Jinal Vyas 1233053785 Part - 1 Data Preparation Report

```
# Here, I am using the data of bands 3 to 7 from Landsat-8 of NASA over the Alaska Mendanhall Glacier

# The product I am using is Landsat 8 OLI/TIRS Collection 2 atmospherically corrected surface reflect
# the raw reflectance values can be influenced by the time of day, weather conditions, and the atmosp

# For the EDA representation purpose, I am taking the data of two months from 1st October 2023 to 1st
# Landsat collects images every 16 days, but here I have derived the images after applying cloud mask
# I have performed EDA on the tif file I derived from the median of pixels from two months of the abo
# In the next stage I will replicate this processing on data files of more years and perform segmenta
```

```
# Rasterio is a Python library used for reading, writing, and processing raster data, typically in Ge
!pip install rasterio
```

```
Collecting rasterio
  Downloading rasterio-1.4.2-cp310-cp310-manylinux_2_17_x86_64.manylinux2014_x86_64.whl.metadata (9.1 kB
Collecting affine (from rasterio)
  Downloading affine-2.4.0-py3-none-any.whl.metadata (4.0 kB)
Requirement already satisfied: attrs in /usr/local/lib/python3.10/dist-packages (from rasterio) (24.2.0)
Requirement already satisfied: certifi in /usr/local/lib/python3.10/dist-packages (from rasterio) (2024.8
Requirement already satisfied: click>=4.0 in /usr/local/lib/python3.10/dist-packages (from rasterio) (8.1
Collecting cligj>=0.5 (from rasterio)
  Downloading cligj-0.7.2-py3-none-any.whl.metadata (5.0 kB)
Requirement already satisfied: numpy>=1.24 in /usr/local/lib/python3.10/dist-packages (from rasterio) (1
Collecting click-plugins (from rasterio)
  Downloading click_plugins-1.1.1-py2.py3-none-any.whl.metadata (6.4 kB)
Requirement already satisfied: pyparsing in /usr/local/lib/python3.10/dist-packages (from rasterio) (3.2
Downloading rasterio-1.4.2-cp310-cp310-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (22.2 MB)
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 22.2/22.2 MB 23.1 MB/s eta 0:00:00
Downloading cligj-0.7.2-py3-none-any.whl (7.1 kB)
Downloading affine-2.4.0-py3-none-any.whl (15 kB)
Downloading click_plugins-1.1.1-py2.py3-none-any.whl (7.5 kB)
Installing collected packages: cligj, click-plugins, affine, rasterio
Successfully installed affine-2.4.0 click-plugins-1.1.1 cligj-0.7.2 rasterio-1.4.2
```

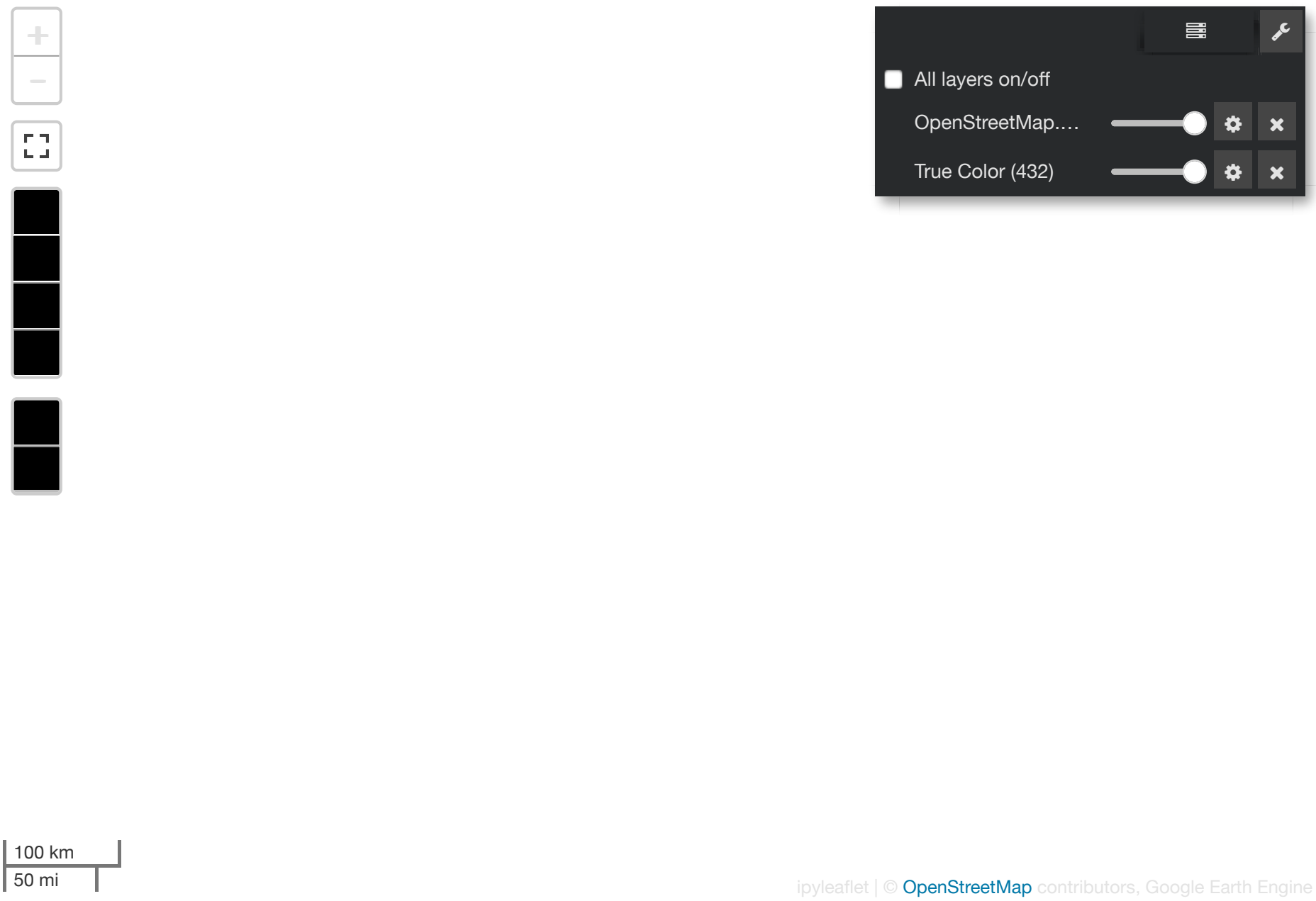
```
# geemap is the Python API of Google Earth Engine
import ee
import geemap.core as geemap
import torch
import rasterio
from torch.utils.data import Dataset, dataloader
from torchvision import transforms
import numpy as np
import matplotlib.pyplot as plt
import numpy as np
from osgeo import gdal
import seaborn as sns
```

```
ee.Authenticate()
ee.Initialize(project='ee-jinalvyasict19')
```

