Temporal Change Detection Using Landsat Earth Observation Images

GNR 617: Image Interpretation Laboratory

Prepared by

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AIM / Data used / Methods used

Aim:

- To perform the change detection using temporal Landsat images

Data used:

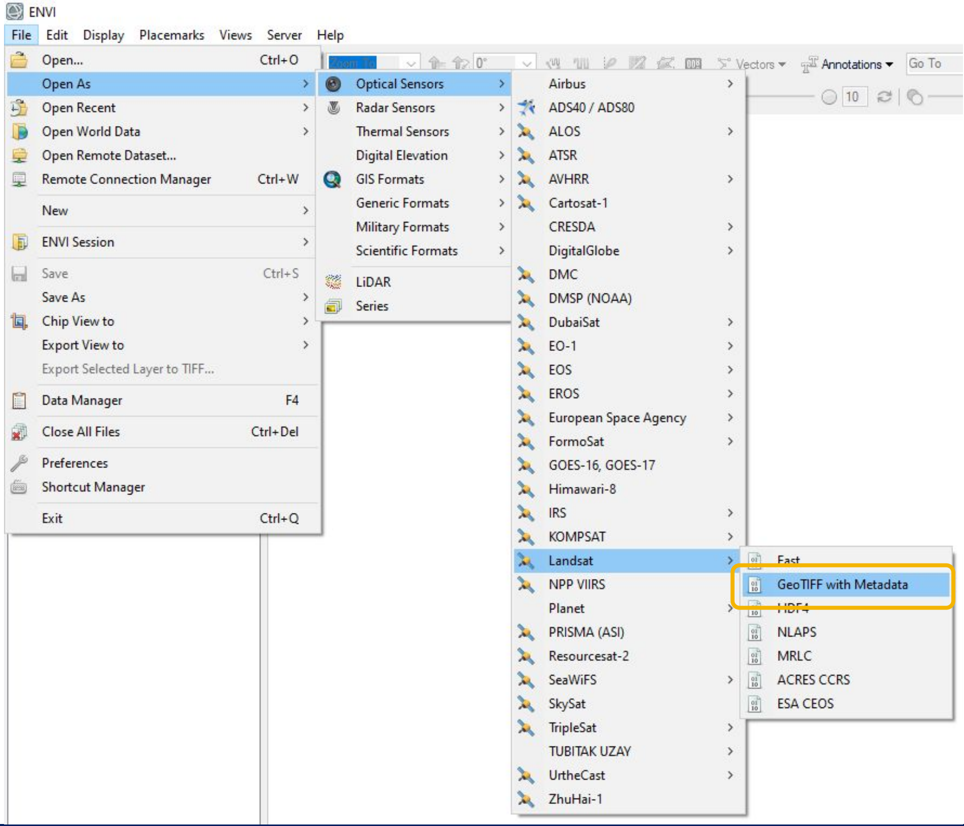
- Landsat 7 acquired over Mumbai (2003)
- Landsat 8 acquired over Mumbai (2018)
- Subset roi (xml/shapefile)

Method/algorithm used:

- Image difference / Image Transform methods
- Otsu / PCA techniques

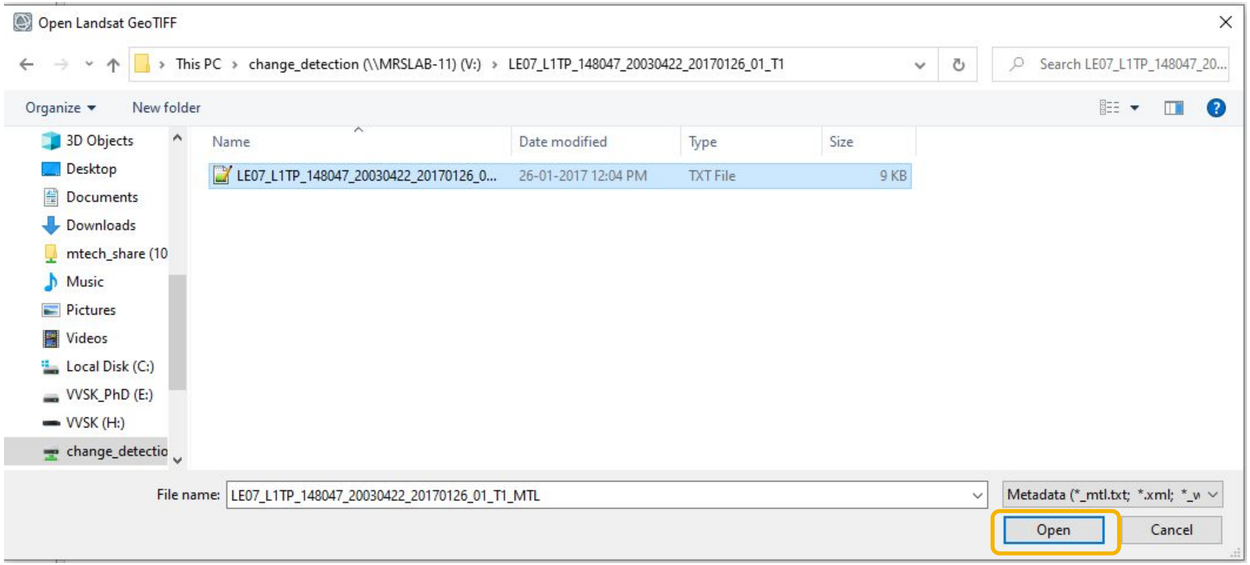
Import datasets

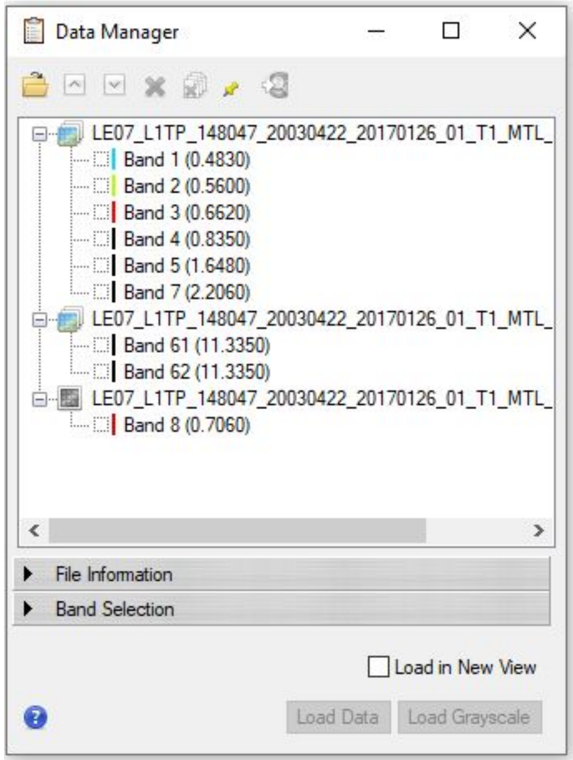
- Import both Landsat-7, 8 datasets



Import datasets

- Import both Landsat-7, 8 datasets

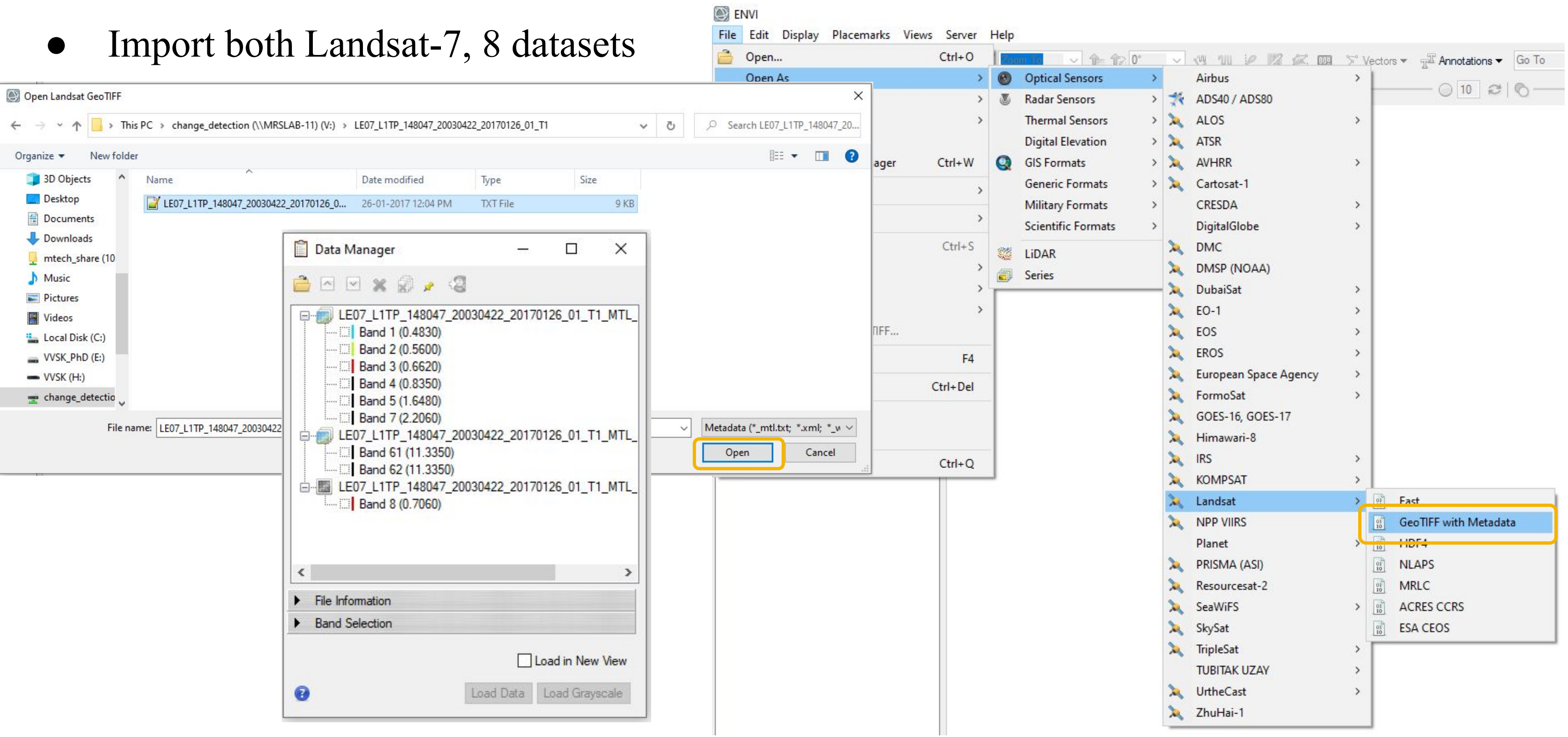




- Similarly, open the Landsat-8 image.

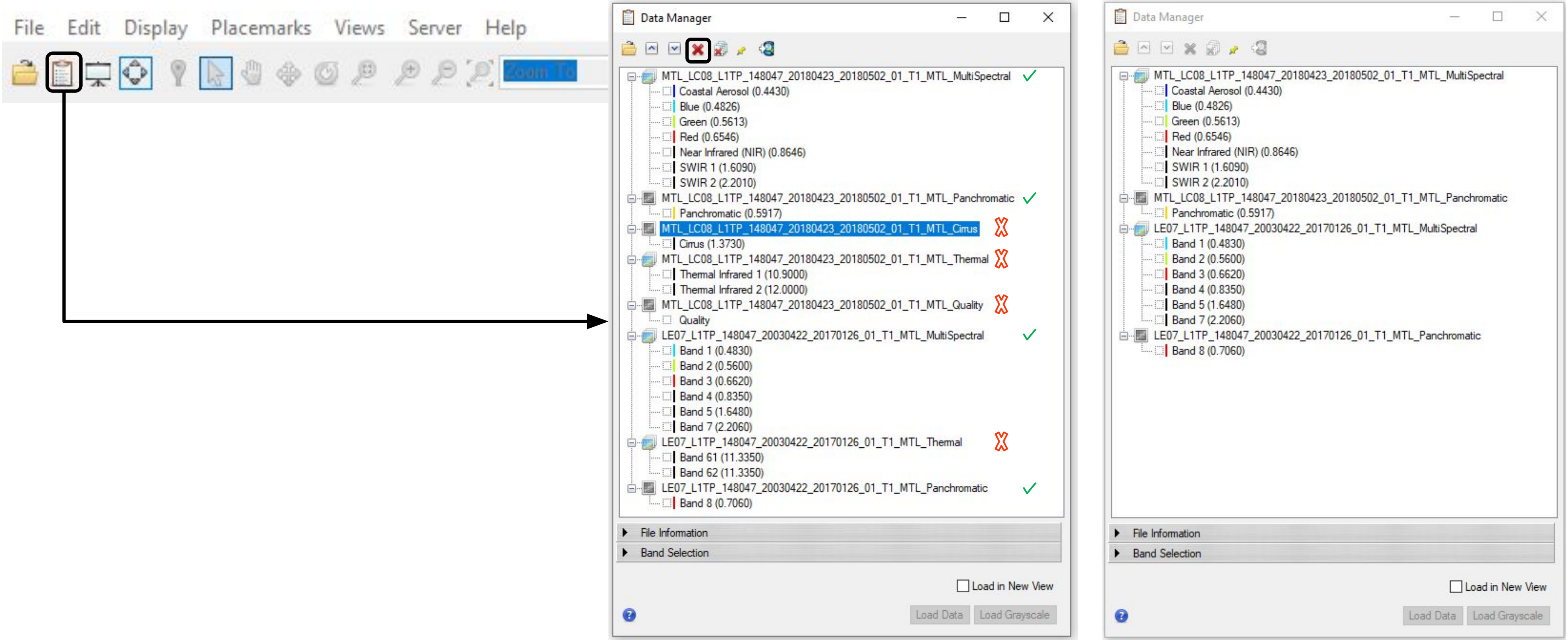
Import datasets

- Import both Landsat-7, 8 datasets



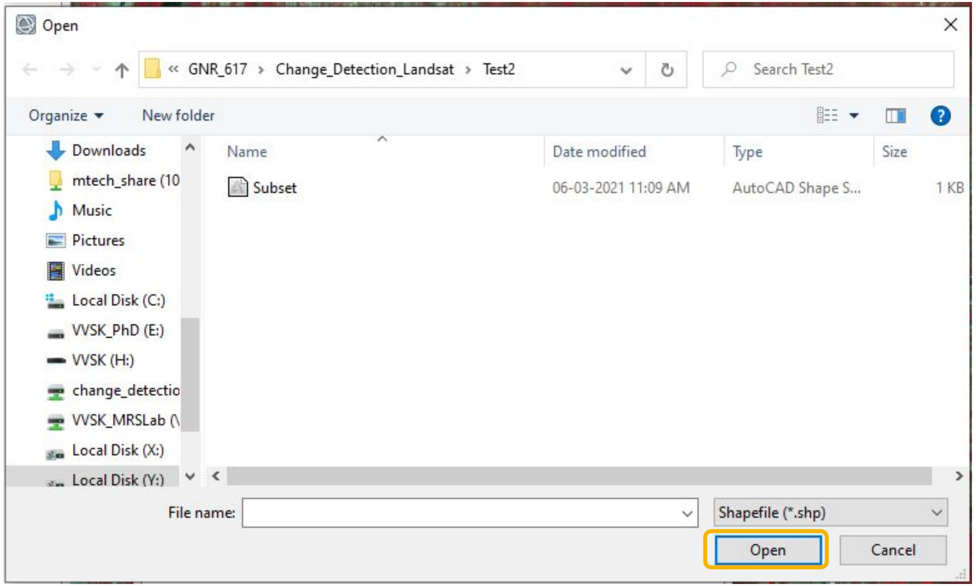
Remove unnecessary images

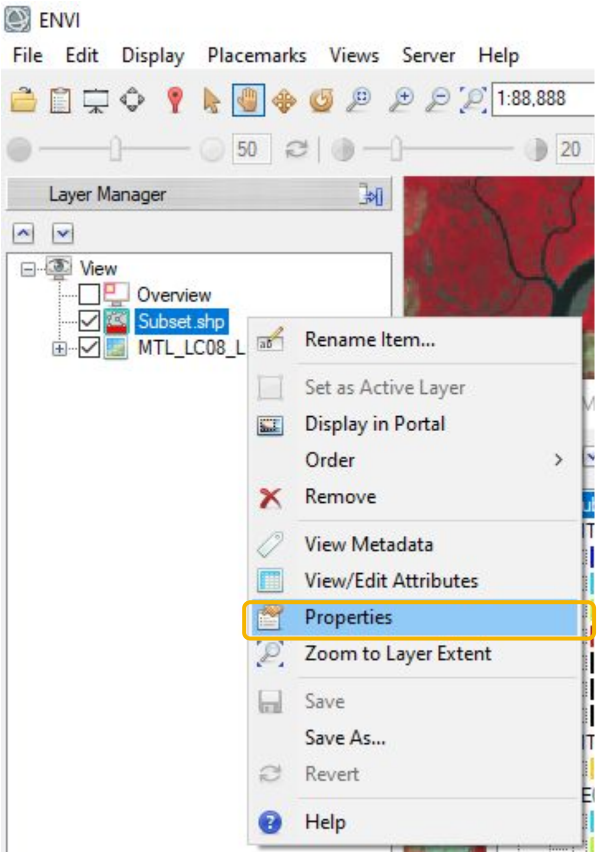
There are Multi-spectral, Panchromatic, Thermal, Cirrus and quality bands available with Landsat images. Remove the unnecessary images from the data manager.



Subset the Landsat images

Import the shapefile/roi to subset the images.





