Evaluation Task 2 for Machine Learning Model for the Albedo of Mercury

Problem Statement 2 :

Predicting Mercury's elemental composition from Albedo with MESSENGER Data

Importing important libraries

```
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import urllib.request
import pandas as pd
from numpy import genfromtxt
from sklearn.metrics import mean_squared_error
from sklearn.linear_model import LinearRegression
import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)
```

Importing Dataset

Getting the data from https://github.com/ML4SCI/ML4SCI_GSoC/tree/main/Messenger/Mercury and converting it into proper format for further processing.

```
data_all = {}


top =
urllib.request.urlopen('https://raw.githubusercontent.com/ML4SCI/ML4SC
I_GSoC/main/Messenger/Mercury/mercury-albedo-top-half.png.csv')
lines = [i.decode('utf-8') for i in top.readlines()]
data_all['top_half'] = genfromtxt(lines, delimiter=',')

bottom =
urllib.request.urlopen('https://raw.githubusercontent.com/ML4SCI/ML4SC
I_GSoC/main/Messenger/Mercury/mercury-albedo-resized-bottom-
half.png.csv')
lines = [i.decode('utf-8') for i in bottom.readlines()]
data_all['bottom_half'] = genfromtxt(lines, delimiter=',')

alsi =
urllib.request.urlopen('https://raw.githubusercontent.com/ML4SCI/ML4SC
I_GSoC/main/Messenger/Mercury/alsimap_smooth_032015.png.csv')
lines = [i.decode('utf-8') for i in alsi.readlines()]
data_all['alsi'] = genfromtxt(lines, delimiter=',')

casi =
urllib.request.urlopen('https://raw.githubusercontent.com/ML4SCI/ML4SC
```

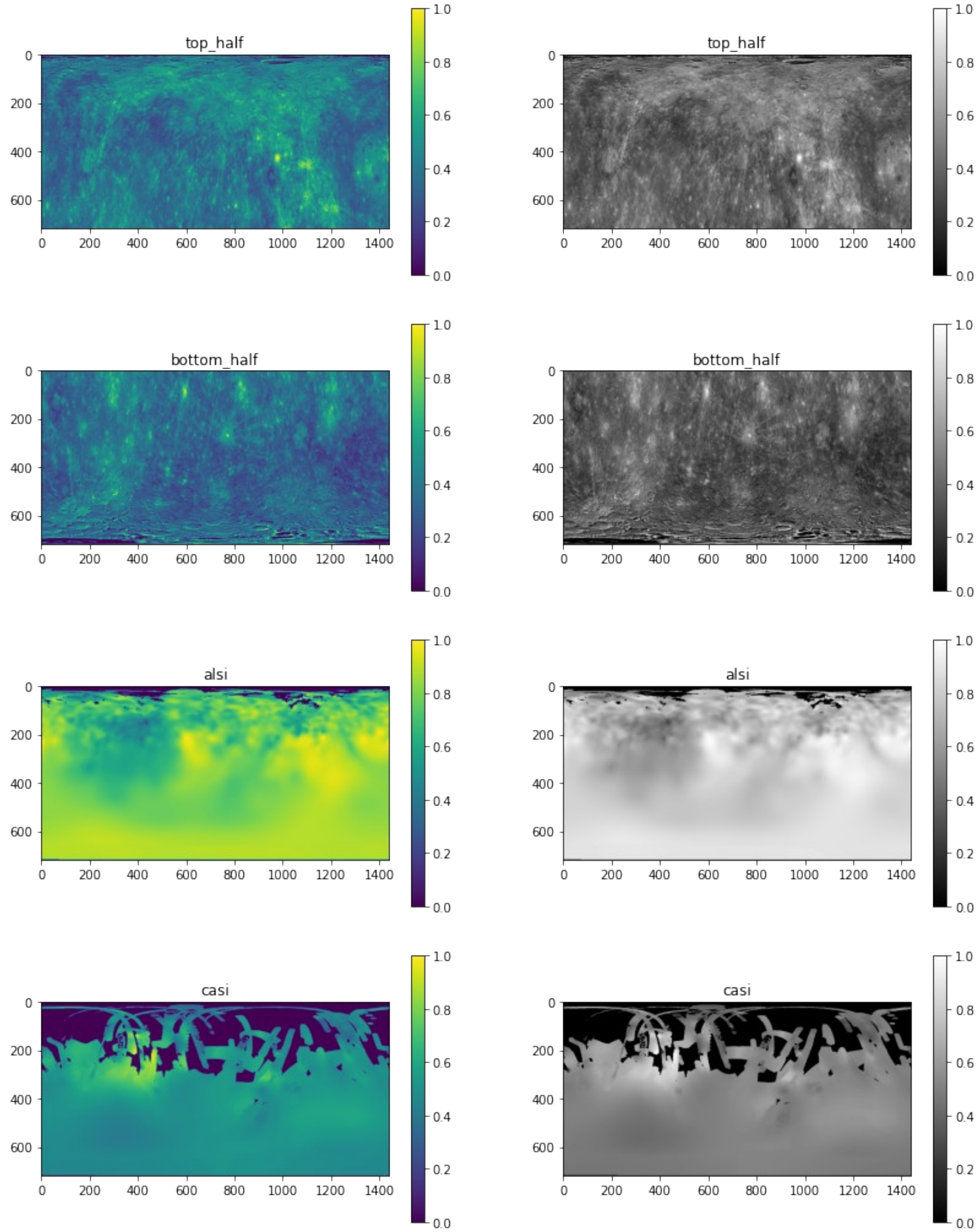
```
I_GSoC/main/Messenger/Mercury/casimap_smooth_032015.png.csv')
lines = [i.decode('utf-8') for i in casi.readlines()]
data_all['casi'] = genfromtxt(lines, delimiter=',')

fesi =
urllib.request.urlopen('https://raw.githubusercontent.com/ML4SCI/ML4SC
I_GSoC/main/Messenger/Mercury/fesimap_smooth_032015.png.csv')
lines = [i.decode('utf-8') for i in fesi.readlines()]
data_all['fesi'] = genfromtxt(lines, delimiter=',')

mgsi =
urllib.request.urlopen('https://raw.githubusercontent.com/ML4SCI/ML4SC
I_GSoC/main/Messenger/Mercury/mgsimap_smooth_032015.png.csv')
lines = [i.decode('utf-8') for i in mgsi.readlines()]
data_all['mgsi'] = genfromtxt(lines, delimiter=',')

ssi =
urllib.request.urlopen('https://raw.githubusercontent.com/ML4SCI/ML4SC
I_GSoC/main/Messenger/Mercury/ssimap_smooth_032015.png.csv')
lines = [i.decode('utf-8') for i in ssi.readlines()]
data_all['ssi'] = genfromtxt(lines, delimiter=',')

data_all["albedo"] = np.concatenate((data_all["top_half"],
data_all["bottom_half"]))
```