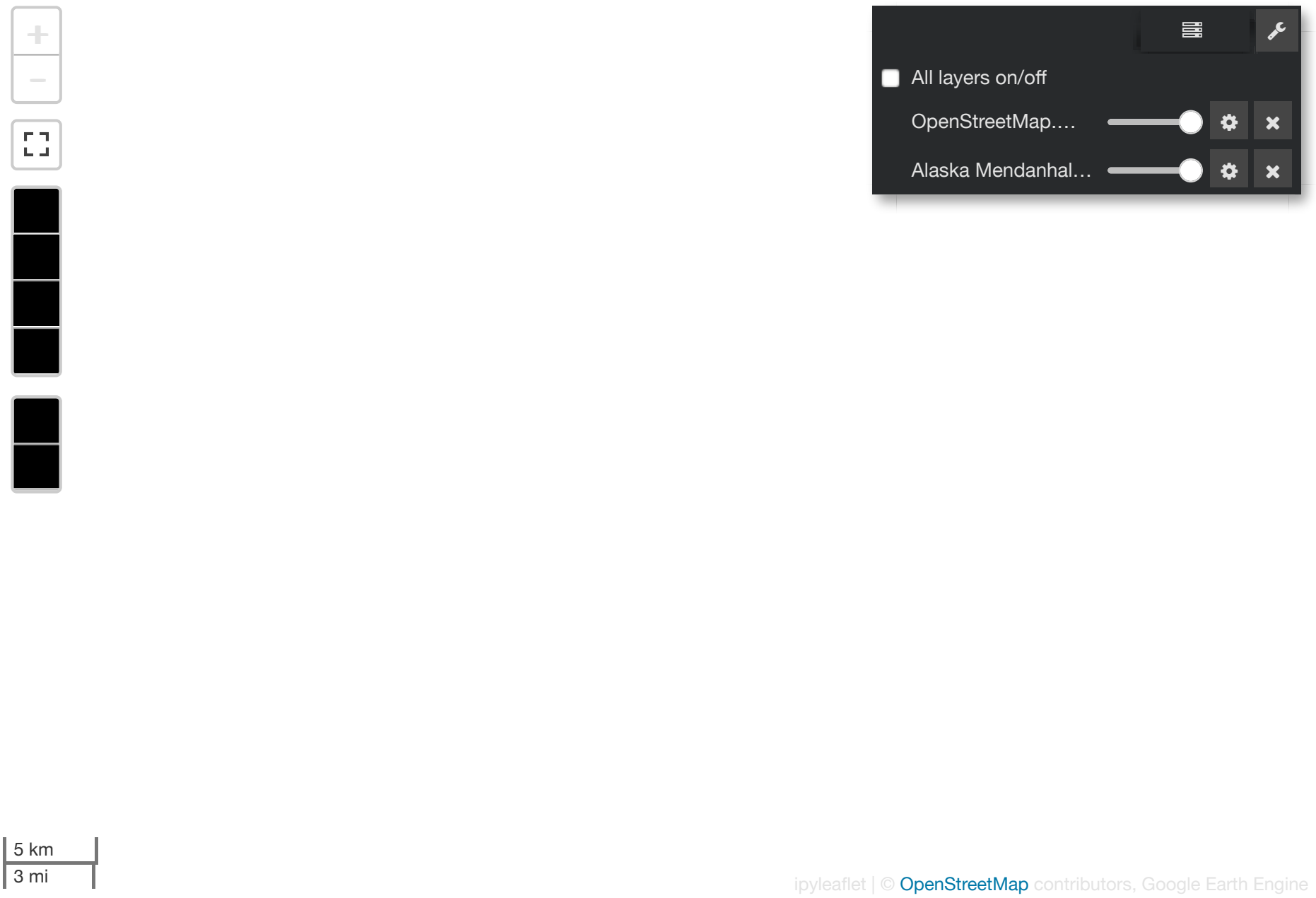
```
# viewing data over entire global map keeping North America as center
dataset = ee.ImageCollection('LANDSAT/LC08/C02/T1_L2').filterDate(
    '2023-10-01', '2023-12-01'
)

def apply_scale_factors(image):
  optical_bands = image.select(['SR_B3', 'SR_B4', 'SR_B5', 'SR_B6', 'SR_B7']).multiply(0.0000275).ad
  thermal_bands = image.select('ST_B.*').multiply(0.00341802).add(149.0)
  return image.addBands(optical_bands, None, True).addBands(
      thermal_bands, None, True
  )


dataset = dataset.map(apply_scale_factors)

visualization = {
    'bands': ['SR_B4', 'SR_B3', 'SR_B2'],
    'min': 0.0,
    'max': 0.3,
}

m = geemap.Map()
m.set_center(-104.88, 50.35, 3)
m.add_layer(dataset, visualization, 'True Color (432)')
m
```

```
# code to apply cloud masking for clear view
def mask_clouds_shadows(image):
  qa_mask = image.select('QA_PIXEL')
  cloud_mask = (qa_mask.bitwiseAnd(1 << 3)).eq(0)
  shadow_mask = (qa_mask.bitwiseAnd(1 << 4)).eq(0)
  mask = cloud_mask.And(shadow_mask)
  return image.updateMask(mask)

dataset = dataset.map(mask_clouds_shadows)
```

```
# # viewing data over entire global map keeping Alaska Mendanhall Glacier as center
m = geemap.Map()
m.set_center(-134.62, 58.42, 6)
m.add_layer(dataset, visualization, 'True Color (432)')
m
```



```
# defining Mendanhall Glacier as region of interest
alaska_bounds = ee.Geometry.Polygon([[-134.62, 58.42], [-134.62, 58.59], [-134.42, 58.59], [-134.42,
map = geemap.Map()
map.centerObject(alaska_bounds, 10)
map.addLayer(alaska_bounds, {'color': 'lightblue'}, 'Alaska Mendanhall Glacier')
map
```




```
# If your dataset is made up of multiple images, you're creating a composite where the pixel value
# from all the images at that location.
image = dataset.median().clip(alaska_bounds)
```

```
# downloading the image, am using high resolution of 10, which will increase data size a bit.
export_task = ee.batch.Export.image.toDrive(
    image = image,
    description = 'alaska_image',
    scale = 10,
    region = alaska_bounds,
    maxPixels = 1e13,
    fileFormat = 'GeoTIFF',
    folder = 'EarthEngineExports_Alaska'
)

export_task.start()
```

```
# I will be using SR_B3 to SR_B7 for now, as they are enough for snow segmentation, other bands rep
# like a fusion of panchromatic and lower-resolution bands for better spatial resolution
image
```

```
▶ Image (19 bands)
```

```
# downloading the dataset into google drive clipped to Mendanhall Glacier's bounds
import time
while export_task.active():
  print('Polling for task (id: {}).'.format(export_task.id))
  time.sleep(5)
```

```
Polling for task (id: MQNN3XYHIUL3XKB4NSE5FM37).
Polling for task (id: MQNN3XYHIUL3XKB4NSE5FM37).
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Polling for task (id: MQNN3XYHIUL3XKB4NSE5FM37).
Polling for task (id: MQNN3XYHIUL3XKB4NSE5FM37).
```

