

geodiv_vignette

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Install *geodiv*

geodiv is an R package that provides methods for calculating gradient surface metrics for continuous analysis of landscape features. There are a couple of ways to download and install the *geodiv* R package. You can install the released version of *geodiv* from CRAN with:

```
install.packages("geodiv")
```

And the development version from GitHub with:

```
install.packages("devtools")
devtools::install_github("bioXgeo/geodiv")
```

Note that Mac OS users may need to install the development tools here to get the package to install:

<https://cran.r-project.org/bin/macosx/tools/>

To begin, let's load the necessary packages for the examples that follow.

```
library(geodiv)
library(raster)
library(rasterVis)
library(mapdata)
library(maptools)
library(rgeos)
library(ggplot2)
library(tidyverse)
library(parallel)
library(sf)
library(rasterVis)
library(ggmap)
library(corrplot)
library(gridExtra)
library(cowplot)
library(factoextra)
library(cluster)
library(rfigshare)
```

Example 1: Simple workflow with Landsat NDVI

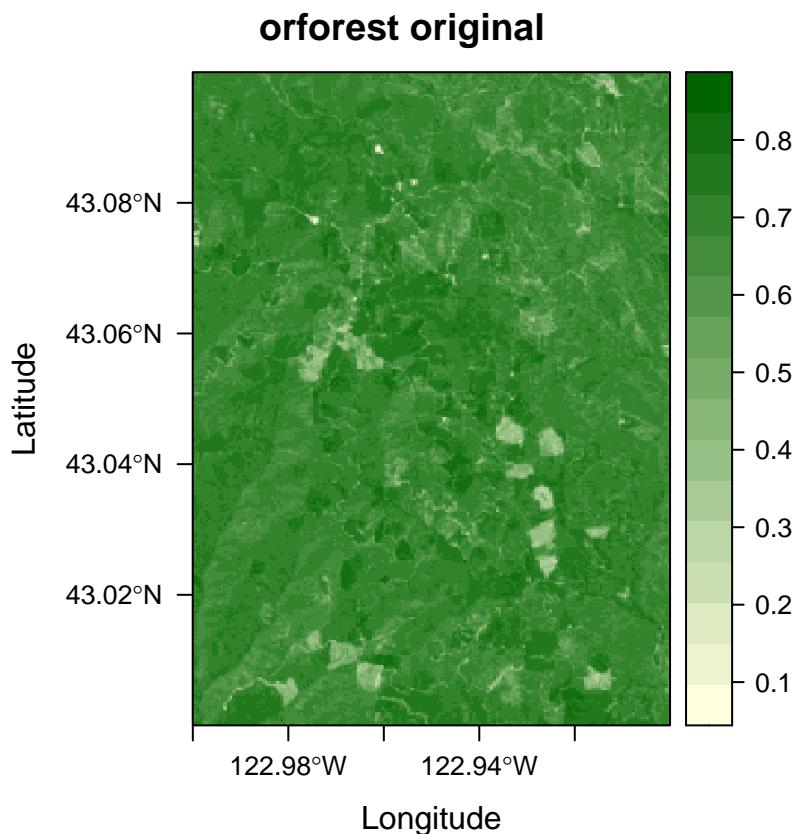
The National Aeronautics and Space Administration (NASA) has been collecting Earth observing images with Landsat for decades. Normalized Difference Vegetation Index (NDVI) is a measure of vegetation or greenness that can be quantified from Landsat images by measuring the difference between near-infrared and red light, which vegetation strongly reflects and absorbs, respectively. For this first example, we generated an NDVI image over a small region in southwestern Oregon using Google Earth Engine. This image is available as a raster layer available as an R data object entitled ‘orforest’ when *geodiv* is installed. Google Earth Engine already has a number of tutorials and sample code and functions for this step that can be accessed on its site: earthengine.google.com. There are also several ways in which to access satellite data from R as well. Given that the focus of this tutorial is on the use of the *geodiv* R package, we provide these data already generated in Google Earth Engine.

Let's begin by loading the example data, which is a raster layer called ‘orforest’.

```
# Load the orforest data into your active session.
data(orforest)
# check out the properties of the orforest raster layer.
orforest
#> class      : RasterLayer
#> dimensions : 371, 371, 137641 (nrow, ncol, ncell)
#> resolution : 0.0002694946, 0.0002694946 (x, y)
#> extent     : -123, -122.9, 43.00002, 43.1 (xmin, xmax, ymin, ymax)
#> crs        : +proj=longlat +datum=WGS84 +no_defs
#> source     : memory
#> names      : summer_ndvi_p45_r30_2000_2016_30m
#> values     : 0.09595944, 0.8357643 (min, max)
```

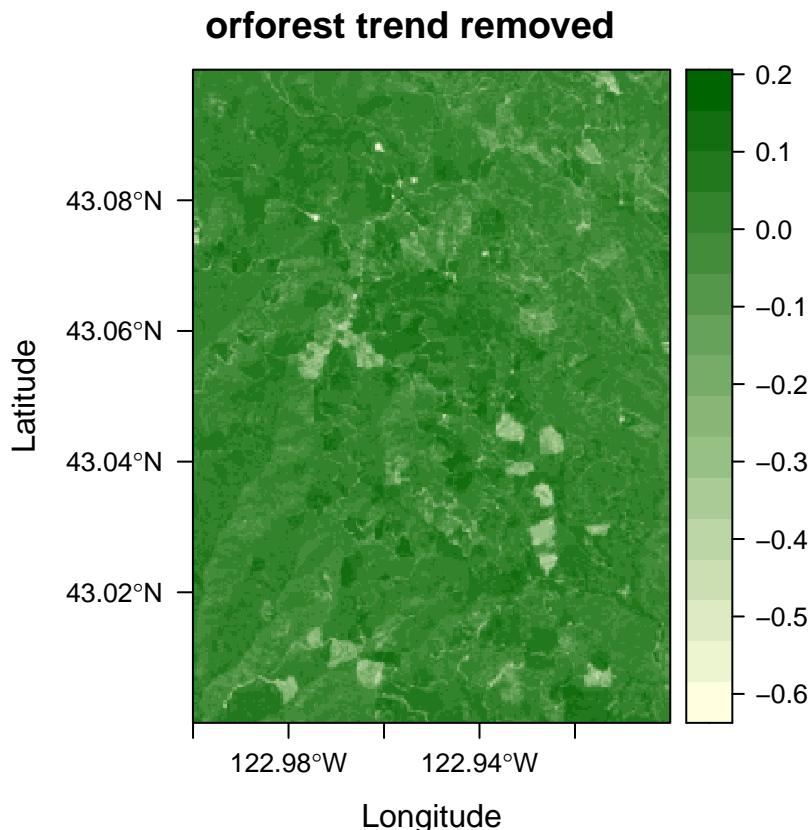
First, we plot the data without any trends removed.

```
# Plot orforest without the trend removed.
eviCols <- colorRampPalette(c('lightyellow1', 'darkgreen'))(100)
eviTheme <- rasterVis::rasterTheme(region = eviCols)
(orig_ndvi <- rasterVis::levelplot(orforest, margin = F,
                                    par.settings = eviTheme, xlab = 'Longitude',
                                    ylab = 'Latitude', main='orforest original'))
```



Use the ‘remove_plane’ function of *geodiv* to remove the best fit polynomial plane from the image. This function searches polynomials of orders 0 - 3 to determine which has the lowest error relative to the surface values. To fit a plane with a user-specified polynomial order, you may use the function ‘fitplane’.

```
# Plot orforest with the trend removed.
orfor_rem <- remove_plane(orforest)
#> [1] "Order of polynomial that minimizes errors: 0"
(orig_rem_plot <- rasterVis::levelplot(orfor_rem, margin = F,
                                         par.settings = eviTheme,
                                         xlab = 'Longitude', ylab = 'Latitude',
                                         main='orforest trend removed'))
```



You can also plot the raw satellite image (as opposed to the NDVI derived from Landsat imagery). To do this, create a Google Maps API key and copy to the indicated location.

```
# Plot the actual satellite image.
coords <- coordinates(orforest)
lon <- mean(coords[, 1], na.rm = TRUE)
lat <- mean(coords[, 2], na.rm = TRUE)
api_key <- NA # ADD AN API KEY HERE
```

Once an API key has been inserted, run the following code to get the satellite image next to the original NDVI image.

```
# Register a Google API key.
register_google(api_key)

# Get a satellite image at the specified longitude and latitude.
img <- get_map(c(lon, lat), zoom = 13, maptype = 'satellite',
```

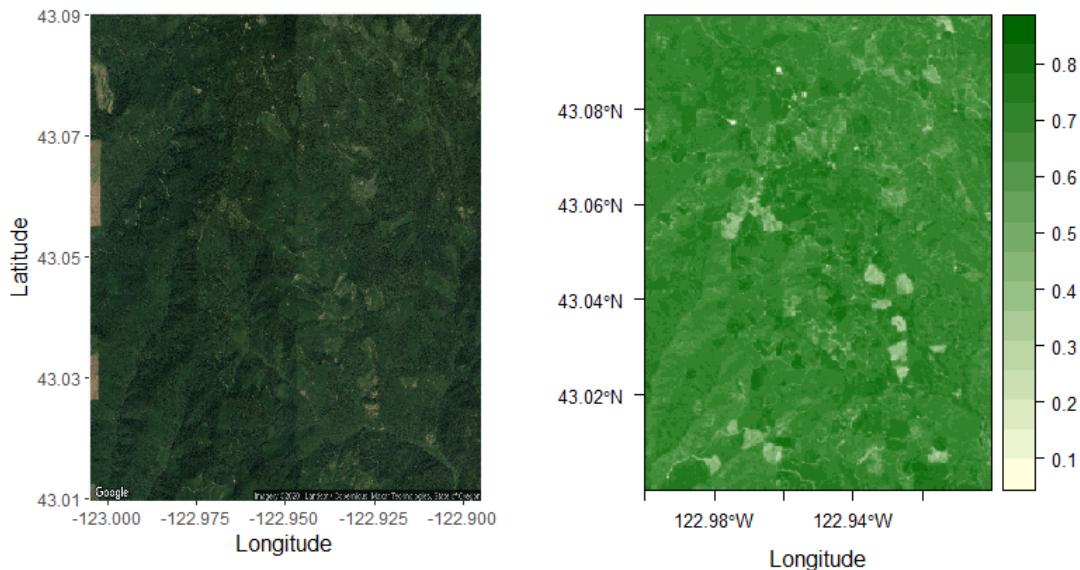
```

source = "google"

# Create a figure with the satellite image using ggplot.
satimg <- ggmap(img) + coord_fixed(1.7) + xlab('Longitude') +
  ylab('Latitude') +
  theme(axis.title.x = element_text(size = 12),
        axis.title.y = element_text(size = 12),
        plot.margin = unit(c(0, 0, 0, 0), "cm"))

# Plot the satellite image next to the original NDVI image.
plot_grid(satimg, orig_ndvi, ncol = 2, nrow = 1, scale = c(0.84, 1))

```



Calculate global surface gradient metrics

The simplest use of the *geodiv* package is to apply metrics globally over an entire image. This returns a measurement of the overall heterogeneity of the image. The ‘sa’ function calculates the average roughness of a surface as the absolute deviation of surface heights from the mean surface height. The ‘sbi’ function calculates the surface bearing index, which is the ratio of the root mean square roughness (S_q) to height at 5% of bearing area (z_{05}). The ‘std’ function calculates texture direction metrics (i.e., the angle of dominating texture and the texture direction of the Fourier spectrum image calculated from the orforest image).

```

# Calculate global metrics over the entire orforest image.
(sa <- sa(orforest)) # average roughness
#> [1] 0.04466675
(sbi <- sbi(orforest)) # surface bearing index
#> [1] 0.085557302
(std <- std(orforest, create_plot = FALSE, option = 1))
#> [1] 90

```

Generate texture images

Another common use case is to look at texture images where a spatial function has been applied locally over focal windows across a landscape. This functionality is provided through both the ‘focal_metrics’ and ‘texture_image’ functions.

The ‘texture_image’ function applies metrics in either square or round windows over the raster. This function tends to be faster than ‘focal_metrics,’ but can use more memory when run on Windows. It is suggested that Windows users use the ‘focal_metrics’ function instead, unless they have a computer with a lot of memory.

The ‘focal_metrics’ function is modified from the ‘window_lsm’ function in *landscapemetrics* (Hesselbarth, et al. 2019). Windows must be rectangular or square, and the ‘metrics’ argument is a list of functions. The output of this function is a list of rasters.

Note that this step can be somewhat time intensive. For users that would like to examine the output, but don’t want to run this step, the code to import the rasters is included below.

```

# Texture image creation using 'focal_metrics' function.
window <- matrix(1, nrow = 7, ncol = 7)
system.time(
output_rasters <- focal_metrics(orforest, window,
                                    metrics = list('sa', 'sbi'),
                                    progress = TRUE)
)

print(output_rasters)

# Texture image creation using 'texture_image' function.
metric_list <- c('sa', 'sbi', 'std')
system.time(output_rasters2 <- lapply(metric_list, FUN = function(m) {
  texture_image(orforest, window_type = 'square', size = 7,
                in_meters = FALSE, metric = m,
                parallel = TRUE, ncore = 4, nclumps = 20)}))

# Download rasters from figshare. The list of data returned here will be used
# throughout the vignette.
url <- fs_download(12834896, mine = FALSE, session = NULL)
#> No encoding supplied: defaulting to UTF-8.

output_rasters2 <- list()
output_rasters2[[1]] <- raster(url[[5]])
output_rasters2[[2]] <- raster(url[[6]])
output_rasters2[[3]] <- raster(url[[7]])

```

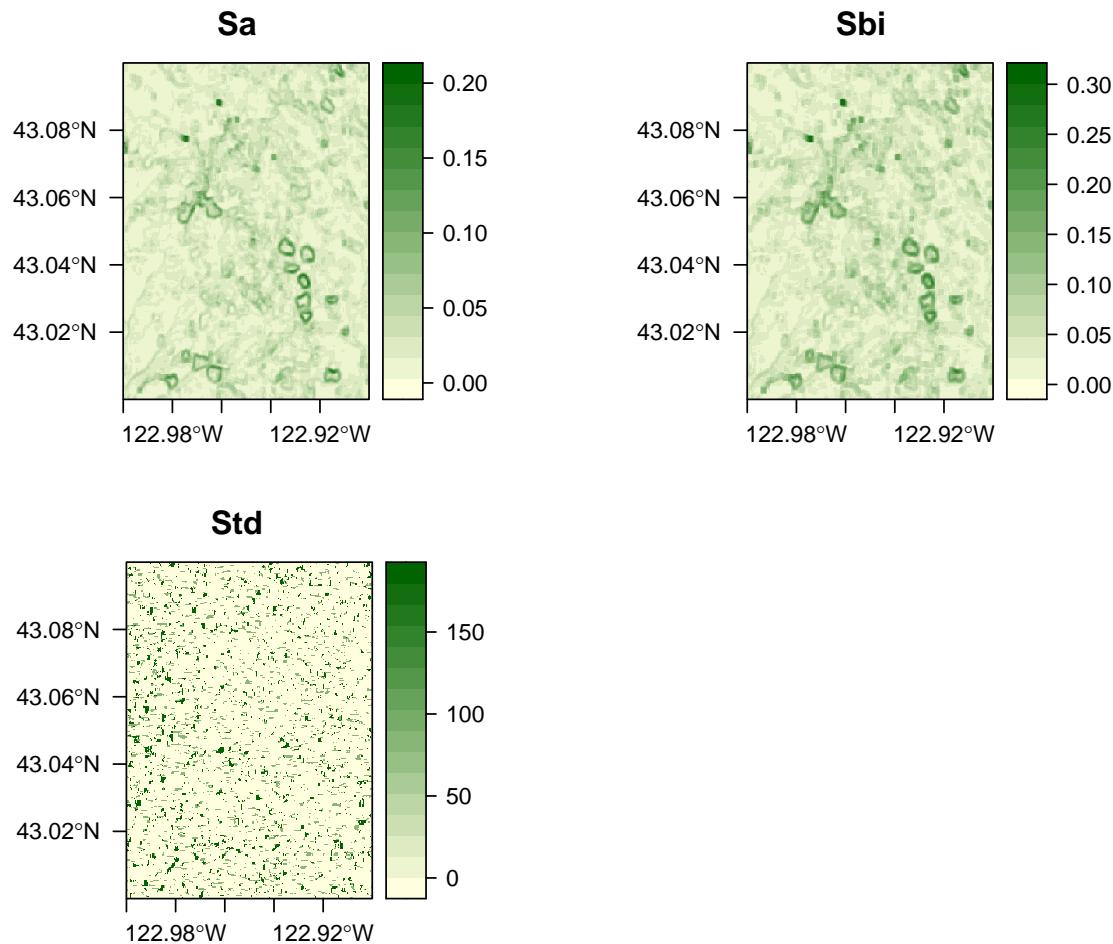
Plot the texture image rasters.

```

# Create list of plots.
names <- c('Sa', 'Sbi', 'Std')
rast_list <- unlist(output_rasters2)
plts <- lapply(seq(1, 3), FUN = function(i) {
  rasterVis::levelplot(rast_list[[i]], margin = F, par.settings = eviTheme,
                        ylab = NULL, xlab = NULL, main = names[i])
})

# Arrange plots in the list into a grid.
grid.arrange(grobs = plts, nrow = 2)

```



Example 2: Applying all surface metrics across the state of Oregon, USA

Motivation

By assessing heterogeneity using a variety of metrics, researchers can gain a more complete picture of heterogeneity than they would with a single metric (Dahlin, 2016). To demonstrate the utility of *geodiv* for this common application, in Example 2 we apply all surface metric functions to images across Oregon, USA

and examine the patterns of, and relationships among, metrics. We calculate metrics for both elevation data from the Shuttle Radar Topography Mission (SRTM) and a commonly-used measure of canopy greenness, Enhanced Vegetation Index (EVI), from NASA's Moderate Resolution Imaging Spectroradiometer (MODIS). We then examine the correlations among metrics along a transect crossing the state, and determine how the metrics cluster using two methods, hierarchical clustering and Principal Components Analysis (PCA). This analysis demonstrates the relationships among metrics, with potential for determining how metrics group and behave with various input data.

