# STAT 585X - Final Project - Report
# Changes in cultivated cropland in CEAP

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## 1 Introduction

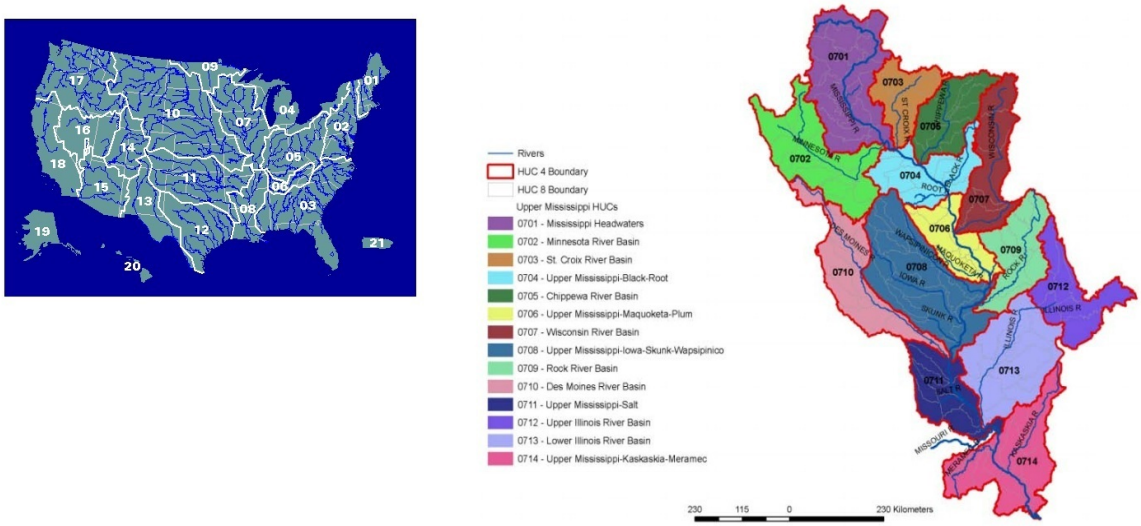
### 1.1 Question of interest

Do changes in land characteristics over time match the Conservation Effects Assessement Project (CEAP) survey design and data collection?

### 1.2 Motivation

National Resources Inventory (NRI) is an annual survey conducted collaboratively by USDA NRCS (Natural Resources Conservation Services) and ISU Center for Survey Statistics and Methodology (CSSM) to provide status and trend estimates for natural resources on nonfederal lands in US. Example of such estimates are soil erosion estimates in relation to land characteristics and programs.

Conservation Effects Assessment Project (CEAP) is a series of surveys intended to quantify environmental effects of conservation prctices and programs by hydrologic unit codes (HUCs). The following image illustrates the division of the United States territory into 2-digits HUCs and the sudivision of the Upper Mississippi region into 4-digit HUCs.




The CEAP sample is a subset of the NRI points classified as cultivated cropland. The data was collected using farmers interviews and NRCS hydrologic, climate and soil databases. The data was then

filtered through an APEX model (black box) and the result is a set of observations for usable points for 19 response variables. The final goal is to produce erosion estimates for 8-digit HUCs.

CEAP is run at both national and regional levels. The Des Moines River Watershed (HUC 0710) is the region of interest in this project, that is subdivided into nine 8-digit HUCs.

For CSSM analysis, data from the Soil Survey is considered, collected over the 2003 to 2006 time period. Hence, the survey frame, consisting of NRI cultivated cropland points, is set in 2003. The information for these eligible points is collected in the following years, 2004-2007. Changes in land characteristics for the sample points may result in frame coverage problems that should not be ignored in the analysis.

In this project we are using publicly available land data to investigate changes in land characteristics over time for a region of interest in CEAP.

### 1.3 Data

The CEAP sample data for the Des Moines River Watershed (HUC 0710) region is not publicly available. Web navigation brings us to different sources of data on the United States counties and regions. In this project, we consider the following sources of information:

- Crop Data Layer (CDL)

  The CDL data is available at `http://nassgeodata.gmu.edu/CropScape/` in the form of Tagged Image File (.tif) Format. We are interested in the state of Iowa data, available for the years of 2003-2007. The information consists of pixel counts and acreage values for different categories of cropland data. Each of the category has an associated value (code), for example 1 stands for Corn and 5 stands for Soybean. A complete list of category codes and class names for the USDA NASS CDL is available at `http://www.nass.usda.gov/research/Cropland/docs/CDL_2013_crosswalk.htm`.

- Census Topologically Integrated Geographic Encoding and Referencing database (Tigerweb)

  The Census Tigerweb data is available at `http://tigerweb.geo.census.gov/tigerwebmain` for both national and regional levels. Also, data for the hydrologic levels is available at `http://tigerweb.geo.census.gov/tigerwebmain/Files/tigerweb_tab10_hydro_poly_ia.html`. We are interested in the state of Iowa data, as well as the Des Moines River data. In particular, we are interested in the points coordinates.

- Public Land Survey System (PLSS)

  The PLSS data can be found on `http://www.geocommunicator.gov/GeoComm/lsis_home/home/index.htm` in the form of shapefiles. Information is available at both state and county levels.

- GIS data on hydrologic basins

  The GIS data can be found at `ftp://ftp.igsb.uiowa.edu/gis_library/basins/` in the form of shapefiles. Information is available for the entire Des Moines River basin.

- Atlas of historical countyu boundaries (AtlasHCB)

  The AtlasHCB data is available at `http://publications.newberry.org/ahcbp/pages/Iowa.html` in the form of shapefiles. Information is available for the entire state of Iowa.

# 2 Data Collection and Processing Steps

We explored all these different data sources using R tools. These data differ in format, in dimension and, most importantly, in the enclosed information. We are interested in a very specific region in the state of Iowa so it is very important to select the sources that provide us with most useful information.

