In [1]:
```
%matplotlib inline
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.linear_model import Ridge
from sklearn.metrics import r2_score,mean_squared_error
from sklearn.preprocessing import StandardScaler
from sklearn.multioutput import MultiOutputRegressor
#from keras.models import Sequential
#from keras.layers import Dense
```

In [2]:
```
albedo_top_data=pd.read_csv("..\ML4SCI_GSoC\Messenger\Mercury\mercury-albedo-top-half.png.cs
v",header=None)
```

In [3]:
```
albedo_top_data.head()
```

Out[3]:

	0	1	2	3	4	5	6	7	8	9	...	1430	1431
0	0.486275	0.498039	0.521569	0.529412	0.541176	0.596078	0.643137	0.678431	0.686275	0.698039	...	0.509804	0.552941
1	0.486275	0.498039	0.521569	0.529412	0.541176	0.596078	0.643137	0.678431	0.686275	0.698039	...	0.509804	0.552941
2	0.027451	0.019608	0.011765	0.007843	0.003922	0.003922	0.007843	0.019608	0.031373	0.035294	...	0.015686	0.019608
3	0.027451	0.019608	0.011765	0.007843	0.003922	0.003922	0.007843	0.019608	0.031373	0.035294	...	0.015686	0.019608
4	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	...	0.000000	0.000000

5 rows × 1440 columns

In [4]:
```
albedo_top_data.describe()
```

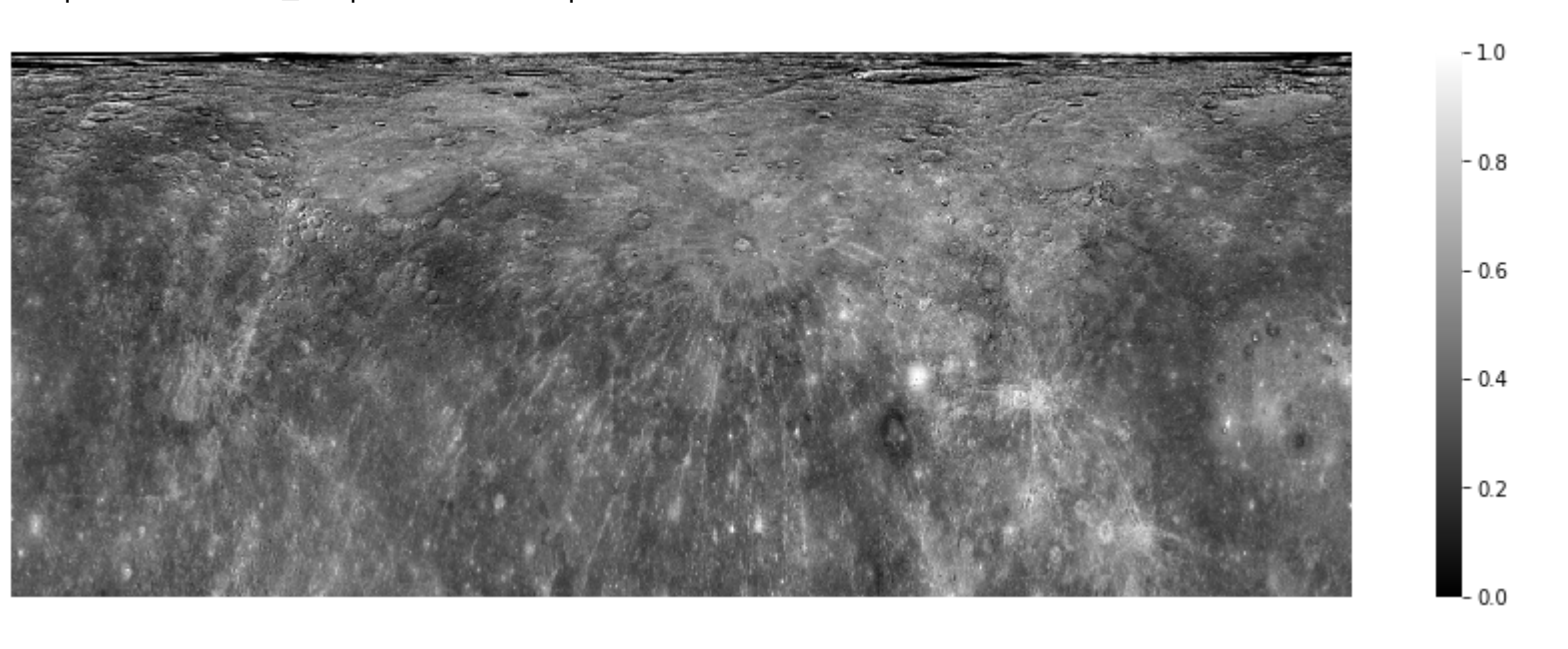
Out[4]:

	0	1	2	3	4	5	6	7	8	
count	720.000000	720.000000	720.000000	720.000000	720.000000	720.000000	720.000000	720.000000	720.000000	720.00000
mean	0.396427	0.394325	0.391678	0.385904	0.385261	0.380229	0.381144	0.380784	0.376122	0.37660
std	0.115433	0.110688	0.105231	0.097998	0.097741	0.101651	0.100978	0.104517	0.106795	0.10653
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.00000
25%	0.329412	0.333333	0.333333	0.329412	0.329412	0.321569	0.325490	0.325490	0.317647	0.31764
50%	0.384314	0.384314	0.388235	0.384314	0.388235	0.380392	0.384314	0.384314	0.372549	0.37254
75%	0.454902	0.447059	0.451961	0.451961	0.447059	0.436275	0.439216	0.436275	0.435294	0.43529
max	0.847059	0.850980	0.737255	0.631373	0.737255	0.741176	0.737255	0.749020	0.749020	0.76862

8 rows × 1440 columns

In [5]:
```
plt.subplots(figsize=(15,5))
sns.heatmap(albedo_top_data,xticklabels=False,yticklabels=False,cmap='gray')
```