Elevation and EVI Data

Elevation and EVI data that are available to use along with this vignette were prepared in Google Earth Engine (Gorelick et al., 2017) and analyzed in R. Void-filled SRTM data (Farr et al., 2007) and quality-filtered, maximum growing season, MODIS EVI data (Didan, 2015) were downloaded in Fall 2019. The code chunk below downloads these data into the current R session from figshare. Again, R may be used to access satellite data, but we provide previously-prepared data for the purpose of this analysis.

```
# Download data from figshare.
elev <- raster(url[4])
evi <- raster(url[3]) * 0.0001
```

Aggregate both datasets to ~2km resolution for comparison between datasets and to reduce computational time.

```
elev <- aggregate(elev, fact = 8)
evi <- aggregate(evi, fact = 8)
```

Pre-processing of rasters

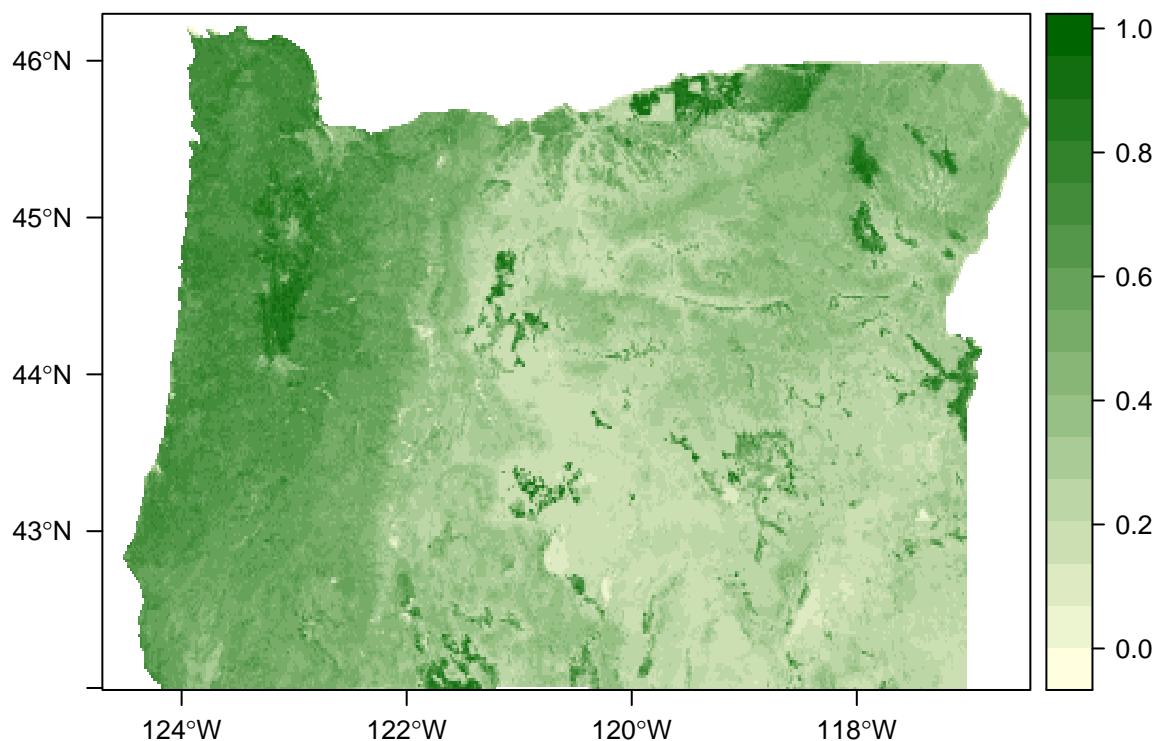
Begin by masking any values that are outside of the boundaries for the state of Oregon.

```
state <- maps::map(database = 'state', regions = 'oregon',
                     fill = TRUE, plot = FALSE)
statePoly <- map2SpatialPolygons(state, IDs = state$names,
                                 proj4string = CRS(proj4string(evi)))
evi_masked <- mask(x = evi, mask = statePoly)
elev_masked <- mask(x = elev, mask = statePoly)
```

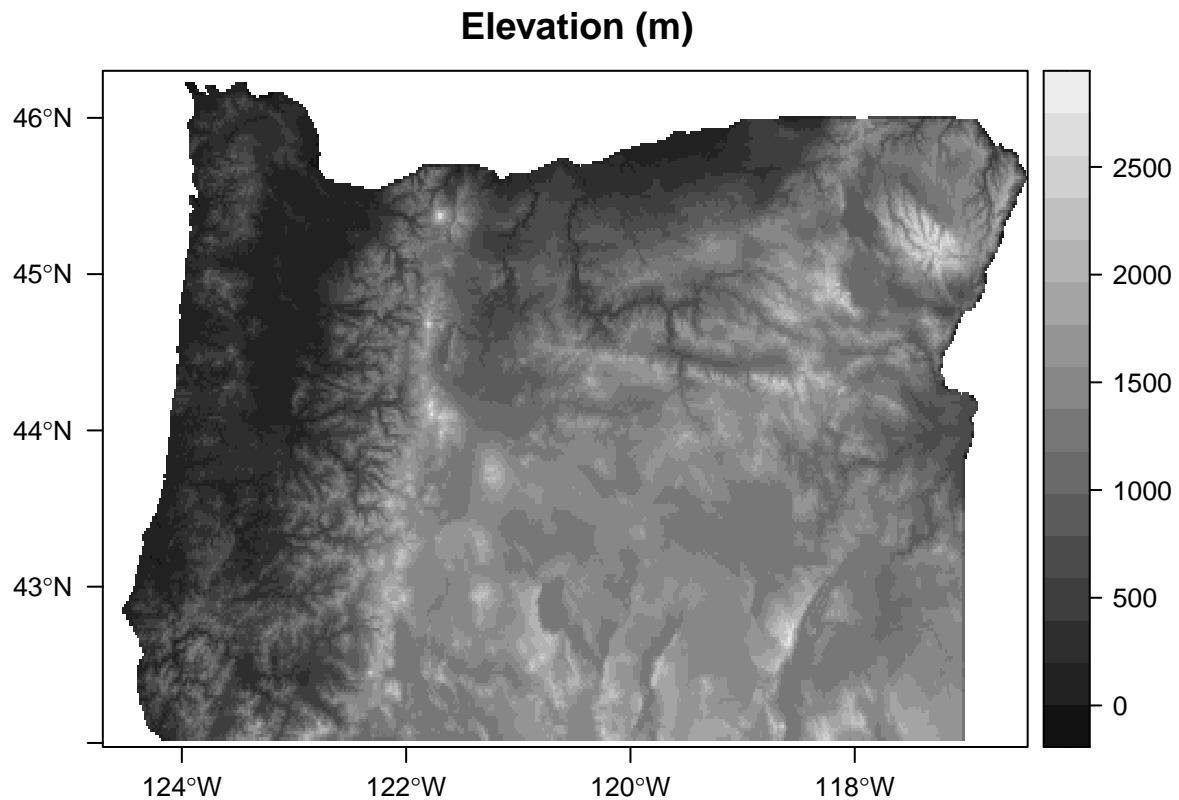
Generate plots to get a sense for the spatial patterns in the data.

```
# plot maximum growing season EVI for Oregon
rasterVis::levelplot(evi_masked, margin = F, par.settings = eviTheme,
                      ylab = NULL, xlab = NULL,
                      main = 'Maximum Growing Season EVI')
```

Maximum Growing Season EVI



```
# plot elevation (in meters) for Oregon
elevCols <- colorRampPalette(c('grey7', 'grey93'))(100)
elevTheme <- rasterVis::rasterTheme(region = elevCols)
rasterVis::levelplot(elev_masked, margin = F, par.settings = elevTheme,
                     ylab = NULL, xlab = NULL, main = 'Elevation (m)')
```

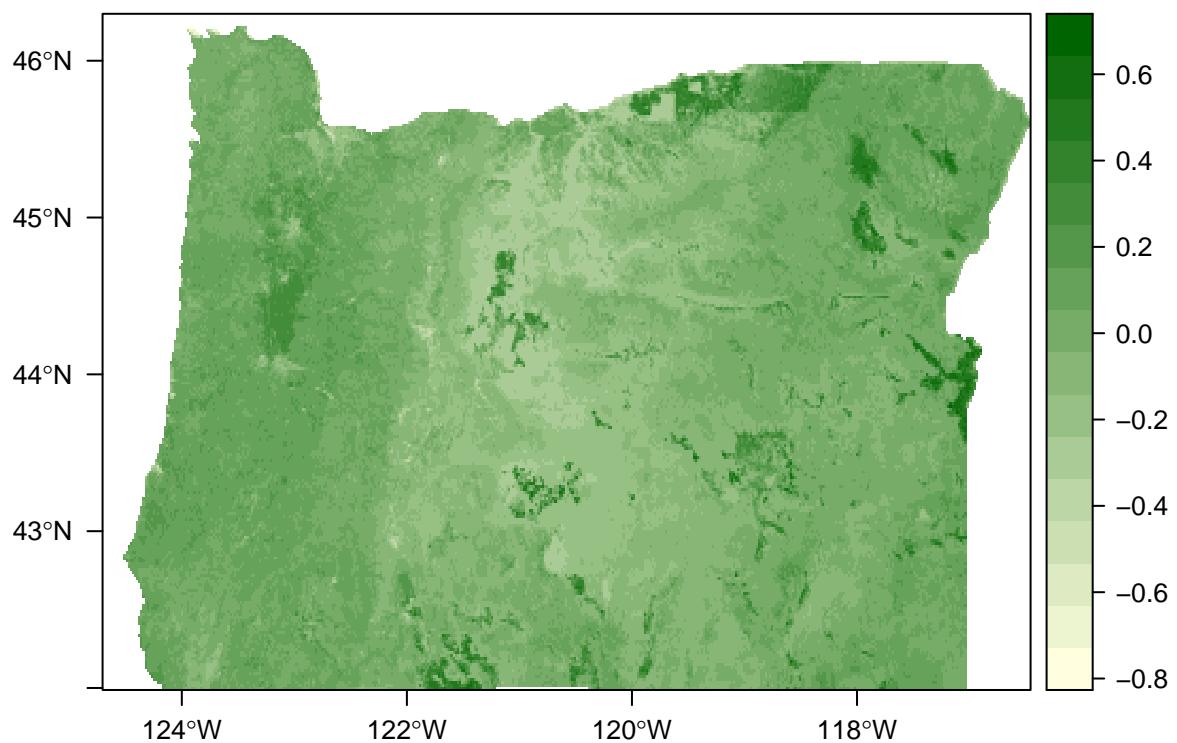


Remove any trends in the data with the ‘remove_plane’ function and take a look at the plots of the images with the trends removed.

```
evi_masked <- remove_plane(evi_masked)
#> [1] "Order of polynomial that minimizes errors: 1"
elev_masked <- remove_plane(elev_masked) # there was no trend
#> [1] "Order of polynomial that minimizes errors: 0"

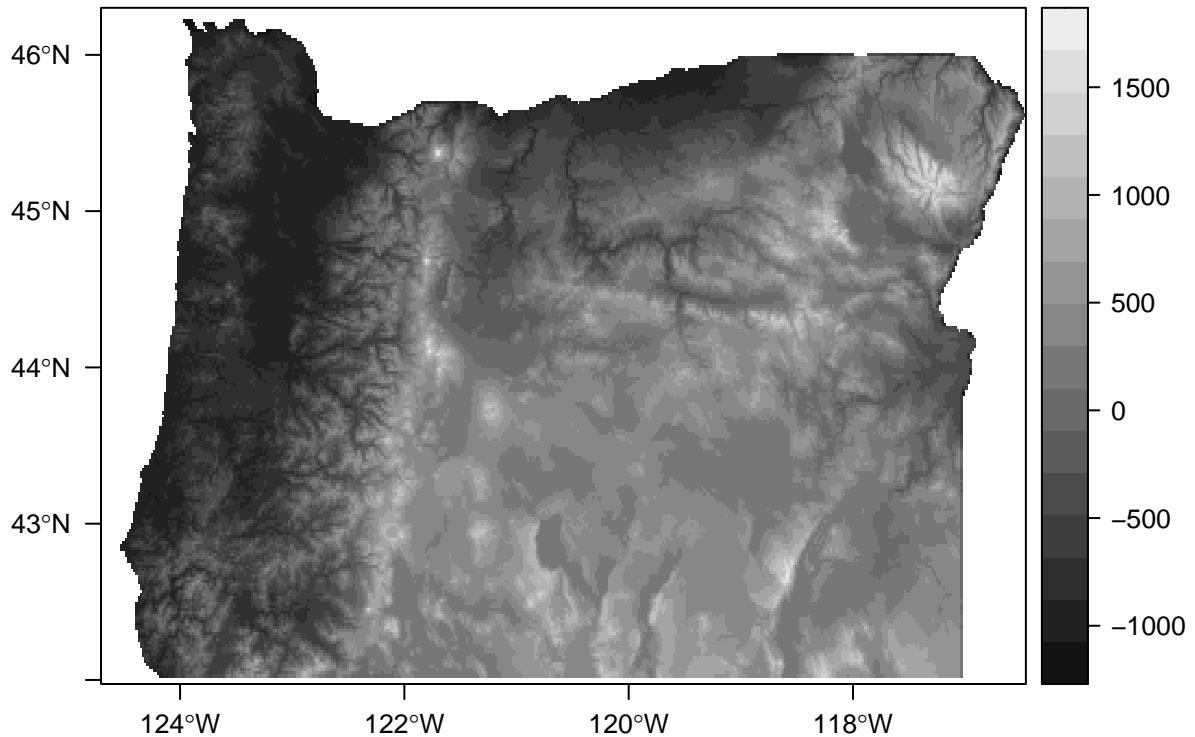
# plot again to see what the new raster looks like
rasterVis::levelplot(evi_masked, margin = F, par.settings = eviTheme,
                      ylab = NULL, xlab = NULL, main = 'EVI without Trend')
```

EVI without Trend



```
rasterVis::levelplot(elev_masked, margin = F, par.settings = elevTheme,  
                      ylab = NULL, xlab = NULL, main = 'Elevation without Trend')
```

Elevation without Trend



Generate texture images of the state of Oregon

Below we generate a texture image for the state of Oregon using the ‘sa’ metric for elevation. Note that the following step may take some time. We provide the output datafile files along with this vignette for all metrics included in geodiv for elevation and EVI over ~30km x 30km square moving windows and scaled following calculation for the subsequent analyses in this vignette.

```
# Calculate elevation sa texture image for state of Oregon
system.time(outrast <- texture_image(elev_masked, window_type = 'square', size = 7,
                                         in_meters = FALSE, metric = 'sa', parallel = TRUE,
                                         ncores = 4, nclumps = 20))
```

The code below illustrates how to convert the raster generated by the ‘texture_image’ function (i.e., outrast) to a dataframe for subsequent analyses.

```
# get raster values
vals <- outrast[]

# Convert output raster of sa metrics (outrast) to a dataframe for
# easier use in subsequent analyses
coords <- coordinates(outrast)
sa_data_elev <- data.frame(x = coords[, 1], y = coords[, 2], v = vals)
```

Generating these data frames can take a while, so we have provided .csv files for all gradient surface metrics

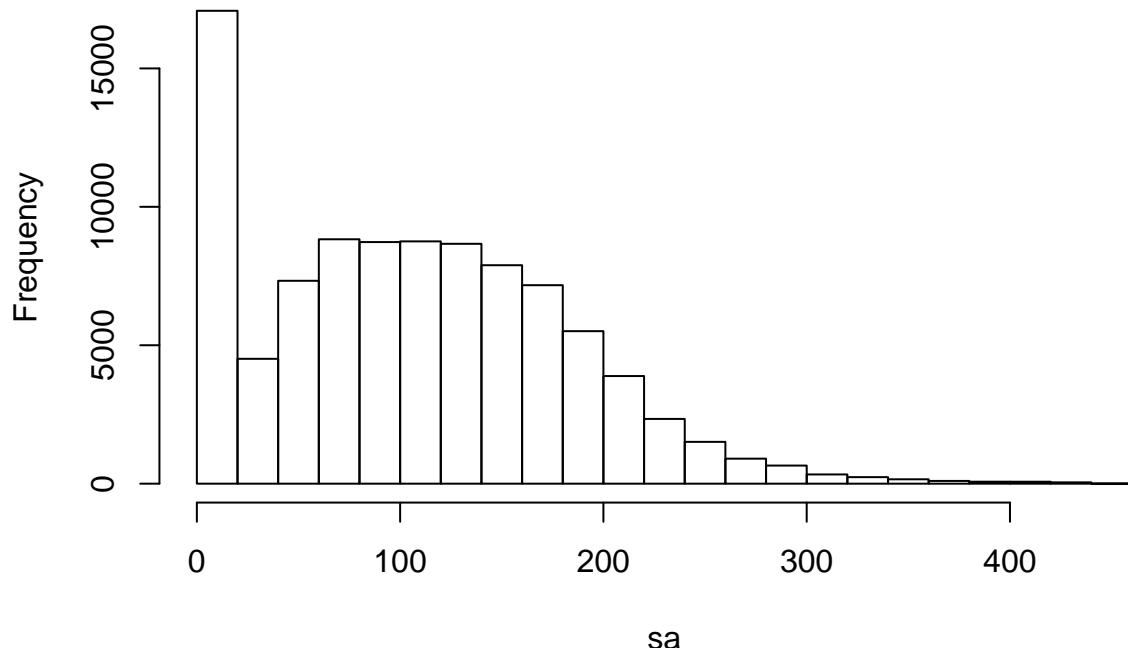
calculated for elevation and EVI in case you find them useful for working with this vignette. The below code reads in these provided .csv files by downloading data from figshare.

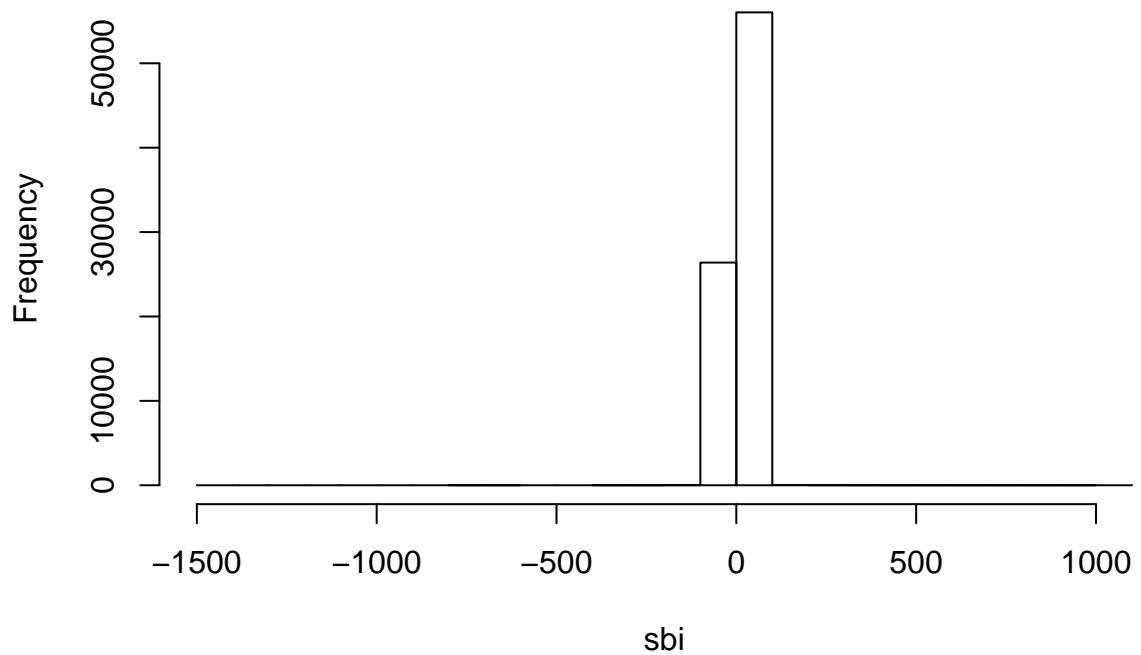
```
# The list of figshare files was completed above, so grab the appropriate files
# for the csv's of all texture image outputs for Oregon.
data_evi <- read.csv(url[2], stringsAsFactors = FALSE)
data_elev <- read.csv(url[1], stringsAsFactors = FALSE)
```

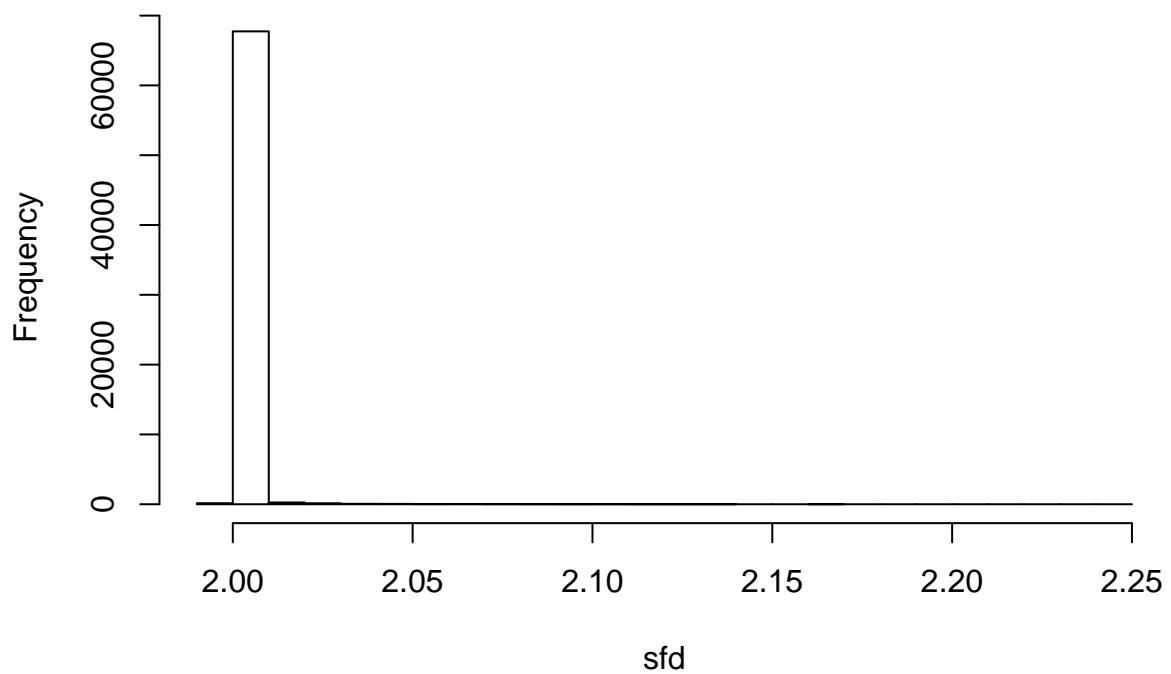
Visualization of texture image outputs

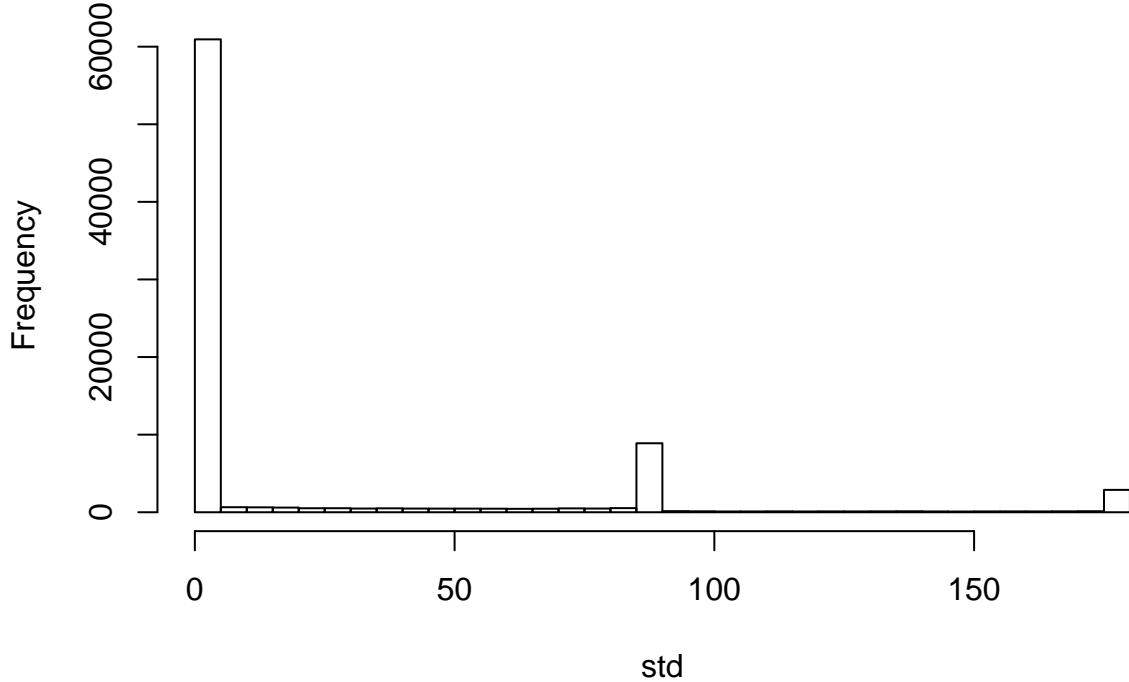
Distributions of a few elevation variables:

```
for (i in c(9, 10, 18, 6)) {
  hist(data_elev[, i], breaks = 30, xlab = names(data_elev)[i], main = '')}
```









The code below visualizes metrics over the entire state in order to capture different aspects of landscape heterogeneity. Individual metrics primarily distinguish mountainous versus flat terrain, and managed versus more natural areas; however, some metrics are difficult to interpret, or do not show very much variation over the region. The difficulty of interpreting metrics is a known complicating factor for their use. Others have addressed this issue and linked metrics with known ecosystem features or patch metrics (McGarigal et al., 2009; Kedron et al., 2018).

```
# New names for plots
plt_names <- data.frame(old = names(data_elev)[3:ncol(data_elev)],
                         new = c('Shw', 'Srw', 'Srwi', 'Std', 'Std1', 'S10z',
                                'Sa', 'Sbi', 'Sci', 'Sdc 50-55%', 'Sdc 80-85%',
                                'Sdc 0-5%', 'Sdq6', 'Sdr', 'Sds', 'Sfd', 'Sk',
                                'Sku', 'Smean', 'Sph', 'Spk', 'Sq', 'Ssc',
                                'Ssk', 'Sv', 'Svi', 'Svk'))
```

```
create_maps <- function(df, r, theme) {
  maps_list <- list()
  for (i in seq(3, ncol(df))) {
    temp <- setValues(r, df[, i])
    temp[is.na(r)] <- NA
    goodname <- as.character(plt_names$new[plt_names$old == names(df)[i]])
    maps_list[[i - 2]] <- rasterVis::levelplot(temp, margin = F,
                                                par.settings = theme,
                                                ylab = NULL, xlab = NULL,
                                                main = goodname)
    maps_list[[i - 2]]$par.settings$layout.heights[
```

```

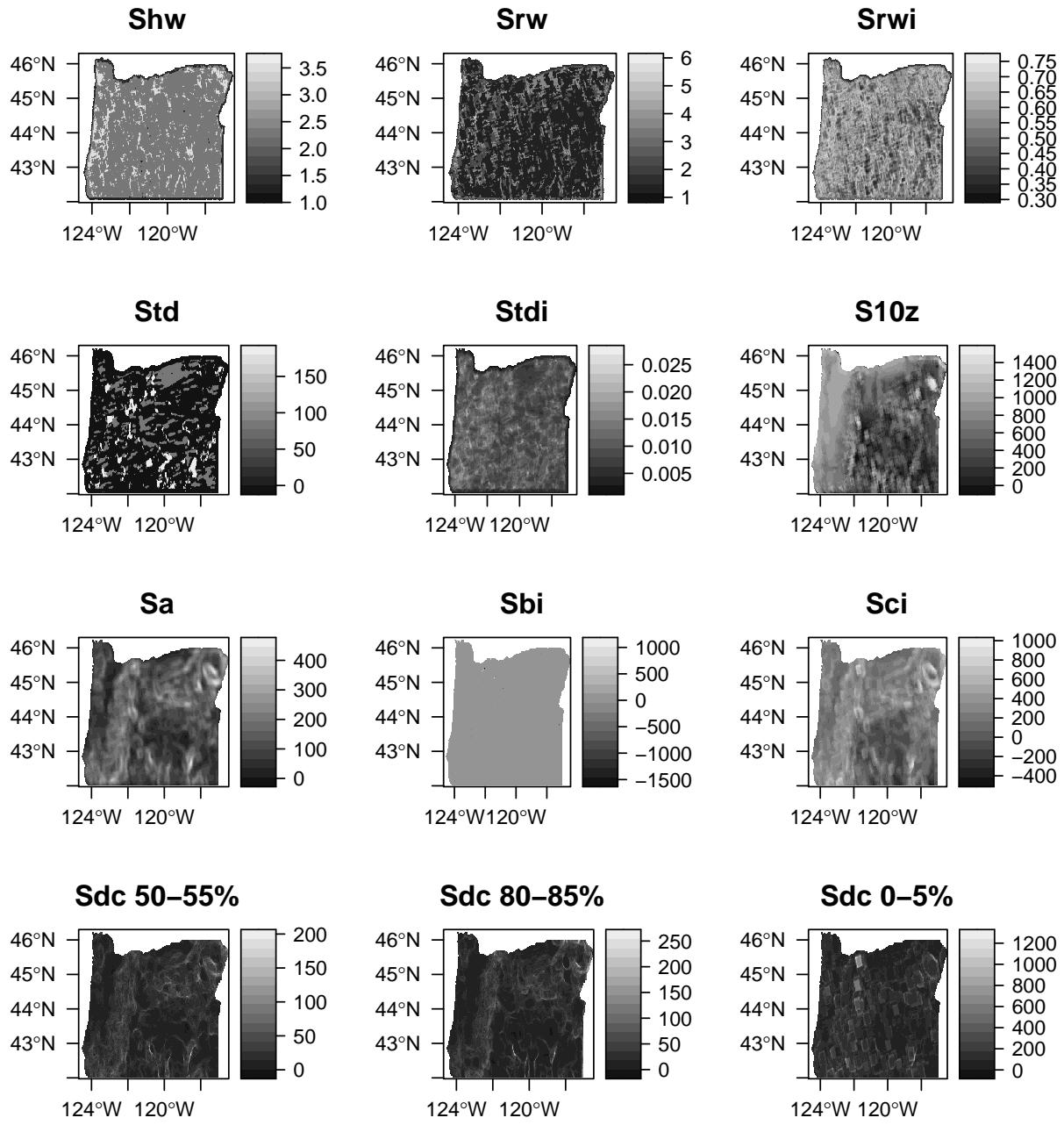
    c( 'bottom.padding',
      'top.padding',
      'key.sub.padding',
      'axis.xlab.padding',
      'key.axis.padding',
      'main.key.padding') ] <- 1
  maps_list[[i - 2]]$aspect.fill <- TRUE
  names(maps_list)[i - 2] <- goodname
}
return(maps_list)
}

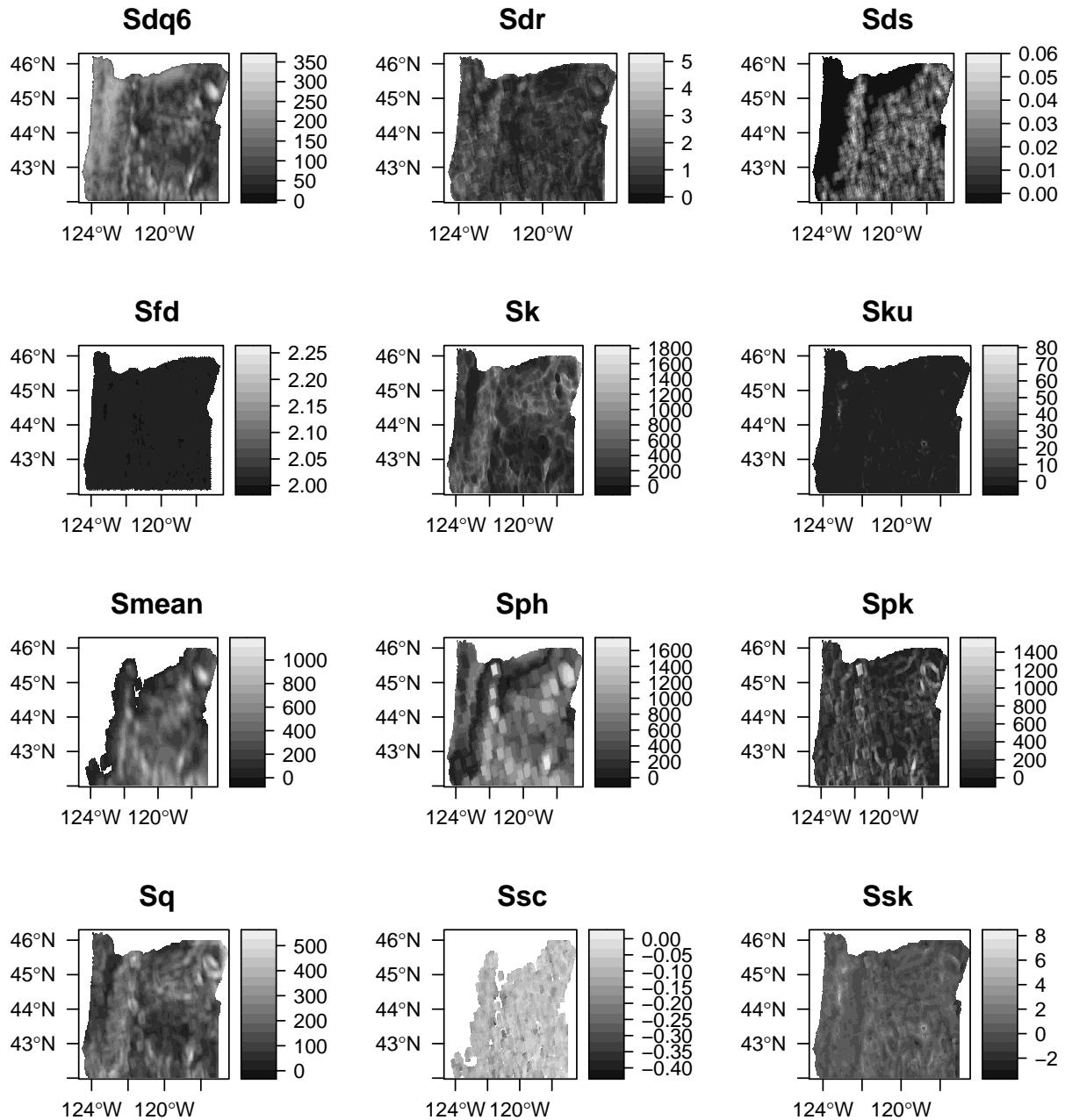
# Create plots of all possible surface gradient metrics that geodiv calculates
# for elevation and EVI.
elev_maps <- create_maps(data_elev, elev_masked, elevTheme)
evi_maps <- create_maps(data_evi, evi_masked, eviTheme)

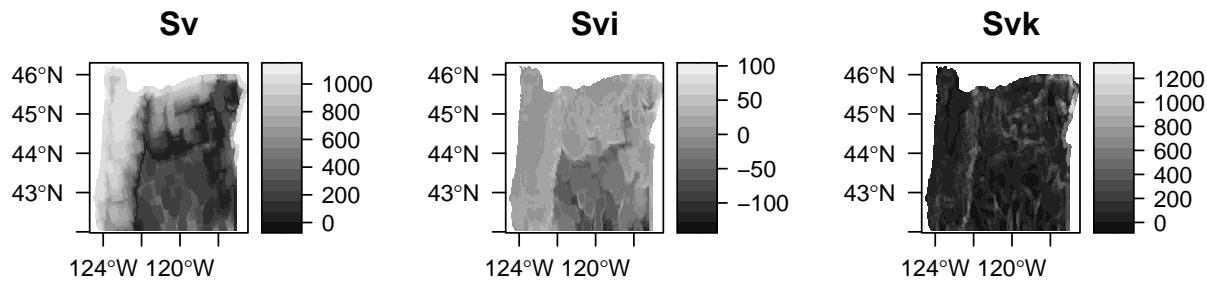
# Make sure that order of maps is the same for both EVI and Elevation.
new_order <- match(plt_names$new, names(evi_maps)) # get order according to names table
evi_maps <- evi_maps[new_order]

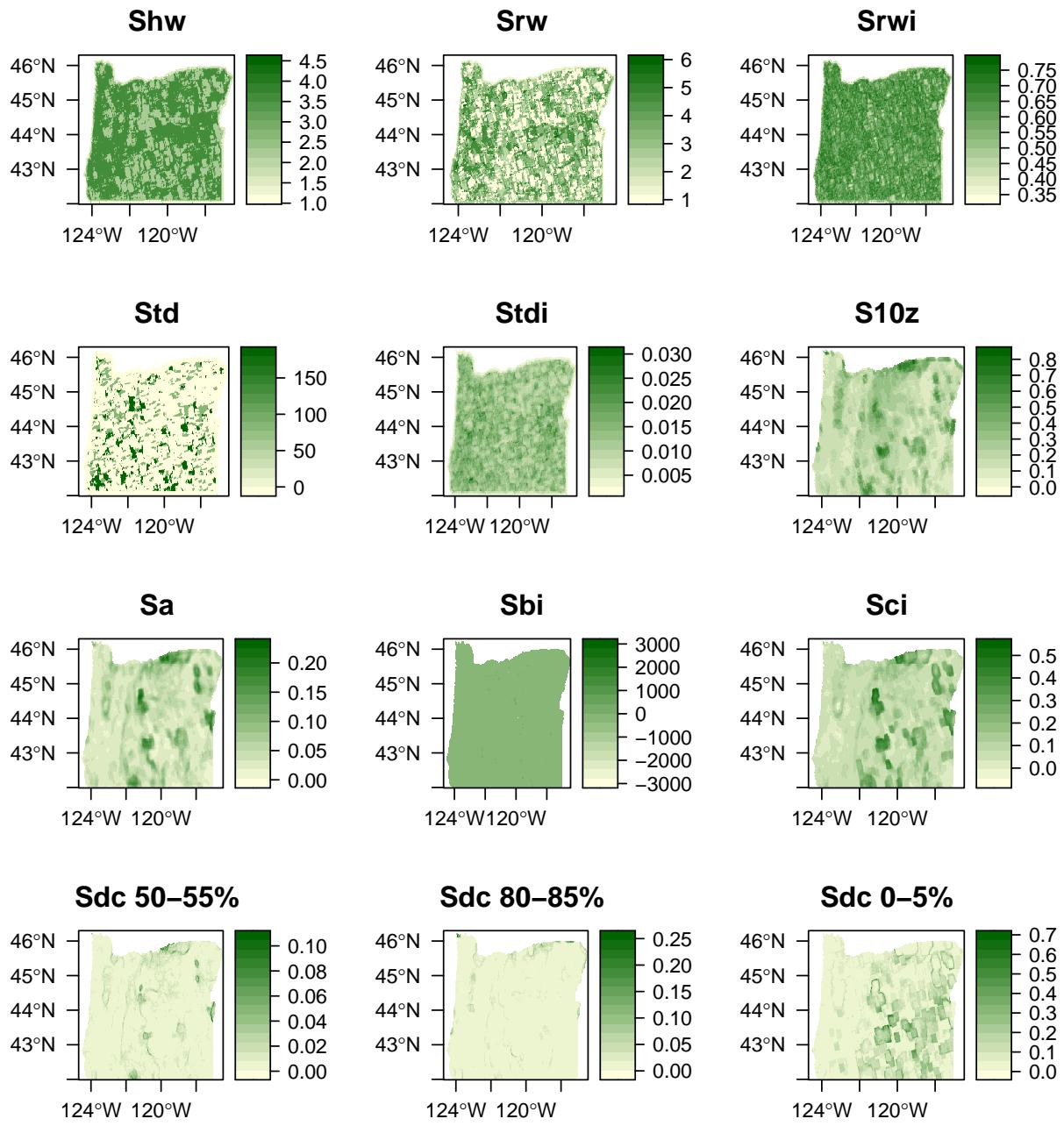
# Create map panels (3 each for EVI and elevation).
for (l in list(elev_maps, evi_maps)) {
  grid.arrange(grobs = l[1:12], nrow = 4, ncol = 3) # 850x800
  grid.arrange(grobs = l[13:24], nrow = 4, ncol = 3) # 850x800
  grid.arrange(grobs = l[25:27], nrow = 4, ncol = 3) # 850x800
}

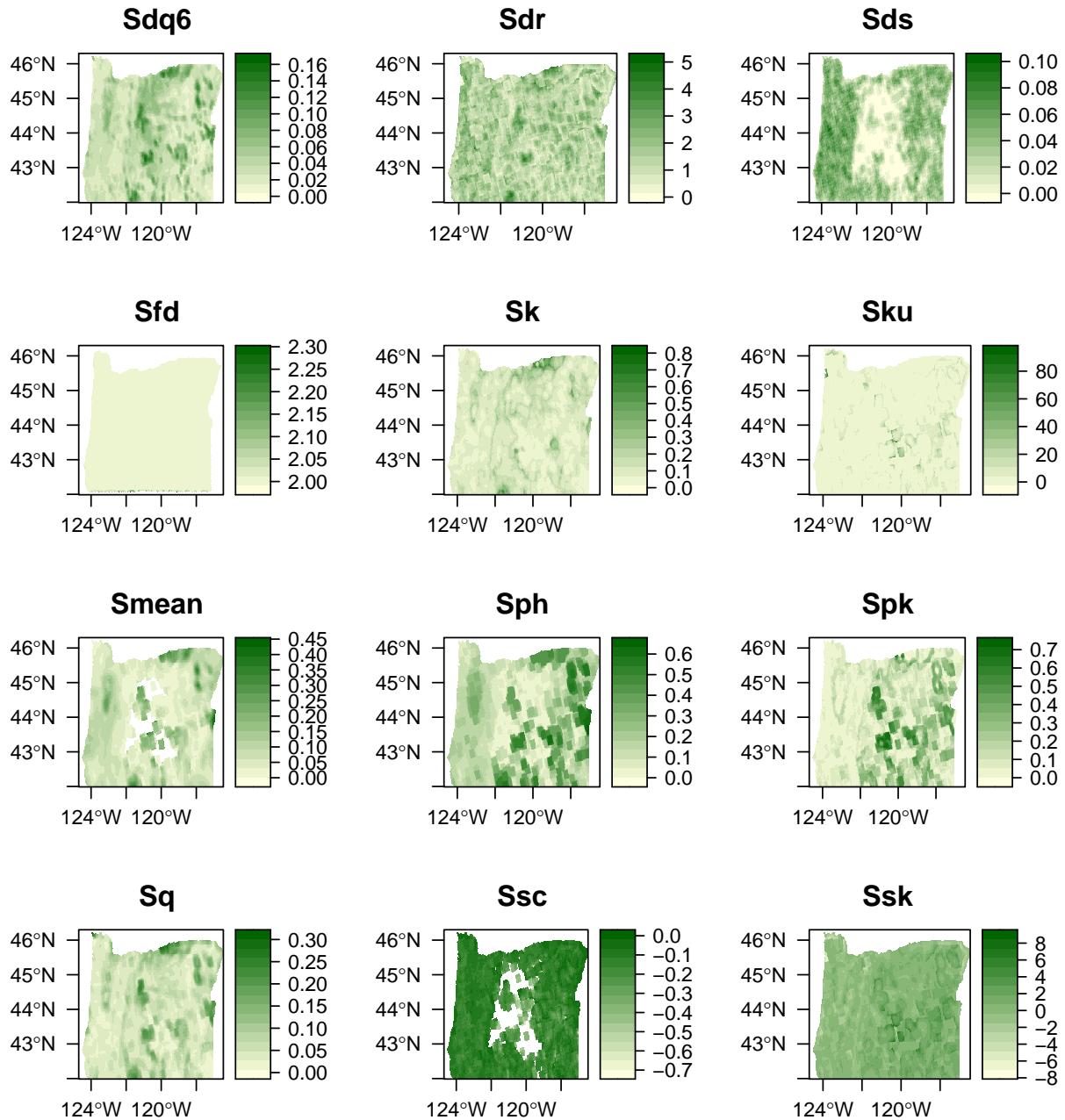
```

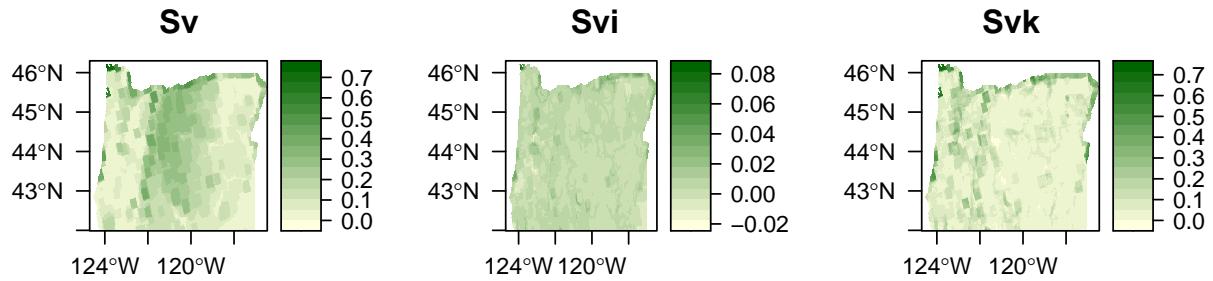












Transect analysis

In the code below, we examine an example of local correlation and clustering among the surface gradient metrics by extracting values over a horizontal transect across central Oregon.

First we convert the raw elevation and EVI data from the NASA's SRTM and MODIS mission, respectively, to a dataframe and add those raw values to the dataframes for EVI and elevation containing the gradient surface metrics we've calculated across the state of Oregon.

```

# Convert the rasters to dataframe format and add value to dataframe with
# metric values.
sp_df <- function(r, df) {
  pixdf <- as.data.frame(as(r, "SpatialPixelsDataFrame"))
  df$value <- pixdf[, 1]
  return(df)
}

data_elev <- sp_df(elev, data_elev)
data_evi <- sp_df(evi, data_evi)

```

Now we extract the data along a latitudinal transect going across the state of Oregon.

```

# Create new dataframe of values along a latitudinal transect.
get_transect <- function(r, df) {
  # Crop raster to center transect (+/- 7 pixels North or South).
  center_row <- round(nrow(r) / 2)
  r_crop <- crop(r, extent(r, center_row - 7, center_row + 7, 1, ncol(r)))

  # Get 8th latitudinal coordinate (center latitude) from the cropped raster.
  central_y <- unique(coordinates(r_crop)[, 2])[8]

  # Get the closest latitude in the dataframe to the central raster coordinate.
  central_y <- unique(df$y[near(df$y, central_y, 0.01))][1]

  # Extract mean EVI and elevation values by raster column.
  r_means <- colMeans(as.matrix(r_crop), na.rm = TRUE)

  # Now limit the dataframe to the central row across the transect.
  transect_vals <- df[df$y == central_y,]

  # Add column means to dataframe.
  transect_vals$value <- r_means

  return(transect_vals)
}

transect_elev <- get_transect(elev, data_elev)
transect_evi <- get_transect(evi, data_evi)

```

The code below places standardizes all metrics by placing them on the same scale from 0 - 1.

```

# Get all metrics on same scale (0-1).
scale_mets <- function(df) {
  for (i in 3:ncol(df)) {
    df[,i] <- (df[, i] - min(df[, i], na.rm = TRUE)) /
      (max(df[, i], na.rm = TRUE) - min(df[, i], na.rm = TRUE))
  }
  return(df)
}

transect_elev <- scale_mets(transect_elev)
transect_evi <- scale_mets(transect_evi)

```

Clustering analysis over transect

For the transect analysis, we will perform hierarchical clustering on metric values using the function ‘`eclust`’ in the package `factoextra` (Kassambara & Mundt, 2020). First, some additional data wrangling is required to prepare the data for the clustering analysis below.