Exploratory Data Analysis

```
from google.colab import drive
drive.mount('/content/drive', force_remount=True)
```

```
Mounted at /content/drive
```

```
# Loading the tiff file derived from median of pixels over multiple images of two months
dataset = gdal.Open('/content/drive/My Drive/EarthEngineExports_Alaska/alaska_image.tif')

print(dataset.GetMetadata())
print("Number of Bands:", dataset.RasterCount)
print("GeoTransform:", dataset.GetGeoTransform())
```

```
{'AREA_OR_POINT': 'Area'}
Number of Bands: 19
GeoTransform: (-134.62000134216848, 8.983152841195215e-05, 0.0, 58.59000929237184, 0.0, -8.98315284119521
```

```
# making sure that the data is not entirely empty, hence loaded properly.
dataset.GetRasterBand(1).ReadAsArray()
```

```
array([[33328., 33328., 33328., ..., 44065., 44065., 43669.],
       [33328., 33328., 33328., ..., 44547., 44547., 44164.],
       [36721., 36721., 36721., ..., 44547., 44547., 44164.],
       ...,
       [ 7658.,  7658.,  7658., ..., 16850., 16850., 16850.],
       [ 7568.,  7568.,  7568., ..., 23831., 23831., 23831.],
       [ 7568.,  7568.,  7568., ..., 23831., 23831., 23831.]])
```

```
np.nanmax(dataset.GetRasterBand(1).ReadAsArray())
```

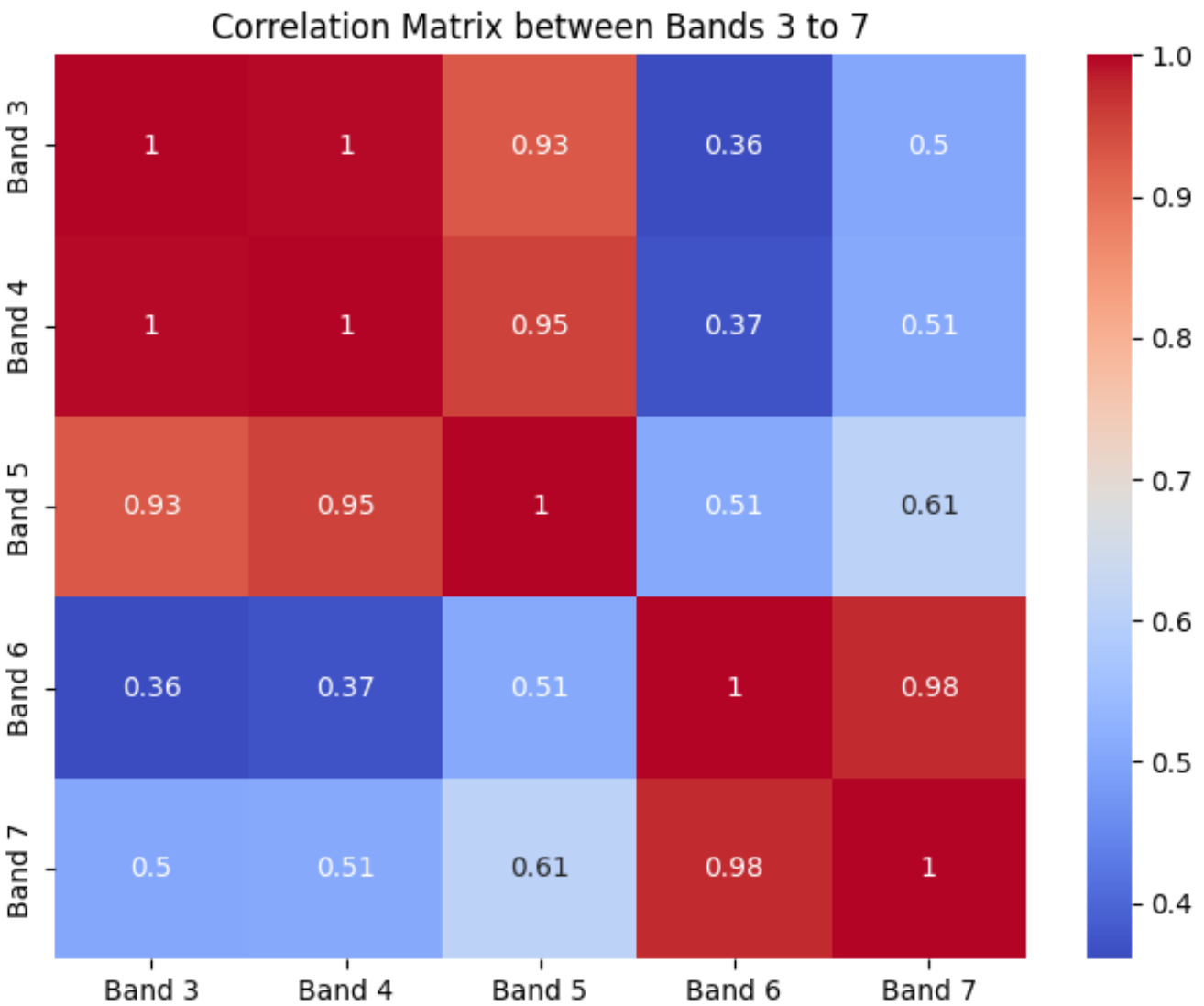
```
65454.0
```

```
# Printing the Meta-Data In Detail
with rasterio.open('/content/drive/My Drive/EarthEngineExports_Alaska/alaska_image.tif') as src:
    print(f"Number of Bands: {src.count}")
    for band in range(1, src.count + 1):
        print(f"Band {band}: {src.descriptions[band - 1]}")
```

