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# GIS Professional Portfolio for William Thoman

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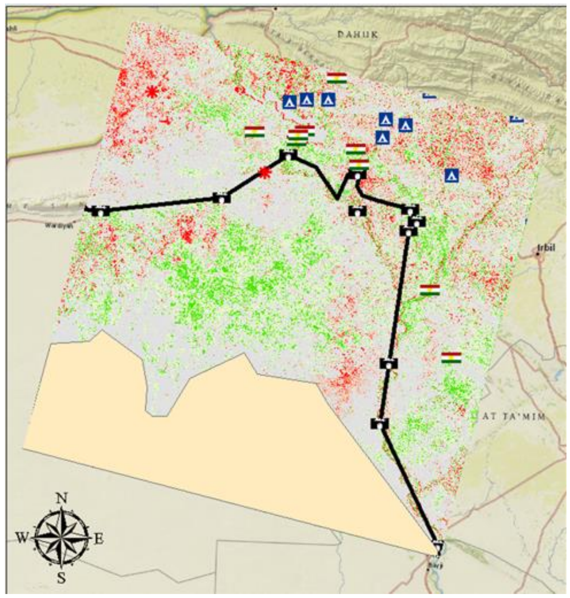
# GIS Professional Portfolio

By William Thoman




Completed as a Requirement for Graduation

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# Portfolio Overview

The following professional portfolio demonstrates the use of Geographic Information Systems and associated fields such as remote sensing, computer programming, and spatial statistics in order to explore environmental and human phenomena and the interactions between humanity and the environment. The following projects transition from more narrowly focused remote sensing or spatial statistics projects to those which combine a number of skills and knowledge bases.

The first project in this collection looks at homicide rates for two 3 year periods in the city of Chicago. Through a combination of hotspot analysis, geographically weighted regression, and Bivariate LISA this projects explores the spatial nature of homicides in the city as well as attempting to model possible explanatory variables such as poverty, education levels and income. This project thus not only exhibits applications of various spatial statistics components but also the use of multiple software types (ArcGIS, Crimestat, and Geoda) to conduct hybrid analysis of vector data. This project demonstrated many trends in homicides; most notably that despite a decreasing overall trend, the murder rate remained relatively high in concentrated hotspot areas which had lower income, education, and employment levels.

The second project is part of a larger project which sought to use multiple remote sensing methods to assess the impact of 2014 drought around Modesto, California. This was done by using Landsat imagery to produce both index and classified imagery and conducting image differencing between three years: 2001, 2003, and 2014. The project component seen here is an analysis of image differencing of NDVI images. The results were categorized in thresholds of standard deviations ranging from negative two to positive two standard deviations away from the mean. This allowed the analysis to highlight areas of extreme loss of vegetation in terms of confidence interval of probability. This project demonstrates use and understanding of basic remote sensing concepts such data downloading, image correction, image enhancement through index use and image comparison in time series to assess land cover change.

In addition to GIS and remote sensing skills projects, a project that demonstrates ability to design and create a program in Python is included. The program created allowed for automated generation of various state or province maps from a larger country shapefile. In addition to map generation the program also allowed for the user to import symbology from other files. While the example only created maps of U.S. states with roads, cities, and water it created a framework that could be modified for many different configurations in terms of included features and unit of display (counties, districts, countries, etc.). This project overall demonstrated the ability to use python and programming skills to create custom automations and functions in order to more efficiently complete processes, especially those which must be completed multiple times.

Following these projects based on comparatively narrow skillsets are projects which combine skills and knowledge bases to look at more complex human-environment interactions through a spatial lens. The first project of this section seeks to model the risk of a chain reaction of volcanic eruption and limnic eruption (mass release of $C0_2$ and methane) around Lake Kivu in the Democratic Republic of the Congo. Using flow and watershed modules this project modeled lava flows and then modeled the possible subsequent limnic eruption from the lake using a model that simulated gas dispersal based on wind speed. Following this we combined these factors to generate a map showing safest areas to evacuate to in the event of said catastrophe. This project demonstrate risk mapping and modeling as well as raster based analysis.

The subsequent project looks at the potential effects of mining in Cajamarca, Peru on the surrounding landscape by looking at changes in vegetation indices and also examines areas of high species biodiversity and their exposure to negative environmental externalities from mining. Zonal statistics were used to look at how both biodiversity and SAVI changed in 500 meter interval buffer polygons around identified mine sites. This project used remotely sensed and ancillary vector data to look at human and environmental interaction. In addition to remote sensing tools, this project also used zonal statistic tool sets.

The final project in this portfolio combines remote sensing, spatial analysis, and review of literature and news sources to explore the impacts of conflict on agriculture in northern Iraq. This project utilized remotely sensed images to compare SAVI images of northern Iraq and looked at areas of clustered negative values for change between 2014 and 2015. This analysis was combined with ancillary vector data contain information about territorial control, ethnic groups, and internally displaced persons (IDPs). Finally a visual analysis was conducted in conjunction with an examination of news sources in order to relate the loss of vegetation in areas to displacement, especially of ethnic minorities, by the contemporary conflict against ISIS. This project demonstrated use of remote sensing techniques in concert with broader research and ancillary vector data and examined human environment interactions.

# Spatial Analysis of Homicide Rates in Chicago for 2001-2003 and 2012-2014

By William Thoman, Zhuoyue Zhou

Throughout 2012 and 2013, the city of Chicago saw a spike in homicides, especially gang-related homicides. This ran contrary to the trend of decreasing homicide numbers since the 1980s (Chicago Police Department 2011). A *New York Times* analysis piece discovered that Chicago was a city divided by its murder rates and in terms of race and wealth (Davey 2013). We decided to test the geographic and statistical veracity of this common account.

Building off of other works that looked at environmental factors of crime, our analysis looked at unemployment, household income, education, and race. These independent variables are used in many analyses of crime hotspots, as well as many spatial analyses of crime (Zhang and Peterson 2007).The examination of socioeconomic variables was conducted by using block-group level 2012 American Community Survey for our period from 2012-2014 and year 2000 census block-group level data for our period from 2001-2003. Chicago crime data was downloaded from the City of Chicago data portal. Points were used to calculate the block-group level annual murder rate, in order to use spatial regression toolsets.

We conducted exploratory analysis using CrimeStat software to look at Nearest Neighbor Hierarchical clustering hotspots. Following this, we ran the Getis-Ord Gi* Statistic to determine the hot and cold spot clusters of homicide within Chicago. Next regression analysis was conducted for the aforementioned variables beginning with Ordinary Least Squares (OLS) Regression. For both time periods the Jarque-Bera statistic was significant, thus we decided to conduct Geographically Weighted Regression. Finally Bivariate LISA was conducted in Geoda to further analyze the spatial nature of our variables.

As can be seen in the following figures, crime in Chicago remains concentrated in the south and west sides of the city, and the factors examined have more explanatory power (higher model R squared value in those areas) in those areas as indicated in our GWR maps. There was also High-High clustering of or independent and dependent variables on the south and west sides of Chicago and Low-Low clustering in the north and east portions of the city. Our model was limited to some degree in effectiveness due to the inability to account for factors such as gang membership or gun ownership which are harder factors to map.

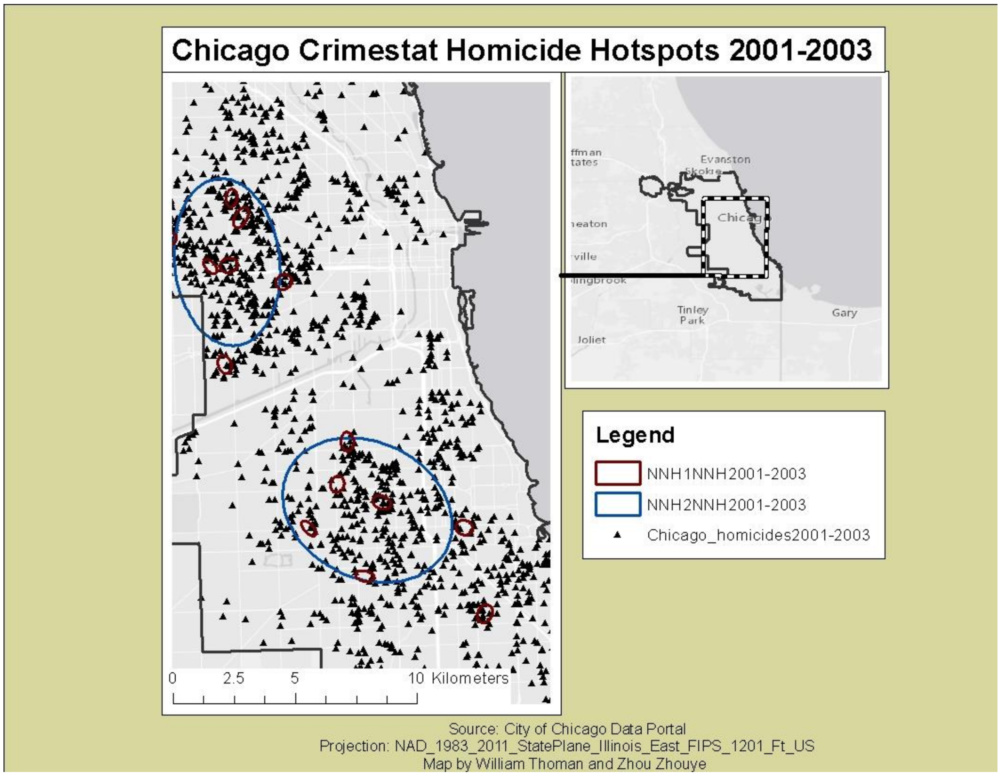



Figure 1: Crime Stat Output for NNH clusters for 2001-2003

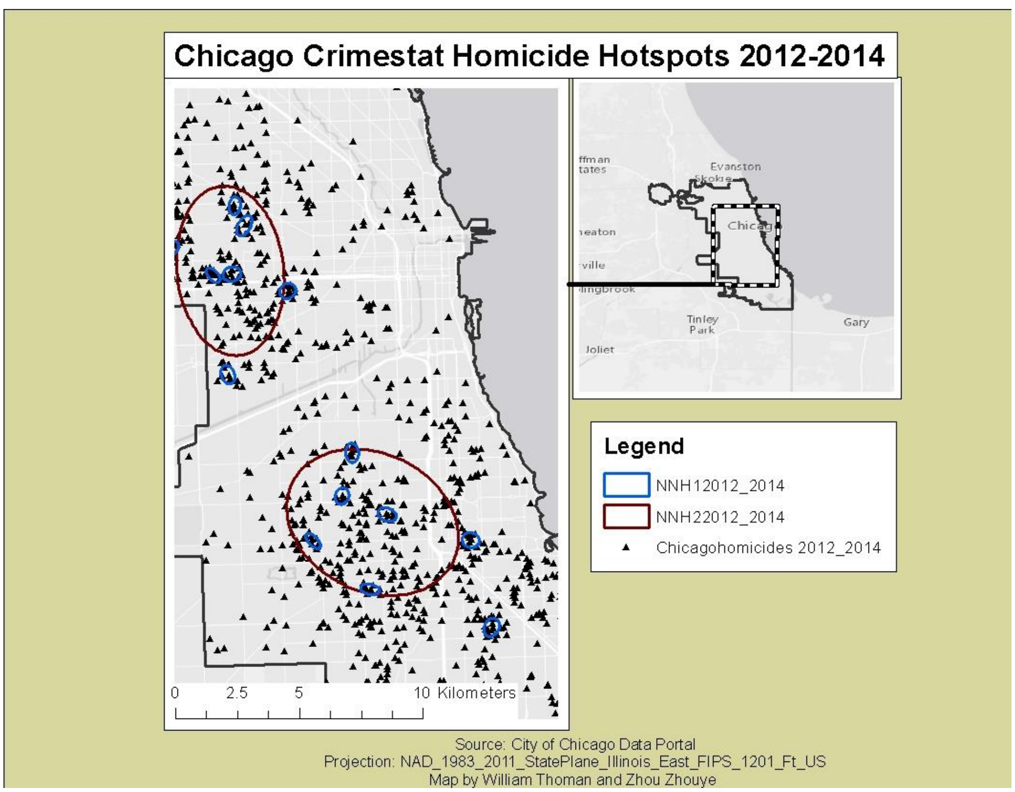



Figure 2: Crime Stat Output for NNH clusters for 2012-2014

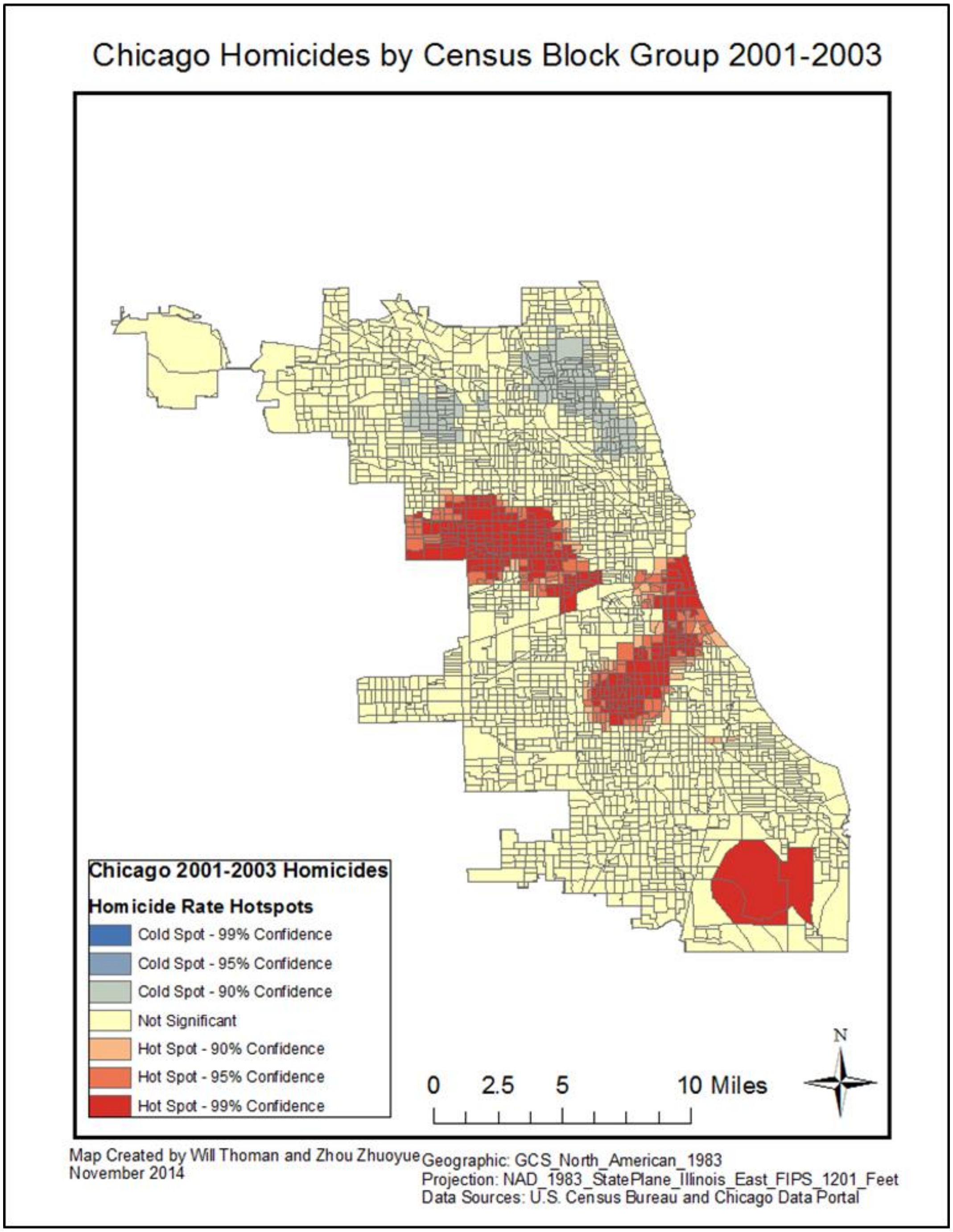



Figure 3: Getis Ord Gi* Hotsposts for 2001-2003

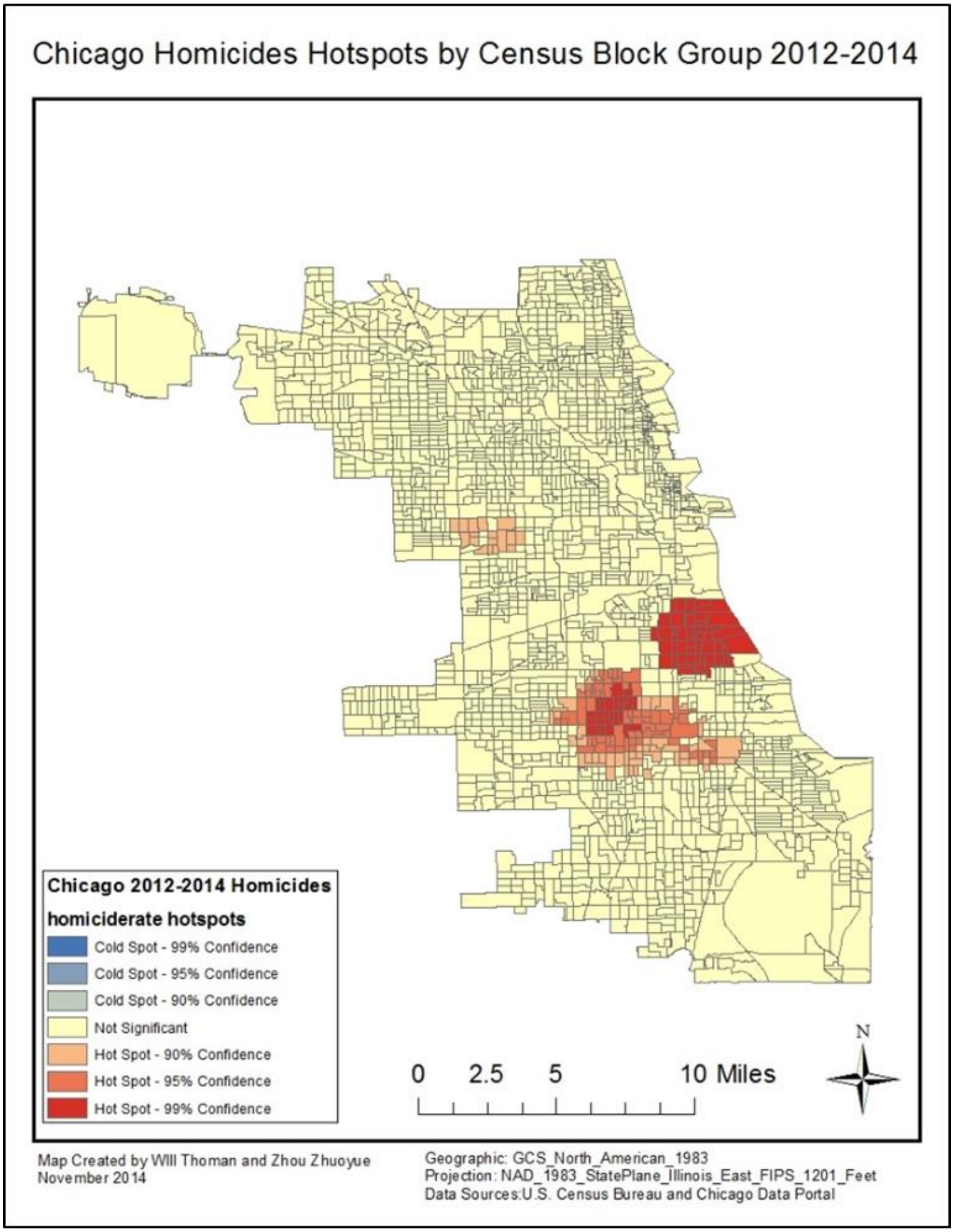



Figure 4: Getis Ord Gi* Hotsposts for 2012-2014

**Summary of OLS Results - Model Variables**

| Variable | Coefficient [a] | StdError | t-Statistic | Probability [b] | Robust_SE | Robust_t | Robust_Pr [b] | VIF [c] |
|---|---|---|---|---|---|---|---|---|
| Intercept | -0.824633 | 0.208377 | -3.957403 | 0.000087* | 0.524894 | -1.571046 | 0.116322 | -------- |
| NONWHTPCT | 1.463926 | 0.236533 | 6.189108 | 0.000000* | 0.347102 | 4.217572 | 0.000031* | 1.274686 |
| UNEMPPCT | 4.891922 | 1.797423 | 2.721630 | 0.006543* | 1.834051 | 2.667276 | 0.007696* | 1.288265 |
| INCOMEPERP | -0.000024 | 0.000004 | -5.554179 | 0.000000* | 0.000020 | -1.246442 | 0.212732 | 1.021460 |
| EDU_PCT | 3.560380 | 0.109344 | 32.561201 | 0.000000* | 3.028710 | 1.175544 | 0.239897 | 1.029419 |