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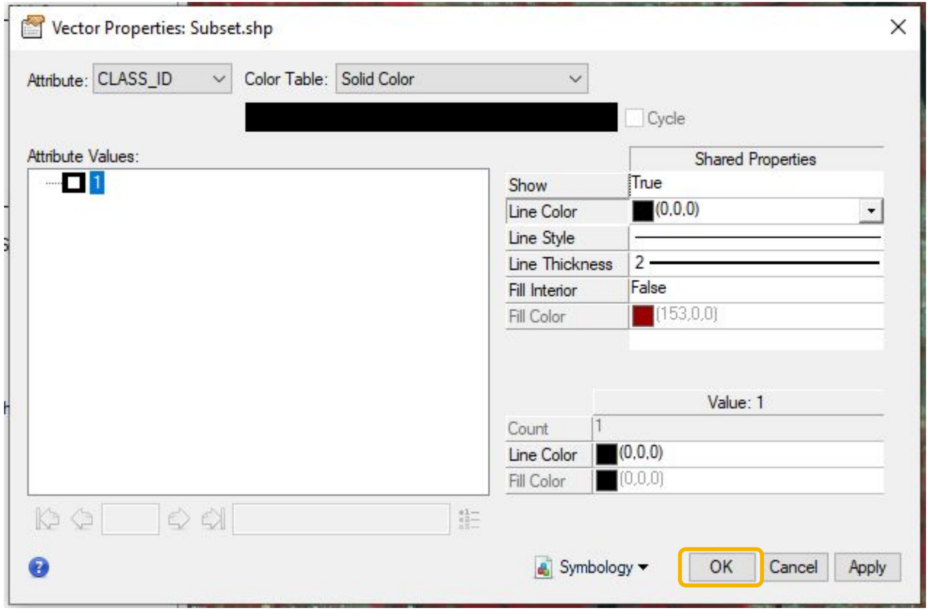

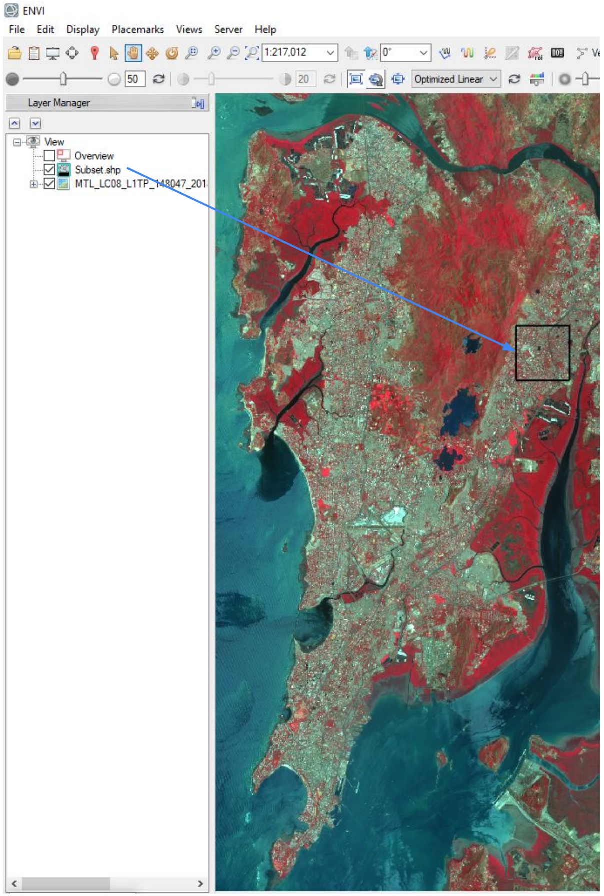

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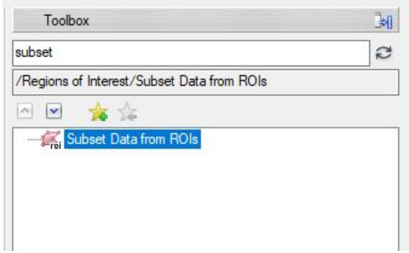
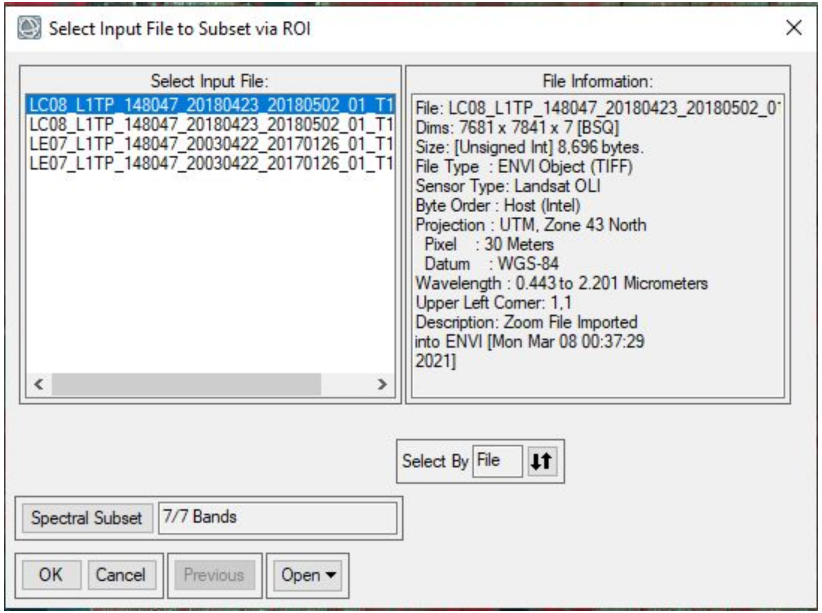
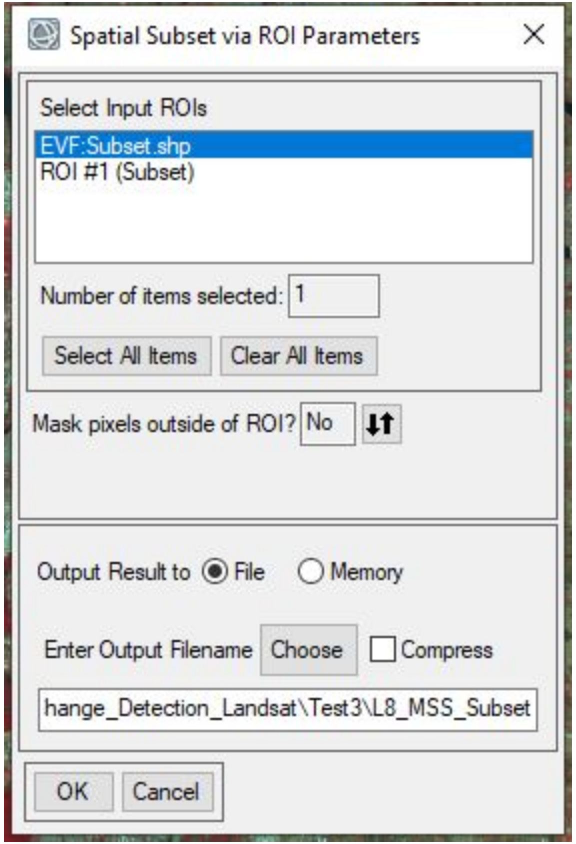
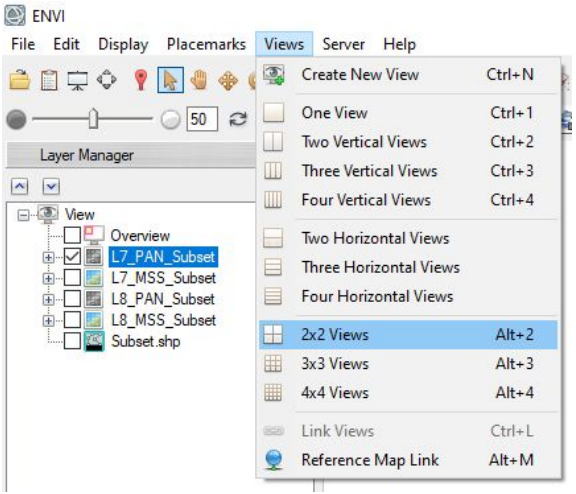


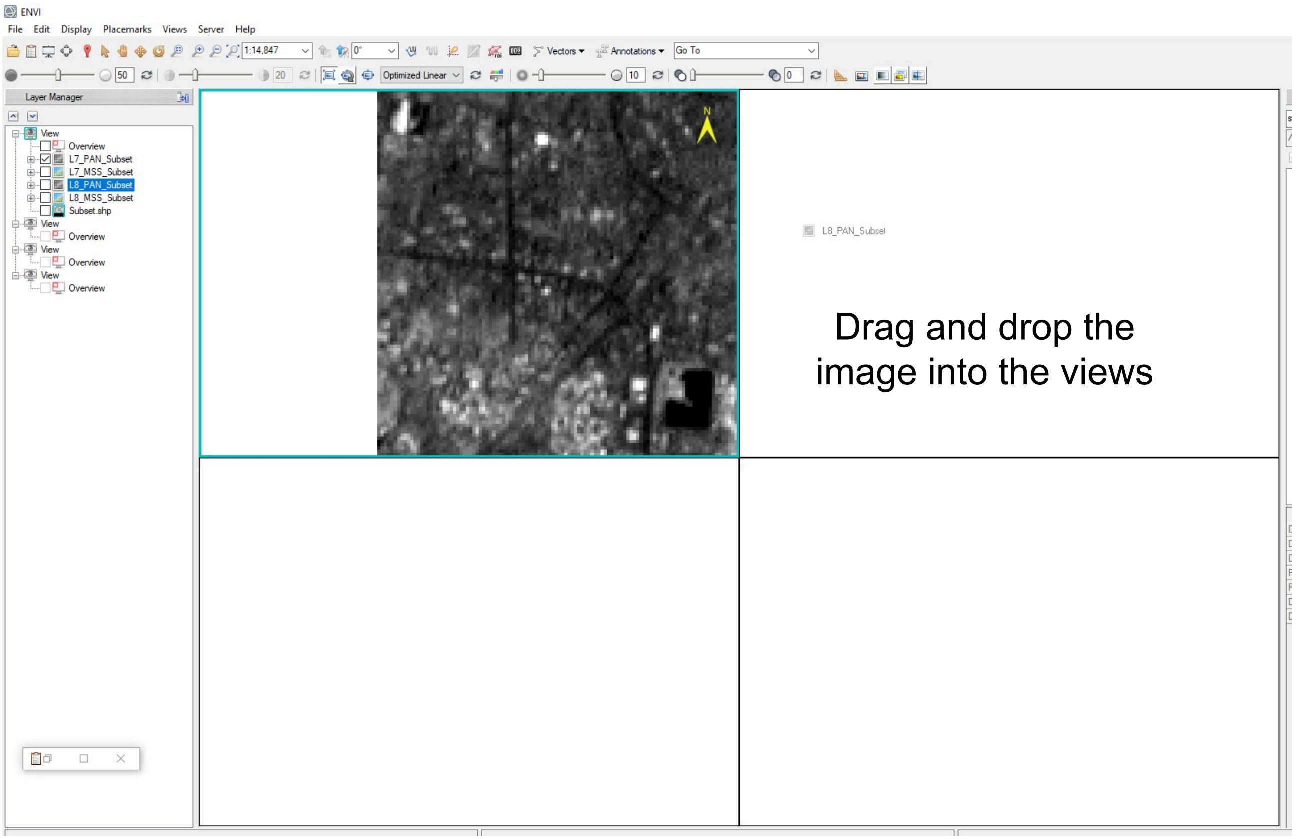




- Repeat this step for all other images (Pan, MSS - L7, L8)