Except for the CENSUS Tigerweb data and the CDL codes and classification data, all other files need to be downloaded and stored in the working folder. If you are not able to download it from the web (steps are presented below), please contact us and we will provide you the data.

## 2.1 CDL data

We first download the data for years 2003-2007 from the website, following these steps:

1. Open this link in an internet browser: `http://nassgeodata.gmu.edu/CropScape/`. We now have the United States map and some tabs on the left and at the top of the map;
2. Click on the *US map -like* tab at the top, hoovering over it says *Define Area of Interest by Region/State/ASD/County*, select *State* as the *Level* and *Iowa* as the *state*. Click *Submit*;
3. Select the years of interest (in this case 2003-2007) and download the data. The file is large, so downloading it takes long time.

At the end of the downloading process, we unzip the file and we have five .tif files, one for each year of interest. These are raster graphics images, spatial data structures that divide the US teritory into pixels that store crop information. This type of data is referred to as a 'grid,' contrasted with 'vector' data that is used to represent points, lines, polygons. The dimensions of the files are large, about 200,000 KB each for the 2003-2005 data and about 60,000 KB each for the 2006-2007 data.

*Note:* The first and greatest challenge in this section was storing the CDL data. We run our of memory on the working drive (U drive) and had to consider document reallocation on web storage clouds.

An useful R package to read and manipulate the CDL data is the *Raster* package, implemented using S4 methods. This package allows us to read the raster values from the files and to convert the cell numbers to coordinates and back.

```
## read the data
cdl.ia03 <- raster("data/CDL_2003_19.tif")
cdl.ia04 <- raster("data/CDL_2004_19.tif")
cdl.ia05 <- raster("data/CDL_2005_19.tif")
cdl.ia06 <- raster("data/CDL_2006_19.tif")
cdl.ia07 <- raster("data/CDL_2007_19.tif")

cdl.ia03

## class       : RasterLayer
## dimensions  : 11672, 17796, 207714912  (nrow, ncol, ncell)
## resolution  : 30, 30  (x, y)
## extent      : -52065, 481815, 1938165, 2288325  (xmin, xmax, ymin, ymax)
## coord. ref. : +proj=aea +lat_1=29.5 +lat_2=45.5 +lat_0=23 +lon_0=-96 +x_0=0 +y_0=0 +ellps=GRS80
## data source : U:\stat585\STAT585X-Project\data\CDL_2003_19.tif
## names       : CDL_2003_19
## values      : 0, 255  (min, max)
```

Notice the attributes of the raster objects. One of the most important attributes, for us, is the coordinate reference system (CRS), or the map projection. We need to pay greater attention to this attribute in order to carefully manipulate the future data on the region of interest, to get the matching coordinate reference (more details follow). The objects we have so far are 'skeletons,' because they only contain attributes of the data, not the actual values stored. In other words, *cdl.ia03 -like* objects are *RatserLayers* that do not contain any cell (pixel) value in (RAM) memory, they only contain the parameters that describe the *RasterLayers*. We are going to read the values for the region of interest using cell numbers and coordinates (xy) in the extraction method using the *cellFromXY* function. For this, we need the coordinates for the Des Moines River Watershed and surrounding area, denoted as the region of interest.

## 2.2 GIS, PLSS, AtlasHCB data

GIS, PLSS, AtlasHCB data sources are considered at first. However, we do not use any in the final results. The dimensions are smaller than the dimensions of the CDL data, so downloading and storing is not as demanding anymore. However, the information in the data is not realible and, as it turns out, not useful for our purposes.

We first download the data from the websites. We read in the data and we extract the polygons information from the shapefiles using the *maptools* library in R and the function developed in one of the STAT 585X labs, to extract the county based information.

For the GIS data, after mapping the region, we realized that it covers the entire basin, more than what we are interested in. Also, the polygon data is in the universal transverse mercador (UTM) and we need to convert it to the longitude-latitude, then to the CRS with the appropriate raster characteristics.

The information in the AtlasHCB data is based on historical records and it is only county based. Hence it is not useful for our purposes because the time period (2003-2007) and the specific region (Des Moines River Watershed) are not included in the specifics of AtlasHCB data.

