APPENDIX E - POPULATION AND RANGEWIDE HABITAT MONITORING PROCEDURES

In developing the original Recovery Plan (USDI FWS 1995), the Recovery Team assimilated, reviewed, and analyzed data generated by the Mexican Spotted Owl Monitoring Program of the FS Southwestern Region. The Recovery Team also compiled and reviewed data from the BLM and the Intermountain and Rocky Mountain Regions, FS. In addition, the Recovery Team evaluated results of a pilot study (Ganey et al. 2004) conducted to test the population-monitoring procedures proposed in USDI FWS (1995) and more recent studies that have estimated the probability of site occupancy by Mexican spotted owls (Lavier 2006, Mullet 2008). Based on lessons learned from these efforts, we offer an alternative design for monitoring the Mexican spotted owl population within the U.S. This approach would measure the critical variables – changes in owl site occupancy rates and changes in habitat – needed for delisting the species (see Part III.E).

Our proposed approach uses occupancy monitoring to evaluate trends in the owl population. Occupancy monitoring is based on mark-recapture theory (MacKenzie et al. 2002, 2003, see also MacKenzie et al. 2006) and allows for estimating detection probabilities and correcting directly observed estimates of occupancy rates. This detail is critical, because it is likely that not all resident owls will be detected in a given year and because detection probabilities may change over time. Such changes in detectability of owls could result in erroneous trend estimates and misguided conservation efforts.

Accurate and efficient protocols for occupancy monitoring require pilot studies to estimate detection probabilities and to estimate variances associated with detection probabilities, occupancy rates, and important habitat variables. For occupancy monitoring, these estimates then can be used to determine the number of call stations per survey plot and to refine the number of visits per plot. Most importantly, the numbers of plots required within predefined strata and EMU can be determined more precisely.

Habitat monitoring should entail remote sensing of habitat across the range of the bird and estimates of desired conditions (Appendix C, Tables C.2, C.3), some of which are best measured on the ground. Although we do not advocate a specific methodology for ground measures, the FS Forest Inventory and Analysis (FIA) program offers some promise. We describe some relevant details of this program below.

1. Population Occupancy Modeling

Monitoring habitat as a singular effort will not adequately reveal the true status of the owl population because numerous factors besides habitat can influence population levels. Thus, it is desirable to simultaneously monitor trends in both habitat and owl abundance (or an acceptable surrogate index).

A limitation of the monitoring scheme proposed here (and all known approaches) is that it monitors primarily territorial birds. The population of non-territorial “floaters” (Franklin 2001) is difficult to detect reliably. Evidence for Mexican spotted owls suggests that a large population

of floaters does not exist, however. Specifically, the proportion of subadult owls successfully holding territories is relatively high, suggesting that surplus older birds do not exist. For example, the proportion of the territorial population comprised of subadult females ranged as high as approximately 30–33% in two demographic study areas in Arizona and New Mexico over a seven-year period (Seamans et al. 1999: Fig. 1). Further, density of territorial owls in these study areas tracked reproduction with a short lag period (Seamans et al. 1999: Fig. 5; Gutiérrez et al. 2003), again suggesting that there were not substantial numbers of floaters available to fill territory vacancies. This evidence supports the use of trends in site occupancy as a reasonably sensitive measure of population trend.

In the following sections, we outline a framework and statistical estimation approach for monitoring owl populations via directly estimating the site occupancy rate of territorial owls. Critical design and sampling details were developed from a pilot study (Ganey et al. 2004). To illustrate the potential utility of FIA, we incorporated FIA into the occupancy monitoring plan so that microhabitat variables can be related to owl occupancy rates. Managers can consider other habitat monitoring programs in lieu of FIA if available or developed.

Monitoring Site Occupancy

Although we support the idea of estimating population size directly and collecting associated demographic data as described in USDI FWS (1995), the results of the pilot study suggest that the costs for such a monitoring program are daunting. Therefore, we propose this alternative monitoring program based on monitoring occupancy rates as an index of population size.

Occupancy

We define occupancy for Mexican spotted owls as the proportion of plots occupied by the species. Plots sampled will be square 1-km^2 (0.36-mi^2) blocks (UTM of 100 ha (247 ac) that can be easily mapped using GIS, located using GPS, and surveyed to detect Mexican spotted owls. The population of plots from which samples are to be drawn will be defined based on FIA Phase 2 state-wide maps. The number of occupied plots divided by the total number of plots sampled (n) provides an estimate of the proportion of sites occupied (O), referred to as occupancy rate.

We suggest that the owl monitoring plots be defined based on overlaying 16 of the 250-m (273-yd) raster cells of the FIA state-wide maps. The advantage of combining FIA plots and occupancy plots is that the FIA data can be used to determine which, if any, habitat variables sampled by FIA are associated with owl occupancy rates. This would allow for estimation of trends in those variables from the full FIA database and from repeated samples over time.

Statistical Model

The proportion of occupied plots (occupancy rate) in year i is taken as $O_i = \mu_O + \delta_i$, where δ_i is distributed with mean zero and variance σ^2, and μ_O is the mean of occupancy across years. The variance σ^2 is the temporal variation in the occupancy rate (i.e., the year-to-year variation in the proportion of sites occupied).

Because not all sites can be surveyed each time an estimate of occupancy is desired, a sample of plots is selected to estimate occupancy. The estimate obtained is $\hat{O}_i = O_i + \varepsilon_i$, where ε_i is distributed with mean zero and sampling variance Var($\hat{O}_i \mid O_i$). In actuality, the occupancy rate will be estimated through a stratified simple random sample without replacement.