Data Visualization

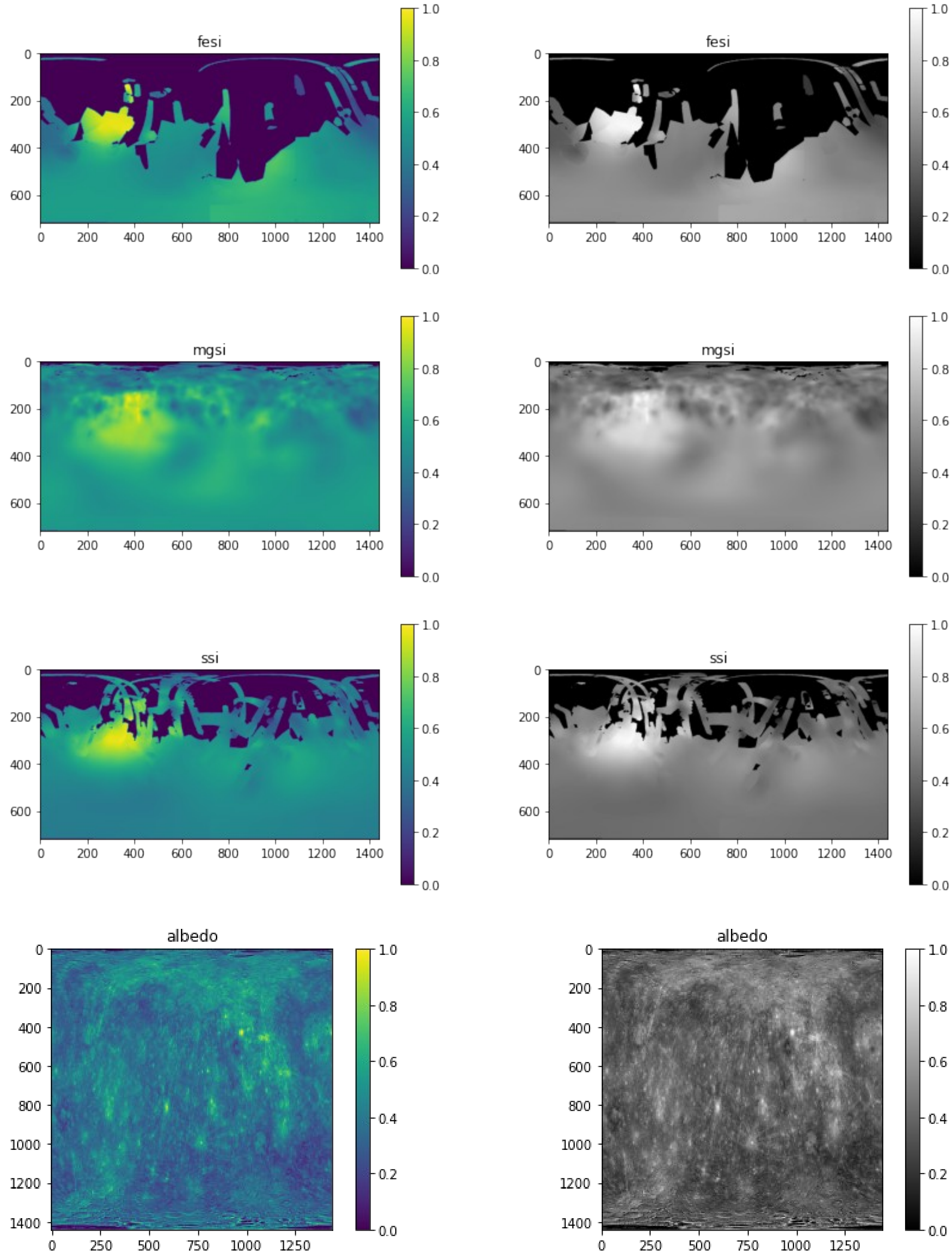
The top-half , bottom-half of Mercury Albedo and chemical composition maps are visualized and present in two forms for better understanding of the data. Furthermore, data correlation matrix is visualized. On the basis of the correlation matrix, it can be said that the correlation between the albedo and elements is low as comapred to the moon.

```
for i, (key, value) in enumerate(data_all.items()):
    plt.figure(i)
    fig, axes = plt.subplots(1, 2, figsize=(14, 4))
    axes[0].set_title(f"{key}")
    original = axes[0].imshow(value)
    plt.colorbar(original, ax=axes[0])
    axes[1].set_title(f"{key}")