Out[5]: <matplotlib.axes._subplots.AxesSubplot at 0x270f0a1e748>

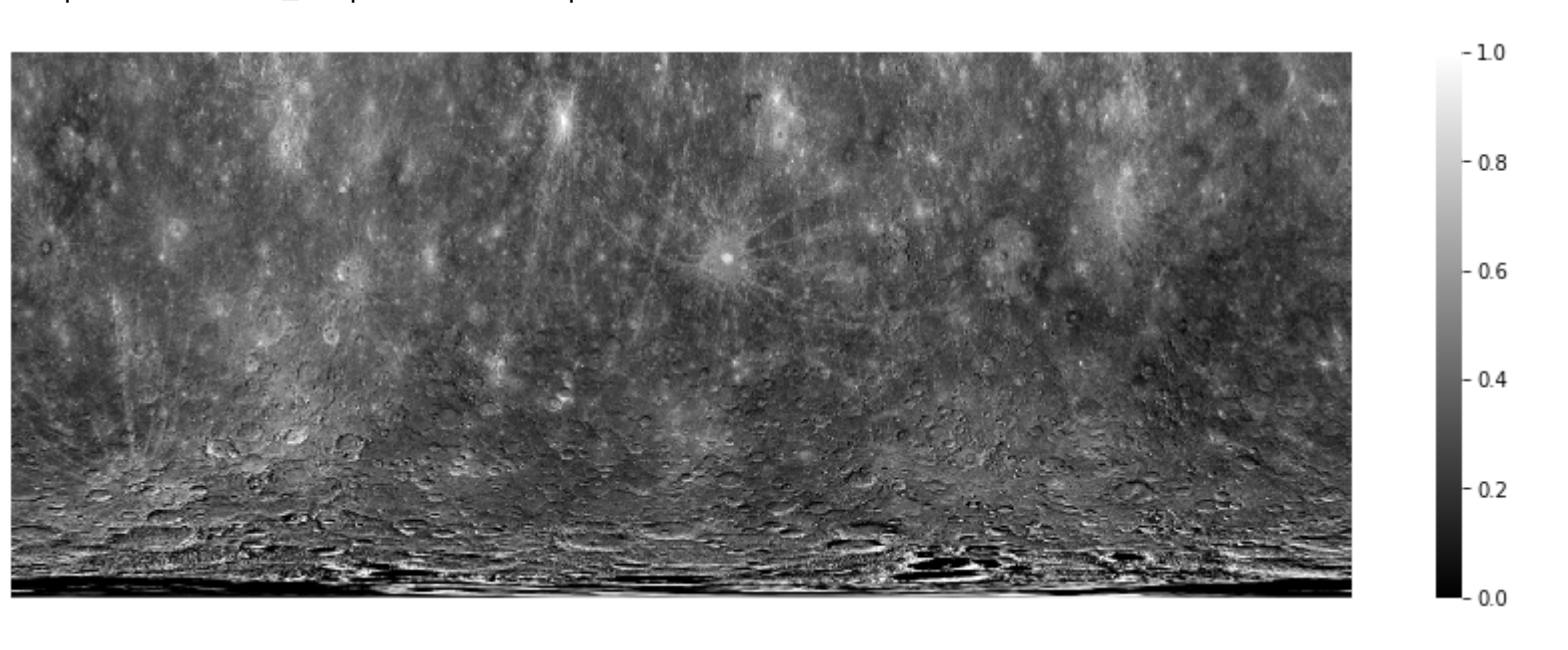


In [6]:
```
scale_al_top=StandardScaler()
scaled_top=scale_al_top.fit_transform(albedo_top_data)
```

In [7]:
```
albedo_bottom_data=pd.read_csv("..\ML4SCI_GSoC\Messenger\Mercury\mercury-albedo-resized-bott
om-half.png.csv",header=None)
```

In [8]:
```
plt.subplots(figsize=(15,5))
sns.heatmap(albedo_bottom_data,xticklabels=False,yticklabels=False,cmap='gray')
```

Out[8]: <matplotlib.axes._subplots.AxesSubplot at 0x270f087a348>



In [9]:
```
mgsi_map_data=pd.read_csv("..\ML4SCI_GSoC\Messenger\Mercury\mgsimap_smooth_032015.png.csv",h
eader=None)
mgsi_map_data.describe()
```

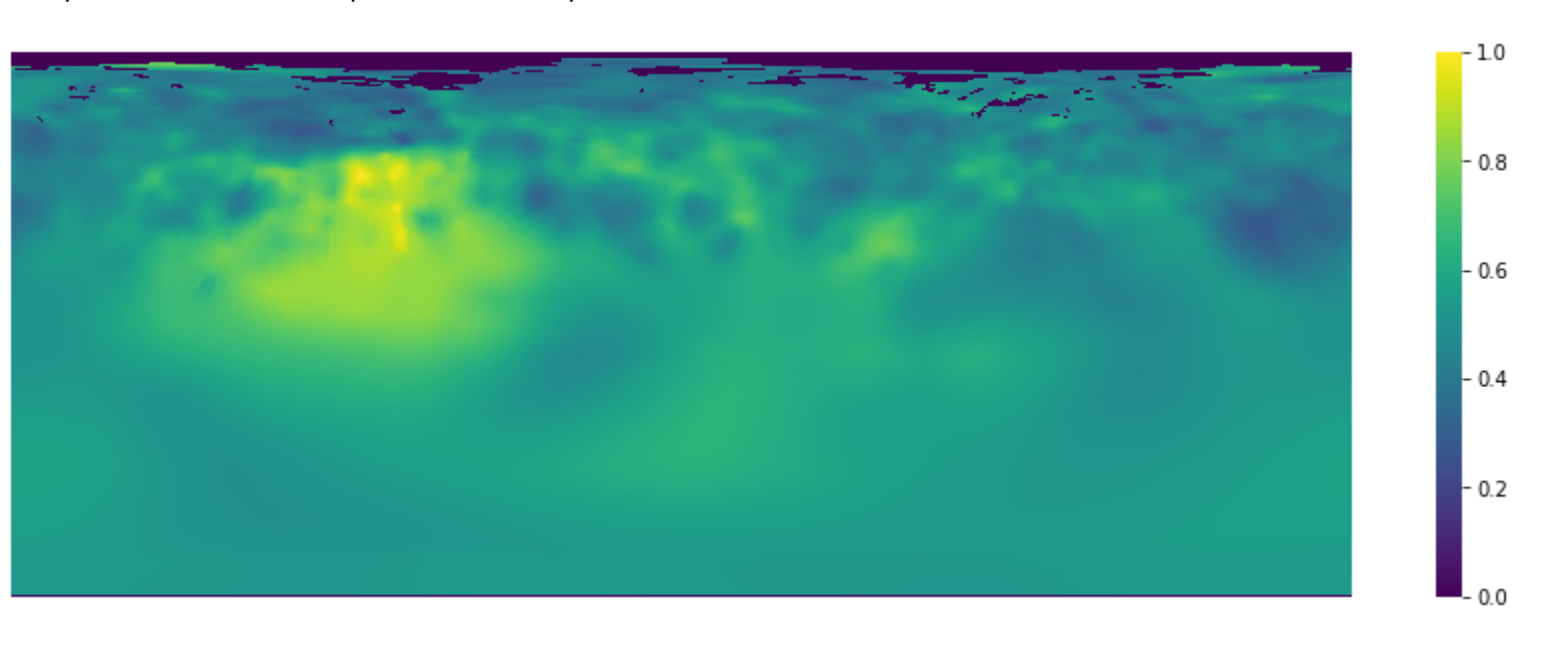
Out[9]:

	0	1	2	3	4	5	6	7	8	
count	720.000000	720.000000	720.000000	720.000000	720.000000	720.000000	720.000000	720.000000	720.000000	720.00000
mean	0.485016	0.485289	0.485528	0.485795	0.485234	0.484722	0.484897	0.485871	0.486068	0.48628
std	0.110547	0.110530	0.110478	0.110411	0.111816	0.113262	0.113268	0.111801	0.111829	0.11188
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.00000
25%	0.450980	0.450980	0.454902	0.454902	0.454902	0.450980	0.450980	0.450980	0.450980	0.45098
50%	0.513726	0.513726	0.513726	0.513726	0.513726	0.513726	0.513726	0.513726	0.513726	0.51372
75%	0.552941	0.552941	0.552941	0.552941	0.552941	0.552941	0.550000	0.549020	0.549020	0.54902
max	0.619608	0.615686	0.615686	0.611765	0.611765	0.607843	0.607843	0.603922	0.600000	0.60000

8 rows × 1440 columns

In [10]:
```
plt.subplots(figsize=(15,5))
sns.heatmap(mgsi_map_data,xticklabels=False,yticklabels=False,cmap='viridis')
```

