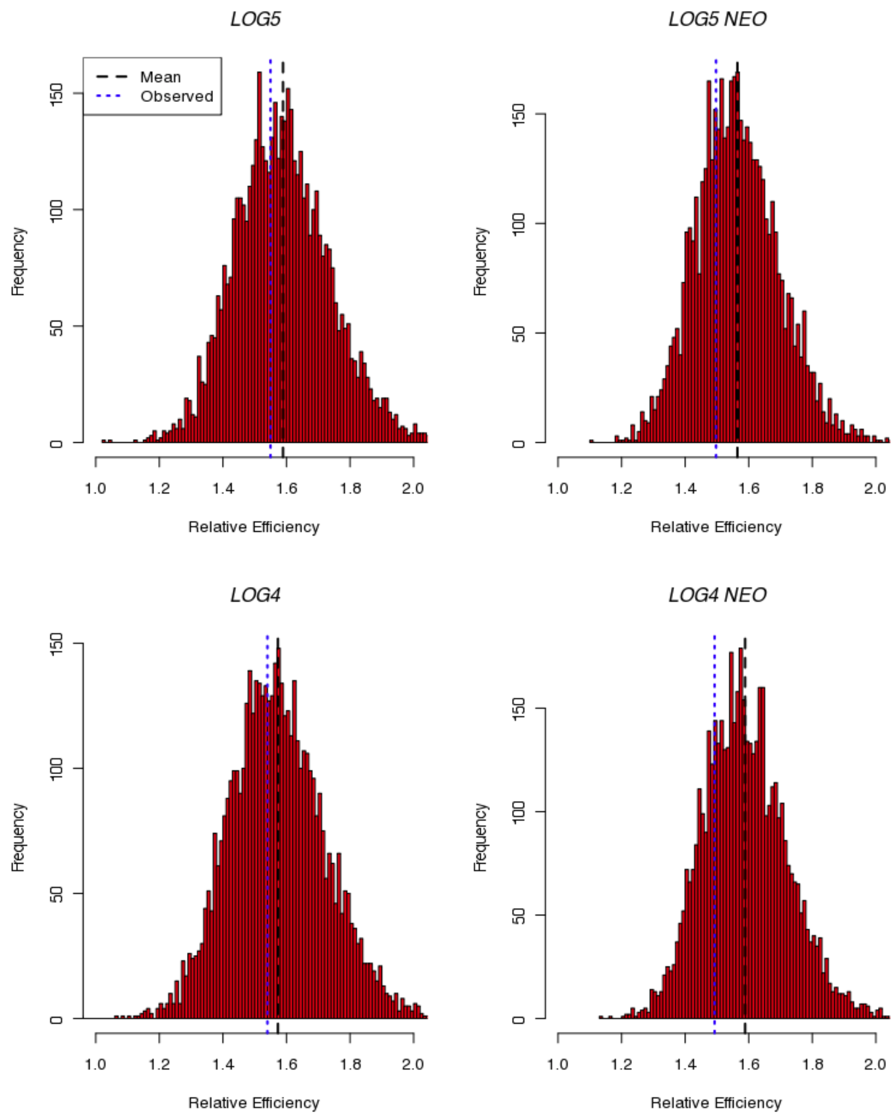

Figure C.1: Histograms of RE from the Minnesota LOG Simulations (*NEO indicates a simulation of a scheme optimized using the sample excluding extreme ovservations*)

