aws

Hands-on tutorials

Get started with Amazon SageMaker AI geospatial capabilities

Get started with Amazon SageMaker AI geospatial capabilities: Hands-on tutorials

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Get started with Amazon SageMaker AI geospatial capabilities

AWS experience	Beginner
Time to complete	45 minutes
Cost to complete	Consult Amazon SageMaker AI Pricing for Geospatial ML to estimate cost for this tutorial.
Services used	Amazon SageMaker AI geospatial capabilities
Last updated	April 19, 2023

Overview

Amazon SageMaker AI geospatial capabilities allow you to build, train, and deploy ML models using geospatial data. You can efficiently transform or enrich large-scale geospatial datasets, accelerate model building with pretrained ML models, and explore model predictions on an interactive map using 3D accelerated graphics and built-in visualization tools.

Geospatial data can be used for a variety of use cases, including natural disaster management and response, maximizing harvest yield and food security, supporting sustainable urban development, and more. For this tutorial, we will use SageMaker AI geospatial capabilities to assess wildfire damage. By creating and visualizing an Earth Observation Job for land cover segmentation organizations can assess the loss of vegetation caused by wildfires and effectively act to mitigate the damage.

What you will accomplish

In this tutorial, you will:

- Onboard an Amazon SageMaker AI Studio Domain with access to Amazon SageMaker AI geospatial capabilities
- Create and run an Earth Observation Job (EOJ) to perform land cover segmentation

- Visualize the input and output of the job on an interactive map
- Export the job output to Amazon S3
- Analyze the exported data and perform further computations on the exported segmentation masks

Prerequisites

Before starting this tutorial, you will need:

An AWS account: If you don't already have an account, follow the Setting Up Your AWS Environment getting started guide for a quick overview.

Implementation

Step 1: Set up your Amazon SageMaker AI Studio domain

In this tutorial, you will use Amazon SageMaker AI Studio to access Amazon SageMaker AI geospatial capabilities.

Amazon SageMaker AI Studio is an integrated development environment (IDE) that provides a single web-based visual interface where you can access purpose-built tools to perform all machine learning (ML) development steps, from preparing data to building, training, and deploying your ML models.

If you already have a SageMaker AI Studio domain in the US West (Oregon) Region, follow the SageMaker AI Studio setup guide to attach the required AWS IAM policies to your SageMaker AI Studio account, then skip Step 1, and proceed directly to Step 2.

If you don't have an existing SageMaker AI Studio domain, continue with Step 1 to run an AWS CloudFormation template that creates a SageMaker AI Studio domain and adds the permissions required for the rest of this tutorial.

1. Launch the stack

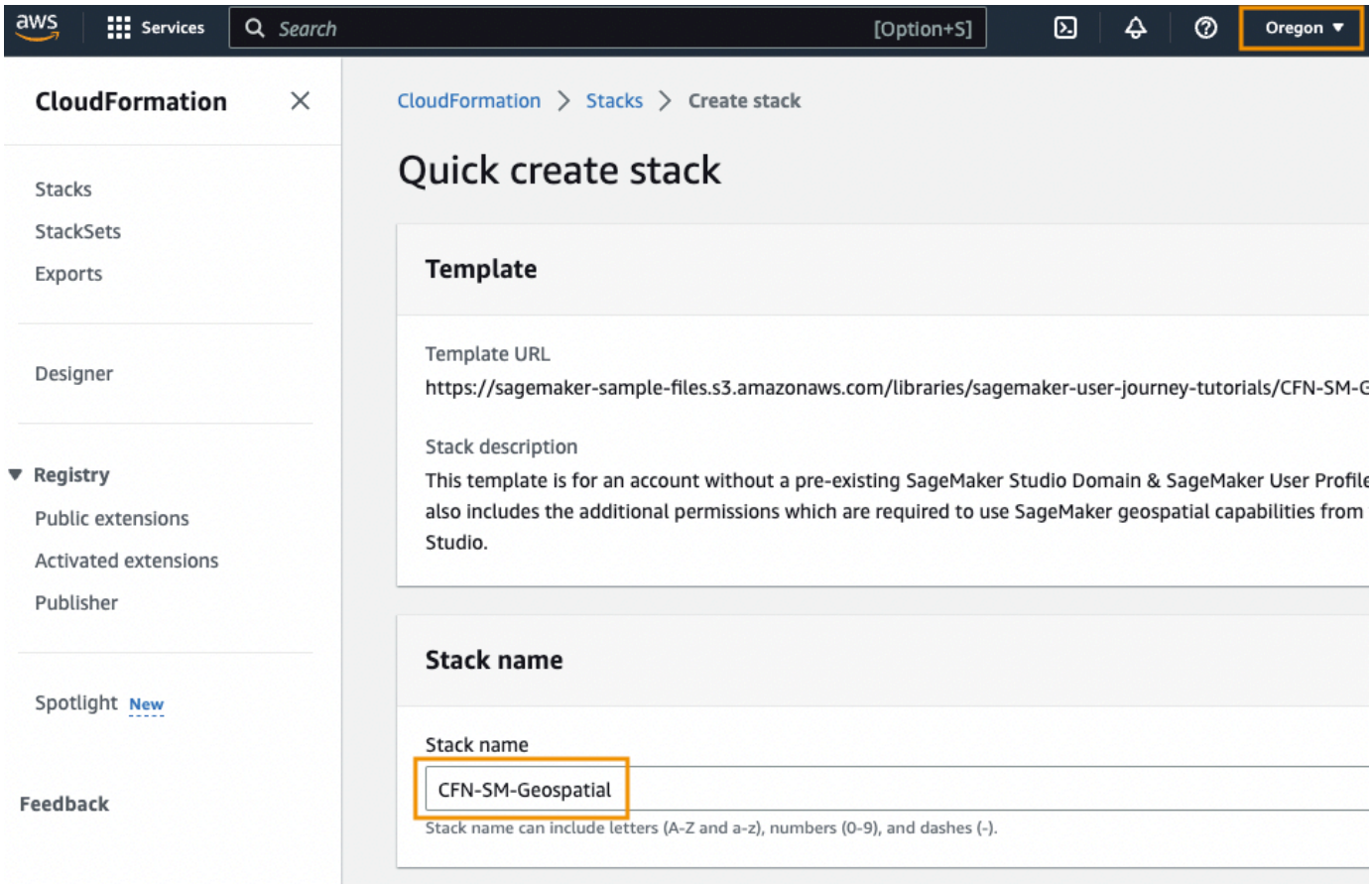
   Choose the AWS CloudFormation stack link.

   This link opens the AWS CloudFormation console and creates your SageMaker AI Studio domain and a user named **studio-user**. It also adds the required permissions to your SageMaker AI Studio account.

In the CloudFormation console, confirm that **US West (Oregon)** is the **Region** displayed in the upper right corner.

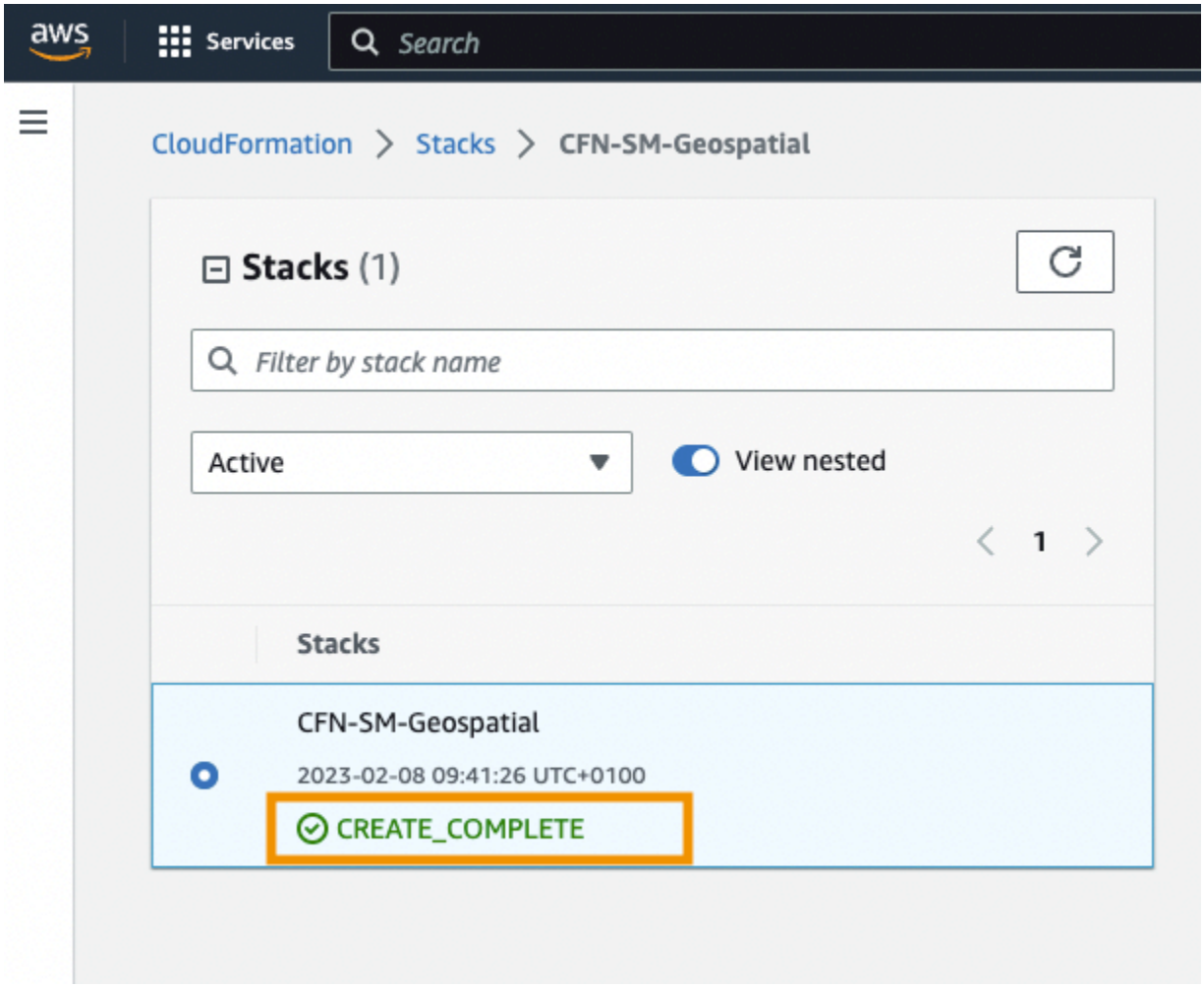
Stack name should be **CFN-SM-Geospatial**, and should not be changed. This stack takes about 10 minutes to create all the resources.

This stack assumes that you already have a public VPC set up in your account. If you do not have a public VPC, see VPC with a single public subnet to learn how to create a public VPC.



2. Confirm creation

When the stack creation has been completed, you can proceed to the next section to set up a SageMaker AI Studio notebook.

