

Vegetation Change in Beijing

An Application of Change Detection & Time Series Analysis

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Introduction

Change detection and time series analysis are powerful tools to understand the dynamics of environmental changes over time. Greenery is a critical component of the urban environment, providing important ecosystem services and contributing to the overall quality of life in cities. While Beijing has undergone rapid urbanization over the last decades, the city has committed to plant million acres of trees since 2012¹. This project utilizes Landsat 8 images through Google Earth Engine to examine changes and patterns in vegetation cover over time in the greater Beijing area.

Google Earth Engine Workflow

Google Earth Engine is a cloud-based geospatial data analysis platform that allows users to access and work with various collections of global data. In the following sections, only critical steps in the Google Earth Engine Workflow will be explained. For complete workflow and graphic output, please visit:

<https://code.earthengine.google.com/d42f4bd3d93a3f4c4137c41ad1be62ed>

Image Preparation

In this project, USGS Landsat 8 Level 2, Collection 2, Tier 1 imageries that covered the greater Beijing area from 2013 to the most recent summer record (2022) were used. The following code chunk demonstrates the image preparation steps.

```
// Set centre of Beijing as point of interest (POI)
var bj_pt = ee.Geometry.Point([116.3868,39.8988])

// Set Landsat-8 data source bounding POI
var landsat8 = ee.ImageCollection('LANDSAT/LC08/C02/T1_L2')
  .filterBounds(bj_pt)

// Create function to apply scale factors
function applyScaleFactors(image) {
  var opticalBands = image.select('SR_B.*').multiply(0.0000275).add(-0.2);
  var thermalBands = image.select('ST_B.*').multiply(0.00341802).add(149.0);
  return image.addBands(opticalBands, null, true)
    .addBands(thermalBands, null, true);
}

// Apply scale factors, select and rename relevant spectral bands
var landsat8_scaled = landsat8.map(applyScaleFactors)
  .select(
    ['SR_B2', 'SR_B3', 'SR_B4', 'SR_B5', 'SR_B6', 'SR_B7'],
    ['blue', 'green', 'red', 'nir', 'swir1', 'swir2']);

// Retrieve 'Pre' and 'Post' images around POI
var preImage = landsat8_scaled
  .filterDate('2013-05-01', '2013-08-30')
  .sort('CLOUD_COVER', true)
  .first();
var postImage = landsat8_scaled
  .filterBounds(point)
  .filterDate('2021-05-01', '2021-08-30')
  .sort('CLOUD_COVER', true)
  .first();
```

¹ http://yllhj.beijing.gov.cn/ztxx/mtjj/mtbd/201602/t20160206_115734.shtml

After the series of queries and filters, the selected `preimage` was taken from May 12, 2013, and the `postImage` from May 2, 2021. A true color composite image with red, green, blue bands, as well as a false color composite image with red, near-infrared (nir), shortwave infrared 2 (swir2) bands were produced for both pre and post Images.