    gray_image = axes[1].imshow(value, cmap='gray')
    plt.colorbar(gray_image, ax=axes[1])
```

```
<Figure size 432x288 with 0 Axes>
```



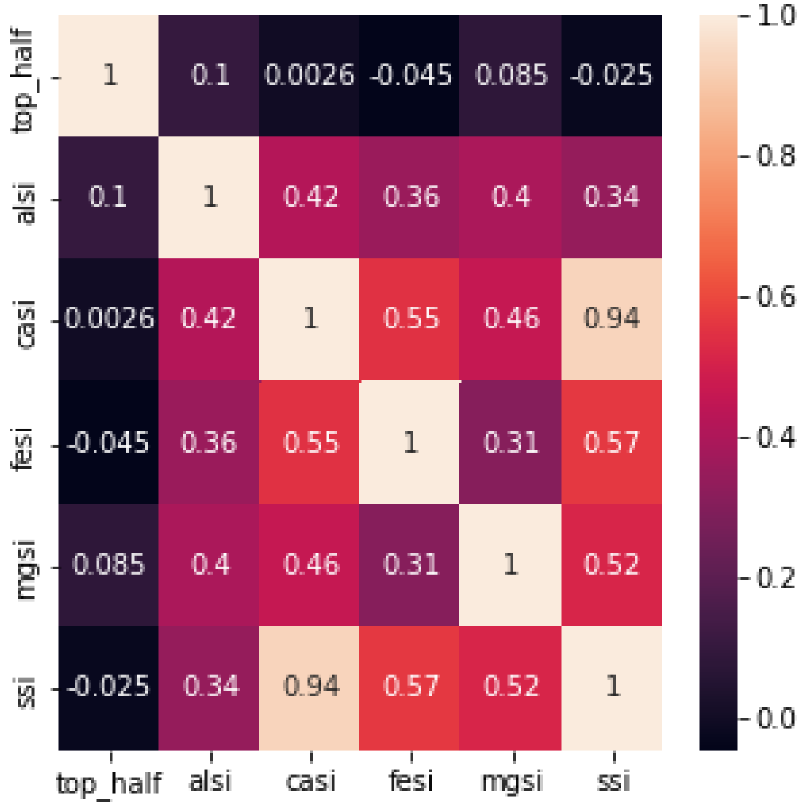
top_half
top_half
bottom_half
bottom_half
alsi
alsi
casi
casi




```
elem = np.array(list(zip(data_all['top_half'].flatten(),
data_all['alsi'].flatten(), data_all['casi'].flatten(),
data_all['fesi'].flatten(),
data_all['mgsi'].flatten(),data_all['ssi'].flatten())))
df =
pd.DataFrame(elem,columns=['top_half','alsi','casi','fesi','mgsi','ssi
```

```
'])
corr = df.corr()
plt.figure(figsize=(5, 5))
sns.heatmap(corr, annot=True)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f4a502fa3d0>
```