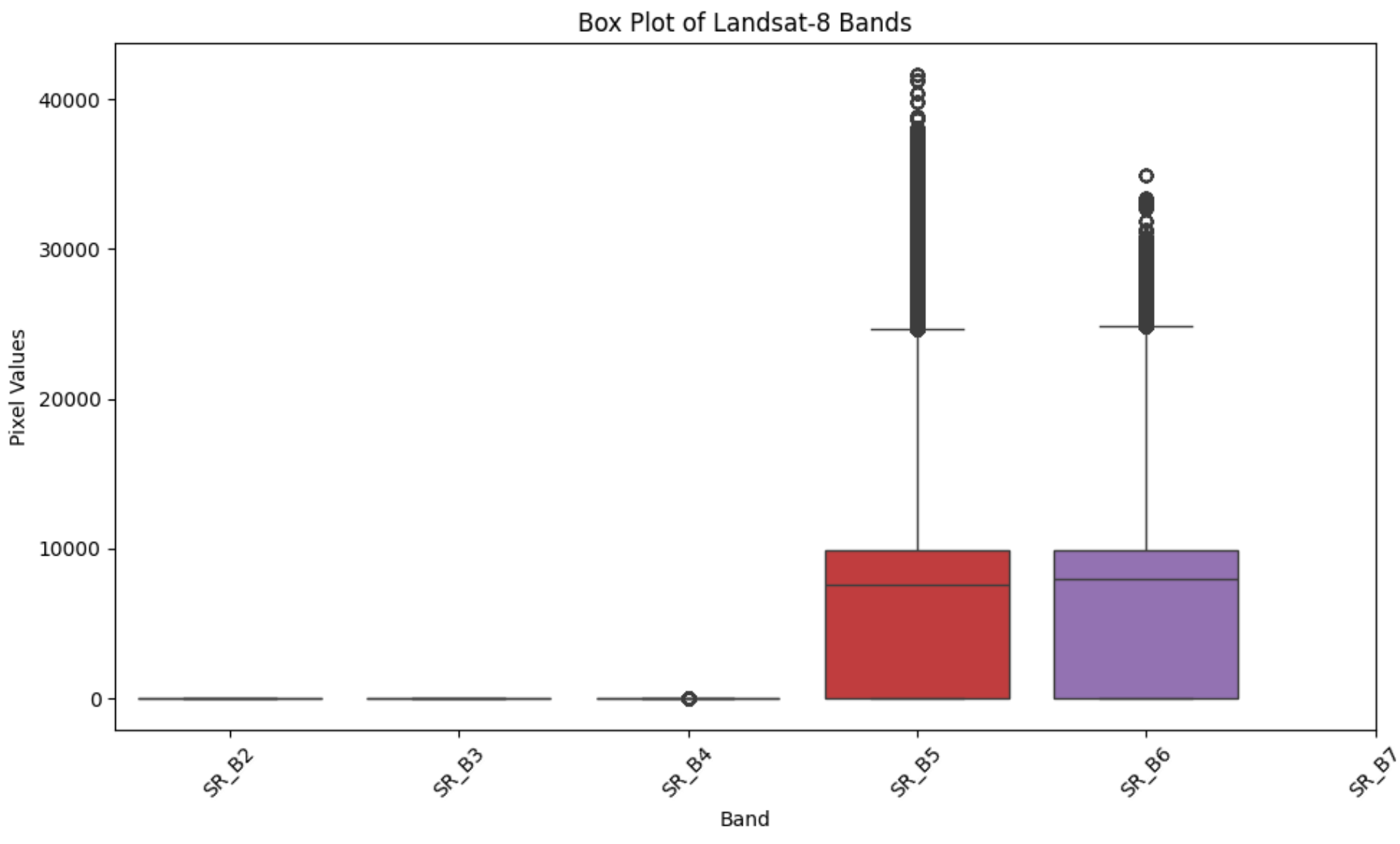
```
Number of Bands: 19
Band 1: SR_B1
Band 2: SR_B2
Band 3: SR_B3
Band 4: SR_B4
Band 5: SR_B5
Band 6: SR_B6
Band 7: SR_B7
Band 8: SR_QA_AEROSOL
Band 9: ST_B10
Band 10: ST_ATRAN
Band 11: ST_CDIST
Band 12: ST_DRAD
Band 13: ST_EMIS
Band 14: ST_EMSD
Band 15: ST_QA
Band 16: ST_TRAD
Band 17: ST_URAD
Band 18: QA_PIXEL
Band 19: QA_RADSAT
```

Data Cleaning and EDA Continued

```
# Here, there are several Nan values because of these reasons:
# Satellite imagery can have NaN values in regions affected by clouds, cloud shadows, or other atmos
# cannot be accurately measured.
# Some pixels may represent areas where no data is available (e.g., out of the image bounds, in remo
# Hence, it is in best interest to replace these NaN values by just zero for simplicity of computat
# values with arbitrary values (e.g., zero or the mean of surrounding pixels) introduces bias. It d
# any further analysis, such as classification, index calculation (like NDSI or NDVI), or any machi

# Plotting heatmap correlation matrix, to see relation between multiple bands, some pairs like 6-7,

with rasterio.open(file_path) as src:
    band_3 = src.read(3)
    band_4 = src.read(4)
    band_5 = src.read(5)
    band_6 = src.read(6)
    band_7 = src.read(7)

band_3 = np.nan_to_num(band_3, nan=0)
band_4 = np.nan_to_num(band_4, nan=0)
band_5 = np.nan_to_num(band_5, nan=0)
band_6 = np.nan_to_num(band_6, nan=0)
band_7 = np.nan_to_num(band_7, nan=0)

band_3_flat = band_3.flatten()
band_4_flat = band_4.flatten()
band_5_flat = band_5.flatten()
band_6_flat = band_6.flatten()
band_7_flat = band_7.flatten()


data = np.stack([band_3_flat, band_4_flat, band_5_flat, band_6_flat, band_7_flat])

correlation_matrix = np.corrcoef(data)

# Create a heatmap of the correlation matrix
plt.figure(figsize=(8, 6))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', xticklabels=["Band 3", "Band 4", "Band
            yticklabels=["Band 3", "Band 4", "Band 5", "Band 6", "Band 7"])
plt.title('Correlation Matrix between Bands 3 to 7')
plt.show()
```