Out[10]: <matplotlib.axes._subplots.AxesSubplot at 0x270f079e7c8>

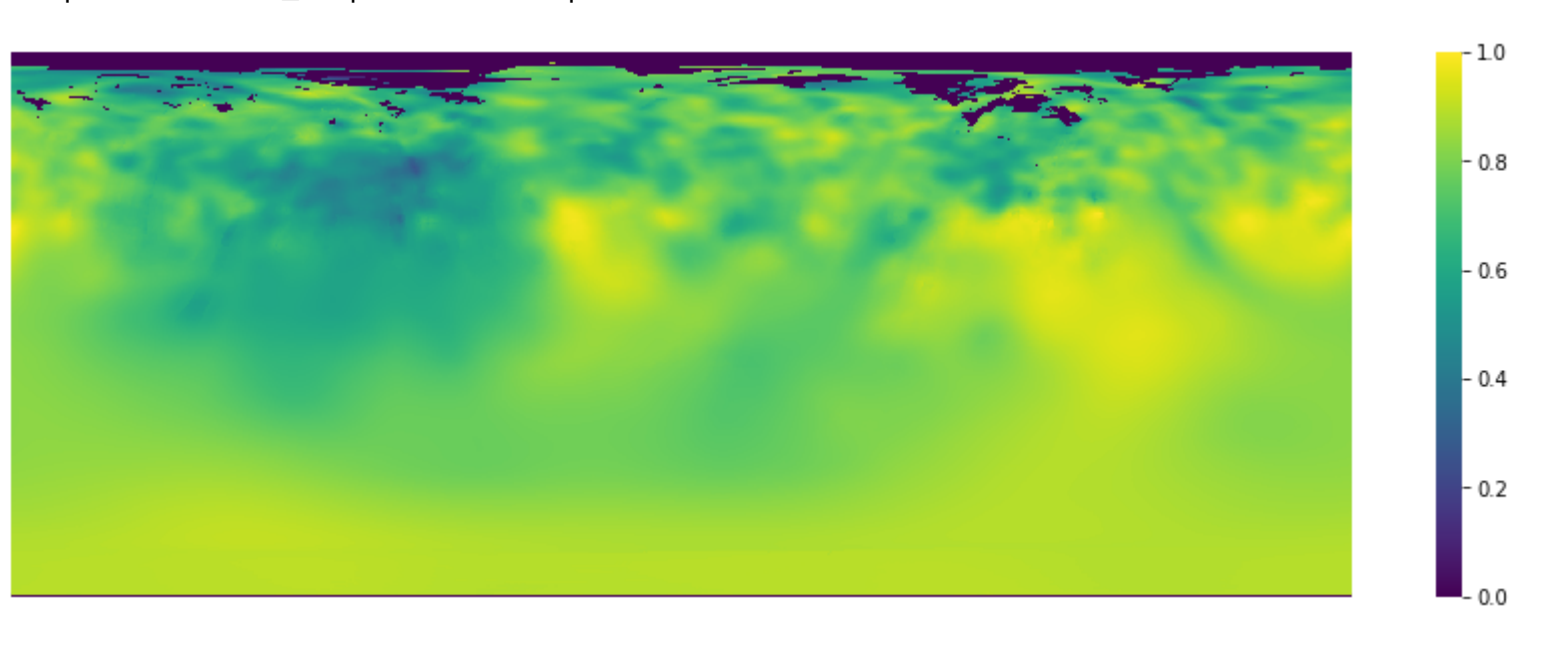


In [11]:
```
scale_mg=StandardScaler()
scaled_mgsi=scale_mg.fit_transform(mgsi_map_data)
```

In [12]:
```
alsi_map_data=pd.read_csv("..\ML4SCI_GSoC\Messenger\Mercury\\alsimap_smooth_032015.png.csv",
header=None)
```

In [13]:
```
plt.subplots(figsize=(15,5))
sns.heatmap(alsi_map_data,xticklabels=False,yticklabels=False,cmap='viridis')
```

Out[13]: <matplotlib.axes._subplots.AxesSubplot at 0x270f05b77c8>

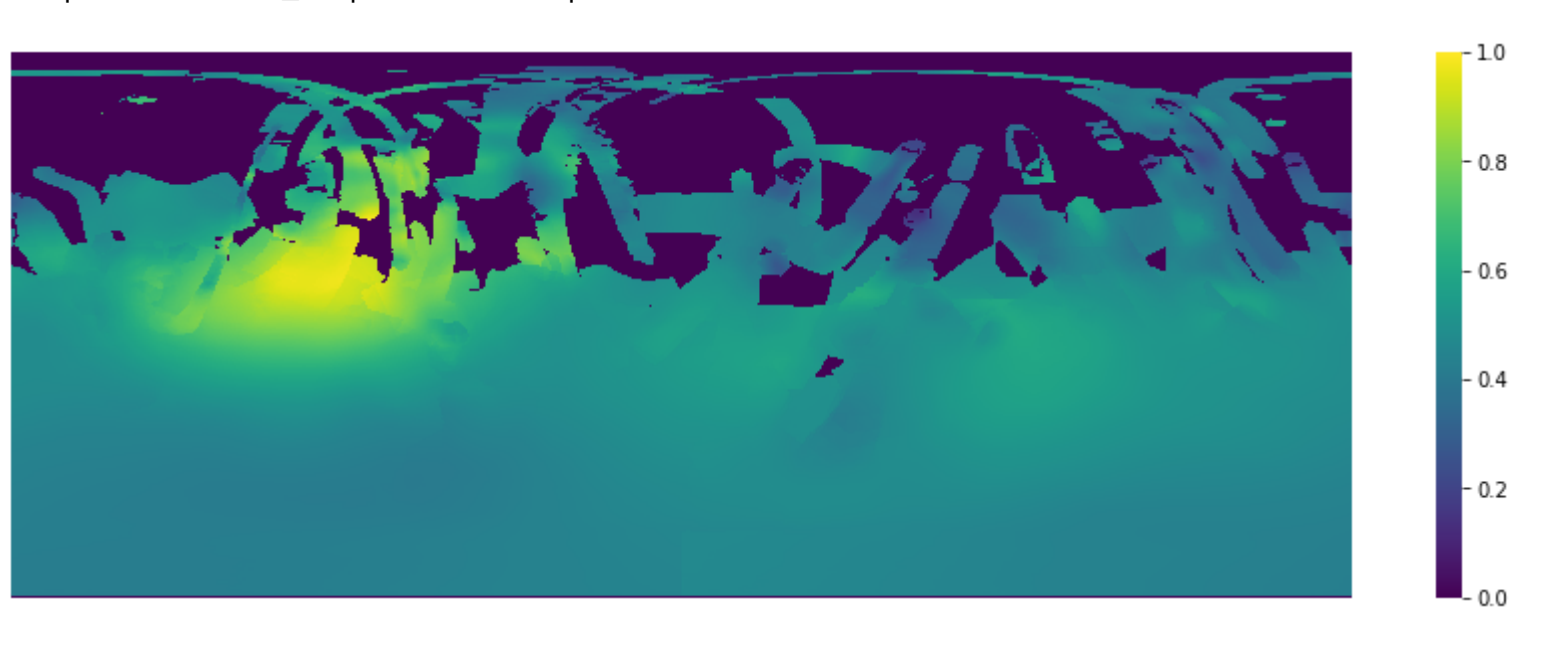


In [14]:
```
scale_al=StandardScaler()
scaled_alsi=scale_al.fit_transform(alsi_map_data)
```

In [15]:
```
ssi_map_data=pd.read_csv("..\ML4SCI_GSoC\Messenger\Mercury\\ssimap_smooth_032015.png.csv",he
ader=None)
```