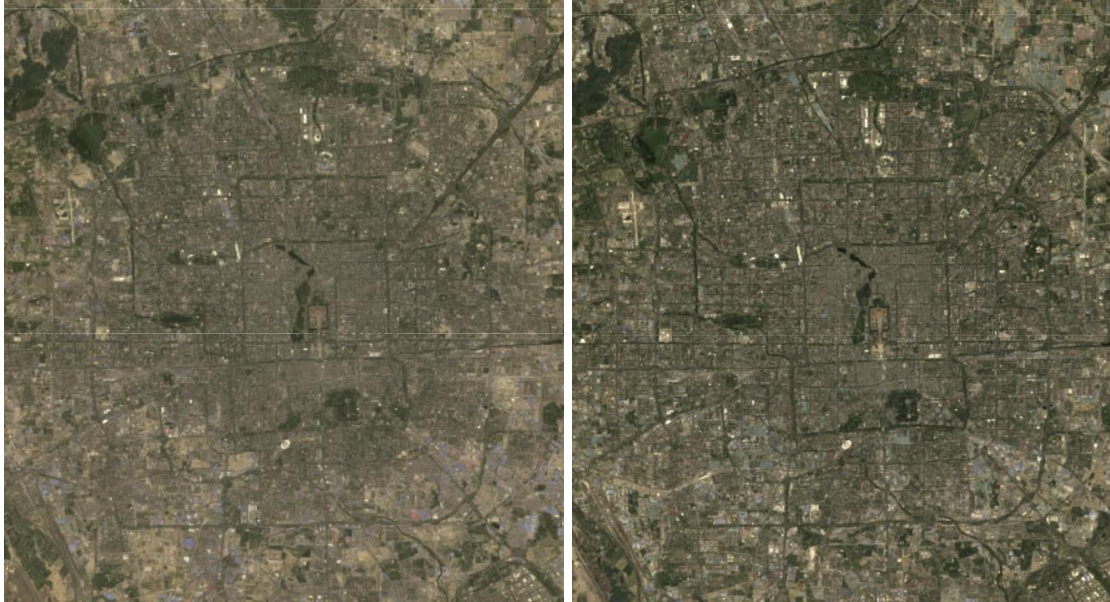


Figure 1. Red/Green/Blue True Color Composite Landsat-8 Images (Left: 2013; Right: 2021)

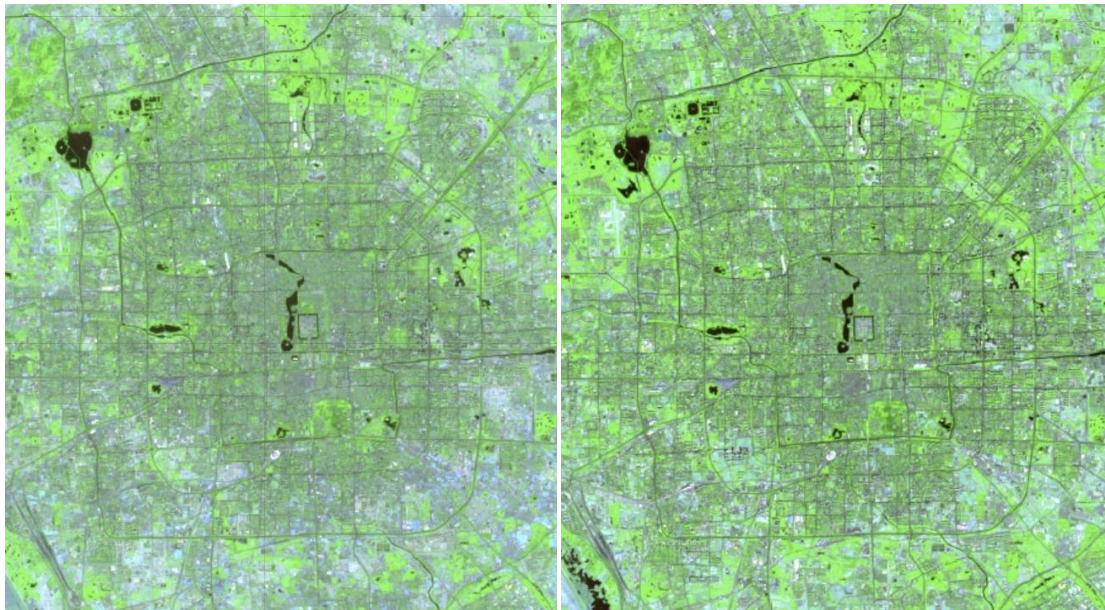


Figure 2. Red/NIR/SWIR2 False Color Composite Landsat-8 Images (Left: 2013; Right: 2021)

Healthy vegetation tends to reflect brighter responses in the NIR bands. While it was difficult to distinguish vegetation changes between the True Color images, there seem to be more 'green' in the 2021 False Color image in comparison to 2013, which represented the NIR bands.

Change Detection

The following plots show the mean Landsat-8 band values within the inner Beijing area in 2013 and 2021 respectively. Note that Landsat8 image initiated in March 2013 and the first qualified image for the area of interest started in May. This project focuses on the summer months when vegetation growth peaks and without effects from snow. Therefore, the period between May and December of the respective years was set as the time range for both plots.

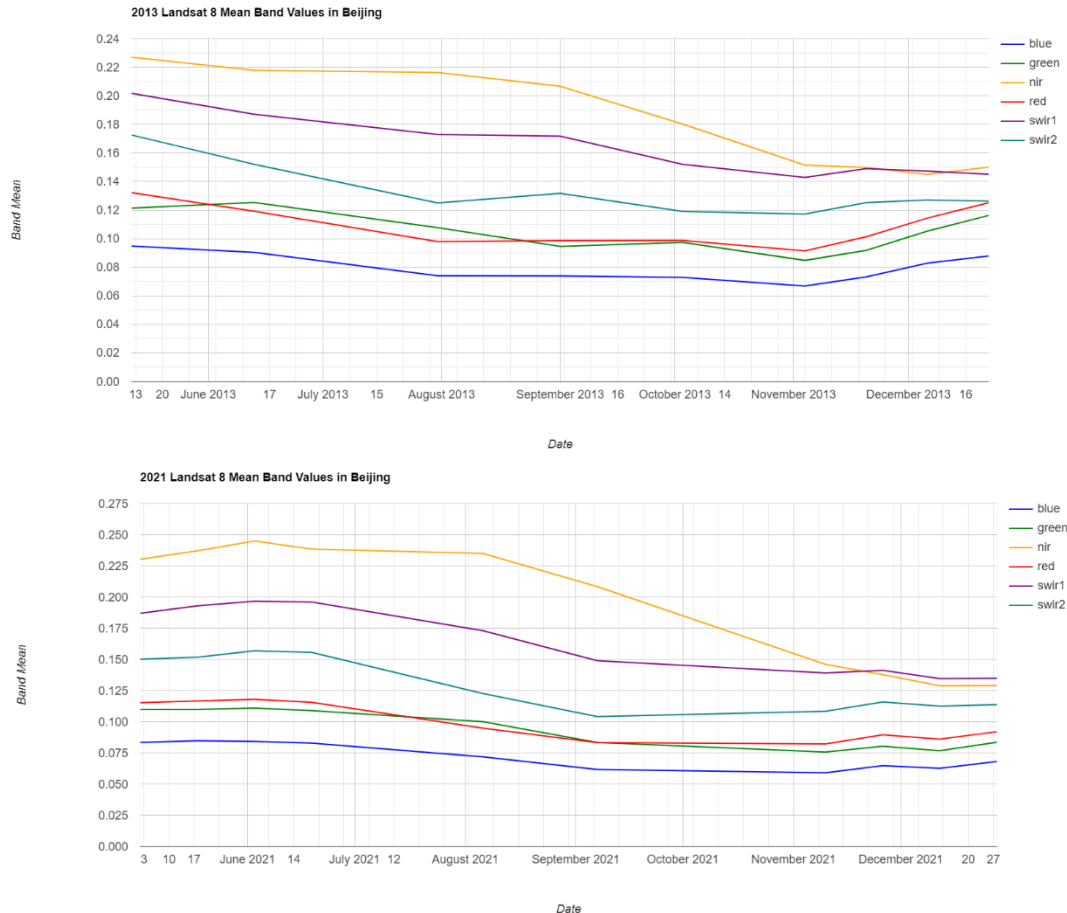


Figure 3. Landsat-8 Band Means within inner Beijing (Top: 2013; Bottom: 2021)

