Informing Reforestation Strategy for the Mendocino National Forest: Integrating climate change into management planning of the North Shore Restoration Project (NSRP)

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Executive Summary

Following the extensive Mendocino Complex Fire in 2018 and subsequent fires in the Mendocino National Forest (MNF) there is now a herculean management challenge and a great need for strategic landscape scale analysis and planning to restore desired conditions to the National Forest. These desired conditions include reforestation to create diverse ecological mosaics of habitat patches that are resilient and responsive to future fire regimes and altered climate dynamics. Of particular concern are the effects of climate change on the potential for revegetating forest lands with high exposure and high vulnerability (Stein et al. 2014) with the goal of maintaining the ecologically dynamic processes that will shape future landscapes. The authors of GTR-270 (Meyer et al. 2021) emphasize the need for prioritizing restoration management activities and this is a major objective of this research study.

This study was conducted using geographic information system (GIS) technology to analyze the biophysical site conditions to produce a site capability model and map to guide future land management decisions within the North Shore Restoration Project (NSRP) area which encompasses approximately 39,300 acres (15,900 ha). This comprehensive site analysis utilizes a 'land facet' approach to discretize the landscape into logical land management units based on key ecological factors (Brost & Beier 2012). Those key factors include integration of four main biophysical variables: (1) **vulnerability** of prefire vegetation communities to climate change, (2) **exposure** of land facets based on topographic slope and aspect, (3) **burn severity** as measured by differences between NDVI (a 'greenness index') values pre- and postfire, and (4) **soil type** that assesses the depth of available water storage (AWS). The first three variables listed above were each broken down into three levels of management concern (high, medium, and low) and subsequently combined into a single map depicting 27 unique combinations. Employing expert opinion, each of the 27 unique combinations were assessed for a planting recommendation. There are three possible planting recommendations: (1) no planting, let the site regenerate on its own (i.e., leave it alone); (2) replant the site using plant species in the prefire vegetation community type; and (3) plant new species because climate change impacts will likely cause a shift in plant community type. Results from this modeling analysis indicate approximately half (47%) of the NSRP site corresponds to the first planting recommendation (i.e., leave it alone to regenerate), about one fifth (18%) of the site corresponds to the second planting recommendation (i.e., replant prefire plant species), and about one third (35%) of the site corresponds to the third planting recommendation (i.e., a plant community type-shift).

To further refine these management recommendations into a more practicable approach, we incorporated the fourth variable listed above: available water storage. AWS measures the depth of the soil and its water holding capacity (in cm), and is used here to prioritize where to first implement the planting recommendations. Soil AWS is split into five classes (1-5) from shallow (Class 1) to deep (Class 5). The highest priority areas for replanting are located in the deepest soil AWS class (Class 5) because it has the greatest buffering capacity to minimize the potential effects of climatic water deficit, which is expected to be one of the most consequential determinants for survival of new reforestation plantings under drought or semi-drought climatic conditions (Stephenson 1998; McDowell et al. 2008; Restaino et al. 2016). The next highest priority would be in Class 4 AWS areas and so on to Class 1 (i.e., the thinnest soils having the lowest priority for reforestation).

Due to the severity of the recent fire effects combined with increasing climate change impacts it is expected that some former conifer-dominated areas may not be capable of supporting the same or similar

plant communities in the future (Shive et al. 2018; Coop et al. 2020; Wang et al. 2022). These areas, where plant community 'type-shifts' are expected, are identified (in planting recommendation #3 above) in order to enable the MNF managers to develop a suite of better adapted plant species and communities that will be resilient to anticipated future conditions (i.e., fire regime and climate change). To help guide land manager's decisions regarding selecting a "new" plant community type, a plant community sequencing model was developed based on two variables: (1) a moisture gradient and (2) elevation position (high and low). This model is based on expert opinion. In some areas oak woodlands are likely to regenerate through stump sprouting in areas where conifers were once dominant (including mixed-conifer forest stands that had a significant component of oak prior to the fire). These areas are logical places to consider managing for oak woodlands at localized spatial scales. Traditionally, aboriginal burning was a local scale endeavor designed to enhance oak woodland resources for Native American people (Kimmerer & Lake 2001) that in today's altered landscape must be integrated at the landscape scale (Wohling 2009). It is well known that without frequent, low intensity fire these areas are vulnerable to Douglas-fir invasion (Hunter & Barbour 2001).

Finally, to assist land managers in selecting specific plant species to plant for reforestation purposes (fulfilling planting recommendations #2 and #3) a database has been constructed linking various vegetation community classification schemes to the individual species that comprise them. The plant communities defined in the California Wildlife Habitat Relationship (CWHR) system (Mayer & Laudenslayer 1988) and the California Native Plant Society's Manual of California Vegetation (MCV) system (Sawyer et al. 2009) have been integrated into the database to create a plant selection tool. The MNF and the NSRP site have several plant community type designations in its prefire vegetation map GIS layer inventory. The most useful of these various systems are the CWHR type and the CALVEG (Classification and Assessment with Landsat of Visible Ecological Groupings) system SAF cover type, including regional dominance type 1 and regional dominance type 2. Each of these vegetation classification systems lists either a single dominant species or a dominant and sub-dominant species, however, they lack detail about other co-occurring species within the community type, especially in the mid-story or ground strata (vegetation layers). This is where the MCV system is very helpful because it lists these commonly associated species. Thus, the plant selection tool database developed for this project will provide land managers at the MNF with the ability to identify not just canopy dominant species, but the other plant species also associated with the dominant type, an aid in developing desired future landscape conditions.

There are some notable limitations of this research study. First and foremost is that this system has not been field tested or verified because it beyond the funding scope of this project. Although this study puts forth a logical and systematic approach to reforestation along with a prioritization scheme, it is necessary to check the planting recommendations against field knowledge and field visits to confirm their validity. It is recommended that a validation study be undertaken to confirm high priority areas for restoration. Another limitation of the study is a lack of error assessment of the mapping variables used in this study. Vegetation maps commonly have classification errors and boundary mapping errors which can alter the management prescriptions determined for a specific site. Verification of each mapping variable would be needed for any planting recommendation prescription for any site selected for reforestation. Despite these limitations, the information in this report can be used immediately to cross-check reforestation treatments that are currently proposed or being planned in the near future.

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1. Introduction

The North Shore Restoration Project (NSRP; see Figure 1) of the Mendocino National Forest (MNF) was initiated by U.S. Forest Service personnel following the devastating effects of the Mendocino Complex Fire. In July 2018 nearly the entire NSRP site burned in the Ranch Fire (the northern portion of the Mendocino Complex Fire), except the extreme southwest corner of the site nearest to the wildland-urban interface (WUI) of towns proximate to Clear Lake. Thousands of homes were threatened by the Ranch Fire. Located in the Upper Lake Ranger District of the MNF, the NSRP site is approximately 40,000 acres and is part of the Berryessa Snow Mountain National Monument in the Inner Coast Range of Northern California.

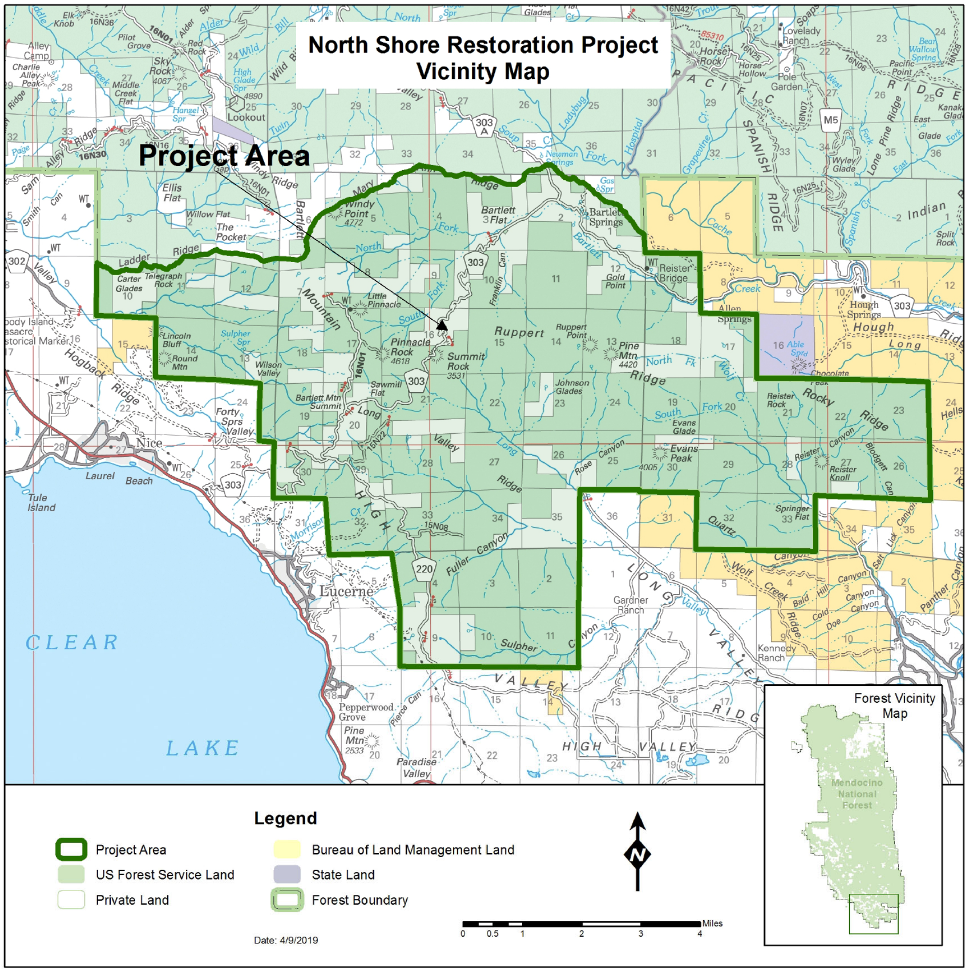


Figure 1: Site location and vicinity map of the North Shore Restoration Project in the Mendocino National Forest. Elevation ranges from 1,350 to 4,770 feet. (Map image courtesy of USFS.)

The NSRP was developed by MNF managers as a region-scale project that could be implemented over time as postfire conditions within the project area changed and management objectives for the landscape evolved. Postfire landscape dynamics within National Forests have emerged as a substantive management and planning concern in an era of increased aridity resulting from climate change and increasingly large and high-severity wildfires, as numerous studies throughout the western U.S. in the past decade have documented a decreasing likelihood that western forests will recover to pre-disturbance conditions (e.g., Anderegg et al. 2013; Serra-Diaz et al. 2018; Meyer et al. 2021; Safford et al. 2022; Wang et al. 2022). While recent studies (e.g., Meyer et al. 2021) have addressed broad conditions under which disturbed landscapes may recover to pre-disturbance conditions, managers seek additional guidance about post-disturbance restoration projects, particularly for the severe disturbances covering extensive landscapes that have occurred since the 1980s.

Two principal, overlapping dynamics have increased disturbance size and severity in western forests. Increasing atmospheric temperatures resulting from climate change result in increased aridity and reduced soil moisture, a direct stressor for vegetation and a cause of reduced fuel moisture and increased fire (Allen et al. 2010; Abatzoglou et al. 2017; Crockett & Westerling 2018). Increased moisture stress also increases competition among individual plants in all landscapes, which also indirectly reduces their resistance to insect attack and a variety of pathogens (Fettig et al. 2019, 2021). A warming atmosphere may be associated with increased likelihood of more severe and/or longer-term drought, exacerbating the effects of moisture stress at the stand level. These effects are entrained in current climate dynamics, although their severity may be moderated during this century by programs that reduce the planetary human production of greenhouse gases.

The second dynamic affecting forested landscapes is a management approach for most federally owned lands during the last century involving fire suppression and a management focus on an extraction of resources with economic value (i.e., merchantable timber), particularly large trees. This focus resulted in altered forest structures, with increased amounts of fuels (including live and dead vegetation, with abundant litter and duff on the ground surface) and a scarcity of large trees that would have survived lower-severity fires in prior landscapes. The result of this failed management paradigm has been a substantial increase in fire dynamics in recent decades, with both larger and more severe fires in western forested landscapes (Parks et al. 2016; Keeley & Syphard 2018; Hessburg et al. 2021; Wayman & Safford 2021; Airey-Lauvaux et al. 2022).

Observing the consequences of fire and other forest disturbances has led to an increasing concern that climate change may drive forest ecosystems beyond the range of known historical conditions, and more specifically that the combination of stressors is leading to “type-conversions” among forest types, or even from forests to non-forested ecosystem types, with resulting consequences for the ecosystem services that these landscapes provide (Shatford et al. 2007; McIntyre et al. 2015; Coppoletta et al. 2016; Liang et al. 2017; Bost et al. 2019; Young et al. 2019; Stevens-Rumann & Morgan 2021; Taylor et al. 2021; Vanderhoof et al. 2021; Guiterman et al. 2022; Safford et al. 2022; Steel et al. 2022; Hill et al. 2023). Type-conversions (or type-shifts) are specifically a concern for forested landscapes in the Klamath ecoregion (Griffith et al. 2016) in northwestern California, as the Klamath ecoregion’s landscapes are already known to exist in multiple “stable” ecosystem states, either forest-dominated or shrubland- and hardwood-dominated, in dynamic successional processes mediated by periodic fire (Whittaker 1960, Taylor & Skinner 1998, 2003; Sawyer 2006; Odion et al. 2010; Halofsky et al. 2011; Estes et al. 2017; Tepley et al. 2017; Miller et al. 2019; Schriver et al. 2018; McCord et al. 2020; Taylor et al. 2021; Jules et al. 2022), including the “dry, frequent-fire” forests in the MNF, in which hardwoods are already a significant component in many low- and mid-elevation landscapes. Given the known conditions in the Klamath ecoregion’s forested landscapes, the project’s study objectives are:

- To create a GIS site analysis model and a map of discrete land management units (using a ‘land facet’ approach) for use in assisting U.S. Forest Service personnel to make decisions regarding potential plant community restoration within the North Shore Restoration Project area

- To identify options and priorities for plant community reforestation that are expected to be adaptive and resilient to future conditions taking climate change into account
- To document the site analysis models, including input variables and results, that define discrete management units for land management (i.e., potential reforestation treatments)
- To create a database of individual plant species linked to the major systems that describe plant communities in California that are potentially suitable or appropriate for the defined management units for reforestation purposes
- To provide GIS datasets of the land facet analysis transferred to appropriate personnel (ArcGIS shapefiles, rasters and geodatabases)

This report provides documentation of all the methods used in developing the multiple biophysical spatial models that culminate in a set of planting recommendations for all areas within the NSRP site. It should be noted that each model is based on expert knowledge, opinion, and literature. The modeling process is briefly summarized here (see Figure 2). The process begins with assessing the 'vulnerability' of all 16 major prefire vegetation communities to climate change impacts (low, medium, and high). Next, a topographic model of land facet 'exposure' is calculated (low, medium, and high) based on 28 combinations of slope and aspect (the direction a slope faces). Burn severity (low, medium, and high) is then assessed from pre- and postburn high resolution RGB aerial photographs with an infrared band to yield NDVI (a "greenness" index) values indicating low to high mortality. These three variables are then combined in a 3x3 matrix to produce 27 unique management scenarios that are each assigned a planting recommendation. The three planting recommendations are: (1) no planting, let the site regenerate on its own (i.e., leave it alone); (2) replant the site using plant species in the prefire vegetation community type; and (3) plant new species because climate change impacts will likely cause a shift in plant community type. A fourth variable is introduced, soil available water storage (AWS), to prioritize where to initiate planting recommendations #2 and #3 to promote seedling survival and reforestation success. Soil AWS is a measure of soil depth and water holding capacity available to plants and is divided into five classes, where Class 5 has the most AWS (i.e., identifying the best planting areas to start; highest priority) and Class 1 has the least (i.e., lowest priority). The datasets provided by this study are described in Appendix A.

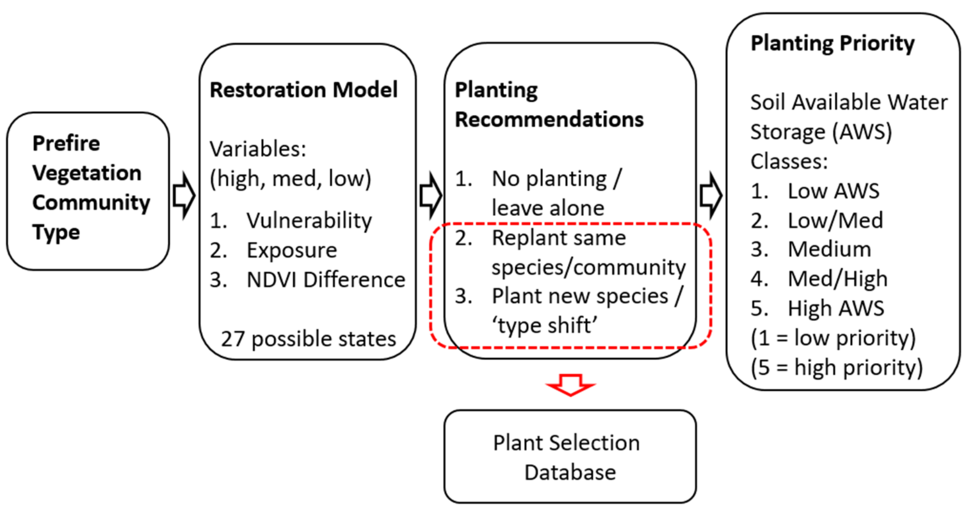


Figure 2: A summary process diagram of the research and modeling approach taken in this study.

2. Data and Methods

This ecological modeling project utilized geographic information system (GIS) software developed by the Environmental System Research Institute (Esri), Redlands, California. We used ArcGIS Desktop version 10.8.1. In addition, output from the GIS software was further analyzed with Microsoft Excel (spreadsheet) and Access (database). Two GIS geodatabases of base data were obtained by the authors from MNF personnel named "MNFLibrary_01302019.gdb" and "Master_NorthShoreRestoration.gdb" both of which use the UTM Zone 10 coordinate system with a 1983 datum and meters as the lineal unit.

2.1 Prefire Vegetation

The NSRP prefire vegetation feature class (vector GIS polygon layer) analyzed in this project was obtained from the "Master_NorthShoreRestoration.gdb" geodatabase and is named "Veg_ExistingVeg_12132019." A summary table was created from the layer using the attribute table tool "Summarize" by summing the "area" field for each CWHR community type. These data were imported to Excel to sort the CWHR types from largest to smallest area.

2.2 Vulnerability of prefire vegetation communities to climate change

Assessment of the vulnerability of prefire vegetation communities to the impacts of climate change was conducted using expert opinion and literature, such as plant community databases. The authors collaborated with other scientists to rate each CWHR vegetation type for its susceptibility to 'type conversion' or a 'type-shift' as either low (1), medium (2) or high (3), where high means high vulnerability to type conversion. High vulnerability implies that the community type has relatively low adaptive capacity (sensu Stein et al. 2014) to increasingly high exposure environments, including higher local temperatures and increased climatic water deficit, and isn't expected to regenerate following high mortality events due to fire effects, nor would planted seedlings be expected to survive in the future. The vulnerability ratings determined for each vegetation type were subsequently joined to the polygons in the prefire GIS data layer as attributes using a table join function in ArcGIS. The attributes were coded as "1" for low, "2" for medium, and "3" for high, as indicated above.

2.3 Vegetation type-shift sequence model

To operationalize the vulnerability ratings for each vegetation type in terms of a vegetation community 'type-shift,' a vegetation type sequence model was constructed, again using expert opinion and literature. The model uses two main variables as gradients for the sequencing: (1) water requirements (soil moisture) and (2) elevation (high and low). Each of the 14 significant CWHR vegetation types at the NSRP site were arrayed according to their relative soil moisture needs and elevational position. The objective of this model is to guide land managers towards where a 'type-shift' might move to for the purpose of selecting new species for reforestation (both dominant species and subdominant species).

2.4 Exposure: topographic analysis

A main variable in assessing climate change impacts to vegetation communities is land facet exposure. Exposure is a function of topographic slope and aspect. Aspect is the direction a slope faces (e.g., east, west, north, or south). A GIS model was constructed using 10 aspect classes (north, northeast, east, southeast, south, southwest, west, northwest, north, and flat) and three slope classes (level = 0 – 14.2

degrees, moderate = 14.2 – 23.3 degrees, and steep = 23.3 – 52.5 degrees). Exposure values (low, medium, high) were then coded for each combined topographic aspect and slope value (land facet) for a total of 28 unique combinations (see Table 4 and Figure 5b). A digital elevation model (DEM) with a cell size of 30 m was obtained from a US Geological Survey (USGS) website covering the NSRP site and using the NSRP project boundary GIS layer ("nsp_project_bnd_12_13_2019") the DEM was clipped using the "Clip" tool in ArcGIS Toolbox. The clipped DEM was then used to run the "Aspect" and "Slope" Surface tools in the ArcGIS Spatial Analyst Toolbox. Degree slope was specified for the slope surface. Two rasters were created: "nsp_aspect" and "nsp_slope_deg." Each was reclassified: "nsp_aspect" was reclassified to "nsp_asp_1to10" (using the 10 values in Table 4) and "nsp_slope_deg" was reclassified to "nsp_slope_123" (using the 3 values in Table 4). These two raster layers were used as input to the following complex Python statement (code) that was written to implement the exposure model using a series of nested conditional statements and run using the ArcGIS Spatial Analyst tool "Raster Calculator":

```
Con(((("nsp_slope_123" == 1) | ("nsp_slope_123" == 2) | ("nsp_slope_123" == 3)) & (("nsp_asp_1to10" == 1) |
("nsp_asp_1to10" == 2) | ("nsp_asp_1to10" == 3))), 1, Con((("nsp_slope_123" == 1) & ("nsp_asp_1to10" == 4)), 1,
Con(((("nsp_slope_123" == 2) | ("nsp_slope_123" == 3)) & (("nsp_asp_1to10" == 4))), 2, Con(((("nsp_slope_123" == 1) |
("nsp_slope_123" == 2)) & (("nsp_asp_1to10" == 5))), 3, Con(((("nsp_slope_123" == 3) & ("nsp_asp_1to10" == 5))), 3,
Con(((("nsp_slope_123" == 1) | ("nsp_slope_123" == 2) | ("nsp_slope_123" == 3)) & (("nsp_asp_1to10" == 6) |
("nsp_asp_1to10" == 7) | ("nsp_asp_1to10" == 8))), 3, Con(((("nsp_slope_123" == 1)) & (("nsp_asp_1to10" == 9))), 2,
Con(((("nsp_slope_123" == 2) | ("nsp_slope_123" == 3)) & (("nsp_asp_1to10" == 9))), 3, Con(((("nsp_slope_123" == 1) |
("nsp_slope_123" == 2) | ("nsp_slope_123" == 3)) & (("nsp_asp_1to10" == 10))), 1, 99)))))))))
```

The final raster layer was named "nsp_exposure" and was used to extract each exposure class (1-3) for each vegetation type in the NSRP site. This was accomplished using the Spatial Analyst Extraction tool called "Extract by Mask." A separate vector layer for each of the 16 CWHR vegetation types was created and used as the input feature mask for the input raster "nsp_exposure." The results (cell counts) of each extraction (vegetation community type) were manually entered into an Excel table for analysis, presentation, and graphing purposes.

2.5 RAVG analysis

The Rapid Assessment of Vegetation Condition after Wildfire (RAVG) program is a service by the USGS to provide forest managers with a quick assessment of burn severity after a fire of greater than 1,000 acres in the western U.S. (and >500 acres in the eastern U.S). RAVG estimates basal area loss of trees. This system compares a pair of images (typically LANDSAT imagery with 30-meter pixel size), one before the fire and one immediately after the burn. A RAVG analysis was conducted for the Mendocino Complex fire in 2019. The polygon feature class dataset used in this project's initial analysis of burn severity is the "Fire_FireSeverityRAVG_12132019" layer from the "Master_NorthShoreRestoration.gdb."

In order to analyze how the vegetation types in the NSRP site were affected by fire severity using RAVG, we first converted the polygon feature class to a raster using a 30 m cell size (to match LANDSAT pixel resolution). This was accomplished using the ArcGIS Toolbox "Conversion" tools and implementing the "Polygon to Raster" tool in the "To Raster" toolbox. We used the "cell center" option and selected the "GRIDCODE" polygon attribute for the raster cell value. The raster cell values were "1" = low severity, "2" = moderate severity, "3" = high severity, and "0" = other. The new raster layer was named "firesevRAVG" and was used to extract each fire severity class (0-3) for each vegetation type in the NSRP site. This was accomplished using the Spatial Analyst Extraction tool called "Extract by Mask." A separate vector layer for each of the 16 CWHR vegetation types was created and used as the input feature mask for the input raster “firesevRAVG.” Cell counts were multiplied by 900 square meters and divided by 10,000 to derive hectares (areal extent). The results of each extraction (vegetation community type) were manually entered into an Excel table for presentation, graphing, and statistical purposes.

Based on the results from this RAVG analysis (see section 3.5 below), it was readily obvious that most vegetation communities were severely affected by the fire immediately following the event. The RAVG analysis results made it difficult to assess relative mortality within each polygon of each vegetation type which is a critical variable to determine restoration or reforestation priority. Therefore, we decided to take a different approach to evaluating burn severity using higher resolution imagery and a slightly wider time period between image comparisons (to account for some plant recovery). This methodology is described in the next section (2.6 below).

2.6 NDVI (greenness index) analysis

To evaluate burn severity and assess relative mortality more effectively for the NSRP site, we compared two high resolution NAIP images (National Agricultural Imagery Program, a product from the USDA). NAIP imagery is typically acquired for every county on a two-year time interval (in California) and is then processed and distributed on-line by the NRCS (Natural Resources Conservation Service). Pixel or cell size of most NAIP images is 1 meter or smaller (i.e., much more detailed than the RAVG LANDSAT images at 30-meter pixels). The two NAIP images used in this analysis have a pixel or cell size resolution of 0.6 meters (about 2 feet). NAIP images are “true color” images, meaning they have three bands representing red, green, and blue (RGB), however, starting in 2016 NAIP images now include an infrared (IR) band in addition to RGB. The inclusion of the IR band now makes it possible to calculate NDVI (Normalized Difference Vegetation Index) values which is a common remote sensing technique (a ratio of IR/R, or more specifically: IR-R/IR+R) to measure relative “greenness” of a site (Campbell 2002). This greenness index can measure the abundance of plant vigor or stress or mortality in response to drought or fire effects.

Since the Ranch Fire (a portion of the Mendocino Complex fire that burned in the MNF) occurred in 2018 and the NAIP image for 2018 had a photo mosaic having both prefire and postfire imagery, we avoided the 2018 image and instead used NAIP images from 2016 (prefire) and 2020 (postfire). Thus, we had an image two years before the fire and two years after the fire. Having an image two years postfire allowed the vegetation that did not completely die to partially recover. This can give land managers a better sense of which vegetation patches have been completely killed versus partial or minor mortality. From this information a prioritization scheme can be developed to target those areas with higher mortality that potentially lack seed sources for regeneration or reforestation.

