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Vulnerability of Giant Sequoia to Moisture Stress in a Changing Climate: A pilot study of potential moisture proxies

Natural Resource Report NPS/SEKI/ NRR—2013/XXX



ON THE COVER

Giant sequoia and white fir seedlings, Sequoia and Kings Canyon National Parks

Vulnerability of Giant Sequoia to Moisture Stress in a Changing Climate: A pilot study of potential moisture proxies

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A Note on this Report

This report was peer-reviewed by the following individuals:

- Koren Nydick, Science Coordinator, Sequoia and Kings Canyon National Parks (NPS project manager for the Task Agreement).
- Nathan Stephenson, Research Ecologist, Sequoia Field Station. Western Ecological Research Center, U.S. Geological Survey
- Marc Meyer, Southern Sierra Nevada Province Ecologist, U.S. Forest Service

The report was not officially published under the National Park Service's Natural Resource Report Series because the reviewers did not agree with all of the conclusions in the report. I believe the report has value, however, in documenting the original ideas, research, and conclusions that began a longer research initiative.

Research on this project continued after the completion of this report and resulted in the following published journal articles:

Ray, R. L. 2016. Moisture Stress Indicators in Giant Sequoia Groves in the Southern Sierra Nevada of California, USA. *Vadose Zone J.* 15. doi:10.2136/vzj2016.03.0018

Su, Y., Bales, R. C., Ma, Q., Nydick, K., Ray, R. L., Li, W., & Guo, Q. (2017). Emerging stress and relative resiliency of Giant sequoia groves experiencing multiyear dry periods in a warming climate. *Journal of Geophysical Research: Biogeosciences*, 122, 3063–3075.

<https://doi.org/10.1002/2017JG004005>

Research on this project also provided the groundwork for a subsequent project: *Giant Sequoia Drought Response from Leaf to Landscape*. A special section with five *Leaf to Landscape* journal articles is forthcoming in *Forest Ecology and Management*.

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December 26, 2017

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Introduction

Giant sequoias are ancient residents of California. The species has grown in the Sierra Nevada for 2.6 million years and individual sequoia trees can persist for thousands of years. Sequoia have survived through large climate fluctuations in the past, including multiple ice ages. While this suggests they are a robust species with a capacity to adapt to a range of climate conditions, the climatic changes of the past 100 years and the expected warming in the next century is occurring at an unprecedented pace. Park resource managers are forced to ask whether the species is adjusting to its changing climatic environment, or whether all or some of the current groves are being stressed by climatic changes, requiring unique management of the species.

Giant sequoias may be vulnerable to climate shifts in California. They are known to prefer moist habitat. Changes in climate are causing warmer temperatures, which in turn lead to changes in patterns of available moisture. More precipitation is predicted to fall as rain rather than snow. The reduced snowpack means less snowmelt will be available in the summer drought typical of Mediterranean climate. This will change hydrology and increase the probability that plants will experience water deficit during the growing season. Extreme heat events will increase and cold spell frequency will decrease. The increase in average temperature will be more pronounced in the summer, which will then increase the evaporative demand from the canopy and the soil.

This project begins to address giant sequoia vulnerability to moisture stress in a changing climate, by looking at giant sequoia and hydrology across the southern Sierra Nevada at the landscape scale.

Historical and current response of giant sequoias to moisture stress:

Literature Review

This literature review was excerpted from the Sequoia and Kings Canyon National Parks (SEKI) Natural Resource Condition Assessment (NRCA Appendix 10b; Harrison 2013).

Paleoecology

Giant sequoias were well established on the western slope of the Sierra Nevada by 2.6 million years ago. The past million years have been climatologically dynamic, with eleven glacial events. Very cold temperatures have been a dominant feature of the period with much briefer warming events. But both warming and cooling presented survival challenges to all plant species, including sequoia (Millar 1996). The period included very rapid shifts in temperature of 3-15°C over years to decades (Millar 2003).

Fossil giant sequoia pollen deposits indicate the trees may have been widespread and common during the early Holocene, 12,000 years ago. Given the longevity of the species, the studies of Anderson and others show that the current groves in the southern Sierra Nevada may perhaps be only two to three generations old, indicating that the current grove locations may represent a reaction to transient

ecological conditions specific to the past few thousands of years rather than adaptations to longer-term environmental conditions.

Groves are arranged in a North-South distribution along the western slope of the Sierra Nevada generally from 1,400 m to 2,150 m in elevation. In general, the groves display a predictable and general rise in elevation with decreasing latitude. There are approximately 77 groves of giant sequoia covering 14,600-17,500 hectares (Stephenson 1996, USDA Forest Service 2010a). Approximately 94% of the land is managed by government agencies and 6% is in private ownership.

Soil and Hydrologic Relationships

Soil moisture patterns play an important role in grove establishment. Rundel (1969, 1971), Halpin (1995), and Hucks (1999) identified a significant increase in soil moisture within the groves studied, compared to the surrounding forest. In some cases more mesic sites are easily observed (margins around meadows, riparian corridors, etc.), but upland stands of sequoia may have no obvious characteristics associated with increased subsurface moisture (Rundel 1969; Anderson et al. 1995). Halpin's work also showed that the water holding capacity of soils within groves was significantly greater than surrounding forested areas (Halpin 1995). Soil type has been eliminated as an important determinant of grove location. Texture does seem to be important, however, with a preference for sandy soils with low clay content (Hartesvelt et al. 1975).

A study conducted at the Packsaddle Grove (Sequoia National Forest) showed that while moisture may have disappeared from soils by late summer (September), moisture reserves were still present in weathered bedrock immediately below. It was estimated that annual precipitation of less than 68 cm (27 inches) would fail to maintain this water reserve on upland sites, resulting in late summer water stress (Anderson et al. 1995). Halpin also indicates the abundance of water reserves below the soil layer, and at depths even greater than Anderson's (Halpin 1995).

It is important to note that groves may not be homogenous with respect to moisture - giant sequoias may be occupying areas within groves with distinct hydrologic characteristics especially suitable for colonization, and these may not be found uniformly throughout any particular grove (see also Rundel 1969, and Weatherspoon 1986).

Halpin (1995) compared interactions of giant sequoia (as well as other associated species) with the environment at spatially hierarchical levels. He found that the abiotic environmental factors he studied, including percent soil, soil depth, topographic flow, potential evapotranspiration (PET), and precipitation, contributed differentially to tree distribution by species, but that the influence of each was based on the size of the area sampled. At 50 hectares (the 'catchment' level) higher topographic flow was the only significant regulating factor for giant sequoia. Topographic flow is defined as water movement over the surface and towards established channels, and this was the only factor that demonstrated any significant effect on sequoia distribution. At the patch (1 hectare) level PET was the most important, and the only value Halpin considered that was statistically significant. Interestingly, he

attributed this to the soil pressure mound created around giant sequoias: when he modeled the importance of PET with this micro-topographic feature removed it was no longer significant. Thus the pressure ridges created by the larger sequoias are environmental features of great importance to the local distribution.

In essence, Halpin demonstrated that the distribution of giant sequoia was not affected by any tested environmental characteristics. However, on a smaller scale, the movement of water over the surface of the ground – before it reaches even ephemeral streams – does have an influence on creating suitable habitat. Finally, at the patch level, the determining factor is the result of interactions between giant sequoias and their environment.

Halpin went on to examine the tendency of sequoias to aggregate. This tendency had already been noted by Bonnickson and Stone (1982), Stohlgren (1991), and Stephenson (1994). Using a “nearest neighbor” point pattern analysis, Halpin found that at the 20 hectare scale giant sequoias were significantly closer than would have been expected with by random distribution, but that this began to degrade with smaller sized scales.

As is discussed in the section on the paleohistory of giant sequoia, groves as we experience them are a recent phenomenon. Over the past few thousand years the species has been able to exploit a limited range of suitable habitats. During this period, these habitats were large enough to allow for (in most cases) the occupation of fairly extensive contiguous areas, but unique enough to prevent the species from expanding beyond these sites. At least in terms of soil nutrients and soil hydrology, it is reasonable to assume that other sites within the Sierra Nevada have comparable qualities, but these have not been colonized by giant sequoia. Either the species did not occur in the vicinity to begin with, or other as yet undetermined environmental factors prevented establishment.

Weather and Climate

At the elevation of the groves a significant portion of precipitation falls as snow, typically from October through April. Total annual precipitation has historically ranged from 900 to 1500 mm (35-55 in.). Dry season precipitation has been described as being typically less than 30 mm (1.2 in., Rundel 1969). Summer precipitation is rare, but when it occurs it is commonly associated with thunderstorms.

Stephenson (1988, cited in Halpin 1995) determined that precipitation on SEKIs western slope increased steadily from low elevations until about 2,000 m (6,600 ft), at which point changes in precipitation were in quality (snow vs. rain) instead of quantity. This means that total annual precipitation should be essentially constant within the elevational range of giant sequoia groves.

Temperature ranges are variable across the range of giant sequoia, but in keeping with the Mediterranean climate, with cool, wet, winters and warm to hot, dry summers. Weather records are lacking for most groves, but the indication is that average summer highs are about 29°C (84°F), with extreme high temperatures reaching 40°C (104°F). Average winter lows of about -5°C (25°F). Extreme

lows can reach -24°C (-12°F) (Rundel 1969; Weatherspoon 1985). Although such extremely cold temperatures are rare within their natural range, some sequoias (though not all) planted elsewhere have survived even greater lows (Libby 1981, 1986; Harrison 2013). These figures are derived from accurate data records, but from only a few weather stations in or near groves, and only extend back into the recent past 100 years or so. Since it is clear that climatic conditions in the groves have been both colder and warmer during the past few thousand years (Swetnam 1993; Swetnam and Baisan 2003), these ranges cannot be considered as representative of the true environmental tolerances of the species. Additionally, the sensitivity of sequoias to environmental conditions is necessarily expressed differently at different life stages, with the seed reproduction and seedling stages being the most sensitive to both heat and cold (Harvey et al. 1980, Stark 1986a, 1986b).

Genetics may play a role in giant sequoia response to moisture stress. There is a low to moderate degree of genetic variability between groves, with some degree of variation from southern to northern populations. There is no clear indication, however, that this North-South variation is associated with fitness based on latitude. On the other hand, within grove variation does seem to display some degree of topographic stratification, with a tendency for families in a grove located at higher elevations performing better in cold-related tests (Melchior and Herrmann (1987); Guinon et al 1982). Heterozygosity displayed a significant correlation with latitude, with the northern groves being less variable than the southern populations. Given the relative isolation and generally smaller sizes of the northern groves, this result is not surprising (Fins and Libby 1982). Concern has been raised over the threat to genetic integrity presented by the presence of non-native sequoia plantings near existing groves.

Indirect effects of climate change include potentially improved habitats for pests and pathogens and possibly introduce novel pathogens to the area. Possible increases in wildfires due to lower humidity, drier fuels, and longer fire seasons, present the risk of an increased level of threat from a problem that is already extreme. The new, warmer, environment could also lead to a gradual shift in species composition to better suited plants, and these in turn may have detrimental impacts on giant sequoia ecology. Even if giant sequoias as a species can adapt in various ways to changing conditions, it is doubtful if all associated species could do so. In that case they would survive as a species while their historic ecosystem dissolves.

End of excerpted text (Harrison 2013).

Giant sequoia moisture stress

Moisture stress in giant sequoias can be defined in many ways and at several space/time scales (Figure 1). At the diurnal and seasonal timescale and at the leaf spatial scale, moisture stress can be quantified as anything that closes stomata and constrains gas exchange, leading to a decrease in energy uptake during photosynthesis. At a longer timescale (years to decades) and the individual tree spatial scale, a compromised energy budget may lead to decreased reserves available to cope with other stressors, including insects, disease, fire, climate change and air pollution. At the longest timescale and at the stand and species scale, moisture stress may be seen as greater mortality, changes in stand structure, changes in forest function like nutrient and water cycling, and shifts and/or contractions in species range.

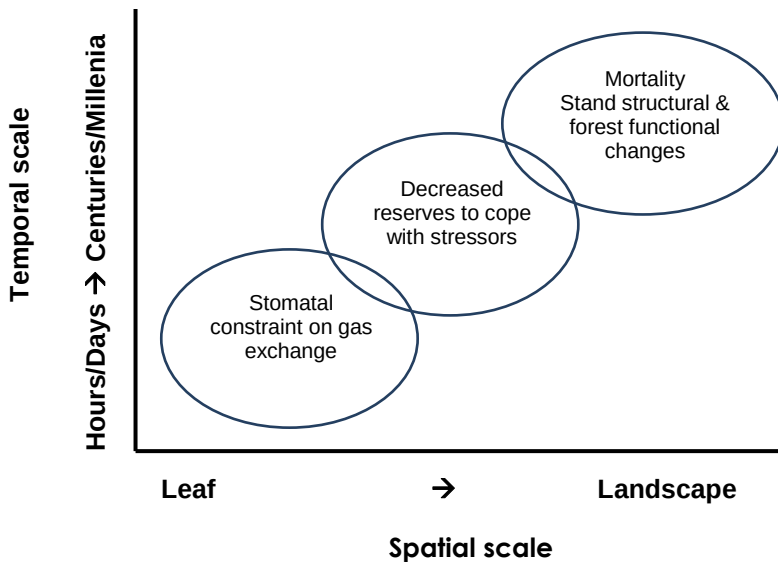
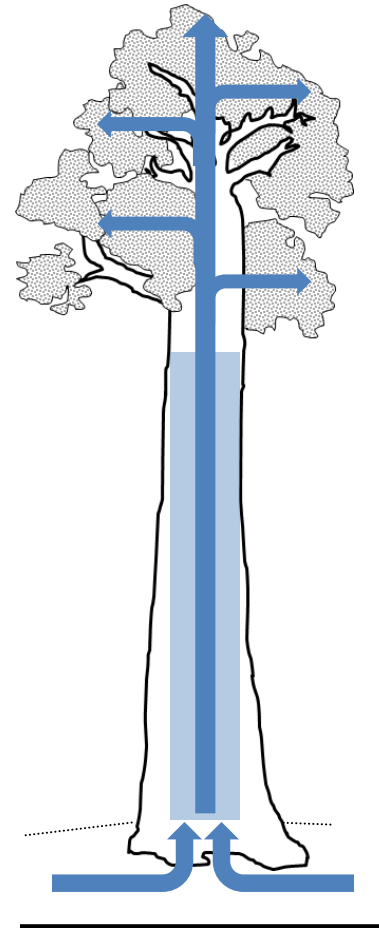


Figure Intro-1. Moisture stress in giant sequoia can be expected to be manifest differently at different spatial and temporal scales. The blue shading indicates the window of influence of measurement and management.



The energy budget of giant sequoia is strongly influenced by soil water availability and water loss from the canopy. Moisture stress = energy loss.

Moisture stress can be a result of either low soil moisture or low atmospheric humidity, or both. Water is drawn up from the soil through the roots into the trunk and upwards to the leaf surface.

Since sequoia trunks are so large, they have the capacity to store huge amounts of water. Water is released into the atmosphere through small pores on the leaves/needles (stomata) that can open and close in response to environmental factors. Stomata typically close when available internal water is not sufficient to meet evaporative demand. Since stomata also control photosynthesis, their closure limits the ability of the tree to produce sugars and thus food energy. So when moisture stress is high, photosynthesis is constrained and the energy budget of the tree is negatively affected.

So, two moisture factors control the sequoia water and energy budgets – soil moisture availability and atmospheric humidity.

Soil moisture availability

In the Mediterranean climate of California, there is little rainfall between May and October. Because there is little rain, the summer is predictably the driest time of the year that sequoias have to cope with, and soil moisture drops from June through October. Soil moisture during this period is often dependent on melting snow either on site, or uphill. Warmer annual temperatures, including those associated with climate change, reduce the snowpack and lengthen this low soil moisture period.

Topographic wetness index (TWI) is a measure of the potential for a landscape to hold water, based on its surface characteristics. It is calculated as a measure of slope within a catchment area. TWI is smallest in areas with steep slopes and diverging topography and TWI is highest in areas where water pools, areas with milder slopes and converging topography.

TWI is a proxy for actual soil moisture at the landscape scale. Few long-term soil moisture measurements exist in sequoia groves, and no soil moisture measurements exist to estimate soil moisture at the landscape scale.

TWI as a proxy for soil moisture may be confounded when surface topographic characteristics do not reflect subsurface terrain. Cracks, fissures, and other subsurface features may pool water. Sequoia roots, although they are typically shallow, may have access to water in these areas. Roots may extend laterally significant distances, adding some uncertainty in pinpointing where water uptake occurs.

Canopy moisture stress

The sequoia canopy is where the majority of moisture loss occurs, and where short-term moisture stress effects will be measurable and visible. To take up carbon dioxide from the air, the energy source for the tree, stomatal pores on sequoia leaves must open. When stomata are open, water evaporates from the



inside of the leaf into the surrounding air. So energy and water are tied. Carbon (energy) uptake requires water loss, but water conservation by closing stomatal pores limits carbon uptake thus results in energy loss. This trade-off is termed “water-use efficiency”.

Canopy moisture stress for this study was assessed with the use of remotely sensed images and algorithms of reflectance data that model water content and “greenness” of the exposed canopy tops. The remotely sensed data were obtained by Landsat5 TM (Thematic Mapper)

The top of the giant sequoia canopy is more moisture stressed than the bottom, thus remotely sensed images—if validated—could be good indicators of grove moisture stress.

sensor. The imagery has a spatial resolution of 30 m and a swath of 185 km, which is detailed enough to characterize at the grove scale, but not the individual tree scale. In this project, about 250 Landsat5 TM images covering the study areas were acquired. The years 1984-2010 were analyzed, only including the driest part of the summer season (mainly July and August) for each year, when canopy moisture stress would be expected to be at its maximum.

Existing studies suggested that near infrared (NIR) wavelengths and shortwave infrared (SWIR) wavelengths are relatively sensitive to liquid water, which provides many advantages in satellite monitoring of vegetation water content (Hunt and Rock, 1989; Gao, 1996). In this project, several vegetation indices derived from NIR and SWIR wavelengths were selected. The index most sensitive to water, the Normalized Difference Water Index (NDWI), is an index of vegetation moisture. The other indices are measures of canopy density or greenness, the most derived of which is the Modified Soil Adjusted Vegetation Index (MSAVI) that improves the separation of canopy from background soils, important for areas with patchy vegetation cover.

Ambrose et al. (2009) and Ambrose et al. (in prep) provide much of what is currently understood about sequoia canopy physiology and leaf-level water use. Their work showed that moisture stress at the top of the canopy is different from the bottom of the canopy. Particularly, at the top of the canopy stomata are closed more of the time and leaf area per unit mass is lower than at the bottom of the canopy. Sequoia

needles are thicker in the sunny canopy tops, more like juvenile foliage. Stomata are open less at the top of the canopy than at the bottom, but the top of the canopy takes up relatively more carbon for the time they are open. In other words, the water-use efficiency is higher at the top of the canopy.

Linear relationships link the physiology at the top of the canopy with that at the bottom (Figure 2). These relationships are key because remotely sensed images represents the top of the canopy only. However, by knowing the moisture stress signal at the top, the results of Ambrose et al. (2009) can be used to estimate how the rest of the

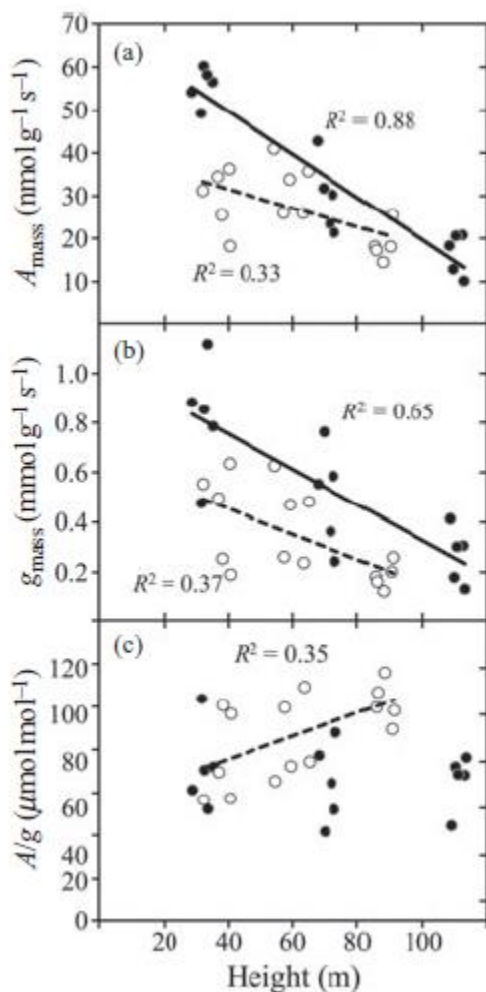


Figure Intro-2. Canopy physiology is different at the top of the canopy of giant sequoia than at the bottom. Stomatal conductance and photosynthesis are lowest at the canopy top, although instantaneous water-use efficiency is greatest. Open circles are giant sequoia. Closed circles are coastal redwood From Ambrose et al. (2009). A refers to maximum photosynthesis per unit leaf mass, and g refers to maximum stomatal conductance per unit leaf mass.

canopy is responding. In this case, stomatal closure will be greatest at the top of the canopy, but stomata are less constrained linearly with canopy depth.

Key points and implications of the Guo et al. report

Topographic Wetness Index (TWI) and Snowcover Persistence

Groves lie within a fairly narrow elevational band on the west side of the Sierra, mostly from 1,200-2,200 m. There is significant variation in the range of TWI between and within groves, although the difference in average TWIs between each grove is small. A mean TWI below 7.5 is seen in only 15% of groves, suggesting a potential threshold minimum soil moisture below which sequoia may not grow. By area most of the groves have mean TWI values in the range of 8-9, perhaps indicating sequoia soil moisture optimum. In general, larger groves have higher maximum TWIs than smaller groves. For example, Belknap and Redwood Mountain groves (9.5 and 13.2 km² area, respectively) had maximum TWI greater than 26 whereas West Redwood Mountain, Clough and Douglass groves (each covering about 0.01 km²) had maximum TWI less than 12.

Other geographic areas within the elevational band that giant sequoias occupy appear to have similar TWI and might be suitable habitat for the species. More work would be required to assess whether vegetation and soils are suitable for giant sequoia in these currently un-colonized areas.

TWI is a measure of surface topography and does not reflect sub-surface water storage potential, which can be large. Snow persistence is an important variable that—together with TWI—can reveal some of the elements key to soil moisture. The current analysis can be used to highlight groves potentially more vulnerable, particularly when considering TWI and snowcover persistence together. But it should be a starting point, not an ending point for informing resource-management actions to reduce stress in specific areas.

Based on the snowcover persistence analysis, it can be concluded that the groves having more stable snowcover persistence should have less vulnerability to soil moisture stress than the groves with shorter or more variable snowcover persistence. Elevation is a predictor of snowcover persistence, but within small elevation gradients other factors, such as aspect, also influence snowpack. Areas with milder slopes and more converging area (higher TWI), plus longer snow persistence, should be less susceptible to low summer soil moisture than areas having steeper slopes and more diverging topography (lower TWI) and earlier snowmelt.

It is probable that lower-elevation sequoia groves that lack significant areas with high TWI are most vulnerable to moisture stress. While steepness is a general indicator, TWI is expected to be a better indicator of moisture stress in this case. Higher-elevation groves should be considered less vulnerable, unless the TWI across the groves is low. For the large number of groves with elevations mainly in the 1,800-2,100 m range, the distribution of TWI values, or possibly the mean plus one standard deviation, can serve as a first-order indicator of relative vulnerability.

While at present about 80% of the grove area is above the 1,800-m rain to snow transition elevation; with a 2°C warming only about 15% of the grove area will be above the future 2,100-m rain-snow transition elevation. Groves that lack significant areas of higher-elevation terrain, topographic convergence and subsurface storage should be the most vulnerable to moisture stress.

Remote-sensing

NDWI appears to be the most informative potential canopy moisture stress index in assessing moisture stress in giant sequoia, because it has the strongest water signature (Gao 1996, Ceccato et al 2001, Ceccato et al 2002, Gu et al. 2008). The other indices presented are estimates of greenness, each with varying sensitivity to canopy gaps and visible soil influence on reflectance. MSAVI is the index most robust to gaps and performs best of all the indices when applied to areas with a high degree of exposed soil surface. MSAVI shows very little variation across the sequoia groves, however, possibly indicating that the groves are consistent in terms of reflectance, so that they provide a uniformity of canopy once gaps are taken into account. While NDWI is a potentially better measure of canopy moisture than the greenness indices, *it is influenced by canopy gaps* (Gao 1996).

In general, averaged NDWI is highest in the middle of the north-to-south range of giant sequoia. Groves to the north and south of the parks show lower NDWI (potentially greater moisture stress). The groves in the southern region of the range have higher NDWI (potentially lower moisture stress). Precipitation, temperature, and NDWI do not show significant changes over the 20-year period of analysis. There is little evidence that temperature is related to NDWI, however precipitation showed significant relationships with both a wet and a dry grove ($R^2 = 63\%$ and $R^2 = 28\%$ respectively).

Other geographic areas within the elevational band that giant sequoias occupy appear to have high NDWI and might be suitable habitat for the species.

The data indicate that groves with higher NDWI have lower variation from year to year, and that groves with lower NDWI have higher variation. Assuming a higher within-grove variance in NDWI indicates a higher vulnerability of a grove to changing climate, drier groves have a higher vulnerability to a drying climate than wetter ones.

The relationship between topographic wetness and NDWI has an R^2 of 0.1, indicating that very little of the variability in TWI is explained by NDWI. The better relationship between snow persistence and NDWI ($R^2 = 0.5$) suggests that snowmelt may play an important role in local canopy water relations.

Gaps in understanding – potential future directions

Interpreting the results of this study with relation to the vulnerability of giant sequoias to moisture stress was difficult because no direct measurements of soil moisture or canopy water content were available to validate the proxies that were measured. So it was unclear whether the proxies used were good indicators of moisture stress in soils and giant sequoia canopies.

Ideally, a study of moisture stress in giant sequoia groves should include *direct measurements* of canopy moisture stress. Canopy moisture stress can physiologically be defined as:

Canopy Leaf Water Content = $f(\text{soil water availability, stem hydraulic conductance, evaporative demand, controls on leaf physiology})$

This framework can help to constrain what measurements need to be made in the future, and give context to where they belong in the relationship. In the Guo et al. report (below), populating a model like the one above with the measurements already made might look like the following, and would be a useful next analysis:

$$\text{NDWI} = f([\text{TWI and/or snowcover}], [\text{temperature, aspect, VPD}])$$

What measurements have been made and what measurements are still needed should be determined in consultation with researchers having expertise in these areas.

The following were noted by reviewers:

- As noted, there is a general lack of ground-level validation of the remote sensing work. The value of different indices can only be answered by looking at performance against independent data, like field data.
- Disturbance, particularly fire, in the landscape was shown to have an impact on the reflectance results, probably unrelated to canopy moisture.
- The indices are sensitive to species composition, canopy structure, leaf area, tree density and other stand-level variation.
- A longer record of remote imagery and climate data would increase confidence in findings.

Further research – soil moisture stress

Potential future work to further the results in this study include: i) more-detailed evaluation of available data, ii) field characterization of landscape features in selected groves, and iii) multi-year measurements of more-direct indicators of moisture stress.

1. *Assess TWI-soil-moisture relationships.* Although we lack soil-moisture data in the 70 groves, there are spatially-distributed, long-term data sets in nearby areas of similar elevation and forest density that could be used to evaluate the TWI-moisture stress relationship. This would allow extending the conclusions and provide more-definite management recommendations.

2. *Evaluate vegetation-TWI relationships.* Using available LiDAR data, supplemented by additional LiDAR flights and/or GPS measurements of where individual giant sequoia trees are located within groves, do a combined spatial analysis of tree location, TWI, and vegetation-stress indices. This will

determine if sequoias are preferentially located in areas with higher TWI, and also if they are located in areas with higher or lower canopy moisture stress.

3. *Establish within-grove heterogeneity in soil moisture.* Shortly after the seasonal snowpack has melted, measure soil-moisture patterns in a late-spring or early-summer synoptic survey at two or more giant sequoia groves to establish differences in water storage across elevation, aspect, TWI and canopy-cover gradients. Evaluate in the context of available, detailed data sets from non-grove areas. Use data to assess TWI-soil moisture relationships in groves.

4. *Carry out longer-term soil-moisture measurements in groves.* Based on the synoptic surveys, install continuous-measurement nodes for soil moisture, which will be put in place and monitored over the long term as indicators of landscape and temporal variability and change. To the extent possible, these measurement nodes should be located at or near sites with other relevant climate, hydrologic and ecosystem data. Two candidate groves that fit this criterion are Giant Forest and Redwood Mountain. Note that Giant Forest has an average elevation of 2058 m, and is among the higher-elevation groves in Sequoia-Kings Canyon; whereas Redwood Mountain has an average elevation of 1816 m, and is a mid to lower elevation grove. Other groves should be considered based on funding. Note that soil moisture generally tracks sap flow measurements in mixed-conifer forests, and is much less expensive and reliable. Sap flow should be considered for groves based on soil-moisture results.

5. *Extend precipitation and meteorological measurements.* Based on current analyses of temperature, precipitation and other meteorological variables, extend multi-year or long-term measurements to cover important climate gradients and microclimates.

6. *Carry out subsurface characterization.* In selected groves, and based on topography, soils, vegetation and geology, carry out seismic surveys to establish depths and profiles of weathered material as a basis for estimating subsurface storage potential of representative landscapes.

7. *Build a convenient GIS data base of all relevant data.* This will include an artifact-free DEM, physiographic and vegetation information, vegetation indices, available remotely sensed snowpack and other vegetation information, LiDAR data and other emerging datasets. Include relevant quality-controlled time-series data if not already publically available.

8. *Do a pilot study of isotopic indicators of water source.* Characterize water isotopes of shallow and deeper water reservoirs in one or more groves, and compare to water use by vegetation

Further research – canopy moisture stress

1. *Field data are needed to calibrate and validate the ground truth information.* Because of the lack of sequoia canopy moisture measurements, only satellite data were used in this project. More climate stations would provide climate data with higher spatial resolution and accuracy. To validate and calibrate remotely sensed data, field data related to vegetation moisture, such as leaf water content,

should be collected. A leaf-sampling campaign of giant sequoia trees should be carried out, and their pure spectra should be collected in controlled laboratory experiments. Also, their water content and nutrient capacity should be measured accurately in the laboratory. Such data are necessary and required to improve current studies.

2. Stand structure and remote imaging. The use of aerial photos in conjunction with reflectance data could help to identify vegetation density and other stand characteristics that relate to remote sensing. Between-pixel variation of these images may be due to within-pixel variation in canopy structure, leaf area, or species composition. Because groves are so small, a useful approach may be to get hi-resolution imagery for a few of the groves. Crown closure, stand density and within-stand gaps have an important influence on reflectance imagery. LIDAR would be useful in supplying stand structure to correct remote imagery.

Other potential approaches to further the understanding of giant sequoia moisture stress

Direct measurement of canopy moisture stress

Multiple techniques exist to measure leaf moisture stress directly, including measurements of leaf water content, leaf water potential, stomatal conductance, and water-use efficiency (Ambrose et al. 2009). These techniques are done at the leaf-level, thus are labor intensive, particularly since accessing the crowns of giant sequoia requires time and specialized equipment. These measurements would provide information on, at most, 15 individuals in one summer.

Vegetation type indicators of moisture stress

The proximity of each grove to different vegetation type either above or below may serve as a biological marker showing steep gradients in water availability.

Tree-ring data

Existing tree ring data show that giant sequoias are responding to climate. Forty to sixty years of tree ring growth show a response to previous years' precipitation and not to temperature (Rob York, personal communication). Tree ring records might be used to validate remote sensing time trend results. Tree rings might also be used to develop a Palmer Drought Severity Index. This would require interpolation with climate data, and adds another element of uncertainty. However, the tree ring record is potentially very long in these long-lived trees.

Direct infrared measurement

Canopy reflectance measurements at the whole-tree scale (from a plane, helicopter, or other low altitude platform) that use thermal imagery (Scherrer et al 2011) could possibly reveal temperature differences within and between groves, but these would also require canopy level validation of physiological and mechanistic relevance to moisture stress. It is possible that the small boundary layers found in needle foliage would limit the effectiveness of thermal imagery.

Atmospheric humidity

Cloud banding along the western flank of the Sierra shows a remarkable similarity in pattern to the distribution of giant sequoia (Eric Waller, personal communication). These cloud bands appear when cold spells in the California central valley force atmospheric humidity to condense in situ (Figure 3 and many other available images). It is possible that these cloud bands reveal areas of generally higher atmospheric humidity which create moist conditions, ideal for giant sequoia because of the reduced evaporative demand. Giant sequoia might inhabit the areas at the conjunction of 1) appropriate soil type, 2) higher soil moisture, 3) high atmospheric humidity, and low evaporative demand. It is also possible that the higher atmospheric humidity in these areas is a *result* of giant sequoia. Giant sequoias transfer huge amounts of water from the soil to the atmosphere. A single sequoia instrumented with sapflow monitors was estimated to move 2,900 L of water in per day from the soil to the atmosphere (Anthony Ambrose, personal communication).

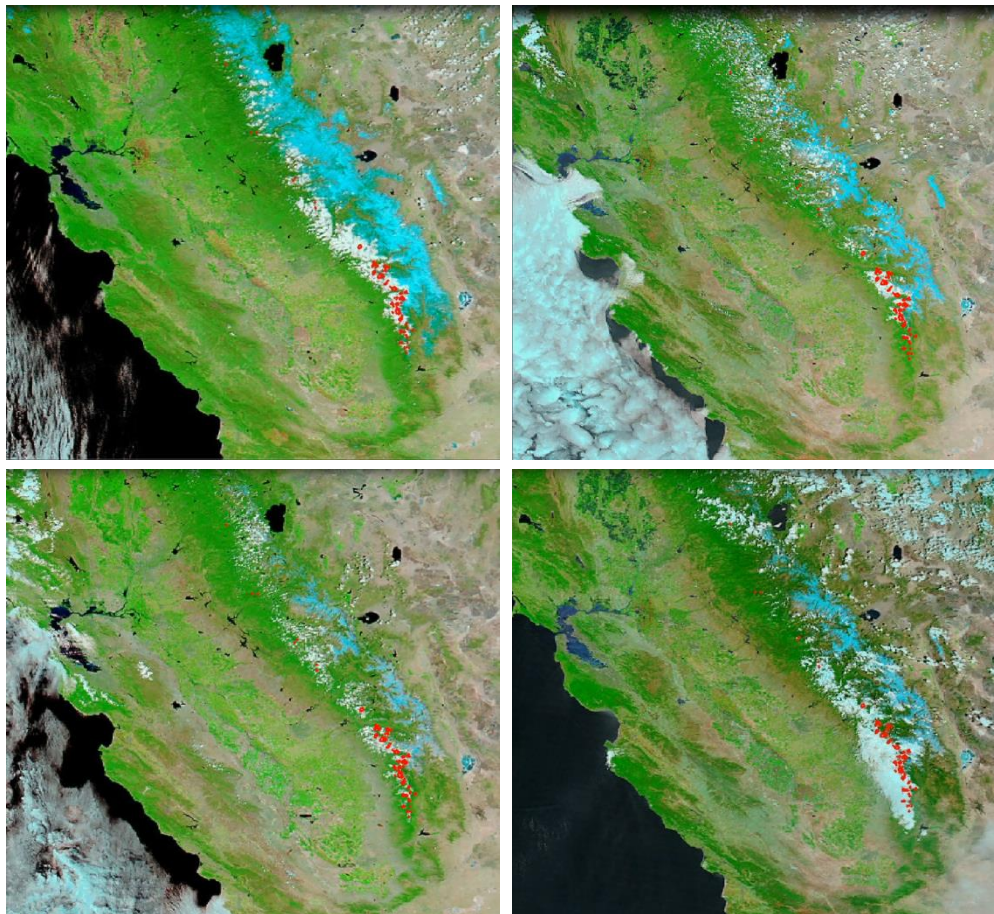


Figure Intro-3. Images of the San Joaquin Valley from space on April 29, 2010 (top left), June 2, 2011 (top right), August 7, 2009 (bottom left) and September 13, 2008 (bottom right). Red dots are giant sequoia groves, light blue is snow, white is clouds (images courtesy of E. Waller).

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***SEQUOIA AND KINGS CANYON NATIONAL PARKS:
VULNERABILITY OF GIANT SEQUOIA TO MOISTURE STRESS IN A
CHANGING CLIMATE: A PILOT STUDY OF POTENTIAL MOISTURE
PROXIES***

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Introduction

Giant sequoia trees and their ecosystems are unique to the Sierra Nevada, where most groves are federally managed. In the southern Sierra Nevada, 70 giant sequoia groves stretch across two jurisdictions, including Sequoia and Kings Canyon National Parks (SEKI) and Giant Sequoia National Monument (GSNM). Giant sequoias are difficult to study, and much of what we understand about them has come out of these groves. Giant sequoias are unique and significant part of the natural heritage of the region, and even of the country, yet their existence may be threatened by climate change. According to a Natural Resources Condition Assessment, increasing temperatures over the next several decades, by inducing earlier snowmelt and prolonging summer droughts, may create conditions unfavorable to giant sequoias (York et al., 2012). A direct effect would probably be a widespread and continuing failure in giant sequoia reproduction, even in the presence of prescribed fires, because giant sequoia seedlings are highly vulnerable to prolonged drought (Harvey et al., 1980; Mutch, 1994). Death rates might increase among adult sequoias and associated species as drought stress makes them more vulnerable to insects, pathogens, air pollution, and intense fires. In order to effectively and efficiently allocate management efforts to conserve giant sequoias, the vulnerability of giant sequoia groves to drought/water stress must be evaluated.

Vegetation stress can be defined as any disturbance that severely impacts growth of vegetation, such as insufficient water or nutrients, adverse climatic conditions, plant disease, and insect damage (Jackson, 1986). Factors leading to water stress include reduced soil moisture, increased canopy temperature and evapotranspiration, and reduced leaf water content, and these influence the canopy moisture conditions to various degrees. Changes that take place as a result of water stress affect the amount and direction of radiation reflected and emitted from plants. Remote sensing techniques, relying on up-to-date information over a large geographical area, are capable of measuring such radiation and therefore offer the possibility of quantitatively assessing plant water stress caused by biotic and abiotic factors (Jackson, 1986).

In addition, topographic gradients may influence vegetation patterns. The relationships among topographic gradients, aspects, and topographic wetness index are very important in understanding the vegetation pattern on any watershed. The topographic wetness index (TWI) is widely used to simulate soil moisture wetness states in a watershed, and it is the most commonly used indicator for locating soil moisture storage and/or soil water stress on a landscape (Beven and Kirkby, 1979). High TWI areas in a catchment tend to saturate first and therefore indicate potential surface or subsurface contributing areas. Thus in principle there is a strong correlation between TWI and wetting/drying cycles, and TWI patterns can be used as a first-order estimate of soil-moisture distribution. However, soil moisture also

depends on other features, e.g. vegetation, bedrock topography, soil properties. Correlations between TWI and actual soil wetness or zones of surface saturation give mixed results (Lin et al., 2006).

The main objectives of this project are: (1) to develop TWI maps for Sequoia and Kings Canyon National Parks (SEKI) and Sequoia National Forest/Giant Sequoia National Monument (SNF/GSNM) at the watershed scale and link them with static parameters/variables such as vegetation and soil types, and dynamic variables such as temperature, snow, and precipitation, in order to identify the most and least water stress regions; (2) to estimate various vegetation and moisture indices, which can directly or indirectly indicate canopy moisture conditions, with a time-series of satellite remotely sensed data [Landsat5 TM (thematic mapper) data]; and 3) to evaluate the vulnerability of giant sequoia groves to water stress based on the index that can best represent the relationship between moisture conditions and climate change.

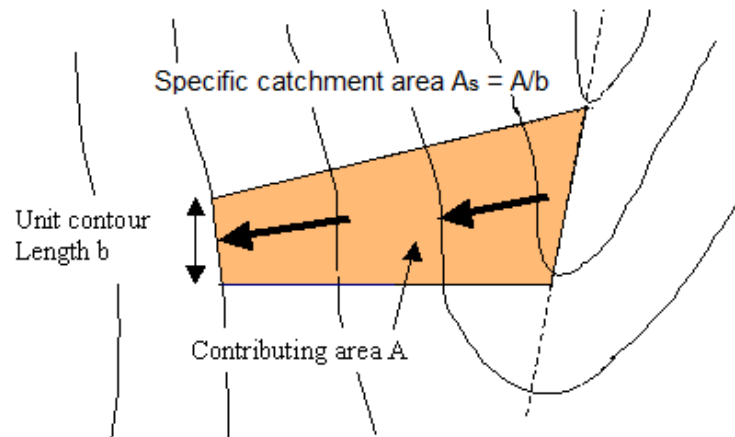
Based on our main objectives, we developed TWI maps for SEKI and SNF/GSNM at the watershed scale, covering 70 sequoia groves, and compared them with static variables such as vegetation and soil types. A 10-m digital elevation model (DEM) was used to develop slope and aspect maps in order to link slopes and aspects with the regions of most and least water stress. We also evaluated historical changes in remotely sensed canopy moisture indices in the summer seasons from 1984 to 2010 for 70 giant sequoia groves in SEKI and SNF/GSNM. We also studied dynamic changes in climate variables in the area covered by the sequoia groves. The climate dataset was developed by the Spatial Lab at UC Merced, for the time range 1930 to 2010, across the western United States, at monthly and yearly temporal resolutions. Climate variables include total precipitation and mean temperature. For the period 1984–2005 (both the climate data and TM images available for the study area are in this time period), we combined the historical maps of vegetation and moisture indices derived from satellite data with the historical climate data, and then analyzed the correlations between them.

I - Soil Water Availability

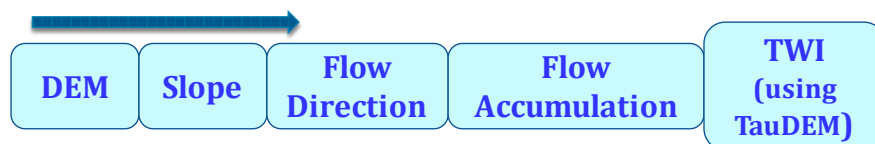
1. Topographic Wetness Index (TWI)

The topographic wetness index (TWI), represents an attempt to integrate topographical information in order to capture the hydrologic variation in soil water content. We used an approach developed by Beven and Kirkby (1979) to calculate *TWI*:

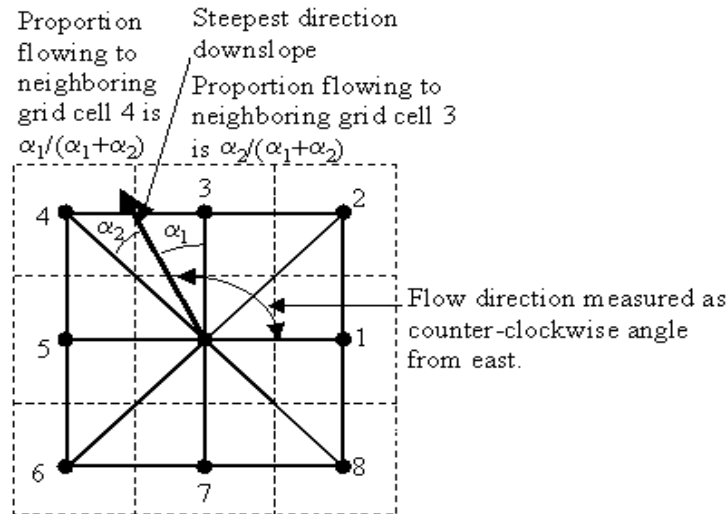
$$TWI = \ln\left(\frac{A_s}{\tan \beta}\right) \quad (I-1)$$



where A_s is the specific catchment area, β is the local slope angle in degrees. When flow accumulation is multiplied by cell area, it refers to contributing area. According to the *TWI* concept, the soil moisture and groundwater level of a location are the result of the accumulated upslope area, A , and the drainage expressed as slope, $\tan \beta$. *TWI* has been used in several studies to spatially estimate hydrological, physical, and chemical properties of soils.



For flow direction, the D_∞ algorithm was used as shown below.



The *TWIs* physical significance is based on water accumulation by gravity, and is thus used as an index of the potential supply of water to meet evaporative demand. It does not take into account other aspects such as soil properties or climatic factors such as precipitation and temperature on soil-moisture content. The improved approach used in the current analysis classified aspect into shady slope, sunny slope, and semi-shady and semi-sunny slope, considering more southerly aspects to be sunny and more northerly aspects to be shady (Ma et al., 2010). For example, the soil-moisture content of a shady slope is expected to be greater than that of a sunny slope; however, it is necessary to analyze if *TWI* values differ on shady versus sunny slopes. Note also that for equal values of A_s , *TWI* decreases with local slope angle.

2. Data and methods

First, a study region was developed to cover all 70 sequoia groves that were identified (Figure I-1). The area of individual groves ranges from 0.01 km² to 15.51 km² (Table A1). Total grove area is about 150 km², with the six largest groves accounting for half of this area (Mountain Home, Converse, Redwood Mountain, Evans, Belknap, Giant Forest); and the smallest two thirds of the groves making up only 10% of the total grove area (Figure I-2).

A 10-m DEM was used to calculate *TWI* for the study region. We initially used a 10-m DEM obtained from Sequoia-Kings Canyon National Parks for the full region. However, due to severe striping in the slope and *TWI* calculations we used a different 10-m DEM obtained from Sequoia-Kings Canyon National Parks in 2005 that had the same elevation patterns but had few artifacts in the slope and *TWI*

calculations.¹ We also evaluated 10-m DEMs currently available for download from USGS; however the same striping problem was evident. The problems were much less apparent in the 30-m USGS DEM; however the TWI calculations showed a much narrower range of values than for the 10-m DEM. Thus for the area outside the Parks we resampled the 30-m DEM to a 10-m resolution and merged this resampled product with 10-m DEM obtained from Sequoia-Kings Canyon National Parks in 2005. While resampling did not provide new information, this allowed doing all calculations at the same spatial resolution, taking advantage of the 10-m DEM inside the Parks. While the area outside the parks is not completely free of striping artifacts, it is much less than when using the 10-m DEMs currently available from the parks or USGS. Using ArcGIS tools, the 10-m DEM was used to derive slope, specific catchment area and aspect of the study region. Elevation, slope and aspect maps were compared with the TWI map to understand the variations of soil-moisture wetness.

¹ The metadata for this 10-m DEM indicated that they were the source files for a National Elevation Data (NED) binary floating point raster dataset.

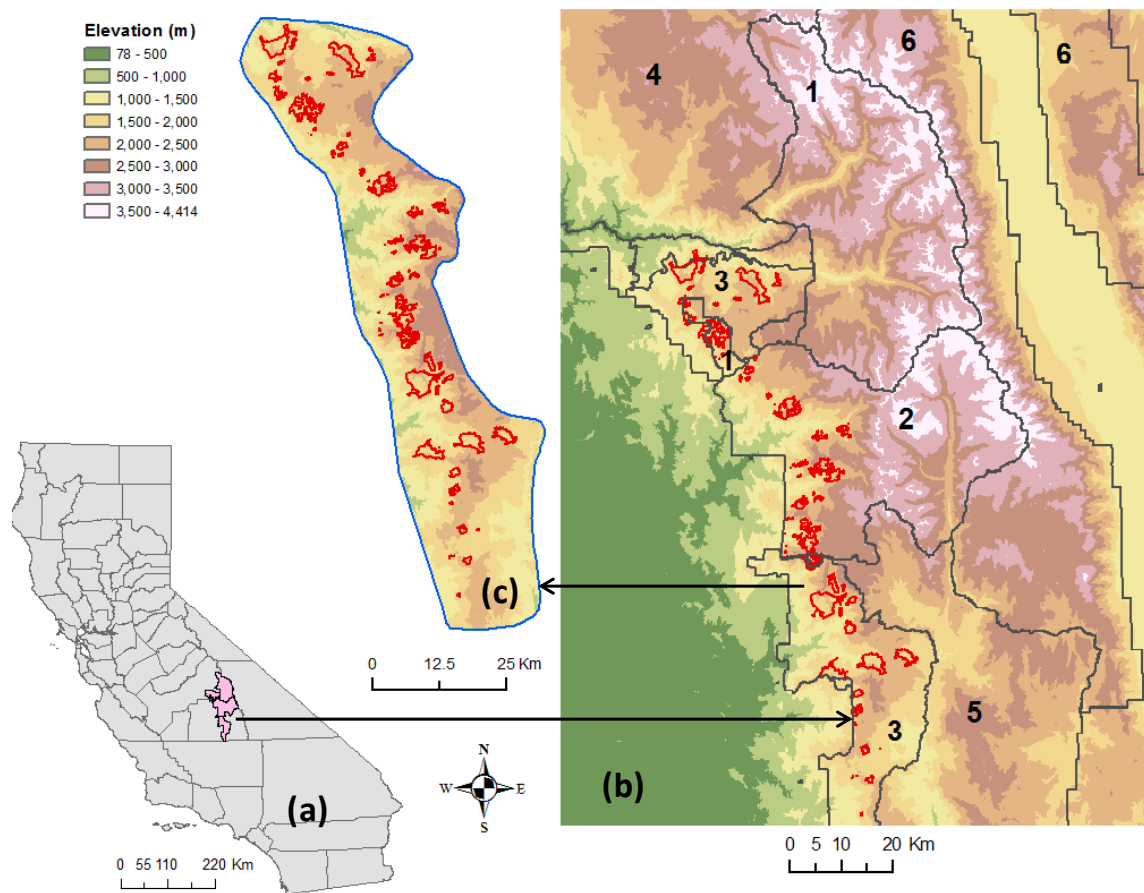


Figure I-1: Locations of the 70 Sequoia Groves (inset polygons in red): a) California; b) DEM for larger region with national parks and forests; c) and selected region for analysis. 1. *Kings Canyon Nat. Park*, 2. *Sequoia Nat. Park*, 3. *Giant Sequoia Nat. Monument*, 4. *Sierra Nat. Forest*, 5. *Sequoia Nat. Forest*.

Soil databases and landcover maps were obtained from STATSGO² and CALVEG³, respectively (Figure I-3). The STATSGO soil map consists of 11 soil layers. One layer (surface soil layer) soil map was developed based on the common or majority of soil textures in 11 soil layers. Based on the STATSGO soil map, the maximum soil depth in sequoia groves is 150 cm. The STATSGO soil depths support the depth used by previous studies, for example, Halpin (1995) wrote “Soil depths in the mixed conifer- giant sequoia forest area have been expected to rarely exceed 150 cm (Rundel 1969, 1971, Hartesveldt et al. 1975, Harvey et al. 1980, Oshumi 1983, Huntington et al. 1985, Reigel et al. 1988)”.

² See <http://soils.usda.gov/survey/geography/statsgo/>

³ See <http://www.fs.fed.us/r5/rsl/projects/mapping/accuracy.shtml>

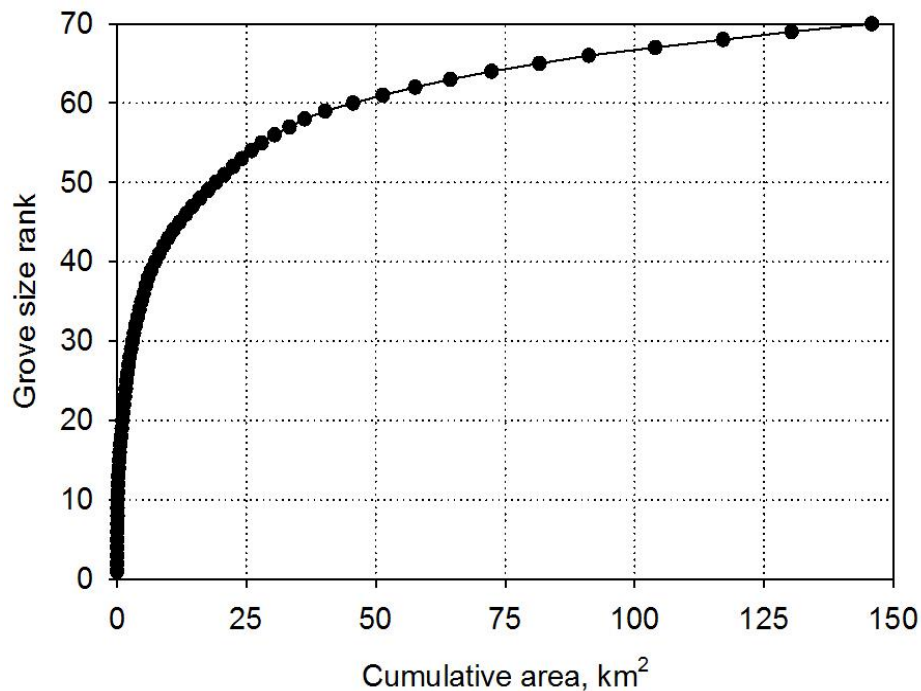


Figure I-2: Cumulative area of groves, summed from smallest to largest

However, it should be noted that soil depth does not indicate relative water storage, as strata deeper than mapped soils account for a significant fraction of water use by forest vegetation and streamflow in Southern Sierra mixed-conifer forests (Arkley, 1981; Rossi and Graham, 2010; Bales et al., 2011).

The CALVEG landcover map, which is derived from LANDSAT reflectances, shows 1 to 5 vegetation types within each sequoia grove (Tables A2, A3)⁴. For example, Redwood Mountain sequoia grove has five types of vegetation; Herbaceous rangeland, shrub and brush rangeland, mixed conifer, conifer and hardwood.

⁴ <http://www.fs.usda.gov/detail/r5/landmanagement/resourcemanagement?cid=stelprdb5365219>

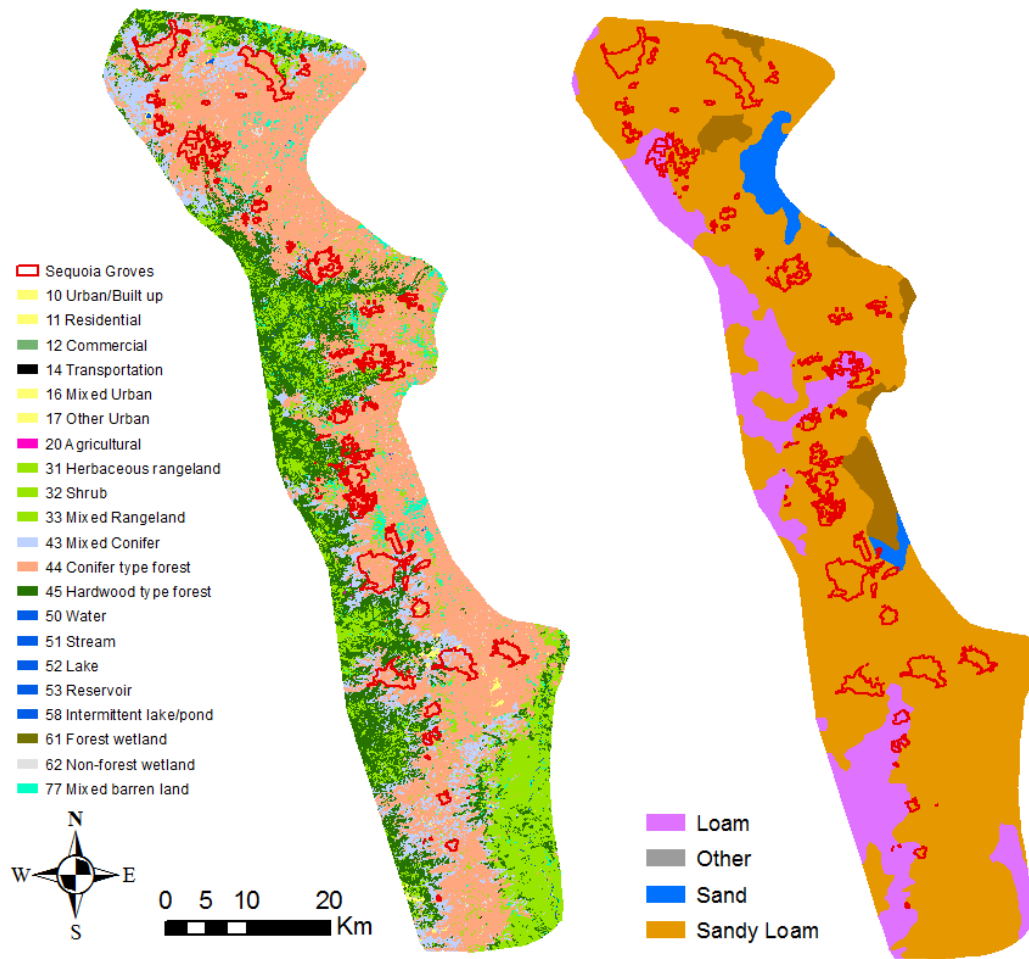


Figure I-3: a) Landcover map and b) soil texture map

In addition to TWI, this study also compared estimated *TWI* with the snowcover persistence in order to evaluate the relationship between high or low *TWI* versus high or low snowcover persistence within the sequoia groves. A 500-m MODIS fractional snowcover product was used to generate 12 years (2000-2011) of snowcover persistence maps for 1st day of each month from March to June (Painter et al., 2009; Rice et al., 2011). The index (0-12) of snowcover persistence is the number of years when each pixel has greater than 20% snowcover for the day of particular month. For example, a pixel value 4 for the 1st of March shows that there was snowcover in least four of the 12 years.

3. Results

First, elevation bands were developed using a 10-m DEM for the larger region. The Sequoia Groves map was used to narrow the study region so that the range of elevation can be small and it covers all of the 70 sequoia groves (Figure I-1). Second, soil and landcover maps were linked with sequoia groves. As shown in Figure I-3a, a majority of the sequoia groves have conifer and mixed-conifer landcover types; however, some of the sequoia groves are very close to the hardwood forest and shrub land. That is, the sequoia groves occur along a very steep climate gradient, which has the potential to undergo rapid changes as climate warms. Based on the STATSGO soil map, only three types of soil texture; loam, sandy loam and other, were found in this study region for the sequoia groves (Figure I-3b). A majority of the sequoia groves have a soil texture of sandy loam.

3.1 Elevation

Elevations in the groves ranged from 1088 m to 2756 m. As shown in Figures I-4 and Figure I-5, about 90% of the sequoia groves have a mean elevation in the range of 1600-2000 m. Within individual groves elevations can span a range of over 1000 m, suggesting that it may be necessary to analyze each grove individually to identify the specific areas that may have more or less soil-moisture stress. Many of the lower-elevation groves are small (Figure I-5a versus I-5b); with the result that about 90% of the mean grove elevations lie in the range of 1800 ± 100 to 2050 ± 100 m (mean $\pm$ stdev) (Figure I-5b). Relatively large groves exist across the elevation range of the groves. Belknap and Redwood Mountain groves lie at the lower end of this elevation range. Evans and Giant Forest occupy the upper end of this range; and Converse and Mountain Home groves are in the middle of the elevation distribution. Values for the mean, minimum, maximum and standard deviation of elevation for each grove are in the Table A1. The mean elevation of all grove area, i.e. aggregating all grove areas together in one analysis, is 1930 m (Figure I-6). Only 21% of the total grove area is below 1800 m, and only 15% is above 2100 m elevation.

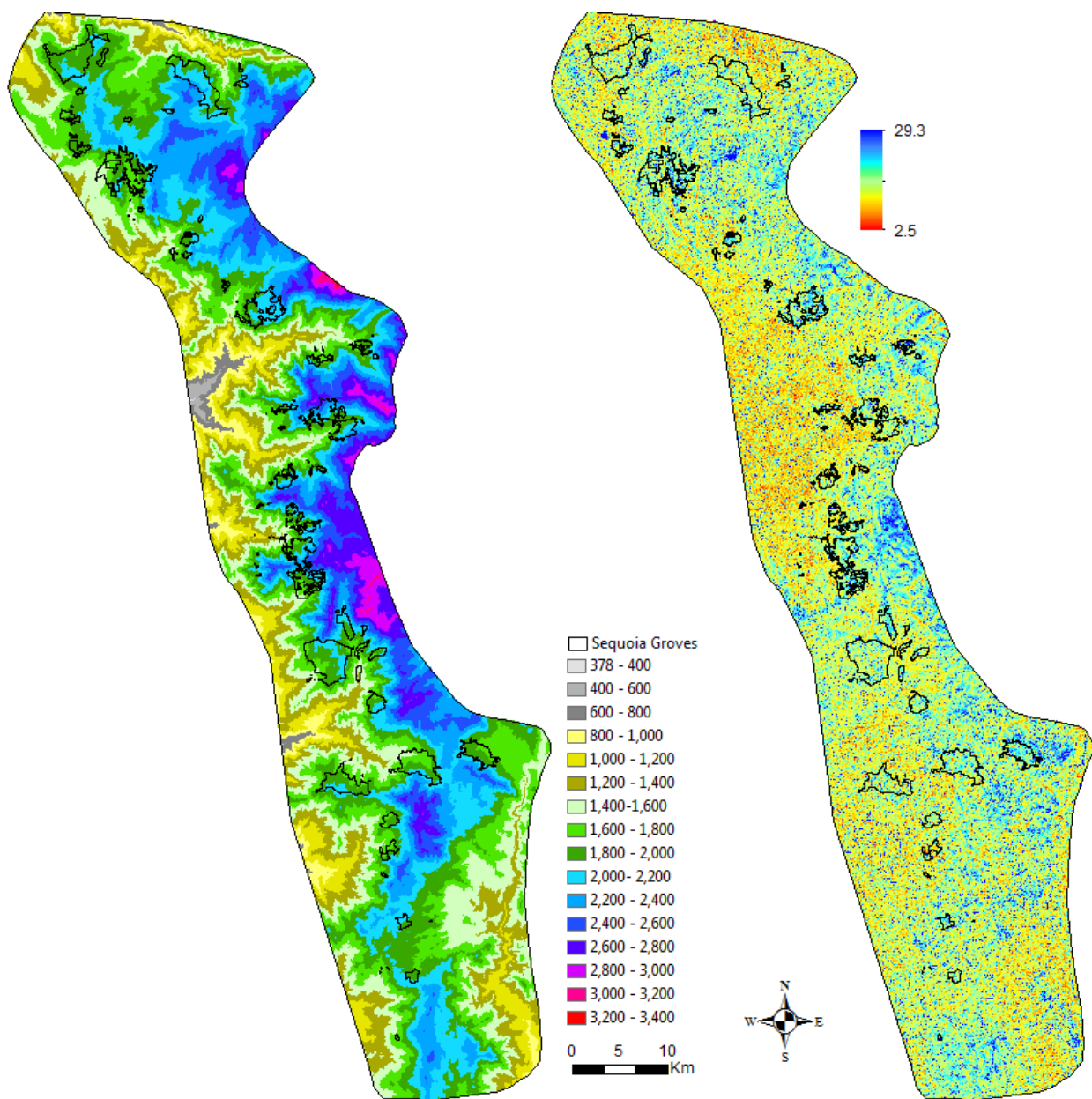


Figure I-4: a) Elevation, and b) TWI.

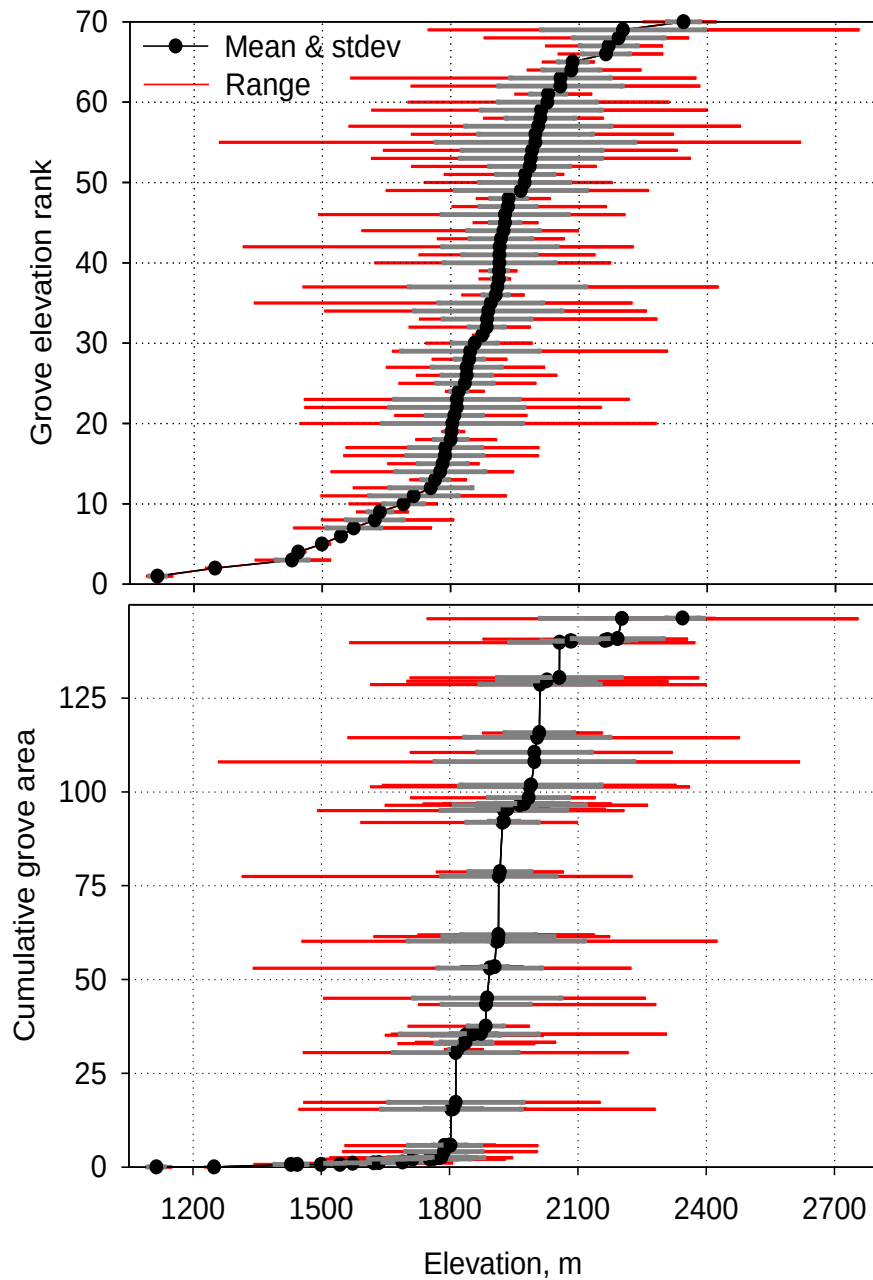


Figure I-5: Distribution of grove elevations: a) ranked from lowest to highest, and b) ranked from lowest to highest, but plotted versus cumulative area.