**OLS Diagnostics**

| | | | |
|---|---|---|---|
| Input Features: | homicide rate | Dependent Variable: | HMCD_RT |
| Number of Observations: | 2339 | Akaike's Information Criterion (AICc) [d]: | 12559.347203 |
| Multiple R-Squared [d]: | 0.324356 | Adjusted R-Squared [d]: | 0.323198 |
| Joint F-Statistic [e]: | 280.120530 | Prob(>F), (4,2334) degrees of freedom: | 0.000000* |
| Joint Wald Statistic [e]: | 260.382240 | Prob(>chi-squared), (4) degrees of freedom: | 0.000000* |
| Koenker (BP) Statistic [f]: | 1583.333940 | Prob(>chi-squared), (4) degrees of freedom: | 0.000000* |
| Jarque-Bera Statistic [g]: | 92135096.502118 | Prob(>chi-squared), (2) degrees of freedom: | 0.000000* |

Figure 5: Results of OLS Analysis 2012-2014

**Summary of OLS Results - Model Variables**

| Variable | Coefficient [a] | StdError | t-Statistic | Probability [b] | Robust_SE | Robust_t | Robust_Pr [b] | VIF [c] |
|---|---|---|---|---|---|---|---|---|
| Intercept | -0.559261 | 0.328654 | -1.701674 | 0.088946 | 0.329513 | -1.697234 | 0.089782 | -------- |
| INC_1999 | -0.000032 | 0.000011 | -2.747272 | 0.006051* | 0.000033 | -0.963210 | 0.335518 | 2.618027 |
| PERC_UNEMP | -3.265848 | 2.132458 | -1.531495 | 0.125784 | 3.037910 | -1.075031 | 0.282453 | 1.415862 |
| PERC_NW | 3.430411 | 0.381573 | 8.990185 | 0.000000* | 0.520691 | 6.588192 | 0.000000* | 1.617136 |
| PERC_BACH | 3.495425 | 0.822003 | 4.252328 | 0.000026* | 2.849558 | 1.226655 | 0.220067 | 2.607689 |

**OLS Diagnostics**

| | | | |
|---|---|---|---|
| Input Features: | Annual Homicide Rate pe | Dependent Variable: | HOM_RATE |
| Number of Observations: | 2599 | Akaike's Information Criterion (AICc) [d]: | 16152.887827 |
| Multiple R-Squared [d]: | 0.040539 | Adjusted R-Squared [d]: | 0.039060 |
| Joint F-Statistic [e]: | 27.400445 | Prob(>F), (4,2594) degrees of freedom: | 0.000000* |
| Joint Wald Statistic [e]: | 269.264571 | Prob(>chi-squared), (4) degrees of freedom: | 0.000000* |
| Koenker (BP) Statistic [f]: | 29.590600 | Prob(>chi-squared), (4) degrees of freedom: | 0.000006* |
| Jarque-Bera Statistic [g]: | 58884357.102045 | Prob(>chi-squared), (2) degrees of freedom: | 0.000000* |

Figure 6: Results of OLS Analysis 2001-2003

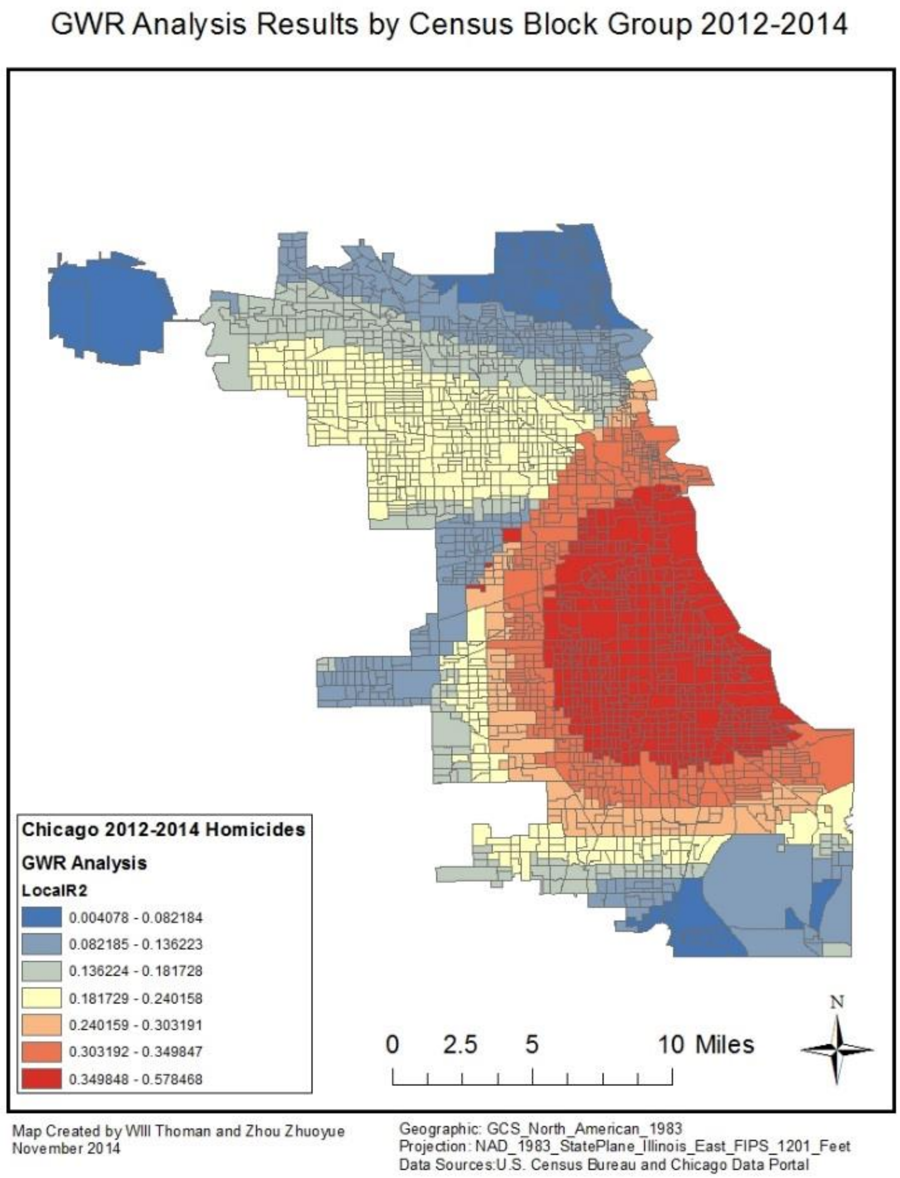



Figure 7: Results of GWR Analysis 2012-2014

| OID | VARNAME | VARIABLE | DEFINITION |
|---|---|---|---|
| 0 | Bandwidth | 0.06716 | |
| 1 | ResidualSquares | 27255.46069 | |
| 2 | EffectiveNumber | 47.598993 | |
| 3 | Sigma | 3.448865 | |
| 4 | AICc | 12453.98545 | |
| 5 | R2 | 0.370653 | |
| 6 | R2Adjusted | 0.357855 | |
| 7 | Dependent Field | 0 | homecide_rate |
| 8 | Explanatory Field | 1 | Income_2000 |
| 9 | Explanatory Field | 2 | Percent_unemployment |
| 10 | Explanatory Field | 3 | Percent_non-white |
| 11 | Explanatory Field | 4 | Percent_bachelor |

Figure 8: GWR Output 2012-2014

| OID | VARNAME | VARIABLE | DEFINITION |
|---|---|---|---|
| 0 | Bandwidth | 0.036823 | |
| 1 | ResidualSquares | 43319.41302 | |
| 2 | EffectiveNumber | 114.919878 | |
| 3 | Sigma | 4.176006 | |
| 4 | AICc | 14859.29514 | |
| 5 | R2 | 0.451431 | |
| 6 | R2Adjusted | 0.426267 | |
| 7 | Dependent Field | 0 | homecide_rate |
| 8 | Explanatory Field | 1 | Income_1999 |
| 9 | Explanatory Field | 2 | Percent_unemployment |
| 10 | Explanatory Field | 3 | Percent_non-white |
| 11 | Explanatory Field | 4 | Percent_bachelor |

Figure 9: GWR Output 2001-2003

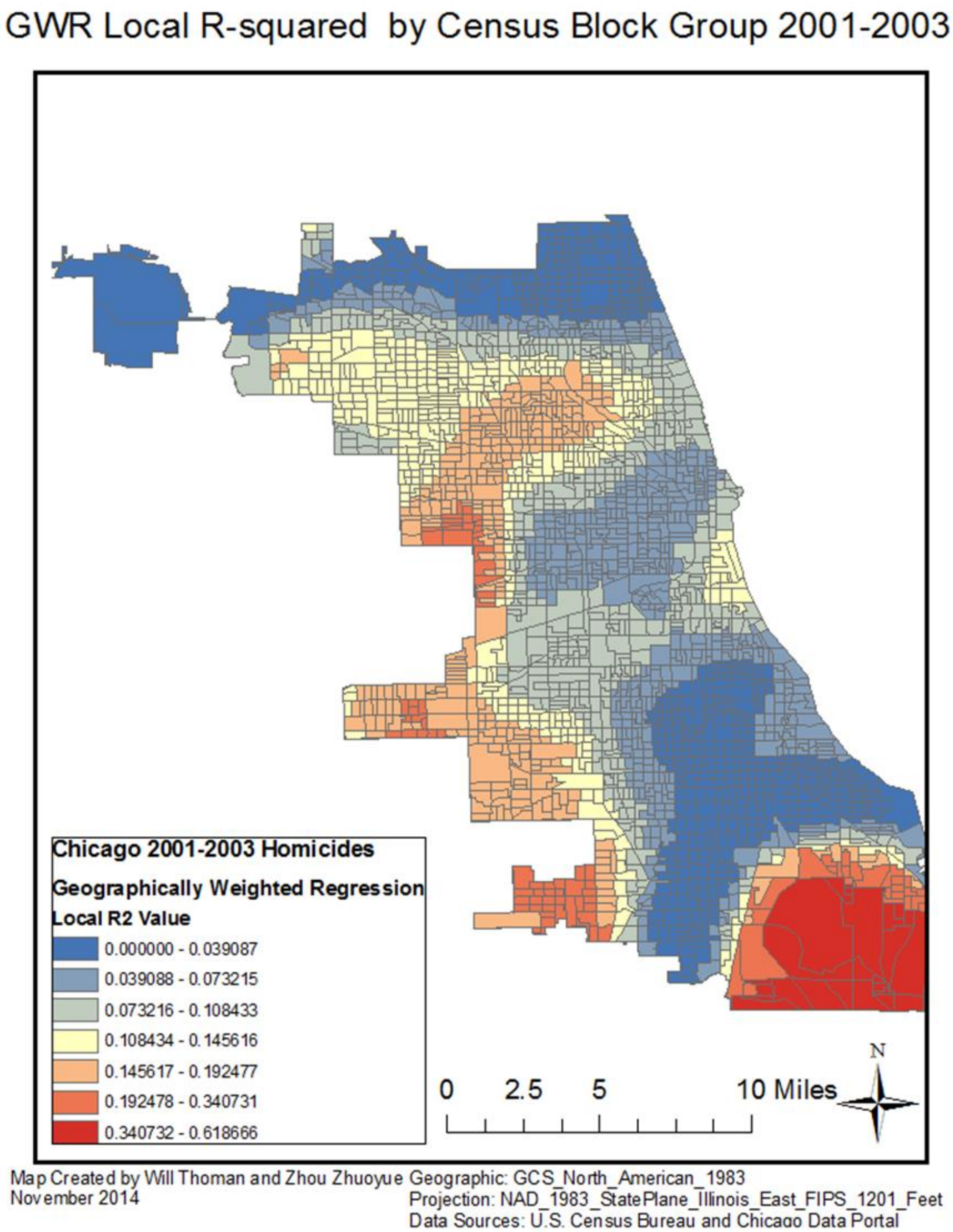



Figure 10: Results of GWR Analysis 2001-2003

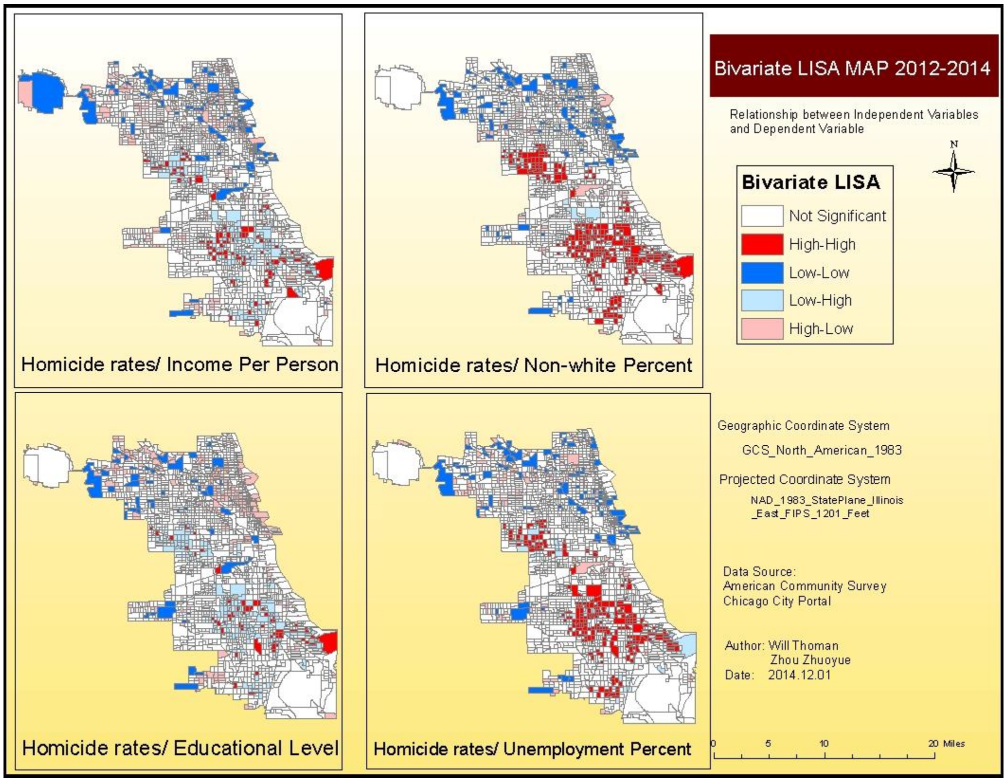



Figure 11 Bivariate LISA MAP for 2001-2003

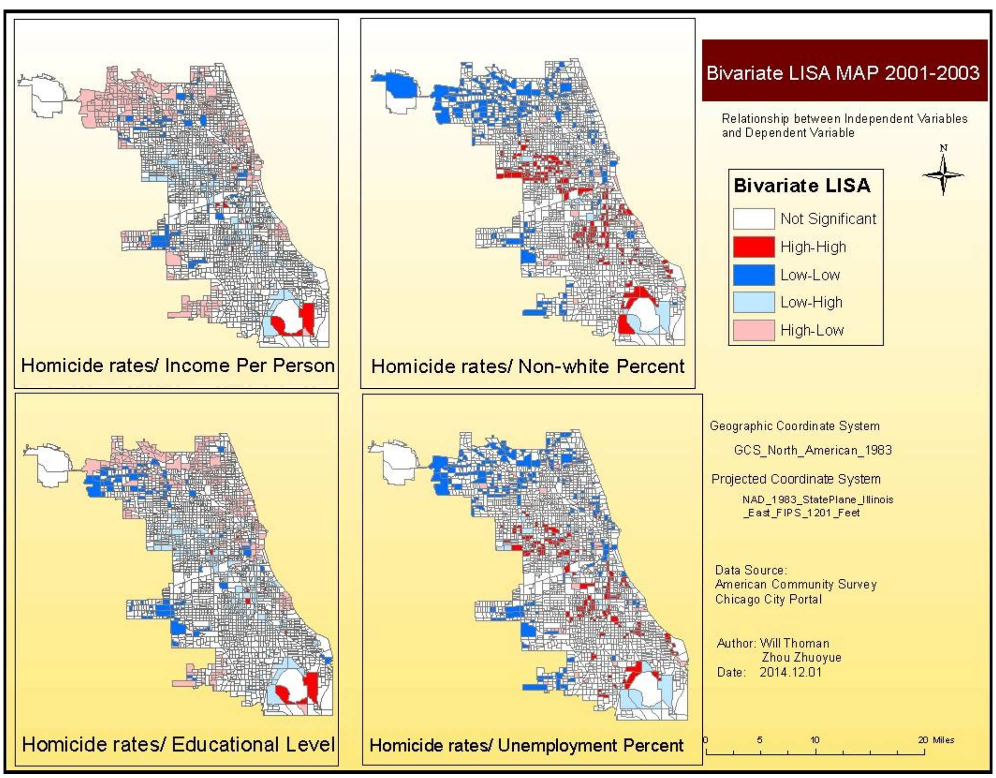



Figure 12 Bivariate LISA MAP for 2012-2014

# An Assessment of The 2013-14 Drought in Modesto, California

by Lei Rong, Nan Ding, William Thoman, and Jennifer Duong

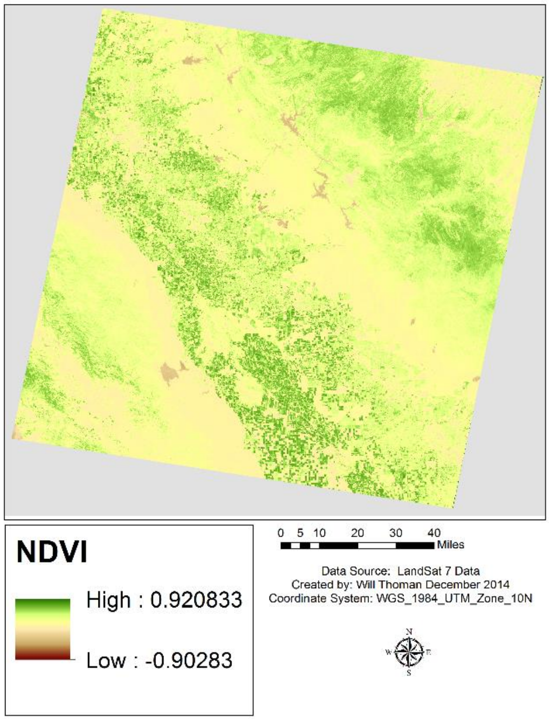
The 2014 drought was one of California's most severe droughts on record. Exacerbating the already severe consequences of this drought is California's status as one of our nation's most productive agricultural regions, making the ramifications of drought extend far beyond the state. In order to assess the spatial nature of drought severity a multifaceted analysis was conducting analysis of land cover change, change in vegetation index, and change in snow index for a Landsat scene around Modesto, California using images from years 2001, 2003, and 2014.

To conduct analysis of the change in vegetation Normalized Difference Vegetation Index images were generated (Figure 13). Following this image differencing was conducted for each of time periods and the results in terms of z-scores were displayed below (Figure 14). To better analyze the trends, thresholding was used to categorize the changes in NDVI by confidence interval (Figures 15-17).