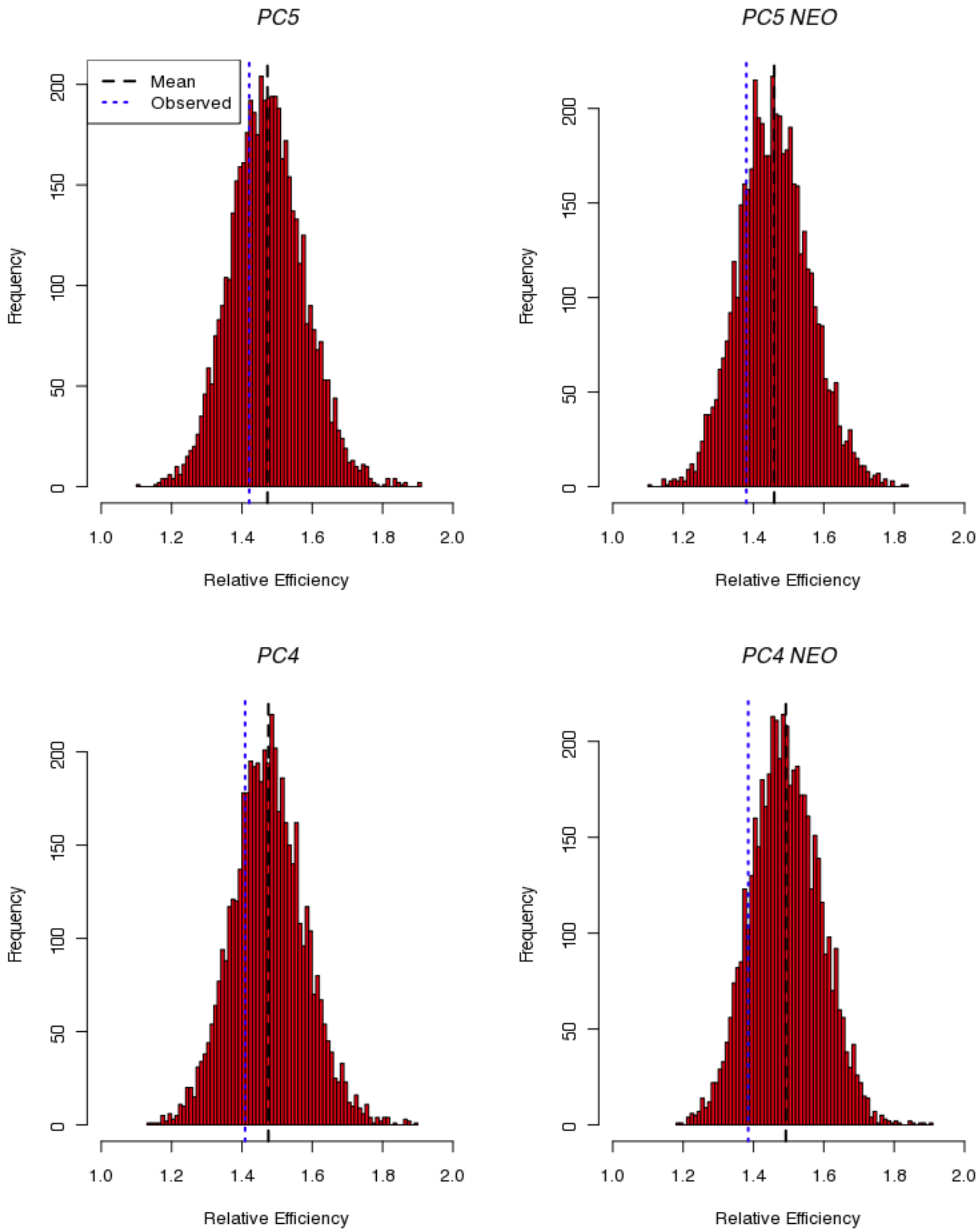

Figure C.2: Histograms of RE from the Minnesota PC Simulations (*NEO indicates a simulation of a scheme optimized using the sample excluding extreme ovservations*)

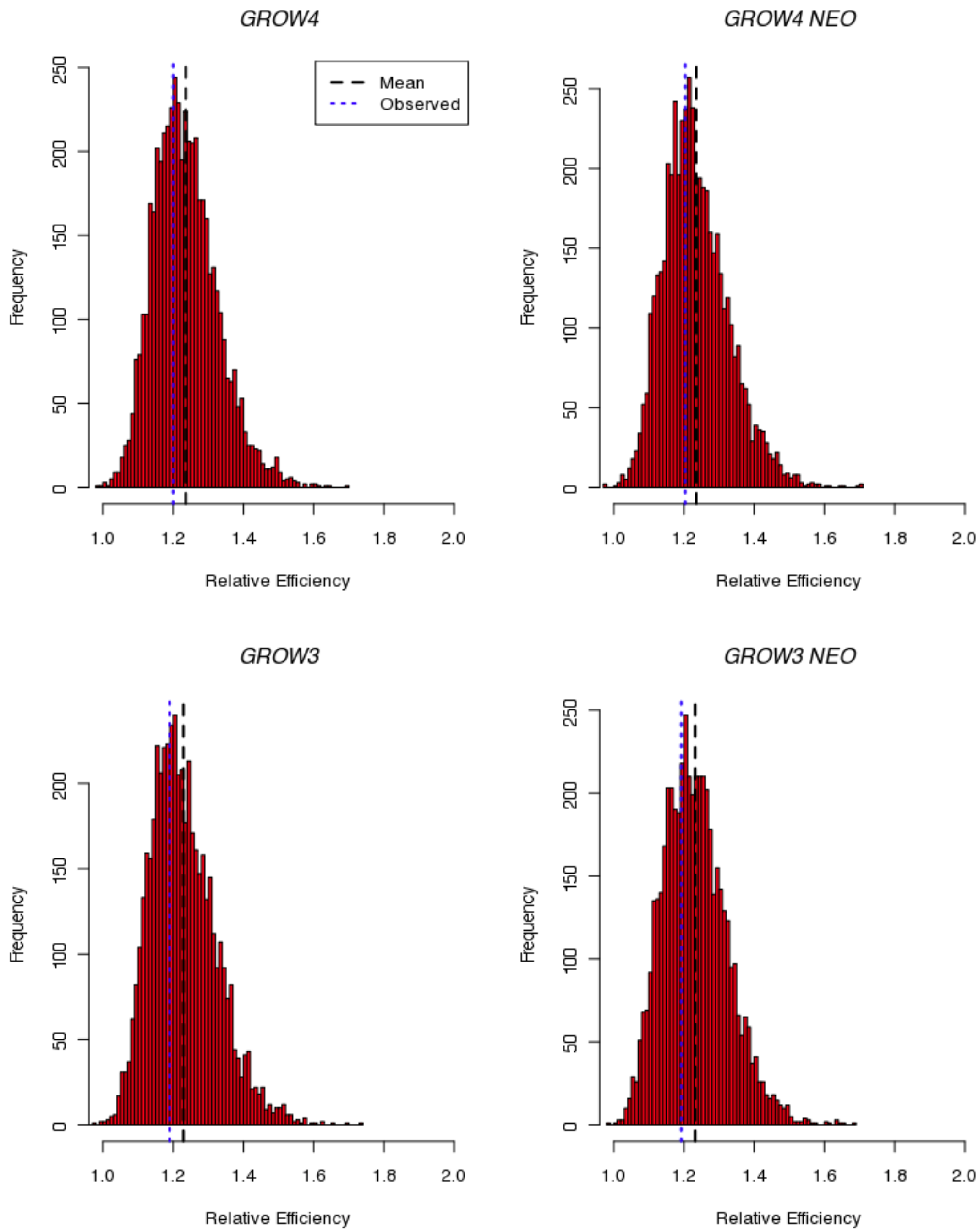

Figure C.3: Histograms of RE from the Minnesota GROW Simulations (*NEO indicates a simulation of a scheme optimized using the sample excluding extreme ovservations*)