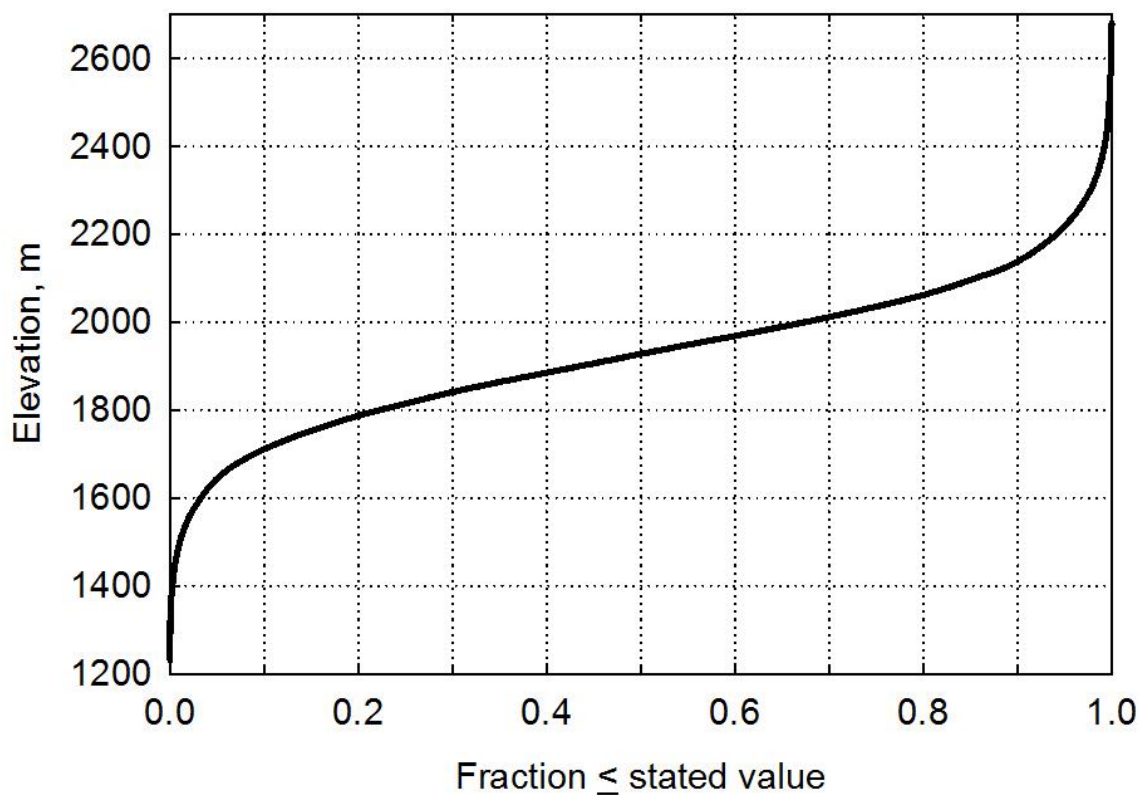


Figure I-6 Aggregate elevation distribution for area within the 70 groves.

3.2 Slope

The slope of sequoia groves ranges from 0° to 66° . As shown in Figures I-7, Figure I-8 and Table A1, there is significant difference in mean slope among the sequoia groves. For example, the lowest mean slope is at Indian Grove (0.8 km^2 , 1819 m) and is 7° , whereas the steepest is 40° at Douglass Grove (0.01 km^2 , 2085 m). Groves with steep slopes potentially have more soil moisture stress than do the groves with shallower slopes; the same would be true for steeper versus less-steep areas within individual groves. About 80% of the groves have mean slopes less than 29° , and half have slopes less than 23° (Figure I-7a). The area-weighted mean slope is 20° (Figure I-7b). The standard deviation of slope for most groves is near 8° , and the range for most groves spans zero to 50° or more. Values are tabulated in Table A1. The larger groves have mean slopes below 25° , with Evans at 21.0° , Mountain Home at 18.3° , Converse at 14.5 and Giant Forest at 13.3° .

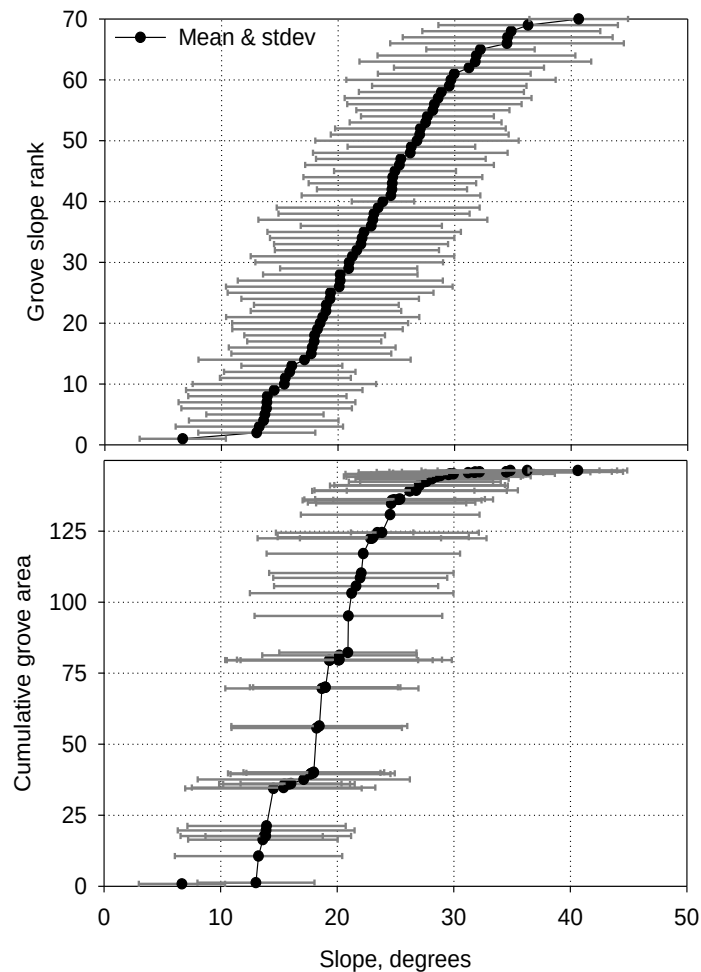


Figure I-7: Distribution of grove slopes: a) ranked from lowest to highest, and b) ranked from lowest to highest, but plotted versus cumulative area.

3.3 Topographic Wetness Index (TWI)

There is a range of TWI values both across and within groves (Figure I-8). In general, the differences between mean TWIs across groves are relatively small compared to the range of TWI values within each grove (Figure I-9). This is in contrast to slope, which does show significant differences across the 70 groves (Figure I-7). It can be seen that only one grove has a mean TWI below 7.5, and also few groves have TWI above 9.2 (Figure I-9a). It can be seen on Figure I-9b that the groves with the highest and lowest TWI values are small groves. Further, by area most of the groves have mean TWI values in the range of 8-9, with standard deviations on the order of ± 2 , or well within the range of 6-11.

Further analysis may be necessary at the grove level to identify vulnerable regions because of this somewhat larger within-grove variability as compared to the between-grove variability. This is also illustrated on the expanded view of TWI patterns in Appendix B.

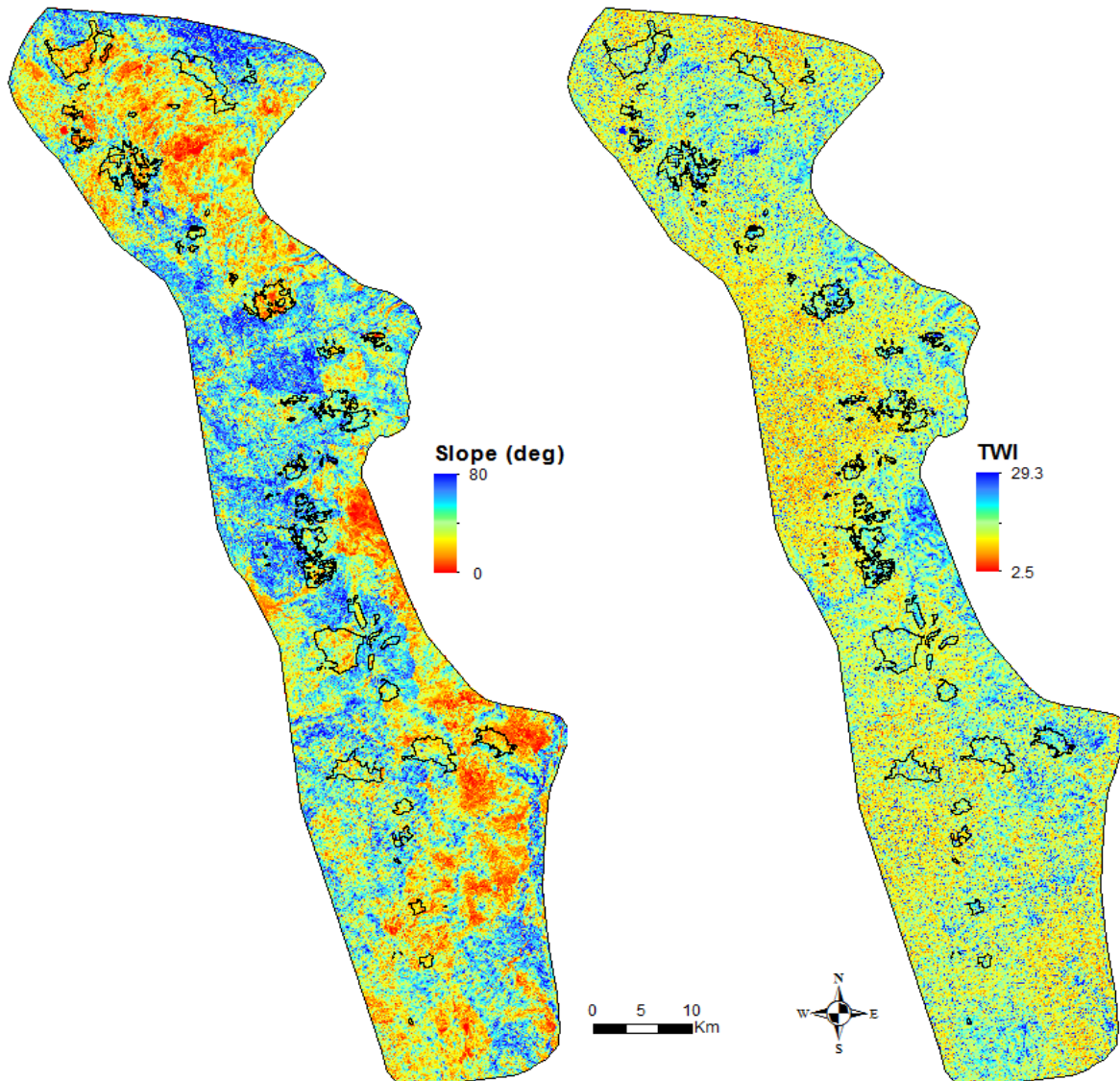


Figure I-8: (a) Slope angle ($^{\circ}$) and (b) TWI distributions. Grove polygons are shown in black. See Appendix B for an expanded view of TWI across groves.

The difference in TWI across groves may still be important in distinguishing groves that have a higher versus lower potential for moisture stress. Assuming that water drainage follows topography, each sequoia grove is less vulnerable to soil-moisture stress at converging areas and more vulnerable at diverging areas. The highest TWI values were in 11 small, relatively less-steep groves, plus 2 medium-sized groves (Redwood Meadow, Long Meadow), with Giant Forest having the highest mean TWI of

the large groves (9.0). Similarly, the lowest TWI values were found in 7 small, steeper groves, with values below 7.6. Of the larger groves, Black Mountain (8.0 km², 1894 m) had a mean TWI of 8.1 and Evan 8.3 (12.8 km², 2012 m). Seventy percent of the groves (49), comprising 82% of the grove area, had mean values in the 6.7-8.8 range. In this range there was also little difference in the standard deviations, going from a TWI of just under 6 to just over 10. TWI ranges (Table A1) are skewed much more toward high than low values (Figure I-10). The actual distributions of TWI values within each grove are shown in Appendix B, illustrating that smaller groves show the most variability.

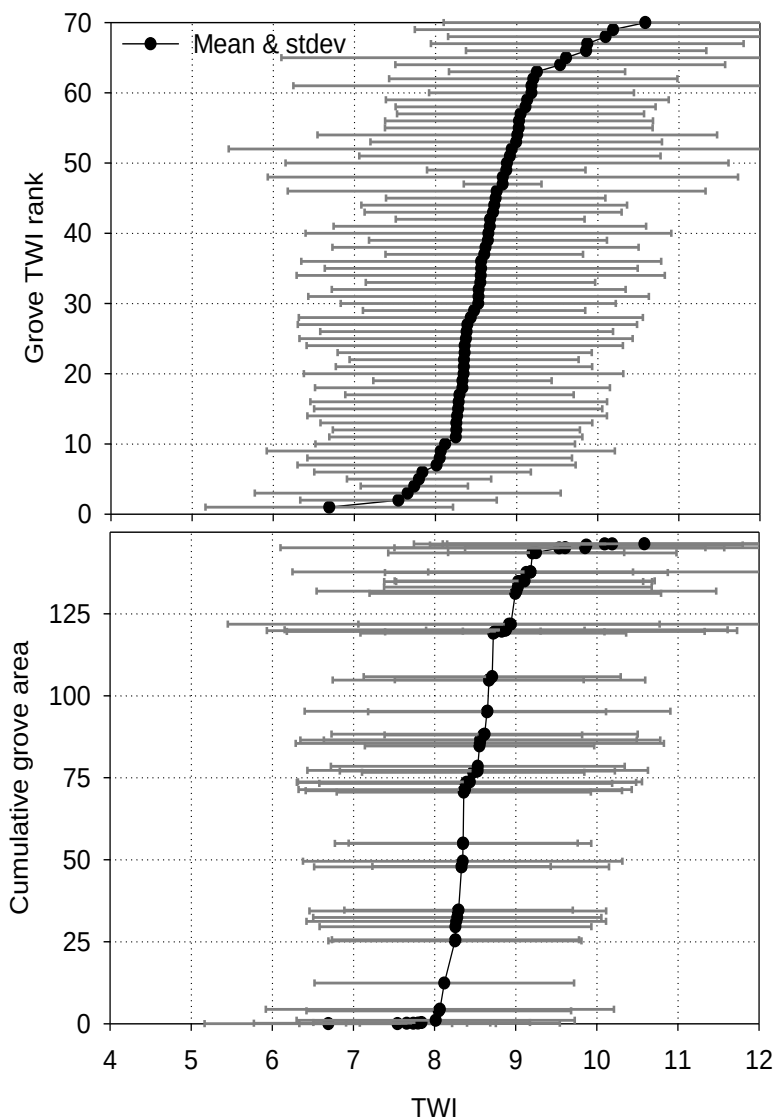


Figure I-9: Distribution of grove TWI values: a) ranked from lowest to highest, and b) ranked from lowest to highest, but plotted versus cumulative area.

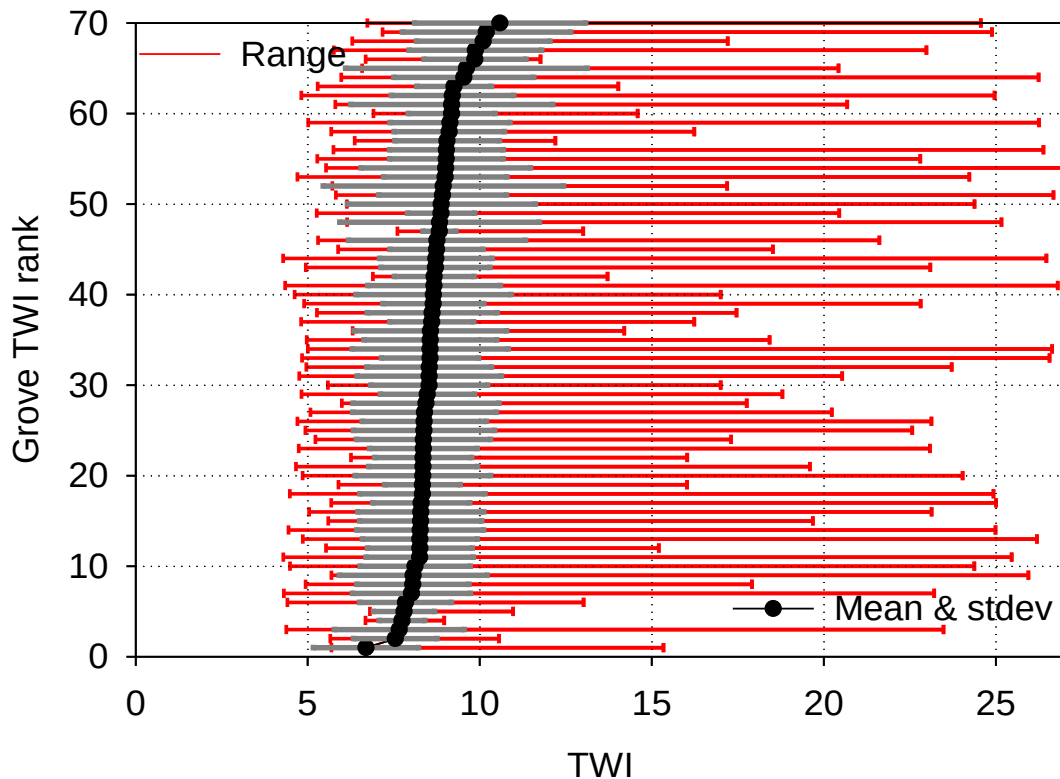


Figure I-10: Mean, standard deviation and range of TWI values for the 70 groves

Maximum TWI across groves potentially indicates where the wettest areas would be expected. Fewer than 11 small groves have maximum TWI values below 15, suggesting that most groves should have some wetter areas (Figure I-11). Further analysis shows 58% of grove area had maximum TWI values in the range of 20-27. Moreover, a majority of the groves comparatively larger in area ($>5 \text{ km}^2$) had maximum TWI greater than 22. This indicates that in general, a larger grove has higher maximum TWI than a smaller grove. For example, Belknap and Redwood Mountain (9.5 and 13.2 km^2) had maximum TWI greater than 26 whereas West Redwood Mountain, Clough and Douglass (0.01 km^2) had maximum TWI less than 12.

Figure I-12 depicts box plots of mean TWI, slope and elevation. Results show medians for TWI, slope and elevation are, respectively, 8.5 , 22.6° and 1900 m . The lower and upper quartiles for TWI, slope and elevation are, respectively, 8.35 and 9.0 , 17.8 and 27.4 , and 1780 and 1990 . Groves with higher TWI tend to have lower slopes, whereas those with lower TWI values tend to have steeper slopes (Figure I-13), as expected from equation I-1. The mean TWI of all grove area (i.e. aggregating all grove areas together in one analysis) is about 8.3 (Figure I-14). About 40% of the total grove area is below 8.0 ,

but only 10% has a value below 7.0. Nearly 70% of the grove area has TWI above 9.0, with 88% having a TWI above 10. Some of the high-TWI areas include stream channels and probably also meadows.

Within-grove spatial variability for all groves is illustrated in Appendix B, both as maps and as statistical distributions.

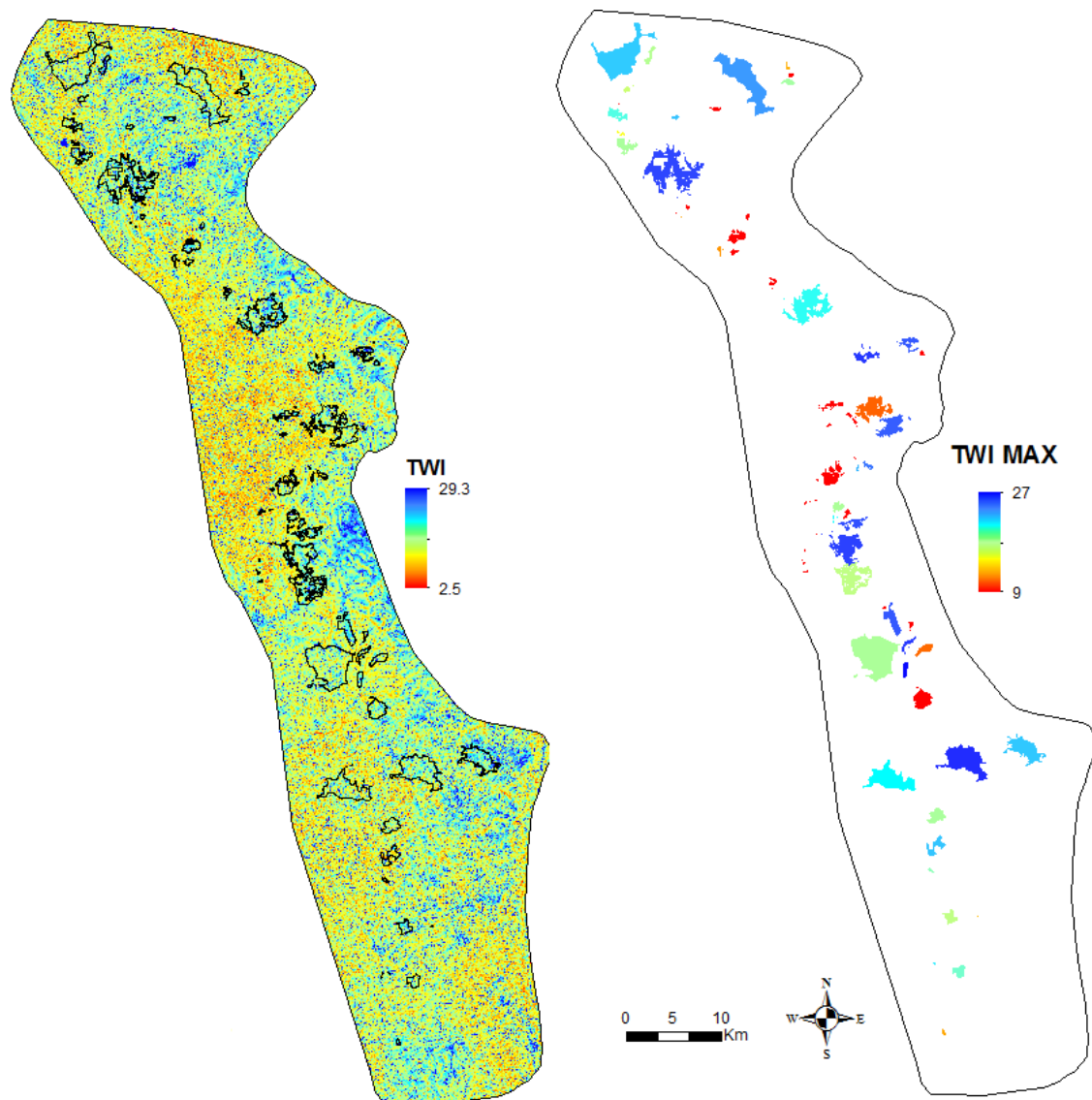


Figure I-11: TWI map with selected groves for less/more exposure to soil moisture stress: a) TWI for whole study domain and b) maximum TWI within each grove.

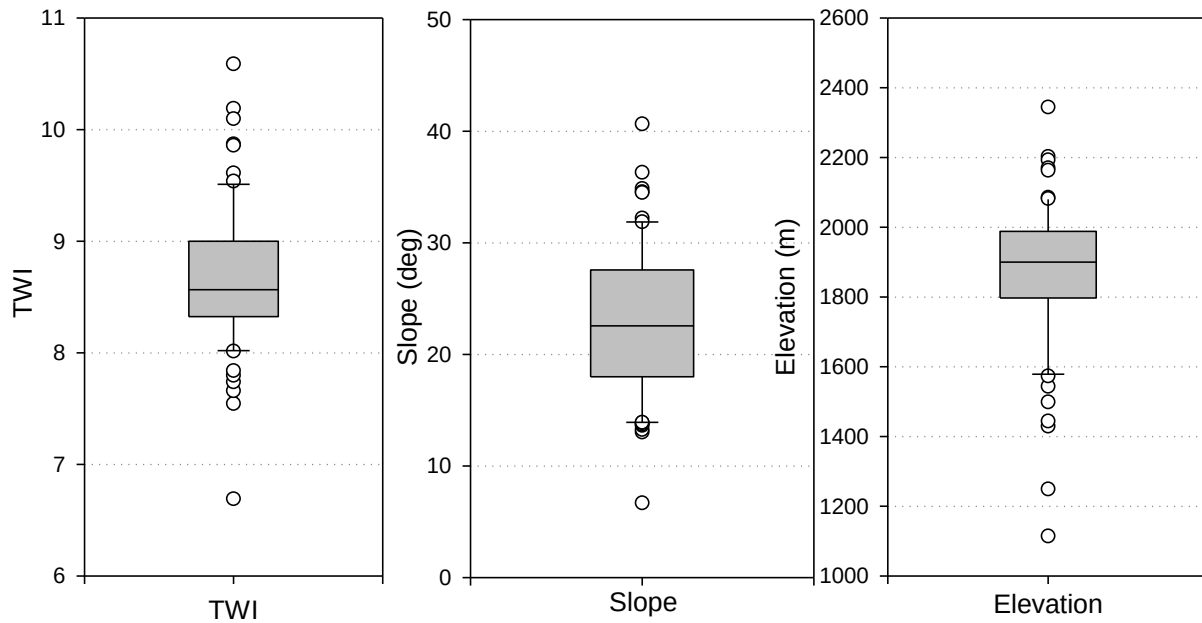


Figure I-12: Box plots for mean TWI, slope and elevation of all sequoia groves

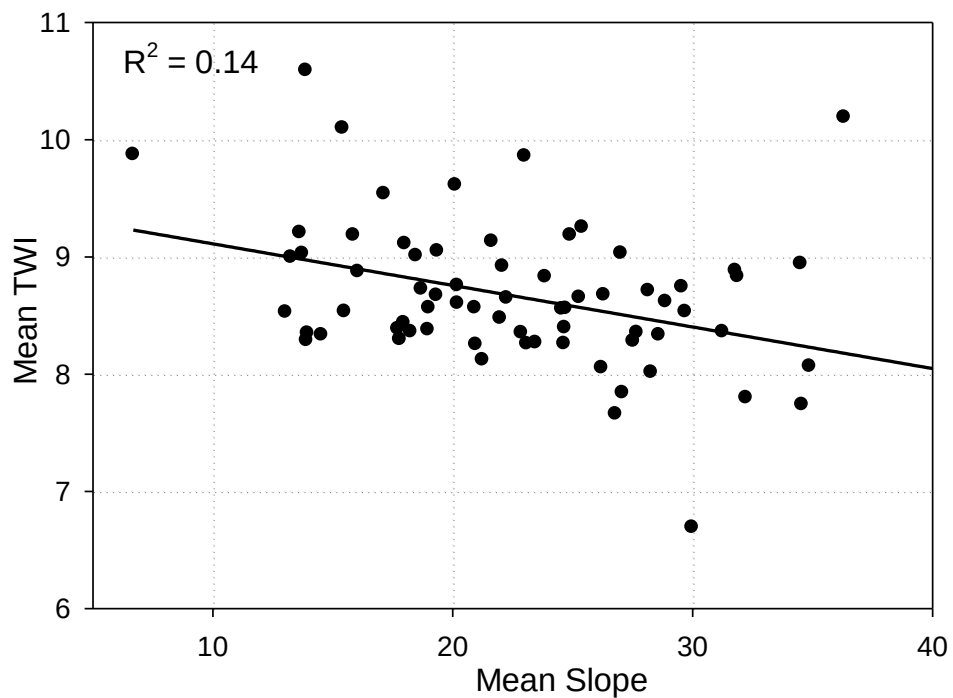


Figure I-13: Mean TWI as a function of mean slope for the 70 groves

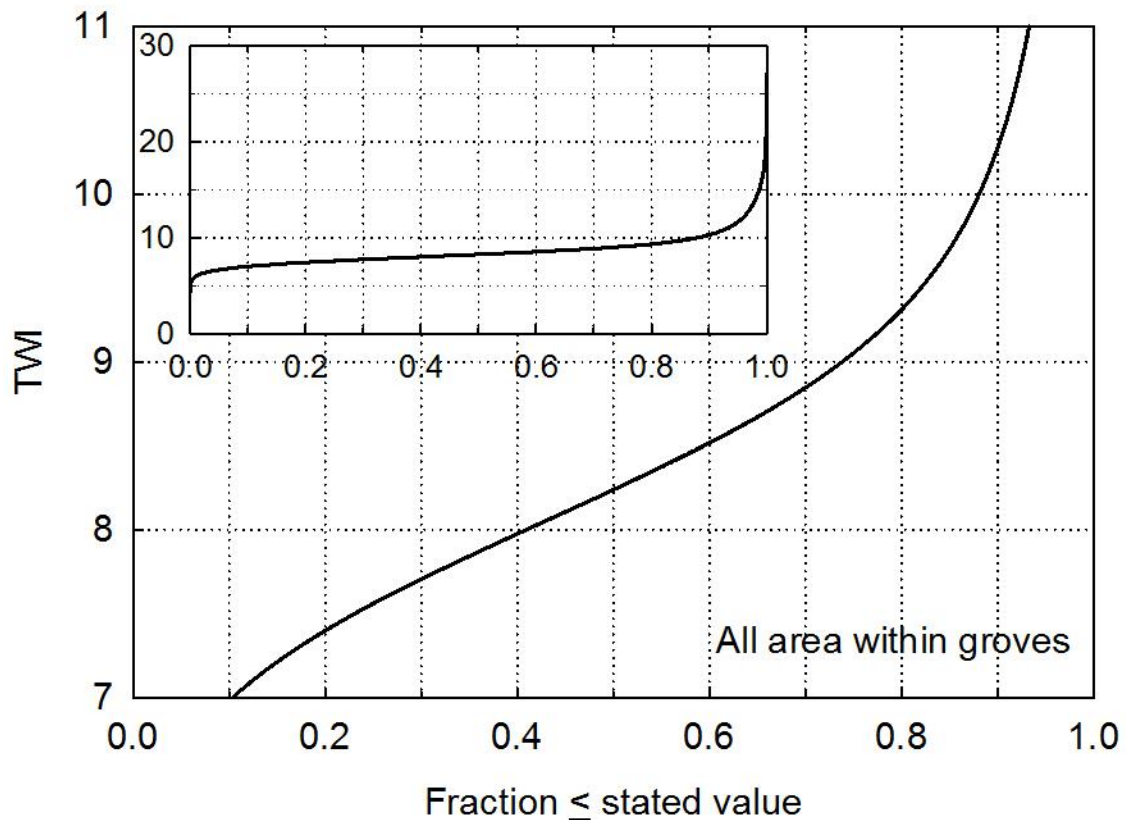


Figure I-14. Aggregate elevation distribution for area within the 70 groves

3.4 Aspect

Table I-1: The calculated TWI values based on re-classified aspect

Aspect	Area , km ²	TWI				
		Min	Max	Range	Mean	STD
Shady slope (0-67.5°)	26	4.3	26.8	22.5	8.4	1.8
Semi-shady slope (67.5-112.5°)	15	4.4	27.1	22.7	8.5	1.6
Sunny slope (112.5-247.5°)	45	4.3	27.1	22.8	8.7	1.8
Semi-sunny slope (247.5-292.5°)	25	4.3	27.1	22.8	8.7	1.7
Shady slope (292.5-360°)	36	4.3	27.1	22.8	8.4	1.7

A general aspect map (Figure I-15a) derived from a 10-m DEM did not provide any relationship or link with TWI values, and no relationship is expected. In order to investigate this further, we classified the aspect into shady slope, sunny slope, and semi-shady and semi-sunny slope following Ma et al.

(2010) (Table I-1, Figure I-15b, I-15c). However, there were no clear patterns of TWI varying with shady slopes versus sunny slopes. It should be noted that TWI values are entirely based on topography (i.e., converging and diverging areas) and thus are not expected to depend on aspect. However, other remotely sensed soil moisture indices might show differences among the various aspects. Note that shady and sunny refer to more-southern versus more-northern aspect and not canopy cover.

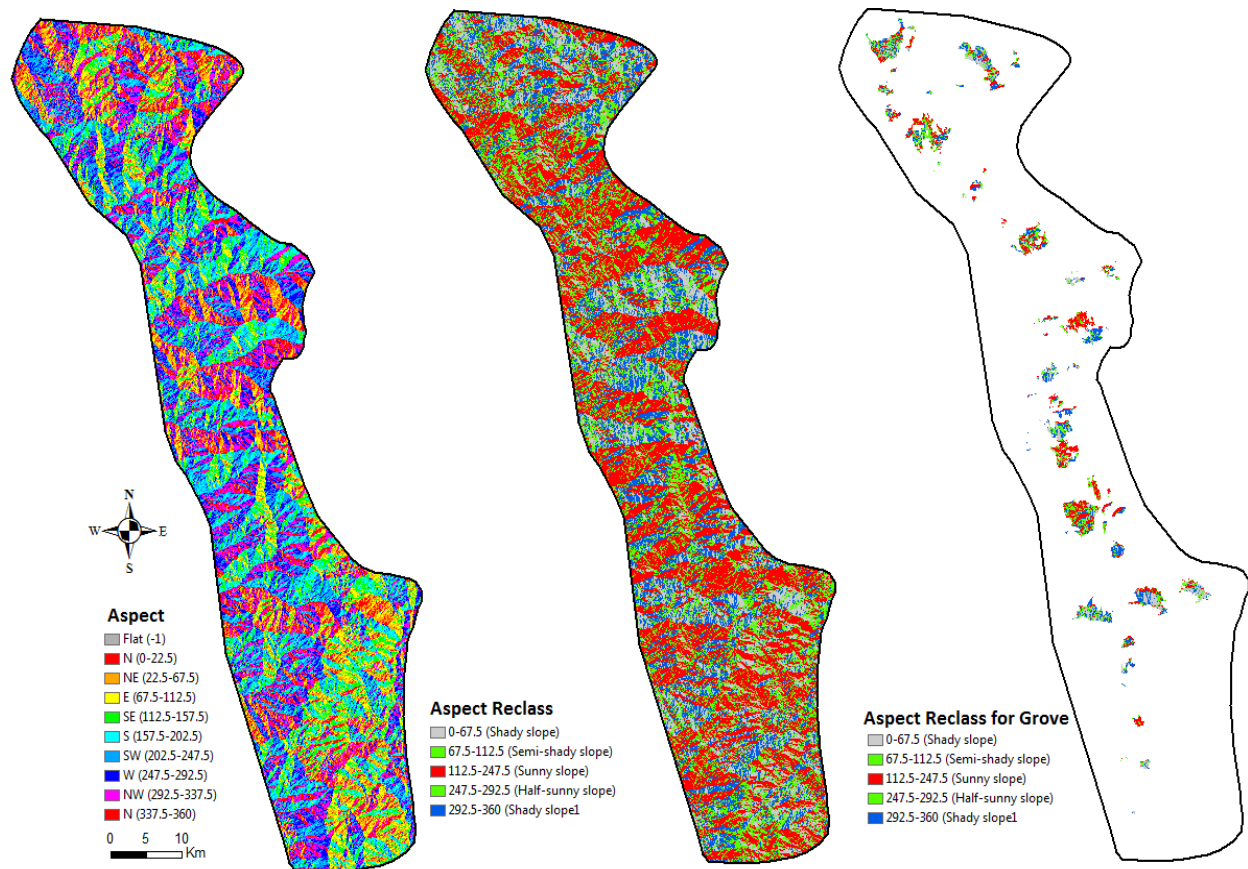


Figure I-15: Aspect map derived from 10m DEM: a) a general aspect map; b) re-classified aspect map for study region and c) re-classified map only for 70 sequoia groves

3.5 Snowcover persistence

Figure I-16 shows snowcover persistence maps at sequoia groves for a 12-year period (2000-2011) for the first of each month, March and April along with the maximum TWI values map. When we compare snowcover persistence in March 1 and maximum TWI at each grove, we found a suggestion that areas with longer snowcover persistence tend also to have higher TWI, however, correlations are poor (Figure I-17). This could indicate that a combination of these two factors, snowcover and TWI, may be associated with lower versus higher vulnerability to soil moisture stress. The majority of the

groves consistently have some snow presence in March 1 and April 1, with differences appearing later in spring.

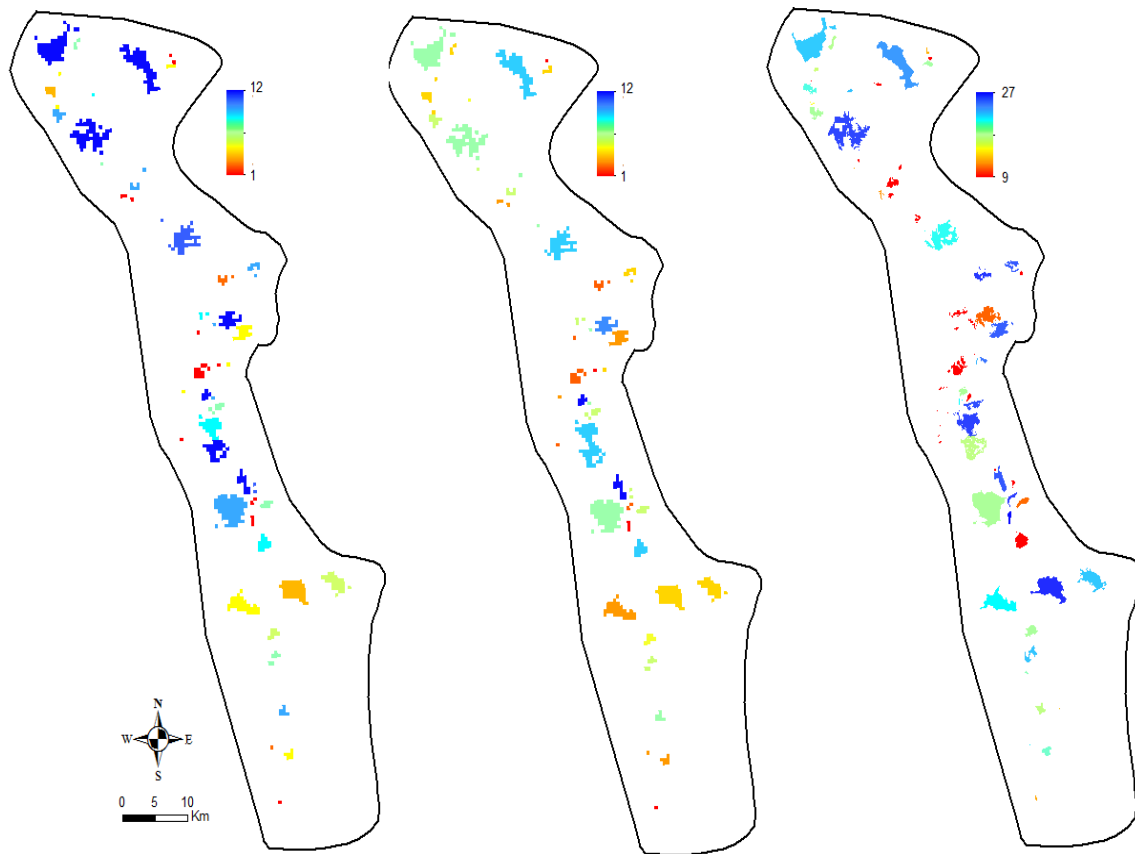


Figure I-16: Comparison of MODIS snowcover persistence (2000-2011): a) March 1; b) April 1 and c) maximum TWI at each Sequoia Grove

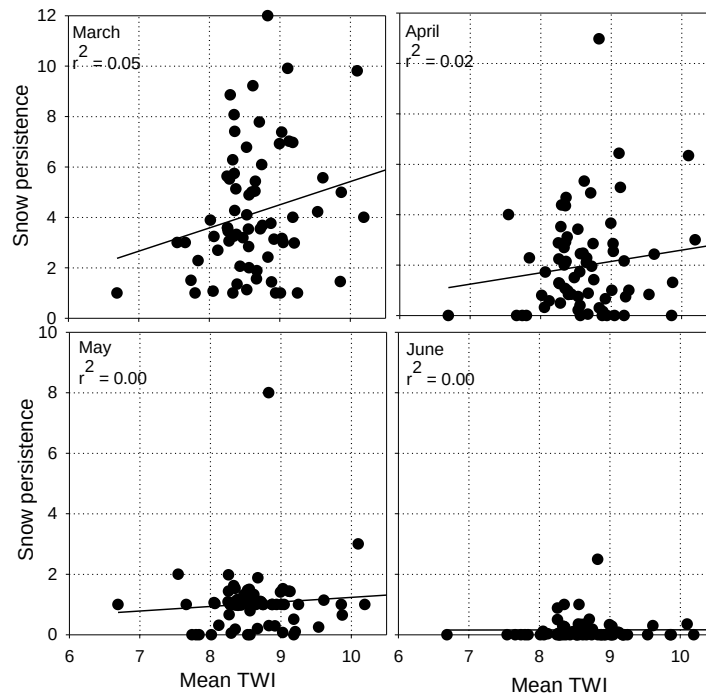


Figure I-17: Comparison of MODIS snowcover persistence (2000-2011): a) March 1; b) April 1 and c) with average TWI at each Sequoia Grove

Figure I-18 depicts mean snowcover persistence for first day of four months; March, April, May and June. As expected, it is clear that snow persistence decreases from March towards June. Snow persistence varies between groves in the same month. When snow starts to melt; some groves also start to lose snow cover on the ground and it continues until June. However, some of the groves have snowcover even in June. The mean snowcover persistence for the first day of four months; March, April, May and June for each grove is presented in Table A4, A5, A6 and A7, respectively. In March and April snowcover persistence is correlated with elevation above about 1800 m elevation, below which there is little seasonal snow accumulation (Figure I-19). However, factors other than elevation influence snowcover persistence (e.g. aspect, canopy cover and radiation) especially during snowmelt.

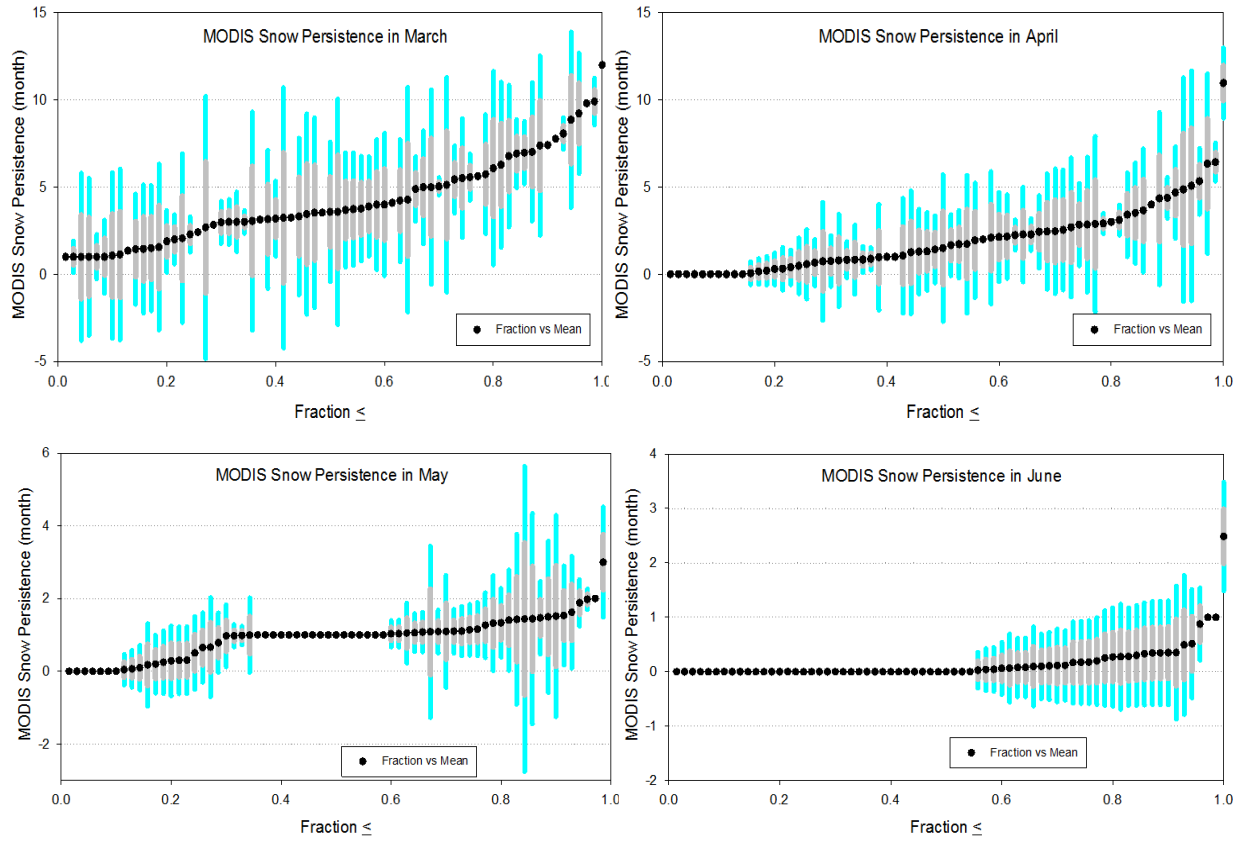


Figure I-18: Variations of mean (black dots), mean $\pm$ 1-Std Dev (gray) and mean $\pm$ 2-Std Dev (cyan) of snowcover persistence for March 1, April 1, May 1 and June 1, the tables for sorted groves based on snowcover persistence are presented in Table A5, A6, A7 and A8

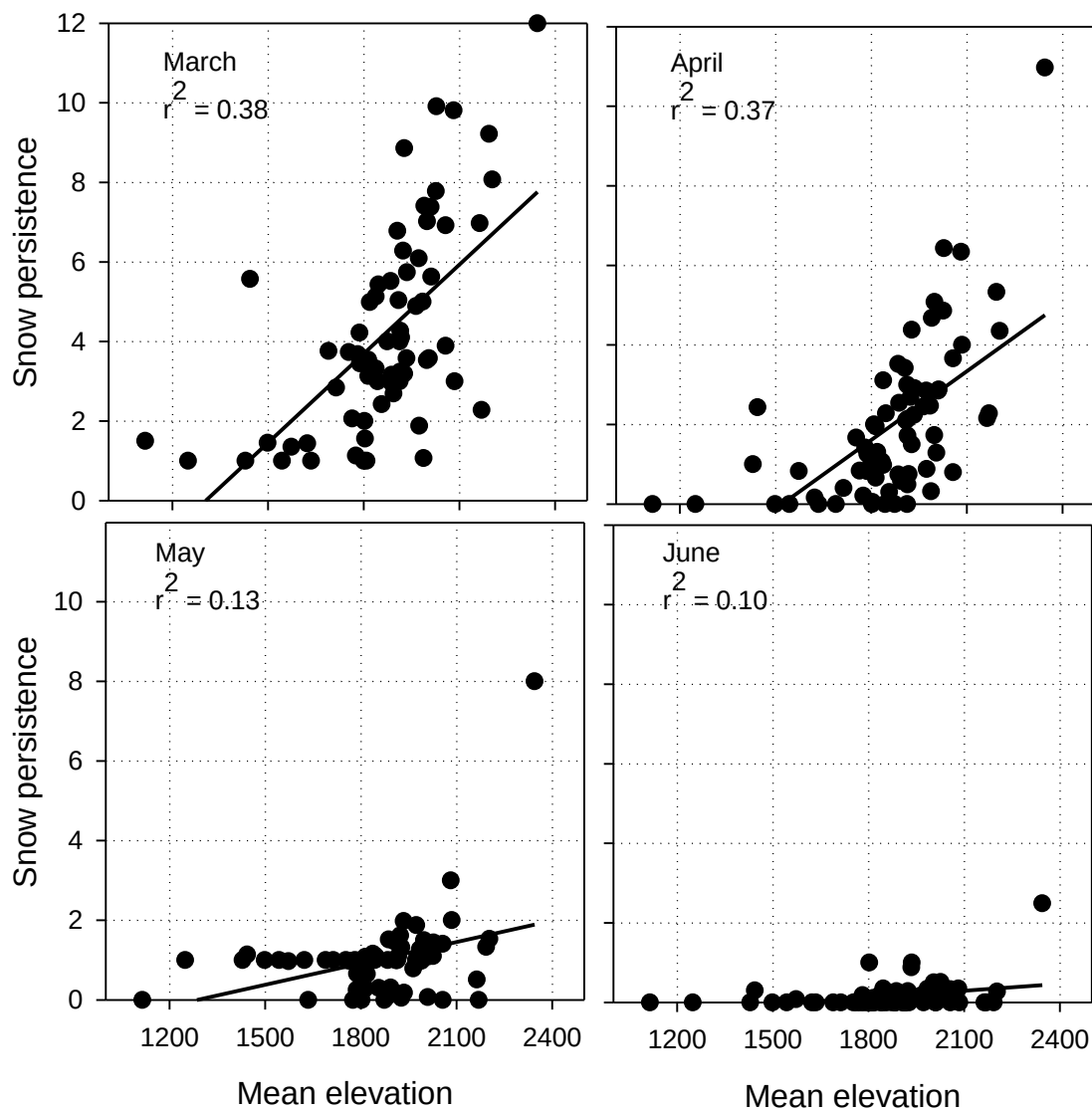


Figure I-19: Snow persistence for March-June versus elevation for the 70 groves

3.6 Background region

A background analysis was conducted to compare the topographic wetness index at a sequoia grove with that of a region near the boundary of the grove having similar elevation, slope and area (Figure I-20 and Table I-2). The Belknap grove (area = 9.52 km²) was chosen, as it represents both the range and mean of TWI values found across the 70 groves. A single adjacent area was chosen for comparison; though an alternate approach would be to randomly select points from the regional population and compare TWI values for non-contiguous sets of points having an area equal to the Belknap Grove. Results indicate a similar but slightly higher TWI and thus lower potential vulnerability to moisture

stress at the Belknap grove versus the non-grove region near the boundary of the grove (Figure I-21). The mean TWI at non-grove region is a little smaller (8.5) than for the grove (8.7) (Table I-2). Moreover, the range of TWI values is 4.3-26.8 at Belknap versus 4.5-24.5 for the non-grove region (Figure I-21). This analysis further supports the findings of Halpin (1995) who found TWI values higher at groves than the non-grove sites.

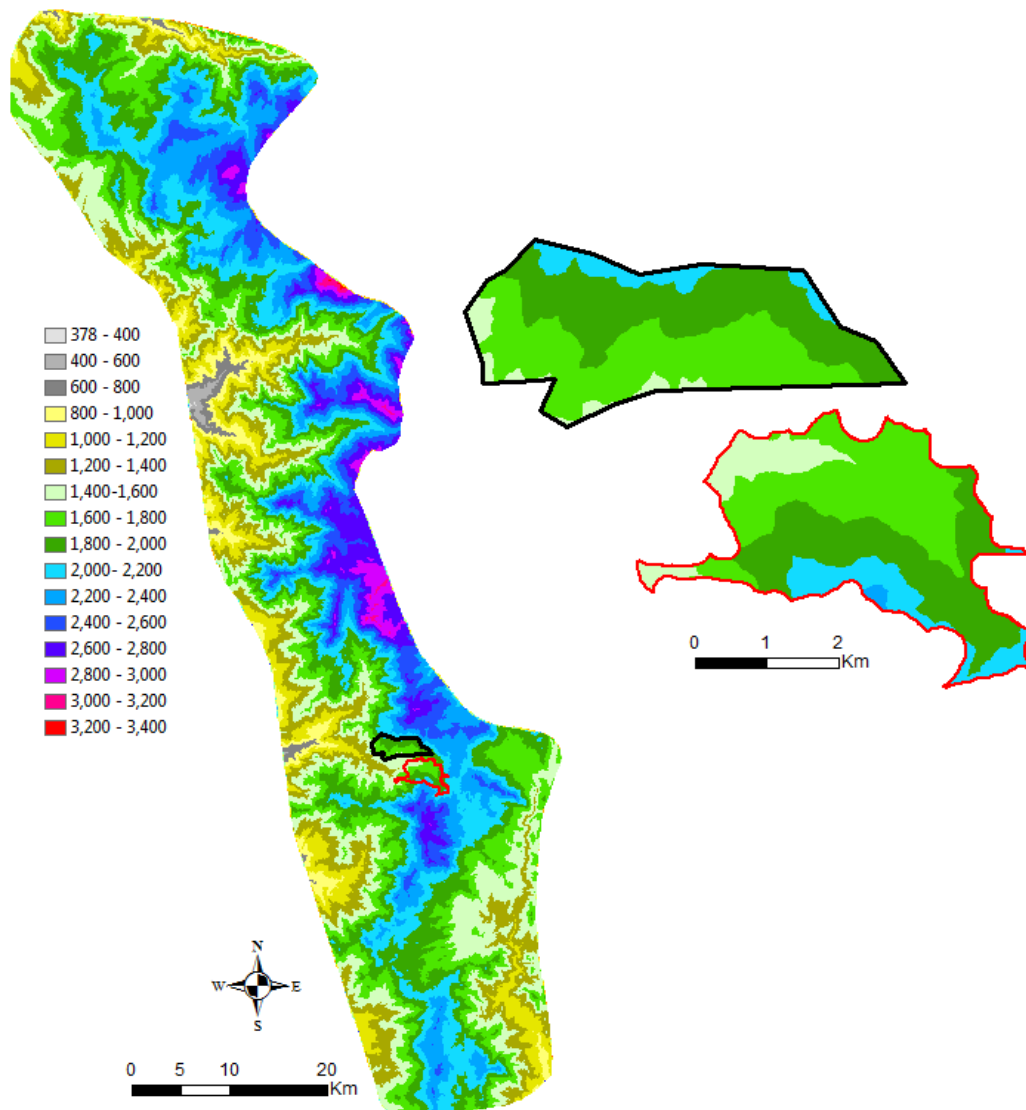


Figure I-20: Selected region (background) and Belknap grove

Table I-2: Comparison of elevation, slope and TWI at selected background region nearby Belknap grove (9.6 km²) and Belknap grove itself (9.5 km²)

	TWI		Elevation, m		Slope, deg	
	Background	Belknap	Background	Belknap	Background	Belknap
MIN	4.5	4.3	1431	1444	0.4	0.1
MAX	24.6	26.8	2130	2281	55.0	55.6
RANGE	20.0	22.5	699	838	54.8	55.5
MEAN	8.5	8.7	1804	1804	20.0	19.3
STD	1.6	1.9	136	164	7.5	7.6

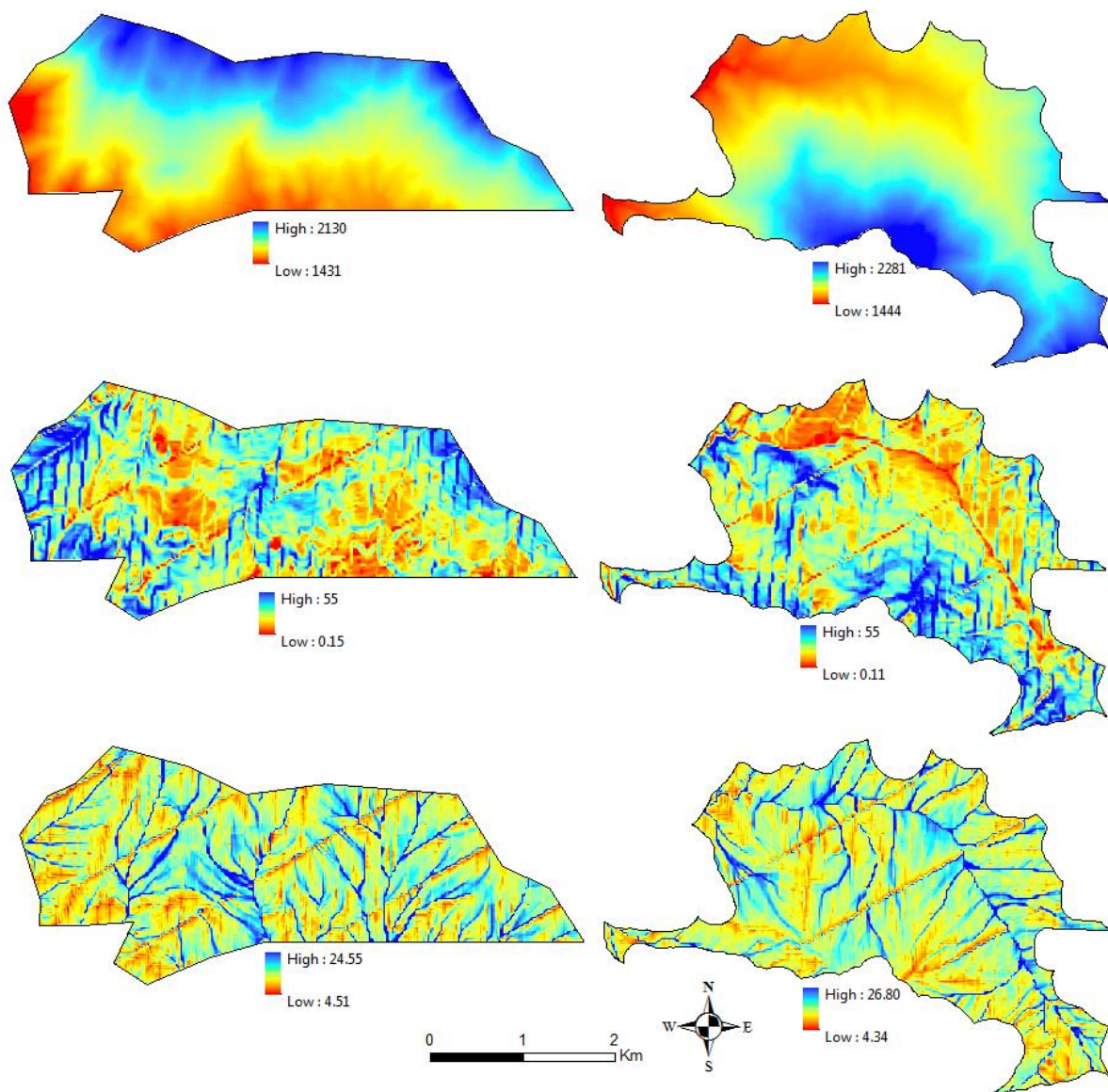


Figure I-21: Spatial comparison of elevation (m), slope (°) and TWI for background and Belknap grove.

Comparing all TWI values in the domain studied, it can be seen that the groves do generally have higher TWI values than does the non-grove area (Figure I-22). The mean value for the grove area is 8.3, versus 7.8, for a random sample of pixels in the surrounding area with the same overall elevation distribution as the grove area. Ten random samples were selected from the full non-grove domain, with the same result. Results show higher and lower TWI values, respectively, at grove and non-grove domains for lower elevation range (1250-1950m) and similar TWI values for the mid-elevation range (1950-2250m). However, both grove and non-grove domains with higher elevation range (2250-2700m) have lower and higher TWI values in some parts of the domain (Figures A1 and A2).

A similar difference between grove and non-grove areas can be seen for a vegetation index, NDWI (Figure I-23). See section II for development of the vegetation index data. The area within groves has a higher NDWI than the same number of pixels, with the same elevation distribution as the grove area, selected from the non-grove area.

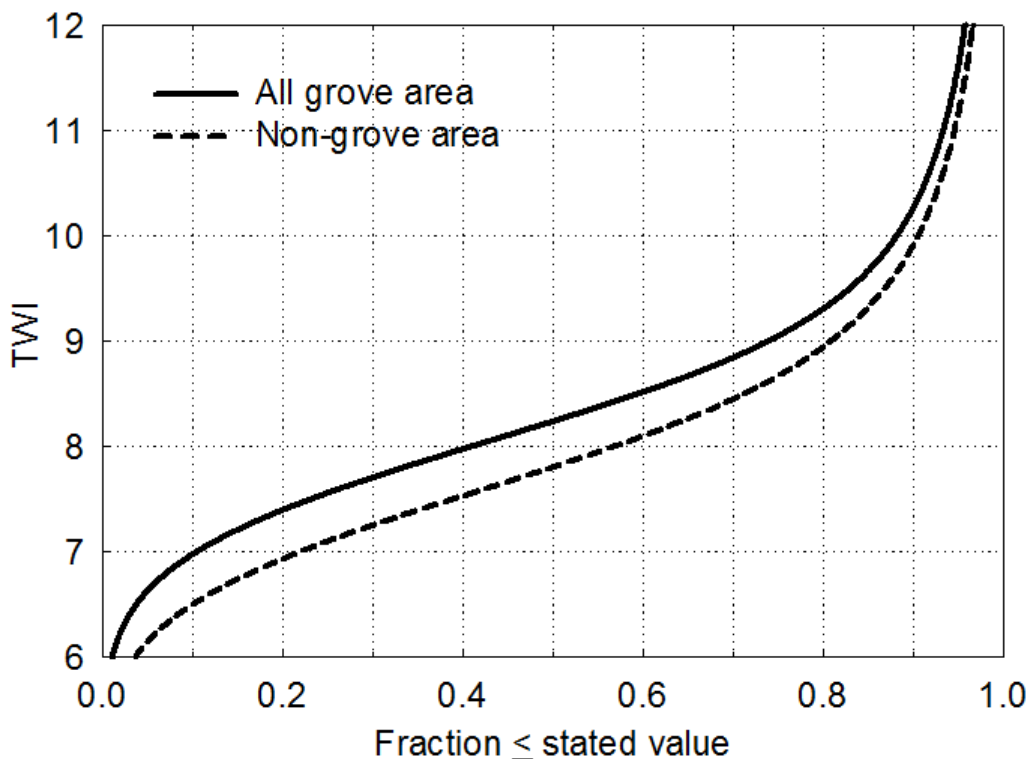


Figure I-22. Aggregate TWI distribution for area within the 70 groves compared to the full domain studied.

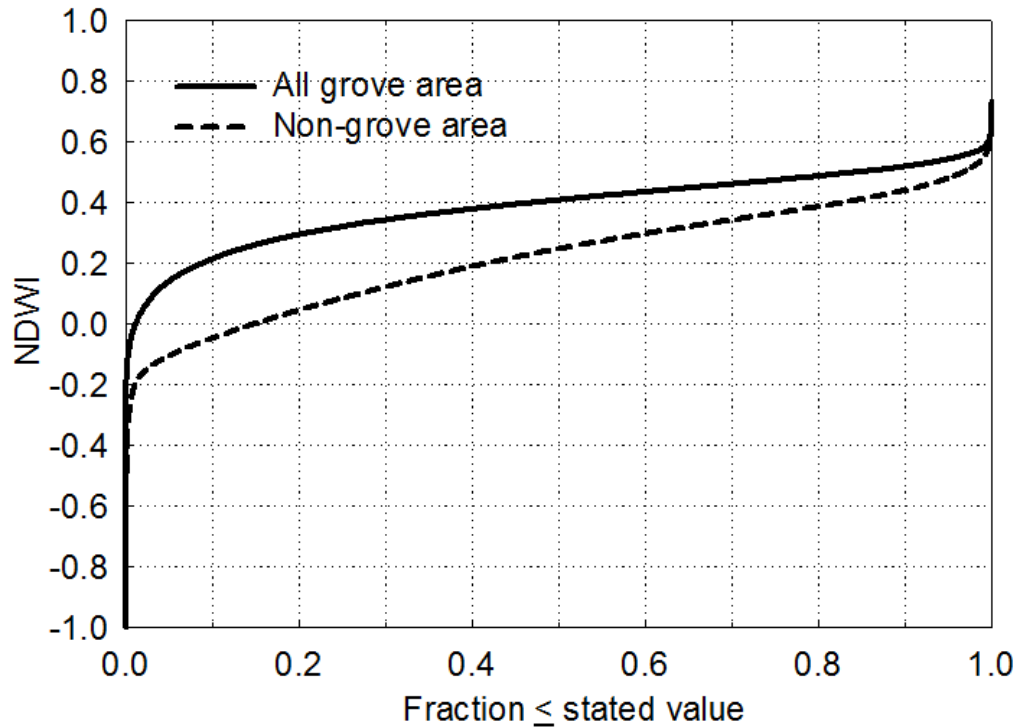


Figure I-23. Aggregate NDWI distribution for area within the 70 groves compared to the full domain studied.

4. Discussion

4.1. Previous studies

We also compared our results with a previous study conducted by Patrick Halpin for his dissertation in 1995. The main aim of this comparison was simply to establish that Halpin's approach and our approach gave similar results. One difference was his use of a 30-m DEM versus our 10-m DEM. Halpin (1995) had identified 75 sequoia groves within the vicinity of Sequoia and King Canyon Parks, that is, 5 more than our 70 identified/provided sequoia groves, however, he did not present comparative results of TWIs for the 75 groves.

Halpin (1995) reported TWIs in detail only at the Log Creek catchment, a 49-ha subarea within the larger 970-ha Giant Forest grove (Figure I-24); for this area he had a 5-m DEM. Therefore, we compared the TWIs at the Log Creek catchment. Interestingly, we found a good match of estimated TWIs between the two studies (Figure I-25). As shown in Figure I-25, Halpin (1995) estimated TWI values ranging from 3.8 to 19.0, with a mean of 8.1 and standard deviation of 1.5. Our TWI values

ranged from 2.8 to 20.2, with a mean of 6.6 and standard deviation of 2.0. A small difference is due to use of two different spatial scales DEM (5-m DEM and 49 ha by Halpin, 1995 and 10-m DEM and 76 ha by us) and little different in catchment area.

