Proposed methods for monitoring “groupy-clumpy” forest cover characteristics at the stand scale

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Introduction

The Front Range Collaborative Forest Landscapes Restoration Project (FR-CFLRP) has broadly defined that desired condition (DC) are to “establish a complex mosaic of forest density, size and age (at stand scales)”. The current FR-CFLRP monitoring plan further specifies that the future forest should have “increased tree clumps and spatial heterogeneity in stands” and an “increased number of openings (>.25 acre)” (Clement and Brown 2011). This desired spatial distribution of the trees within a stand has been nicknamed “groupy-clumpy”. While the FR-CFLRP Science and Monitoring Team has not been able to specify parameters that define “groupy-clumpy” forest conditions, there is consensus that stands of similarly-sized evenly-spaced trees (plantation-like stands) are undesirable. Repeatable monitoring that quantifies tree spatial structure is therefore necessary to ensure post-treatment forest condition goals are met.

The Science and Monitoring Team’s difficulties agreeing on specific parameters that define the DC are partially due to a lack of information on the historic spatial distribution of trees in these forests. We also lack information about how spatial distribution of trees may influence important ecological processes such as fire behavior, wildlife habitat and tree growth. Working group projects are attempting to address these knowledge gaps and results will eventually help the Science and Monitoring Team define DC. For example, the historic-forest reconstruction study will provide estimates of pre-settlement forest density and spatial pattern that can help us estimate historic fire behavior (Paula Fornwalt, Peter Brown, Laurie Huckabee, Mike Battaglia, CFRI and others). The wildlife subgroup is developing monitoring methods and DC in terms of wildlife and wildlife habitat. However, the results of these studies will take time to produce so consensus on the definition of DC for treatment areas is not likely in the near term.

The Science and Monitoring Team is obligated to monitor the FR-CFLRP forest restoration treatments and cannot afford to wait for further information before designing monitoring protocol. We have taken the general directives in the current FR-CFLRP plan and begun refining them to include specific measures of “groupy-clumpy” forests. In the lack of better scientific information, this data-based monitoring of “groupy-clumpy” restoration treatments can provide statistical information that can inform future management decisions through adaptive management. These techniques will allow us to compare stands to DCs once defined.

The current FR-CFLRP monitoring plan calls for the collection of plot-based measures of tree density (both basal area and trees per acre), size (quadratic mean diameter) and age in each treatment unit (stand). This data can provide the within- and among-plot means and among-plot ranges and variances of tree densities, sizes and age values. However, these variables cannot quantify the spatially explicit distribution of trees that is essential to monitoring for "groupy-clumpy" forest conditions. There were strong feelings within the Science and Monitoring Team that the current FR-CFLRP monitoring plan should include a metric of spatial distribution of trees "to define and assess the mosaic condition beyond simple averages and distributions of the identified monitoring variables as measured in the plots" (Clement and Brown 2011) but there was difficulty devising such a method and none was included in the current plan. The protocol outlined here will allow quantification of forest canopy cover spatial distribution that, in conjunction with plot-based statistics, will present a more complete picture of forest structure that will allow the FR-CFLRP to monitor its goals.

Proposed Methods

Traditional metrics of tree spatial distributions involve intensive fieldwork to precisely map the location of each tree. The spatial heterogeneity subgroup has been exploring a range of methods to more easily and efficiently quantify "groupy-clumpy" forest characteristics.

Jenny Briggs, Paula Fornwalt, Jonas Feinstein and Craig Hansen's and work with the SRLCC (Southern Rockies Landscape Conservation Cooperative) study has focused on developing a field based measure of "groupy-clumpy" conditions using transect-intercept methods. The results of the post-treatment re-measurement of these plots are pending. These methods should be considered alongside those presented below.

Yvette Dickinson and Kristen Pelz have been investigating the use of aerial imagery to map tree crowns and scaled-down traditional landscape ecology metrics to quantify the spatial distribution of the forest canopy within a treatment unit. The following is a discussion of these methods for monitoring forest structural complexity within-treatment units.

One of the advantages of using aerial imagery is that the National Aerial Imagery Program (NAIP) collects and makes publicly available aerial imagery for the entire US on a four-year cycle. This imagery is of a moderately high resolution (1 m) includes the three visible bands of light (red, green and blue) and a near-infrared band. Vegetation strongly reflects light in the near-infrared wavelengths, and as such is very useful for the remote sensing of forests. Similar 4-band imagery is also collected at finer resolutions for the National Forests specifically (Forest Resource Imagery).

We propose to use multispectral analysis methods using the ENVI software package (Exelis Visual Information Solutions) to delineate areas of coniferous canopy, shadow, herbaceous ground cover and bare soil (e.g. unpaved roads) from the NAIP imagery. The combination of the reflected wavelengths of these cover types are unique and can be used to map land cover within each pixel. We can use this classification of pixels to identify isolated crowns and groups of adjoining crowns.

Various supervised classification algorithms and the inclusion of additional derived bands were tested for accuracy in identifying coniferous canopy, shadow, herbaceous ground cover and bare soil cover types. Supervised classification algorithms utilize user-defined training data to classify ever pixel in the image into the specified classes. The training data (aka Regions of Interest, ROIs) were identified manually ensuring a separability value greater than 1.8 (a value of 2.0 indicates perfect separation between the user-defined classes in terms of their spectral signature). Parallelepiped, Minimum Distance, Mahalanobis Distance and Maximum Likelihood supervised classification algorithms were tested, with the

Mahalanobis distance algorithm resulting in superior classification accuracy. The Maximum likelihood algorithm also produced satisfactory results. The addition of derived bands was also investigated. These derived bands are calculated from the original bands and have been shown to improve the accuracy of classification in other remote sensing applications. We assessed accuracy improvement from adding Normalized Difference Vegetation Index (NDVI, the normalized difference between the near-infrared and red bands), Simple Ratio (SR, the ratio of the near-infrared to red bands) and Red Green Index (RGI, the ratio of the red to green band). While the addition of each of these derived bands individually improved accuracy of the classification, we concluded that the combination of the Simple Ratio derived band, red, green, blue and near infrared bands analyzed using the Mahlanobis distance supervised classification algorithm produced most accurate results for image classification into coniferous canopy, shadow, herbaceous ground cover and bare soil cover types.

Shadow is a perennial concern in aerial image analysis, and unfortunately little can be done to eliminate it. The amount of shadow in aerial photography is influenced by the time of day and season of capture as well as characteristics of forest canopy and topography. Thankfully, aerial photographers attempt to minimize shadowing as much as possible so large areas of shadowing are unusual in the NAIP and Forest Resource Imagery. However, areas of deep shadows due to steep topography will necessarily be excluded from the analysis. Small areas of shadow within the forest canopy area common, and we cannot definitively know what is hidden in these shadows. We can reduce the uncertainty due to shadow by resampling the data to a slightly larger resolution (2.4 m as recommended by Meddens et al., 2011). Small within-crown shadows are then "averaged-out"; however, larger deep shadows still remain a problem. Shadows can also be classified as part of the "background" to reduce their influence on statistical analyses. Background pixels are considered uninformative and therefore are ignored.

The spatial distribution of forest canopy within a stand can be described as a series of patches (clumps or groups of adjoining tree-crowns) in a matrix of bare-ground and herbaceous groundcover (gaps between trees). Metrics developed by landscape ecologists may be scaled-down and used to describe spatial characteristics of canopy patches and gaps between tree crowns within treatment units. Metrics calculated using FragStats (McGarigal et al. 2012) such as the percent cover, largest patch index, edge density, patch size, patch density, patch perimeter-to-area ratio, Euclidean distance between patches, and proximity index can be used to quantify the size, shape, and distribution of canopy patches and gaps across the treatment unit (Table 1, Appendix 1).

We used the 8-neighbour rule for defining neighboring pixels. Under the 8-neighbour rule pixels adjacent vertically, horizontally and on the diagonal are classified as neighbors. This is a more accurate representation of the real-world adjacency of cover classes than the alternative 4-neighbor rule, which only defines pixels adjacent directly vertically and horizontally as neighbors.

Table 1. Proposed metrics to monitor "groupy-clumpy" forest characteristics within treatment units using aerial imagery.

Metric	Definition, interpretation and units	Expected trend with "clumpy-groupy" restoration treatments by patch type	
		Coniferous canopy	***Gaps***
Percentage of landscape [treatment unit] (PLAND) occupied by coniferous canopy cover and canopy gaps.	Area of each patch type as a percent of total landscape area(%).	Decrease	Increase
Largest patch index (LPI) for coniferous canopy cover and canopy gaps.	The percentage of total landscape area comprised by the largest patch (%). It is a measure of the dominance of the largest patch of each patch type.	Decrease	Increase
Edge density (ED) of coniferous canopy cover and canopy gaps.	The length of patch edge per unit area (m/ha) for each patch type. Edge effects where adjacent patches influence each other are an important driver of ecological processes in complex landscapes. Edge density is therefore the likely influence of edge effects in the landscape.	Increase for both coniferous canopy cover and canopy gaps.	
Patch area (PA) of coniferous canopy cover and canopy gaps. Mean, range, standard deviation reported. Frequency distribution graphs of patch area may also be plotted.	The size of a patch by type (ha).	Decrease in mean with increase in range and standard deviation	Increase in mean with increase in range and standard deviation
Perimeter area ratio (PARA). for canopy cover and canopy gaps. Mean, range, and standard deviation reported. Frequency distribution graphs may also be plotted.	A ratio of the perimeter of a patch to its area is a measure of the shape of a patch (unitless). Edge effects where adjacent patches influence each other are an important driver of ecological processes in complex landscapes. Large perimeter-to-area ratios indicate convoluted or complex edges with greater proportions of the area influenced by neighboring patches.	As the stand becomes more fragmented and/or patches become more irregular with complex and convoluted edges the perimeter-to-area ratio will increase for all patch types.	
Patch density (PD) of coniferous canopy cover and canopy gaps.	Simple measure of the density of patches per 100 hectares. Patch density is an indication of the prevalence of patch types (i.e. canopy or opening) and is strongly influenced by the size of patches.	Increase	Decrease

Metric *(cont.)*	Definition, interpretation and units *(cont.)*	Expected trend with "clumpy-groupy" restoration treatments by patch type *(cont.)*	
		Coniferous canopy	***Gaps***
Euclidean distance (ED) to nearest similar patch of coniferous canopy cover and canopy gaps. Mean, range and standard deviation reported. Frequency distribution graphs may also be plotted.	The shortest straight-line distance between the focal patch (m) and its nearest neighbor of the same type is a simple measure of patch context used to quantify patch isolation.	Increase in mean with increase in range and standard deviation	Decrease in mean with increase in range and standard deviation
Proximity index (PI) of coniferous canopy cover and canopy gaps, with a defined search radius (10 m in the following example). Mean, range and standard deviation reported. Frequency distribution graphs may also be plotted.	Unitless index of the size and proximity of all patches whose edges are within specified search radius (neighborhood) of the focal patch. PI is 0 if no neighbors are found within the search radius. PI increases with occupation of the neighborhood by patches of the same type and as those patches become closer and larger. The upper limit is influenced by the search radius and the minimum distance between patches.	Decrease in mean, with increase in range and standard deviation	Increase in mean with increase in range and standard deviation

Example: Application of methods to a test area of the Front Range landscape

We present results of a test run using an area of Front Range forest used to develop this protocol. We used two small sub-areas that are used to compare an area with a fragmented forest canopy (Area 1) with a more contiguously forested area (Area 2).

Figure 1. Aerial image (a) and classification of image into cover classes at with 1m (b) and 2.4m (c) resolution for low-density forest Area 1. Classes include coniferous canopy (green), bare soil (yellow), herbaceous cover (red) and shadow (blue). For analysis, herbaceous and bare soil were combined into the canopy gap class and shadows were classified as background.

