# **Earth Engine 101**

This workbook is an introdution to Earth Engine analysis in an IPython Notebook, using the Python API. The content is similar to what is covered in the Introduction to the Earth Engine API workshop using the Earth Engine Javascript "Playground".

Let's get started by importing a few moduled used in this tutorial.

In [19]:

from IPython.display import Image

## Hello, World

To get used to using IPython Notebooks, let's print some simple output back to the notebook. Click on the box below, and then press the play (run) button from the toolbar above.

```
print("Hello, world!")
In [20]:
```

Hello, world!

That works, but we can also first store the content in a variable, and then print out the variable.

```
In [21]:
```

```
string = "Hello, world!"
print(string)
```

Hello, world!

### Hello, Images

Let's work with something more interesting... a dataset provided by Earth Engine.

Assuming that this server has been setup with access to the Earth Engine Python API, we should be able to import and initialise the Earth Engine Python module (named 'ee'). If the module loads successfully, nothing will be returned when you run the following code.

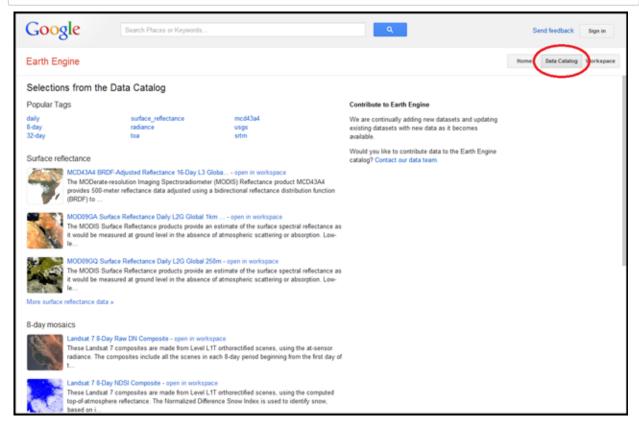
```
In [22]:
```

```
import ee
ee.Initialize()
```

Next, let's locate a dataset to display. Start by going to the Earth Engine Public Data Catalog (https://earthengine.google.org/#index (https://earthengine.google.org/#index)).

In [23]: Image('http://www.google.com/earth/outreach/images/tutorials\_eeintro\_05\_data\_cata

Out[23]:



Type in the term **SRTM** in the search box, click the search button, and then select the dataset **SRTM Digital Elevation Data Version 4** from the list of results. This will bring up a data description page for the <u>SRTM Digital Elevation Data 30m</u>

(https://earthengine.google.org/#detail/CGIAR%2FSRTM90\_V4) dataset. The data description page provide a short description of the dataset and links to the data provider, but the key piece of information that we need for working with the dataset in Earth Engine is the **Image ID**, which for this dataset is **CGIAR/SRTM90\_V4**. Let's use the Image ID to store a reference to this image dataset:

```
In [24]: srtm = ee.Image("CGIAR/SRTM90_V4")
```

And now, we can print out information about the dataset, using the .getInfo() method.

In [25]: info = srtm.getInfo()
print(info)