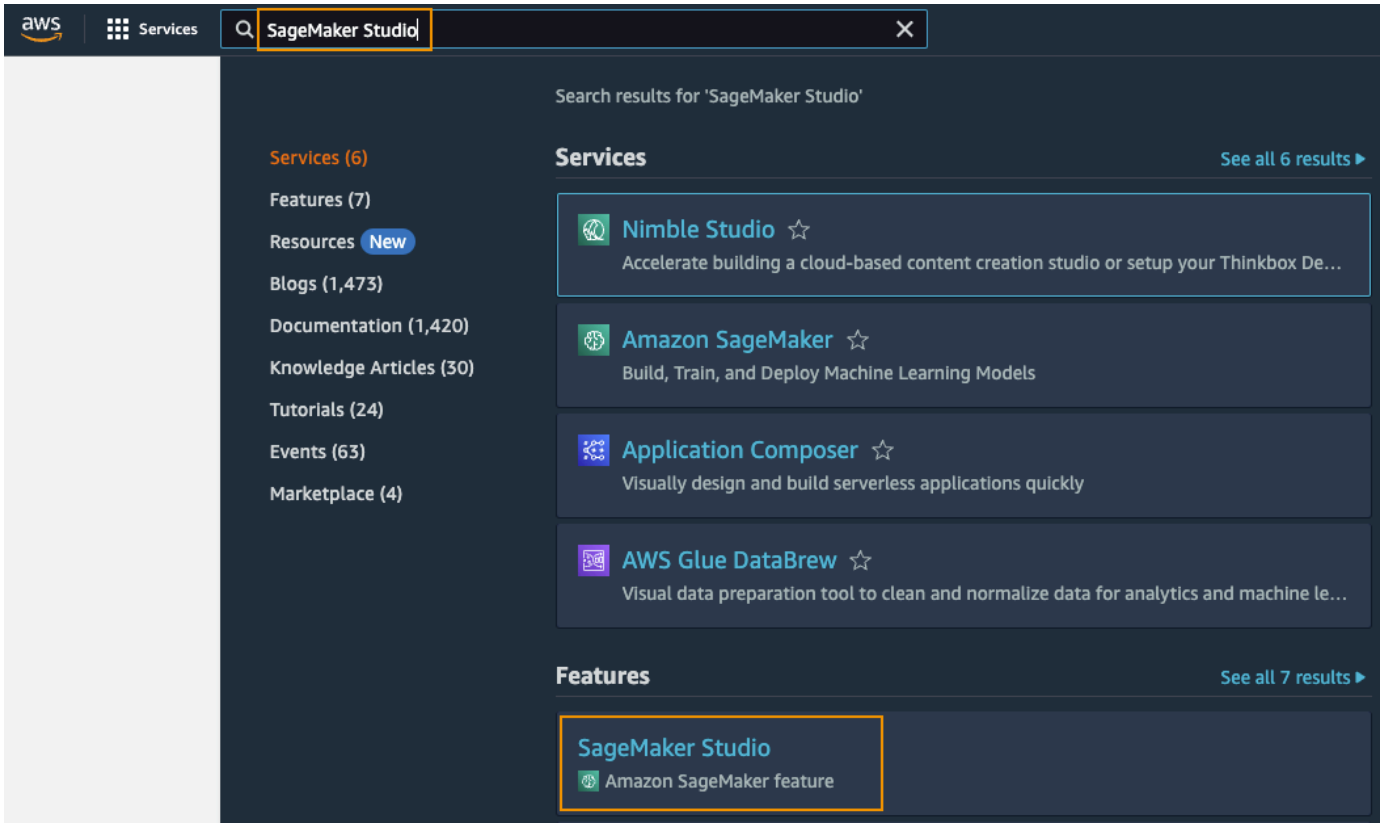


Step 2: Set up a SageMaker AI Studio notebook

In this step, you'll launch a new SageMaker AI Studio notebook with a SageMaker AI geospatial image, which is a Python image consisting of commonly used geospatial libraries such as GDAL, Fiona, GeoPandas, Shapely, and Rasterio, and allows you to visualize geospatial data within SageMaker AI.

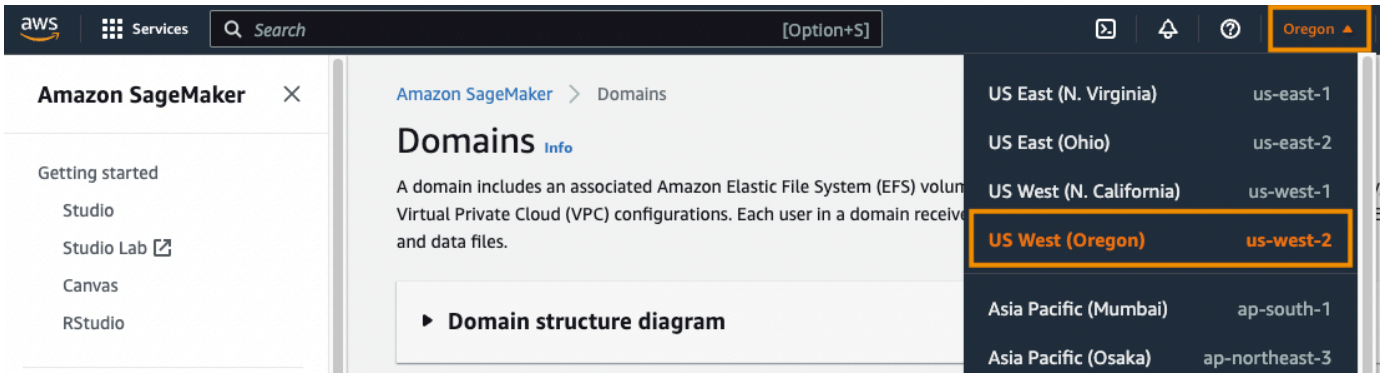
1. Open SageMaker AI Studio

   Enter **SageMaker AI Studio** into the console search bar, and then choose **SageMaker AI Studio**.



2. Choose a region

   Choose **US West (Oregon)** from the **Region** dropdown list on the upper right corner of the SageMaker AI console.



3. Choose Open Studio

   To launch the app, select **Studio** from the left console and select **Open Studio** using the studio-user profile.

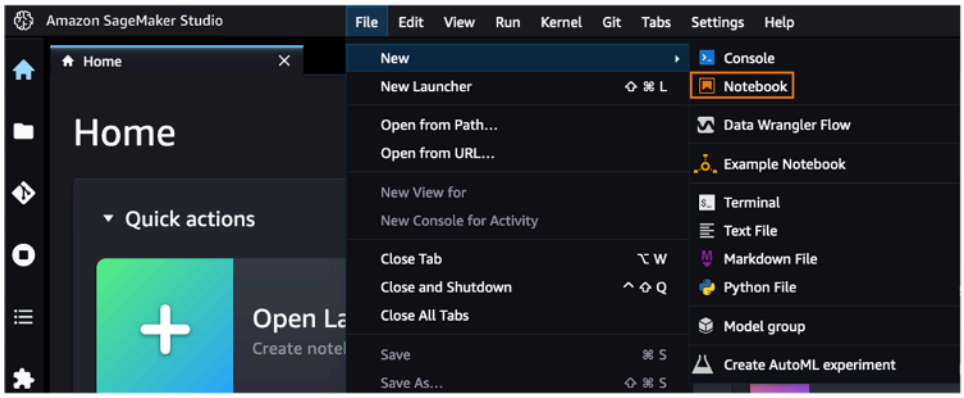
4. Wait for application to launch

   The SageMaker AI Studio **Creating application screen** will be displayed.

   The application will take a few minutes to load.

5. Create a notebook

   Open the SageMaker AI Studio interface. On the navigation bar, choose **File > New > Notebook**.

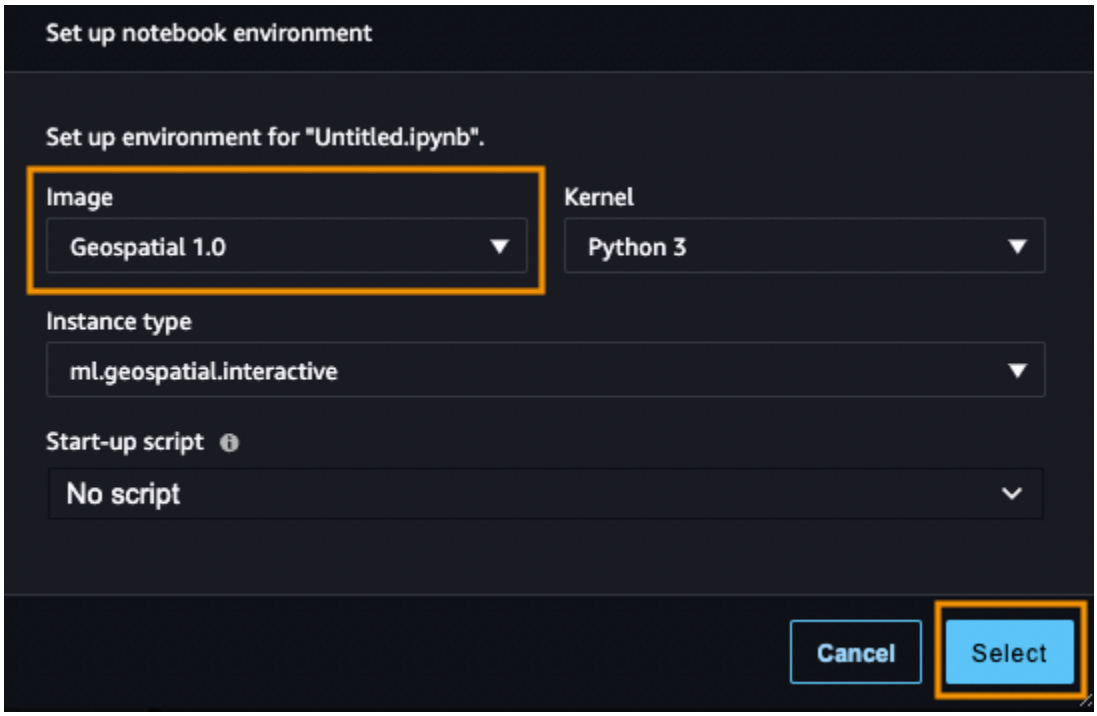


6. Set up environment

   In the Set up notebook environment dialog box, under **Image**, select **Geospatial 1.0**.

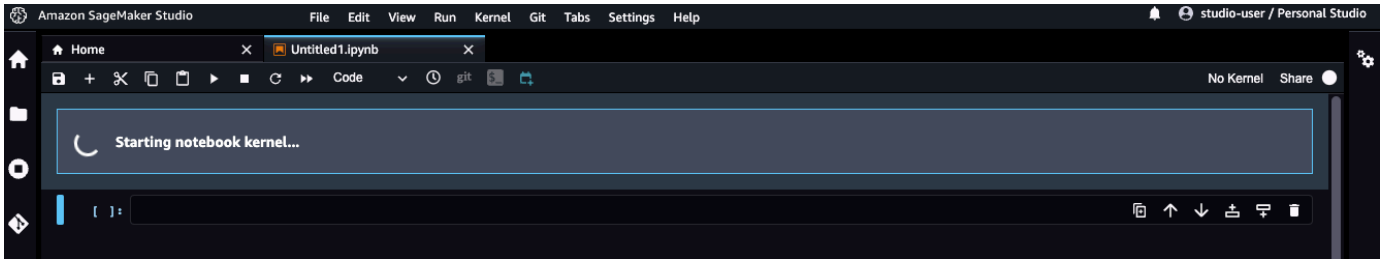
   The Python 3 kernel is selected automatically. Under **Instance type**, choose **ml.geospatial.interactive**.

   Then, choose **Select**.



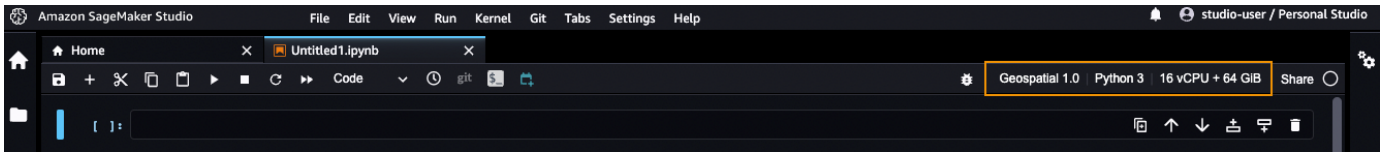
7. Verify kernel started

   Wait until the notebook kernel has been started.