The two Lake County NAIP images were downloaded from the following USDA NRCS website on 3/10/22: https://nrcs.app.box.co/v/naip/folder/73962678696?page=2. The Lake County NAIP imagery code is 06033 or sometimes abbreviated as “ca033.” The two files downloaded were: “ortho_1-1_hc_s_ca033_2016_1.zip” and “ortho_1-1_hc_s_ca033_2020_1.zip.” The decompressed files used for analysis were ‘.sid’ files: “ortho_1-1_hn_s_ca033_2020_1.sid” and “ortho_1-1_hn_s_ca033_2016_1.sid.” These two image files were subsequently clipped with the NSRP site boundary feature class using the “Image Clip” tool in the ArcGIS Image Analysis window to create ‘.tif’ files. The two clipped images were named: “2016_nsp_clip_naip_sid1.tif” and “2020_nsp_clip_naip_sid1.tif” and were input for NDVI analysis using the Image Analysis window. To conduct NDVI analysis in ArcGIS, the following preprocessing procedure was used for each clipped image file: the layer 'properties' were opened from the TOC (the ArcGIS table of contents) and the symbology tab was selected where the "green" and "blue" channels were deselected; then the "alpha" channel box was checked and set to Band_3. In the Image Analysis window the "options" icon was clicked and the NDVI tab was selected where the "Red Band" was set to "1" and the "Infrared Band" was set to "3." By clicking the "Leaf" icon in the Image Analysis window the NDVI calculation is executed. The last step is saving the temporary raster files by exporting them. The final file names for the NSRP site NDVI calculations are: "NDVI_2016" and "NDVI_2020" (these are included in the GIS datasets provided to the CLERC and MNF personnel).

The next step in the NDVI analysis is to create a "difference map" between the two time periods. Using the "Raster Calculator" in the Spatial Analyst Map Algebra Toolbox, the "NDVI_2020" raster was subtracted from the "NDVI_2016" raster to create a new raster called "NDVI_1620diff." This new map shows in great detail (0.6 m pixels) the difference between the NDVI value in 2016 and 2020. This highly detailed information is made more useful if we calculate the average (mean) "difference value" for all the cells that compose whole polygons in the prefire vegetation polygon layer. Thus, we can calculate a single value for each vegetation polygon signifying whether there are large or small differences pre- and postfire. Large average differences would indicate significant mortality and small average differences are minor impacts due to the fire.

To accomplish the task of averaging the NDVI difference values within each vegetation polygon, we employed the use of the ArcGIS Zonal Toolbox tool called "Zonal Statistics." This tool uses a polygon layer to analyze a raster layer by calculating one of many types of statistical metrics (e.g., mean, standard deviation, maximum value, minimum value, coefficient of variation, etc.). The boundary of the polygon encompasses the cell values that are input into the statistical metric, then each cell within the polygon boundary of the output raster is filled with the value of the calculated metric. For the NSRP site we are calculating the average (mean) value of the NDVI differences (between 2016 and 2020) within each vegetation polygon to yield a single value. The settings for the "Zonal Statistics" tool were as follows: the input feature zone data was set to the "Veg_existingVeg_12_13_2019" (the vegetation polygons); the zone field was set to the "Object ID" (of each respective polygon); the input value raster was set to "NDVI_1620diff" (the raster of the difference between the NDVI value in 2016 and 2020); the statistics type was set to "mean"; and finally, the output raster was set to "NDVI_diffmean" (this output raster is included in the GIS datasets provided to the CLERC and MNF personnel in Appendix A). An alternate method to calculate NDVI mean difference is described in Appendix B.

The mean NDVI difference raster, calculated above, ranges in values from -42.63 to 53. A negative value would indicate that a polygon in 2020 is "greener" than in 2016 indicating the polygon probably did not experience a burn (i.e., it was unburned in the Ranch Fire). Small positive values mean there is little difference between the two time periods and there were minor fire effects on the vegetation (e.g., values between 1-10). High positive values indicate high mortality in 2020 as compared to 2016 (e.g., values from 15-53). High positive values are important polygons for land managers to prioritize because they more likely need reseeding or reforestation prescription treatments; 'priority' implies management concern and high priority is high management concern. Therefore, to make this information more usable for land management decision-making, the mean NDVI difference raster ("NDVI_diffmean") was reclassified into high, medium and low categories using the ‘Natural Breaks’ (Jenks method) option in the “Reclassify” tool in the ArcGIS Spatial Analyst Reclass Toolbox. The input raster was “NDVI_diffmean” and the output raster was named “NDVI_priority.” The range of values for each class in the “NDVI_priority” raster are as follows: low (-42.63 to 8.36); medium (8.37 to 16.994); and high (16.995 to 53). The output raster (“NDVI_priority”) is included in the GIS datasets provided to the CLERC and MNF personnel.

The final step in the NDVI analysis is to assess the three NDVI priority levels (low, medium, and high) in terms of each vegetation type at the NSRP site. This was accomplished using the Spatial Analyst Extraction tool called “Extract by Mask.” A separate vector layer for each of the 16 CWHR vegetation types was created and used as the input feature mask for the input raster “NDVI_priority.” The 16 output rasters were named “<vegtype>_ndviprior” (where “<vegtype>” refers to each CWHR type acronym). Cell counts were multiplied by 0.36 square meters (0.6 m cell size) and divided by 10,000 to derive hectares (areal extent). The results of each extraction (vegetation community type) were manually entered into an Excel table for presentation, graphing, and statistical purposes.

2.7 Restoration model and planting recommendations

A decision support “restoration model” was constructed to help guide specific management actions for reforestation by combining three of the products described above into a single framework. The three variables that are implemented in the decision support restoration model are: (1) vulnerability of prefire vegetation communities to climate change, (2) exposure of land facets based on topographic slope and aspect, and (3) burn severity as measured by differences between NDVI (a ‘greenness index’) values pre- and postfire. Each of these variables has been broken down into three levels of management concern (high, medium, and low) as described in their respective sections above. The three variables plus three concern levels for each variable produces 27 unique management combinations. Each unique management combination has a planting recommendation, and in some cases, can have more than one planting recommendation depending on the context. The three planting recommendations are: (1) no planting, let the site regenerate on its own (i.e., leave it alone); (2) replant the site using plant species in the prefire vegetation community type; and (3) plant new species because climate change impacts will likely cause a shift in plant community type. The planting recommendations were determined by expert opinion.

The first step to combine the three variables into a single unique three-digit number is to reclassify two of the rasters such that they can all be added together to produce the three-digit number. The vulnerability raster was reclassified from values of 1, 2, and 3 to values 100, 200, and 300. The exposure raster was reclassified from values of 1, 2, and 3 to values 10, 20, and 30. The NDVI difference raster was left as values of 1, 2, and 3. By doing this the three variables could be added together using the Spatial Analyst Raster Calculator to produce a single three-digit number with the first digit representing vulnerability, the second digit representing the exposure and the third digit representing NDVI difference. The output raster was named “rmodel2_add.” This raster was subsequently reclassified into the planting recommendations based on the unique three-digit number from the restoration model. The final raster for the planting recommendations is named “pmodel3.”

The final raster layer (“pmodel3”) was used to extract each planting recommendation (1-3) for each vegetation type in the NSRP site. This was accomplished using the Spatial Analyst Extraction tool called

“Extract by Mask.” A separate vector layer for each of the 16 CWHR vegetation types was created and used as the input feature mask for the input raster “pmodel3.” The results of each extraction (vegetation community type) were manually entered into an Excel table for presentation, graphing, statistical purposes.

2.8 Soil available water storage (AWS)

To further specify *where* to undertake the planting recommendations and prioritize those actions, a fourth reforestation management variable is introduced based on soil type. A key factor in the success of reforestation plantings in mountainous terrain is the survival of seedlings and that success is influenced by soil depth and soil moisture, both of which can exhibit great variation in areas with steep slopes, ridges, and valleys. To identify and select an existing mapped soil variable to inform this objective, the county-level soil survey program was examined and queried. The digital (GIS) version of the county soil survey is named SSURGO (Soil Survey Geographic) and the spatial data and database tables are managed and distributed by the NRCS (a USDA program). The SSURGO data model (version 2.2.2) is sophisticated and extensive in terms of integrating hundreds of soil variables in over 70 tables through a relational database model.

By carefully reviewing the metadata tables (the Table Column Descriptions) in SSURGO we identified the best single integrative soil variable as “available water storage” (AWS). Specifically, the Available Water Storage 0-150 cm weighted average (named “aws0150wta” as a column in the database) in the Map Unit Aggregate Attribute table (named “muaggatt”). The metadata description is as follows: “Available water storage (AWS). The volume of water that the soil, to a depth of 150 centimeters, can store water that is available to plants. It is reported as the weighted average of all components in the map unit, and is expressed as centimeters of water. AWS is calculated from AWC (available water capacity) which is commonly estimated as the difference between the water contents at 1/10 or 1/3 bar (field capacity) and 15 bars (permanent wilting point) tension, and adjusted for salinity and fragments” (USDA No date; page 78 from SSURGO Metadata - Table Column Descriptions, SSURGO Metadata Version: 2.2.2).

The SSURGO soil variable ‘minimum bedrock depth’ (i.e., soil depth) was also evaluated, but it lacked any water holding capacity information and since it largely correlated with the AWS information it was dropped for modeling parsimony reasons. AWS has the advantage of indicating both soil depth and water holding capacity available to plants. AWS measures the depth of the soil and its water holding capacity (in cm), and is used here to prioritize where to first implement the planting recommendations. Soil AWS is split into five classes (1-5) from shallow (Class 1) to deep (Class 5). The highest priority areas for replanting are located in the deepest soil AWS class (Class 5) because it has the greatest buffering capacity to minimize the potential effects of climatic water deficit, which is expected to be one of the most consequential determinants for survival of new reforestation plantings under drought or semi-drought climatic conditions (Stephenson 1998; McDowell et al. 2008; Restaino et al. 2016). The next highest priority would be in Class 4 AWS areas and so on to Class 1 (i.e., the thinnest soils having the lowest priority for reforestation). The following paragraph describes the methodology of creating the AWS variable.

The Lake County (CA033) SSURGO GIS database used in the project was downloaded on July 13, 2022 from https://websoilsurvey.nrcs.usda.gov/app/WebSoilSurvey.aspx in the Spatial Data Format of an ESRI

Shapefile with a Geographic map projection and a WGS84 datum. The download file is named "wss_SSA_CA033_soildb_US_2003_[2021-09-06].zip." It is Tabular version 16 (9/6/21) and Spatial version 7 (9/16/21). Once unzipped the database consists of a folder named "CA033" which contains a Spatial data folder, a Tabular data folder, and several metadata files. The Lake County SSURGO shapefile is named "soilmu_a_ca033" and it is in the Spatial folder and all the table files are contained in the Tabular folder. The shapefile was imported into a geodatabase as a polygon feature class and two tables were joined to it. First, the "mapunit.txt" table was imported into MS Excel and then converted to a geodatabase table using the ArcGIS Conversion Toolbox tool called "Excel To Table." Then a relational table join was performed using the common "MUKEY" database field. Next, the same procedure was used for the Mapunit Aggregate Attribute table (named "muaggatt.txt"). Once the attribute information was complete we clipped the SSURGO data to the NSRP site boundary. Then we converted the polygon data to raster data using the ArcGIS Conversion Toolbox tool called "Polygon to Raster" with the following settings: the "aws0150wta" field was set for the raster cell value; 10 m cell size; output filename was "soil_aws150fp" (fp means 'floating point' raster—i.e., a raster with decimal point values). Finally, the floating point raster was reclassified to an integer (whole number) raster using the ArcGIS Spatial Analyst Reclass Toolbox tool called "Reclassify." The AWS values (in cm) were reclassified into five classes using a slightly modified Equal Interval method to yield the following integer values: 1 = 1.73 to 5.0; 2 = 5.1 to 10.0; 3 = 10.1 to 15.0; 4 = 15.1 to18.0; and 5 = 18.1 to 22.47. The output filename was set to "soilaws150rc."

2.9 Plant selection database tool

To assist land managers in selecting specific plant species to plant for reforestation purposes (fulfilling planting recommendations #2 and #3) a series of database tables have been constructed linking various vegetation community classification schemes to the individual species that comprise them. The plant communities defined in the California Wildlife Habitat Relationship (CWHR) system (Mayer & Laudenslayer 1988) and the California Native Plant Society's *Manual of California Vegetation* (MCV) system (Sawyer et al. 2009) have been integrated into the database to create a plant selection tool. The MNF and the NSRP site have several plant community type designations in its prefire vegetation map GIS layer inventory. The most useful of these various systems are the CWHR type and the CALVEG (Classification and Assessment with Landsat of Visible Ecological Groupings) system SAF (Society of American Foresters) cover type, including regional dominance type 1 and regional dominance type 2. The fields "SAF_COVER_TYPE", "REGIONAL_DOMINANCE_TYPE_1", and "REGIONAL_DOMINANCE_TYPE_2" (from the layer "Veg_ExistingVeg_12132019") were concatenated in ArcGIS and added to the MS Excel table as a column.

Each of the vegetation classification systems described above lists either a single dominant species or a dominant and sub-dominant species, however, they lack detail about other co-occurring species within the community type, especially in the mid-story or ground strata (vegetation layers). This is where the MCV system is very helpful because it lists these commonly associated species. We referenced the CalFlora database with documented species occurrences to manually create this list. This MS Excel sheet was also populated with information obtained from CalFlora on all of the known animal species associated with each plant species as well as bloom periods for each species. Thus, the plant selection tool database tables developed for this project will provide land managers at the MNF with the ability to identify not just canopy dominant species, but the other plant species also associated with the dominant type, an aid in developing desired future landscape conditions.

3. Results

3.1 Prefire Vegetation

The prefire vegetation of the NSRP site is summarized by CWHR community type in Table 1 and a map is shown in Figure 3. Low elevation mixed chaparral (MCH) is the dominant community comprising 35% of the site and second most abundant vegetation type is montane hardwood (MHW) covering 18% of the site. Adding all three types of chaparral (MCH, CRC, and MCP) together shows 50% of the site is composed of these vegetation types. Adding both types of montane hardwood (MHW and MHC) together shows 26% of the site is composed of this vegetation type. The most abundant conifer type is closed-cone pine-cypress (CPC) covering 7% of the site. Timber production conifer types, including Douglas-fir (DFR), ponderosa pine (PPN), and mixed conifer (SMC) together comprise about 11% of the site. Low elevation oaks, including blue oak-foothill Pine (BOP), valley oak woodland (VOW), blue oak woodland (BOW), coastal oak woodland (COW) together comprise about 3% of the site. It should be noted that four insignificant land cover types were removed due to very limited area or lack of relevance (i.e., urban, pasture, lacustrine, and wet meadow).

Table 1: The prefire percentage, area (ha), and number of polygons of CWHR vegetation types (data layer date: 12-13-2019) within the MNF NSRP study area. Four insignificant land cover types were removed due to very limited area or lack of relevance (i.e., urban, pasture, lacustrine, and wet meadow).

CWHR Vegetation Type (prefire)	Number of Polygons	Area (ha)	Percent
Mixed Chaparral (MCH)	1,649	5,502.8	34.7
Montane Hardwood (MHW)	1,165	2,808.3	17.7
Chamise-Redshank Chaparral (CRC)	544	1,862.6	11.7
Montane Hardwood-Conifer (MHC)	465	1,280.3	8.1
Closed-Cone Pine-Cypress (CPC)	463	1,091.1	6.9
Sierran Mixed Conifer (SMC)	264	845.0	5.3
Montane Chaparral (MCP)	150	609.6	3.8
Annual Grassland (AGS)	192	600.9	3.8
Ponderosa Pine (PPN)	220	553.2	3.5
Douglas-fir (DFR)	96	276.4	1.7
Blue Oak-Foothill Pine (BOP)	114	168.7	1.1
Valley Oak Woodland (VOW)	57	113.7	0.7
Blue Oak Woodland (BOW)	49	92.5	0.6
Barren (BAR)	12	21.5	0.1
Coastal Oak Woodland (COW)	11	18.5	0.1
Montane Riparian (MRI)	8	13.2	0.1
	5,459	15,858.3	

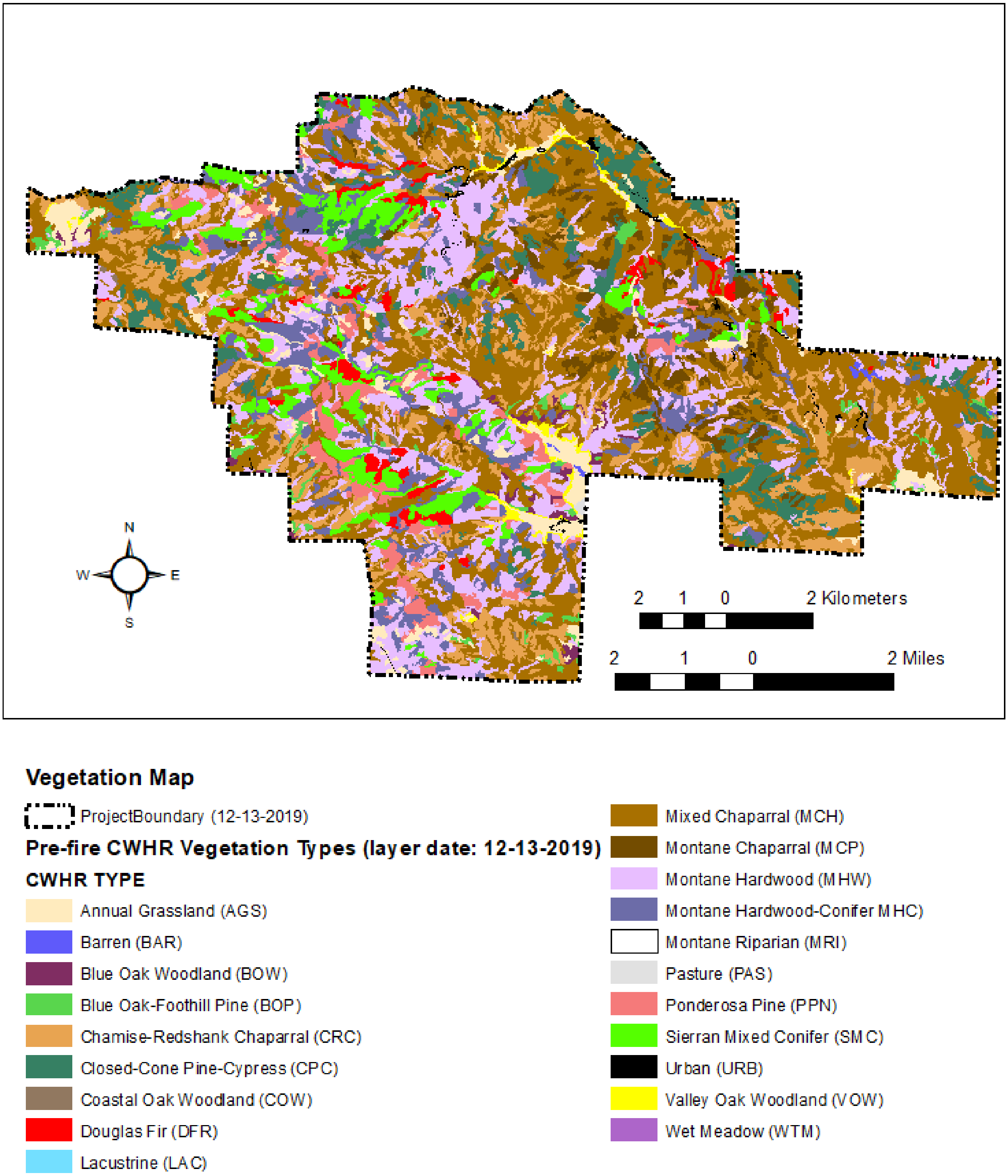


Figure 3: Prefire CWHR vegetation map of the MNF NSRP study area.

3.2 Vulnerability of prefire vegetation communities to climate change

The results of the vulnerability assessment of 16 prefire CWHR vegetation communities to the impacts of climate change is shown in Table 2. The vegetation types are sorted from low to high vulnerability. Only two vegetation types were rated as high vulnerability: Douglas-fir (DFR) and mixed conifer (SMC). The majority were rated as medium (eight types) including all the hardwood, oak, and the remaining conifer types: ponderosa pine (PPN) and closed-cone pine-cypress (CPC). The remaining six were rated as low, including all the chaparral community types (MCP, MCH, and CRC), annual grassland (AGS) and montane riparian (MRI). Using the vulnerability attributes joined to the prefire polygon layer of existing vegetation, a map depicting the spatial distribution of each vulnerability rating in the NSRP is shown in Figure 4.

Table 2: Vulnerability ratings of CWHR vegetation types to climate change (CC) and type conversions within the MNF NSRP study area. Four insignificant land cover types were removed due to very limited area or lack of relevance (i.e., urban, pasture, lacustrine, and wet meadow).

CWHR Vegetation Type (prefire)	CC Vulnerability
Annual Grassland (AGS)	Low
Barren (BAR)	Low
Mixed Chaparral (MCH)	Low
Chamise-Redshank Chaparral (CRC)	Low
Montane Chaparral (MCP)	Low
Montane Riparian (MRI)	Low
Montane Hardwood (MHW)	Medium
Montane Hardwood-Conifer (MHC)	Medium
Closed-Cone Pine-Cypress (CPC)	Medium
Blue Oak-Foothill Pine (BOP)	Medium
Coastal Oak Woodland (COW)	Medium
Blue Oak Woodland (BOW)	Medium
Valley Oak Woodland (VOW)	Medium
Ponderosa Pine (PPN)	Medium
Douglas-fir (DFR)	High
Sierran Mixed Conifer (SMC)	High

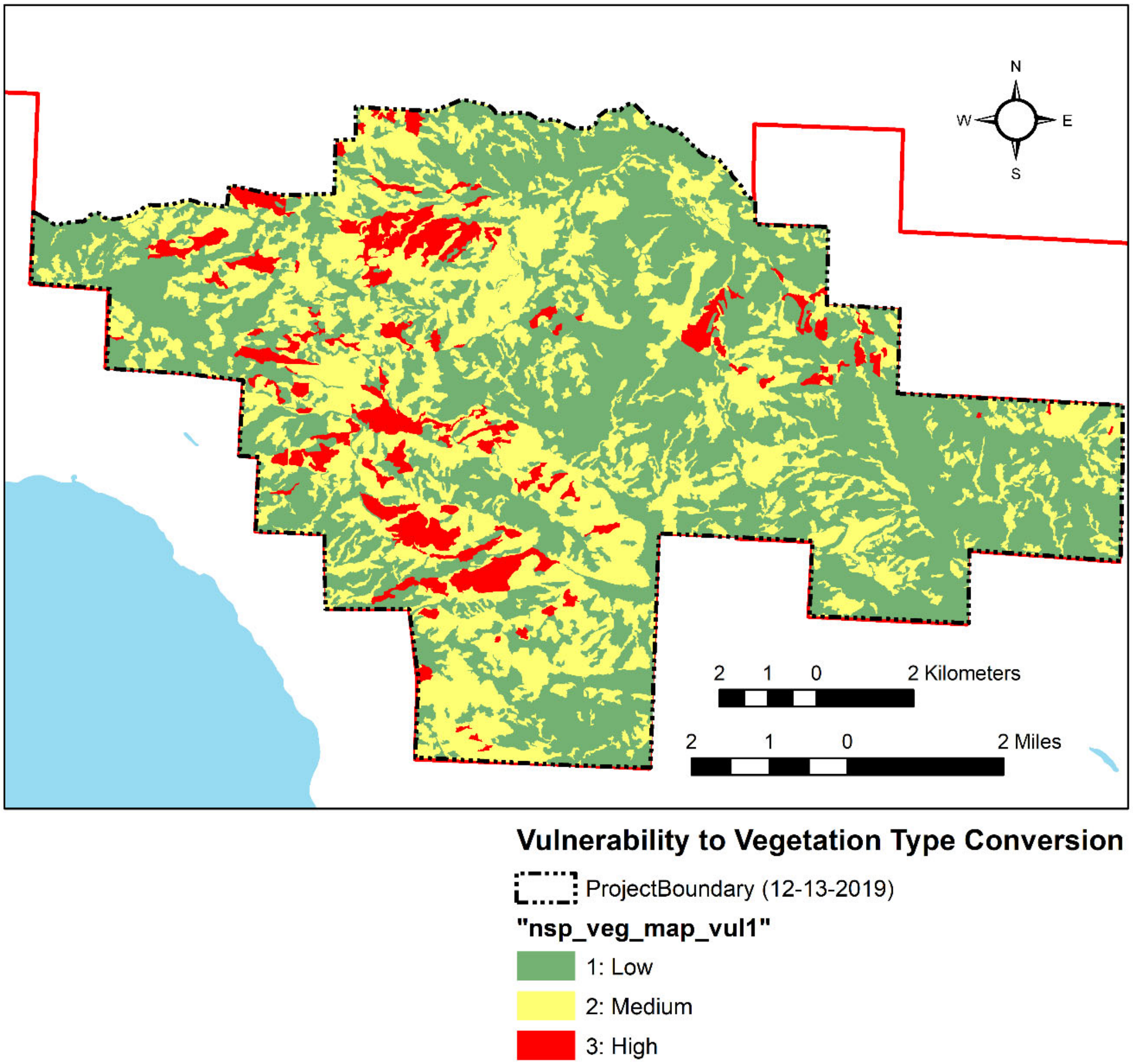


Figure 4: Vulnerability to vegetation community type-shift conversion of the MNF NSRP study area.

3.3 Vegetation type-shift sequence model

The vegetation type sequence model results are shown in Table 3. Each vegetation type is ordered in an array on a soil moisture gradient ranging from dry to mesic to wet and according to topographic position (high or low elevation). Type-shifts are expected to move to the left in Table 3, by one or more boxes, (depending on expert judgement from forest ecologists, botanists, and silviculturists) from wetter or mesic community types (on the right side) to drier community types (on the left side). For example, if a Douglas-fir (DFR) polygon is rated as likely to shift to a new type based on the planting recommendation model (covered below), then the new vegetation type could be ponderosa pine (PPN) which is one box to the left in the table. Or, if there is a large component of hardwood that is stump sprouting at the site, then the new type could be montane hardwood-conifer (MHC) or montane hardwood (MHW). This will require real time judgement calls by site experts (land managers with much experience in the MNF).

Table 3: Vegetation community 'type-shift' sequence. Type-shifts occur to the left (one or more boxes), from wetter or mesic community types (on the right side) to drier community types (on the left side).

Vulnerability Rating →	**1** Low	**1** Low	**2** Med	**2** Medium	**2** Medium	**2** Med	**2** Med	**2** Med	**2** Med	**3** High	**1** Low
High Elevation	AGS	MCP	CPC				MHW	MHC	PPN	SMC DFR	MRI
Low Elevation	AGS	MCH CRC	CPC	BOW (hillside)	BOP (hillside)	VOW (flats)	COW				
Moisture Gradient	Dry	<--				Mesic	<------------------------------------				Wet

Table notes:
AGS = Annual Grassland
MCP = Montane Chaparral
MCH = Mixed Chaparral
CRC = Chamise-Redshank Chaparral
CPC = Closed-Cone Pine-Cypress
BOW = Blue Oak Woodland
BOP = Blue Oak-Foothill Pine
VOW = Valley Oak Woodland
MHW = Montane Hardwood
COW = Coastal Oak Woodland
MHC = Montane Hardwood-Conifer
PPN = Ponderosa Pine
SMC = Sierran Mixed Conifer
DFR = Douglas-fir
MRI = Montane Riparian

3.4 Exposure: topographic analysis

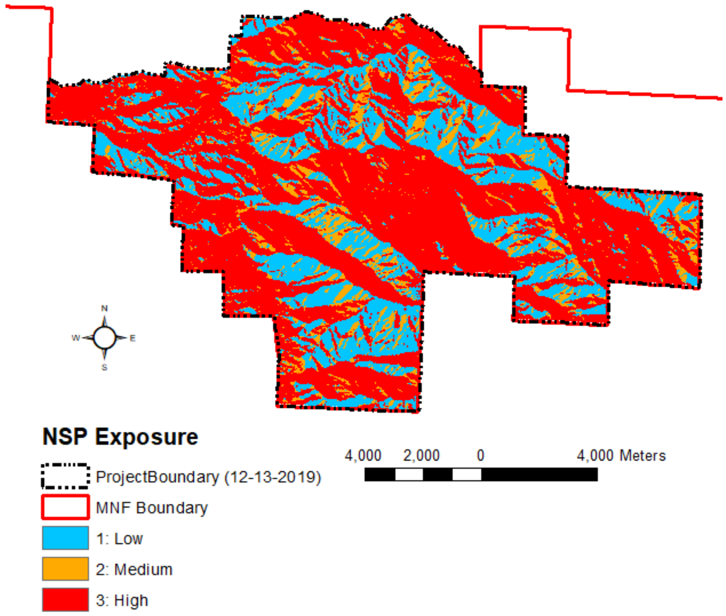
The land facet exposure model (Table 4) results for the MNF NSRP study area is shown in the map in Figure 5a. The exposure map shows 26.5% of the site is in the low exposure class, 11.4% is in the medium exposure class, and 62.1% is in the high exposure class.

