

Vegetation Dynamics from NDVI Time Series Analysis at Carmel Valley

1. Project Motivation and Objectives

Remote sensing (RS) imagery has been most commonly used to generate several land use and land cover (LULC) maps and to conduct LULC change analysis because of the ability to observe landscape across regions in a synoptic and timely. Since vegetation is the majority of land covers on earth, understanding vegetation dynamics is important to promote our lives in many perspectives (e.g., urban planning and management).

The normalized difference vegetation index (NDVI) is the most predominant vegetation indices for monitoring vegetation dynamics. However, previous research on vegetation dynamics primarily emphasized the area of vegetation change or vegetation NDVI value change. Therefore, this pilot study aims to provide more comprehensive aspects of vegetation dynamics based on three indicators:

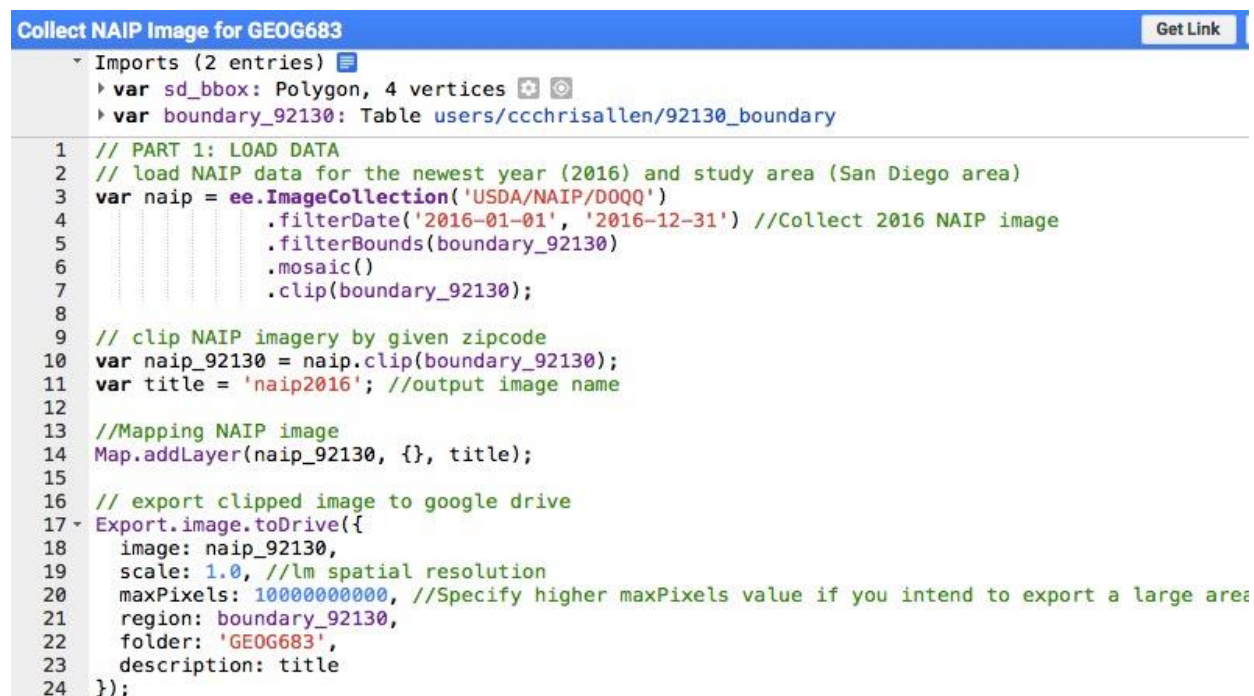
- Vegetation NDVI value change
- Speed of vegetation NDVI value change
- Acceleration of vegetation NDVI value change

Another merit of this study is to automate the entire image processing routines of vegetation dynamics via Python 2.7 and ArcPy. Hopefully, the python script used in this project can be partially reused for other research purposes, specifically in the part of I/O (read/write) image information.

