Geoprocessing in python (SS 2019)

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Assignment V

| Due date | Su | Sunday, 26.5.2019 10pm | |
|---------------------|----|--|--|
| Submission form | 1. | Upload greatest disturbance raster as geotiff. | |
| | 2. | py-Script | |
| Evaluation criteria | • | Correctness of the asked results (50%). | |
| | • | Functionality of the py-script (50%). | |

Goal of this assignment

- Strengthen NumPy skills
- GDAL write multi-band raster
- Visualization with Matplotlib

Exercise I

In recent years, time series-based methods for mapping land cover changes at the pixel level have started to replace image-based change detection methods. One example is the widely-used LandTrendr algorithm (Kennedy et al., 2010), which has been commonly applied to detect and characterize forest changes in various biomes. LandTrendr fits a series of interconnected linear segments to an annual pixel time series to separate interannual noise caused by variations in phenology and atmospheric conditions from the disturbance and recovery signal. More recently, LandTrendr has been implemented in the cloud-platform Google Earth Engine (Kennedy et al., 2018). In this exercise, we will work with one of the LandTrendr outputs from the Google Earth Engine to extract and map the greatest disturbance year.

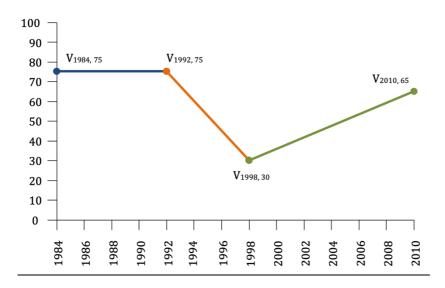


Fig 1. Example LandTrendr fitted time series with 3 segments and 4 vertices. If LandTrendr was run with a maximual number of 6 segments (7 vertices), then the pixel output would look as follows:

| # | Layer | Pixel value |
|----|-----------------------|-------------|
| 1 | Vertex year 1 | 1984 |
| 2 | Vertex year 2 | 1992 |
| 3 | Vertex year 3 | 1998 |
| 4 | Vertex year 4 | 2010 |
| 5 | Vertex year 5 | 0 |
| 6 | Vertex year 6 | 0 |
| 7 | Vertex year 7 | 0 |
| 8 | Vertex raw value 1 | 71 |
| 9 | Vertex raw value 2 | 77 |
| 10 | Vertex raw value 3 | 33 |
| 11 | Vertex raw value 4 | 62 |
| 12 | Vertex raw value 5 | 0 |
| 13 | Vertex raw value 6 | 0 |
| 14 | Vertex raw value 7 | 0 |
| 15 | Vertex fitted value 1 | 75 |
| 16 | Vertex fitted value 2 | 75 |
| 17 | Vertex fitted value 3 | 30 |
| 18 | Vertex fitted value 4 | 65 |
| 19 | Vertex fitted value 5 | 0 |
| 20 | Vertex fitted value 6 | 0 |
| 21 | Vertex fitted value 7 | 0 |
| 22 | Mean square error | 22 |

You are supplied with a spatial subset (514 x 461 pixels) of a LandTrendr output over western Poland. The output was created by fitting 6-segments to a spectral index called "tasseled cap wetness". Hence the results will include information on the timing (year) and fitted spectral values for 7 vertices. Important (!): prior to running LandTrendr, the spectral index was multiplied by -10000, which means that removal of forest cover leads to an increase in spectral value (positive magnitude change), and revegetation leads to a decrease in spectral value. You also have a forest mask (1: forest, 0: non-forest) for the same extent.

1) Vertex image: gpy_poland_landtrendr_tcw_vertex_8618.tif

2) Forest mask: gpy_poland_forestmask.tif

- 1. Create greatest disturbance image: Create a single layer raster where each pixel has the year of the greatest disturbance (largest positive change magnitude) if it was disturbed or 0 if it was undisturbed or non-forest. Save the resulting raster as Geotiff and submit it to moodle.
- 2. Create a histogram that shows the annual forest disturbance frequency between 1987 and 2018 for the study area. Submit the graph to moodle.
- Kennedy, R.E., Yang, Z., Cohen, W.B., 2010. Detecting trends in forest disturbance and recovery using yearly Landsat time series: 1. LandTrendr Temporal segmentation algorithms. Remote Sens. Environ. 114, 2897–2910. https://doi.org/10.1016/j.rse.2010.07.008
- Kennedy, R.E., Yang, Z., Gorelick, N., Braaten, J., Cavalcante, L., Cohen, W.B., Healey, S., 2018. Implementation of the LandTrendr algorithm on Google Earth Engine. Remote Sens. 10, 1–10. https://doi.org/10.3390/rs10050691