8. Verify Geospatial 1.0 shows

   The kernel on the top right corner of the notebook should now display **Geospatial 1.0**.



Step 3: Create an Earth Observation Job

In this step, you'll use Amazon SageMaker AI Studio geospatial notebook to create an Earth Observation job (EOJ) which allows you to acquire, transform, and visualize geospatial data.

In this example, you'll be using a pre-trained machine learning model for land cover segmentation. Depending on your use case, you can choose from a variety of operations and models when running an EOJ.

1. Initialize the geospatial client

   In the Jupyter notebook, in a new code cell, **copy** and **paste** the following code and select **Run**.

   - This will initialize the geospatial client and import libraries for geospatial processing.
   - As the geospatial notebook image comes with these libraries already pre-installed and configured, there is no need to install them first.

```
import boto3
import sagemaker
import sagemaker_geospatial_map

import time
import datetime
import os
from glob import glob
```

```
import rasterio
from rasterio.plot import show
import matplotlib.colors
import matplotlib.patches as mpatches
import matplotlib.pyplot as plt
import numpy as np
import tifffile

sagemaker_session = sagemaker.Session()
export_bucket = sagemaker_session.default_bucket() # Alternatively you can use your
 custom bucket here.

session = boto3.Session()
execution_role = sagemaker.get_execution_role()
geospatial_client = session.client(service_name="sagemaker-geospatial")
```

2. Start a new Earth Observation Job

   Next you will define and start a new Earth Observation Job (EOJ).

   In the EOJ configuration, you can define an area of interest (AOI), a time range and cloud-cover-percentage-based filters. Also, you can choose a data provider.

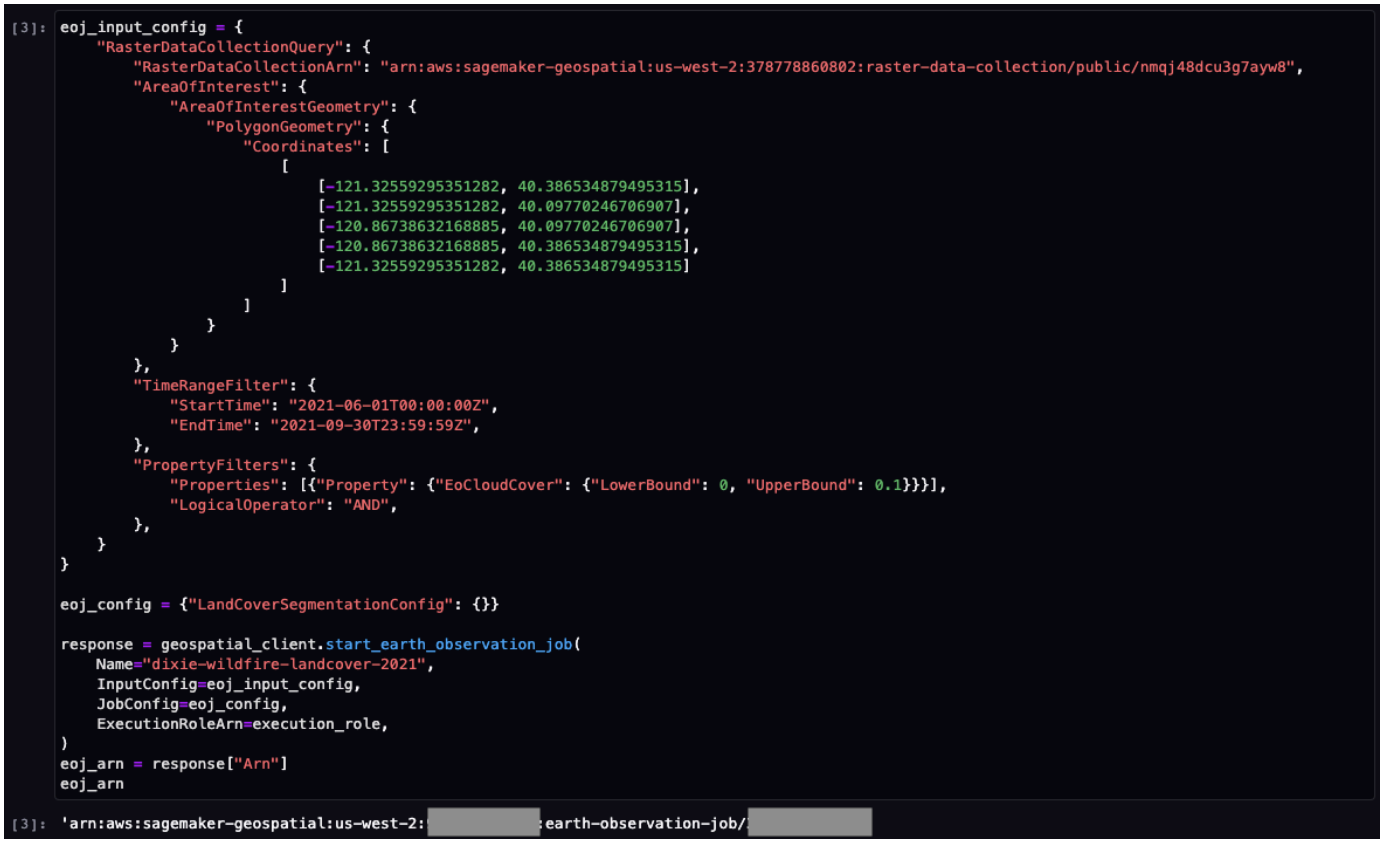
   In the provided configuration, the area of interest is an area in California which was affected by the Dixie wildfire. The underlying data is from the Sentinel-2 mission.

   Copy and **paste** the following code into a new code cell. Then, select **Run**.

   When the job is created, it can be referenced with a dedicated ARN.

```
eoj_input_config = {
```

```
    "RasterDataCollectionQuery": {
        "RasterDataCollectionArn": "arn:aws:sagemaker-geospatial:us-
west-2:378778860802:raster-data-collection/public/nmqj48dcu3g7ayw8",
        "AreaOfInterest": {
            "AreaOfInterestGeometry": {
                "PolygonGeometry": {
                    "Coordinates": [
                        [
                            [-121.32559295351282, 40.386534879495315],
                            [-121.32559295351282, 40.09770246706907],
                            [-120.86738632168885, 40.09770246706907],
                            [-120.86738632168885, 40.386534879495315],
                            [-121.32559295351282, 40.386534879495315]
                        ]
                    ]
                }
            }
        },
        "TimeRangeFilter": {
            "StartTime": "2021-06-01T00:00:00Z",
            "EndTime": "2021-09-30T23:59:59Z",
        },
        "PropertyFilters": {
            "Properties": [{"Property": {"EoCloudCover": {"LowerBound": 0,
 "UpperBound": 0.1}}}],
            "LogicalOperator": "AND",
        },
    }
}

eoj_config = {"LandCoverSegmentationConfig": {}}

response = geospatial_client.start_earth_observation_job(
    Name="dixie-wildfire-landcover-2021",
    InputConfig=eoj_input_config,
    JobConfig=eoj_config,
    ExecutionRoleArn=execution_role,
)
eoj_arn = response["Arn"]
eoj_arn
```



```
[3]: eoj_input_config = {
         "RasterDataCollectionQuery": {
             "RasterDataCollectionArn": "arn:aws:sagemaker-geospatial:us-west-2:378778860802:raster-data-collection/public/nmqj48dcu3g7ayw8",
             "AreaOfInterest": {
                 "AreaOfInterestGeometry": {
                     "PolygonGeometry": {
                         "Coordinates": [
                             [
                                 [-121.32559295351282, 40.386534879495315],
                                 [-121.32559295351282, 40.09770246706907],
                                 [-120.86738632168885, 40.09770246706907],
                                 [-120.86738632168885, 40.386534879495315],
                                 [-121.32559295351282, 40.386534879495315]
                             ]
                         ]
                     }
                 }
             },
             "TimeRangeFilter": {
                 "StartTime": "2021-06-01T00:00:00Z",
                 "EndTime": "2021-09-30T23:59:59Z",
             },
             "PropertyFilters": {
                 "Properties": [{"Property": {"EoCloudCover": {"LowerBound": 0, "UpperBound": 0.1}}}],
                 "LogicalOperator": "AND",
             },
         }
     }

     eoj_config = {"LandCoverSegmentationConfig": {}}

     response = geospatial_client.start_earth_observation_job(
         Name="dixie-wildfire-landcover-2021",
         InputConfig=eoj_input_config,
         JobConfig=eoj_config,
         ExecutionRoleArn=execution_role,
     )
     eoj_arn = response["Arn"]
     eoj_arn

[3]: 'arn:aws:sagemaker-geospatial:us-west-2:          :earth-observation-job/          '
```

3. Explore the raster data

   While the job is running, you can explore the raster data which is used as input for the EOJ.

   Use the geospatial SDK to retrieve image URLs in a cloud optimized GeoTIFF (COG) format.

   Copy and **paste** the following code into a new code cell. Then, select **Run**.

```
search_params = eoj_input_config.copy()
search_params["Arn"] = "arn:aws:sagemaker-geospatial:us-west-2:378778860802:raster-
data-collection/public/nmqj48dcu3g7ayw8"
search_params["RasterDataCollectionQuery"].pop("RasterDataCollectionArn", None)
search_params["RasterDataCollectionQuery"]["BandFilter"] = ["visual"]

cog_urls = []
search_result = geospatial_client.search_raster_data_collection(**search_params)
for item in search_result["Items"]:
    asset_url = item["Assets"]["visual"]["Href"]
    cog_urls.append(asset_url)

cog_urls
```

```
[4]: search_params = eoj_input_config.copy()
     search_params["Arn"] = "arn:aws:sagemaker-geospatial:us-west-2:378778860802:raster-data-collection/public/nmqj48dcu3g7ayw8"
     search_params["RasterDataCollectionQuery"].pop("RasterDataCollectionArn", None)
     search_params["RasterDataCollectionQuery"]["BandFilter"] = ["visual"]

     cog_urls = []
     search_result = geospatial_client.search_raster_data_collection(**search_params)
     for item in search_result["Items"]:
         asset_url = item["Assets"]["visual"]["Href"]
         cog_urls.append(asset_url)

     cog_urls

[4]: ['https://sentinel-cogs.s3.us-west-2.amazonaws.com/sentinel-s2-l2a-cogs/10/T/FK/2021/9/S2A_10TFK_20210926_0_L2A/TCI.tif',
      'https://sentinel-cogs.s3.us-west-2.amazonaws.com/sentinel-s2-l2a-cogs/10/T/FK/2021/9/S2B_10TFK_20210921_0_L2A/TCI.tif',
      'https://sentinel-cogs.s3.us-west-2.amazonaws.com/sentinel-s2-l2a-cogs/10/T/FK/2021/7/S2B_10TFK_20210713_0_L2A/TCI.tif',
      'https://sentinel-cogs.s3.us-west-2.amazonaws.com/sentinel-s2-l2a-cogs/10/T/FK/2021/6/S2A_10TFK_20210628_0_L2A/TCI.tif',
      'https://sentinel-cogs.s3.us-west-2.amazonaws.com/sentinel-s2-l2a-cogs/10/T/FK/2021/6/S2A_10TFK_20210618_0_L2A/TCI.tif',
      'https://sentinel-cogs.s3.us-west-2.amazonaws.com/sentinel-s2-l2a-cogs/10/T/FK/2021/6/S2B_10TFK_20210603_0_L2A/TCI.tif']
```