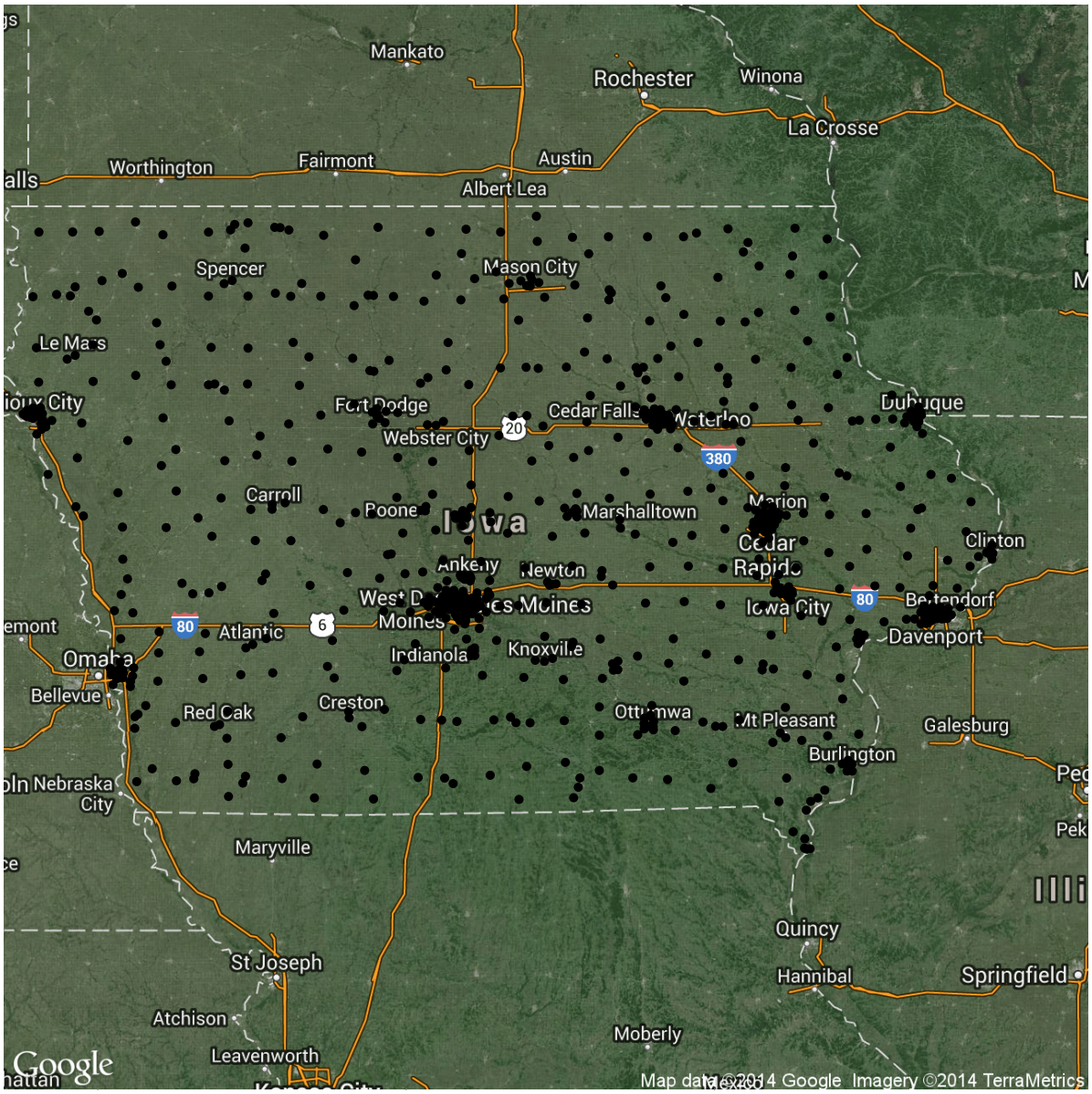
On the other hand, PLSS data have large dimensions and storage space has been a challenge in this project. The processing steps are similar to the ones described above, in this section, because we are once again dealing with shapefiles. Also, the data is available at both state and county levels, but not at hydrologic levels. Hence, we decide to search for another source of data. Census data turns out to be very useful for us, and we decribe it in the next section.

## 2.3 Census data

We pull both the Iowa data and the Des Moines River data from the web using the *XML* library in R. The Iowa data is used to extract the point coordinates and construct a map. First, we pull the point coordinates for the available points and save them in a dataframe containing the numeric values. We use the *ggplot2* library in R to construct a plot of the data and the *maps* and *ggmap* libraries to construct a map of the data. These visualisations serve as both a nice representation of the data and as a verification that we are working with the desired region. We constructed maps using both *qplot* and *qmap* functions but we only present the google maps.

```
### pull the iowa census data from the web
src <- "http://tigerweb.geo.census.gov/tigerwebmain/Files/tigerweb_acs13_tract_ia.html"
tables <- readHTMLTable(src)
ldply(tables, dim)
```

```
##                                                                    .id  V1 V2
## 1 State of Iowa Census Tracts - Current/ACS13 - Data as of January 1, 2013 825 17

tigeria <- tables[[1]]
head(tigeria)

##   MTFCC            OID       GEOID STATE COUNTY  TRACT BASENAME              NAME LSADC
## 1 G5020 20790328763043 19001960100    19    001 960100     9601 Census Tract 9601    CT
## 2 G5020 20790328763062 19001960200    19    001 960200     9602 Census Tract 9602    CT
## 3 G5020 20790328763079 19001960300    19    001 960300     9603 Census Tract 9603    CT
## 4 G5020 20790155900148 19003950100    19    003 950100     9501 Census Tract 9501    CT
## 5 G5020 20790155900144 19003950200    19    003 950200     9502 Census Tract 9502    CT
## 6 G5020 20790692090375 19005960100    19    005 960100     9601 Census Tract 9601    CT
##   FUNCSTAT  AREALAND AREAWATER UR     CENTLAT      CENTLON    INTPTLAT     INTPTLON
## 1        S 707919439   1124009  ÃĆ +41.4204490 -094.4773809 +41.4226701 -094.4754745
## 2        S 666068268   1098841  ÃĆ +41.2402687 -094.4593481 +41.2403358 -094.4634803
## 3        S 100416467    375146  ÃĆ +41.2975066 -094.5025203 +41.2964752 -094.5071226
## 4        S 879308484   4856978  ÃĆ +41.0477119 -094.6732029 +41.0509146 -094.6680804
## 5        S 217392267    496426  ÃĆ +40.9528920 -094.8044597 +40.9482672 -094.8079792
## 6        S 335670054  27231318  ÃĆ +43.3462135 -091.2527640 +43.3464049 -091.2647941

### transform the data to the desired format

## first we need to pull the coordinates
dsmriv <- tigeria
poly.coords.ia <- as.data.frame(dsmriv[, c("INTPTLAT", "INTPTLON")])
row.names(poly.coords.ia) <- NULL
names(poly.coords.ia) <- c("x", "y")

poly.coords.ia[, 1] <- as.numeric(as.vector(poly.coords.ia[, 1]))
poly.coords.ia[, 2] <- as.numeric(as.vector(poly.coords.ia[, 2]))

## plot the area qplot(y,x,data=poly.coords.ia)

qmap(location = "iowa", zoom = 7, maptype = "hybrid") + geom_point(data = poly.coords.ia, mapping =
    y = x), size = 2)
### always remember, longitude first, then latitude!!!!!!
```