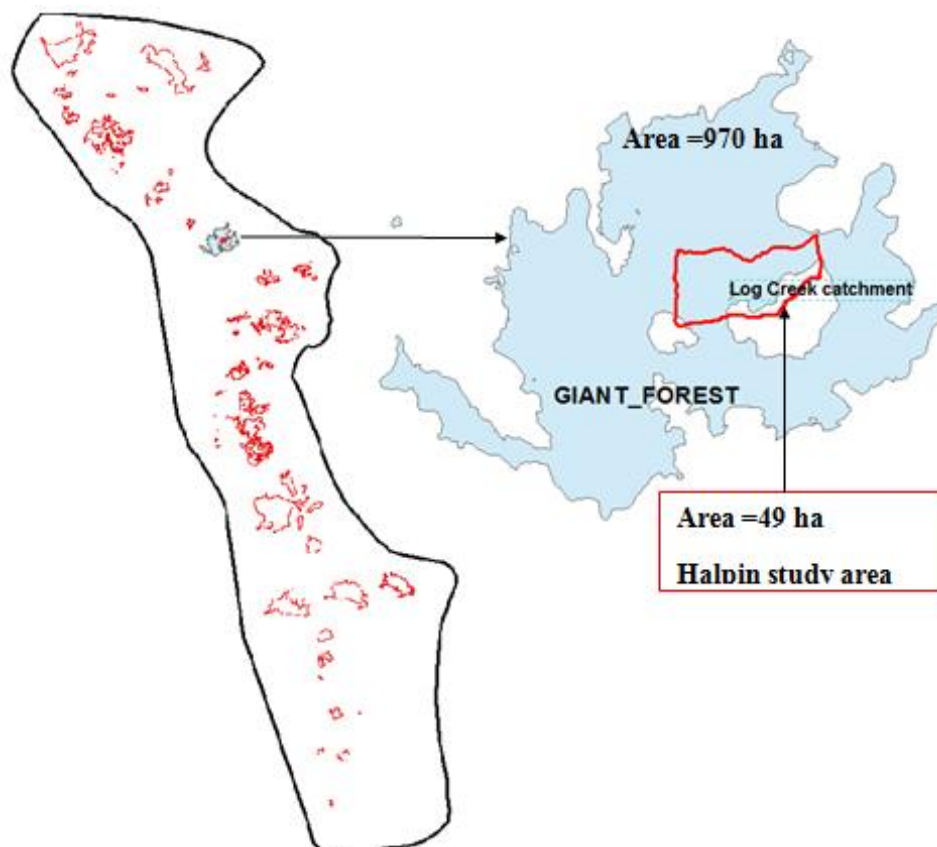


Figure I-24: Selected Log Creek catchment at Giant Forest Grove

4.2. Implications for moisture stress

Periodic soil-moisture surveys at a slightly higher-elevation mixed-conifer/red-fir site in the Sierra Nevada, Teakettle Experimental Area, show that soil moisture depends on slope above about 7° slope (Kirchner et al., 2008) (Figure I-25). Below 7° slope this dataset showed no dependence of soil moisture on slope. No variability in soil moisture due to canopy cover or aspect was found at this site; however it is dominated by south and west aspects.

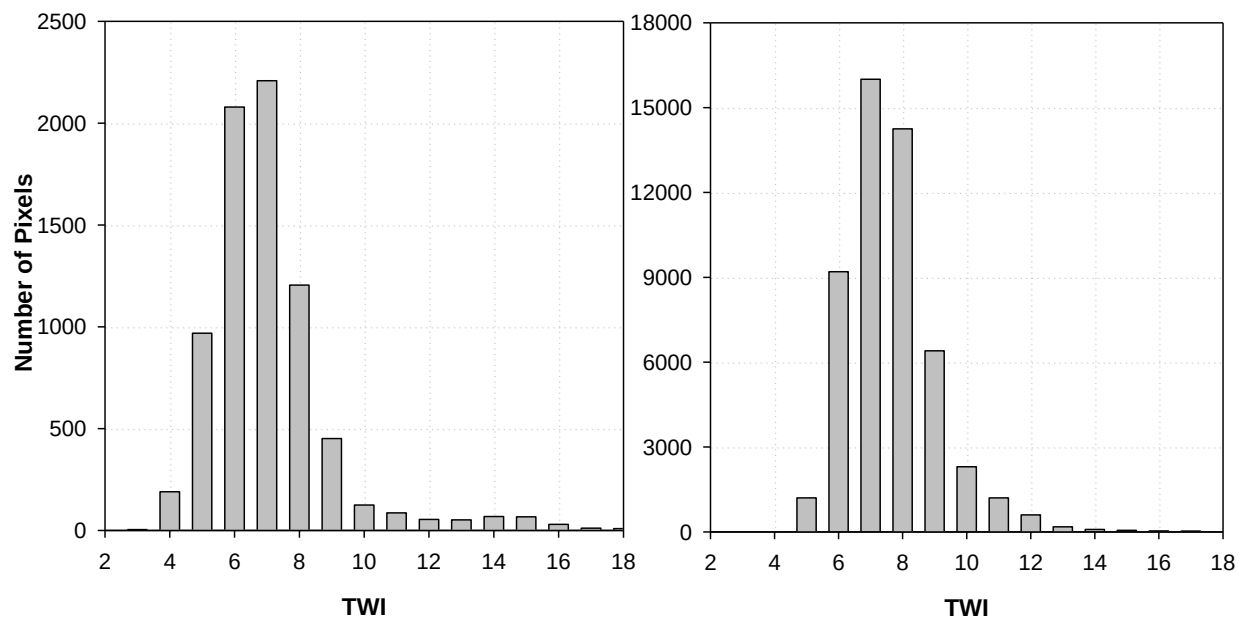


Figure I-25: Comparison between frequency distribution of TWIs from two studies at log Creek catchment, present study on the left and past study (Halpin, 1995) on the right.

Snowcover persistence provides added information beyond what a topographic index can provide. It is an index of how late in the year soil moisture will remain high versus drop off. This is illustrated in Figure I-26, where soil moisture remains high until snow is melted across the basin, followed by about a 3-month recession (Bales et al., 2011). Note that streamflow, which is sustained by soil drainage, continues to decline after soil-moisture storage reaches a plateau. Later-season streamflow (and evapotranspiration) is supplied by deeper strata that were not measured in this research. Note that later-season rainfall causes only a small rise in moisture storage, pointing to the importance of seasonal snow for summer moisture.

It should be noted that soil depth does not indicate relative water storage, as strata deeper than mapped soils account for a significant fraction of water use by forest vegetation and streamflow in Southern Sierra mixed-conifer forests (Arkley, 1981; Rossi and Graham, 2010; Bales et al., 2011). Nor has it been established that TWI alone indicates relative water storage in the subsurface. However, in principle it may indicate longer versus shorter water storage given that contributing area is part of the calculation. An additional information need is for subsurface porosity, or water-storage potential. One approach to get a first-order estimate is to use seismic velocity, as illustrated on Figure I-28 for the Providence Creek headwaters in the Sierra Nevada National Forest, elevation about 2000 m. This is the same area from which the Figure I-27 results came.

The current analysis did not include analyzing areas within groves where giant sequoia do or do not grow relative to low versus high TWI values. But is it apparent that most groves do have some areas with higher versus lower TWI. While some of this area is in or near stream channels and meadows, as seen in Appendix B, there are hillslope areas of higher TWI in most groves.

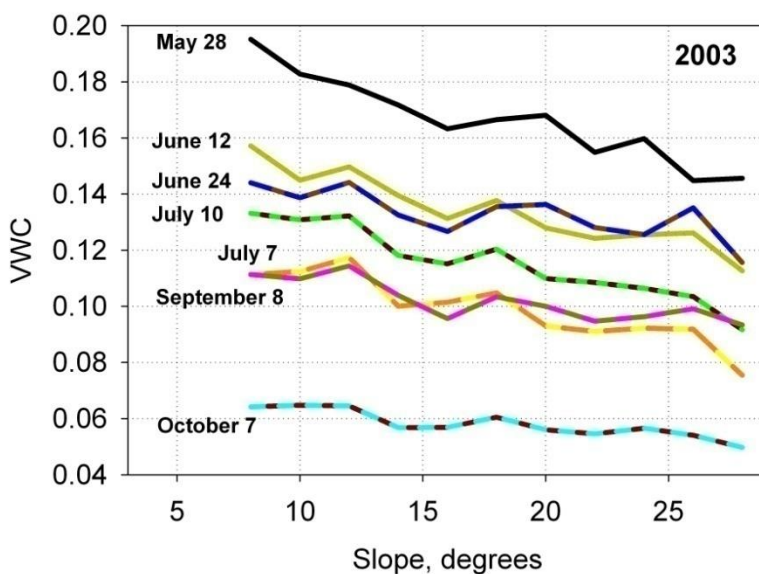


Figure I-26: Mean soil moisture as a function of from repeated surveys, at Teakettle Experimental Area. VWC is volumetric water content. Data from Teakettle Experimental area, courtesy M. North (Kirchner et al., 2008)

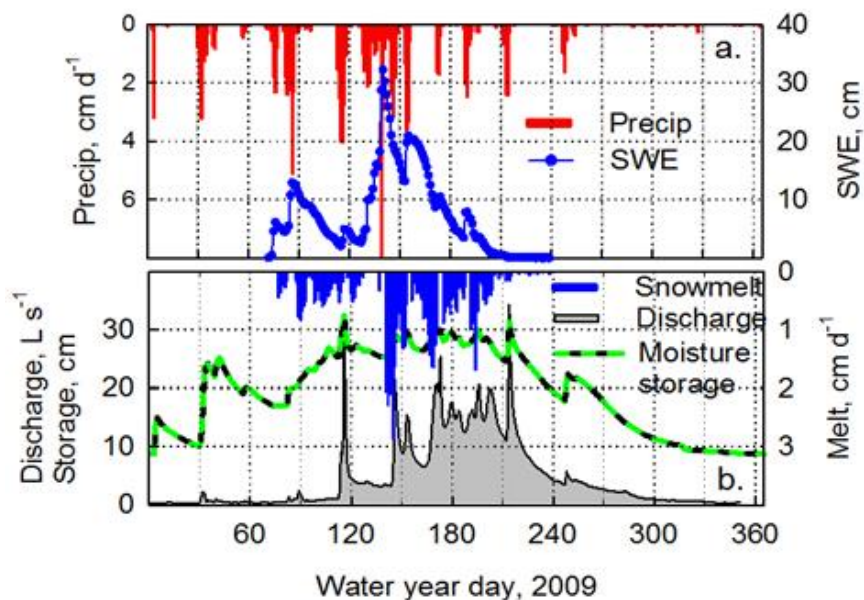


Figure I-27: Catchment-scale precipitation, snowpack, snowmelt, soil-moisture storage and discharge at P303 catchment, Kings River Experimental Watershed (Bales et al., 2011)

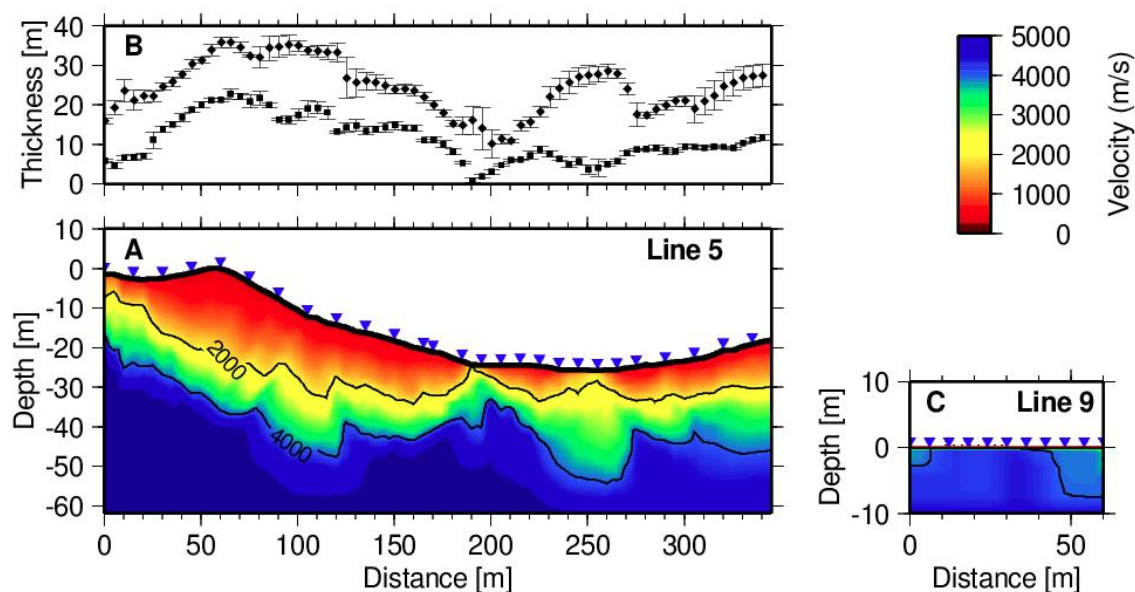


Figure I-28. (A) Velocity model of a transect spanning a forested slope and swampy meadow in the headwaters of the Southern Sierra Critical Zone Observatory based on inversion of first-arrival travel times. (B) Depth from the surface to the 2000 m/s and 4000 m/s contours. Error bars reflect variations observed in a Monte Carlo ensemble of solutions that result from a range of starting models. Depth to the 4000 m/s contour varies from 10 to 35 m (average 23 m) and is highest at the crest of the forested slope. In contrast, under the swampy meadow, depth to the 4000 m/s contour is shallowest and most variable, ranging from ~10 to 30 m over just 60 m of horizontal distance. (C) Velocity model of Line 9 from inversion of first-arrival travel times. Velocities of 4000 m/s at the surface on Line 9, acquired on an extensive granite outcrop, enable interpretation of 4000 m/s velocities (blue shades) on Line 5 as coherent bedrock at depth. After Holbrook et al., in review.

4.3. Implications of climate warming

Snowcover patterns, including persistence, are projected to change with further climate warming. Considering that this region of the Sierra Nevada has about a 6-7°C per 1000 m ground-based lapse rate, an average temperature increase of about 2°C is thus equivalent to moving about 300 m down in elevation under the current climate (Rice and Bales, 2013). Thus with 2°C warming, a consistent seasonal snowpack that provides summer moisture would shift above 2100 m elevation, versus the current 1800 m elevation. While at present about 80% of the grove area is above the 1800-m midpoint of the rain-snow transition elevation (approximately 50% each rain and snow); with a 2°C warming only about 15% of the grove area will be above the 2100-m rain-snow transition midpoint elevation. Groves

that lack significant areas of higher-elevation terrain, topographic convergence and subsurface storage should be the most vulnerable to moisture stress.

5. Conclusions

This analysis found that TWI and snow persistence do differ between groves, with TWI also having significant variability within each grove. This distinction provides a basis for identifying potential sequoia groves that are more or less vulnerable to soil moisture stress. This is based on the assumptions that areas with milder slopes and more converging area (higher TWI), plus longer snow persistence, should be less susceptible to low summer soil moisture than areas having steeper slopes and more diverging topography (lower TWI) and earlier snowmelt. Although we can analyze TWI at the 10-m scale, and thus get sub-grove variability; snowcover data are only available at the 500-m scale.

Snow persistence is an excellent complement to TWI, as it is a readily available index of seasonal moisture availability. It is most useful above about 1800 m elevation, and should be used in conjunction with regional precipitation and meteorological data. However, it has the distinct advantage over precipitation data in that it is measured on site, versus extrapolated from a measurement site based on topography. Snow persistence is also potentially ecologically very important for giant sequoia because of its overall contribution to seasonal water storage.

Two limitations of this analysis are lack of site-specific field data for evaluation of patterns, and lack of detailed within-grove analysis. As soil moisture is not measured in these groves, no evaluation was done. Detailed within-grove analysis was beyond the scope of this initial study.

It should be emphasized that although topographic water availability shows some important distinctions between groves, across the landscape and between hillslope-scale areas within groves, we currently have not validated its ability to predict moisture stress through use of more-direct measures such as soil moisture, deeper moisture storage, evapotranspiration, or vegetation-stress indices. The current analysis can be used to highlight groves potentially more vulnerable, particularly when considering TWI and snowcover persistence together. But it should be a starting point, not an ending point for informing resource-management actions to reduce stress in specific areas. Thus TWI can help identify areas potentially vulnerable to moisture stress, though it is not a sufficient indicator of water stress. For example, soil-water storage also depends on the depth of properties of the subsurface media.

In continuing this analysis and planning resource-management activities, it should be assumed that lower-elevation sequoia groves that lack significant areas with high TWI are most vulnerable to moisture stress. While steepness is a general indicator, TWI is expected to be a better indicator of moisture stress in this case. Higher-elevation groves should be considered less vulnerable, unless the

TWI across the groves is low. For the large number of groves with elevations mainly in the 1800-2100 m range, the distribution of TWI values, or possibly the mean plus one standard deviation, can serve as a first-order indicator of relative vulnerability.

6. Recommendations

It is recommended that the current analysis be extended by: i) more-detailed evaluation of available data, ii) field characterization of landscape features in selected groves, and iii) multi-year measurements of more-direct indicators of moisture stress.

1. **Assess TWI-soil-moisture relationships.** Although we lack soil-moisture data in the 70 groves, there are spatially-distributed, long-term data sets in nearby areas of similar elevation and forest density that could be used to evaluate the TWI-moisture stress relationship. This would allow extending the conclusions and provide more-definite management recommendations.
2. **Evaluate vegetation-TWI relationships.** Using available LiDAR data, supplemented by additional LiDAR flights and/or GPS measurements of where Giant Sequoia trees are located within groves, do a combined spatial analysis of tree location, TWI, and vegetation-stress indices. This will determine if sequoias are preferentially located in areas with higher TWI, and also if they are located in areas with higher or lower canopy moisture stress.
3. **Establish within-grove heterogeneity in soil moisture.** Shortly after the seasonal snowpack has melted, measure soil-moisture patterns in a late-spring or early-summer synoptic survey at two or more Giant Sequoia groves to establish differences in water storage across elevation, aspect, TWI and canopy-cover gradients. Evaluate in the context of available, detailed data sets from non-grove areas. Use data to assess TWI-soil moisture relationships in groves.
4. **Carry out longer-term soil-moisture measurements in groves.** Based on the synoptic surveys, site continuous-measurement nodes for soil moisture, which will be put in place and monitored over the long term as indicators of landscape and temporal variability and change. To the extent possible, these measurement nodes should be located at or near sites with other relevant climate, hydrologic and ecosystem data. Two candidate groves that fit this criterion are Giant Forest and Redwood Mountain. Note that Giant Forest has an average elevation of 2058 m, and is among the higher-elevation groves in Sequoia-Kings Canyon; whereas Redwood Mountain has an average elevation of 1816 m, and is a mid to lower elevation grove. Other groves should be considered based on resource availability.

Note that soil moisture generally tracks sap flow measurements in mixed-conifer forests, and is much less expensive and reliable. Sap flow should be considered for groves based on soil-moisture results.

5. *Extend precipitation and meteorological measurements.* Based on current analyses of temperature, precipitation and other meteorological variables, extend multi-year or long-term measurements to cover important climate gradients and microclimates.
6. *Carry out subsurface characterization.* In selected groves, and based on topography, soils, vegetation and geology, carry out seismic surveys to establish depths and profiles of weathered material as a basis for estimating subsurface storage potential of representative landscapes.
7. *Build a convenient GIS data base of all relevant data.* This will include an artifact-free DEM, physiographic and vegetation information, vegetation indices, available remotely sensed snowpack and other vegetation information, LiDAR data and other emerging datasets. Include relevant quality-controlled time-series data if not already publically available.
8. *Do a pilot study of isotopic indicators of water source.* Characterize water isotopes of shallow and deeper water reservoirs in one or more groves, and compare to water use by vegetation.

II - Remotely-Sensed Canopy Moisture Stress and Climate Change

In this part, we use a time-series of satellite remotely sensed data [Landsat5 TM (thematic mapper) data] to estimate various vegetation and moisture indices, which can directly or indirectly indicate canopy moisture conditions; and to evaluate the vulnerability of giant sequoia groves to water stress based on the index that can best represent the relationship between moisture conditions and climate change. Here, it's critical to note that for medium spatial resolution images, remote sensing signals for groves will be most heavily dominated by things that are not giant sequoias such as white fir, sugar pine, oaks, shrubs, rocks, bare soil, litter and duff, meadows, etc. Reflectance from giant sequoia crowns themselves may make up only 5 to 10% on average of any grove's signal.

1. Data

1.1 Database

Remotely sensed images used in this project were obtained by the Landsat5 TM sensor. TM images from 1984 to 2011 were downloaded from the USGS website (<http://www.usgs.gov>), which allows us to detect temporal and spatial changes of interest. The images have a moderate spatial resolution at 30 m and a swath of 185 km. Table II-1 shows the wavelengths and spatial resolutions of seven bands of the TM sensor. In the project, about 250 Landsat5 TM images (Level-1, L1) covering the study areas were acquired. The time range is 1984–2010, including only the summer seasons (mainly July and August) for each year.

Table II-1: Wavelengths and spatial resolutions of seven bands of Landsat5 TM sensor

Landsat 5 (TM sensor)	Wavelength (μm)	Resolution (m)
Band 1	0.45–0.52	30
Band 2	0.52–0.60	30
Band 3	0.63–0.69	30
Band 4	0.76–0.90	30
Band 5	1.55–1.75	30
Band 6	10.40–12.50	120
Band 7	2.08–2.35	30

1.2 Data pre-processing

Most vegetation models and algorithms for remotely sensed imagery are applicable to land surface reflectance. However, the original TM L1 data provide at-sensor digital numbers (*DNs*) derived from signals received by the sensor, which are scaled integers from quantization rather than a physical quantity. The *DN* value contains radiant information from the main target, adjacent land surface, atmosphere, etc. (Figure II-1). It is necessary to eliminate environmental influences to refine and maximize the target information. Thus, first of all, the original images should be pre-processed, including radiometric calibration, atmospheric and topographic corrections, and haze and cloud removal. After these processes, the *DN* value in the original image can be converted into the surface reflectance of the target.

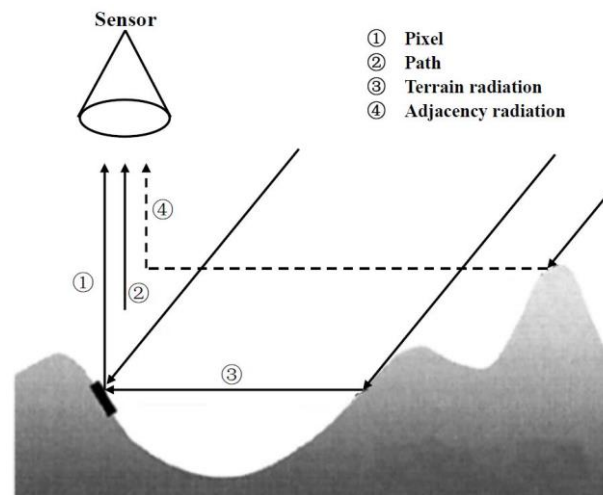


Figure II-1: Composition of sensor-received radiant information. Including: (1) target pixel; (2) path radiance; (3) terrain radiation; (4) adjacency radiation.

The software ERDAS IMAGINE (Leica Geosystems Geospatial Imaging, LLC) and ENVI (ITT Industries, Inc., USA) were used to perform data pre-processing. Specifically, the ATCOR-3 module (Atmospheric/Topographic Correction, Richter and Schläpfer, 2011) embedded in ERDAS IMAGINE was applied to correct atmospheric and topographic effects simultaneously. The programming language IDL was used to perform mathematical calculations. Figure II-2 displays the major steps of the pre-processing procedure.

1.2.1 Radiometric calibration

Radiometric calibration is an essential step in converting *DNs* into meaningful physical quantities such as radiance. The pixel's *DN* values from TM L1 images are represented as Q_{cal} . During radiometric calibration, Q_{cal} values are converted to units of absolute spectral radiance (L_λ) using 32-bit floating-point calculations. The equation is as follows (Markham and Barker, 1986):

$$L_{\lambda} = \left(\frac{LMAX_{\lambda} - LMIN_{\lambda}}{Q_{cal\ max} - Q_{cal\ min}} \right) (Q_{cal} - Q_{cal\ min}) + LMIN_{\lambda} \quad (II-1)$$

where L_{λ} is the spectral radiance at the sensor's aperture [$W/(m^2\ sr\ \mu m)$]; Q_{cal} is the quantized calibrated pixel value[DN]; $Q_{cal\ min}$ is the minimum quantized calibrated pixel value corresponding to $LMIN_{\lambda}$ [DN]; $Q_{cal\ max}$ is the maximum quantized calibrated pixel value corresponding to $LMAX_{\lambda}$ [DN]; $LMIN_{\lambda}$ is the spectral at-sensor radiance scaled to $Q_{cal\ min}$ [$W/(m^2\ sr\ \mu m)$]; and $LMAX_{\lambda}$ is the spectral at-sensor radiance scaled to $Q_{cal\ max}$ [$W/(m^2\ sr\ \mu m)$].

All parameters in the equation are specified in the header files of the TM imagery data. Since $Q_{cal\ min}$ and $Q_{cal\ max}$ are equal to 0 and 255 respectively for the TM5 sensor, the equation can be simplified as:

$$L_{\lambda} = \left(\frac{LMAX_{\lambda} - LMIN_{\lambda}}{255} \right) Q_{cal} + LMIN_{\lambda} \quad (II-2)$$

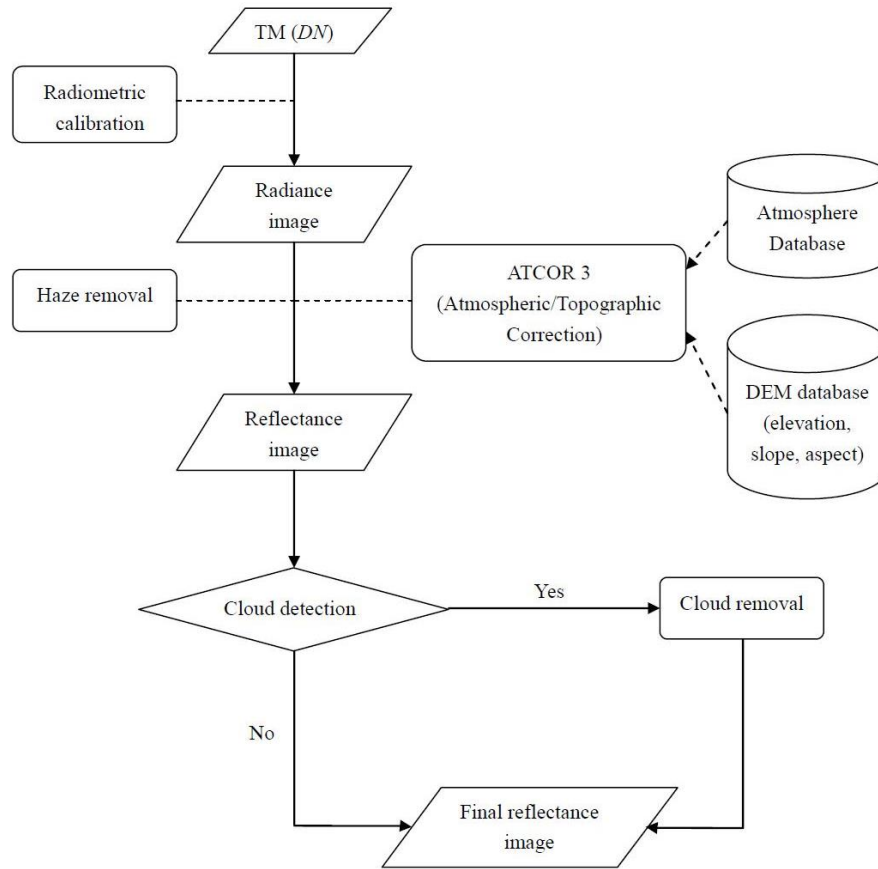


Figure II-2: Pre-processing procedure for TM imagery, including radiometric calibration, atmospheric/topographic correction and haze/cloud removal.

1.2.2 Atmospheric/topographic correction

The radiation signals collected by satellites in the solar spectrum are modified by scattering and absorption by gases and aerosols while travelling through the atmosphere from the Earth's surface to the sensor. The original imagery can be potentially more useful if these disturbances can be removed by atmospheric correction. For images dominated by mountainous terrain, topography is also a key factor impacting signals received by the sensor. Shadows, where apparent brightness is much darker than that of the same land surface in non-shadows, pervade images of rugged mountainous terrain. In this case, topographic correction is also necessary and imperative.

In this project, we used the ATCOR-3 module (Richter, 1996, 1998), which is available in the ERDAS IMAGE software, to eliminate the influences of the atmosphere, solar illumination, sensor viewing geometry, and terrain shadowing simultaneously, after which the at-sensor radiance (L_λ) of each pixel is converted to target surface reflectance (R_λ). ATCOR requires high-resolution and accurate DEM data, and empirical determination of atmospheric parameters for the study areas. The atmospheric correction of ATCOR mainly applies radiative transfer calculation results, based on the MODTRAN-4 code. An integral part of ATCOR is a large database of atmospheric correction functions (look-up tables, LUT) covering a wide range of weather conditions, sun angles, and ground elevations. For topographic corrections, a more sophisticated algorithm, developed by Dozier and his colleagues (Dozier and Frew, 1981, 1990; Dozier 1989), has been incorporated into the Image Processing Workbench (IPW), a digital-image-processing software system. This method assumes that the total incoming shortwave irradiance to a surface (F) is composed of direct solar radiation (F_I), diffuse solar radiation (F_D), and radiation reflected from the neighboring pixels (F_T):

$$F = F_I + F_D + F_T \quad (\text{II-3})$$

F_I , F_D , and F_T can be separately derived from information on solar and sensor geometry, and surrounding DEM data (Dozier, 1989). Accordingly, the surface reflectance (ρ) can be obtained as follows:

$$\rho = \frac{\pi L}{F} \quad (\text{II-4})$$

where L is the observed radiance of the pixel.

We first used DEM data with a 30-m spatial resolution to calculate the required topographic parameters, such as elevation, slope, aspect, and shadow of each pixel, and these were used as the inputs for ATCOR; secondly, we set up the required atmospheric parameters based on a supplementary dataset. Finally, reflectance images after topographic and atmospheric correction were obtained.

1.2.3 Haze/cloud removal

Thin haze and thick clouds can often be observed in about one-quarter of the image being used. Clouds often block the satellite's view of the surface and saturate signals in visible bands of pixels under their influence. The conventional atmospheric correction mentioned above cannot remove them effectively, and, thus, such images were additionally performed with haze/cloud removal processing.

For thin haze, ATCOR provided a basic algorithm to detect and remove its impacts. For thick clouds, we used a removing algorithm, neighborhood similar pixel interpolator (NSPI, Zhu et al., 2011), to remove clouds regions and fill in the clouds gaps (see Figure II-3). The cloudy area was first visually interpreted and the clouds mask was produced manually for the cloudy image acquired at current time (t_2); then another cloud-free image acquired at previous time (t_1) was selected as an auxiliary image. Within these two images, a certain amount of neighboring pixels, that was spectrally and spatially similar to each of the clouded pixels around the detected cloud area, are detected and selected. Then a weighted linear model was applied to predict the spectral value of the cloudy pixel. In doing so, more accurate reflectance cloud-free products could be generated.

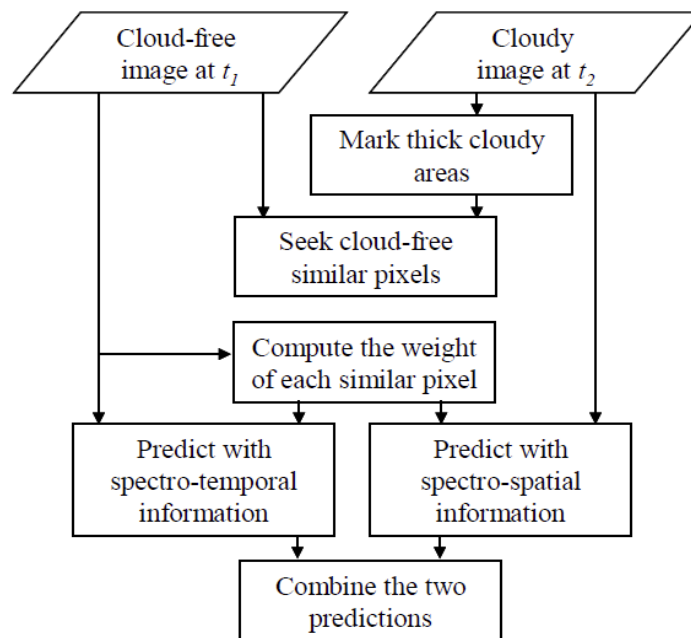


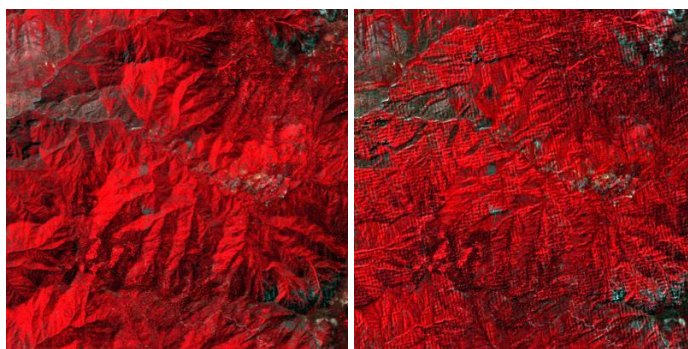
Figure II-3: Flowchart of NSPI approach for thick cloud removal (Zhu et al., 2011)

1.2.4 Results of pre-processing

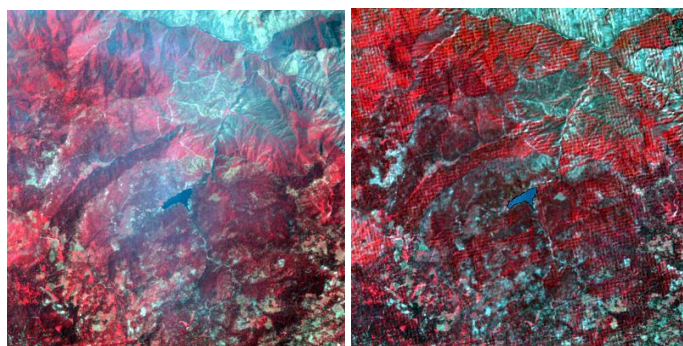
Figure II-4 displays the comparisons between corresponding images before and after atmospheric and topographic corrections, haze removal and clouds removal, respectively. Before topographic

correction, shadows covers up the optical feature of land surface; while the shaded regions become clearer to represent their surface features after topographic correction (Figure II-4a). For haze or cloudy images, the correction also performed very well. Obviously, the contaminated regions were removed and the spectral features of surface were recovered (Figure II-4b and c).

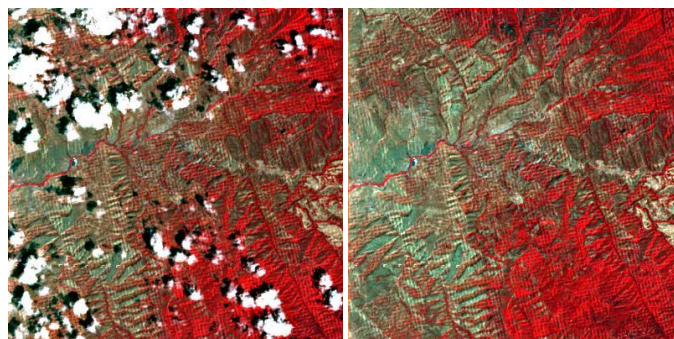
In addition, we also visually examined the spectra of ground objects before and after the pre-processing. Figure II-5 presents the spectra comparisons of typical land covers between images before and after correction, including vegetation, soil, roads, broad-leaved and coniferous forest. It can be seen that the corrected spectra were closer to standard spectra in shape and value ranges. The typical characteristics of surface target were also enhanced. In general, corrected images illustrated obvious advantages over original *DN* images.



(a) Before (left) and after (right) atmospheric and topographic correction

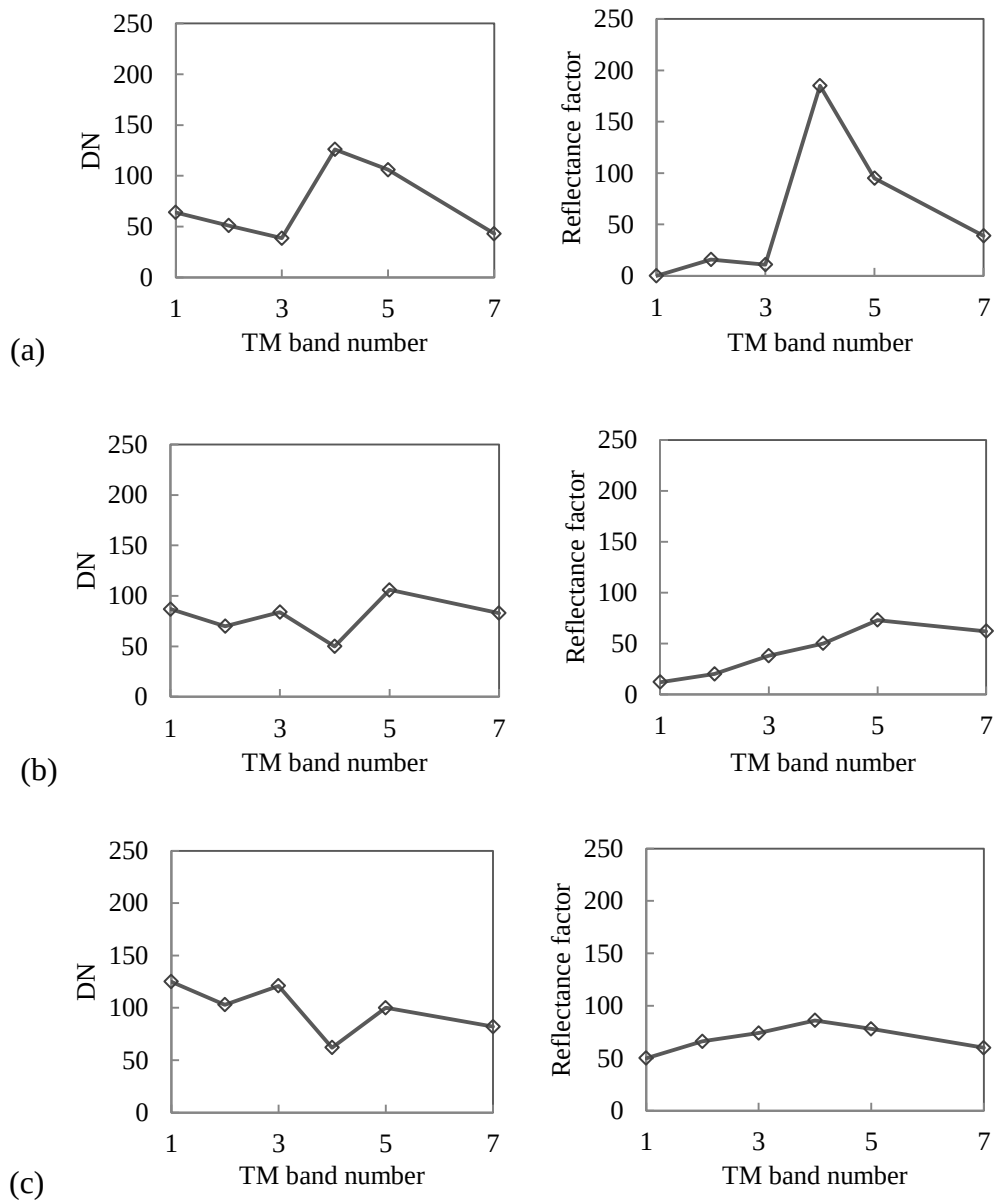


(b) Before (left) and after (right) haze removal



(c) Before (left) and after (right) cloud removal

Figure II-4: Visual comparisons of original images (*DN* value) and pre-processed images (reflectance) (NIR-red-green composite): (a) before (left) and after (right) atmospheric and topographic correction; (b) before (left) and after (right) haze removal; (c) before (left) and after (right) cloud removal.



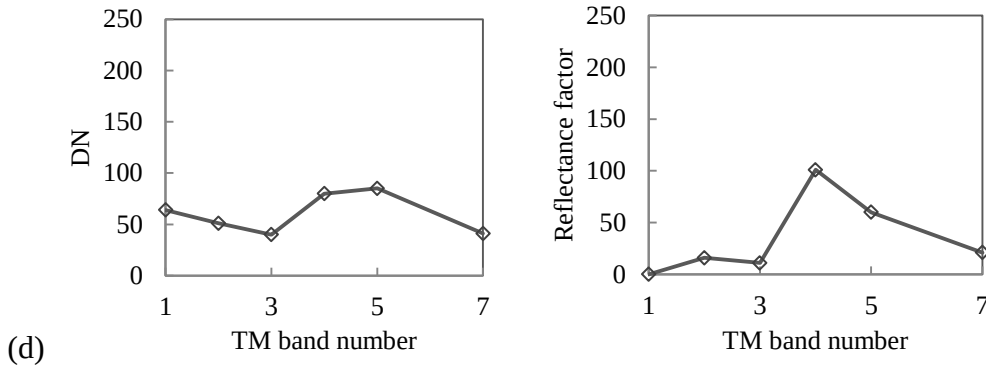


Figure II-5: Comparisons between pixel's spectra in original image (*DN* value) and pre-processed image (reflectance rescaled to 0–255) for typical land covers: (a) vegetation; (b) soil; (c) road; and (d) coniferous forest.

1.3 Moisture indices

As mentioned above, factors leading to water stress include soil moisture, canopy temperature and evapotranspiration, and leaf water content. These factors therefore affect the canopy moisture status to a greater or lesser extent. In this project, we applied several commonly used remotely sensed vegetation indices to evaluate vegetation growth and biological conditions. Some indices directly reflect the vegetation water content, and others mainly indicate the vegetation intensity and growth conditions. Here, all the selected indices were considered as potential indicators of vegetation moisture and were named moisture indices. The objective is to uncover the dynamic changes of these indices in the past 27 years, and also to determine which indices can better represent the moisture conditions of giant sequoia groves.

In this project, two types of indices were introduced: general vegetation indices and tasseled cap (TC) transformation indices. The former index is usually a mathematical combination of several vegetation optical bands. The latter, however, is a linear combination of all information from all available bands (except TM band 6, the thermal band).

1.3.1 Vegetation indices

Existing studies suggest that near infrared (NIR) and shortwave infrared (SWIR) wavelengths are relatively sensitive to liquid water; this provides many advantages in satellite monitoring of vegetation water content (Hunt and Rock, 1989; Gao, 1996). In this project, several vegetation indices derived from NIR and SWIR wavelengths were selected. Note that, since the corrected TM images can better represent the optical features of the target surface, all these indices were calculated from corrected reflectance data, rather than from raw images.

1.3.1.1 Normalized difference vegetation index (NDVI)

NDVI is a simple indicator that can be used to analyze remote-sensing measurements, typically but not necessarily from a space platform, and assess whether the target being observed contains live green vegetation or not (Tucker, 1979). In general, if there is much more reflected radiation at NIR wavelengths than at visible wavelengths, vegetation in that pixel is likely to be dense and may contain some type of forest. If there is very little difference between the intensities of the visible and NIR wavelengths, the vegetation is probably sparse and may consist of grassland, tundra, or desert. Based on this principle, NDVI can be written mathematically as:

$$NDVI = \frac{\rho_{NIR} - \rho_{red}}{\rho_{NIR} + \rho_{red}} \quad (II-5)$$

where ρ_{NIR} is the reflectance value of the NIR band (TM band 4) and ρ_{red} is the reflectance value of the red band (TM band 3).

The NDVI for a given pixel always results in a number in the range -1 to $+1$. A zero or negative value means no live vegetation, and a value close to $+1$ ($0.8-0.9$) indicates the highest possible density of green vegetation.

1.3.1.2 Enhanced vegetation index (EVI)

EVI is an “optimized” index, designed to enhance the vegetation signal with improved sensitivity in high biomass regions and improve vegetation monitoring through a decoupling of the canopy background signal and a reduction in atmospheric influences (Huete et al., 2006). EVI is calculated similarly to NDVI, but does not become saturated as easily as NDVI does when viewing forests with large amounts of chlorophyll. The formula is:

$$EVI = G * \frac{\rho_{NIR} - \rho_{red}}{\rho_{NIR} + 6\rho_{red} - 7.5\rho_{blue} + L} \quad (II-6)$$

where ρ_{blue} is the reflectance value of the blue band (TM band 1); the L factor equals 1.0; and G is the “Gain” factor, equal to 2.5.

1.3.1.3 Soil adjusted vegetation index (SAVI)

SAVI is based on NDVI after eliminating the influences of background soils using various observed data (Huete, 1988). This index is mainly used for areas where vegetative cover is low and significant soil surface is exposed. SAVI is structured similarly to NDVI but with the addition of a “soil-brightness correction factor”:

$$SAVI = (1 + L) * \frac{\rho_{NIR} - \rho_{red}}{\rho_{NIR} + \rho_{red} + L} \quad (II-7)$$

where L is the soil-brightness correction factor, which equals 0.5. In theory, a lower SAVI indicates a lower amount or cover of green vegetation.

1.3.1.4 Modified soil adjusted vegetation index (MSAVI)

MSAVI was developed from SAVI. In the definition of SAVI, L is a coefficient varying with vegetation density and is difficult to optimize. Accordingly, Qi et al. (1994) suggested a self-adjusting L , resulting in a new index—MSAVI. It avoids finding the soil line from a feature-space plot or even explicitly specifies the soil-brightness correction factor:

$$MSAVI = \frac{2\rho_{NIR} + 1 - \sqrt{(2\rho_{NIR} + 1)^2 - 8(\rho_{NIR} - \rho_{red})}}{2} \quad (II-8)$$

SAVI also ranges from -1 to 1 ; a high SAVI indicates a high level of greenness of vegetation.

1.3.1.5 Normalized difference water index (NDWI)

NDWI is defined as the ratio of the difference between reflected SWIR and reflected NIR and the sum of the two bands; it gives a measurement of the vegetation moisture (Gao, 1996; McFeeters, 1996; Ceccato et al., 2001). The SWIR reflectance reflects changes in both the vegetation water content and the spongy mesophyll structure in vegetation canopies, whereas the NIR reflectance is affected by leaf internal structure and leaf dry matter content, but not by water content. Combination of the NIR with the SWIR removes variations induced by leaf internal structure and leaf dry matter content, improving the accuracy in retrieving the vegetation water content. Previous studies suggested that NDWI is a good indicator for vegetation liquid water and can be used as a drought indicator (Gu et al., 2008). The formula is defined as:

$$NDWI = \frac{\rho_{NIR} - \rho_{SWIR}}{\rho_{NIR} + \rho_{SWIR}} \quad (II-9)$$

where ρ_{SWIR} is the reflectance of SWIR band (TM band 7).

1.3.2 Tasseled cap (TC) transformation indices

TC transformation is a conversion of the records in a set of channels into composite values, i.e., the weighted sums of separate band values. TC transformation produces three components: brightness (B),

greenness (G), and wetness (W). Brightness roughly measures the brightness level of each pixel in the scene; greenness and wetness represent the degree of greenness and water content of a pixel, respectively. The three indices can be directly correlated to physical characteristics of vegetation and have potential use in uncovering forest features. When compressing spectral data into a few bands associated with physical scene characteristics, the TC transformation of TM data represents examples of linear combination features, which have achieved a degree of acceptance in the remote-sensing community (Crist, 1985; Crist and Kauth, 1986). Currently, there is no available TC transformation equation for surface reflectance data from the Landsat5 TM sensor. Thus, in this project, we have to apply the transformation to at-sensor *DN* data of original images, rather than of corrected reflectance images.

The formulation of TC transformations is sensor dependent. The coefficients are identical for all images derived from the same sensor, regardless of when and where they are collected. Table II-2 shows TC transformation parameters for at-sensor *DN* data from the Landsat5 TM sensor (Crist 1985; Crist and Kauth, 1986). The TC indices were calculated from the data of the related six TM bands. With respect to our project, we only calculate the TC wetness index, which is closely related to vegetation moisture. The formula is as follows:

$$Wetness = 0.1446(TM1) + 0.1761(TM2) + 0.3322(TM3) + 0.3396(TM4) - 0.6210(TM5) + 0.4186(TM7) \quad (II-10)$$

where *TM1*, *TM2*, *TM3*, *TM4*, *TM5*, and *TM7* are the *DN* values of TM bands 1, 2, 3, 4, 5, and 7, respectively.

Table II-2: Tasseled cap transformation parameters for *DN* imagery from Landsat5 TM sensor.

Parameters are coefficients for each TM band, and they fit the transformation formula

$$y = \beta_1 * TM1 + \beta_2 * TM2 + \beta_3 * TM3 + \beta_4 * TM4 + \beta_5 * TM5 + \beta_6 * TM7.$$

	Band1	Band2	Band3	Band4	Band5	Band7
Brightness	0.2909	0.2493	0.4806	0.5567	0.4438	0.1706
Greenness	-0.2728	-0.2174	-0.5508	0.7220	0.0733	-0.1648
Wetness	0.1446	0.1761	0.3322	0.3396	-0.6210	0.4186

In theory, the NDWI and TC wetness are indices related to vegetation water content, and can directly represent the moisture condition of the vegetation or canopy. Indices such as NDVI, EVI,

SAVI, and MSAVI, which were designed to present the vegetation growth conditions (intensity, healthy situation, etc.), can indirectly indicate the moisture conditions.

2. Data analysis and results

Vegetation indices derived from corrected reflectance data and TC wetness derived from raw *DN* data were used to analyze the temporal and spatial variations of moisture in the summer seasons from 1984 to 2010. Climate data covering the giant sequoia groves from 1931 to 2005 were available, including monthly total precipitations and mean temperatures. From 1984 to 2005 (a period for which both climate data and TM images are available for the study area), correlations between the moisture indices and climate data were analyzed. The historical dynamic of climate change was firstly presented through a longtime-series of precipitation and temperature. The changing trends in these indices were analyzed temporally and spatially. Secondly, the performances of these indices were compared, to determine which one can better represent the vegetation moisture. In addition, the relationship between moisture and fire, snow cover, and TWI were also discussed. Finally, the vulnerabilities of all groves to moisture stress under climate change were analyzed, based on the sensitivity of moisture to precipitation and on within-grove variances in moisture over time.

2.1 Temporal trends in climate (precipitation and temperature)

The climate data used in this project were collected from four weather stations surrounding giant sequoia groves (see Figure II-6). Data were available for 1931–2005 at the study area, including monthly total precipitation, mean temperatures, maximum temperatures, and minimum temperatures. Herein, we mainly focus on the total precipitations and mean temperatures.

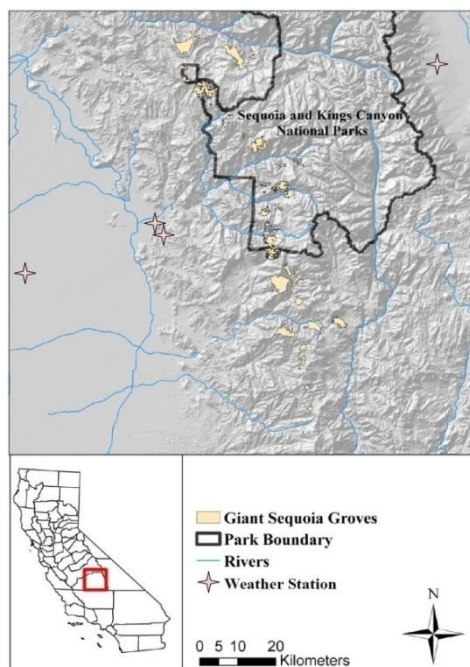
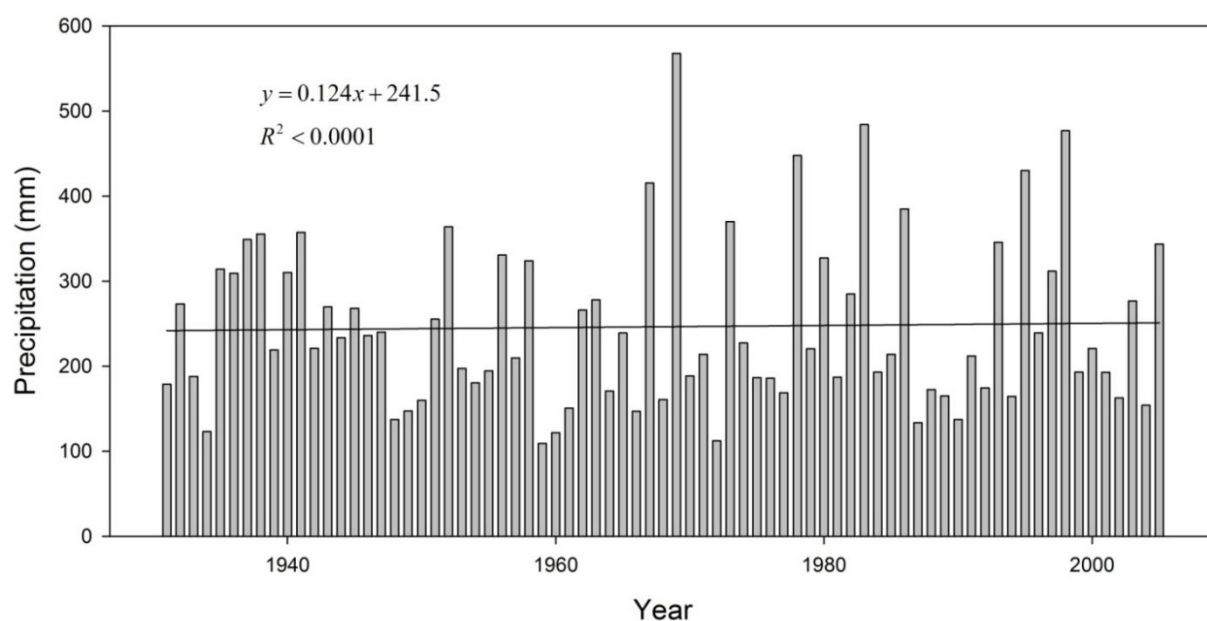
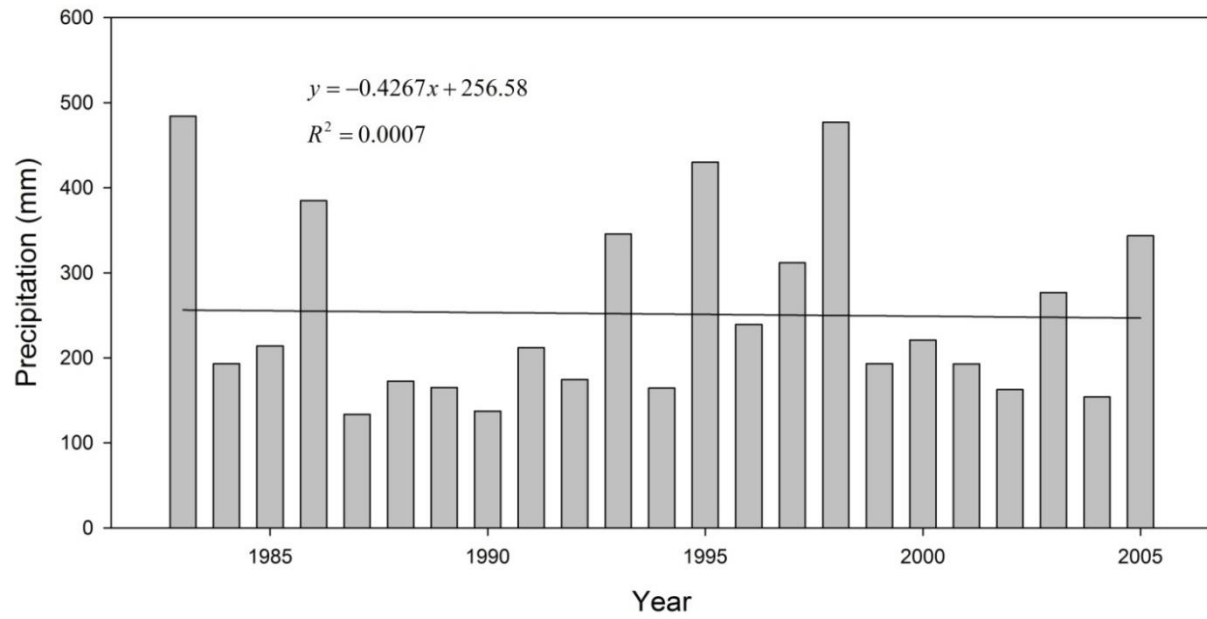


Figure II-6: Distribution of four weather stations used in this project.

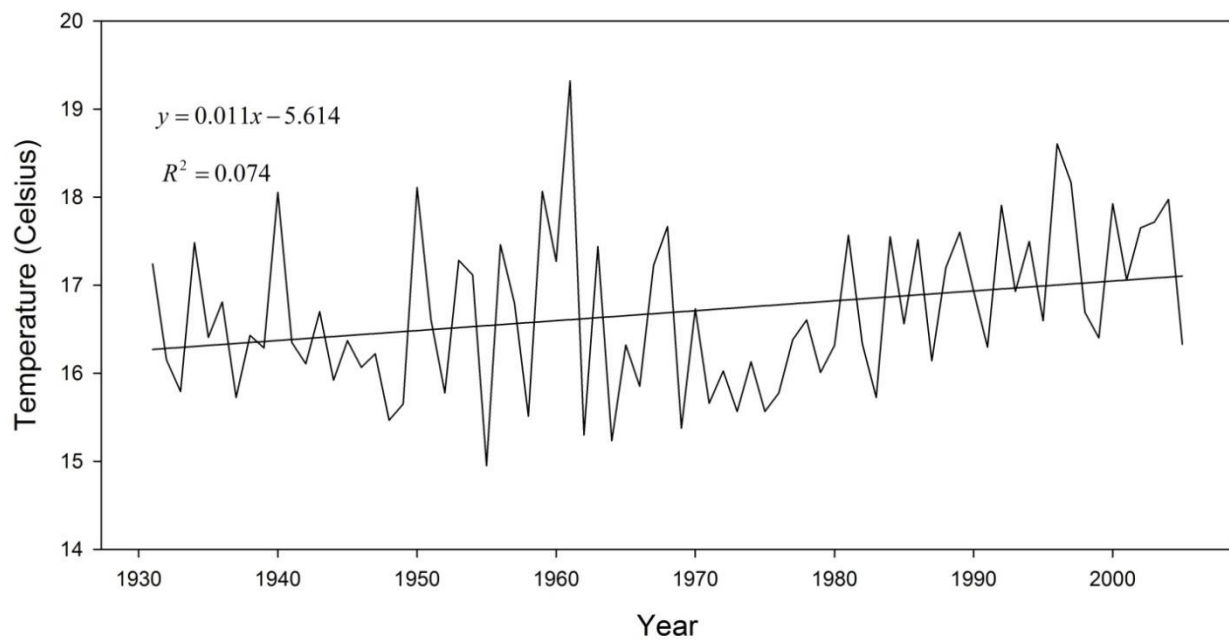
Since the TM images used in this project mainly cover the summer season, the precipitation and temperature dynamics before this time probably affect the vegetation moisture conditions. Considering the vegetation growth lags in response to temperature and precipitation in giant sequoias (York et al., 2006), we took the total precipitation and mean temperature value from September of the previous (x) year to August of the current ($x+1$) year as the annual climate data of the current ($x+1$) year to match the timing of our imagery, which came from July to August. Figure II-7 displays the yearly precipitation and temperature trends in the study area for the whole period for which climate data are available (from 1931 to 2005), and the period of interest in this project (from 1984 to 2005).



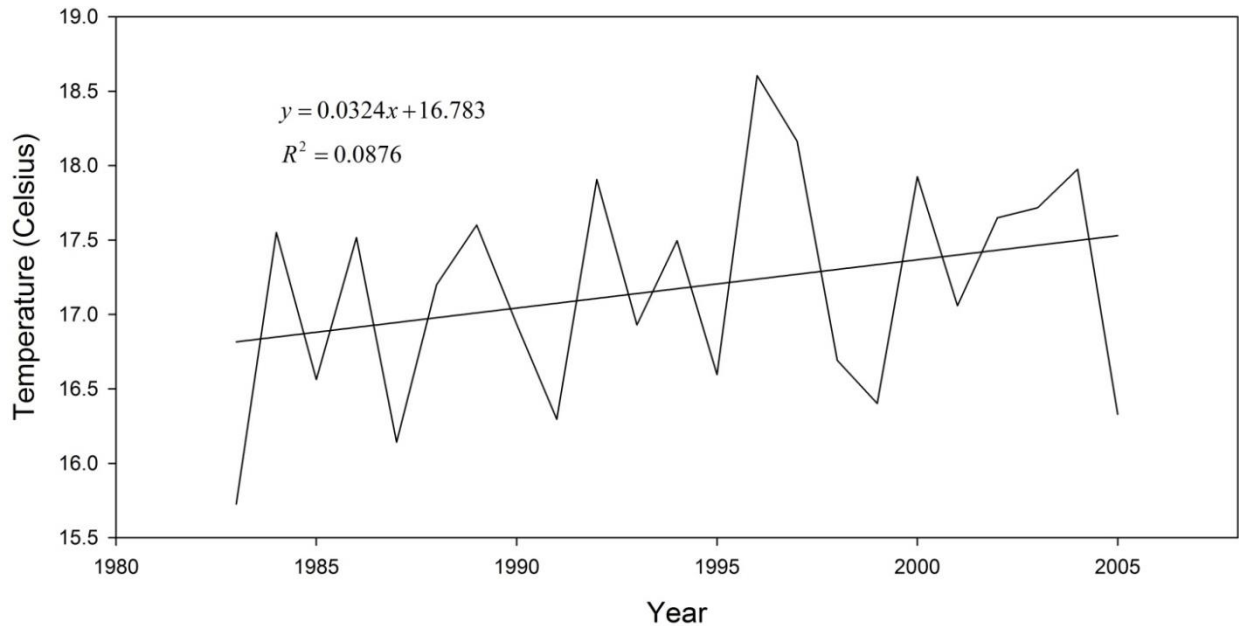
(a)



(b)



(c)



(d)

Figure II-7: Yearly precipitation and temperature trends in the study area in two periods (1931 to 2005, 1984 to 2005). Values shown here are average values for the four weather stations shown in Figure II-6 in each year: (a): pre-total precipitation from 1931 to 2005; (b) pre-total precipitation from 1984 to 2005; (c): pre-mean temperature from 1931 to 2005; and (d) pre-mean temperature from 1984 to 2005. Here, “pre” means, e.g., for 1951, the sum or average value from September 1950 to August 1951.

As we can see, for the period from 1931 to 2005, the mean temperature shows a slightly increasing trend ($R^2=0.074$, $P\text{-value}=0.0174$), which can be visually detected the total precipitation, however, increased very slightly ($R^2<0.0001$, $P\text{-value}=0.8137$), but with a strong fluctuation (the precipitation range is from 100mm to 600 mm). For example, in 1959 or 1972 (or 1987 or 1990), the value is around 100mm, and such years are referred to as “dry” years; in 1969 or 1983 (or 1995 or 1998), the value is larger than 500mm, and such years are referred to as “wet” years. For the period of interest, from 1984 to 2005, the total precipitation also shows no significant change ($R^2=0.0007$, $P\text{-value}=0.9044$); the mean temperature shows an increasing trend, which is more significant than the total precipitation ($R^2=0.0876$, $P\text{-value}=0.0536$) but still weak in the statistical meaning. In addition, years 1993, 1995, 1998, and 2005 can be considered as wet years, whereas 1987 and 1990 were dry years. It could help us to understand the mechanism of vegetation response under such climate changes.

2.2 Temporal trends in vegetation moisture indices

Vegetation indices and TC wetness indices were calculated for the images collected in July and August from 1984 to 2010.

First, to identify the significant level of temporal changes of these indices, linear regression and F -tests were performed for each index on a 27-year time-series (1984–2010) (Lomax, 2007) (Table II-3). Apparently, from the values of slope within the linear regressions between time and vegetation moisture indices, NDWI, NDVI, EVI, SAVI, and MSAVI show possibilities of decreasing trends with the negative slopes, while the slope for TC wetness is positive, implying an opposite behavior compared with other indices. However, considering about the confidence level, the P -values of these indices suggest very significant trends for NDVI, EVI, SAVI, and MSAVI (P -values<0.001), but insignificant trends for NDWI (P -value=0.4295) and TC wetness (P -value=0.7202).

Table II-3: Regression and F -test results between moisture indices and time from 1984 to 2010. Regression equation is $y = ax + b$; x is an integer from 0 to 26 (representing 27 years from 1984 to 2010); y represents the average value of the moisture indices for all groves in the corresponding year.

	NDWI	NDVI	EVI	SAVI	MSAVI	TC wetness
Slope (a)	−0.0003	−0.0059	−0.0257	−0.0087	−0.0035	0.0211
Intercept (b)	0.3740	0.9268	2.0381	1.3795	0.9570	18.9432
F value	0.6450	23.0500	26.5106	22.7848	19.2199	0.1313
P -value	0.4295	<0.001	<0.001	<0.001	0.0002	0.7202

The preceding approach of taking the average of all the groves as representative for the whole study area smoothes the detailed information for individual groves and weakens the trends of the indices over time. Therefore, to illustrate the detailed temporal variations and to reveal the relationship between moisture conditions and vulnerability of giant sequoias, two groves, DEER_CREEK and DOUGLASS (Figure II-8), where NDWI has the highest (i.e., wettest) and lowest (i.e., driest) values, respectively, among all the groves, were selected for analysis in this project. The average value of each pixel within both groves for each index are shown in a time-series in Figure II-9, and the corresponding linear regression results are shown in Table II-4.