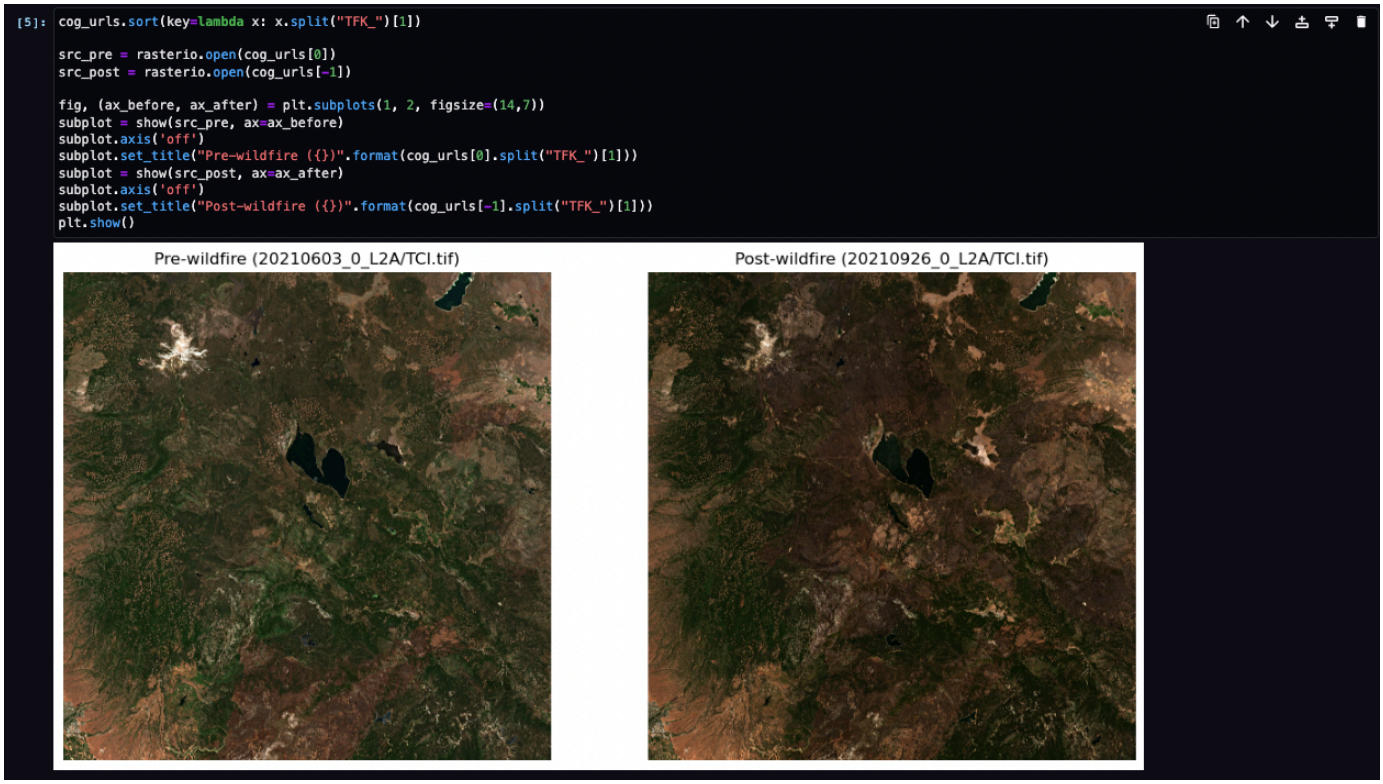
4. Visualize input data

   Next, you will use the COG URLs to visualize the input data for the area of interest.

   This provides you with a visual comparison of the area before and after the wildfire.

   Copy and **paste** the following code into a new code cell. Then, select **Run**.

```
cog_urls.sort(key=lambda x: x.split("TFK_")[1])

src_pre = rasterio.open(cog_urls[0])
src_post = rasterio.open(cog_urls[-1])

fig, (ax_before, ax_after) = plt.subplots(1, 2, figsize=(14,7))
subplot = show(src_pre, ax=ax_before)
subplot.axis('off')
subplot.set_title("Pre-wildfire ({})".format(cog_urls[0].split("TFK_")[1]))
subplot = show(src_post, ax=ax_after)
subplot.axis('off')
subplot.set_title("Post-wildfire ({})".format(cog_urls[-1].split("TFK_")[1]))
plt.show()
```



5. Output job status

   Before you can proceed with further steps, the EOJ needs to complete.

   Copy and **paste** the following code into a new code cell. Then, select **Run**.

   This code will continuously output the current status of the job and execute until the EOJ is complete.

   Wait until the displayed status has changed to **COMPLETED**. This might take up to 20-25 minutes.

```
# check status of created Earth Observation Job and wait until it is completed
eoj_completed = False
while not eoj_completed:
    response = geospatial_client.get_earth_observation_job(Arn=eoj_arn)
    print("Earth Observation Job status: {} (Last update:
 {})".format(response['Status'], datetime.datetime.now()), end='\r')
    eoj_completed = True if response['Status'] == 'COMPLETED' else False
    if not eoj_completed:
        time.sleep(30)
```

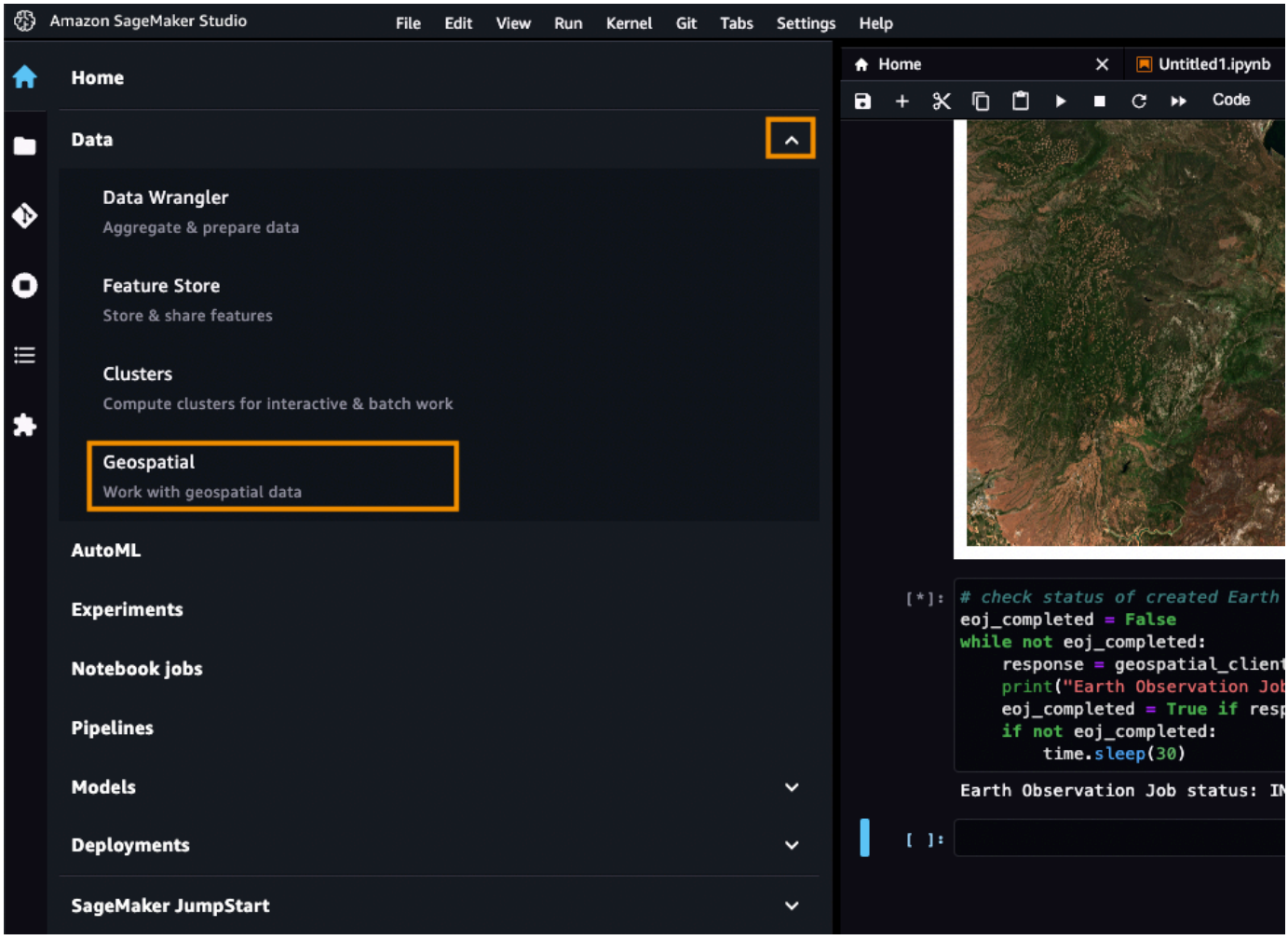
```
[6]: # check status of created Earth Observation Job and wait until it is completed
eoj_completed = False
while not eoj_completed:
    response = geospatial_client.get_earth_observation_job(Arn=eoj_arn)
    print("Earth Observation Job status: {} (Last update: {})".format(response['Status'], datetime.datetime.now()), end='\r')
    eoj_completed = True if response['Status'] == 'COMPLETED' else False
    if not eoj_completed:
        time.sleep(30)

Earth Observation Job status: COMPLETED (Last update: 2023-02-08 09:36:33.451051)8)
```

Step 4: Visualize the Earth Observation Job

In this step, you'll use visualization functionalities provided by Amazon SageMaker AI geospatial capabilities to visualize the input and outputs of your Earth Observation Job.

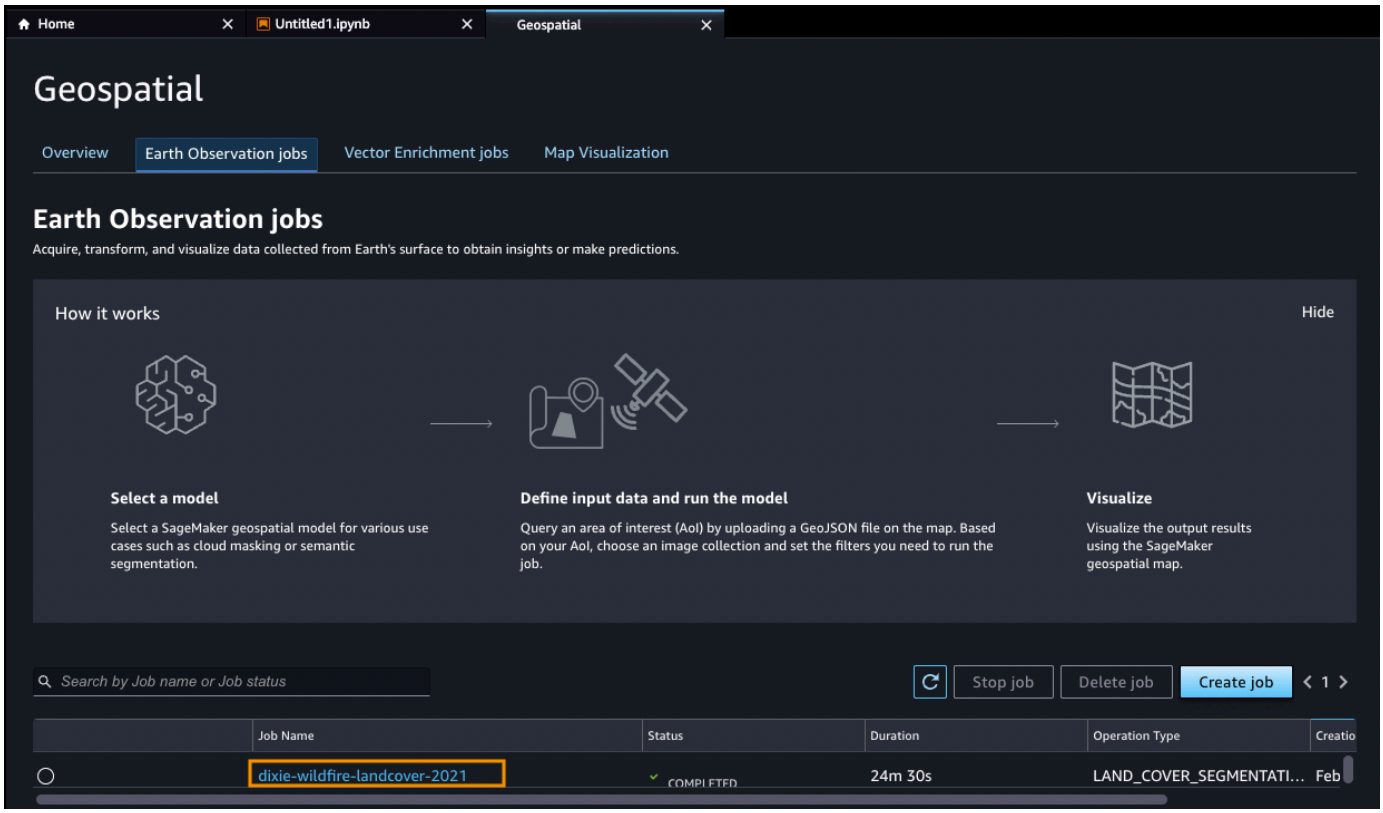
1. Navigate to your EOJs

   In the left-hand navigation, click on the arrow to expand the **Data** section. Then, choose **Geospatial**.



2. Select the applicable EOJ

In the new Geospatial tab, you will find an overview of all your EOJs. Select the **job dixie-wildfire-landcover-2021**.



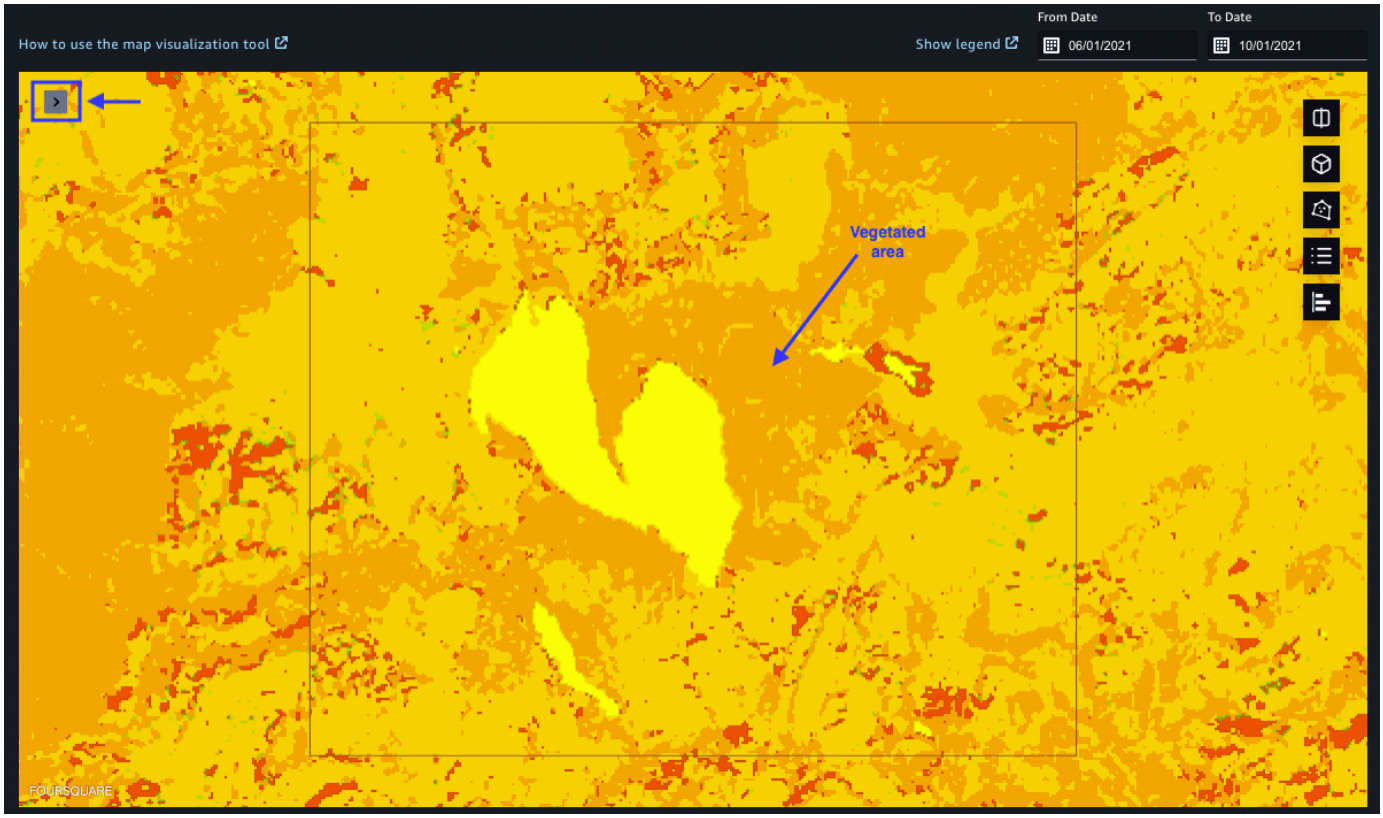
3. Visualize job output

   On the job detail page, choose **Visualize job output**.

4. View the visualization

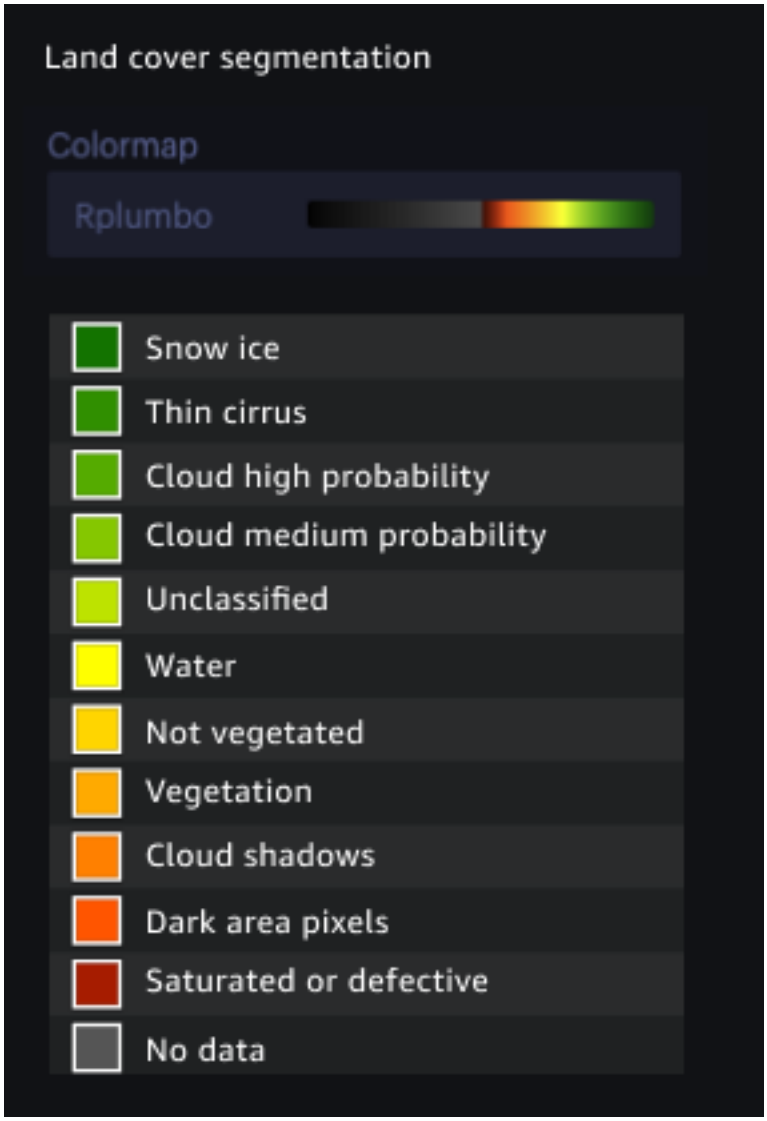
   The visualization will show you the output for the landcover segmentation for the most recent date in the **To Date field**.

   - The image presented is the land cover data after the wildfire.
   - The pixels in dark orange represent vegetated areas (as described in legends for EOJ).
   - Select the arrow on the left side to open the visualization options.



5. Use the legend to understand the data

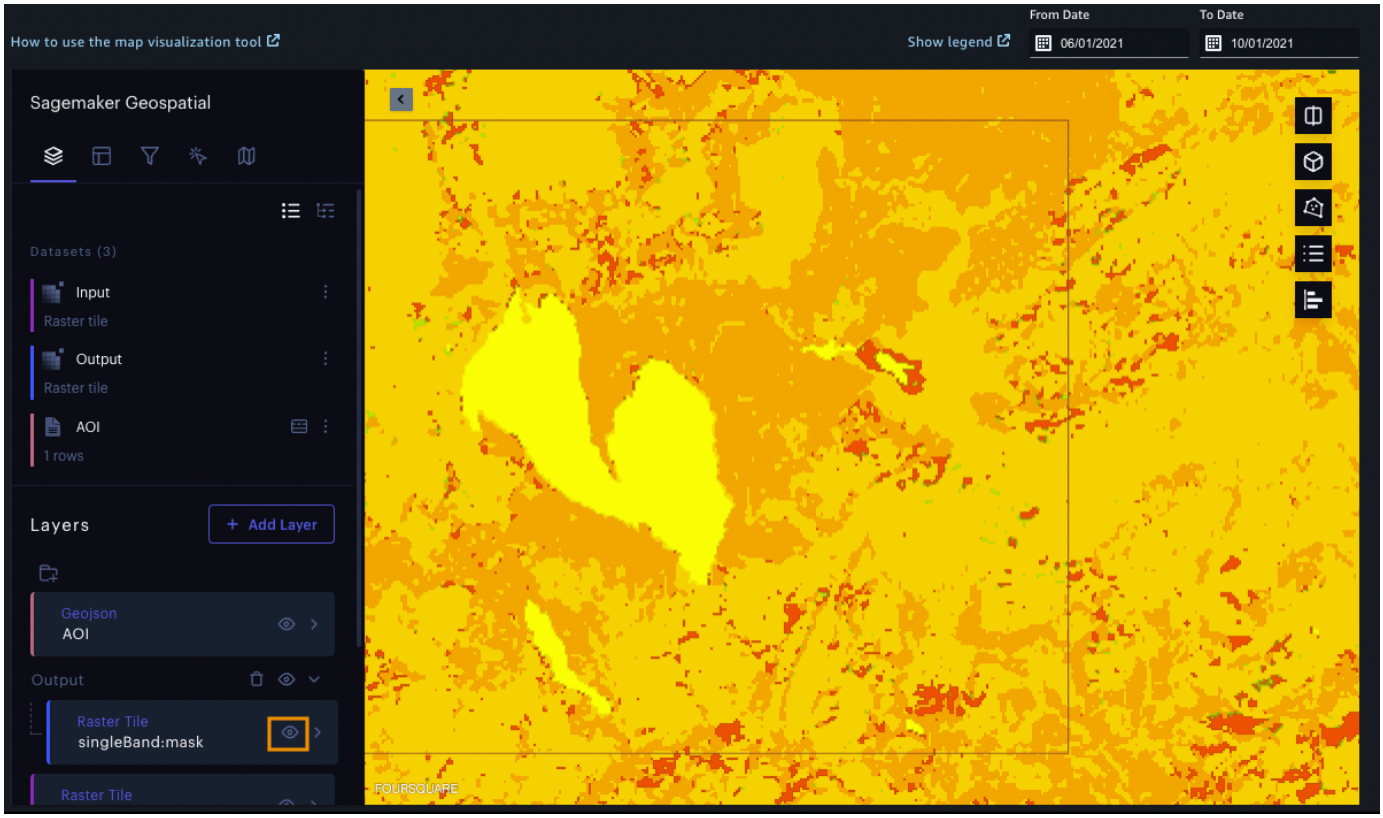
   View the legend.