Table 5 shows the results of the analysis of each topographic exposure class (low, medium, and high) within each of the 16 prefire CWHR vegetation types in area units (hectares) within in the MNF NSRP study area. It is notable that the three CWHR community types with the greatest abundance of high exposure areal extent were: mixed chaparral (MCH), chamise chaparral (CRC), and montane hardwood (MHW), respectively (Table 5). Figure 6 graphically depicts the areal (ha) proportions of each topographic exposure class (low, medium, and high) within each prefire CWHR vegetation type, while Figure 7 graphically depicts the percentage proportions of each topographic exposure class (low, medium, and high) within each prefire CWHR vegetation type in within the MNF NSRP study area.

Table 4: Exposure values (low, medium, high) for combined topographic aspect and slope values to define 'land facets.'

Aspect	**Aspect (degrees)**	**Slope (degrees)**		
		Level = 0° – 14.2°	Mod = 14.2° – 23.3°	Steep = 23.3° -52.5°
North	0° - 22.5°	Low	Low	Low
Northeast	22.5° - 67.5°	Low	Low	Low
East	67.5° - 112.5°	Low	Med	Med
Southeast	112.5° – 157.5°	Med	Med	High
South	157.5° – 202.5°	High	High	High
Southwest	202.5° – 247.5°	High	High	High
West	247.5° -292.5°	High	High	High
Northwest	292.5° – 337.5°	Med	High	High
North	337.5° – 360°	Low	Low	Low
Flat	-1	Low	NA	NA

(a)



(b)

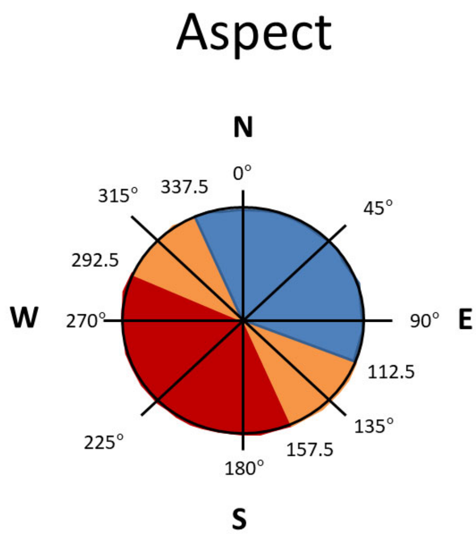


Figure 5: **(a)** Exposure map of the MNF NSRP study area: 26.5% is in the low exposure class, 11.4% is in the medium exposure class, and 62.1% is in the high exposure class. **(b)** Aspect color-coded diagram.

Table 5: Analysis of prefire CWHR vegetation type areal extent (in hectares) within each topographic exposure class (low, medium, and high) in the MNF NSRP study area.

CWHR Vegetation Type	1 - Low Exposure	2 - Medium Exposure	3 - High Exposure
Annual Grassland (AGS)	124.5	31.8	444.7
Barren (BAR)	9.5	1.4	10.6
Blue Oak-Foothill Pine (BOP)	24.2	9.4	135.1
Blue Oak Woodland (BOW)	2.6	2.6	87.3
Coastal Oak Woodland (COW)	4.2	1.5	12.7
Closed-Cone Pine-Cypress (CPC)	410.6	151.0	529.5
Chamise-Redshank Chaparral (CRC)	87.1	102.7	1,672.8
Douglas-fir (DFR)	212.4	26.4	37.6
Mixed Chaparral (MCH)	998.7	615.5	3,888.5
Montane Chaparral (MCP)	174.2	112.3	323.1
Montane Hardwood-Conifer (MHC)	520.8	197.9	561.6
Montane Hardwood (MHW)	948.5	391.0	1,468.8
Montane Riparian (MRI)	4.5	0.3	8.5
Ponderosa Pine (PPN)	151.6	66.2	335.4
Sierran Mixed Conifer (SMC)	502.0	102.9	240.1
Valley Oak Woodland (VOW)	29.1	3.7	80.9

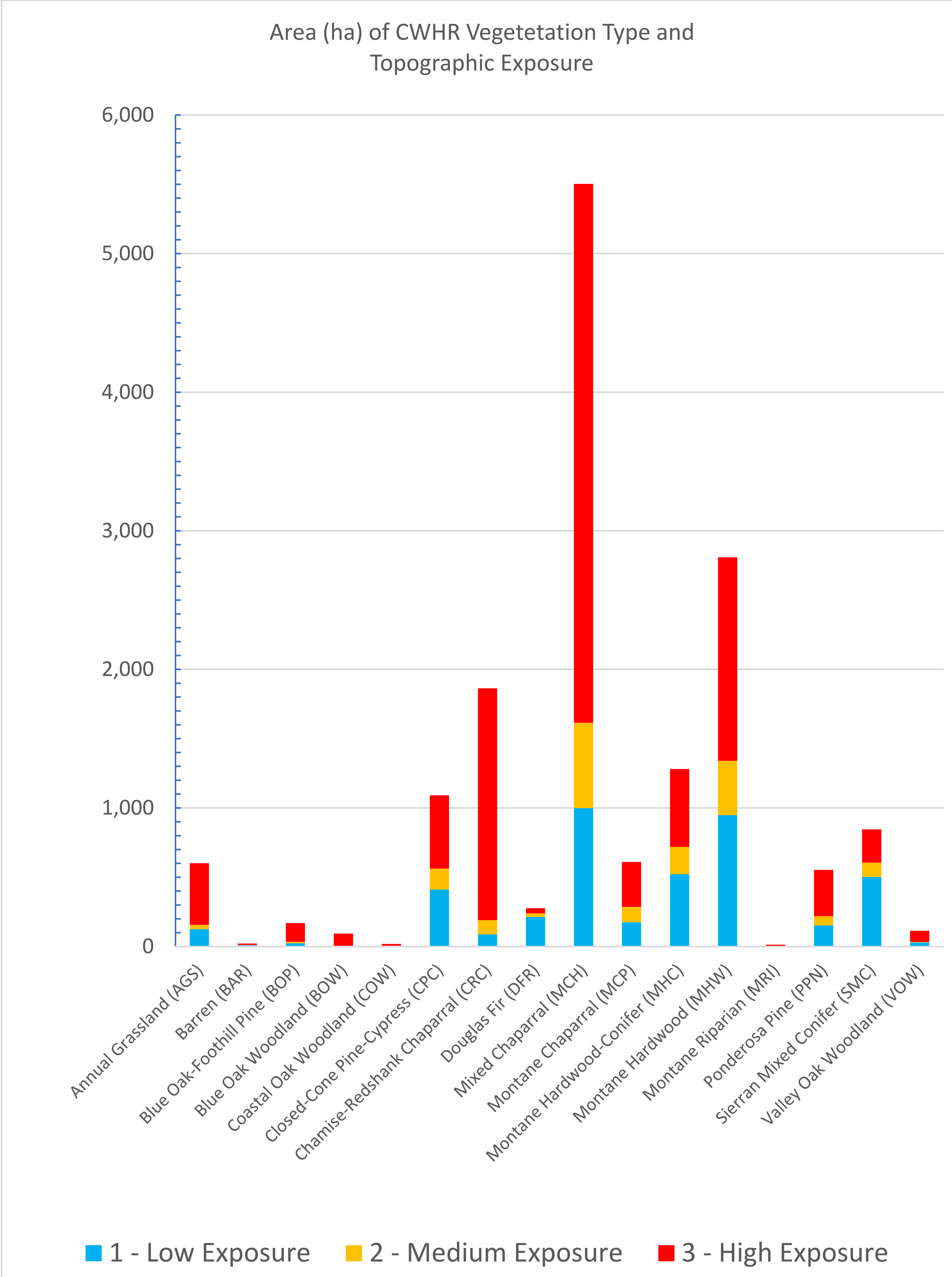


Figure 6: The area (ha) proportions of each topographic exposure class (low, medium, and high) within each prefire CWHR vegetation type in the MNF NSRP study area.

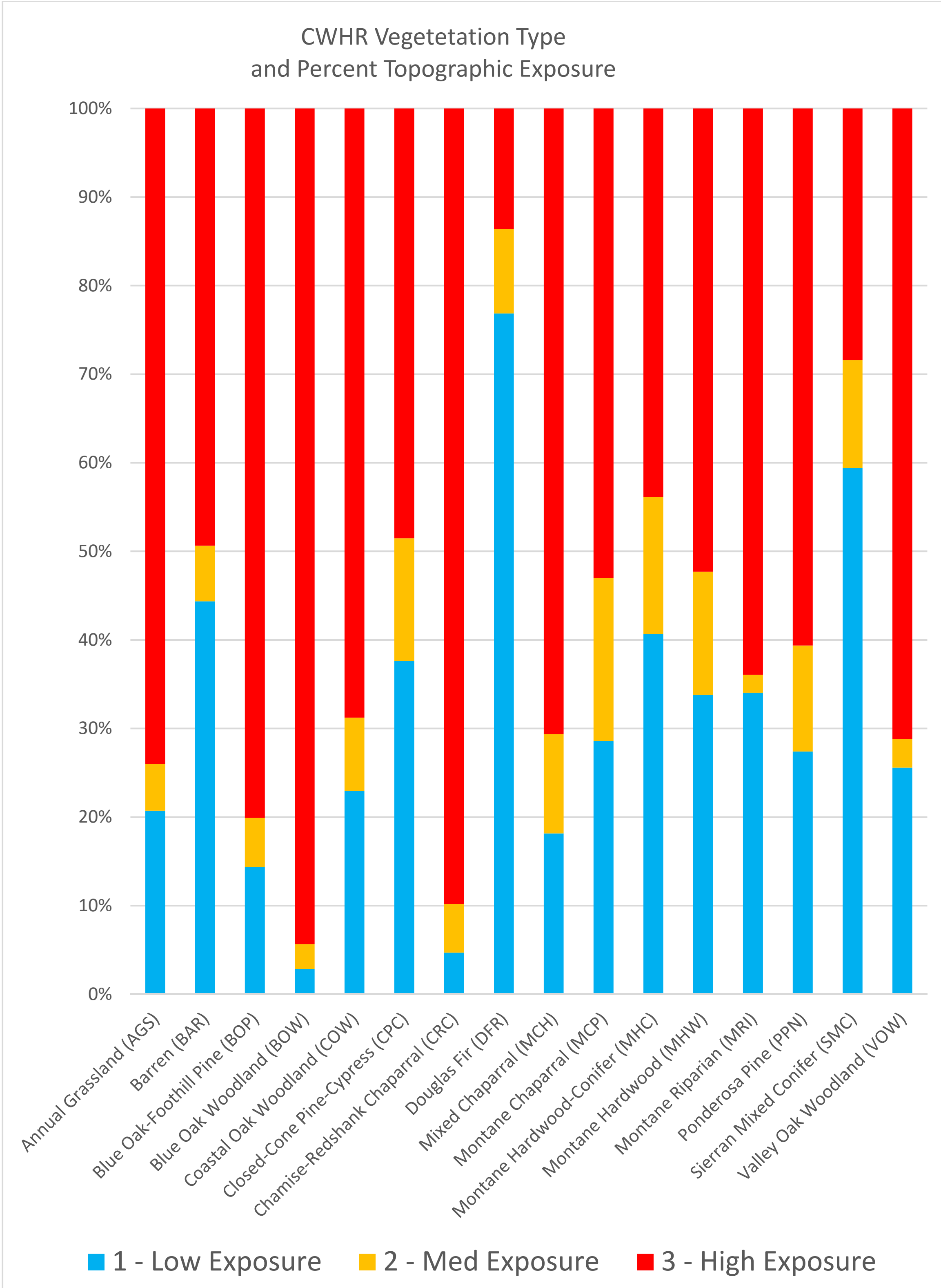


Figure 7: The percentage proportions of each topographic exposure class (low, medium, and high) within each prefire CWHR vegetation type in the MNF NSRP study area.

3.5 RAVG analysis

The RAVG analysis results are presented in Table 6 and Figures 8, 9 and 10. The areal extent (in hectares) of each of the four RAVG burn severity classes (0-3) for each CWHR vegetation type is shown in Table 6 and is graphed in Figure 9. From Figure 10, the relative proportions of each burn severity class for each vegetation type, it is very clear that the Mendocino Complex fire was an extreme event dramatically affecting each vegetation type. Of the 16 most significant vegetation types at the NSRP site, high severity fire effects were most impactful to the chamise chaparral (CRC) vegetation type, affecting 97% of that plant community. Least affected was the valley oak (VOW) vegetation type with 45% of that type experiencing high severity. On average for all 16 types, 73% were impacted by high severity fire effects. This overall high level of impact across almost all vegetation types made using this variable of little value to guide specific management actions and therefore the NDVI approach was taken instead (see next section).

Table 6: Analysis of prefire CWHR vegetation type area (in hectares) within each fire severity (RAVG) class (other, low, moderate, and high) in the MNF NSRP study area

CWHR Vegetation Type Name	0 - other	1 - Low Severity	2 - Moderate Severity	3 - High Severity
Annual Grassland (AGS)	3.7	23.5	128.3	405.8
Barren (BAR)	3.6	4.5	6.6	6.5
Blue Oak-Foothill Pine (BOP)	1.4	10.4	26.2	113.7
Blue Oak Woodland (BOW)	0.1	1.7	28.9	57.2
Coastal Oak Woodland (COW)	0.1	0.8	2.7	13.3
Closed-Cone Pine-Cypress (CPC)	1.6	11.8	54.8	1,026.6
Chamise-Redshank Chaparral (CRC)	1.8	9.1	35.9	1,720.2
Douglas-fir (DFR)	5.3	36.7	66.6	170.5
Mixed Chaparral (MCH)	24.9	95.5	335.7	4,856.7
Montane Chaparral (MCP)	0.3	3.8	39.1	565.8
Montane Hardwood-Conifer (MHC)	18.6	134.6	302.0	786.1
Montane Hardwood (MHW)	56.6	212.6	515.8	1,900.1
Montane Riparian (MRI)	0.9	4.5	8.5	0.0
Ponderosa Pine (PPN)	9.8	92.4	157.1	270.3
Sierran Mixed Conifer (SMC)	14.6	105.8	196.9	501.4
Valley Oak Woodland (VOW)	2.6	14.8	45.6	52.4

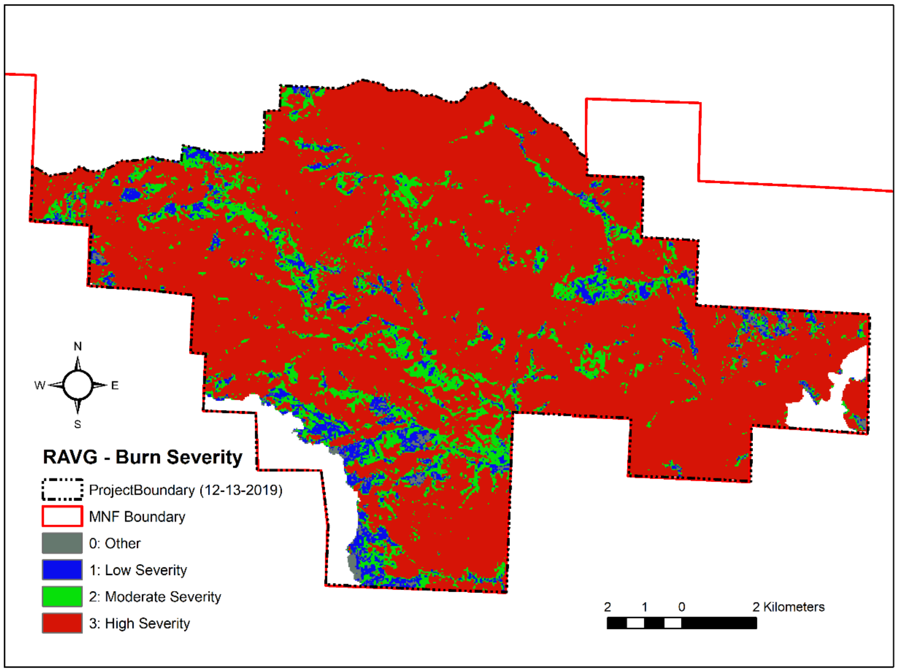


Figure 8: RAVG map of burn severity at the MNF NSRP study area.

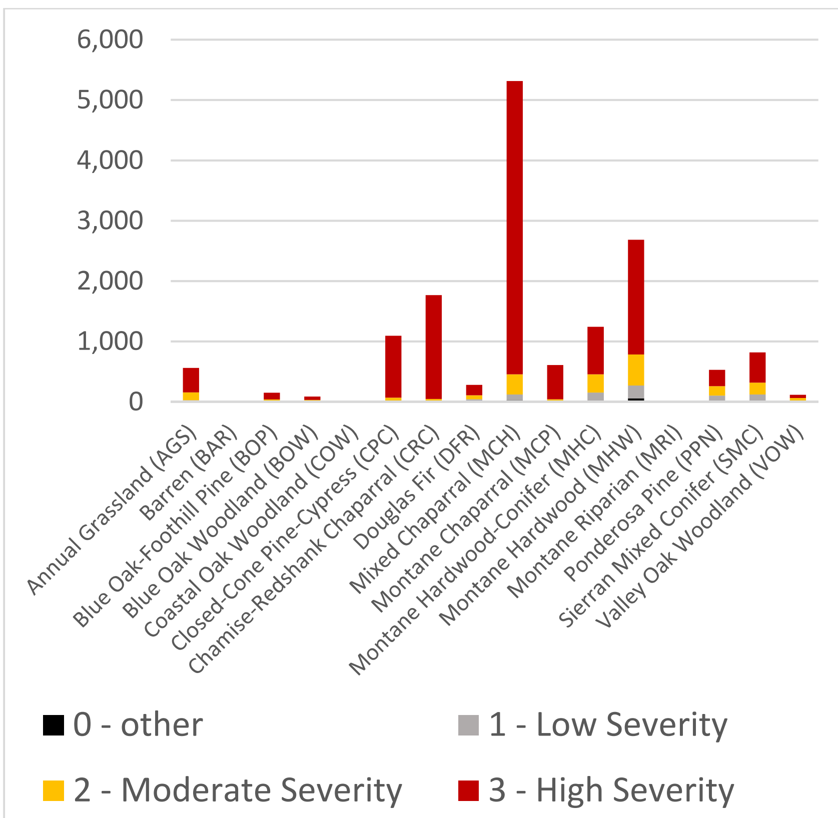


Figure 9: The areal (ha) extent of each fire severity (RAVG) class (other, low, moderate, and high) within each prefire CWHR vegetation type in the MNF NSRP study area.

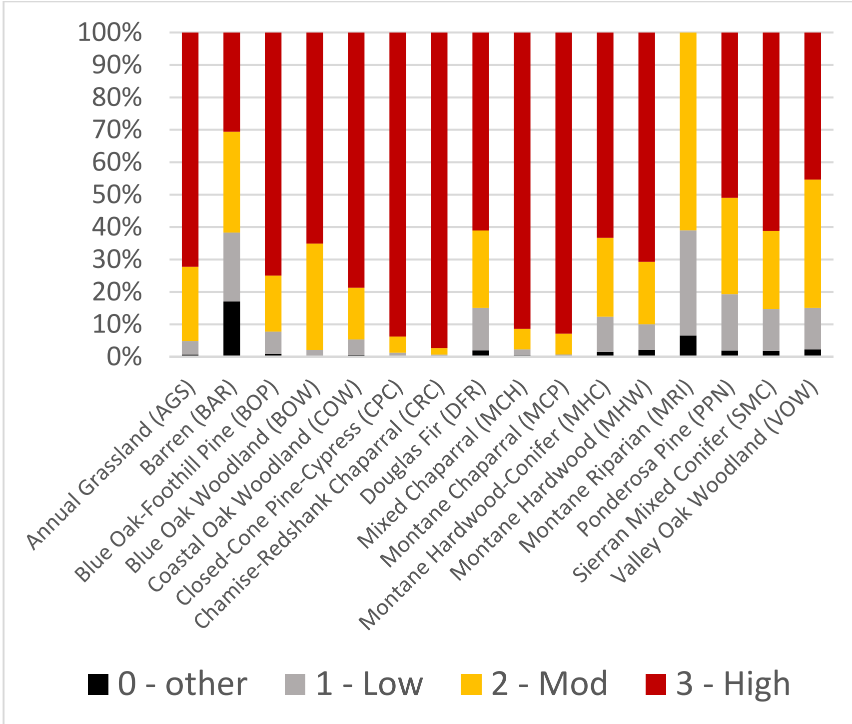


Figure 10: The percentage proportions of each fire severity (RAVG) class (other, low, moderate, and high) within each prefire CWHR vegetation type in the MNF NSRP study area.

3.6 NDVI (greenness index) analysis

The prefire (2016) and postfire (2020) NDVI greenness index values within the MNF NSRP study area are depicted in map images in Figure 11. The prefire image is markedly "greener" than the postfire image, as expected. The 2016 image ranges in index value from 49 to 200 (mean = 116.5, std. dev. = 12.2) and the 2020 image ranges in value from 0 to 200 (mean = 101.1, std. dev. = 16.2). When the two images were subtracted to assess their corresponding cell differences the values ranged from -127 to 169 (mean = 14.5, std. dev. = 15.9). After the zonal average (mean) was calculated (from the difference raster) for each vegetation polygon, the values ranged from -42.6 to 53 (mean = 14.5 and std. dev. = 6.5). A map of the mean NDVI difference values that were reclassified into three priority classes (high, medium, and low) within the MNF NSRP study area is shown in Figure 12. "Priority," in this context, is a function of management concern. Low priority is defined as small differences between 2016 and 2020 mean NDVI polygon values (i.e., low mortality) and high priority are large differences (i.e., high mortality).

The assessment of mean NDVI difference values between 2016 and 2020 (of each NDVI priority class) within each prefire CWHR vegetation type polygons in areal extent (hectares) in the MNF NSRP study area is shown in Table 7 and graphed in Figure 13. Mixed chaparral (MCH) and chamise chaparral (CRC), respectively, exhibited the most and next-most area burned in the high priority class. A graph of the percentage proportions of each NDVI difference priority class (low, medium, and high) within each CWHR vegetation type in is shown in Figure 14. Closed cone pine-cypress (CPC) and mixed conifer (SMC) had the highest and second highest proportion of high priority, respectively. Of least concern, are valley oak woodland (VOW), annual grassland (AGS), and montane riparian (MRI).

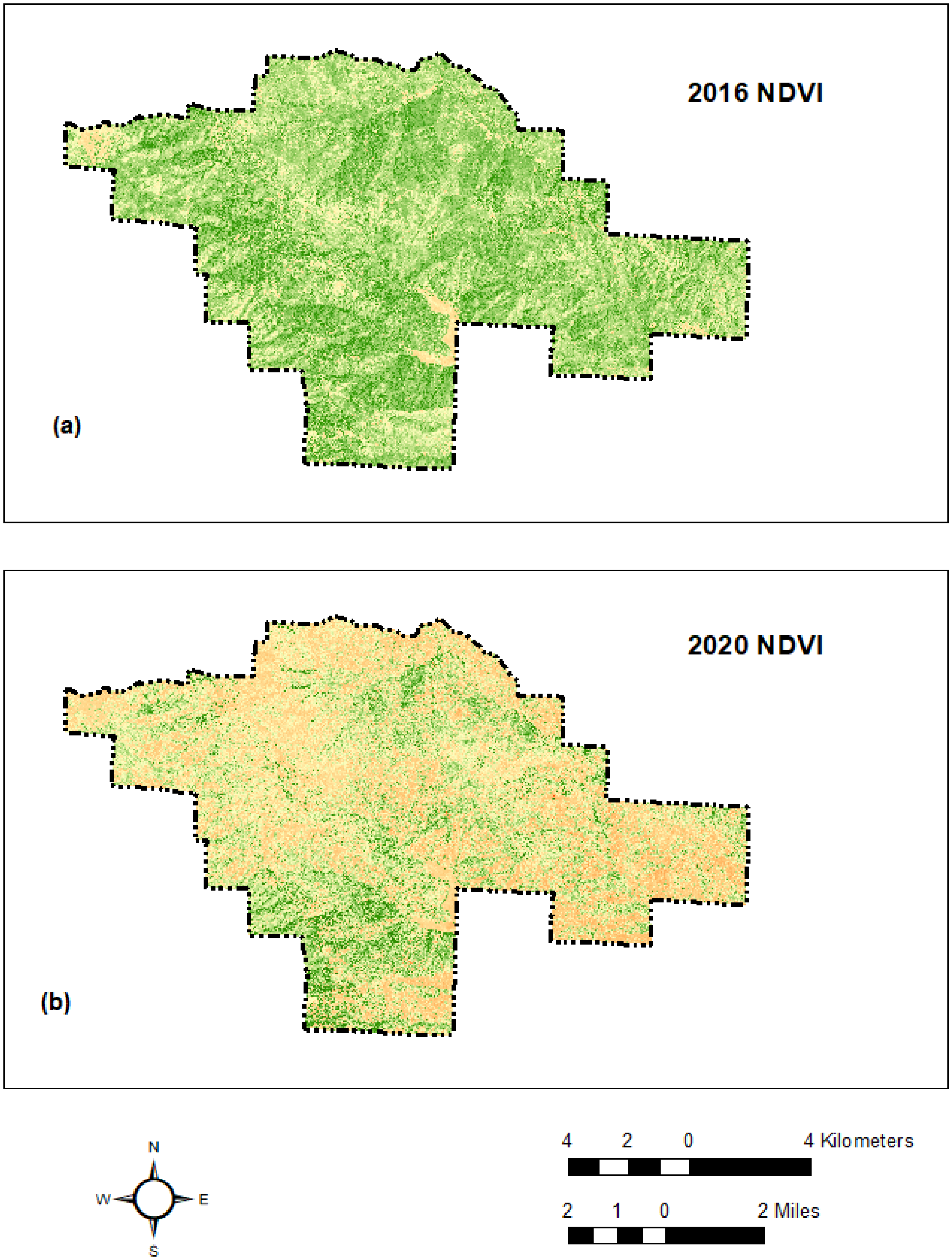


Figure 11: **(a)** Prefire (2016) and **(b)** postfire (2020) NDVI greenness index values within the MNF NSRP study area. These images were derived from NAIP (USDA) images of Lake County, CA.