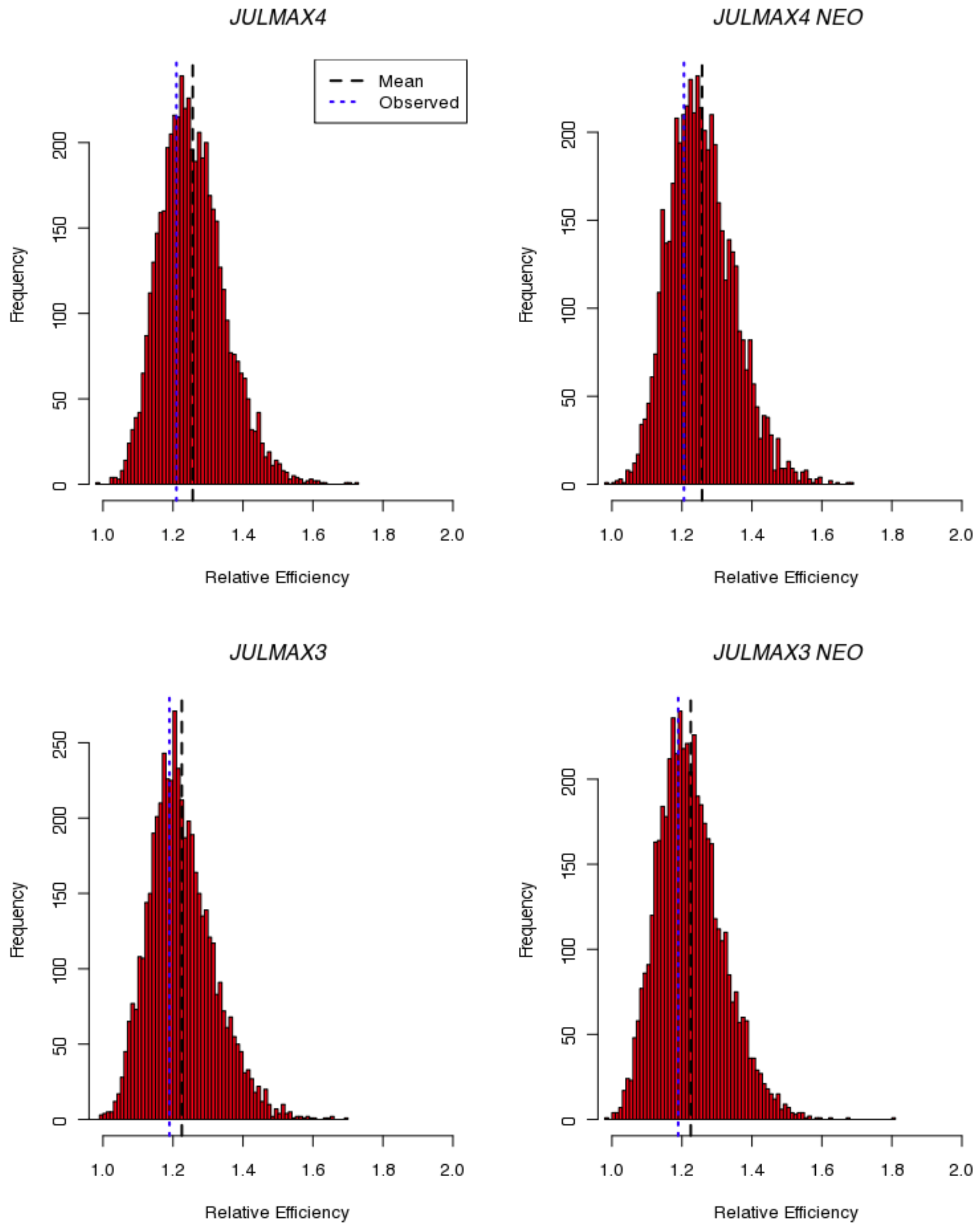

Figure C.4: Histograms of RE from the Minnesota JULMAX Simulations (*NEO indicates a simulation of a scheme optimized using the sample excluding extreme ovservations*)

