ZOO955 - Satellite Imagery

Hilary Dugan

4/9/2018

LANDSAT

Freely available: https://earthexplorer.usgs.gov/

Sentinel

https://scihub.copernicus.eu/dhus/#/home

LANDSAT Bands

Load imagery and create raster brick

```
library(raster)
library(sp)

l.blue <- raster('LC08_L1TP_024030_20170602_20170615_01_T1/LC08_L1TP_024030_20170602_20170615_01_T1_B2.'
l.green <- raster('LC08_L1TP_024030_20170602_20170615_01_T1/LC08_L1TP_024030_20170602_20170615_01_T1_B3
l.red <- raster('LC08_L1TP_024030_20170602_20170615_01_T1/LC08_L1TP_024030_20170602_20170615_01_T1_B4.T
l.nir <- raster('LC08_L1TP_024030_20170602_20170615_01_T1/LC08_L1TP_024030_20170602_20170615_01_T1_B5.T
l.swir1 <- raster('LC08_L1TP_024030_20170602_20170615_01_T1/LC08_L1TP_024030_20170602_20170615_01_T1_B6
l.swir2 <- raster('LC08_L1TP_024030_20170602_20170615_01_T1/LC08_L1TP_024030_20170602_20170615_01_T1_B7
l.pc <- raster('LC08_L1TP_024030_20170602_20170615_01_T1/LC08_L1TP_024030_20170602_20170615_01_T1_B8.TI
l.cirrus <- raster('LC08_L1TP_024030_20170602_20170615_01_T1/LC08_L1TP_024030_20170602_20170615_01_T1_B
l.t1 <- raster('LC08_L1TP_024030_20170602_20170615_01_T1/LC08_L1TP_024030_20170602_20170615_01_T1_B10.T
l.t2 <- raster('LC08_L1TP_024030_20170602_20170615_01_T1/LC08_L1TP_024030_20170602_20170615_01_T1_B11.T

# Create raster brick
ls = brick(l.red,l.green,l.blue,l.nir,l.swir1,l.swir2,l.cirrus,l.t1,l.t2)

# CROP
e <- extent(280000, 330000, 4750000, 4800000)
ls.c = crop(ls,e)

names(ls.c) <- c('red','green','blue','NIR','SWIR1','SWIR2','cirrus','thermal1','thermal2')
writeRaster(ls.c,filename = 'Madison_Landsat_20170602.tif', format="GTiff", overwrite=TRUE)
```

Load cropped imagery

```
library(raster)
```

```
## Loading required package: sp
```

Landsat sensor	LS 1–5 MSS	LS 4–5 TM	LS 7 ETM+	LS 8 OLI/TIRS	Pixel size (m)
Coastal aerosol				B1 (0.43–0.45)	30
Blue		B1 (0.45–0.52)	B1 (0.45–0.52)	B2 (0.45–0.51)	30
Green	B1 (0.5–0.6)	B2 (0.52–0.60)	B2 (0.52–0.60)	B3 (0.53–0.59)	30 (60 [a] for MSS)
Red	B2 (0.6–0.7)	B3 (0.63–0.69)	B3 (0.63–0.69)	B4 (0.64–0.67)	30 (60 [a] for MSS)
NIR 1	B3 (0.7–0.8)				60
NIR	B4 (0.8–1.1)	B4 (0.76–0.90)	B4 (0.77–0.90)	B5 (0.85–0.88)	30 (60 [a] for MSS)
SWIR 1		B5 (1.55–1.75)	B5 (1.55–1.75)	B6 (1.57–1.65)	30
SWIR 2		B7 (2.08–2.35)	B7 (2.09–2.35)	B7 (2.11–2.29)	30
Thermal		B6 (10.40–12.50)	B6 [b] (10.40–12.50)	B10 (10.60–11.19) B11 (11.50–12.51)	30 [a]
Pan-Chromatic			B8 (0.52–0.90)	B8 (0.50–0.68)	15
Cirrus				B9 (1.36–1.38)	30

Figure 1:

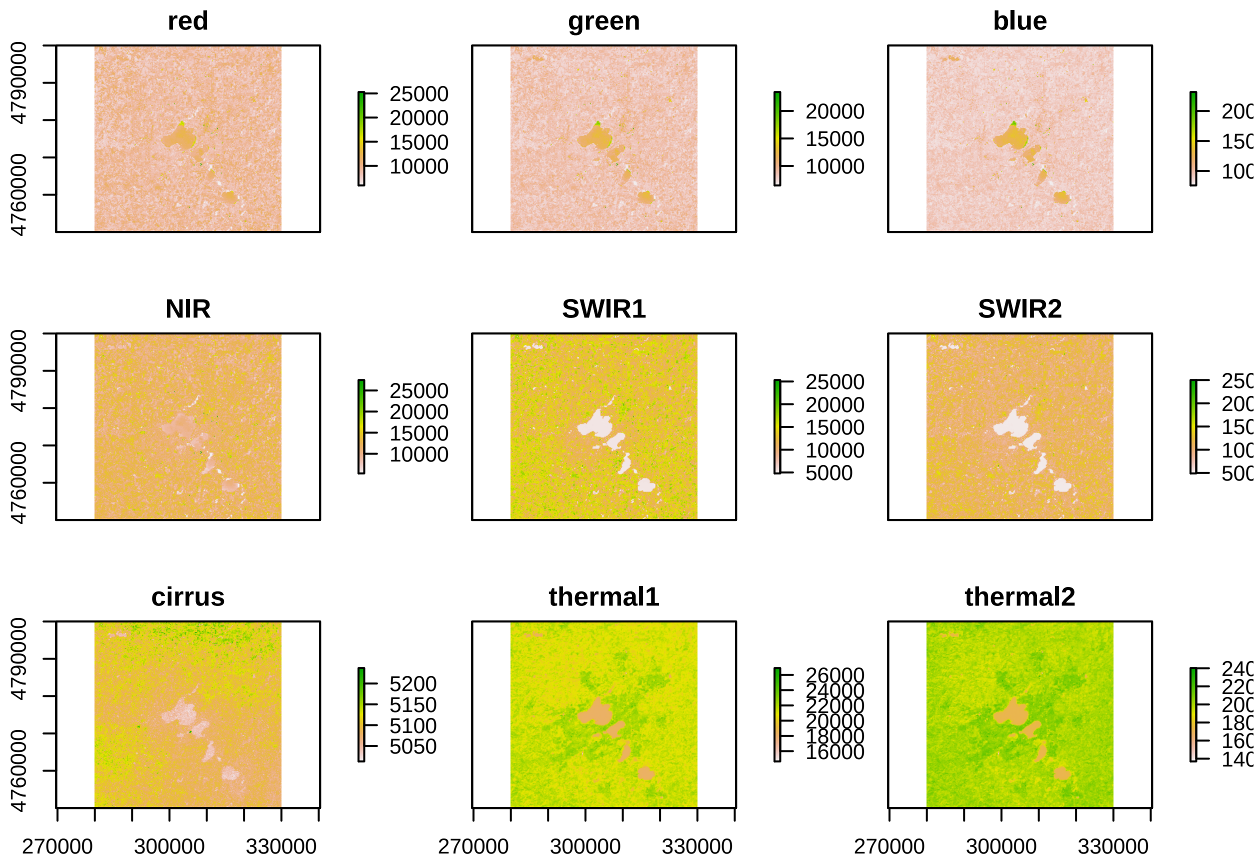
```r
library(sp)
r1 = brick('Madison_Landsat_20170602.tif')
r2 = brick('Madison_Landsat_20180317.tif')
names(r1) <- c('red','green','blue','NIR','SWIR1','SWIR2','cirrus','thermal1','thermal2')
names(r2) <- c('red','green','blue','NIR','SWIR1','SWIR2','cirrus','thermal1','thermal2')

r1
```

```
## class       : RasterBrick
## dimensions  : 1667, 1667, 2778889, 9  (nrow, ncol, ncell, nlayers)
## resolution  : 30, 30  (x, y)
## extent      : 280005, 330015, 4750005, 4800015  (xmin, xmax, ymin, ymax)
## coord. ref. : +proj=utm +zone=16 +datum=WGS84 +units=m +no_defs +ellps=WGS84 +towgs84=0,0,0
## data source : /Users/hilarydugan/Documents/Zoo955/Lecture9_SatelliteImagery/Madison_Landsat_20170602
## names       :   red, green,  blue,   NIR, SWIR1, SWIR2, cirrus, thermal1, thermal2
## min values  :  3868,  5598,  7421,  5232,  5142,  5058,   4995,    20368,    19692
## max values  : 65535, 65535, 61486, 65535, 65535, 65535,   6626,    38316,    32482
```

Plot imagery

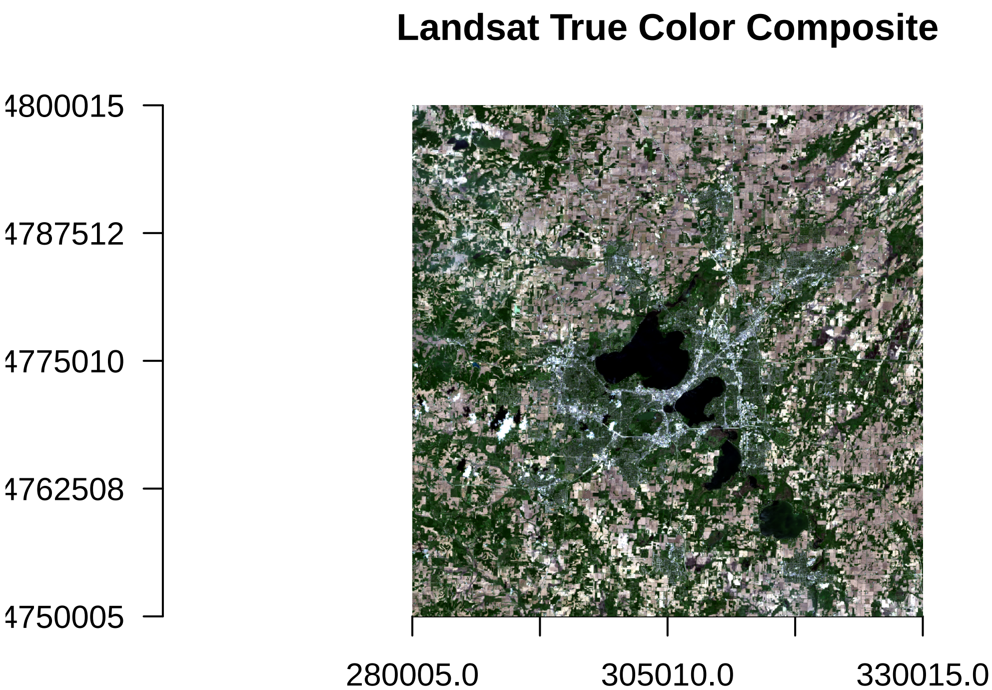
```r
plot(r2)
```



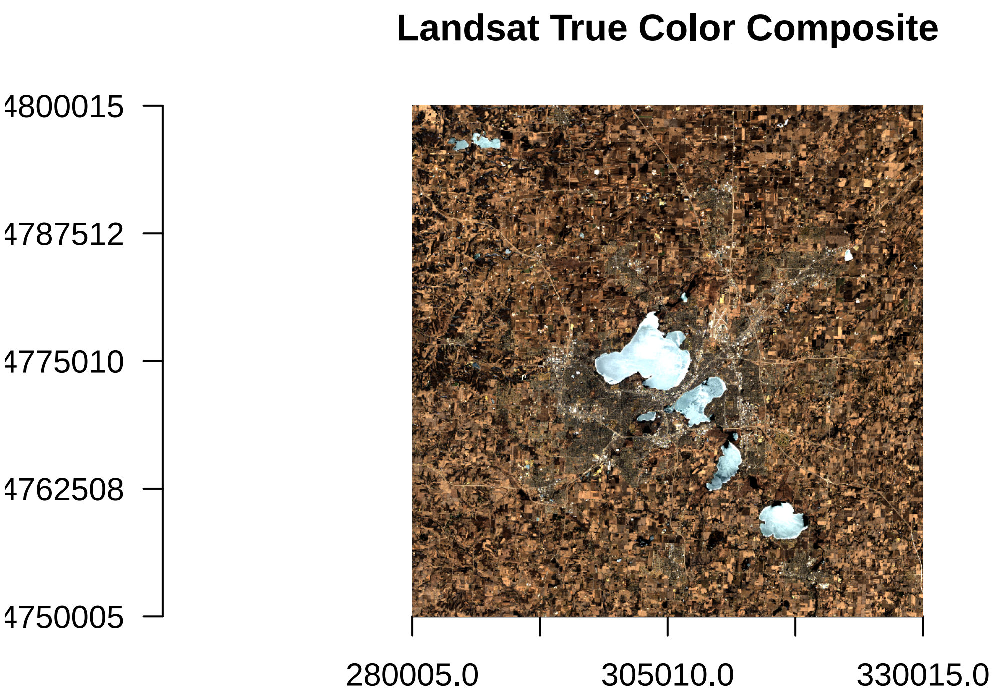
Plot RGB

- Can plot indivudal layers of a multi-spectral image, but they are often combined
- To combine three bands, use plotRGB
- Select bands that render in the red, green and blue regions
- Additional arguments to plotRGB to improve the visualization (e.g. a linear stretch of the values, using strecth = "lin").

```r
plotRGB(r1, r = 1, g = 2, b = 3, axes = TRUE, stretch = "lin",
        main = "Landsat True Color Composite")
```




```r
plotRGB(r2, r = 1, g = 2, b = 3, axes = TRUE, stretch = "lin",
        main = "Landsat True Color Composite")
```



Extract values

```r
# Load Lake shapefile
library(sf)
```

```
## Warning: package 'sf' was built under R version 3.4.4
```

```
## Linking to GEOS 3.6.1, GDAL 2.1.3, proj.4 4.9.3
```

```r
mendota <- st_read('../Lecture2_CRS/Data/LakeMendota.shp') %>%
  st_transform('+proj=utm +zone=16 +datum=WGS84 +units=m +no_defs +ellps=WGS84 +towgs84=0,0,0')
```

```
## Reading layer `LakeMendota' from data source `/Users/hilarydugan/Documents/Zoo955/Lecture2_CRS/Data/
## Simple feature collection with 1 feature and 12 fields
## geometry type:  POLYGON
## dimension:      XY
## bbox:           xmin: -89.48369 ymin: 43.07384 xmax: -89.36737 ymax: 43.14706
## epsg (SRID):    4269
## proj4string:    +proj=longlat +datum=NAD83 +no_defs
```

```r
# random sample of 100 points
l.pts <- st_sample(mendota, size = 100) %>% st_sf
lake.s <- extract(r1, as(l.pts,'Spatial')) #summer values
lake.w <- extract(r2, as(l.pts,'Spatial')) #winter values

# Load watershed shapefile
```

```r
watershed <- st_read('../Lecture3_Shapefiles/Data/YaharaBasins/Mendota_Basin.shp') %>%
  st_transform('+proj=utm +zone=16 +datum=WGS84 +units=m +no_defs +ellps=WGS84 +towgs84=0,0,0')
```

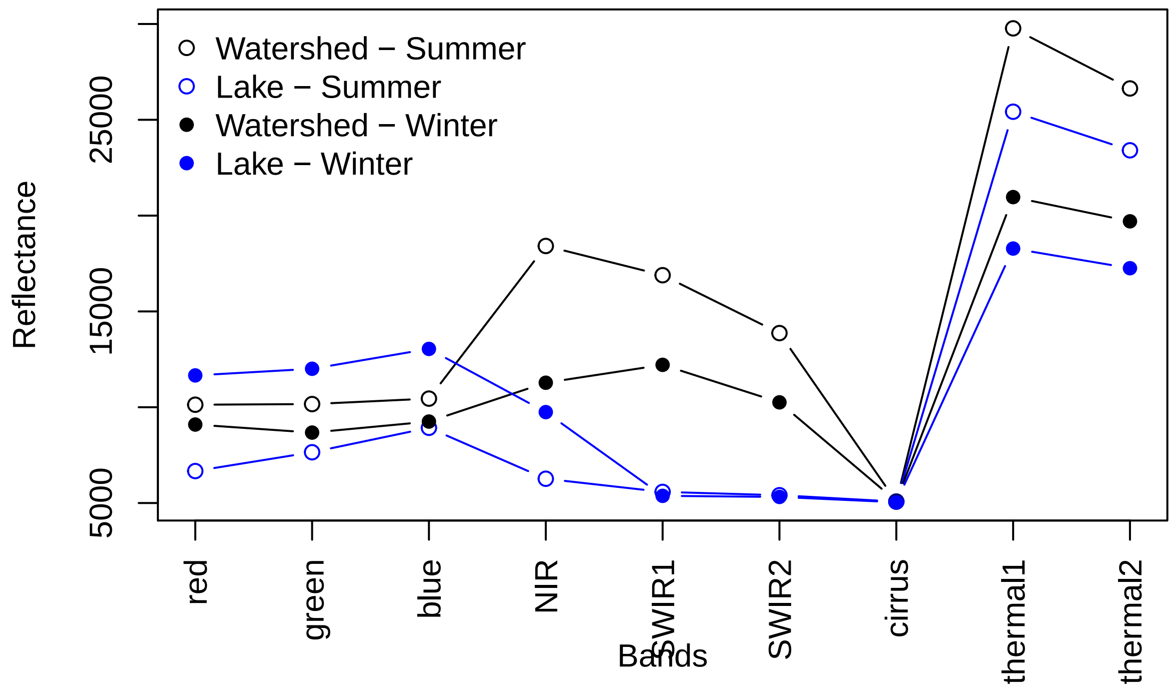
```
## Reading layer `Mendota_Basin' from data source `/Users/hilarydugan/Documents/Zoo955/Lecture3_Shapefil
## Simple feature collection with 1 feature and 3 fields
## geometry type:  MULTIPOLYGON
## dimension:      XY
## bbox:           xmin: 552122.5 ymin: 286231.1 xmax: 584702.5 ymax: 321699.8
## epsg (SRID):    NA
## proj4string:    +proj=tmerc +lat_0=0 +lon_0=-90 +k=0.9996 +x_0=520000 +y_0=-4480000 +ellps=GRS80 +tow
```

```r
# random sample of 100 points
ws.pts <- st_sample(watershed, size = 100) %>% st_sf
ws.s <- extract(r1, as(ws.pts,'Spatial'))
ws.w <- extract(r2, as(ws.pts,'Spatial'))

# To see some of the reflectance values
lake.S <- colMeans(lake.s)
lake.W <- colMeans(lake.w)
ws.S <- colMeans(ws.s,na.rm = T)
ws.W <- colMeans(ws.w,na.rm = T)

plot(ws.S,xlab='Bands',ylab='Reflectance',type='b',xaxt='n')
axis(1,at = 1:9,labels = names(r2),las=2)

lines(lake.S,type='b',col='blue')
lines(ws.W,type='b',col='black',pch=16)
lines(lake.W,type='b',col='blue',pch=16)
legend('topleft',legend = c('Watershed - Summer','Lake - Summer','Watershed - Winter','Lake - Winter'),c
       pch=c(21,21,16,16),bty='n')
```

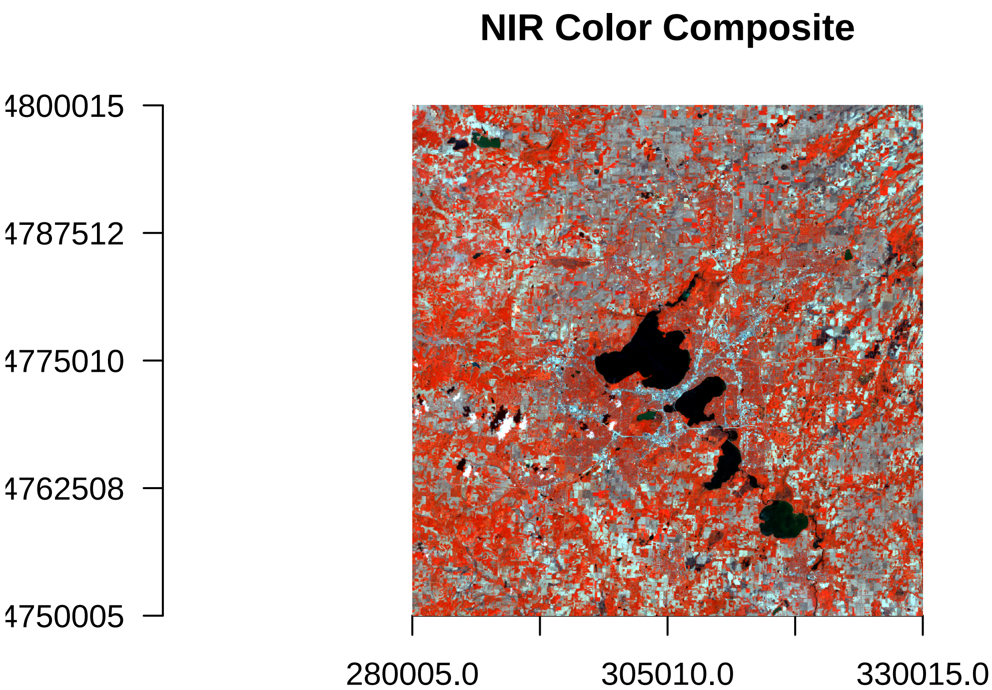


Indices

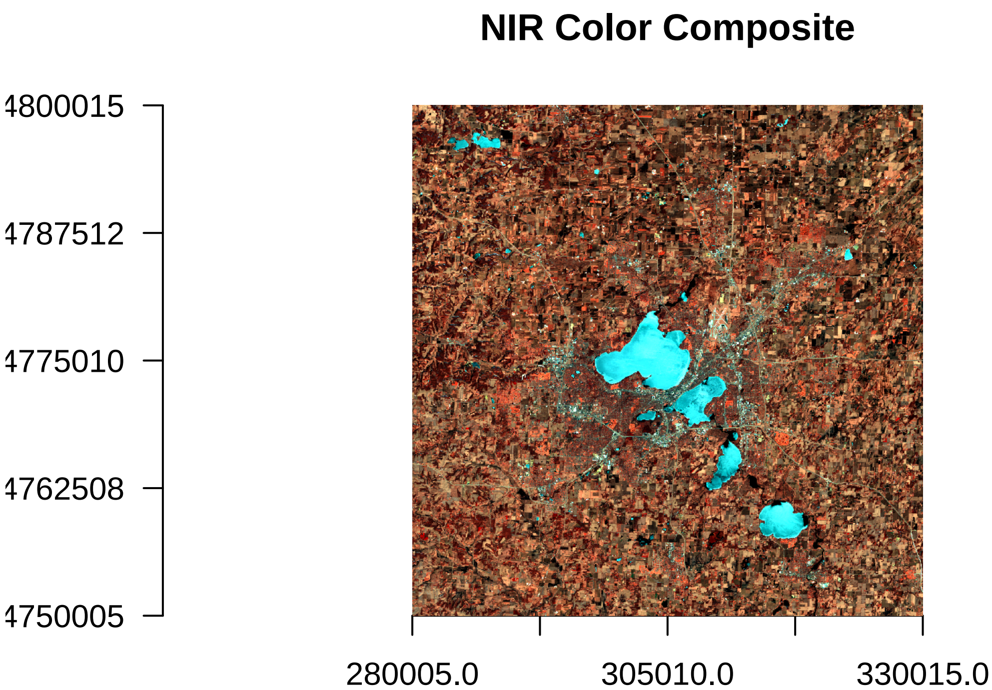
Normalized Difference Vegetation Index - NDVI

Vegetation strongly reflects near-infrared. Plot NIR band as red

```r
plotRGB(r1, r = 4, g = 2, b = 3, axes = TRUE, stretch = "lin", main = "NIR Color Composite")
```




```r
plotRGB(r2, r = 4, g = 2, b = 3, axes = TRUE, stretch = "lin", main = "NIR Color Composite")
```

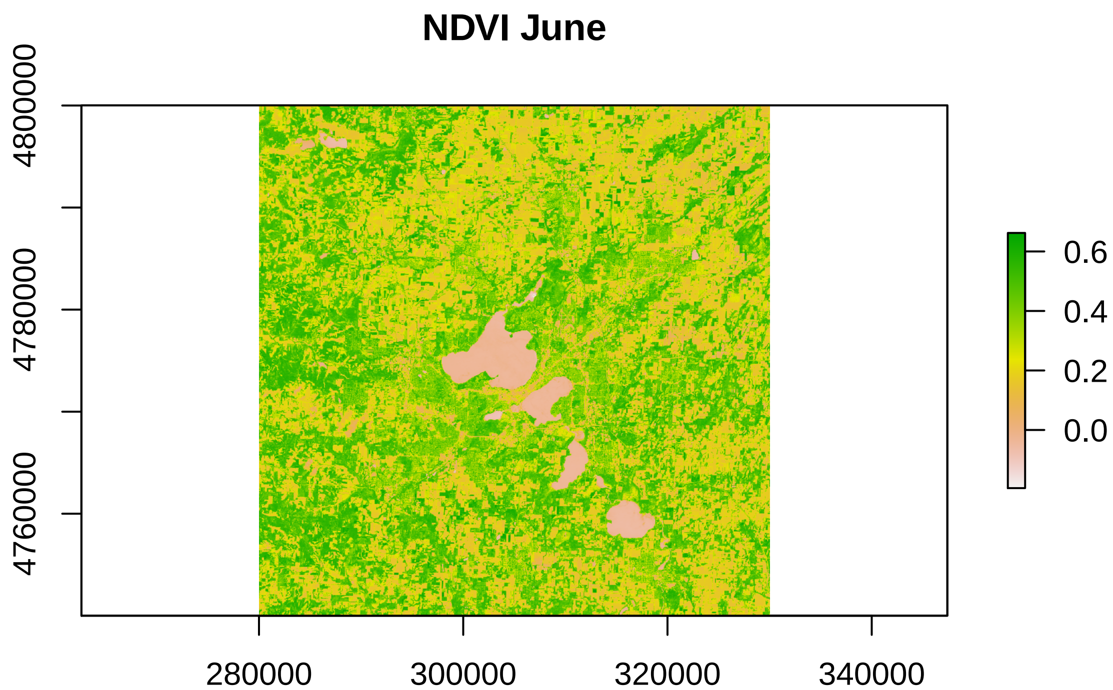


- Normalized Difference Vegetation Index (NDVI) quantifies vegetation by measuring the difference between near-infrared (which vegetation strongly reflects) and red light (which vegetation absorbs)
- Satellite sensors like Landsat and Sentinel-2 both have the necessary bands with NIR and red

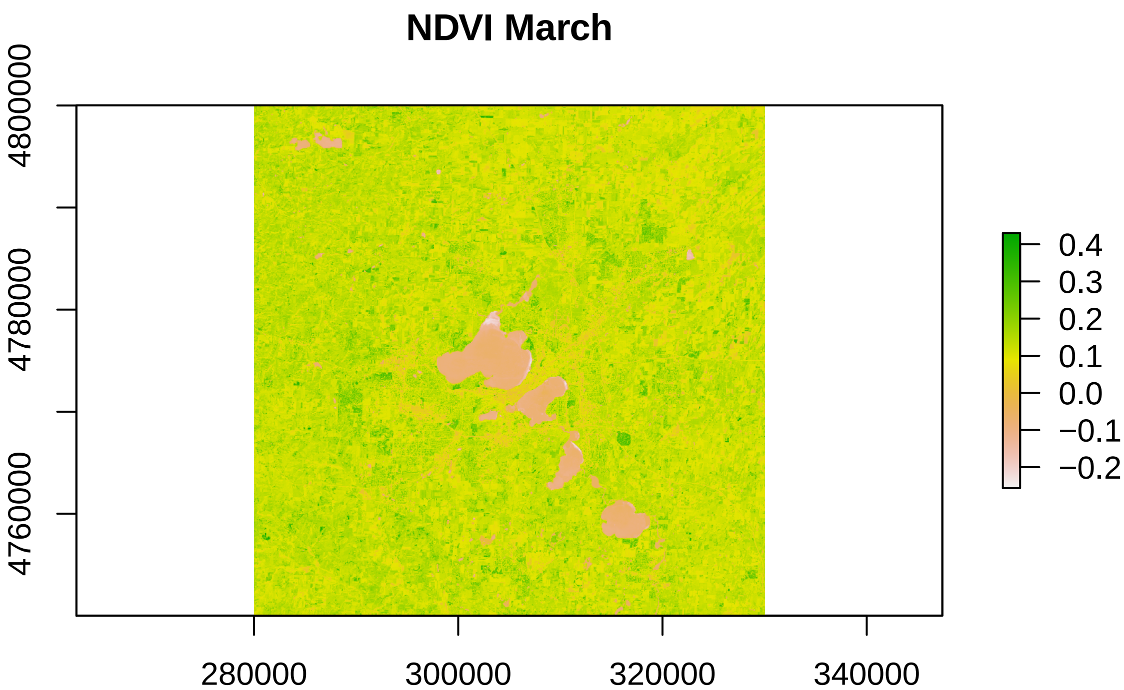
NDVI = (NIR - Red) / (NIR + Red)

```
ndvi1 <- (r1[[4]] - r1[[1]]) / (r1[[4]] + r1[[1]])
ndvi2 <- (r2[[4]] - r2[[1]]) / (r2[[4]] + r2[[1]])

plot(ndvi1, main = 'NDVI June')
```




```
plot(ndvi2, main = 'NDVI March')
```



Areas of barren rock, sand, or snow usually show very low NDVI values (for example, 0.1 or less). Sparse vegetation such as shrubs and grasslands or senescing crops may result in moderate NDVI values (approximately 0.2 to 0.5). High NDVI values (approximately 0.6 to 0.9) correspond to dense vegetation such as that found in temperate and tropical forests or crops at their peak growth stage.

As expected the NDVI is higher during the summer

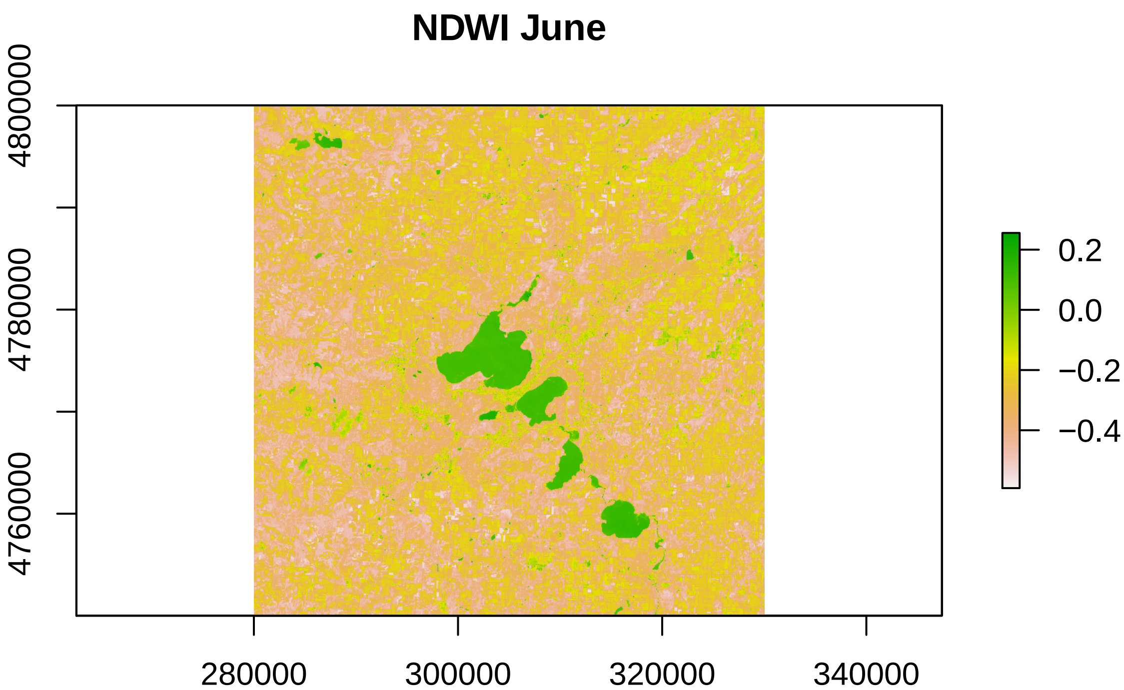
Normalized Difference Water Index - NDWI

Normalized Difference Water Index (NDWI), as described by McFeeters (1996), to differentiate water from non-water

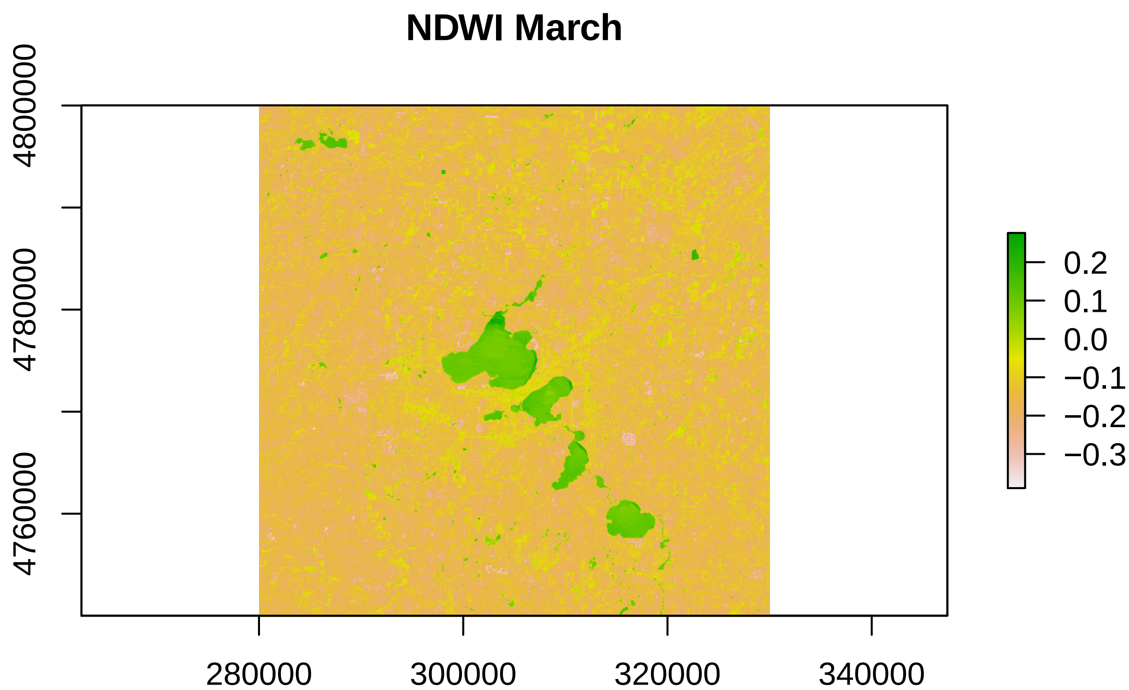
NDWI <- (NIR - GREEN)) / (NIR + GREEN)

```
ndwi1 <- (r1[[2]] - r1[[4]]) / (r1[[4]] + r1[[2]])
ndwi2 <- (r2[[2]] - r2[[4]]) / (r2[[4]] + r2[[2]])

plot(ndwi1, main = 'NDWI June')
```




```
plot(ndwi2, main = 'NDWI March')
```