2. Data and Study Area

Four images (2010, 2012, 2014, 2016) were collected from National Agriculture Imagery Program (NAIP) using Google Earth Engine, scripted in JavaScript. The collected NAIP images have the following characteristics:

- Spatial resolution: 1 m
- Spectral resolution: R, G, B, NIR
- Radiometric resolution: 8-bit unsigned (0 – 255)



The screenshot shows the Google Earth Engine code editor interface. At the top, there is a blue header bar with the text "Collect NAIP Image for GEOG683" and a "Get Link" button on the right. Below the header, the "Imports (2 entries)" section is expanded, showing two imported variables: "sd_bbox" (a Polygon with 4 vertices) and "boundary_92130" (a Table from the user "users/ccchrisallen/92130_boundary"). The main code area contains a JavaScript script with 24 lines. The script is organized into three parts: loading data, processing the image, and exporting it. It uses the "ee" library to load NAIP data for the year 2016, filter it by date and bounds, mosaic the images, and clip them to the study area boundary. Finally, it exports the clipped image to Google Drive with a specific scale, maxPixels, region, folder, and description.

```

1 // PART 1: LOAD DATA
2 // load NAIP data for the newest year (2016) and study area (San Diego area)
3 var naip = ee.ImageCollection('USDA/NAIP/DOQQ')
4   .filterDate('2016-01-01', '2016-12-31') //Collect 2016 NAIP image
5   .filterBounds(boundary_92130)
6   .mosaic()
7   .clip(boundary_92130);
8
9 // clip NAIP imagery by given zipcode
10 var naip_92130 = naip.clip(boundary_92130);
11 var title = 'naip2016'; //output image name
12
13 //Mapping NAIP image
14 Map.addLayer(naip_92130, {}, title);
15
16 // export clipped image to google drive
17 Export.image.toDrive({
18   image: naip_92130,
19   scale: 1.0, //1m spatial resolution
20   maxPixels: 1000000000, //Specify higher maxPixels value if you intend to export a large area
21   region: boundary_92130,
22   folder: 'GEOG683',
23   description: title
24 });

```

Figure 1. Collecting NAIP images through code editor of Google Earth Engine

This project chose zip code 92130, Carmel Valley (Figure 2), as the study area where urbanization has contributed to substantial change of vegetation coverage in 6 years (2010 – 2016).

3. Methods

The entire image processing routine is divided into three parts:

- Reading image information from .csv file

- Classifying vegetation
- Performing vegetation dynamics based on NDVI time-series change detection

The following ArcPy methods were adopted to develop each part of image processing routine of this project:

- `arcpy.GetParameterAsText`
- `arcpy.env.workspace`
- `arcpy.CheckOutExtension`
- `arcpy.AddMessage`
- `arcpy.Raster`
- `arcpy.GetRasterProperties_management`
- `arcpy.sa` (e.g., `Int`, `Float`, `SetNull`, `RemapRange` and `Reclassify`)

3.1. Reading Image Information From CSV File

In the beginning, users need to specify image absolute path, time stamp, and NDVI threshold for each image input in csv file. This design is time-efficient for users since no need to add each image input on ArcMap every time. Moreover, this part of code can be easily customized and reused to read image information for different research purposes. In this project, there are two options of image input for users: either 30m or 1m NAIP images (Figure2). Performing four 1m resolution images for vegetation dynamics generally takes 20 minutes. To quickly look at vegetation dynamics, please select 30m resolution images.