Sampling Plan to Estimate O_i

Occupancy will be estimated by sampling occupancy sampling units (plots), consisting of square 1-km^2 areas. A plot size of 1 km^2 was selected to keep sampling units small and for operational simplicity. Small sampling units are desirable in this monitoring scheme because the response variable is basically owl presence-absence, and so it varies only from zero to one. As the number of owls present in a sample block increases above one, the occupancy index becomes less sensitive as an index of actual population change (i.e., as long as one owl remains, one or more birds could disappear with no change detected). Thus, it is desirable to minimize the probability that a sample unit overlays >1 owl territory. In addition, spacing constraints should be applied so that sampled blocks are separated by >4 km (2.5 mi), to minimize the probability of detecting the same owl(s) on >1 sampled unit. For example, mean nearest-neighbor distances between territorial owls in two study areas in Arizona (2.4 km [1.4 mi], n = 42 pairs, May and Gutiérrez 2002) and New Mexico (2.1 km [1.3 mi], n = 31 pairs, Peery et al. 1999), suggested that a separation of 4 km (2.4 mi) is appropriate. Both of these constraints (size and spacing) should help ensure that occupancy rate actually tracks abundance (i.e., no sampled unit should contain large numbers of owls and no owls should be sampled on >1 unit). We envision drawing a random sample of plots and sampling these same plots each year to minimize the variation between years. Drawing a new sample of plots each year has some advantages (see below) but would increase year-to-year variation over our proposed design.

Each of the Mexican spotted owl EMUs to be included in monitoring must be partitioned into occupancy sampling units consisting of existing FIA Phase 2 plots. This partitioning must be done before a sample is drawn so that a random sample can be drawn from the entire population of occupancy sampling units. Habitat characteristics of all sampling units must be known to estimate and implement a ratio estimator based on the estimated probability of occupancy for each potential plot (Cochran 1977, Bowden et al. 2003) and to estimate occupancy rate for all the plots in the sampling frame.

The sampling scheme will be a stratified random sample without replacement, with stratification consisting of at least the EMUs. Additional stratification should be based at least on elevation, as was done for the previous quadrat sampling scheme (Ganey et al. 2004), on topographic indices (see Bowden et al. 2003), and/or on FIA habitat maps. We expect that one stratum in each EMU will consist of non-habitat for owls, defined as low elevation, unforested areas lacking canyons or other topographic relief. Delineation of non-habitat will be based on validated owl habitat models and through Phase 1 FIA data and Phase 2 FIA state-wide maps. One important aspect of classifying owl habitat is that non-forested areas must be included in some locales, particularly owl habitat that occurs in non-forested canyons. Stratification variables such as forest type also should be used where available, and clearly the FIA Phase 1 and Phase 2 data can be used to provide stratification information. Likely, three forest types should be defined within each of the five EMUs: mixed conifer, ponderosa pine-Gambel oak,

and Madrean pine-oak. In addition, some plots should be placed in a canyon stratum in each EMU. The canyon stratum should be defined based on topographic roughness. Thus, we envision up to five strata in each of the five EMUs, for a potential total of 25 strata.

Stratification serves two purposes here. First, and most importantly, stratification distributes the sample across the sampling frame (and thus provides an argument for stratifying by EMU). With a simple random sample, there is a risk that all or most of the sampled plots are in one localized area. As a result, the sample is not considered representative of the sampling frame (even though such a sample has the same probability of being selected as a sample where the plots are more evenly distributed). Second, stratification provides improved estimates because proper stratification reduces the variability among plots, and thus results in more precise estimates. There is a need to make inferences from individual stratum estimates for the EMUs because each of these units must demonstrate a stable or increasing occupancy rate (see Part III.E). When inferences are stratum-specific, then each stratum must be considered a separate sampling frame. In the monitoring scheme we describe, the stratum-specific estimates are viewed as essential information, and it is thus necessary to obtain precise estimates of occupancy for each stratum. As we describe below, data from all the plots where owls are detected, regardless of which stratum a plot occupies, will be used to generate models of owl detection probabilities. Therefore, the effect of combining data across strata will improve the precision of the estimates across strata, but it will also result in a sampling covariance across strata that must be handled with the methods presented by Bowden et al. (2003).

Plots within strata should either be selected with simple random sampling, or preferably, using generalized random tessellation stratified (GRTS) sampling (Stevens and Olsen 1999, 2003, 2004) to obtain a spatially balanced sample within each stratum. GRTS sampling ranks the order of sampling of the plots within each stratum. Computer code for Windows is available at on the West-Inc web site, www.west-inc.com, for selecting a GRTS sample.

Estimation of occupancy for each sampling unit will be made from two or more visits, because detection rate can be estimated only when plots are visited >1 time. Based on at least two visits, estimates of the detection rate of owls on an occupancy sampling unit and occupancy rate for the sample can be estimated using the maximum likelihood approach of MacKenzie et al. (2002, 2003). Parameters estimated are the occupancy probability for the sampling unit (ψ) and probability of detection given owls are present (p) for the sample. To determine the proportion of false negative plots (i.e., proportion of plots that are occupied but on which owls are not detected), the modeling approach requires at least two visits to a sample of plots to be able to estimate p and then ψ.