{u'bands': [{u'crs': u'EPSG:4326', u'crs\_transform': [0.000833333333333, 0.0, -180.0, 0.0, -0.000833333333333, 60.0], u'id': u'elevation', u'data\_type': {u'ma x': 32767, u'type': u'PixelType', u'precision': u'int', u'min': -32768}, u'dime nsions': [432000, 144000]}], u'version': 1475598656017000, u'type': u'Image', u'id': u'CGIAR/SRTM90\_V4', u'properties': {u'system:time\_end': 951177600000, u'system:visualization\_0\_max': 10000, u'thumb': u'https://mw1.google.com/ges/d d/images/SRTM90\_V4\_thumb.png', u'system:visualization\_0\_gamma': 1.6, u'provider \_url': u'http://srtm.csi.cgiar.org/', u'description': u"The Shuttle Radar To 029/2005RG000183/full'>Farr et al. 2007</a>) digital elevation dataset was or iginally produced to provide consistent, high-quality elevation data at near This version of the SRTM digital elevation data has been proc global scope. data voids, and to facilitate its ease of use. The SRTM 90m has essed to fill a resolution of 90m at the equator. This dataset contains one band, 'elevation' (meters).For the creation of any reports, publications, new data sets, derived products, or services resulting from the data set, us Jarvis, A., H.I. Reuter, A. Nelson, E. Guevara. 200 ers should cite: 8. Hole-filled SRTM for the globe Version 4, available from the CGIAR-CSI SRT <a href='http://srtm.csi.cgiar.org'>http://srtm.csi.cgiar.org M 90m Database: </a>.", u'title': u'SRTM Digital Elevation Data Version 4', u'period': 0, u'system:visualization\_0\_name': u'Elevation', u'date\_range': [950227200000, 95 1177600000], u'sample': u'https://mw1.google.com/ges/dd/images/SRTM90\_V4\_sampl e.png', u'link': u'srtm90 v4', u'provider': u'NASA / CGIAR', u'system:time star t': 950227200000, u'system:visualization\_0\_min': 0, u'system:asset\_size': 18827 626666, u'tags': [u'nasa', u'cgiar', u'srtm', u'elevation', u'topography', u'de m', u'geophysical'], u'system:visualization\_0\_bands': u'elevation'}}

What is returned by the .getInfo() command is a Python dictionary. If needed, we could parse out this information and make use of it in our analysis.

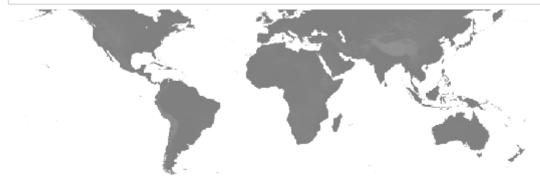
#### Add an Image to the Map

IPython Notebooks can be used to display an image, using the Image module:

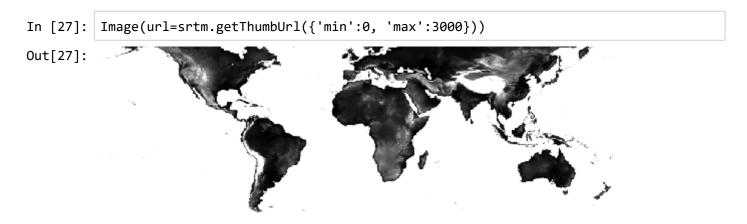
In [26]: from IPython.display import Image

Image(url=srtm.getThumbUrl())

Out[26]:

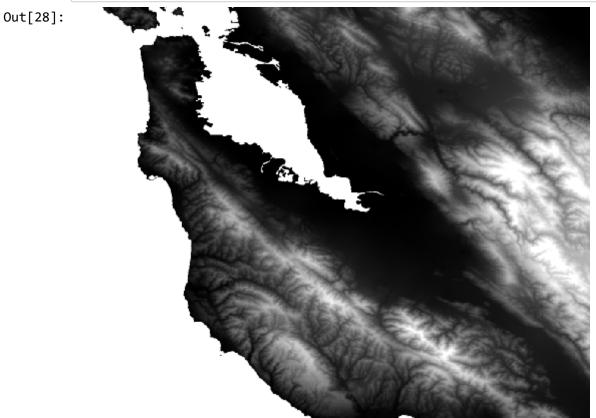


Ok, we can see the outlines of the continents, but there is not a lot of contrast between different elevation areas. So let's improve upon that, but adding some visualization parameters.



By default, the **.getThumbUrl()** method returns the entire extent of the image, which in this case is global. We can also specify a region, to show a smaller area.

```
In [28]: point = ee.Geometry.Point(-122.0918, 37.422)
    region_bay_area = point.buffer(50000).bounds().getInfo()['coordinates']
    Image(url=srtm.getThumbUrl({'min':0, 'max':1000, 'region':region_bay_area}))
```



## Load and Filter an Image Collection

So far we have been working with a single image, but there are also interesting datasets that are distributed as a series of images (such as images collected by satellite). Head back to the <u>Earth Engine Public Data Catalog (https://earthengine.google.org/#index)</u>, search for **landsat 8 toa**, and

load up the data description page for the **USGS Landsat 8 TOA Reflectance (Orthorectified)** dataset. The ID for this Image Collection is **LANDSAT/LC8\_L1T\_TOA**.

Out[29]:



### **Playing with Image Bands**

Using the default image visualization parameters, that doesn't look like much. So we add some visualization data, to display a true color image.

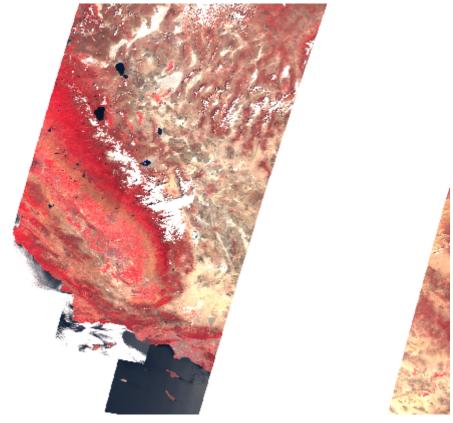
Out[30]:



And by changing the bands displayed, we can also display a false color image.

```
In [31]: Image(url=18_image.getThumbUrl({
         'region':region_california,
         'bands':'B5,B4,B3',
         'min':0,
         'max':0.3
}))
```

Out[31]:



# **Play with Reducing Image Collections**

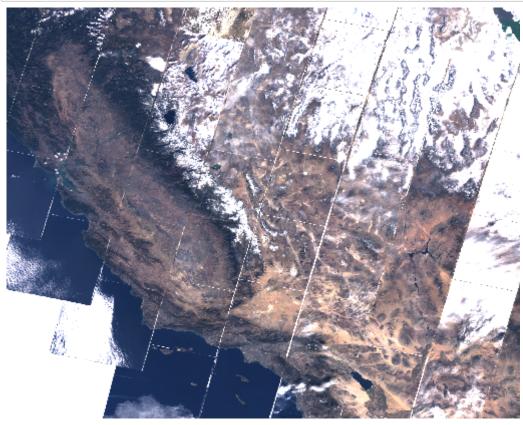
Next expand the date range to cover an entire year, so that there are many overlapping images. We will continue to use the **.mosaic()** reducer, which retains the last (most recent) pixels in areas of image overlap. Clouds are readily apparent.

```
In [32]: filtered = 18.filterDate('2013-01-01', '2014-01-01')
```

## ImageCollection.mosaic Reducer

```
In [33]: l8_image = filtered.mosaic()
    Image(url=18_image.getThumbUrl({
        'region':region_california,
        'bands':'B4,B3,B2',
        'min':0,
        'max':0.3
}))
```

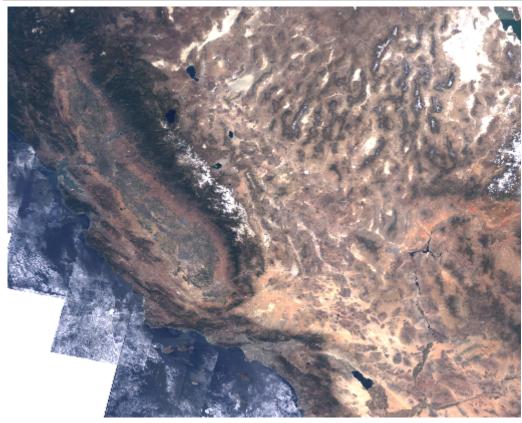
Out[33]:



ImageCollection.median Reducer

```
In [34]: l8_image = filtered.median()
    Image(url=18_image.getThumbUrl({
        'region':region_california,
        'bands':'B4,B3,B2',
        'min':0,
        'max':0.3
    }))
```

Out[34]:



ImageCollection.min Reducer

```
In [35]: l8_image = filtered.min()
    Image(url=18_image.getThumbUrl({
        'region':region_california,
        'bands':'B4,B3,B2',
        'min':0,
        'max':0.3
    }))
```

Out[35]:



ImageCollection.max Reducer ¶

```
In [36]: l8_image = filtered.max()
    Image(url=18_image.getThumbUrl({
         'region':region_california,
         'bands':'B4,B3,B2',
         'min':0,
         'max':0.3
}))
```

Out[36]:



In [ ]: