In [11]:
```
#!pip install rasterio
#!pip install pyspatialml

"""
In order to run this notebook, please ensure that
you start by installing the
necessary libraries into your python environment,
preferably in jupyter notebooks.
The usable libraries are listed below, this will
ensure that all processes run perfectly without fail,
notably, please intall the pyspatial libraries
with some functionalities of handling geotiffs/raster datasets.

"""
```

In [1]:
```
import pandas as pd
import numpy as np
import rasterio
from rasterio import *
from rasterio.plot import show
from pyspatialml import Raster
from sklearn.ensemble import RandomForestRegressor
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split,GridSearchCV
from sklearn.pipeline import Pipeline
from scipy.stats import pearsonr
import matplotlib.pyplot as plt
plt.rcParams["figure.figsize"] = (10,6.5)
```

In [ ]:
```
"""
This notebook uses machine learning to
predict/estimate yields of crops and also generate
crop mask maps using
machine learning specifically Random Forest method.
The general process/pattern include the following

Extracting data points
Training your model and testing it
Predicting the outputs i.e crop masks or yield estimation
"""
```

In [ ]:
```
"""
Ensure that you you read your CSV file as shown below.
The CSV files need to extract the satellite imagery values and mutate
the columns that will be used to train your model.
Preferably, you can run the process of extraction in R using the following
code. Ensure proper libraries are also installed in your short R code.
dt <- sentinel %>%
  extract(y = samples) %>%
  as.data.frame %>%
  mutate(yield = samples$Type_3)
dt

"""
```

In [12]:
```
import geopandas as gpd

# Read the shapefile
# gdf = gpd.read_file("AUS_GEDI_UPDATED.shp")
gdf = pd.read_csv("predicted_yield_data_extacted_2.csv")
```

```
# Print the first few rows of the GeoDataFrame
print(gdf.tail())
```

```
          B4      B3      B2      B5      B8     yield
2997  2381.0  2204.5  2233.5  2626.0  3427.0  1.218750
2998  2170.5  1978.0  2029.0  2427.0  3123.0  4.450625
2999  2054.0  1968.0  1990.0  2286.0  3398.0  1.502500
3000  2705.5  2249.5  2212.0  2950.0  3654.5  1.157500
3001  2402.5  2097.0  2077.0  2670.0  3587.0  2.130000
```

In [13]:

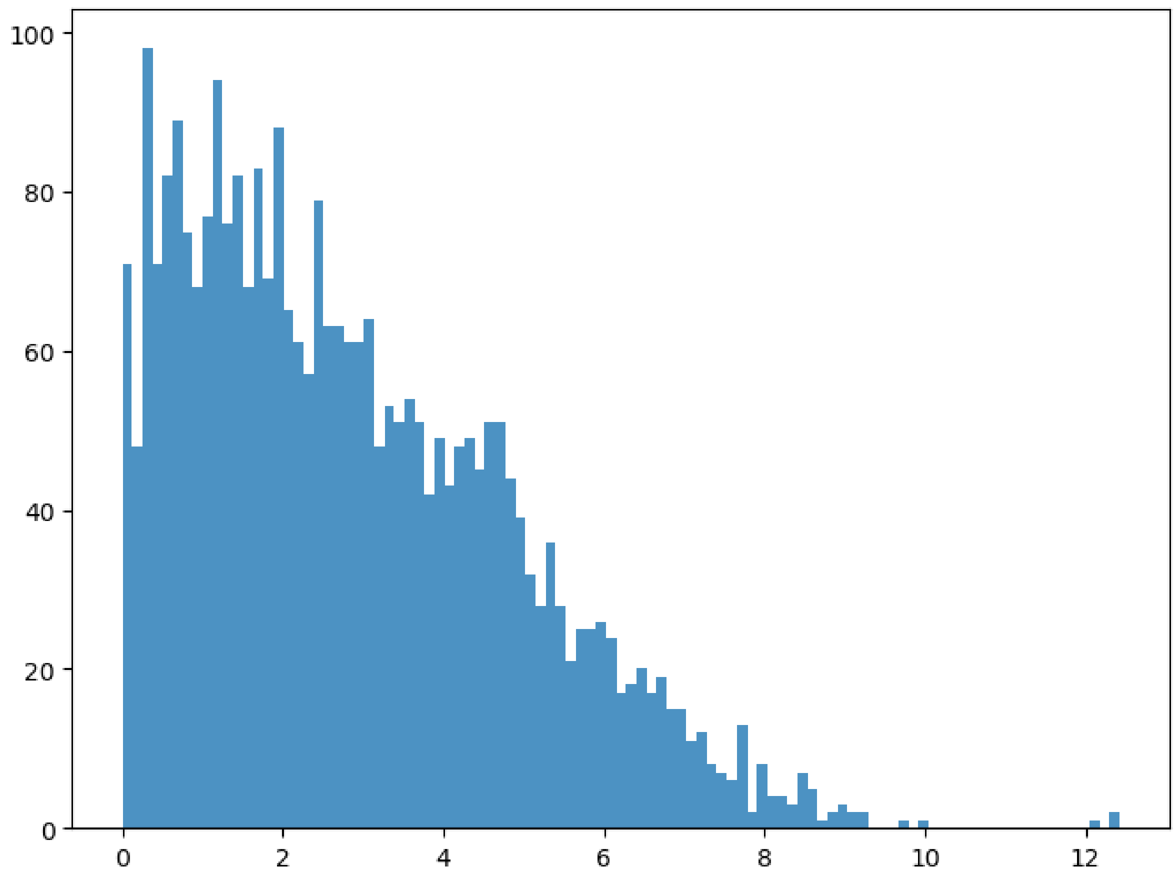
```
"""
Read the CSV as a dataframe, ofcourse not mandatory though
"""
df1 = pd.DataFrame(gdf)
df1.head()
```

Out[13]:

	B4	B3	B2	B5	B8	yield
0	2419.5000	2187.0	2194.5	2655.5	3344.0	0.050625
1	2.8275	2008.5	2075.0	2387.5	3039.5	0.104375
2	2234.0000	2039.5	2101.5	2486.5	3187.5	0.126250
3	2081.5000	1981.5	2054.5	2311.0	3076.5	0.143125
4	2109.0000	1964.0	2001.0	2325.0	3025.0	0.155625

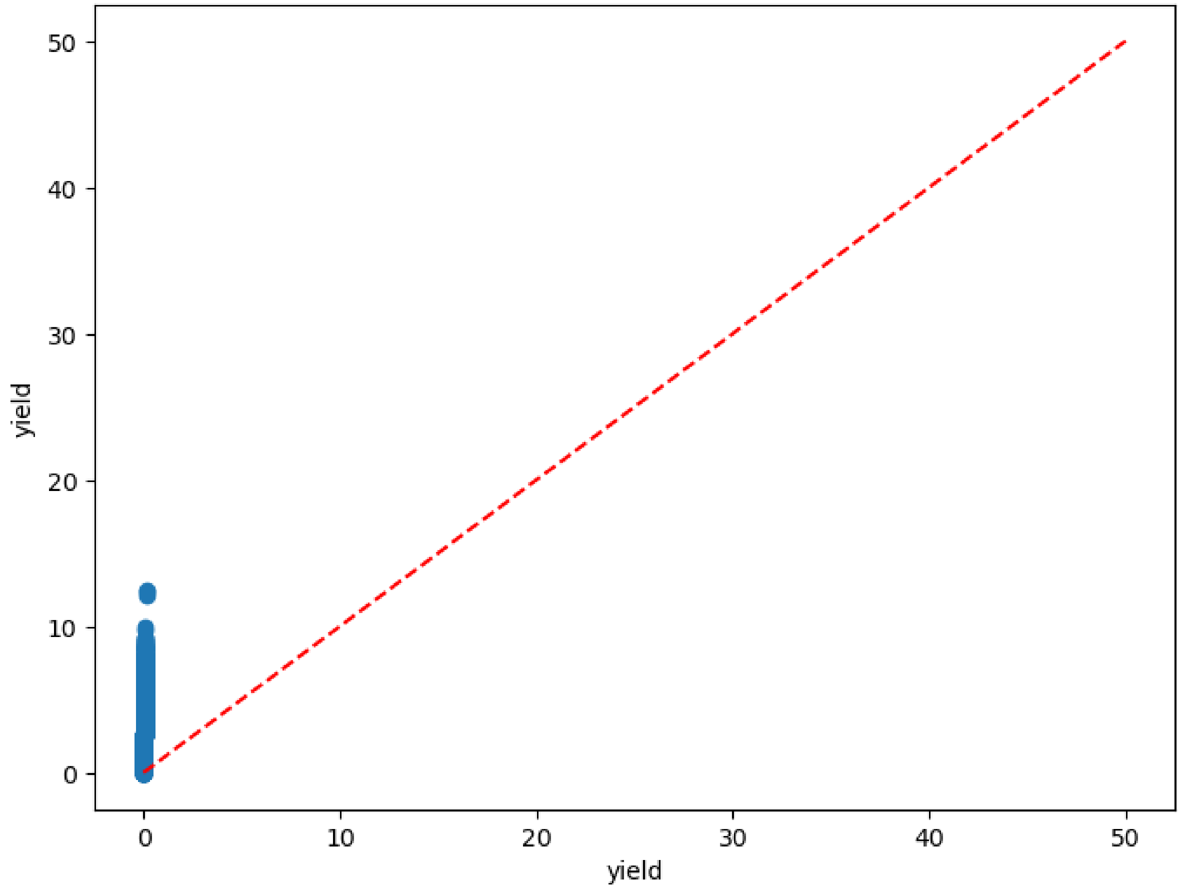
In [14]:

```
"""
Plotting a histogram of the crop cuts data in Mg/ha as collected from the fi

"""
predictors =  df1
bins = np.linspace(min(predictors['yield']),max(predictors['yield']),100)
plt.hist((predictors['yield']),bins,alpha=0.8);
```