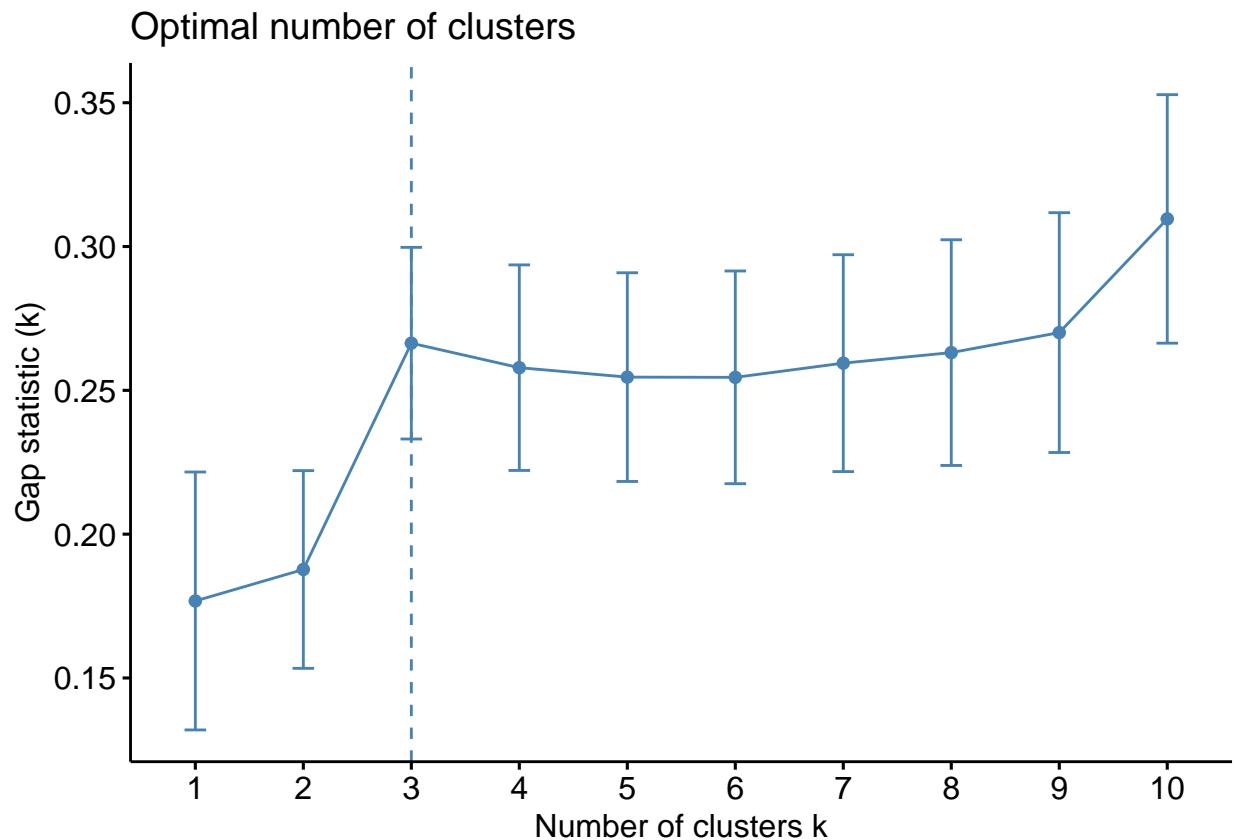
```
# Remove NA values from the metric columns.
rm_nas <- function(df) {
  for (i in 3:ncol(df)) {
    df <- df[!is.na(df[, i]),]
  }
  return(df)
}

transect_elev <- rm_nas(transect_elev)
transect_evi <- rm_nas(transect_evi)
```

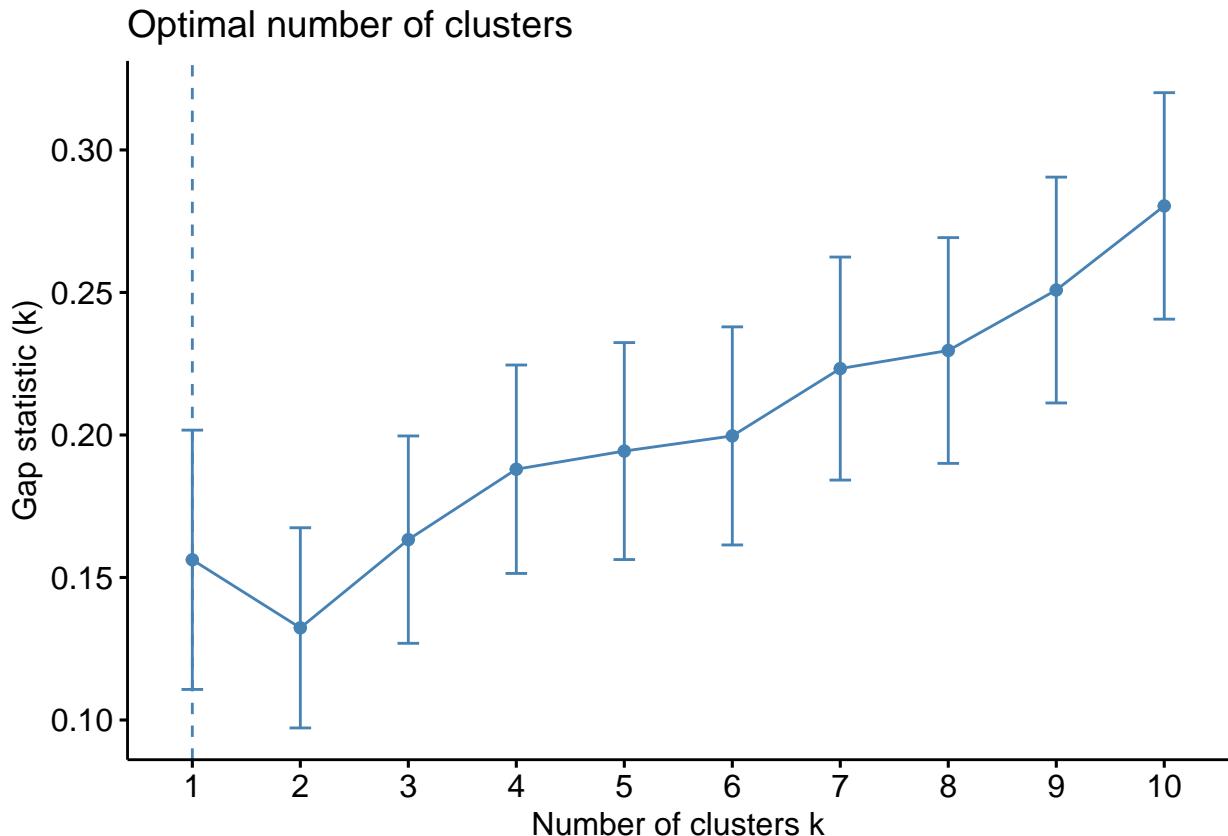
The code below performs the clustering analysis on the surface gradient metrics. We first determine the optimal number of clusters by examining the gap statistic, and then plot the clustered variables to see the relationships among them.

```
### Plot optimal number of clusters
plot_gap <- function(df) {
  # enhanced k-means clustering
  res.km <- clusGap(t(df)[3:(ncol(df) - 1), ], stats::kmeans, K.max = 10,
                      B = 100, nstart = 25)
  # gap statistic plot
  factoextra::fviz_gap_stat(res.km)
}

plot_gap(transect_evi)
```



```
plot_gap(transect_elev)
```



```

#### Dendrogram and scatterplot of clusters
get_clusters <- function(df, nclust) {
  # Enhanced hierarchical clustering using optimal # of clusters.
  res.hc <- factoextra:::elclust(t(df)[3:(ncol(df) - 1),],
                                 "hclust", k = nclust)

  return(res.hc)
}

plot_dendrogram <- function(res.hc, nclust){
  # Plot colors
  plt_cols <- c('lightgoldenrod1', 'lightblue', 'grey', 'lightsteelblue4')

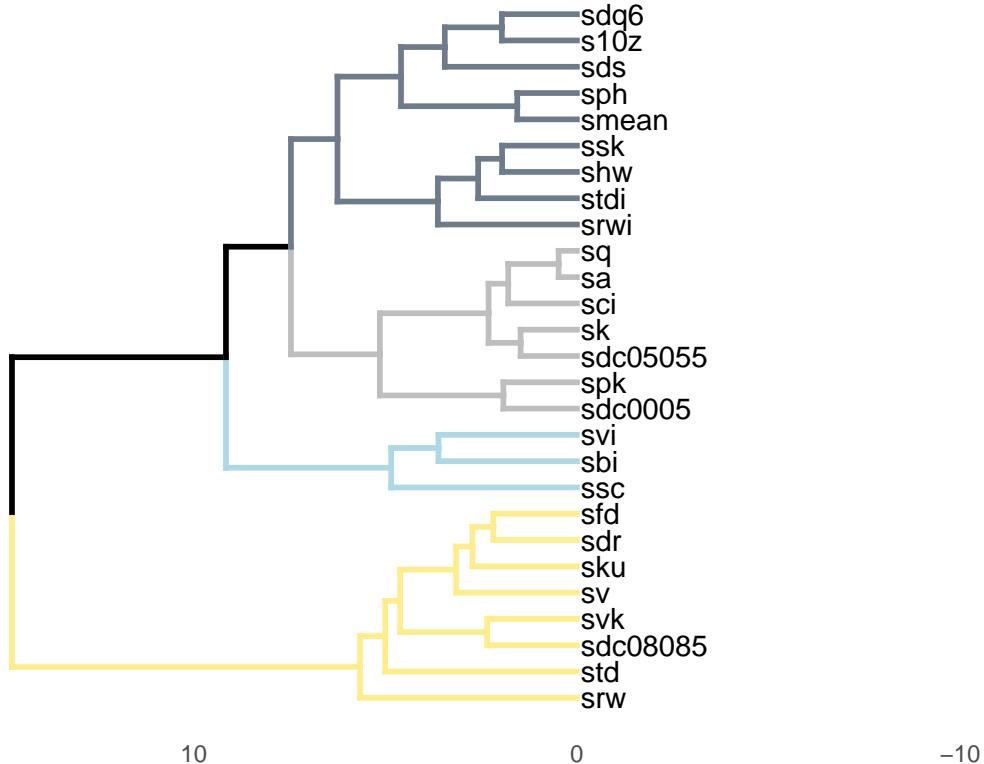
  # Dendrogram plot
  fviz_dend(res.hc, rect = FALSE, k_colors = plt_cols[1:nclust],
            lwd = 1, label_cols = 'black', cex = 0.8, main = "", ylab = "",
            type = 'rectangle', horiz = TRUE, labels_track_height = 14) +
    theme(axis.text.y = element_blank(), axis.ticks = element_blank())
}

plot_scatter <- function(res.hc) {
  # Scatterplot
  fviz_cluster(res.hc)
}

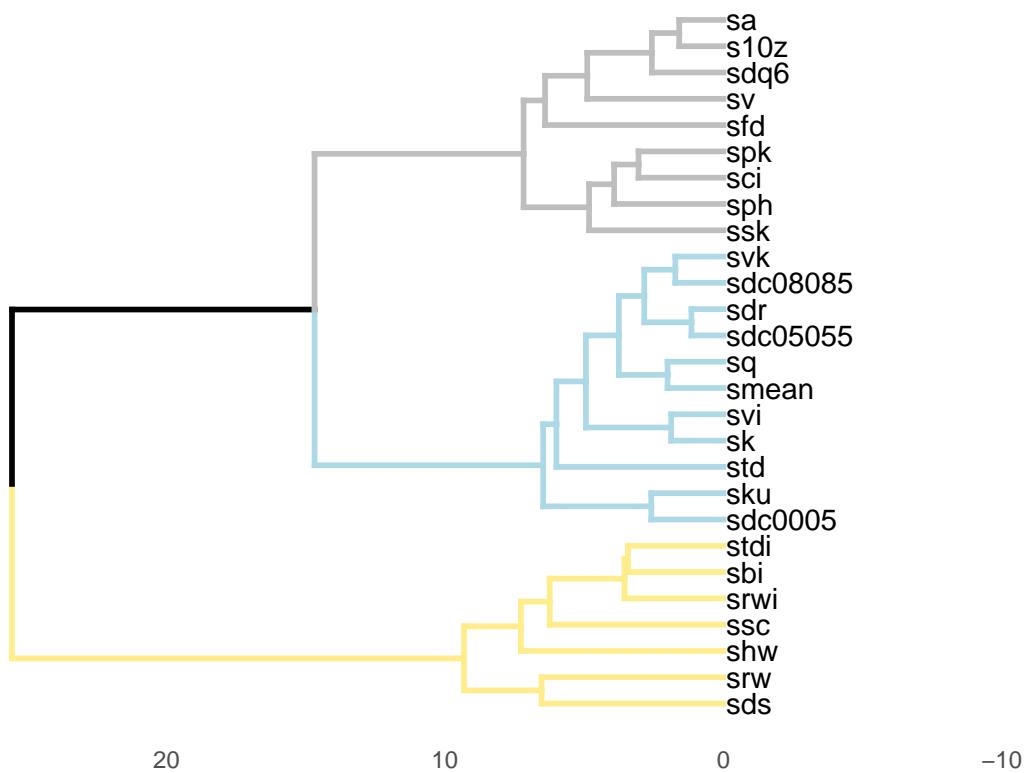
```

```
res.hc_elev <- get_clusters(transect_elev, nclust = 4)
res.hc_evi <- get_clusters(transect_evi, nclust = 3)

plot_dendrogram(res.hc_elev, nclust = 4)
```

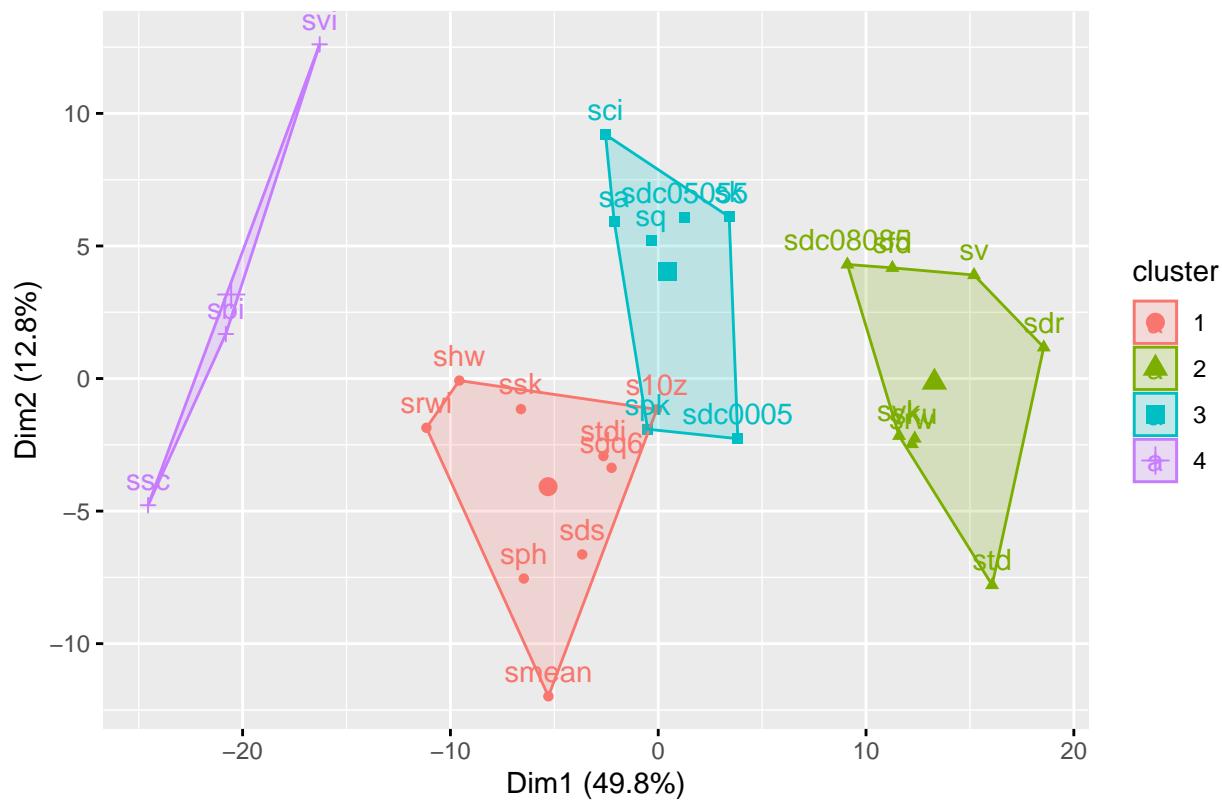


```
plot_dendrogram(res.hc_evi, nclust = 3)
```



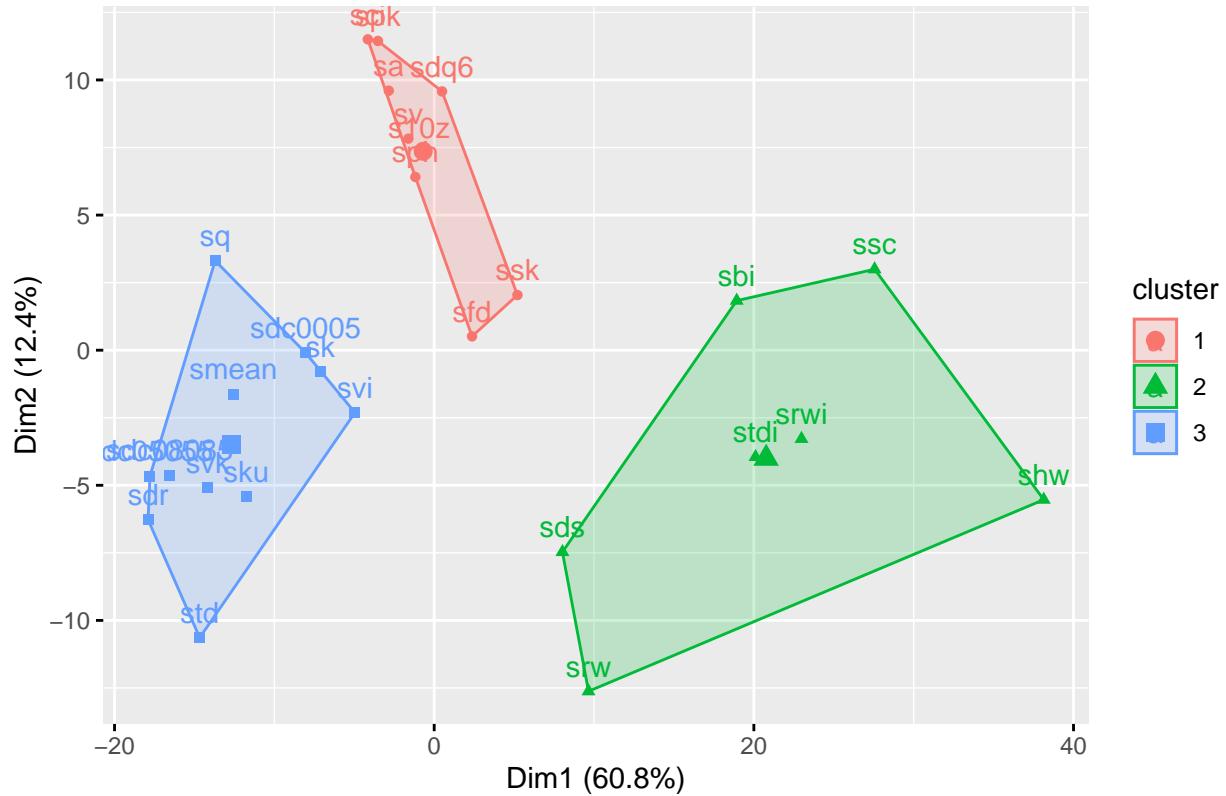
```
plot_scatter(res.hc_elev)
```

Cluster plot



```
plot_scatter(res.hc_evi)
```

Cluster plot



Now we generate plots that show the EVI and elevation surface gradient metrics along the Oregon state transect.

First, the data have to be gathered into a longer format for this visualization.

```
# Create gathered (long) version of dataframe for the clustering analysis.
gather_data <- function(df) {
  df <- df %>% tidyr::gather(key = 'var', value = 'value',
                                names(df[, seq(3, ncol(df))]))

  # Order variables.
  df <- df[order(df$var),]

  return(df)
}

gathered_elev <- gather_data(transect_elev)
gathered_evi <- gather_data(transect_evi)
```

Now we can plot the metrics along the transect, labeling the cluster.

```
# Plot metrics along transect, with cluster labeled.
plot_transect_mets <- function(df, res.hc, varname) {
  # Map colors to cluster or variable names.
  col_map <- c("1" = "lightgoldenrod1", "2" = "lightblue", "3" = "grey",
```

```

    "4" = "lightsteelblue4", "EVI" = "white", "Elev" = "white")

# Create a dataframe to match variable names with cluster number.
clust_df <- data.frame(var = res.hc$labels, clust = res.hc$cluster)
clust_df <- clust_df[order(clust_df$clust),]

# Convert var to character.
clust_df$var <- as.character(clust_df$var)

# Join cluster number with main dataframe to get cluster labels for plotting.
df <- left_join(df, clust_df, by = 'var')

# Anything not labeled with a cluster (i.e., the actual value) gets labeled.
df$clust[is.na(df$clust)] <- varname

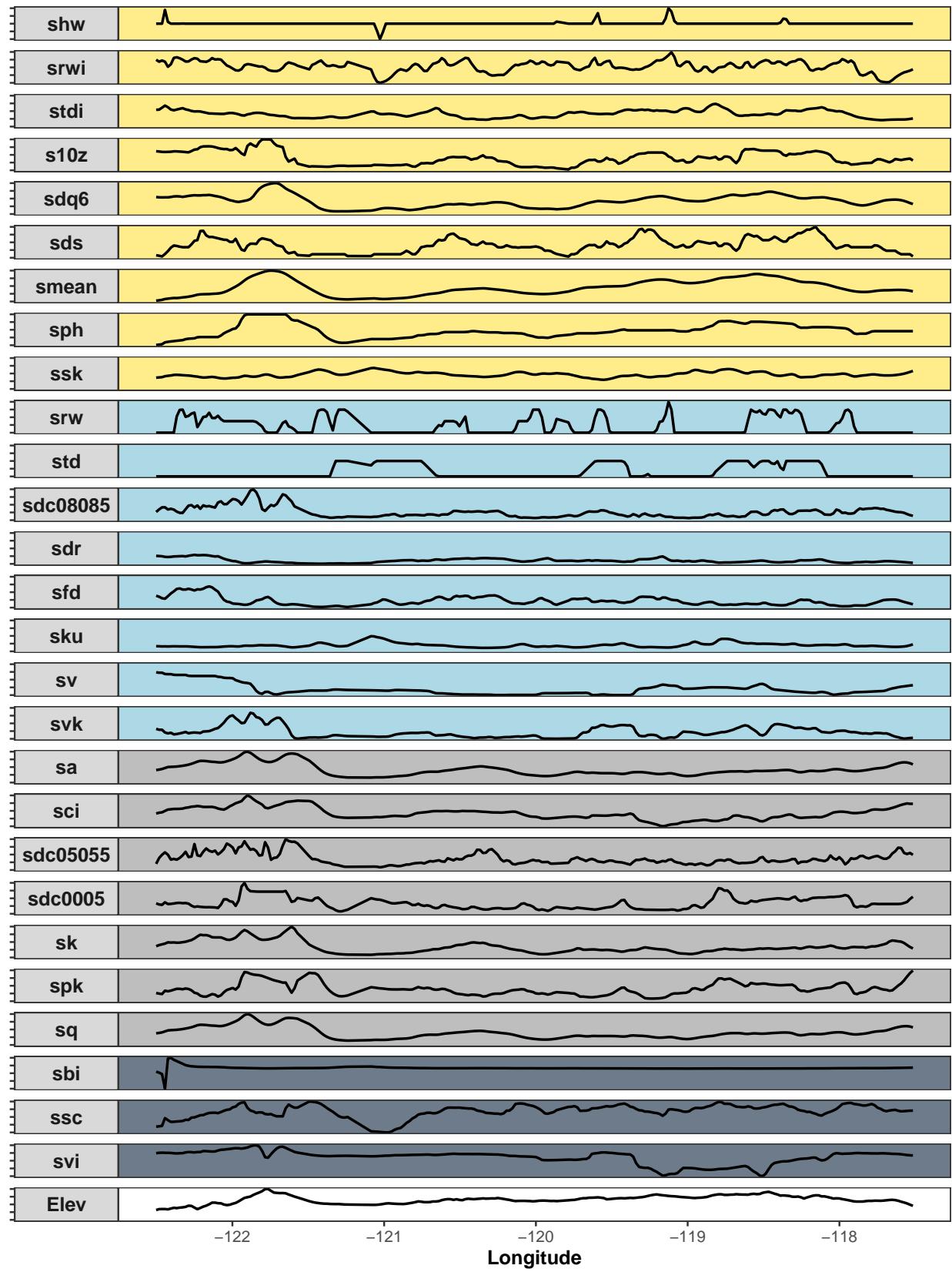
# Change 'value' label to actual variable name.
df$var[df$var == 'value'] <- varname

# Convert cluster names to factors and match with colors.
df$clust <- as.factor(df$clust)
df$var <- factor(df$var, levels = c(clust_df$var, varname))
cols_to_use <- col_map[names(col_map) %in% df$clust]

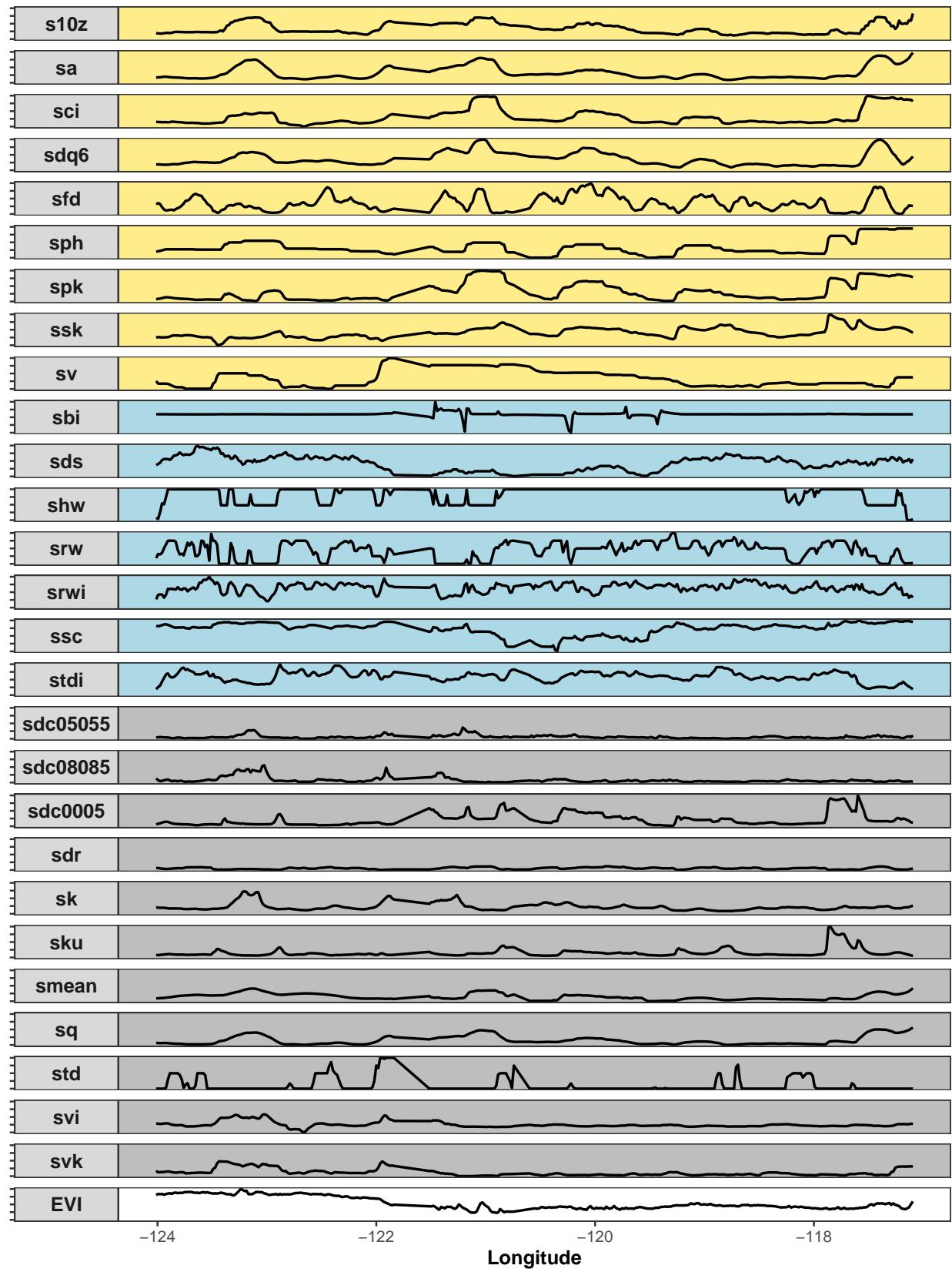
ggplot(df, aes(x = x, y = value)) +
  geom_rect(aes(xmin = -Inf, xmax = Inf, ymin = -Inf, ymax = Inf,
                 fill = clust)) +
  geom_line(lwd = 0.7) +
  xlab('Longitude') +
  facet_grid(var ~ ., switch = 'y') +
  scale_fill_manual(values = cols_to_use, name = 'Cluster') +
  theme_bw() +
  theme(axis.title.y = element_blank(),
        axis.text.y = element_blank(),
        strip.text.y.left = element_text(face = 'bold', size = 11, angle = 0),
        legend.position = 'none',
        axis.title.x = element_text(face = 'bold', size = 11))
}

plot_transect_mets(gathered_elev, res.hc_elev, "Elev")

```



```
plot_transect_mets(gathered_evi, res.hc_evi, "EVI")
```



Summary of transect cluster analysis

Overall trends along the transect were similar among metrics, with more variation at smaller intervals. Using hierarchical clustering, we found four clusters of metrics for elevation, and three for EVI. The metrics fell into different combinations based on the variable considered (elevation or EVI). For example, Sdq6 and S10z grouped together for both variables, but Std and Srw were in the same group for elevation, and different groups for EVI.

Principal Components Analysis (PCA)

Next, we will determine the statewide elevation and EVI variance explained by metrics using PCA. First, we need to get the data ready for the PCA. In the code below, we remove several variables due to their large number of NA values, caused either by windows containing too few values, or windows lacking ‘peaks’ or ‘valleys’ (pixels surrounded by lower or higher values, respectively). After cleaning the data, 21 metrics remain in the analysis.

```
# Get data ready for PCA by removing NA values.
clean_data <- function(df) {
  # Remove columns with very large numbers of NAs.
  NAs <- sapply(df, function(x) sum(is.na(x)))
  rm_cols <- which(NAs >= 20000)
  df <- df[, -rm_cols]
  # Remove NAs from remaining columns.
  df <- na.omit(df)
  return(df)
}

data_elev_noNA <- clean_data(data_elev)
data_evi_noNA <- clean_data(data_evi)
```

In the code below, the PCA is performed with the remaining metrics using the ‘prcomp’ function in the *stats* package.

```
# Calculate the principal components.
elev_prc <- prcomp(data_elev_noNA[, 3:22], center = TRUE, scale = TRUE)
evi_prc <- prcomp(data_evi_noNA[, 3:22], center = TRUE, scale = TRUE)
summary(elev_prc)
#> Importance of components:
#>              PC1     PC2     PC3     PC4     PC5     PC6     PC7
#> Standard deviation   2.3592  1.7964  1.5836  1.28897 1.12823  1.02005 0.99978
#> Proportion of Variance 0.2783  0.1613  0.1254  0.08307 0.06365  0.05203 0.04998
#> Cumulative Proportion 0.2783  0.4396  0.5650  0.64810 0.71174  0.76377 0.81374
#>                  PC8     PC9     PC10    PC11    PC12    PC13    PC14
#> Standard deviation   0.91966 0.79134 0.72898 0.60892 0.58858 0.52619 0.50061
#> Proportion of Variance 0.04229 0.03131 0.02657 0.01854 0.01732 0.01384 0.01253
#> Cumulative Proportion 0.85603 0.88734 0.91391 0.93245 0.94978 0.96362 0.97615
#>                  PC15    PC16    PC17    PC18    PC19    PC20
#> Standard deviation   0.42315 0.34368 0.29564 0.27348 0.11043 0.07380
#> Proportion of Variance 0.00895 0.00591 0.00437 0.00374 0.00061 0.00027
#> Cumulative Proportion 0.98510 0.99101 0.99538 0.99912 0.99973 1.00000
summary(evi_prc)
#> Importance of components:
#>              PC1     PC2     PC3     PC4     PC5     PC6     PC7
```

```

#> Standard deviation      2.5246 1.9870 1.37645 1.25486 1.09009 0.99925 0.96783
#> Proportion of Variance 0.3187 0.1974 0.09473 0.07873 0.05941 0.04992 0.04683
#> Cumulative Proportion  0.3187 0.5161 0.61081 0.68955 0.74896 0.79889 0.84572
#>                         PC8     PC9     PC10    PC11    PC12    PC13    PC14
#> Standard deviation      0.82448 0.79386 0.70303 0.53013 0.50317 0.47567 0.40850
#> Proportion of Variance 0.03399 0.03151 0.02471 0.01405 0.01266 0.01131 0.00834
#> Cumulative Proportion  0.87971 0.91122 0.93593 0.94998 0.96264 0.97396 0.98230
#>                         PC15   PC16   PC17   PC18   PC19   PC20
#> Standard deviation      0.38320 0.30381 0.2531  0.1547  0.14751 0.07128
#> Proportion of Variance 0.00734 0.00461 0.0032  0.0012  0.00109 0.00025
#> Cumulative Proportion  0.98964 0.99426 0.9975  0.9987  0.99975 1.00000

```

Now let's look at some diagnostic plots for the principal components. Scree plots indicate the importance of the principal components with a broken stick criterion. The point at which the scree plot curve crosses the broken stick model distribution, which we will plot in red, is considered to indicate the maximum number of components to retain.

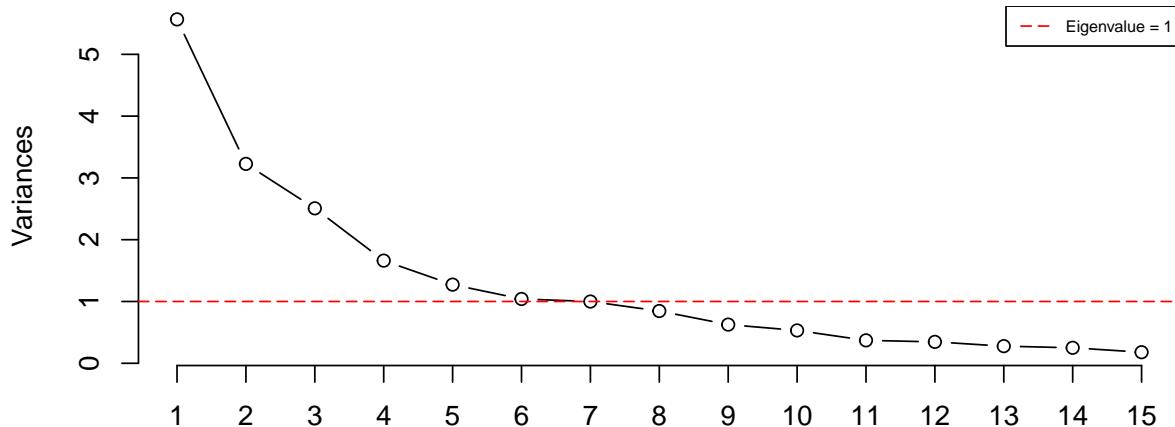
```

# Take a look at the components using a screeplot.
plot_scree <- function(pc_dat) {
  screeplot(pc_dat, type = "l", n pcs = 15,
            main = "Screeplot of the first 10 PCs")
  abline(h = 1, col = "red", lty = 5)
  legend("topright", legend = c("Eigenvalue = 1"),
         col = c("red"), lty = 5, cex = 0.6)
}

plot_scree(elev_prc)

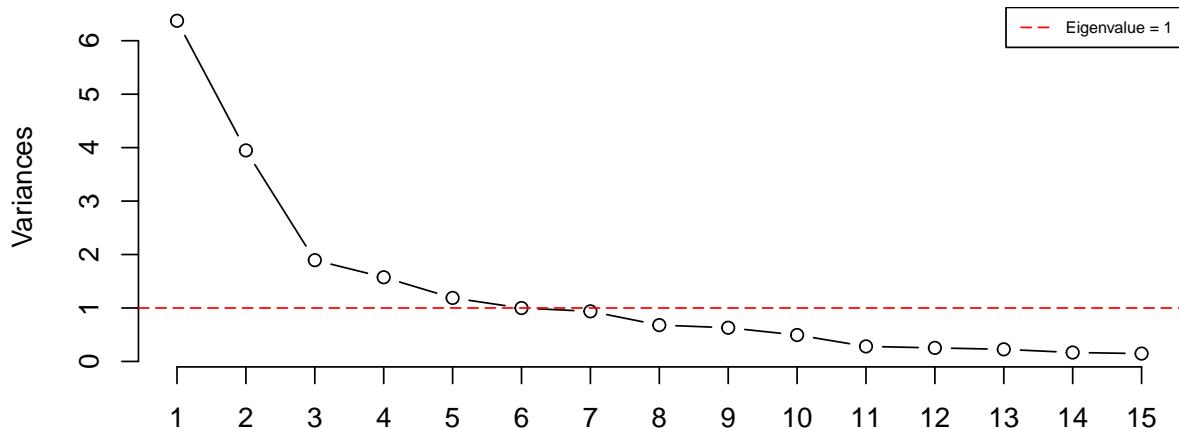
```

Screeplot of the first 10 PCs



```
plot_scree(evi_prc)
```

Screeplot of the first 10 PCs



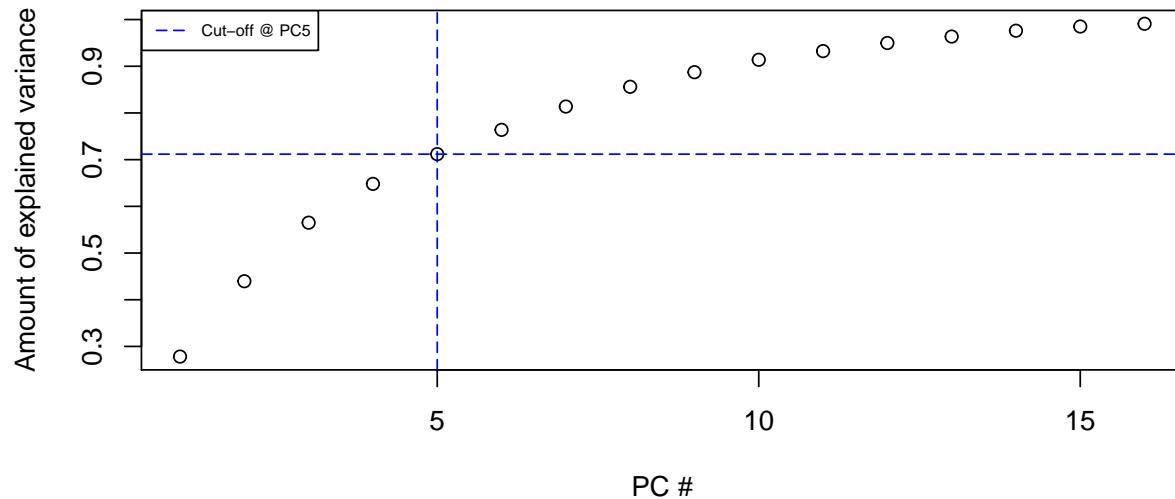
We can also take a look at the components for elevation and EVI to see how much variance the surface metrics explain with cumulative variance plots.

```
# Look at how much variance is explained using a cumulative variance plot.
plot_cvar <- function(pc_dat) {
  # Get cumulative variance explained.
  cumpro <- summary(pc_dat)$importance[3, ][1:16]

  # Create plot of cumulative variance, marking the 5th component as the cutoff.
  plot(cumpro, xlab = "PC #", ylab = "Amount of explained variance",
       main = "Cumulative variance plot")
  abline(v = 5, col = "blue", lty = 5)
  abline(h = cumpro[5], col = "blue", lty = 5)
  legend("topleft", legend = c("Cut-off @ PC5"),
         col = c("blue"), lty = 5, cex = 0.6)
}

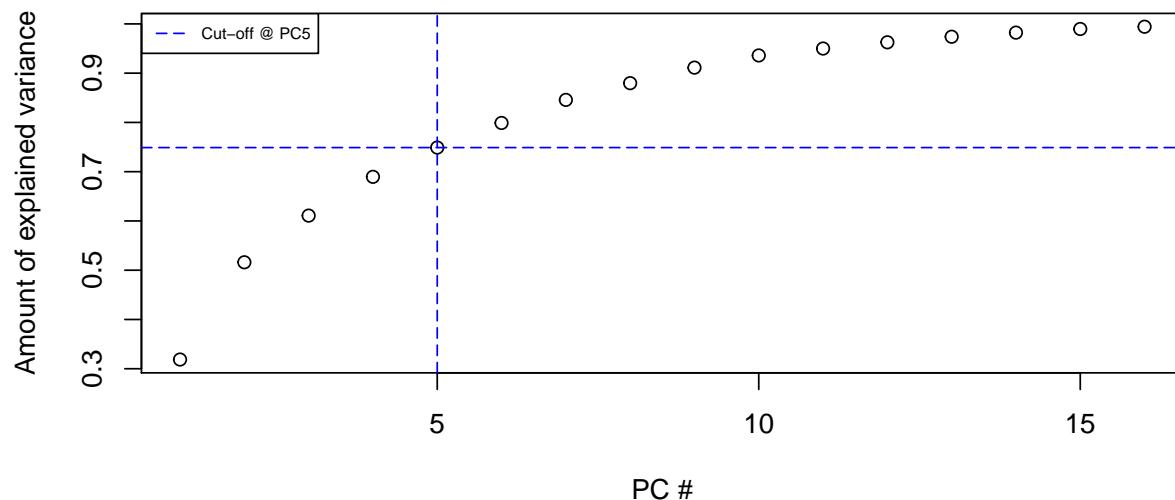
plot_cvar(elev_prc)
```

Cumulative variance plot



```
plot_cvar(evi_prc)
```

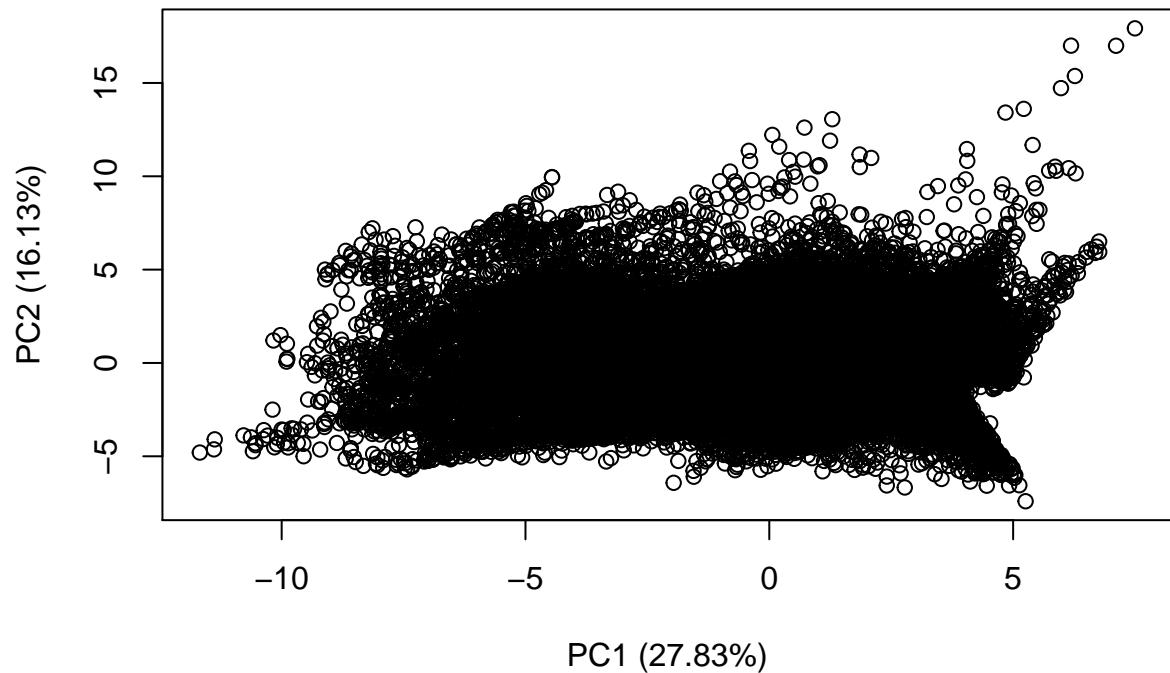
Cumulative variance plot



For both elevation and EVI, the first 5 principal components explained >70% of the variation. Now, let's plot the first components for elevation.

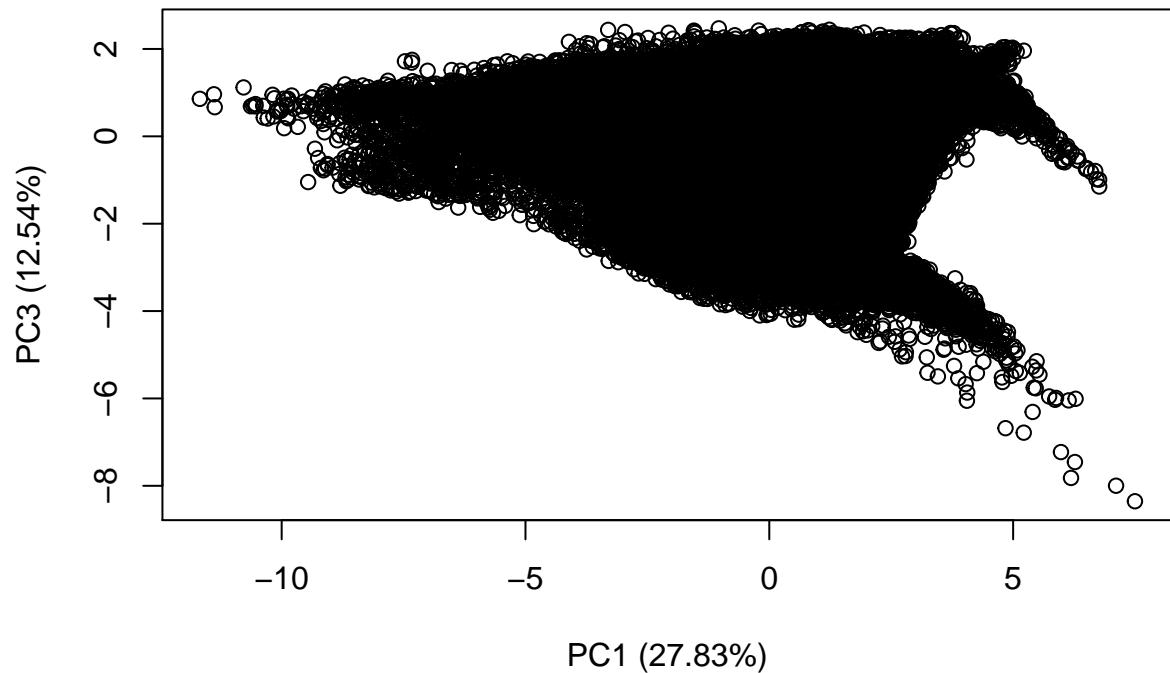
```
# Create scatterplots to look at relationships among principal components.  
plot(elev_prc$x[, 1], elev_prc$x[, 2], xlab = "PC1 (27.83%)",  
     ylab = "PC2 (16.13%)", main = "PC1 / PC2 - plot")
```

PC1 / PC2 – plot



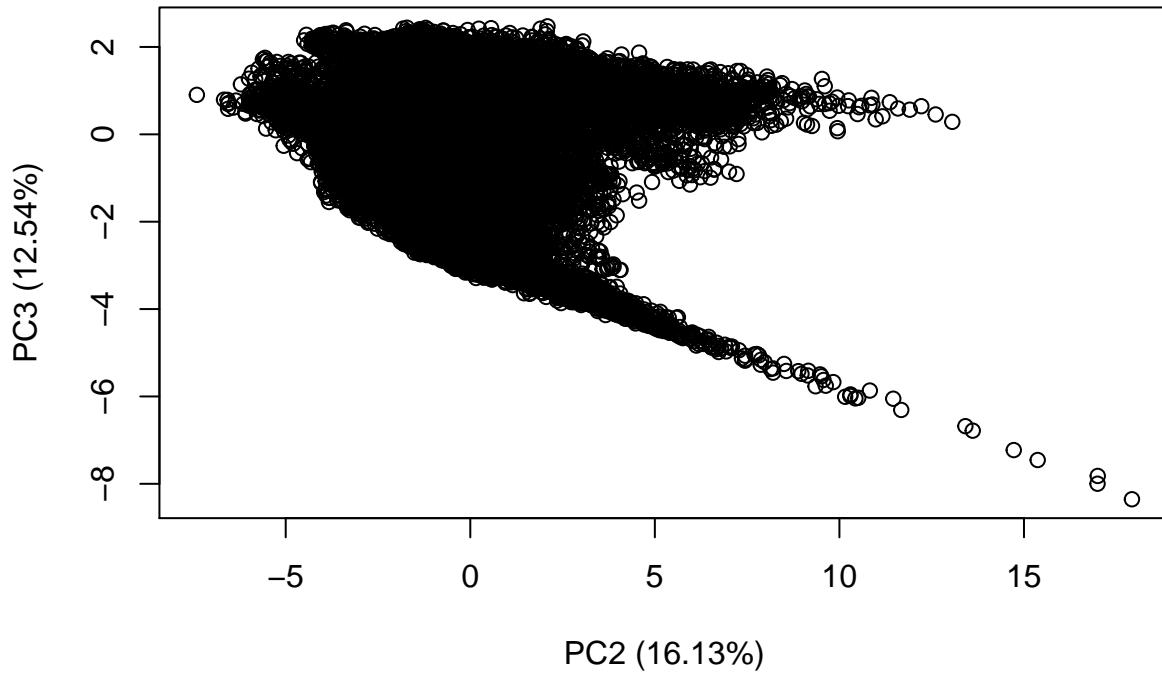
```
plot(elev_prc$x[, 1], elev_prc$x[, 3], xlab = "PC1 (27.83%)",
     ylab = "PC3 (12.54%)", main = "PC1 / PC3 - plot")
```

PC1 / PC3 – plot



```
plot(elev_prc$x[, 2], elev_prc$x[, 3], xlab = "PC2 (16.13%)",
      ylab = "PC3 (12.54%)", main = "PC2 / PC3 - plot")
```

PC2 / PC3 – plot



In the code below, we map the components to see if there are any spatial patterns readily identifiable.

```
# Map components across state.
map_comps <- function(pc_dat, noNA_df, full_df, r, theme) {
  # Add pc values to no-NA dataframe.
  for (i in 1:5) {
    colname <- paste0('prc', i)
    noNA_df[, colname] <- pc_dat$x[, i]
  }

  # Add PCA results back to full raster dataframe.
  full_dat <- full_df %>% left_join(noNA_df)
  # Cut to only the prc columns.
  full_dat <- full_dat[, grep('prc', names(full_dat))]

  # Create rasters and maps with principle component values.
  out_maps <- list()
  for (i in 1:5) {
    new_rast <- setValues(r, full_dat[, i])
    pc_map <- rasterVis::levelplot(new_rast, margin = F,
                                    par.settings = theme,
                                    ylab = NULL, xlab = NULL,
                                    main = paste0('PC', i))
    pc_map$par.settings$layout.heights[c('bottom.padding',
                                         'top.padding',
                                         'key.sub.padding',
                                         'key.title.padding')] <- 1
    out_maps[[i]] <- pc_map
  }
}
```

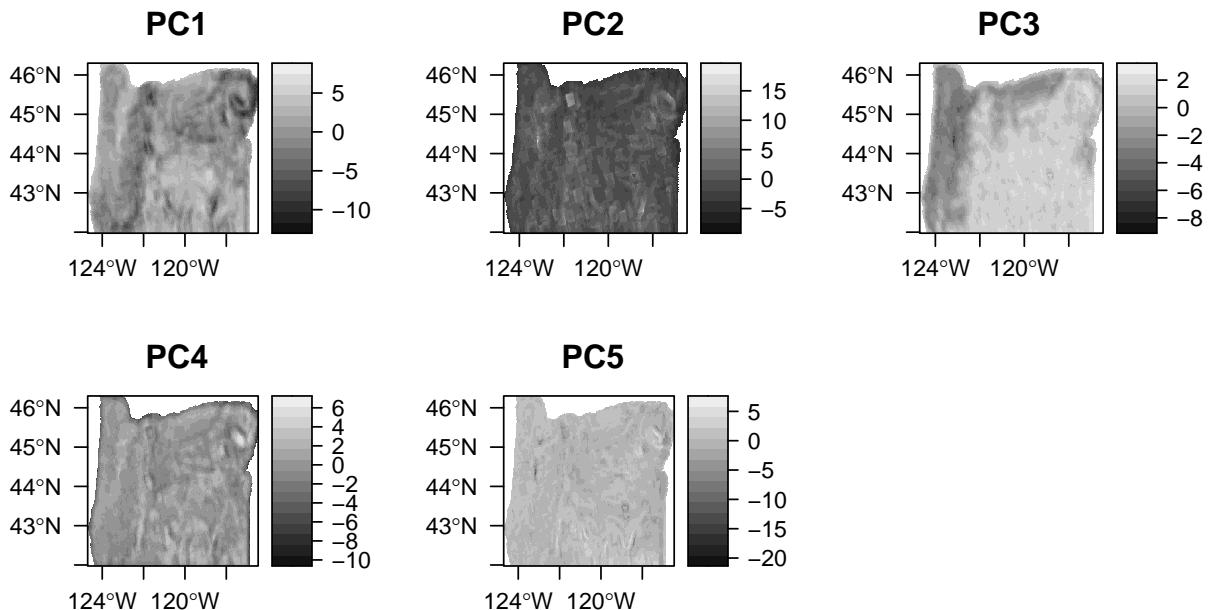
```

    'axis.xlab.padding',
    'key.axis.padding',
    'main.key.padding') ] <- 1
pc_map$aspect.fill <- TRUE
out_maps[[i]] <- pc_map
}

# Plot in a grid.
grid.arrange(grobs = out_maps, nrow = 2, ncol = 3)
}

map_comps(elev_prc, data_elev_noNA, data_elev, elev, elevTheme)
#> Joining, by = c("x", "y", "std", "s10z", "sa", "sbi", "sci", "sdc05055", "sdc08085", "sdc0005", "sdq6")

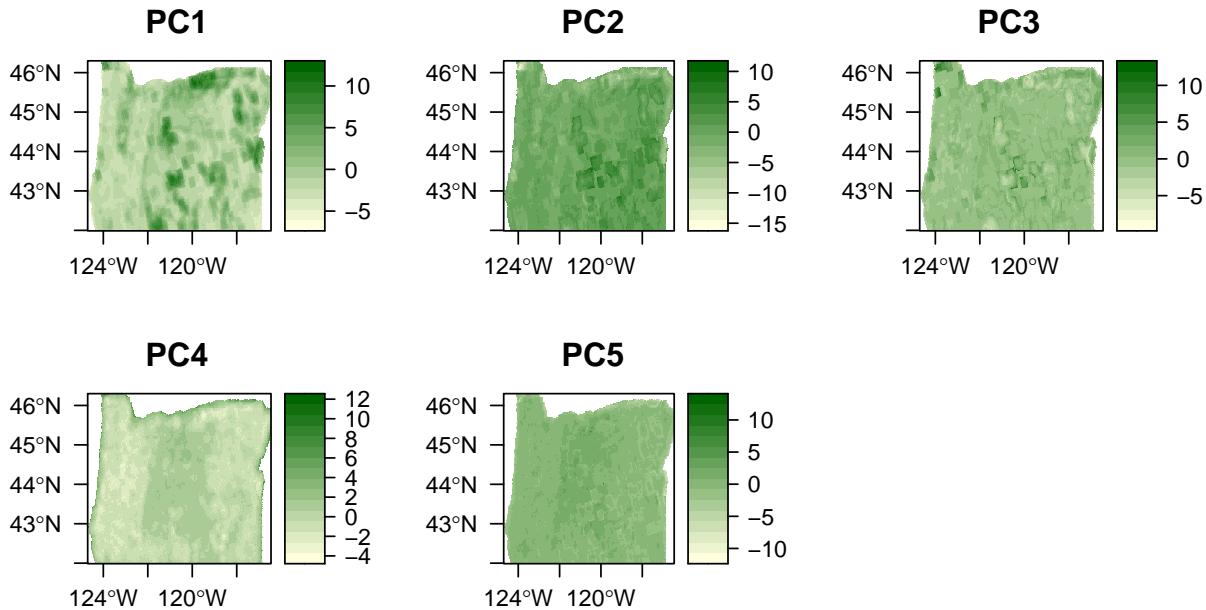
```



```

map_comps(evi_prc, data_evi_noNA, data_evi, evi, eviTheme)
#> Joining, by = c("x", "y", "s10z", "sa", "sbi", "sci", "sdc05055", "sdc08085", "sdc0005", "sdq6", "sdq7")

```



What are the principal component loadings for elevation?

```
# Plot principal component loadings.
plot_loadings <- function(pc_dat) {
  # Get rotation for top 5 components.
  loadings <- pc_dat$rotation[, 1:5]

  # Figure out the relative loadings.
  aload <- abs(loadings)
  rel <- sweep(aload, 2, colSums(aload), "/")

  # Convert relative loadings to dataframe.
  rel <- as.data.frame(rel)
  # Get good variable names (from dataframe created earlier).
  rel$var <- plt_names$new[match(rownames(rel), plt_names$old)]

  # Create importance plots.
  imp_plts <- list()
  for (i in 1:5) {
    temp <- rel
    # Determine whether component loading is positive or negative.
    temp$sign <- factor(sapply(loadings[, i], FUN = function(x) x / abs(x)),
                         levels = c(-1, 1))

    # Order loadings by value.
    temp <- temp[order(temp[, i]),]

    temp$var <- factor(temp$var, levels = temp$var)

    temp_plt <- ggplot(temp, aes(x = temp[, i], y = var)) +
      geom_point(size = 3, aes(pch = sign)) +
      scale_shape_manual(name = element_blank(),
                         values = c(15, 17))
    imp_plts[[i]] <- temp_plt
  }
}
```

```

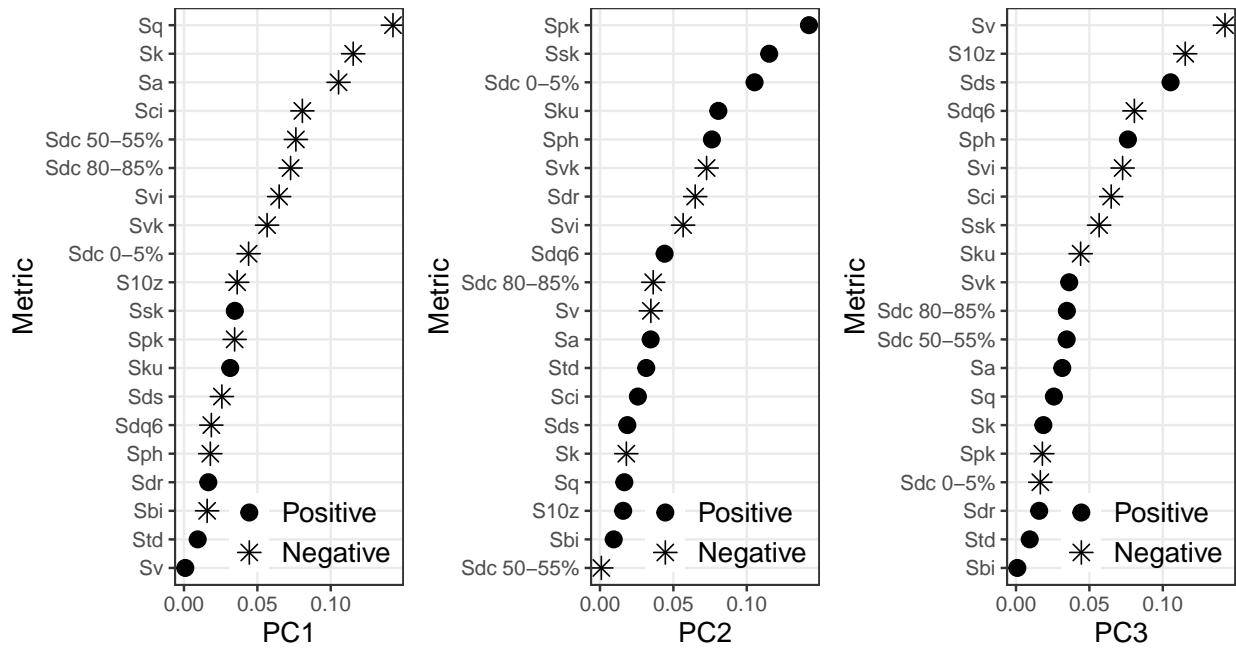
            breaks = c(1, -1),
            values = c(19, 8),
            labels = c("Positive", "Negative")) +
  xlab(paste0('PC', i)) +
  ylab('Metric') +
  theme_bw() +
  theme(panel.grid.minor = element_blank(),
        legend.justification = c(1, 0),
        legend.position = c(1, 0),
        legend.background = element_blank(),
        legend.text = element_text(size = 12),
        axis.title = element_text(size = 12))

  imp_plts[[i]] <- temp_plt
}

# Return grid of first three components.
grid.arrange(grobs = imp_plts[1:3], ncol = 3)
}

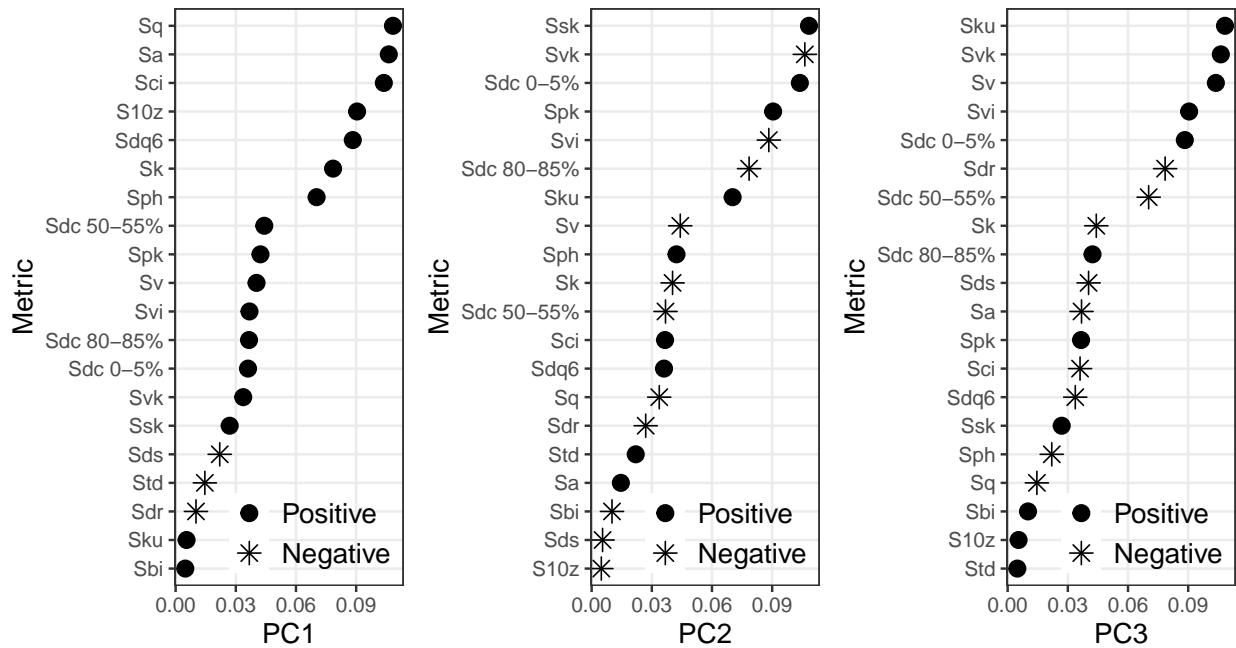
plot_loadings(elev_prc)

```



What are the principal component loadings for EVI?

```
plot_loadings(evi_prc)
```



Summary of PCA

Looking at the PCA components and loadings, the first component for both elevation and EVI described general surface heterogeneity, whereas the second was related to the shape of the regional value distribution. The metric groupings observed match previous findings, and the first two components represent the same groupings (roughness and distribution) found by McGarigal et al. (2009).

Overall summary

The contrast in metric groupings between the transect hierarchical clustering analysis and statewide PCA demonstrate that there may be differences in metric information depending on the landscape size and scale. As the PCA results were more in line with previous results in the literature, this suggests that those results show the broader metric grouping habits. The transect results demonstrate that this grouping does not always hold across different regions.

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