In [16]:
```
plt.subplots(figsize=(15,5))
sns.heatmap(ssi_map_data,xticklabels=False,yticklabels=False,cmap='viridis')
```

Out[16]: <matplotlib.axes._subplots.AxesSubplot at 0x270f063bf88>

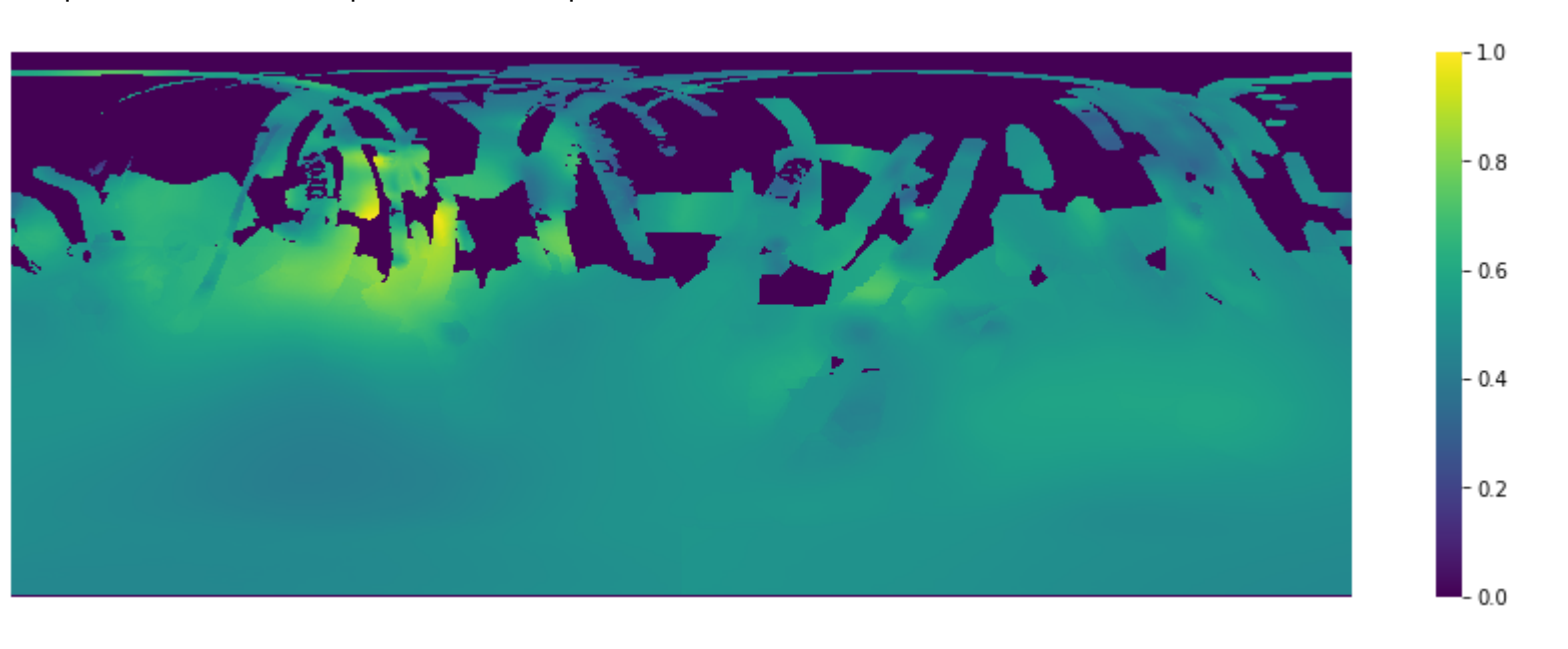


In [17]:
```
scale_s=StandardScaler()
scaled_ssi=scale_s.fit_transform(ssi_map_data)
```

In [18]:
```
casi_map_data=pd.read_csv("..\ML4SCI_GSoC\Messenger\Mercury\\casimap_smooth_032015.png.csv",
header=None)
```

In [19]:
```
plt.subplots(figsize=(15,5))
sns.heatmap(casi_map_data,xticklabels=False,yticklabels=False,cmap='viridis')
```

Out[19]: <matplotlib.axes._subplots.AxesSubplot at 0x270f06a8ac8>

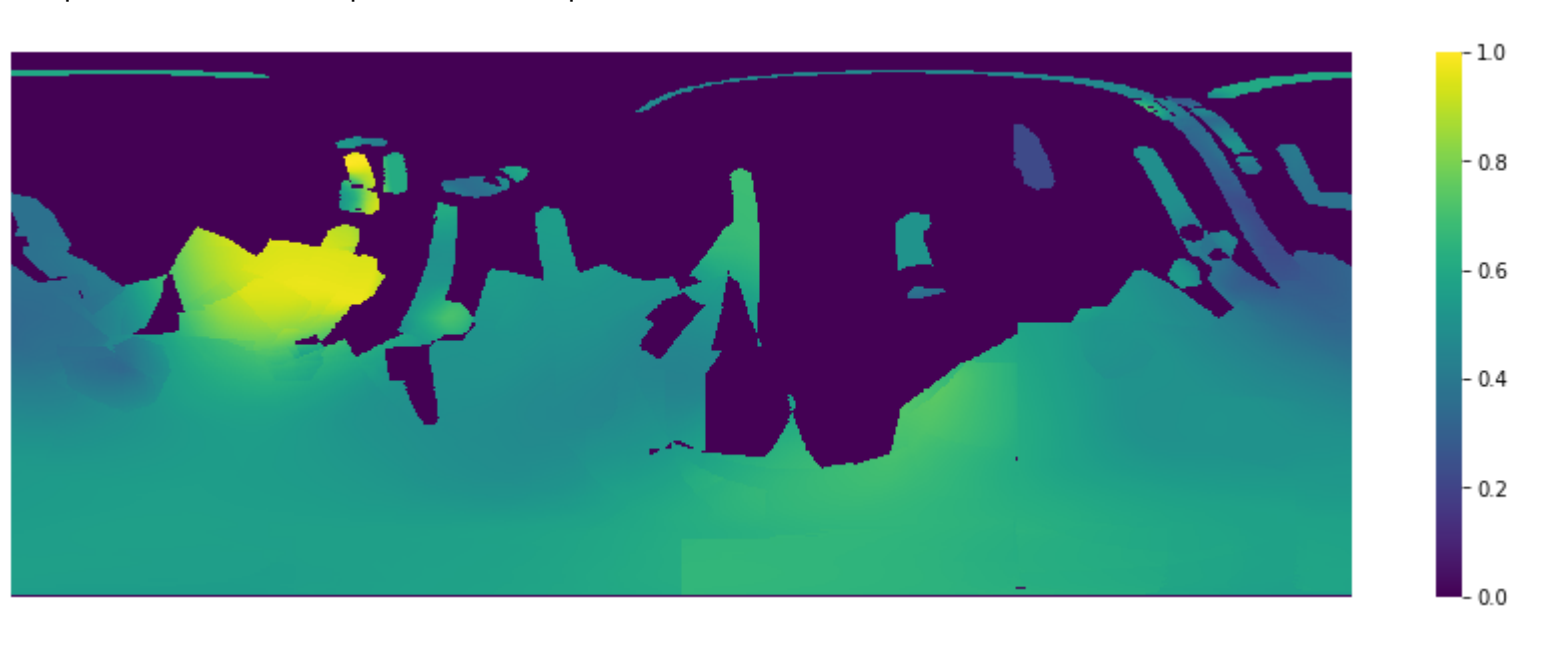


In [20]:
```
scale_ca=StandardScaler()
scaled_casi=scale_ca.fit_transform(casi_map_data)
```

In [21]:
```
fesi_map_data=pd.read_csv("..\ML4SCI_GSoC\Messenger\Mercury\\fesimap_smooth_032015.png.csv",
header=None)
```

In [22]:
```
plt.subplots(figsize=(15,5))
sns.heatmap(fesi_map_data,xticklabels=False,yticklabels=False,cmap='viridis')
```

Out[22]: <matplotlib.axes._subplots.AxesSubplot at 0x270f08ef908>



In [23]:
```
scale_fe=StandardScaler()
scaled_fesi=scale_fe.fit_transform(fesi_map_data)
```

In [24]:
```
# this is the function for converting every dataset into a column vector.
def column_converter(data):
    column_arr=data.reshape(-1,1,order='F') # here order='F' specifies that it will read col
umn vice
    return column_arr
# returned value will be a column vector of type ndarray
```

In [25]:
```
albedo_top_column=column_converter(scaled_top)
mgsi_map_column=column_converter(scaled_mgsi)
alsi_map_column=column_converter(scaled_alsi)
ssi_map_column=column_converter(scaled_ssi)
casi_map_column=column_converter(scaled_casi)
fesi_map_column=column_converter(scaled_fesi)
```

In [26]:
```
mgsi_map_column.shape
```

Out[26]: (1036800, 1)

In [27]:
```
X_train=albedo_top_column
```

In [28]:
```
Y_train=np.concatenate((mgsi_map_column,alsi_map_column,ssi_map_column,casi_map_column,fesi_
map_column),axis=1)
```

In [29]:
```
Y_train.shape
```

Out[29]: (1036800, 5)

I wanted to use deep multioutput neural network regression algorithm,but after several hours of training, the algorithm didn't responded due to high computational cost becaure data is very large.......no. of rows in dataset=1.036Million. define the model model = Sequential() model.add(Dense(10, input_dim=1, kernel_initializer='he_uniform', activation='relu')) model.add(Dense(5)) model.compile(loss='mae', optimizer='adam') model.fit(X_train,Y_train,verbose=0,epochs=100) pred=model.predict(X_train)

In [30]:
```
model=LinearRegression(normalize=True)
```

In [31]:
```
model.fit(X_train,Y_train)
```

Out[31]: LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=True)

In [32]:
```
pred=model.predict(X_train)
```

In [33]:
```
pred.shape
```

Out[33]: (1036800, 5)

In [34]:
```
r2_score(Y_train,pred)
```

Out[34]: 0.004471946894451739

In [35]:
```
model3=DecisionTreeRegressor()
model3.fit(X_train,Y_train)
```

Out[35]:
```
DecisionTreeRegressor(ccp_alpha=0.0, criterion='mse', max_depth=None,
                      max_features=None, max_leaf_nodes=None,
                      min_impurity_decrease=0.0, min_impurity_split=None,
                      min_samples_leaf=1, min_samples_split=2,
                      min_weight_fraction_leaf=0.0, presort='deprecated',
                      random_state=None, splitter='best')
```

In [36]:
```
pred3=model3.predict(X_train)
```

In [37]:
```
r2_score(Y_train,pred3)
```

Out[37]: 0.43223810735350715

In [38]:
```
model5=Ridge()
```

In [39]:
```
model5.fit(X_train,Y_train)
```

Out[39]:
```
Ridge(alpha=1.0, copy_X=True, fit_intercept=True, max_iter=None,
      normalize=False, random_state=None, solver='auto', tol=0.001)
```

In [40]:
```
pred7=model5.predict(X_train)
```

In [41]:
```
r2_score(Y_train,pred7)
```

Out[41]: 0.004471946894440327

In [42]:
```
modelk=RandomForestRegressor()
```

In [43]:
```
modelk.fit(X_train,Y_train)
```

Out[43]:
```
RandomForestRegressor(bootstrap=True, ccp_alpha=0.0, criterion='mse',
                      max_depth=None, max_features='auto', max_leaf_nodes=None,
                      max_samples=None, min_impurity_decrease=0.0,
                      min_impurity_split=None, min_samples_leaf=1,
                      min_samples_split=2, min_weight_fraction_leaf=0.0,
                      n_estimators=100, n_jobs=None, oob_score=False,
                      random_state=None, verbose=0, warm_start=False)
```

In [44]:
```
val=modelk.predict(X_train)
```

In [45]:
```
r2_score(Y_train,val)
```

Out[45]: 0.4276435386051533

cross validation score

In [46]:
```
from sklearn.model_selection import cross_val_score
```

In [47]:
```
# function for cross validation score.
def crossval_score(model,X,Y):
    score=cross_val_score(model,X,Y,scoring='neg_mean_squared_error')
    score1=np.sqrt(-score)
    return score1.mean(),score1.std()
```

In [48]:
```
#dataset for cross validation.
X_cval=X_train[0:150,:]
Y_cval=Y_train[0:150,:]
```

In [49]:
```
# random forest cross validation score
cv2_mean,cv2_std=crossval_score(modelk,X_cval,Y_cval)
print("mean:decision tree model:",cv2_mean)
print("std:decision tree model:",cv2_std)
```

```
mean:decision tree model: 1.4416537581891533
std:decision tree model: 0.5870498301579595
```

In [50]:
```
# decision tree cross validation score
cv2_mean,cv2_std=crossval_score(model3,X_cval,Y_cval)
print("mean:decision tree model:",cv2_mean)
print("std:decision tree model:",cv2_std)
```

```
mean:decision tree model: 1.548658178018396
std:decision tree model: 0.5408618481738284
```

In [51]:
```
# ridge cross validation score
cv2_mean,cv2_std=crossval_score(model5,X_cval,Y_cval)
print("mean:ridge model:",cv2_mean)
print("std:ridge model:",cv2_std)
```