The plots provide an overview of spectral responses and their differences across time. Note that NIR values are generally higher in 2021 with larger gap between NIR and other band values during the summer months than in 2013. To better quantify vegetation greenness, Normalized Difference Vegetation Index (NDVI) is calculated to assess vegetation density. The following code chunk demonstrates the steps towards change detection between the 2 images.

```
// Calculate NDVI
var ndviPre = preImage.normalizedDifference(['nir', 'red']).rename('ndvi_pre')
var ndviPost = postImage.normalizedDifference(['nir', 'red']).rename('ndvi_post')

// Calculate NDVI difference between 2 images, and map the difference
var diff = ndviPost.subtract(ndviPre).rename('change');
```



```

var visParams = {
  palette: ['ee4d5a', 'f97b57', 'efc47e', 'efc47e', 'ecda9a',
    '97e196', '6cc08b', '217a79', '217a79', '074050'],
  min: -0.5,
  max: 0.5
};
Map.addLayer(diff, visParams, 'NDVI change');

// Set change threshold and reclassify the pixels accordingly
var thresholdGain = 0.3;
var thresholdLoss = -0.3;

var diffClassified = ee.Image(0);

// Reclassified as '1' if the pixel value difference is greater than '0.3'
// and as '2' if the difference is lower than '-0.3'
diffClassified = diffClassified.where(diff.gte(thresholdGain), 1);
diffClassified = diffClassified.where(diff.lte(thresholdLoss), 2);

var changeVis = {
  palette: 'white,2659eb,fa1373',
  min: 0,
  max: 2
};
Map.addLayer(diffClassified.selfMask(),
  changeVis,
  'NDVI change over +/- 0.3');