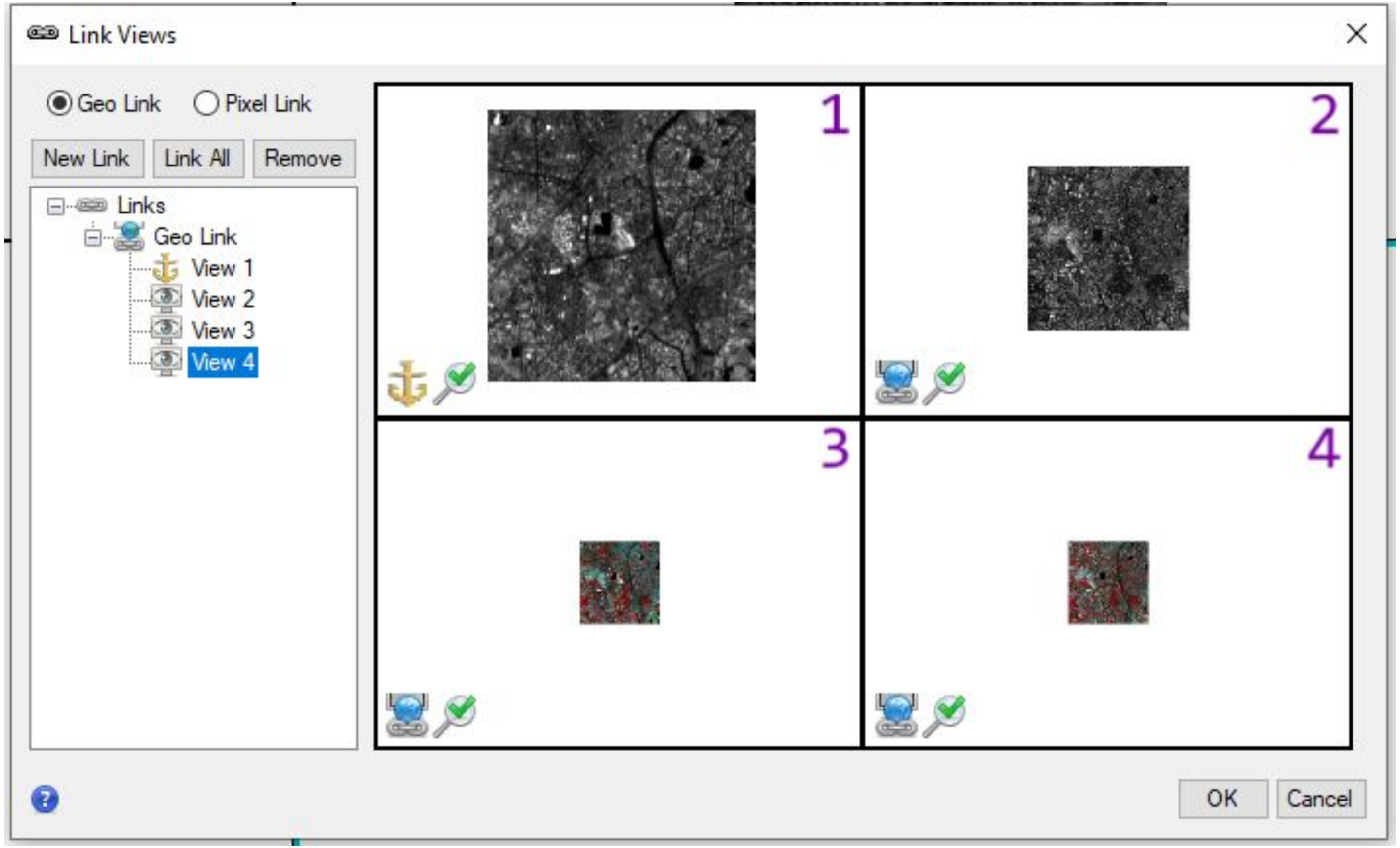
View input datasets



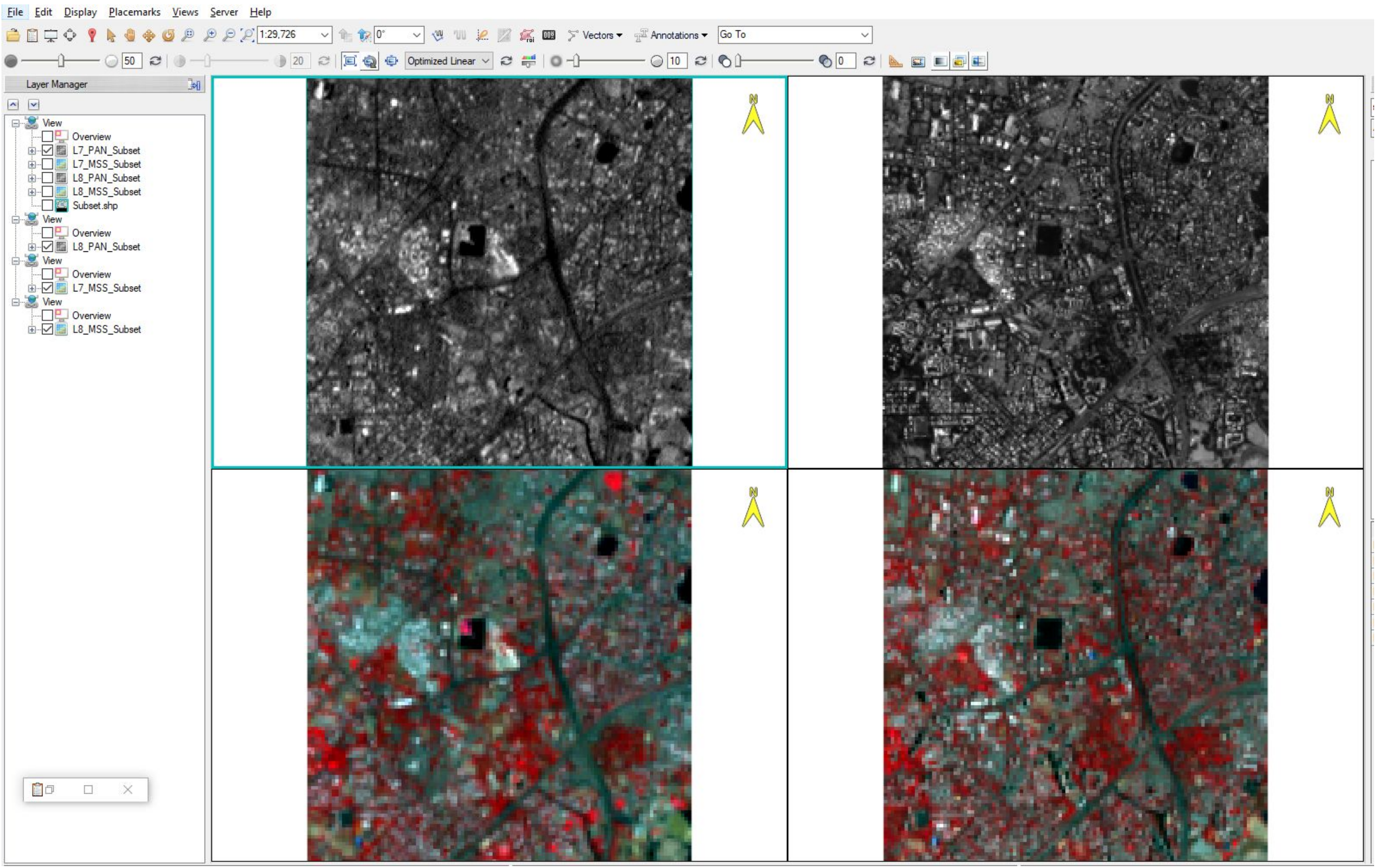


Drag and drop the image into the views

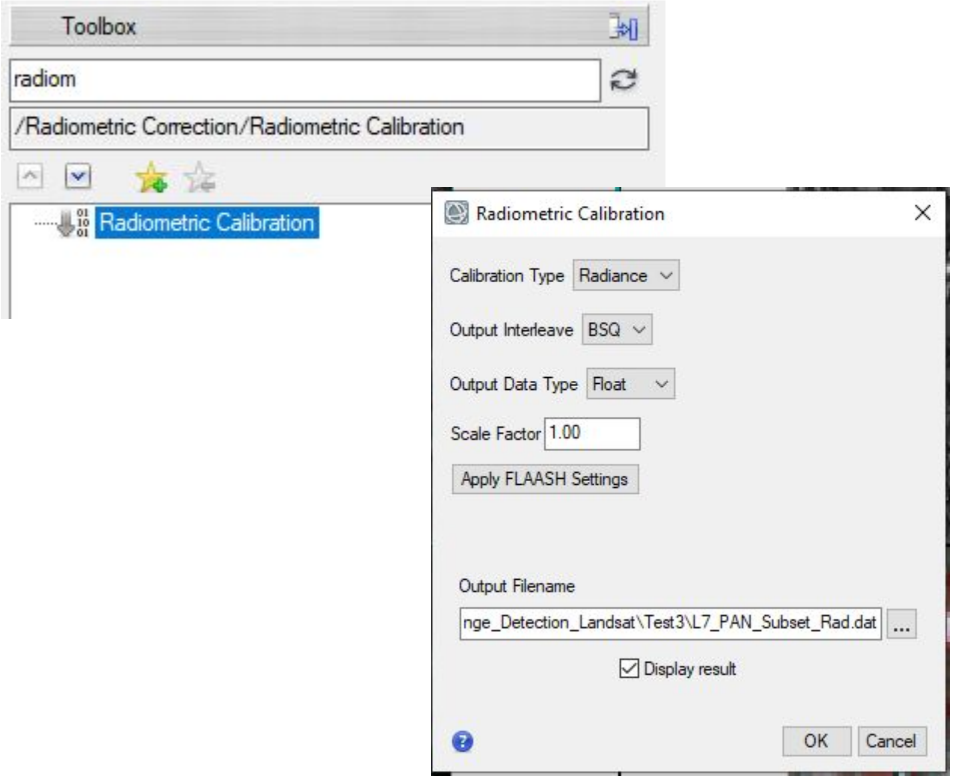
View input datasets

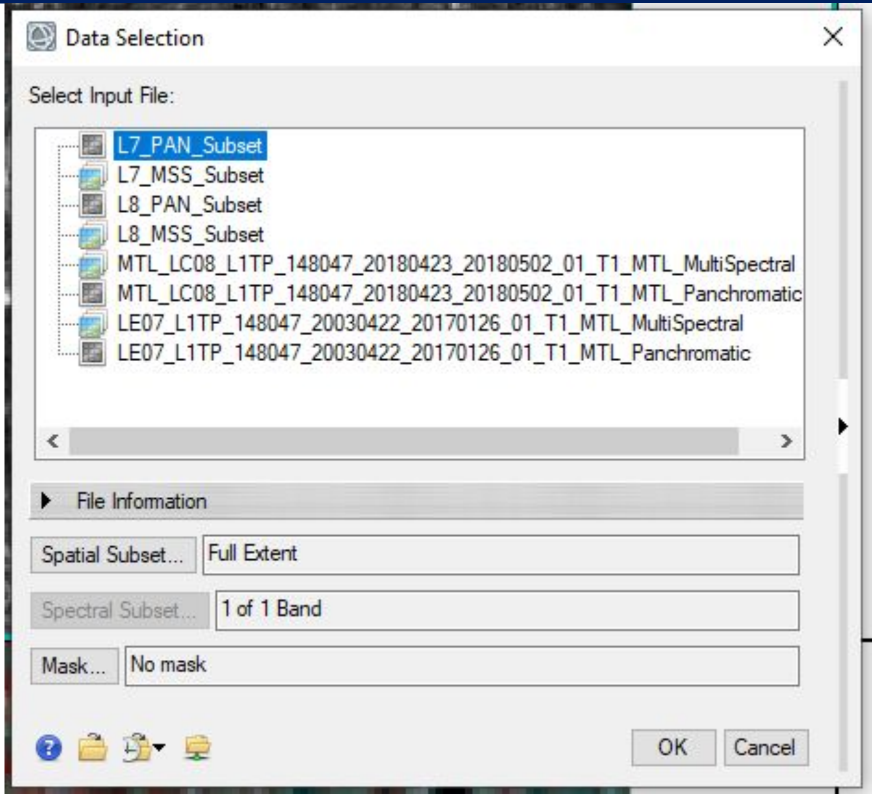


View subset datasets



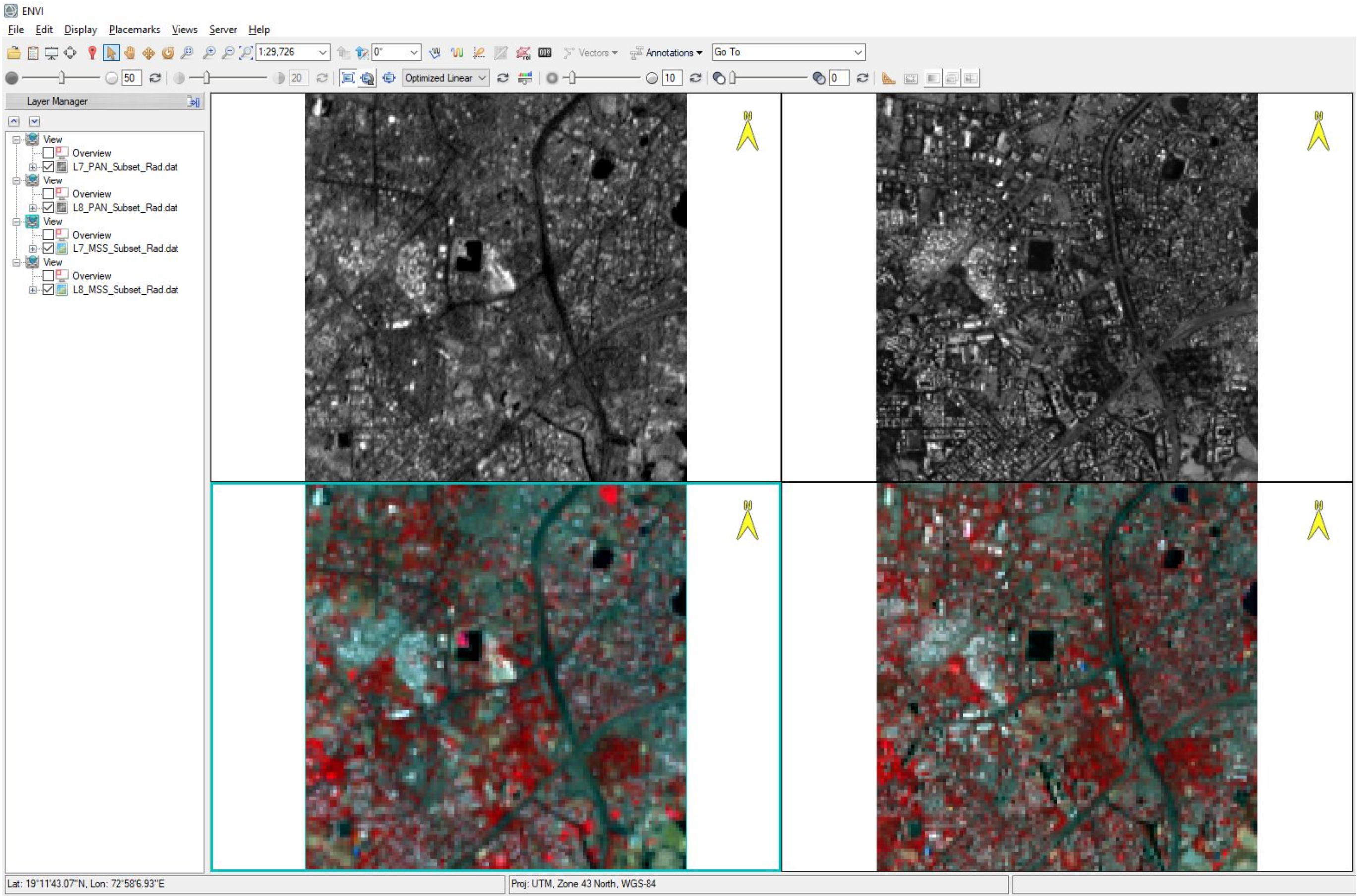
Radiometric calibration (Radiance)



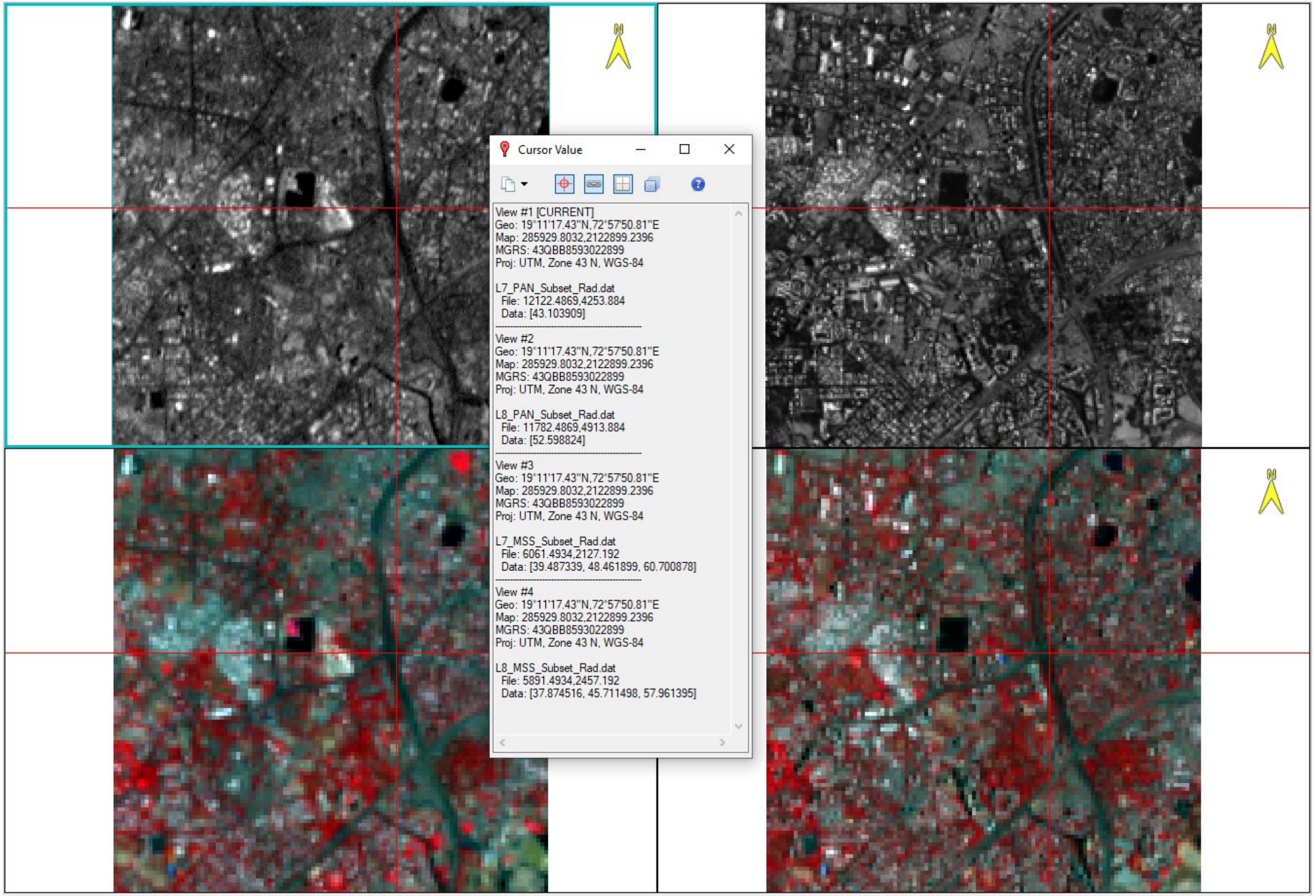


Repeat this process for subset images (PAN, MSS) of L7, L8.