Table 7: Analysis of mean NDVI difference values between 2016 and 2020 of CWHR vegetation type polygons reported as areal extent (in hectares) within each NDVI priority class in the MNF NSRP study area. Low priority is defined as small differences between 2016 and 2020 mean NDVI polygon values (i.e., low mortality) and high priority are large differences (i.e., high mortality).

CWHR Vegetation Type	1 - Low Priority	2 - Medium Priority	3 - High Priority
Annual Grassland (AGS)	320.5	233.6	58.7
Barren (BAR)	9.9	6.3	5.4
Blue Oak-Foothill Pine (BOP)	38.6	102.1	32.6
Blue Oak Woodland (BOW)	15.7	531.9	28.4
Coastal Oak Woodland (COW)	5.7	10.8	2.1
Closed-Cone Pine-Cypress (CPC)	56.8	405.6	647.3
Chamise-Redshank Chaparral (CRC)	132.2	885.7	879.3
Douglas-fir (DFR)	47.5	112.6	118.5
Mixed Chaparral (MCH)	476.8	3,033.2	2,065.7
Montane Chaparral (MCP)	50.2	427.7	134.4
Montane Hardwood-Conifer (MHC)	272.0	559.4	455.4
Montane Hardwood (MHW)	643.6	1,411.2	780.1
Montane Riparian (MRI)	6.6	7.1	0.0
Ponderosa Pine (PPN)	127.4	235.4	194.4
Sierran Mixed Conifer (SMC)	180.9	263.4	405.1
Valley Oak Woodland (VOW)	81.4	30.9	3.4

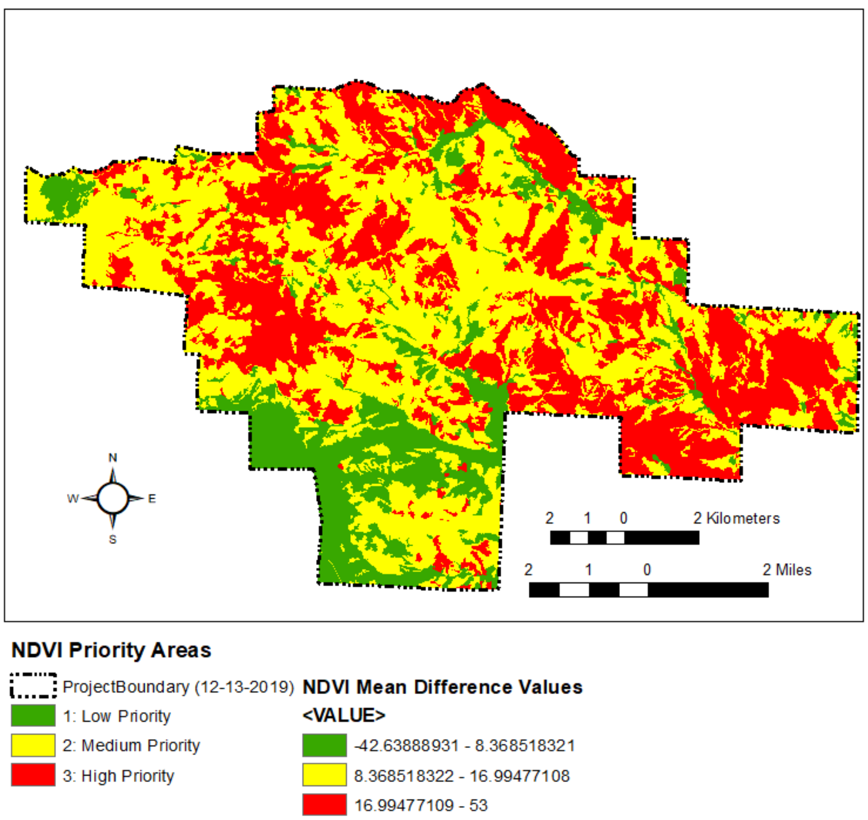


Figure 12: Mean NDVI difference values classified into three priority classes within the MNF NSRP study area. Low priority is defined as small differences between 2016 and 2020 mean NDVI polygon values (i.e., low mortality) and high priority are large differences (i.e., high mortality).

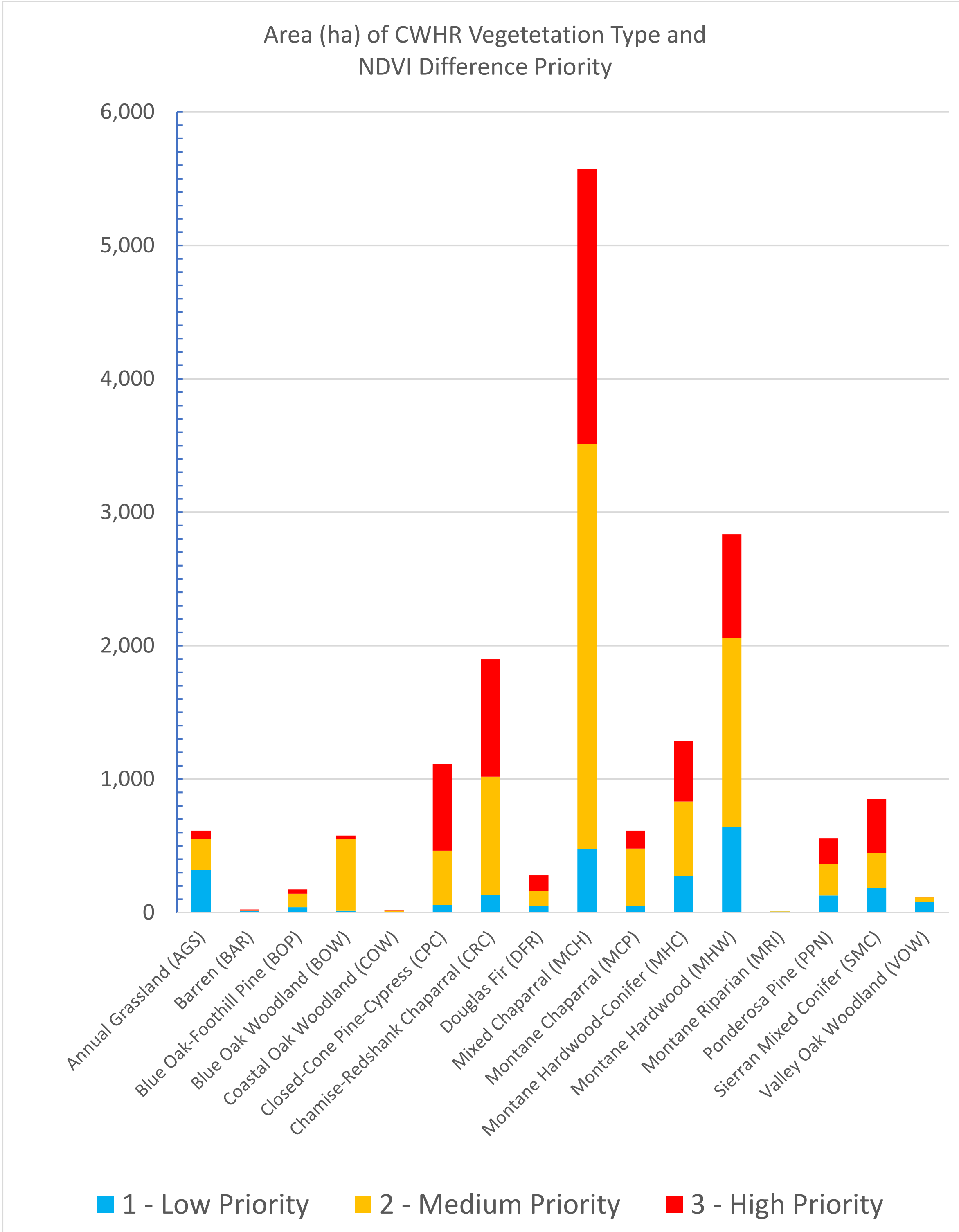


Figure 13: The area (ha) proportions of each mean NDVI difference priority class (low, medium, and high) within each prefire CWHR vegetation type in the MNF NSRP study area.

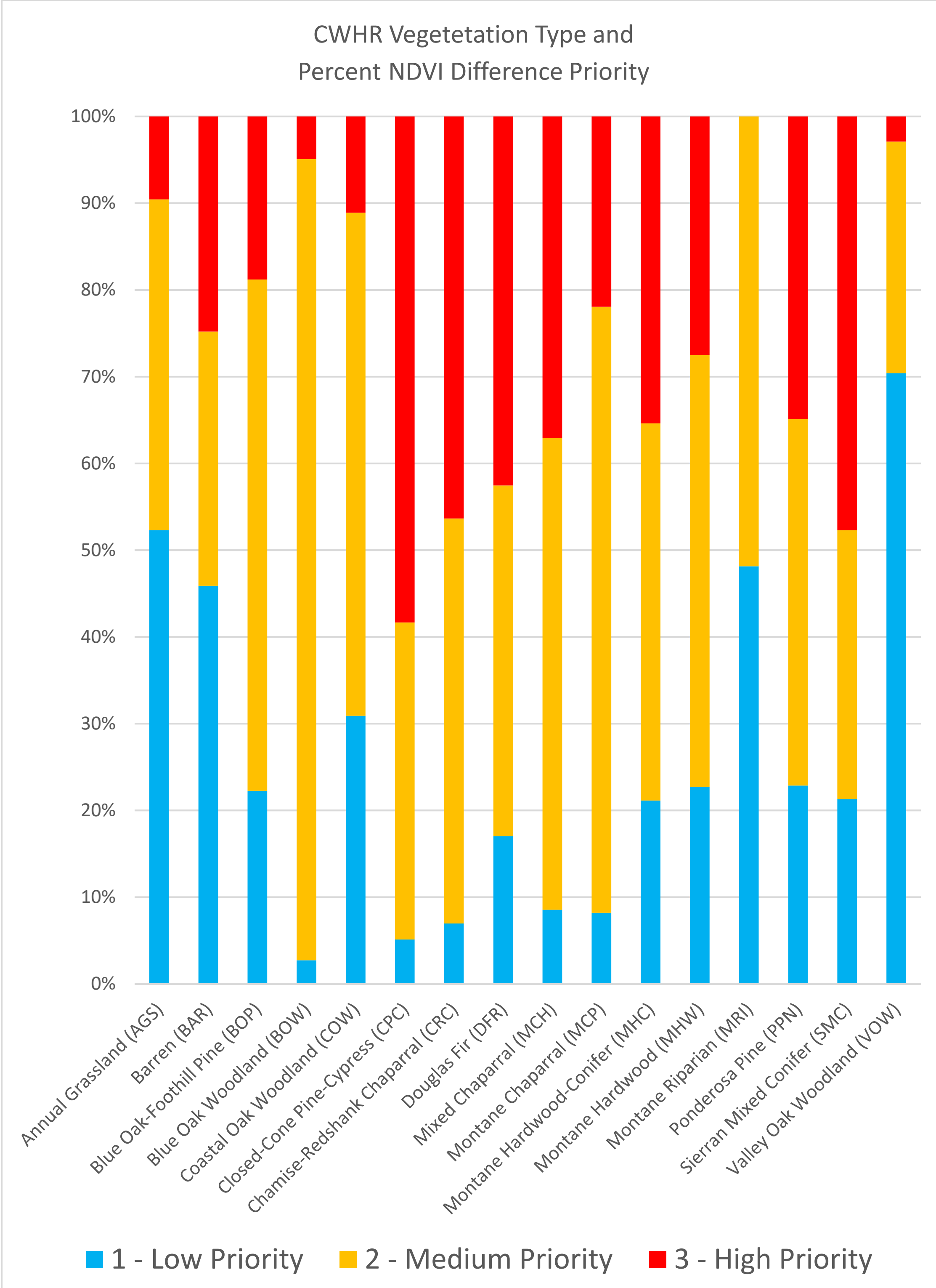


Figure 14: The percentage proportions of each mean NDVI difference priority class (low, medium, and high) within each prefire CWHR vegetation type in the MNF NSRP study area.

3.7 Restoration model and planting recommendations

The 27 unique combinations of the three variables in the decision support restoration model, together with the three planting recommendations are presented in Table 8 and Figures 15-23. The figures graphically depict the decision support model variables and planting recommendations; they are presented in groups of thee where each group has the same exposure and vulnerability levels (i.e., low-low, low-medium, low-high, and so on) and the mean NDVI difference (burn impacts) levels vary from low to high. The relative proportions of each planting recommendation were calculated as 47%, 18% and 35% for planting recommendations #1, #2 and #3, respectively (Figure 24). For reference, the three planting recommendations are: (1) no planting, let the site regenerate on its own (i.e., leave it alone); (2) replant the site using plant species in the prefire vegetation community type; and (3) plant new species because climate change impacts will likely cause a type-shift in plant community.

It is notable that four of the 27 unique variable combinations have two possible outcomes depending on the context. In Table 8 those exceptions are indicated with "or" in parentheses and in Figures 17, 20, and 22 the exceptions are denoted with a dashed line arrow. Those four exceptions are: (1) combination 133 with planting recommendation 3 or 1; (2) combination 232 with planting recommendation 3 or 2; (3) combination 322 with planting recommendation 3 or 2; and (4) combination 323 with planting recommendation 3 or 2. Again, this model is based on expert opinion and these exceptions are based on uncertainty about possible outcomes. For example, combination 133 consists of low vulnerability, high exposure, and high mean NDVI difference (i.e., high mortality) where mixed chaparral (MCH) fits this scenario (see Table 2 and Figures 6 and 13). In this scenario, due to assumed high mortality and where root crowns are expected to be killed by high intensity fire, it is expected in most cases it would receive planting recommendation #3 (i.e., plant new species due to a vegetation type-shift), where MCH would likely shift to grassland (AGS) as indicated in Table 3 (the vegetation type-shift table); however, in some cases mortality may not be as extreme and it could regenerate on its own (i.e., planting recommendation #1). There are probably *more* than four exceptions among these three model variables, but these four were readily apparent to the authors and collaborators who reviewed the model.

A map of the distribution of each planting recommendation (1-3) within the MNF NSRP site is shown in Figure 25. The results of the of the three planting recommendations analysis within each prefire vegetation type are presented in Table 9 and in Figures 26 and 27. Although blue oak-pine (BOP) and blue oak woodland (BOW) occupy only 1.1% and 0.6% of the NSRP site, respectively, a notable result from this analysis is that both of these vegetation communities are projected to type-shift by over 60% and 75%, respectively, from its prefire distribution (Figure 27). Montane hardwood (MHW) is also projected to type-shift by over 40% in its prefire distribution (Figure 27). These results of potential climate change impacts to the oak communities in the NSRP are supported by previous modeling studies examining the potential effects of climate change on California vegetation communities (McIntyre et al. 2015; Coop et al.2020).

In terms of the merchantable timber community types in the NSRP site (that prefire occupied just 10.5% of the NSRP site, see Table 1), for ponderosa pine (PPN), mixed conifer (SMC), and Douglas-fir (DFR), each of these types is projected to type-shift by 45%, 33%, 20%, respectively. Thus, the best opportunities for replanting prefire sites for merchantable timber are SMC (959 acres) followed by DFR (428 acres) and PPN (428 acres). However, it should also be noted that the SMC and DFR sites that are projected to type-shift could shift to PPN (or MHC), depending on the exposure of the site (Table 3), and therefore augment planting sites of merchantable timber.

Another notable result is the impact of climate change on the three chaparral communities, which together occupy half (50%) of the prefire site. The most dominant vegetation type at the NSRP site is mixed chaparral (MCH) (occupying 35% prefire site) and 30% is projected to type-shift to grassland (AGS), depending on local fire severity effects. Though not as abundant as MCH, chamise chaparral (CRC) is projected to lose 42% of its prefire distribution and type-shift to AGS. Montane chaparral (MCP) is the least impacted, where just 14% is projected to type-shift to AGS, and nearly all the remainder are expected to regenerate naturally (i.e., planting recommendation #1).

Table 8: Restoration management model (combined variables) with planting recommendations.

	Restoration Management Model Code	Vulnerability	Exposure	NDVI Difference	Planting Recommendation Code	Planting Recommendation
1	111	Low	Low	Low	1	No planting / Leave alone / Prefire CWHR type
2	112	Low	Low	Medium	1	No planting / Leave alone / Prefire CWHR type
3	113	Low	Low	High	1	No planting / Leave alone / Prefire CWHR type
4	121	Low	Medium	Low	1	No planting / Leave alone / Prefire CWHR type
5	122	Low	Medium	Medium	1	No planting / Leave alone / Prefire CWHR type
6	123	Low	Medium	High	1	No planting / Leave alone / Prefire CWHR type
7	131	Low	High	Low	1	No planting / Leave alone / Prefire CWHR type
8	132	Low	High	Medium	1	No planting / Leave alone / Prefire CWHR type
9	133	Low	High	High	3 (or 1)	Plant new species / Postfire CWHR type-shift
10	211	Medium	Low	Low	1	No planting / Leave alone / Prefire CWHR type
11	212	Medium	Low	Medium	2	Replant prefire species / Prefire CWHR type
12	213	Medium	Low	High	2	Replant prefire species / Prefire CWHR type
13	221	Medium	Medium	Low	1	No planting / Leave alone / Prefire CWHR type
14	222	Medium	Medium	Medium	2	Replant prefire species / Prefire CWHR type
15	223	Medium	Medium	High	2	Replant prefire species / Prefire CWHR type
16	231	Medium	High	Low	1	No planting / Leave alone / Prefire CWHR type
17	232	Medium	High	Medium	3 (or 2)	Plant new species / Postfire CWHR type-shift
18	233	Medium	High	High	3	Plant new species / Postfire CWHR type-shift
19	311	High	Low	Low	1	No planting / Leave alone / Prefire CWHR type
20	312	High	Low	Medium	2	Replant prefire species / Prefire CWHR type
21	313	High	Low	High	2	Replant prefire species / Prefire CWHR type
22	321	High	Medium	Low	1	No planting / Leave alone / Prefire CWHR type
23	322	High	Medium	Medium	3 (or 2)	Plant new species / Postfire CWHR type-shift
24	323	High	Medium	High	3 (or 2)	Plant new species / Postfire CWHR type-shift
25	331	High	High	Low	1	No planting / Leave alone / Prefire CWHR type
26	332	High	High	Medium	3	Plant new species / Postfire CWHR type-shift
27	333	High	High	High	3	Plant new species / Postfire CWHR type-shift

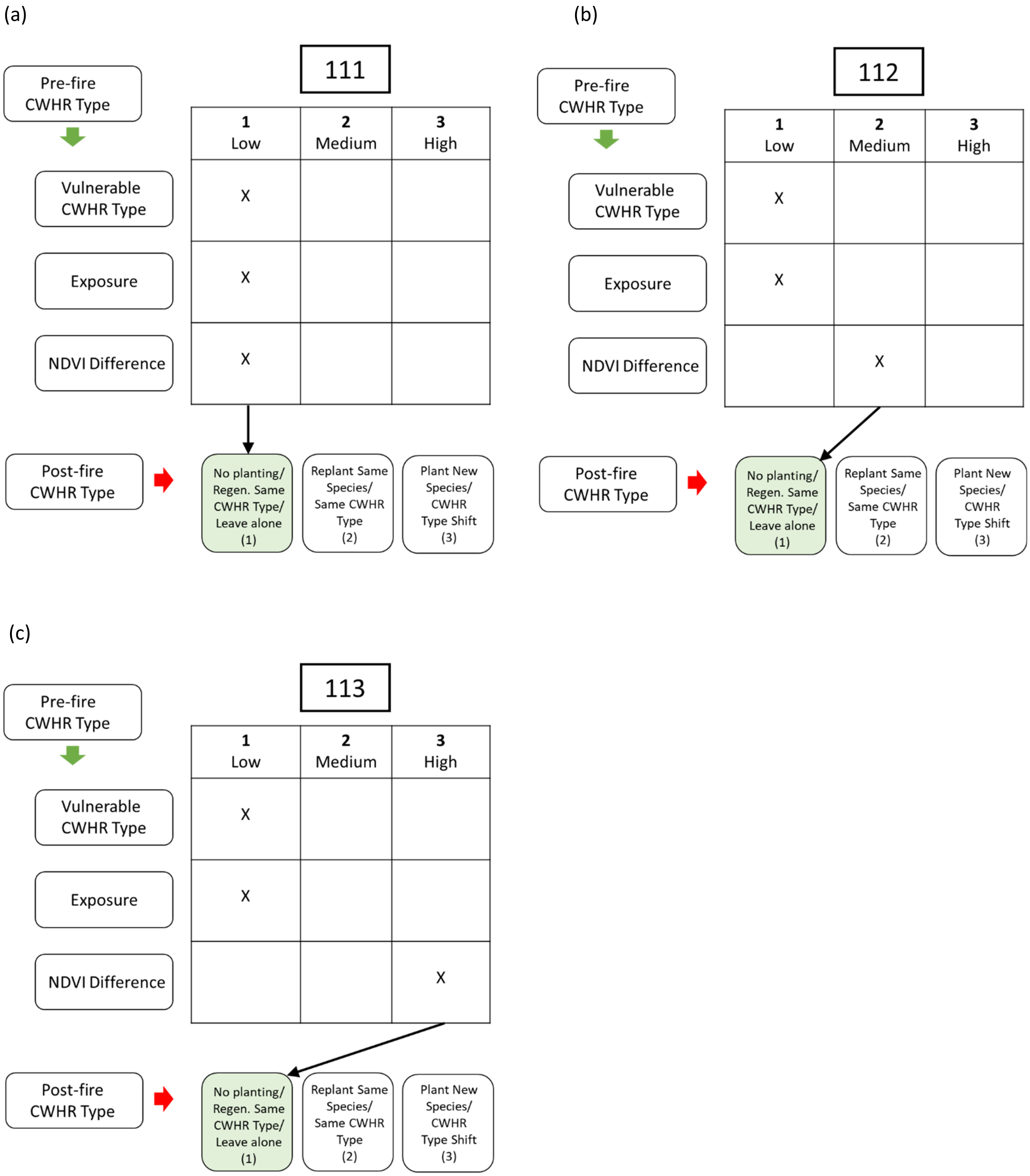


Figure 15: Restoration management model with planting recommendations. These figures depict low vulnerability and low exposure.

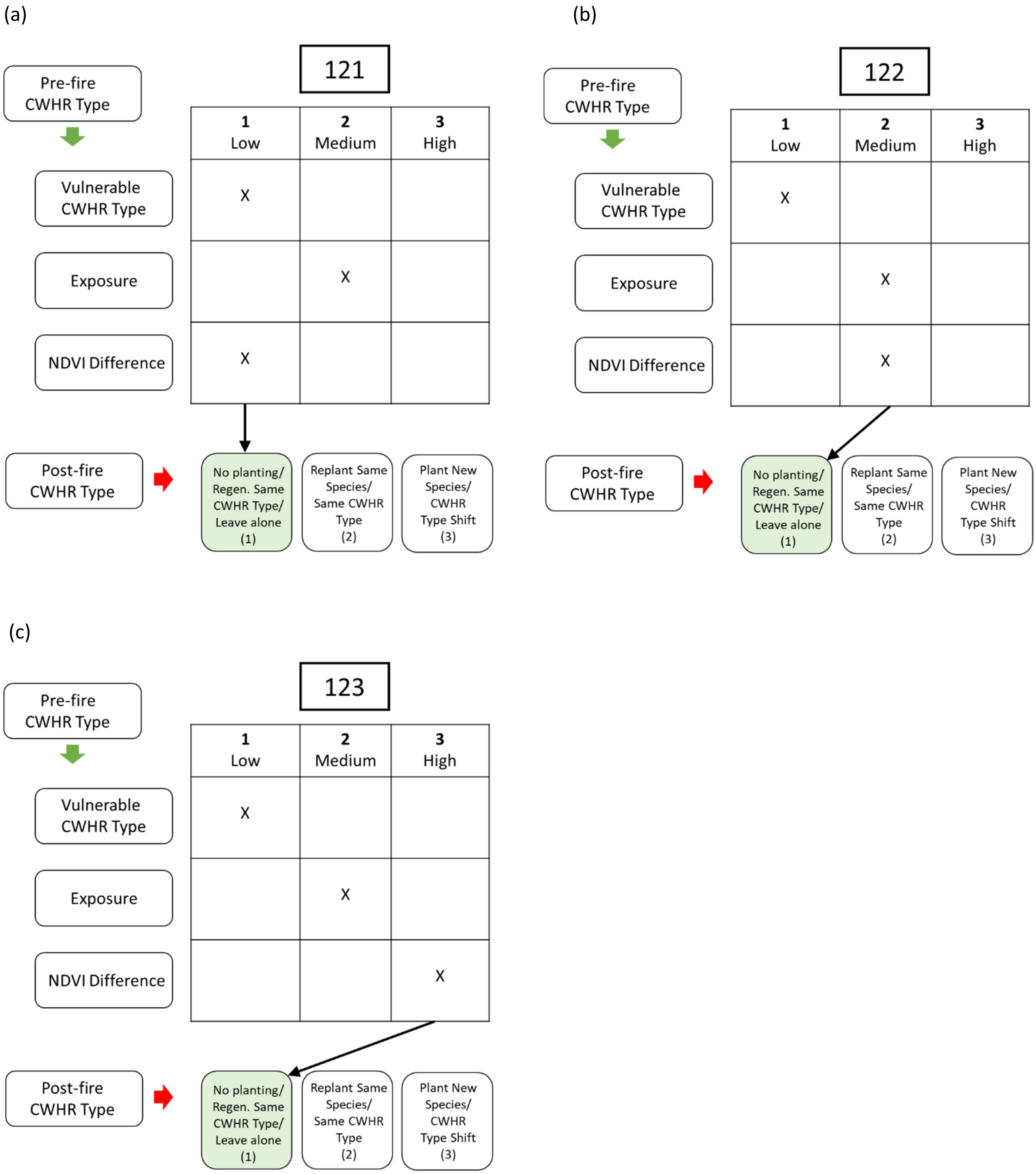


Figure 16: Restoration management model with planting recommendations. These figures depict low vulnerability and medium exposure.