Several examples will now be given to explain this estimator. First, assume one or more owls are detected on occupancy sampling unit j on each of the $t = 2$ visits, and assume that the probability of detection is not occasion-specific. The probability of this series of events is $\psi_j p_j p_j$. If owls are detected only on the first visit, then the probability is $\psi_j p_j (1 - p_j)$. If they are only detected on the last visit, then the probability is $\psi_j (1 - p_j) p_j$. If owls are never detected, then the probability is $\psi_j (1 - p_j)(1 - p_j) + (1 - \psi_j)$. These four probabilities sum to one because they are the only possible observations. Thus, these probabilities can be modeled in

a maximum likelihood estimation framework (using numerical optimization of the log likelihood) based on observed histories of owl detections on sampled units.

We expect that habitat information provided by FIA Phase 2 state-wide maps will provide useful predictors of owl occupancy rates. We envision two separate analyses of the occupancy data that incorporate habitat information. The first analysis would link FIA variables to occupancy rates, specifically the key variables listed above. Models that incorporate multiple covariates and possibly their interactions should be developed to identity habitat variables important for further analysis. That is, the trends in the identified variables will be examined with the FIA data base. These habitat variables will be constructed from the means or sums of variables provided by the 16 250-m (273-yd) cells of the FIA state-wide maps that underlie each of the 1-km^2 (0.36-mi^2) occupancy plots.

The FIA covariates may not prove useful as predictors of owl occupancy. If so, this should not necessarily be interpreted as evidence that owl occupancy is not related to habitat conditions. Several alternative explanations may better explain this outcome. For example, the variables included in the analysis may not relate directly to owls, or spatial scale issues may mask any existing relationship.

The second analysis will be to identity functions of the FIA variables that can be used in a ratio estimator sampling model (Cochran 1977). Typically, ratio estimators use a single variable to improve the precision of the desired estimate. For example, Ganey et al. (2004) found that the triangulated irregular network (TIN) ratio was an important variable for use as a ratio estimator, and the TIN ratio reduced the variance of the estimate by nearly a factor of four. We hope to identify ratio covariates that will be useful in improving precision of the occupancy estimates, although these models will likely need to be stratum-specific to accommodate the differences in the strata identified.

If plot-specific covariates from Phase 2 FIA state-wide maps do not improve the estimation of occupancy rate within a strata, then the estimate of ψ obtained without covariates for the plots would be an appropriate estimate of O, or model averaging might be used to average $\hat{\psi}$ from multiple models but still providing an estimate of O. However, plot-specific covariates would be expected to improve the estimate of occupancy probability for each plot, and also of p (see Bowden et al. 2003). The occupancy estimator has been implemented in Program MARK (White and Burnham 1999) so that the use of individual covariates, AICc model selection, and variance components capabilities already available in this software package (White et al. 2001) can be used with this model. In addition, Bayesian estimation methods were added to MARK in 2004, allowing estimation of process variances through the use of hyper-distributions. Plot-specific covariates can be used to build a model from the data on the sampled plots to estimate the probability of occupancy of a plot. The resulting model on a logit scale then could be used in a ratio (or regression) estimator to estimate the number of occupied plots for the sampling frame as we describe above. Thus the occupancy rate (O_i) for a stratum for year i would be estimated based on the covariate values for each of the plots in the strata. If the model (and associated covariates) predicting the probability of occupancy of a sampling unit is poor, in the sense that the model does not improve the predictions of the probability of occupancy, then the occupancy estimate from the sample is still a valid estimator of the occupancy rate of the stratum. However,

if the model is a good predictor, then using the covariate information from each potential sampling unit in the stratum will improve the estimate for the stratum. That is, the additional information available for each unsampled plot in the stratum is used, resulting in a less biased and more precise stratum-level estimate.

Multiple strata might be pooled in a MARK analysis to obtain better estimates of detection probabilities and the functional relationship between a covariate and probability of occupancy, but estimates of occupancy rate would still be specific to each stratum. However, if multiple strata are pooled to estimate occupancy, then a sampling covariance is induced between the strata estimates, necessitating the use of a ratio estimator incorporating this sampling covariance (Bowden et al. 2003).

Another possibility that could be explored is to use cluster sampling to sample plots (but see above concern about spacing of sample units). Biologists conducting the surveys could decrease travel time between plots, increasing the number of plots that could be surveyed on one occasion. The difficultly with cluster sampling is how to handle the lack of independence of plots within the same cluster and the effect of this lack of independence on estimation of ψ. Further, cluster sampling improves efficiency of the sampling design when the variance among cluster totals is small and, conversely, variance within the cluster is large (Scheaffer et al. 1986). Likely exactly the opposite is the case for clusters of 1-km^2 (0.36-mi^2) plots because of a high spatial autocorrelation between plots. Clusters would have to be quite large to make cluster sampling more efficient than random sampling. However, cluster sampling should still be an option that is considered to decrease travel time.

One fundamental part of the field methodology is yet to be resolved fully. We lean toward basing occupancy estimates on whether or not a bird was detected from a call point in a sample plot, for operational simplicity. That is, if a surveyor calls from within the plot and hears a response, the plot is considered occupied, regardless of whether the owl was physically on the plot. The alternative approach is to require the surveyor to verify that the owl responding is physically on the plot being sampled, which is a time-intensive (and often dangerous) nighttime activity. However, not requiring the owl to physically exist on the plot at the time of the survey will cause detection probabilities to be lower because of the heterogeneity caused by owl responses from varying distances off the plot. Peripheral birds may be detected on some occasions and not others. In contrast, birds residing on the plot would generally be detected with higher probability. As a result, there is a tradeoff here – if keeping detection probabilities high is a priority, only plots where owls are detected on the plot should be considered occupied. However, because of the objectivity of monitoring when the detections are not limited to just the plot being sampled, we tend to prefer this simpler approach.