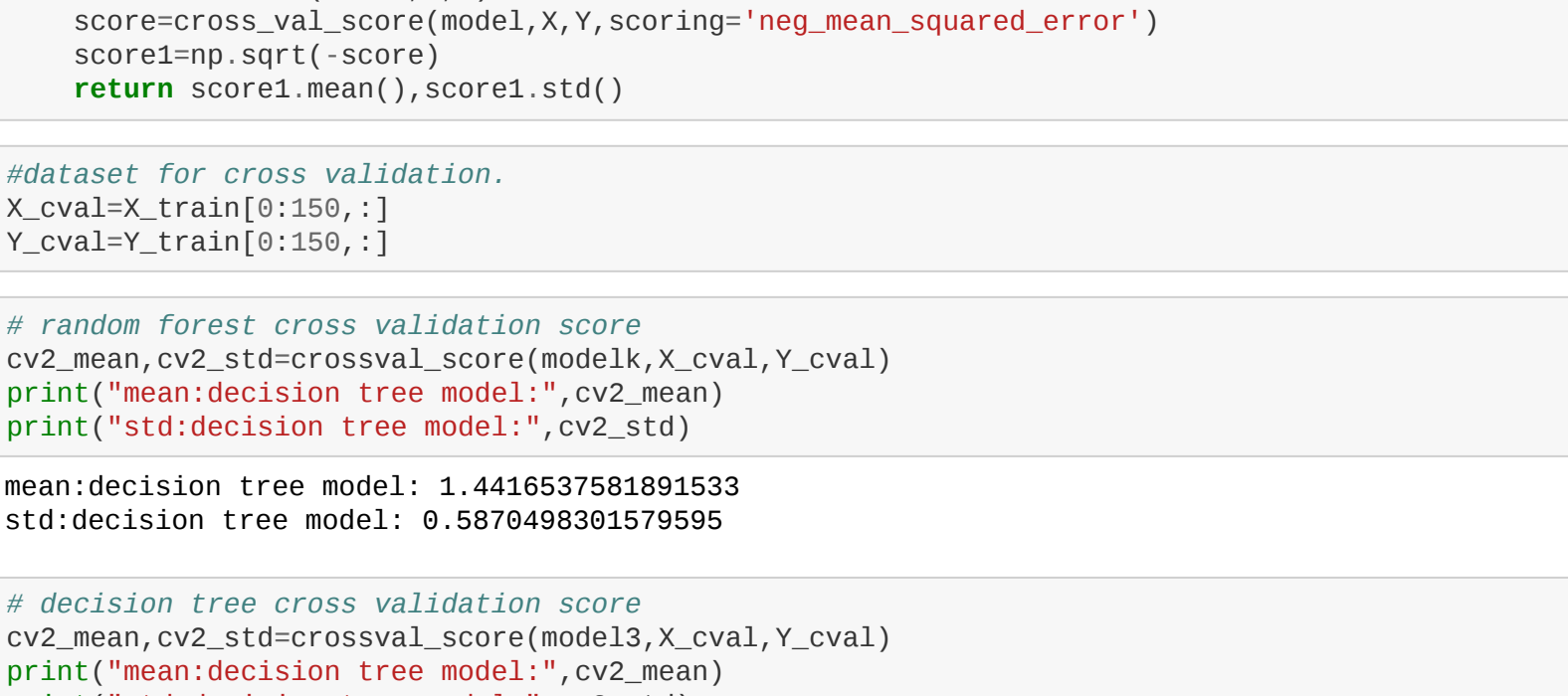
```
mean:ridge model: 1.184835277781369
std:ridge model: 0.7324476044215636
```

In [52]:
```
k=val[:,0].reshape(-1,1)
```

In [53]:
```
l=k.reshape(-1,1440,order='F')
data=pd.DataFrame(l)
original_constrain_mgsi=scale_mg.inverse_transform(data)
```

In [54]:
```
plt.subplots(figsize=(15,5))
sns.heatmap(original_constrain_mgsi,xticklabels=False,yticklabels=False,cmap='viridis')
```

Out[54]: <matplotlib.axes._subplots.AxesSubplot at 0x270f081d848>



testing data preprocessing.

In [55]:
```
scale_bottom=StandardScaler()
albedo_scaled_bottom=scale_bottom.fit_transform(albedo_bottom_data)
```

In [56]:
```
albedo_bottom_column=column_converter(albedo_scaled_bottom)
```

In [57]:
```
predicted_chemicals_composition=modelk.predict(albedo_bottom_column)
```

In [58]:
```
predicted_chemicals_composition.shape
```

Out[58]: (1036800, 5)

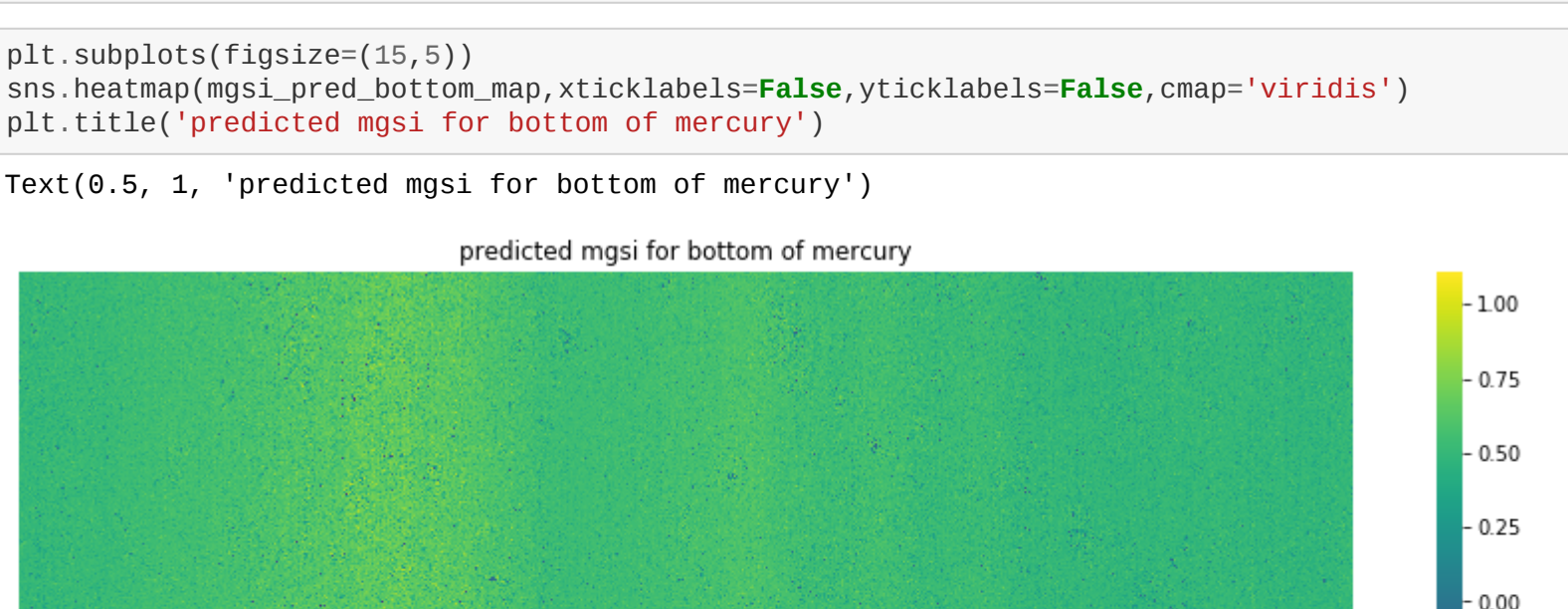
In [59]:
```
#chemical columns
mgsi_predicted_column=predicted_chemicals_composition[:,0].reshape(-1,1)
alsi_predicted_column=predicted_chemicals_composition[:,1].reshape(-1,1)
ssi_predicted_column=predicted_chemicals_composition[:,2].reshape(-1,1)
casi_predicted_column=predicted_chemicals_composition[:,3].reshape(-1,1)
fesi_predicted_column=predicted_chemicals_composition[:,4].reshape(-1,1)
```

In [60]:
```
# scaled predicted chemical columns
scaled_mgsi_predicted_map=mgsi_predicted_column.reshape(-1,1440,order='F')
scaled_alsi_predicted_map=alsi_predicted_column.reshape(-1,1440,order='F')
scaled_ssi_predicted_map=ssi_predicted_column.reshape(-1,1440,order='F')
scaled_casi_predicted_map=casi_predicted_column.reshape(-1,1440,order='F')
scaled_fesi_predicted_map=fesi_predicted_column.reshape(-1,1440,order='F')
```