6. Configure visualization options

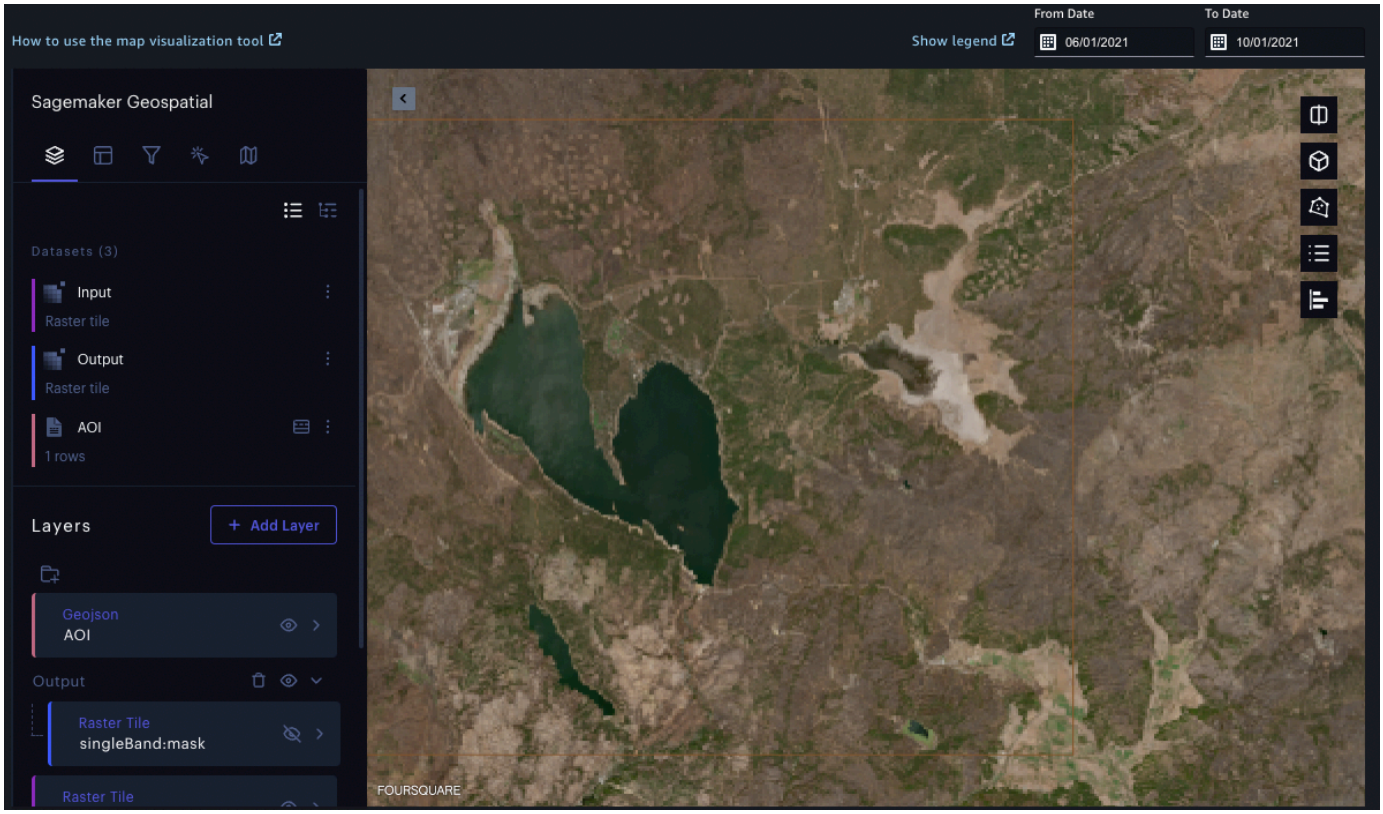
   Within the visualization options you can select and configure all geospatial and data layers.

   Select the **Hide symbol** for the output raster tile layer.



7. View the underlying input data layer

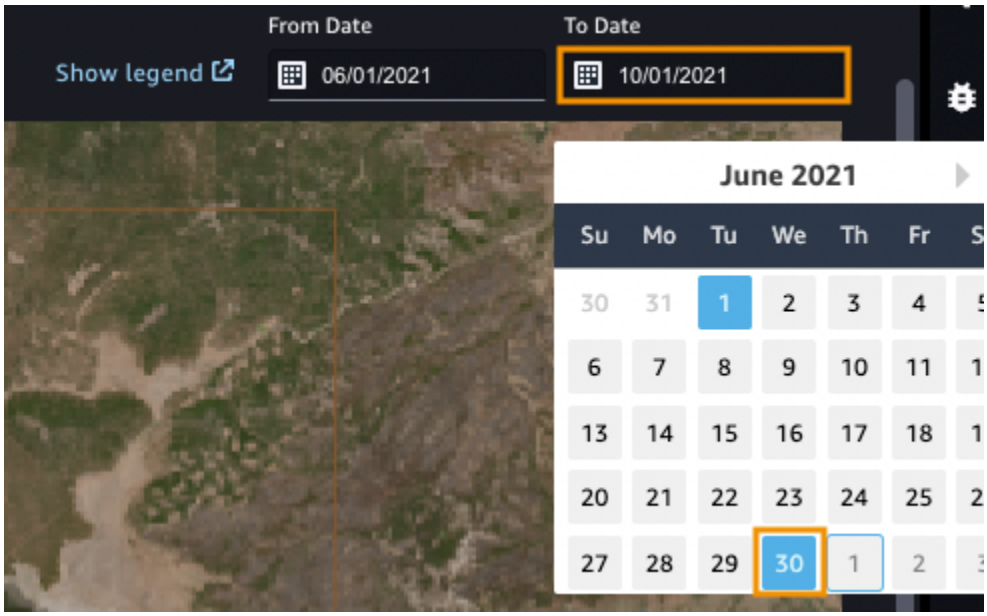
   After you select the **Hide symbol**, you will be able to see the underlying input data layer.



8. Change the date

   You are also able to visualize different time periods of the input and output data of your EOJ.

   Select the **30th of June 2021** in the **To Date** field.

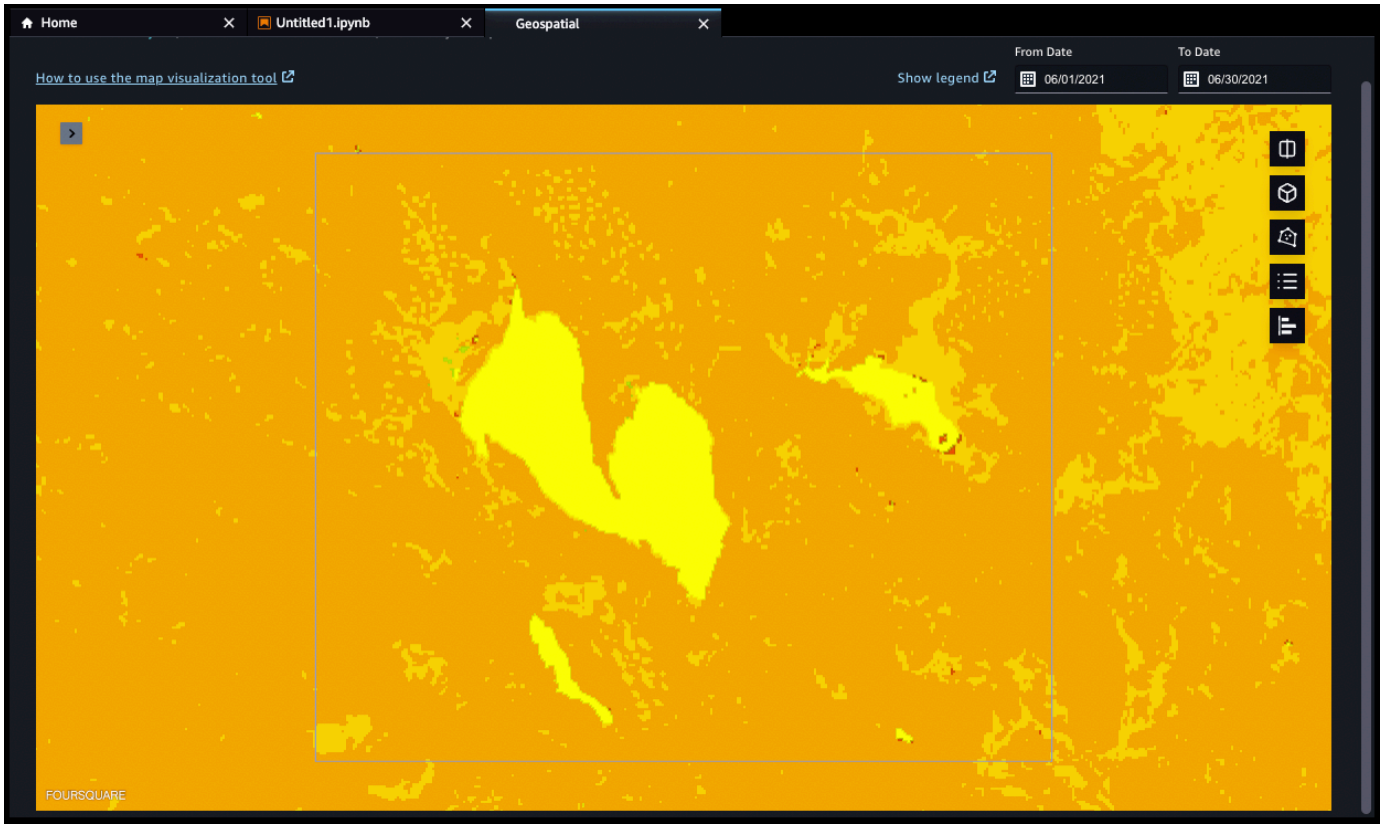


9. View the updated imagery

The data displayed is satellite imagery from before the 30th of June 2021.

This timeframe was before the wildfire, and the amount of vegetation (dark orange) is much higher than on the output viewed previously.

You can again select to hide the output layer to see the underlying input satellite image (as in the step before).



10. Navigate to the notebook

To proceed, select the tab **Untitled1.ipynb** to switch back to the notebook.

Step 5: Export the Earth Observation Job to Amazon S3

In this step, the output data from the Earth Observation Job will be exported to an Amazon Simple Storage Service (Amazon S3) bucket and the exported segmentation masks will be downloaded for further processing.

1. Export the EOJ to S3

   You will use the geospatial SDK to export the output of the Earth Observation Job to S3.

   This operation takes between 1-2 minutes to complete.

   Copy and **paste** the following code into a new code cell. Then, select **Run**.