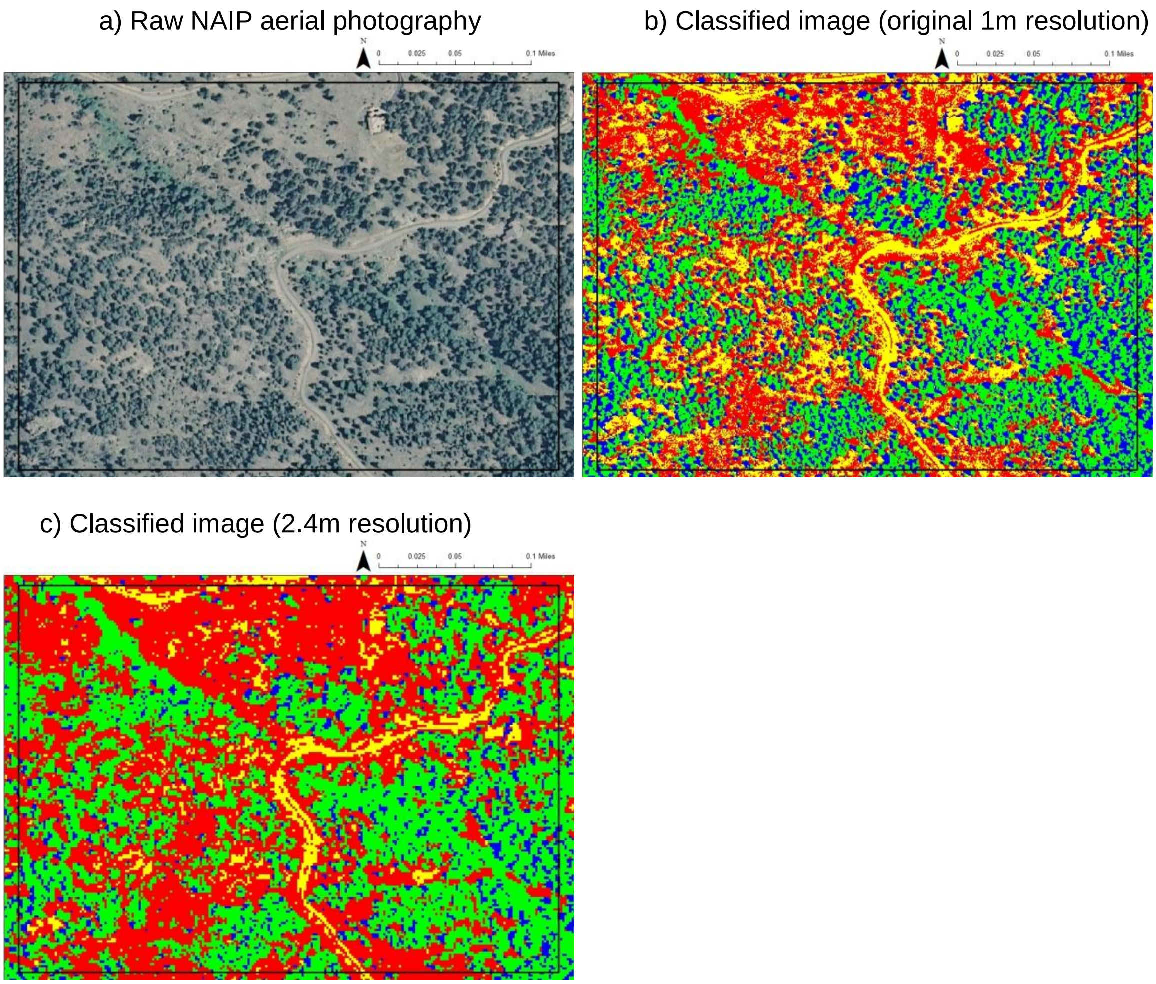
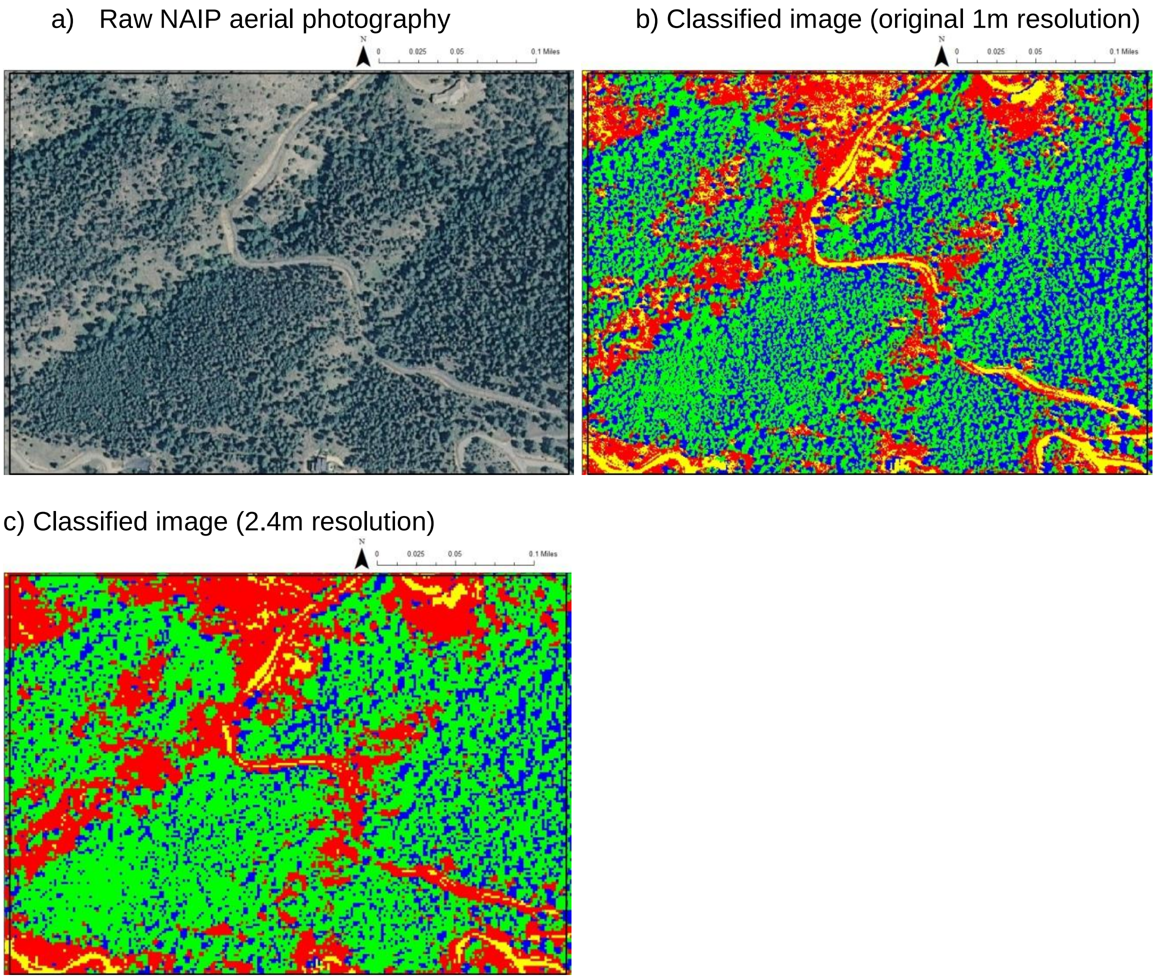