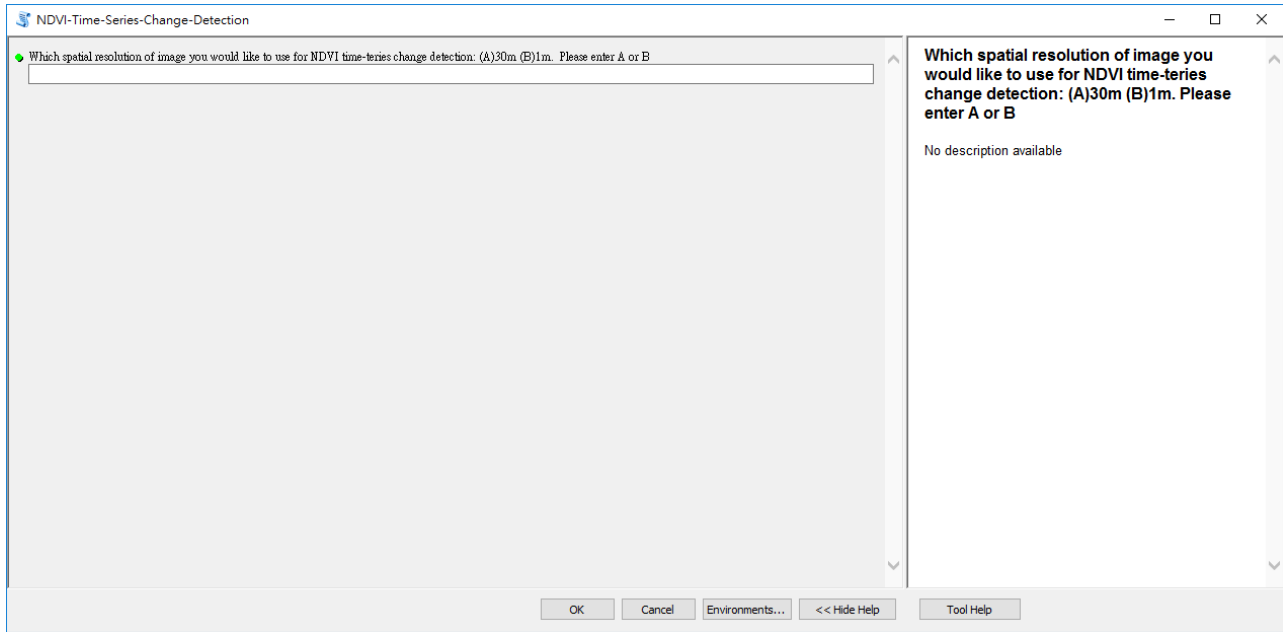


Figure2. A user interface of NDVI time-series change detection tool.

3.2 Classifying Vegetation

Here I created two functions, **NDVI_Calculation** and **Vegetation_Classification**, to iteratively classify multi-temporal vegetation coverage from NDVI time-series. The first function (Figure 3) will generate and output NDVI time-series based on the following algorithm, modified from (Jensen, 2017):

$$\left[\left(\frac{NIR - R}{NIR + R} \right) \times 100 \right] + 100$$

This equation stretches NDVI value from 0 to 200 that avoids negative NDVI value and promotes the efficiency of NDVI threshold interpretation. Next, I visually interpreted the NDVI layers to find the most appropriate NDVI value as the threshold for vegetation classifications. The thresholds will be manually entered on csv file. For example, if the threshold is 122, NDVI value over 122 will be classified as vegetation; in the opposite, it will be classified as non-vegetation.

```

98 def NDVI_Change_Detection(ndviList, num_img, time_stamp):
99     ##Vegetation Coverage Change (T1, T2, T3)
100     arcpy.AddMessage("\nCalculating the Change of NDVI Value...")
101     #Set up workspace
102     arcpy.env.workspace = r"C:/Program/Output/CN"
103     #Calculating the Change of NDVI Value
104     CN = []
105     for i in range(num_img-1):
106         CN.append(ndviList[i+1]-ndviList[i]) #Vegetation Coverage Change = T1(201
107         result = ("T{}_CN.tif".format(i+1))
108         CN[i].save(result)
109
110     ##Vegetation Coverage Change Speed
111     arcpy.AddMessage("\nCalculating the Speed of NDVI Value Change...")
112     #Set up workspace
113     arcpy.env.workspace = r"C:/Program/Output/SNC"
114     #Calculating the Speed of NDVI Value Change
115     SNC = []
116     for i in range(num_img-2):
117         SNC.append((CN[i+1]-CN[i])/(time_stamp[i+1]-time_stamp[i])) #Vegetation C
118         result = ("S{}_SNC.tif".format(i+1))
119         SNC[i].save(result)
120
121     ##Vegetation Coverage Change Acceleration
122     arcpy.AddMessage("\nCalculating the Acceleration of NDVI Value Change...")
123     #Set up workspace
124     arcpy.env.workspace = r"C:/Program/Output/ANC"
125     #Calculating the Acceleration of NDVI Value Change
126     ANC = []
127     for i in range(num_img-3):
128         ANC.append((SNC[i+1]-SNC[i])/(time_stamp[i+1]-time_stamp[i])) #Vegetation C
129         result = ("A{}_ANC.tif".format(i+1))
130         ANC[i].save(result)