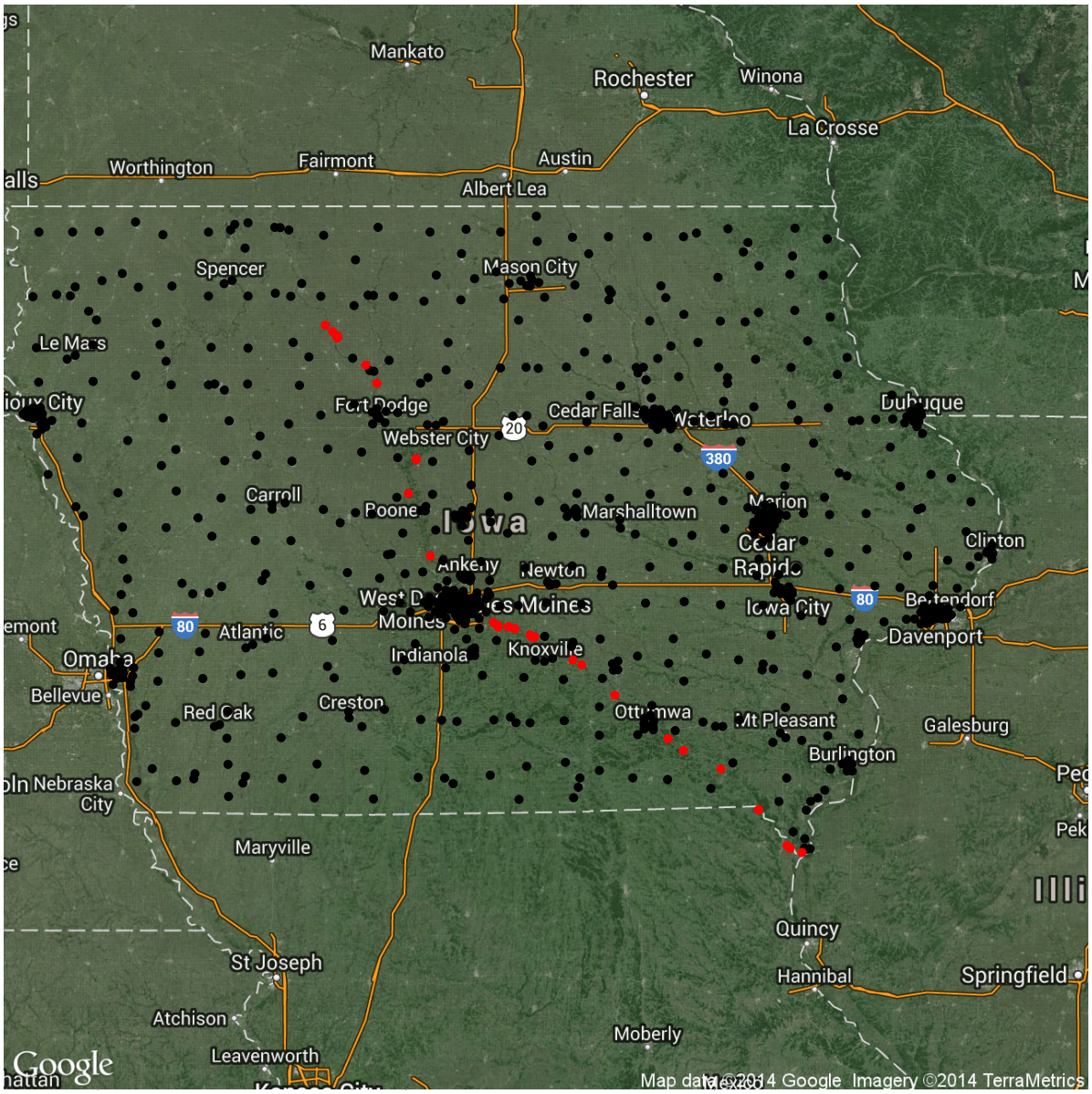



The data for the Des Moines River is extracted from the full dataframe on the hydrologic levels in Iowa. Again, we construct a dataframe with numeric values for the point coordinates and we overlay this data on the previous map.

```
### pull the hydrologic iowa data from the web

src <- "http://tigerweb.geo.census.gov/tigerwebmain/Files/tigerweb_tab10_hydro_poly_ia.html"
tables <- readHTMLTable(src)
ldply(tables, dim)

##                                                                .id    V1 V2
## 1 U.S. Polygon Hydrography for Iowa - Data as of January 1, 2010 16448 15

tigeria <- tables[[1]]
head(tigeria)
```

```
##   MTFCC          OID PRETYP PRETYPEABRV SUFTYP SUFTYPEABRV                  BASENAME
## 1 H3010 110697284649      ÃĆ           ÃĆ      ÃĆ           ÃĆ              Ackerman Cut
## 2 H3010 110420222385      ÃĆ           ÃĆ    225         Crk                   Allen
## 3 H2030 110438005187      ÃĆ           ÃĆ    361          Lk                Alligator
## 4 H2030 110417623043      ÃĆ           ÃĆ    361          Lk                Arrowhead
## 5 H2030 110196632486      ÃĆ           ÃĆ      ÃĆ           ÃĆ Artesian Lake County Park
## 6 H2030 110434989248      ÃĆ           ÃĆ    361          Lk                 Backbone
##                         NAME ISLOCAL AREALAND AREAWATER     CENTLAT     CENTLON
## 1              Ackerman Cut       N        0    105436 +42.7714854 -91.0771683
## 2                 Allen Crk       N        0     78271 +41.4781465 -95.9224417
## 3              Alligator Lk       N        0     52834 +42.0869879 -90.1785601
## 4              Arrowhead Lk       N        0    114486 +42.2967329 -95.0512242
## 5 Artesian Lake County Park       N        0     99969 +42.1501453 -94.6802219
## 6               Backbone Lk       N        0    455483 +42.6081368 -91.5457812
##      INTPTLAT    INTPTLON
## 1 +42.7714854 -91.0771683
## 2 +41.4702610 -95.9181765
## 3 +42.0869879 -90.1785601
## 4 +42.2967329 -95.0512242
## 5 +42.1501453 -94.6802219
## 6 +42.6017186 -91.5372706
```