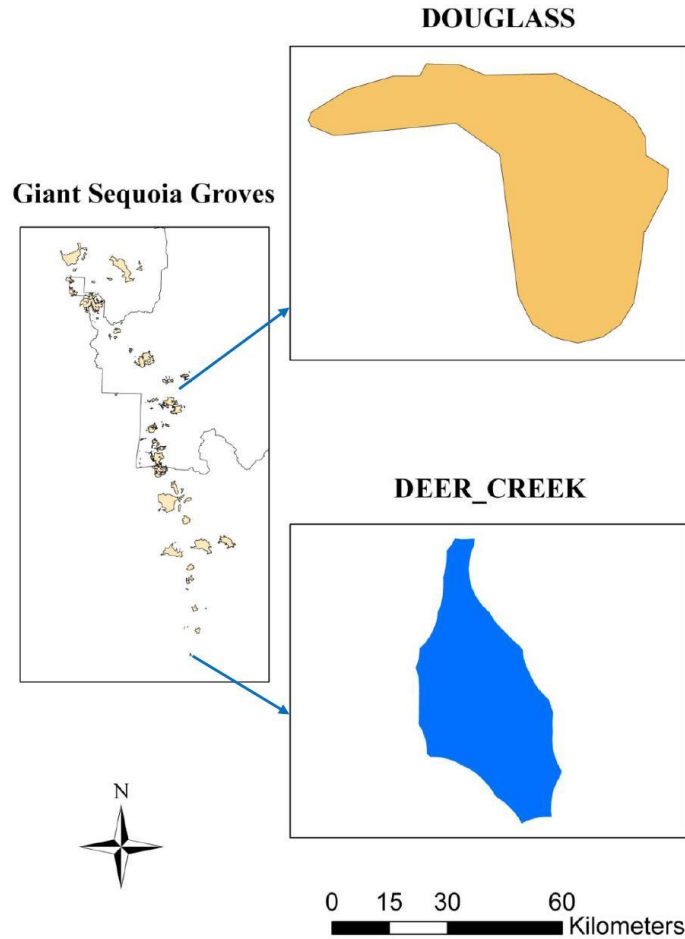
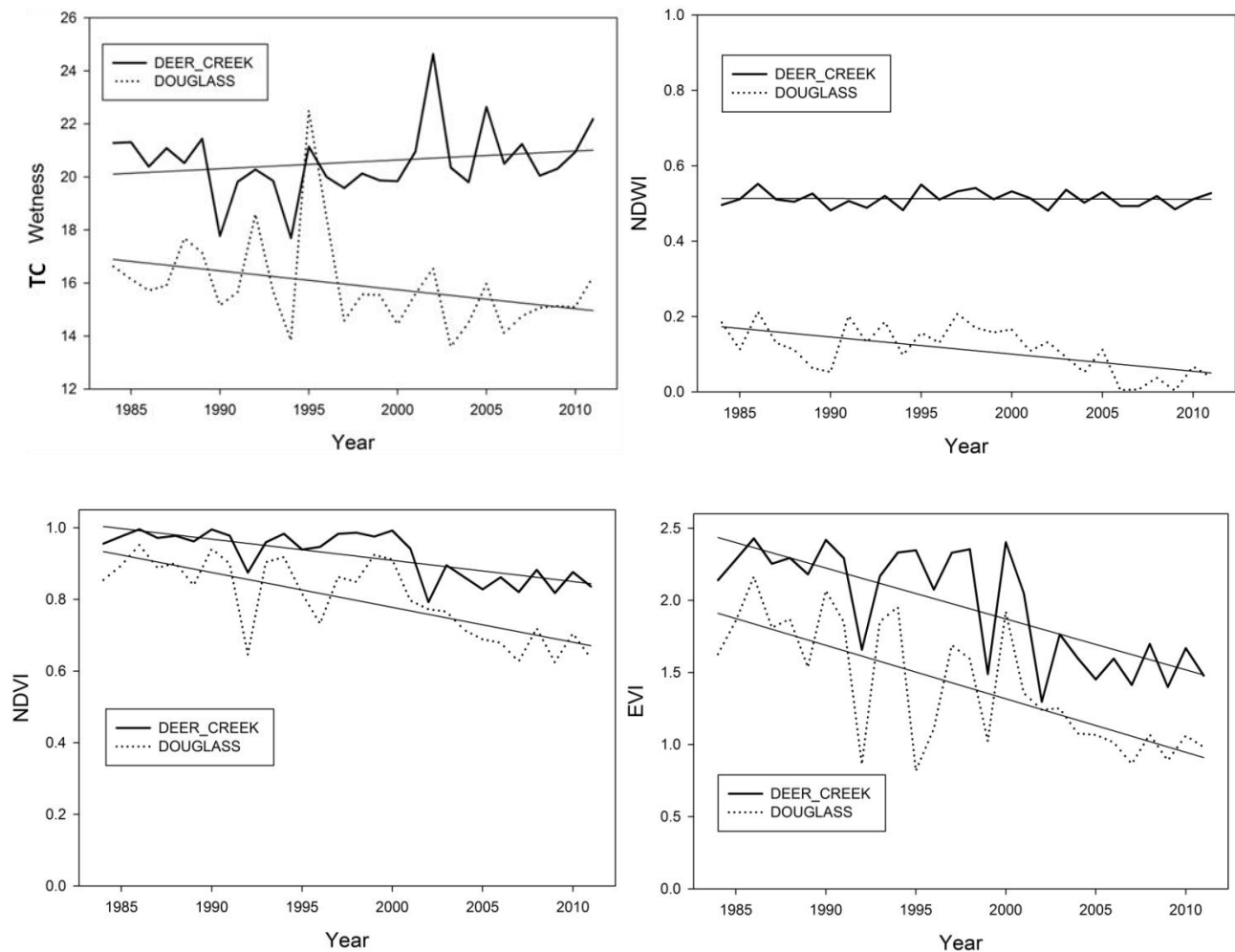


Figure II-8: Locations and characteristics of giant sequoia groves selected for analysis in this project. DOUGLASS (above) is the driest grove with the lowest NDWI, at 0.1114, and DEER_CREEK (below) is the wettest grove with the highest NDWI, at 0.5143.

As we can see from Figure II-9 and Table II-4, (1) NDVI, EVI, SAVI, and MSAVI were relatively stable from 1984 to 2000, and jumped down to lower levels since 2001. Moreover, the variability before 2001 is greater than after 2001. Overall, the decreasing trends are obvious, which is consistent with the results shown in Table II-4. (2) Similarly, for NDWI, both selected groves also have a more or less decreasing trend over time, but such trends are less significant than those for above indices (NDVI, EVI, SAVI, and MSAVI); this is consistent with the results shown in Table II-4 where the regression slope for NDWI is the lowest. Apparently, DOUGLASS grove shows a significant trend over time ($P\text{-value}=0.007$), while DEER_CREEK illustrates a changing trend lack of significance ($P\text{-value}=0.8672$). This suggests that the temporal fluctuation for the drier grove (DOUGLASS), is stronger than that for the relatively wetter grove (DEER_CREEK).

For TC wetness index, based on its behavior illustrated in Table II-3, Figure II-9 and Table II-4, we found that TC wetness generally varies around certain values with an increasing trend (regression slope = 0.0211 for all groves); and compared with the other indices, TC wetness shows an opposite fluctuation direction. Considering that TC wetness behaves differently from the other five indices and that the significance level is too low to indicate a meaningful trend over time, we exclude it from the subsequent analysis in this project. The opposite and poor performance of TC wetness is probably because it was calculated directly from TM *DN* imagery, which was not atmospherically or topographically corrected, and might contain many erroneous signals.



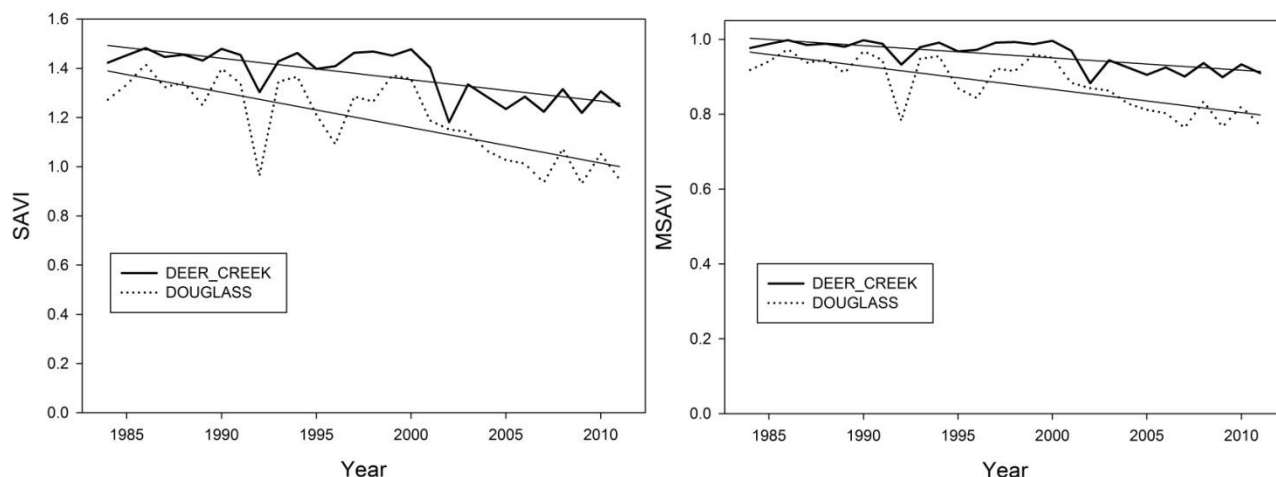


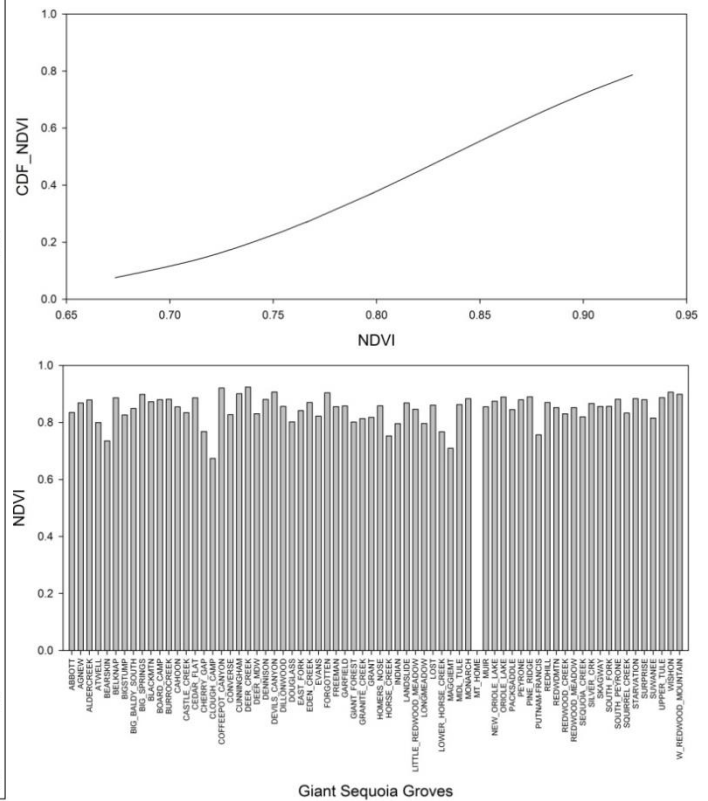
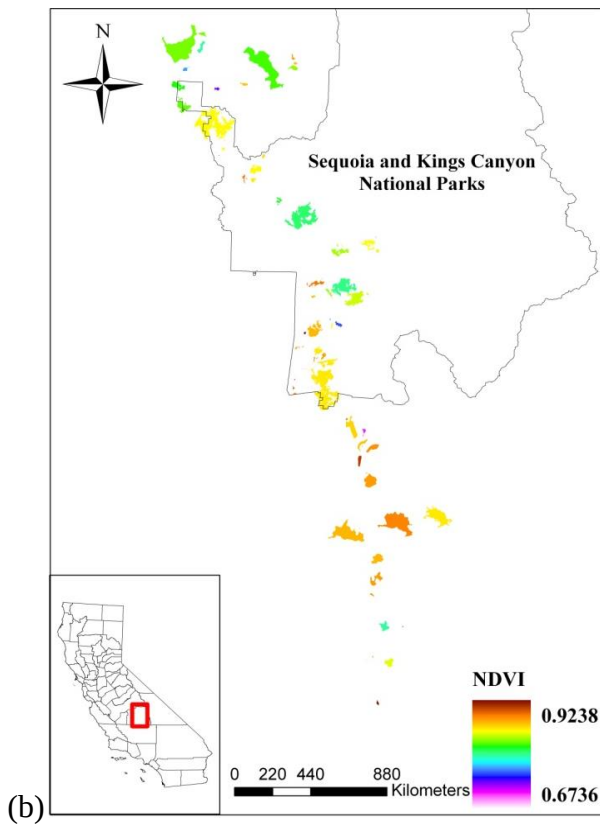
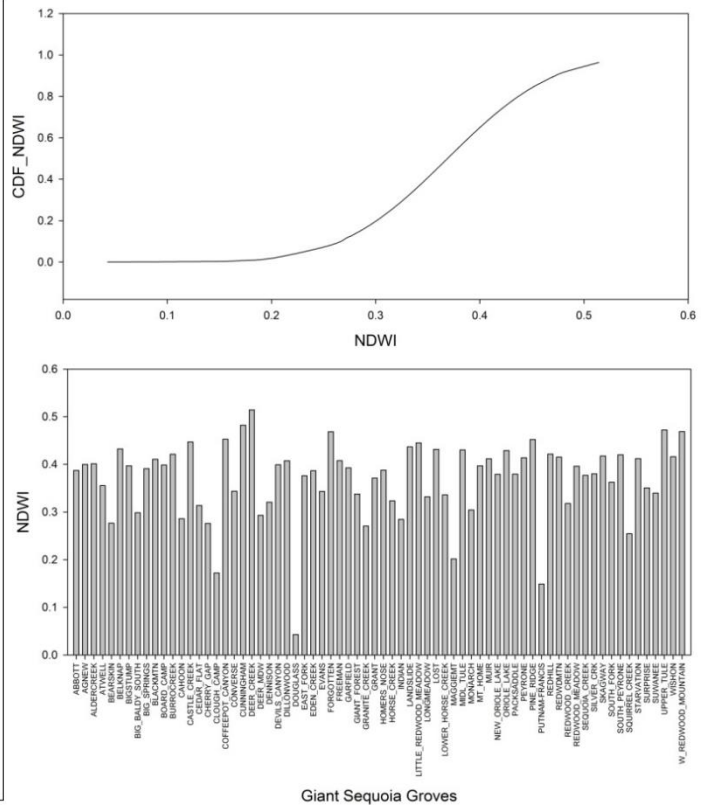
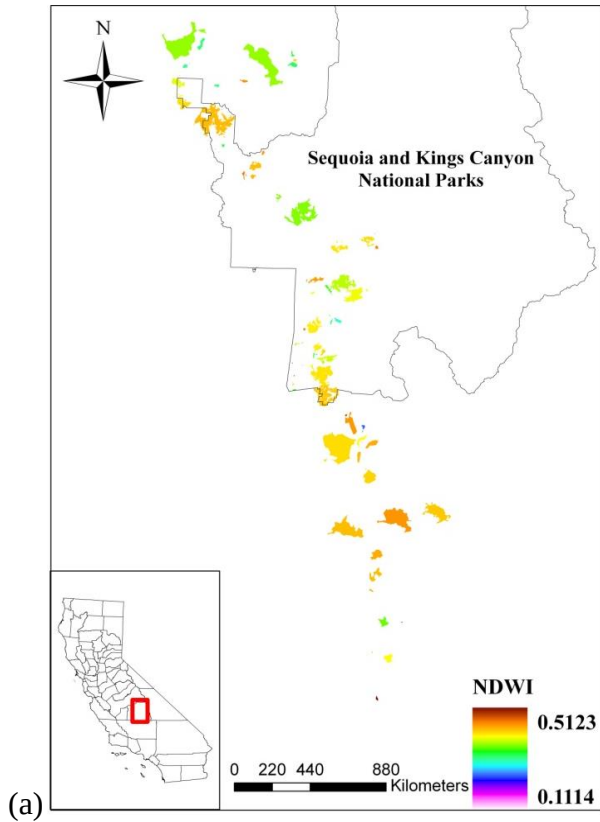
Figure II-9: Yearly variations in moisture indices from 1984 to 2010 of the two selected giant sequoia groves: DEER_CREEK and DOUGLASS. (TC wetness index, NDWI, NDVI, EVI, SAVI and MSAVI are each shown).

Table II-4: Regression results between moisture indices and time for the two selected groves: DEER_CREEK and DOUGLASS (see corresponding curves in Figure II-9). Regression equation is $y = ax + b$; x is an integer from 0 to 26 (representing 27 years from 1984 to 2010); y represents the average moisture index values within each grove in the corresponding year.

		NDWI	NDVI	EVI	SAVI	MSAVI	TC wetness
DEER_CREEK	Slope (a)	-8.3E-05	-0.0059	-0.0353	-0.0087	-0.0033	0.0335
	R^2	0.0011	0.5552	0.5575	0.5528	0.5508	0.0432
	P -value	0.8672	1.51E-6	1.39E-6	1.65E-6	1.78E-6	0.2917
DOUGLASS	Slope (a)	-0.0045	-0.0097	-0.0371	-0.0144	-0.0062	-0.0714
	R^2	0.3510	0.5554	0.5009	0.5566	0.5499	0.1078
	P -value	0.0007	1.50E-6	1.02E-5	1.43E-6	1.84E-6	0.0882

2.3 Spatial patterns of vegetation moisture

As shown in Figure II-9, different groves have different values of moisture indices. To explore the spatial distribution of moisture, the average value in the summer seasons in the 27 years from 1984 to 2010 for each index was calculated at grove level, as shown in Figure II-10 (original data shown in Table A9). As a supplement, the cumulative distribution function (CDF) plot for each index was also calculated, and these are displayed in Figure II-10.



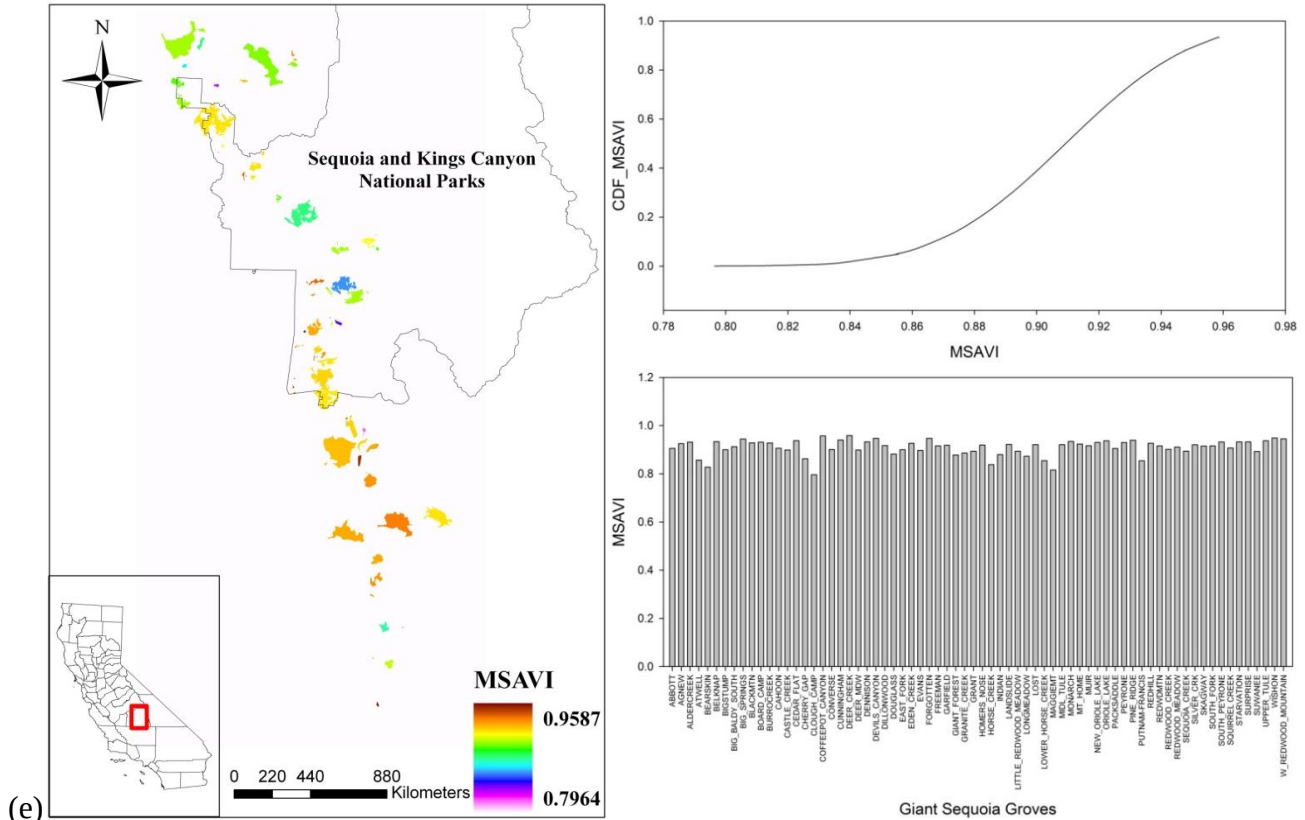


Figure II-10: Grove-based distributions and bar diagrams, and corresponding cumulative distribution function (CDF) plots, of (a) NDWI, (b) NDVI, (c) EVI, (d) SAVI, and (e) MSAVI. Values shown here are the average values over 27 years (1984–2010) for each giant sequoia grove. Original data are shown in Table A9. (See large-scale figures in Figure A-22 and Figure A-23)

Generally, the moisture indices are greater in southern groves than in northern groves and in the middle parts. The spatial variations between different groves are obvious. We can see that about 80% of sequoia groves have average NDWI, NDVI, EVI, SAVI, and MSAVI values less than 0.4, 0.9, 1.9, 1.3, and 0.9 respectively. Moreover, NDWI and EVI have stronger spatial variations compared with the other indices; NDVI, EVI, SAVI, and MSAVI, however, do not vary among groves very much.

In addition, to identify locations outside the current extent of groves where conditions may be favorable for giant sequoia, the spatial distribution of the average NDWI in 1984–2010 within an extended area, is shown in Figure II-11. The absence of data in the top-right corner is a result of the image boundary constraint. With these data, we can identify areas on the landscape with high NDWI values and thus determine potentially desirable places to plant the species.

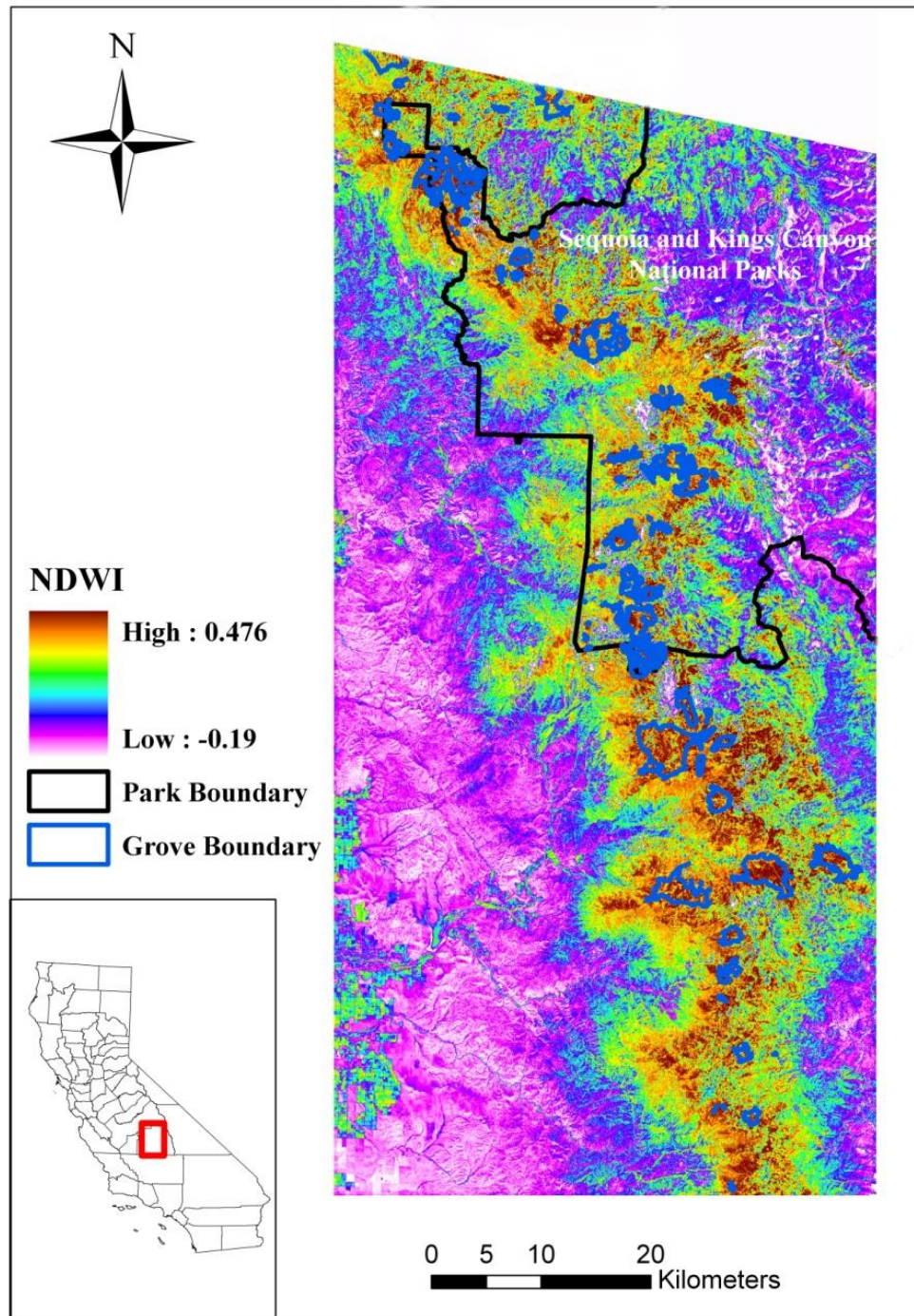


Figure II-11: Pixel-based distribution of NDWI within an extended area. Values shown here are average NDWI values over 27 years (1984–2010) for each pixel. The extent is the sub-area from the entire TM area where we performed pre-processing in this project. Corrected image data and calculated moisture indices are not available outside this region. Absence of data in the top-right corner is the result of image boundary constraints. (See large-scale figures in Figure A-24)

2.4 Vegetation moisture vs. climate (precipitation and temperature)

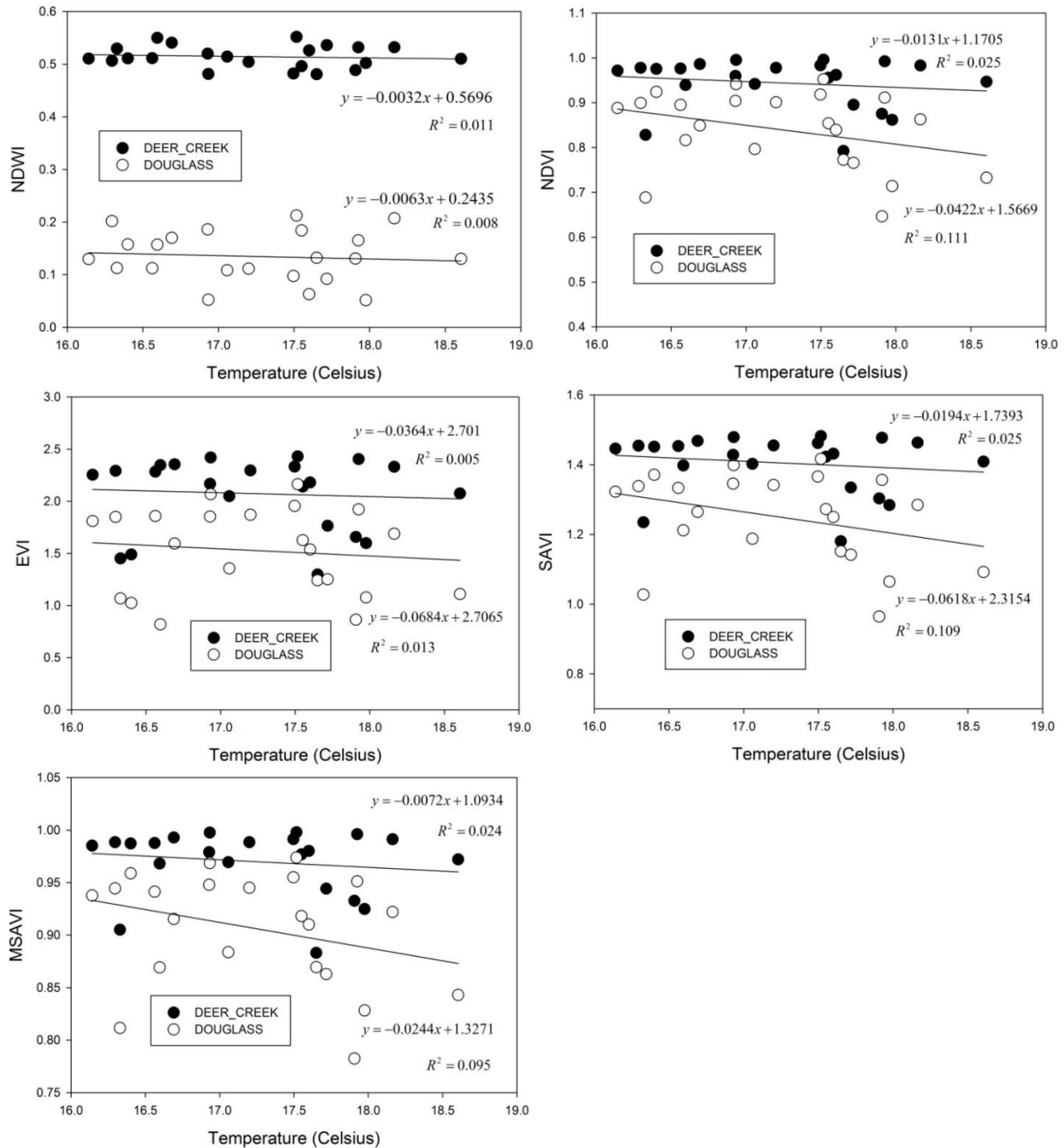


Figure II-12: Relationship between moisture indices and annual mean temperature. Moisture indices are the calculated averages of NDWI, NDVI, EVI, SAVI, and MSAVI within the two selected giant sequoia groves. Temperatures (annual mean) are the average values for the four weather stations shown in Figure II-6 in the corresponding years. Each point for a given grove represents a different year.

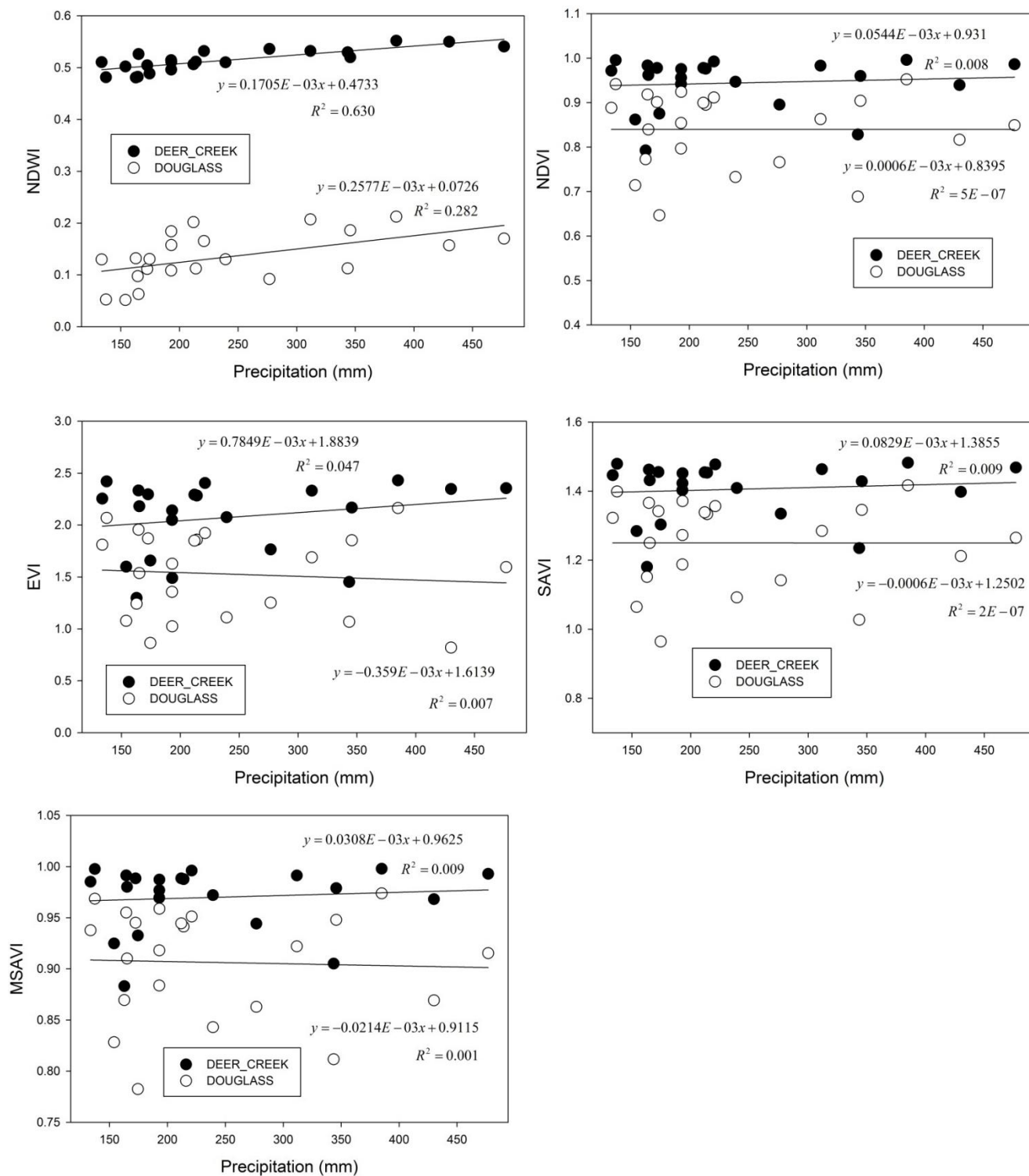


Figure II-13: Relationship between moisture indices and annual total precipitation. Moisture indices are the calculated averages of NDWI, NDVI, EVI, SAVI, and MSAVI within the two selected giant sequoia groves. Precipitation (annual total) is the average values for the four weather stations shown in Figure II-6 in the corresponding years. Each point for a given grove represents a different year.

One of the main objectives is to explore the influence of climate change on giant sequoia moisture. Hence, it is necessary and important to analyze the relationship between the moisture indices and precipitation and temperature. The two selected groves, DEER_CREEK and DOUGLASS, were used to represent the wettest and driest moisture regions in this section. Based on the data from Figure II-7 and Figure II-9, comparisons between these indices and climate data are displayed in Figure II-12 and Figure II-13. The corresponding regression results are provided in Table II-5 (including slope and correlation coefficient R^2). Note that the available time range for both sets of data is from 1984 to 2005.

Table II-5: Regression results for moisture indices with temperature and precipitation for the two selected groves: DEER_CREEK and DOUGLASS. Regression equation is $y = ax + b$; x represents the climate data (temperature or precipitation); y represents the average moisture index values within each grove in the corresponding year. R^2 represents the correlation coefficient.

		DEER_CREEK Grove				
		NDWI	NDVI	EVI	SAVI	MSAVI
Temperature	Slope (a)	-0.0030	-0.0130	-0.0360	-0.0190	-0.0070
	R^2	0.0110	0.0250	0.0050	0.0250	0.0240
	P -value	0.6511	0.4844	0.7573	0.4848	0.4936
Precipitation	Slope (a)	0.17E-3	0.05E-3	0.79E-3	0.08E-3	0.03E-3
	R^2	0.6300	0.0080	0.0470	0.0090	0.0090
	P -value	2.38E-6	0.6805	0.3344	0.6707	0.6753
		DOUGLASS Grove				
		NDWI	NDVI	EVI	SAVI	MSAVI
Temperature	Slope (a)	-0.0060	-0.0420	-0.0680	-0.0620	-0.0240
	R^2	0.0080	0.1110	0.0130	0.1090	0.0950
	P -value	0.6927	0.1295	0.6151	0.1323	0.1640
Precipitation	Slope (a)	0.26E-3	-0.00E-3	-0.36E-3	-0.00E-3	-0.02E-3
	R^2	0.2820	5.00E-7	0.0070	2.00E-7	0.0010
	P -value	0.0099	0.9977	0.7065	0.9984	0.8656

From Figure II-12 and Table II-5, we can see that all indices are more or less responsive to changing temperatures, and a negative relationship is generally suggested between these indices and temperature with the negative values of regression slopes. However, all these regression relationships are insignificant ($R^2 < 0.11$, P -values > 0.05).

From Figure II-13 and Table II-5, we can see that the precipitation trend does not have a strong influence on these indices, except for NDWI. Compared with other indices, the relationship between

precipitation and NDWI shows the largest R^2 values and the significant P -values for both the high-NDWI (DEER_CREEK: $R^2=0.63$, $P\text{-value}=2.38\text{E-}6$) and low-NDWI (DOUGLASS: $R^2=0.28$, $P\text{-value}=0.0099$), suggesting that NDWI is more sensitive to precipitation changes. Moreover, NDWI shows a positive relationship with precipitation (regression slope=0.1710 and 0.26E-3 for DEER_CREEK and DOUGLASS groves). This makes sense because more water falling to the ground probably leads to greater moisture.

Apparently, the factors of temperature and precipitation behaved differently on moisture. For example, temperature explains only about 1% of the variation in NDWI for both the high-NDWI (DEER_CREEK) and low-NDWI (DOUGLASS) groves, while precipitation can explain 63% of the variation in NDWI for high-NDWI grove but only 28% in the low-NDWI grove. However, except for NDWI, both temperature and precipitation don't have strong relationships with other indices (NDVI, EVI, SAVI, and MSAVI). Even for NDWI, only precipitation shows a significant correlation with NDWI, and temperature still correlates poorly with NDWI. Consequently, we can obtain an insight into the vulnerability of giant sequoia groves to moisture stress. In the wetter grove, precipitation explains more of the variation in NDWI than that in the drier grove. In addition, when the same amount of precipitation falls into the wetter grove as the drier grove, the variation in NDWI is larger in the drier grove (inferred from the regression slope between precipitation and NDWI, which is 0.26E-3 for the DOUGLASS grove with the lowest NDWI and 0.17E-3 DEER_CREEK grove with the highest NDWI).

Based on previous analysis, we can see that NDWI shows stronger correlations to climate variations compared to NDVI, EVI, SAVI, and MSAVI. It correlates positively very well with precipitation but has no significant relationship with temperature. Moreover, we can find that the average NDWI values of all the groves are almost not changing ($P\text{-value}=0.4295$) in the 27 years from 1984 to 2010 (Table II-3). For the wetter selected grove with high NDWI (DEER_CREEK), its NDWI also shows a very weak trend over time ($P\text{-value}=0.8672$), for the drier one with low NDWI, however, there is a significant decreasing trend of NDWI during this period ($P\text{-value}=0.0007$) (Table II-4). This is probably because of the stable precipitation ($P\text{-value}=0.9044$) and slightly increasing temperature ($P\text{-value}=0.0536$) in this period. On the one hand, almost no change in the precipitation counterbalanced changes in NDWI; on the other hand, the increasing temperature led to more evapotranspiration, resulting in a slight decrease in NDWI. Furthermore, the sensitive characteristics of NDWI rely on the use of TM band 7, whose wavelength is very sensitive to liquid water and is often used to derive water content information. Accordingly, the water contents of the vegetation would be more or less reflected by the responses of this band; soil water or surface water could also affect this band. The complex trade-off between vegetation water and soil water makes the mechanism between vegetation and climate more complicated. Other unexpected events may lead to large variations (such as the peaks and troughs in Figure II-9) of moisture indices. To some extent, NDWI efficiently represents the moisture variations

under climate change. Its behavior can be partly explained by temperature and precipitation variations, and it can also be affected by other environmental factors. Accordingly, in the following analysis, we mainly focus on NDWI and explore other possible influences from fire, snow, etc.

2.5 Vegetation moisture vs. fire

Fire is an important factor affecting the moisture indices of giant sequoia groves, and may be the reason for some abnormal cases of these moisture indices. In this project, we used fire history polygons data of SEKI from 1984 to 2010, which were derived from “IRMA Portal Integrated Resource Management Applications”, and tried to reveal the influence of fire perimeters on moisture indices in the related groves. The fire data were from the website

<https://irma.nps.gov/App/Reference/Profile/2182078?code=2182078>. NDWI and NDVI were selected to present the result.

Contrasting the fire polygons with giant sequoia grove polygons, we found that five groves (ATWELL, EAST_FORK, GARFIELD, GRANT, and REDWDMTN) had experienced fire events at different times. It should be noted that if only a tiny part of a grove was in a fire region, we didn't include this grove into fire analysis, considering it's not enough to influence the average water content of the whole grove. Table II-6 shows details of the fire events which occurred in the five groves. Here, since our TM images were mainly obtained in July and August, fires occurring after September 1st are assumed to affect the next year in the analysis (see “Affected year” in Table II-6).

Figure II-14 shows the influence of fire on NDVI and NDWI values for the five groves. Since the fire area has a different unit from NDVI and NDWI, it was rescaled to the range [0, 1] (divided by 1000) prior to the analysis. As we can see, as a result of variations in temperature and precipitation, the two indices both have normal fluctuations. However, abrupt descents, which were unlikely to be caused by changing climate, also occurred in certain years. These abnormalities can be attributed to fire events in the corresponding years. The occurrence of fires explains the obvious descent of NDVI and NDWI in the time-series, and, basically, the fire area also has a positive correlation with the depths of the valley points, especially in ATWELL and EAST_FORK. These results make sense because fire could destroy the trees and damage the living environment, including creating gaps and bare landscape and changing species composition and canopy densities, which consequently influence the growth statement of the trees, the water content within the grove, and the landscape viewing. As a result, such changes within groves could be captured by satellite sensors and be reflected in the reflectance signals, which finally be illustrated in the reflectance-derived moisture indices in this study. Considering that fire may has an effect on the reflectance properties of groves, including creating gaps, charred (non-reflective) landscape, and changing species composition and canopy densities, fire may be considered as one of the

factors that has influence on the growth and water content of giant sequoia groves. However, it should be noted that fire effects can continue for years and even decades after the fire, the result therefore is probably a complex and long-term set of changes in reflectance.

Table II-6: Summary for five giant sequoia groves (ATWELL, EAST_FORK, GARFIELD, GRANT, and REDWDMTN) affected by fire events in the period from 1984 to 2011. Grove name, fire start date, fire out date, fire area, and affected year are included. Affected year is identical to fire out date if the latter is no later than September 1st; otherwise affected year is defined as the year after that of the fire out date. The date format is “YYYYMMDD”.

Grove	Start date	Out date	Area (Ha)	Affected year
ATWELL	19860908	19860908	0.09	1987
	19940114	19940125	55.71	1994
	19951011	19951222	843.13	1996
	19971013	19971115	168.55	1998
	19991122	19991230	159.07	2000
	20060505	20060710	8.91	2006
	20081118	20090106	316.39	2009
EAST_FORK	19910926	19911206	309.33	1992
	19920705	19921030	0.09	1992
	19991122	19991230	159.07	2000
	20021010	20021113	489.39	2003
	20061019	20061229	143.40	2007
	20081118	20090106	316.39	2009
GARFIELD	19850807	19851001	95.85	1985
	19851001	19851020	40.95	1986
	19860724	19861024	157.77	1986
GRANT	19901015	19901126	14.58	1991
	19900629	19900725	0.09	1990
	19920923	19921030	79.47	1993
	19931013	19931207	18.33	1994
	19950824	19960115	178.21	1996
	19960731	19960731	0.09	1996
	19961007	19961105	85.92	1997
	20040928	20041015	0.09	2005
	20040928	20041215	24.15	2005
	20050922	20051129	145.14	2006
REDWDMTN	19870830	19870930	266.43	1988
	19880705	19880714	0.09	1988
	19920507	19920826	0.09	1992
	20021009	20021114	0.09	2003
	20030802	20030915	0.09	2003
	20040520	20041029	44.88	2004
	20060705	20061114	247.90	2006
	20060516	20060815	4.85	2006
	20090705	20091102	328.40	2009
	20110710	20111208	254.07	2011

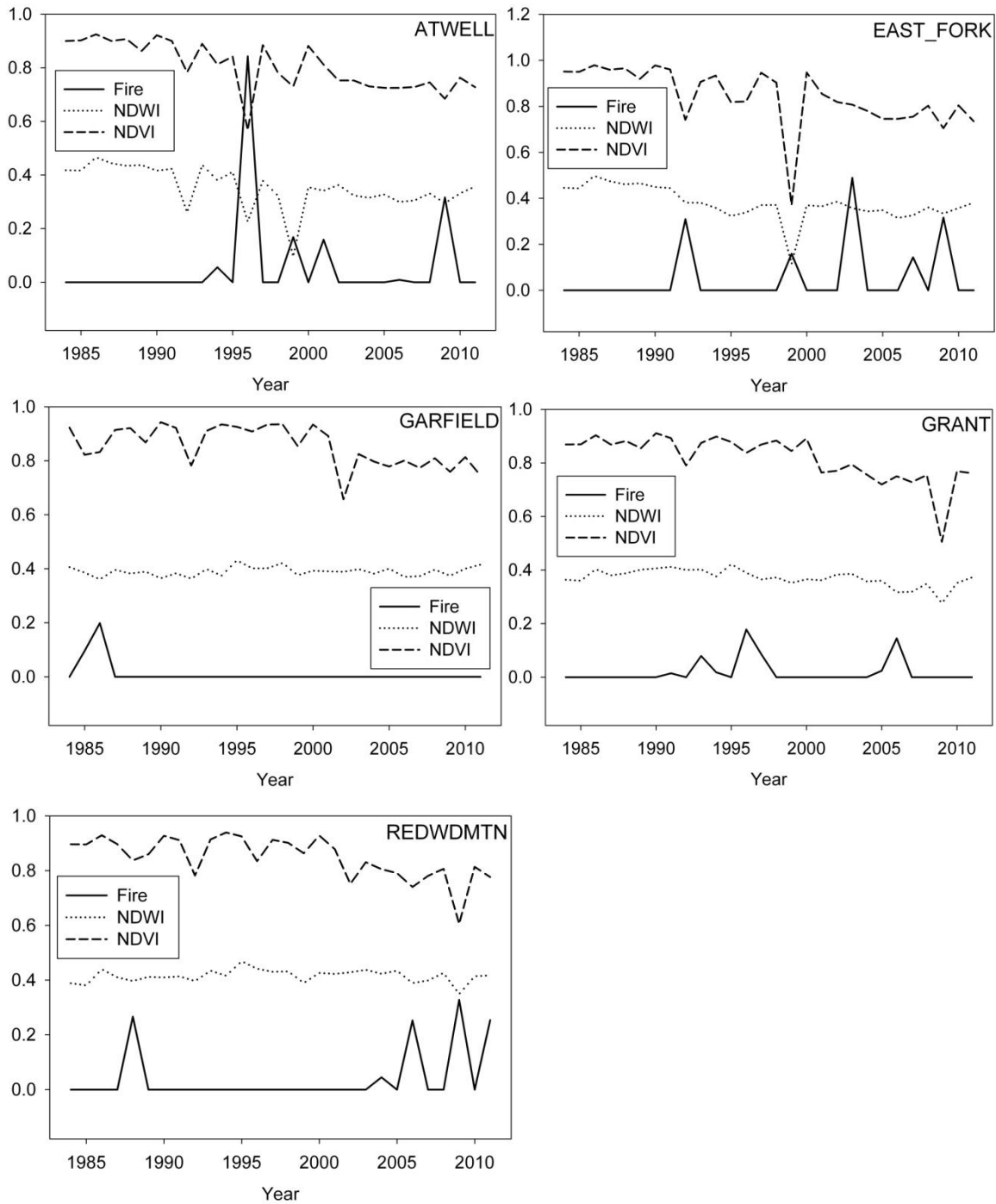


Figure II-14: Impact of fire events on NDWI and NDVI in the five affected giant sequoia groves (ATWELL, EAST_FORK, GARFIELD, GRANT, and REDWDMTN) in time-series (1984–2011). All the fire area is rescaled to 0-1 (divided by 1000) based on the data in Table II-6 firstly. They are rescaled based on every individual grove’s fire dataset. NDWI and NDVI are the average values within each grove.

2.6 Vegetation moisture vs. snow

Snowmelt is an important water resource for mountain areas in the Sierra Nevada. Traditional measurements of precipitation cannot precisely cover the contribution from snowfall. Moreover, snowfall has a lag effect on water runoff, which usually accumulates in winter and melts in spring. It is therefore necessary to explore the potential influence of snow persistence on moisture.

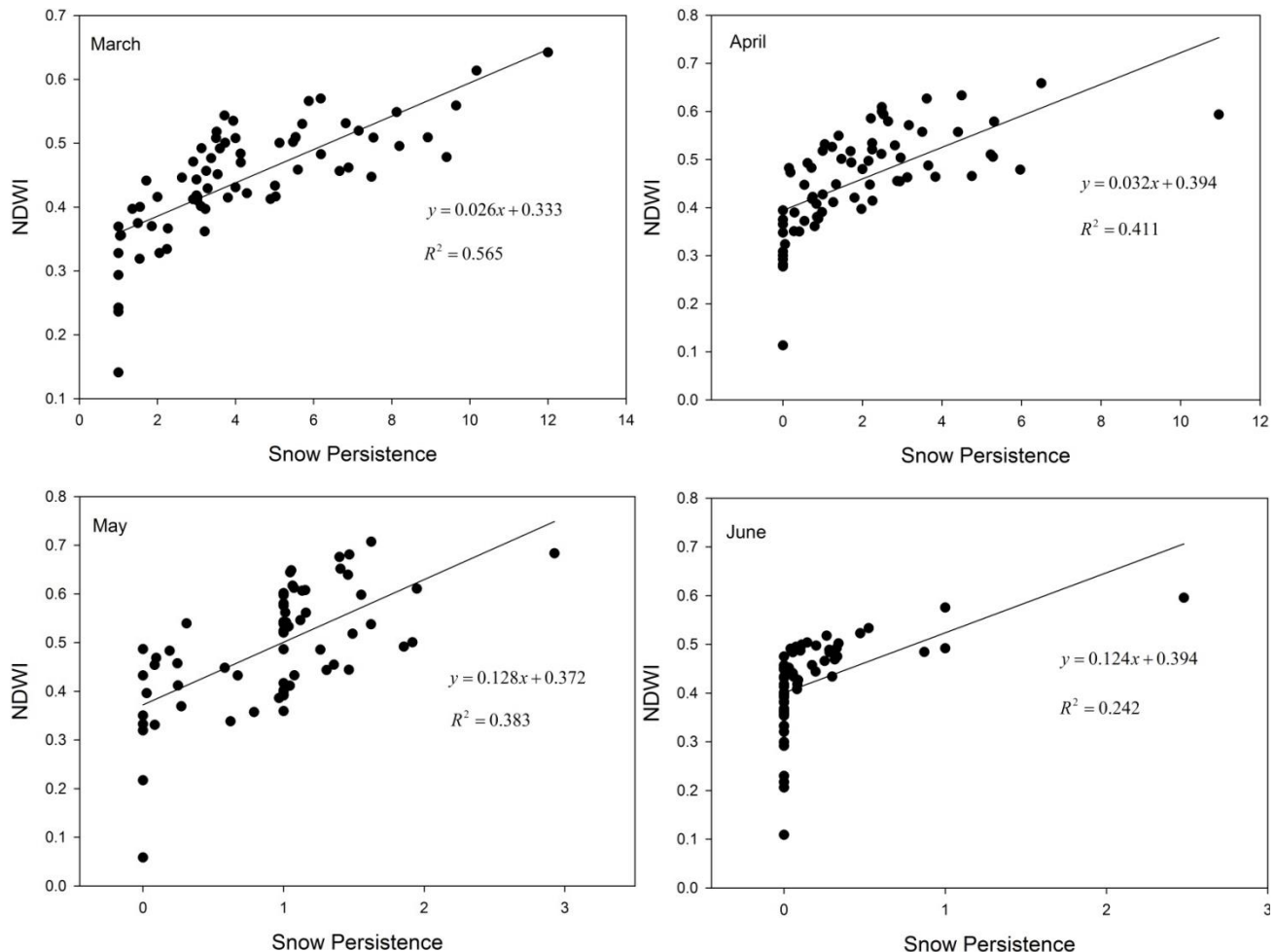


Figure II-15: Grove-based relationship between NDWI and snow persistence in March, April, May, and June. Snow persistence is the average value over 12 years (2000–2011) derived from MODIS imagery for each giant sequoia grove. NDWI is the average value in this period (2000–2011) for each corresponding grove.

Figure II-15 shows the grove-based relationship between NDWI and snow persistence in March, April, May, and June. The snow data were based on the average of snow persistence in the four months using 12 years' Moderate Resolution Imaging Spectroradiometer (MODIS) images (2000–2011) for each giant sequoia grove. Herein, the value of snow persistence at a certain grove describes the number

of years snow occurs at this grove in the 12 years for which snow persistence data exist. For example, if snow persistence is 8.86, it means that in the 12 years, there was an average of 8.86 years that snow existed at a certain time of year in this area. NDWI here is the average value in the same period (2000–2011) for each corresponding grove. Accordingly, three conclusions can be obtained from the regression results. (1) Snow persistence successively decreases from March to June through snow-melting processes, until most groves are out of snow cover in June. (2) NDWI and snow persistence have a positive correlation in all four months, which can be attributed to the fact that more snow appears in these months, and more runoff is probably generated in the later summer season, when the TM images were obtained. (3) In March, when snow cover is greatest, the two quantities have the strongest correlation ($R^2=0.536$, $P\text{-value}<0.0001$), followed by April ($R^2=0.349$, $P\text{-value}<0.0001$), May ($R^2=0.346$, $P\text{-value}<0.0001$), and June ($R^2=0.204$, $P\text{-value}<0.0001$).

2.7 Moisture vs. TWI (topographic wetness index)

Soil water content may influence the moisture conditions of giant sequoia trees. As mentioned above, TWI is frequently used to simulate soil moisture wetness status in a watershed, and it is the most commonly used indicator for locating soil moisture storage and/or soil water stress on a landscape. Figure II-16 shows a comparison between NDWI and TWI; NDWI is the average value in 27 years from 1984 to 2010 for each grove, and TWI is the average value for the corresponding grove. It can be seen that NDWI has a positive but very weak correlation with TWI ($R^2=0.117$, $P\text{-value}=0.0034$), indicating that the variations in local soil water content have a little contribution to changes in tree moisture. It should be noted that the correlation is probably an artifact. Specifically, TWI is strongly determined by slope steepness which also affects reflectance, and adjustments aimed at correcting for slope steepness might be imperfect, so that there's a correlation between slope steepness and NDWI that is unrelated to water.

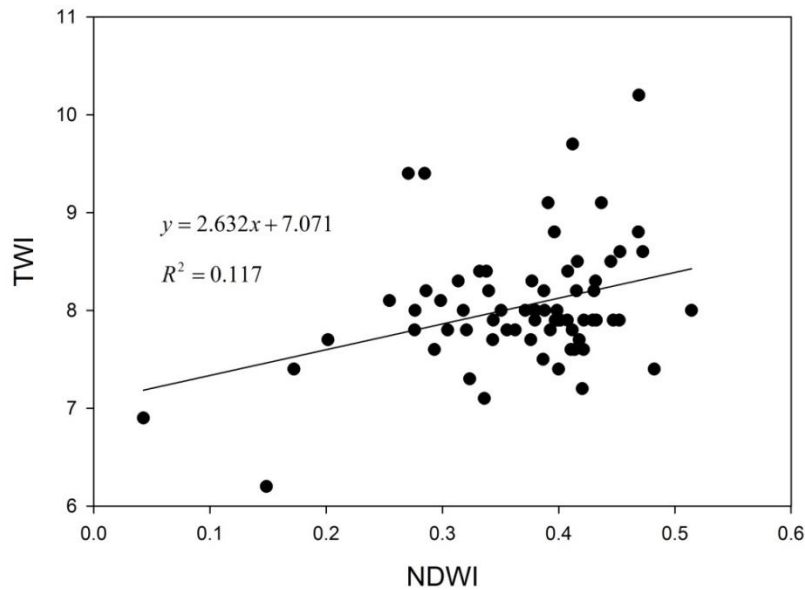


Figure II-16: Grove-based relationship between NDWI and TWI. NDWI is the average value over 27 years (1984–2010) for each giant sequoia grove.

2.8 Vulnerability of giant sequoia groves

To some extent, NDWI is useful as an index for the overall moisture conditions of vegetation in sequoia groves, and here is taken as one of the hypothesized components of the vulnerability of giant sequoia trees to moisture stress under a changing climate. It should be noted that additional field data will be needed to verify the efficacy of NDWI in the future. Based on the average NDWI within each grove, we calculated the within-grove variance of the 27-year time-series from 1984 to 2010. The descending rank of the groves based on this variance is displayed in Figure II-17. It should be noted that abnormal values resulting from fire events were modified by interpolation to exclude the influence of fire from the analysis. Meanwhile, variation of 27-year average NDWIs (rescaled to comparable level with within-grove variance) over all groves were also shown in Figure II-17 to reveal the relationship between average moisture condition and the inter-annual variability in moisture condition of each grove. Reasonably, a higher within-grove temporal variance indicates a higher inter-annual variability in NDWI-based moisture condition of this grove to changing climate. As we can see, for the two selected groves, DOUGLASS ranks third (within the top 5%) and DEER_CREEK ranks sixth lowest (within the bottom 10%), indicating that a drier grove with lower NDWI may have a higher vulnerability than that of a wetter one, a finding that well matches the results discussed in section 2.4. Furthermore, also seen in Figure II-17, with the decrease of inter-annual variability over groves, the within-grove average NDWI presents an obvious increasing trend, which also suggests a negative relationship between vulnerability and NDWI-based moisture condition of giant sequoia groves.

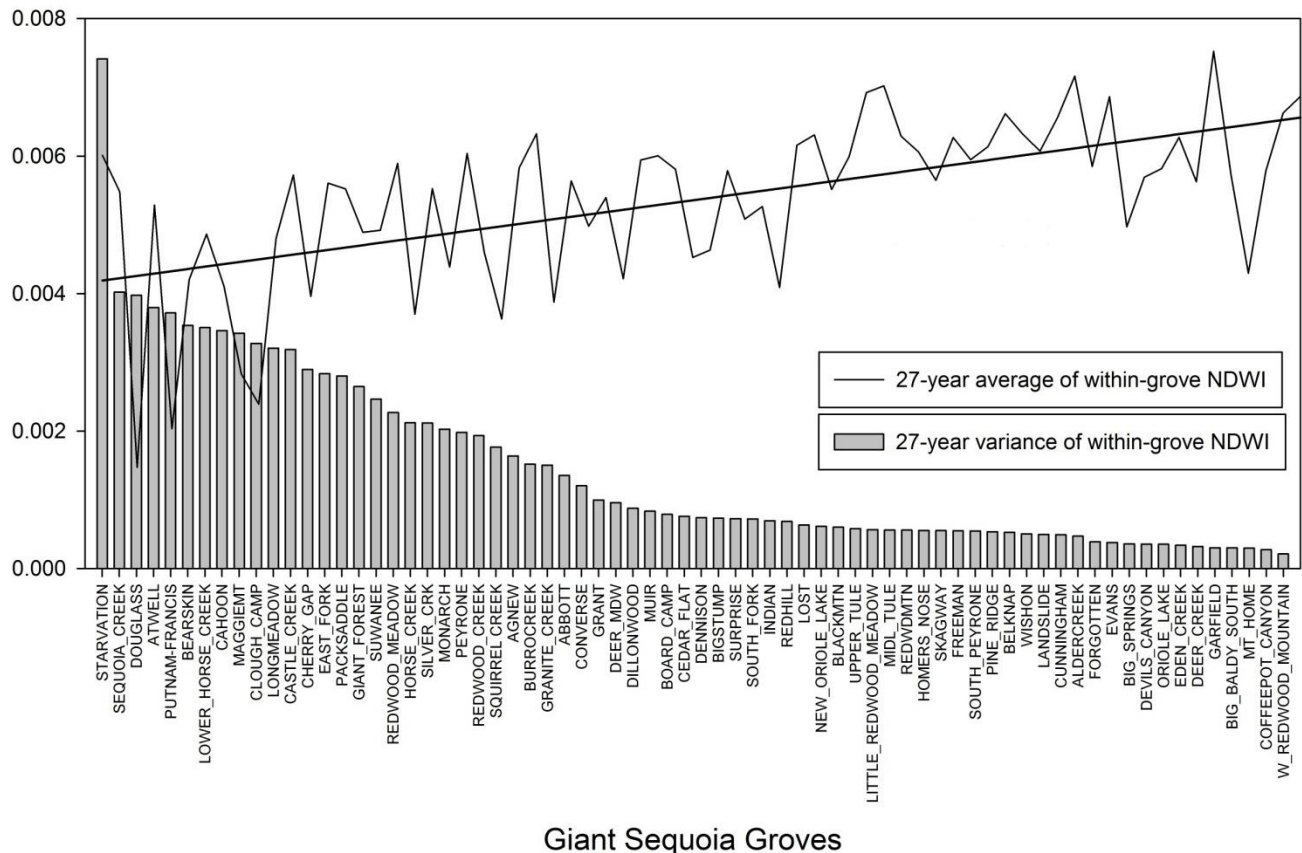


Figure II-17: Ranking of giant sequoia groves based on the within-grove variance of NDWI over 27 years (1984–2010), and variation of 27-year average NDWIs (rescaled to comparable level with within-grove variance) over all groves. Each grove has one NDWI in a year, and within-grove variance here is the variance of this yearly value in the time series (1984–2010) of each grove.

For a further step, we performed a combined analysis of relationship between NDWI inter-annual variability and TWI, grove elevation, and 27-year NDWI average (indicating general moisture condition). It should be noted that since the data of snow persistence has a different time range (2000–2011) with others, it’s not reasonable to include snow persistence into the analysis. From the results shown in Figure II-18, it can be seen that both TWI (Figure II-18a, $R^2 = 0.12$, $P\text{-value} = 0.0032$) and NDWI-based average moisture condition (Figure II-18b, $R^2 = 0.42$, $P\text{-value} < 0.001$) have significant negative relationships with the inter-annual variability in NDWI. However, the elevation of sequoia groves was not significantly related to NDWI inter-annual variability (Figure II-18c, $R^2=0.008$, $P\text{-value} = 0.4589$).

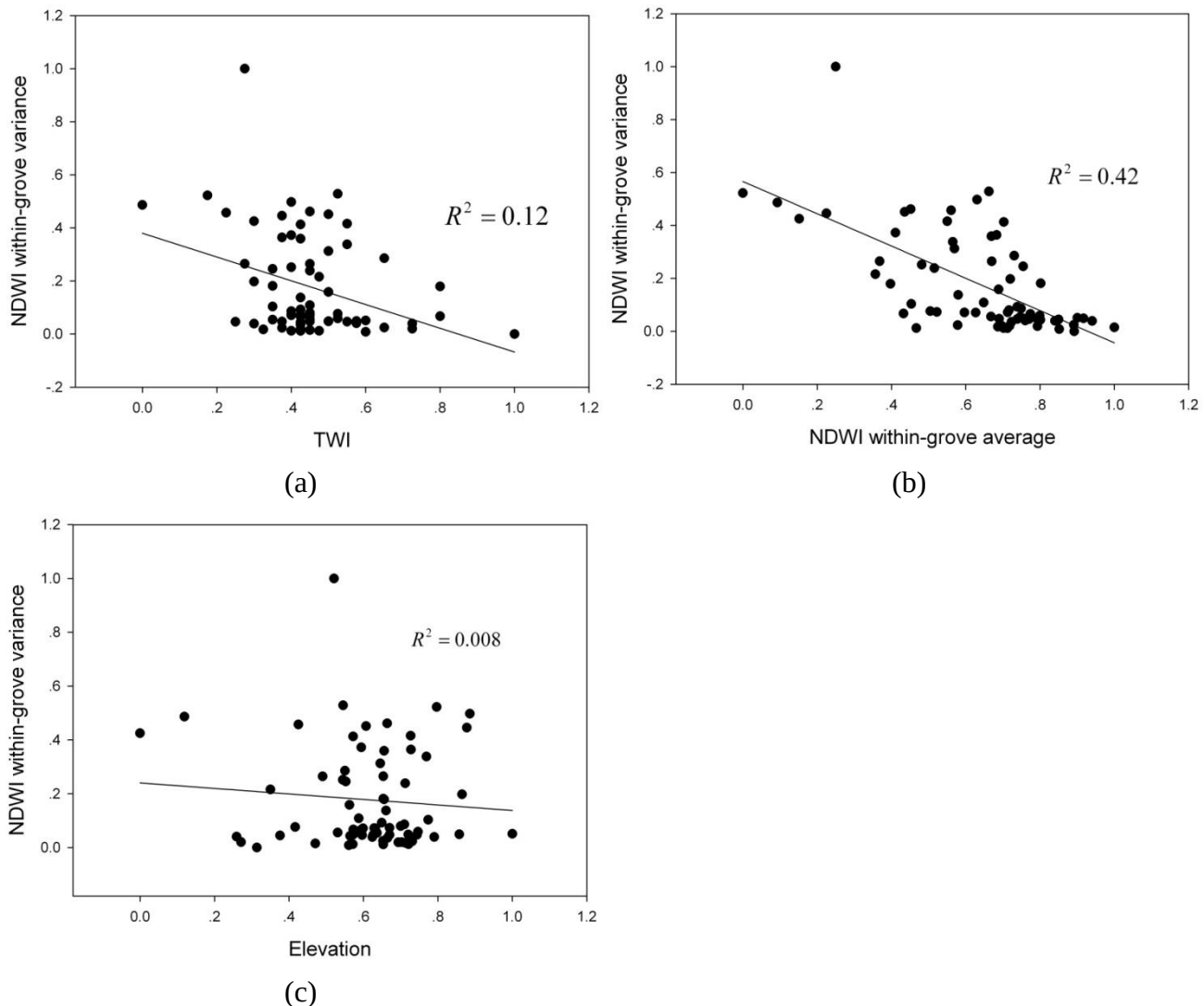


Figure II-18: Relationship between NDWI inter-annual variability of giant sequoia grove to moisture stress and (a) TWI, (b) general moisture condition (indicated by NDWI within-grove average of the 27-year time-series), and (c) elevation of grove.

Accordingly, we plotted TWI, NDWI-based average moisture condition, and inter-annual variability in NDWI. Figure II-19 shows the result in a three dimensional curve. It can be seen that in general, the vulnerability is low where both TWI and moisture condition are high, and is high where both or any one of them is low, which indicates a similar result with that of Figure II-18. Consequently, combining TWI and general moisture condition of a sequoia grove is a potential way to measure its vulnerability to moisture stress.