```

Figure 3. Definition of NDVI_Calculation function

The second function (Figure 4) performs the classification based on this rule. The classified NDVI, called ndviVEG, will be returned and appended into a list, named ndviList, for iterative vegetation dynamics calculation. To visually interpret the change of vegetation coverage over time, binary vegetation classifications (0: non-veg; 1: veg) will be generated by reclassifying ndviVEG layers.

```

68 def Vegetation_Classification(img_path, time_stamp, ndvi_threshold): #4/27 transf
69     ##NDVI Calculation (2010NDVI, 2012NDVI, 2014NDVI, 2016NDVI)
70     NDVI = NDVI_Calculation(img_path, time_stamp)
71
72     #Set up workspace
73     arcpy.env.workspace = r"C:/Program/Output/ndviVEG"
74     result = ("{}ndviVEG.tif".format(time_stamp))
75
76     #Vegetation Classification
77     ndvi_threshold = int(ndvi_threshold)
78     whereClause = ("VALUE < {}".format(ndvi_threshold)) #Set local variables (con
79     arcpy.AddMessage("Classifying {}Vegetation...".format(time_stamp))
80     ndviVEG = arcpy.sa.SetNull(NDVI, NDVI, whereClause)
81     #ndviVEG.save(result)
82
83     ##Generate Binary Vegetation Classification Map
84     arcpy.AddMessage("Generating {}Binary Vegetation Map...".format(time_stamp))
85
86     # Define the RemapValue Object
87     maxNDVI = arcpy.GetRasterProperties_management(NDVI, "MAXIMUM")
88     arcpy.env.workspace = r"C:/Program/Output/VEG"
89     result = ("{}VEG.tif".format(time_stamp))
90     VEG_Range = RemapRange([[0, ndvi_threshold, 0], [ndvi_threshold, maxNDVI, 1]])
91
92     # Execute Reclassify
93     VEG = Reclassify(NDVI, "VALUE", VEG_Range)
94     VEG.save(result)
95
96     return ndviVEG

```

Figure 4. Definition of Vegetation_Classification function

3.3 Performing Vegetation Dynamics Based on NDVI Time-Series Change Detection

This study defined three functions to iteratively generate three indicators for vegetation dynamics (Figure 5):