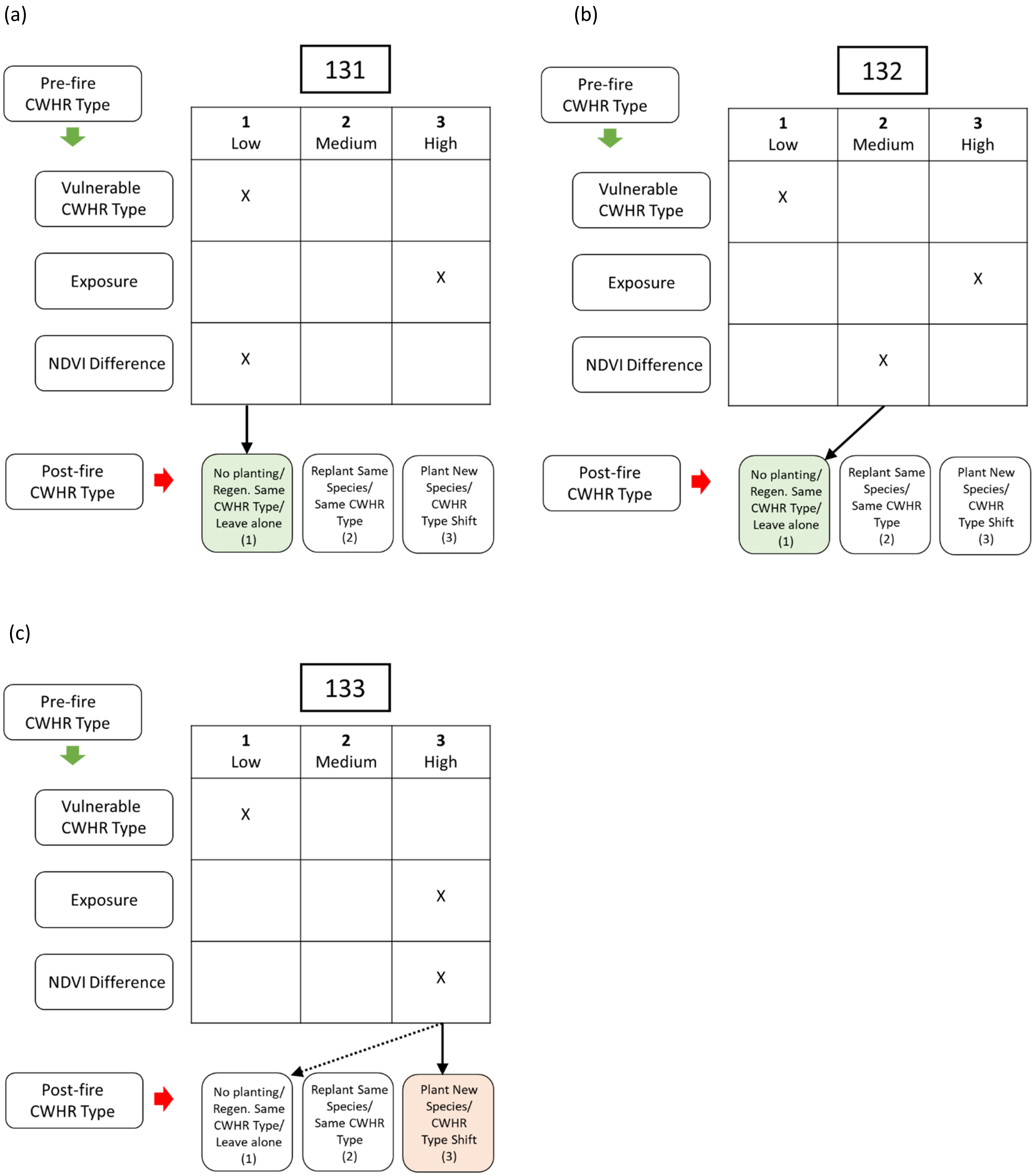


Figure 17: Restoration management model with planting recommendations. These figures depict low vulnerability and high exposure.

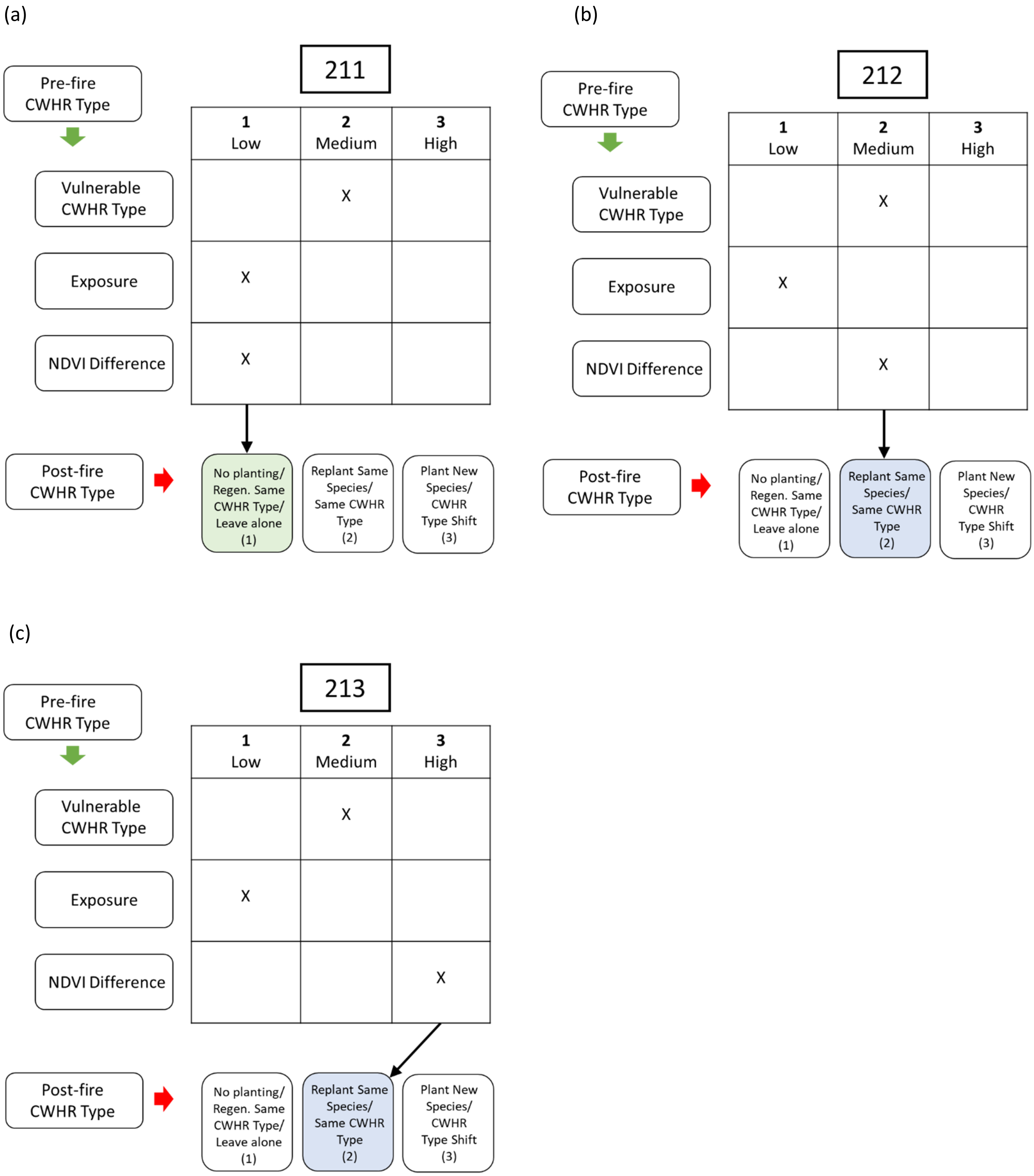


Figure 18: Restoration management model with planting recommendations. These figures depict medium vulnerability and low exposure.

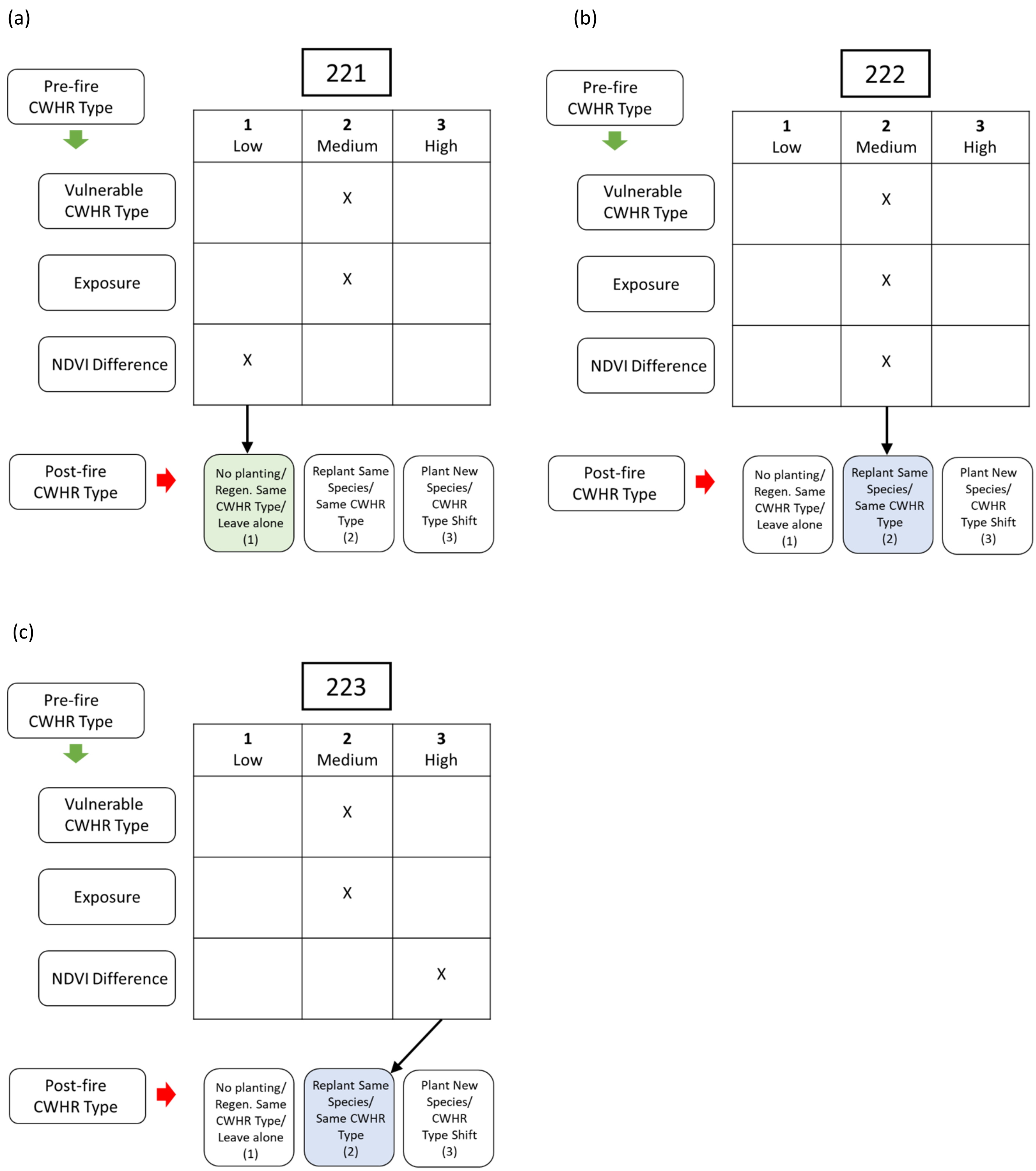


Figure 19: Restoration management model with planting recommendations. These figures depict medium vulnerability and medium exposure.

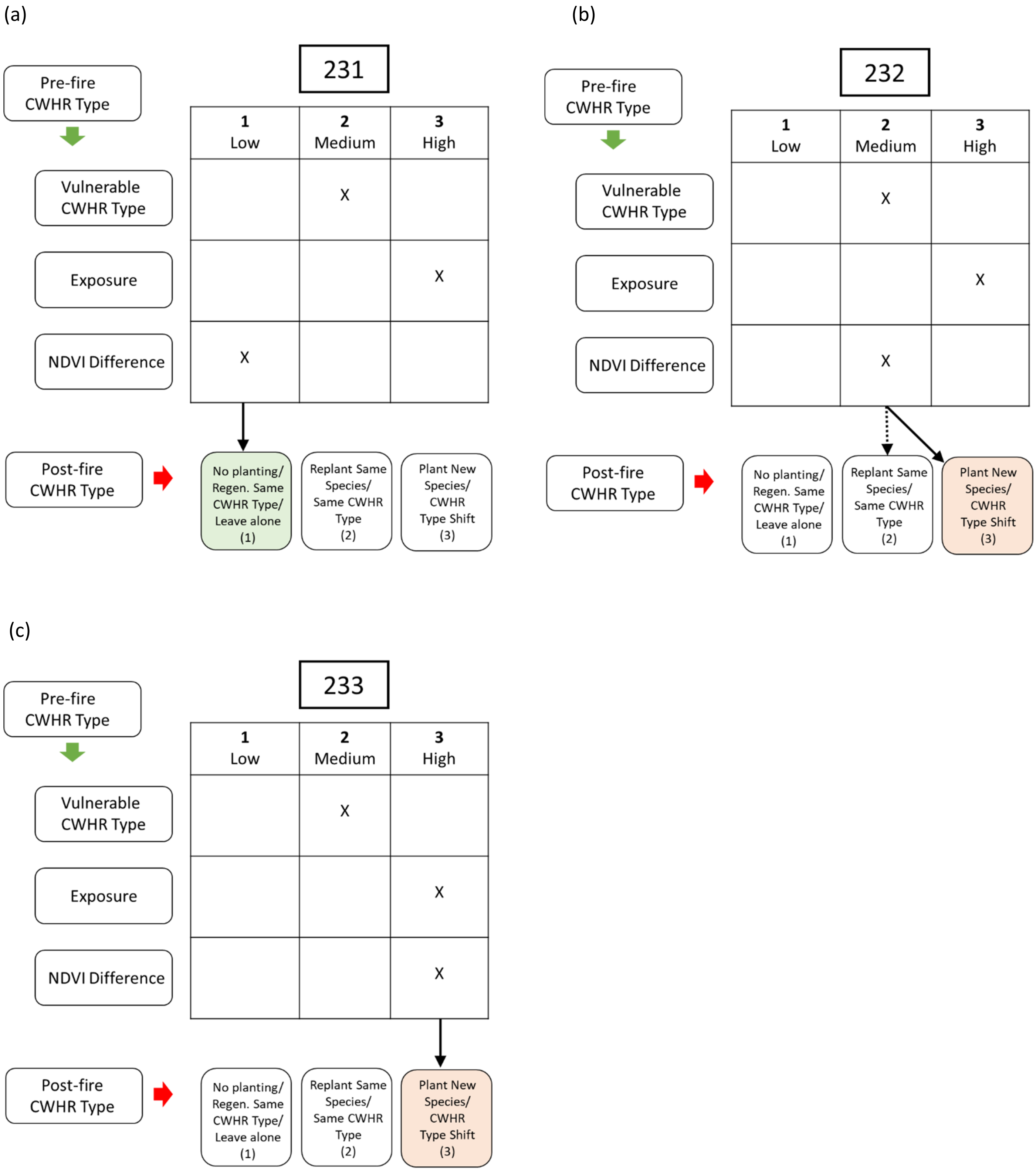


Figure 20: Restoration management model with planting recommendations. These figures depict medium vulnerability and high exposure.

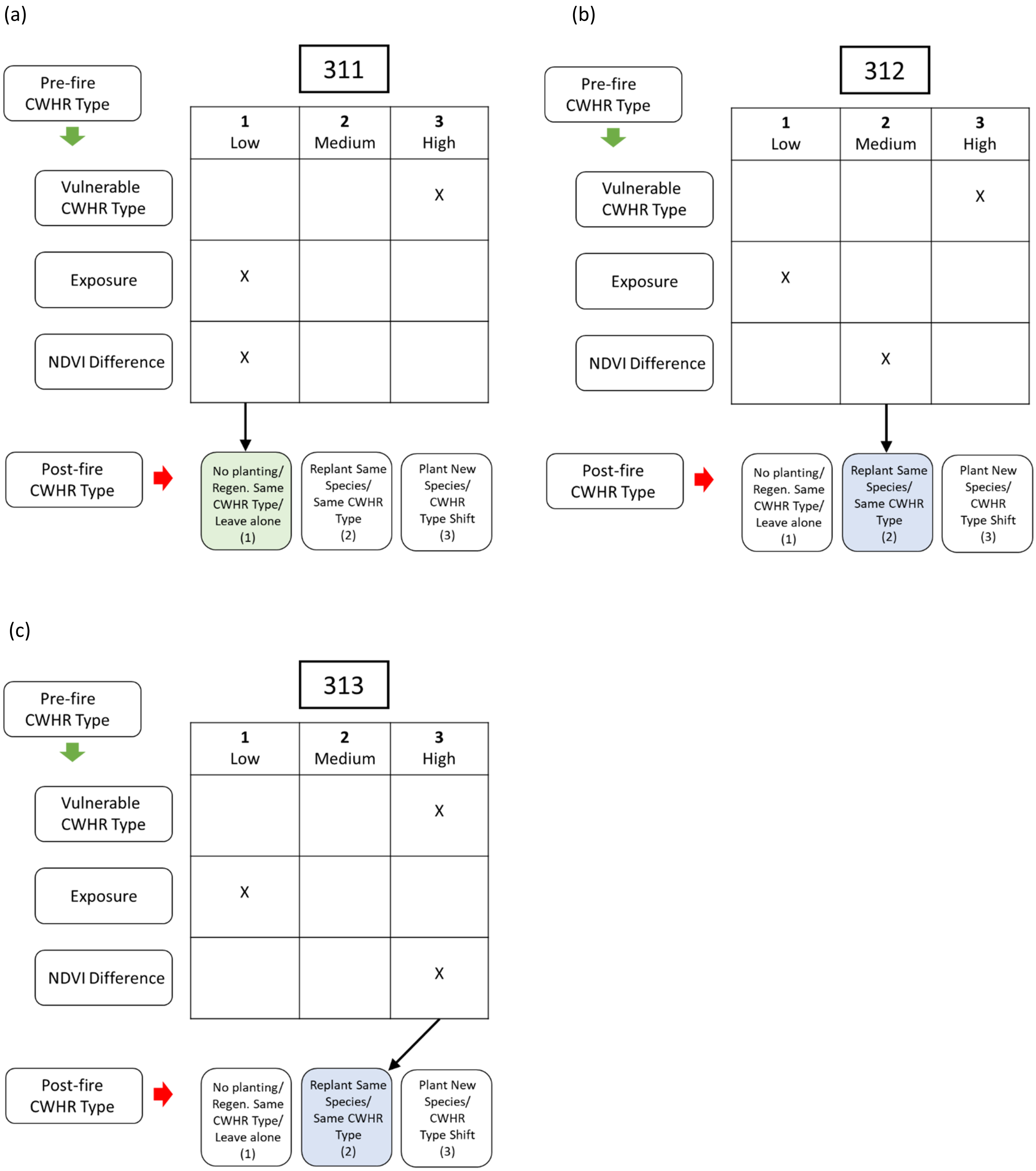


Figure 21: Restoration management model with planting recommendations. These figures depict high vulnerability and low exposure.

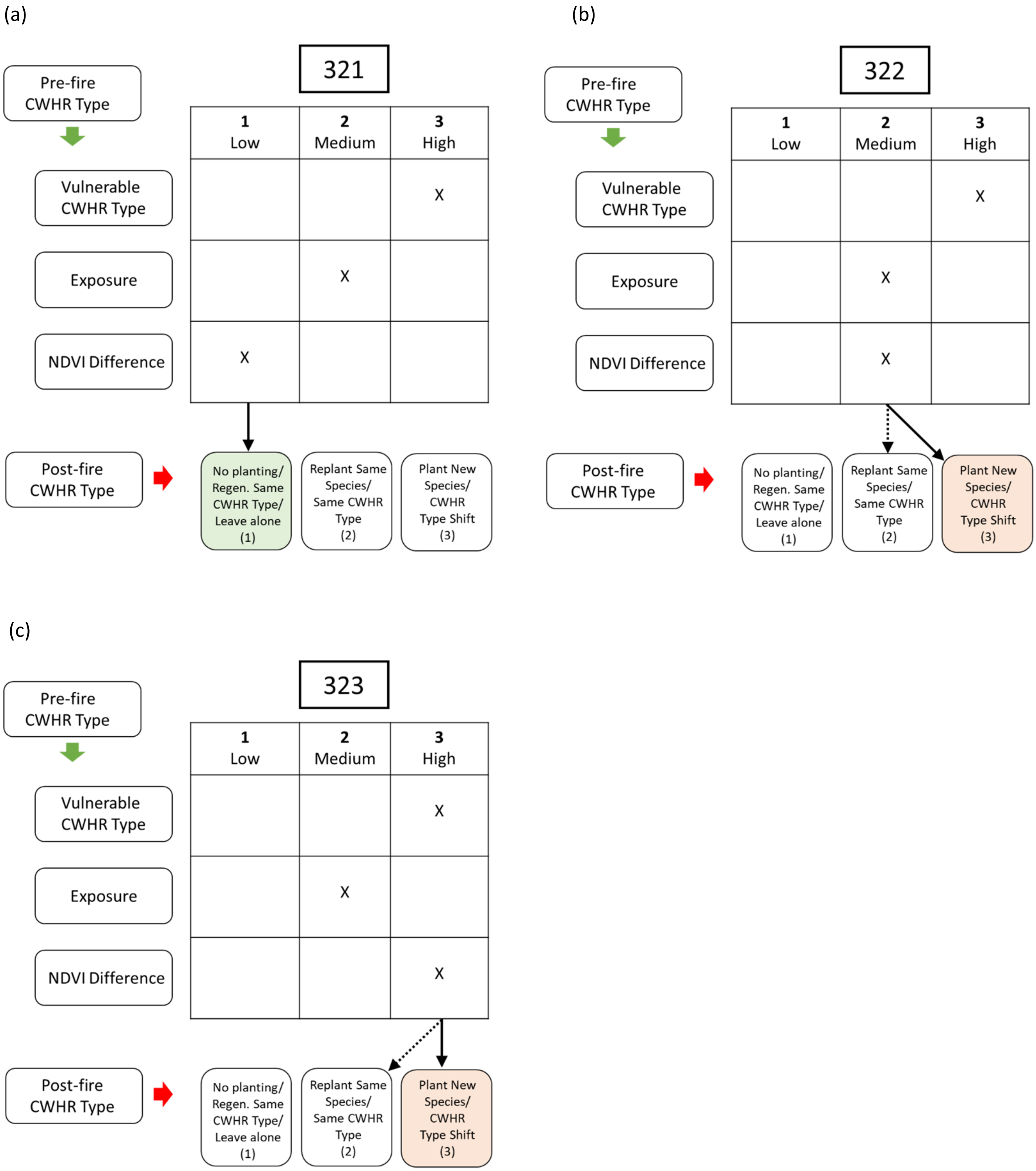


Figure 22: Restoration management model with planting recommendations. These figures depict high vulnerability and medium exposure.

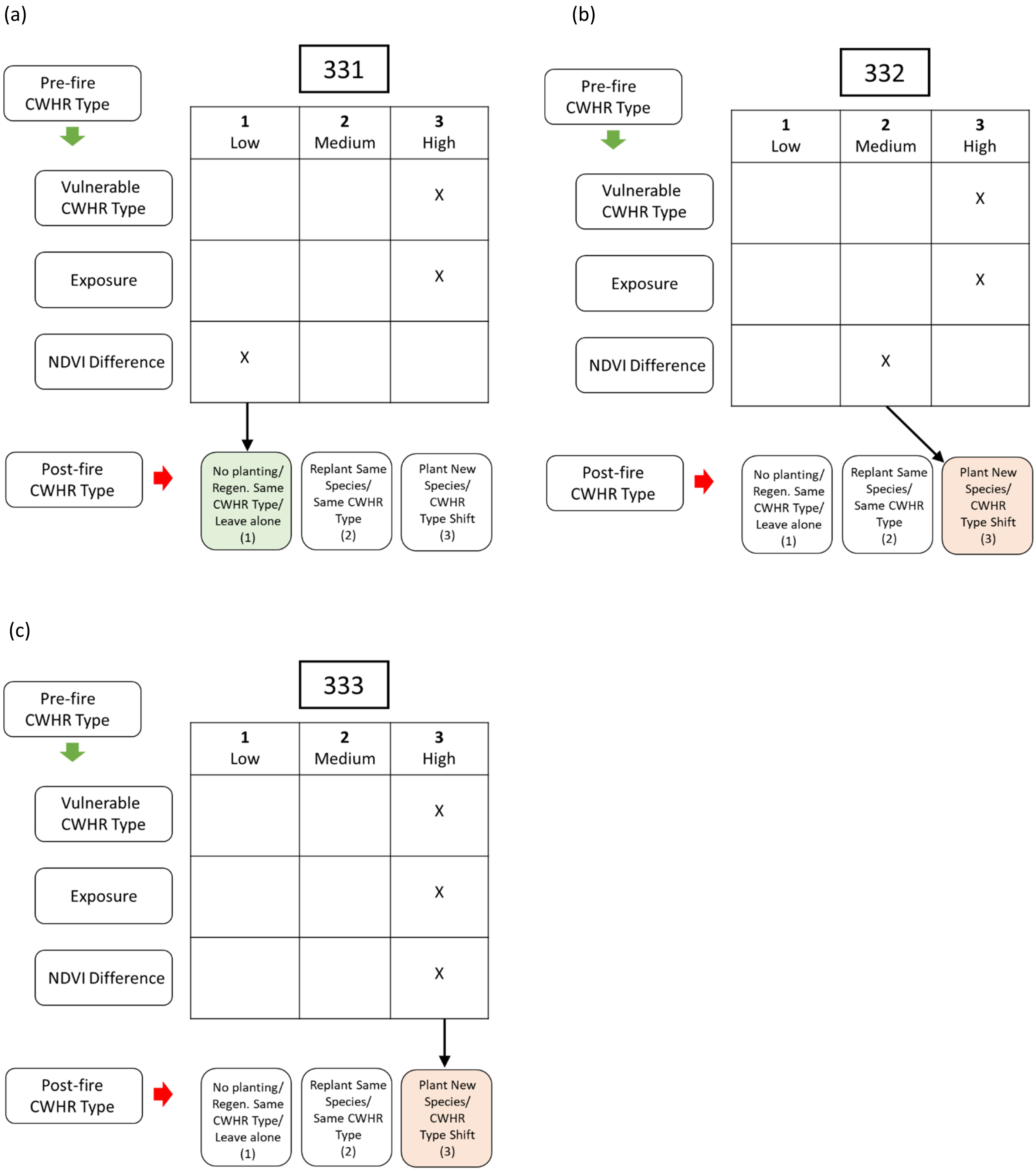


Figure 23: Restoration management model with planting recommendations. These figures depict high vulnerability and high exposure.

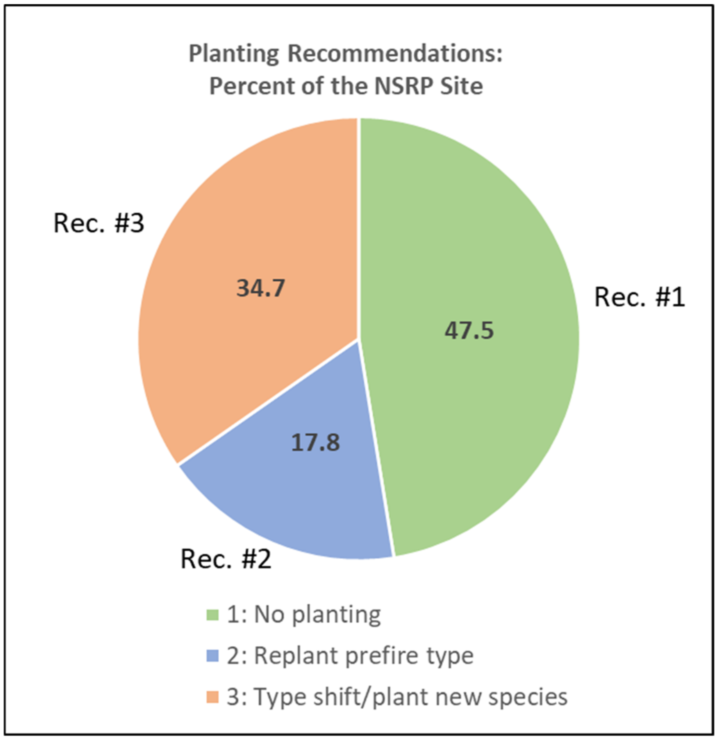


Figure 24: Percent of the NSRP site covered by each planting recommendation from the restoration model.

Table 9: Analysis of prefire CWHR vegetation type area (in hectares) within each planting recommendation (1, 2, and 3) class in the MNF NSRP study area.