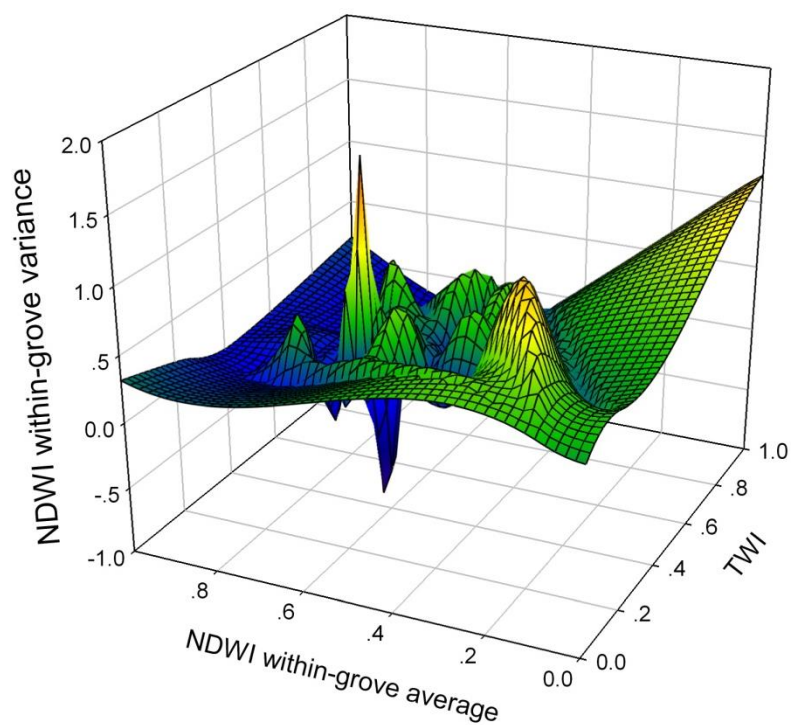


Figure II-19: Relationship between vulnerability of giant sequoia grove to moisture stress (indicated by NDWI within-grove variance of the 27-year time-series) and combined TWI and general moisture condition (indicated by NDWI within-grove average of the 27-year time-series).

3. Conclusion

In part-II, we used a time-series of remotely sensed satellite images (Landsat5 TM L1) from 1984 to 2010 to explore the vulnerability of giant sequoias to moisture stress under climate change in SEKI and SNF/GSNM. Several moisture indices, namely NDWI, NDVI, EVI, SAVI, MSAVI, and TC wetness, were calculated to estimate the water and growth conditions of giant sequoia groves. Temporal trends in the moisture indices and climate data are presented, and the relationship between these indices and temperature and precipitation are analyzed. As supplements, the relationships of moisture conditions with fire, snow cover, and TWI are also provided. Finally, the vulnerabilities of all groves to moisture conditions under climate change are analyzed based on sensitivity of moisture to precipitation and on within-grove moisture variances over time. Several conclusions can be drawn from our analysis:

(1) In the past 27 years (from 1984 to 2010), through the overall analysis of all the groves, the vegetation indices NDVI, EVI, SAVI, and MSAVI show a generally decreasing trend; NDWI shows the possibility of a decreasing trend, but the trend is insignificant; TC wetness shows a slightly increasing trend which, however, is the most insignificant index. Further analysis was performed within two selected groves – the relatively wetter (higher NDWI) one and drier (lower NDWI) one. From 1984 to 2010, NDVI, EVI, SAVI, and MSAVI within the two groves show similar changing patterns as the overall analysis of all the groves; the temporal variation of NDWI is insignificant for the wetter grove ($P\text{-value}=0.8672$), but significant for the drier one ($P\text{-value}=0.0007$), indicating that the drier the grove, the more sensitive to climate change it might be; TC wetness shows insignificant trends for both groves, and is thus excluded from the following analysis.

(2) The temporal and spatial variations of these indices can be explained by the changing temperature and precipitation to some extent. Generally, these indices correlate negatively with temperature changes, but poorly; the precipitation variations don't have strong relationships with these indices, except NDWI. For the two selected groves, NDWI shows a positive relationship with precipitation, and this relationship is more significant for the wetter grove (high-NDWI grove). In sum, except for NDWI, both temperature and precipitation don't have strong relationship with other indices (NDVI, EVI, SAVI, and MSAVI). Even for NDWI, only precipitation shows a significant correlation with NDWI, and temperature still correlates poorly with NDWI.

(3) According to the behaviors of these indices, NDWI was chosen as the most effective indicator of climate change. NDWI shows a slightly negative response to temperature, but their correlation is poor; NDWI has a positive response to precipitation, and their correlation is significant. Specifically, for the two selected groves, temperature explains only about 1% of the variation in NDWI for both high-NDWI and low-NDWI groves, while precipitation explain 63% of the variation in NDWI for high-NDWI grove

and 28% in the low-NDWI grove. Moreover, the overall increasing temperature and stable precipitation from 1984 to 2005 account for the decreasing trend of NDWI in the study area, especially for drier groves.

(4) Climate change might explain the variations of these indices (especially NDWI) to some extent. Other factors, such as fire event, snow, can also affect these indices. The occurrence of fire events matches well with obvious decreases in NDVI and NDWI in the temporal analysis, explaining the rough peaks and troughs within these indices variations that climate factors cannot explain, indicating that fire may be one of the factors that influence on the growth and water content of giant sequoia groves. As well, NDWI and snow persistence have a positive correlation in March, April, May, and June, attributed to the fact that more snow appears in these months, and more runoff is probably generated in the later summer season, when the TM images were obtained.

(6) NDWI has a positive but very weak correlation with TWI ($R^2=0.117$, $P\text{-value}=0.0034$), implying that variations in local soil water content might have a little contribution to changes in tree moisture. However, this correlation might be an artifact considering that there's a correlation between slope steepness and NDWI that is unrelated to water.

(7) Based on the assumption that NDWI can effectively represent the overall moisture condition, analysis of the sensitivity of NDWI to precipitation shows that, in general, a lower NDWI grove has a higher vulnerability to climate change (especially to reduction in precipitation), and a higher NDWI grove one has a lower vulnerability. Also, a comparison between within-grove NDWI variances over the 27 years and 27-year average NDWIs over all groves indicates a similar result. Moreover, combined TWI and 27-year average NDWI can function as an indicator of the vulnerability to moisture stress.

4. Future study/research

Further studies should focus on the following areas:

(1) More data analysis and evidence are needed to specify the changing patterns of canopy moisture. Currently, only July and August have been included. Other months should be studied and seasonal trends should be analyzed to better understand the relationship between canopy moisture and climate factors. The average values for certain groves were used for comparison. Pixel-scale comparison and analysis should be considered to derive more accurate and more local variation patterns. Supplementary land use and geometric data could also be combined to uncover the factors affecting the responses and changes.

(2) Field data are needed to calibrate and validate the ground truth information. Because of the lack of field investigations, only satellite data were used in this project. More weather stations would provide climate data with higher spatial resolution and accuracy. Field data related to vegetation moisture, such as leaf water content, should also be collected to validate and calibrate the satellite data results. A leaf-sampling campaign of giant sequoia trees should be carried out, and their pure spectra should be collected in controlled laboratory experiments. Also, their water content and nutrient capacity should be measured accurately in the laboratory. Such data are necessary and required to improve current studies.

(3) Vegetation moisture algorithms based on remote sensing data should be studied to develop more accurate moisture estimation results, including empirical algorithms and physical models. As a result, better moisture products could then be generated and future vegetation moisture conditions could be predicted.

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Conclusions and Recommendations

Giant sequoia trees and their ecosystems are unique to the Sierra Nevada, where most groves are federally managed. In the southern Sierra Nevada, 70 giant sequoia groves stretch across three jurisdictions, including Sequoia and Kings Canyon National Parks (SEKI), Sequoia National Forest (SNF), and Giant Sequoia National Monument (GSNM). Increasing temperatures over the next several decades, by inducing earlier snowmelt and prolonging summer droughts, may create conditions unfavorable to giant sequoias. Death rates might increase among adult sequoias and associated species as drought stress makes them more vulnerable to insects, pathogens, air pollution, and intense fires. In order to effectively and efficiently allocate management efforts to conserve giant sequoias, the vulnerability of giant sequoia groves to drought/water stress must be evaluated.

In this project, we achieved two scopes of objectives. In scope-I, we developed TWI maps for SEKI, SNF, and GSNM and linked them with static parameters/variables such as vegetation and soil types, and dynamic variables such as temperature, snow, and precipitation, by which we identified the most and least water stress regions. In scope-II, we estimated various vegetation and moisture indices with a time-series of Landsat TM5 images; and based on NDWI, which is the best index indicating the relationship between moisture conditions and climate data, we evaluated the vulnerability of giant sequoia groves to moisture stress.

Accordingly, we obtained five major findings / hypothesis: 1) TWI can contribute to identify potential sequoia groves that are more or less vulnerable to soil moisture. This assumes that areas having mild slope and more converging area are less susceptible to low summer soil moisture than areas having steeper slopes and more diverging topography. 2) Snow persistence is an excellent complement to TWI, and it is most useful above about 1800 m elevation, and should be used in conjunction with regional precipitation and meteorological data; 3) NDWI performs the best as an indicator of relationship between moisture condition and climate change. It shows a slightly negative response to temperature and a strong positive response to precipitation. Due to the relatively stable trend in precipitation and slightly increasing trend in temperature from 1984 to 2005, the drier grove (with lower NDWI) shows a significant decreasing trend ($P\text{-value}=0.0007$) in this period. Meanwhile, the wetter grove (with higher NDWI) shows almost no changing ($P\text{-value}=0.8672$), indicating that the drier the grove, the more sensitive to climate change it might be; 4) NDWI has a positive but very weak correlation with TWI, implying that variations in local soil water content might have a little contribution to changes in canopy moisture. 5) In general, a lower-NDWI grove, which is usually with lower TWI and considered as a drier grove, has a higher vulnerability to climate change (especially to precipitation), and a higher-NDWI grove (relatively wetter grove) has a lower vulnerability.

Through this project, it is recommended that the current analysis be extended by: i) more-detailed evaluation of available data, ii) field characterization of landscape features in selected groves, and iii) multi-year measurements of more-direct indicators of moisture stress.

1. Assess TWI-soil-moisture relationships. Although we lack soil-moisture data in the 70 groves, there are spatially-distributed, long-term data sets in nearby areas of similar elevation and forest density that could be used to evaluate the TWI-moisture stress relationship. This would allow extending the conclusions and provide more-definite management recommendations.
2. Evaluate vegetation-TWI relationships. Using available LiDAR data, supplemented by additional LiDAR flights and/or GPS measurements of where Giant Sequoia trees are located within groves, do a combined spatial analysis of tree location, TWI, and vegetation-stress indices. This will determine if sequoias are preferentially located in areas with higher TWI, and also if they are located in areas with higher or lower canopy moisture stress.
3. Establish within-grove heterogeneity in soil moisture. Shortly after the seasonal snowpack has melted, measure soil-moisture patterns in a late-spring or early-summer synoptic survey at two or more Giant Sequoia groves to establish differences in water storage across elevation, aspect, TWI and canopy-cover gradients. Evaluate in the context of available, detailed data sets from non-grove areas. Use data to assess TWI-soil moisture relationships in groves.
4. Carry out longer-term soil-moisture measurements in groves. Based on the synoptic surveys, site continuous-measurement nodes for soil moisture, which will be put in place and monitored over the long term as indicators of landscape and temporal variability and change. To the extent possible, these measurement nodes should be located at or near sites with other relevant climate, hydrologic and ecosystem data. Two candidate groves that fit this criterion are Giant Forest and Redwood Mountain. Note that Giant Forest has an average elevation of 2058 m, and is among the higher-elevation groves in Sequoia-Kings Canyon; whereas Redwood Mountain has an average elevation of 1816 m, and is a mid to lower elevation grove. Other groves should be considered based on resource availability. Note that soil moisture generally tracks sap flow measurements in mixed-conifer forests, and is much less expensive and reliable. Sap flow should be considered for groves based on soil-moisture results.
5. Extend precipitation and meteorological measurements. Based on current analyses of temperature, precipitation and other meteorological variables, extend multi-year or long-term measurements to cover important climate gradients and microclimates.
6. Carry out subsurface characterization. In selected groves, and based on topography, soils, vegetation and geology, carry out seismic surveys to establish depths and profiles of weathered material as a basis for estimating subsurface storage potential of representative landscapes.

7. Build a convenient GIS data base of all relevant data. This will include an artifact-free DEM, physiographic and vegetation information, vegetation indices, available remotely sensed snowpack and other vegetation information, LiDAR data and other emerging datasets. Include relevant quality-controlled time-series data if not already publically available.
8. Do a pilot study of isotopic indicators of water source. Characterize water isotopes of shallow and deeper water reservoirs in one or more groves, and compare to water use by vegetation.
9. Manage and protect giant sequoia based on NDWI conditions. Figure II-11 provides the general NDWI condition in and surrounding giant sequoia grove area, through which we can identify areas on the landscape with high NDWI values and thus determine potentially desirable places to plant the species.
10. Measure the vulnerability of giant sequoia to moisture stress by combining TWI and general moisture condition. Both TWI and 27-year average NDWI obviously show negative relationship with the vulnerability to moisture condition, and it's still effective when combining these two indices.

We also recognize that some limitations exist in this project. For medium spatial resolution images, remote sensing signals for groves will be most heavily dominated by things that are not giant sequoias, leading to interpretations of results have bias compared to real situation. Lack of field data and relatively coarse climate data arise difficulty in a complete validation of our results. Installing more weather stations and conducting laboratory measurements for giant sequoia leaves may contribute to this issue in the future study. In addition, detailed within-grove analysis at pixel scale could have improved the result to derive more accurate and more local variation patterns.

APPENDIX A

Table A1: Summary of TWI, slope and elevation for each grove

GROVE	AREA (km ²)	TWI				Slope (deg)				Elevation (m)			
		MIN	MAX	MEAN	STD	MIN	MAX	MEAN	STD	MIN	MAX	MEAN	STD
ABBOTT	0.02	6.30	14.20	8.56	2.22	7.30	37.48	19.01	6.21	1778	1834	1802	14
AGNEW	0.17	4.41	13.02	7.84	1.34	2.50	50.73	27.08	7.32	2021	2296	2170	67
ALDERCREEK	2.91	4.82	18.80	8.48	1.37	0.60	48.65	21.98	7.46	1490	2209	1927	148
ATWELL	5.40	4.66	19.59	8.35	1.58	0.29	45.40	22.86	6.06	1746	2756	2203	191
BEARSKIN	0.26	5.68	25.01	8.30	1.41	0.59	40.98	17.79	7.15	1851	2005	1927	35
BELKNAP	9.52	4.34	26.79	8.67	1.93	0.11	55.62	19.33	7.61	1446	2282	1804	164
BIGSTUMP	1.96	5.04	23.13	8.29	1.83	0.00	44.47	13.91	7.58	1702	1987	1885	42
BIG_BALDY_SOUTH	0.15	5.89	16.03	8.33	1.10	9.62	50.93	28.59	8.02	1668	1979	1809	66
BIG_SPRINGS	0.01	6.58	20.43	9.61	3.51	4.67	37.46	20.11	9.72	1428	1463	1444	7
BLACKMTN	7.99	4.48	24.37	8.12	1.60	0.04	58.49	21.25	8.73	1339	2225	1894	122
BOARD_CAMP	0.40	5.88	18.52	8.74	1.35	6.53	50.08	29.55	6.63	1737	2179	1973	106
BURROCREEK	1.21	5.60	19.68	8.28	1.78	3.15	50.87	27.52	6.52	1621	2175	1914	131
CAHOON	0.13	6.14	25.16	8.83	2.90	4.97	51.05	31.88	8.49	1741	1992	1856	53
CASTLE_CREEK	1.69	5.82	26.67	8.92	1.86	0.61	59.51	22.08	7.91	1458	2153	1815	157
CEDAR_FLAT	0.13	6.14	24.38	8.88	2.73	3.94	59.94	31.78	9.94	1496	1808	1623	67
CHERRY_GAP	0.35	4.93	22.57	8.38	2.05	1.41	41.91	18.97	6.46	1719	2049	1838	59
CLOUGH_CAMP	0.01	6.68	8.97	7.74	0.66	16.13	48.58	34.56	9.00	1088	1151	1115	19
COFFEEPOT_CANYON	0.10	5.29	14.03	9.25	1.09	10.76	44.91	25.40	7.28	1717	1908	1800	39
CONVERSE	13.12	4.48	24.93	8.33	1.82	0.00	52.56	14.53	7.57	1591	2100	1924	84
CUNNINGHAM	0.02	5.80	20.68	9.19	2.94	0.07	25.96	15.86	5.64	1850	1891	1874	9
DEER_CREEK	0.17	5.26	20.45	8.87	0.98	0.28	25.87	16.05	4.33	1561	1770	1690	47
DEER_MDW	0.68	4.31	23.21	8.01	1.71	3.11	54.50	28.27	7.48	1706	2384	2057	145
DENNISON	0.08	6.25	16.03	8.35	1.41	8.27	42.17	27.68	5.70	1859	2034	1936	42
DEVILS_CANYON	0.06	6.90	13.71	8.68	1.16	7.52	40.29	26.30	5.48	1784	2065	1974	67
DILLONWOOD	6.78	4.89	22.81	8.65	1.47	0.19	56.93	22.25	8.30	1453	2426	1910	207
DOUGLASS	0.01	5.66	10.56	7.54	1.21	29.68	48.48	40.66	4.23	2013	2137	2085	34
EAST_FORK	3.96	4.86	26.19	8.26	1.67	1.02	49.56	24.64	6.44	1561	2479	2005	171
EDEN_CREEK	2.90	4.94	17.91	8.05	1.63	0.81	55.57	26.21	8.35	1614	2362	1988	165
EVANS	12.84	4.29	25.46	8.25	1.56	0.16	58.06	20.96	8.05	1614	2401	2012	141
FORGOTTEN	0.02	6.36	12.20	9.05	1.52	5.72	41.23	19.36	8.83	1865	1941	1913	16
FREEMAN	5.77	4.82	24.96	9.21	1.78	0.07	40.19	13.63	6.41	1726	2283	1885	103
GARFIELD	6.22	4.83	26.56	8.55	1.41	0.37	65.84	24.55	7.67	1258	2619	1998	233
GIANT_FOREST	9.25	4.70	24.22	9.00	1.80	0.00	48.55	13.26	7.18	1565	2375	2057	117
GRANITE_CREEK	0.01	7.18	24.88	10.19	2.45	15.95	49.28	36.31	7.70	1866	1956	1913	21
GRANT	1.57	4.85	24.04	8.35	1.97	0.01	48.98	13.95	6.79	1678	2000	1834	66
HOMERS_NOSE	0.94	4.94	23.09	8.71	1.58	2.86	54.19	28.15	6.57	1699	2312	2026	115
HORSE_CREEK	0.44	5.69	25.94	8.07	2.15	4.31	54.43	34.87	7.63	1725	2139	1914	86

INDIAN	0.83	5.76	22.98	9.87	1.93	0.72	31.03	6.69	3.70	1786	1880	1819	19
Table A1: Contd.													
LANDSLIDE	0.33	6.29	17.21	10.10	1.94	2.02	35.53	15.40	7.87	1978	2246	2082	67
LITTLE_RED_Med	0.19	6.91	14.59	9.18	1.26	7.45	37.70	24.90	5.23	2050	2297	2163	56
LONGMEADOW	1.24	5.28	22.80	9.03	1.65	0.38	32.12	13.73	5.03	1876	2158	2010	81
LOST	0.21	5.68	16.23	9.11	1.60	6.15	34.56	18.00	6.04	1948	2131	2028	42
LOWER_HRS_CR	0.03	6.81	10.97	7.80	0.89	13.04	41.93	32.22	4.65	1579	1702	1635	28
MAGGIEMT	0.27	5.27	17.46	8.62	1.89	10.83	60.33	28.87	7.08	1877	2357	2193	107
MIDL_TULE	2.51	5.02	26.25	9.13	1.74	2.70	52.88	21.63	7.04	1707	2322	1998	134
MONARCH	0.22	4.76	20.53	8.53	2.10	4.13	55.63	29.69	8.98	1519	1948	1776	105
MT_HOME	15.51	4.74	23.08	8.36	1.57	0.00	48.77	18.25	7.31	1314	2228	1915	134
MUIR	1.54	4.81	16.24	8.60	1.22	0.94	52.43	20.20	6.63	1708	2142	1985	94
NEW_ORIOLE_LK	0.15	5.99	17.76	8.44	2.12	2.51	32.57	17.96	5.75	1703	1838	1764	32
ORIOLE_LAKE	0.99	4.97	18.42	8.56	1.93	0.70	46.40	20.92	5.89	1648	2264	1964	154
PACKSADDLE	1.21	4.96	23.71	8.53	1.81	0.27	42.13	15.49	5.61	1768	2067	1918	73
PEYRONE	1.61	4.44	24.99	8.27	1.85	0.50	53.58	23.45	8.70	1554	2007	1788	85
PINE RIDGE	0.29	5.08	20.23	8.39	2.09	5.07	51.53	24.67	7.19	1432	1757	1573	64
PUTNAM-FRANCIS	0.00	5.69	15.34	6.69	1.53	13.53	41.65	29.98	6.56	1225	1264	1249	10
REDHILL	1.87	4.70	23.13	8.39	1.80	0.27	44.13	17.71	6.86	1648	2021	1838	81
REDWDMTN	13.23	4.29	26.47	8.72	1.64	0.01	50.73	18.69	8.28	1457	2218	1815	146
REDWOOD_CREEK	0.42	5.23	17.30	8.36	1.95	6.75	49.58	31.24	6.43	1641	2331	1991	164
REDWOOD_MEADOW	1.46	5.98	26.24	9.54	2.03	0.33	50.40	17.13	9.10	1549	2006	1787	89
SEQUOIA_CREEK	0.14	5.30	21.62	8.76	2.57	0.39	50.07	20.20	8.80	1651	1868	1781	58
SILVER_CRK	0.77	5.00	26.63	8.56	2.27	0.96	45.77	24.71	7.67	1495	1931	1714	104
SKAGWAY	0.35	5.53	15.20	8.26	1.52	5.25	50.12	23.09	8.20	1802	2166	1934	66
SOUTH_FORK	1.67	5.75	26.38	9.03	1.65	2.70	52.84	27.01	7.63	1504	2259	1888	173
SOUTH_Peyrone	0.13	4.38	23.48	7.66	1.88	2.28	52.29	26.78	8.73	1755	1933	1844	34
SQUIRREL CREEK	0.00	5.72	17.19	8.94	3.49	10.31	47.81	34.50	10.02	1531	1559	1544	9
STARVATION	0.04	6.73	24.56	10.59	2.49	0.27	38.05	13.88	7.31	1571	1841	1754	97
SURPRISE	0.15	4.62	17.00	8.65	2.25	5.44	55.34	25.28	8.09	1663	2308	1846	162
SUWANEE	0.42	5.59	17.00	8.53	1.69	1.46	31.36	13.04	5.02	1825	1973	1905	30
UPPER_TULE	0.09	7.61	13.01	8.83	0.48	17.34	30.47	23.86	2.67	2249	2422	2345	38
WISHON	0.69	5.53	27.12	9.01	2.46	2.03	48.28	18.47	7.55	1341	1520	1429	38
W_RED_MTN	0.01	6.68	11.76	9.86	1.48	9.31	38.35	23.00	9.82	1483	1520	1499	10

Table A2: Landcover classification and associated codes for sequoia groves

Groves	Area (km ²)	Landcover Codes
ABBOTT	0.02	44
AGNEW	0.17	44
ALDERCREEK	2.91	32, 43, 44, 45, 11
ATWELL	5.42	31, 32, 44, 45, 62, 77
BEARSKIN	0.27	44
BELKNAP	9.55	11, 17, 32, 43, 44, 45
BIGSTUMP	1.97	10, 17, 31, 32, 43, 44, 45, 62
BIG_BALDY_SOUTH	0.15	32, 43, 44, 45, 77
BIG_SPRINGS	0.01	44, 45, 61
BLACKMTN	8.01	32, 43, 44, 45, 77
BOARD_CAMP	0.40	43, 44, 45, 77
BURROCREEK	1.21	32, 43, 44
CAHOON	0.13	44, 45, 77
CASTLE_CREEK	1.70	32, 43, 44
CEDAR_FLAT	0.13	33, 44, 45, 77
CHERRY_GAP	0.35	31, 43, 44
CLOUGH_CAMP	0.01	32, 45, 61
COFFEEPOT_CANYON	0.10	32, 44, 45
CONVERSE	13.17	17, 32, 43, 44, 45, 62
CUNNINGHAM	0.02	43, 44
DEER_CREEK	0.17	43, 44
DEER_MDW	0.68	43, 44
DENNISON	0.08	32, 43, 44
DEVILS_CANYON	0.06	32, 44, 77
DILLONWOOD	6.80	32, 43, 44, 45, 77
DOUGLASS	0.01	44, 77
EAST_FORK	3.97	31, 32, 43, 44, 45, 77
EDEN_CREEK	2.90	32, 43, 44, 45, 62, 77
EVANS	12.86	32, 43, 44, 45, 62
FORGOTTEN	0.02	44
FREEMAN	5.78	44, 45, 77
GARFIELD	6.24	31, 32, 43, 44, 45, 62, 77
GIANT_FOREST	9.35	31, 32, 43, 44, 45, 62, 77
GRANITE_CREEK	0.01	32, 44
GRANT	1.58	10, 31, 32, 43, 44, 62, 77
HOMERS_NOSE	0.94	32, 43, 44, 45, 77
HORSE_CREEK	0.44	32, 44, 45, 50, 77
INDIAN	0.83	17, 32, 44, 62
LANDSLIDE	0.33	32, 43, 44
LITTLE_REDWOOD_MEADOW	0.19	32, 44, 45
LONGMEADOW	1.25	17, 32, 43, 44, 45

LOST	0.21	32, 44, 62
Table A2: Contd.		
LOWER_HORSE_CREEK	0.03	43, 44, 45, 50
MAGGIEMT	0.27	32, 43, 44, 77
MIDL_TULE	2.52	32, 43, 44, 77
MONARCH	0.22	32, 43, 44
MT_HOME	15.58	32, 43, 44, 45, 52, 62, 77
MUIR	1.54	32, 43, 44, 45, 77, 62
NEW_ORIOLE_LAKE	0.15	44, 45
ORIOLE_LAKE	0.99	32, 44, 45
PACKSADDLE	1.21	32, 43, 44, 45
PEYRONE	1.61	32, 43, 44, 45
PINE_RIDGE	0.29	43, 44, 45
PUTNAM-FRANCIS	0.00	45, 77
REDHILL	1.88	43, 44, 45, 77
REDWDMTN	13.26	17, 31, 32, 43, 44, 45, 61, 62, 77
REDWOOD_CREEK	0.42	32, 44, 45, 77
REDWOOD_MEADOW	1.47	32, 43, 44, 45, 62, 77
SEQUOIA_CREEK	0.14	32, 44, 45, 77
SILVER_CRK	0.78	32, 43, 44, 45, 77
SKAGWAY	0.35	32, 44, 45
SOUTH_FORK	1.67	32, 43, 44, 45, 77
SOUTH_Peyrone	0.14	43, 44
SQUIRREL CREEK	0.00	43, 44
STARVATION	0.04	43, 44, 45
SURPRISE	0.15	44, 45, 77
SUWANEE	0.42	32, 44, 77
UPPER_TULE	0.09	32, 44, 77
WISHON	0.69	43, 44, 45
W_REDWOOD_MOUNTAIN	0.01	44, 61

Table A3: Landcover types and associated codes

Code	Description	Code	Description
10	Urban or build-up land	44	Conifer type forest land
11	Residential	45	Hardwood type forest land
12	Commercial and services	50	Water
14	Transportation, communications, utilities	51	Stream or canal
16	Mixed urban or built-up land	52	Perennial Lake or Pond
17	Other urban or built-up land	53	Reservoir
20	Agricultural land	58	Intermittent Lake or Pond
31	Herbaceous rangeland	61	Forested wetland
32	Shrub and brush rangeland	62	Non-forested wetland
33	Mixed rangeland	70	Barren land
43	Mixed conifer hardwood type forest land		

Source: CalVeg, <http://www.fs.fed.us/r5/rsi/projects/frdb/tables/table182.html>

Table A4: Snow persistence for March 1, ranked from lowest to highest

Groves	Fraction	Mean	1-Std Dev	2-Std Dev
BIG_SPRINGS	0.01	1.00	0.00	0.00
COFFEEPOT_CANYON	0.03	1.00	0.45	0.90
LOWER_HORSE_CREEK	0.04	1.00	2.39	4.78
PUTNAM-FRANCIS	0.06	1.00	2.25	4.51
SQUIRREL CREEK	0.07	1.00	0.63	1.27
W_REDWOOD_MOUNTAIN	0.09	1.00	1.05	2.09
EDEN_CREEK	0.10	1.07	2.37	4.74
MONARCH	0.11	1.13	2.45	4.90
PINE_RIDGE	0.13	1.35	0.00	0.00
CEDAR_FLAT	0.14	1.44	1.58	3.15
WISHON	0.16	1.45	1.83	3.66
CLOUGH_CAMP	0.17	1.50	1.79	3.58
BELKNAP	0.19	1.56	2.37	4.75
DEVILS_CANYON	0.20	1.88	0.89	1.77
ABBOTT	0.21	2.00	0.70	1.40
NEW_ORIOLE_LAKE	0.23	2.06	2.41	4.83
AGNEW	0.24	2.28	0.50	1.00
CAHOON	0.26	2.42	0.00	0.00
BLACKMTN	0.27	2.69	3.75	7.51
SILVER_CRK	0.29	2.84	0.00	0.00
FREEMAN	0.30	2.98	0.60	1.20
DOUGLASS	0.31	3.00	0.64	1.28
FORGOTTEN	0.33	3.00	0.85	1.70
SOUTH_PEYRONE	0.34	3.00	0.32	0.64
BURROCREEK	0.36	3.06	3.12	6.25
CASTLE_CREEK	0.37	3.13	0.00	0.00
SOUTH_FORK	0.39	3.16	1.98	3.95
ALDERCREEK	0.40	3.19	1.07	2.14
HORSE_CREEK	0.41	3.24	3.73	7.46
GRANT	0.43	3.25	0.00	0.00
REDHILL	0.44	3.32	2.24	4.48
PEYRONE	0.46	3.45	2.87	5.74
GARFIELD	0.47	3.53	2.72	5.43
REDWDMTN	0.49	3.54	0.00	0.00
SKAGWAY	0.50	3.58	2.00	3.99
EAST_FORK	0.51	3.58	3.24	6.47
SEQUOIA_CREEK	0.53	3.68	1.64	3.27
STARVATION	0.54	3.73	1.61	3.22
DEER_CREEK	0.56	3.76	1.50	3.00
DEER_MDW	0.57	3.89	1.42	2.85
CUNNINGHAM	0.59	4.00	1.86	3.72
GRANITE_CREEK	0.60	4.00	2.04	4.07

Table A4: Contd.

PACKSADDLE	0.61	4.10	0.00	0.00
REDWOOD_MEADOW	0.63	4.22	1.75	3.50
MT_HOME	0.64	4.27	3.22	6.44
ORIOLE_LAKE	0.66	4.89	0.92	1.84
INDIAN	0.67	4.99	1.61	3.22
MUIR	0.69	5.00	2.79	5.57
DILLONWOOD	0.70	5.04	0.25	0.49
CHERRY_GAP	0.71	5.13	3.07	6.15
SURPRISE	0.73	5.43	0.96	1.91
BIG_BALDY_SOUTH	0.74	5.52	1.70	3.39
BIGSTUMP	0.76	5.57	0.66	1.32
EVANS	0.77	5.63	0.00	0.00
DENNISON	0.79	5.74	1.70	3.40
BOARD_CAMP	0.80	6.09	2.77	5.55
CONVERSE	0.81	6.28	2.36	4.73
SUWANEE	0.83	6.78	2.03	4.06
GIANT_FOREST	0.84	6.92	0.98	1.95
LITTLE_REDWOOD_MEADOW	0.86	6.97	0.89	1.78
MIDL_TULE	0.87	7.02	1.98	3.96
LONGMEADOW	0.89	7.38	2.57	5.13
REDWOOD_CREEK	0.90	7.41	0.00	0.00
HOMERS_NOSE	0.91	7.78	0.00	0.00
ATWELL	0.93	8.07	0.44	0.88
BEARSKIN	0.94	8.86	2.51	5.02
MAGGIEMT	0.96	9.22	1.72	3.44
LANDSLIDE	0.97	9.81	0.00	0.00
LOST	0.99	9.91	0.66	1.32
UPPER_TULE	1.00	12.00	0.00	0.00

Note: Mean snow persistence is ranked from low to high (This table was used for Fig.13 in report)

Table A5: Snow persistence for April 1, ranked from lowest to highest

Groves	Fraction	Mean	1-Std Dev	2-Std Dev
ABBOTT	0.01	0.00	0.00	0.00
CLOUGH_CAMP	0.03	0.00	0.00	0.00
CUNNINGHAM	0.04	0.00	0.00	0.00
DEER_CREEK	0.06	0.00	0.00	0.00
FORGOTTEN	0.07	0.00	0.00	0.00
LOWER_HORSE_CREEK	0.09	0.00	0.00	0.00
PUTNAM-FRANCIS	0.10	0.00	0.00	0.00
SOUTH_PEYRONE	0.11	0.00	0.00	0.00
SQUIRREL CREEK	0.13	0.00	0.00	0.00
WISHON	0.14	0.00	0.00	0.00
BELKNAP	0.16	0.05	0.32	0.64
CEDAR_FLAT	0.17	0.16	0.36	0.73
MONARCH	0.19	0.21	0.41	0.81
CAHOON	0.20	0.30	0.46	0.92
EDEN_CREEK	0.21	0.32	0.61	1.22
SILVER_CRK	0.23	0.40	0.49	0.98
BURROCREEK	0.24	0.49	0.79	1.59
BLACKMTN	0.26	0.58	0.99	1.99
CASTLE_CREEK	0.27	0.66	0.66	1.33
FREEMAN	0.29	0.74	1.68	3.37
PACKSADDLE	0.30	0.75	0.72	1.45
DEER_MDW	0.31	0.80	1.32	2.64
PINE_RIDGE	0.33	0.83	0.52	1.03
REDWOOD_MEADOW	0.34	0.83	0.99	1.97
NEW_ORIOLE_LAKE	0.36	0.84	0.37	0.74
DEVILS_CANYON	0.37	0.88	0.32	0.64
REDHILL	0.39	0.98	1.51	3.02
COFFEEPOT_CANYON	0.40	1.00	0.00	0.00
W_REDWOOD_MOUNTAIN	0.41	1.00	0.00	0.00
GRANT	0.43	1.07	1.64	3.28
PEYRONE	0.44	1.26	1.76	3.52
EAST_FORK	0.46	1.29	1.21	2.43
INDIAN	0.47	1.31	1.11	2.22
SEQUOIA_CREEK	0.49	1.42	0.95	1.91
ALDERCREEK	0.50	1.50	2.10	4.20
STARVATION	0.51	1.67	0.87	1.74
HORSE_CREEK	0.53	1.72	0.96	1.93
GARFIELD	0.54	1.73	1.97	3.93
REDWDMTN	0.56	1.95	1.63	3.27
BIG_SPRINGS	0.57	2.00	0.00	0.00
DILLONWOOD	0.59	2.10	1.89	3.78
MT_HOME	0.60	2.14	1.27	2.55

Table A5: Contd.

LITTLE_REDWOOD_MEADOW	0.61	2.16	1.20	2.39
SKAGWAY	0.63	2.24	0.43	0.86
SURPRISE	0.64	2.28	1.36	2.71
AGNEW	0.66	2.28	0.45	0.90
BIGSTUMP	0.67	2.43	1.04	2.07
ORIOLE_LAKE	0.69	2.45	1.65	3.30
MUIR	0.70	2.47	1.78	3.57
SOUTH_FORK	0.71	2.54	1.72	3.43
CONVERSE	0.73	2.69	1.99	3.98
LONGMEADOW	0.74	2.85	1.17	2.34
BOARD_CAMP	0.76	2.85	1.93	3.86
EVANS	0.77	2.88	2.51	5.02
DENNISON	0.79	2.91	0.28	0.57
GRANITE_CREEK	0.80	3.00	0.00	0.00
CHERRY_GAP	0.81	3.11	0.43	0.86
SUWANEE	0.83	3.42	1.20	2.40
BIG_BALDY_SOUTH	0.84	3.52	1.43	2.87
GIANT_FOREST	0.86	3.66	1.76	3.53
DOUGLASS	0.87	4.00	0.00	0.00
ATWELL	0.89	4.35	2.47	4.93
BEARSKIN	0.90	4.38	0.57	1.15
REDWOOD_CREEK	0.91	4.68	1.31	2.62
HOMERS_NOSE	0.93	4.86	3.20	6.39
MIDL_TULE	0.94	5.08	3.29	6.58
MAGGIEMT	0.96	5.33	0.94	1.89
LANDSLIDE	0.97	6.34	2.57	5.15
LOST	0.99	6.43	0.54	1.08
UPPER_TULE	1.00	10.97	1.00	2.00

Note: Mean snow persistence is ranked from low to high (This table was used for Fig.13 in report)

Table A6: Snow persistence for May 1, ranked from lowest to highest

Groves	Fraction	Mean	1-Std Dev	2-Std Dev
ABBOTT	0.01	0.00	0.00	0.00
AGNEW	0.03	0.00	0.00	0.00
CLOUGH_CAMP	0.04	0.00	0.00	0.00
CUNNINGHAM	0.06	0.00	0.00	0.00
DEER_MDW	0.07	0.00	0.00	0.00
LOWER_HORSE_CREEK	0.09	0.00	0.00	0.00
MONARCH	0.10	0.00	0.00	0.00
BEARSKIN	0.11	0.05	0.21	0.42
LONGMEADOW	0.13	0.07	0.25	0.50
FREEMAN	0.14	0.10	0.31	0.61
DENNISON	0.16	0.18	0.57	1.13
BELKNAP	0.17	0.20	0.40	0.79
REDWOOD_MEADOW	0.19	0.25	0.43	0.86
CASTLE_CREEK	0.20	0.29	0.48	0.96
CAHOON	0.21	0.30	0.46	0.92
BLACKMTN	0.23	0.31	0.46	0.92
LITTLE_REDWOOD_MEADOW	0.24	0.51	0.50	1.00
INDIAN	0.26	0.65	0.48	0.95
PEYRONE	0.27	0.66	0.68	1.36
ORIOLE_LAKE	0.29	0.79	0.41	0.82
PINE_RIDGE	0.30	0.97	0.43	0.85
REDWOOD_CREEK	0.31	0.98	0.15	0.31
NEW_ORIOLE_LAKE	0.33	0.98	0.13	0.25
DILLONWOOD	0.34	1.00	0.51	1.02
BIG_BALDY_SOUTH	0.36	1.00	0.00	0.00
BIG_SPRINGS	0.37	1.00	0.00	0.00
BOARD_CAMP	0.39	1.00	0.00	0.00
BURROCREEK	0.40	1.00	0.00	0.00
CEDAR_FLAT	0.41	1.00	0.00	0.00
COFFEEPOT_CANYON	0.43	1.00	0.00	0.00
DEER_CREEK	0.44	1.00	0.00	0.00
FORGOTTEN	0.46	1.00	0.00	0.00
GRANITE_CREEK	0.47	1.00	0.00	0.00
PUTNAM-FRANCIS	0.49	1.00	0.00	0.00
SEQUOIA_CREEK	0.50	1.00	0.00	0.00
SILVER_CRK	0.51	1.00	0.00	0.00
SOUTH_PEURONE	0.53	1.00	0.00	0.00
SQUIRREL CREEK	0.54	1.00	0.00	0.00
STARVATION	0.56	1.00	0.00	0.00
WISHON	0.57	1.00	0.00	0.00
W_REDWOOD_MOUNTAIN	0.59	1.00	0.00	0.00
HORSE_CREEK	0.60	1.03	0.18	0.36

Table A6: Contd.

CHERRY_GAP	0.61	1.03	0.18	0.37
MT_HOME	0.63	1.05	0.41	0.82
EDEN_CREEK	0.64	1.06	0.26	0.52
REDWDMTN	0.66	1.08	0.27	0.54
EVANS	0.67	1.09	1.18	2.35
GRANT	0.69	1.09	0.29	0.59
PACKSADDLE	0.70	1.10	0.77	1.54
SURPRISE	0.71	1.10	0.30	0.60
HOMERS_NOSE	0.73	1.10	0.34	0.68
BIGSTUMP	0.74	1.14	0.35	0.70
REDHILL	0.76	1.16	0.36	0.73
MUIR	0.77	1.27	0.45	0.89
ALDERCREEK	0.79	1.32	0.65	1.31
MAGGIEMT	0.80	1.33	0.47	0.94
GIANT_FOREST	0.81	1.41	0.69	1.38
MIDL_TULE	0.83	1.43	1.17	2.34
EAST_FORK	0.84	1.44	2.10	4.19
LOST	0.86	1.44	1.44	2.89
SUWANEE	0.87	1.47	0.50	1.00
GARFIELD	0.89	1.50	1.04	2.08
SOUTH_FORK	0.90	1.52	1.38	2.77
ATWELL	0.91	1.53	0.68	1.36
CONVERSE	0.93	1.62	0.77	1.54
DEVILS_CANYON	0.94	1.88	0.32	0.64
SKAGWAY	0.96	1.98	0.14	0.29
DOUGLASS	0.97	2.00	0.00	0.00
LANDSLIDE	0.99	3.00	0.76	1.51
UPPER_TULE	1.00	8.00	0.00	0.00

Note: Mean snow persistence is ranked from low to high (This table was used for Fig.13 in report)

Table A7: Snow persistence for June 1, ranked from lowest to highest

Groves	Fraction	Mean	1-Std Dev	2-Std Dev
AGNEW	0.01	0.00	0.00	0.00
BEARSKIN	0.03	0.00	0.00	0.00
BELKNAP	0.04	0.00	0.00	0.00
BIG_BALDY_SOUTH	0.06	0.00	0.00	0.00
BIG_SPRINGS	0.07	0.00	0.00	0.00
BOARD_CAMP	0.09	0.00	0.00	0.00
BURROCREEK	0.10	0.00	0.00	0.00
CAHOON	0.11	0.00	0.00	0.00
CASTLE_CREEK	0.13	0.00	0.00	0.00
CEDAR_FLAT	0.14	0.00	0.00	0.00
CHERRY_GAP	0.16	0.00	0.00	0.00
CLOUGH_CAMP	0.17	0.00	0.00	0.00
COFFEEPOT_CANYON	0.19	0.00	0.00	0.00
CUNNINGHAM	0.20	0.00	0.00	0.00
DEER_CREEK	0.21	0.00	0.00	0.00
DEER_MDW	0.23	0.00	0.00	0.00
DOUGLASS	0.24	0.00	0.00	0.00
EVANS	0.26	0.00	0.00	0.00
FORGOTTEN	0.27	0.00	0.00	0.00
FREEMAN	0.29	0.00	0.00	0.00
GRANITE_CREEK	0.30	0.00	0.00	0.00
HORSE_CREEK	0.31	0.00	0.00	0.00
INDIAN	0.33	0.00	0.00	0.00
LITTLE_REDWOOD_MEADOW	0.34	0.00	0.00	0.00
LONGMEADOW	0.36	0.00	0.00	0.00
LOWER_HORSE_CREEK	0.37	0.00	0.00	0.00
MAGGIEMT	0.39	0.00	0.00	0.00
MONARCH	0.40	0.00	0.00	0.00
NEW_ORIOLE_LAKE	0.41	0.00	0.00	0.00
PUTNAM-FRANCIS	0.43	0.00	0.00	0.00
REDWOOD_MEADOW	0.44	0.00	0.00	0.00
SILVER_CRK	0.46	0.00	0.00	0.00
SOUTH_PEYRONE	0.47	0.00	0.00	0.00
SQUIRREL CREEK	0.49	0.00	0.00	0.00
STARVATION	0.50	0.00	0.00	0.00
SUWANEE	0.51	0.00	0.00	0.00
WISHON	0.53	0.00	0.00	0.00
W_REDWOOD_MOUNTAIN	0.54	0.00	0.00	0.00
BLACKMTN	0.56	0.03	0.17	0.33
PEYRONE	0.57	0.04	0.19	0.38
REDHILL	0.59	0.04	0.20	0.40
PACKSADDLE	0.60	0.06	0.24	0.48

Table A7: Contd.

MIDL_TULE	0.61	0.07	0.31	0.62
PINE_RIDGE	0.63	0.08	0.27	0.54
LOST	0.64	0.08	0.27	0.54
ALDERCREEK	0.66	0.10	0.36	0.73
DILLONWOOD	0.67	0.10	0.30	0.59
REDWDMTN	0.69	0.11	0.31	0.62
EDEN_CREEK	0.70	0.11	0.33	0.67
DEVILS_CANYON	0.71	0.12	0.32	0.64
ORIOLE_LAKE	0.73	0.17	0.37	0.75
GRANT	0.74	0.17	0.38	0.76
SEQUOIA_CREEK	0.76	0.18	0.38	0.76
MT_HOME	0.77	0.20	0.40	0.80
REDWOOD_CREEK	0.79	0.25	0.44	0.87
ATWELL	0.80	0.27	0.45	0.90
SOUTH_FORK	0.81	0.28	0.48	0.96
CONVERSE	0.83	0.28	0.45	0.90
BIGSTUMP	0.84	0.30	0.46	0.92
GIANT_FOREST	0.86	0.33	0.47	0.94
MUIR	0.87	0.34	0.47	0.95
LANDSLIDE	0.89	0.35	0.48	0.95
SURPRISE	0.90	0.35	0.48	0.95
GARFIELD	0.91	0.35	0.61	1.22
EAST_FORK	0.93	0.50	0.64	1.28
HOMERS_NOSE	0.94	0.51	0.50	1.00
SKAGWAY	0.96	0.88	0.33	0.66
ABBOTT	0.97	1.00	0.00	0.00
DENNISON	0.99	1.00	0.00	0.00
UPPER_TULE	1.00	2.49	0.50	1.00

Note: Mean snow persistence is ranked from low to high (This table was used for Fig.13 in report)

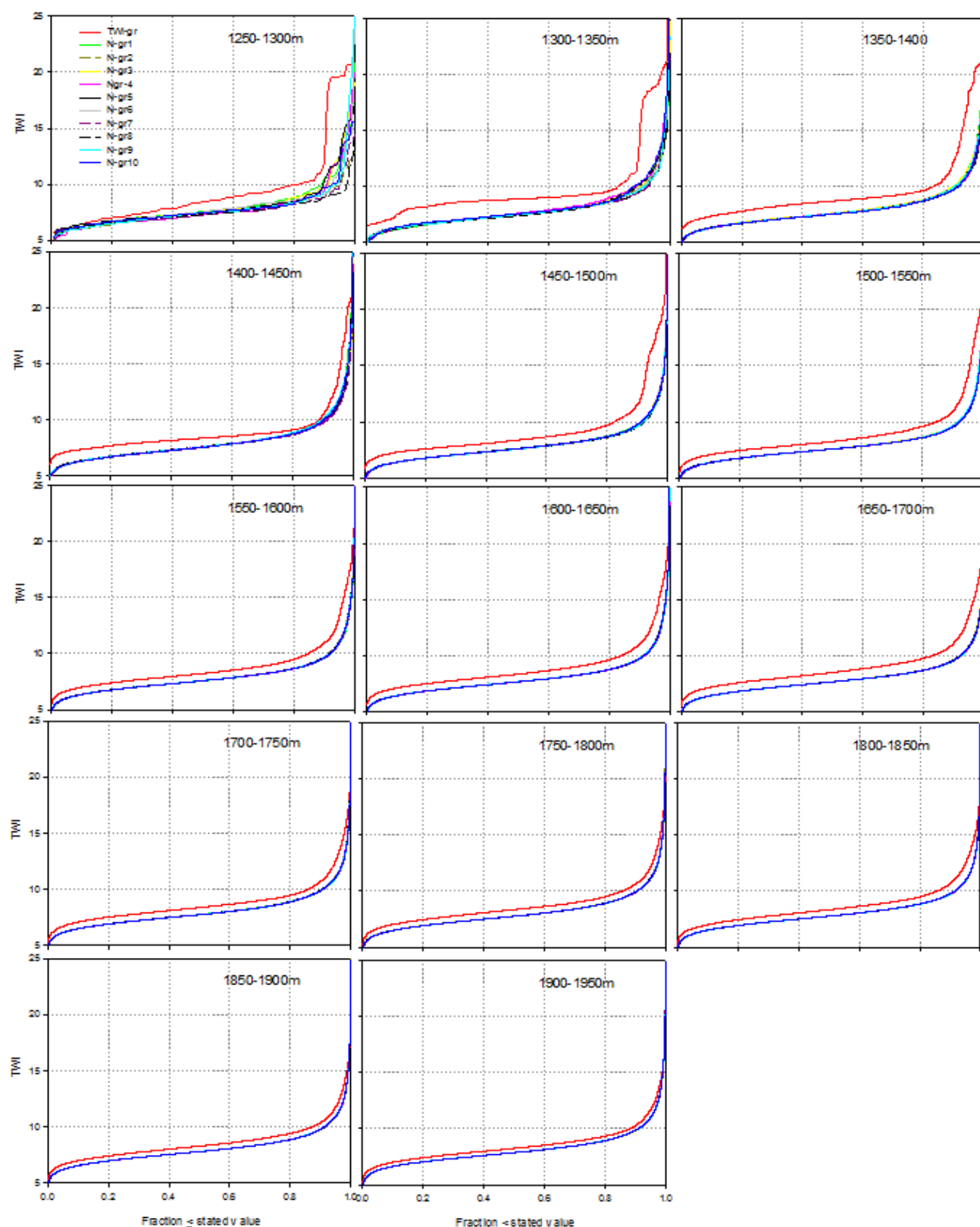


Figure A1: Comparison of TWIs at grove and non-grove domains based on 10 sets of randomly selected equal number (grove-domain) of pixels from non-grove domain (1250-1950m)

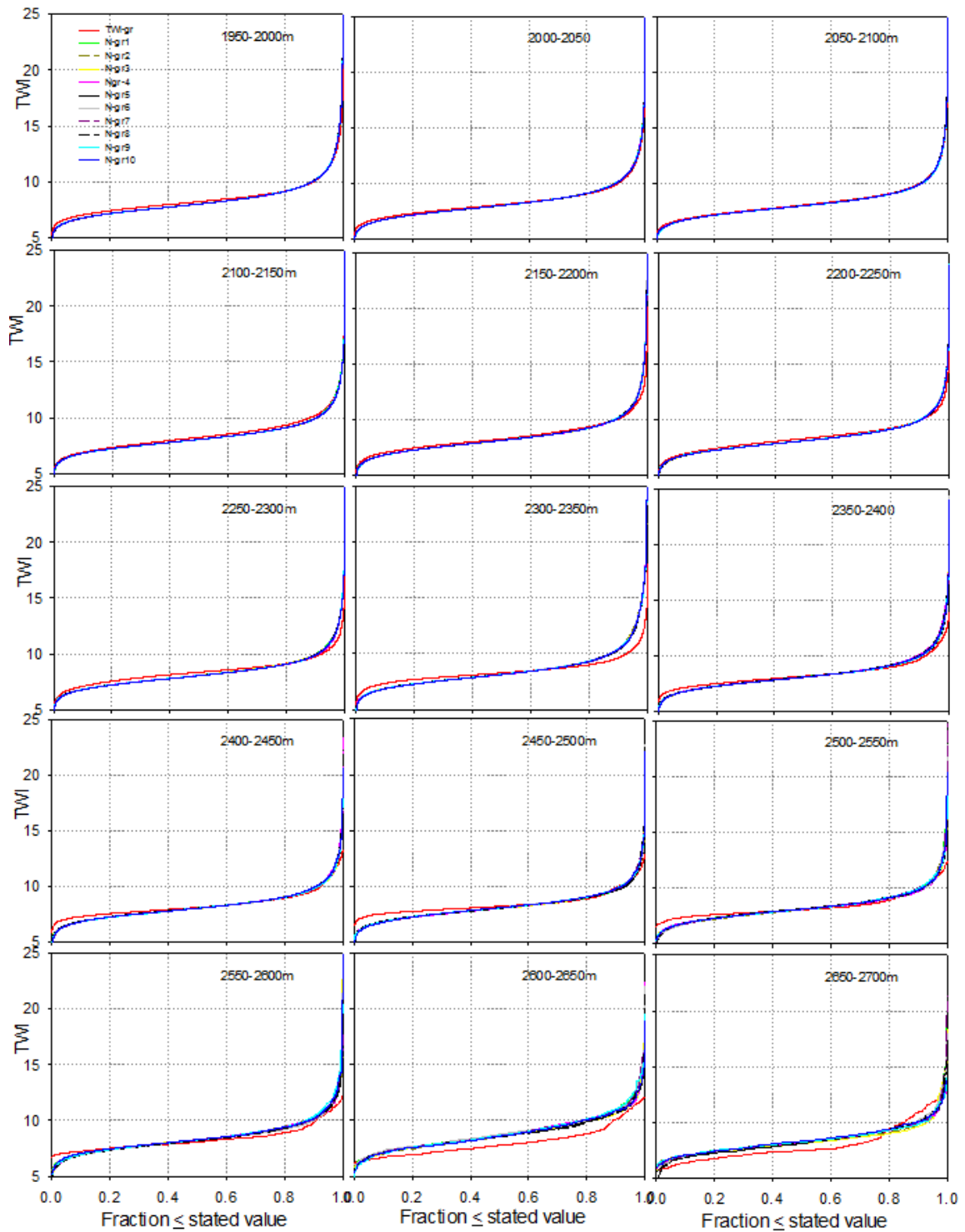
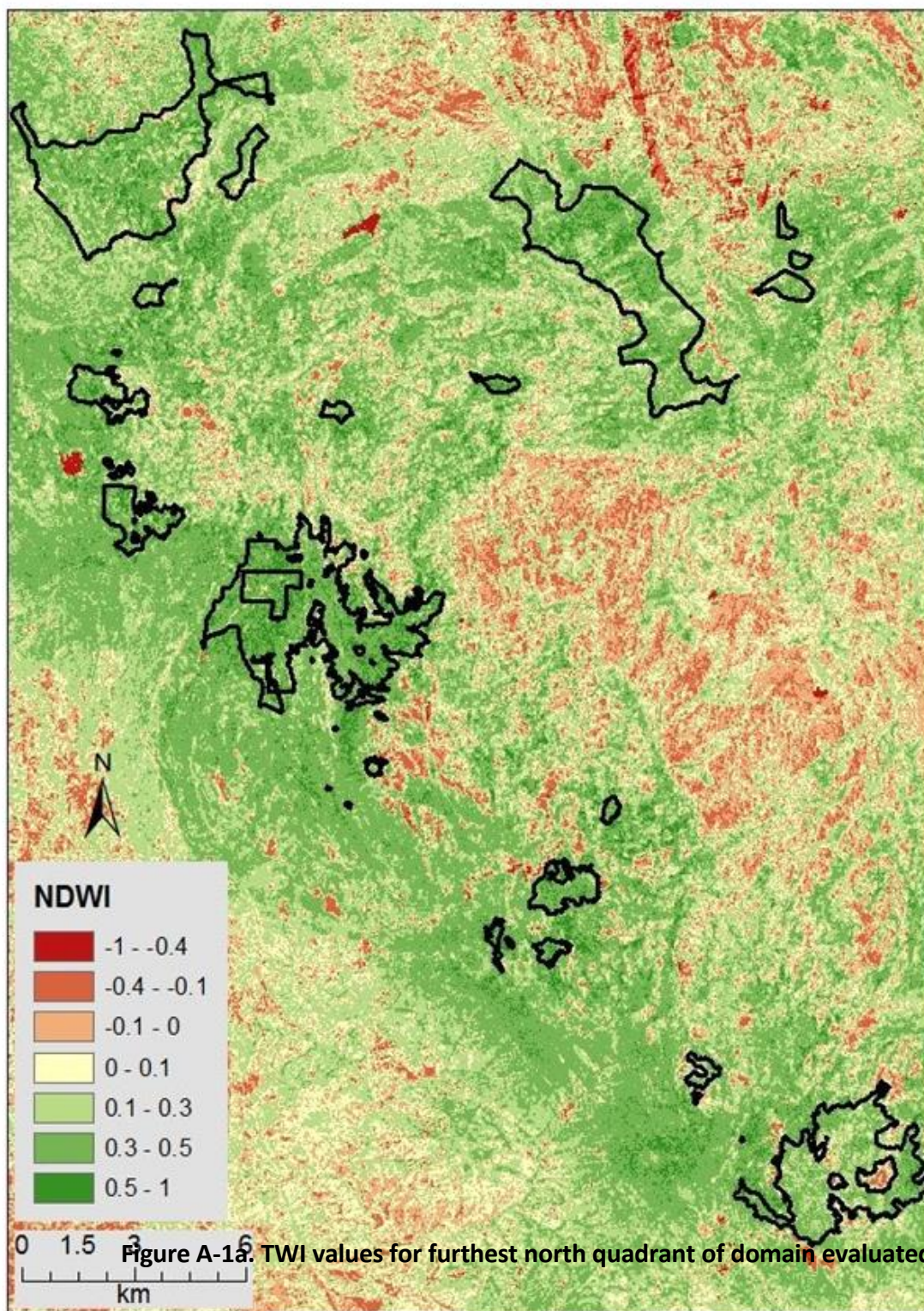
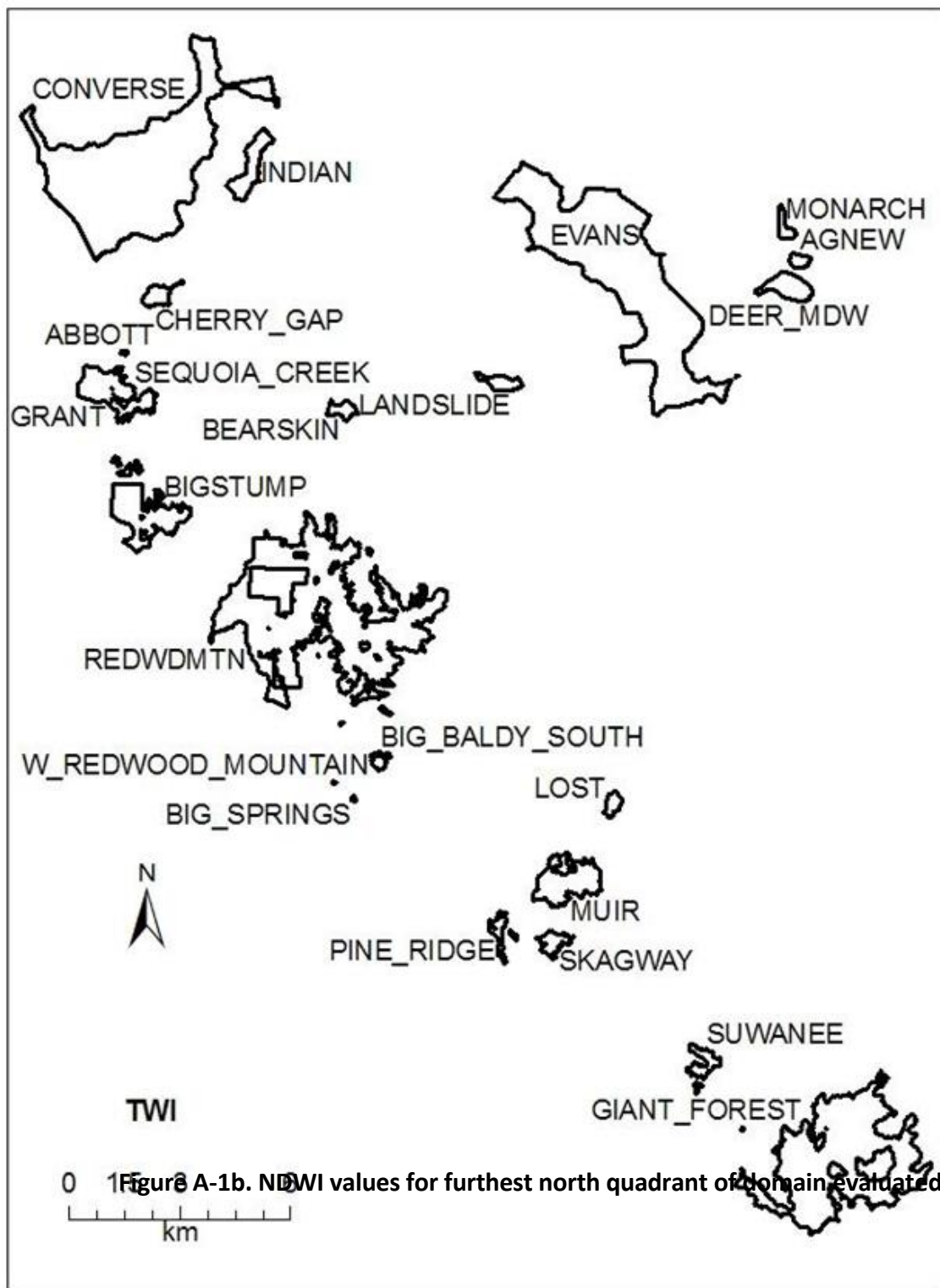


Figure A2: Comparison of TWIs at grove and non-grove domains based on 10 sets of randomly selected equal number (grove-domain) of pixels from non-grove domain (1950-2700m)

Appendix B

Larger-scale maps of spatial patterns of TWI in groves, Aug 2008 NDWI values, and grove-by-grove analyses