Spliting Dataset into Test and Train sets

```
n = len(elem)//2
train = elem[:n]
test = elem[n:]
x_train, y_train = train[:,:1], train[:,1:]
x_test, y_test  = test[:,:1],  test[:,1:]
```

Training ML model and calculation of the MSE and accuracy.

I decided to use the Linear Regression for this task. MSE(mean squared error) is used as a performance metric for this model. The mean squared error is found out to be 0.05845956007038442.

```
model = LinearRegression().fit(x_train, y_train)
y_pred=model.predict(x_test)
mse=mean_squared_error(y_test, y_pred)
print("MSE for LinearRegression: ",mse)
```

```
MSE for LinearRegression:  0.05845956007038442
Model Accuracy for Test set: -6.466
Model Accuracy for Train set: 0.009
```

Results:

Prediction about chemical composition for the top half of the planet using the albedo is shown below

```python
prediction = model.predict(data_all['top_half'].reshape(-1,1))
elem = ["alsi","casi", "fesi","mgsi", "ssi"]

for i, name in enumerate(elem):
    img = data_all[name]
    predicted_img = prediction[:,i].reshape(720,-1)
    prediction_error = np.abs(predicted_img - img)
    plt.figure(i)
    fig, axes = plt.subplots(nrows=1, ncols=3, figsize=(18, 4))
    axes[0].set_title(f"{name}")
    im = axes[0].imshow(img, vmin=0, vmax=1)
    plt.colorbar(im, ax=axes[0])
    axes[1].set_title(f"Predicted {name}")
    im = axes[1].imshow(predicted_img, vmin=0, vmax=1)
    plt.colorbar(im, ax=axes[1])
    axes[2].set_title(f"Prediction error {name}")
    im = axes[2].imshow(prediction_error, vmin=0, vmax=1)
    plt.colorbar(im, ax=axes[2])
    fig.tight_layout()
```

```
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```
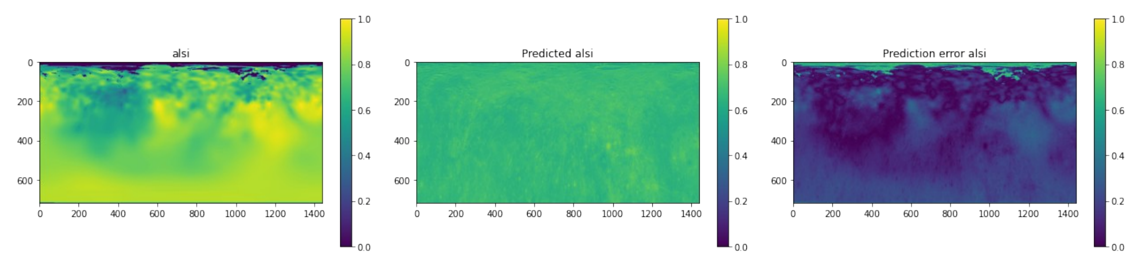
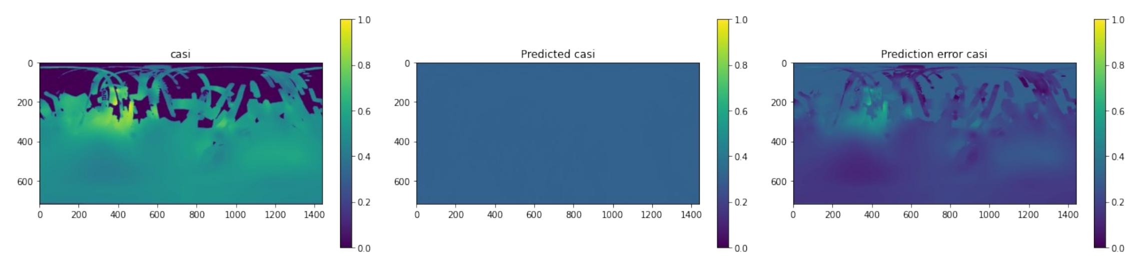
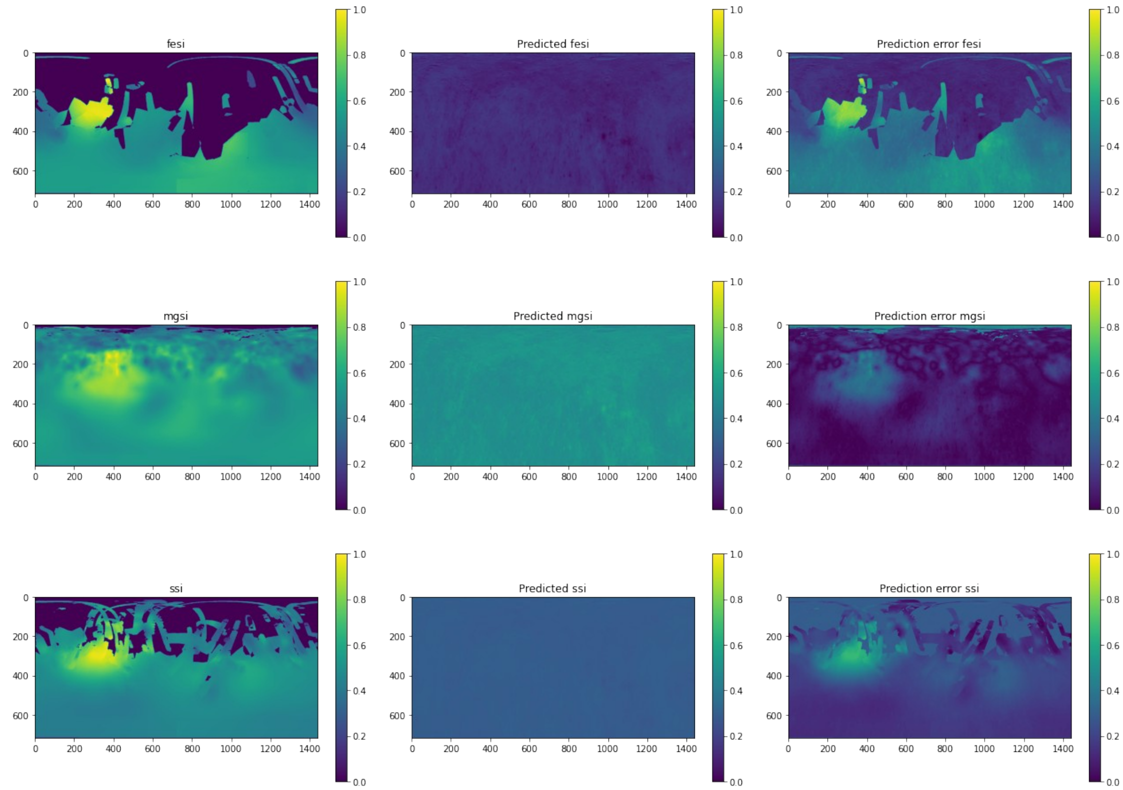



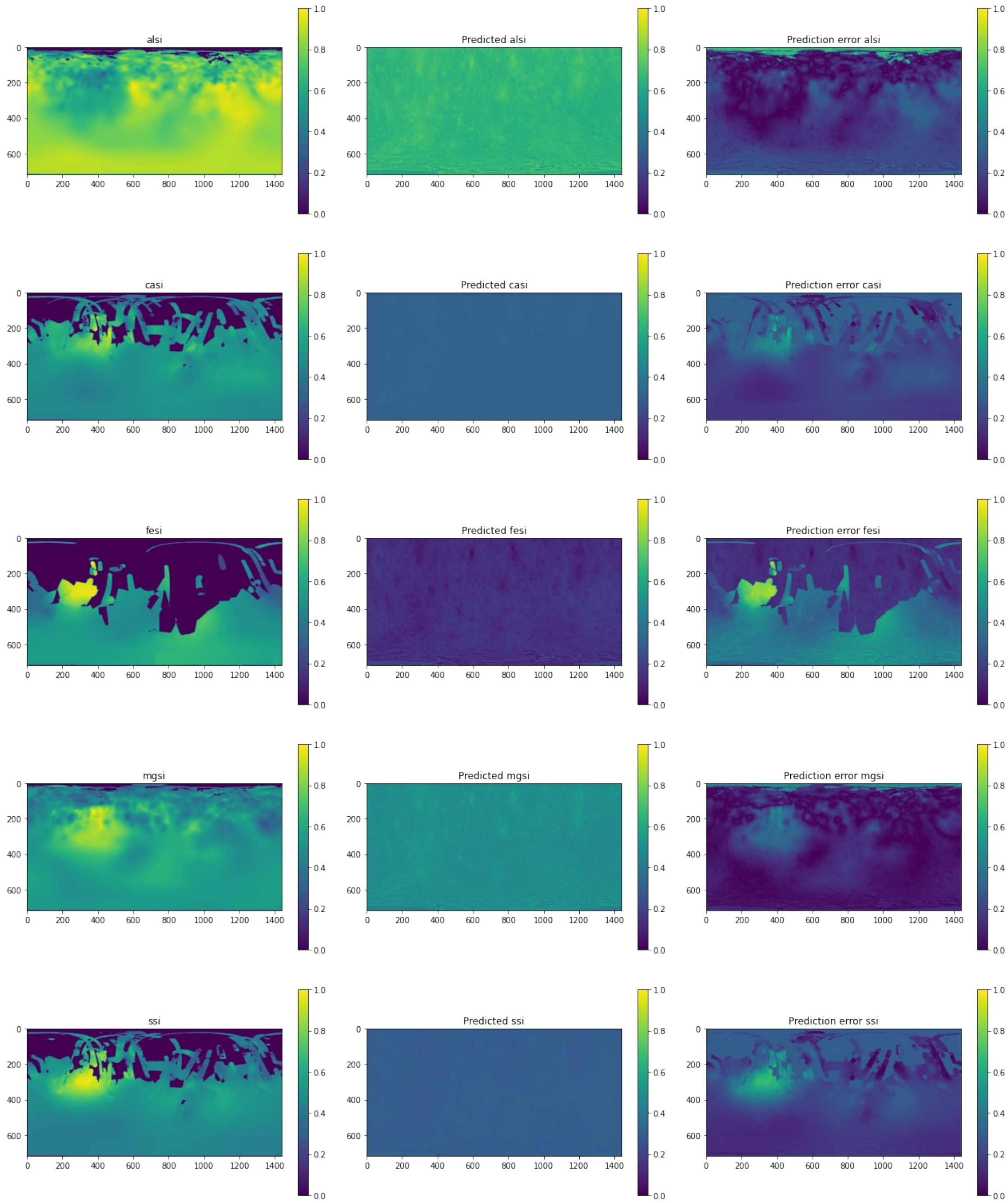




Prediction about chemical composition for the bottom half of the planet using the albedo is shown below