An approach that could encompass both types of detections is the multi-state occupancy model developed by MacKenzie et al. (2009). That is, each plot would conceptually be classified into one of three states: unoccupied, owl(s) detected but unsure if phyisically on the plot, and owl(s) definitely detecton on the plot. Detections for which the observer is not sure if the owl is on the plot could define a lower state, and detections that are unquestionably on the plot are defined as a higher state. These observer-driven extensions are characterized by ambiguity in both species presence and correct state classification, caused by imperfect detection. A second applicaton of

the multi-state occupancy model might be to define the lower state as one or more owls detected on the plot, and a higher state as reproduction having occurred on the plot because young are present. This latter example is illustrated in MacKenzie et al. (2009) with California spotted owls.

Based on data from the pilot study on population monitoring (Ganey et al. 2004), detection probabilities for two occasions were sufficiently high when six to seven call points were visited within the 1-km^2 plot (Fig. E.1). The population monitoring pilot study was not intended to provide call points well-spaced to cover 1-km^2 plots, however, so this figure may present a worst-case scenario. It is suspected that five call points would be adequate for most UTM blocks. Further, because a site is classified as occupied if an owl is detected, the number of call points that a surveyor must actually visit will depend on when an owl is first detected (i.e., if an owl is detected from the first call point, the remaining call points need not be visited).

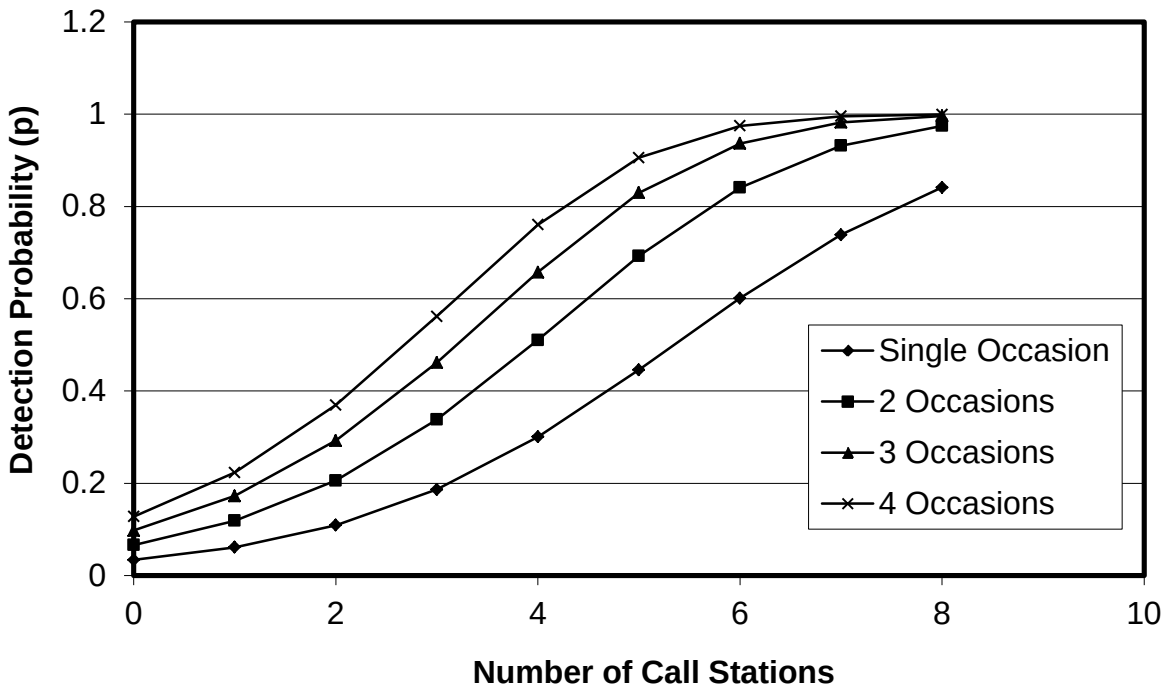

Figure E.1 Probability of detection for a 1-km^2 (0.36-mi^2) plot for the number of points on the plot from which owls are called and the number of occasions on which the plot is visited. For example, a plot with two visits and six points called would have a detection probability of >0.8 that an owl was detected on at least one of the visits. Note, however, that even though detection probabilities are provided for a single visit, a sample of plots must be visited twice to be able to estimate the probability of detection (p) and hence the probability of occupancy, ψ.

The results in Fig. E.1 above also demonstrate that increasing the number of visits to the plot from two to three or more provides only small increases in probability of detection. Thus, we suggest visiting more plots two times rather than fewer plots three or more times.

Statistical Estimation of Trend in Occupancy

The sequence of years for which occupancy rates are measured can be viewed as either a sample of all years, or as a fixed interval in time about which we desire to make inferences. Different statistical models are appropriate for these different sets of assumptions. A random effects model assumes that the sequence of years is a representative sample from a sampling frame of years. As a result, inferences are being made to the entire sampling frame. In contrast, the fixed effects model is only making inferences to the sequence of years measured.