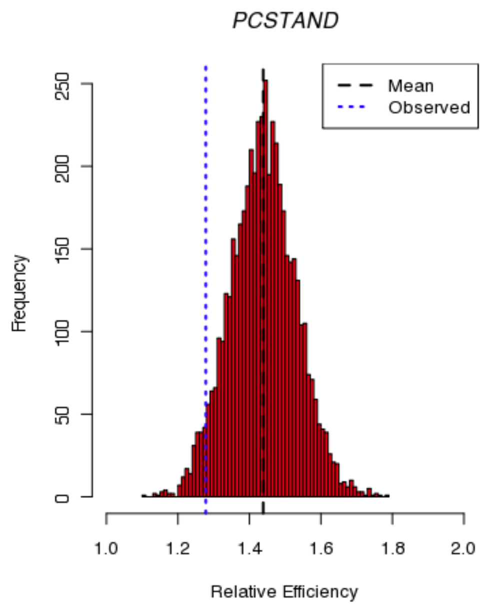

Figure C.5: Histograms of RE from the Minnesota PCSTAND Simulation

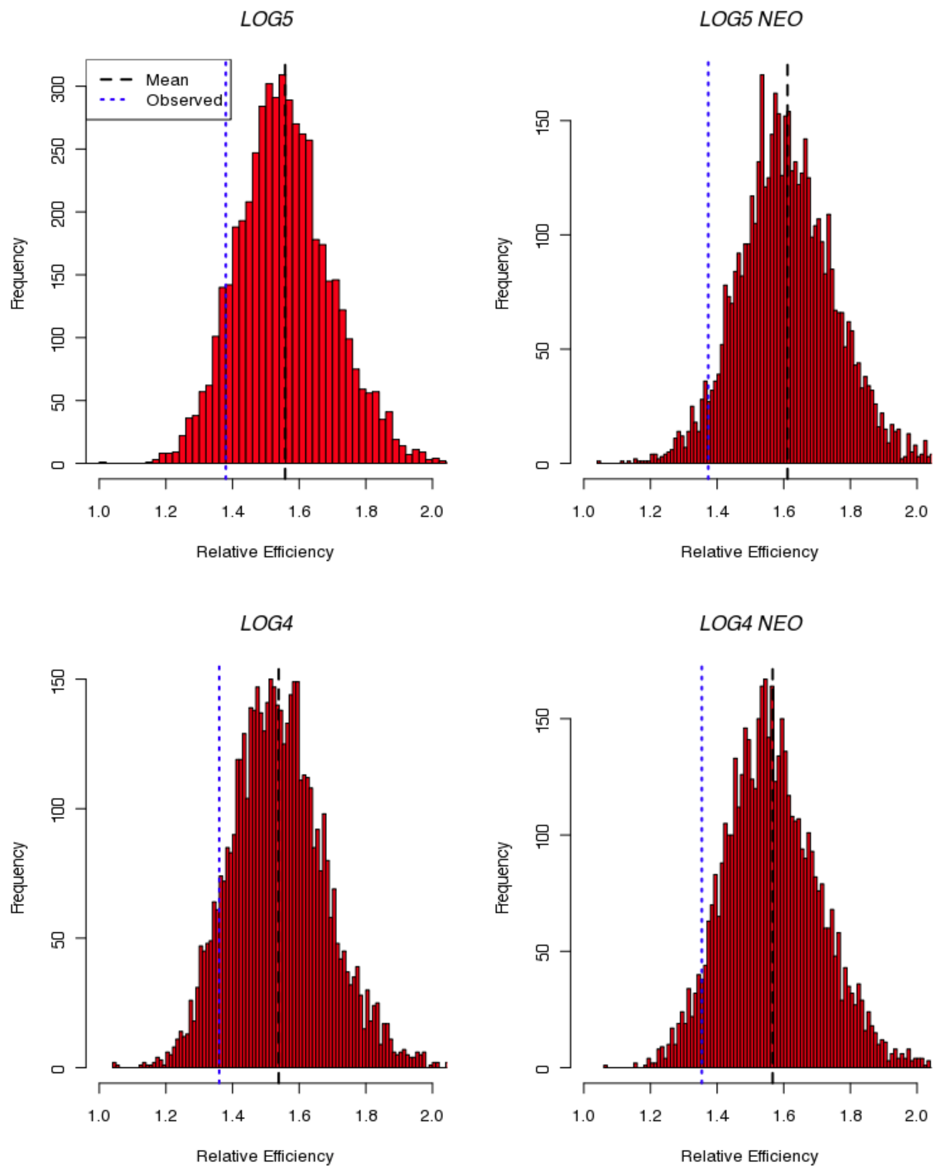

Figure C.6: Histograms of RE from the Wisconsin LOG Simulations (*NEO indicates a simulation of a scheme optimized using the sample excluding extreme ovservations*)

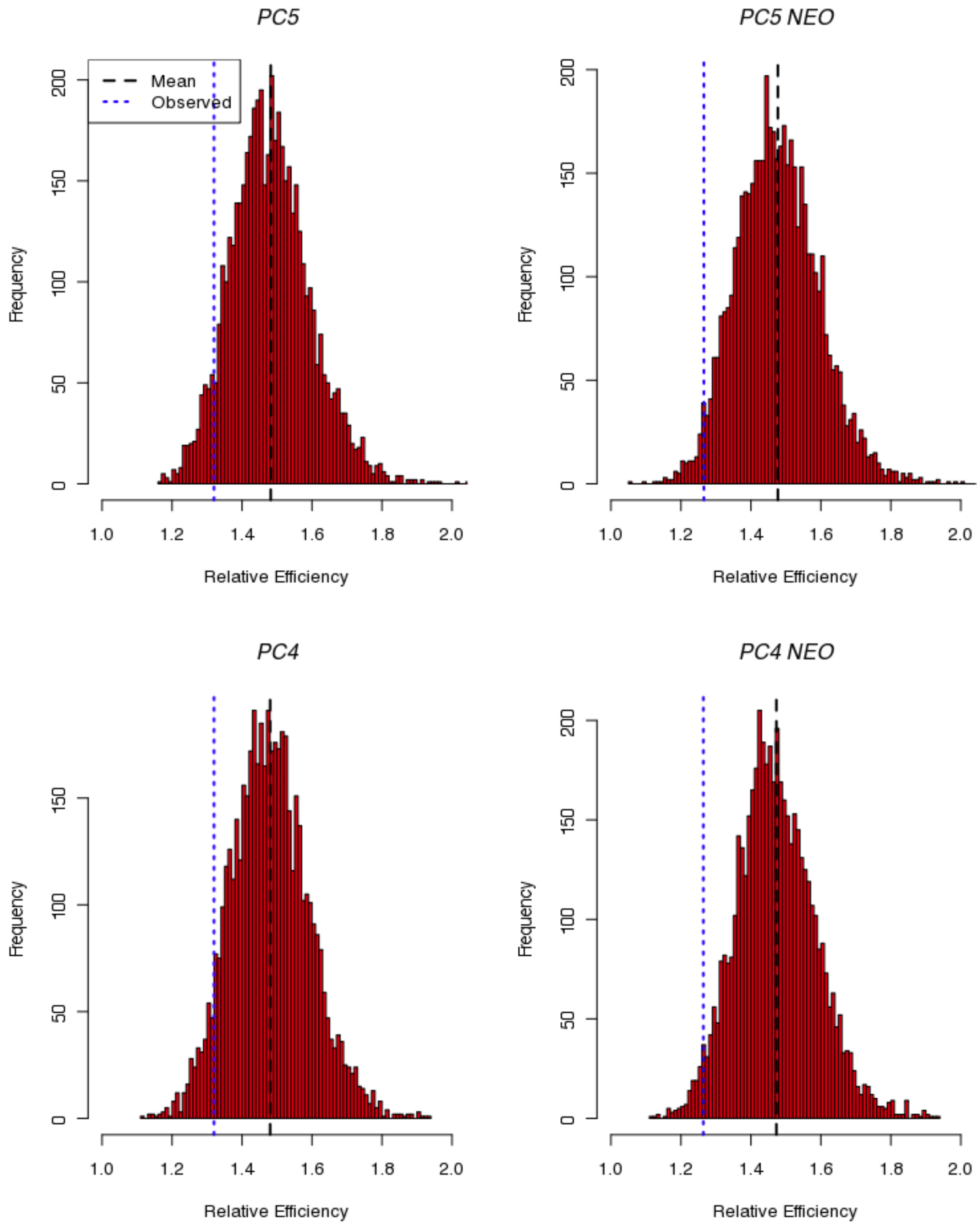

Figure C.7: Histograms of RE from the Wisconsin PC Simulations (*NEO indicates a simulation of a scheme optimized using the sample excluding extreme ovservations*)