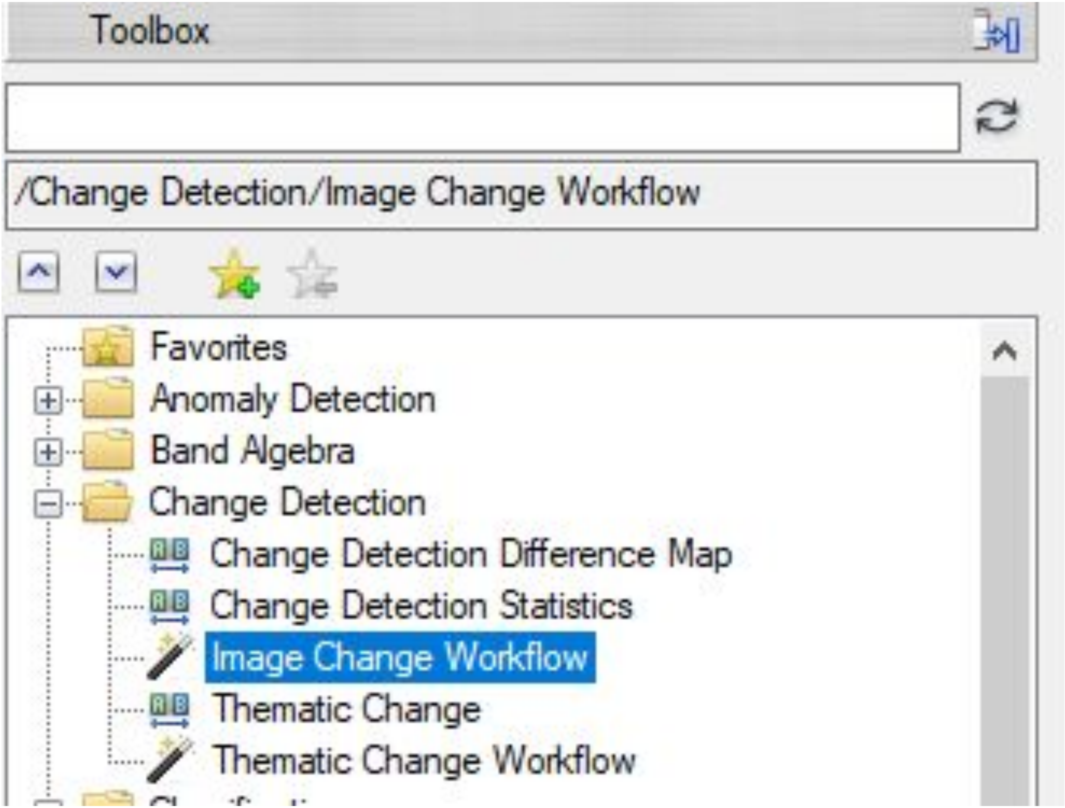
View input datasets



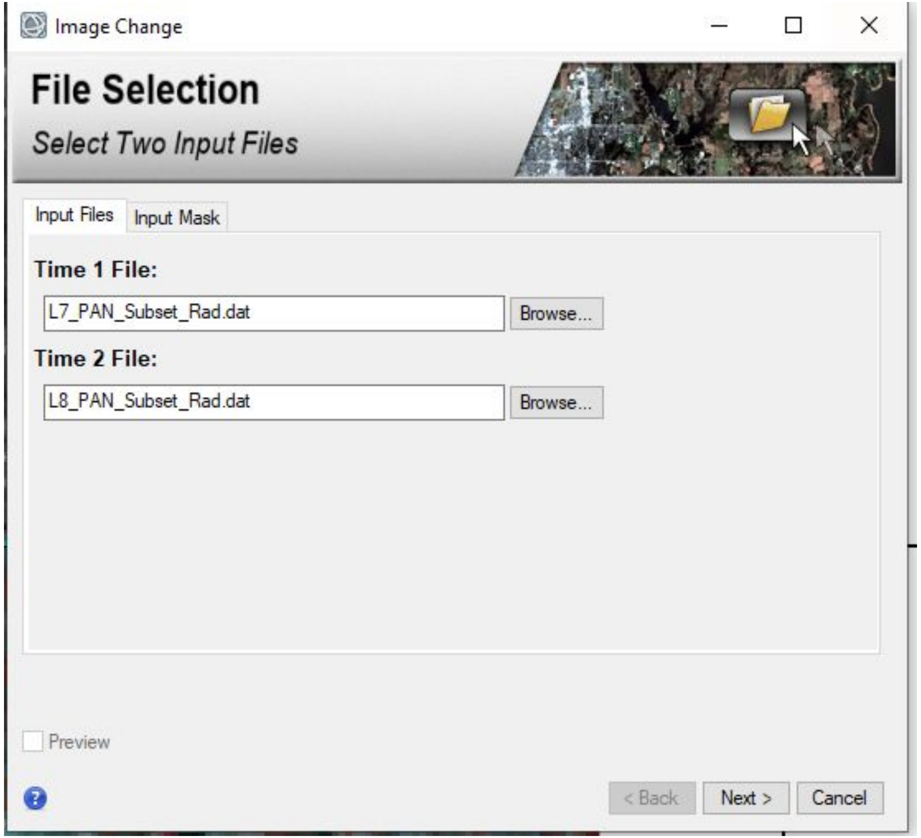
View cursor values

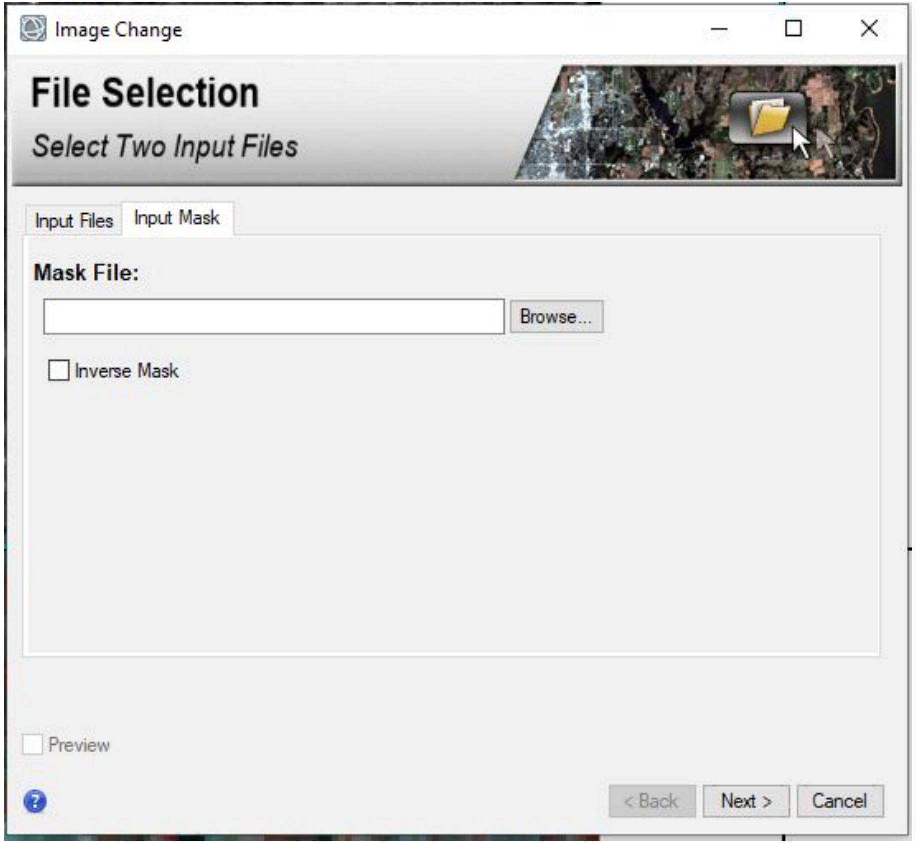


Change Detection with PAN images

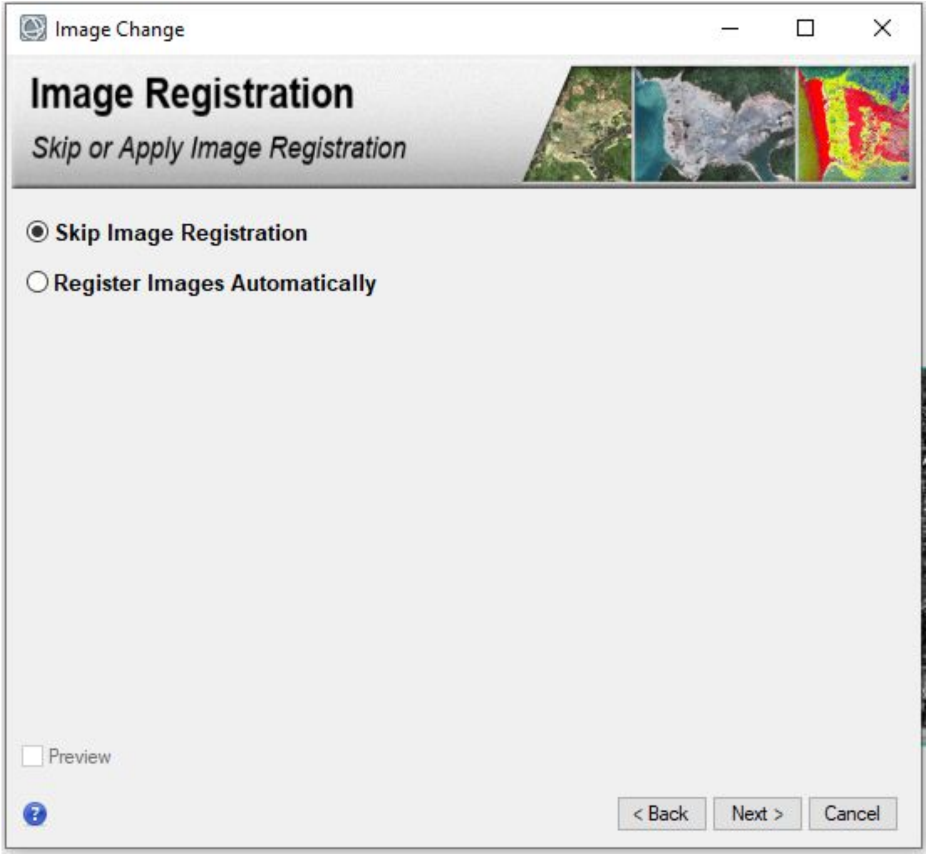


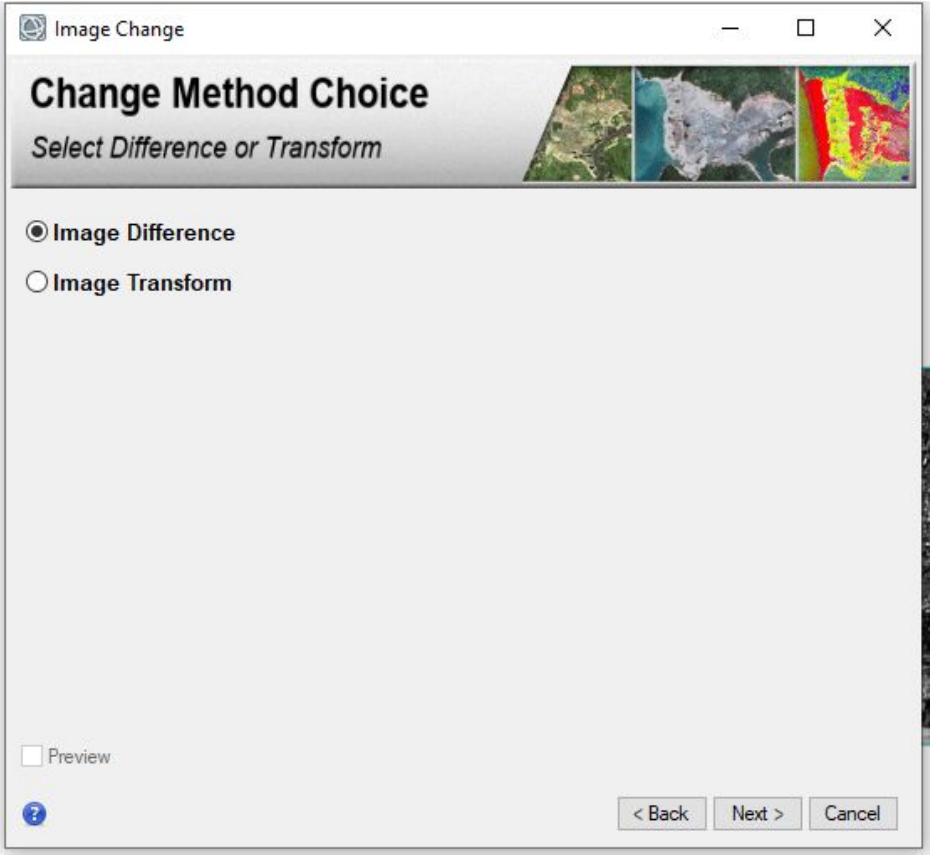
Change Detection with PAN images



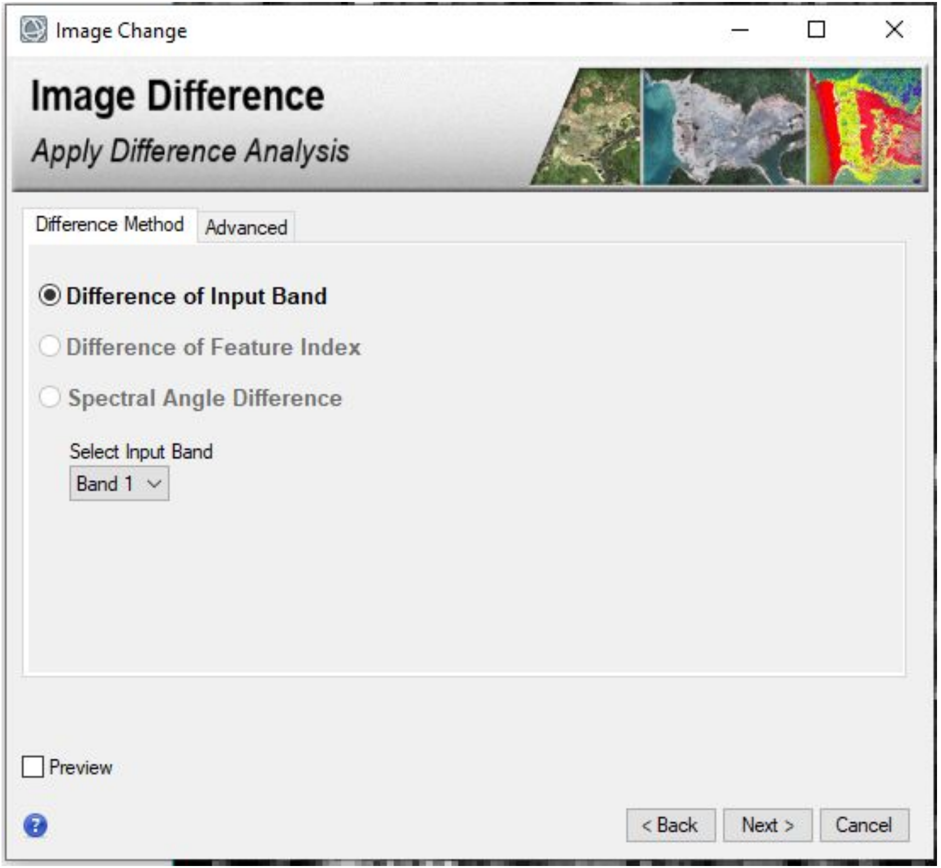


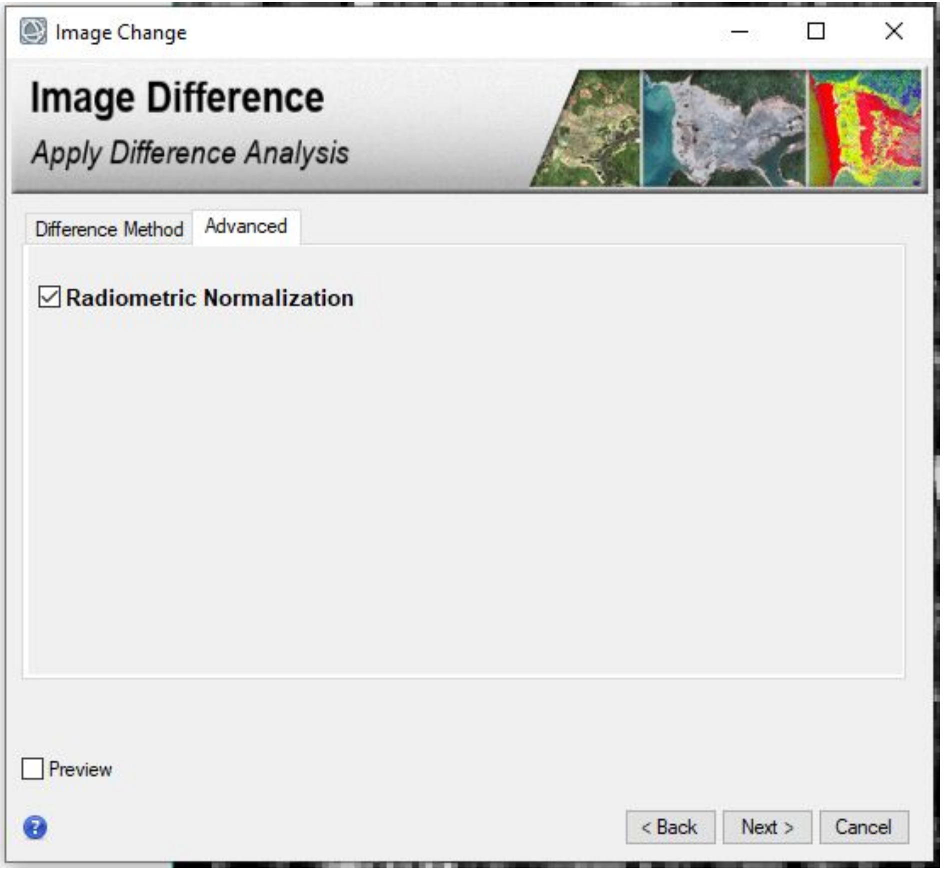
Change Detection with PAN images



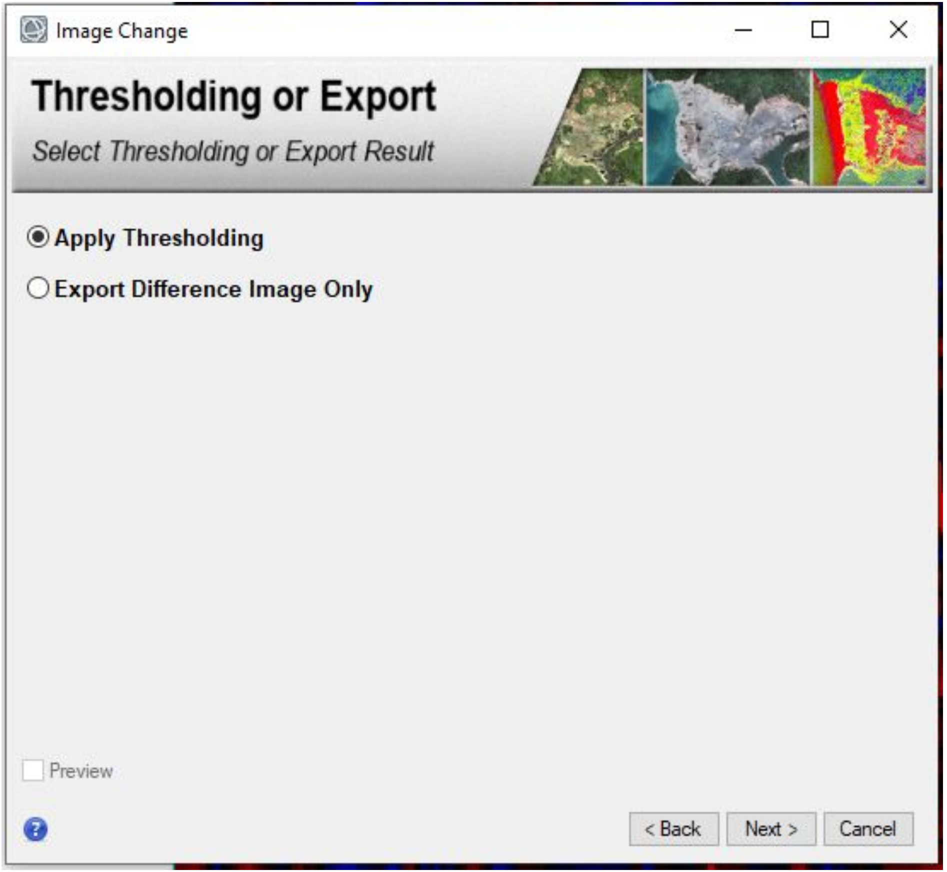


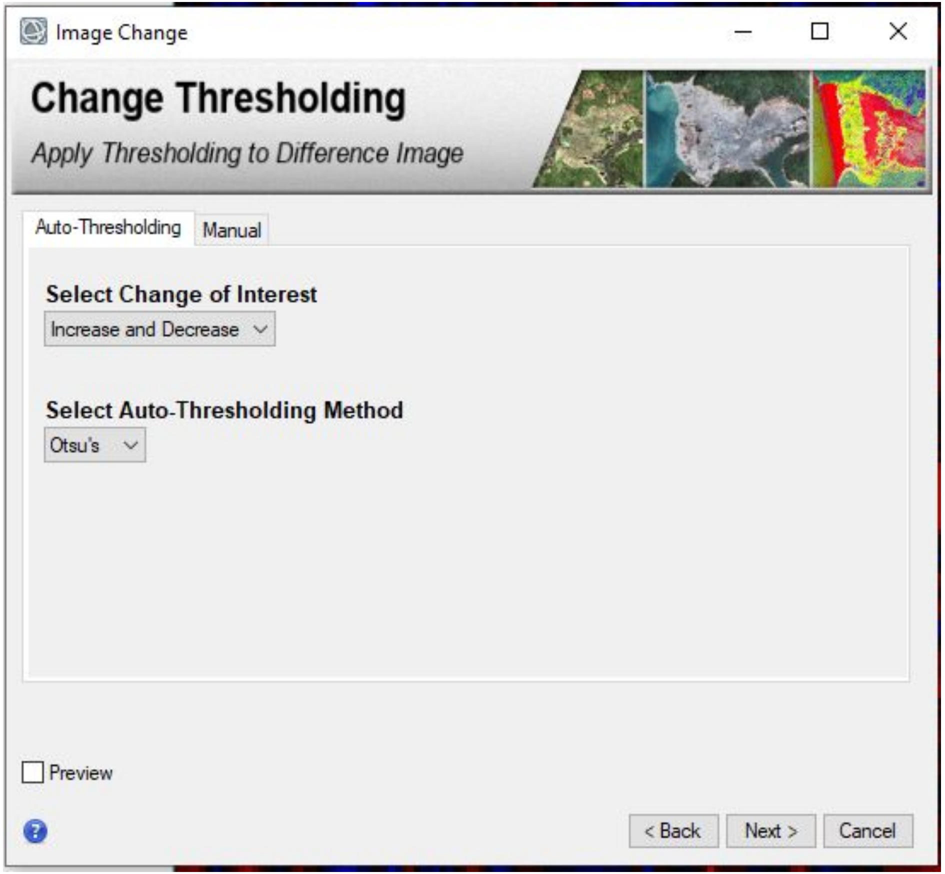
Change Detection with PAN images



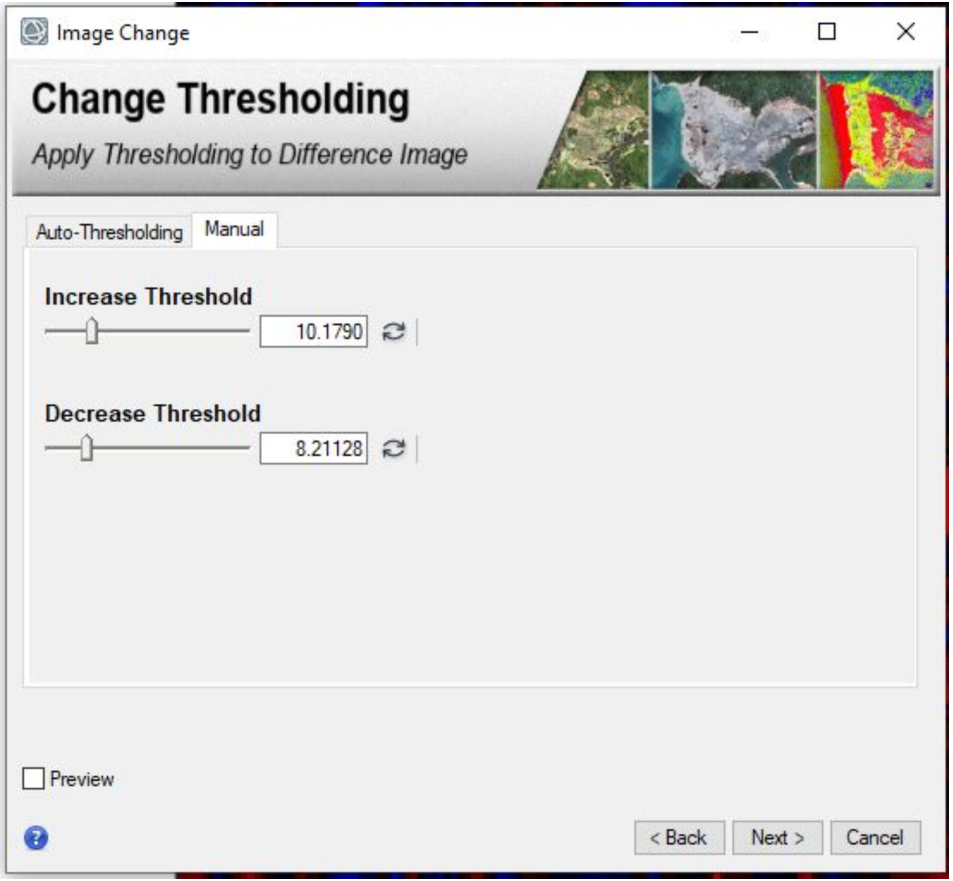


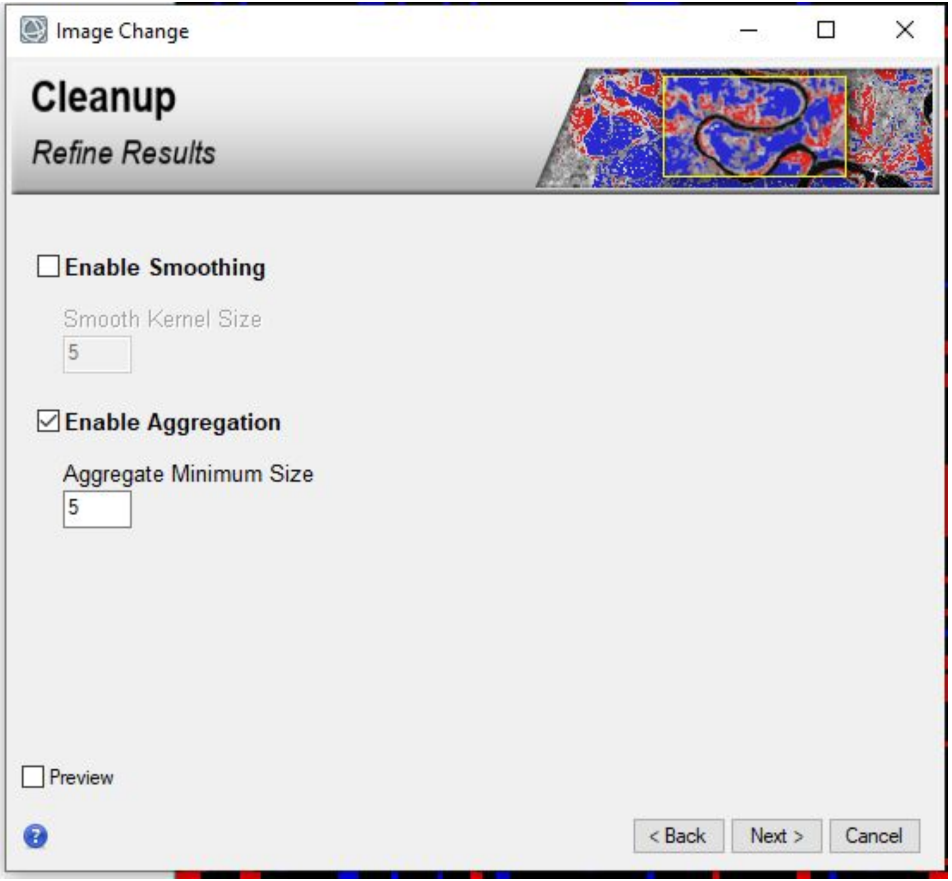