```

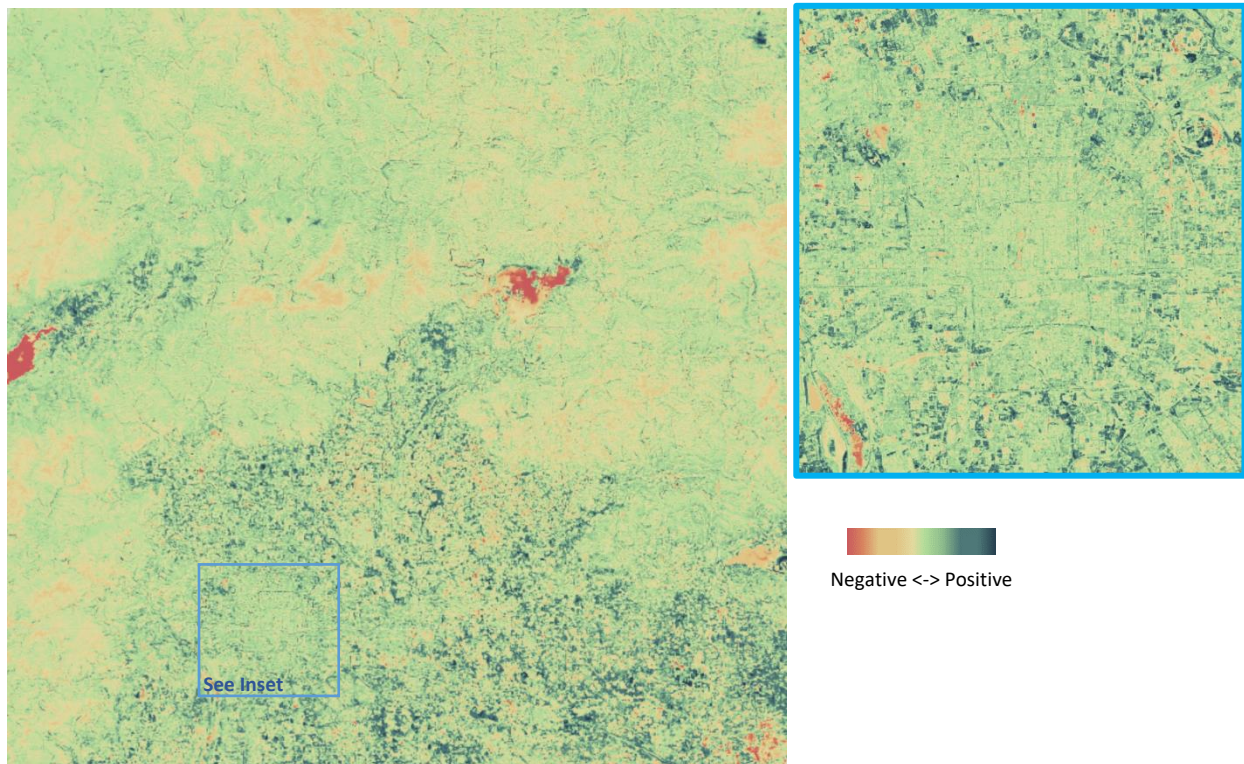


Figure 4. NDVI Difference (Main: Landsat-8 scene; Inset: Inner Beijing)

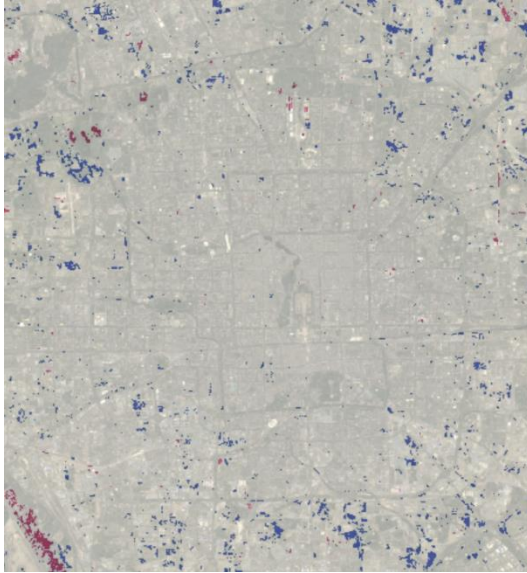


Figure 5. NDVI Difference over ± 0.3 (Blue: positive change; Purple: negative change)

As shown in Figure 4, the overall difference within inner Beijing is positive and shows a green tone in general, meaning there is more vegetation coverage in 2021 than 2013. However, it's worth noting that the area east of the city reflects the most intense increase in NDVI. Upon referencing to the True Color composite images, the strong negative changes are mostly due to expansion of water surface (larger water surface areas in 2021).

By setting the change thresholds to ± 0.3 , areas with most significant changes over or under the threshold can be identified and mapped out. In Figure 5, areas in blue indicate an increase in NDVI (i.e. vegetation presence) while purple indicate a decrease. Most changes occurred along the outskirts of the city, close to previously established green areas and edges of city blocks.

Time Series Analysis

While Change Detection allowed us to compare 2 selected images and identify areas of changes, Time Series Analysis provides insights of changes and trends throughout the years in between. In addition to plotting the median values for Landsat-8 bands, NDVI is calculated and appended to the image properties. To highlight vegetation growth and to minimize the effects from snow, only images collected during the summer months (i.e. May 1 to August 31) were included, and a total of 32 images were used in the analysis. The following code chunk demonstrates how an annual image composite is created and added to the map display.

```
// Define a function to retrieve annual composite for specified year
// The median values at each pixel of all bands across all images in a given year are used
// to produce the annual composite.
function getAnnualComposite(year) {
  var startDate = ee.Date.fromYMD(year, 1, 1);
  var endDate = startDate.advance(1, 'year');
  var composite = collection.filterDate(startDate, endDate).median();
  return composite;
}

// Define a function to update the map with the selected year
function updateMap(year) {
  var image = getAnnualComposite(year);
  var visParams = {bands: ['red', 'green', 'blue'], min: 0, max: 0.3};
  Map.layers().set(0, ui.Map.Layer(image, visParams, 'Image for ' + year));
}

var initialYear = 2013;
var initialImage = getAnnualComposite(initialYear);
var visParams = {bands: ['red', 'green', 'blue'], min: 0, max: 0.3};

// Create and add a slider widget for selecting the year
var slider = ui.Slider({
  min: 2013,
```

```

max: 2022,
step: 1,
onChange: updateMap,
style: {width: '400px', padding: '10px'}
});

```

```
Map.add(slider);
```

Scrolling through the true color composite images from 2013 to 2022, it was difficult to determine any changes in vegetation in the densely urbanized Beijing. The plot below highlights the median band values for Red, NIR, and the calculated NDVI from selected images between summer 2013 and 2022. While there are variations throughout the years that may be attributed to cloud, haze, weather patterns (start of spring may vary in different years), there is an upward trend as seen in the NDVI trendline, indicating an overall increase in vegetation areas throughout the years.