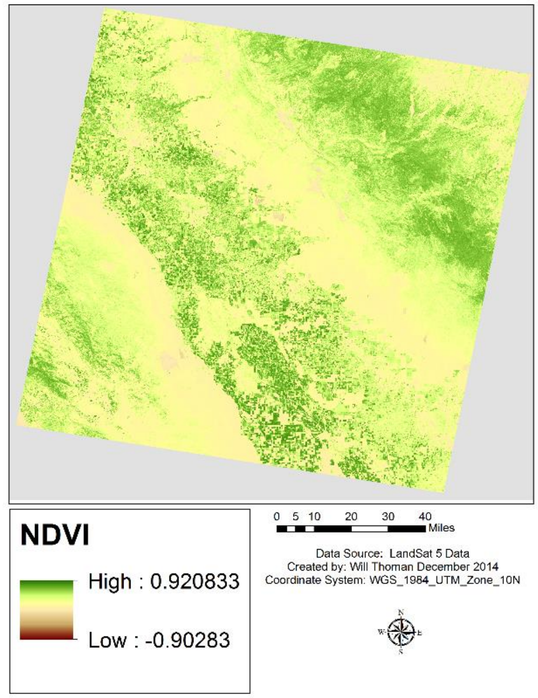
While there is a great deal of loss and net loss in 2014 compared to the 2001-2003 image differencing images much of it can be explained by the fire damage from the Rim Fire, which was the 953 square km in total. While there were other contributing human factors contributing to the fire, it is highly likely that drought did play some role in its spread and duration. As can be seen in the following figures, many areas of significant change (as determined by confidence intervals) were concentrated in areas that were either damaged by a fire or had recovered after a fire as can be determined by visual analysis.

Despite some limitations, the results of the project's various processes yielded results that were consistent with the extreme drought of recent years. We saw noticeable decreases in areas of healthy vegetation and snowpack between our two earlier years and 2014 to a much greater degree than the difference between 2001 and 2003. While there are many other factors that would need be taken into consideration for a more full analysis of our observations, it appears that there is a correlation between loss of vegetation indicated by vegetation indices and land cover analysis between our earlier years and 2014. This is consistent with our overall knowledge of the drought as well as our findings from the drought index which identified this area as having severe drought.

2001 NDVI Values




2003 NDVI Values




2014 NDVI Values

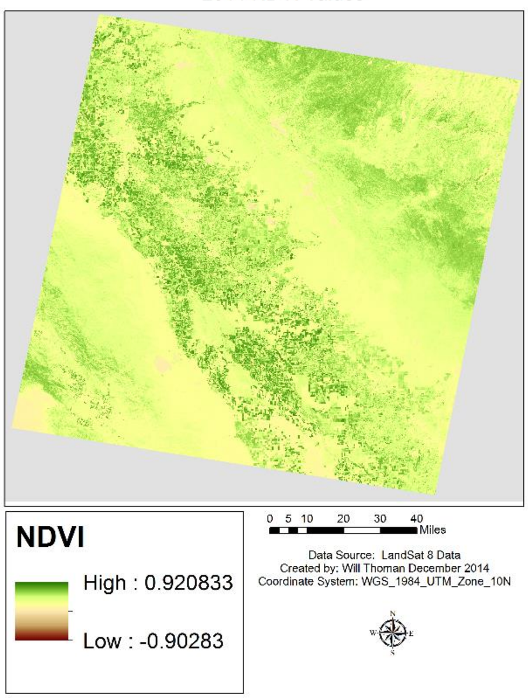
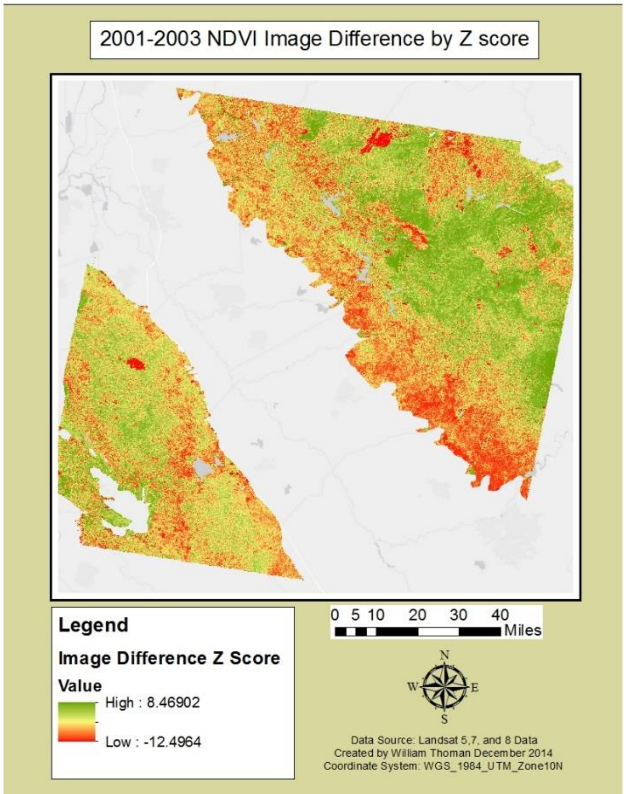
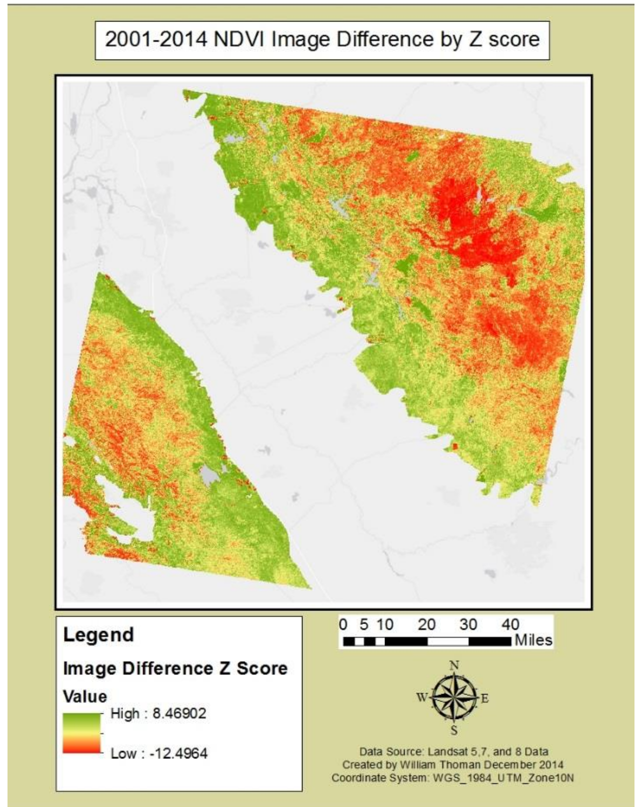



Figure 14: NDVI Images from 2001,2003, and 2014 from Landsat 5,7, and 8 respectively



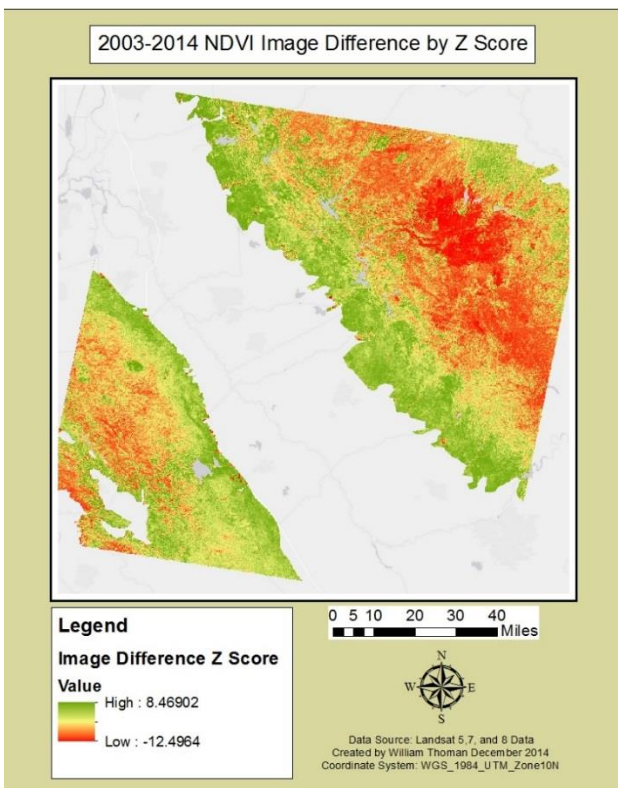




Figure 15: Image difference images for NDVI by Z-score

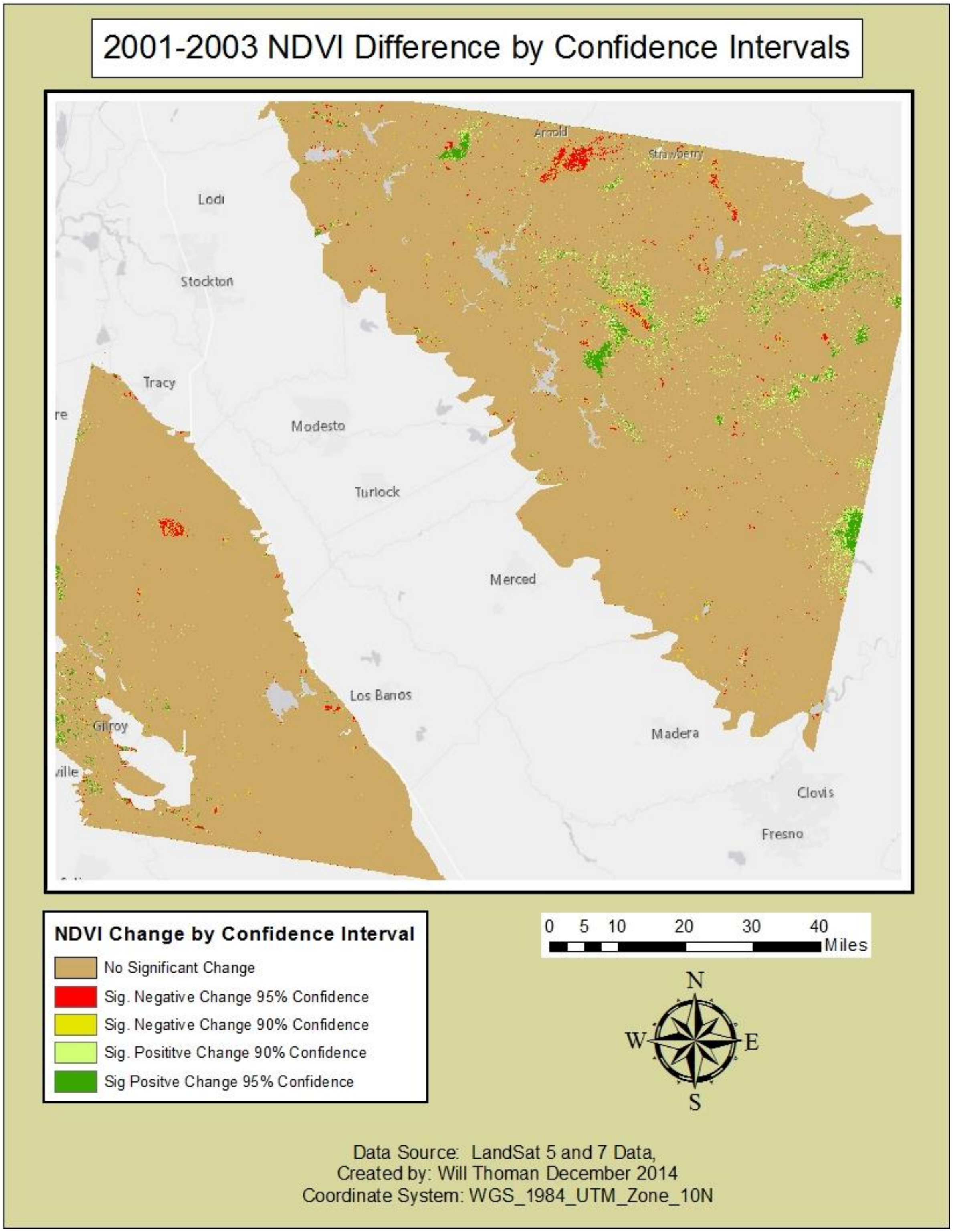



Figure 16:2001-2003 NDVI Difference by Confidence Intervals

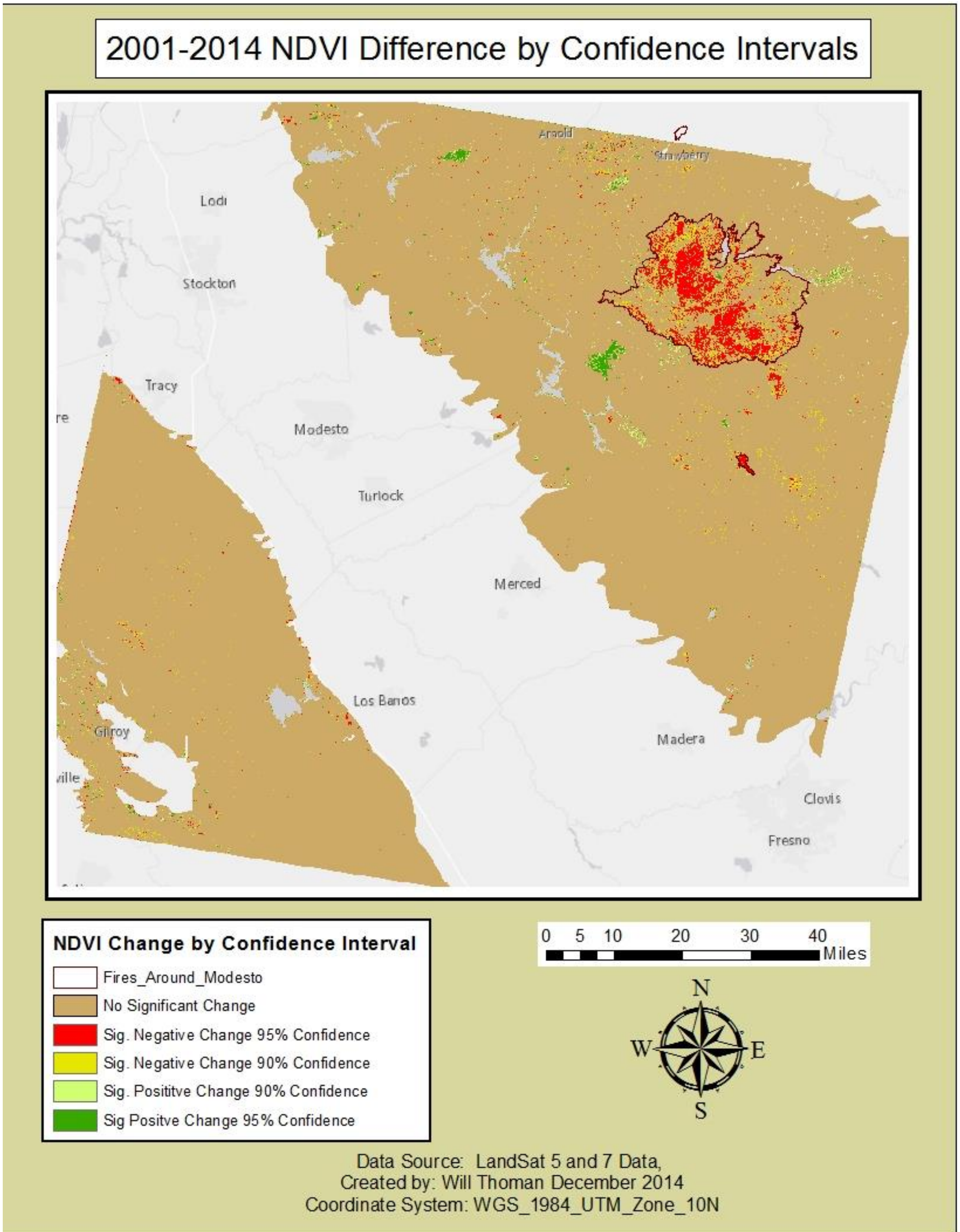



Figure 17:2001-2014 NDVI Difference by Confidence Intervals

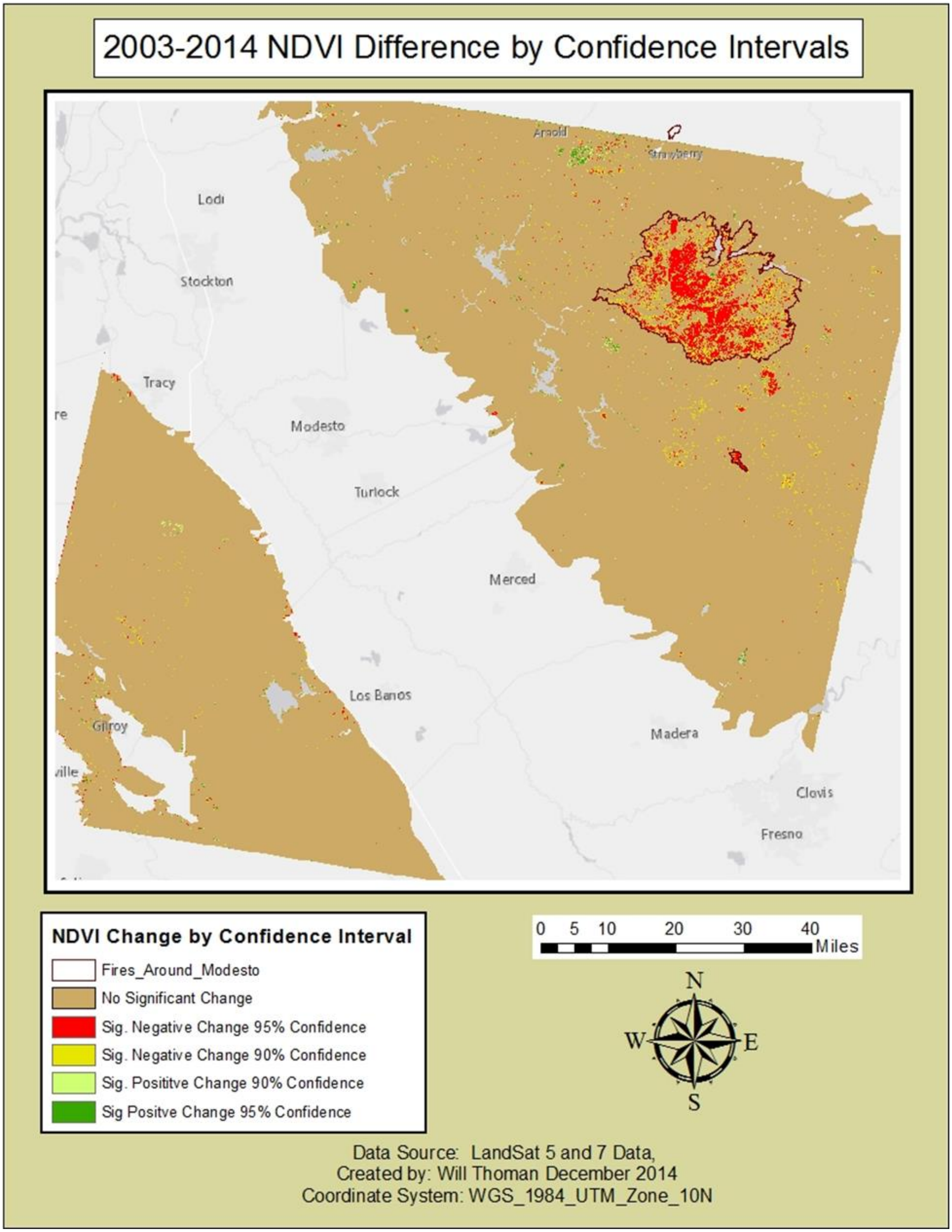



Figure 16:2003-20014 NDVI Difference by Confidence Intervals

# Creating a Python Programming Script for Map Automation in GIS

By Jennifer Duoung, Garfield Barclay, and William Thoman

This project set out with the objective to create a program which automated map generation for smaller administrative districts from a larger shapefile, in this case creating state maps from a larger United States shapefile. In addition to generating these maps, the script is designed to add other layers to the map, in our case roads, water bodies, and cities that our program clipped from another shapefile. In order to keep consistent design in our maps we created a function designed to import symbology of several layer files which were designed as templates. In addition the display and layout of the resulting maps would depend on the dimensions, as maps with width exceeding length would be displayed in landscape and those where length exceeded width would be displayed in portrait format. Finally a pdf and mxd would be exported with the corresponding state name.