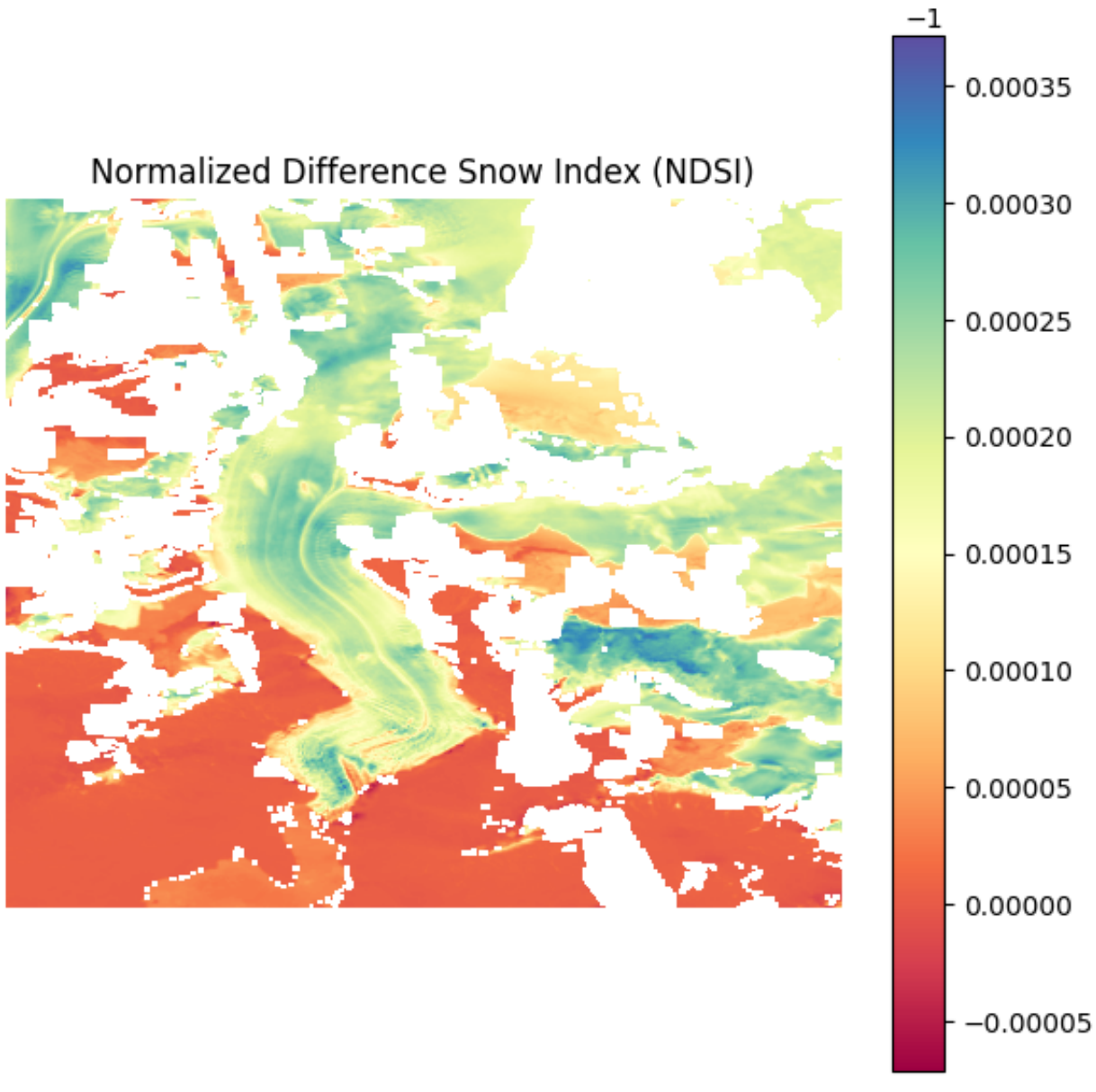
```
# Here, though there are outliers, but they may represent extreme temperature components like snow,
all_bands = [band_3_flat, band_4_flat, band_5_flat, band_6_flat, band_7_flat]
band_names = ['SR_B2', 'SR_B3', 'SR_B4', 'SR_B5', 'SR_B6', 'SR_B7']

plt.figure(figsize=(10, 6))
sns.boxplot(data=all_bands)
plt.xticks(np.arange(len(band_names)), band_names, rotation=45)
plt.title("Box Plot of Landsat-8 Bands")
plt.xlabel("Band")
plt.ylabel("Pixel Values")
plt.tight_layout()
plt.show()
```



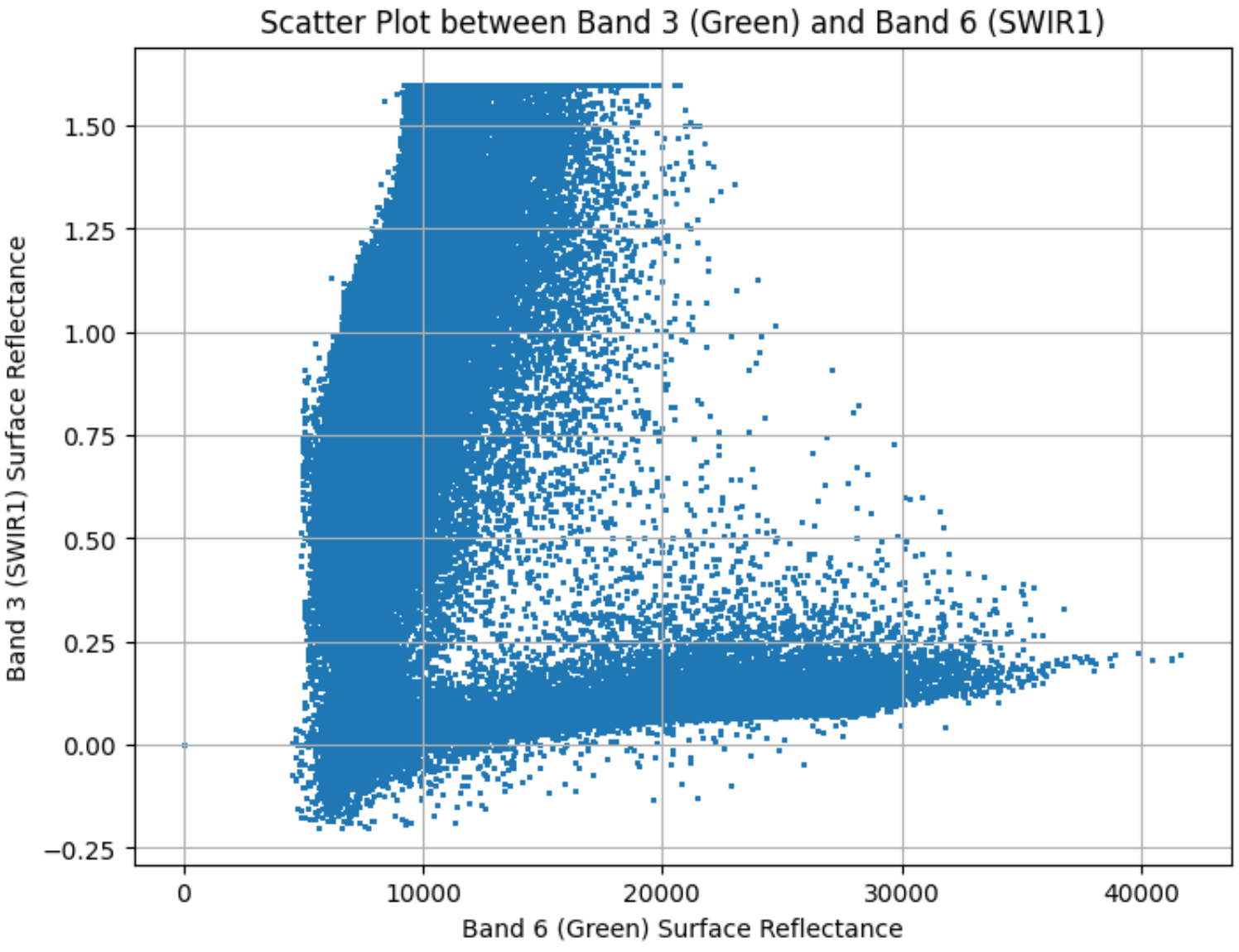
Feature Engineering

```
# Performing Feature Engineering, i.e. deriving a new feature named NDSI (Normalized Difference Snow
# NDSI is typically used to detect snow and ice, as these features often have a high reflectance in
# a lower reflectance in the SWIR bands, which yields positive NDSI values

NDSI = (band_3 - band_6) / (band_3 + band_6)

# Plot NDSI
plt.figure(figsize=(7, 7))
plt.imshow(NDSI, cmap='Spectral')
plt.title('Normalized Difference Snow Index (NDSI)')
plt.colorbar()
plt.axis('off')
plt.show()
```

```
<ipython-input-185-277dda5d0dc9>:3: RuntimeWarning: invalid value encountered in divide
  NDSI = (band_3 - band_6) / (band_3 + band_6)
```