In [61]:
```
#predicted original chemical map.
mgsi_pred_bottom_map=scale_mg.inverse_transform(scaled_mgsi_predicted_map)
alsi_pred_bottom_map=scale_al.inverse_transform(scaled_alsi_predicted_map)
ssi_pred_bottom_map=scale_s.inverse_transform(scaled_ssi_predicted_map)
casi_pred_bottom_map=scale_ca.inverse_transform(scaled_casi_predicted_map)
fesi_pred_bottom_map=scale_fe.inverse_transform(scaled_fesi_predicted_map)
```

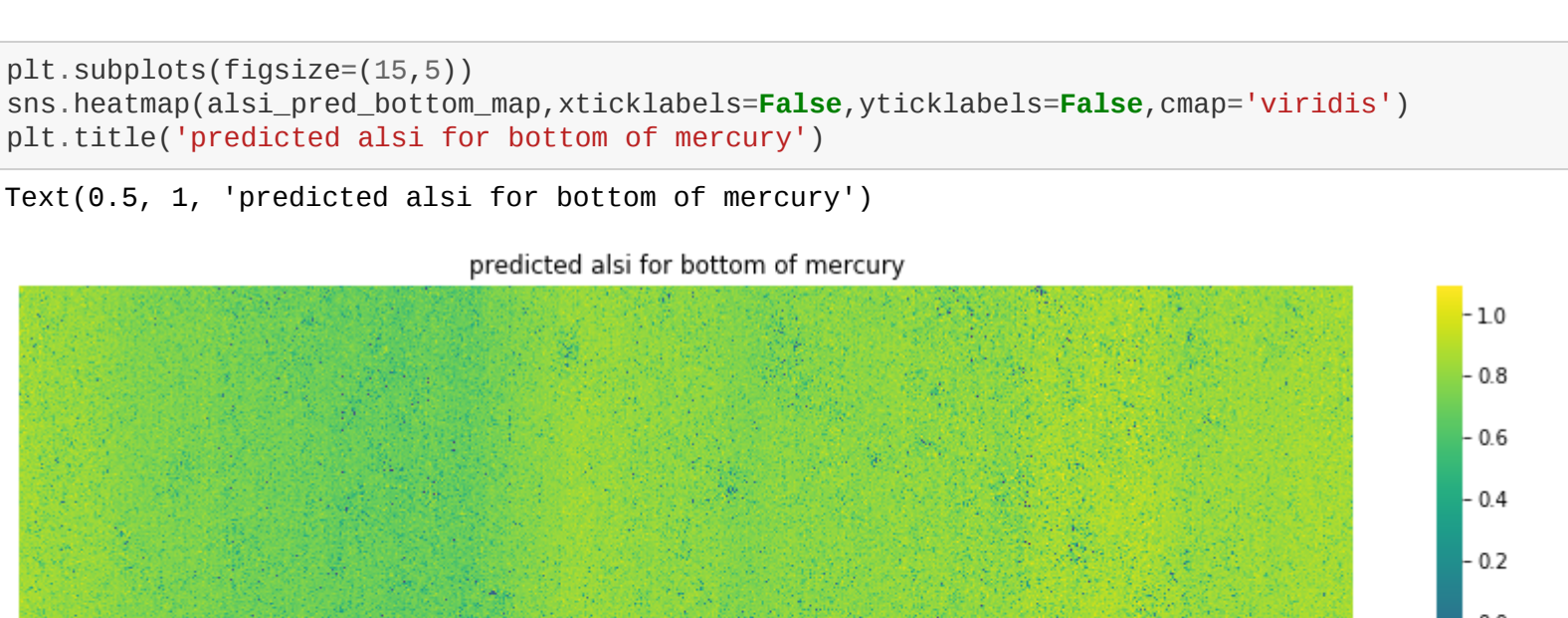
In [81]:
```
plt.subplots(figsize=(15,5))
sns.heatmap(mgsi_pred_bottom_map,xticklabels=False,yticklabels=False,cmap='viridis')
plt.title('predicted mgsi for bottom of mercury')
```

Out[81]: Text(0.5, 1, 'predicted mgsi for bottom of mercury')



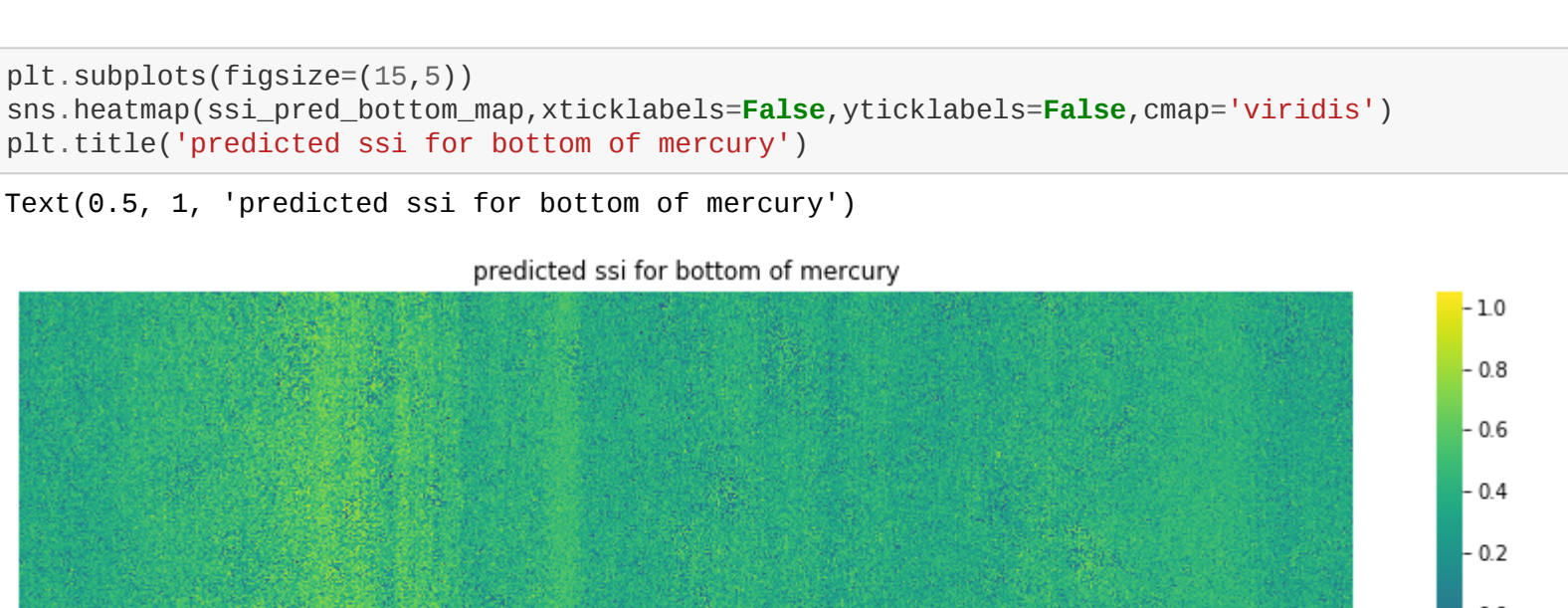
In [82]:
```
plt.subplots(figsize=(15,5))
sns.heatmap(alsi_pred_bottom_map,xticklabels=False,yticklabels=False,cmap='viridis')
plt.title('predicted alsi for bottom of mercury')
```

Out[82]: Text(0.5, 1, 'predicted alsi for bottom of mercury')