The structure of our program can be divided into the following areas: creation of a graphic user interface (GUI), functions designed to clip various features to the extent of states, functions designed to apply symbology from templates, functions to design map layout based on dimensions, and functions designed to export PDF and mxd files from the generated maps. The logic of the program can be seen in the flowchart shown below (Figure 17). The script itself, shown in entirety below, begins with a long series of function definitions and then proceeds to a series of function calls to be activated depending on user input from the GUI. The modular nature of the script allowed for easier debugging as errors could be identified within specific functions rather than errors appearing throughout the script that would be more difficult to isolate. Options were designed to generate a map for one selected state or all states depending on user input. An example of an output map can be seen below (Figure 18).

While some limitations on the script did appear, overall the script completed the objectives set out by the project. The script also serves as a potential template for many different types of map generation with minor edits, and as it stands the script can be used to create maps of any administrative sub districts such as counties, regions, or provinces. More different features could easily be added as could different designs and layouts depending on the need of the user.

```
##Script name: Automation of Map Creation
##Date: December 8, 2015
##Authors: Garfield Barclay, Jennifer Duong, and William Thoman
##Final Project for Comp Programming for GIS, Fall 2015
#__________________________________________________________________#

#Imports modules
import arcpy,sys,os
from arcpy import env
from arcpy import mapping

#____________________________Parameters for GUI__________________________#

#para input folder with all 4 shapefiles
infolder=r'D:\Comp_final\InputFolder'
#para boundary shapefile
fc=r'D:\Comp_final\InputFolder\us_states.shp'
#para statename
statename="Maine"
#Check box for all states
ischecked='true'

#__________________________Set_up_for_running_script_____________________#
#set workspace
arcpy.env.workspace=infolder

#allow overwrites
arcpy.env.overwriteOutput = True

#set up links to template mxd's
mxdLandscape = arcpy.mapping.MapDocument(infolder+r'\landscape.mxd')
mxdPortrait = arcpy.mapping.MapDocument(infolder+r'\portrait.mxd')
#Used to test extent of layer
mxdBlank=arcpy.mapping.MapDocument(infolder+r'\portrait.mxd')

#____________________________Function Definitions_______________________#


#creates layerfile from shapefile
def shapetolayer(incl,infold,statename):
    print "Converting shapefile to Layer file"
    obj=arcpy.Describe(incl)
    title=obj.name[0:-4]
    del obj
    feat=arcpy.MakeFeatureLayer_management(incl,str(statename)+"lyr_file")
    del incl
    layer_file=title+"temp.lyr"
    del title
    arcpy.SaveToLayerFile_management(feat, layer_file, "ABSOLUTE")
    del feat
    del layer_file
```

```
#creates a layerfile for state boundaries
def cliptostate(infc,clipfc,infolder,outfold,namest):
    print "Clipping to Boundary"
    obj=arcpy.Describe(infc)
    title=obj.name[0:-8]
    clipdfile=outfold+"\\"+title+'_'+namest+r"_clip.lyr"
    arcpy.Clip_analysis(infc,clipfc,clipdfile)
    del title
    del obj

#clips input shapefiles to state boundary, converts to layers and adds to
maps
def addclippedtomap(incl,mapdoc,data,outfold):
    print "Adding features to map"
    desc=arcpy.Describe(incl)
    lyr_name=desc.name
    #creates lake lyr
    if "lake" in lyr_name:
        arcpy.MakeFeatureLayer_management(incl,"Lakes")
        lake_layerfile=outfold+'\\'+"Lake.lyr"
        arcpy.SaveToLayerFile_management("Lakes", lake_layerfile,
"ABSOLUTE")
        add_lake = arcpy.mapping.Layer(lake_layerfile)
        arcpy.mapping.AddLayer(data,add_lake, "AUTO_ARRANGE")
    #creates road layer
    if "road" in lyr_name:
        arcpy.MakeFeatureLayer_management(incl,"Roads")
        road_layerfile=outfold+'\\'+"Road.lyr"
        arcpy.SaveToLayerFile_management("Roads", road_layerfile,
"ABSOLUTE")
        add_road = arcpy.mapping.Layer(road_layerfile)
        arcpy.mapping.AddLayer(data,add_road, "AUTO_ARRANGE")
    #creates city layer
    if "cit"in lyr_name:
        arcpy.MakeFeatureLayer_management(incl,"State Cities")
        city_layerfile=outfold+'\\'+"City.lyr"
        arcpy.SaveToLayerFile_management("State Cities", city_layerfile,
"ABSOLUTE")
        add_city = arcpy.mapping.Layer(city_layerfile)
        arcpy.mapping.AddLayer(data,add_city,"TOP")

#shows labels for city layer in mxd
def addlabels(mapdoc,layer_name):
    layer = arcpy.mapping.ListLayers(mapdoc, layer_name)[0] #Indexing list
for 1st layer
    if layer.supports("LABELCLASSES"):
        for lblclass in layer.labelClasses:
            lblclass.showClassLabels = True
    layer.showLabels = True
#creates map and adds symbology
def createmap(mxd,infolder,outfolder,stlyr,stname,layout):
    #defining layout for input into genlayers function
    if layout=="landscape":
        lay="landscape"
```

```
    if layout=="portrait":
        lay="portrait"
    #function call for creating layers, clipping layers and adding layers
to map
    df = arcpy.mapping.ListDataFrames(mxd, "Layers")[0]
    inclasses=arcpy.ListFiles('*.shp')
    print inclasses
    for inclass in inclasses:
        shapetolayer(inclass,outfolder,stname)
    path=infolder
    inlyrs=arcpy.ListFiles('*.lyr')
    print inlyrs
    clip=arcpy.mapping.Layer(stlyr)
    arcpy.env.workspace=infolder
    for inlyr in inlyrs:
        cliptostate(path+'\\'+inlyr,clip,infolder,outfolder,statename)
    arcpy.env.workspace= outfolder
    clippedshps=arcpy.ListFiles('*clip.shp')
    for clippedshp in clippedshps:
        addclippedtomap(clippedshp,mxd,df,outfolder)
    del path
    del clip
    print clippedshps
    df = arcpy.mapping.ListDataFrames(mxd, "Layers")[0]
    #sets up list of template layerfiles
    lyr1 = arcpy.mapping.ListLayers(mxd, "", df)[0]
    lyr2 = arcpy.mapping.ListLayers(mxd, "", df)[1]
    lyr3 = arcpy.mapping.ListLayers(mxd, "", df)[2]
    lyr4 = arcpy.mapping.ListLayers(mxd, "", df)[3]
    refList = [infolder + "\\Symbology\\us_cities.lyr",
               infolder + "\\Symbology\\us_roads.lyr",
               infolder + "\\Symbology\\us_lakes.lyr",
           infolder + "\\Symbology\\us_states.lyr"]
    lyrList = [lyr1, lyr2, lyr3, lyr4]
    print lyrList
    #applies symbology to layers in our mxd
    i = 0
    while i < 4:
        refpath=os.path.abspath(refList[i])
        sourceLayer = arcpy.mapping.Layer(refpath)
        arcpy.mapping.UpdateLayer(df, lyrList[i], sourceLayer, True)
        i +=1

    #function call for adding labels
    addlabels(mxd,"State Cities")

    df.zoomToSelectedFeatures() #zoom to selected features
    arcpy.RefreshActiveView() #just added

    #function call for genlayout which formats the layout for the map
    genlayout(mxd,stname,outfolder,lay)

    #cleanning out lists
```

```
    for inlyr in inlyrs:
        if arcpy.Exists(inlyr):
            fildes=arcpy.Describe(inlyr)
            filnam=fildes.name
            filtype=fildes.extension
            if filtype != ".lock.":
                 arcpy.Delete_management(inlyr)

#function formats the layout items for the mxd and items
def genlayout(mxd,state,outfolder,lay):
    print "Generating map layout"

##Adding title for MXD

    # the Element Name of the Title MUST be "Map Title" in the source mxd
file
    text = arcpy.mapping.ListLayoutElements(mxd,"TEXT_ELEMENT","Map
Title")[0]

    text.text = "Map of "+ state #INSERT STATE NAME

    text = arcpy.mapping.ListLayoutElements(mxd,"TEXT_ELEMENT","Map
Title")[0]

    letter_Width = 11.0
    if lay=="landscape":
        text.elementPositionX = letter_Width/2 -float(text.elementWidth/2)

    #sets up map element variables
    northArrow = arcpy.mapping.ListLayoutElements(mxd,
"MAPSURROUND_ELEMENT", "North Arrow")[0]
    df = arcpy.mapping.ListDataFrames(mxdLandscape,
northArrow.parentDataFrameName)[0]

    ScaleBar = arcpy.mapping.ListLayoutElements (mxd,
"MAPSURROUND_ELEMENT", "") [0]
    df2 = arcpy.mapping.ListDataFrames(mxdLandscape,
ScaleBar.parentDataFrameName)[0]

    legend = arcpy.mapping.ListLayoutElements(mxd, "LEGEND_ELEMENT",
"Legend")[0]
    df3 = arcpy.mapping.ListDataFrames(mxd, legend.parentDataFrameName)[0]

    #positions the map elements for a landscape map
    if lay=="landscape":
        northArrow.elementPositionX = df.elementPositionY +
(df.elementWidth/1.05)
        northArrow.elementPositionY = df.elementPositionX +
(df.elementHeight/150)

        ScaleBar.elementPositionX = df2.elementPositionY +
(df2.elementWidth/2.5)
        ScaleBar.elementPositionY = df2.elementPositionX +
(df2.elementHeight/50)
```

```
        legend.elementPositionX = df3.elementPositionY +
(df3.elementWidth/18)
        legend.elementPositionY = df3.elementPositionX +
(df3.elementHeight/50)

        arcpy.RefreshActiveView()
        arcpy.RefreshTOC()

        #saves an mxd with the name of the state
        mxd.saveACopy(state+"_landscape.mxd")

        #exports map to pdf
        arcpy.mapping.ExportToPDF(mxdLandscape, state+"_landscape.pdf")
        del mxd
    #positions the map elements for a portrait map

    if lay=="portrait":
        northArrow.elementPositionX = df.elementPositionY +
(df.elementWidth*0.66)
        northArrow.elementPositionY = df.elementPositionX +
(df.elementHeight/25)

        ScaleBar.elementPositionX = df2.elementPositionY +
(df2.elementWidth/4)
        ScaleBar.elementPositionY = df2.elementPositionX +
(df2.elementHeight/50)

        legend.elementPositionX = df3.elementPositionY +
(df3.elementWidth/18)
        legend.elementPositionY = df3.elementPositionX +
(df3.elementHeight/30)

        arcpy.RefreshActiveView()
        arcpy.RefreshTOC()

        #saves an mxd with the name of the state
        mxdPortrait.saveACopy(outfolder+'\\'+state+r".mxd")

        #exports map to pdf
        arcpy.mapping.ExportToPDF(mxd,state+"_portrait.pdf" )
        del mxd




#____________________________Function Calls___________________________#

#creates list of statenames
statelist=[]
rows=arcpy.SearchCursor(fc)
statelist=sorted(list(set(r.getValue('NAME') for r in rows)))
```

```
#_______________________________For All States____________________________#
#sets up a checkmark box to create maps of all states
if ischecked=='true':
    for statename in statelist:
        #create output folder for each state
        outname=statename+"_folder"
        if arcpy.Exists(infolder+"\\"+outname):
            arcpy.Delete_management(infolder+"\\"+outname)
        print "Creating Output Folder"
        arcpy.CreateFolder_management (infolder,outname)
        outfolder=infolder+'\\'+outname

        #creares state boundary layer from selected states
        arcpy.MakeFeatureLayer_management(fc,"State Boundary for
"+str(statename),"\"NAME\" = '" + statename + "'")
        state_layerfile=infolder+'\\'+statename+".lyr"
        arcpy.SaveToLayerFile_management("State Boundary for
"+str(statename), state_layerfile,"ABSOLUTE")
        layerpath=os.path.abspath(infolder+'\\'+statename+'.lyr')

        #adds statelayer to blank mxd to find extent
        df = arcpy.mapping.ListDataFrames(mxdBlank, "Layers")[0]
        add_layer = arcpy.mapping.Layer(layerpath)
        arcpy.mapping.AddLayer(df,add_layer)
        del add_layer
        df.zoomToSelectedFeatures()
        state_lyr = arcpy.mapping.ListLayers(mxdBlank,"*", df)[0]
        extent = state_lyr.getSelectedExtent()
        #Generates a Landscape Map
        if extent.width > extent.height:
            print r"Extent width is "+str(extent.width)
            print "Landscape Layout selected"
            layout="landscape"
            print "Adding boundary layer to map"
            df = arcpy.mapping.ListDataFrames(mxdLandscape, "*")[0]
            add_layer = arcpy.mapping.Layer(layerpath)
            arcpy.mapping.AddLayer(df,add_layer)
            del add_layer
            df.zoomToSelectedFeatures()

createmap(mxdLandscape,infolder,outfolder,state_layerfile,statename,layout
)
            del state_layerfile
            del layerpath
            del mxdLandscape

mxdLandscape=arcpy.mapping.MapDocument(infolder+r'\landscape.mxd')
        #Generates a Portrait Map
        if extent.height > extent.width:
            print r"Extent height is "+str(extent.height)
            print "Portrait Layout selected"
            layout="portrait"
            print "Adding boundary layer to map"
            df = arcpy.mapping.ListDataFrames(mxdPortrait, "*")[0]
```

```
            add_layer = arcpy.mapping.Layer(layerpath)
            arcpy.mapping.AddLayer(df,add_layer)
            del layerpath
            df.zoomToSelectedFeatures()

createmap(mxdPortrait,infolder,outfolder,state_layerfile,statename,layout)
            del state_layerfile
            del mxdPortrait

mxdPortrait=arcpy.mapping.MapDocument(infolder+r'\portrait.mxd')
        arcpy.env.workspace=infolder
        infilelist=arcpy.ListFiles()
        for fil in infilelist:
            if arcpy.Exists(fil):
                fildes=arcpy.Describe(fil)
                filnam=fildes.name
                filtype=fildes.extension
                if filtype != ".lock.":
                    if "temp" in filnam:
                        try:
                            arcpy.Delete_management(fil)
                        except:
                            pass
                if filtype==".lyr":
                    arcpy.Delete_management(fil)
        print "Map created for "+str(statename)

#____________________________For Selected State_________________________#

else:
     #create output folder for each state
    outname=statename+"_folder"
    if arcpy.Exists(infolder+"\\"+outname):
         arcpy.Delete_management(infolder+"\\"+outname)
    print "Creating Output Folder"
    arcpy.CreateFolder_management (infolder,outname)
    outfolder=infolder+'\\'+outname

    #creares state boundary layer from selected states
    arcpy.MakeFeatureLayer_management(fc,"State Boundary for
"+str(statename),"\"NAME\" = '" + statename + "'")
    state_layerfile=infolder+'\\'+statename+".lyr"
    arcpy.SaveToLayerFile_management("State Boundary for "+str(statename),
state_layerfile,"ABSOLUTE")
    layerpath=os.path.abspath(infolder+'\\'+statename+'.lyr')
    #adds statelayer to blank mxd to find extent
    df = arcpy.mapping.ListDataFrames(mxdBlank, "Layers")[0]
    add_layer = arcpy.mapping.Layer(layerpath)
    arcpy.mapping.AddLayer(df,add_layer)
    del add_layer
    df.zoomToSelectedFeatures()
    state_lyr = arcpy.mapping.ListLayers(mxdBlank,"*", df)[0]
    extent = state_lyr.getSelectedExtent()
    #Generates a Landscape Map
```

```
    if extent.width > extent.height:
        print r"Extent width is "+str(extent.width)
        print "Landscape Layout selected"
        layout="landscape"
        print "Adding boundary layer to map"
        df = arcpy.mapping.ListDataFrames(mxdLandscape, "*")[0]
        add_layer = arcpy.mapping.Layer(layerpath)
        arcpy.mapping.AddLayer(df,add_layer)
        del add_layer
        df.zoomToSelectedFeatures()

createmap(mxdLandscape,infolder,outfolder,state_layerfile,statename,layout
)
        del state_layerfile
        del layerpath
        del mxdLandscape
        mxdLandscape=arcpy.mapping.MapDocument(infolder+r'\landscape.mxd')
    #Generates a Portrait Map
    if extent.height > extent.width:
        print r"Extent height is "+str(extent.height)
        print "Portrait Layout selected"
        layout="portrait"
        print "Adding boundary layer to map"
        df = arcpy.mapping.ListDataFrames(mxdPortrait, "*")[0]
        add_layer = arcpy.mapping.Layer(layerpath)
        arcpy.mapping.AddLayer(df,add_layer)
        del layerpath
        df.zoomToSelectedFeatures()

createmap(mxdPortrait,infolder,outfolder,state_layerfile,statename,layout)
        del state_layerfile
        del mxdPortrait
        mxdPortrait=arcpy.mapping.MapDocument(infolder+r'\portrait.mxd')
    arcpy.env.workspace=infolder
    infilelist=arcpy.ListFiles()
    #cleaning up temp files
    for fil in infilelist:
        if arcpy.Exists(fil):
            fildes=arcpy.Describe(fil)
            filnam=fildes.name
            filtype=fildes.extension
            if filtype != ".lock.":
                if "temp" in filnam:
                    try:
                        arcpy.Delete_management(fil)
                    except:
                        pass
            if filtype==".lyr":
                arcpy.Delete_management(fil)
    print "done"
```

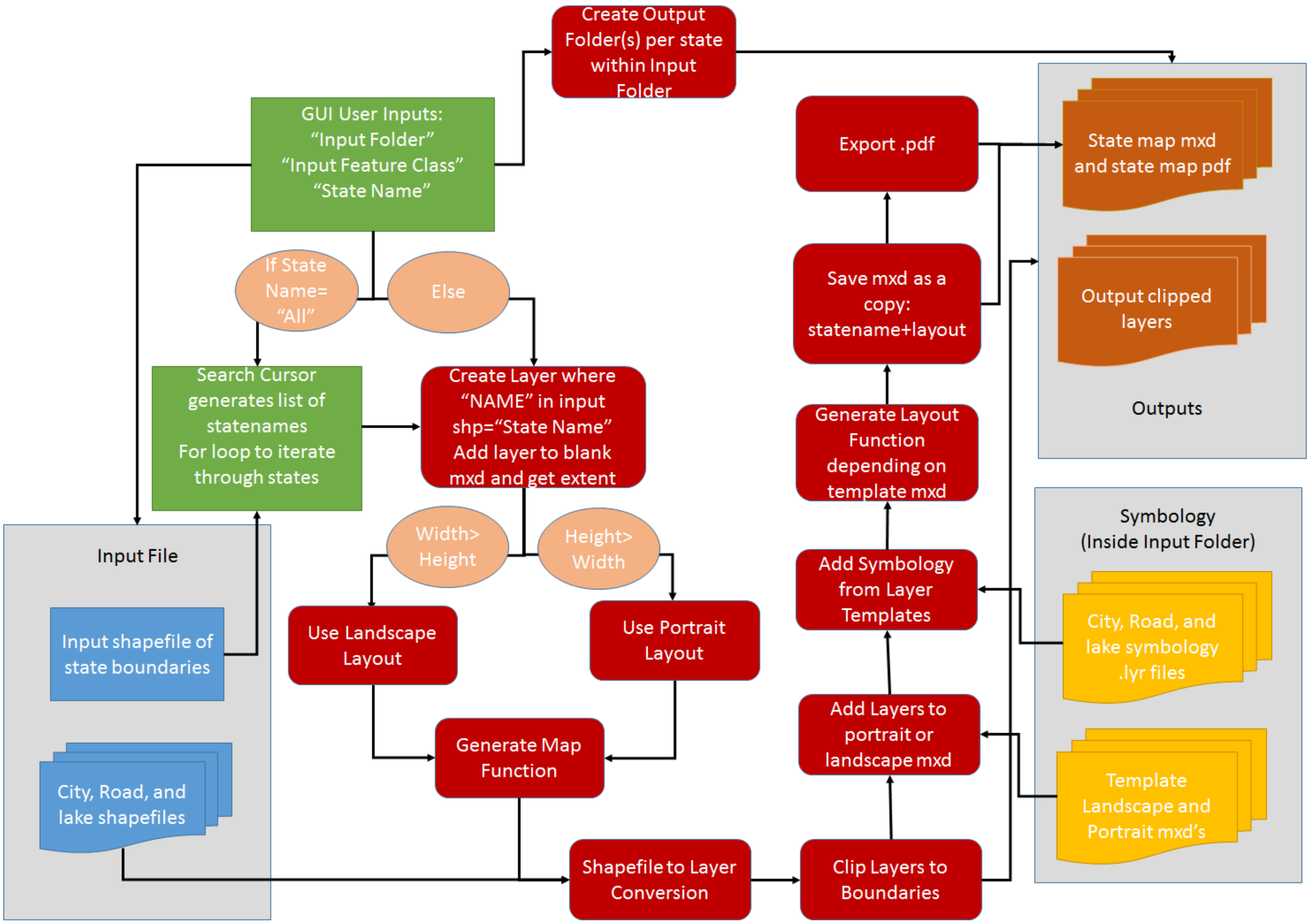



Figure 17: Project Flow Chart

*<u>Color Key:</u>*
*Green = GUI User input for single states or SearchCursor for all maps to be outputted*
*light pink = if/else statements*
*blue = file inputs*
*red = processes*
*yellow = symbology*
*burnt orange = outputs*

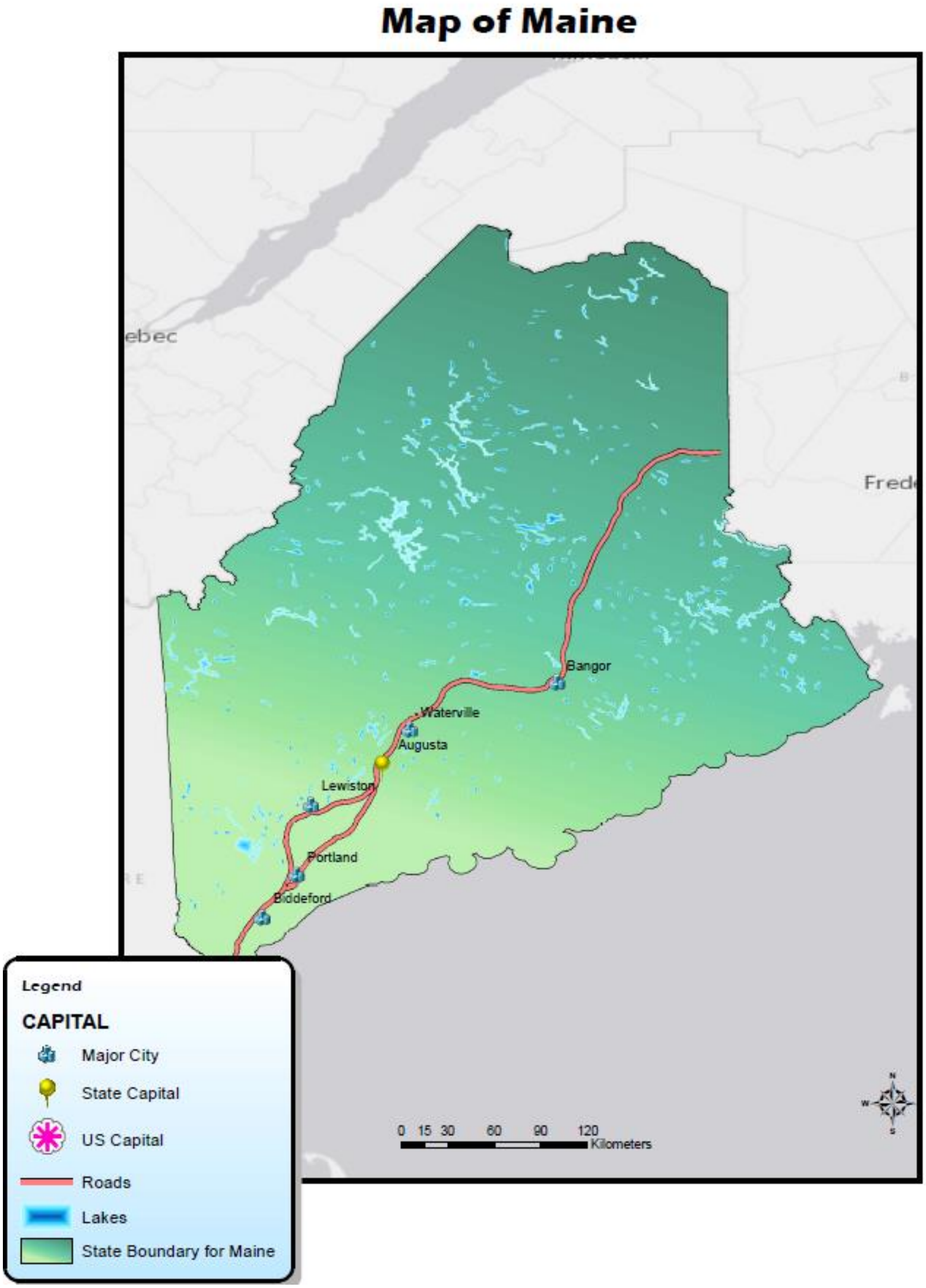



Figure 18: Example of Map produced by using the above script

# Risk Modeling of Lava Flows and Subsequent Limnic Eruption near Lake Kivu, East Africa

By Dan Auerbach and William Thoman

Lake Kivu is a large lake (2,700 km2) on the border between Rwanda and the Democratic Republic of the Congo. The area around the lake has been the site of much geopolitical strife and many refugees live in the area, especially in the city of Goma, which lies on the shores of Lake Kivu and is near an active volcano, Mt. Nyriagongo, which has destroyed large areas of the city as recently as 2002. Outside of the threat of conflict and volcanic eruptions, Goma faces a threat from the lake itself which sits above large pockets of methane and carbon dioxide. If these gas pockets are disturbed it could unleash a limnic eruption of deadly gases, the only precedents of which occurred in Cameron with much smaller lakes and less population density. These limnic eruptions killed over 1700 people as the gases are both colorless, odorless, and disperse quickly. This project set out to model the potentially devastating chain reaction of a volcanic eruption leading to a limnic eruption in terms of its possible effects on Goma.

Initially lava flows were modeled using currently existing lava vents and ASTER elevation data. The extremely low viscosity of the lava produced by Nyriagongo allowed for the use of flow accumulation and direction modeling, as unlike most lava, this lava behaved similarly to water. Past fissures were identified by use of Google Earth and used as source points for flow modeling (Figure 19). Next limnic eruptions were simulated by using tools designed to model gas dispersal, with the points where our modeled lava flows entered the lake as sources, and accounting for both wind directions blowing towards and away from the city of Goma at 5km/hr (Figures 20-21). Following the creation of these models the results were aggregated to produce a map showing suitability of evacuation from the deadly chain reaction (Figure 22).

Due to the unpredictable nature of both volcanic eruptions (fissures could open anywhere) and limnic eruptions (which could occur at any time), our model may be limited in its effectiveness. However it did suggest that in event of an eruption, residents should counterintuitively flee towards the higher ground of the volcano to avoid the deadly gases from the lake. With further expansion of this model and increased data we could generate an even more comprehensive risk model.

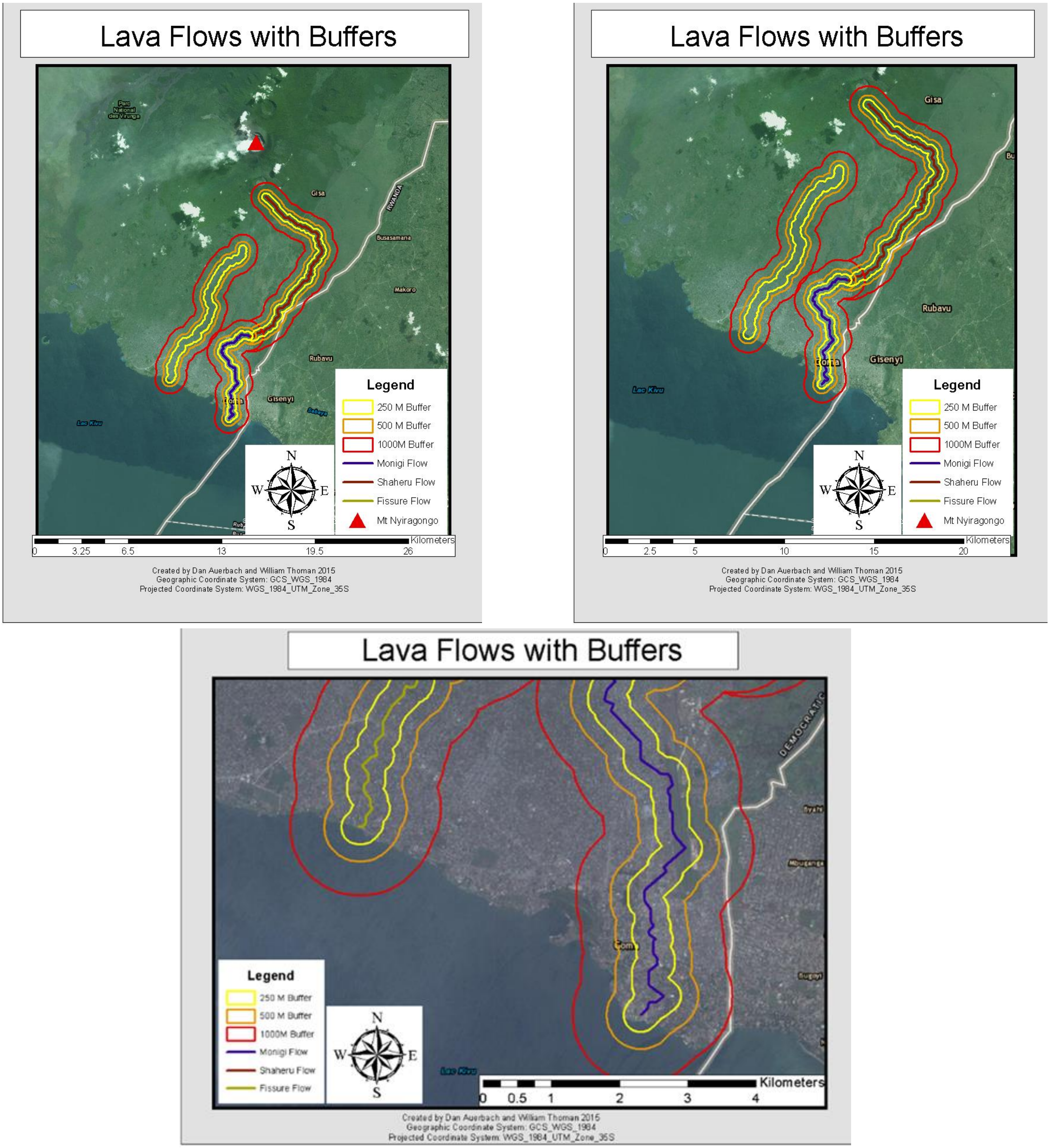



Figure 19: Lava flow maps from different vents with buffers of potential damage

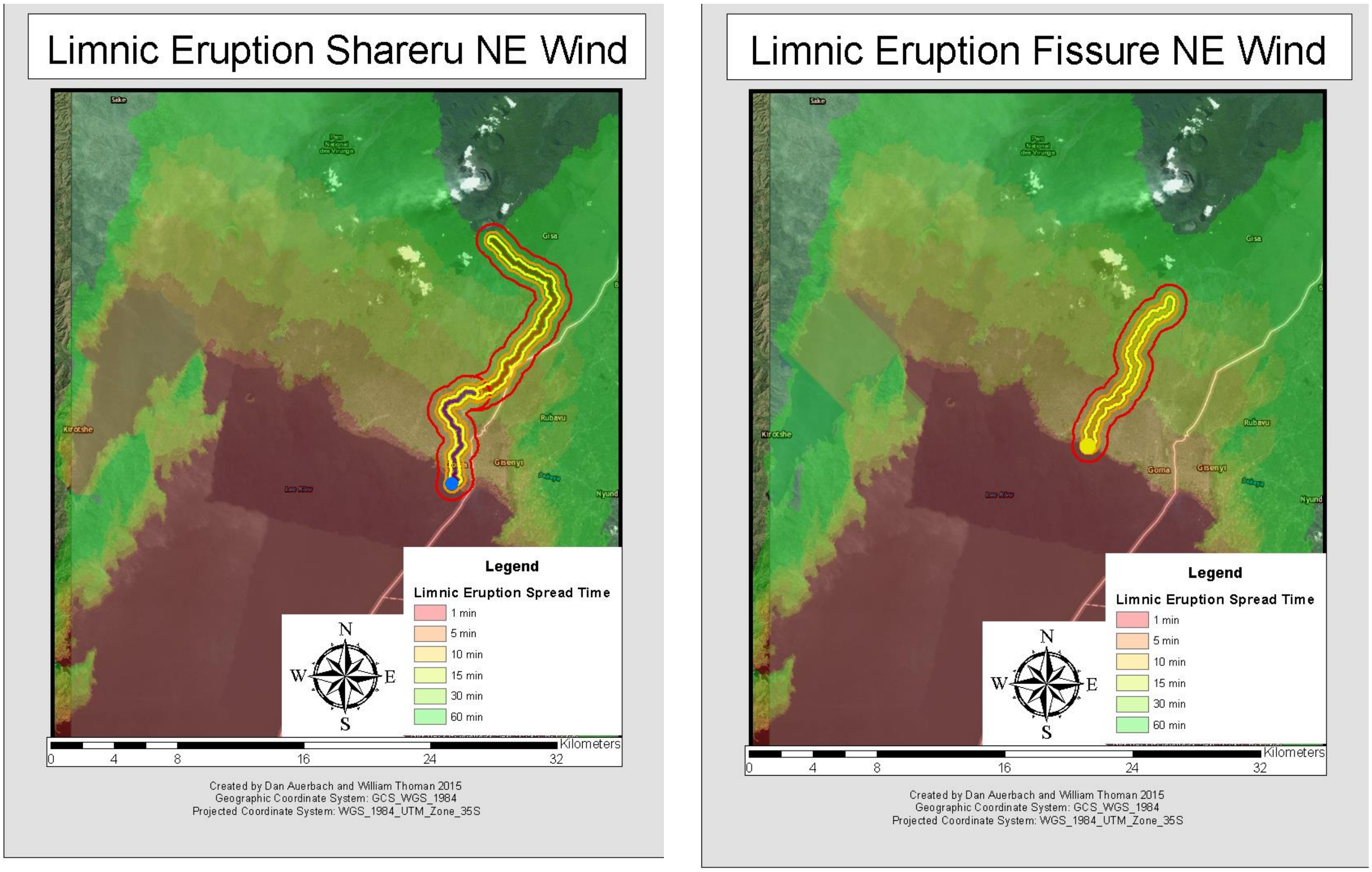



Figure 20: Limnic eruption from both sources with Northeast wind direction

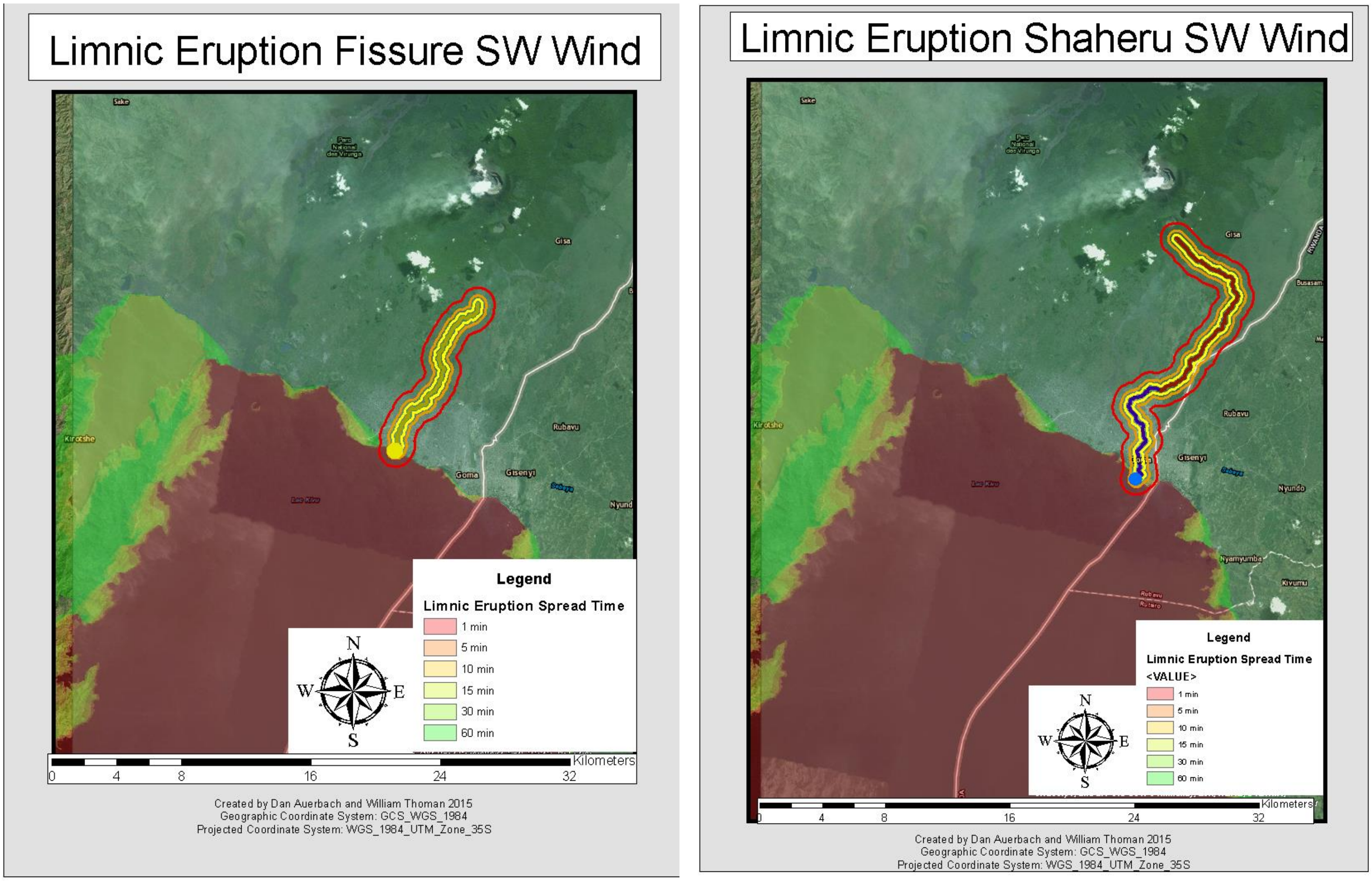



Figure 21: Limnic eruption from both sources with Southwest wind direction

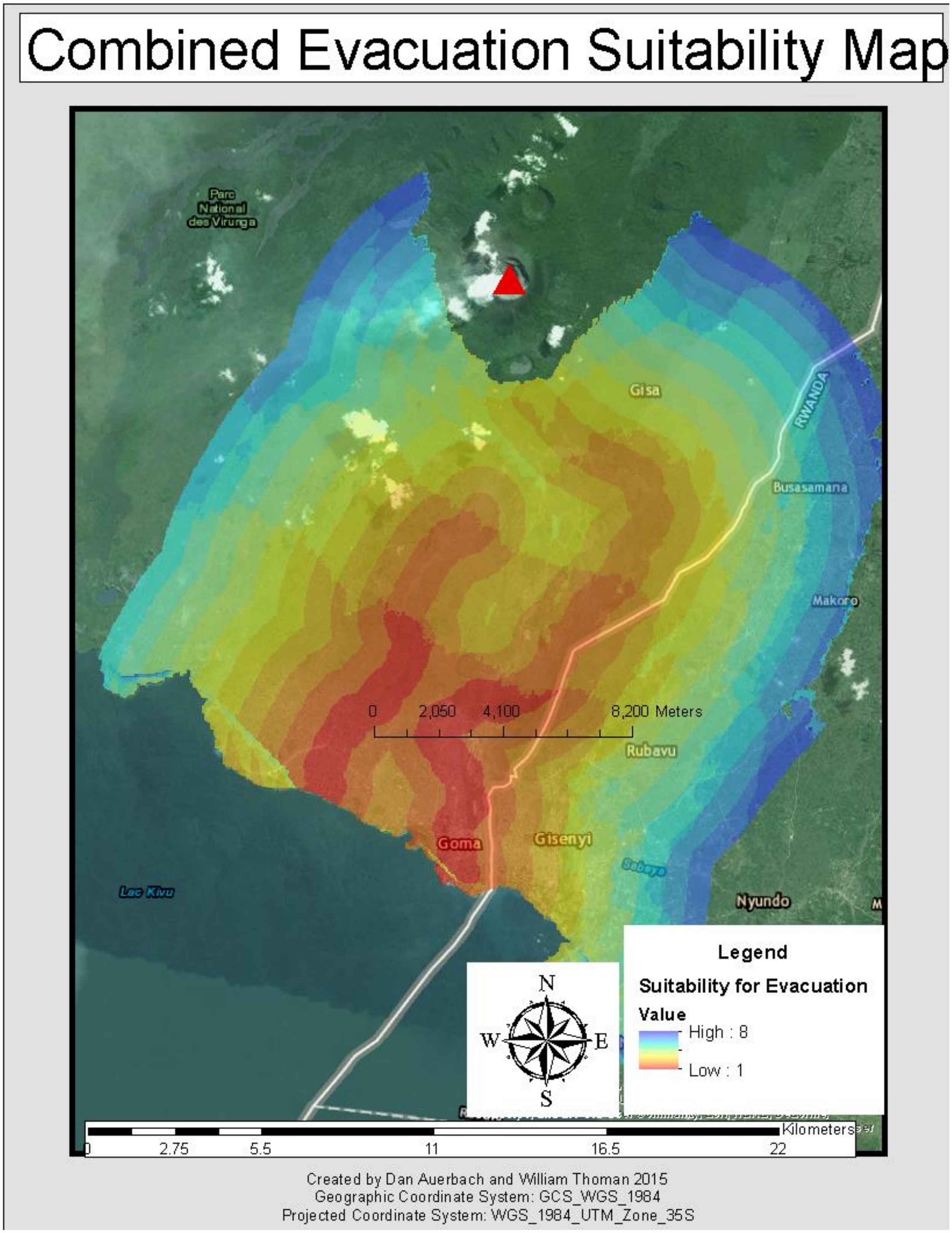



Figure 22: Combined Evacuation Suitability map from volcanic and limnic eruptions

**The Effects on Amphibian and Reptilian Biodiversity, due to the Operation of the Yanacocha Gold Mining Operation from 1991 to 2014**

By William Thoman and Matt Zimmerman

Gold mining has been a part of Peru's history since before arrival of Europeans, and the mining trade has been revitalized in recent years as Peru sought to better its stagnating economy. While economic benefits have been undeniable, so to have negative effects on the environment and communities living near the mining areas. This project focused its investigation on the environmental impacts of the Yanacocha gold mine, the fourth largest open pit gold mine in the world located in the Cajamarca region of northern Peru. Rather than merely look at impact on vegetation this project uses biodiversity measurements to assess biodiverse areas that are most at risk in order to inform conservation efforts Being able to identify loss of habitats, biodiversity and the drivers thereof  in an area can lead to better protection and allocation of conservation resources (Jarvis et al., 2010).

We began by looking at the land cover impacts of the mine's construction using image comparison of Landsat imagery from 1991, 2001, and 2014 and using the Soil Adjusted Vegetation Index, or SAVI to compare changes between the years (Figure 24). We conducted zonal statistics for 500 meter buffer regions to look how proximity to mines affected decrease in vegetation and graphed the results for each buffer region in terms of z-score of standard deviations away from the mean decrease (Figure 25). Following this IUCN polygons of reptile and amphibian species were used to generate maps of alpha biodiversity (Figure 26) which were analyzed by conducting zonal statistics for each of the buffer polygons in terms of biodiversity (Figure 27).

For the time period of 1991 to 2014 the significant losses in vegetation are located in some of the active mine areas that are identified, especially at and around the Yanacocha mine and around the city of Cajamarca. Biodiversity analysis was less conclusive as the polygons were coarser although there are some clear areas of high biodiversity threatened by mining impacts. With additional data more comprehensive analysis could be conducted. While mining is unlikely to stop assessments of its impacts on the environment, especially spatial ones could better inform stewardship policies generated by the government and mining companies.