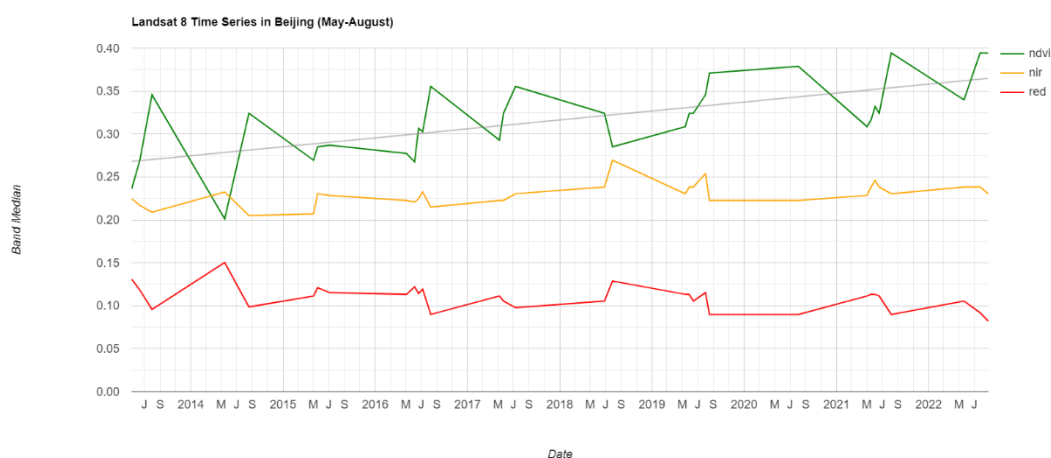


Figure 6. Landsat-8 Time Series Median Band Values in Beijing (May – August)

Summary

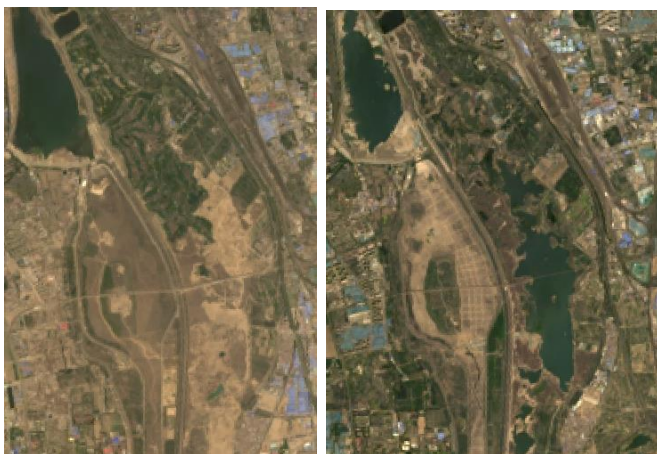


Figure 6. Pre- and Post- Image zoomed in to the Forest Park

Results from the change detection and time series analysis have shown that there has been an increase in greenery cover in the city of Beijing over time. In addition, as discussed in the Change Detection section, there are noticeable differences in some of the water bodies. Upon closer examination, a new Forest Park with wetland and forested features (see Figure 7) was developed in recent years to the southwest of the city, which contributed to a negative NDVI change due to new water surface, and positive NDVI change adjacent to the water features.

The findings from this project highlight the potential for remote sensing and geospatial tools such as Google Earth Engine to provide valuable insights into changes in urban environments, policy adherence, and long-term monitoring.