- Vegetation NDVI value change (CN): $T1(2012-2010)$, $T2(2014-2012)$, $T3(2016-2014)$
- Speed of vegetation NDVI value change (SNC): $S1:(T2-T1)/2$, $S2:(T3-T2)/2$
- Acceleration of vegetation NDVI value change (ANC): $A1:(S2-S1)/2$

```
98 def NDVI_Change_Detection(ndviList, num_img, time_stamp):
99     ##Vegetation Coverage Change (T1, T2, T3)
100     arcpy.AddMessage("\nCalculating the Change of NDVI Value...")
101     #Set up workspace
102     arcpy.env.workspace = r"C:/Program/Output/CN"
103     #Calculating the Change of NDVI Value
104     CN = []
105     for i in range(num_img-1):
106         CN.append(ndviList[i+1]-ndviList[i]) #Vegetation Coverage Change = T1(201
107         result = ("T{}".format(i+1))
108         CN[i].save(result)
109
110     ##Vegetation Coverage Change Speed
111     arcpy.AddMessage("\nCalculating the Speed of NDVI Value Change...")
112     #Set up workspace
113     arcpy.env.workspace = r"C:/Program/Output/SNC"
114     #Calculating the Speed of NDVI Value Change
115     SNC = []
116     for i in range(num_img-2):
117         SNC.append((CN[i+1]-CN[i])/(time_stamp[i+1]-time_stamp[i])) #Vegetation C
118         result = ("S{}".format(i+1))
119         SNC[i].save(result)
120
121     ##Vegetation Coverage Change Acceleration
122     arcpy.AddMessage("\nCalculating the Acceleration of NDVI Value Change...")
123     #Set up workspace
124     arcpy.env.workspace = r"C:/Program/Output/ANC"
125     #Calculating the Acceleration of NDVI Value Change
126     ANC = []
127     for i in range(num_img-3):
128         ANC.append((SNC[i+1]-SNC[i])/(time_stamp[i+1]-time_stamp[i])) #Vegetation C
129         result = ("A{}".format(i+1))
130         ANC[i].save(result)
```

Figure 5. Definition of NDVI_Change_Detection function

4. Results (Take 1m NAIP as an example)

4.1. Binary Vegetation Classifications

According to Table 1, vegetation coverage and percentage were decreasing from 2010 to 2016 at Carmel Valley. The following maps (Figure 6) show the spatial distribution of vegetation coverage over time. The east-southern Carmel Valley might have the large amount decrease of vegetation coverage.

Table 1. The change of vegetation coverage and percentage from 2010 to 2016

Year	Vegetation Coverage (m ²)	Percentage of Vegetation Coverage (%)
2010	45423760	16.1
2012	32251308	11.4
2014	20784488	7.4
2016	14123916	5.0