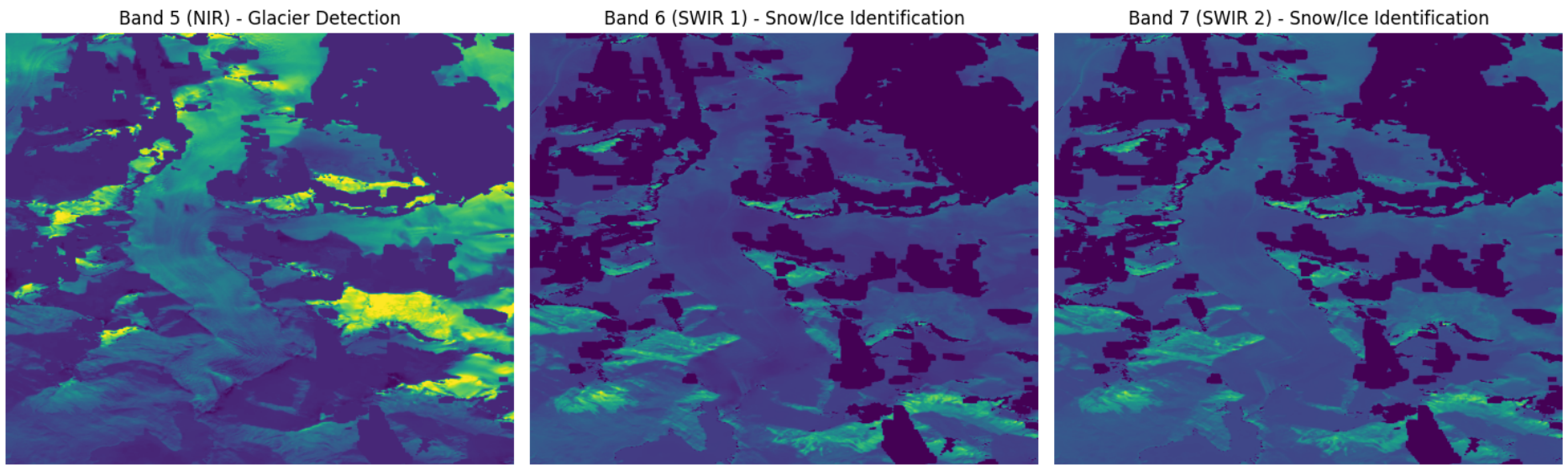


```
# visualizing correlation between 3 and 6 to understand NDSI further
# For Snow/Ice: The Green band (Band 3) will have higher values (as snow reflects visible light), ar
#  (since snow absorbs infrared light). This results in a positive NDSI values.
plt.figure(figsize=(8, 6))
plt.scatter(band_6_flat, band_3_flat, alpha=0.5, s=1)  # s=1 for small points, alpha for transparen
plt.title("Scatter Plot between Band 3 (Green) and Band 6 (SWIR1)")
plt.xlabel("Band 6 (Green) Surface Reflectance")
plt.ylabel("Band 3 (SWIR1) Surface Reflectance")
plt.grid(True)
plt.show()
```



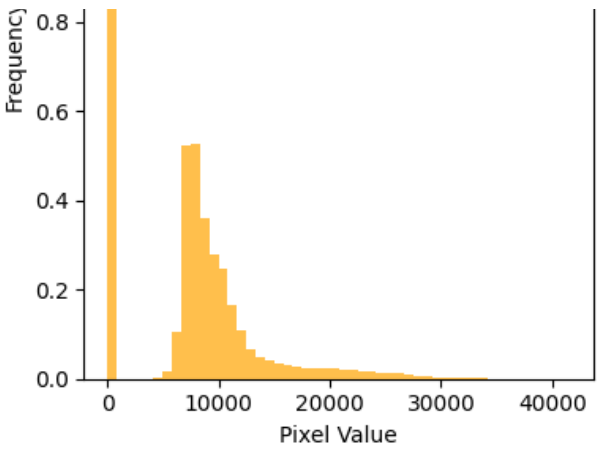
EDA Continued

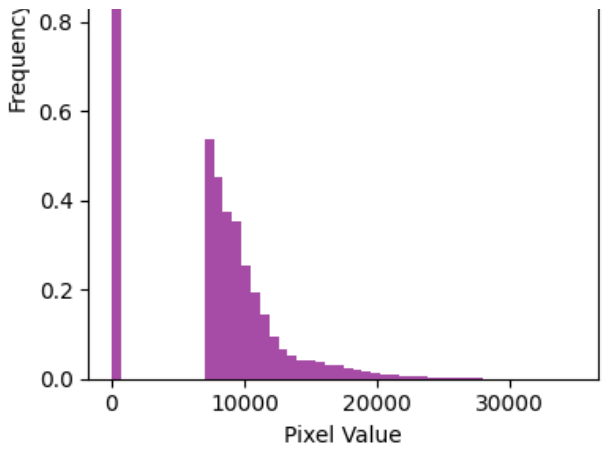
```
# Plotting band 5, 6 and 7.
# NIR (Band-5)  is useful for vegetation monitoring, SWIR1 (Band-6) is sensitive to moisture content
# water tend to reflect differently in this band. SWIR2 (Band-7) is important for detecting moisture
# distinguishing water from other land covers.
file_path = "/content/drive/My Drive/EarthEngineExports_Alaska/alaska_image.tif"

with rasterio.open(file_path) as src:
    band_5 = src.read(5)  # NIR (Near Infrared)
    band_6 = src.read(6)  # SWIR 1
    band_7 = src.read(7)  # SWIR 2

band_5 = np.nan_to_num(band_5, nan=0)
band_6 = np.nan_to_num(band_6, nan=0)
band_7 = np.nan_to_num(band_7, nan=0)

fig, axes = plt.subplots(1, 3, figsize=(15, 5))

axes[0].imshow(band_5)
axes[0].set_title('Band 5 (NIR) - Glacier Detection')
axes[0].axis('off')

axes[1].imshow(band_6)
axes[1].set_title('Band 6 (SWIR 1) - Snow/Ice Identification')
axes[1].axis('off')


axes[2].imshow(band_7)
axes[2].set_title('Band 7 (SWIR 2) - Snow/Ice Identification')
axes[2].axis('off')

plt.tight_layout()
plt.show()
```