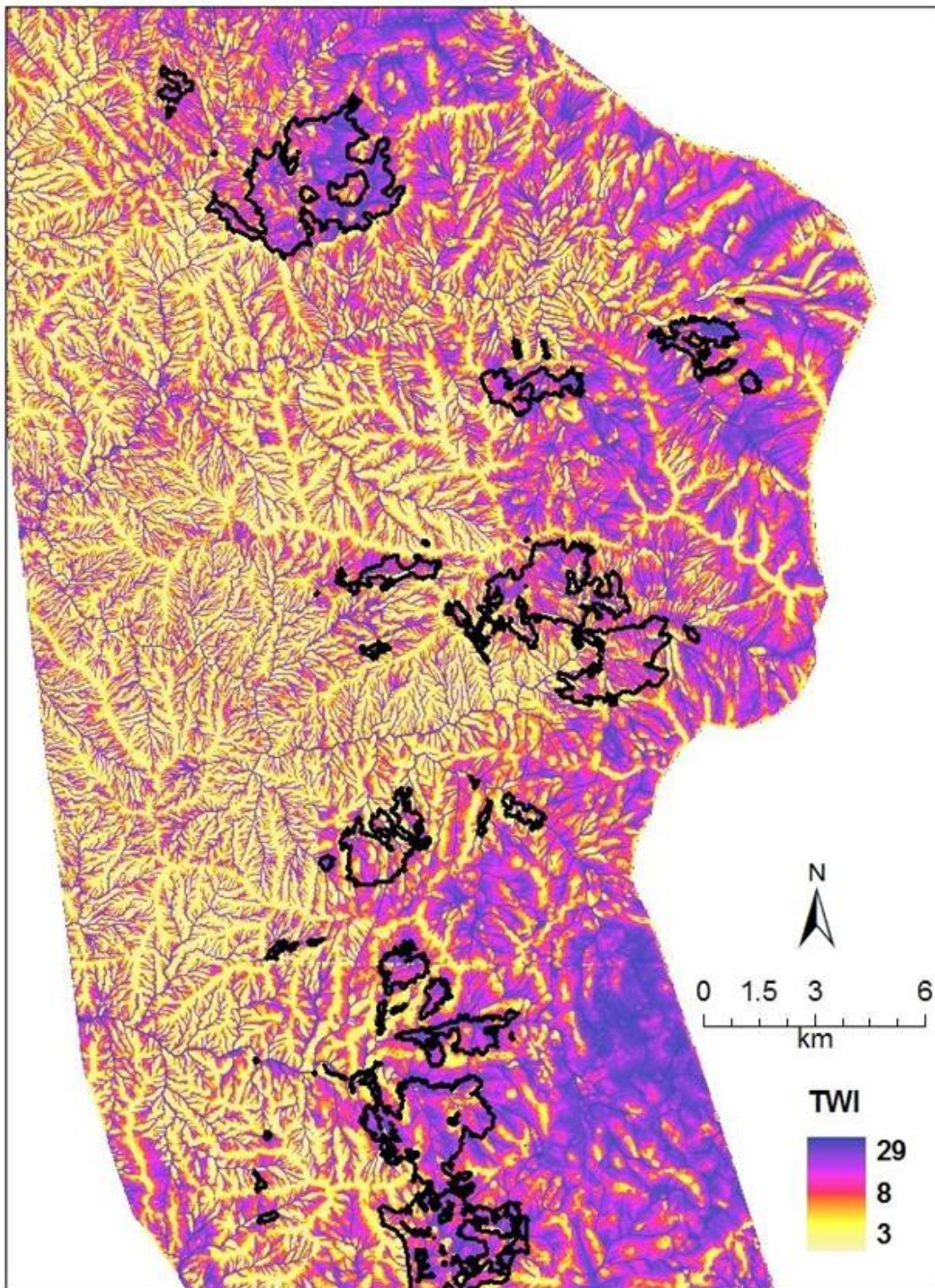


Figure A-2a. TWI values for second quadrant from north for domain evaluated

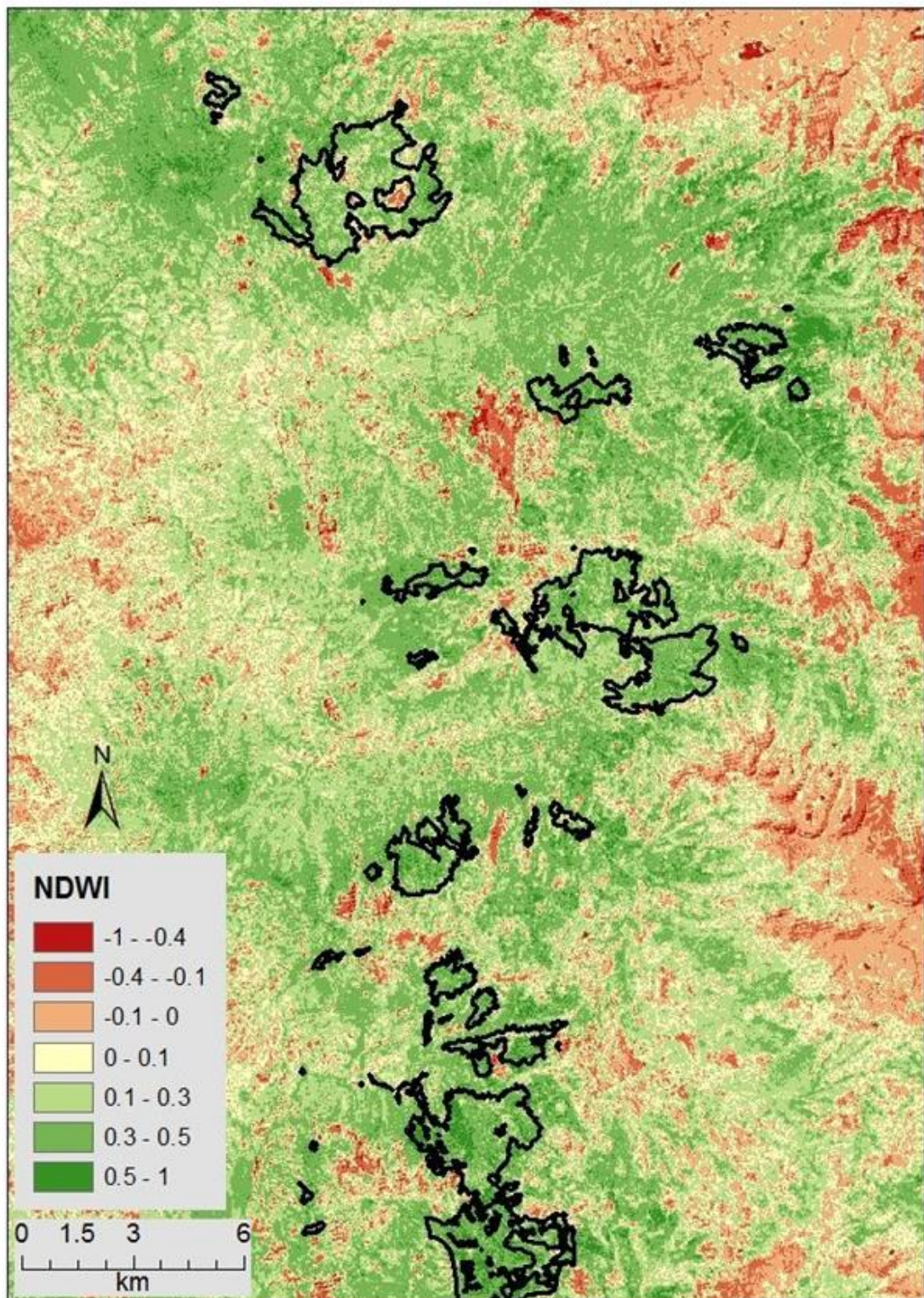


Figure A-2b. NDWI values for second quadrant from north for domain evaluated

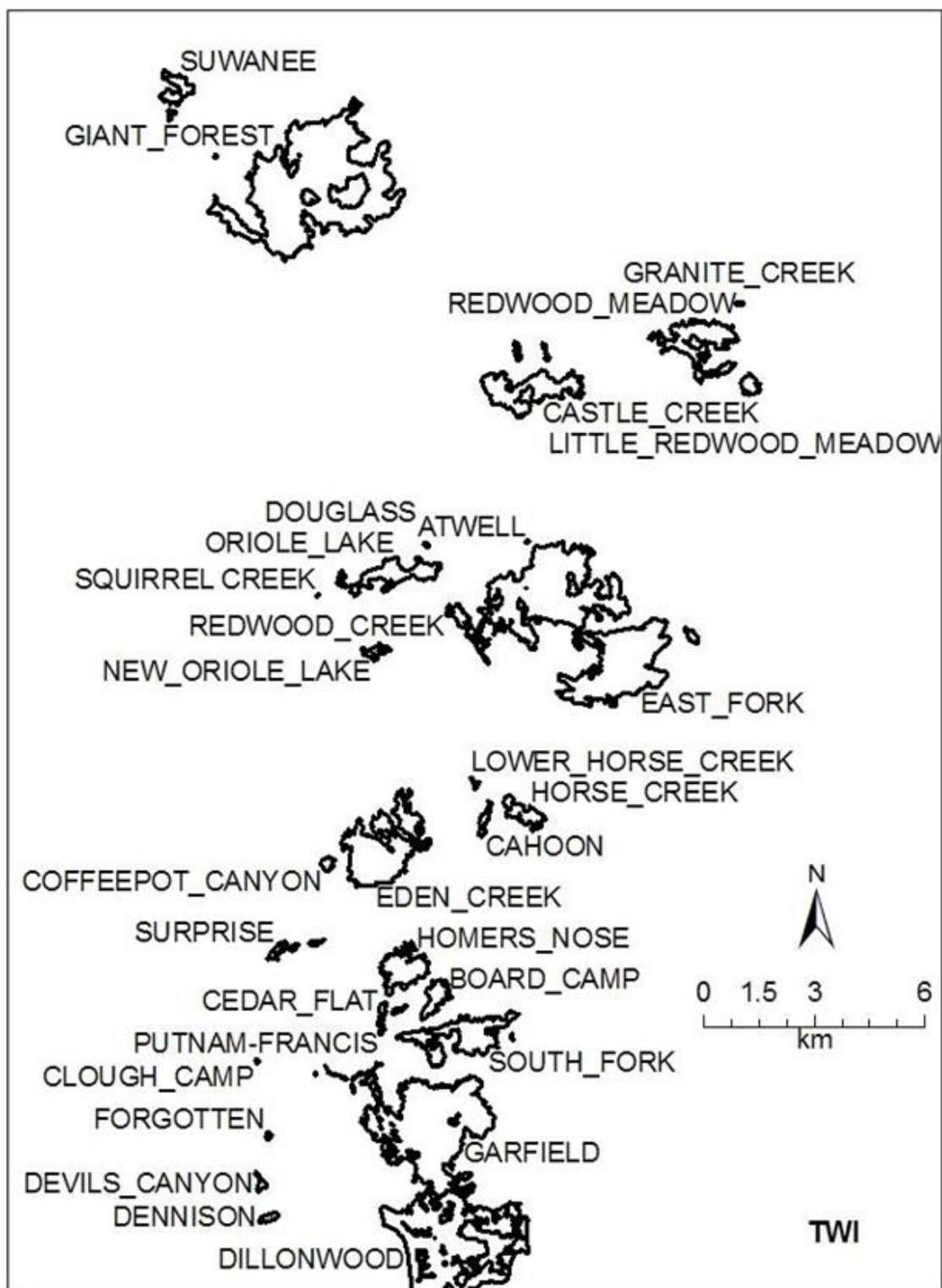


Figure A-2c. Grove names for second quadrant from north for domain evaluated

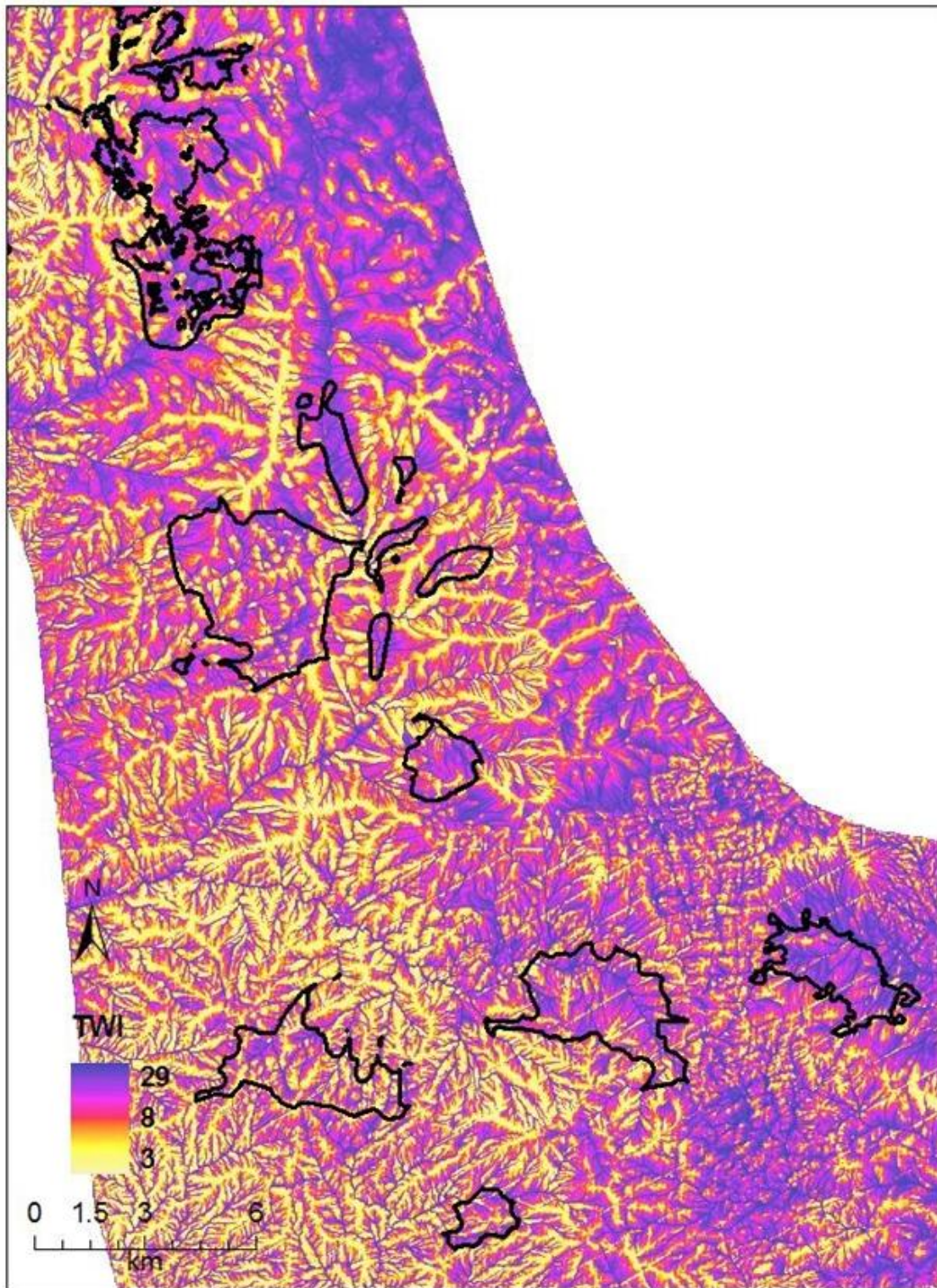


Figure A-3a. TWI values for third quadrant from north for domain evaluated

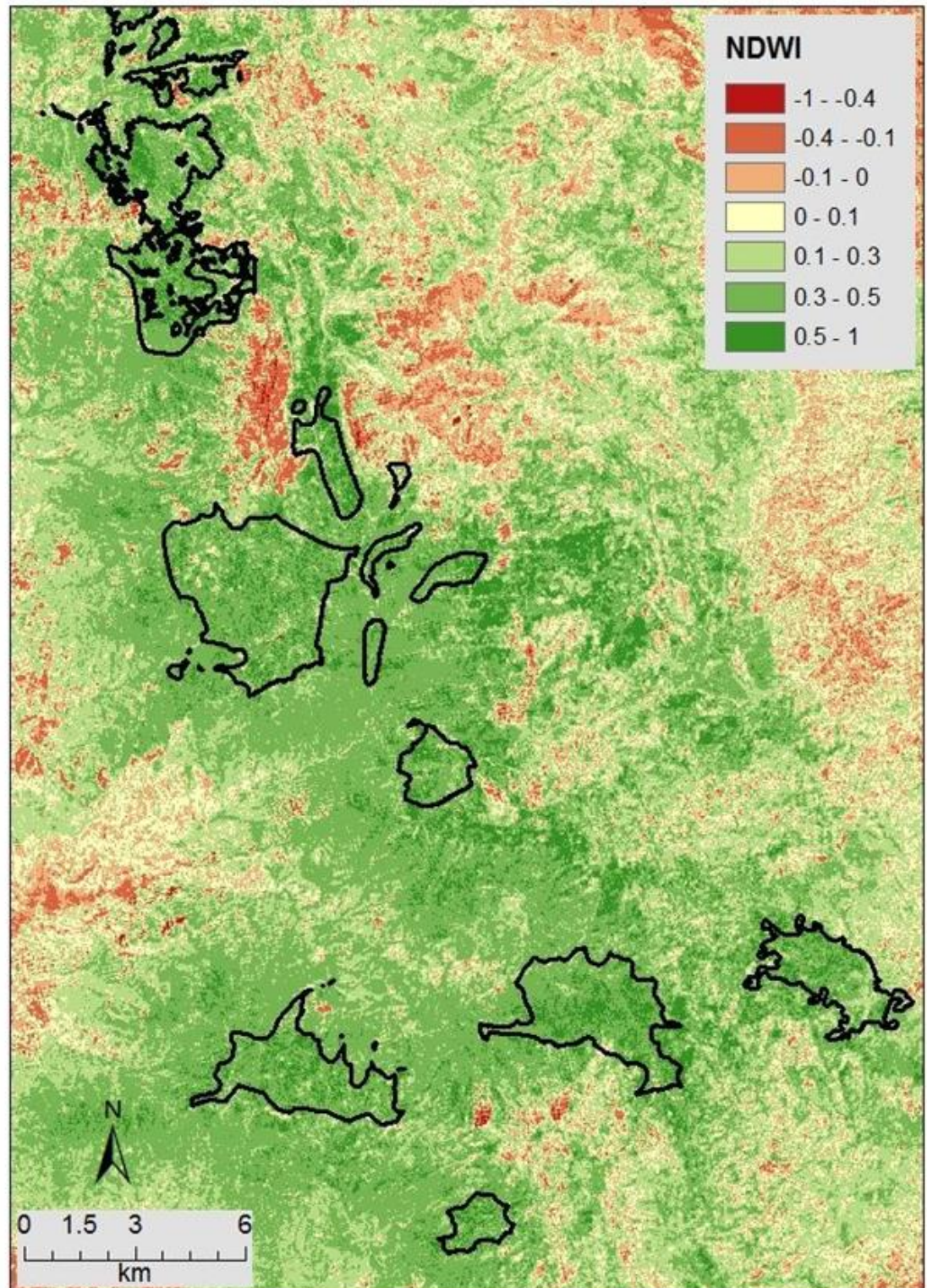


Figure A-3b. NDWI values for third quadrant from north for domain evaluated

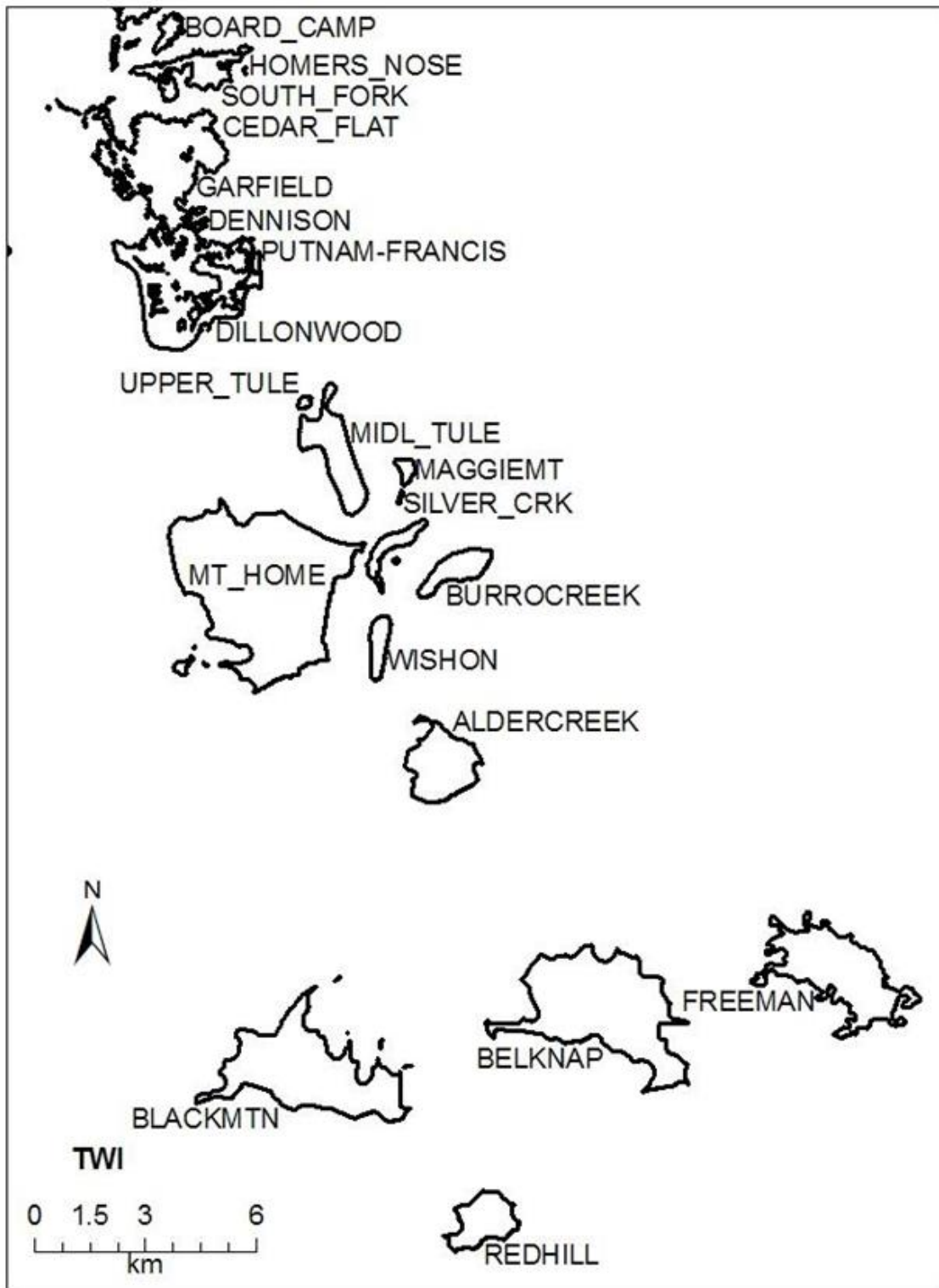


Figure A-3c. Grove names for third quadrant from north for domain evaluated

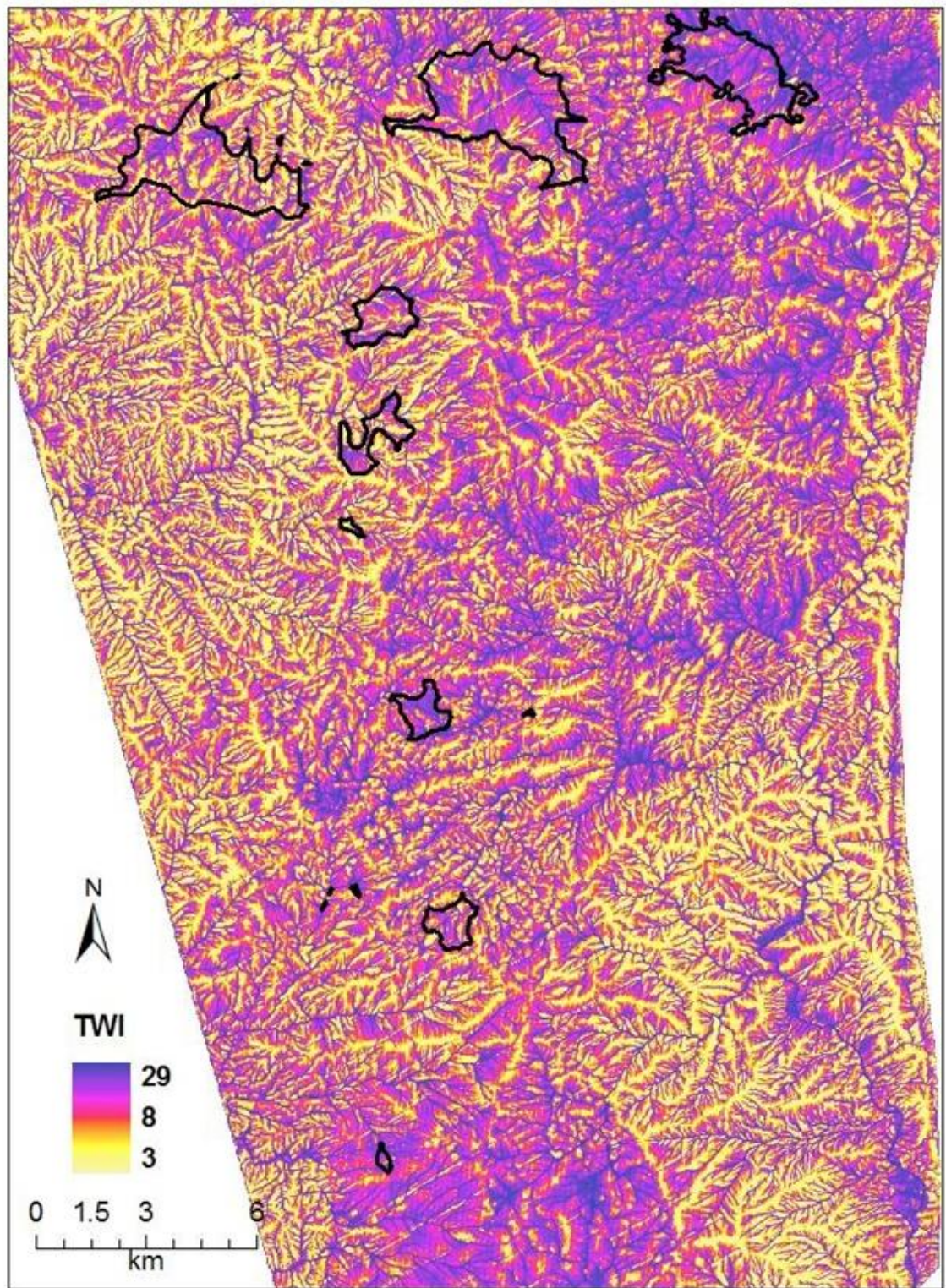


Figure A-4a. TWI values for furthest south quadrant for domain evaluated

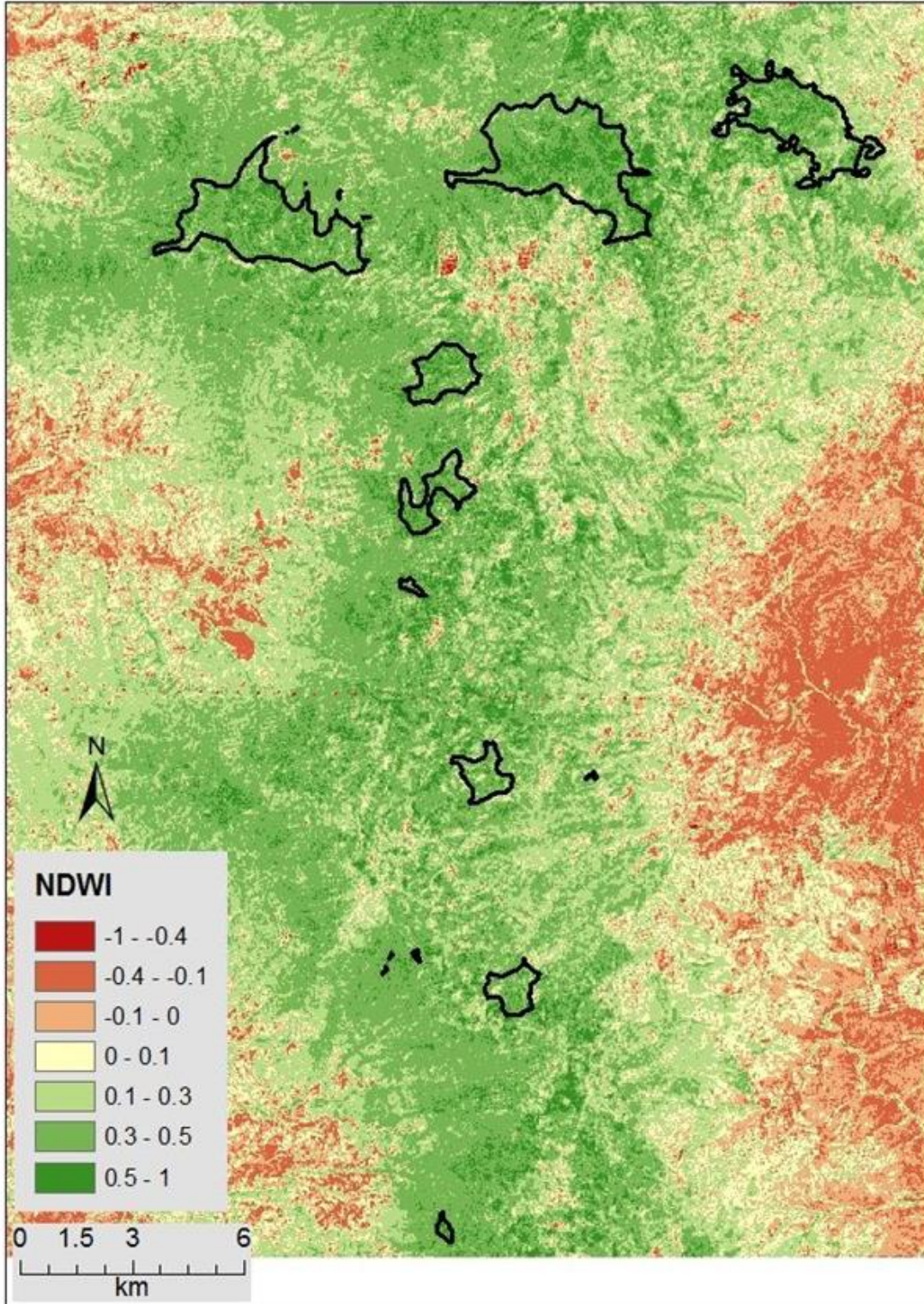


Figure A-4b. NDWI values for furthest south quadrant for domain evaluated

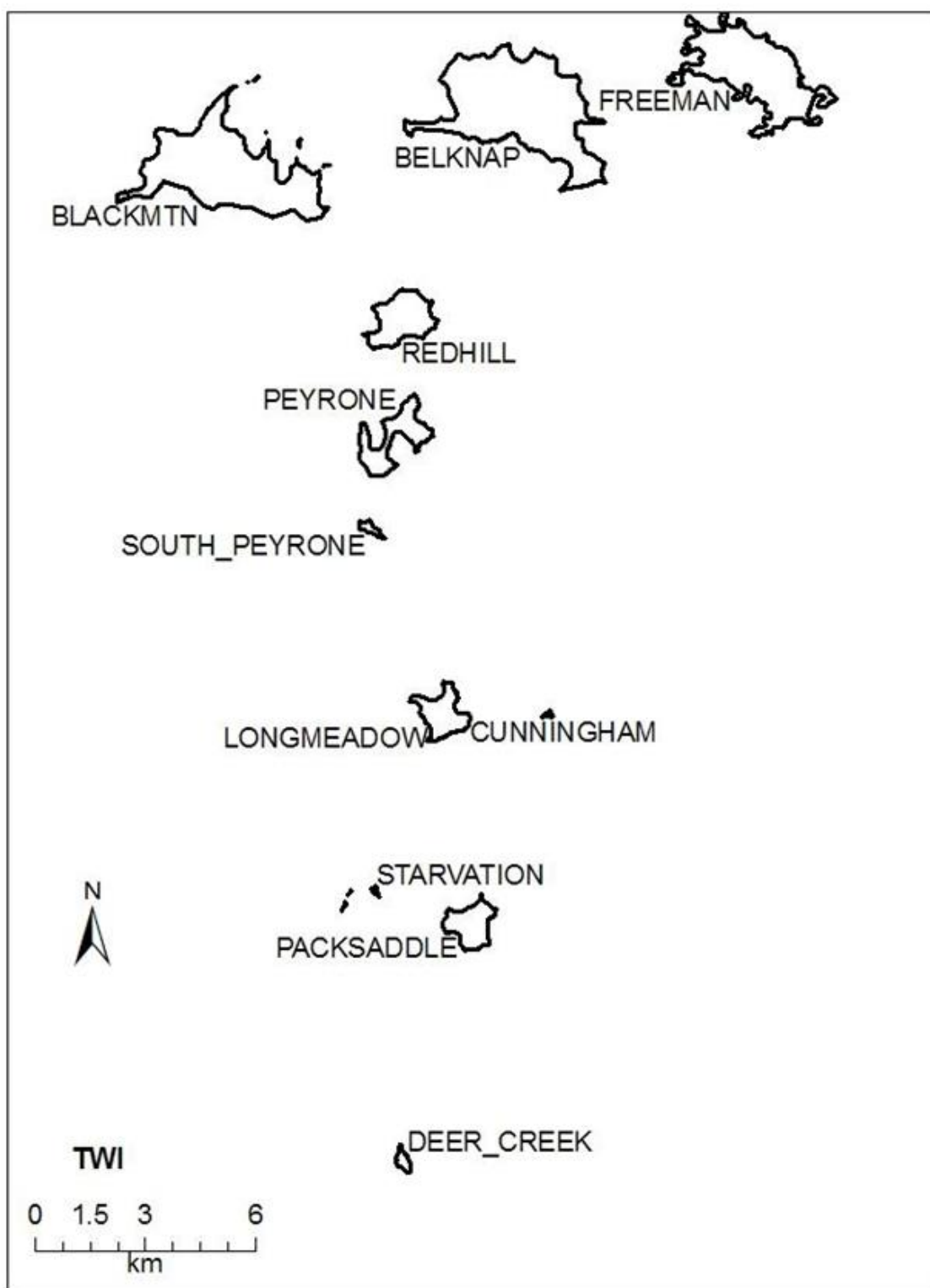


Figure A-4c. Grove names for furthest south quadrant for domain evaluated

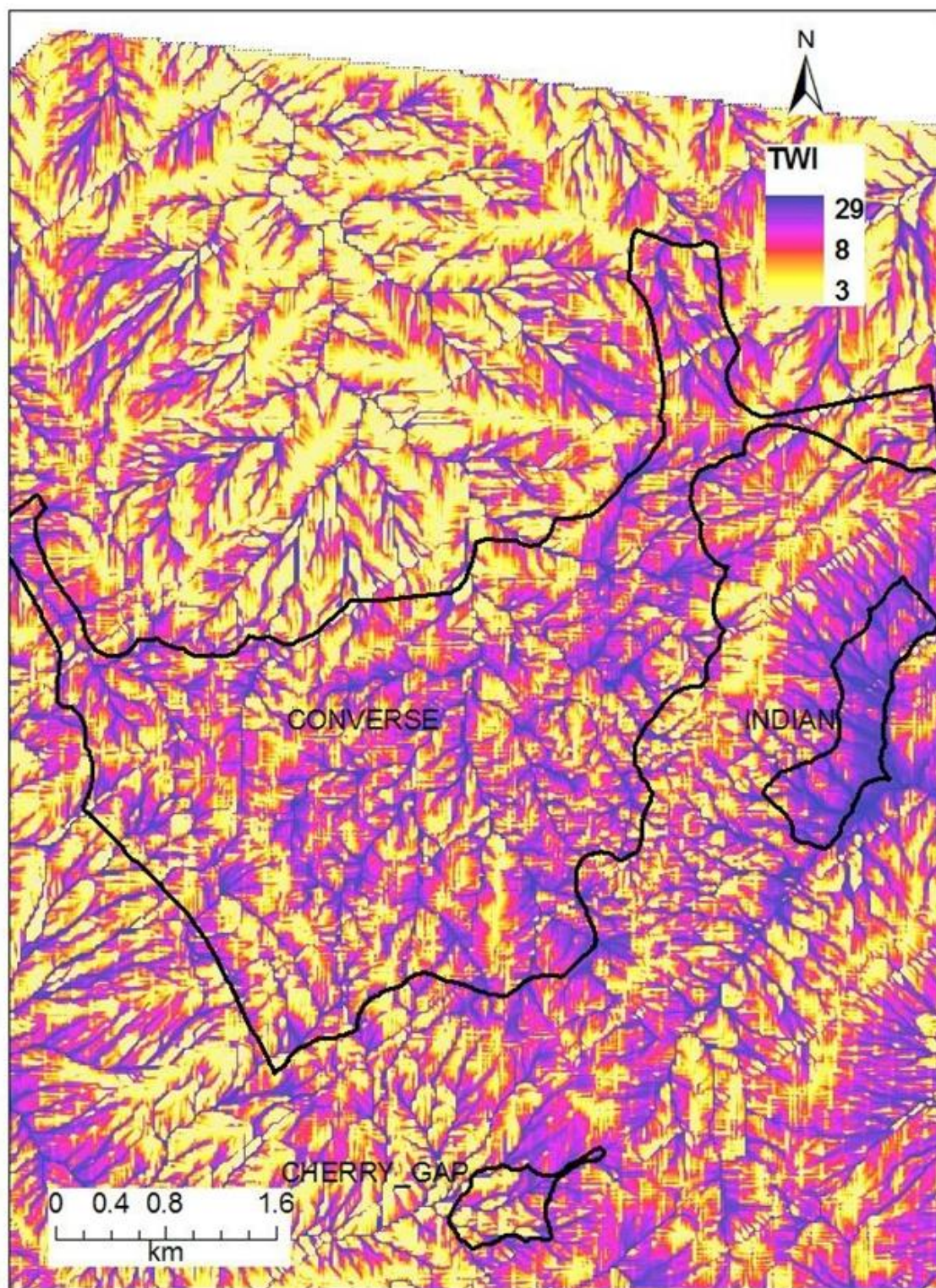


Figure A-5a. TWI values for Converse, Cherry Gap and Indian groves, and surrounding area.

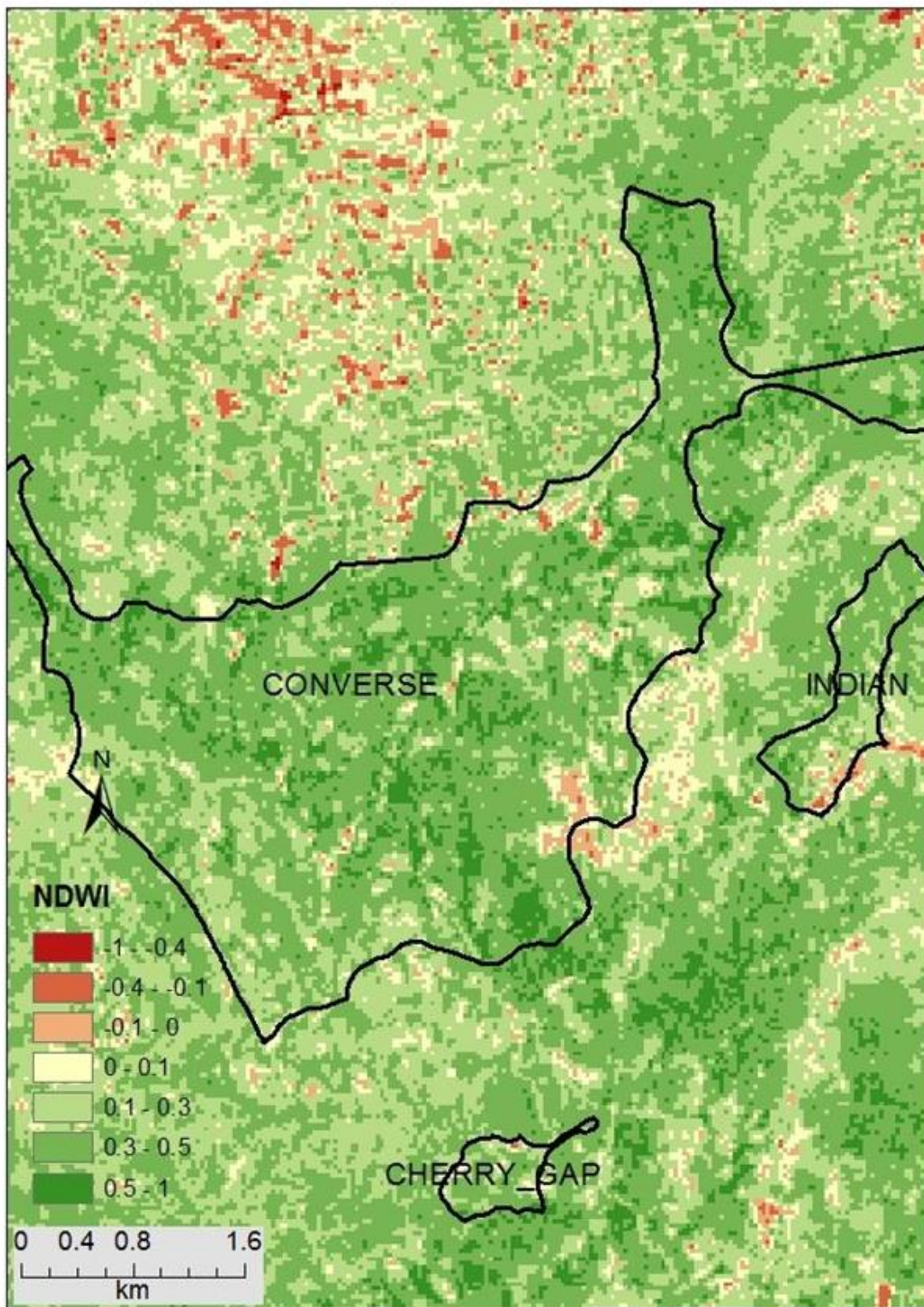


Figure A-5b. NDWI values for Converse, Cherry Gap and Indian groves, and surrounding area

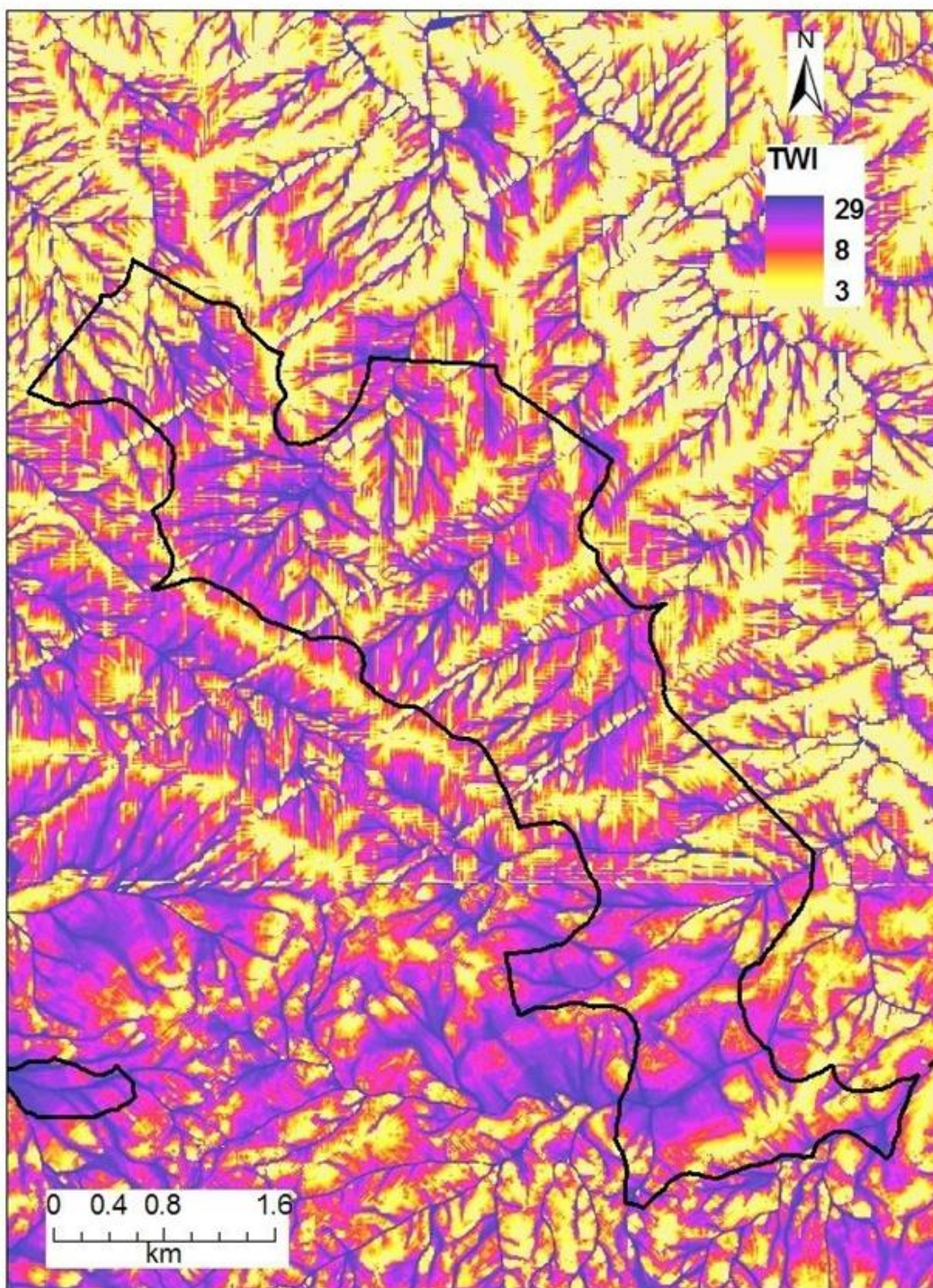


Figure A-6a. TWI values for Evans grove and surrounding area.

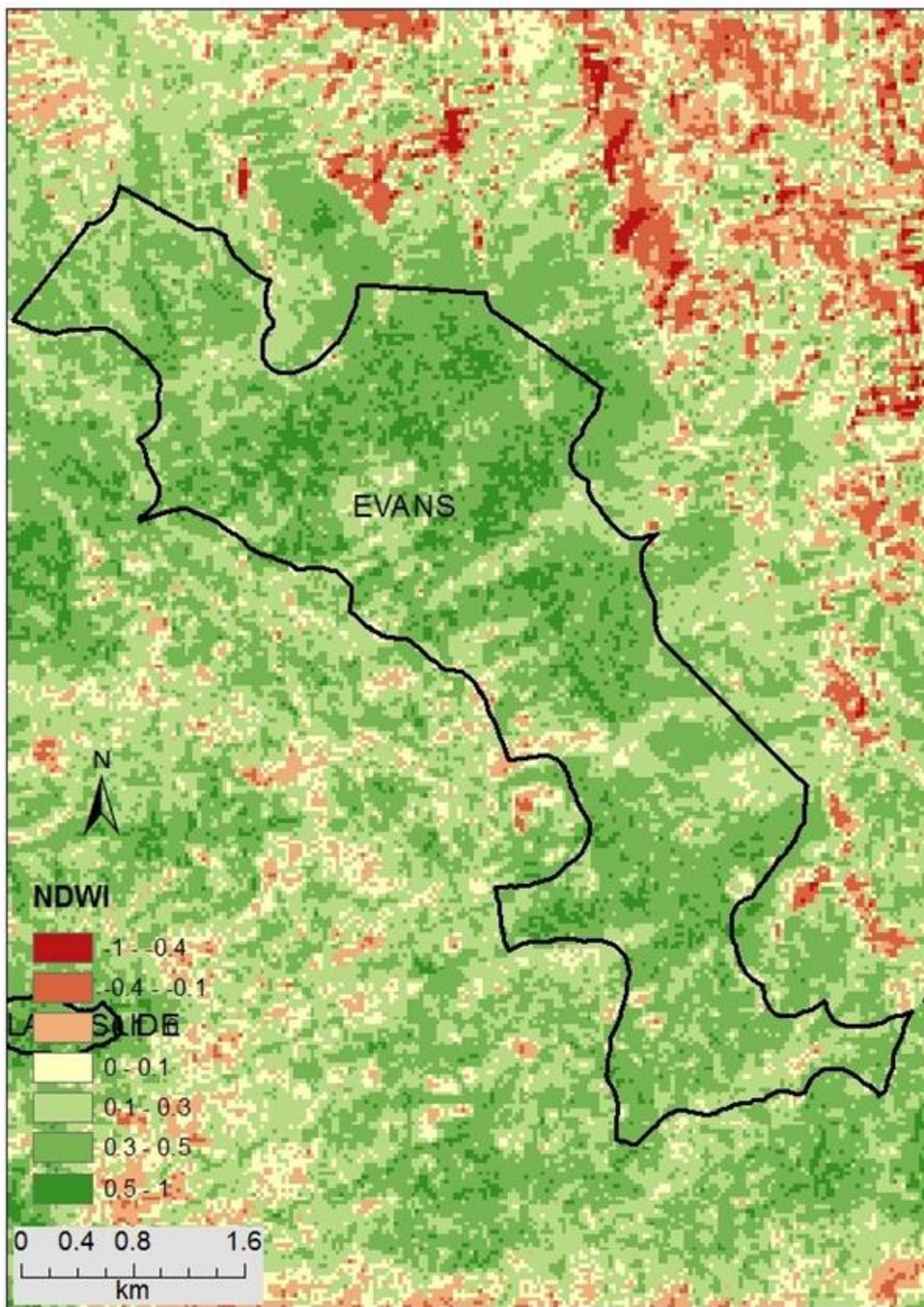


Figure A-6b. NDWI values for Evans grove and surrounding area.

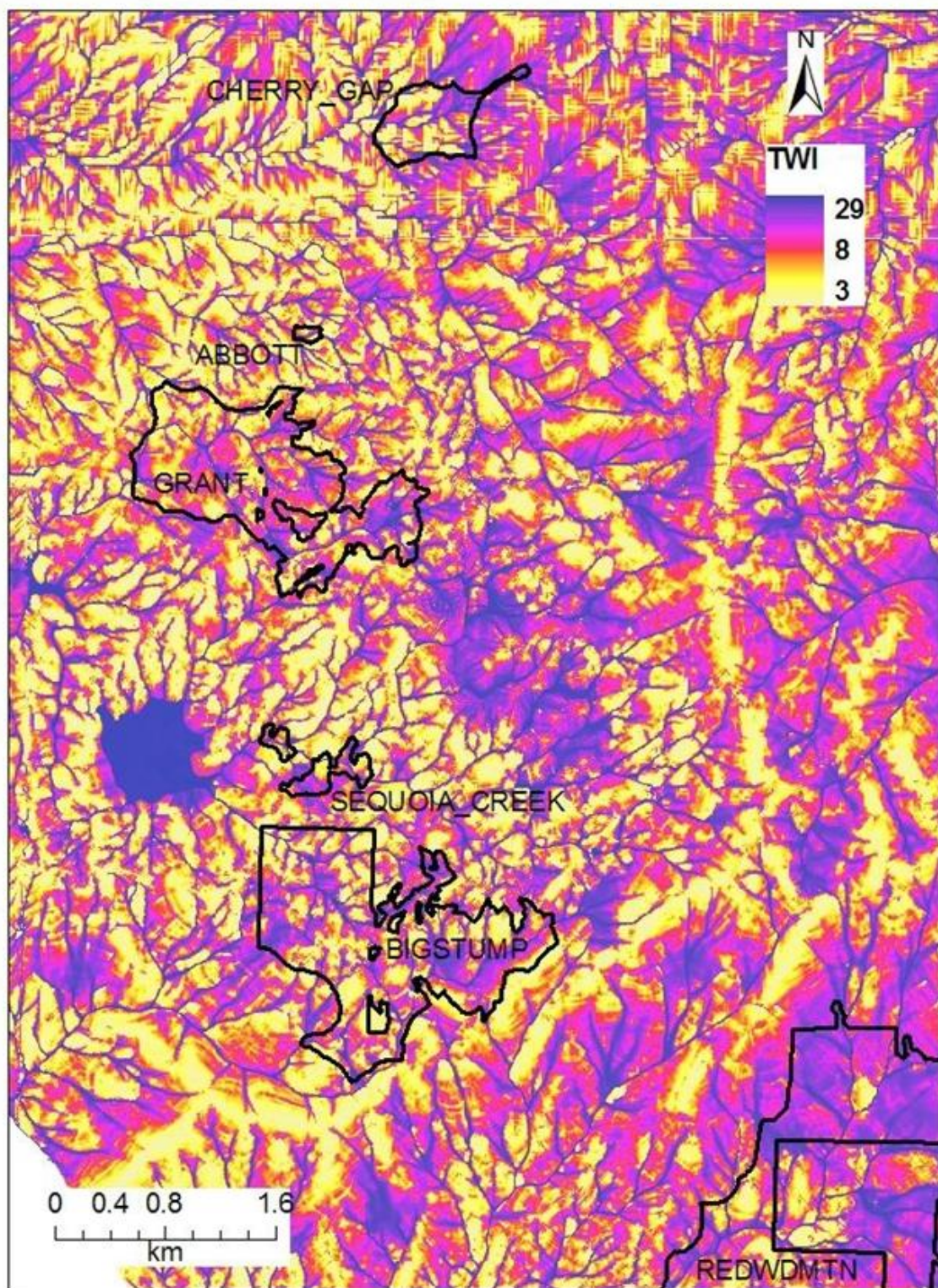


Figure A-7a. TWI values for Grant and nearby groves and surrounding area.

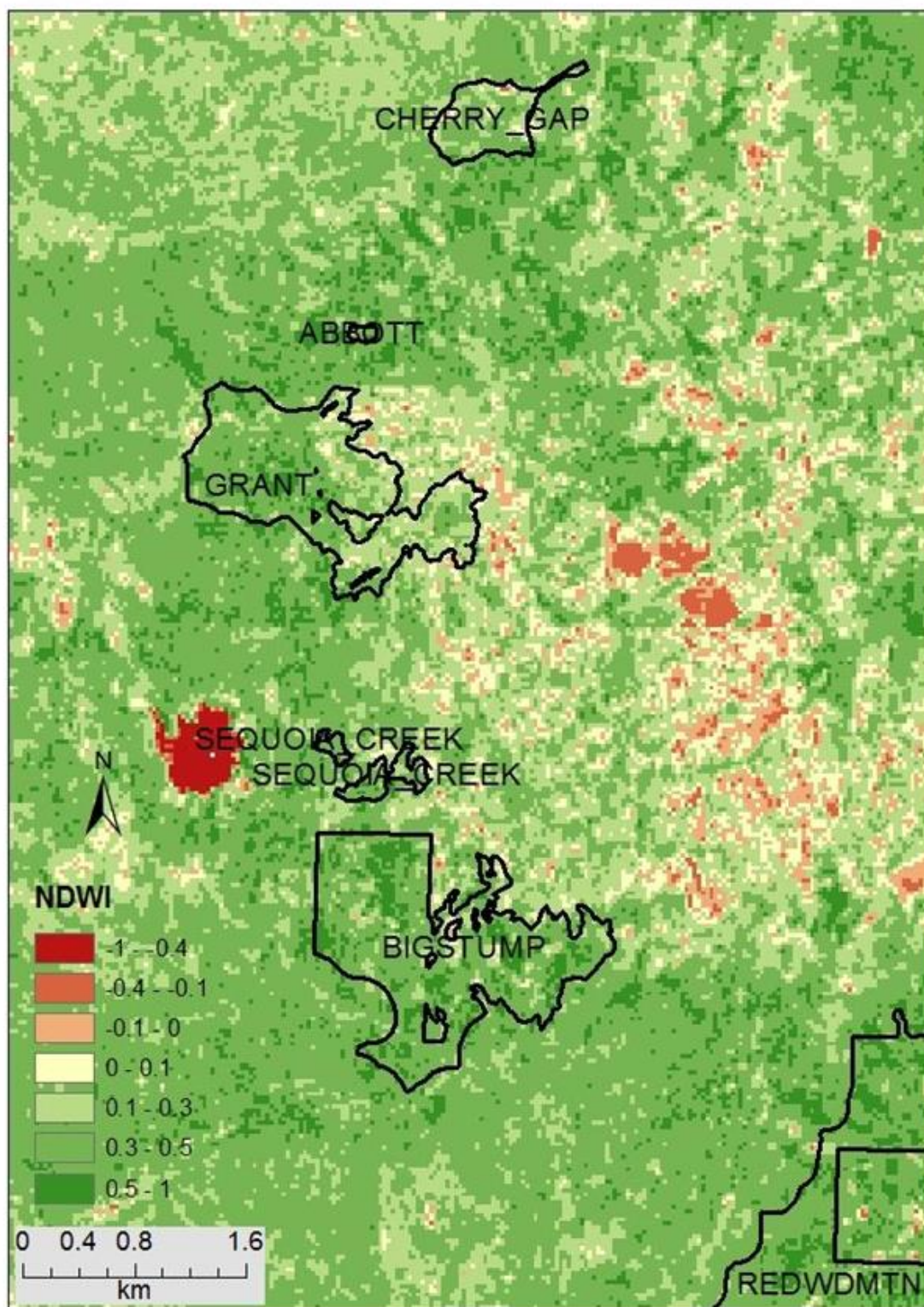


Figure A-7b. NDWI values for Grant and nearby groves and surrounding area.

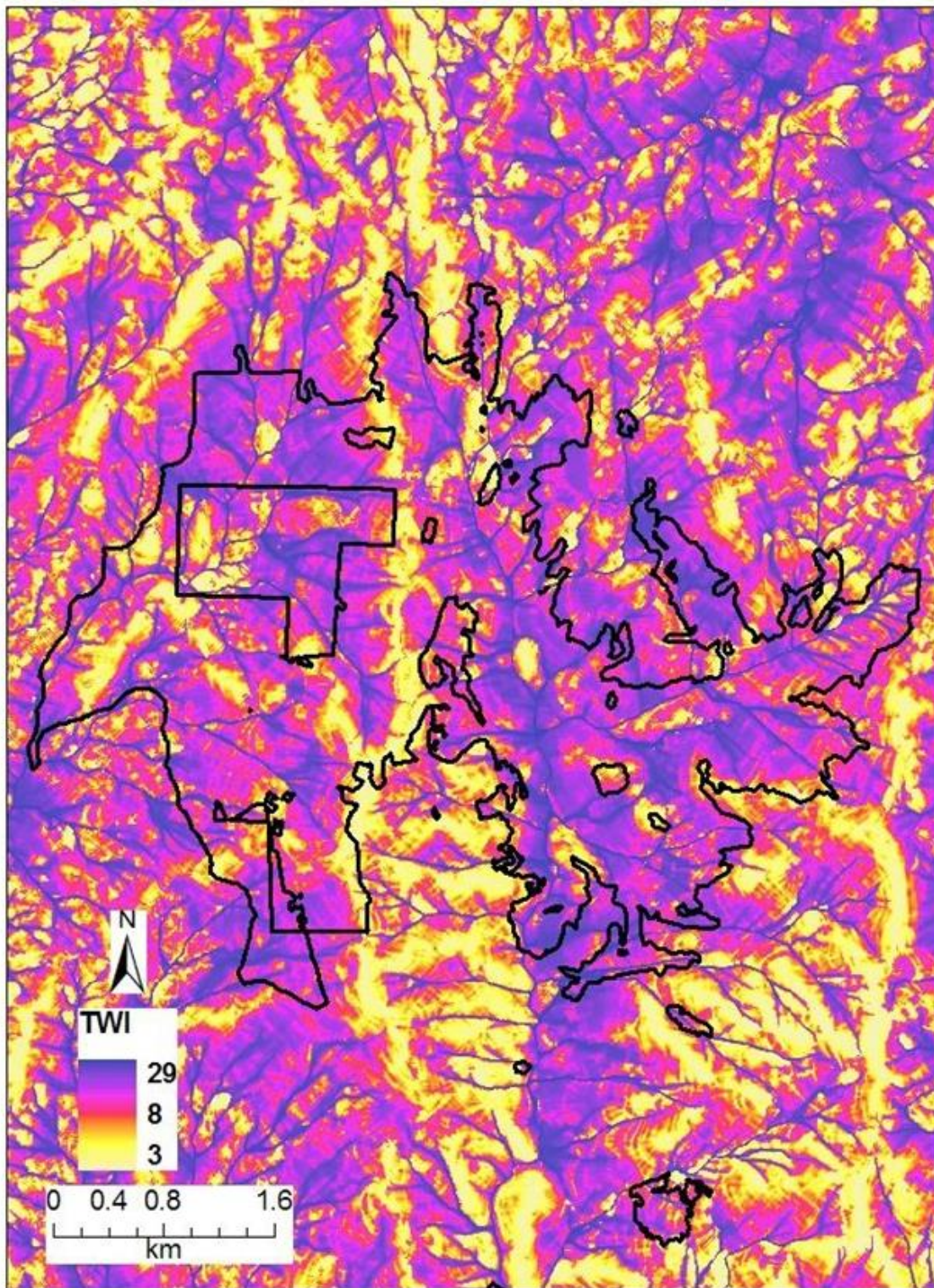


Figure A-8a. TWI values for Redwood Mountain and nearby smaller groves, and surrounding area.

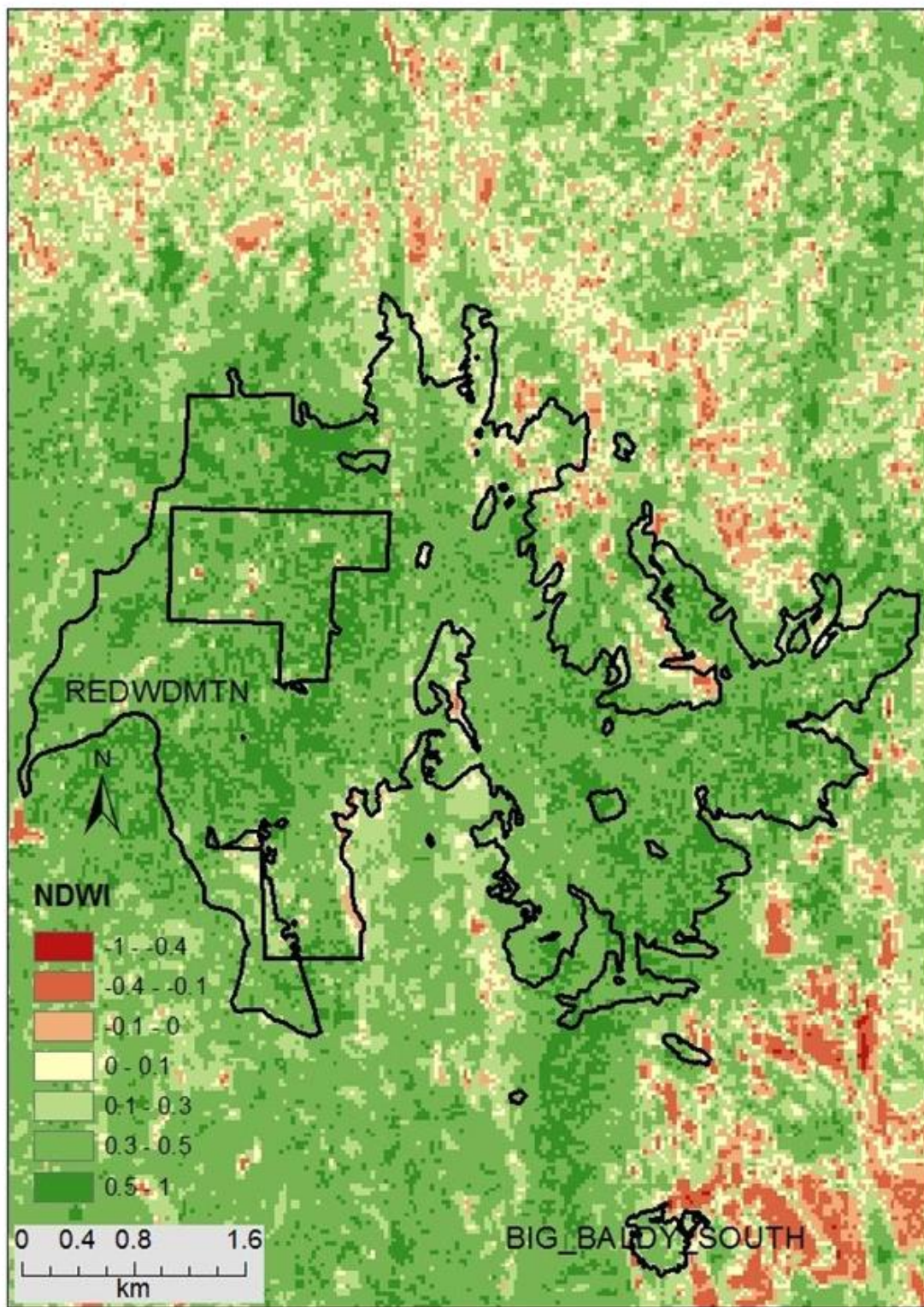


Figure A-8b. NDWI values for Redwood Mountain and nearby smaller groves, and surrounding area.

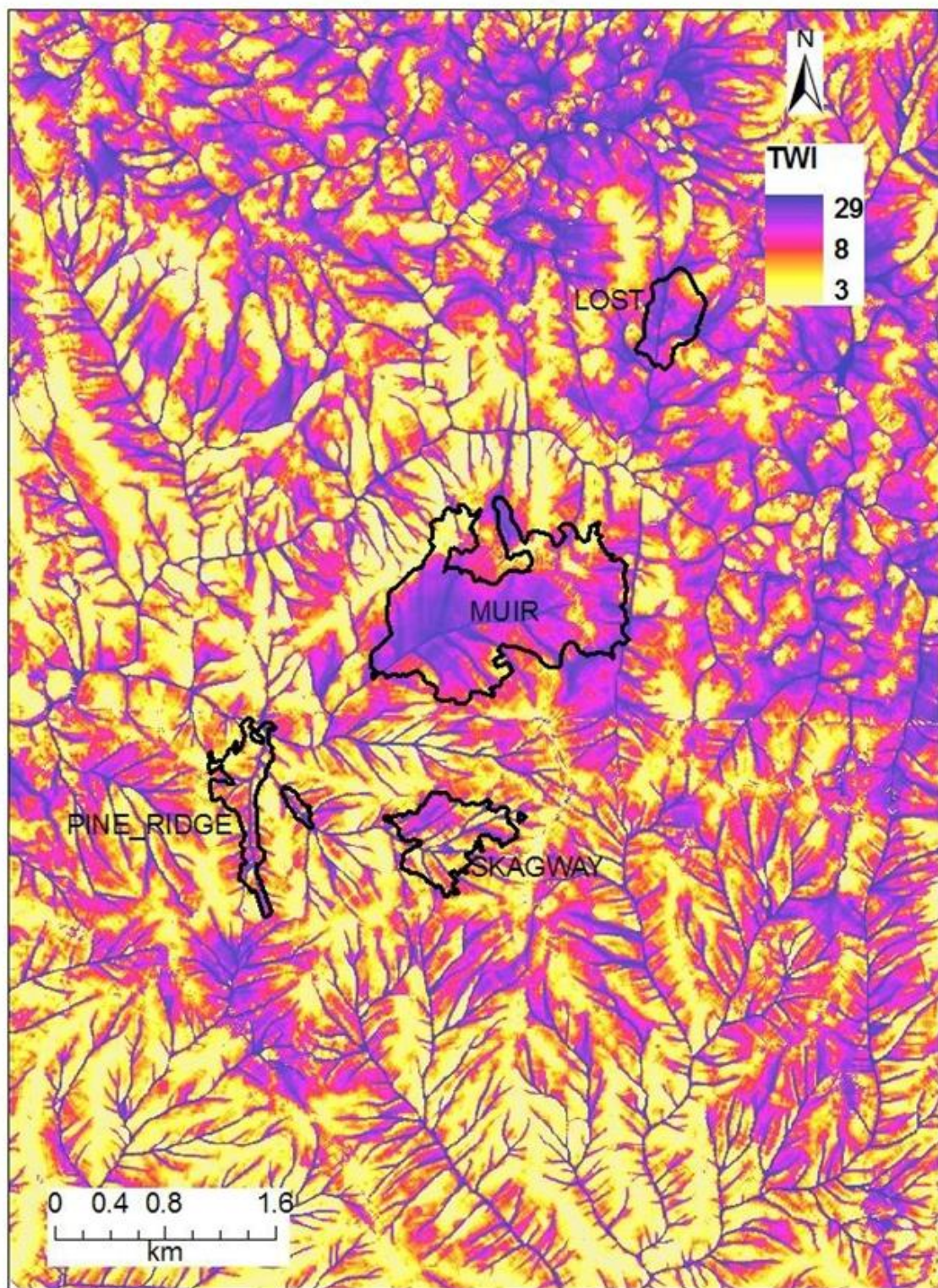


Figure A-9a. TWI values for Muir, Lost, Pine Ridge and Skagway groves, and surrounding area.

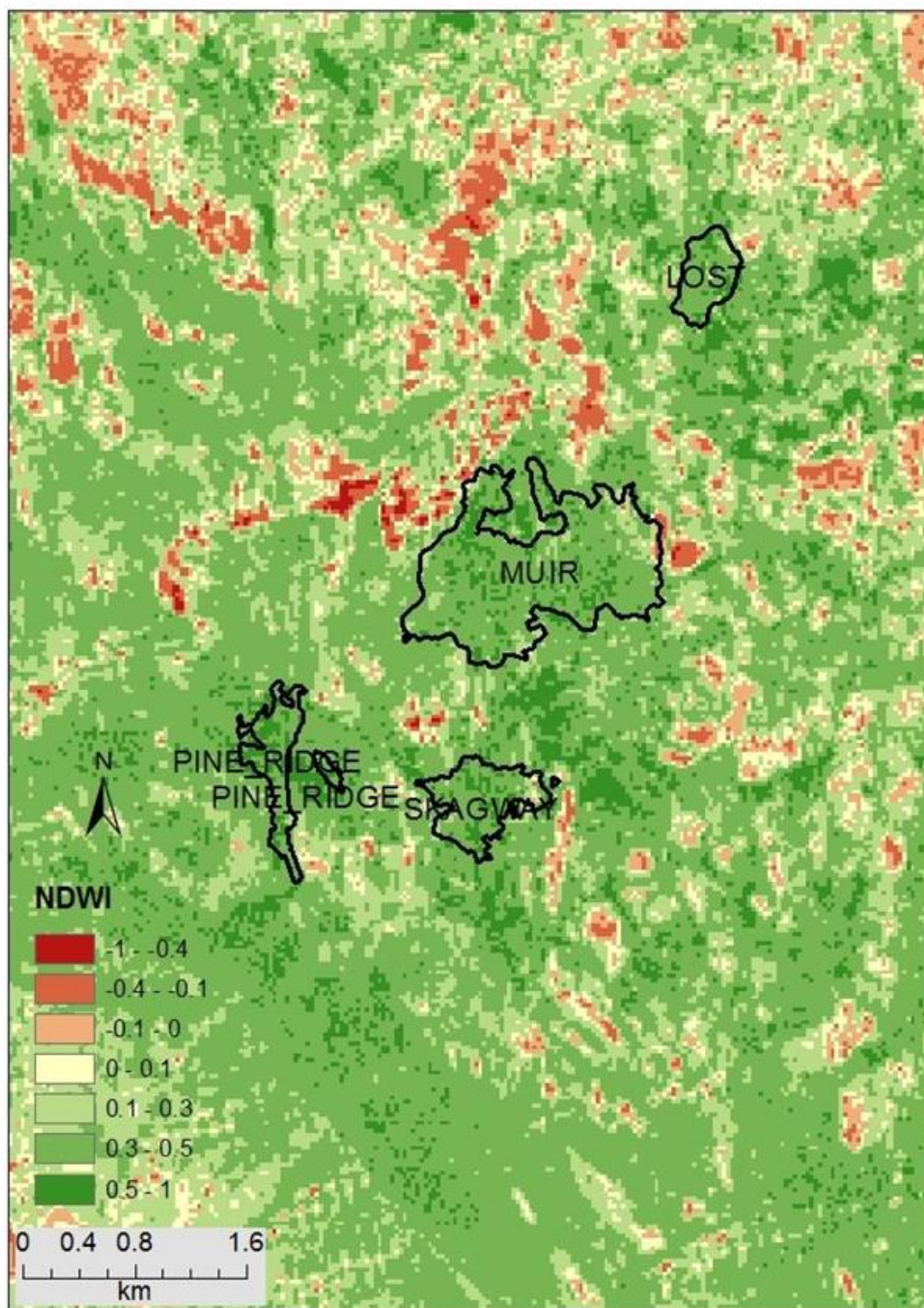


Figure A-9b. NDWI values for Muir, Lost, Pine Ridge and Skagway groves, and surrounding area.

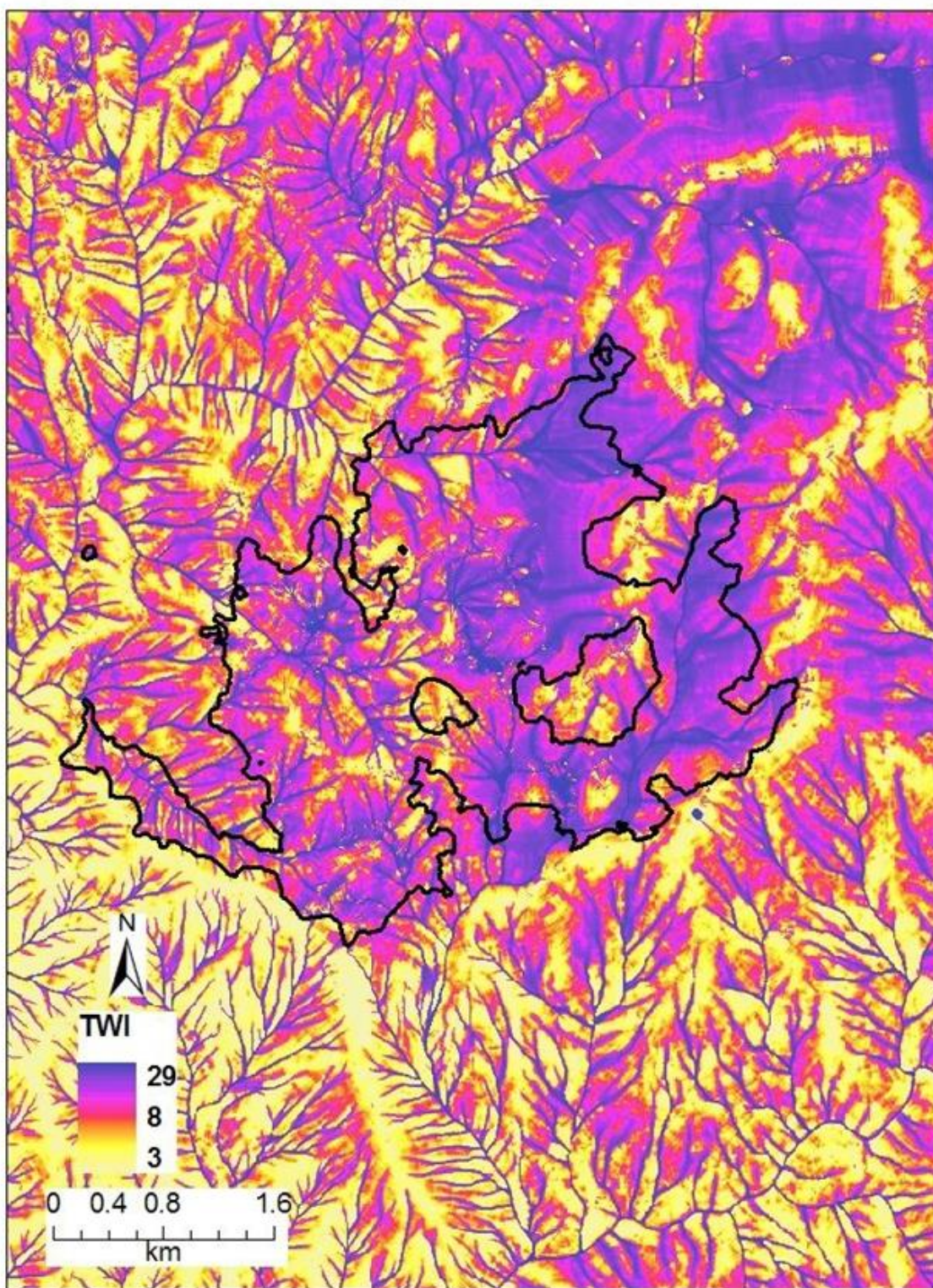


Figure A-10a. TWI values Giant Forest grove and surrounding area.

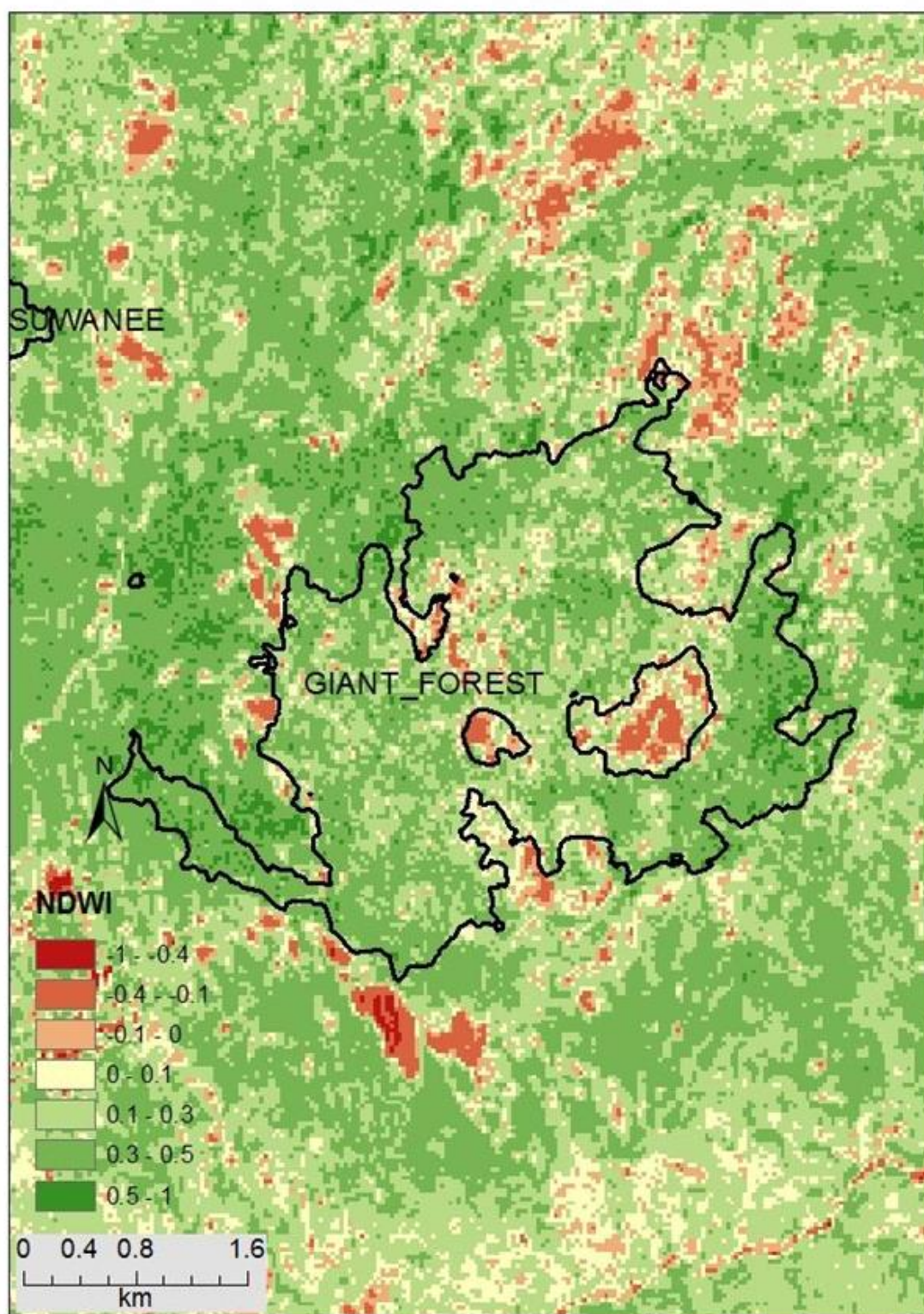


Figure A-10b. NDWI values Giant Forest grove and surrounding area.

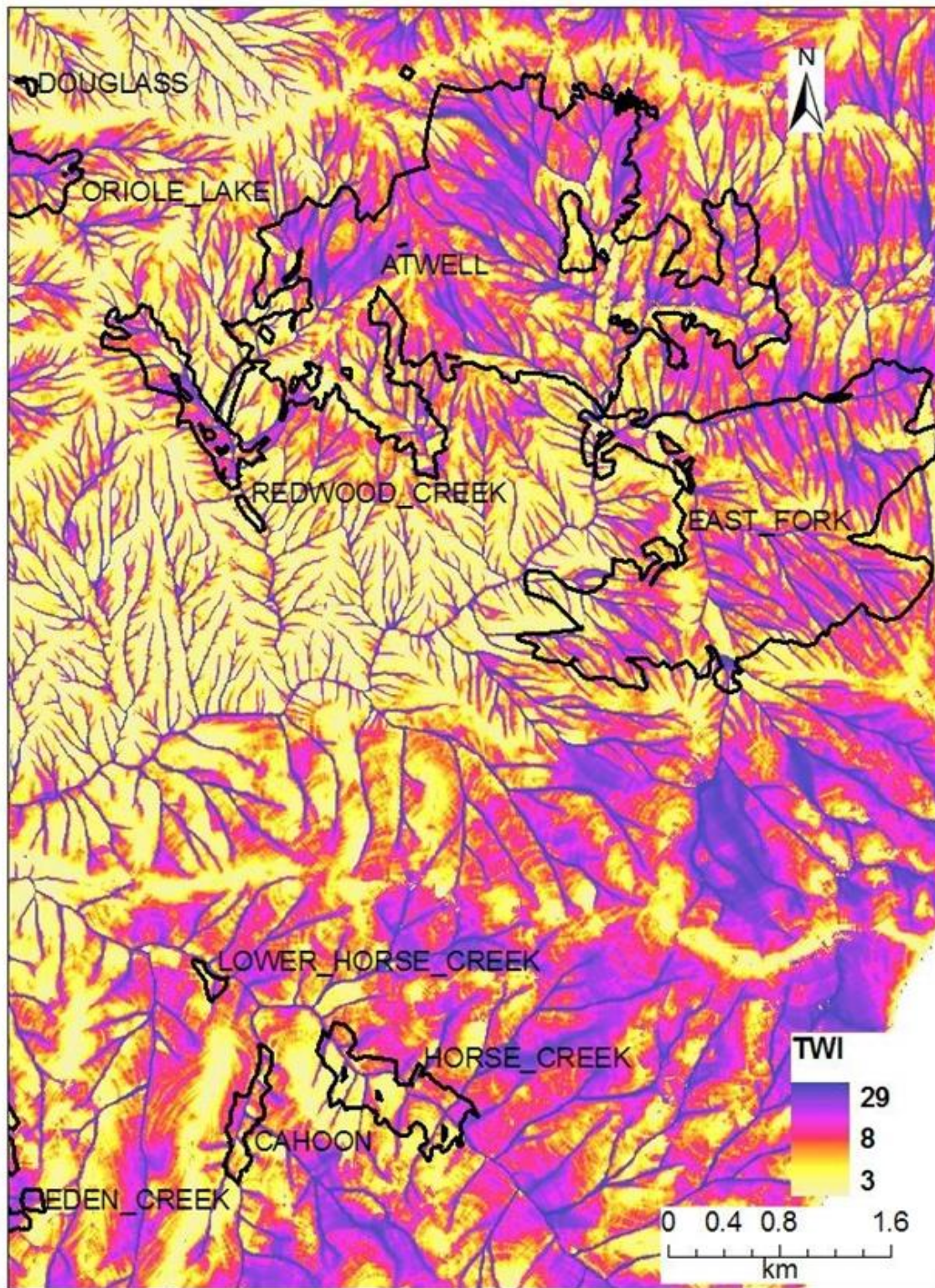


Figure A-11a. TWI values for Atwell, East Fork and other nearby groves, and surrounding area.

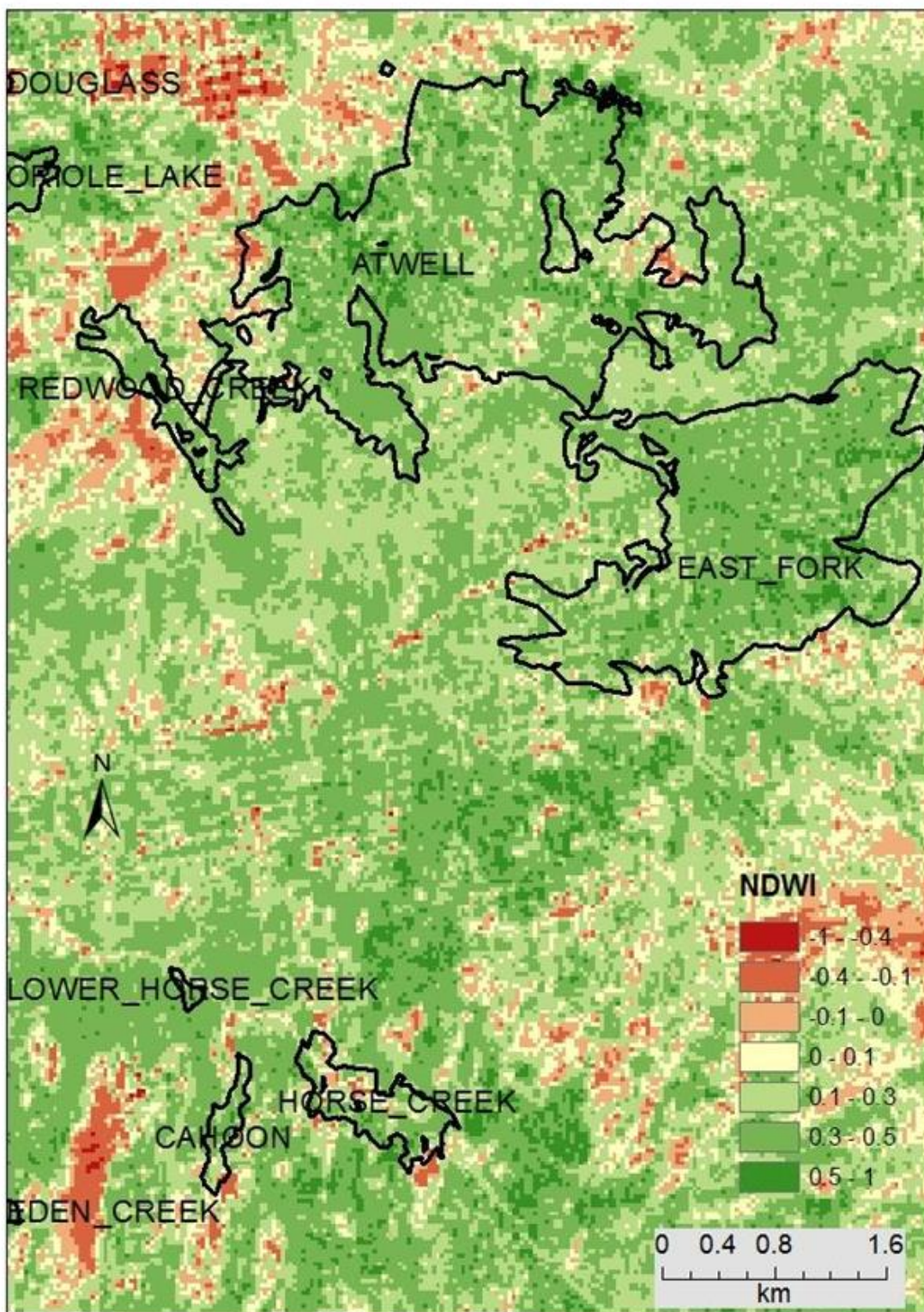


Figure A-11b. NDWI values for Atwell, East Fork and other nearby groves, and surrounding area.

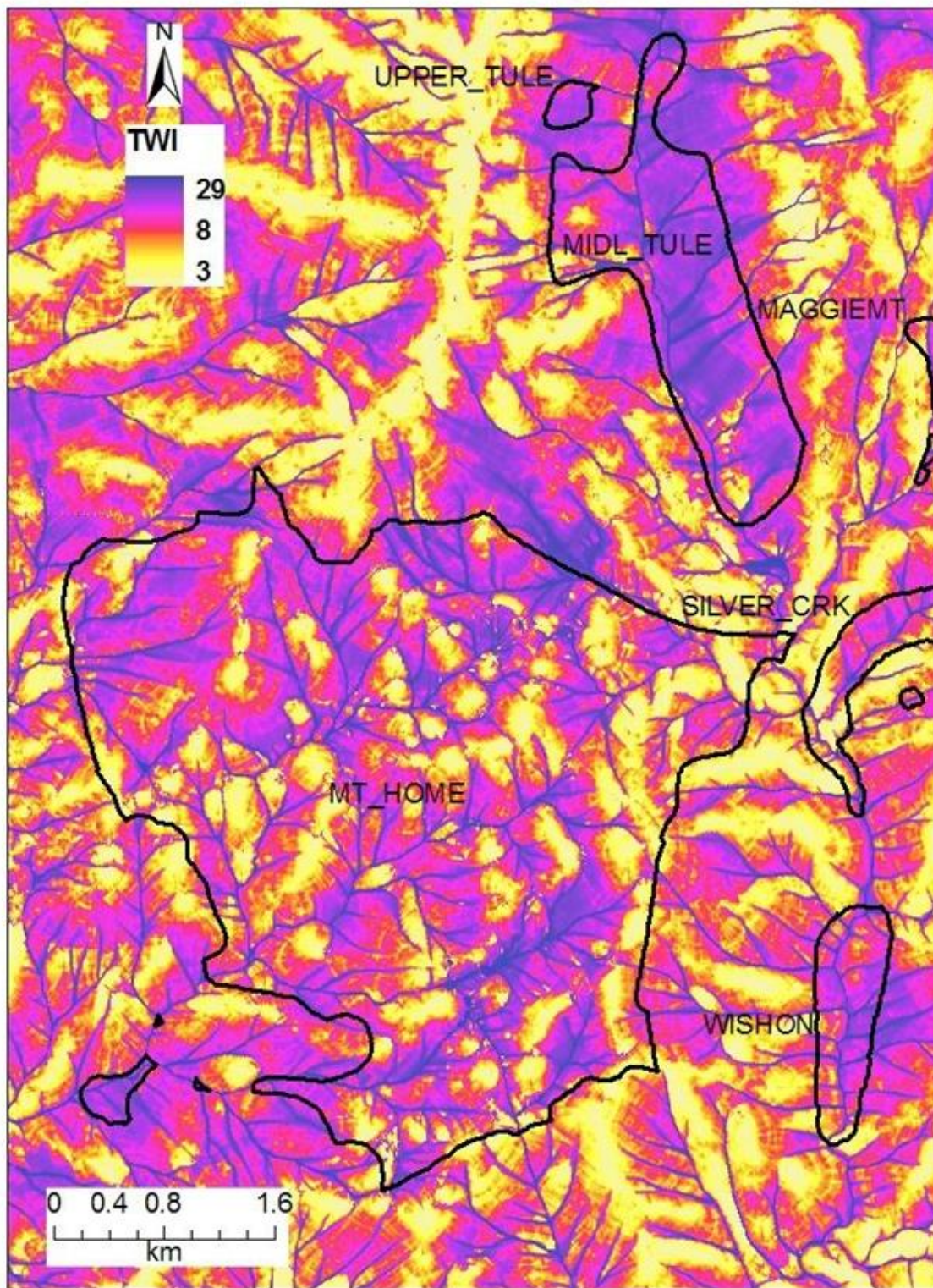


Figure A-12a. TWI values for Mountain Home and nearby groves, and surrounding area.

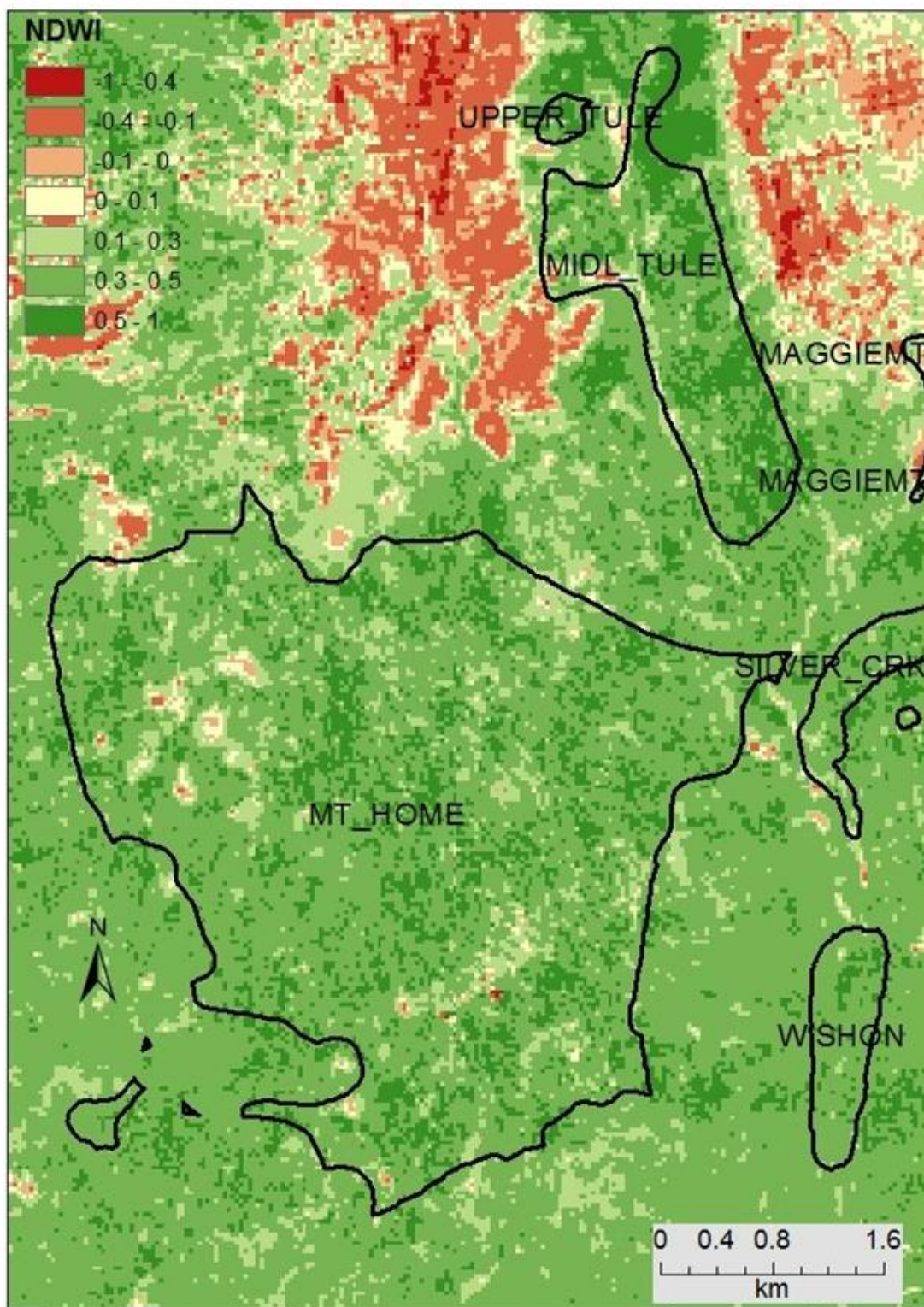


Figure A-12b. NDWI values for Mountain Home and nearby groves, and surrounding area.

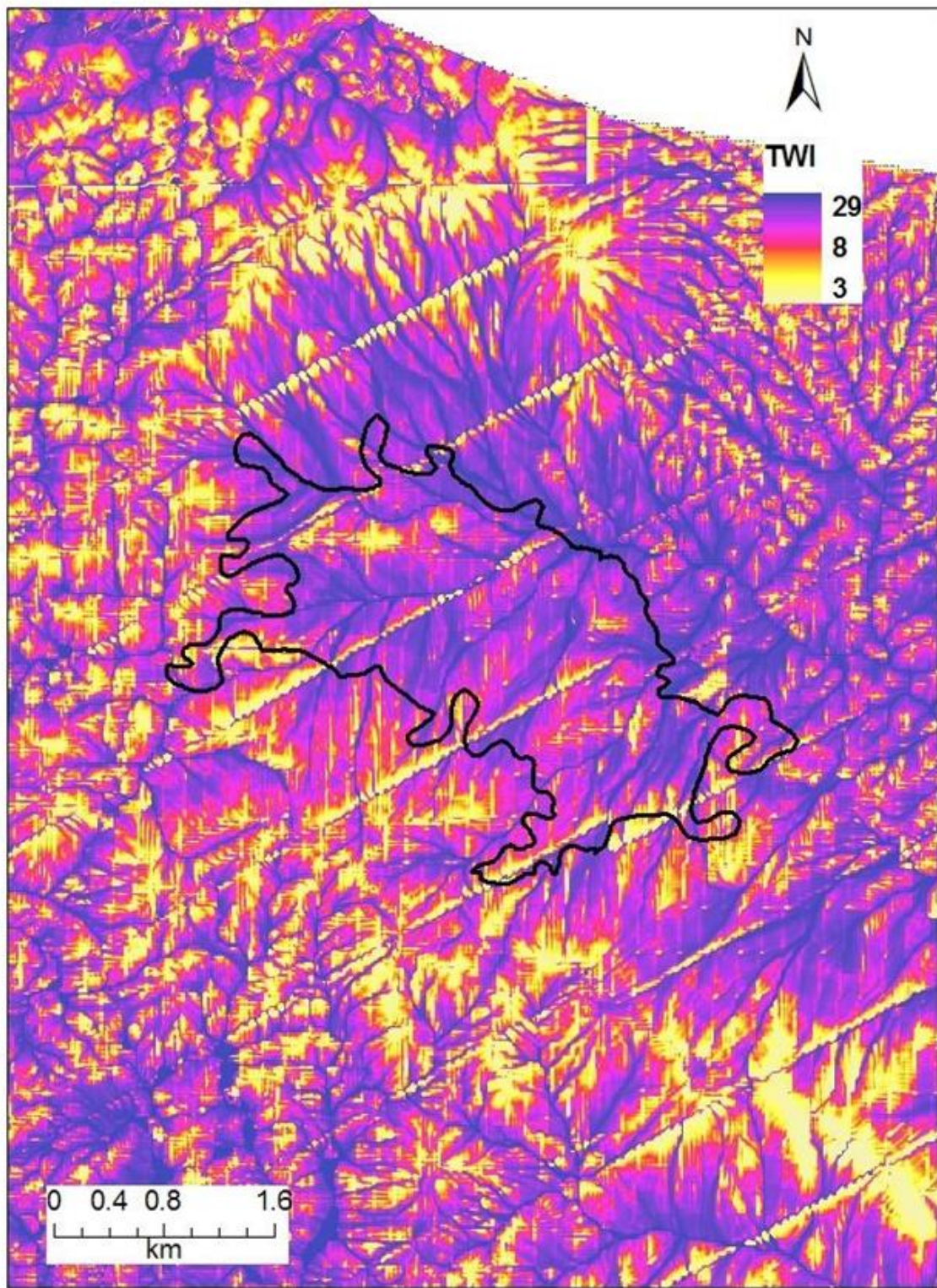


Figure A-13a. TWI values for Freeman grove and surrounding area.

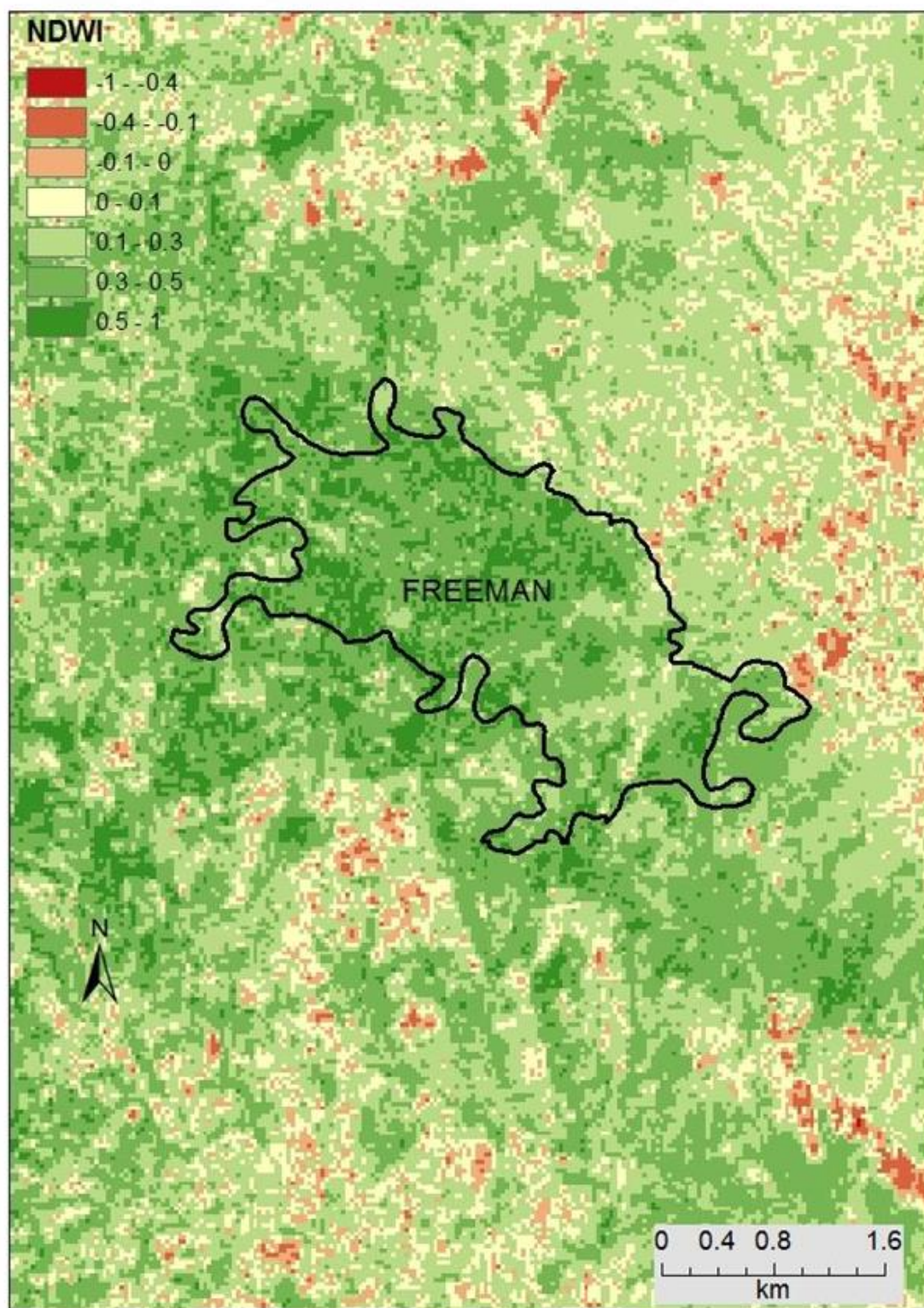


Figure A-13b. NDWI values for Freeman grove and surrounding area.

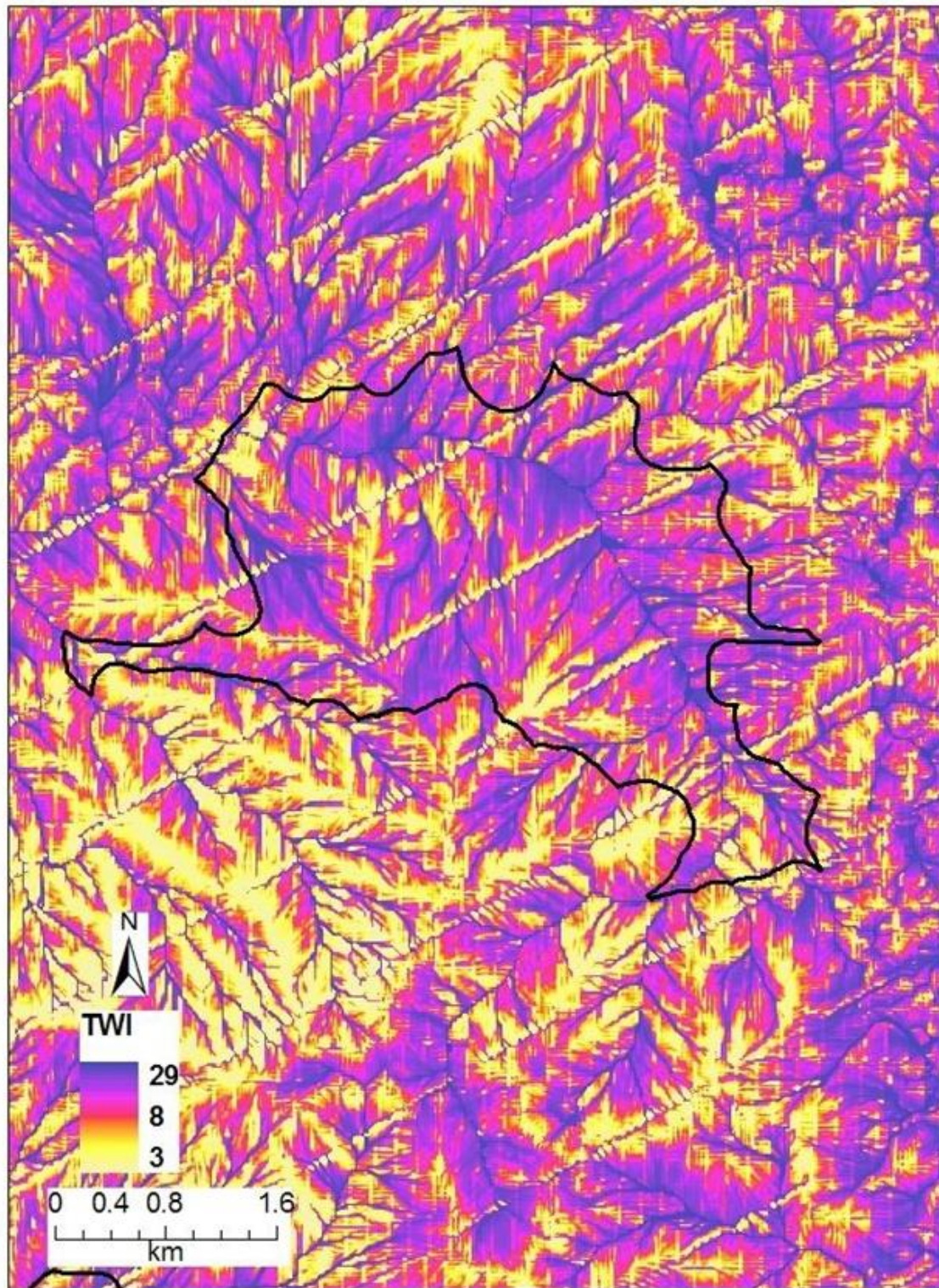


Figure A-14a. TWI values for Belknap grove and surrounding area.

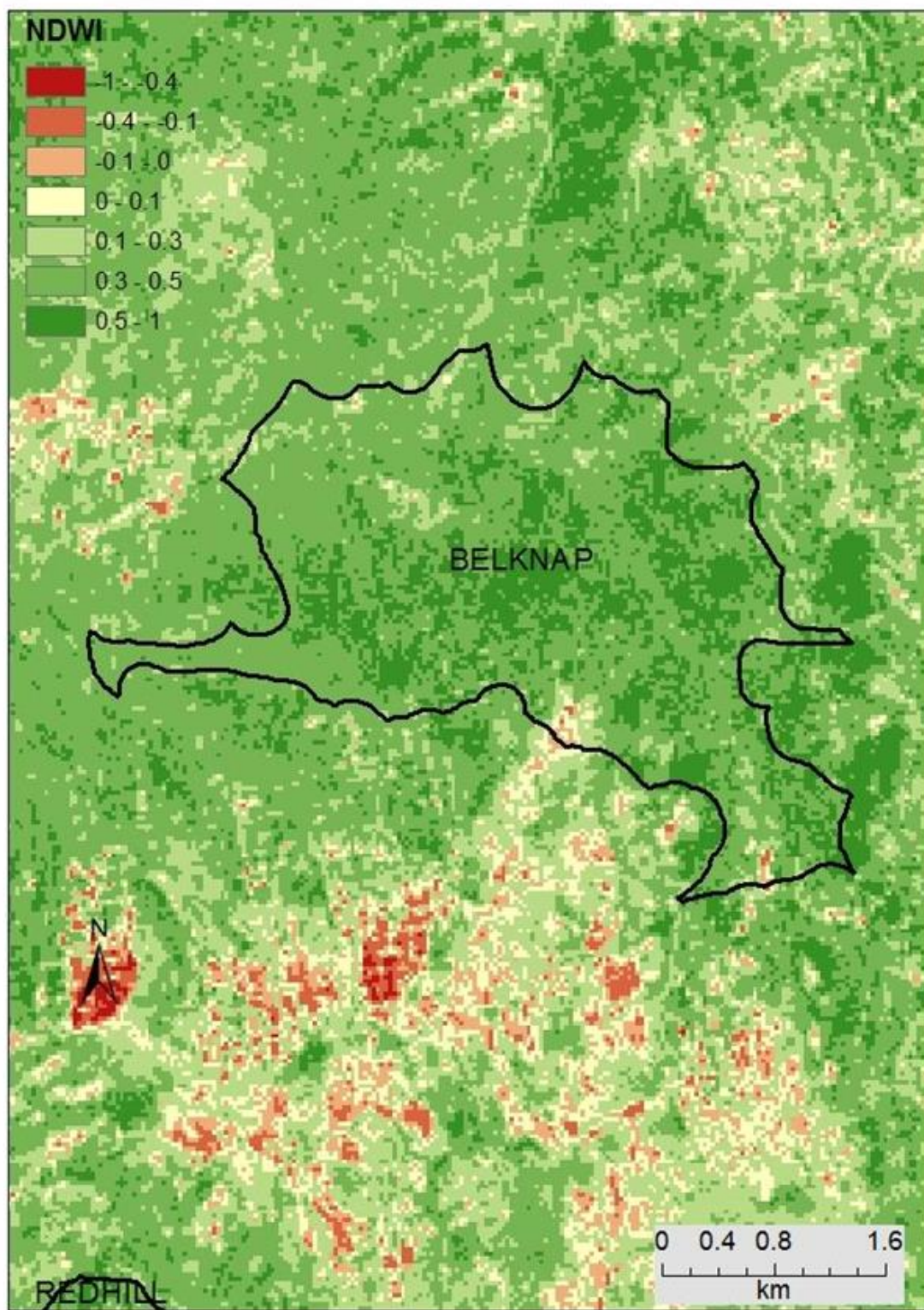


Figure A-14b. NDWI values for Belknap grove and surrounding area.

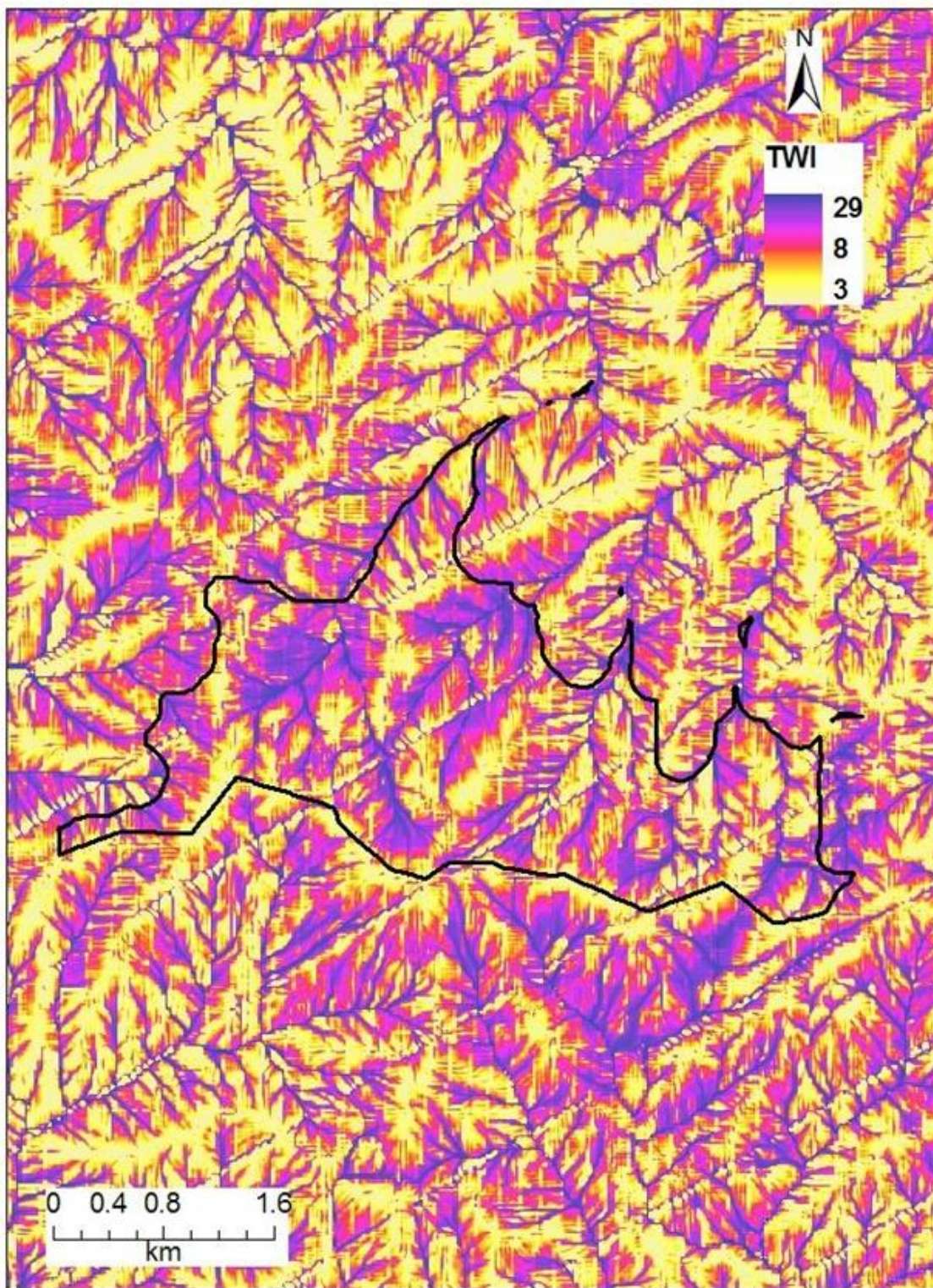


Figure A-15a. TWI values for Blackcap Mountain grove and surrounding area.

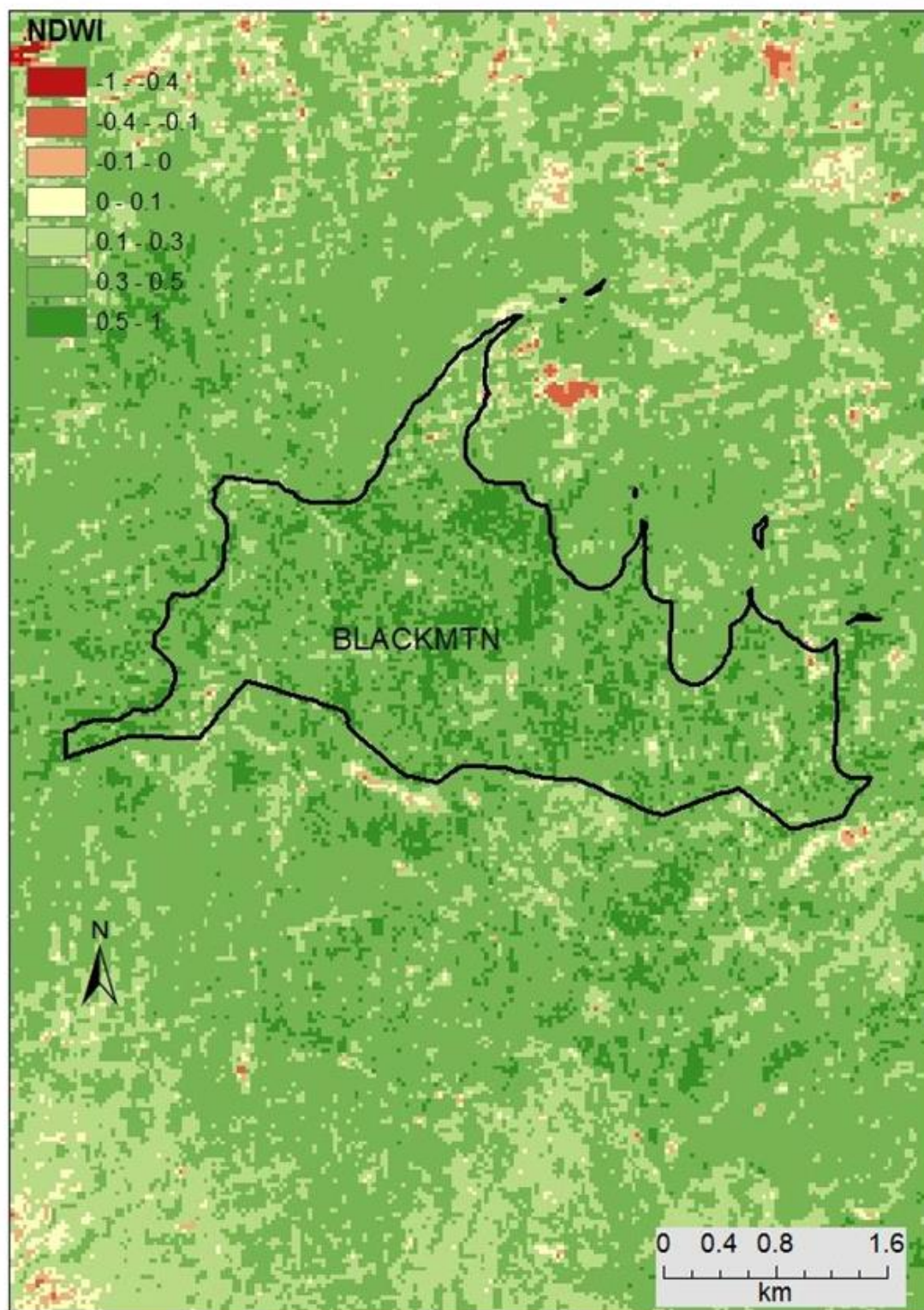


Figure A-15b. NDWI values for Blackcap Mountain grove and surrounding area.

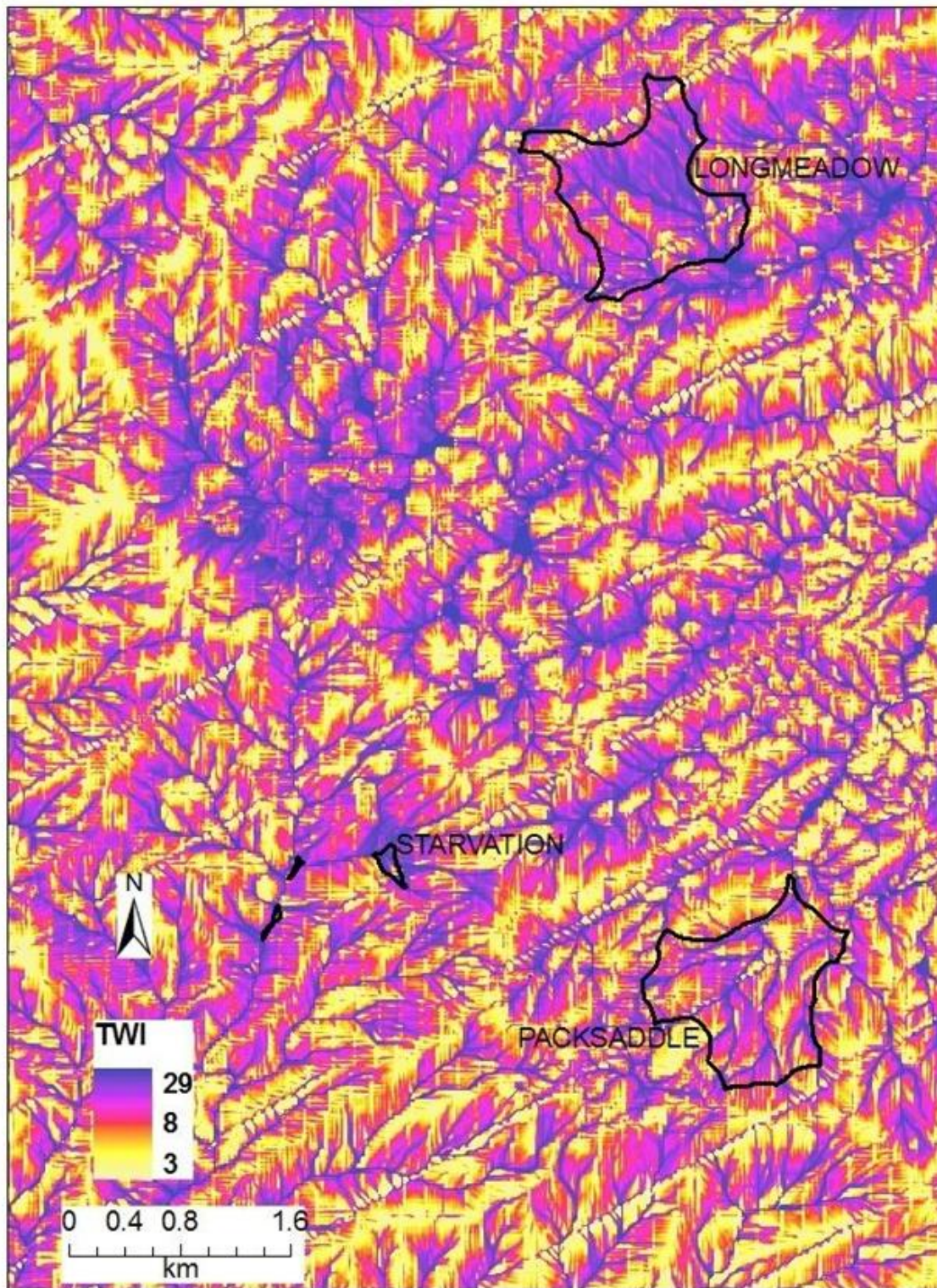


Figure A-16a. TWI values for Long Meadow, Starvation, Packsaddle groves and surrounding area

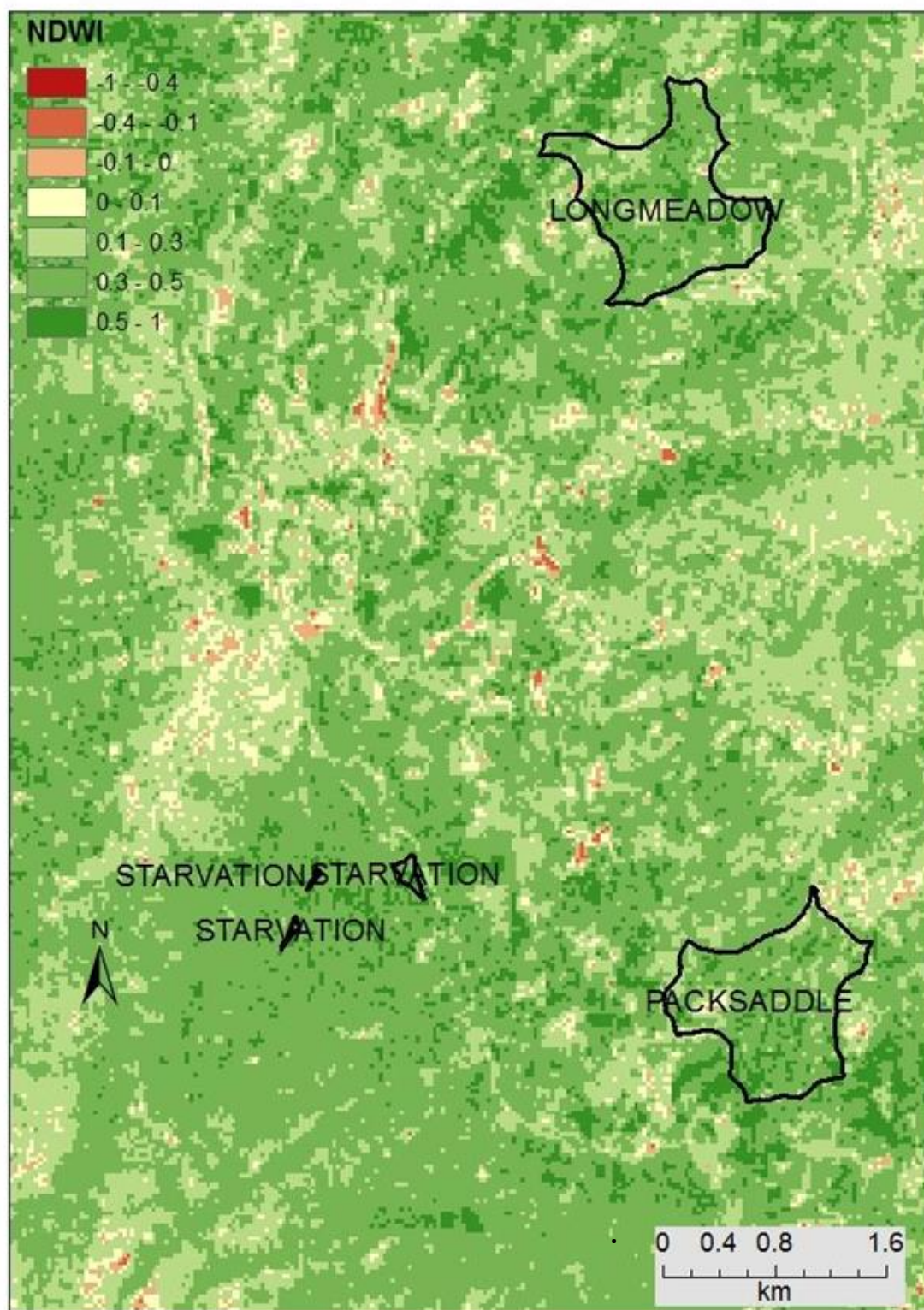


Figure A-16b. NDWI values for Long Meadow, Starvation, Packsaddle groves and surrounding area.

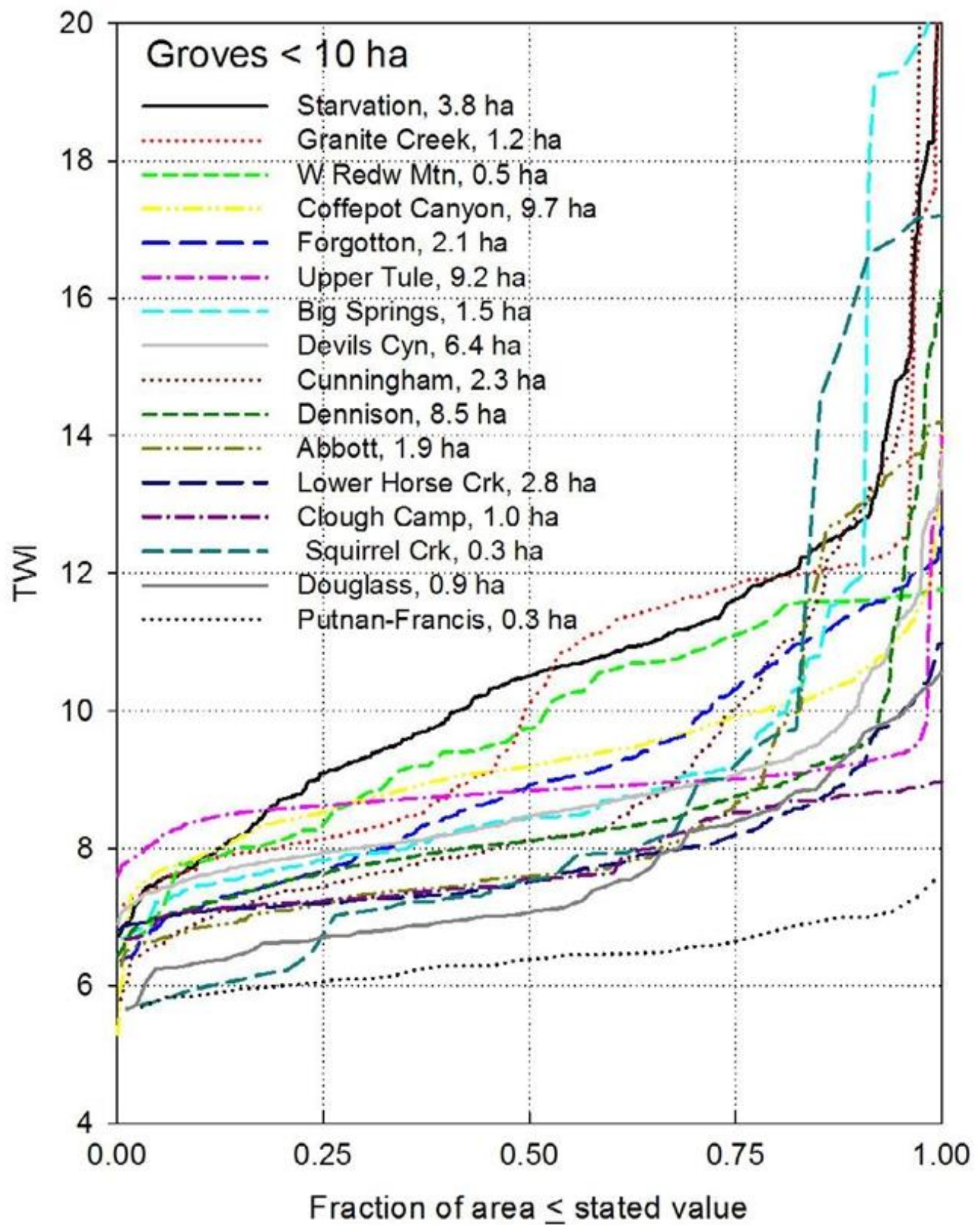


Figure A-17. Distribution of TWI values for smallest groves.

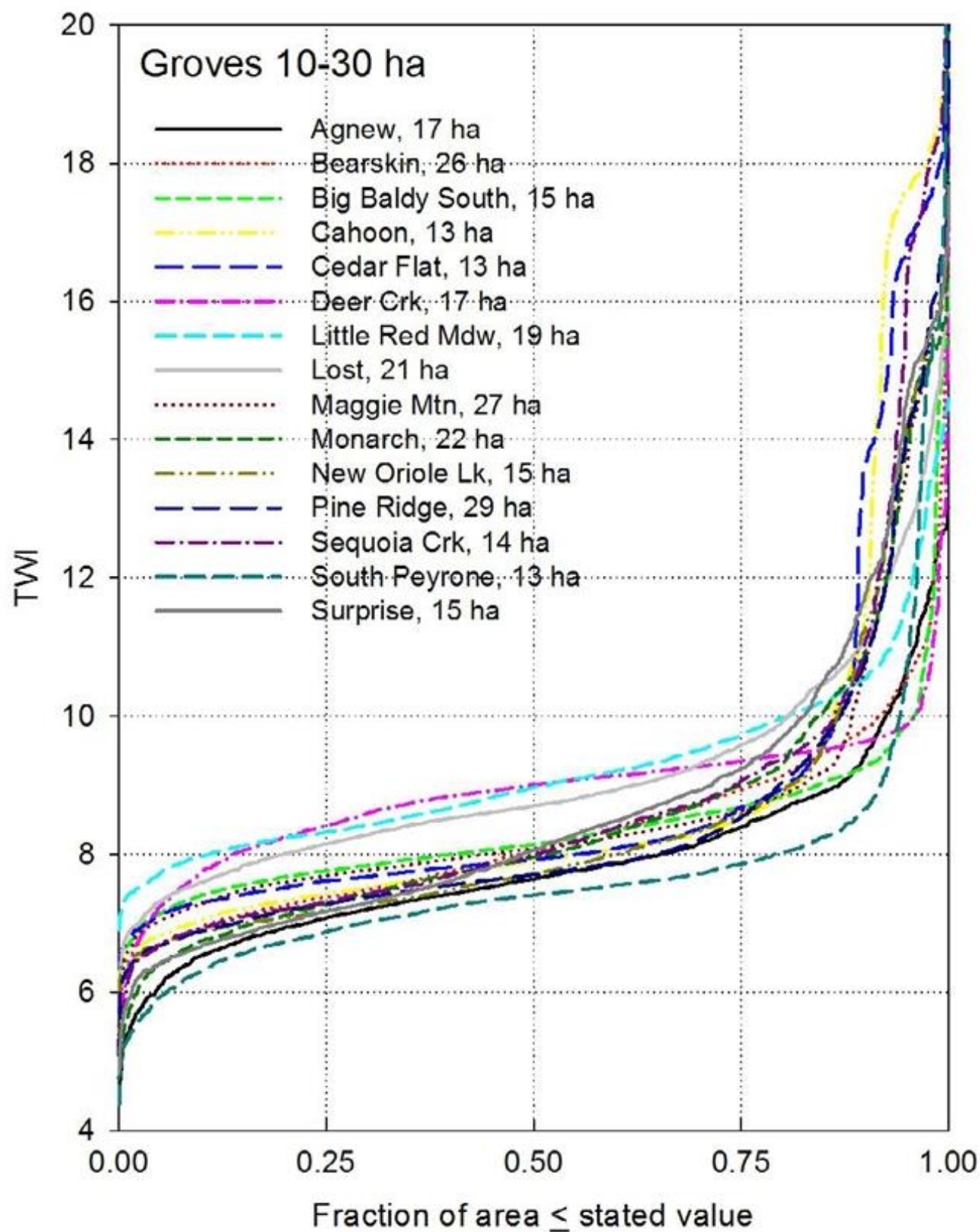


Figure A-18. Distribution of TWI values for small groves > 10 ha.

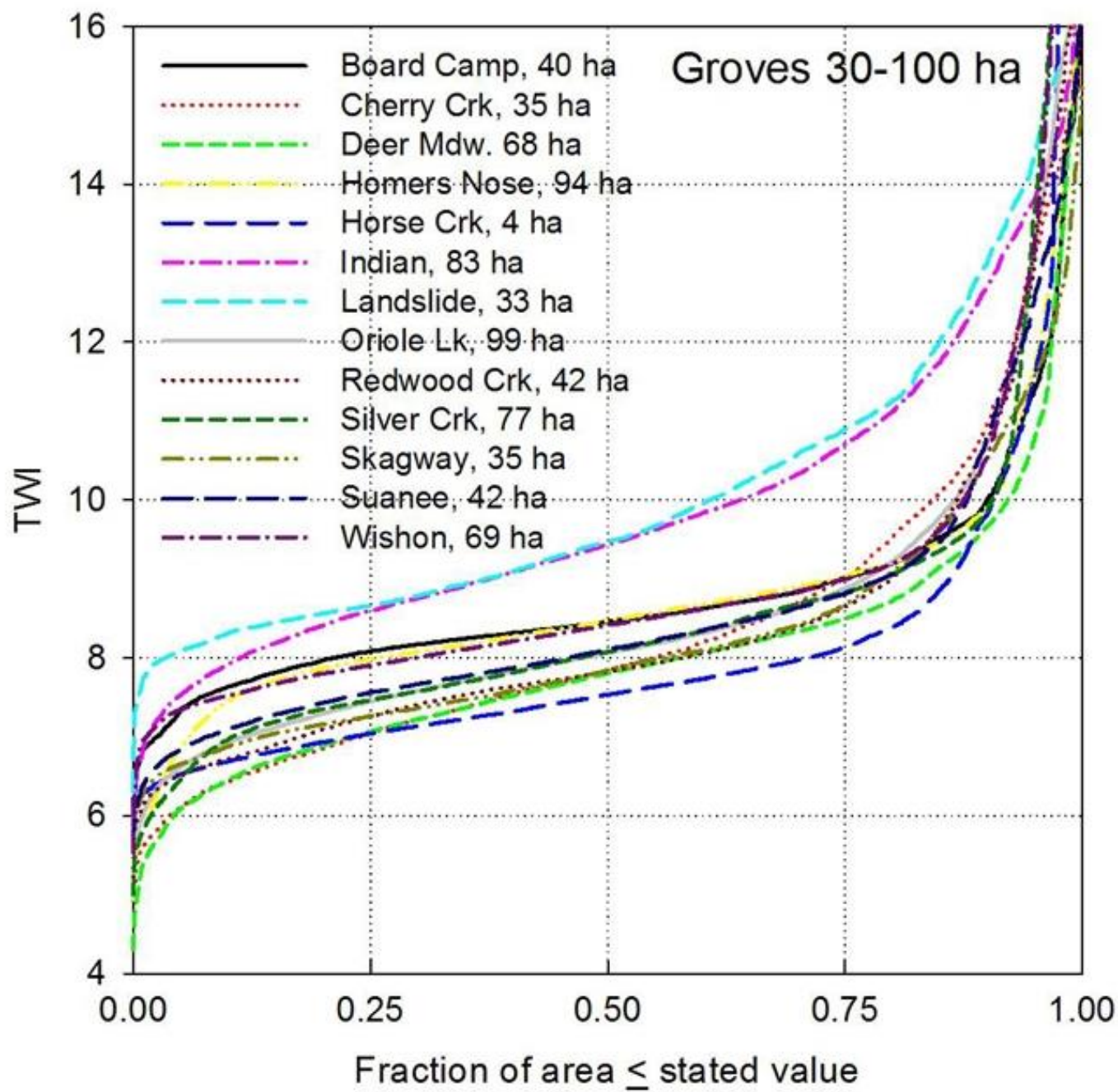


Figure A-19. Distribution of TWI values for medium-sized groves.