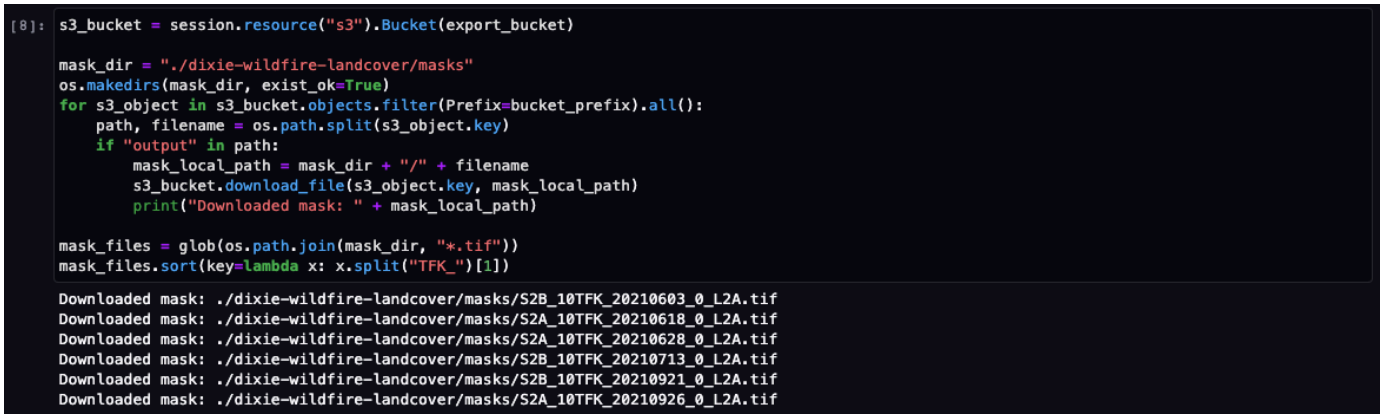
```
bucket_prefix = "eoj_dixie_wildfire_landcover"
response = geospatial_client.export_earth_observation_job(
    Arn=eoj_arn,
    ExecutionRoleArn=execution_role,
    OutputConfig={
        "S3Data": {"S3Uri": f"s3://{export_bucket}/{bucket_prefix}/"}
    },
)

while not response['ExportStatus'] == 'SUCCEEDED':
    response = geospatial_client.get_earth_observation_job(Arn=eoj_arn)
    print("Export of Earth Observation Job status: {} (Last update:
 {})".format(response['ExportStatus'], datetime.datetime.now()), end='\r')
    if not response['ExportStatus'] == 'SUCCEEDED':
        time.sleep(30)
```

2. Download the mask files

   Next, you will download the mask files from S3 into SageMaker Studio.

Copy and paste the following code into a new code cell. Then, select **Run**.

```
s3_bucket = session.resource("s3").Bucket(export_bucket)

mask_dir = "./dixie-wildfire-landcover/masks"
os.makedirs(mask_dir, exist_ok=True)
for s3_object in s3_bucket.objects.filter(Prefix=bucket_prefix).all():
    path, filename = os.path.split(s3_object.key)
    if "output" in path:
        mask_local_path = mask_dir + "/" + filename
        s3_bucket.download_file(s3_object.key, mask_local_path)
        print("Downloaded mask: " + mask_local_path)

mask_files = glob(os.path.join(mask_dir, "*.tif"))
mask_files.sort(key=lambda x: x.split("TFK_")[1])
```



Step 6: Analyze the exported segmentation masks

In this step, you'll use geospatial Python libraries included in the SageMaker AI geospatial image to perform further operations on the exported data.

1. Extract segmentation classes

   Using the **numpy** and **tifffile** libraries, you will extract dedicated segmentation classes (vegetation and water) out of the mask data and store this data in variables for later usage.

   Copy and **paste** the following code into a new code cell. Then, select **Run**.

```
landcover_simple_colors = {"not vegetated": "khaki","vegetated": "olivedrab",
 "water": "lightsteelblue"}

def extract_masks(date_str):
    mask_file = list(filter(lambda x: date_str in x, mask_files))[0]
    mask = tifffile.imread(mask_file)
    focus_area_mask = mask[400:1100, 600:1350]

    vegetation_mask = np.isin(focus_area_mask, [4]).astype(np.uint8) # vegetation
 has a class index of 4
    water_mask = np.isin(focus_area_mask, [6]).astype(np.uint8) # water has a class
 index of 6
    water_mask[water_mask &gt; 0] = 2
    additive_mask = np.add(vegetation_mask, water_mask).astype(np.uint8)

    return (focus_area_mask, vegetation_mask, additive_mask)

masks_20210603 = extract_masks("20210603")
masks_20210926 = extract_masks("20210926")
```

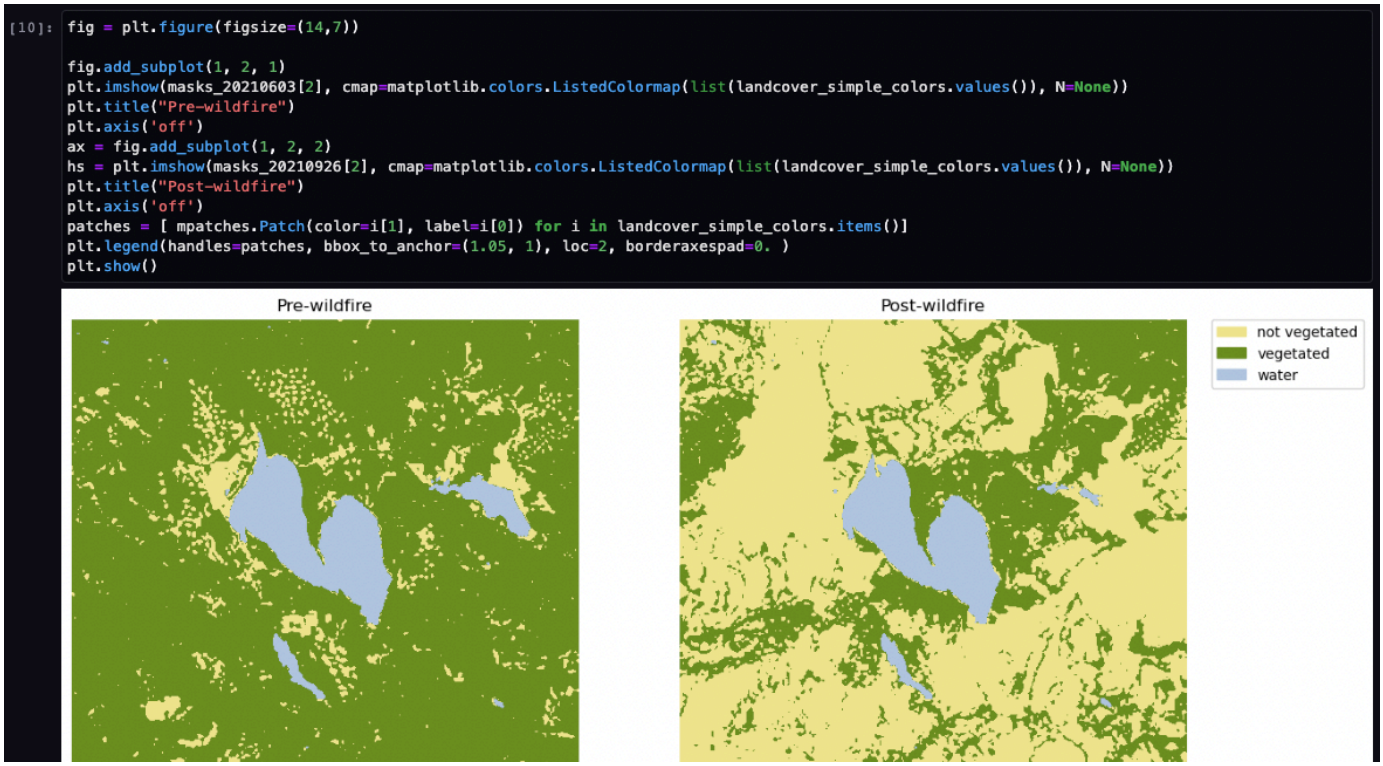
2. Visualize the extracted classes

   You will use now the preprocessed mask data to visualize the extracted classes.

   Copy and **paste** the following code into a new code cell. Then, select **Run**.

```
fig = plt.figure(figsize=(14,7))

fig.add_subplot(1, 2, 1)
plt.imshow(masks_20210603[2],
 cmap=matplotlib.colors.ListedColormap(list(landcover_simple_colors.values()),
 N=None))
plt.title("Pre-wildfire")
```

```
plt.axis('off')
ax = fig.add_subplot(1, 2, 2)
hs = plt.imshow(masks_20210926[2],
 cmap=matplotlib.colors.ListedColormap(list(landcover_simple_colors.values()),
 N=None))
plt.title("Post-wildfire")
plt.axis('off')
patches = [ mpatches.Patch(color=i[1], label=i[0]) for i in
 landcover_simple_colors.items()]
plt.legend(handles=patches, bbox_to_anchor=(1.05, 1), loc=2, borderaxespad=0. )
plt.show()
```



3. Compute and visualize the difference

   Finally, you will compute and visualize the difference between the post- and pre-wildfire mask.

   This shows the impact the wildfire had on the vegetation in the observed area. More than 60% of vegetation was lost as a direct impact of the fire.

   Copy and **paste** the following code into a new code cell. Then, select **Run**.

```
vegetation_loss = round((1 - (masks_20210926[1].sum() / masks_20210603[1].sum())) *
 100, 2)
```

```
diff_mask = np.add(masks_20210603[1], masks_20210926[1])
plt.figure(figsize=(6, 6))
plt.title("Loss in vegetation ({}%)".format(vegetation_loss))
plt.imshow(diff_mask, cmap=matplotlib.colors.ListedColormap(["black","crimson",
 "silver"], N=None))
plt.axis('off')
patches = [mpatches.Patch(color="crimson", label="vegetation lost")]
plt.legend(handles=patches, bbox_to_anchor=(1.05, 1), loc=2, borderaxespad=0. )
plt.show()
```

(Optional) Clean up resources

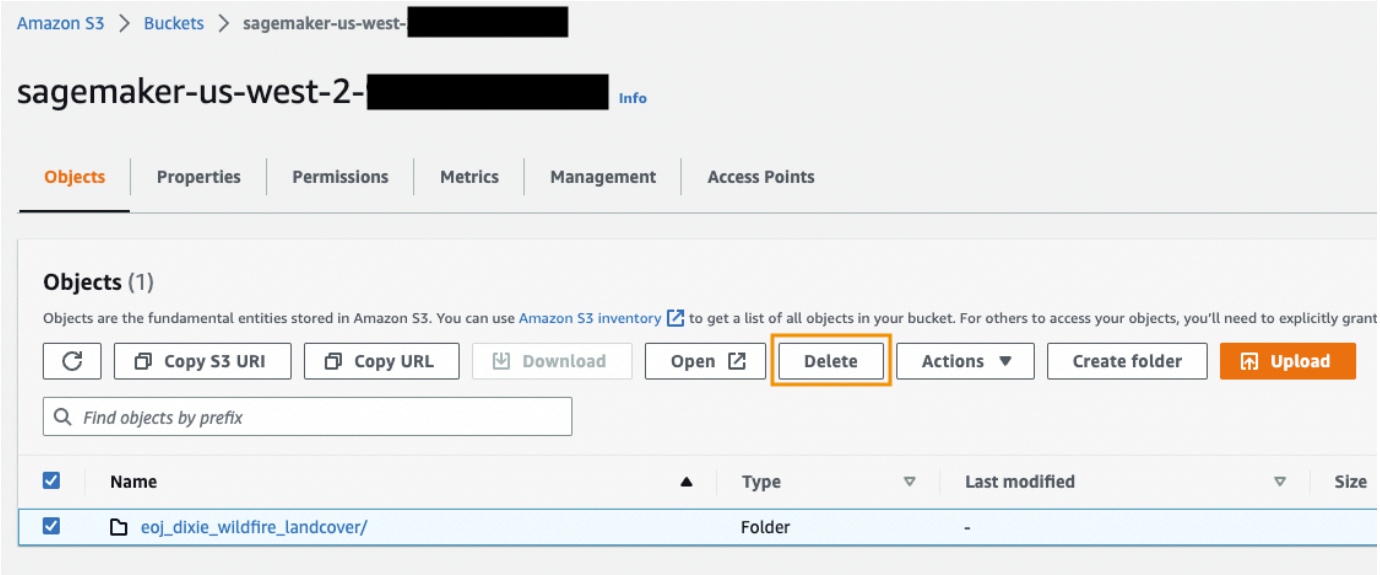
It is a best practice to delete resources that you no longer need so that you don't incur unintended charges.

1. Delete the bucket

   To delete the S3 bucket, complete the following steps:

   - Open the Amazon S3 console. On the navigation bar, choose **Buckets**, **sagemaker-<your-Region>-<your-account-id>**, and then select the checkbox next to **eoj_dixie_wildfire_landcover**. Then, choose **Delete**.
   - On the **Delete objects** dialog box, verify that you have selected the proper object to delete and enter **permanently delete** into the **Permanently delete objects** confirmation box.

- Once this is complete and the bucket is empty, you can delete the **sagemaker-<your-Region>-<your-account-id>** bucket by following the same steps again.

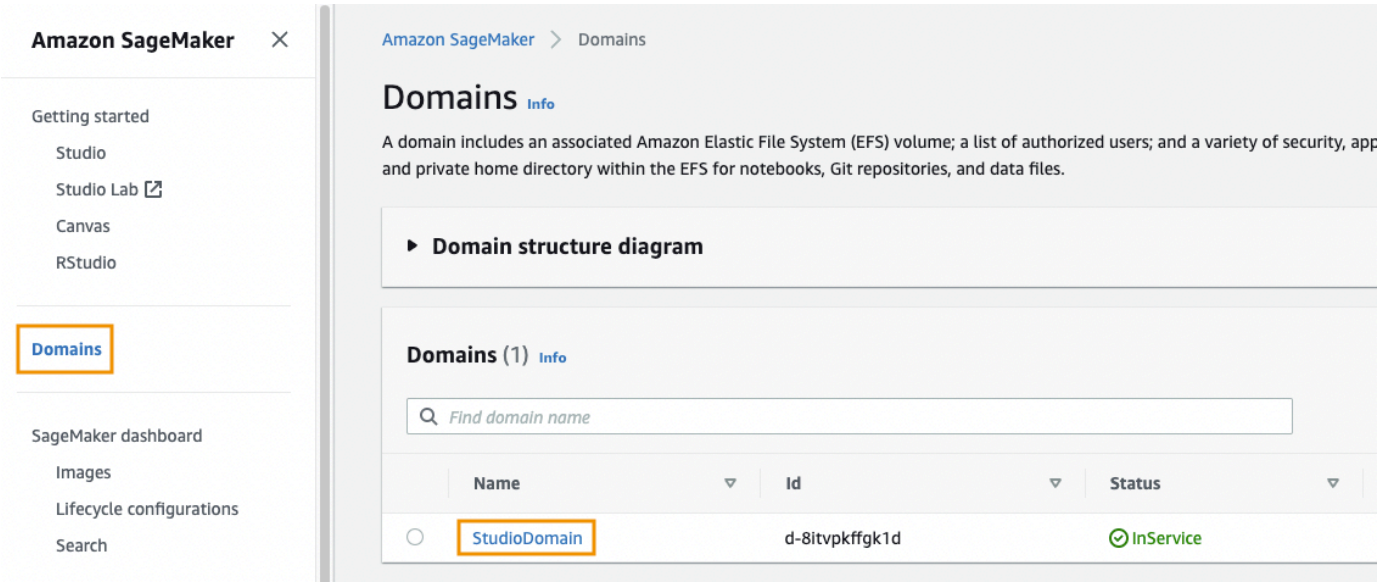


2. Choose the SageMaker AI Studio domain

> **Note**
>
> The Geospatial kernel used for running the notebook image in this tutorial will accumulate charges until you either stop the kernel or perform the following steps to delete the apps. For more information, see Shut Down Resources in the **Amazon SageMaker AI Developer Guide**.

To delete the SageMaker AI Studio apps, perform the following steps:

- In the SageMaker AI console, choose **Domains,** and then choose **StudioDomain**

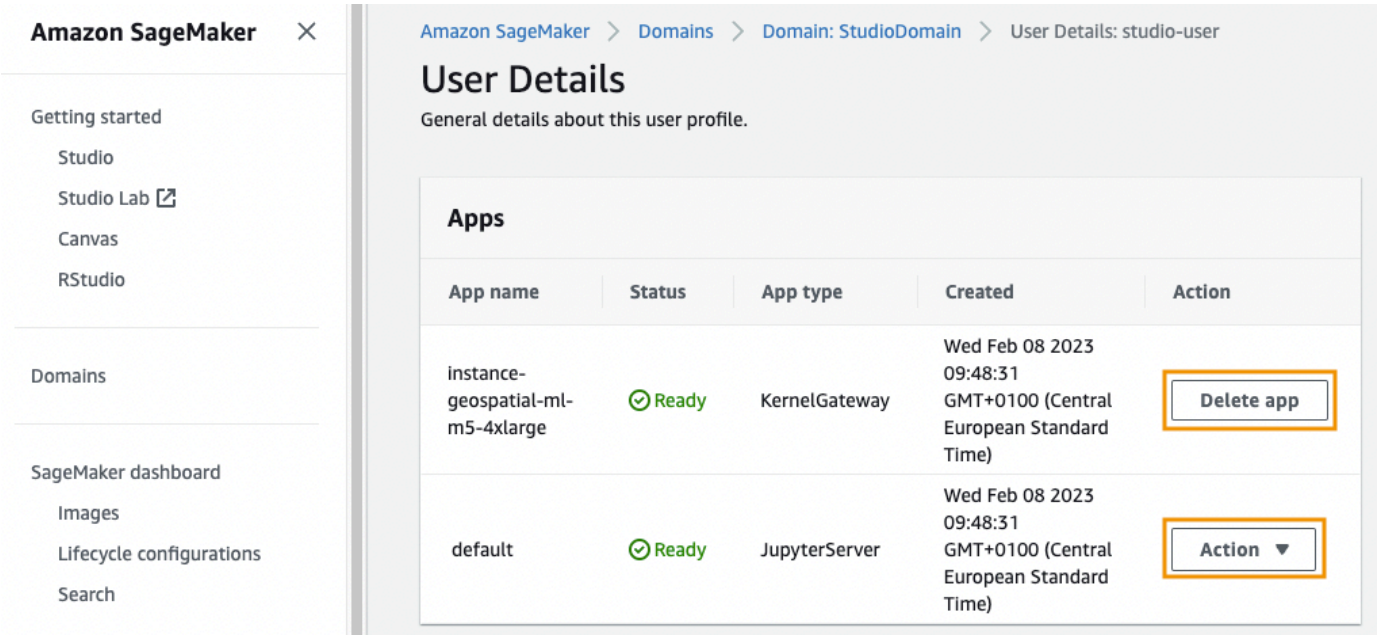


3. Delete the SageMaker AI Studio apps

   From the **User profiles** list, select **studio-user,** and then delete all the apps listed under Apps by choosing **Delete app**.

   To delete the JupyterServer, choose **Action**, then choose **Delete**.

   Wait until the Status changes to Deleted.



Delete the CloudFormation Stack

If you used an existing SageMaker AI Studio domain, you can skip the rest of the steps, and proceed directly to the conclusion section.

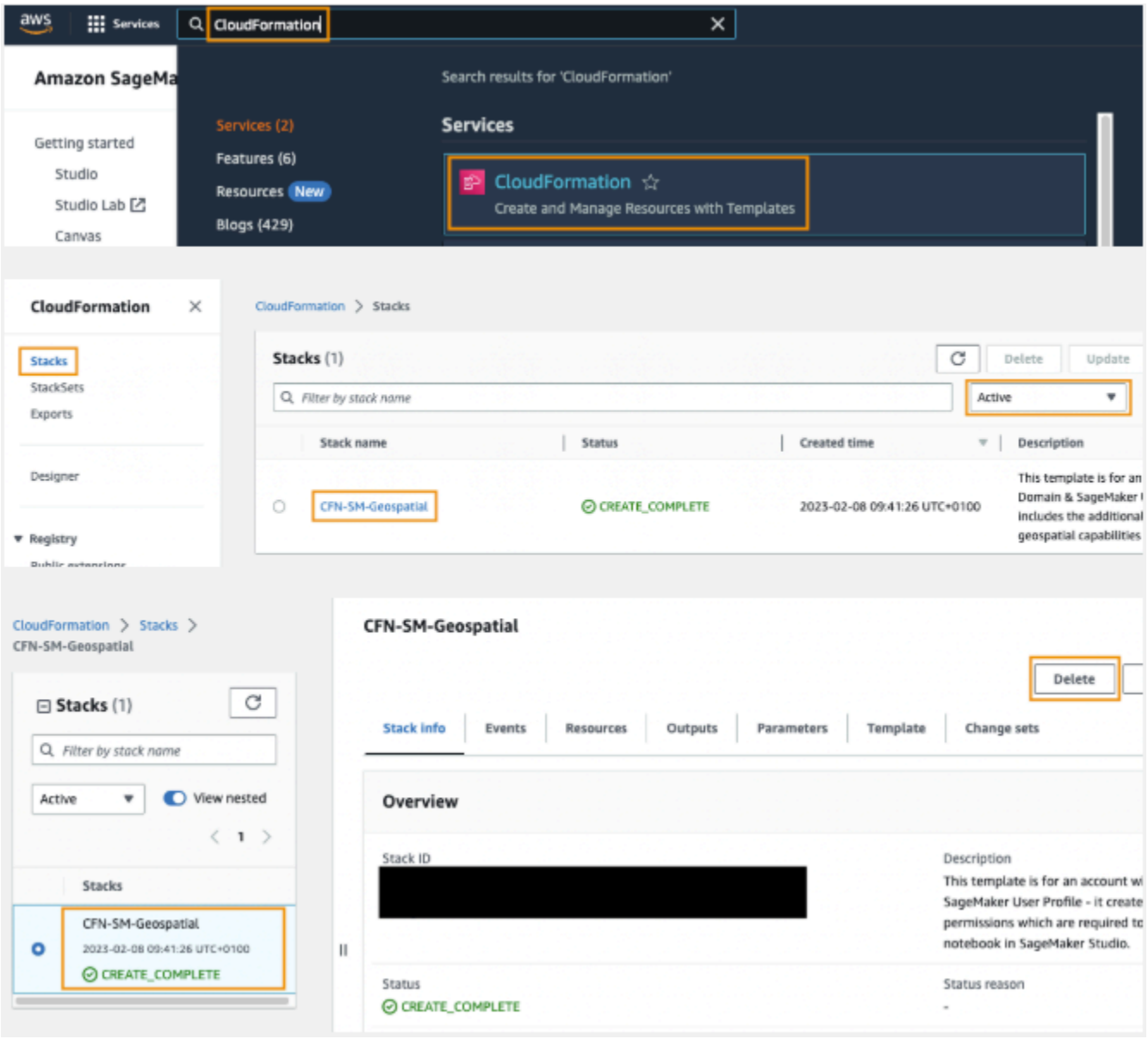
If you ran the CloudFormation template to create a new SageMaker AI Studio domain, continue with the following step to delete the domain, user, and the resources created by the CloudFormation template.

- Delete the CloudFormation stack

  Navigate to the CloudFormation console.

  In the CloudFormation pane, choose **Stacks**. From the status dropdown list, select **Active**. Under Stack name, choose **CFN-SM-Geospatial** to open the stack details page.

  On **CFN-SM-Geospatial** stack details page, choose **Delete** to delete the stack along with the resources it created.



Conclusion

Congratulations! You have finished the tutorial on how to assess wildfire damage with Amazon SageMaker AI geospatial capabilities.

In this tutorial, you used Amazon SageMaker AI geospatial capabilities to create and visualize an Earth Observation Job, exported its data to S3 and performed further computations on the data.