Change Detection with PAN images



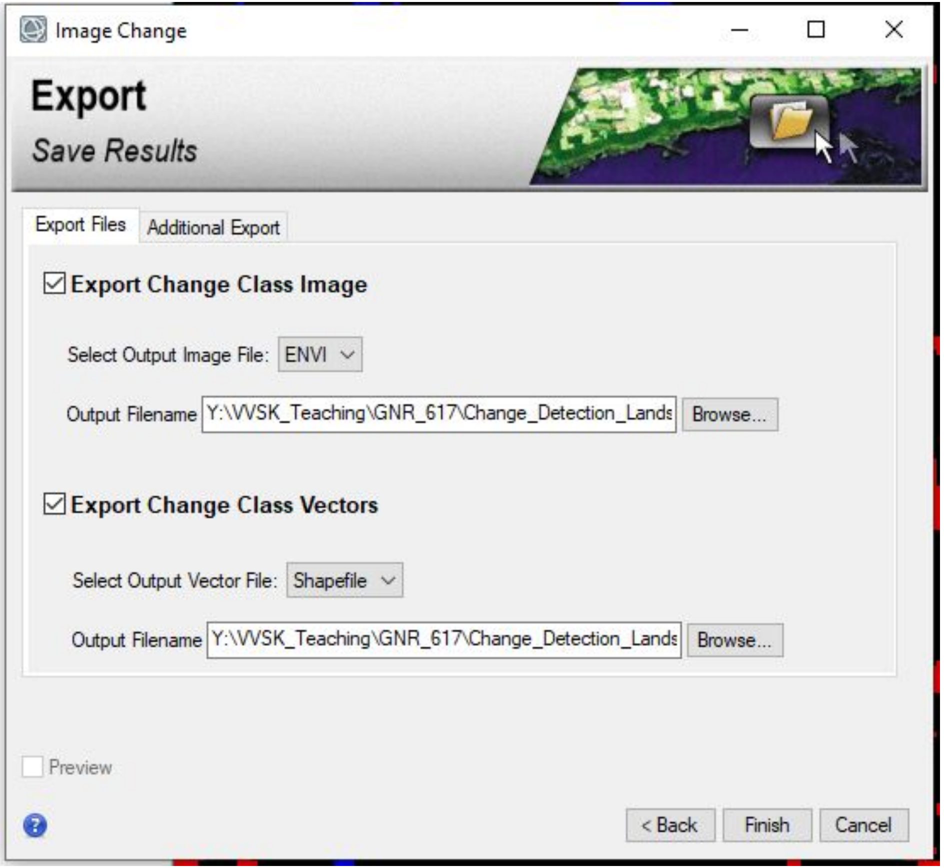


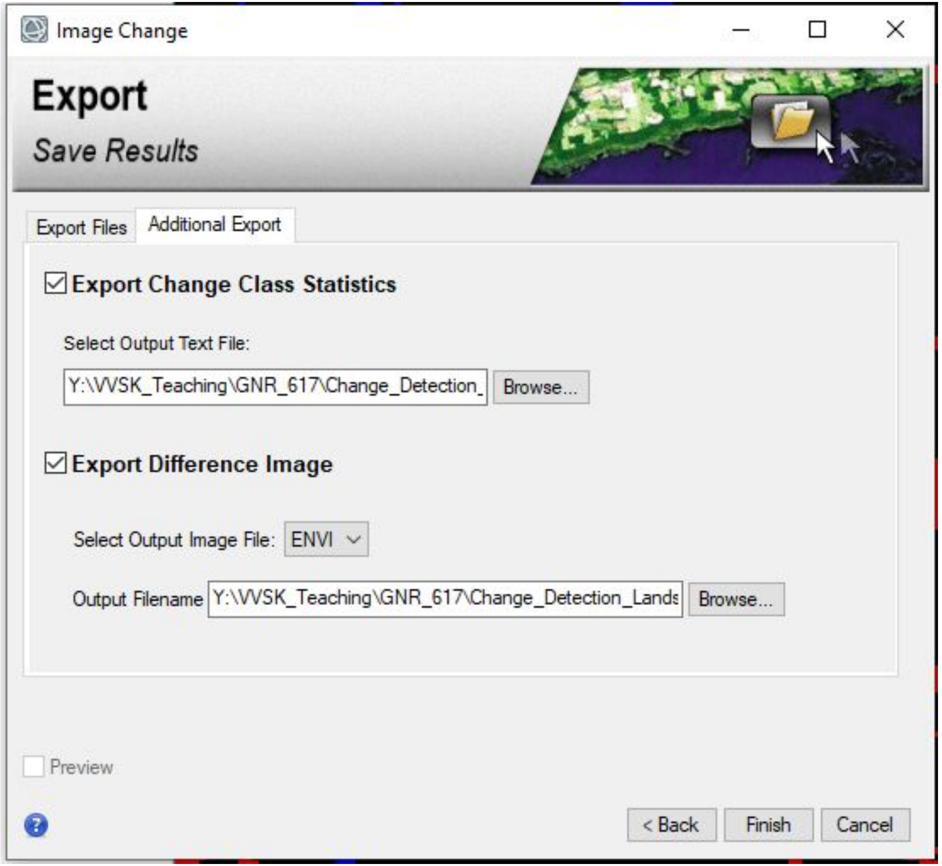
Change Detection with PAN images





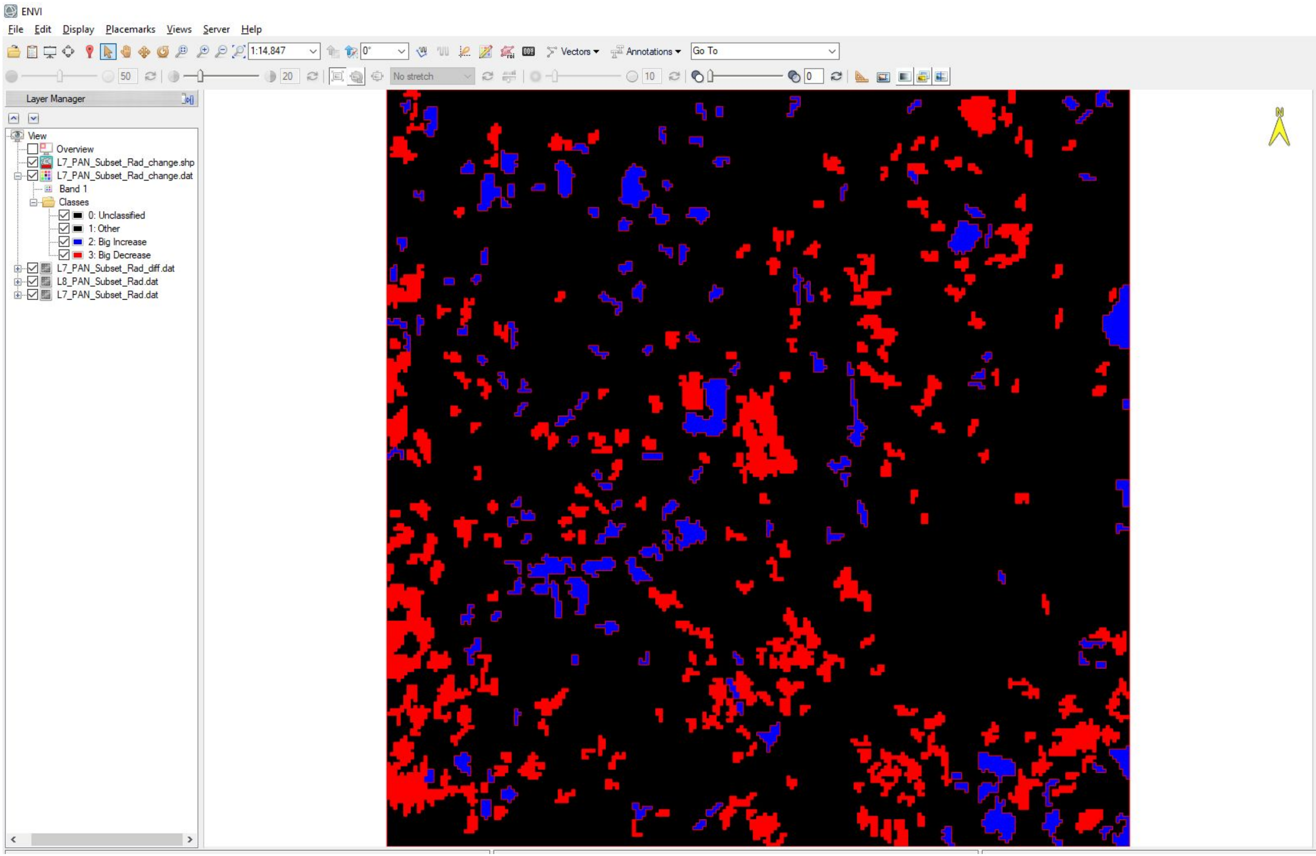
Change Detection with PAN images



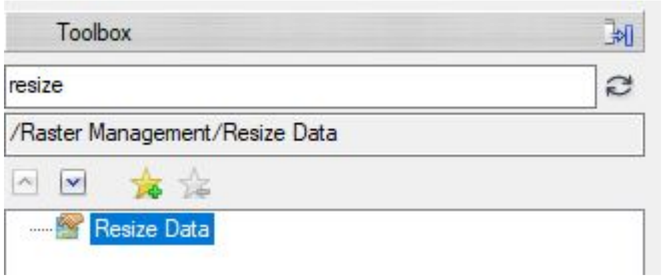


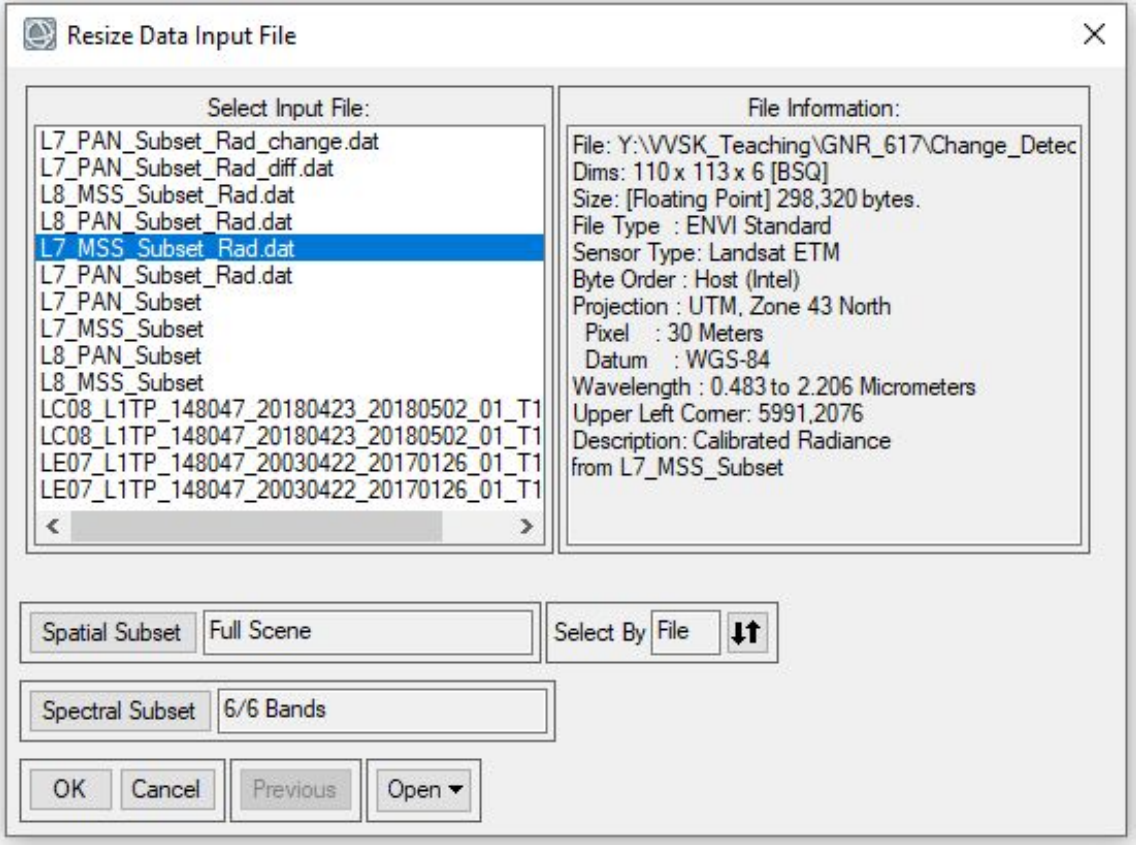
Change Detection with PAN images

The output represents the changes that happened from 2003 to 2015. The pixel values (radiance) may increase/decrease due to the changes happened on the earth surface. On the right side figure, the positive change is shown in blue colour and negative change is shown in red colour.