CWHR Vegetation Type	#1 – No Planting	#2 – Plant Prefire	#3 – Type-Shift	Total
Annual Grassland (AGS)	533.8	8.3	58.9	600.9
Barren (BAR)	15.7	0.1	5.2	21.0
Blue Oak-Foothill Pine (BOP)	40.8	24.8	103.5	169.0
Blue Oak Woodland (BOW)	16.6	5.3	70.3	92.2
Coastal Oak Woodland (COW)	6.1	3.7	8.1	17.9
Closed-Cone Pine-Cypress (CPC)	72.9	510.8	507.4	1,091.1
Chamise-Redshank Chaparral (CRC)	1,076.7	4.7	785.4	1,866.8
Douglas-fir (DFR)	49.0	173.2	54.7	276.8
Mixed Chaparral (MCH)	3,799.8	29.3	1,666.1	5,495.1
Montane Chaparral (MCP)	519.6	3.5	87.7	610.7
Montane Hardwood-Conifer (MHC)	282.2	549.3	455.2	1,286.7
Montane Hardwood (MHW)	663.5	966.6	1,174.7	2,804.8
Montane Riparian (MRI)	14.0	0.1	0.1	14.1
Ponderosa Pine (PPN)	129.2	173.3	252.2	554.7
Sierran Mixed Conifer (SMC)	182.5	388.1	275.1	845.7
Valley Oak Woodland (VOW)	81.8	3.2	27.9	113.0
Total	7,484.0	2,844.0	5,532.5	15,860.5

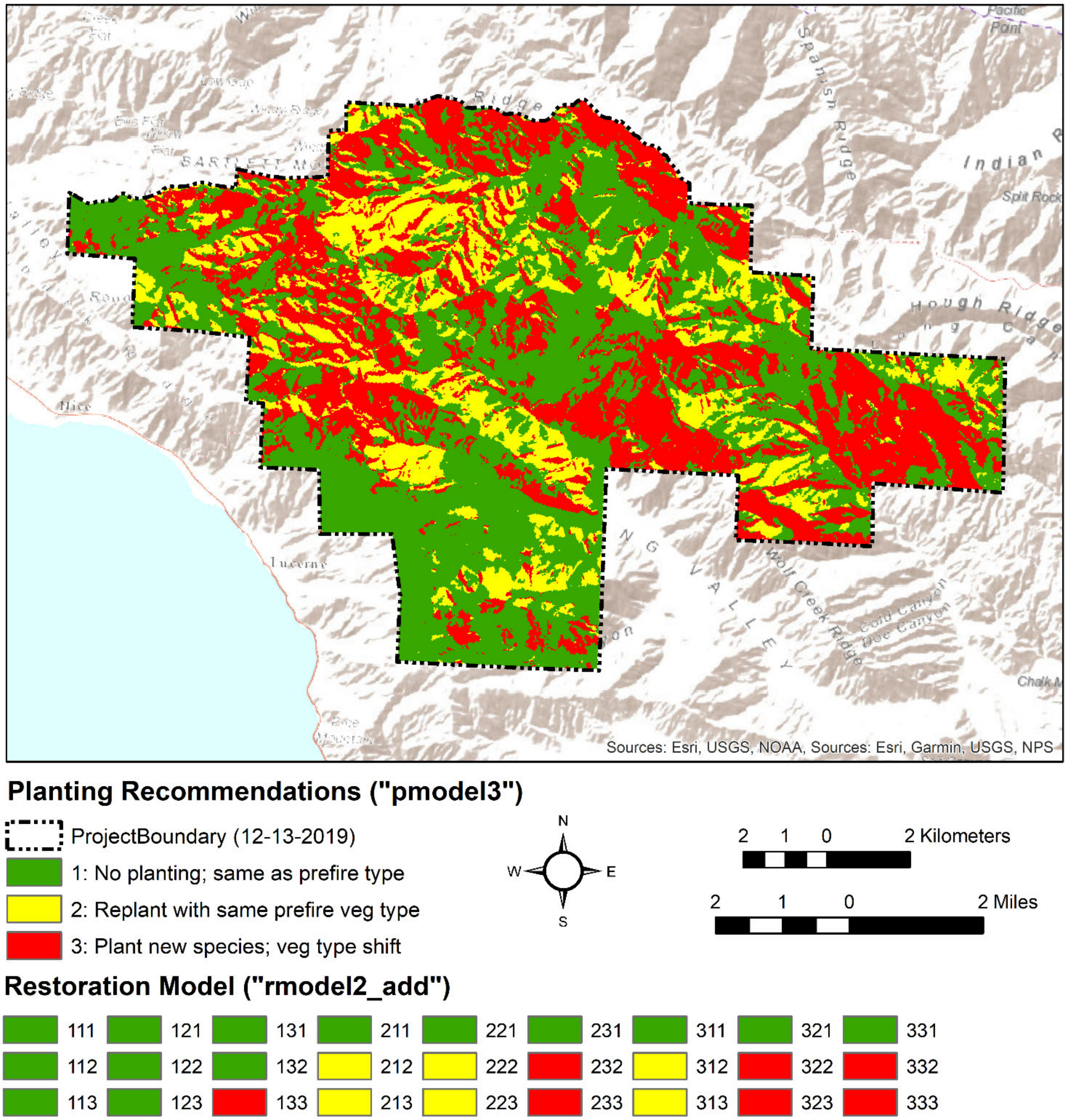


Figure 25: The decision support restoration model with each of the 27 unique combinations of the three variables: (1) vegetation vulnerability, (2) exposure, and (3) NDVI difference. The three planting recommendations derived from the restoration model are shown for the NSRP site in the MNF.

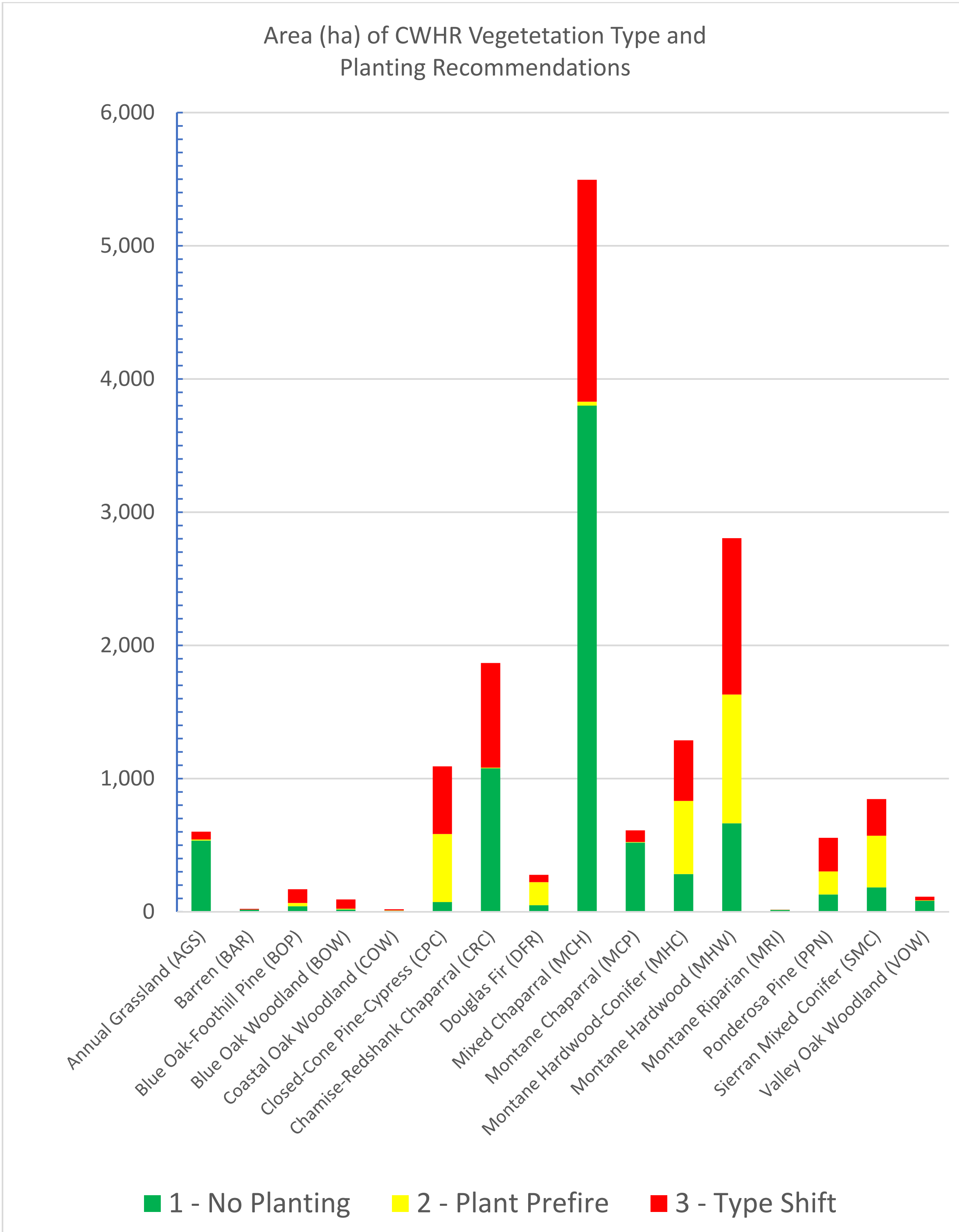


Figure 26: The area (ha) proportions of each planting recommendation class (1, 2, and 3) within each prefire CWHR vegetation type in the MNF NSRP study area.

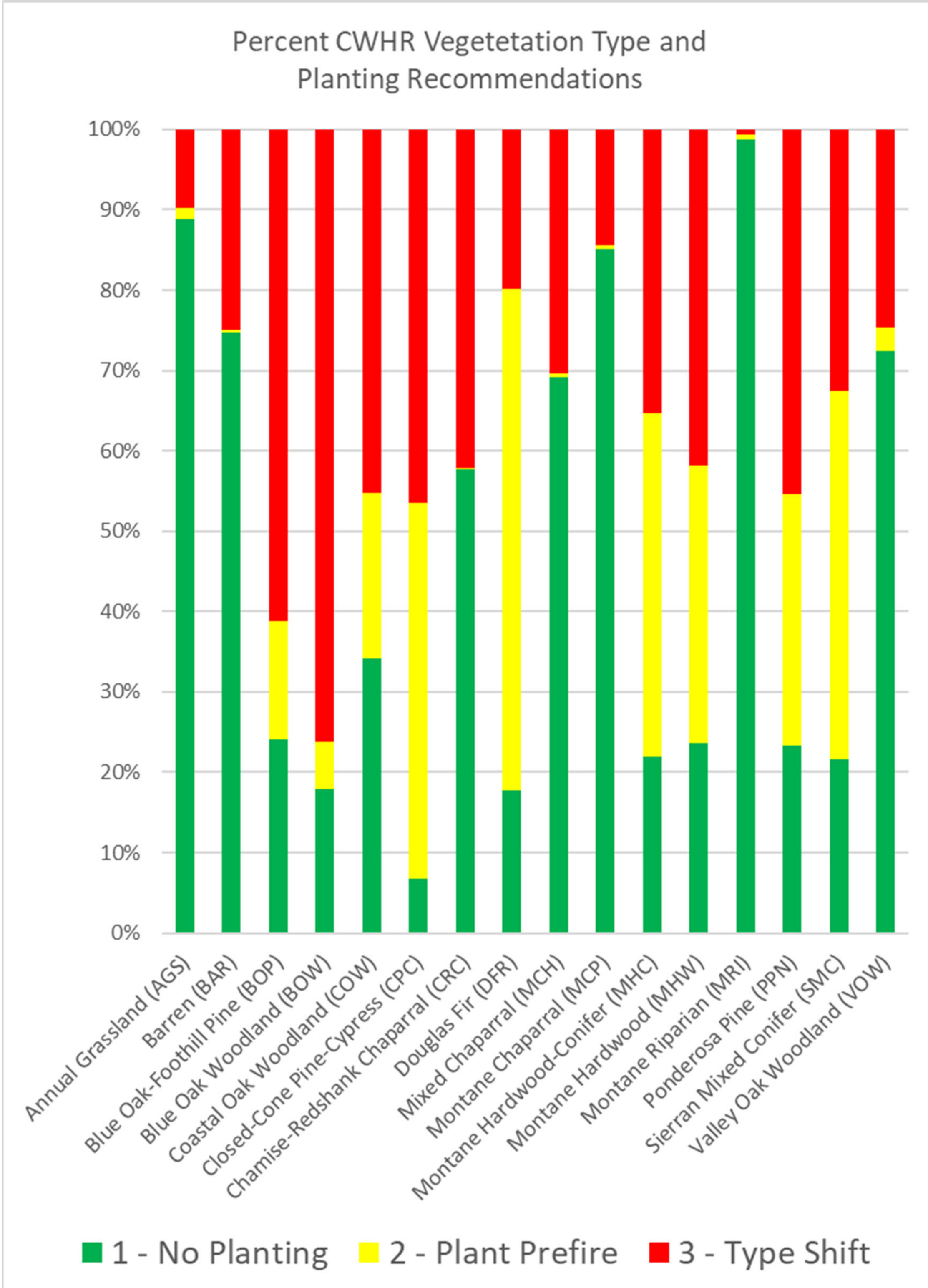


Figure 27: The percentage proportions of each planting recommendation (1, 2, and 3) class within each prefire CWHR vegetation type in the MNF NSRP study area.

3.8 Soil available water storage (AWS)

As described above (in the Data and Methods section), AWS measures the depth of the soil and its water holding capacity (in cm) available to plants, and is used in this study to prioritize where to first implement the planting recommendations. A map of the distribution of the five classes of soil AWS within the NSRP site is shown in Figure 28 and the areal extent (in hectares and acres) of each class and their relative proportions are shown in Table 10. Results from the analysis examining how soil AWS is distributed among the prefire vegetation communities at the NSRP site is presented in Table 11 with graphs by areal extent (Figure 29) and by their relative proportions (Figure 30).

It is notable that AWS Class 5 (the greatest AWS depth) is rather limited in extent occupying just 5.7% (2,223 acres) within the NSRP site. Class 4 is even more limited in extent, however, Class 3 is rather extensive covering almost 25% of the site (9,530 aces). The authors recommend prioritizing reforestation efforts in Class 5, then in Class 4 and Class 3 to have the best chance of successful plantings (i.e., maximizing potential survival rates of reforestation plantings and seedlings).

The three merchantable timber vegetation types, mixed conifer (SMC), Douglas-fir (DFR), and ponderosa pine (PPN) are shown on individual maps (Figures 31-33, respectively) at more zoomed-in scale to show their respective distributions in relation to soil AWS Class 5. As can be seen in Figure 31, there are numerous reforestation opportunities for SMC. Several opportunities exist for DFR (Figure 32) and PPN has the fewest replanting opportunities (Figure 33). It should be noted that 'type-shift' polygons (planting recommendation #3) for SMC and DFR might be able to be planted with PPN (according to Table 3, the vegetation community 'type-shift' sequence table).

Table 10: Analysis of soil available water storage (AWS) to a depth of 150 cm from the Lake County SSURGO GIS data

Soil AWS Class	Water Storage Depth (cm)	Area (ha)	Area (ac)	Percent
1	1.73 to 5.0	6,255.2	15,456.5	39.7
2	5.1 to 10.0	4,692.1	11,594.1	29.8
3	10.1 to 15.0	3,856.9	9,530.4	24.5
4	15.1 to 18.0	65.6	162.2	0.4
5	18.1 to 22.47	899.8	2,223.3	5.7
Total		15,769.5	38,966.4	100.0

Table 11: Analysis of soil available water storage (AWS) to a depth of 150 cm from Lake County SSURGO GIS data of CWHR vegetation type polygons reported as areal extent (in hectares) within each AWS class in the MNF NSRP study area. AWS is the volume of water that the soil can store that is available to plants. Low = 1.73-5 cm, Low/Med = 5.1-10 cm, Medium = 10.1-15 cm, Med/High = 15.1-18 cm, High = 18.1-22.47 cm. Due to limited coverage this table omits the following four CWHR types: Lacustrine, Pasture, Urban, Wet Meadow.

CWHR Vegetation Type	1 - Low Soil Water	2 - Low/Med Soil Water	3 - Medium Soil Water	4 - Med/High Soil Water	5 - High Soil Water
Annual Grassland (AGS)	59.6	160.1	140.6	40.4	117.9
Barren (BAR)	16.6	1.1	0.0	0.0	0.3
Blue Oak-Foothill Pine (BOP)	46.8	96.0	19.3	3.5	5.1
Blue Oak Woodland (BOW)	17.1	66.7	7.3	0.0	4.4
Coastal Oak Woodland (COW)	15.3	2.9	0.1	0.0	0.0
Closed-Cone Pine-Cypress (CPC)	596.2	262.1	146.9	2.7	67.6
Chamise-Redshank Chaparral (CRC)	1,236.5	561.0	65.5	4.7	13.3
Douglas Fir (DFR)	25.8	67.3	149.0	0.0	32.0
Mixed Chaparral (MCH)	2,954.1	1,764.6	706.4	5.9	80.3
Montane Chaparral (MCP)	245.4	255.0	89.8	0.0	14.8
Montane Hardwood-Conifer (MHC)	159.7	320.1	614.4	0.0	151.3
Montane Hardwood (MHW)	802.8	792.5	1,089.8	7.3	119.8
Montane Riparian (MRI)	1.7	1.4	5.0	0.0	0.0
Ponderosa Pine (PPN)	9.5	143.2	346.7	0.0	47.6
Sierran Mixed Conifer (SMC)	8.7	109.8	444.5	0.0	226.9
Valley Oak Woodland (VOW)	16.3	54.1	7.7	0.1	6.8

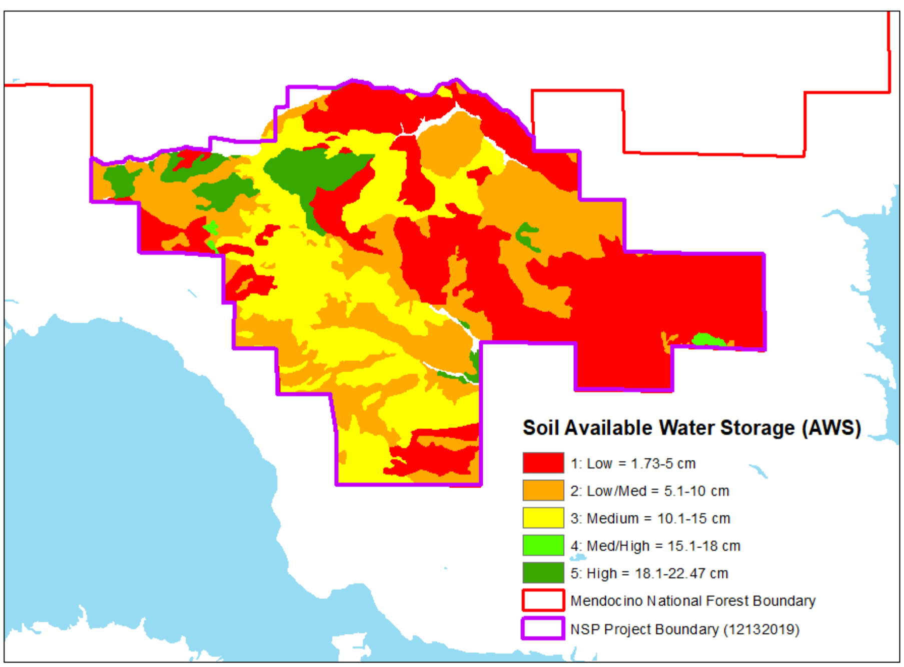


Figure 28: SSURGO soil available water storage (AWS) classified into five classes in the MNF NSRP site.

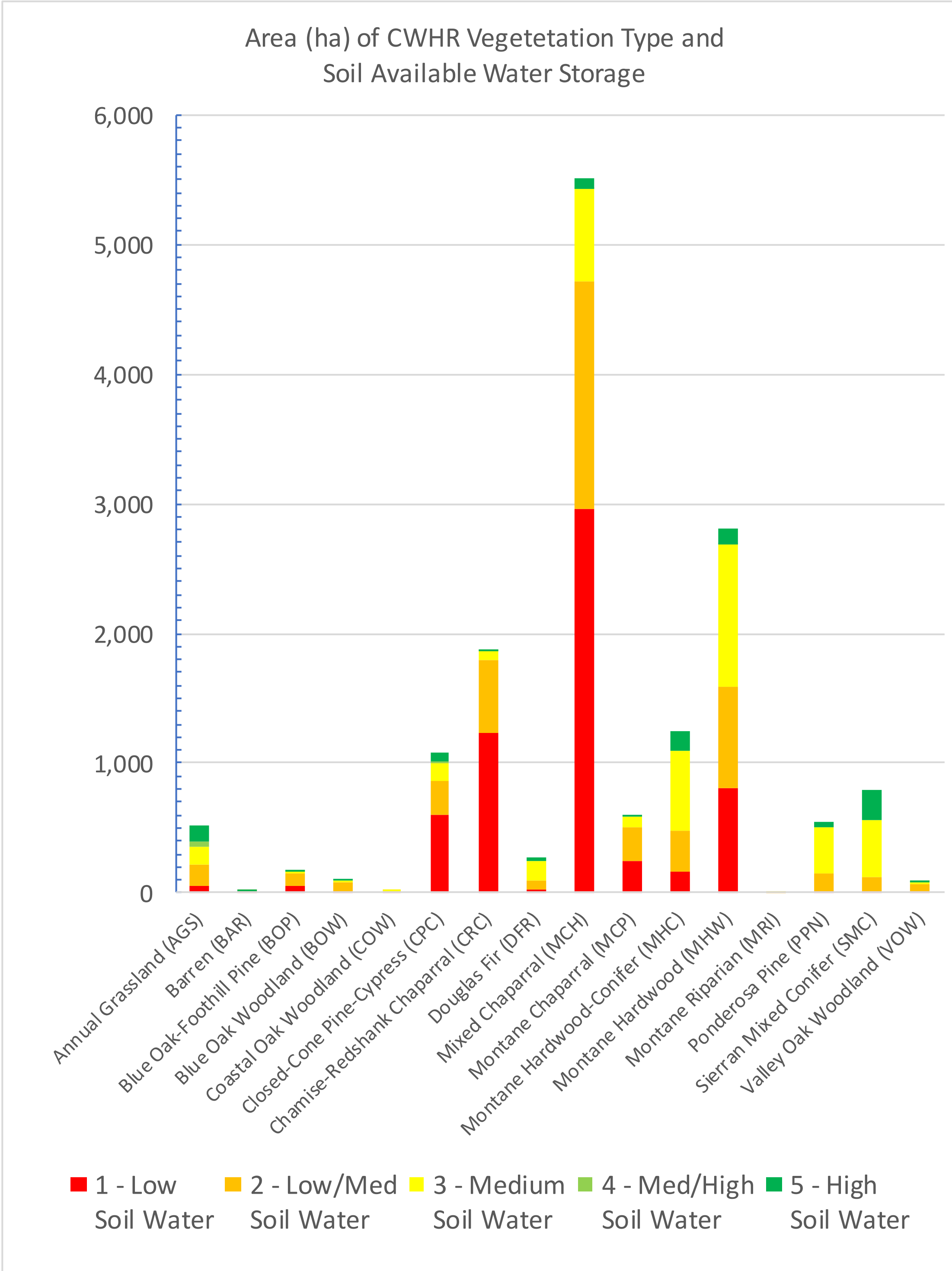


Figure 29: Soil available water storage (AWS) was classified into five classes: Low = 1.73-5 cm, Low/Med = 5.1-10 cm, Medium = 10.1-15 cm, Med/High = 15.1-18 cm, High = 18.1-22.47 cm. The areal (in hectares) proportions of each AWS class are shown for each CWHR vegetation type in the MNF NSRP study area.

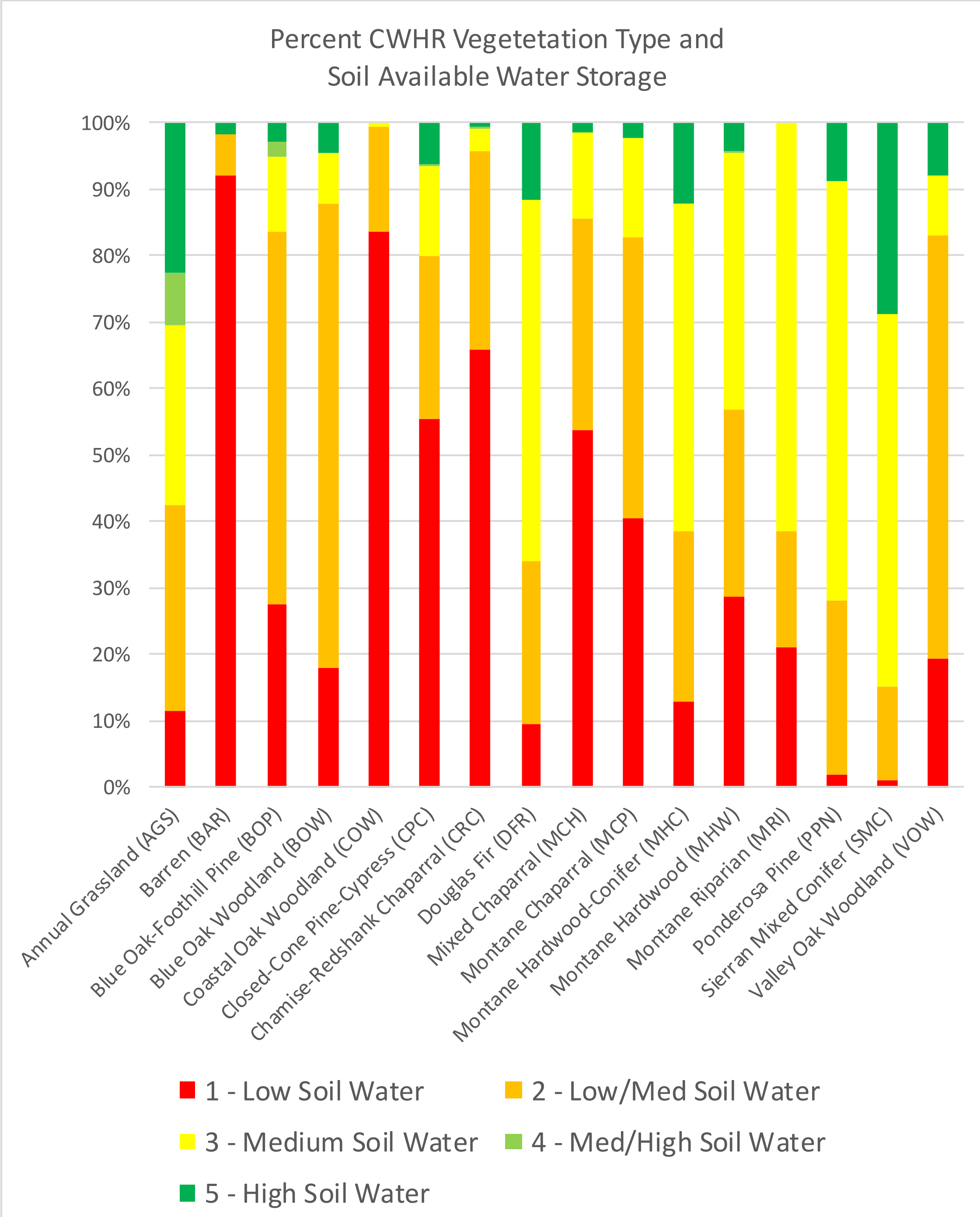


Figure 30: The five classes of soil available water storage (AWS) are shown as a percentage for each CWHR vegetation type in the MNF NSRP study area.