Figure 2. Aerial image (a) and classification of image into cover classes at with 1m (b) and 2.4m (c) resolution for high-density forest Area 2. Classes include coniferous canopy (green), bare soil (yellow), herbaceous cover (red) and shadow (blue). For analysis, herbaceous and bare soil were combined into the canopy gap class and shadows were classified as background.



Accuracy of the image classification

The accuracy of the supervised image classification was tested against an independent dataset of manually classified pixels. For the classification at the original resolution, overall accuracy of classification for all classes was 88.4%, with a Kappa statistic of 0.84. Landis and Koch (1977) suggest that Kappa statistics > 0.8 show strong agreement between the classified image and manually classified pixels. The confusion matrix (Table 2) shows that 80.3% of the coniferous pixels were correctly identified.

Table 2: Confusion matrix of classified image at the original resolution using independent dataset of manually classified pixels.

		Ground Truth (%)				
		Herbaceous	Conifer	Shadow	Bare Ground	Total
Classification	Herbaceous	85.57	14.10	0.55	2.99	22.29
	Conifer	0.00	80.30	1.74	0.00	32.06
	Shadow	0.00	5.42	97.55	0.00	24.88
	Bare Ground	14.43	0.19	0.16	97.01	20.76
	Total	100.00	100.00	100.00	100.00	100.00

After the aerial imagery was resampled to 2.4m resolution, the overall accuracy of the classification was 87.1% with a kappa statistic of 0.82. The confusion matrix (Table 3) shows that 86.67% of the coniferous pixels were correctly identified.