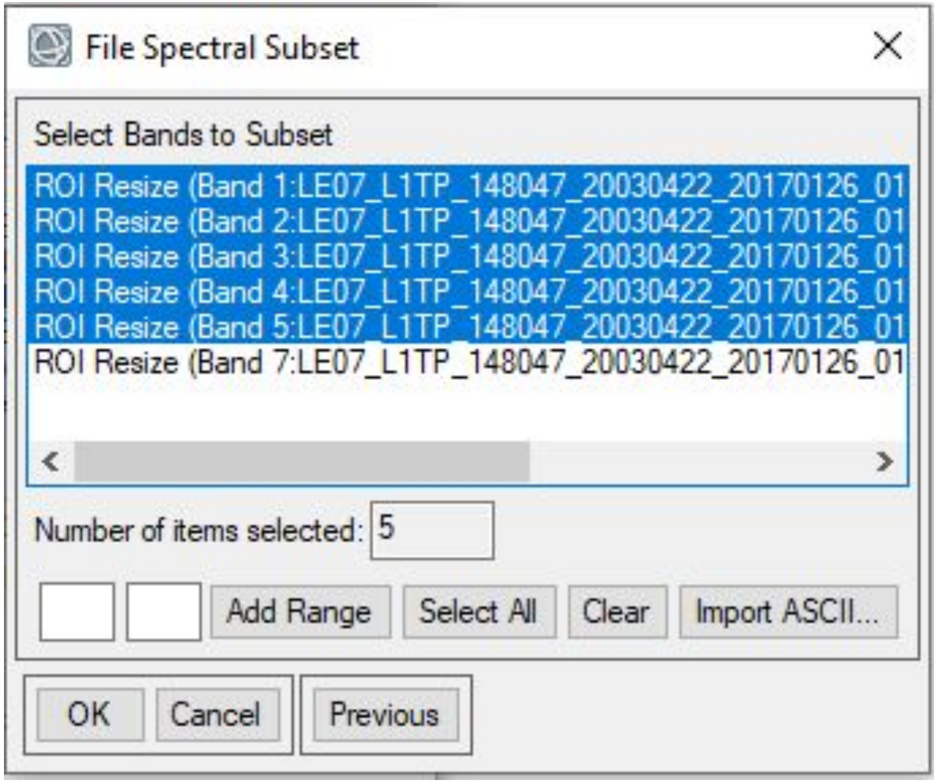


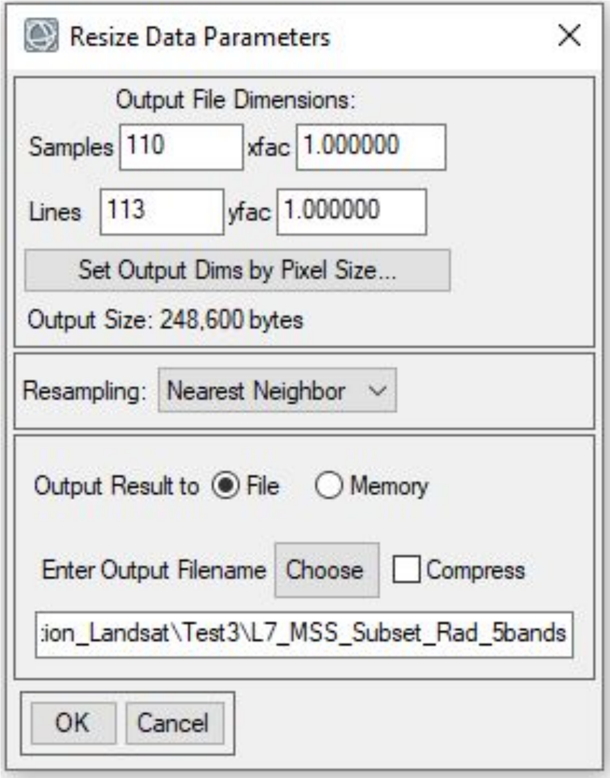
Spectral Subset (Landsat-7)



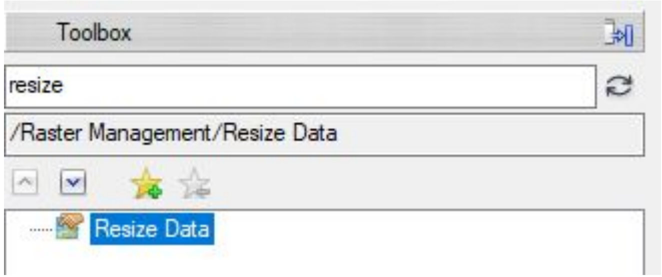


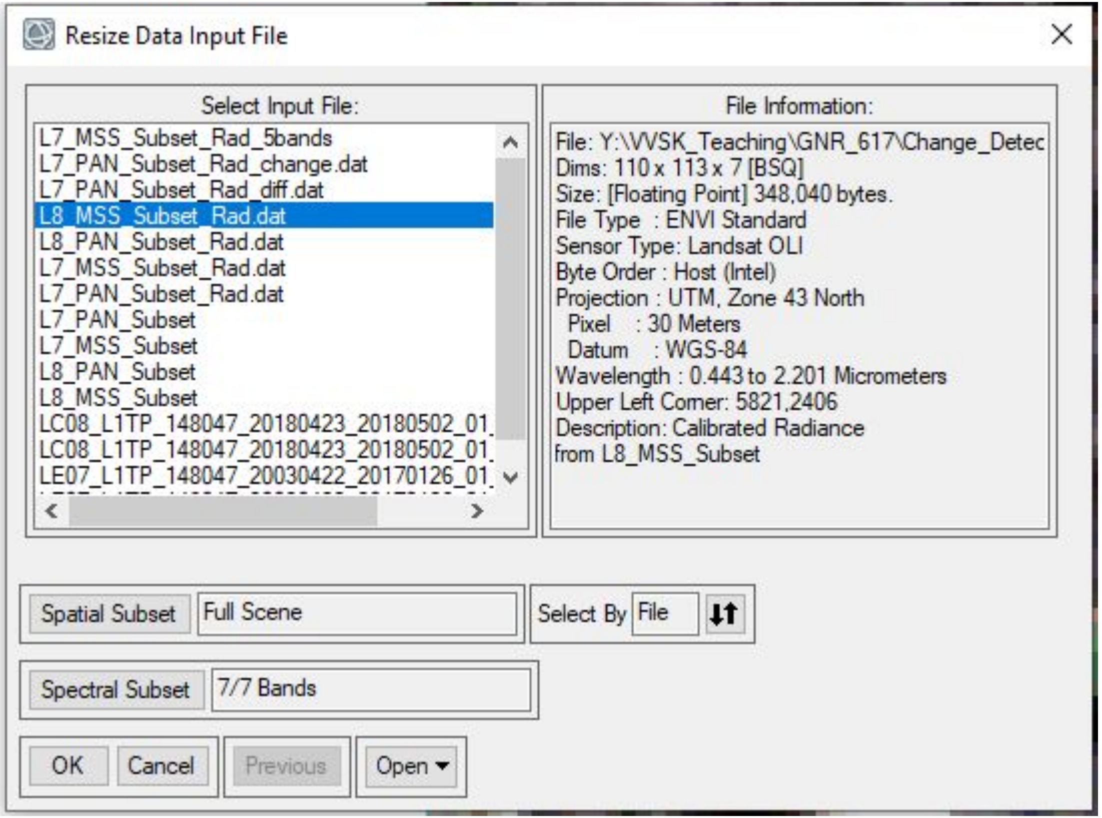
Spectral Subset (Landsat-7)



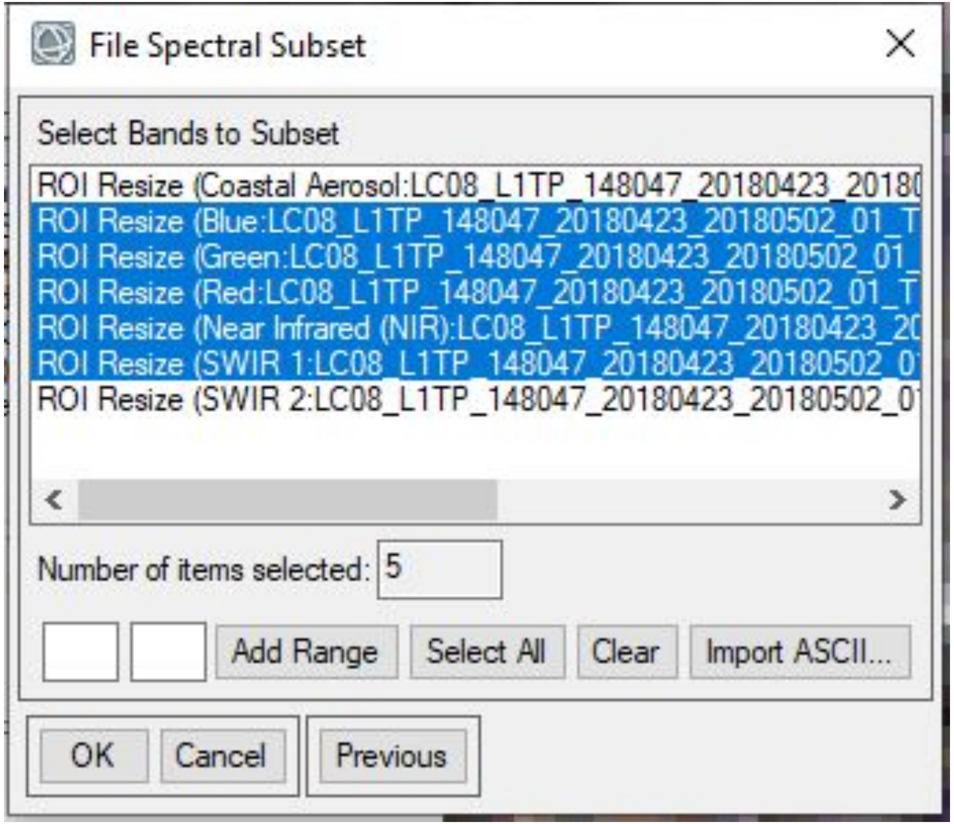


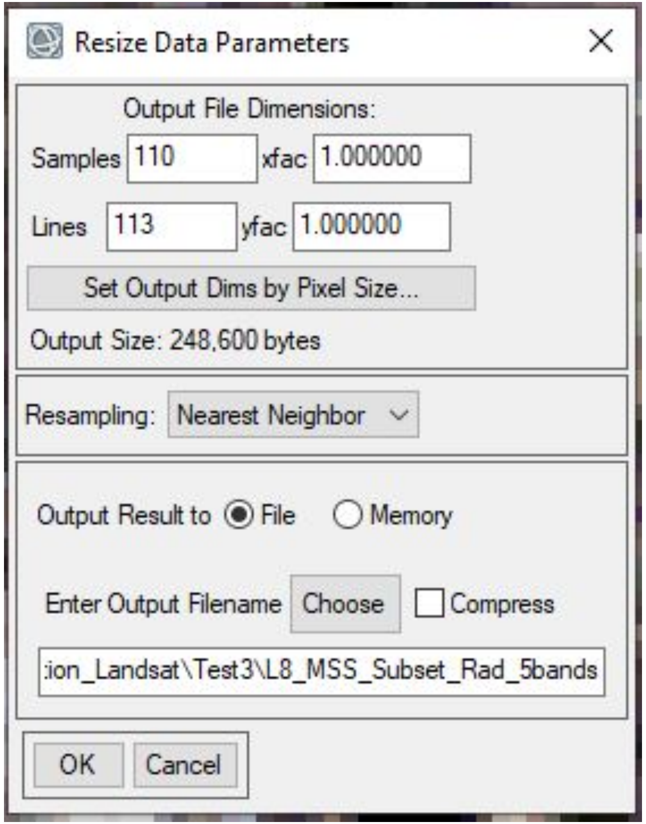
Spectral Subset (Landsat-8)



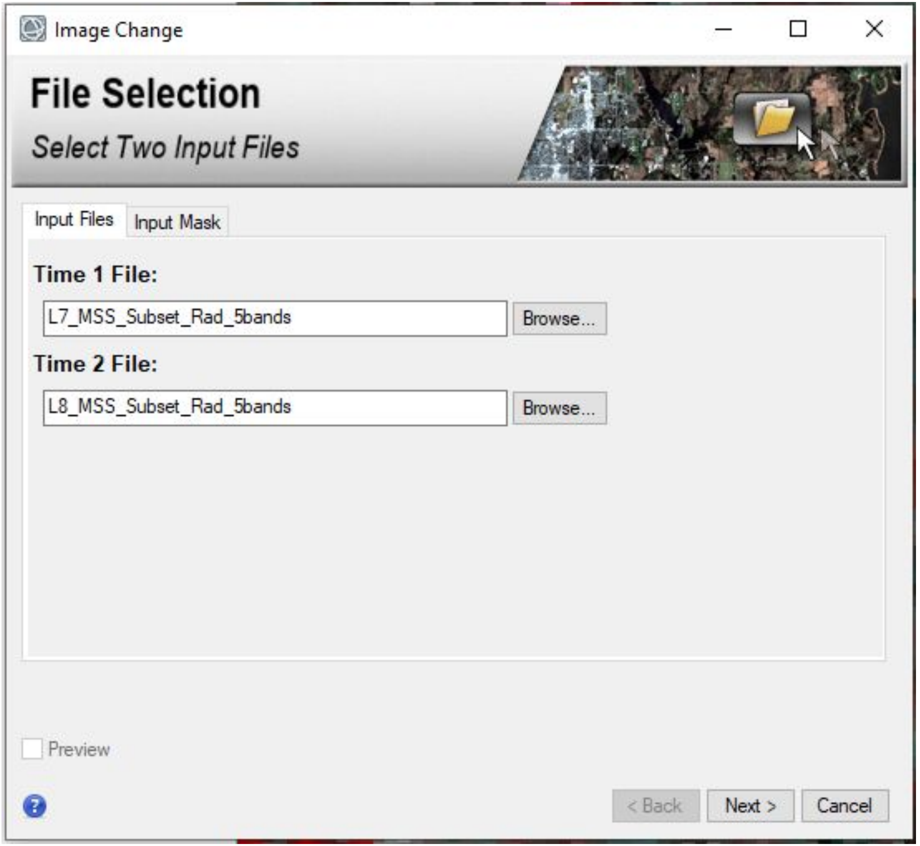


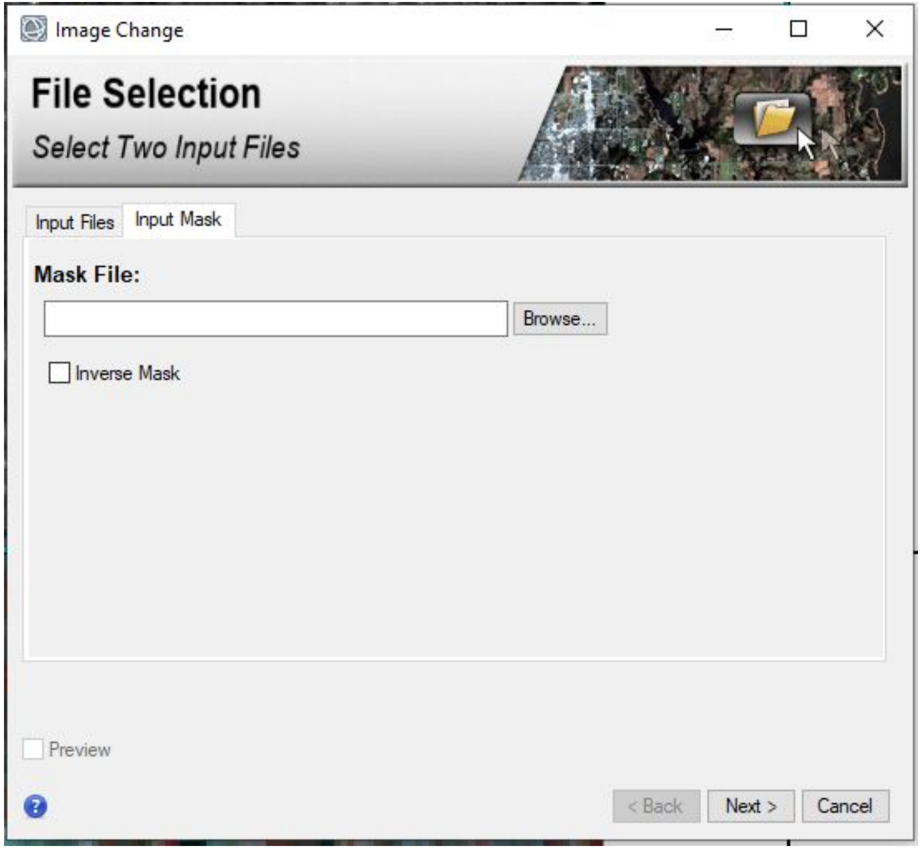
Spectral Subset (Landsat-8)



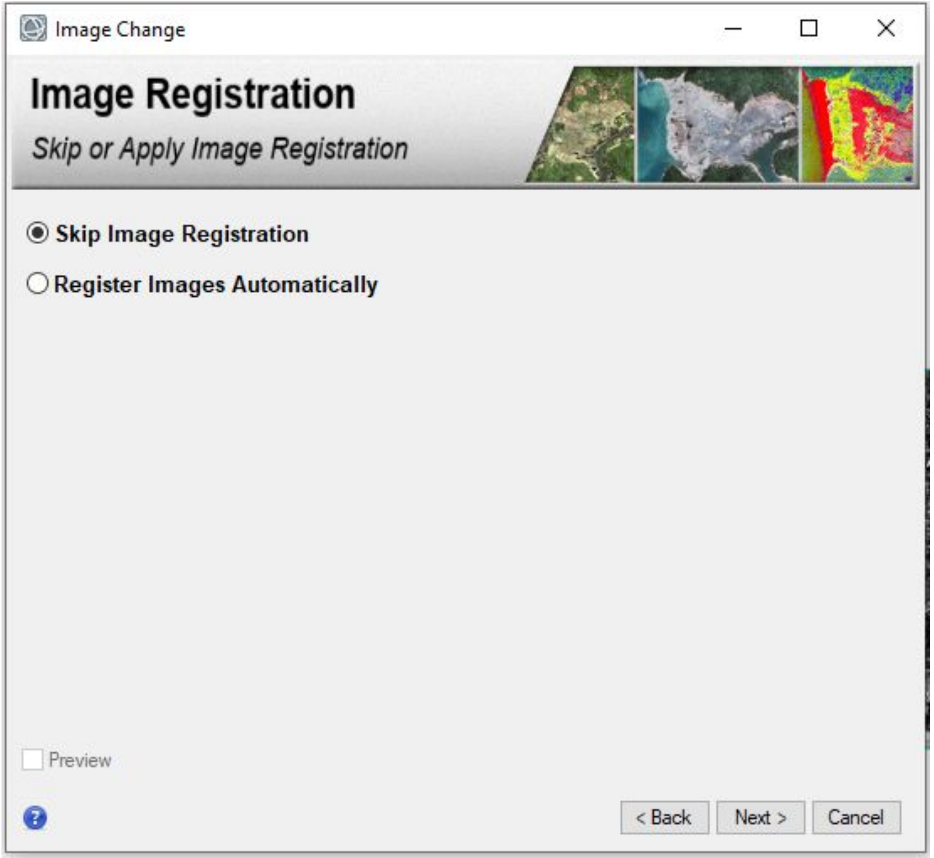


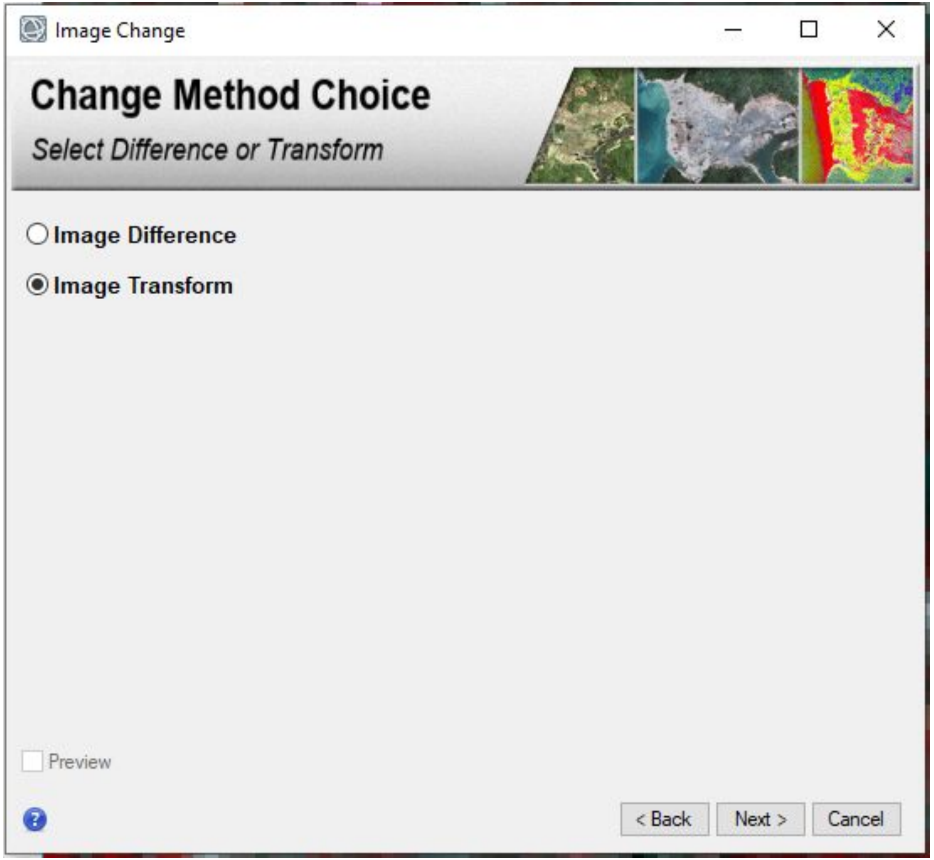
Change Change Detection with MSS images



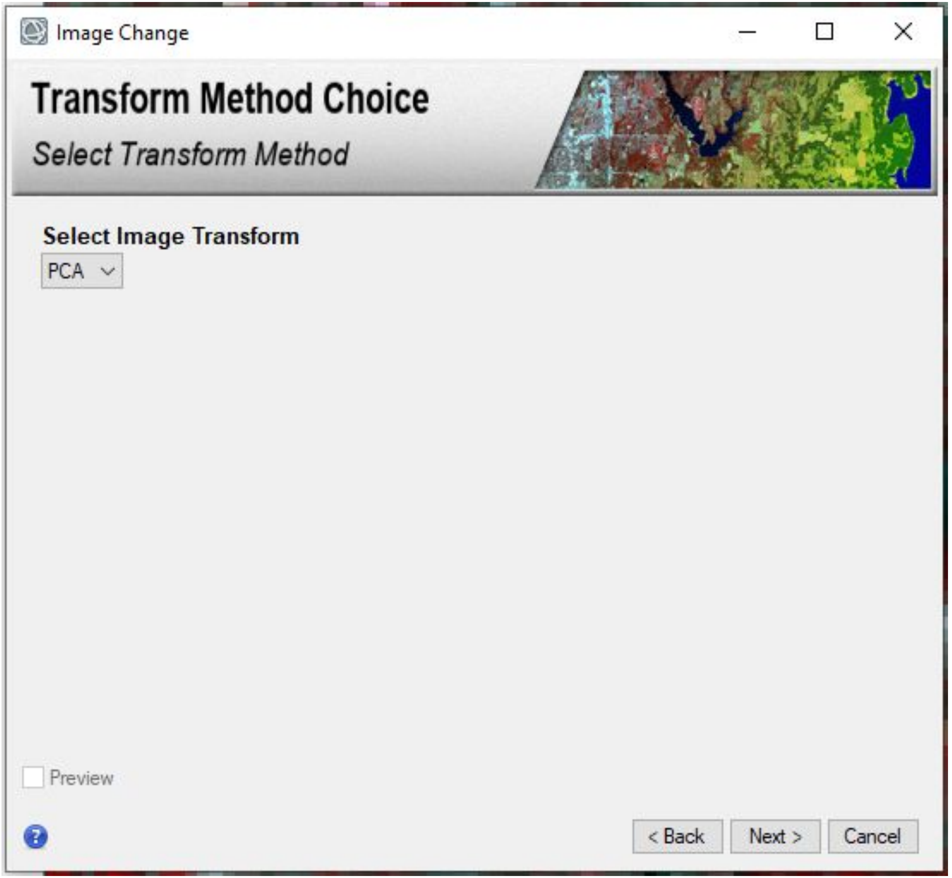


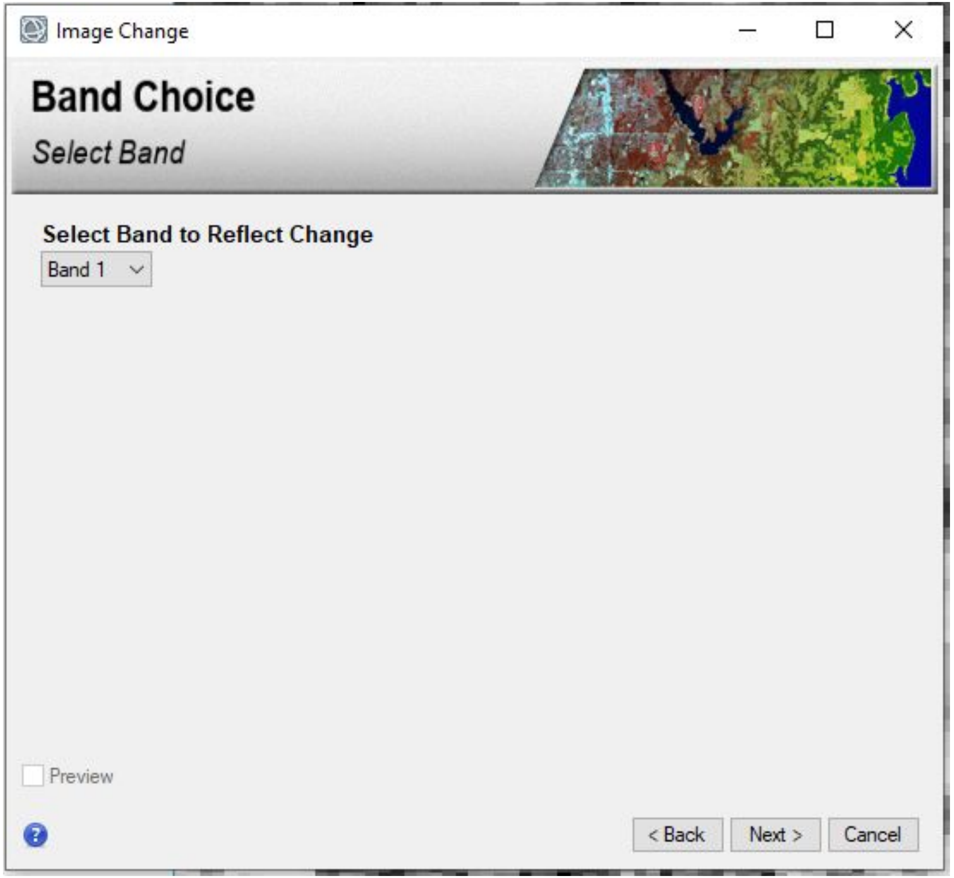
Change Change Detection with MSS images



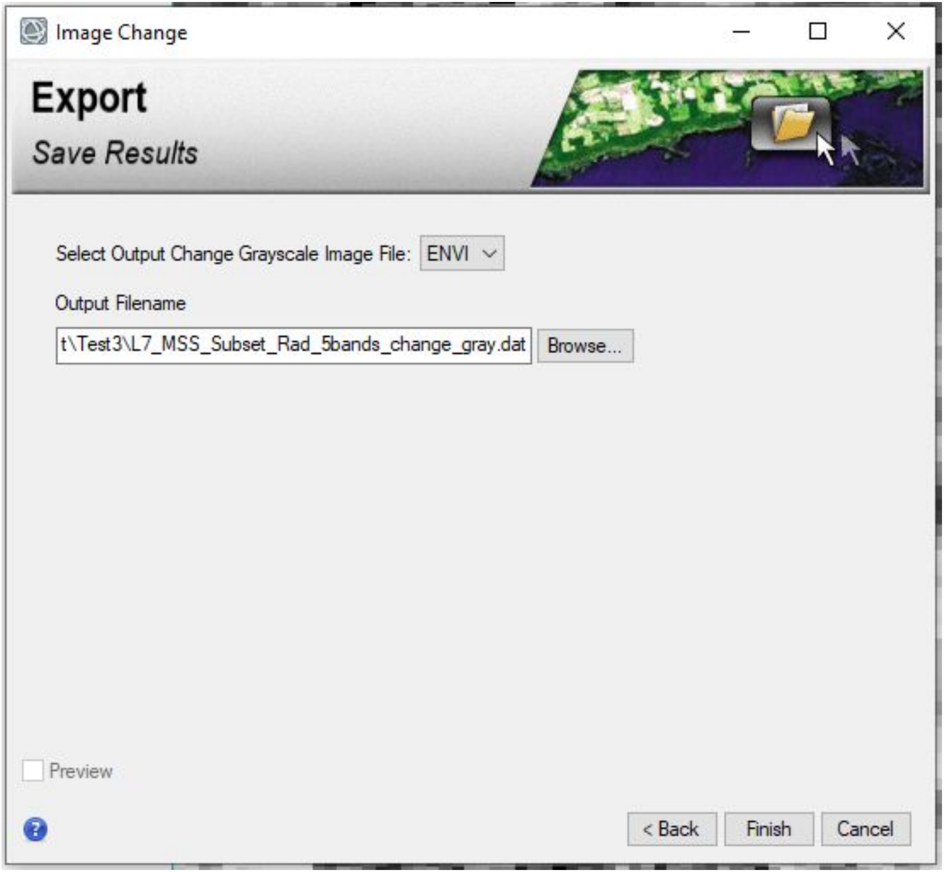


Change Change Detection with MSS images



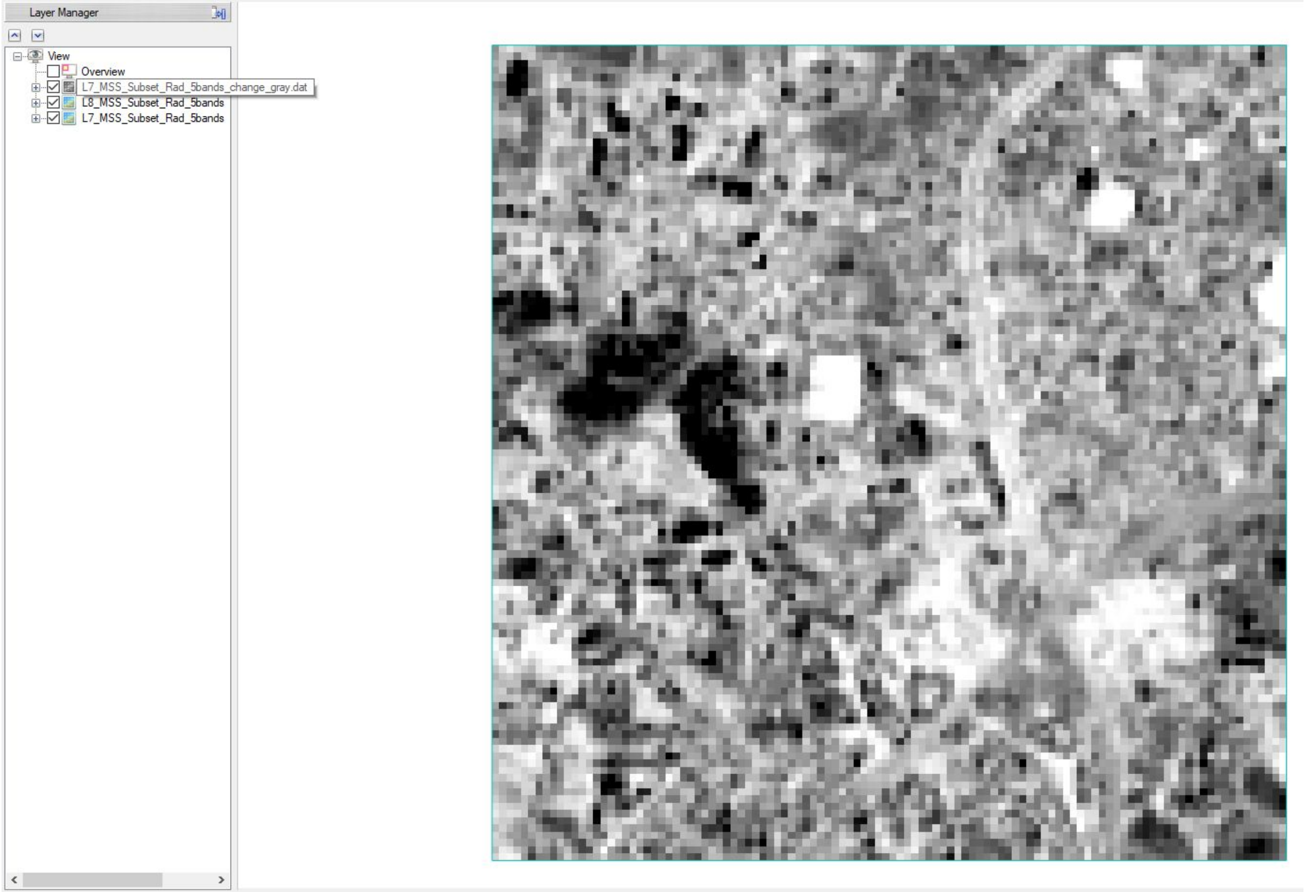


Change Change Detection with MSS images

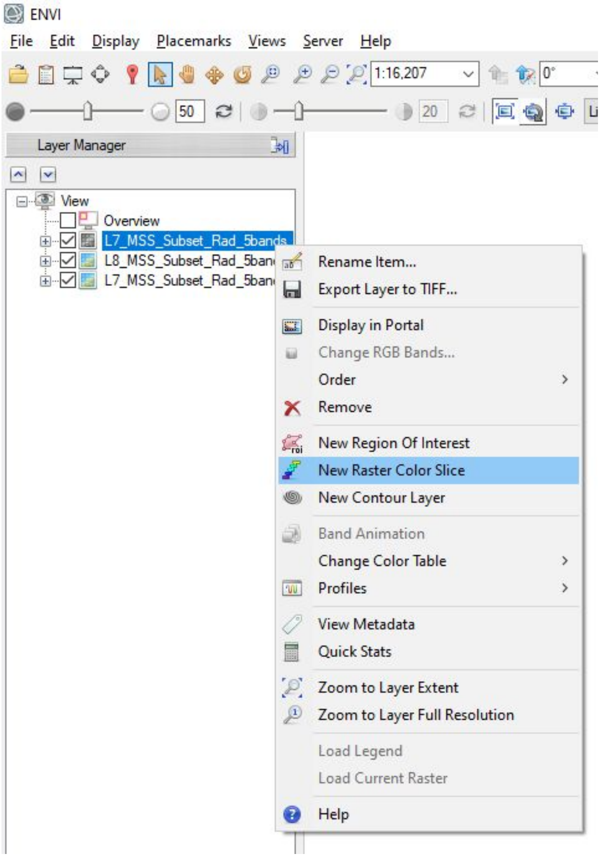


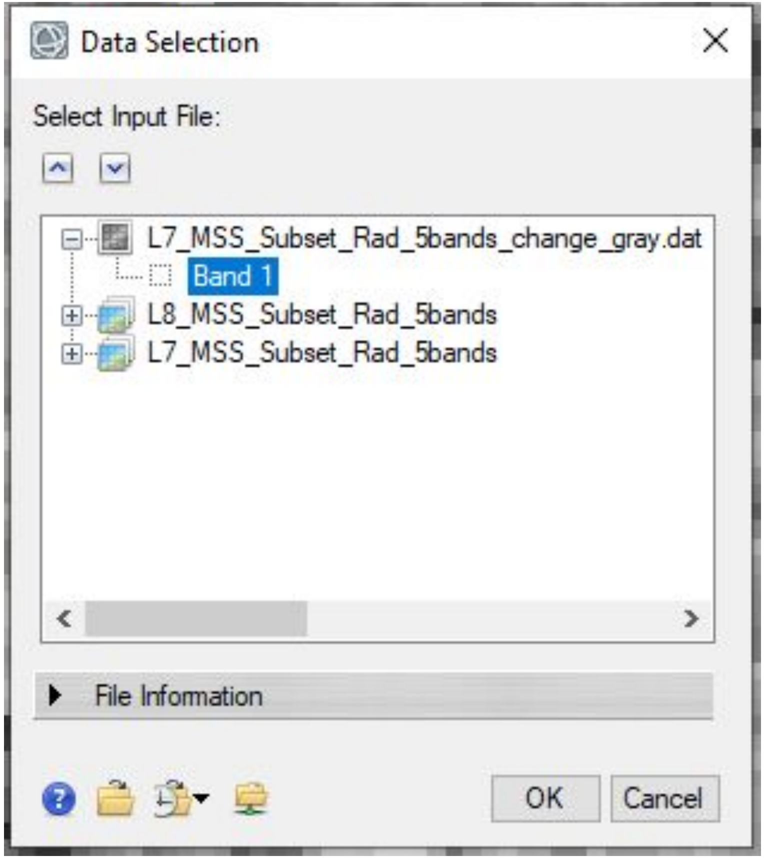
Change Change Detection with MSS images

The changes obtained using PCA method with respect to band 1 (blue) is shown here. Dark pixels show the negative changes and bright pixels show the positive change.