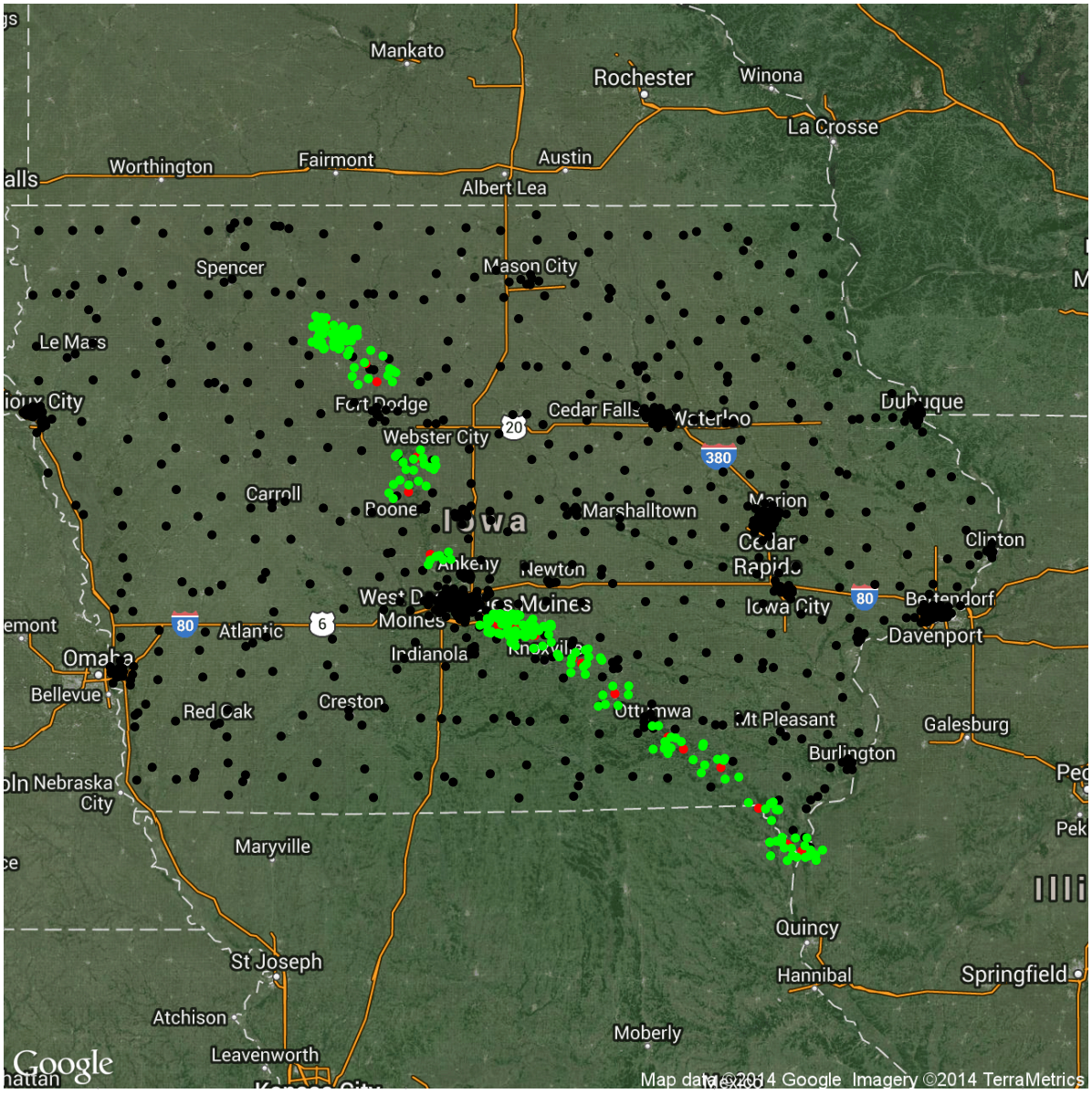
```
### transform the data to the desired format and pull the information of interest
tigeria$NAME <- as.character(tigeria$NAME)

## pull the des moines river data
dsmriv <- tigeria[tigeria$NAME == "Des Moines Riv", ]

poly.coords <- as.data.frame(dsmriv[, c("INTPTLAT", "INTPTLON")])
row.names(poly.coords) <- NULL
names(poly.coords) <- c("x", "y")

poly.coords[, 1] <- as.numeric(as.vector(poly.coords[, 1]))
poly.coords[, 2] <- as.numeric(as.vector(poly.coords[, 2]))

## overlay the des moines river area over the iowa plot

# qplot(y,x,data=poly.coords.ia)+geom_point(data=poly.coords,aes(x=y,y=x),color='red')

# qmap(location = 'iowa', zoom=7, maptype = 'hybrid') + geom_point(data=poly.coords,
# mapping=aes(x=y, y=x), size=2)

qmap(location = "iowa", zoom = 7, maptype = "hybrid") + geom_point(data = poly.coords.ia, mapping =
    y = x), size = 2) + geom_point(data = poly.coords, mapping = aes(x = y, y = x), size = 2,
    color = "red")
```