Table 3: Confusion matrix of classified image resampled to a 2.4m resolution using independent dataset of manually classified pixels.

		Ground Truth (%)				
		Herbaceous	Conifer	Shadow	Bare Ground	Total
Classification	Herbaceous	82.57	10.08	2.77	8.16	36.25
	Conifer	5.85	86.67	3.78	0.00	26.32
	Shadow	0.00	3.25	93.45	0.00	17.18
	Bare Ground	11.58	0.00	0.00	91.84	20.25
	Total	100.00	100.00	100.00	100.00	100.00

Comparison of 1m and 2.4m resolutions

The classified images demonstrate that the resampling to a 2.4 m resolution reduced the prevalence of small within-canopy shadows (Figures 1, 2; b, c). While there is a loss of detail with this generalization, it also creates a more realistic picture of the distribution of canopy clumps and open gaps.

The metrics of patch characteristics differ between the two resolutions due to a change in the individual pixel size. The percent of the landscape and largest patch index are relatively consistent across the resolutions. The density of patches, edge density, perimeter area ratio, mean patch area and mean proximity index decline with increasing pixel size. This is because patches smaller than the larger resampled pixel size are no longer identified. Euclidean nearest neighbor distance increases with pixel size as small patches are no longer identified and closely neighboring patches converge.While the change in resolution influences metrics, if resolution is kept consistent we will be able to make comparisons between treatment units through time for monitoring.

Interpretation of proposed metrics-based monitoring at 2.4m resolution

Area 1 has a smaller percentage of openings (43%) than canopy coverage (57%), but with a similar density of both openings and canopy clumps (Table 4). In contrast, Area 2 has a greater percentage opening than Area 1 (66%) and less coverage of canopy (34%) with a higher density of openings (1843/ha) than canopy clumps (837/ha). The largest patch index (LPI) shows that 44% of Area 1 was occupied by a single opening; in comparison, 36% of Area 2 was occupied by a single canopy clump. The edge density of Area 1 (1113m/ha) was higher than Area 2 (805m/ha), suggesting that Area 1 is more fragmented with a greater influence of edge effects on the ecological processes within the canopy clumps and open gaps (e.g. side shading of canopy over open gaps).

Within Area 1, the canopy clumps and openings had similar mean sizes with a large variation in sizes (mean and standard deviation of 0.04 ha ± 0.28 and 0.05 ha ± 0.59 respectively; Table 4). In comparison, within area 2, the canopy clumps were much larger than the openings on average (mean of 0.08 ha and 0.02 ha respectively). The perimeter area ratios were similar in both areas, suggesting that in both areas the edges of openings and canopy clumps were convoluted and complex.

The proximity index (PI) is a measure of both the distance between patches and their size. High PI values indicate large patches that are close together while low PI values indicate small patches that dispersed. In Area 1 PI for canopy was low while PI was high for openings, indicating that the canopy clumps were relatively sparse compared to the openings. Area 2 demonstrated the opposite trend with a high PI for canopy clumps and low for openings.

Euclidean nearest neighbor distance is also a measure of proximity. This was consistent across the board at approximately 6m. However, there was greater standard deviation in this distance for openings in Area 2; therefore, the distance between open gaps that was occupied by closed forest canopy varied more greatly. The frequency distribution plots of the Euclidean nearest neighbor distance for canopy clumps and open gaps vary between Area 1 and Area 2 (Figure 3; please note that the scales on the axes differ between the plots). The maximum distance between open gaps was greater in Area 2 (>50m) than Area 1 (~20m).