Random Effects Model. Changes in occupancy across years are assumed to be a stochastic process, as we describe above. When the mean of the process (μ_O) is assumed to be constant in the stochastic model described above, changes in occupancy are strictly random. However, trends in occupancy may still be present, although the process generating these trends is purely random. That is, by chance alone, a set of realized temporal observations may show a trend, even though the mean of the underlying process is not changing. The hypothesis examined with a random effects model is that a trend in the occupancy process is taking place (i.e., that there is a trend in μ_O through time). The random effects estimator is supposed to detect a change only in the process. Therefore, potentially important trends in occupancy may be missed with the random effects estimator because these trends are only from variation due to δ_i, not from changes in μ_O. In addition, to detect trends in μ_O, a long time span of data is required. That is, the random effects model will not have much power to detect trends in relatively short spans (i.e., ≤10 years).

An important assumption of the random effects model is that the sample of $\hat{O}_i$ across years is a random sample from all possible years to which inferences are being made. In reality, this assumption is unobtainable because the years sampled are not randomly selected from a population of years.

Fixed Effects Model. The fixed effects model evaluates the trend in the realized sequence of occupancy estimates. That is, the process generating the occupancy rates may not be changing (i.e., μ_O is constant across time), but by chance alone, a realized sequence may show a trend. The fixed effects model will detect this trend, whereas the random effects model we describe above should not detect such "random" trends. Realistically, the statistical procedure used to detect such random trends is desired because the interest is in providing management action as soon as possible given a downward trend in occupancy rates. In such a situation, management actions will not have an impact because the process has not changed. However, this is the price paid to achieve a more sensitive monitoring system.

Therefore, we suggest that the sequence of occupancy estimates, $\hat{O}_i$, be analyzed with a fixed effects model. It is recognizing that the years sampled were not drawn at random from a population of years and that the interest is in detecting downward trends in occupancy, even if the underlying process has not changed, because management actions require some lead time to have an impact on the Mexican spotted owl population.

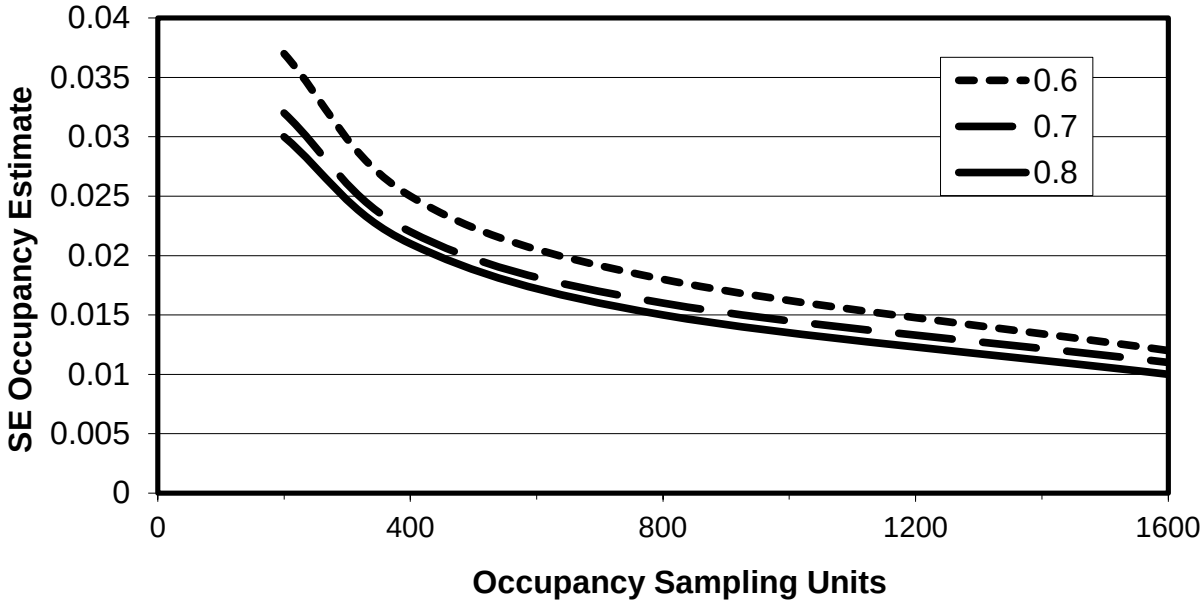

Figure E.2. Standard error of the estimate of site occupancy rate for three levels of the detection probability, *p*, and two visits per site, as a function of the number of occupancy sites sampled.

Expected Precision of Occupancy Estimates

We conducted simulations with Program MARK to determine the precision of the estimate of occupancy without individual covariates. We simulated a factorial design of N = 200, 400, 800, and 1,600 occupancy sampling units, p = 0.6, 0.7, 0.8, and ψ = 0.2. For each scenario, we conducted 1,000 simulations to estimate the expected precision. We based the detection probabilities of p = 0.6, 0.7, and 0.8 on the probability of detection from the quadrat sample (Ganey et al. 2004), where detection of an *individual* owl was ~0.5 in roadless areas, and ~0.9 in roaded areas. We also based the occupancy rate of 0.2 on results of the pilot study (Ganey et al. 2004), where >50% of the high elevation quadrats were occupied. However, because the quadrats were much larger than the occupancy sampling units, the expected occupancy rate of the occupancy sampling units will be considerably less, so we chose 0.2 as a reasonable value. Simulation results for the standard error of $\hat{\psi}$ are shown in Fig. E.2 above for three values of p and a range of sample sizes.

These results (Fig. E.2) suggest that a large number of occupancy sampling units must be measured in each stratum (or within an EMU) to obtain reasonable precision for $\hat{O}$. For example, sampling 1,600 occupancy sampling units in one stratum using a stratified random sample design would result in a standard error of 0.011 for p = 0.7. If three strata in an EMU with this same standard error were combined, the overall estimate would have a standard error of $0.011/\sqrt{3}$ = 0.00635, or approximately a ±6% confidence interval. With this sampling precision, two consecutive year's estimates with a 10% decline between years would likely be considered statistically different. However, if only 200 occupancy sampling units were sampled in one stratum, giving a standard error of 0.032, a ±18% confidence interval would result. This level of

precision would be adequate to detect a 25% decline between consecutive years. What this result suggests is that any occupancy monitoring scheme implemented will only be able to detect changes over a large geographic area. That is, multiple strata must be combined in order to obtain precise estimates of occupancy that will be useful in detecting changes.

Power of Fixed Effects Analysis of Occupancy Estimates

We conducted simulations using Program MARK and SAS to estimate the power of occupancy monitoring to detect trends in percent occupancy. We simulated all combinations of the following models: a linear trend in ψ = 0.00, −0.01, −0.02, and −0.03 each year; ψ values in year zero of 0.10, 0.15, and 0.20; process standard deviation of ψ of 0, 0.05, 0.10, 0.15, and 0.20; p = 0.6, 0.7, 0.8, and 0.9; years of sampling 10, 15, ..., 30; and 200, 400, 800, and 1600 sampling units. Note that annual declines of 1, 2, and 3% result in declines of 10, 18, and 26% over 10 years, respectively.

For 10 years of sampling, power of >90% was generally found for 1,600 sampling units and for 800 sampling units with a process standard deviation of zero and a trend in ψ of −0.03. Thus, this power analysis confirms that large sample sizes will be required to detect changes in occupancy. However, this power analysis does not incorporate plot-specific covariates that might greatly improve the precision of the annual occupancy estimates. For example, plot-specific covariates reduced the variance by half in the pilot population monitoring survey (Bowden et al. 2003, Ganey et al. 2004). Hence, the sample sizes we determine here to provide adequate power may be more than needed to achieve the same power with a ratio estimator. Without a pilot study to determine these relationships (i.e., the degree of correlation between occupancy and plot-specific covariates) and to provide some idea of the temporal process variation in site occupancy rate, inadequate information is available to estimate the necessary sample sizes and/or power of a site occupancy monitoring design at this time.

Relationship Between Occupancy Estimates and Population Abundance

In theory and practice, there is some relationship between occupancy rate and population abundance. Further, Royle and Nichols (2003) describe an approach for estimating occupancy rate or the proportion of an area occupied when heterogeneity in detection probability exists as a result of variation in abundance of the organism under study. Variation in abundance induces variation in detection probability so that heterogeneity in abundance can be modeled as heterogeneity in detection probability. Their method allows estimation of abundance from repeated observations of the presence or absence of animals without having to uniquely mark individuals in the population.

However, we do not foresee the method of Royle and Nichols (2003) as useful in quantifying population abundance. Their method requires some strong assumptions that will not be met with spotted owl data collected on 1-km^2 plots. First, their model assumes that owls are randomly distributed on a homogeneous landscape, i.e., that the number of owls observed on a plot follows a Poisson distribution. Clearly, this strong assumption is invalid for spotted owl data. Second, their model basically assumes that the plots are geographically closed, i.e., no immigration or emigration from the plots. As discussed above, there are issues with this

sampling plan about how well detections can be classified as coming from owls on the plot versus near the plot. Obviously the closure assumption is not met, and hence population abundance estimated from this model will not be useful.

2. Potential Experiments

Many habitat variables important to Mexican spotted owls cannot be monitored by remote sensing. Further, it is important to ensure that adequate habitat is provided for key prey as well. Thus, we propose some potential experiments to relate habitat conditions to owl population dynamics where key habitat characteristics would be measured on the ground. On-the-ground monitoring of relevant habitat characteristics would quantify their change at a local (i.e., within plot) scale and relate them to owl population dynamics.

Monitoring of owl population size based on randomly selected quadrats (as proposed in USDI FWS 1995) provides the opportunity to conduct experiments to extend our knowledge of the impact of habitat manipulation on Mexican spotted owl population dynamics. These experiments are proposed to produce credible, defensible, and reliable results (sensu Murphy and Noon 1991). Quadrats within the population monitoring design would serve as experimental units for examining the effects of future management such as fires, grazing, timber harvest, and recreation.

Given that a treatment is identified prior to its occurrence, vegetation measurements can take place on the site of the expected treatment and on a second, control quadrat that is selected based on its similarity to the expected treatment quadrat. This experimental design is not a true experiment because the treatment is not randomly allocated to one of the pair of quadrats. However, this quasi-experiment is still more powerful in developing cause-and-effect relationships between habitat manipulations and owl population dynamics than the more common correlative designs used by past researchers. Further, the capability to replicate the treatment exists because of the extensive number of quadrats that would be required for measuring changes in population size.

Areas where planned treatments result in some form of habitat alteration provide excellent opportunities for quasi-experiments. Vegetation measures should be taken immediately before and after the habitat-modifying event and thereafter at 5-year intervals. Vegetation measurements that seem especially important to examine are tree size-class distribution, log size-class distribution, canopy cover, and shrub cover. Results from these experiments, coupled with results of population monitoring, provide the basis for a predictive model of spotted owl habitat quality (assuming that owl occupancy reflects habitat quality).

Unfortunately, for logistic reasons we describe above, this revision of the Recovery Plan shifts from direct monitoring of population size to monitoring site occupancy. This modification in monitoring approach reduces our ability to detect impacts of management on owl populations because occupancy is not as sensitive a measure of the response of the owl population to manipulations as is the measurement of population change.

3. Alternative Designs for Occupancy Modeling

In developing the monitoring scheme proposed here, we considered many alternative schemes. Some of these are discussed here, simply to illustrate some of the alternatives considered and why they were rejected.

Drawing a New Sample of Plots Each Year

Instead of the proposed scheme of drawing an initial sample of plots from the sampling frame and monitoring these same plots through time, an alternative approach would be to draw a completely new random sample of plots each year. For repeated sampling of a set of plots to be legitimate, normal activities that occur in spotted owl habitat should continue during the monitoring program, provided these activities meet the requirements of Section 7(a)(2) of the Act by not likely jeopardizing the continued existence of the Mexican spotted owl. Because this Recovery Plan requires that PACs be placed around locations occupied by owls, management activities may be modified if an occupied site is found during the occupancy sampling. Thus, the monitoring process affects the management of occupied sites, an undesirable situation. The main advantage of a new sample each year is that it guards against the potential for land managers to manage areas within the plots differently than the remainder of the landscape. Such differences in management will likely occur because of the establishment of PACs. The price of this protection is relatively great, as illustrated by these three points: 1) the logistics of conducting the surveys each year would increase because of the new plots; 2) quasi-experiments to detect the relationship between habitat manipulations and owl occupancy rates would not be possible; and, 3) higher sampling intensities would be required because this design is less efficient (i.e., less precise) for estimating change. Our proposed design is to draw an initial sample of plots and monitor those same plots each year. Because the plots are small and randomly distributed, management activities probably cannot avoid them, even though PACs are established. As a result, a fixed sample of plots likely is appropriate, so we do not deem it necessary to draw a new sample of plots each year.

Conducting Surveys Less Often Than Yearly

Instead of surveying plots each year, effort and cost could be saved by conducting the surveys at longer intervals, such as every five years. An advantage of this approach is that costs will be lowered, and more precise estimates of population size could possibly be obtained by pooling money to conduct a few very good surveys instead of more frequent surveys with lower effort per survey. The main disadvantage of this approach is that funding would not be allocated each year, which would likely make procuring funding for intense efforts every five years difficult. Finally, the ability to detect relationships between habitat manipulations and occupancy would be greatly decreased because this approach is more sensitive to variability introduced by the years chosen for sampling. That is, less information is provided on temporal variation when samples are only taken every five years. Therefore, we recommend sampling each year as the most effective approach to occupancy monitoring.

PACs as Sampling Units for Monitoring Occupancy

The PACs would seem to be a natural sampling unit to monitor occupancy. The difficulty with this scenario is that PACs are not a representative sample of available owl habitat. The PACs can only be established by the presence of an owl. As a result, the occupancy rate of PACs can only decline, since each PAC is initially occupied. Additionally, PAC boundaries may change as neighboring sites are found to be occupied, creating a non-static sampling frame. Therefore, we recommend that the sampling frame consist of 1-km^2 plots rather than PACs.

One important use of PACs would be to improve stratification of the proposed sampling plan, since the presence of a PAC suggests the area is likely occupied, and a large number of PACs would suggest that much of an area is occupied.

4. Rangewide Habitat Monitoring

The primary objective of rangewide habitat monitoring is to validate the results of population occupancy monitoring. For example, if occupancy monitoring indicates stable (or increasing) occupancy rates, habitat monitoring will provide a general measure of whether there will be sufficient nest and roost habitat for occupancy rates to remain stable. We advocate no specific method for habitat monitoring and leave it up to management agencies to determine the best method(s) to use. One possible approach is to use data from Forest Inventory and Analysis (FIA). We provide a brief overview of that program below.

Introduction to the Forest Inventory and Analysis (FIA) Program

Habitat monitoring depends on remote-sensing and stand-level vegetation data of habitat across the owl's range, using vegetation measures from the FIA program. The FIA has been in continuous operation since 1930 with a mission to "…make and keep current a comprehensive inventory and analysis of the present and prospective conditions of and requirements for the renewable resources of the forest and rangelands of the U.S…"

The core design of FIA consists of three phases (http://fia.fs.fed.us/about.htm). Phase 1 is a remote sensing phase aimed at classifying the land into forest and non-forest and taking spatial measurements such as fragmentation, urbanization, and distance variables. This phase has historically been conducted using aerial photography, but it is changing to a system based on satellite imagery. Data from this phase will be useful for monitoring macrohabitat changes in the range of the Mexican spotted owl.

Phase 2 consists of field samples distributed across the landscape, based on a permanent grid system with an FIA plot approximately every 2430 ha (6,000 ac). Field plots are located systematically on a 5-km (3.1-mi) grid regardless of whether they are forest or non-forest, and regardless of land ownership. Permanent plots are installed on all land ownerships (after permission is granted by the landowner), but the actual locations are kept secret to prevent tampering with the site and to prevent the knowledge of plot presence to influence decisions. Plot locations that are in forested vegetation are visited by field crews who collect a variety of forest ecosystem data. Data are collected at the forested plots regardless of the landowner's

intended use or specific management actions. Non-forest locations are also visited as necessary to quantify rates of land use change. The following data are collected at FIA plots:

i. The general land use that was projected in Phase 1 is verified;
ii. On forested plots, general stand characteristics are collected, such as forest type, stand age, and evidence of disturbance;
iii. Individual tree measures such as diameter, height, damage, cull, and grade are recorded;
iv. Tree regeneration is documented.

The FIA Phase 3 program is based on a subset of the Phase 2 plots (located on a 22-km [13.7-mi] grid, sampling approximately 0.0405 ha every 38,881 ha [1 ac for every 96,000 ac]), from which an extended suite of ecological data (see list below) are collected. These measures relate to forest ecosystem function, condition, and health. Due to the seasonality associated with some of these measurements, the Phase 3 data are generally collected during a three-month window (Jun, Jul, and Aug). The measurements on the Phase 3 subset of plots can be grouped into the following categories:

i. Crown Conditions – generally, poor crown conditions are symptoms of trees under stress, and trees with good crown conditions are vigorous.
ii. Soil Erosion Potential – estimates of soil erosion potential help identify areas that may contribute to water quality degradation.
iii. Soil Chemical Analyses – collection and analysis of soil samples include estimates of site fertility and in some cases potential toxicity relating to acidic soils that relate to productivity.
iv. Lichen Communities – the presence or absence of certain lichen species is indicative of air quality and climate changes.
v. Ozone Bioindicator Plants – these plants have known sensitivities to ground-level ozone, although they are not necessarily collected on the Phase 3 plots (this effort can occur in the general plot area).
vi. Vegetation Structure – the composition of vegetation (species and growth forms), abundance, and spatial arrangement in the forest. Also the presence of exotic and introduced plant species can be extracted from the collected data.
vii. Down Woody Debris – this measurement is useful in determining fire fuel potential, and this information with the vegetation structure data can be used in wildlife habitat models.

Though the FIA program has been in existence since the 1930s, the data collection methods have been modified periodically, and the grid system was recently revamped to improve the statistical validity of the sampling. Currently, 10% of the plots in the western U.S. are scheduled to be sampled every year.

Regardless of whether a plot is Phase 2 or Phase 3, after two or more visits have occurred at a single plot location, it is possible to analyze the data to derive estimates of trends in desired conditions (see Tables C.1 and C.2 in Appendix C).

Habitat Monitoring Methods

As mentioned above, an essential feature of the FIA program is the confidentiality of the data. Because data are collected from all land ownerships and because the data would be biased if landowners or others knew the location of the plots and treated them differently than areas outside the plots, these locations and much of the data from them are not available directly to agencies. Instead, the agencies must craft specific questions for the FIA program, and then FIA responds with answers to the data queries.

We believe existing FIA sampling schemes for all three phases provide adequate data to meet the proposed delisting criteria. Owl-relevant FIA variables should be used to monitor trends in owl habitat, providing a range-wide habitat sampling scheme. Phase 1 data provide a comprehensive coverage of changes amount and type of forest habitat. Phase 2 provides information on changes in forest-stand structure. Phase 3 provides information on additional habitat variables important to owls, such as down woody debris

For purposes of Mexican spotted owl recovery planning, the FIA plots would be aggregated into strata that would be based on 1) EMU, 2) elevation, and 3) forest type. Stratification is important because it distributes samples throughout an EMU and improves precision of the habitat estimates.

5. Relating Habitat and Owl Occupancy Modeling

For purposes of understanding progress towards recovery of the Mexican spotted owl, monitoring should document the changes in the owl population and its habitat when, in fact, such changes are occurring. Thus, an effective monitoring program requires measuring changes in both habitat quantity and owl occurrence across the landscape. To link the monitoring of owl occupancy in forest habitat with the habitat conditions, analysis of occupancy monitoring data should incorporate FIA data.

Linking occupancy monitoring to FIA monitoring is recommended for three reasons. First, the FIA inventory (both Phase 2 and Phase 3) provides microhabitat measurements that can be used to improve the occupancy monitoring scheme, providing predictor variables that will improve the estimation of the probability of occupancy and detection for the plots sampled.

Second, important microhabitat variables that are correlated with owl occupancy will be determined that can then be used to evaluate temporal trends in microhabitat. A strength of this approach is that FIA data collected prior to occupancy monitoring can also be analyzed to determine long-term trends in these variables. In summary, linking FIA data with the occupancy monitoring sampling plots will provide: 1) the opportunity to identify microhabitat variables that relate to owl occupancy and detection rates, and 2) the ability to evaluate trends in these microhabitat variables through time.

Third, FIA is a well-funded, ongoing effort. Thus, it provides a unique opportunity to collect data potentially useful in monitoring trend in owl habitat, without requiring a separate and prohibitively expensive sampling effort.

6. Conclusions

The technology and expertise are available to monitor trends in Mexican spotted owl habitat and population size. Clearly, the objectives and design of the monitoring program must be defined explicitly, and they must be attainable. To implement the process, knowledgeable, dedicated people must be assigned the task. Adequate training and constant feedback mechanisms are critical aspects to a successful monitoring program, as tenable conclusions can be based only on reliable data.