The next challenge is to mimic the CEAP sample. The Des Moines River data contains points only on the river, but not on the entire watershed. We are using the *plyr* package in R to expand this sample of points, in order to capture the region along the river. The approach we decide to use is to add noise to each of the existing points, using the *jitter* function. Also, we create six more points in the nearest neighborhood of the existing points. A map of the final region is presented below.

```
## create a region of interest around the des moines river

set.seed(2013)
add.poly.coords <- as.data.frame(t(ldply(llply(poly.coords, function(x) {
    ldply(x, function(y) jitter(rep(y, 7), 0.075))
}), unlist)[, -1]))
names(add.poly.coords) <- c("x", "y")

# qplot(y,x,data=poly.coords.ia)+ geom_point(data=poly.coords,aes(x=y,y=x),color='red')+
# geom_point(data=add.poly.coords,aes(x=y,y=x),color='green')
```

```
qmap(location = "iowa", zoom = 7, maptype = "hybrid") + geom_point(data = poly.coords.ia, mapping =
    y = x), size = 2) + geom_point(data = poly.coords, mapping = aes(x = y, y = x), size = 2,
    color = "red") + geom_point(data = add.poly.coords, mapping = aes(x = y, y = x), size = 2,
    color = "green")
d <- nrow(add.poly.coords)
```




Once we have the desired region and a fairly sizeable sample (a number of 224), we extract the information from the CDL data. First, we create the matrix of point coordinates in coordinate reference system (CRS) using the attributes of the raster objects described previously. Next we use the *cellFromXY* function to extract the pixel count information available in the CDL data for the points in the region, for each year of interest. The results are numeric vectors of size 224, containing the crop codes for the points. We construct the proportions of crops, by category, by year and the results are in the code chunk below.

```
# get the coordinates in CRS
loc.newcoords <- project(cbind(add.poly.coords[, 2], add.poly.coords[, 1]), proj = "+proj=aea +lat_

# gets the values of the pixels
cdl.pts3 <- cdl.ia03[cellFromXY(cdl.ia03, loc.newcoords)]
table(cdl.pts3)/length(cdl.pts3[-which(is.na(cdl.pts3))]) * 100

## cdl.pts3
##       1       5      25      28      36      61      63      82      83     176
## 23.9024 30.7317  1.4634  0.4878  2.4390  6.3415  4.3902  2.4390  3.9024 23.9024

cdl.pts4 <- cdl.ia04[cellFromXY(cdl.ia04, loc.newcoords)]
table(cdl.pts4)/length(cdl.pts4[-which(is.na(cdl.pts4))]) * 100

## cdl.pts4
##       1       5      25      28      36      61      63      70      81      82      83
## 28.7805 22.4390  1.9512  0.4878  2.9268  2.9268 11.2195  0.4878  0.9756  2.9268  4.8780
##      88     176
##  0.4878 19.5122

cdl.pts5 <- cdl.ia05[cellFromXY(cdl.ia05, loc.newcoords)]
table(cdl.pts5)/length(cdl.pts5[-which(is.na(cdl.pts5))]) * 100

## cdl.pts5
##       1       5      36      44      61      63      70      82      83      88     176
## 25.3659 26.3415  1.4634  0.4878  2.9268 13.6585  0.4878  1.9512  4.3902  1.4634 21.4634

cdl.pts6 <- cdl.ia06[cellFromXY(cdl.ia06, loc.newcoords)]
table(cdl.pts6)/length(cdl.pts6[-which(is.na(cdl.pts6))]) * 100

## cdl.pts6
##       1       5      28      36      61     111     121     122     141     143     176
## 27.3171 25.3659  0.4878  2.4390  1.9512  4.3902  3.9024  0.4878 14.6341  0.4878 16.0976
##     190     195
##  1.4634  0.9756

cdl.pts7 <- cdl.ia07[cellFromXY(cdl.ia07, loc.newcoords)]
table(cdl.pts7)/length(cdl.pts7[-which(is.na(cdl.pts7))]) * 100

## cdl.pts7
##       1       5     111     121     141     176     190     195
## 27.8049 18.0488  5.3659  9.7561 12.6829 22.4390  2.9268  0.9756
```

However, we would like to present the results in a nicer way, displaying the crop classes corresponding the codes, in order to better understand the changes over this time period. For this, we pull the codes and classes data from the NASS website. These HTML data need more cleaning because there are multiple tables on the page, as well as paragraphs of text. We only need the table containg the codes and the associated classes so we need to filter out some rows and columns from the table pulled using the *readHTMLTable* function.One way of doing this is simply exclude the rows and the columns that are not of interest. Another, more elegant, way of accomplishing this task is to navigate on the source page and use the *XML* root and childern information. However, the source code is not in a compact format, the objects are not uniquely identifiable (there are no options, no values and

such). So we can not track the path to the only one table of interest and we use decide to simply exclude some rows and columns. We save the data into a dataframe, containg two columns, one column of codes and one column of classes, and we give the appropriate names.

Next, we merge the codes and classes dataset with the yearly CDL point datasets, saving only the proportion of points in each code. We start by writing a general function to complete this task but, using the *debug/browser* functions in *R* we are able to identify challenges as we continue coding.

```
src <- "http://www.nass.usda.gov/research/Cropland/docs/CDL_2013_crosswalk.htm"
tables <- readHTMLTable(src)
ldply(tables, dim)

##    .id  V1 V2
## 1 NULL 316 13

codes <- tables[[1]]
head(codes)

##   V1
## 1
## 2
## 3
## 4
## 5
## 6
##
## 1                                The 1997-2013 CDLs were recoded and\r\n  re-released in Januar
## 2                      ÃĆÂăcategory named Grass/Pasture (code 176)\r\n  collapses the following
## 3                       ÃĆÂă(code\r\n  171), and Pasture/Hay (code 181). This was done to elimin
## 4                      ÃĆÂăclassified definitionally consistent from\r\n  state to state or year
## 5                      ÃĆÂăthe\r\n  recoding of the entire CDL archive in January 2012 to better
## 6 ÃĆÂăof the category name and code\r\n  changes, please visit the Frequently Asked Questions (F
##   V3 V4   V5   V6   V7   V8   V9  V10  V11  V12  V13
## 1                           <NA> <NA> <NA> <NA> <NA>
## 2                      <NA> <NA> <NA> <NA> <NA> <NA>
## 3                      <NA> <NA> <NA> <NA> <NA> <NA>
## 4                           <NA> <NA> <NA> <NA> <NA>
## 5                           <NA> <NA> <NA> <NA> <NA>
## 6       <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA>

## keep only the codes/classes information

## one way is to navigate on the source page and use root/children XML ideas but the source
## code is not in a compact format, it is written such that the objects on the page are not
## uniquely identified (no options, values, etc)

url <- "http://www.nass.usda.gov/research/Cropland/docs/CDL_2013_crosswalk.htm"

doc <- htmlParse(url)
root <- xmlRoot(doc)

length(xmlChildren(root))

## [1] 2
```

```
xmlName(xmlChildren(root)[[2]])

## [1] "body"

length(xmlChildren(xmlChildren(root)[[2]]))

## [1] 21

length(getNodeSet(root, "//table"))

## [1] 1

length(getNodeSet(root, "//@width"))

## [1] 452

length(getNodeSet(root, "//table[@width]"))

## [1] 1

## since we only need the first two columns, we select them using 1:2 as for the rows, we
## need to count the first 9 rows of text and skip them and also we need to through away the
## last chunck of rows

codes <- as.data.frame(codes[-c(1:9, 266:316), 1:2])
names(codes) <- c("code", "class")
codes[, "class"] <- as.character(codes[, "class"])

## function to merge the points and the codes datasets, by the common codes
merging <- function(x) {

    pts <- as.data.frame(x[-which(is.na(x))])
    names(pts) <- "code"
    res <- join(codes, pts, by = "code")
    res2 <- res[match(pts[, "code"], res[, "code"]), ]

    return(table(res2[, "class"])/nrow(pts) * 100)
}

pts37 <- as.data.frame(cbind(cdl.pts3, cdl.pts4, cdl.pts5, cdl.pts6, cdl.pts7))

d <- apply(pts37, 2, merging)  ###or alply

d2 <- laply(d, length)  ###different sizes

allcrops <- unlist(llply(d, function(x) names(x)))
cropmaxno <- length(unique(allcrops))
```

The first challenge is due to the fact that the sizes differ. The data for each year contains information on the crop classes planted that year, a subset of the total number of crop classes.

We write a function using the *join* in *plyr* and the *match* functions in R to complete this task and apply it to the yearly information.

| Total | 2003 | 2004 | 2005 | 2006 | 2007 |
|---|---|---|---|---|---|
| 21 | 10 | 13 | 11 | 13 | 8 |

Table 1: Number of crop classes by year

The next challenge is to complete yearly information so that all the years have the same number of crop classes. The approach we decide to take is to introduce missing data for the classes that are missing in a year. Our first option for tools is the *–ply* function from the *plyr* package but we do not find a direct way of completing this task. Also, we try to apply a function that imputes missing values and new crop classes for each year, where the yearly data is an element in a list. This is not successful either because we can not make changes to elements in the list.

```
## bring all the years to same number of crop categoris by imputing NA for the years where a
## crop is missing
dat <- d

laply(dat, function(x) names(x) <- unique(allcrops))  ## doesn't do it automatically


### this function should work!!!!!!!!
llply(dat, function(x) {
    for (i in 1:cropmaxno) if (length(grep(unique(allcrops)[i], names(x))) < 1) {
        x <- c(x, NA)
        names(x)[i] <- unique(allcrops)[i]
    }
})

## the problem is that we cannot assign the changes to each element
```

So we decide to write a function that verifies the matching between the existing classes in a year data and the set of all classes, using regular expressions. In particular, we use the *grep* and *identical* functions. The idea turns out to be the final product idea, however there is one more challenge. Some crop classes have names that include other crop classes, for example *Developed* and *Developed/Low Intensity* or *Developed/Open Space*. The *grep* function verifies for elements in a set, but only as substrings of strings. This function does not verify for a perfect string match. Using a few *if* statements and the *debug/browser* functions we complete the task. The resulting function is applied to the existing data and it creates a list of yearly data, each element containing crop classes and proportion of cultivated land in each class. The data is then combined into a final product dataframe.

*Note:* Ideally, we would have preferred using the *plyr* package to complete this task, by assigning a function to each element in a list and obtain a dataframe (i.e *dlply* function), however the number of crop classes differs by year (elements in the list have different sizes) and a dataframe can not have columns of different sizes. We would further investigate if there are functions to handle these challenges.

```
## try
fxn <- function(data) {
    for (x in 1:length(data)) {
        for (i in 1:cropmaxno)
        if (length(grep(unique(allcrops)[i], names(data[[x]]))) < 1) {
            data[[x]] <- c(data[[x]], NA)
```

```
            names(data[[x]])[i] <- unique(allcrops)[i]
        }
        paste("change number", data)
    }
    return(data)
}

# fxn(d) -> newd

## it works, except for the last year, where the categories are developed, developed open
## space, developed etc... the grep function fails because developed is subset ...need to
## match exactly...

## next try
fxn <- function(data) {

    # browser()
    for (x in 1:length(data)) {
        for (i in 1:cropmaxno) {

            cnt <- 0
            subset <- grep(unique(allcrops)[i], names(data[[x]]))
            len <- length(subset)

            if (len < 1) {
                data[[x]] <- c(data[[x]], NA)
                names(data[[x]])[length(data[[x]])] <- unique(allcrops)[i]
            }

            if (len >= 1)
                for (j in 1:len) if (!identical(unique(allcrops)[i], names(data[[x]])[[subset[j]]]))
                  cnt <- cnt + 1

            if (cnt >= 1) {
                data[[x]] <- c(data[[x]], NA)
                names(data[[x]])[length(data[[x]])] <- unique(allcrops)[i]
            }
        }

    }
    return(data)
}

newd <- fxn(d)

# debug(fxn(d))

laply(newd, length)  ###works!!!!! all years have same number of crop classes

## [1] 21 21 21 21 21

## now combine all the years cdl.pts into one data frame

d <- as.data.frame(newd)
```

# 3 Results

We present summaries for all the crop classes, by year in the following table.

| Crop Code | 2003 | 2004 | 2005 | 2006 | 2007 |
|---|---|---|---|---|---|
| Alfalfa | 2.439 | 2.9268 | 1.4634 | 2.439 | 27.8049 |
| Corn | 23.9024 | 0.4878 | 0.4878 | 27.3171 | 12.6829 |
| Developed | 2.439 | 0.9756 | 25.3659 | 14.6341 | 9.7561 |
| Fallow/Idle Cropland | 6.3415 | 28.7805 | 1.9512 | 0.4878 | 22.439 |
| Forest | 4.3902 | 2.9268 | 2.9268 | 3.9024 | 0.9756 |
| Grass/Pasture | 23.9024 | 2.9268 | 13.6585 | 1.9512 | 5.3659 |
| Oats | 0.4878 | 11.2195 | 21.4634 | 16.0976 | 18.0488 |
| Other Small Grains | 1.4634 | 19.5122 | 1.4634 | 0.9756 | 2.9268 |
| Soybeans | 30.7317 | 0.4878 | 0.4878 | 0.4878 | NA |
| Water | 3.9024 | 0.4878 | 26.3415 | 0.4878 | NA |
| Christmas Trees | NA | 1.9512 | 4.3902 | 4.3902 | NA |
| Clouds/No Data | NA | 22.439 | NA | 25.3659 | NA |
| Nonag/Undefined | NA | 4.878 | NA | 1.4634 | NA |
| Other Crops | NA | NA | NA | NA | NA |
| Deciduous Forest | NA | NA | NA | NA | NA |
| Developed/Low Intensity | NA | NA | NA | NA | NA |
| Developed/Open Space | NA | NA | NA | NA | NA |
| Herbaceous Wetlands | NA | NA | NA | NA | NA |
| Mixed Forest | NA | NA | NA | NA | NA |
| Open Water | NA | NA | NA | NA | NA |
| Woody Wetlands | NA | NA | NA | NA | NA |

Table 2: Proportion of land by crop class, by year.

# 4 Conclusions/ Future work

The following conclusions hold only for the region we have described in the previous section. Whether they still hold for the real CEAP data needs future investigation.

Notice that 8 out of the 21 total crop classes are missing for all the years, for this particular region. Also, some of the crop classes are present only in some years, for example *Christmas trees* are not recorded, for this region, in 2003 and in 2007.

There seem to be missing records in 2004 and 2006 due to clouds and to undefined records. These proportions are significantly larger than most of the crop classes proportions. However, the records from 2003, 2005 and 2007 seem to have better records of crop classes, not being affected of missing data.

We notice significant changes in some important crops over the years, for example corn and soybeans. The corn proportion of land is low in 2004 and 2005, while the soybean proportion of land is low in all but 2003, even missing in 2007. This trend would affect the analysis because the frame was designed in 2003 and we see greater changes in the follwoing years, when the data was collected. Some points seem to have changes classes.

We have successfully worked with big data in different formats (.tif, web, coordinates in different measurement system, text and general expressions use) and developed tools to manipulate and extract useful information out of it. The next step is to utilize the tools constructed in this project to analyze changes in the real CEAP data. We would also like to investigate the CDL data as possible source of covariates in CEAP small area models. Another possible extension of this work with be the implementation of a web application, such as shiny. This would allow the users to better interact with CEAP data from yearly surveys, from different regions across United States.

# 5 Final note

This work is completed under the theme of reproducible research and we have created a GitHub repository containing all the files. There have been challenges in maintaining a flow in the pull/commit/push steps throughout the work. Not only we have filled up the *U:* drive space when downloading the large CDL data, but also we have confused GitHub when trying to upload the data on the web repository. When we tried to upload the data, the commit went through but we were not able to push. Hence, we had to use linux commands, such as *git commit -m "commit message"* and take control in the command line. Also, the terminal server ts2.stat.iastate.edu crashed due to heavy load one day, when we were completing a commit. The files remained checked when git crushed. Once again, we used the linux commands, such as *rm -f ./.git/index.lock* to unlock everything and be able to commit and push. Finally, in order to remove the extra folder created from the *.pdf* compilation using *knitr*, we used the command line *git rm -r –cached 'foldername'*. For example, *git rm -r –cached cache* for the cached chunks (web scrapping the census data takes some time) and *git rm -r –cached figure* for the figures (making the google maps takes some time, too).

This report is available in my current GitHub repository, `https://github.com/andreeae/STAT585X-Project`, under *FinalReport.Rnw*. The .pdf and the data are available upon request, as it can not be updated due to large size.

# 6 References


1. Hijmans, R. (2014), "Package 'plyr'," *http://cran.r-project.org/web/packages/plyr/plyr.pdf*
2. Wickham, H. (2014), "Package 'raster'," *http://cran.at.r-project.org/web/packages/raster/raster.pdf*