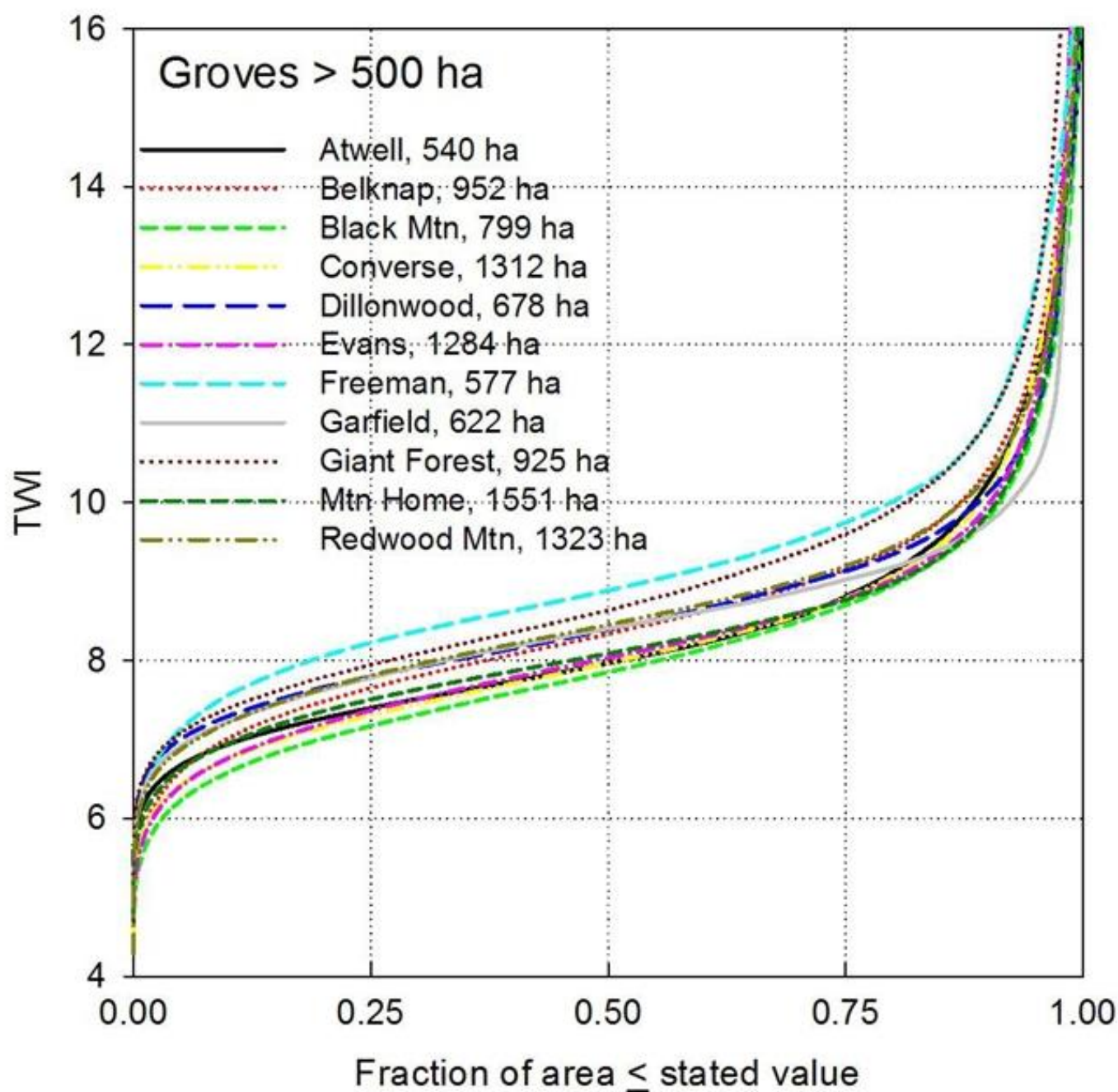


Figure A-20. Distribution of TWI values for larger groves.

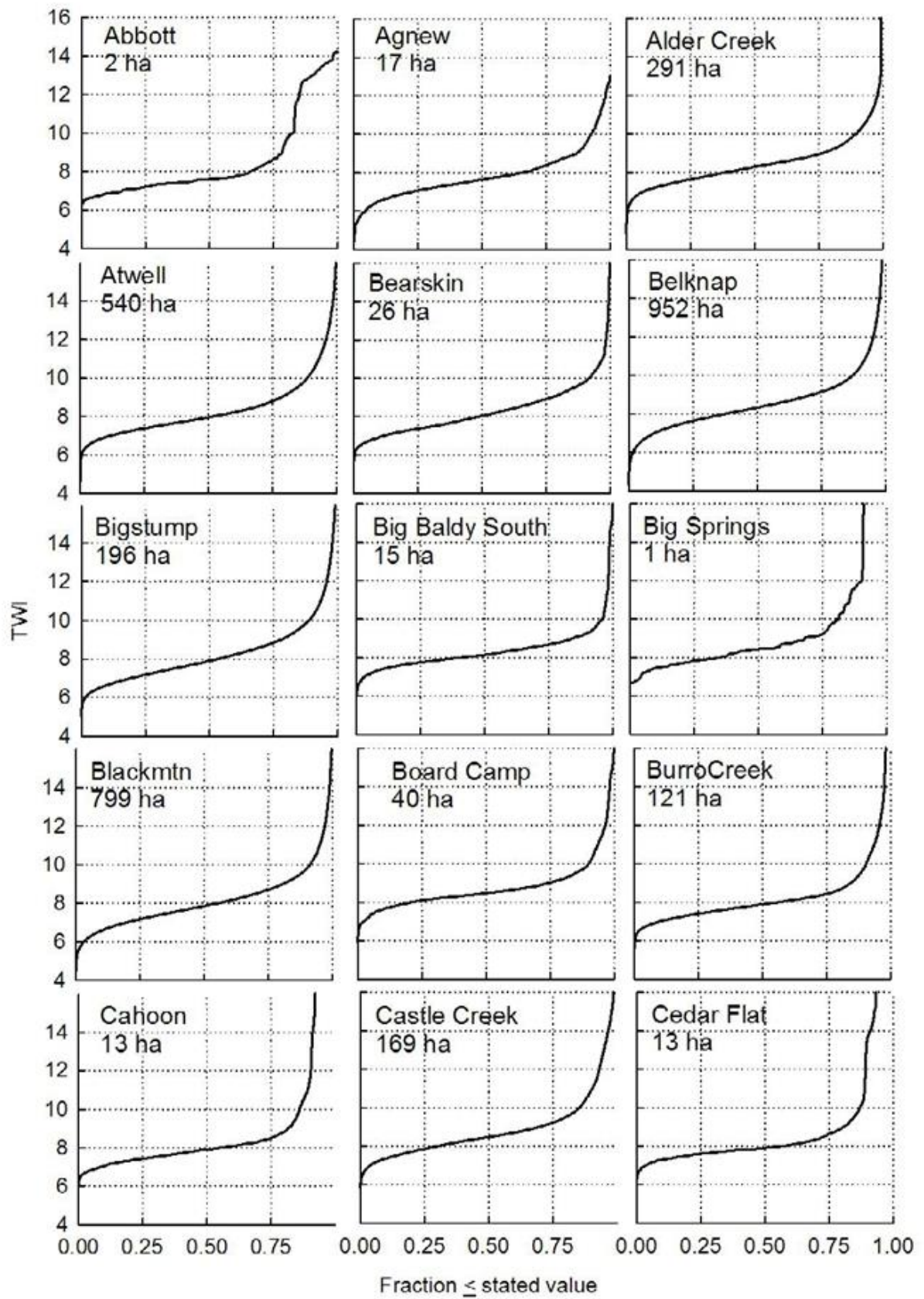
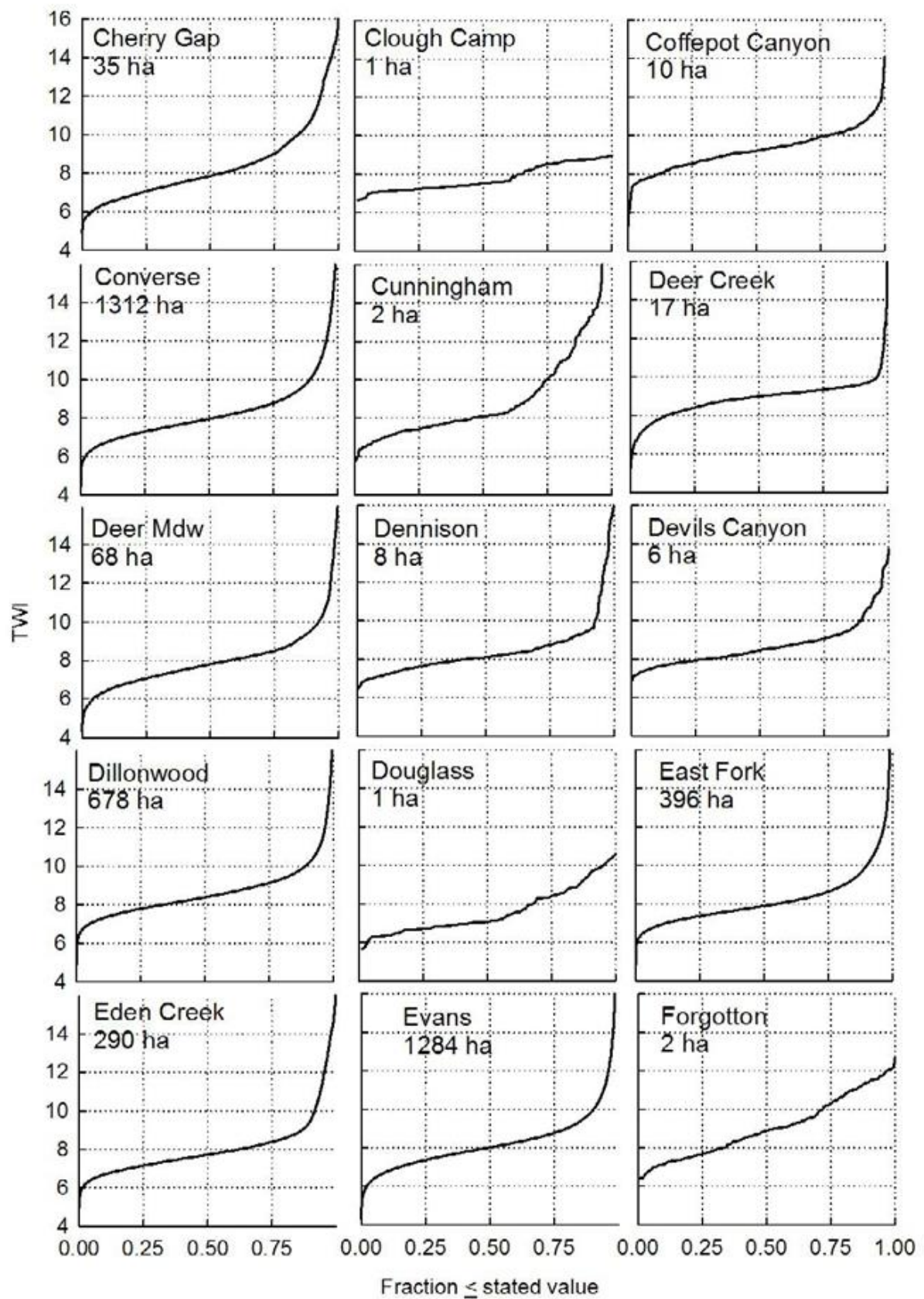
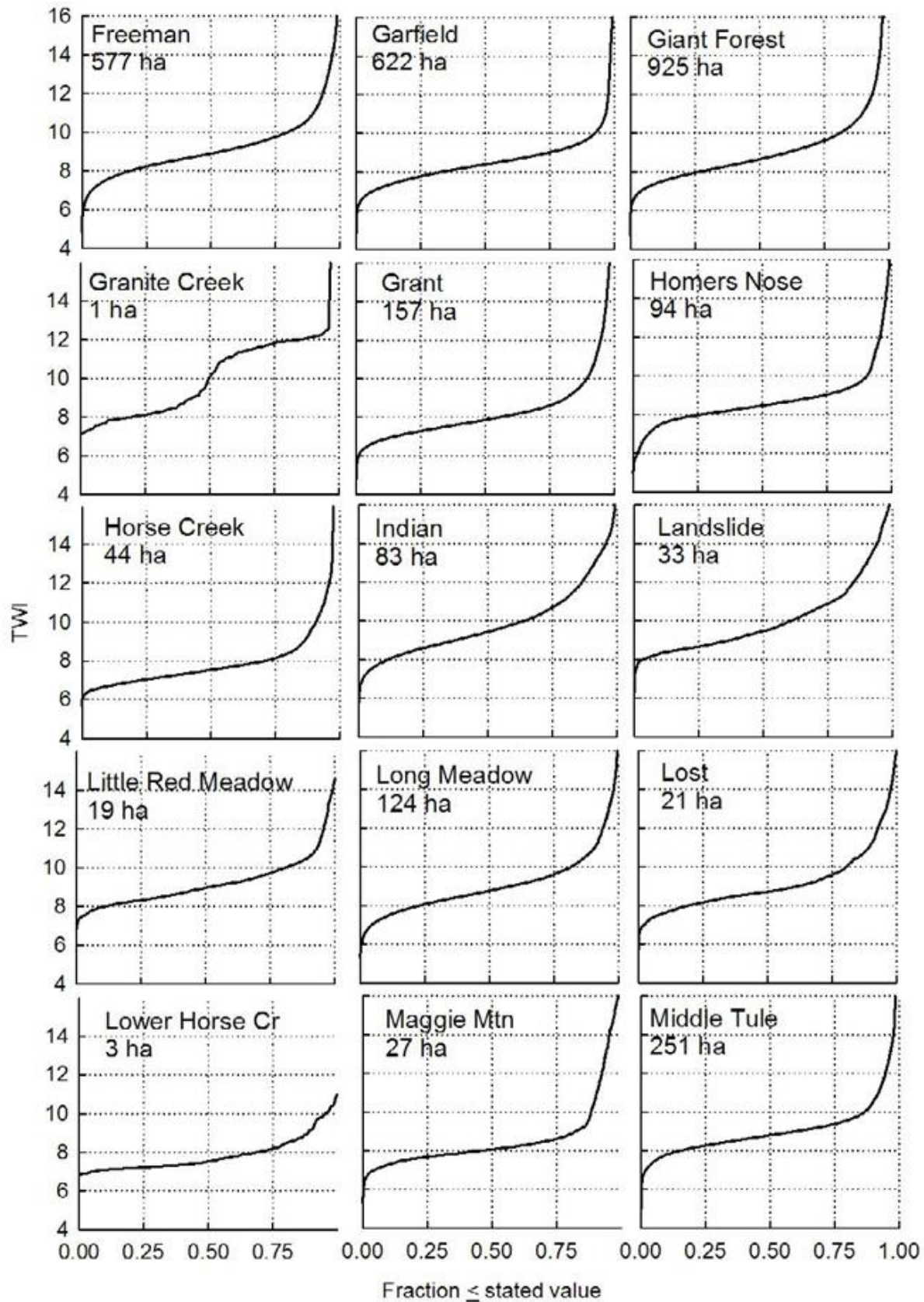
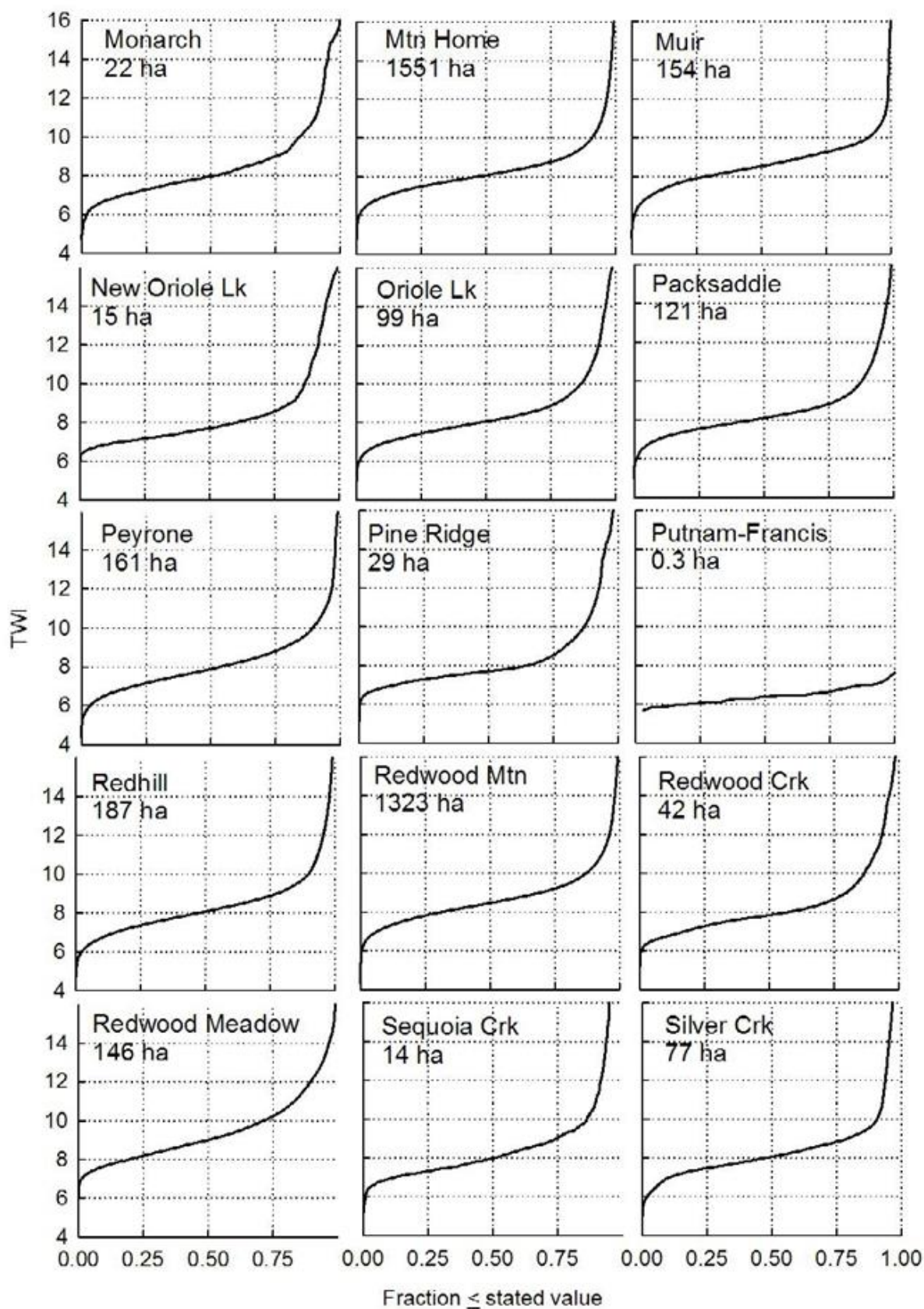
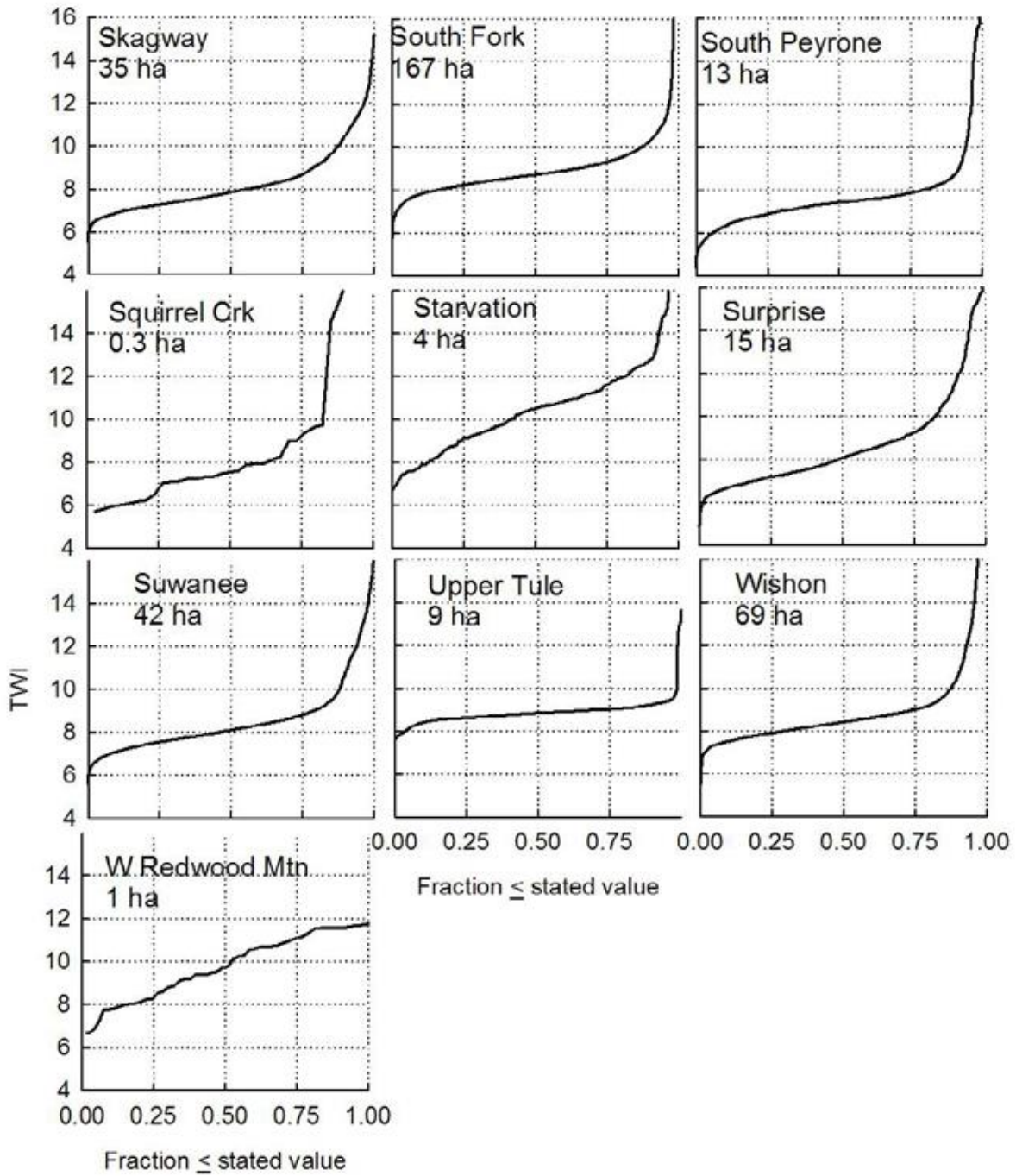


Figure A-21. Distribution of TWI values for largest groves.









Appendix C

Large-scale maps of spatial patterns of moisture indices in groves

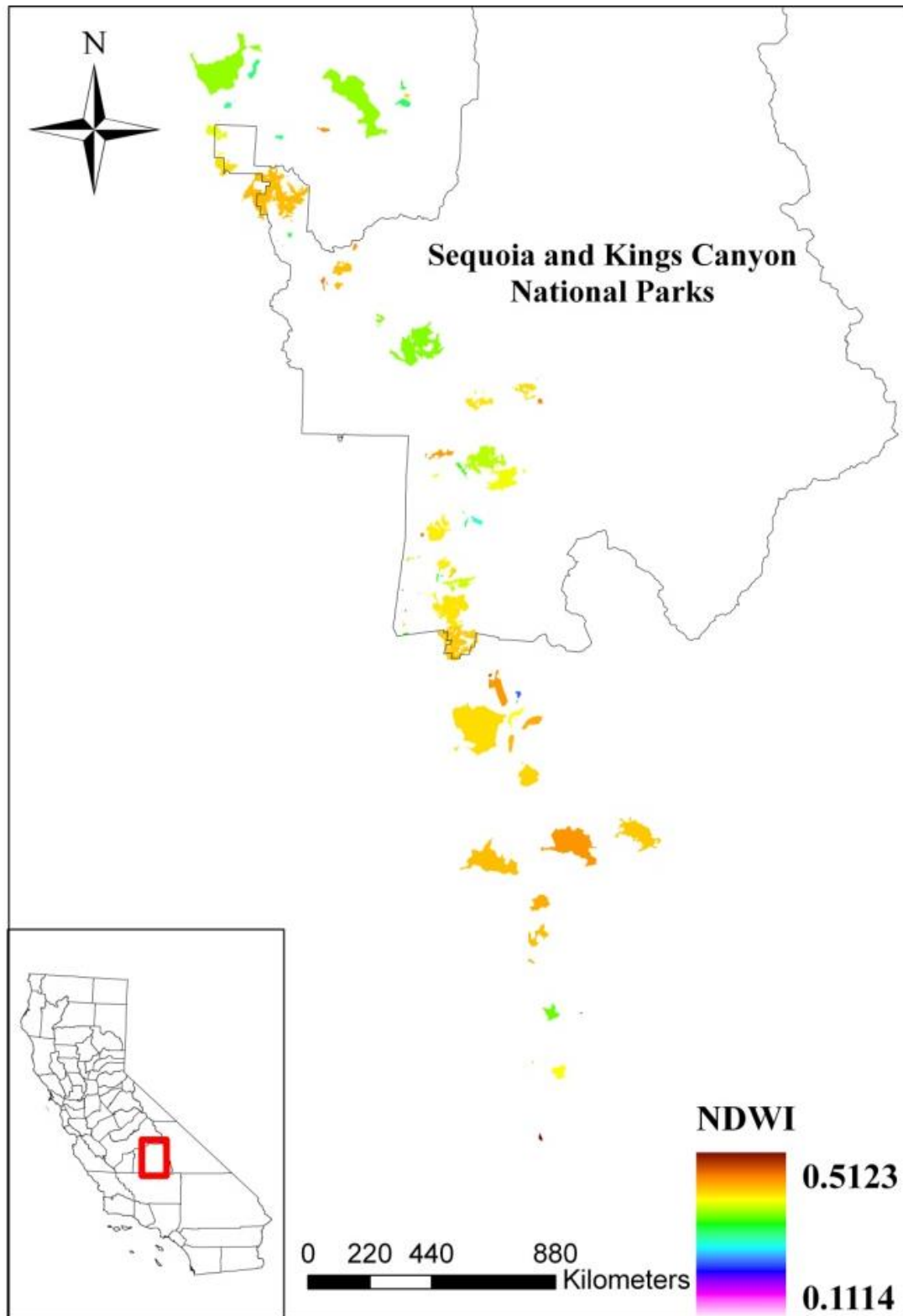


Figure A-22a. Grove-based distributions of NDWI. Values shown here are the average values over 27 years (1984–2010) for each giant sequoia grove.

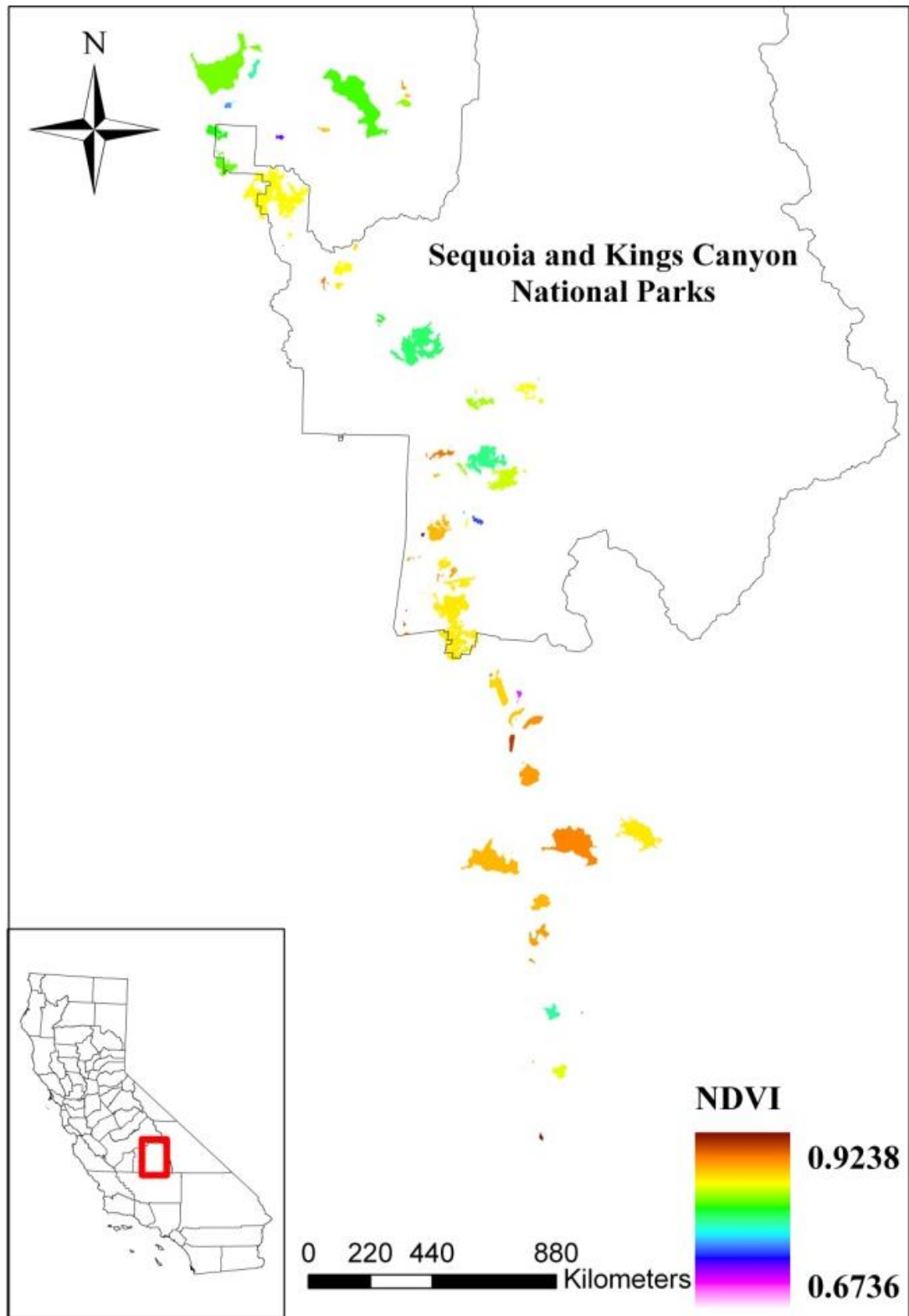


Figure A-22b. Grove-based distributions of NDVI. Values shown here are the average values over 27 years (1984–2010) for each giant sequoia grove.

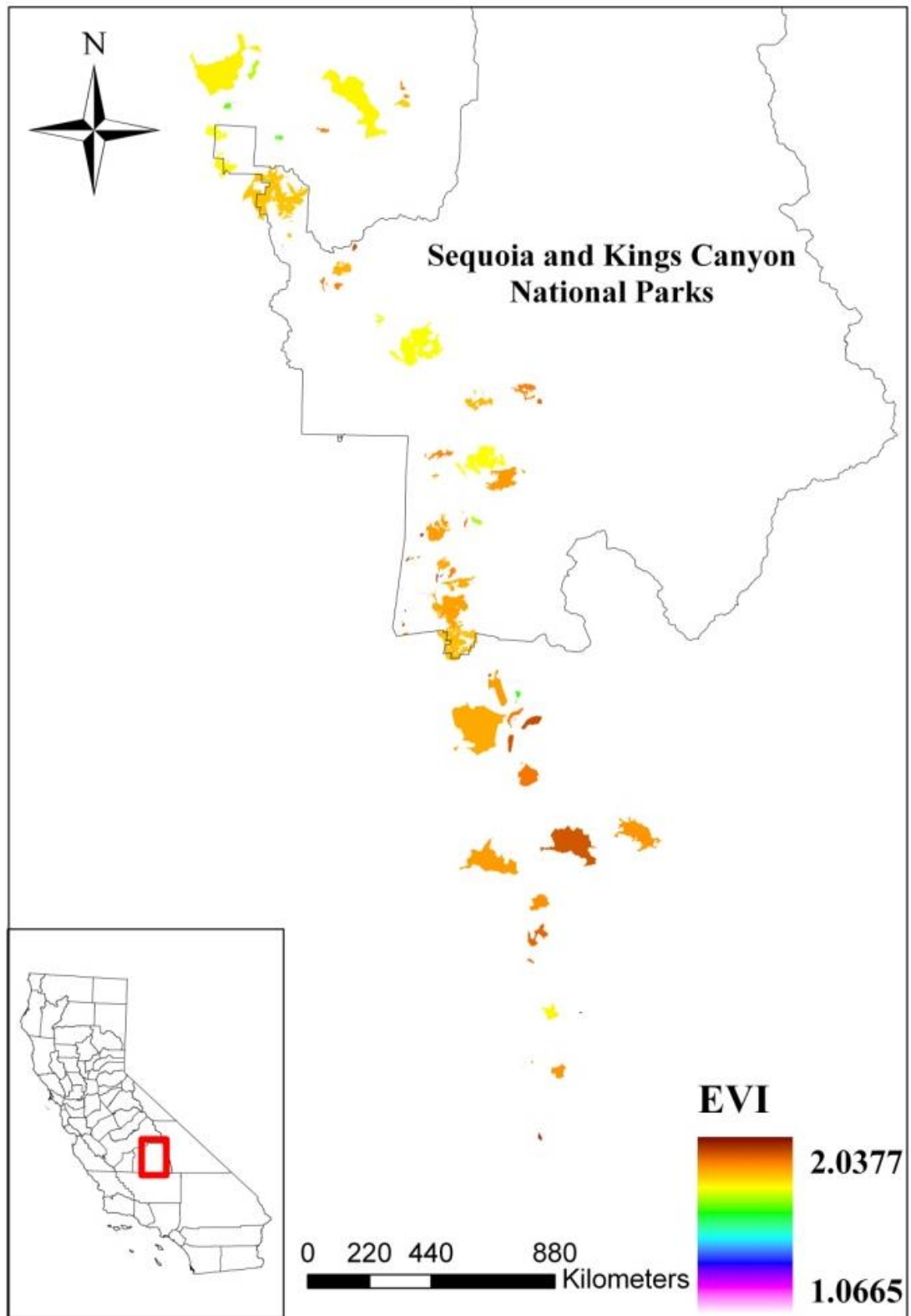


Figure A-22c. Grove-based distributions of EVI. Values shown here are the average values over 27 years (1984–2010) for each giant sequoia grove.

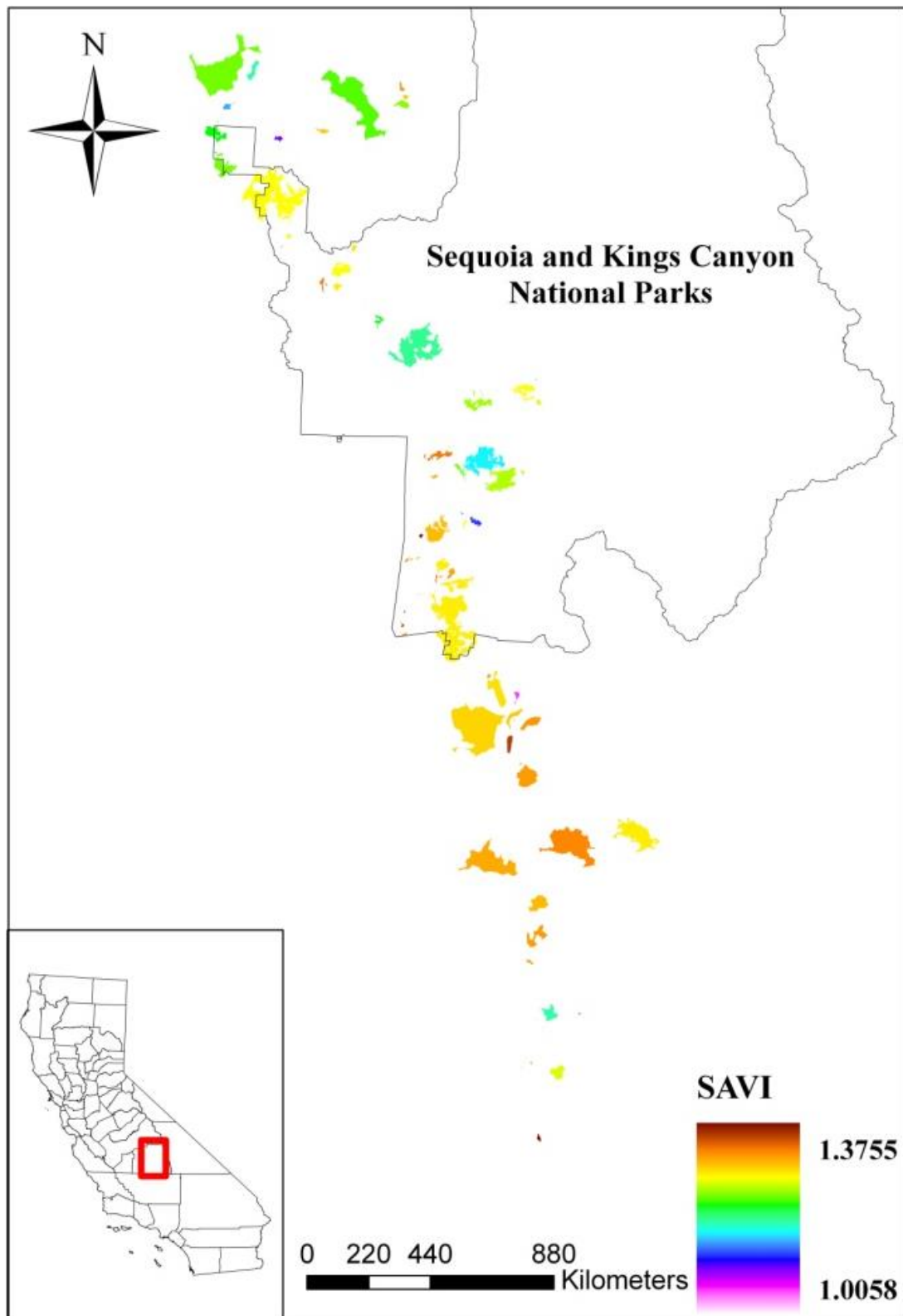


Figure A-22d. Grove-based distributions of SAVI. Values shown here are the average values over 27 years (1984–2010) for each giant sequoia grove.

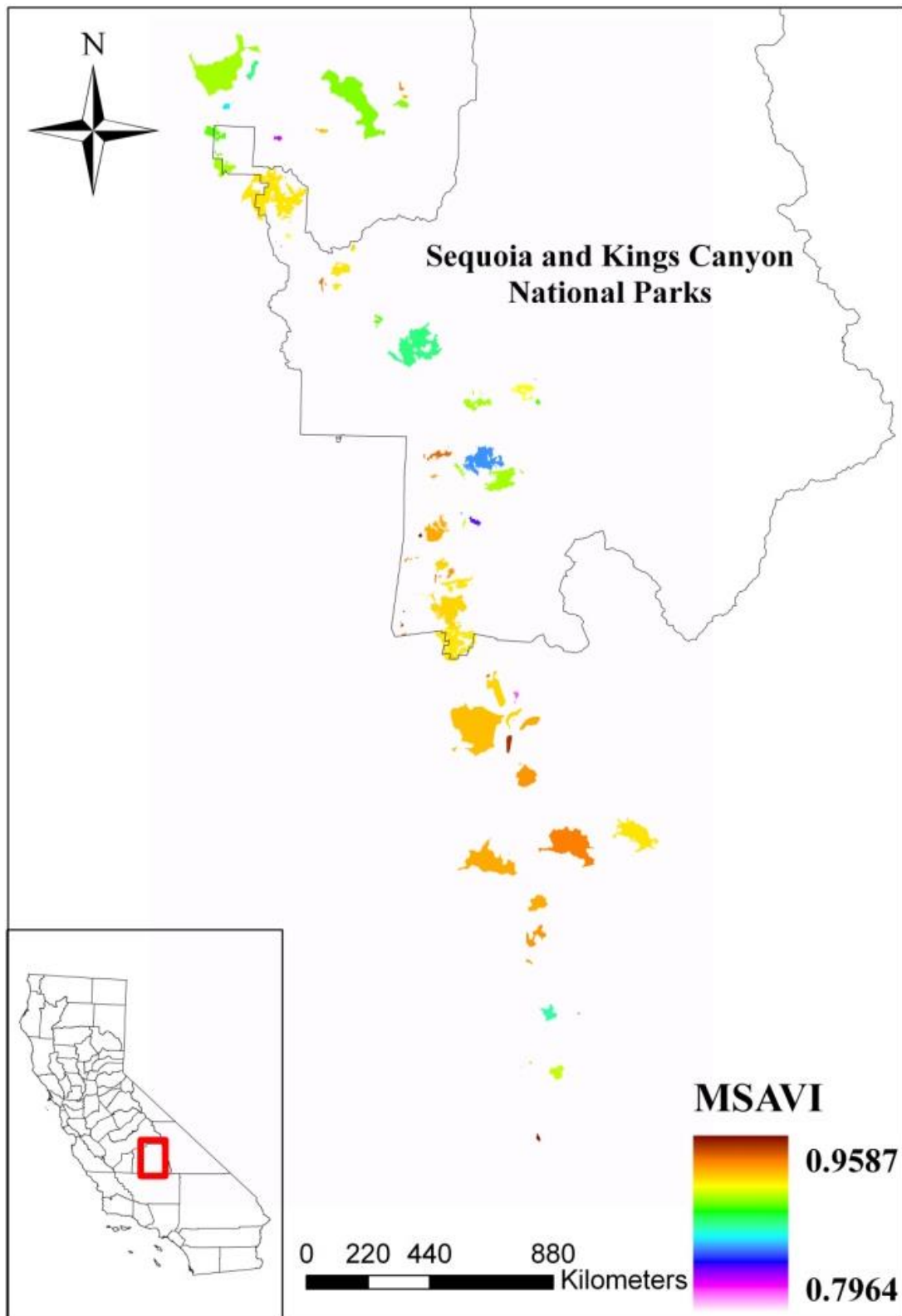


Figure A-22e. Grove-based distributions of MSAVI. Values shown here are the average values over 27 years (1984–2010) for each giant sequoia grove.

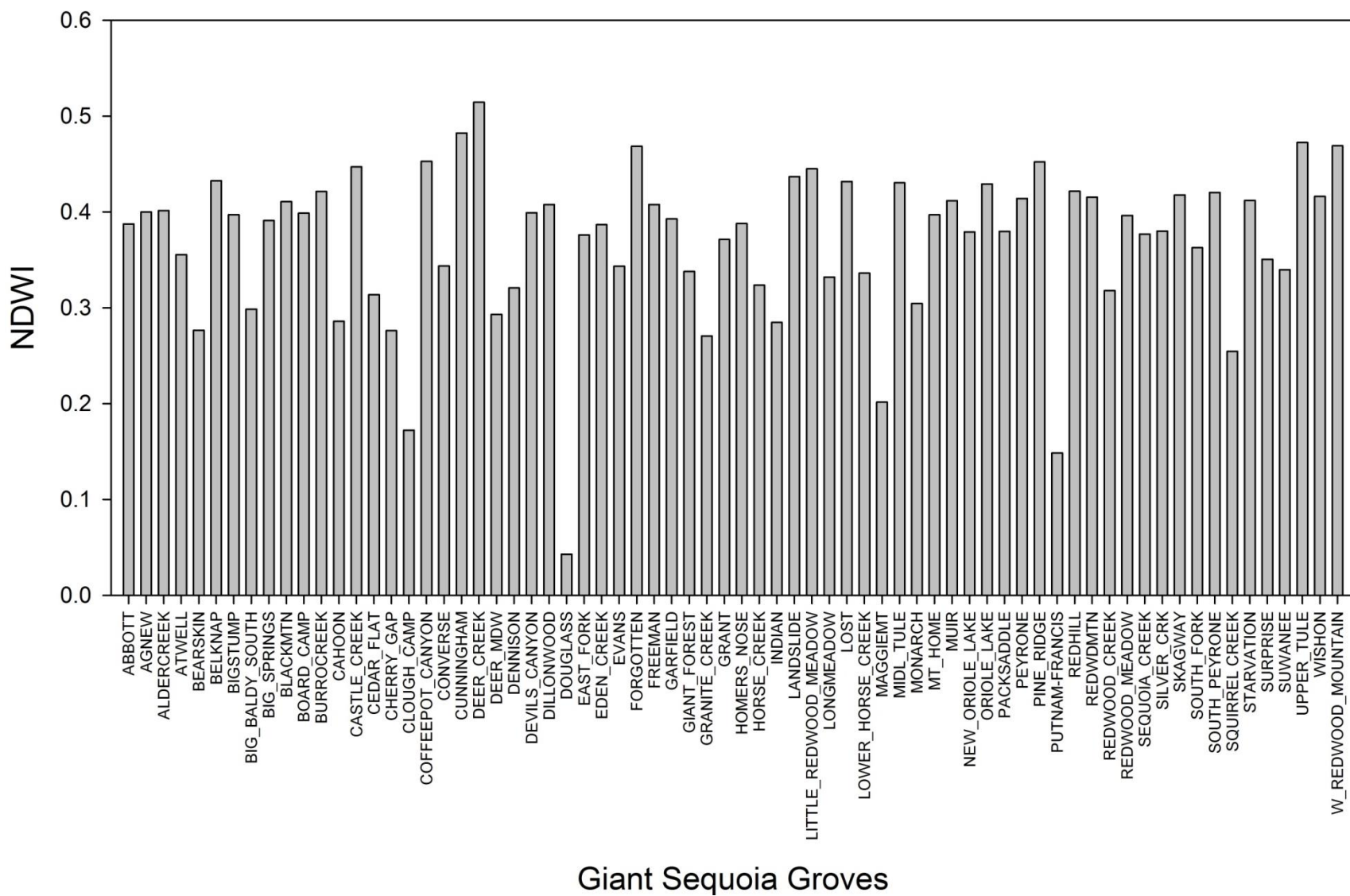


Figure A-23a. Average NDWI over 27 years (1984–2010) for each giant sequoia grove

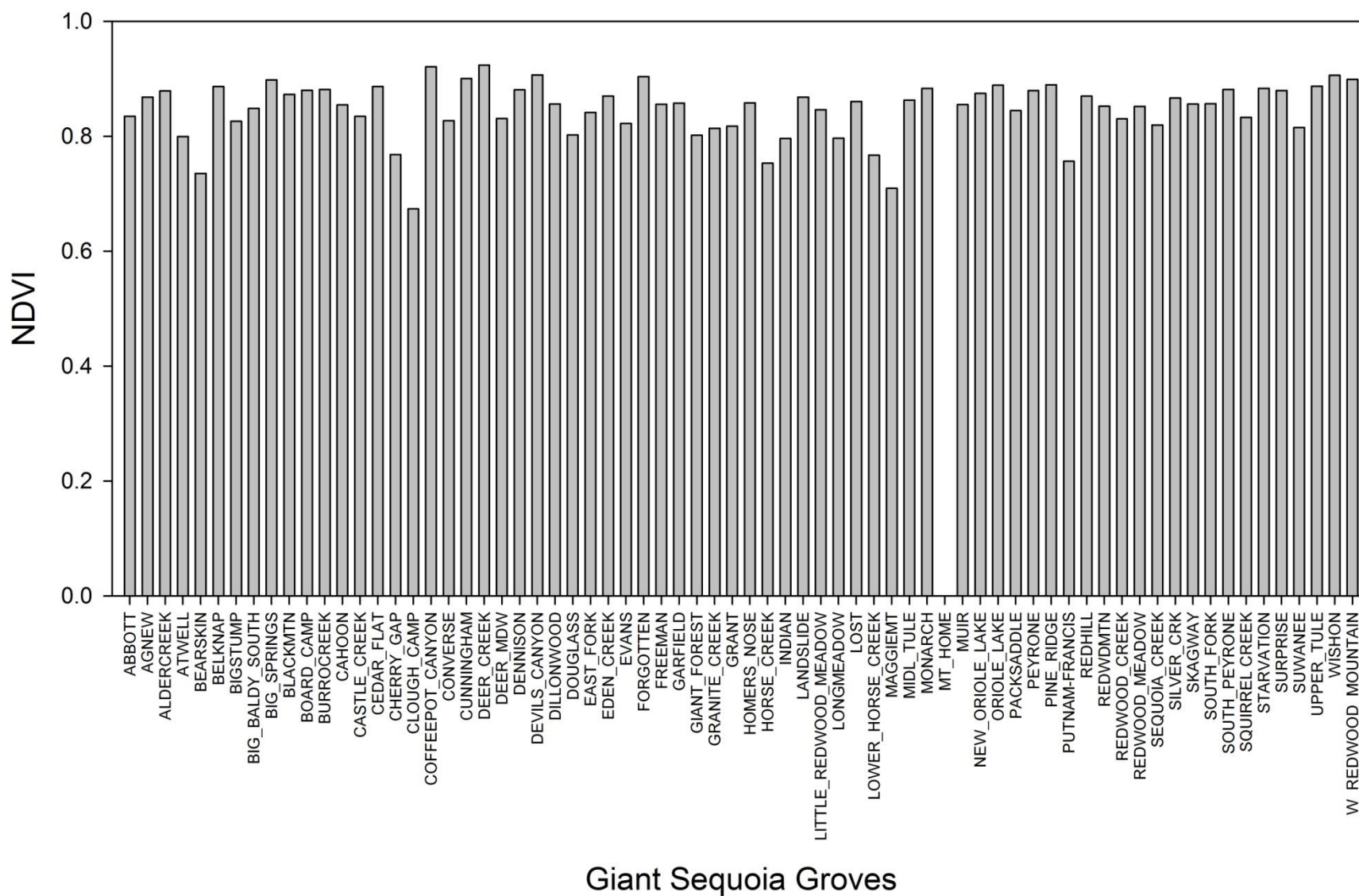


Figure A-23b. Average NDVI over 27 years (1984–2010) for each giant sequoia grove

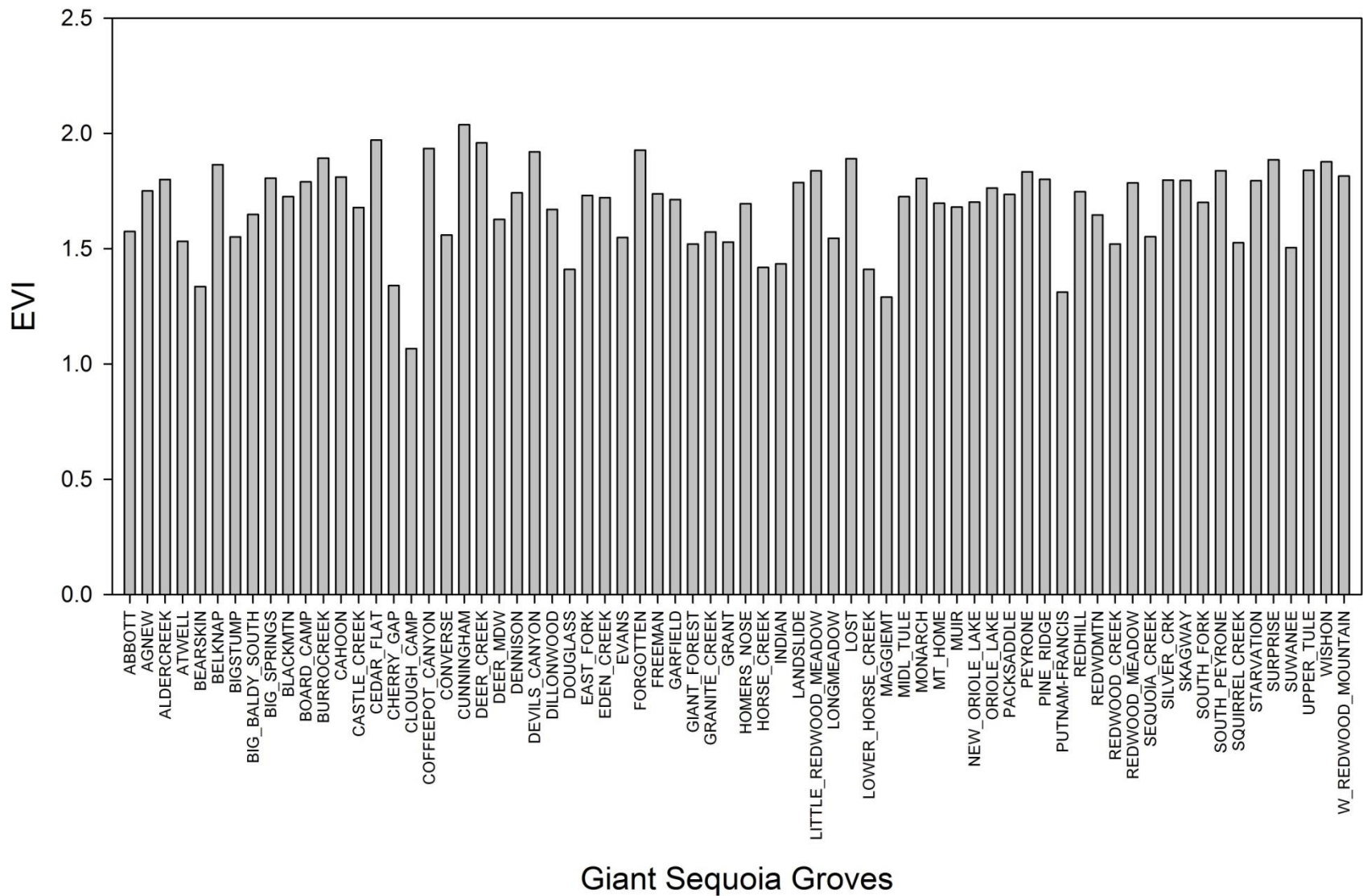


Figure A-23c. Average EVI over 27 years (1984–2010) for each giant sequoia grove

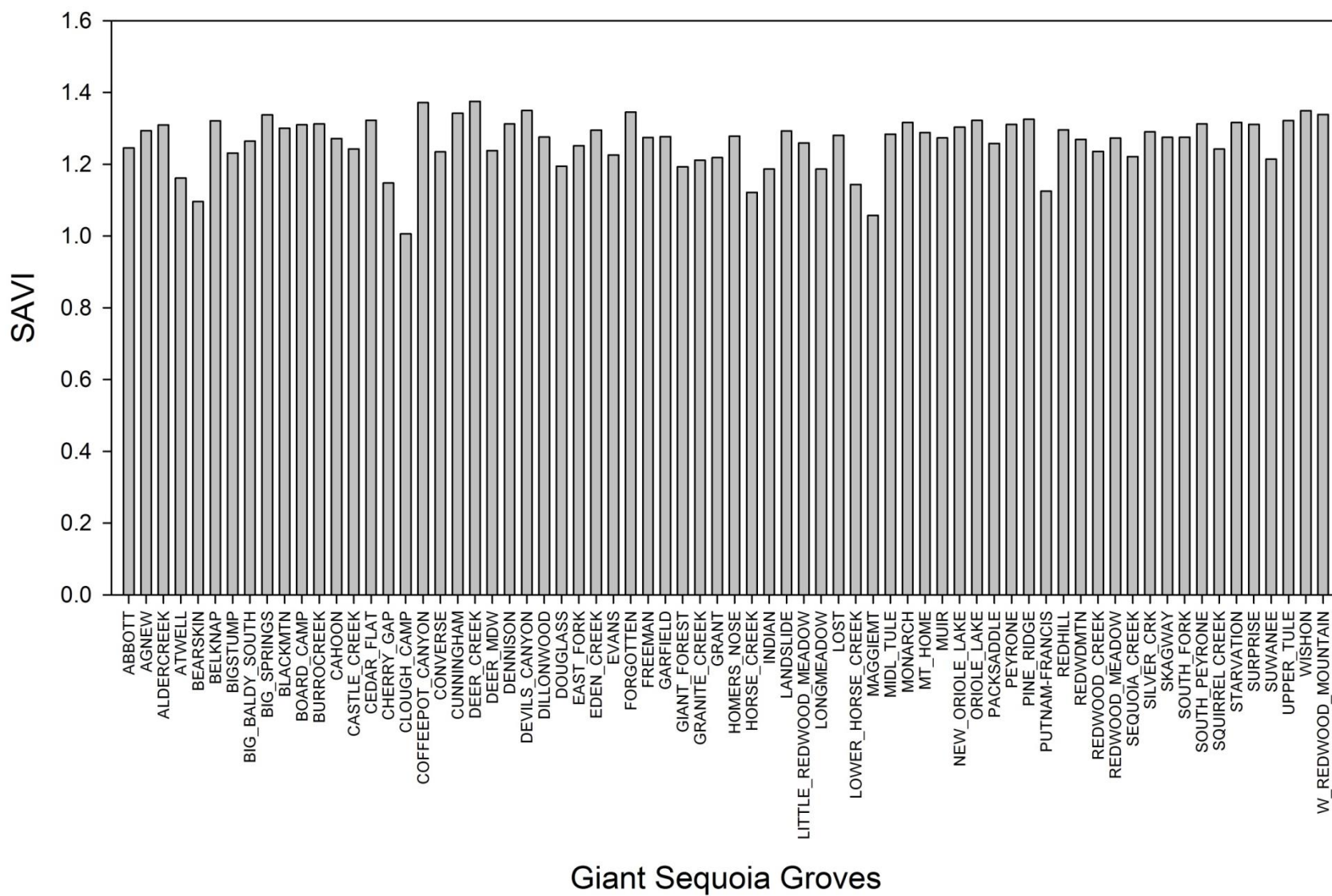


Figure A-23d. Average SAVI over 27 years (1984–2010) for each giant sequoia grove

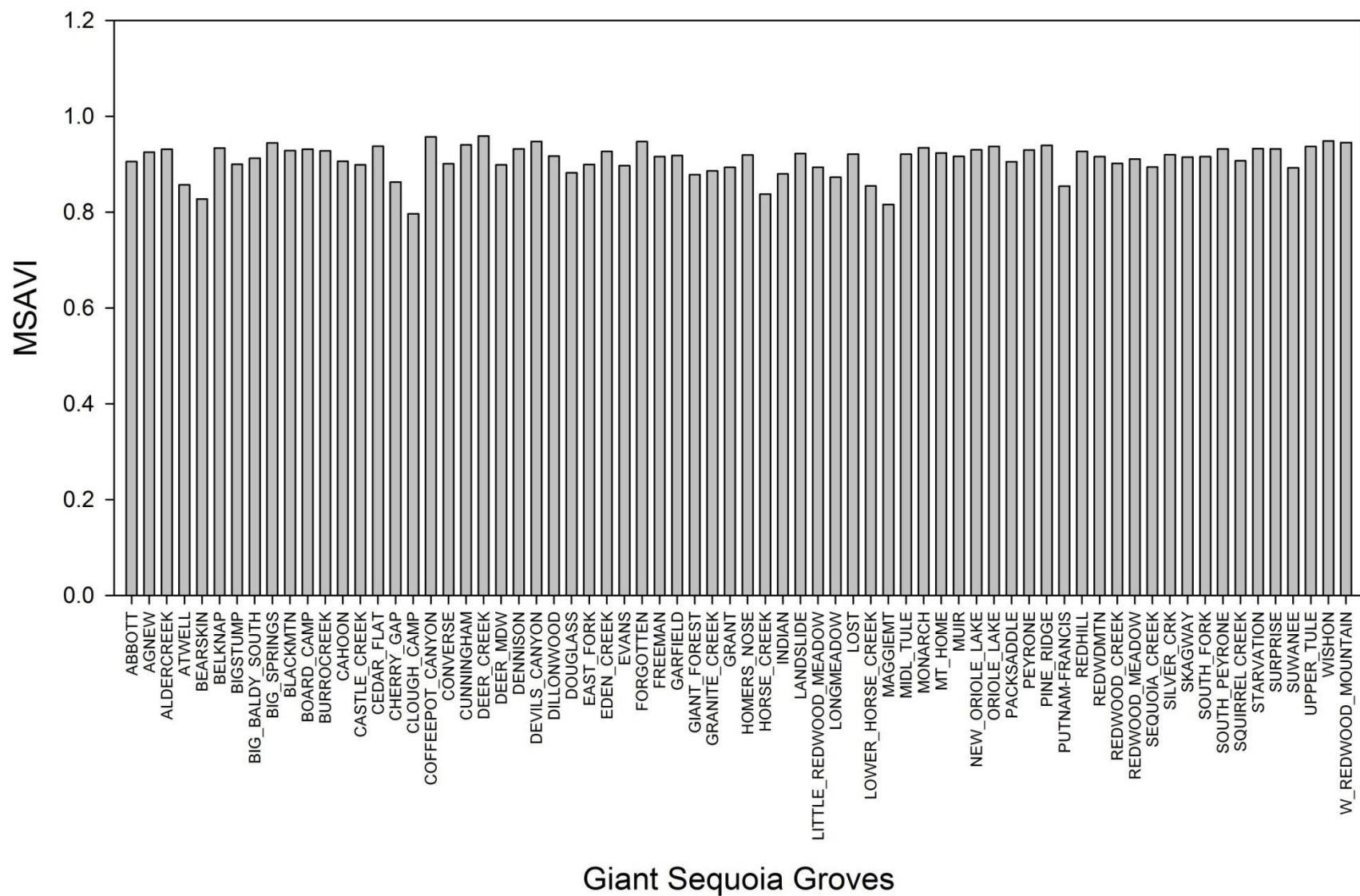


Figure A-23e. Average MSAVI over 27 years (1984–2010) for each giant sequoia grove

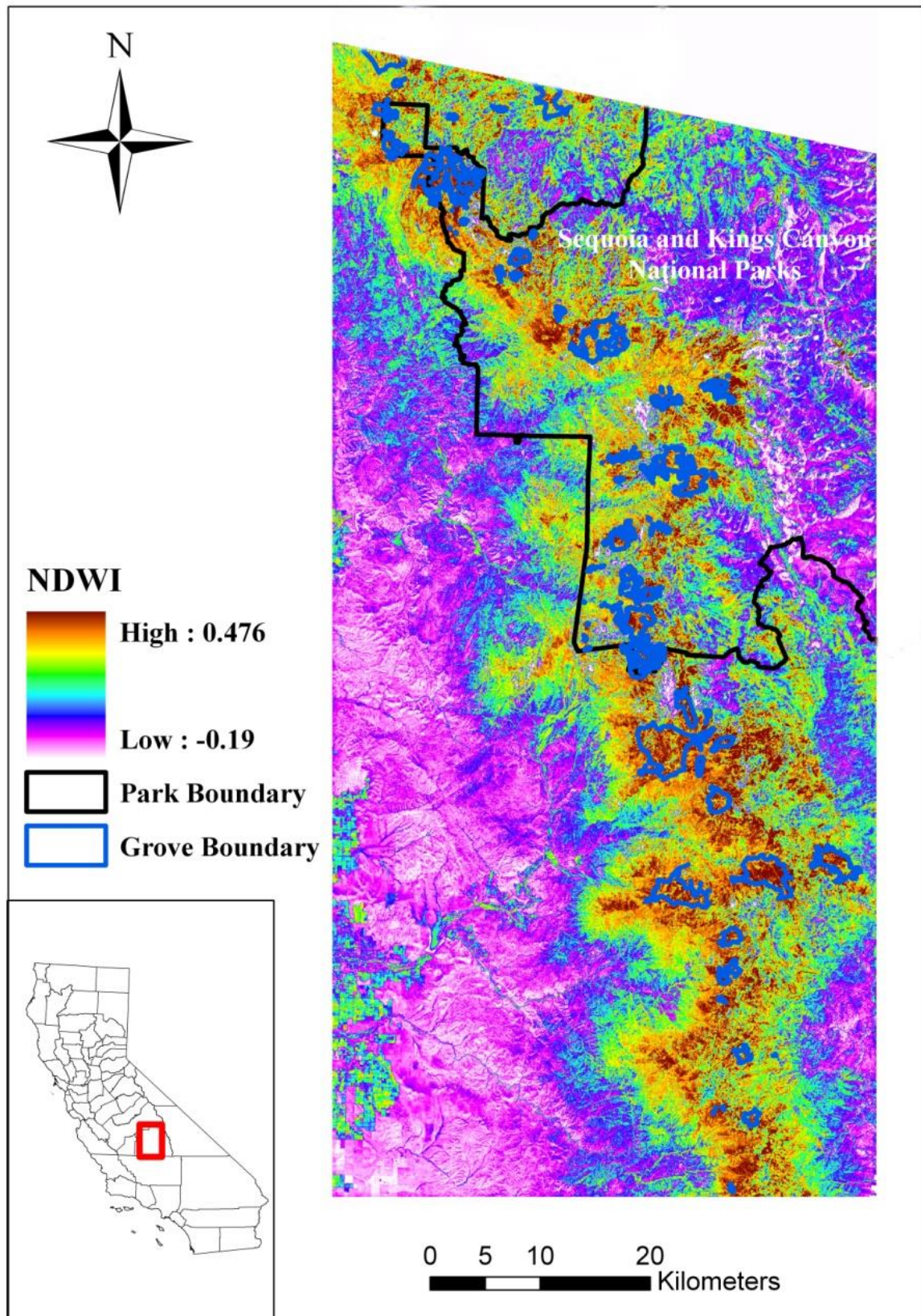


Figure A-24. Average NDWI over 27 years (1984–2010) for each pixel within an extended area.