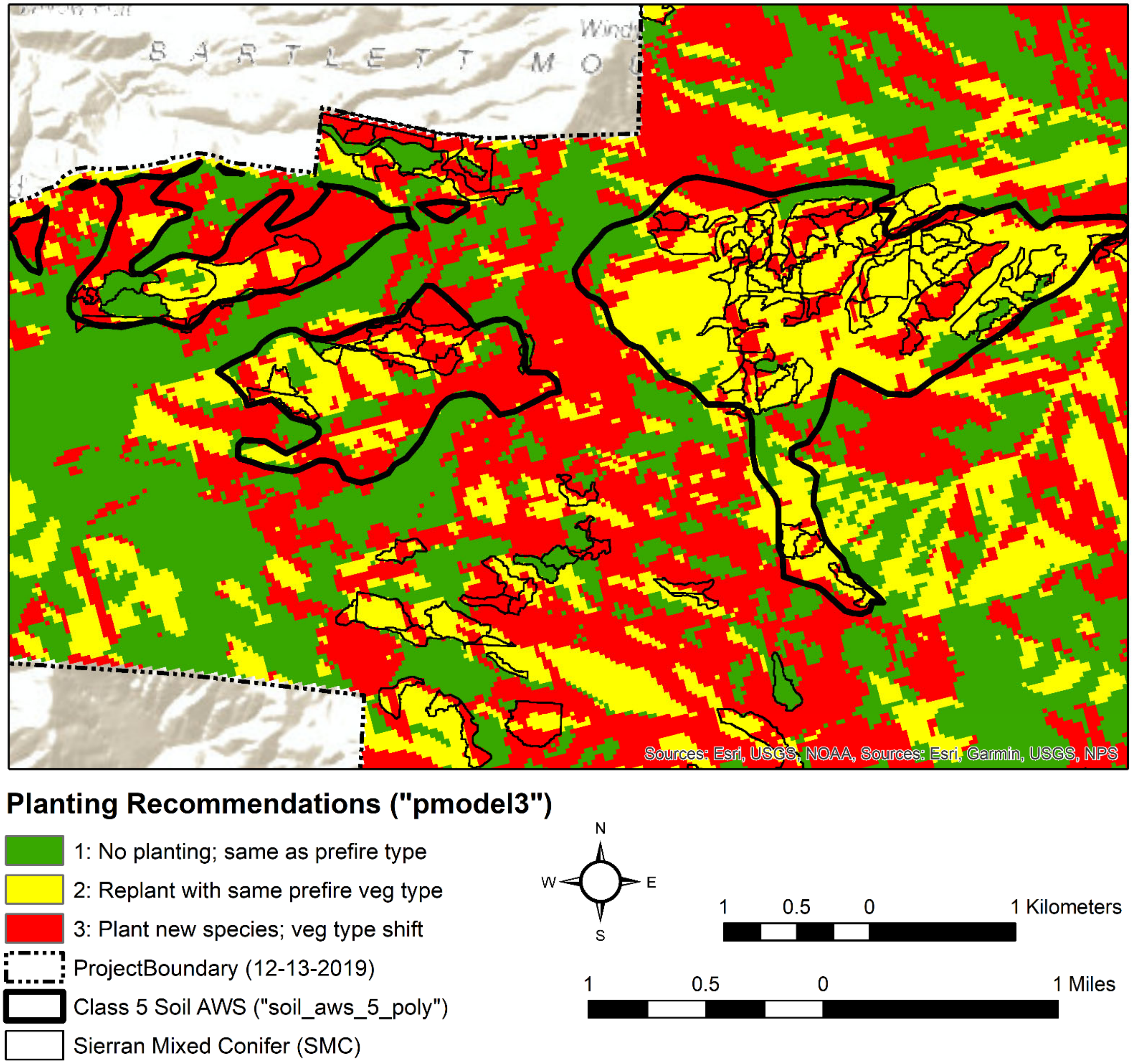


Figure 31: Mixed conifer (SMC) is shown in relation to soil AWS Class 5 with the planting recommendations. There are numerous polygons for replanting opportunities (see yellow areas) within soil AWS Class 5. SMC polygons that reflect planting recommendation #3 (red areas) may be able to be planted with Ponderosa Pine (PPN).

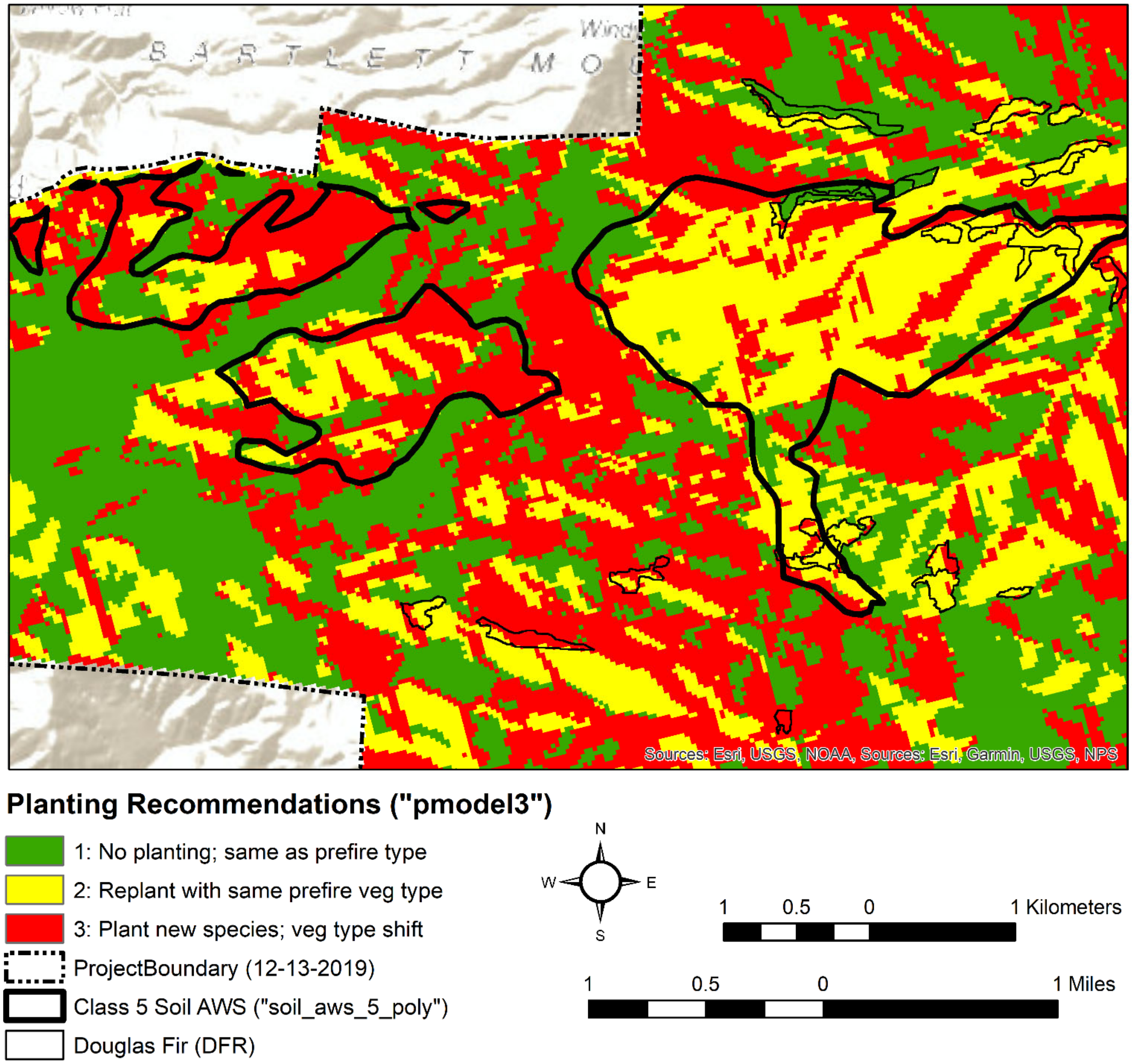


Figure 32: Douglas-fir (DFR) is shown in relation to soil AWS Class 5 with the planting recommendations. There are several polygons for replanting opportunities (see yellow areas) within soil AWS Class 5. DFR polygons that reflect planting recommendation #3 (see red areas) may be able to be planted with Ponderosa Pine (PPN).

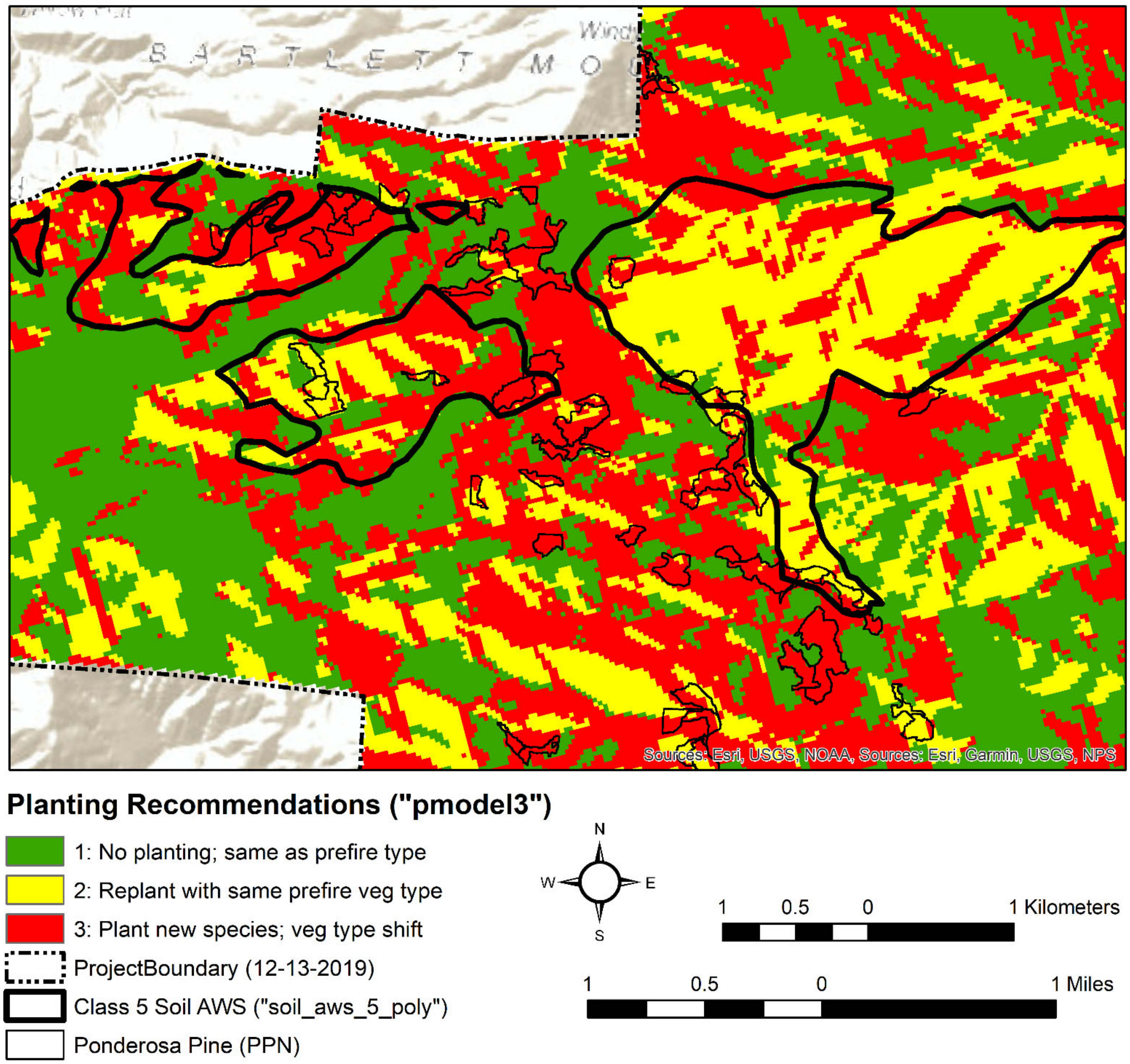


Figure 33: Ponderosa Pine (PPN) is shown in relation to soil AWS Class 5 with the planting recommendations. There are a limited number of polygons for replanting opportunities within soil AWS Class 5.

3.9 Plant selection database tool

To capture information on the NSRP project area plant communities and species, we created an Excel document consisting of four sheets. The first sheet, named “Guide” (see Figure 34 for a sample portion), contains a list of the project area plant communities. Using the land cover dataset provided by MNF, we identified the regionally appropriate CNPS vegetation alliances associated with each of the CWHR broad vegetation types. We found a total of 40 alliances that potentially occurred prefire in the NSRP boundary. We then created a table that contains the major plant species that can comprise each of the 35 alliances (Sawyer et al. 2009). Each row in the table includes CWHR types as identified by CNPS and CDFW, alliance name as identified by CNPS and CDFW (including the page number in Sawyer et al. 2009 with the alliance description), the name of the vegetation type found in the geodatabase provided by MNF, and dominant and subdominant plant species associated with the alliance. Note that the CWHR type “MHC” is not found in the CNPS system, so we used the “MHW” type in its place.

The second sheet, named “Plants” (Figure 35), contains a list of the plant species likely to have been found in the project area prior to the fire. We referenced the CalFlora database with documented species occurrences to manually create this list. This sheet was also populated with information obtained from CalFlora on all of the known animal species associated with each plant species as well as bloom periods for each species. The animal species are included as columns in this sheet, using abbreviations for the sake of table clarity. A total of 796 plant species are included in this sheet. The final two sheets list the insects (Figure 36) and bird species (respectively) that the abbreviations refer to.

This set of tables is meant to provide guidance to project site managers for potential species to include in palettes developed for site revegetation. For example, using the decision matrix described previously, a manager could decide to replant a ponderosa pine stand (i.e., “PPN” in the CWHR scheme). Using the table, a description of the “Ponderosa pine forest” alliance could be referenced in Sawyer et al. (2009). The table shows that ponderosa pine is the dominant species in this alliance, but the manager could also find that black oak and incense cedar are often part of the alliance as well. Referring to the “plants” sheet in the document, the manager can note that if they include incense cedar in the plantings, they will be providing host resources for Nelson’s hairstreak (for example).

	A	B	C	D	E	F	G	H	I	J
1	**CWHR (CNPS)**	**CWHR (CDFW)**	**CNPS Alliance (CNPS 2009)**	**Page**	**CNPS Alliance (CDFW 2005)**	**veg_existingveg_12132019**	**Species1 (dom)**	**Species 1a (dom**	**Species2**	**Species3**
8	PPN	PPN	Ponderosa pine forest	191	Ponderosa pine forest	Pacific ponderosa pine : Ponderosa Pine : Black Oak, Pa	*Pinus ponderosa*		*Abies concolor*	*Calocedru*
9	SMC	MHW, PPN, SMC	Ponderosa pine - Douglas fir fores	199	Douglas fir - ponderosa pine forest	Pacific ponderosa pine - Douglas-fir : Douglas-Fir - Ponc	*Pinus ponderosc*	*Pseudotsuga m*	*Abies concolor*	*Arbutus n*
10	BOP	BOP	Ghost pine woodland	206	Foothill pine	Blue oak - digger pine : Gray Pine : Interior Mixed Hardv	*Pinus sabiniana*		*Aesculus califorr*	*Juniperus*
11	DFR	DFR, SMC	Douglas fir forest	232	Douglas fir	Pacific Douglas-fir : Pacific Douglas-Fir : Canyon Live Oa	*Pseudotsuga menziesii*		*Abies concolor*	*Acer macr*
12	SMC	DFR, SMC	Douglas fir - Incense cedar forest	236	Douglas fir - Incense cedar forest		*Pseudotsuga m*	*Calocedrus decurrens*		*Abies con*
13	MHW	MHW, MHC	Canyon live oak forest	249	Canyon live oak forest	Canyon live oak : Canyon Live Oak : <null>	*Quercus chrysolepis*		*Abies concolor*	*Acer macr*
14	BOW, BOP	BOW	Blue oak woodland	252	Blue oak woodland	Blue oak - digger pine : Blue Oak : <null>	*Quercus douglasii*		*Aesculus califorr*	*Pinus sab*
15	MHW	MHW, MHC	Oregon white oak woodland	258	Oregon white oak woodland	Oregon white oak : Oregon White Oak : <null>	*Quercus garryana*		*Juniperus occide*	*Pinus jeff*
16	MHW	MHW, MHC	California black oak forest	261	Black oak forest and woodland	California black oak : Black Oak : <null>, California black	*Quercus kelloggii*		*Abies concolor*	*Arbutus n*
17	VOW	VOW	Valley oak woodland	265	Valley oak woodland (and forests)	Blue oak - digger pine : Valley Oak : <null>	*Quercus lobata*		*Alnus rhombifol*	*Fraxinus l*
18	BOW, MHW	MHW, BOW, BOP	Interior live oak woodland	273	Interior live oak woodland	Canyon live oak : Interior Live Oak : <null>	*Quercus wislizeni*		*Aesculus califorr*	*Arbutus n*
19	COW	MHW, MHC, COW	California bay forest	296	California bay forest	California coast live oak : California Bay : <null>	*Umbellularia californica*		*Acer macrophyll*	*Aesculus c*
20	SMC	PPN, SMC	Mixed conifer forest	196	Ponderosa pine - Incense cedar forest		*Pinus ponderosc*	*Calocedrus decu*	*Abies concolor*	*Pinus jeff*
21	MRI	MRI	Black cottonwood forest	222	Black cottonwood riparian forests and woodlands		*Populus trichocarpa*		*Abies concolor*	*Acer macr*
22	CRC	CRC	Chamise chaparral	317	Chamise chaparral	Hard chaparral : Chamise : <null>	*Adenostoma fasciculatum*		*Arctostaphylos (*	*Arctostap*
23	MCH, CRC	MCH	Eastwood manzanita chaparral	350	Eastwood manzanita chaparral	Hard chaparral : Manzanita Chaparral : <null>	*Arctostaphylos glandulosa*		*Adenostoma fa:*	*Baccharis*
24	MCP	MCP	Green leaf manzanita chaparral	371	Greenleaf manzanita chaparral	Hard chaparral : Greenleaf Manzanita : <null>	*Arctostaphylos patula*		*Amelanchier aln*	*Arctostap*
25	MCH, MCP	MCH, MCP	White leaf manzanita chaparral	379	Whiteleaf manzanita chaparral	Hard chaparral : Manzanita Chaparral : <null>	*Arctostaphylos viscida*		*Adenostoma fa:*	*Amelanch*

guide | plants | insects | birds

Ready

Figure 34: A portion of the plant selection table describing plant alliances in the project area.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
1	**Species - S**	**Species -**	**ID**	**T/S/G/H/F**	**Bloom (s)**	**Bloom (e)**	**Bees**	**Native be**	**Bumble b**	**Honey be**	**datory ins**	**Beetles**	**Butterflies**	***AdeBre***	***AdBrCa***
2	*Abies concolor*	white fir		T	5-May	6-Jun							Y		
3	*Abies magnifica*	red fir		T	5-May	6-Jun							Y		
4	*Acer macrophyllum*	bigleaf maple		T	4-Apr	5-May	Y	pollen/nectar		pollen/nectar					
5	*Achillea millefolium*	yarrow		H	4-Apr	8-Aug	Y	pollen/nectar					Y		
6	*Achyrachaena mollis*	Blow-Wives		H	4-Apr	5-May									
7	*Acmispon americanus*	Spanish lotus		H	4-Apr	7-Jul							Y		
8	*Acmispon brachycarpus*	short podded lotus		H	3-Mar	6-Jun							Y		
9	*Acmispon denticulatus*	toothed lotus		H	5-May	7-Jul							Y		
10	*Acmispon grandiflorus*	large leaved lotus		H	4-Apr	7-Jul							Y		
11	*Acmispon heermannii*	Heermann's lotus		H	4-Apr	7-Jul							Y		
12	*Acmispon nevadensis*	Sierra lotus		H	5-May	8-Aug							Y		
13	*Acmispon parviflorus*	Hill lotus		H	3-Mar	6-Jun							Y		
14	*Acmispon wrangelianus*	Chilean trefoil		H	3-Mar	4-Apr							Y		
15	*Aconogonon davisiae*	Davis knotweed		H	6-Jun	8-Aug									
16	*Actaea rubra*	Baneberry		H	5-May	7-Jul									
17	*Adenocaulon bicolor*	Trail plant		H	7-Jul	8-Aug									
18	*Adenostoma fasciculatum*	Chamise		S	6-Jun	8-Aug	Y	pollen/nectar							
19	*Adiantum aleuticum*	Five finger fern		F											

Figure 35: A portion of the table with potentially occurring plant species and their ecological associations.

	A	B	C
1	**Abbreviation**	***Scientific name***	**Common name**
2	*AdeBre*	*Adelpha bredowii*	California sister
3	*AdBrCa*	*Adelpha bredowii californica*	California Sister
4	*AntCet*	*Anthocharis cethura*	Desert Orangetip
5	*AntLan*	*Anthocharis lanceolata*	Gray Marble
6	*AntSar*	*Anthocharis sara*	Pacific Orangetip
7	*ApoMor*	*Apodemia mormo*	Mormon Metalmark
8	*AtaCam*	*Atalopedes campestris*	field skipper
9	*AtlHal*	*Atlides halesus*	great purple hairstreak
10	*BatPhi*	*Battus philenor*	pipevine swallowtail
11	*BreExi*	*Brephidium exile*	pygmy blue
12	*CalAug*	*Callophrys augustinus*	Brown Elfin
13	*CalEry*	*Callophrys eryphon*	Western Pine Elfin
14	*CalNel*	*Callophrys nelsoni*	Nelson's Hairstreak
15	*CalNem*	*Calephelis nemesis*	Fatal Metalmark
16	*CalPer*	*Callophrys perplexa*	Bramble Hairstreak Butterfly
17	*CaShCo*	*Callophrys sheridanii comstocki*	Comstock's Hairstreak
18	*CaShLe*	*Callophrys sheridanii lemberti*	Green Hairstreak
19	*CelLad*	*Celastrina ladon*	spring azure
20	*CeLaEc*	*Celastrina ladon echo*	Echo Blue

Figure 36: A portion of the table listing insect and bird species associated with potential plant species.

4. Discussion

The goal of this study is to identify a vegetation management program at the NSRP site in the MNF to maintain ecological integrity and to establish desired future conditions within the project area through a combination of active and passive management. The impacts of the Mendocino Complex Fire in 2018 were extensive and severe as seen in the RAVG analysis and the NDVI analysis in this study. Limited personnel and funding for restoration planting and direct manipulation of landscape factors requires that prioritization (sensu Meyer et al. 2021) be given to those areas with the best chances of success within the next 5-10 years to set a positive trajectory for recovery of ecosystem composition, structure, and functional process needed to maintain the ecological services provided by those landscapes. Towards these ends, this study's objectives sought to inform management personnel and triage readily identifiable portions of the site (land facets) that are likely to return to prefire vegetation communities and portions that are not, and to provide a possible roadmap to traditional and practicable alternative management scenarios. The planting recommendations are designed for this purpose. Planting recommendation #1 is passive management because it identifies areas at the site that can be expected to allow natural processes to regenerate the prefire vegetation type. Planting recommendations #2 and #3 are active management actions designed to guide land managers to either replant the prefire vegetation type (planting recommendation #2) or plant new species because the site has been assessed to likely 'type-shift' to a new vegetation community (planting recommendation #3).

The relative proportions of each planting recommendation (Figure 24) were calculated as 47%, 18% and 35% for planting recommendations #1, #2 and #3, respectively. The result for planting recommendation #1 (i.e., no planting; allow natural regeneration) is somewhat expected, given 50.2% of the NSRP site is covered by chaparral vegetation types (MCH, CRC, MCP) and reproduction and recovery of the species in those vegetation types are driven by frequent fire cycles (Keeley & Davis 2007). In addition, a large proportion of those types occur on high exposure land facets (Figure 6). The result for planting recommendation #2 (i.e., replant with the same species as the prefire vegetation type) is also not surprising given only 10.5% of the site is merchantable timber types (DFR, SMC, PPN); 6.9% is Closed-Cone Pine-Cypress (CPC); and 2.4% are low elevation oak communities (BOP, BOW, VOW). The magnitude of the result for planting recommendation #3 is somewhat surprising because more than one third of the site is projected to 'type-shift' to a new plant community.

Due to the severity of the fire effects of the Mendocino Complex Fire and combined with increasing climate change impacts it is expected that some former conifer-dominated areas may not be capable of supporting the same or similar plant communities in the future (Shive et al. 2018; Coop et al. 2020; Wang et al. 2022). These areas, where plant community 'type-conversions' may be expected, are identified (in planting recommendation #3) in order to enable the MNF managers to develop a suite of better adapted plant species and communities that will be resilient to anticipated future conditions (i.e., fire regime and climate change). To help guide land manager's decisions regarding selecting a "new" plant community type, a plant community sequencing model (Table 3) was developed based on two variables: (1) a moisture gradient and (2) elevation position (high and low). It will require expert judgement by MNF personnel (ecologists, botanists, and silviculturists) to assess to what degree the plant community is likely to shift (i.e., one or more boxes to the left in Table 3) so that appropriate species can be chosen for the particular site in question. Those personnel could decide to maintain the prefire vegetation if upon a site visit the site has a microclimatic effect not reflected in the modeled variables for the restoration management model. The plant selection database tool for this project is designed to assist MNF personnel in choosing appropriate plant species for a reforestation site.

We recognize that MNF forest management personnel might desire reforestation of prefire areas with merchantable timber. At the NSRP site these vegetation types are dominated by conifer vegetation community types such as Douglas-fir (DFR), mixed conifer (SMC), and ponderosa pine (PPN). Prior to the Mendocino Complex Fire, these three types comprised 4,138 acres (10.5%) of the NSRP site. However, 1,515 acres (representing 37% of the prefire distribution of DFR, SMC, and PPN at the site) occupy high exposure land facets which likely will not be able to support these vegetation types in the future. According to the vegetation community 'type-shift' sequence model developed for this project (Table 3) it is expected that SMC and DFR on high exposure land facets could shift to PPN or Montane Hardwood (MHW) and PPN to shift to MHW. As stated above in the Results section, it should also be noted that the SMC and DFR sites that are projected to type-shift could shift to PPN, depending on the exposure of the site (see Table 3).

The other vegetation types are expected to either regenerate on their own or be actively managed with plantings or broadcast seeding. In some prefire areas dominated by conifers that experienced nearly complete mortality, oak woodlands are likely to regenerate through stump sprouting (including mixed-conifer forest stands that had a significant component of oak prior to the fire). These areas are logical places to consider managing for oak woodlands at localized spatial scales. Active management to promote this new oak vegetation community is recommended by planting (e.g., acorns) or broadcast seeding understory species associated with oak woodlands. Efforts should be made to protect the stump sprouts from damage by equipment and field personnel. These new oak communities should be maintained by prescribed fire in future years. Traditionally, aboriginal burning was a local scale endeavor designed to enhance oak woodland resources for Native American people (Kimmerer & Lake 2001). However, in today's altered landscape these activities must be integrated at the landscape scale (Wohling 2009) to achieve larger spatial scale management objectives (i.e., maintaining healthy oak woodlands). It is well known that without frequent, low intensity fire these areas are vulnerable to Douglas-fir invasion (Hunter & Barbour 2001).

Plant diversity in California reflects adaptation to biogeographic and geological conditions that are restricted to western North America, most significantly the Mediterranean-type (summer dry) climate. As with the four other geographic regions on the planet with Mediterranean-type climates, fire has been a significant evolutionary factor for most California plant species. Many forest-associated California plant lineages, including conifers and broadleaved deciduous angiosperms, are derived from ancestors that differentiated in temperate northern North America after the end of the Cretaceous Period, and these lineages evolved with significant exposure to summer drought and periodic fire (Keeley et al. 2011; Pausas & Schwilk 2012; Rundel et al. 2018). These evolutionary histories have important implications for developing management responses to the effects of climate change, which include increased aridity, longer and/or deeper drought, and increased fire.