```
prediction = model.predict(data_all['bottom_half'].reshape(-1,1))
elem = ["alsi","casi", "fesi","mgsi", "ssi"]

for i, name in enumerate(elem):
    img = data_all[name]
    predicted_img = prediction[:,i].reshape(720,-1)
    prediction_error = np.abs(predicted_img - img)
    plt.figure(i)
    fig, axes = plt.subplots(nrows=1, ncols=3, figsize=(18, 4))
    axes[0].set_title(f"{name}")
    im = axes[0].imshow(img, vmin=0, vmax=1)
    plt.colorbar(im, ax=axes[0])
    axes[1].set_title(f"Predicted {name}")
    im = axes[1].imshow(predicted_img, vmin=0, vmax=1)
    plt.colorbar(im, ax=axes[1])
    axes[2].set_title(f"Prediction error {name}")
    im = axes[2].imshow(prediction_error, vmin=0, vmax=1)
    plt.colorbar(im, ax=axes[2])
    fig.tight_layout()
```

```
<Figure size 432x288 with 0 Axes>
```



alsi
Predicted alsi
Prediction error alsi
casi
Predicted casi
Prediction error casi
fesi
Predicted fesi
Prediction error fesi
mgsi
Predicted mgsi
Prediction error mgsi
ssi
Predicted ssi
Prediction error ssi