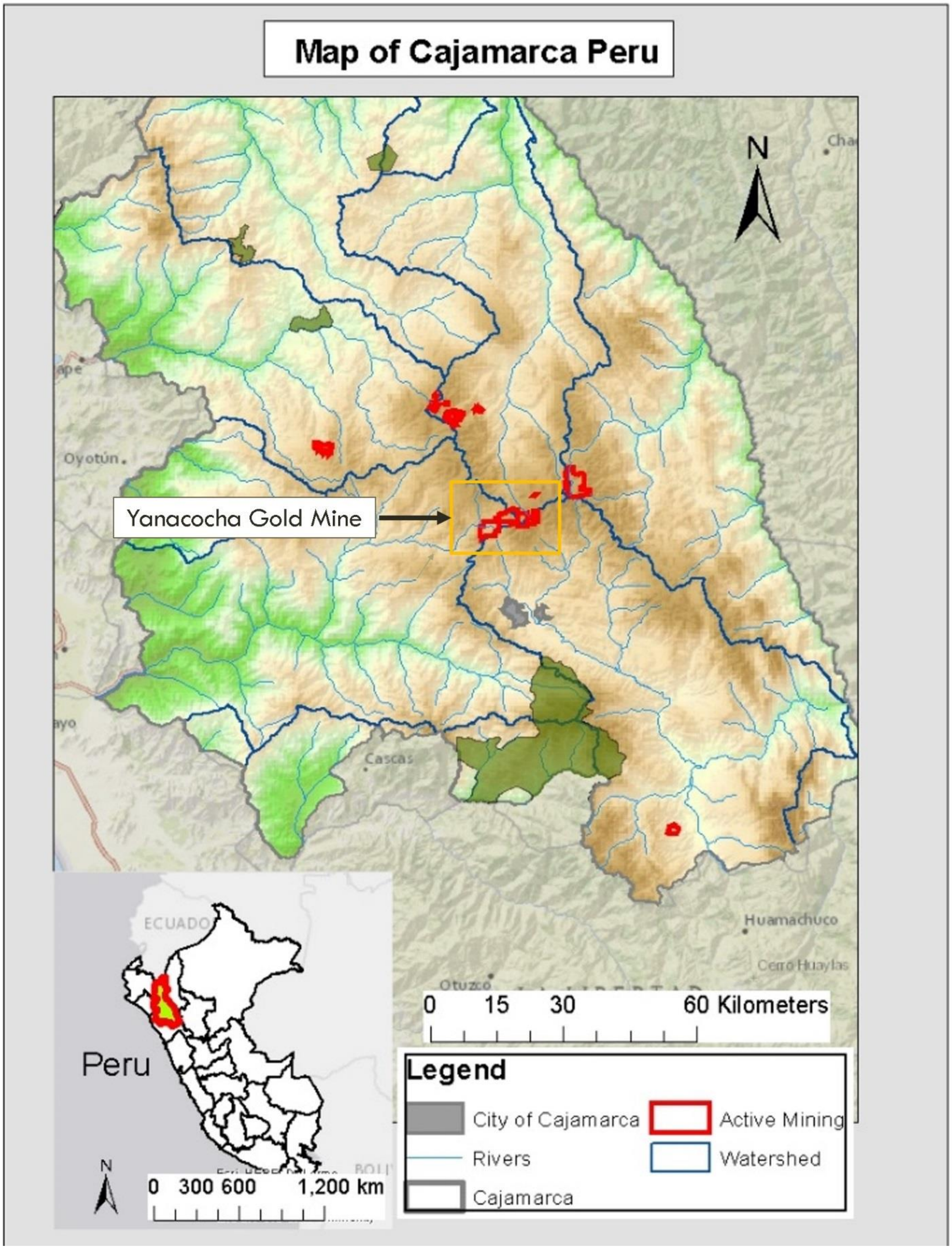



Figure 23: Map of Study area of Cajamarca, Peru

# SAVI Image Differences by Standard Deviations

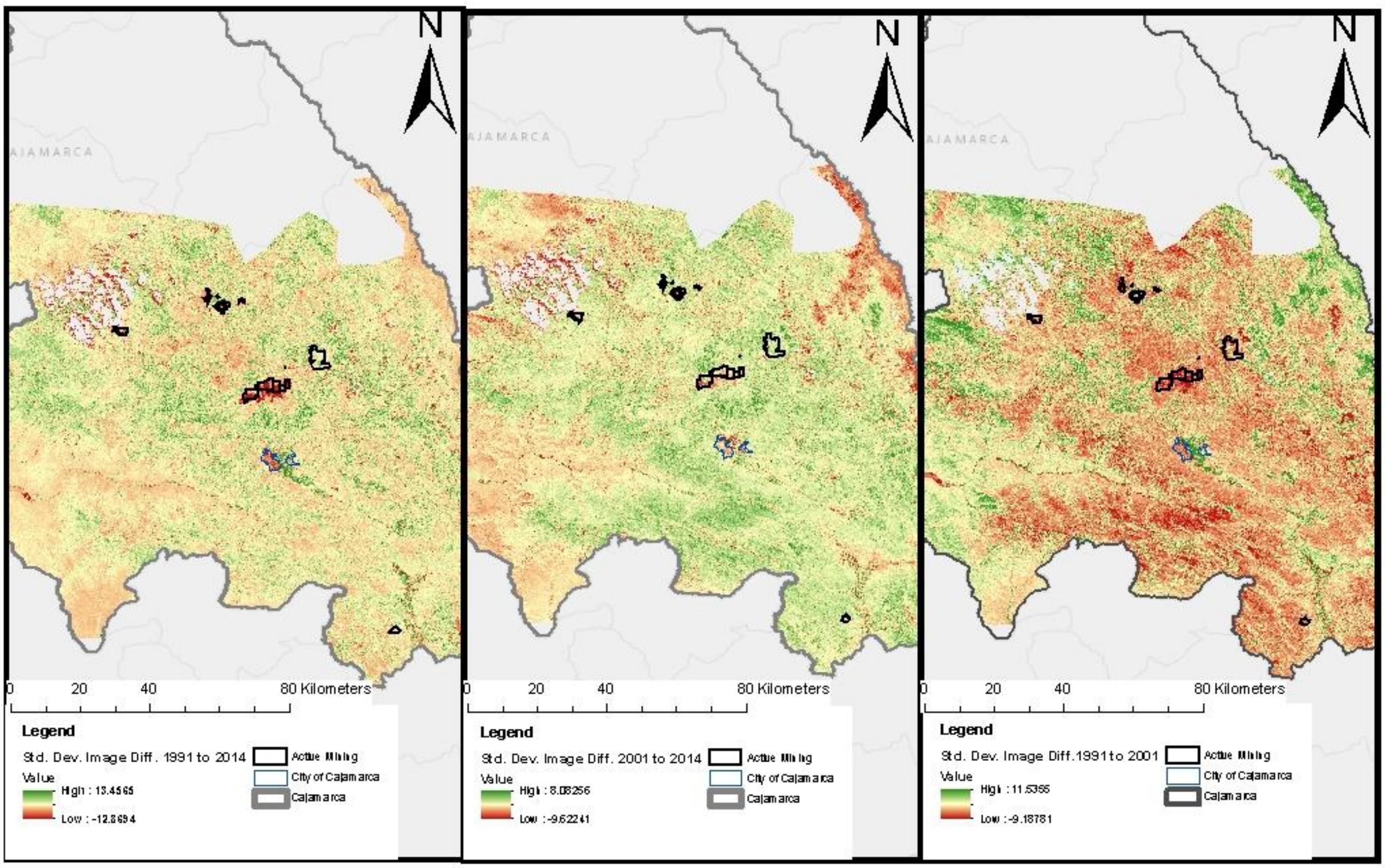



Figure 24: SAVI image difference images for our three Landsat images

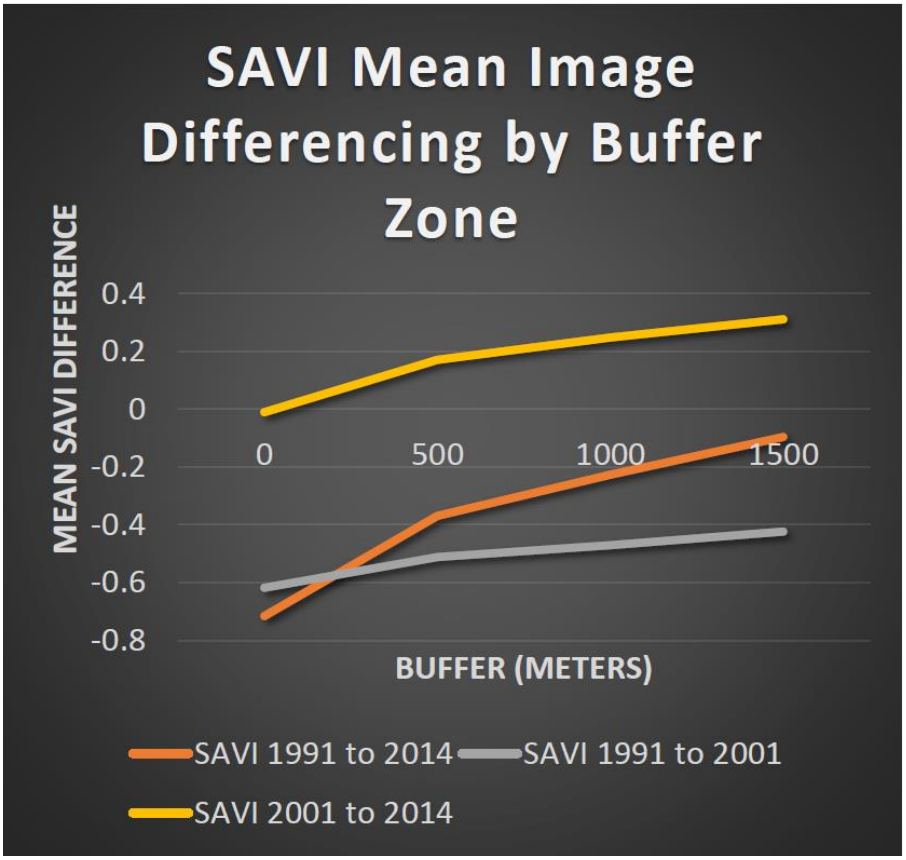



Figure 25:SAVI mean image difference by buffer zone

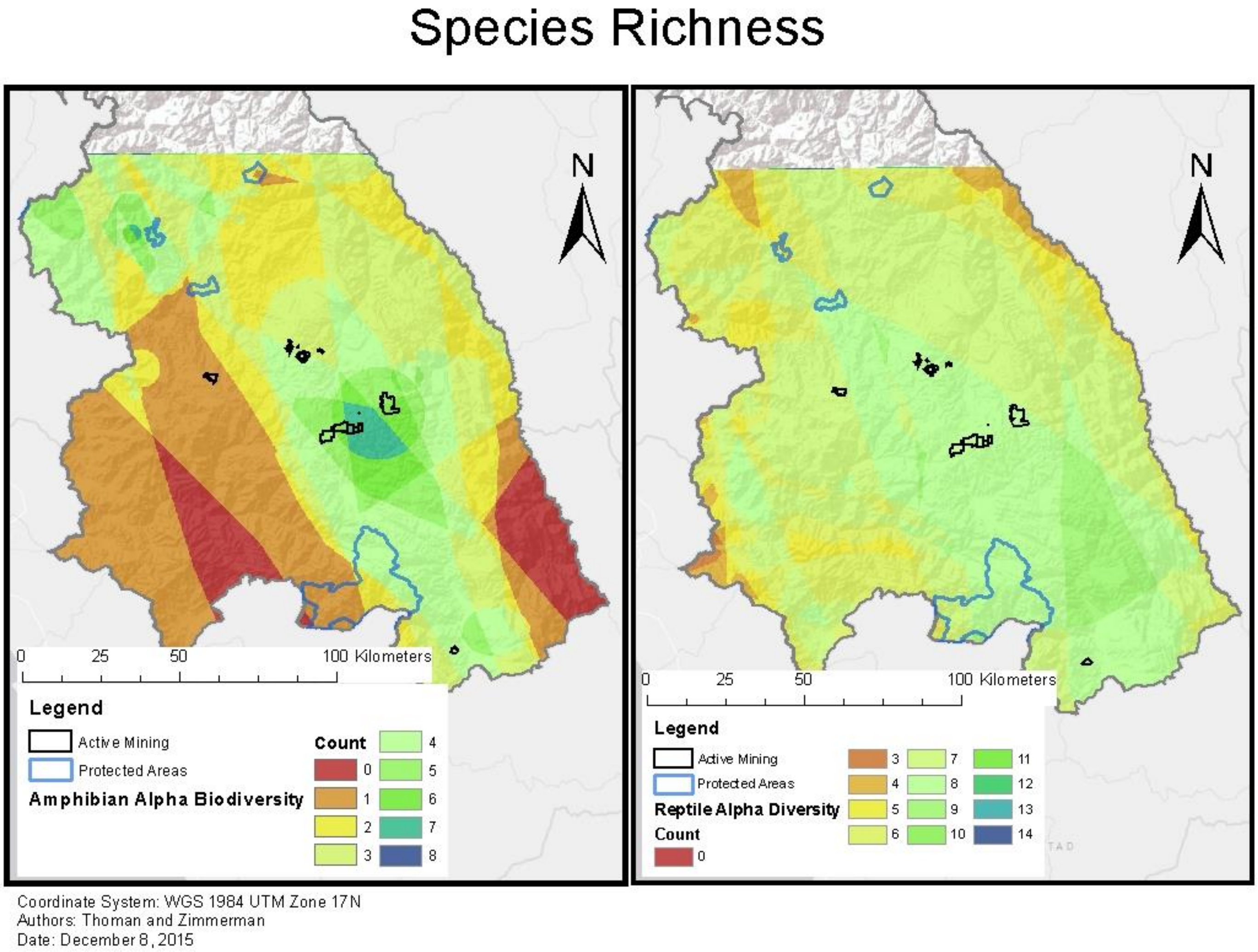



Figure 26: Alpha biodiversity maps for amphibians and reptile in study area

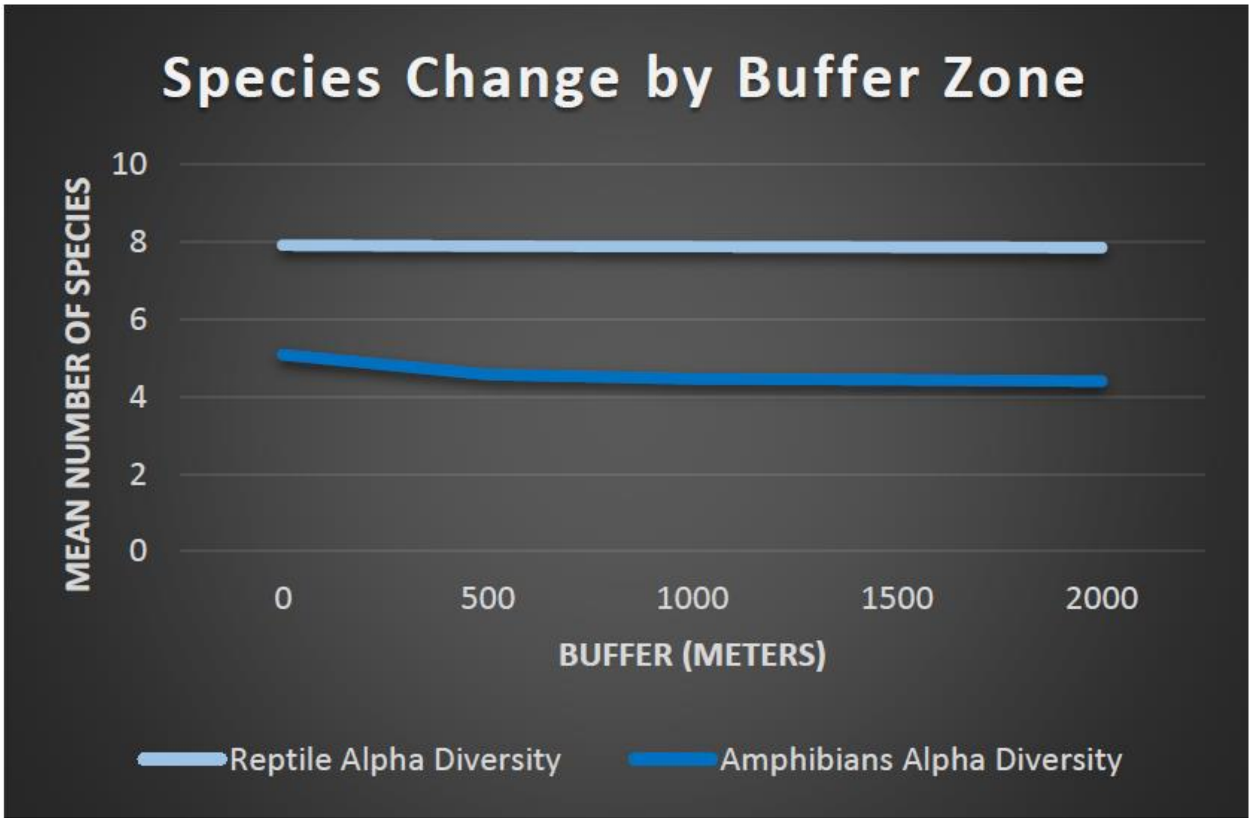



Figure 27: Species richness by buffer zone

# Use of Landsat Data to Monitor Change in Landcover and SAVI values to Examine Effects of Conflict in Iraqi Kurdistan

By William Thoman

The conflict in Syria and Iraq is a multifaceted and complex conflict that has killed hundreds of thousands, displaced millions, and leveled entire cities. Often with such conflicts, gaining intelligence on the amount of devastation is difficult from ground data and as such, remote sensing has proven itself a crucial tool in assessing damage from both human and natural disasters. Much of this data is focused on building damage assessments using high resolution SPOT and Digital Globe data, assessments of landscape level effects are less common. This project examines the landscape using comparison of Landsat imagery, using SAVI to focus on areas of lost vegetation which likely indicate lost farmland due to displacement and conflict.

After correction of Landsat 8 bands from 2014 and 2015 images, false color composites were generated (Figure 28) and Soil Adjusted Vegetation Index images were generated (Figure 29). Following this point data on towns controlled by ISIS and Kurdish forces was added as was point data on Internally Displaced Person (IDP) camps. Finally ethnic data from the Iraq census was added showing what areas were inhabited by Kurds and Sunnis (Figure 30). Image differencing was then conducted for our SAVI images and visual analysis was conducted based on standardized SAVI difference based on z scores (Figure 31).Census data was overlaid with these maps, with focus on areas that were identified as having mixed Sunni and Kurdish populations as this would likely be on the front lines of the conflict between the mostly Sunni Arab ISIS terror group and Kurdish Peshmerga forces (Figure 32).

The results clearly show 3 clusters of strong decrease in SAVI in areas that were identified as mixed Sunni and Kurdish and were close to towns controlled by ISIS (Figure 33). In addition, by use of news media sources it is clear that some of these points are near towns where mass displacement occurred, most notably near the town of Sinjar where the Yazidi religious minority lived before being killed and displaced by ISIS. Noting an upward trend in SAVI due in part to seasonal differences, these areas of decrease in SAVI are notable aberrations. While there are some data limitations due to the conflict in the region, Landsat data is shown to be able to detect broader landscape changes caused by conflict, as long as context is understood.

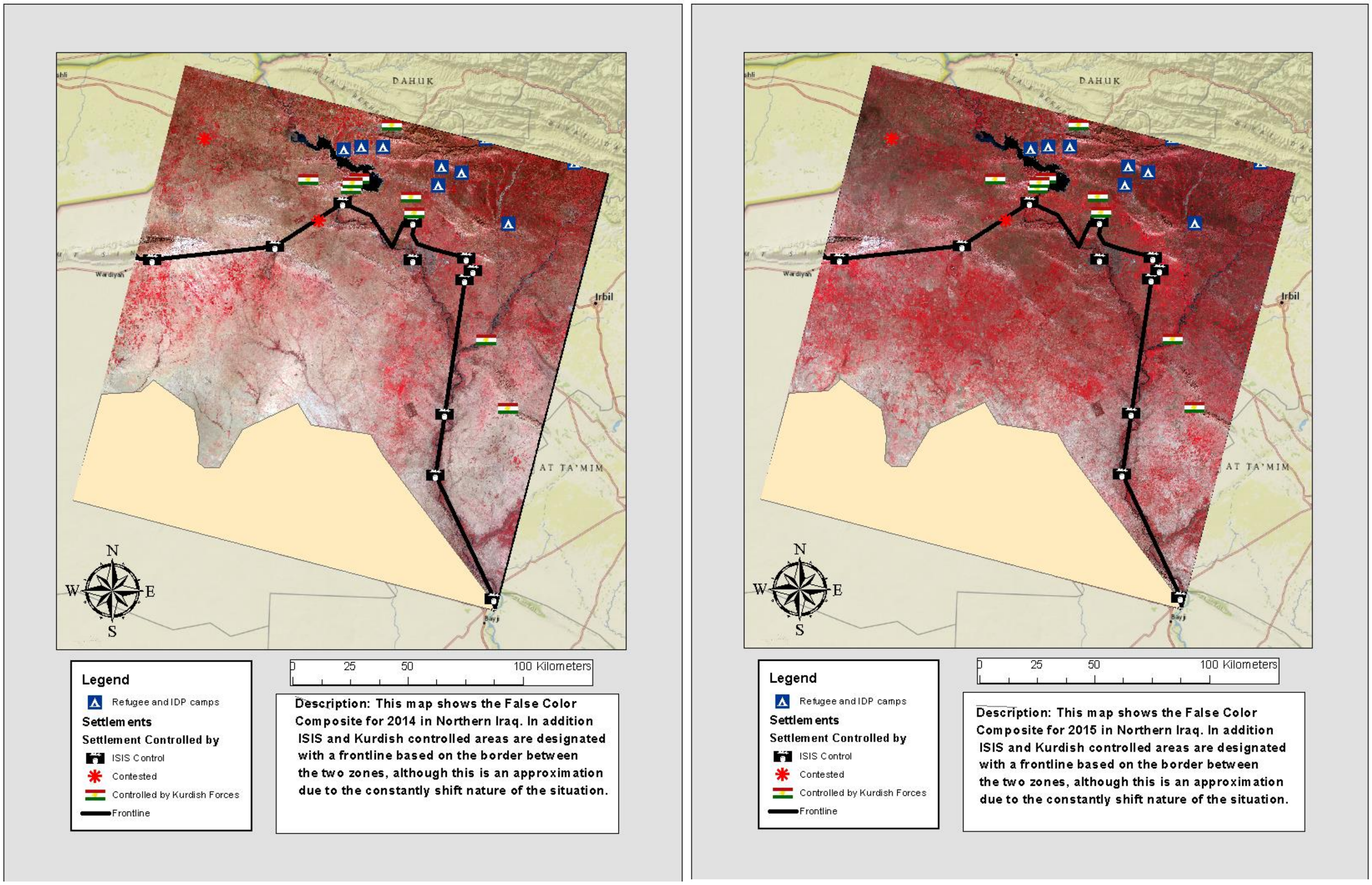
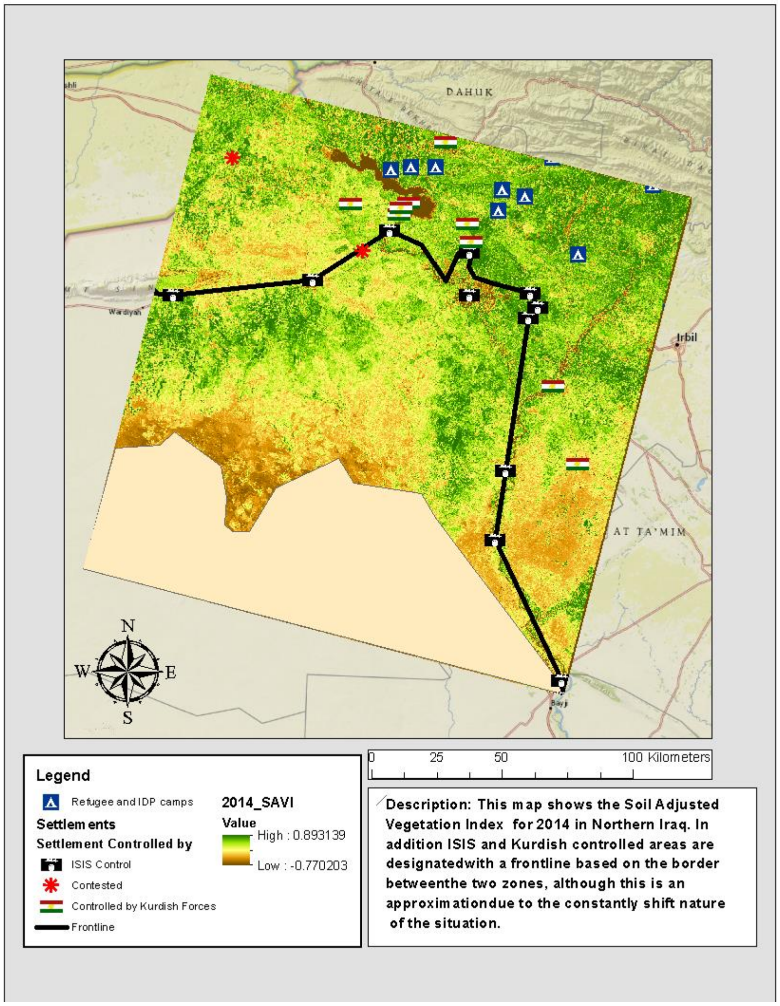



Figure 28: False Color Composites for 2014 and 2015 using Landsat 8 bands 3,4, and 5



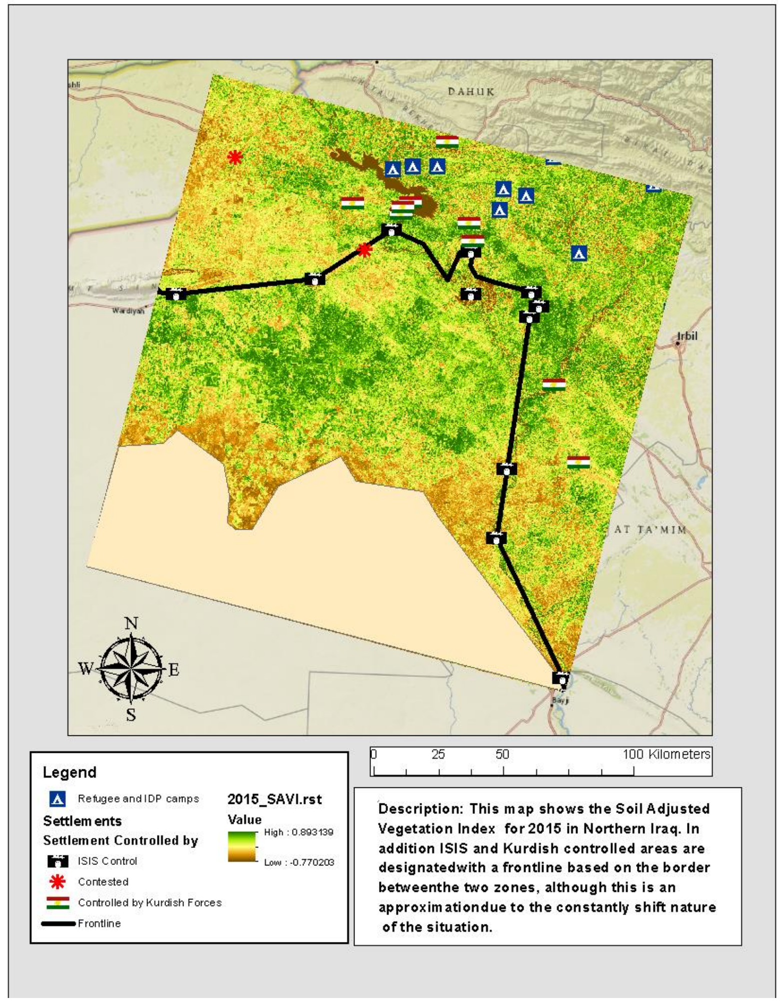




Figure 29: SAVI Images for 2014 and 2015

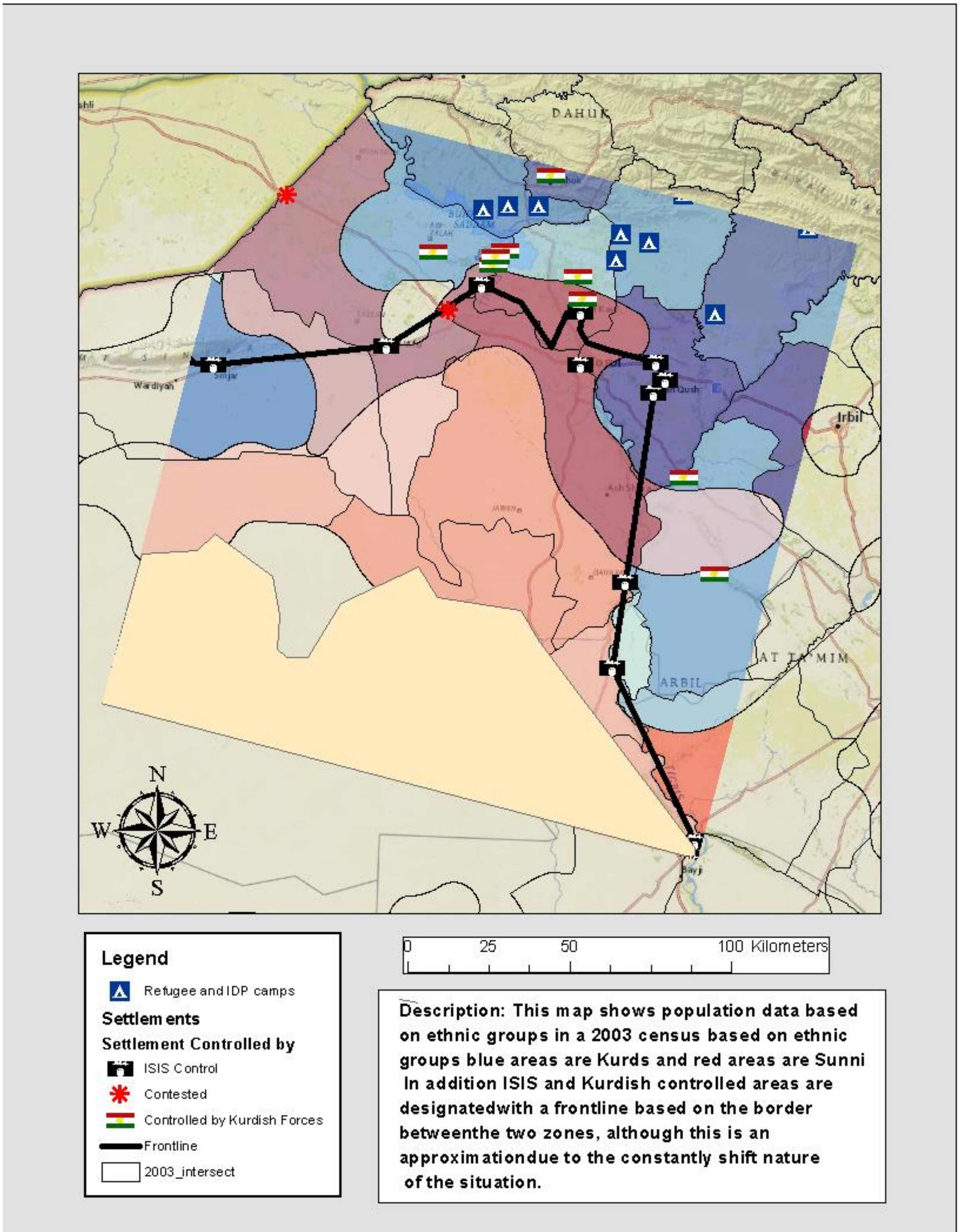



Figure 30: Map showing areas inhabited by Kurds and Sunni Arabs

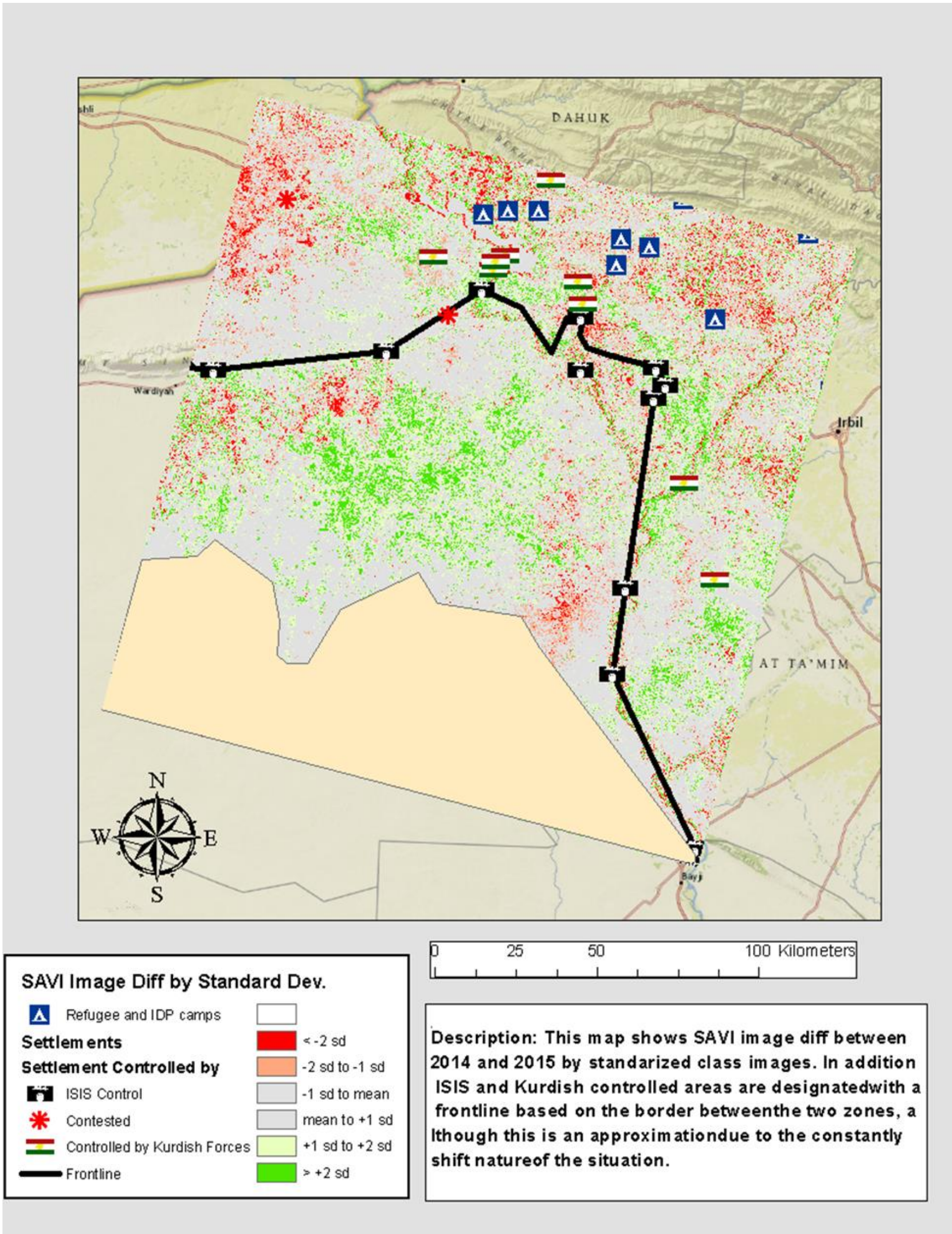



Figure 31: SAVI image difference by standard deviations

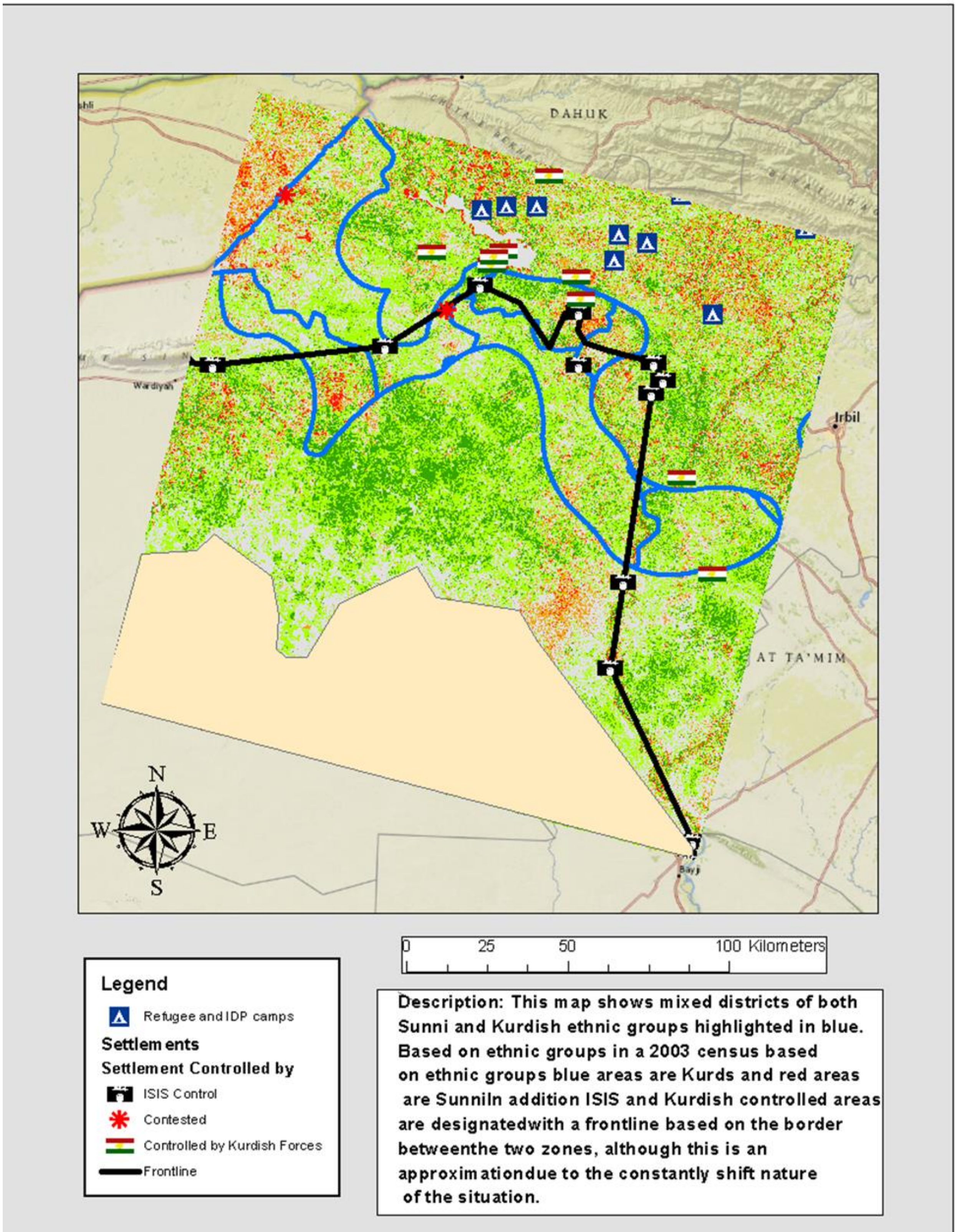



Figure 32: SAVI image difference image with mixed ethnic areas

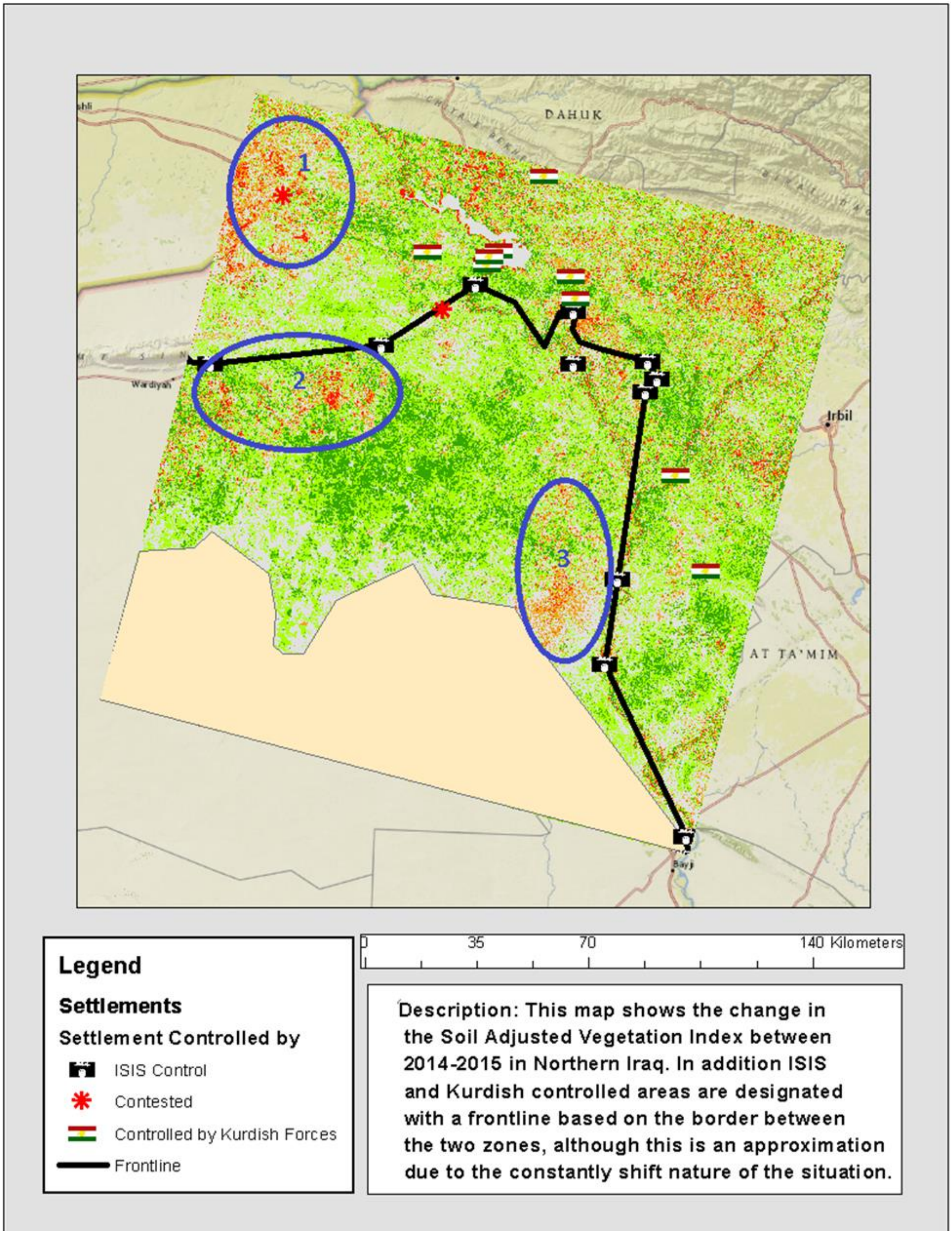



Figure 33: Map of SAVI Image difference with clusters of high negative values circled

# References

**For Project 1: Analysis of Crime in Chicago…**

Burgess, Melissa (2011). ”Understanding crime hotspot maps.” NSW Bureau Crime Statistics and Research: 60.2011: http://www.bocsar.nsw.gov.au/agdbasev7wr/bocsar/documents/pdf/bb60.pdf.

Chicago Police Department (2011). *Chicago Murder Analysis 2011*. Chicago Police Department Research and Development Division, Chicago, IL: 2011.

Colorado State Demography Office (2010). “Margins of Error and their Size”. 2010: http://www.colorado.gov/cs/Satellite?blobcol=urldata&blobheadername1=Content-Disposition&blobheadername2=Content-Type&blobheadervalue1=inline%3B+filename%3D%22MOE+Guidelines.pdf%22&blobheadervalue2=application%2Fpdf&blobkey=id&blobtable=MungoBlobs&blobwhere=1251731975702&ssbinary=true

Gonzales, Alberto R.; Regina B. Schofield; Sarah V. Hart(2005). Mapping Crime: Understanding Hot Spots.[M] National Institute of Justice: 2005 https://www.ncjrs.gov/pdffiles1/nij/209393.pdf.

Grubesic, Tony H.; Alan T. Murray(2001). ”Detecting Hot Spots Using Cluster Analysis and GIS.” Proceedings from the Fifth Annual International Crime Mapping Research Conference: 2001.

Mohler, George (2014). “Marked point process hotspot maps for homicide and gun crime prediction in Chicago”. International Journal of Forecasting: (July-Sept 2014), 491-, 2014.

Ratcliffe, Jerry(2010). “Crime Mapping: Spatial and Temporal Challenges.” *Handbook of Quantitative Criminology*, Eds Piquero, Alex R and Weisburd, David. Springer: 2010

Sherman, Lawrence; Michael Buerger; and Patrick Gartin (1989). "Repeat Call Address Policing: The Minneapolis RECAP Experiment," *Final Report to the National Institute of Justice*, Washington, DC: Crime Control Institute: 1989.

Spencer, Chainey; Lisa Tompson; Sebastian Uhlig(2008). “The Utility of Hotspot Mapping for Predicting Spatial Patterns of Crime”.[J] *Security Journal*: 2008, 21, 4–28.

*US Census Bureau Handbook* (2008).“Compass for Understanding and Using American Community Survey Data” U.S. Department of Commerce Economics and Statistics Administration U.S. CENSUS BUREAUA

Zhang, Haifeng and Michael Peterson (2001). “A Spatial Analysis of Neighborhood Crime in Omaha, Nebraska Using Alternative Measures of Crime Rates” *Internet Journal of Criminology*: 2001.

**For Project 2: Drought Assessment in Modesto, California….**

Chopra, Parul. *Drought Risk Assessment Using Remote Sensing and GIS.* Thesis. The Netherlands/ International Institute for Geo-Information Science and Earth Observation, 2006. Enschede: n.p., 2006.

"California Snowpack Measure Shows No End in Sight for Drought," last modified August 5, 2014. Access at: http://news.nationalgeographic.com/news/2014/08/140805-yosemite-snowpack-sectrometry-california-drought-science/

"U.S. Drought Monitor." *Tabular Data Archive*. USDA, n.d. Web. 01 Dec. 2014.

Eastman, J.R. 2009. "ImageDiff," IDRISI Help System. Accessed in IDRISI Selva. Worcester, MA: Clark University.

**For Project 4: Risk Modeling of Lava Flows and Subsequent Limnic Eruption…**

Akinyede, J.O., et al. "HYDROLOGIC MODELLING OF KATSINA-ALA RIVER BASIN: AN EMERGING SCENARIO FROM LAKE NYOS THREAT." *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences,* Volume XXXIX-B8, 2012. http://www.int-arch-photogramm-remote-sens-spatial-inf-sci.net/XXXIX-B8/7/2012/isprsarchives-XXXIX-B8-7-2012.pdf

Chirico, G., Favalli, M., Papale, P., Boschi, E., Pareschi, M., & Mamou-Mani, A. (2008). Lava flow hazard at Nyiragongo Volcano, DRC. Bulletin of Volcanology, 375-387. Retrieved March 13, 2015, from http://link.springer.com/article/10.1007/s00445-008-0232-z/fulltext.html

Costa et al. "Numerical Model of Gas Dispersal Emitted from Volcanic Sources." *ANNALS OF GEOPHYSICS*. VOL. 48, N. 4/5. August/October 2005. http://www.earth-prints.org/bitstream/2122/941/1/18Costa.pdf

Favalli, et. al." Computer simulations of lava flow paths in the town of Goma, Nyiragongo volcano, Democratic Republic of Congo" JOURNAL OF GEOPHYSICAL RESEARCH, VOL. 111, B06202,doi:10.1029/2004JB003527, 2006

Global Volcanism Program | Nyiragongo. (n.d.). Retrieved April 1, 2015, from http://www.volcano.si.edu/volcano.cfm?vn=223030

Pasche, Natacha. "Methane sources and sinks in Lake Kivu" *JOURNAL OF GEOPHYSICAL RESEARCH*. VOL. 116, 2011. http://onlinelibrary.wiley.com/doi/10.1029/2011JG001690/pdf

Smets, Benoit, et al. "Dry gas vents ("mazuku ") in Goma region (North-Kivu, Democratic Republic of Congo): Formation and risk assessment" *Journal of African Earth Sciences*. Vol 58(5):787-798. 12/2010; https://www.researchgate.net/publication/236841263_Dry_gas_vents_%28_mazuku_%29_in_Goma_region_%28North-Kivu_Democratic_Republic_of_Congo%29_Formation_and_risk_assessment

Schmid, J et al. “Weak mixing in Lake Kivu: New insights indicate increasing risk of uncontrolled gas eruption.” *Geochemistry Geophysics Geosystems,* Volume 6, Number 7. 26 July 2005. http://onlinelibrary.wiley.com/doi/10.1029/2004GC000892/pdf

Sumner, T. (2014, December 13). War Zone: An Uphill Battle to Reveal Mount Nyiragongo's Fiery Past and Forecast Its Future. Science News.

**For Project 5: Effects of the Yanacocha Mine on Amphibian and Reptilian Biodiversity**

Bury, J. (2006). Mining Migrants: Transnational Mining and Migration Patterns in the Peruvian Andes. *The Professional Geographer, 59*(3), pp. 378-389.

Bury, J. (2005). Mining mountains: Neoliberalism, land tenure, livelihoods,. *Environment and Planning, 37,* pp. 221-239. doi:DOI:10.1068/a371

Dagua and Valle del Cauca(2013). Mercury Bioaccumulation on Tadpoles of a Gold Mining Zone in Dagua River. *Acta Biologica Colombiana 18*: pp. 341-348

Eisler, R. (2004). *Biogeochemical, Health, and Ecotoxicological Perspectives on Gold and Gold Mining*. CRC Press 2004

Eisler and Wiemeyer (2004). Cyanide Hazards to Plants and Animals from Gold Mining and Related Water Issues. *Rev Environ Contam Toxicol* 183: pp. 21–54.

Palacios-Berrios (2006). *Assessing Landscape Change in a Mining Area of the Peruvian Andes: A case study in the Yanacocha Mine, Cajamarca*. Department of Geography, UNiversity of Bergen.

Jarvis, A., Touval, Schmitz, M., Sotomayor, L., & Hyman, G. (2009). Assessment of threats to ecosystems in South America. *Journal for Nature Conservation, 18,* pp. 180-188.

Jeronimo, R.P., Rap, E., Vos, J. (2015). The Politics of Land Use Planning: Gold Mining in Cajamarca, Peru. *Land Use Policy 49:* pp.104-117. Mining conflicts in Peru: Condition critical. (2009).

Newmont Mining Corporation. Yanacocha-Peru Overview. Accessed November 10, 2015. http://www.newmont.com/operations-and-projects/south-america/yanacocha-peru/overview/default.aspx

Perlez and Johnson(2010). Behind Gold's Glitter: Torn Lands and Pointed Questions. *The New York Times* June 14, 2010. http://www.nytimes.com/2005/10/24/world/behind-golds-glitter-torn-lands-and-pointed-questions.html?_r=0

Sonter, L., Barrett, D., Moran, C., & Soares-Filho, B. (2013). A Land System Science meta-analysis suggests we underestimate intensive land uses in land use change dynamics. *Journal of Land Use Science*, 191-204. Swenson JJ, Carter CE, Domec J-C, Delgado CI (2011) Gold Mining in the Peruvian Amazon: Global Prices, Deforestation, and Mercury Imports. PLoS ONE 6(4): e18875. doi:10.1371/journal.pone.0018875

**For Project 6: Use of Landsat Data to Examine Effects of Conflict in Iraqi Kurdistan**

Baker, William. "Iraq's 2015/16 Winter Grains Have Favorable Weather for Planting" U.S. Department of Agriculture. . January 12, 2015. http://pecad.fas.usda.gov/highlights/2015/01/Iraq/index.htm
"Battle for Iraq and Syria in maps". 2015. BBC. March 11 2015. http://www.bbc.com/news/world-middle-east-27838034

Filkins, Dexter. 2014. The Fight of Their Lives: ISIS vs. the Kurds. The New Yorker. September 29, 2014: http://www.newyorker.com/magazine/2014/09/29/fight-lives

"Serious Food Security Concerns Following Escalation of Conflict." *Global Information and Early Warning System on Food and Agriculture*. Food and Agriculture Organization of the United Nations. June 25, 2014. http://www.fao.org/3/a-i3898e.pdf

Gorsevski, Virginia, et. al. 2005. Analysis of the Impacts of armed conflict on the Eastern Afromontane forest region on the South Sudan — Uganda border using multitemporal Landsat imagery. Remote Sensing of Environment. Vol 118 (2012) 10–20

Hawramy, Fazel. 2014. Winter brings fresh threat to Iraq's refugees who fled the Isis advance. The Guardian. December 6, 2014: http://www.theguardian.com/world/2014/dec/06/winter-threat-iraq-refugees-kurdish-region-camps-isis

"ISIS advance through Iraq: Interactive Map." *The Financial Times*. Last Updated: April 30, 2015. http://www.ft.com/ig/sites/2014/isis-map/

Jacobsen, Karen. 1997. Refugees' Environmental Impact: The Effect of Patterns of Settlement. Journal of Refugee Studies. 01/1997

Johannessen, Ola M et al. 2001. Environmental monitoring of refugee camps using high-resolution satellite images, final report. August 2001.

Krans, Olaf, et. al. 2015. Assessment of environmental changes induced by internally displaced person (IDP) camps in the Darfur region, Sudan, based on multitemporal MODIS data. International Journal of Remote Sensing. Volume 36, Issue 1, 190-210

"Kurdistan's geography and climate". 2015. Kurdistan Regional Government. http://cabinet.gov.krd/p/p.aspx?l=12&p=213

UNOSAT Home Page. 2015.UNOSAT. http://www.unitar.org/unosat/

Witmer, Frank D. 2008. Detecting war-induced abandoned agricultural land in northeast Bosnia using multispectral, multitemporal Landsat TM imagery. International Journal of Remote Sensing. Volume 29, Issue 13, 2008

Wilson, Cyril. 2014. Spectral analysis of civil conflict-induced forced migration on land-use/land-cover change: the case of a primate and lower-ranked cities in Sierra Leone International Journal of Remote Sensing. Volume 35, Issue 3, February 2014, 1094-1125