Recent advances in genomic studies of the beech family (Fagaceae), coupled with physiological studies of responses to moisture stress, demonstrate that the 'California' clades of oaks (*Quercus*), which include characteristic species defining many California landscapes in terms of both vegetation structure and biomass, exhibit traits that have been shaped by their evolution in western landscapes. Oak species in the three primary California clades (as well as those of their close California relatives, tanoak [*Notholithocarpus*] and the golden chinkapins [*Chrysolepis*]) have differentially adapted to environmental conditions that are important for climate-change response (Baldocchi & Xu 2007, Hipp et al. 2018. Cavender-Bares 2019, Kremer & Hipp 2020, Manos & Hipp 2021).

An existing (and fundamental) ecological pattern long-known for California is a decline in ambient moisture availability from north to south, with a secondary pattern of declining moisture availability as distance increases inland from the coast. Ecological studies of various plant and animal clades have documented decreased biodiversity trends in parallel with those gradients, particularly in clades from ancestors with a northern temperate origin (Hawkins et al 2003, Ackerly 2009, Lancaster & Kay 2013). California's native oak species also demonstrate species-richness patterns correlated with ambient moisture availability, although the patterns are interwoven with the degree that each species tolerates moisture stress (Skelton et al. 2018, 2021). The pattern is related evolutionarily to the time of differentiation of species in each oak clade: earlier-evolving species are typically less-adapted to moisture stress than are later-evolving species. The patterns are associated with development of California's Mediterranean-type climate, which began about the middle of the Miocene Epoch ca. 15 million years ago (Ackerly 2009, Rundel et al. 2018). Notably, many earlier-evolving species commonly occur as trees in moist-forest landscapes, which also have northern-affinity conifer species, while most of the later-evolving oak species occur as dominant or codominant shrubby species in warmer and drier inland and southerly landscapes.

The evolutionary adaptations of California's native plant species to moisture stress is highly relevant for climate-change adaptation. Physiological studies of drought tolerance often focus on the ability of plant hydraulic systems (xylem tissues in root, stem, and leaf) to withstand decreases in atmospheric and soil moisture, which can lead to xylem 'cavitation' and loss of hydraulic function, loss of photosynthetic capability, or even hydraulic failure and death. Water transport in plants is fundamentally a physical process mediated by a cell-turgor gradient from root to leaves, which is ultimately driven by transpiration through stomata. In consequence, plant evolution is deeply affected in multiple ways by the tradeoff between potential hydraulic fracture and maintenance of photosynthesis (McDowell et al. 2008, Brodribb & Cochard 2009, Choat et al. 2018, Brodribb et al. 2020).

Climate-change studies that incorporate increased moisture stress often indicate that low- and mid-elevation conifer forests are likely to undergo changes in structure and composition to include more drought-tolerant species, typically hardwoods, and specifically to be dominated by the oak species that already occur in those landscapes (e.g., McIntyre et al. 2015, Liang et al. 2017). Oaks exhibit a variety of adaptations in response to increasing moisture stress (summarized in Baldocchi & Xu 2007), including physical modifications in xylem characteristics to resist cavitation; changes in root architecture to access available groundwater; changes in leaf size, specific area, and deciduousness; and even plant size at maturity. Less drought-tolerant California oak species (i.e., those typically associated with moist landscapes dominated by forests) generally reach reproductive maturity as trees, while the shrubbiness typical of oak species that occur in shrublands represents an adaptation among California's oak clades to an increasing summer moisture deficit (Skelton et al. 2018, 2021; Roberts *in review*).

Interactions among groundwater depth and plant hydraulic processes affect local survival and competition among species. In the Klamath ecoregion, relatively drought-tolerant Douglas-fir and ponderosa pine are widely involved in regional competition with Oregon white oak (aka Garry oak; *Quercus garryana*) and California black oak (*Quercus kelloggii*) for light and for soil moisture. Landscapes in which this evolutionary dynamic is played out include lower-elevation habitat types like Mixed Evergreen Forest and Northern Oak Woodland, as well as mid-elevation habitat types like Mixed Conifer Forest. The dynamics of such competition are well-described for the contest involving Garry oak and Douglas-fir (e.g., by Schriver et al. 2018, and other earlier studies), in which oak-dominated woodlands can be invaded by shade-tolerant Douglas-firs, which are able to overtop and shade out the oaks unless low-intensity surface fires occur that kill the young conifers.

Recent studies (e.g., Hahm et al. 2018, 2019), however, have also shown that the competition between these two species occurs for soil moisture. Focused studies of stem hydraulics in these two species indicate that both are relatively intolerant of intense moisture deprivation (not surprisingly, as both species are modern representatives of specific clades that first appeared in the Oligocene Epoch in western North America, in the temperate northern forests of the late Paleogene Period). However, Garry oaks share a characteristic trait with other California oaks in varying the development of subsurface root systems according to the presence of groundwater (Garry oak also has a somewhat greater tolerance for stem hydraulic stress than does Douglas-fir). In addition, Garry oak sprouts abundantly from root-crowns of trees killed in higher-intensity fires, which typically remove most Douglas-fir trees, reducing competition for light for the sprouting oaks. The ecological outcome of these interactions is that both Douglas-fir and Garry oak are well-adapted to the current ranges of climate and ecological dynamics that exist in lower elevations in the Klamath ecoregion.

A similar dynamic occurs among black oak, Douglas-fir, and ponderosa pines in mid-elevation mixed-conifer landscapes. Black oak is somewhat more tolerant of stem hydraulic stress than is Garry oak, and ponderosa pine is somewhat more tolerant than is Douglas-fir. Black oak can tap deeper subsurface water than do the conifers, but the conifers can overtop and shade out the oaks in the absence of periodic low-intensity fire. In addition, black oaks killed in higher-intensity fires sprout abundantly from root-crowns, a trait that gives this species a competitive advantage in landscapes that experience larger, more common, or higher-intensity fires. Black oak seedlings are moderately shade-tolerant, and can frequently be detected scattered widely in second-growth mixed-conifer stands when there are parent trees in the vicinity (Steller's jays [*Cyanocitta stelleri*] are 'scatter-hoarding' residents that commonly cache acorns far outside the seedfall perimeter of parent oaks). Within the Klamath ecoregion, it appears likely that similar dynamics exist for canyon live oaks, which are often widely dispersed in low- and mid-elevation forested landscapes, but that relationship is not currently well-documented.

As noted in the Introduction, in the Klamath ecoregion the propensity toward, and stability of, alternative states is a consequence of the geological and evolutionary age of the physical landscape, the moisture availability resulting from its geographical location in the state's northwestern (moist) corner, and the length of the evolutionary history of the species that occur in these landscapes (Whittaker 1960, Sawyer 2006, Ackerly 2009, Odion et al. 2010, Halofsky et al. 2011, Lancaster & Kay 2013, Estes et al. 2017, Tepley et al. 2017, Miller et al. 2019, Schriver et al. 2018, McCord et al. 2020, Jules et al. 2022). The antiquity of the Klamath Mountains as a geographic feature is widely regarded as a principal factor supporting high biodiversity in the Klamath ecoregion. The importance of the length of evolutionary time in which the clades of both conifers and anthophytes that produced the species present today have been exposed to the selective factors in these landscapes is, however, a relatively recent outcome of the development of genomic technology and the ability of scientists to apply it to evolutionary issues, and further insights into these relationships are likely.

Assessing plant hydraulic functional capability provides insight into climate-change adaptation in California landscapes. Hydraulic functions vary among species in many clades of plant families in California (both within and between clades), and this variation is already known to be an important trait in adapting to changing ecological conditions. However, characterizing variability in moisture stress tolerance among plant lineages remains to be achieved for most lineages. Importantly, the relationships of most species to locally available groundwater is not known, but existing evidence indicates that this is a significant factor in plant species resilience in a changing climate. A perceptive recent synthesis of hydraulic considerations for California's oaks is that subsurface moisture availability (i.e., the 'weather underground') is an essential element in assessing climate-change resilience (McLaughlin et al. 2017, 2020), and this is likely to be no less a fundamental relationship for most other California plant clades.

Limited evidence exists about the role of past climates on vegetation composition in California landscapes, although one significant study of pollen from Clear Lake showed that previous periods of warmer and drier climate favored oaks in Northern California landscapes (and likely other hardwoods; Adam & Robinson 1988). In the Klamath ecoregion, hydraulic adaptations are likely to favor hardwoods (especially evolutionarily more-recently differentiated oak species) over conifers in a time of warming atmosphere and increased aridity (although the importance of 'developmental plasticity' is another factor with uncertain but probably high importance in climate-change adaptation, for which additional scientific study is needed). Nonetheless, the significance of local hydrology (particularly the availability and dynamics of groundwater) and its importance for hydraulic functioning in plant species requires a consideration of soil moisture in climate-change (and fire) adaptation programs. The inclusion of SSURGO soil data in the design of this NSRP study is a first step in that direction.

Larger-scale considerations are also relevant in developing planting programs for the NSRP. Planning frameworks for National Forest landscapes have evolved in recent decades to incorporate a focus on larger regions rather than on individual stands. Such focuses fundamentally require that restoration projects incorporate region-scale processes, such as the kinds of spatiotemporal variation that regularly occur within entire watersheds. Providing scientific guidance for planning and executing landscape-scale management exceeds the scope of this report, but both historical and (increasingly) recent examples exist that can assist managers (e.g., Pickett & Thompson 1978, Pickett & Cadenasso 1995, Franklin et al. 2007, Franklin & Johnson 2012, Filotas et al 2014, Turner & Gardner 2015, North et al. 2019, Hessburg et al. 2019, Gaines et al. 2022). A principal concern that can largely be addressed only at landscape scales is ecological connectivity (Noss & Daly 2006; Brost & Beier 2010, 2012; Hilty et al. 2019; Estes et al. 2021). Restoration within the NSRP that is adaptive to the effects of climate change cannot be achieved without incorporating these landscape-scale elements.

Managing for climate-change resilience in an unknown future is clearly an uncertain process, as is indicated in the variety of approaches suggested by various scientists, from a variety of perspectives (e.g., Jackson et al. 2009, Pausas & Schwilk 2011, Millar & Stephenson 2015, Parks et al 2016, Rissman et al.

2018, Hessburg et al 2019). There is little doubt that the fundamental recommendation of Millar & Stephenson (2015) to anticipate future ecological conditions and manage appropriately to maintain ecological services provided by forested landscapes, even with those changes, is good advice.

Still, intrinsic environmental characteristics in the Klamath ecoregion may buffer ecosystems in the region to some expected changes, and the variety of complex adaptive systems already present in forested landscapes in the Klamath region represents an advantage for managers: community assemblages in the Klamath ecoregion are already adapted to shifting to alternative states as conditions change. 'Novel communities' in the Klamath ecoregion may be composed of species combinations that are outside the 'Historical Range of Variability,' but they're likely to be composed largely of species that already occur in the region. Moreover, the genomes of plant species in the region may possess substantial developmental 'plasticity' that will support their roles in shifted future conditions. For example, Oregon white oaks at study sites in the Willamette Valley and southwestern Oregon, stands identified in other studies as genetically closely related, displayed alternative sets of physical traits in clines from valley bottoms to hilltops (Thilenius 1968, Riegel et al. 1992, Gilligan & Muir 2011), indicating substantial developmental flexibility without significant genetic differentiation. Similar results have been documented for several other California oak species; some native oak species seem to respond well to altered climate conditions (Roberts, in review), although research focused on such relationships is only at its beginning.

There are some notable limitations of this research study. First and foremost is that this system of planting recommendations has not been field tested or verified because it was beyond the funding scope of this project. Although this study puts forth a logical and systematic approach to reforestation along with a prioritization scheme, it is necessary to check the planting recommendations against field knowledge and field visits to confirm their validity. It is recommended that a validation study be undertaken to confirm or refute high priority areas for reforestation. Another limitation of the study is a lack of error assessment of the mapping variables used in this study. Vegetation maps commonly have classification errors and boundary mapping errors which can alter the management prescriptions determined for a specific site. Verification of each mapping variable would be needed for a planting prescription for any site selected for reforestation. The intent of this research work was to develop an intuitive framework for prioritizing restoration efforts in an efficient manner at a landscape scale. It is anticipated that with future funding some variables in this framework will be refined, modified, replaced, or eliminated as knowledge of how the system of planting recommendations develops through field experience over time. This project offers opportunities for developing future research questions and monitoring programs in the MNF.

5. Conclusion

This study created a decision support framework for evaluating site potential regarding prioritization of reforestation efforts in the NSRP site within the MNF. The strategy defined discrete land management units using four biophysical variables that informed a set of planting recommendations that incorporates the effects of climate change. As such, the planting framework is expected to be adaptive and resilient to future conditions. This report documents all the computational methods used to produce the restoration model and the planting recommendations. The plant selection tool (database) developed for this project will provide land managers at the MNF with the ability to identify both canopy dominant species and other plant species associated with the dominant type, an aid in developing desired future landscape conditions. The information in this report can be used immediately to cross-check reforestation treatments that are currently proposed or being planned in the near future. The GIS datasets developed in this project have been transmitted to MNF personnel for future use and reference.

6. References

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7. Appendix

Appendix A

Datasets provided to the CLERC and MNF

The key datasets produced in this study are provided in digital format for personnel at the CLERC or the MNF to utilize. All the data are in one compressed zip file named "Greco_Data_to_CLERC_and_MNF.zip" (2.3 gb) and when the file is extracted one folder holds all the datasets (29.2 gb). Within the top-level folder the data have been organized into seven thematic folders that are numbered. Many of the folders contain "layer" files (*.lyr) which are feature classes or rasters with their symbology predefined. It is recommended to load the layer files into the table of contents of whatever ArcGIS program (Esri products) is being used (e.g., ArcGIS Desktop or ArcGIS Pro). The contents of folders 1-6 should be viewed with ArcGIS 'Catalog' software (see Figure A-1). A brief description of each folder and their respective contents is below.

The first folder is named "1_Vegetation_Vulnerability" and contains one shapefile named "nsp_veg_map_vul1.shp" and one layer file named "Vulnerability to Vegetation Type Conversion.lyr."

The second folder is named "2_Topography_Exposure_Analysis" and contains six rasters and five layer files along with the "con" (conditional) statement that calculated the exposure model.

The third folder is named "3_NDVI_Data_Burn_Severity" that contains three folders: (1) "NDVI_images" which contains two RGB aerial photos from 2016 and 2020; (2) "NDVI_method2" that contains eight rasters and seven layer files; and (3) "NDVI_rasters" which contains six rasters and four layer files.

The fourth folder is named "4_Restoration_Model_and_Planting_Recs" and contains two rasters and two layer files.

The fifth folder is named "5_SSURGO_Soil_AWS" which contains one folder and one geodatabase. The folder is named "SSURGO_Soil_Data_NSRP" and contains seven shapefiles, one raster, and one layer file. The geodatabase is named "SSURGO Soil Data.gdb" and contains five polygon feature classes, four rasters, and three tables.

The sixth folder is named "6_CWHR_Vegetation_Shapefiles" and it contains 20 shapefiles. Each CWHR vegetation type from the feature class named "Veg_ExistingVeg_12132019" (from the geodatabase named "Master_NorthShoreRestoration.gdb") was extracted into a separate shapefile. This allows for viewing or analysis of any particular vegetation type of interest. Each file is named with the CWHR acronym of the respective vegetation type (e.g., grassland = ags.shp, ponderosa pine = ppn.shp, Douglas-fir = dfr.shp, etc.).

The seventh folder is named "7_Plant_Selection_Tool" and it contains just one Excel file with three "sheets" (tables) within it. See the report text for more details about each table.

The zip file named "Greco_Data_to_CLERC_and_MNF.zip" can be downloaded from this link for approximately 1-2 months following the distribution of this report in March 2023 or by contacting the lead author: https://drive.google.com/drive/folders/1Maz0vsmooV3psQWbUUYmrsl7zCgSJvMa?usp=sharing

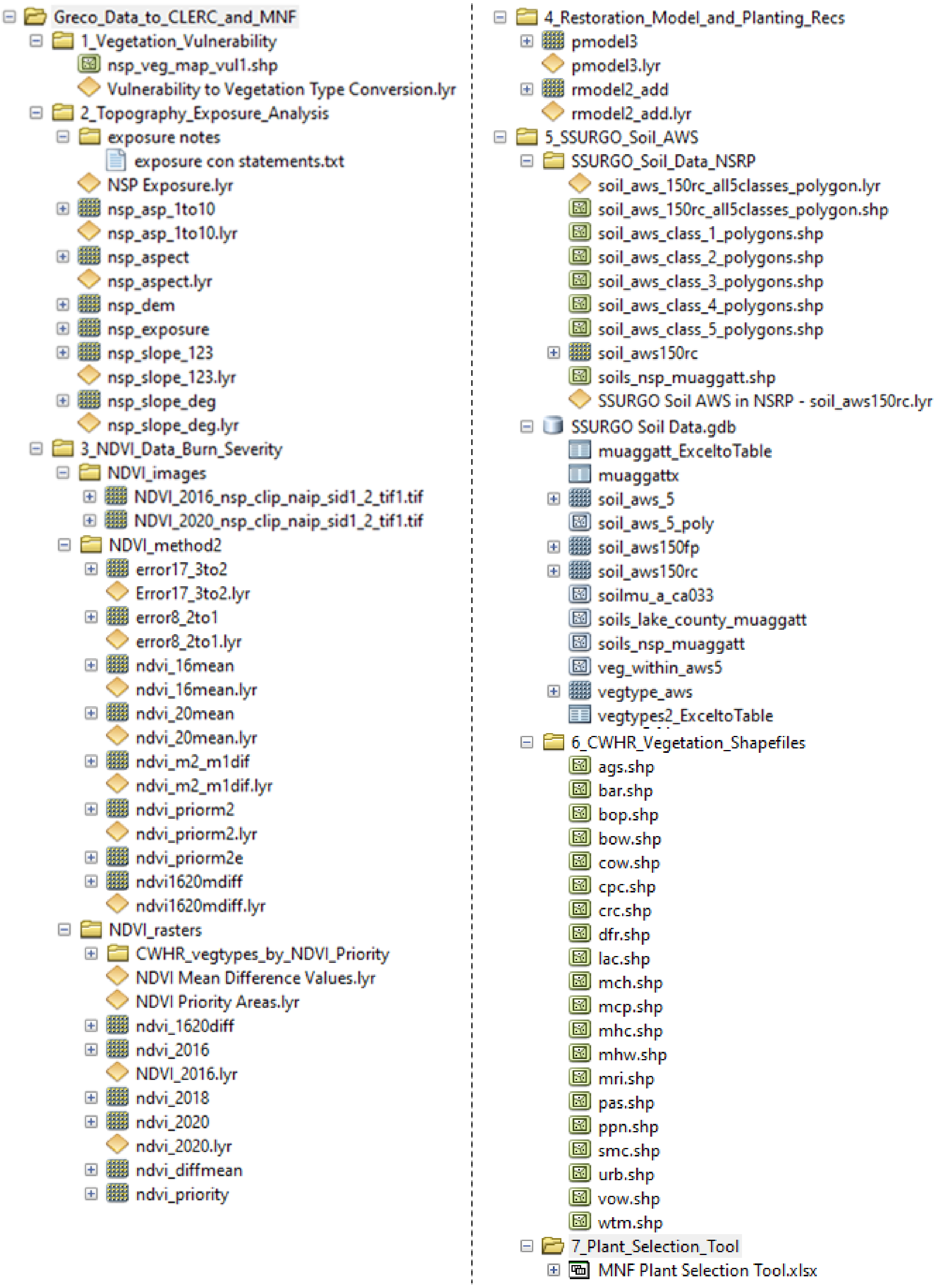

Figure A-1: An expanded tree diagram (using ArcGIS 'Catalog' software) of the data provided to the CLERC and MNF personnel.

Appendix B

An alternate method to calculate mean NDVI difference

This appendix documents an alternate method that was explored to calculate NDVI mean difference between the 2016 and 2020 NAIP aerial photos of the NSRP site. This is called 'NDVI Method 2' in the datasets provided. In NDVI Method 2 the existing vegetation layer ("Veg_ExistingVeg_12132019") was used to calculate the zonal mean of each vegetation polygon covering the datasets "NDVI_2016" and "NDVI_2020" before subtracting them. This is in contrast to the chosen method in the report Methods section that calculates the zonal mean of each vegetation polygon covering the dataset "NDVI_1620diff" after subtracting them. The two methods were then directly compared by conducting an error assessment between them to quantify their agreements and differences.

NDVI Method 2:

First, the zonal mean is calculated within each vegetation polygon for each time period using the ArcGIS Spatial Analyst tool 'Zonal Statistics.' For 2016 the input feature class is "Veg_ExistingVeg_12132019," the Zone Field is set to "Object ID," the input value raster is "NDVI_2016_nsp_clip_naip_sid1_2_tif1.tif," the output raster is named "ndvi_16mean" and the Statistic Type is set to "Mean." The same procedure was repeated for 2020, supplanting "2020" for "2016." To calculate the mean NDVI difference between the two time periods, the ArcGIS Spatial Analyst tool 'Raster Calculator' is used to subtract 2020 from 2016 with the following equation: [ndvi_16mean] – [ndvi_20mean]. The output raster of this calculation is named "ndvi1620mdiff" and resulted in a maximum value of 52.9, a minimum value of -42.6, mean value of 14.5 and a standard deviation of 6.45. Since it is an index, it has no units. The last step is to reclassify the final floating point output raster to an integer raster with three classes (i.e., high, medium, and low). To accomplish this task the ArcGIS Spatial Analyst tool 'Reclassify' was implemented and set to three classes with break points determined using the Natural Breaks (Jenks) method (the same method used in NDVI Method 1). This set breaks at 8.6, 17.3, and 52.9. The input raster is "ndvi1620mdiff" and the output raster is named "ndvi_priorm2" (which is comparable to "ndvi_priority" using NDVI Method 1, described above in the Methods section in the report).

Error analysis between NDVI Method 1 and NDVI Method 2:

The objective of this analysis is to quantify the differences between the two methods in terms of their respective NDVI priority classes (high, medium, and low). The two rasters being compared are: "ndvi_priority" (the results from NDVI Method 1) and "ndvi_priorm2" (the results from NDVI Method 2). The three classes in each of the two time periods result in a 3x3 error matrix (nine possible values) with the three diagonal values being values in agreement and all remaining values in the 3x3 matrix being differences. The process begins with reclassifying one of the two rasters from values of 1, 2, and, 3 to values 10, 20, and 30. When combined, this will create unique numbers for each location (box) in the 3x3 matrix so that errors or agreements can be precisely determined.

For this analysis we reclassified the NDVI Method 2 results ("ndvi_priorm2") and left alone the NDVI Method 1 results ("ndvi_priority"). Using the ArcGIS Spatial Analyst tool 'Reclassify' the input raster is set to "ndvi_priorm2" and the values 1, 2, and, 3 were changed to values 10, 20, and 30 and the output raster is named "ndvi_priorm2e." To calculate the differences between the two methods, NDVI Method 1 is subtracted from NDVI Method 2 using the ArcGIS Spatial Analyst tool 'Raster Calculator' using the following equation: [ndvi_priorm2e] – [ndvi_priority]. The output raster is named "ndvi_m2_m1dif" which resulted in nine unique numbers where the values 9, 18, and 27 indicate agreement (no difference) between the two models and the remaining six values (7, 8, 17, 19, 28, 29) are potential errors indicating disagreement (differences between the two methods).

Results show 97.1% agreement between the two mean NDVI difference methods. The 2.9% error (disagreement) is attributable to two error values: value 8 (0.6%) and value 17 (2.3%). An error with a value of "8" indicates that Method 1 calculated an NDVI priority of 2 (medium impact) and Method 2 calculated an NDVI priority of 1 (high impact), meaning more mortality is predicted using Method 2. An error with a value of "17" indicates that Method 1 calculated an NDVI priority of 3 and Method 2 calculated an NDVI priority of 2, again, meaning more mortality is predicted using Method 2. A portion of these errors is shown in Figure B-1 on a detailed map that shows the majority of the soil AWS Class 5 polygons. The figure depicts three mixed conifer vegetation polygons with error value 17 and one polygon with error value 8. To determine which method is more accurate, a field study would need to be conducted. NDVI Method 1 is used in this study, however, the alternate method could be an improvement and an opportunity to fine tune this overall methodology.

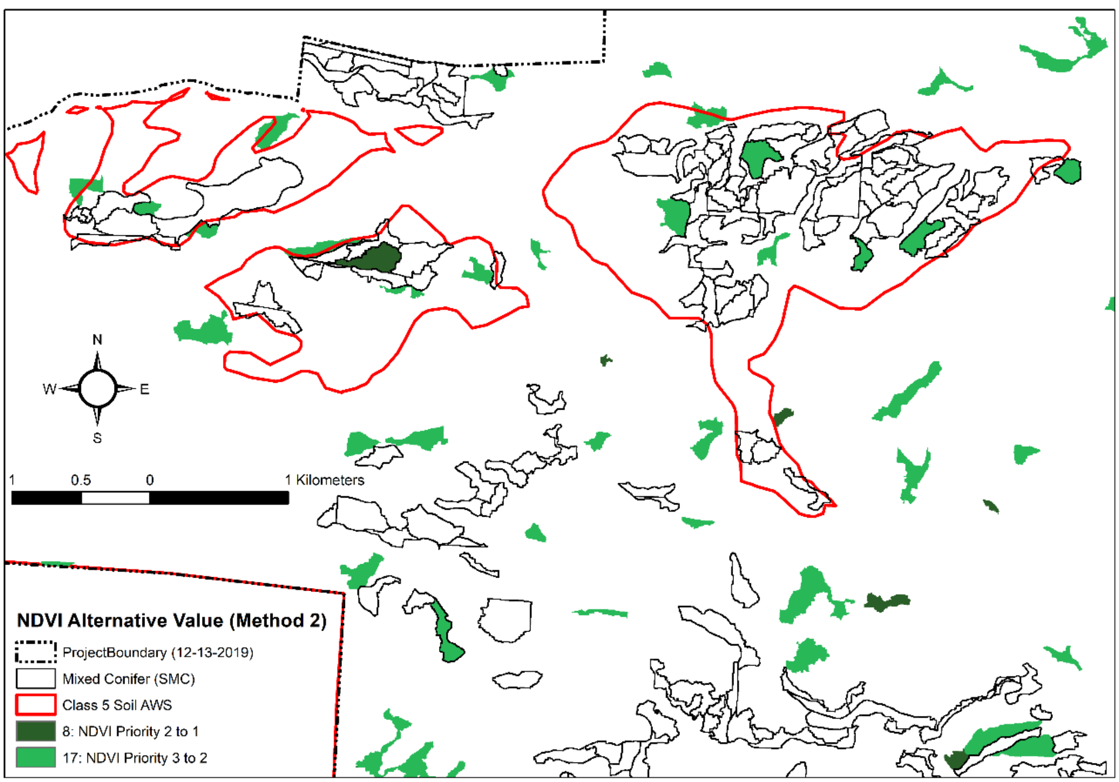

Figure B-1: Results from Method 2 (green polygons) of calculating mean NDVI differences. Four polygons of mixed conifer (SMC) that differ from Method 1 can be seen within soil AWS Class 5 polygons. See text for more details.