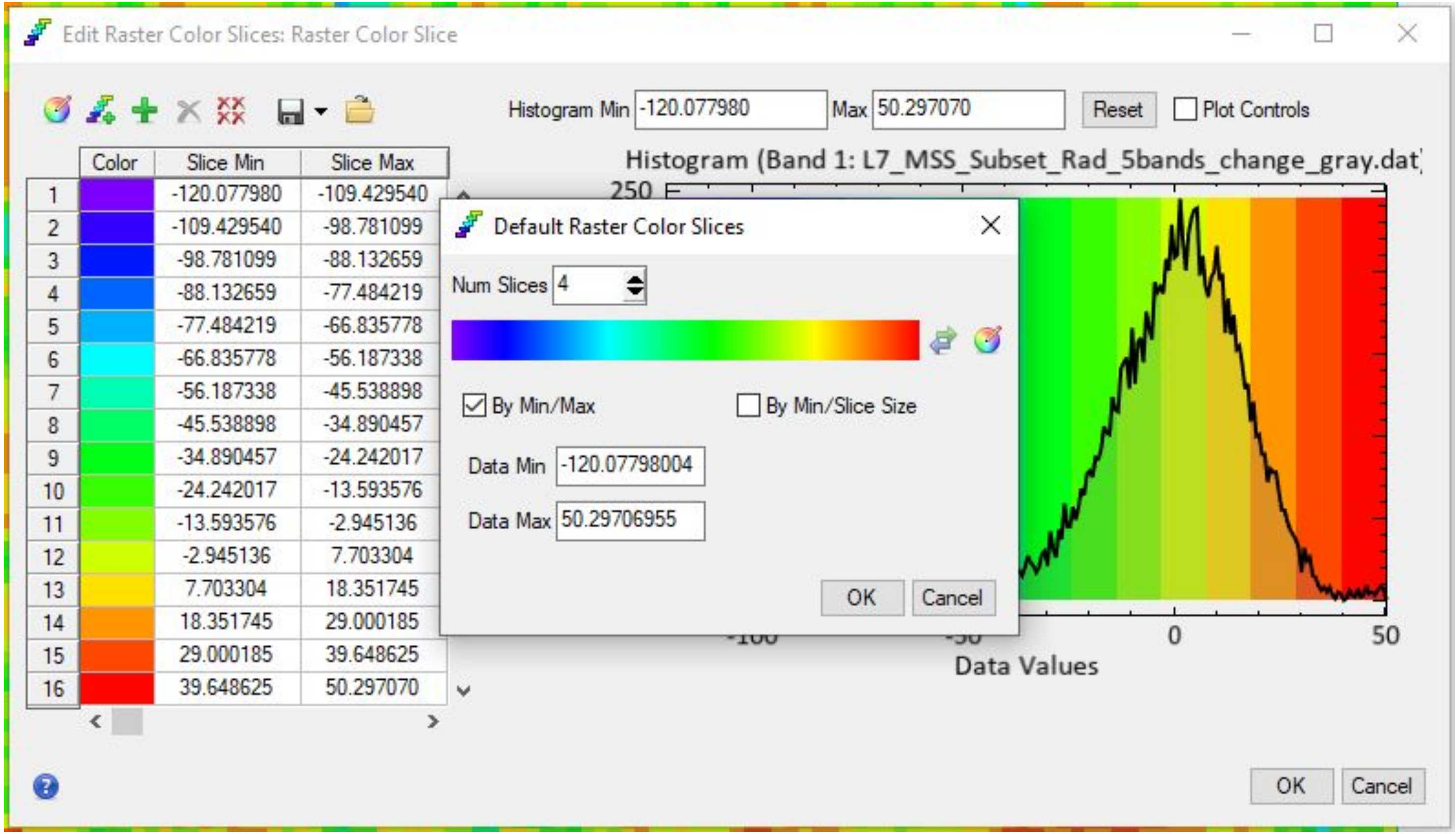


Change Change Detection with MSS images



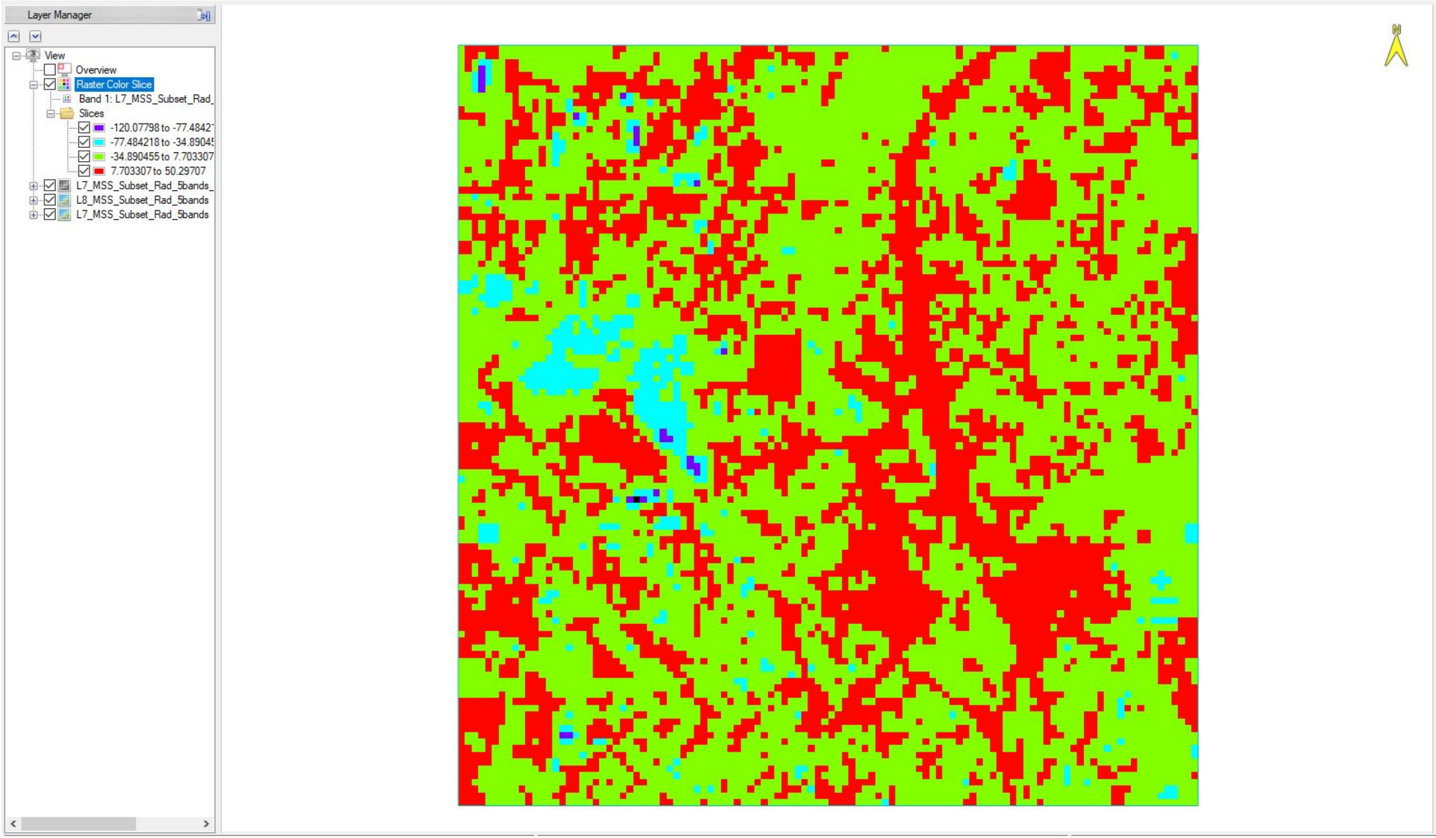


Change Change Detection with MSS images



Change Change Detection with MSS images

In PCA based change detection, the positive change is shown in red/green colour and the negative change is shown in cyan/purple colour. Comparingly, the image difference methods is providing better results. Also, the selection of the method is subjective to the research objectives.



Algorithm description

Otsu's Algorithm

II. Formulation

Let the pixels of a given picture be represented in L gray levels $[1, 2, \cdots, L]$. The number of pixels at level i is denoted by n_i and the total number of pixels by $N = n_1 + n_2 + \cdots + n_L$. In order to simplify the discussion, the gray-level histogram is normalized and regarded as a probability distribution:

$$p_i = n_i/N, \qquad p_i \geq 0, \sum_{i=1}^{L} p_i = 1. \tag{1}$$

Now suppose that we dichotomize the pixels into two classes C_0 and C_1 (background and objects, or vice versa) by a threshold at level k; C_0 denotes pixels with levels $[1, \cdots, k]$, and C_1 denotes pixels with levels $[k+1, \cdots, L]$. Then the probabilities of class occurrence and the class mean levels, respectively, are given by

$$\omega_0 = \Pr(C_0) = \sum_{i=1}^{k} p_i = \omega(k) \tag{2}$$

$$\omega_1 = \Pr(C_1) = \sum_{i=k+1}^{L} p_i = 1 - \omega(k) \tag{3}$$

and

$$\mu_0 = \sum_{i=1}^{k} i \Pr(i|C_0) = \sum_{i=1}^{k} ip_i/\omega_0 = \mu(k)/\omega(k) \tag{4}$$

$$\mu_1 = \sum_{i=k+1}^{L} i \Pr(i|C_1) = \sum_{i=k+1}^{L} ip_i/\omega_1 = \frac{\mu_T - \mu(k)}{1 - \omega(k)}, \tag{5}$$

where

$$\omega(k) = \sum_{i=1}^{k} p_i \tag{6}$$

and

$$\mu(k) = \sum_{i=1}^{k} ip_i \tag{7}$$

are the zeroth- and the first-order cumulative moments of the histogram up to the kth level, respectively, and

$$\mu_T = \mu(L) = \sum_{i=1}^{L} ip_i \tag{8}$$

is the total mean level of the original picture. We can easily verify the following relation for any choice of k:

$$\omega_0\mu_0 + \omega_1\mu_1 = \mu_T, \qquad \omega_0 + \omega_1 = 1. \tag{9}$$

The class variances are given by

$$\sigma_0^2 = \sum_{i=1}^{k} (i - \mu_0)^2 \Pr(i|C_0) = \sum_{i=1}^{k} (i - \mu_0)^2 p_i/\omega_0 \tag{10}$$

$$\sigma_1^2 = \sum_{i=k+1}^{L} (i - \mu_1)^2 \Pr(i|C_1) = \sum_{i=k+1}^{L} (i - \mu_1)^2 p_i/\omega_1. \tag{11}$$

Otsu's Algorithm

These require second-order cumulative moments (statistics).

In order to evaluate the "goodness" of the threshold (at level k), we shall introduce the following discriminant criterion measures (or measures of class separability) used in the discriminant analysis [5]:

$$\lambda = \sigma_B^2/\sigma_W^2, \qquad \kappa = \sigma_T^2/\sigma_W^2, \qquad \eta = \sigma_B^2/\sigma_T^2, \tag{12}$$

where

$$\sigma_W^2 = \omega_0\sigma_0^2 + \omega_1\sigma_1^2 \tag{13}$$

$$\sigma_B^2 = \omega_0(\mu_0 - \mu_T)^2 + \omega_1(\mu_1 - \mu_T)^2$$
$$= \omega_0\omega_1(\mu_1 - \mu_0)^2 \tag{14}$$

(due to (9)) and

$$\sigma_T^2 = \sum_{i=1}^{L} (i - \mu_T)^2 p_i \tag{15}$$

are the within-class variance, the between-class variance, and the total variance of levels, respectively. Then our problem is reduced to an optimization problem to search for a threshold k that maximizes one of the object functions (the criterion measures) in (12).

The optimal threshold k^* that maximizes η, or equivalently maximizes σ_B^2, is selected in the following sequential search by using the simple cumulative quantities (6) and (7), or explicitly using (2)–(5):

$$\eta(k) = \sigma_B^2(k)/\sigma_T^2 \tag{17}$$

$$\sigma_B^2(k) = \frac{[\mu_T\omega(k) - \mu(k)]^2}{\omega(k)[1 - \omega(k)]} \tag{18}$$

and the optimal threshold k^* is

$$\sigma_B^2(k^*) = \max_{1 \le k < L} \sigma_B^2(k). \tag{19}$$

From the problem, the range of k over which the maximum is sought can be restricted to

$$S^* = \{k;\ \omega_0\omega_1 = \omega(k)[1 - \omega(k)] > 0, \qquad \text{or } 0 < \omega(k) < 1\}.$$

We shall call it the effective range of the gray-level histogram. From the definition in (14), the criterion measure σ_B^2 (or η) takes a minimum value of zero for such k as $k \in S - S^* = \{k; \omega(k) = 0$ or $1\}$ (i.e., making all pixels either C_1 or C_0, which is, of course, not our concern) and takes a positive and bounded value for $k \in S^*$. It is, therefore, obvious that the maximum always exists.

Otsu's Algorithm

Assumptions:

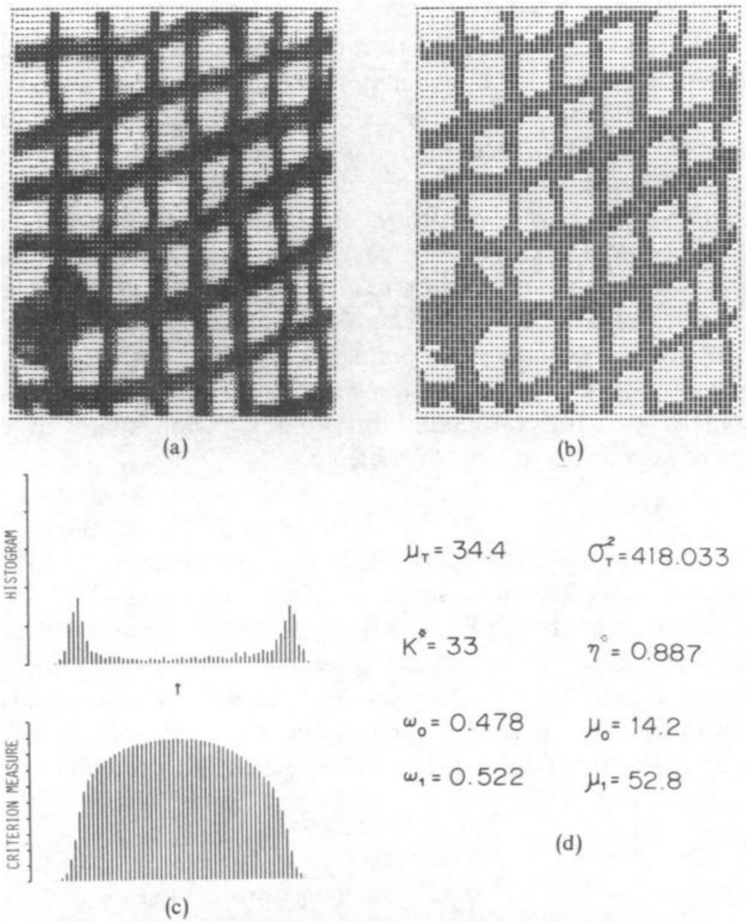
- Class density function - Gaussian
- Similar class sizes and variances

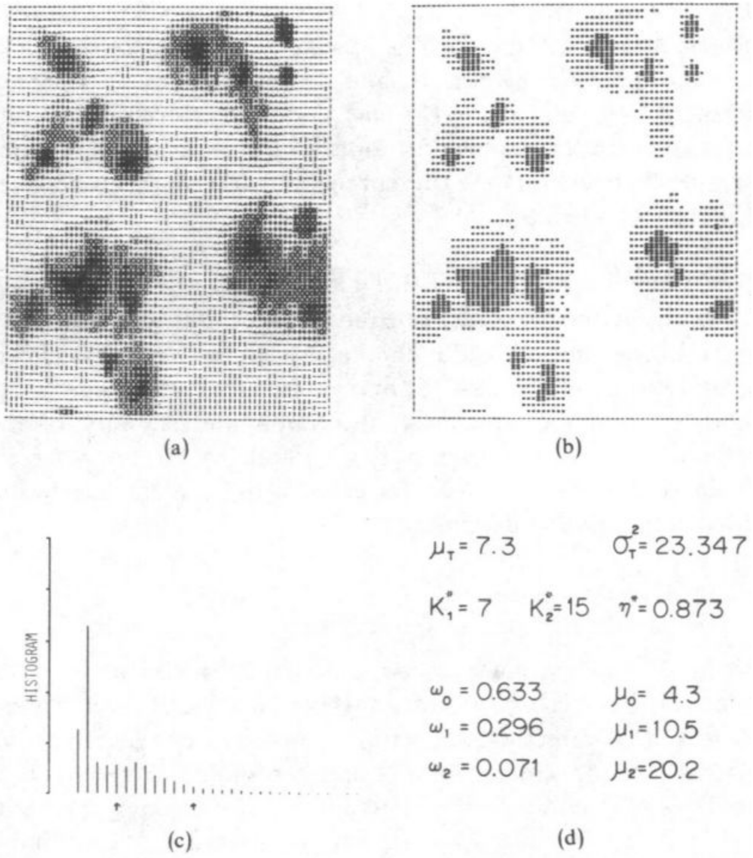
If violated,

- Split the class of the larger size or variance

A skewed density fn or the presence of outliers will cause a bias in the calculated class means

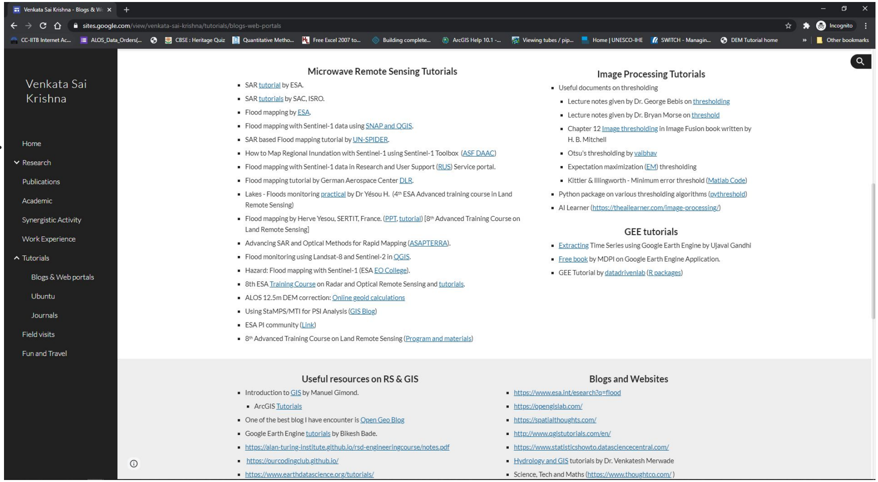
Otsu’s Algorithm





Useful Resources

- Global Exposure Analysis on Floods/Drought and Poverty (Slides)
- Flood mapping by ESA.
- Flood mapping with Sentinel-1 data using SNAP and QGIS.
- SAR based Flood mapping tutorial by UN-SPIDER.
- How to Map Regional Inundation with Sentinel-1 using Sentinel-1 Toolbox (ASF DAAC)
- Flood mapping with Sentinel-1 data in Research and User Support (RUS) Service portal.
- Flood mapping tutorial by German Aerospace Center DLR.
- Lakes - Floods monitoring practical by Dr Yésou H. (4th ESA Advanced training course in Land Remote Sensing)
- Flood mapping by Herve Yesou, SERTIT, France. (PPT, tutorial) [8th Advanced Training Course on Land Remote Sensing]
- Advancing SAR and Optical Methods for Rapid Mapping (ASAPTERRA).
- Flood monitoring using Landsat-8 and Sentinel-2 in QGIS.
- Hazard: Flood mapping with Sentinel-1 (ESA EO College).
- 8th ESA Training Course on Radar and Optical Remote Sensing and tutorials.



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Thank you