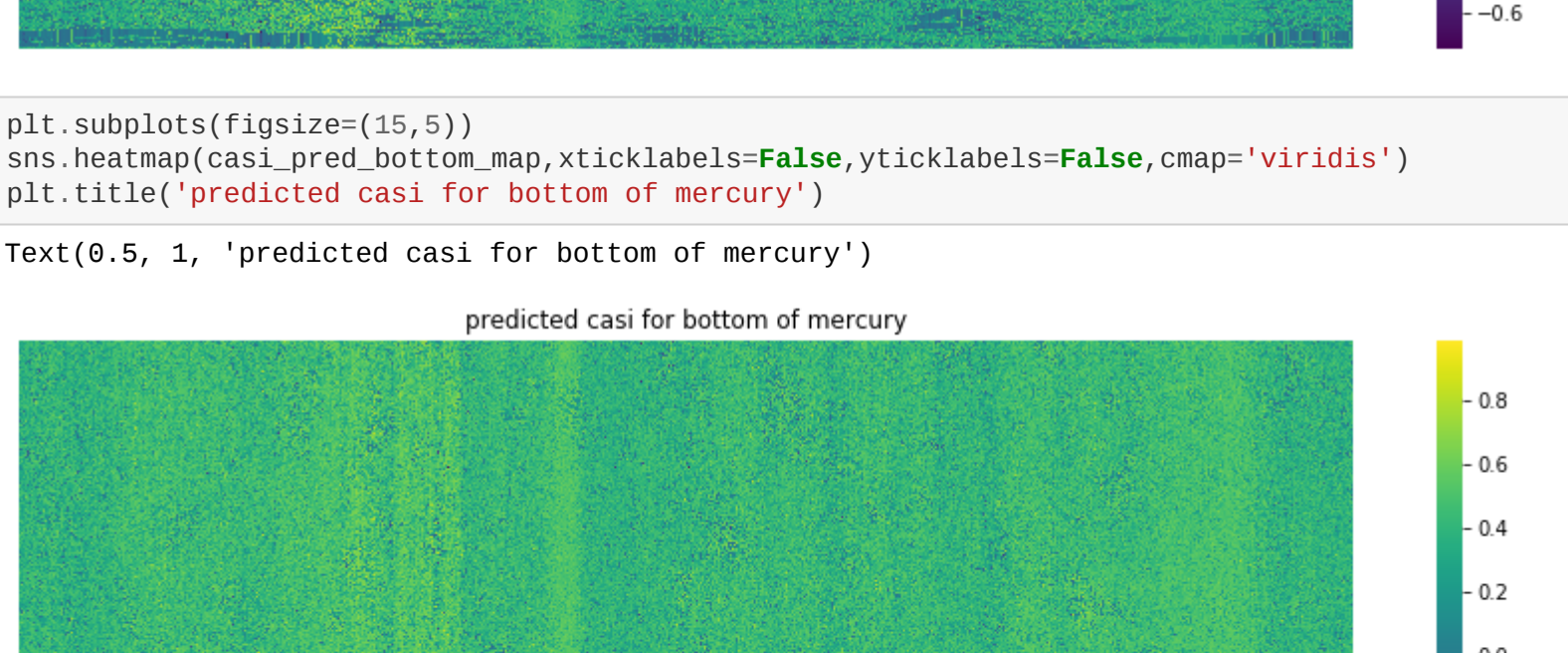
In [83]:
```
plt.subplots(figsize=(15,5))
sns.heatmap(ssi_pred_bottom_map,xticklabels=False,yticklabels=False,cmap='viridis')
plt.title('predicted ssi for bottom of mercury')
```

Out[83]: Text(0.5, 1, 'predicted ssi for bottom of mercury')



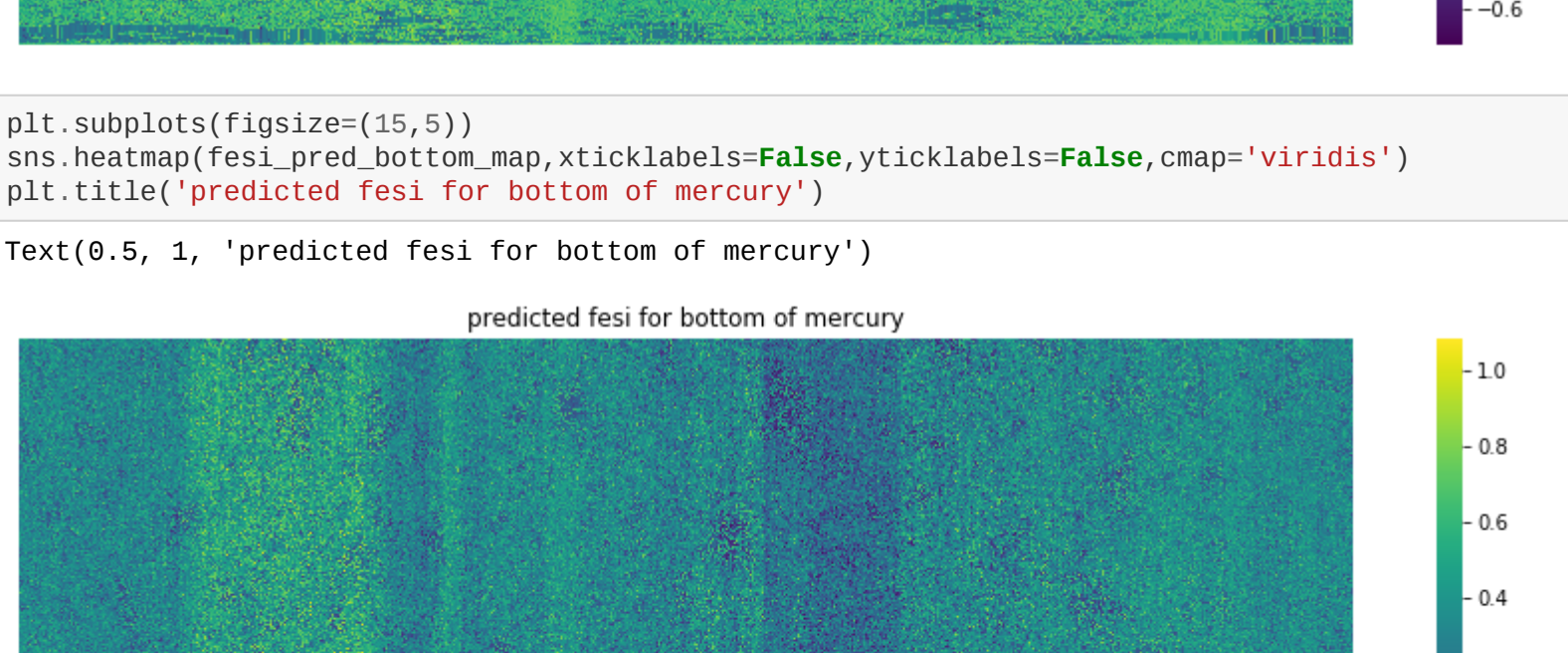
In [84]:
```
plt.subplots(figsize=(15,5))
sns.heatmap(casi_pred_bottom_map,xticklabels=False,yticklabels=False,cmap='viridis')
plt.title('predicted casi for bottom of mercury')
```

Out[84]: Text(0.5, 1, 'predicted casi for bottom of mercury')



In [85]:
```
plt.subplots(figsize=(15,5))
sns.heatmap(fesi_pred_bottom_map,xticklabels=False,yticklabels=False,cmap='viridis')
plt.title('predicted fesi for bottom of mercury')
```

Out[85]: Text(0.5, 1, 'predicted fesi for bottom of mercury')



In [ ]: