Land Use Land Cover classification

CIAT

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Objectives

This manual will help you conduct a land use land cover classification of a 6-band Landsat 8 image. At the end of this session, you will be able to:

1. Import a Landsat image into R
2. Import training data inform of a shapefile into R
3. Extract pixel data to train and fit a RandomForests model
4. Speed up image classification through parallel processing (Bonus)

You can download raw satellite images from this site. Otherwise, download the sample dataset we will use in this session from this link https://drive.google.com/open?id=0B_Gkb_0tNKkQbktFWUFBLU9CV2c

Before you start this session, it is important you have (i) the latest R software and (ii) Rstudio installed in your computer.

Clear your workspace

```
rm(list = ls(all = TRUE))
```

Let's set the start of data processing

```
startTime <- Sys.time()
cat("Start time", format(startTime),"\n")
```

```
## Start time 2016-10-23 19:53:16
```

Loading the data in R

You need to first set your working directory

```
setwd("C:/LDN_Workshop/Sample_dataset/Land_Use_Land_Cover")
```

Let's list down the packages to be used in this session. Packages will be installed if not already installed. They will then be loaded into the session.

```
.packages = c("rgdal","raster","caret")
.inst <- .packages %in% installed.packages()
if(length(.packages[!.inst]) > 0) install.packages(.packages[!.inst])
lapply(.packages, require, character.only=TRUE)
```

```
## Loading required package: rgdal
```

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

```
## rgdal: version: 1.1-8, (SVN revision 616)
##  Geospatial Data Abstraction Library extensions to R successfully loaded
##  Loaded GDAL runtime: GDAL 2.0.1, released 2015/09/15
##  Path to GDAL shared files: C:/Users/jymutua/Documents/R/win-library/3.1/rgdal/gdal
##  GDAL does not use iconv for recoding strings.
##  Loaded PROJ.4 runtime: Rel. 4.9.1, 04 March 2015, [PJ_VERSION: 491]
##  Path to PROJ.4 shared files: C:/Users/jymutua/Documents/R/win-library/3.1/rgdal/proj
##  Linking to sp version: 1.2-3
```

```
## Loading required package: raster
```

```
## Loading required package: caret
```

```
## Loading required package: lattice
```

```
## Loading required package: ggplot2
```

```
## [[1]]
## [1] TRUE
##
## [[2]]
## [1] TRUE
##
## [[3]]
## [1] TRUE
```

To enable us reproduce the results next time, let's set the seed

```r
set.seed(322)
```

Now let's import the Landsat image into R as a 'RasterBrick' object using the brick function from the 'raster' package. Also let's replace the original band names with shorter ones ('B1' to 'B7').

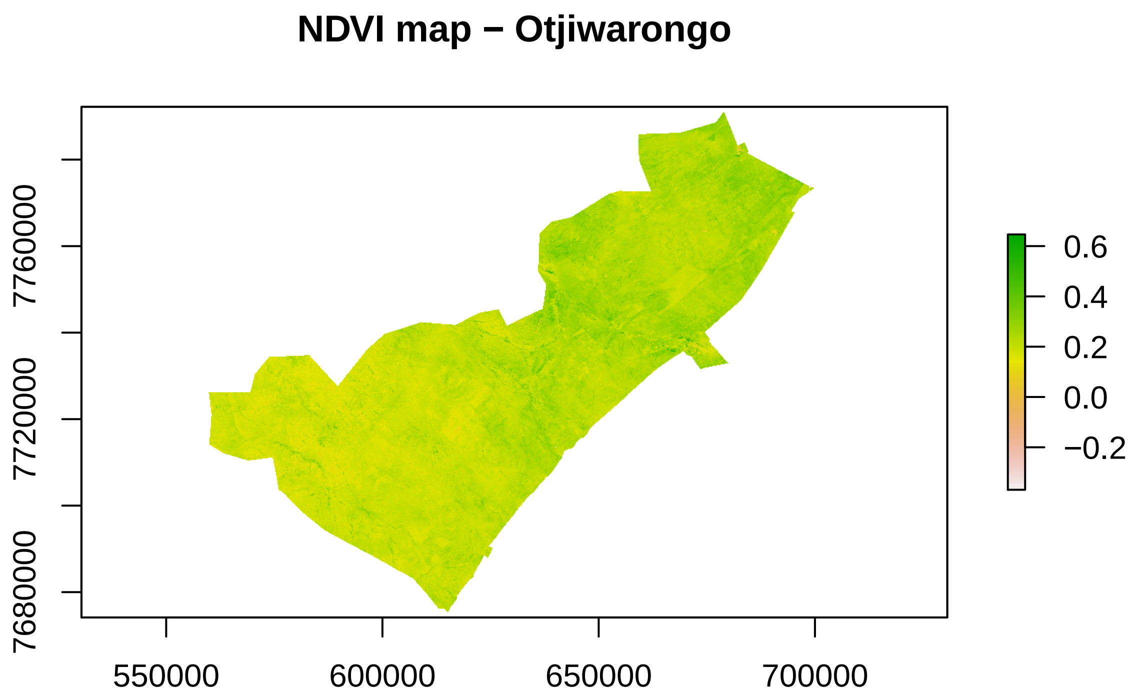
```r
img <- brick("TOA/Otji_TOA.tif")
names(img) <- c(paste0("B", 2:7, coll = ""))
img
```

```
## class       : RasterBrick
## dimensions  : 3936, 4713, 18550368, 6  (nrow, ncol, ncell, nlayers)
## resolution  : 30, 30  (x, y)
## extent      : 559815, 701205, 7674145, 7792225  (xmin, xmax, ymin, ymax)
```

```
## coord. ref. : +proj=utm +zone=33 +south +datum=WGS84 +units=m +no_defs +ellps=WGS84 +towgs84
## data source : C:\LDN_Workshop\Sample_dataset\Land_Use_Land_Cover\TOA\Otji_TOA.tif
## names       :    B2,    B3,    B4,    B5,    B6,    B7
## min values  :   696,   382,   239,     1,    44,    46
## max values  :  4751,  6510,  6164,  7215, 11800,  9882
```

Calculate NDVI and save the output for use in the next session. The resulting NDVI can be plotted as a map, values range from 0.2 (bare soils) to 0.6 (dense vegetation) in the area.

```
NDVI <- (img[[4]] - img[[3]]) / (img[[4]] + img[[3]])
writeRaster(NDVI, "Otji_NDVI.tif", overwrite=TRUE)
plot(NDVI, main="NDVI map - Otjiwarongo")
```



We can make a natural colour visualization of the Landsat image in R using the ‘plotRGB’ command, for example, a natural colour composite 4:3:2 (Red - Green - Blue).We use the expression ‘img * (img >= 0)’ to convert the negative values to zero.

```
plotRGB(img * (img >= 0), r = 4, g = 3, b = 2, scale = 10000)
```

I had initially created a set of training areas in a polygon shapefile ('Otji_trainingData.shp') which stores the id for each land cover type in a column in the attribute table called 'LC_Code' as shown below:

Let's import the training data into R as an object of class 'SpatialPolygonsDataFrame' and create a variable to store the name of the 'class' column. Codes used in the training data include: 1-Forest, 2-Woodland, 31-Bushland, 32-Grassland, 42-Cultivated area, 51-Wetland, 52-Water body, 61-Artificial Surface, 71-Bareland, forest and Woodland classes later combined to Forest/woodland.

```
trainData <- shapefile("Training_data/Otji_trainingData.shp")
responseCol <- "LC_Code"
```

Let's plot the training data

```
plot(trainData, main="Distribution of training data", axes=FALSE)
```