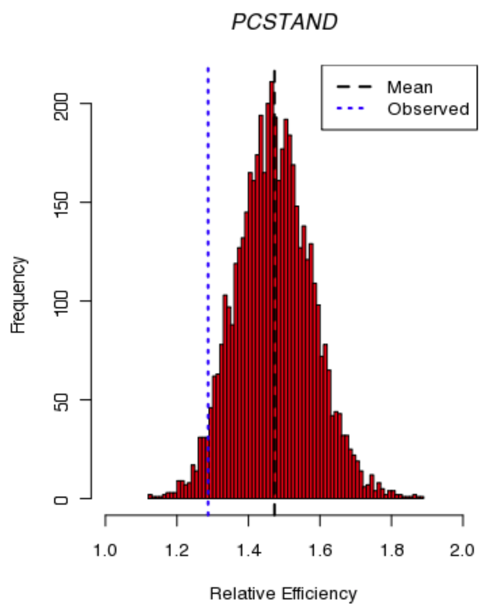

Figure C.8: Histograms of RE from the Wisconsin PCSTAND Simulation

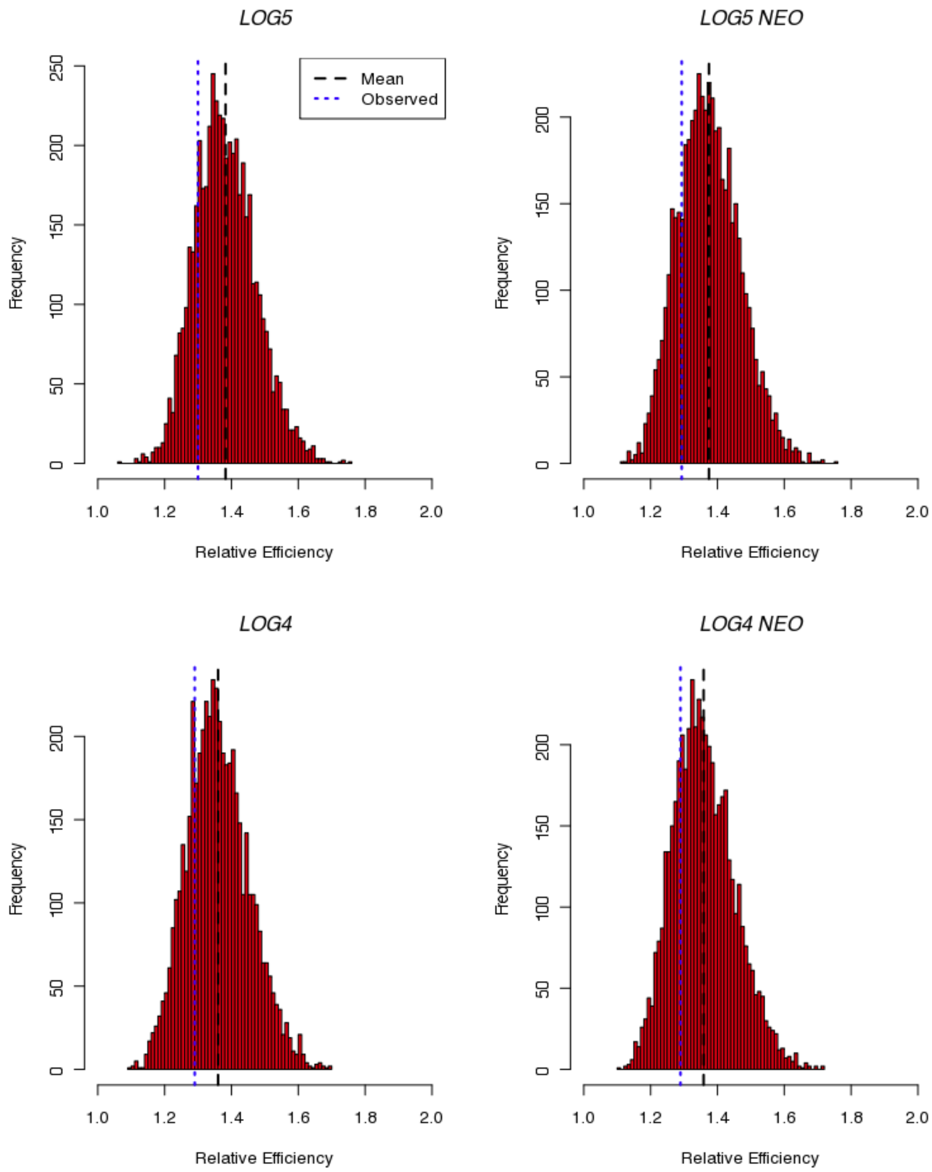

Figure C.9: Histograms of RE from the Michigan LOG Simulations (*NEO indicates a simulation of a scheme optimized using the sample excluding extreme observations*)