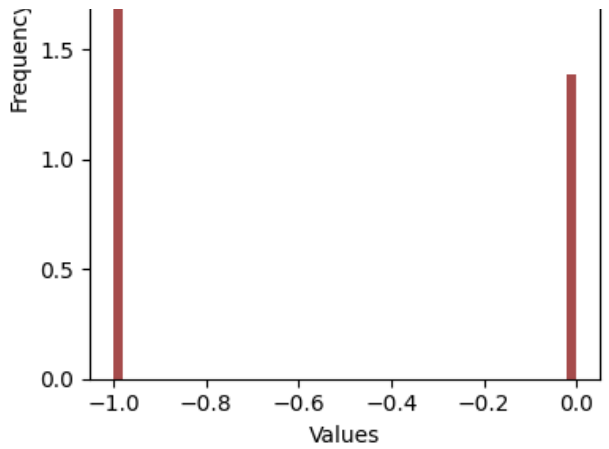



```
# Plotting the histogram to understand the data distribution, and what natural phenomenon is represe

# Summary of ALL BANDS and NDSI:
# Band 3 (Green) represents the visible green light reflected by vegetation, useful for vegetation s
# Band 4 (Red) corresponds to the visible red light and is sensitive to chlorophyll absorption, help
# Band 5 (NIR) captures near-infrared light, with high reflectance from healthy vegetation, making i
# Band 6 (SWIR1) detects moisture content in soil, vegetation, and water, with lower reflectance fro
# Band 7 (SWIR2) also measures moisture, with snow and ice showing low reflectance, and is used for
# The NDSI (Normalized Difference Snow Index) uses Band 3 and Band 6 to highlight snow and ice by co
# in the visible and SWIR bands; values close to 0 indicate non-snow surfaces, while higher values (

# here, normalizing any of the band values, can deteriorate the characteristics separation of glacie

plt.figure(figsize=(12, 10))

```

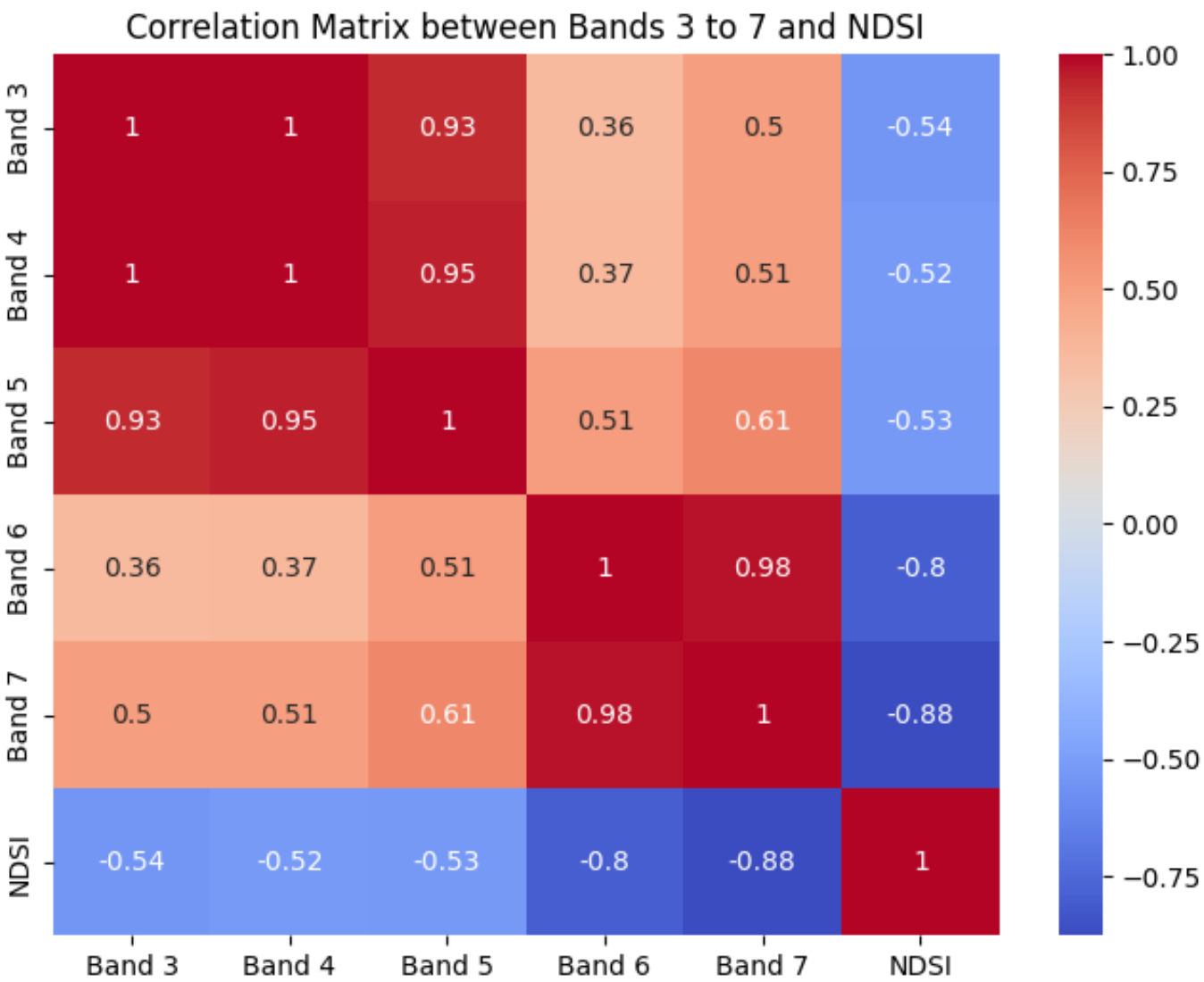
```
# Band 3: Green
plt.subplot(2, 3, 1)
plt.hist(band_3_flat, bins=50, color='green', alpha=0.7)
plt.title('Band 3: Green')
plt.xlabel('Pixel Value')
plt.ylabel('Frequency')

# Band 4: Red
plt.subplot(2, 3, 2)
plt.hist(band_4_flat, bins=50, color='red', alpha=0.7)
plt.title('Band 4: Red')
plt.xlabel('Pixel Value')
plt.ylabel('Frequency')

# Band 5: NIR
plt.subplot(2, 3, 3)
plt.hist(band_5_flat, bins=50, color='blue', alpha=0.7)
plt.title('Band 5: NIR')
plt.xlabel('Pixel Value')
plt.ylabel('Frequency')

# Band 6: SWIR1
plt.subplot(2, 3, 4)
plt.hist(band_6_flat, bins=50, color='orange', alpha=0.7)
plt.title('Band 6: SWIR1')
plt.xlabel('Pixel Value')
plt.ylabel('Frequency')

# Band 7: SWIR2
plt.subplot(2, 3, 5)
plt.hist(band_7_flat, bins=50, color='purple', alpha=0.7)
plt.title('Band 7: SWIR2')
plt.xlabel('Pixel Value')
plt.ylabel('Frequency')

plt.subplot(2, 3, 6)
plt.hist(NDSI_flat, bins=50, color='maroon', alpha=0.7)
plt.title('NDSI')
plt.xlabel('Values')
plt.ylabel('Frequency')

plt.tight_layout()
plt.show()
```








```
# Replotting the correlation matrix with NDSI included, and it is obvious that it will be highly co
# But the high correlation between band 7 and NDSI can be due to the fact that there are similar sp
# SWIR (Shortwave Infrared) bands, particularly Band 6 (SWIR1) and Band 7 (SWIR2).
NDSI = np.nan_to_num(NDSI, nan=0)
NDSI_flat = NDSI.flatten()
data = np.stack([band_3_flat, band_4_flat, band_5_flat, band_6_flat, band_7_flat, NDSI_flat])

correlation_matrix = np.corrcoef(data)

# Create a heatmap of the correlation matrix
plt.figure(figsize=(8, 6))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', xticklabels=["Band 3", "Band 4", "Band
            yticklabels=["Band 3", "Band 4", "Band 5", "Band 6", "Band 7", "NDSI"])
plt.title('Correlation Matrix between Bands 3 to 7 and NDSI')
plt.show()
```