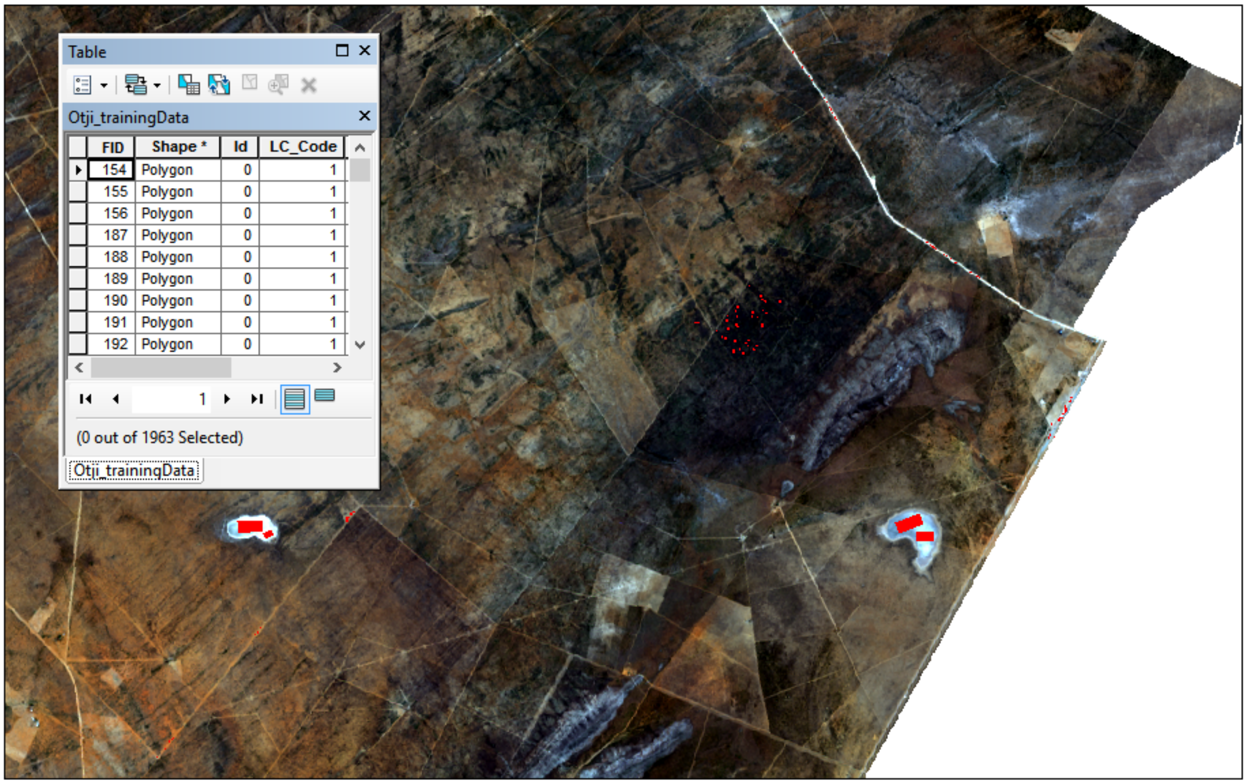


Figure 1: Training data as seen in ESRI ArcGIS

Extracting training pixels values

Let's extract the pixel values in the training areas for every band in the Landsat image and store them in a data frame along with the corresponding land cover class id extract training data using both point and polygon shapefiles

```
trainSet = data.frame(matrix(vector(), nrow = 0, ncol = length(names(img)) + 1))
for (i in 1:length(unique(trainData[[responseCol]]))){
  category <- unique(trainData[[responseCol]])[i]
  categorymap <- trainData[trainData[[responseCol]] == category,]
  dataSet <- extract(img, categorymap)

  if(is(trainData, "SpatialPointsDataFrame")){
    dataSet <- cbind(dataSet, class = as.numeric(category))
    trainSet <- rbind(trainSet, dataSet)
  }
  if(is(trainData, "SpatialPolygonsDataFrame")){
    dataSet <- lapply(dataSet, function(x){cbind(x, class =
                                                    as.numeric(rep(category,
                                                                   nrow(x))))})
    df <- do.call("rbind", dataSet)
    trainSet <- rbind(trainSet, df)
  }
}
```

We can now partition the data into training and testing, this will enable us conduct accuracy tests.

```
inData <- createDataPartition(y = trainSet$class, p = 0.7, list = FALSE)
training <- trainSet[inData,]
testing <- trainSet[-inData,]
```

As you can see below, the training and testsing 'data.frames' contains values for each of six 'Landsat' TOA bands plus the class attribute.

```
table(training$class)
```

```
##
##    1    2   31   32   52   71
##  225  392 2656  874    5 1855
```

```
table(testing$class)
```

```
##
##    1    2   31   32   52   71
##  111  152 1139  378    1  792
```

In our case, we will use 1000 observations which are randomly sample from the training data.frame to train the RF model

```
train_sample <- training[sample(1:nrow(training), 1000), ]
table(train_sample$class)
```

```
##
##   1   2  31  32  71
##  42  48 476 145 289
```

Fitting the Random Forests model

Next let's define and fit the .RandomForests. model using the 'train' function from the 'caret' package by specifying the model as a formula with the dependent variable (i.e., the land cover types ids) encoded as factors.

```
rf_Otji <- train(as.factor(class) ~ B3 + B4 + B5, method = "rf", data =
                   train_sample)
```

```
## Loading required package: randomForest
```

```
## randomForest 4.6-12
```

```
## Type rfNews() to see new features/changes/bug fixes.
```

```
##
## Attaching package: 'randomForest'
```

```
## The following object is masked from 'package:ggplot2':
##
##     margin
```

```
## note: only 2 unique complexity parameters in default grid. Truncating the grid to 2 .
```