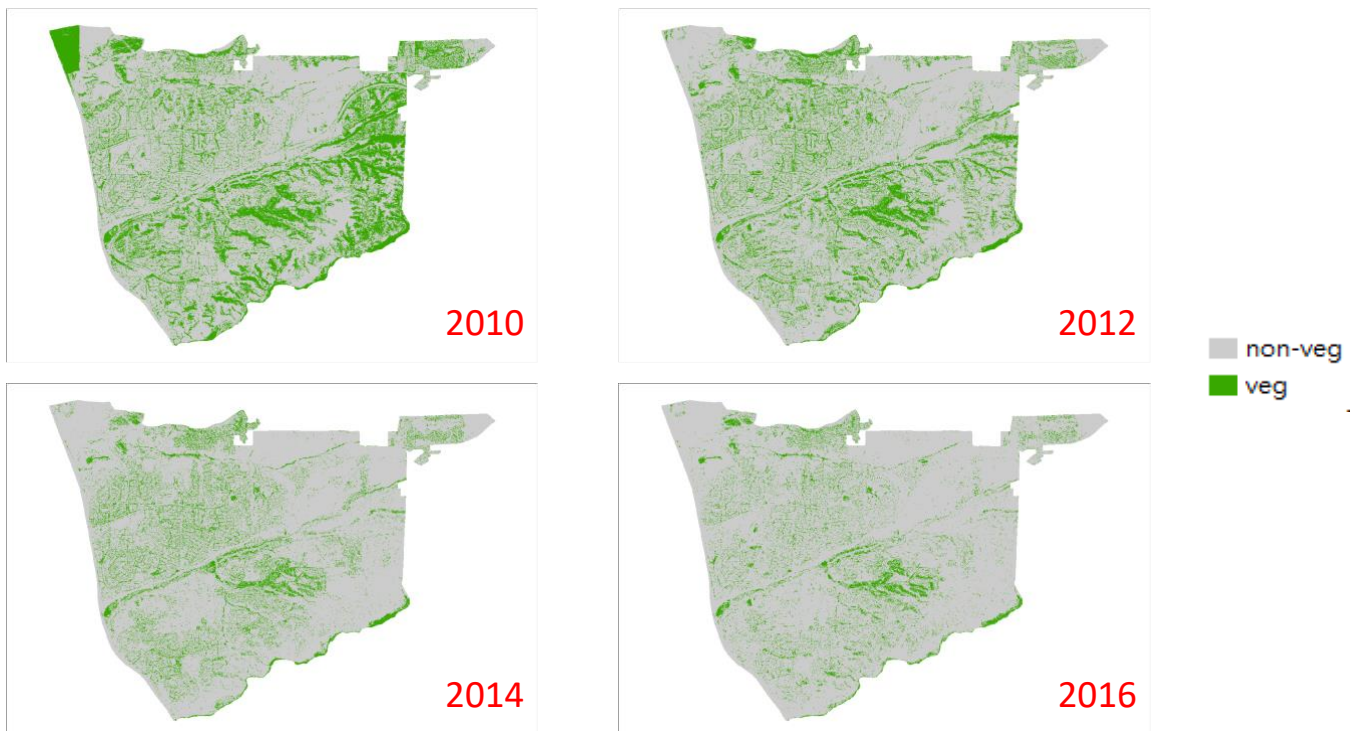


Figure 6. Binary vegetation classifications from 2010 to 2016

4.2. The Change of Vegetation NDVI Value

Table 2 indicates the average vegetation NDVI value is decreasing since 2010. The standard deviation vegetation NDVI value slightly increased in period of 2010 to 2014 but decreased from 2012 to 2016 eventually. Similarly, the east-southern Carmel Valley might have the large amount decrease of vegetation NDVI value change (Figure 7).

Table 2. The change of vegetation NDVI value from 2010 to 2016

Time	Avg. VEG_NDVI Value Change	Std. VEG_NDVI Value Change
T1 (2012 - 2010)	13.55	10.68
T2 (2014 - 2012)	7.54	11.73
T3 (2016 - 2014)	-20.08	9.86