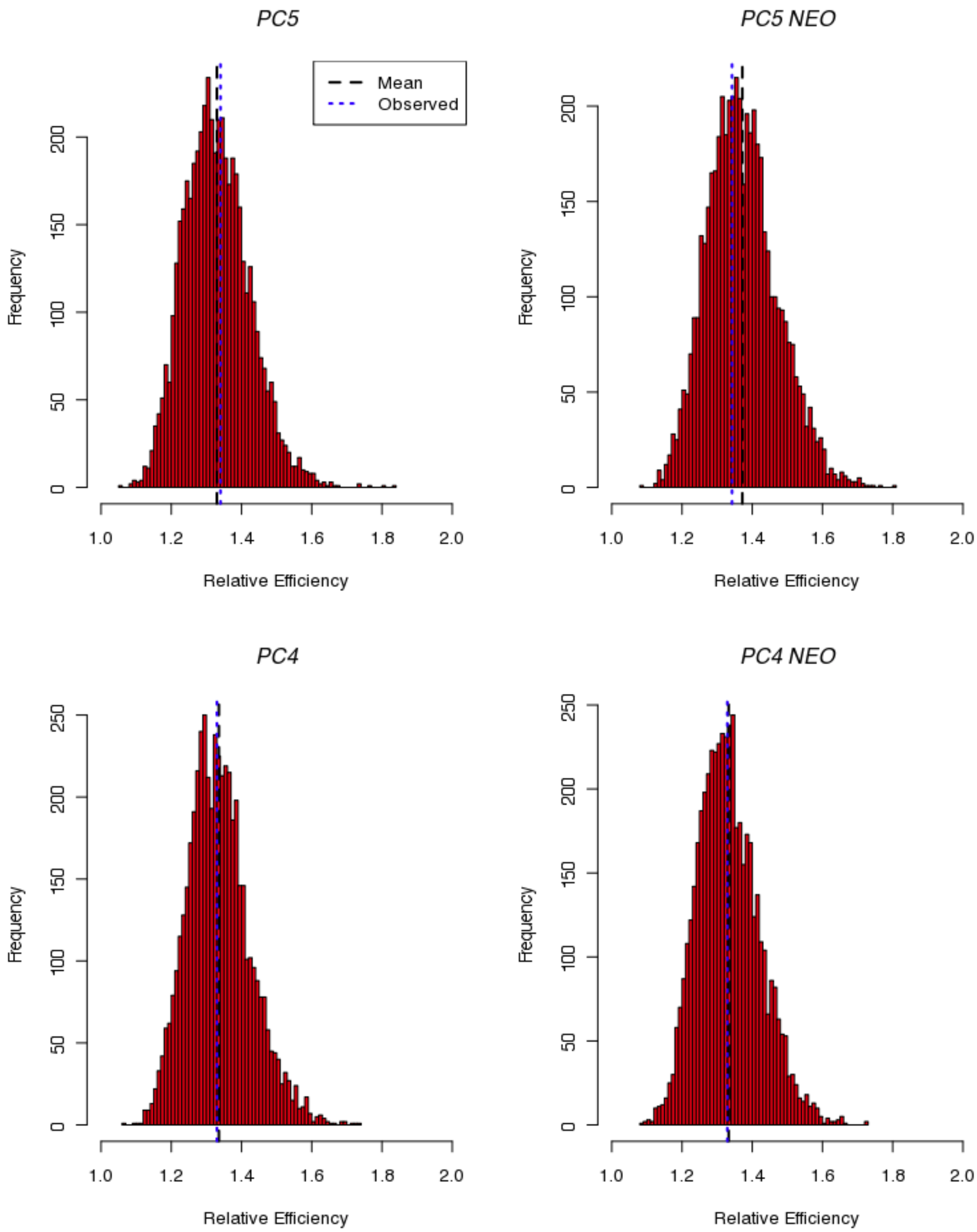

Figure C.10: Histograms of RE from the Michigan PC Simulations (*NEO indicates a simulation of a scheme optimized using the sample excluding extreme observations*)

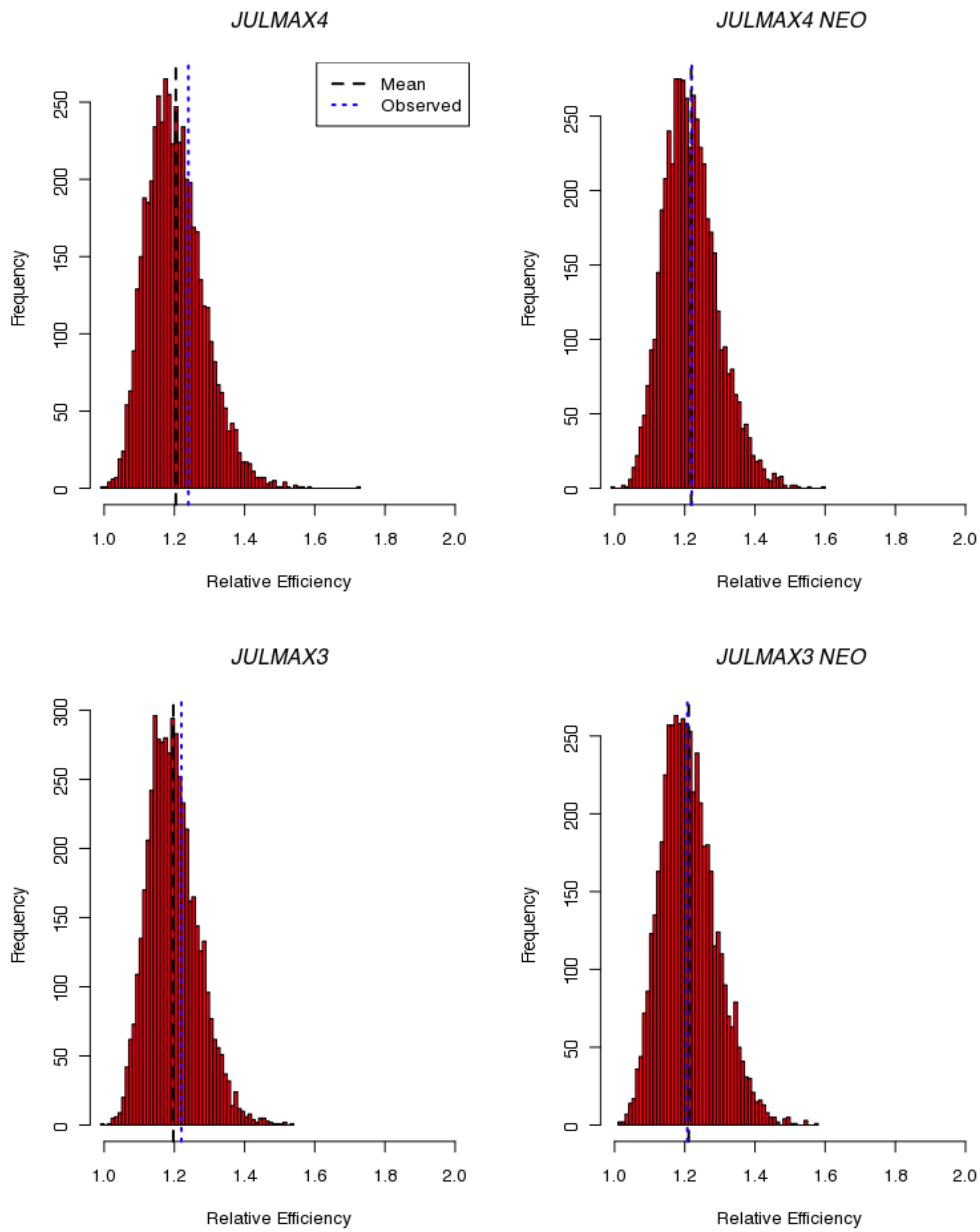

Figure C.11: Histograms of RE from the Michigan JULMAX Simulations (*NEO indicates a simulation of a scheme optimized using the sample excluding extreme observations*)