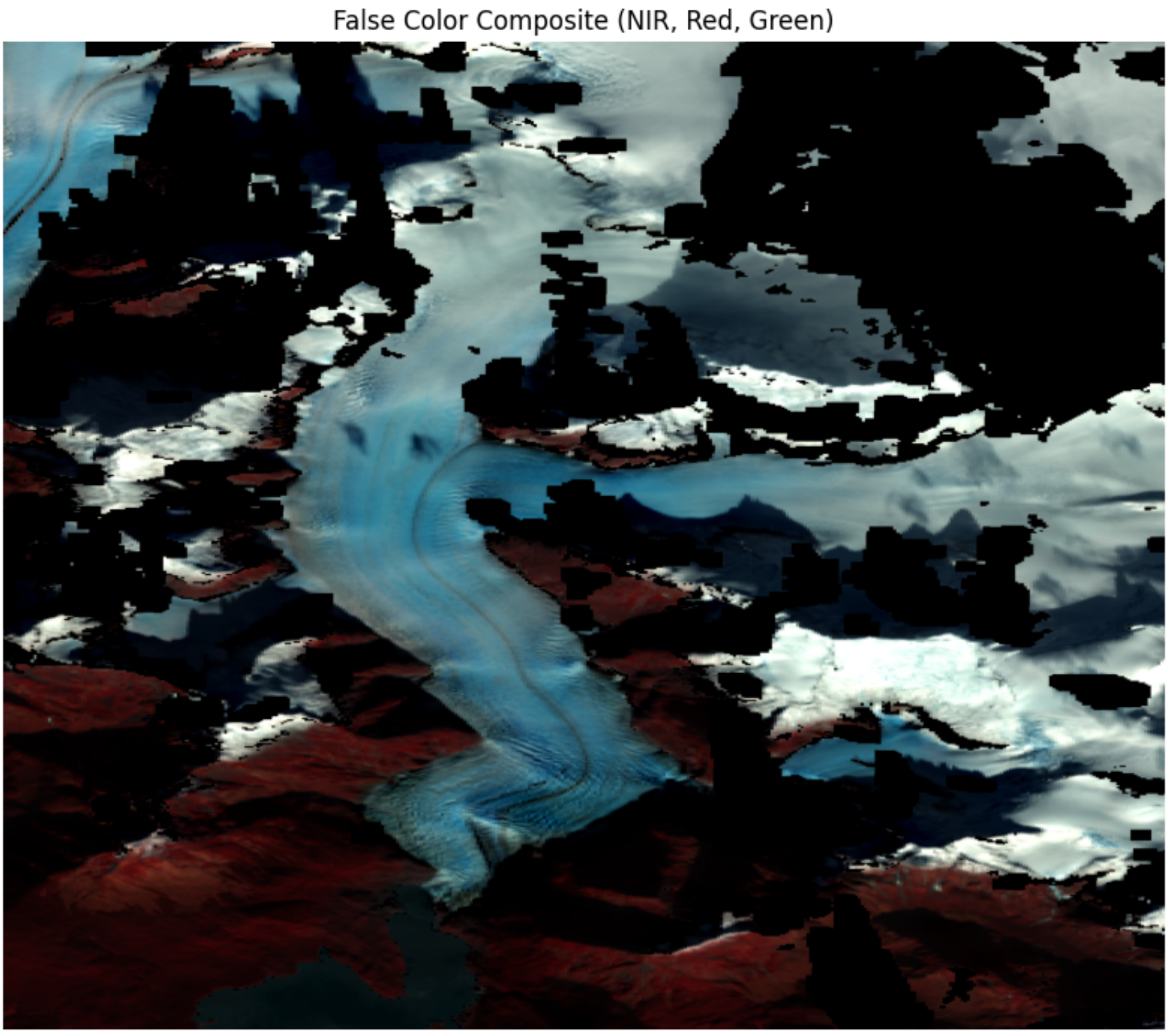


```
# Min value of NDSI being -1.0:
# This suggests that in some areas, the difference between the Green band (Band 3) and the SWIR banc
# the reflectance in the SWIR band is much higher than in the Green band. The minimum value of -1.0
# extremely small or close to zero compared to the SWIR band in these areas.
# Max value of 0.0:
# The maximum value of 0.0 suggests that in all of the image, there are no areas where the Green re
# point that the result is positive.
# Mean of -0.67:
# A mean value of -0.67 indicates that, on average, the Green reflectance is significantly lower tha
# This is usually expected for non-snow/ice-covered areas (e.g., forests, urban areas), where the SW
# the Green reflectanc

NDSI = np.nan_to_num(NDSI, nan=0)
print("NDSI min:", NDSI.min(), "max:", NDSI.max(), "mean:", NDSI.mean())
```

```
NDSI min: -1.0000713605834395 max: 0.0 mean: -0.6704336916204889
```

```
# Using the three bands to plot an RGB image of glacier characteristics measured over 2 months
band_5_norm = band_5 / band_5.max()
band_4_norm = band_4 / band_4.max()
band_3_norm = band_3 / band_3.max()

rgb_image = np.stack((band_5_norm, band_4_norm, band_3_norm), axis=-1)

plt.figure(figsize=(10, 10))
plt.imshow(rgb_image)
plt.title("False Color Composite (NIR, Red, Green)")
plt.axis('off')
plt.show()

```

```
WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGB data ([0..1] for floa
```



```
# Further Steps: I will either use the NDSI image or the RGB Image to perform segmentation (Model p
# (may be with Swin Backbone)), and then I will perform classification, on initial stage I will kee
# (whether snow is present or absent), which if time permits will further include classes like wate
```