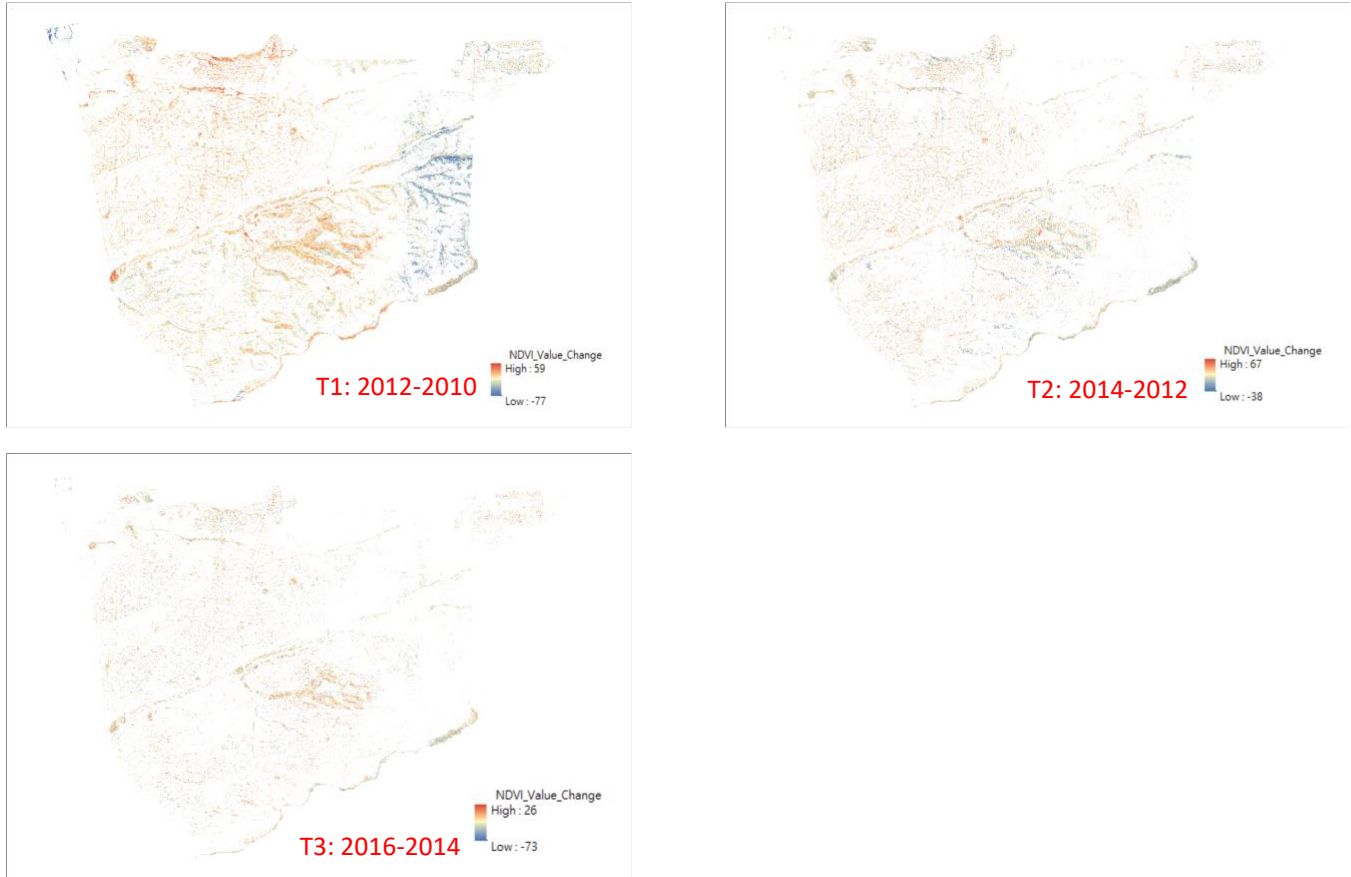


Figure 7. The change of vegetation NDVI Value from 2010 to 2016

4.3. The Speed of Vegetation NDVI Value Change

Apparently, Table 2 shows the identical temporal trend of vegetation dynamics with Table 1(The change of vegetation coverage and percentage). The average speed of vegetation NDVI value change is slow down but the standard deviation increases. However, it is not easy to tell the spatial distribution of the

speed change from Figure 8 because of per-pixel-based classification and very small minimum mapping unit (1m).

Table 3. The speed of vegetation NDVI value from 2010 to 2016

Time	Avg. Speed of VEG_NDVI Value Change	Std. Speed of VEG_NDVI Value Change
S1:(T2-T1)/2	-5.73	8.93
S2:(T3-T2)/2	-13.41	9.69