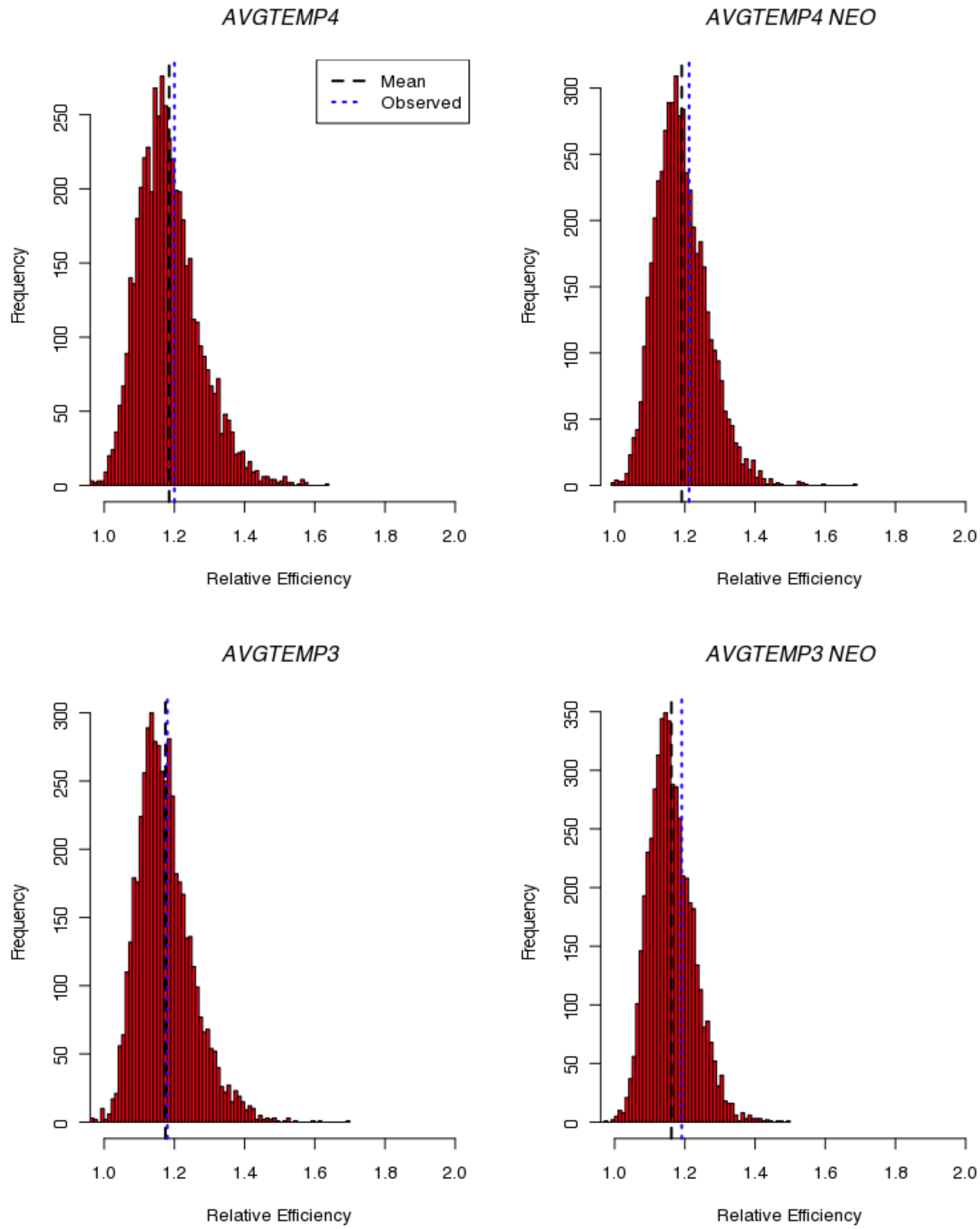

Figure C.12: Histograms of RE from the Michigan AVGTEMP Simulations (*NEO indicates a simulation of a scheme optimized using the sample excluding extreme observations*)