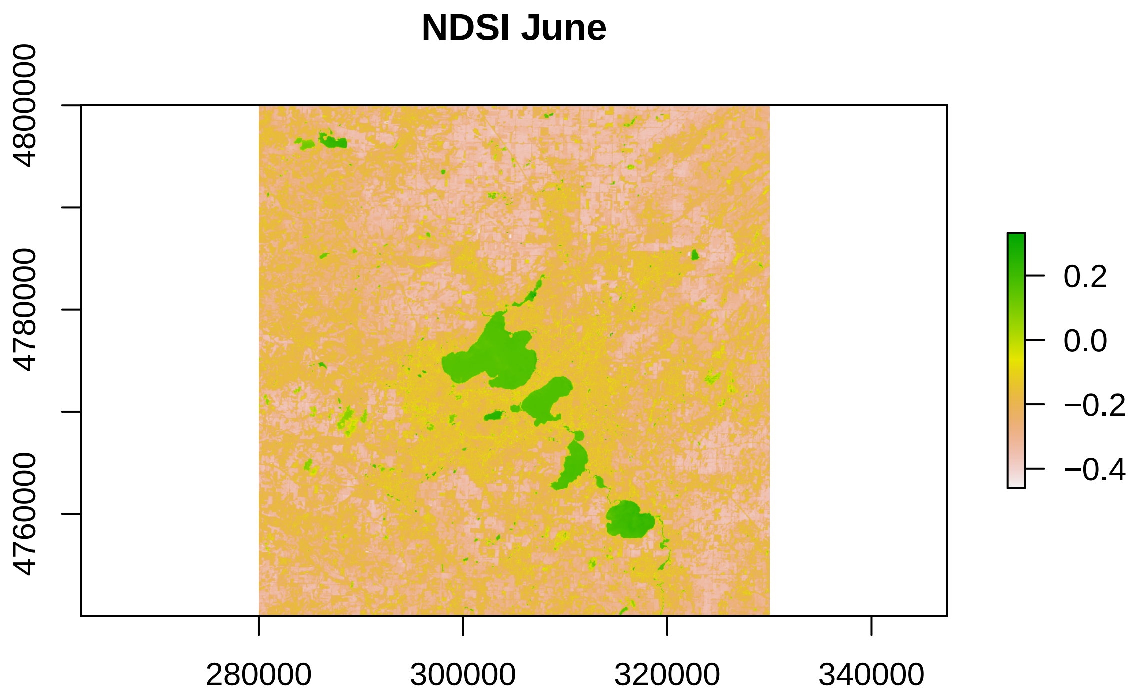
Normalized Difference Snow Index - NDWI

Normalized Difference Water Index (NDSI), to differentiate snow/ice

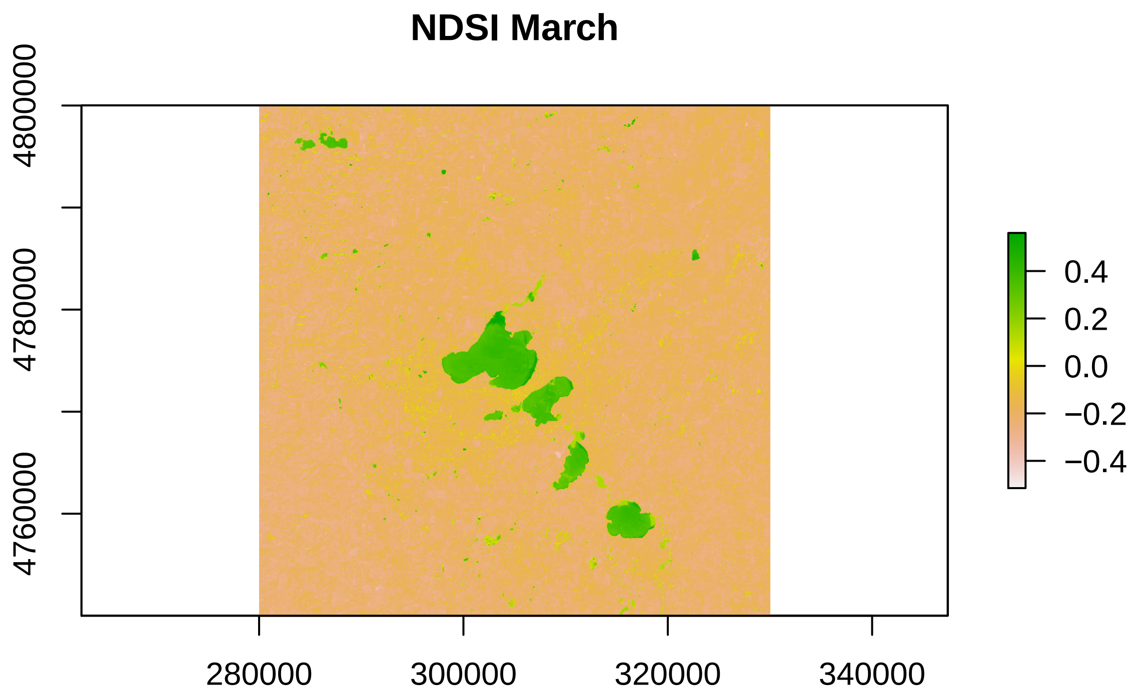
NDSI <- (GREEN - SWIR)) / (SWIR + GREEN)

```
ndsi1 <- (r1[[2]] - r1[[5]]) / (r1[[5]] + r1[[2]])
ndsi2 <- (r2[[2]] - r2[[5]]) / (r2[[5]] + r2[[2]])

plot(ndsi1, main = 'NDSI June')
```




```r
plot(ndsi2, main = 'NDSI March')
```

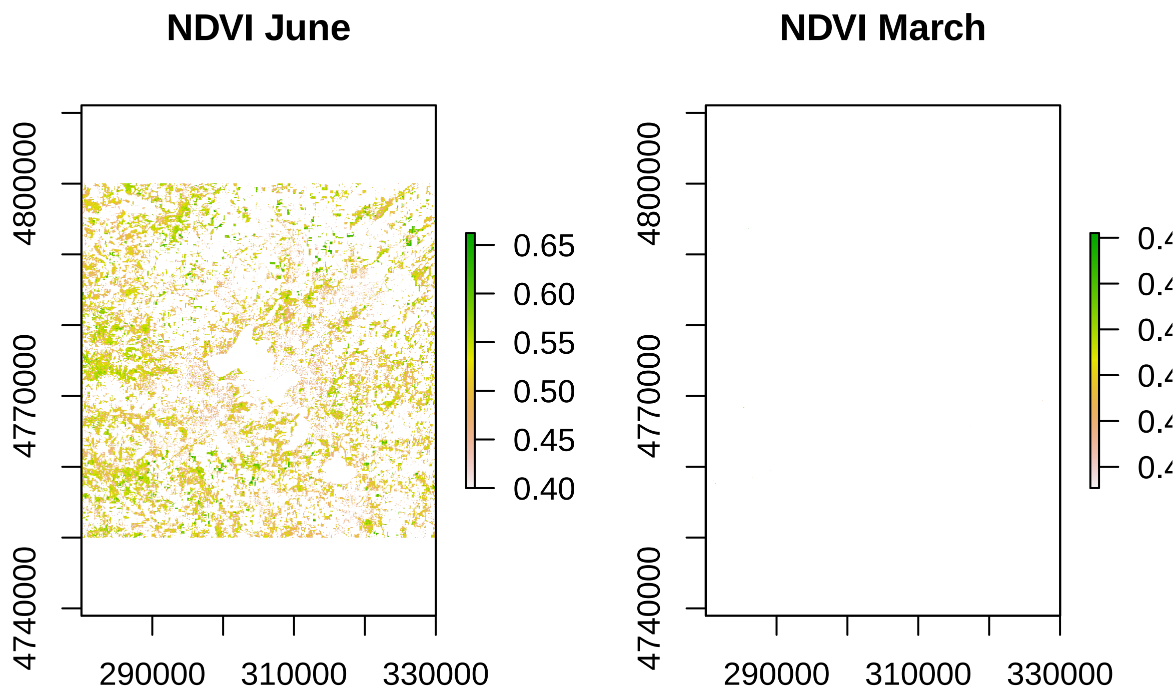


Thresholding

Get an estimate of spatial extent of different features

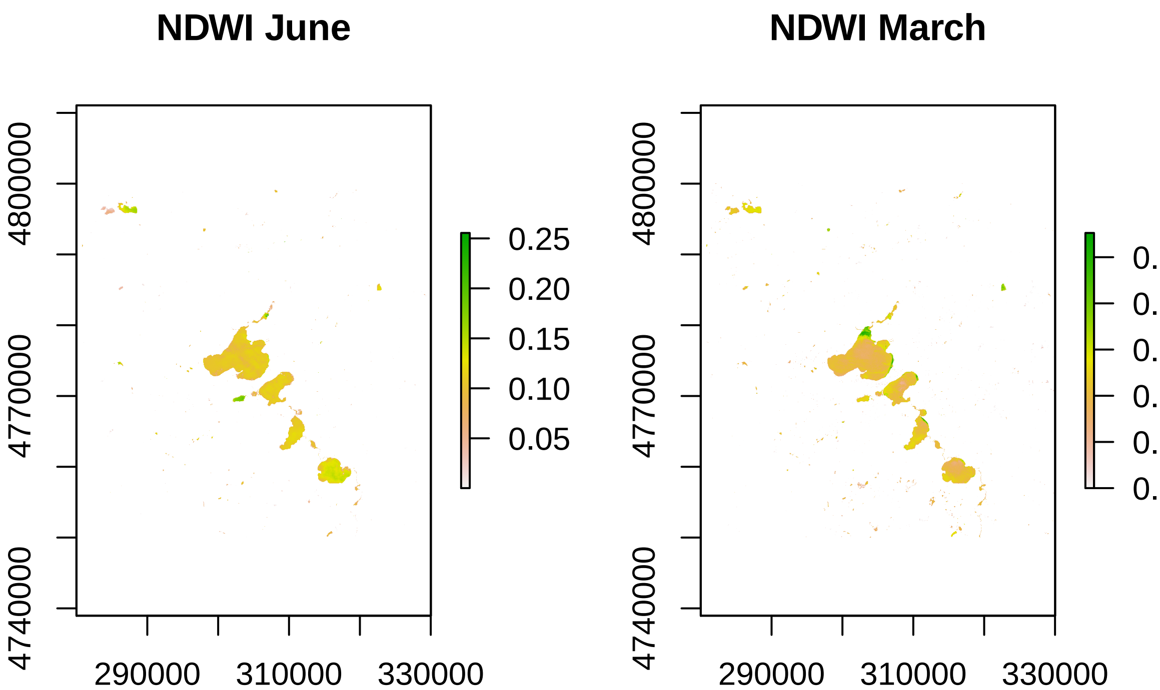
NDVI: Pixels having NDVI values greater than 0.4 are definitely vegetation. Following operation masks all non-vegetation pixels.

```
par(mfrow=c(1,2))
ndvi1[ndvi1 < 0.4] = NA
plot(ndvi1, main = 'NDVI June')
ndvi2[ndvi2 < 0.4] = NA
plot(ndvi2, main = 'NDVI March')
```



NDWI: Pixels having NDVI values greater than 0.2 may be water.

```r
par(mfrow=c(1,2))
ndwi1[ndwi1 < 0] = NA
plot(ndwi1, main = 'NDWI June')
ndwi2[ndwi2 < 0] = NA
plot(ndwi2, main = 'NDWI March')
```


NDWI June
4800000
4770000
4740000
290000
310000
330000
0.25
0.20
0.15
0.10
0.05
NDWI March
4800000
4770000
4740000
290000
310000
330000