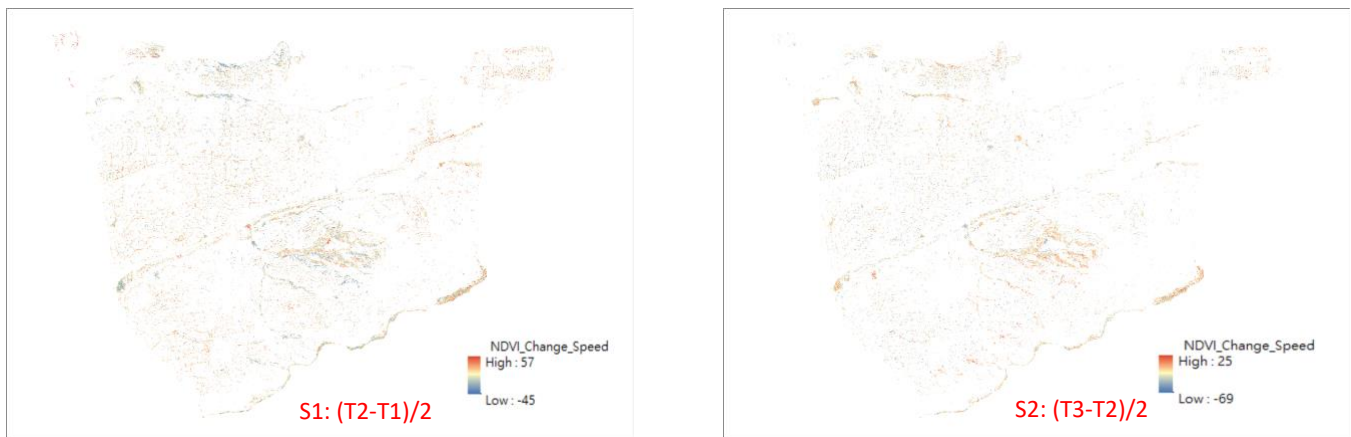


Figure 8. The speed of vegetation NDVI value from 2010 to 2016

4.4. The Acceleration of Vegetation NDVI Value Change

Table 4 demonstrates the average acceleration of vegetation NDVI value is -8.94 and the standard deviation is 13.03. Likewise, it is not easy to tell the spatial distribution of the speed change from Figure 9 because of per-pixel-based classification and very small minimum mapping unit (1m). However, the maximum and minimum acceleration is 44 and -83, respectively.

Table 4. The acceleration of vegetation NDVI value from 2010 to 2016

Time	Avg. Acceleration of VEG_NDVI Value Change	Std. Acceleration of VEG_NDVI Value Change
A1:(S2-S1)/2	-8.94	13.03

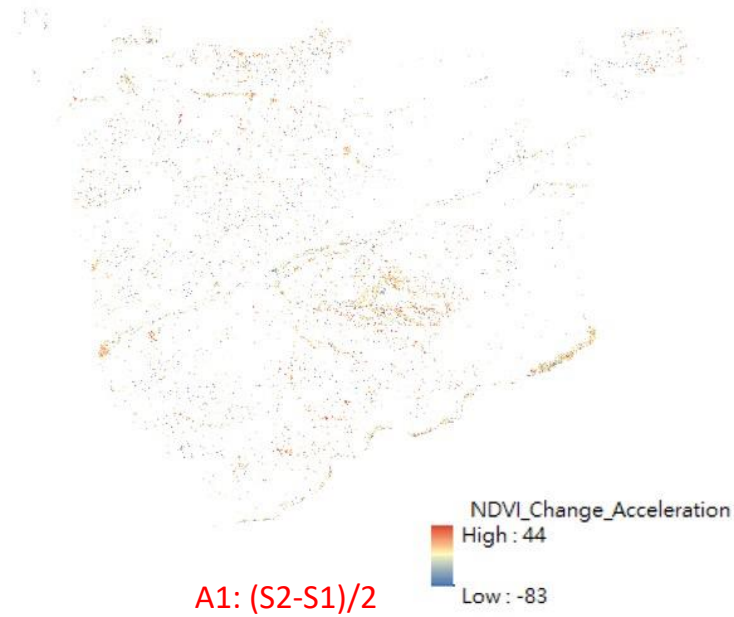


Figure 9. The acceleration of vegetation NDVI value from 2010 to 2016

5. Technical Limitations, Challenges and Problems

Subjective NDVI threshold selection is the primary limitation of this project. Namely, it affects the results of vegetation dynamics based on NDVI time-series. The major technical challenge of this project is the difficulty in appropriately visualizing the results, particularly the speed and acceleration of vegetation NDVI value change. I tried to use brighter color and darker background to highlight the pixels, but it did not work. Grouping pixels into a larger spatial unit for visualization purpose might be worth to try.

6. Lessons Learned

The major lesson I learned from this class is how to use ArcPy to develop various geospatial projects. Specifically, the lab assignments are really helpful exercises. Most of the functions I used in here have been introduced in the class or the lab assignments. I am glad that I am able to automate geospatial workflow through coding Python.

7. Reference

Jensen, J. R. (2017). *Introductory Digital Image Processing: A Remote Sensing Perspective* (4th ed.): Prentice Hall Press.