We can now use the 'predict' command to make a raster with predictions from the fitted model object (i.e., 'rf_Otji') but then we can speed up computations using the 'clusterR' function from the 'raster' package which supports multi-core computing for functions such as predict (NB: install 'snow' package).

```
beginCluster()
```

```
## 4cores detected
```

```r
prediction <- clusterR(img, raster::predict, args = list(model = rf_Otji))
endCluster()
```

We can now test the accuracy using the testing set as it is an independent set of data and let's examine the producer's accuracy (aka sensitivity in the caret package) for the model.

```r
prediction_2 <- predict(rf_Otji, testing)
confusionMatrix(prediction_2, testing$class)$overall[1]
```

```
## Warning in levels(reference) != levels(data): longer object length is not a
## multiple of shorter object length
```

```
## Warning in confusionMatrix.default(prediction_2, testing$class): Levels are
## not in the same order for reference and data. Refactoring data to match.
```

```
##  Accuracy
## 0.9560824
```

```r
confusionMatrix(prediction_2, testing$class)$byClass[, 1]
```

```
## Warning in levels(reference) != levels(data): longer object length is not a
## multiple of shorter object length

## Warning in levels(reference) != levels(data): Levels are not in the same
## order for reference and data. Refactoring data to match.
```

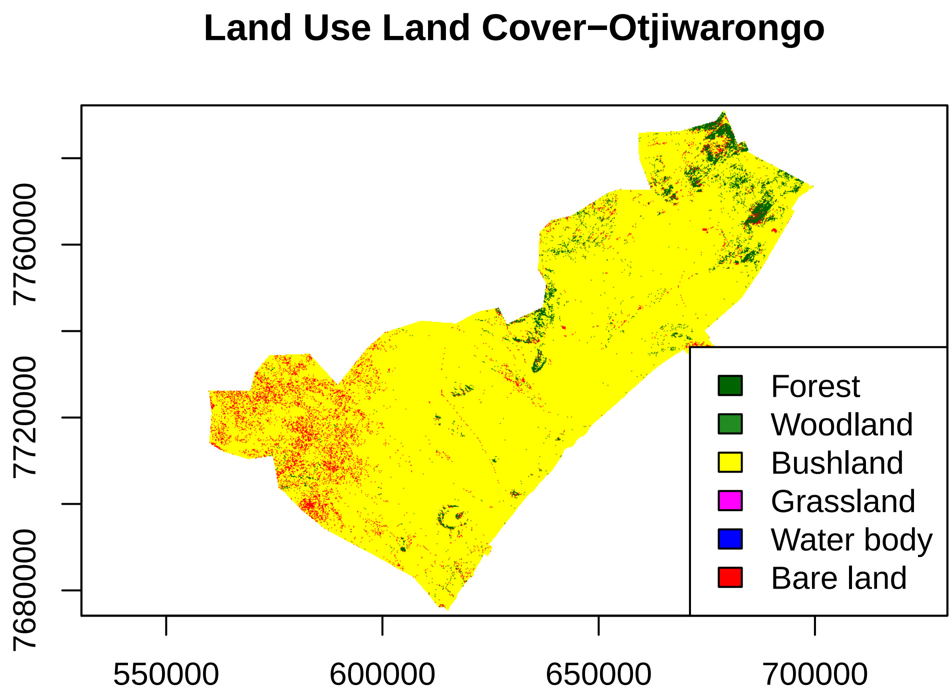
```
##  Class: 1  Class: 2 Class: 31 Class: 32 Class: 52 Class: 71
## 1.0000000 1.0000000 0.9446883 0.9206349 0.0000000 0.9760101
```

Save your classified image as a GeoTIFF

```r
writeRaster(prediction, "Otji_classified.tif", overwrite=TRUE)
```

You can visualize your classified image and add a legend to the plot. Can you recall this categories 1-Forest, 2-Woodland, 31-Bushland, 32-Grassland, 42-Cultivated area, 51-Wetland, 52-Water body, 61-Artificial Surface, 71-Bareland?

```r
cols <- c("dark green", "forestgreen", "yellow", "magenta", "blue", "red")
plot(prediction, col=cols, legend=FALSE, main="Land Use Land Cover-Otjiwarongo")
legend("bottomright",
       legend=c("Forest", "Woodland", "Bushland", "Grassland", "Water body",
                "Bare land"), fill=cols, bg="white")
```



Finally check the amount of time you spent conducting this analysis.

```
timeDiff <- Sys.time() - startTime
cat("\nProcessing time", format(timeDiff), "\n")
```

```
##
## Processing time 38.09907 mins
```