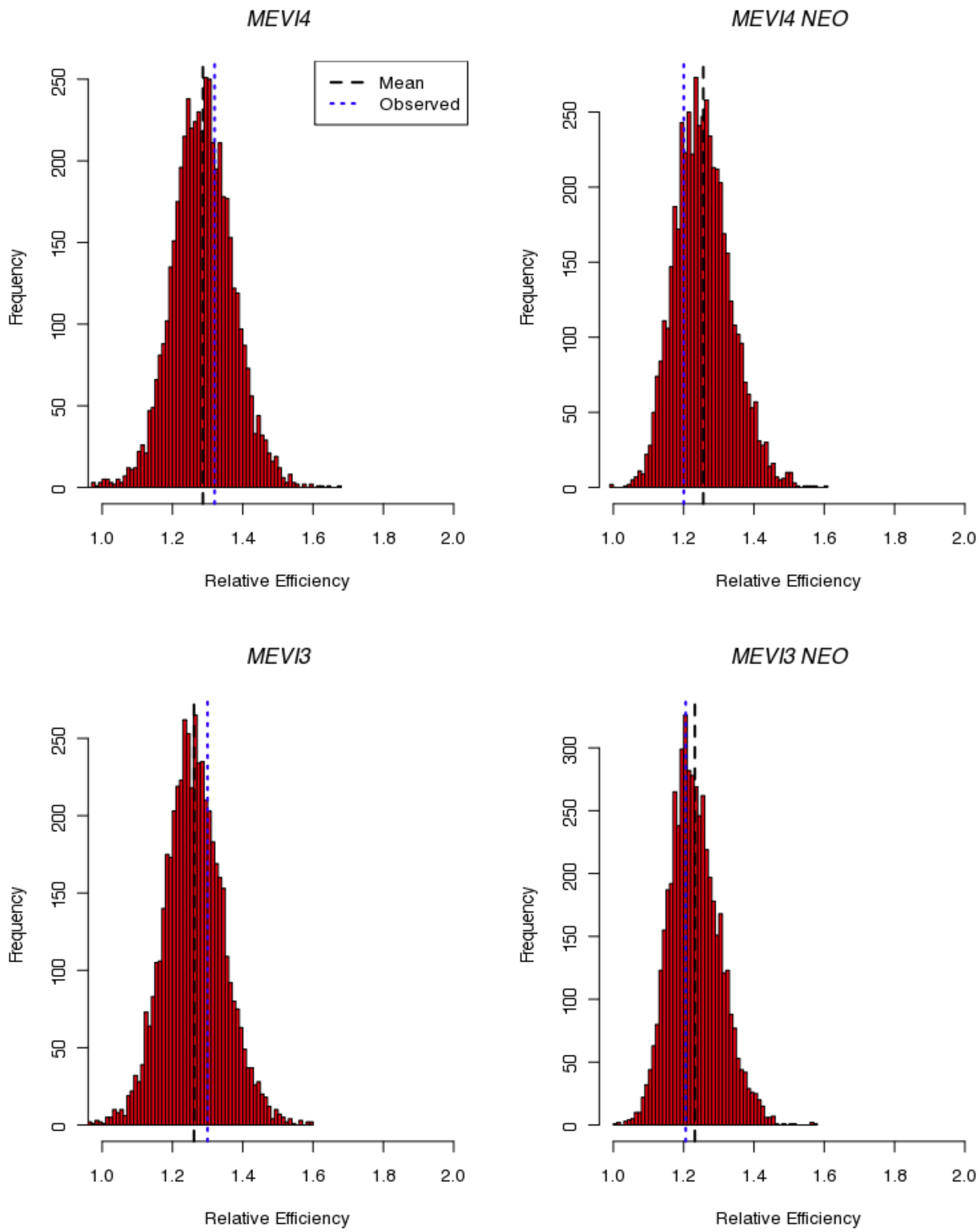

Figure C.13: Histograms of RE from the Michigan MEVI4 & 5 Simulations (*NEO indicates a simulation of a scheme optimized using the sample excluding extreme observations*)

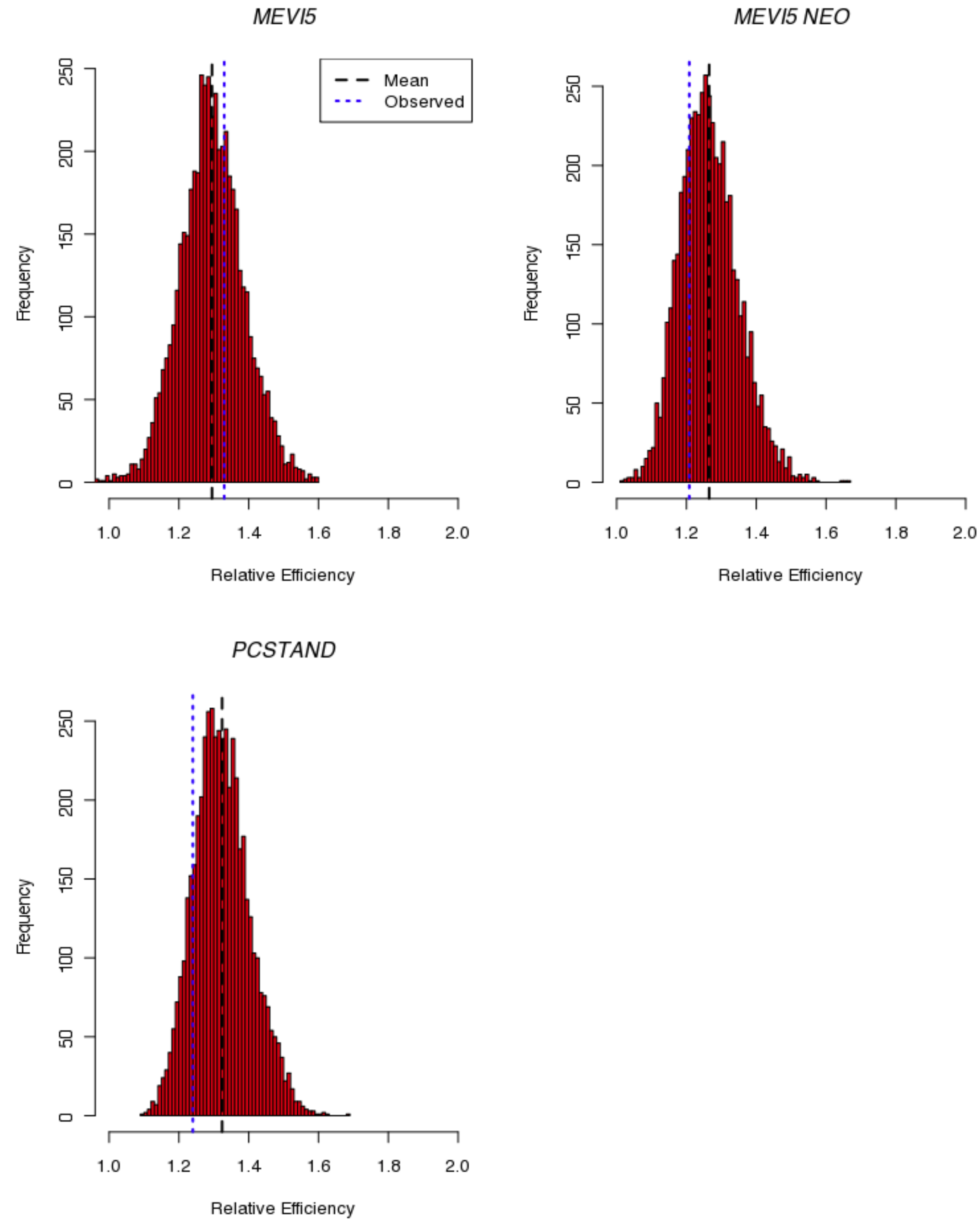

Figure C.14: Histograms of RE from the Michigan MEVI5 and PCSTAND Simulation (*NEO indicates a simulation of a scheme optimized using the sample excluding extreme observations*)