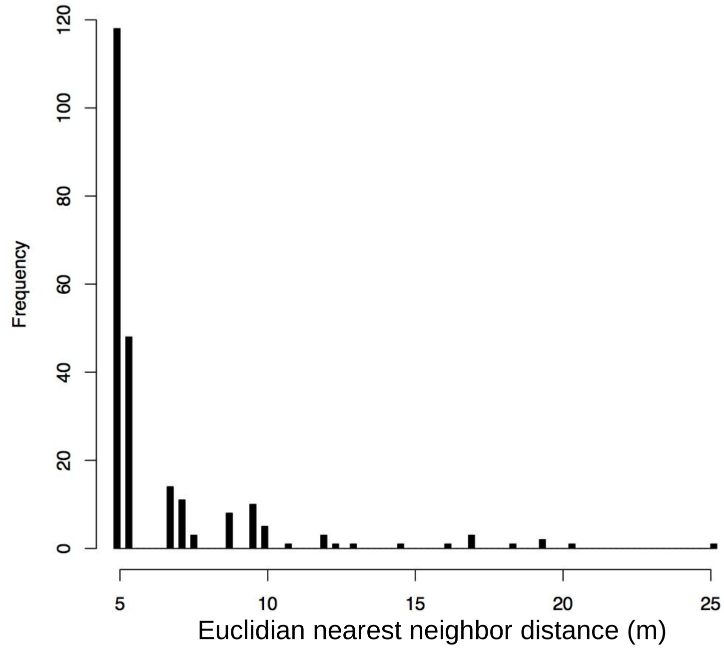
Overall, these metrics indicate Area 1 is more open with greater fragmentation of the canopy and a greater variety in the distances between and sizes of canopy clumps. We suggest that area 1 is closer to the desired future conditions that the FR-CFLRP is aiming to create within treatment units.

Table 4: Metrics measuring "clumpy-groupy" forest characteristics for areas 1 and 2 at 1 and 2.4 m resolutions.

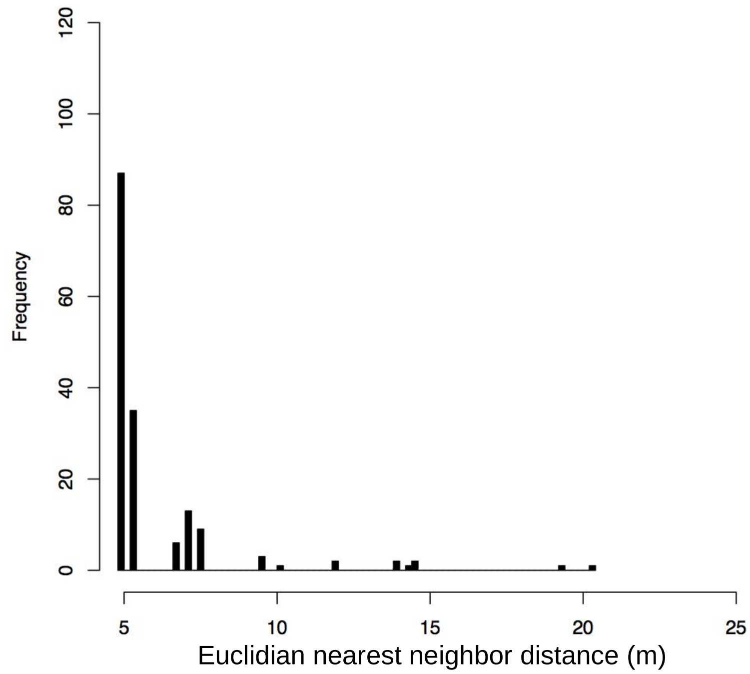
		Area 1				Area 2			
	Resolution:	1 m		2.4 m		1 m		2.4 m	
	Cover:	**Conifer**	**Opening**	**Conifer**	**Opening**	**Conifer**	**Opening**	**Conifer**	**Opening**
% of Landscape		37.34	62.65	42.52	57.48	61.17	38.82	65.95	34.05
Patch density (/ha)		7004	8055	1079	1195	6321	12018	837	1843
Largest patch index (%)		12.11	45.94	15.49	43.91	36.75	13.82	36.56	12.97
Edge density (m/ha)		1808		1113		1431		805	
Patch area (ha)	***Mean***	0.0053	0.0078	0.0394	0.0481	0.0097	0.0032	0.0788	0.0185
	Range	2.3048	8.7370	3.3420	9.4781	5.9470	2.2365	12.3800	2.5263
	Std. dev.	0.0682	0.2245	0.2789	0.5913	0.1952	0.0557	0.9665	0.1447
Perimeter:area	***Mean***	27967	34372	11616	12945	27132	35497	12796	13472
	Range	32670	36408	13243	14732	33204	37114	13052	14863
	Std. dev.	11163	8510	4476	4602	10907	7570	4056	4101
Proximity index	***Mean***	728.6	6929.8	331.1	1291.0	5230.4	523.8	2711.4	129.9
	Range	5837.8	22698.0	1452.0	4548.7	18594.2	6214.0	5377.4	1114.8
	Std. dev.	1495.3	8486.7	461.6	1600.7	5748.2	1309.9	2326.9	282.3
Euclidian nearest neighbor distance (m)	***Mean***	2.63	2.52	6.40	5.81	2.50	3.29	6.0	6.85
	Range	20.09	12.42	20.26	13.94	15.03	21.54	15.6	48.49
	Std. dev.	1.35	1.14	3.13	1.88	1.06	2.31	2.5	4.75

Figure 3. Frequency distribution histograms of the Euclidean distance to the nearest neighbor for canopy clumps in Area 1 (a) and 2 (b). Distance in meters is on x-axis and frequency on y-axis.

a) Area 1



b) Area 2



Conclusions

The monitoring method described here is a robust way of comparing the horizontal distribution of canopy cover among treatment units and through time. These methods can quantify forest spatial structure before treatment and then can be repeated each time the NAIP or forest resource imagery is taken (approximately every 5 years).

Inherent limitations of aerial photography will restrict the use of and inference we can draw from these methods. We recommend using the 2.4m resolution to mitigate problems caused by small within-canopy shadowing; however, the problem of occasional large, deep shadows due to steep topography cannot be completely resolved. Furthermore, the use of aerial imagery can only provide information in the horizontal distribution of canopy but not the vertical forest structure. Field collected common stand exam plot data will provide data on the means and ranges of tree sizes and densities within treatment units.

Importantly, these methods provide quantitative tools with which the FR-CFLRP could define the desired future conditions for forest spatial structure once we better understand the historic conditions, influence of spatial heterogeneity on fire behavior, wildlife and understory plant habitat. The majority of the metrics proposed are intuitive to understand (e.g. patch mean size and distance between patches) and can provide a common language for discussing difficult-to-explain "groupy-clumpy" forest characteristics.

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Appendix 1: Formulae for proposed metrics

% of Landscape

$$\text{PLAND} = P_i = \frac{\sum_{j=1}^{n} a_{ij}}{A}(100)$$

P_i = proportion of the landscape occupied by patch type (class) i.
a_{ij} = area (m^2) of patch ij.
A = total landscape area (m^2).

Patch density

$$\text{PD} = \frac{n_i}{A}(10{,}000)(100)$$

n_i = number of patches in the landscape of patch type (class) i.
A = total landscape area (m^2).

Largest patch index

$$\text{LPI} = \frac{\max_{j=1}^{n}(a_{ij})}{A}(100)$$

a_{ij} = area (m^2) of patch ij.
A = total landscape area (m^2).

Edge density

$$\text{ED} = \frac{\sum_{k=1}^{m} e_{ik}}{A}(10{,}000)$$

e_{ik} = total length (m) of edge in landscape involving patch type (class) i; includes landscape boundary and background segments involving patch type i.
A = total landscape area (m^2).

Patch area

$$\text{AREA} = a_{ij}\left(\frac{1}{10{,}000}\right)$$

a_{ij} = area (m^2) of patch ij.

Perimeter:area

$$\text{PARA} = \frac{p_{ij}}{a_{ij}}$$

p_{ij} = perimeter (m) of patch ij.
a_{ij} = area (m^2) of patch ij.

Proximity index (10m search radius)

$$\text{PROX} = \sum_{s=1}^{n} \frac{a_{ijs}}{h_{ijs}^2}$$

a_{ijs} = area (m^2) of patch ijs within specified neighborhood (m) of patch ij.
h_{ijs} = distance (m) between patch ijs and patch ijs, based on patch edge-to-edge distance, computed from cell center to cell center.

Euclidian nearest neighbor distance

$$\text{ENN} = h_{ij}$$

h_{ij} = distance (m) from patch ij to nearest neighboring patch of the same type (class), based on patch edge-to-edge distance, computed from cell center to cell center.