In [15]:
```
plt.rcParams["figure.figsize"] = (8,6)
plt.scatter(predictors['yield']/100,predictors['yield'])
plt.xlabel('yield')
plt.ylabel('yield')
ident = [0, 50]
plt.plot(ident,ident,'r--')
```

Out[15]:
```
[<matplotlib.lines.Line2D at 0x7ff516761960>]
```



In [17]:
```
"""
fit the values/predictors i.e independent variables and dependent variables.
The numbers represent column indexes that represent the ind vs dep variables
Y will always be data collected from the field
"""
X = predictors.iloc[:,[0,1,2,3,4]].values

Y = predictors.iloc[:,5:6].values
feat = predictors.iloc[:,[0,1,2,3,4]].columns.values
feat
Y
# Y.shape
# X.shape
```

Out[17]:
```
array([[0.050625],
       [0.104375],
       [0.12625 ],
       ...,
       [1.5025  ],
       [1.1575  ],
       [2.13    ]])
```

In [18]:
```
"""
subdiving your samples into training and testing samples,
test size is 0.5 represent training with 50% data and testing
the model with another 50% of the data. Ideally, ML models are
```

```
trained by 0.7 size of the samples for most models
"""
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.5, ran
y_train = np.ravel(Y_train)
y_test = np.ravel(Y_test)
y_test
```

Out[18]:

```
array([1.413125, 3.0275  , 4.6525  , ..., 0.75    , 2.045625, 3.9925  ])
```

In [19]:

```
"""
Calling an RF model and orinting the parameters,
these parameters can be passed into the RF model
"""

rf = RandomForestRegressor(random_state = 42)
rf.get_params()
```

Out[19]:

```
{'bootstrap': True,
 'ccp_alpha': 0.0,
 'criterion': 'squared_error',
 'max_depth': None,
 'max_features': 1.0,
 'max_leaf_nodes': None,
 'max_samples': None,
 'min_impurity_decrease': 0.0,
 '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': 42,
 'verbose': 0,
 'warm_start': False}
```

In [20]:

```
"""
Calling an RF model in preparation for
predcition and prints the fit between training datasets.
.fit(X_train, Y_train): This is a method call on the rfReg object. The .fit(
method is used to train the Random Forest
regression model on your training data.
Here's what the arguments mean:

X_train: This should be a 2D array or
DataFrame containing the feature predictors
(input variables) for your training data.
Each row represents a data point,
and each column represents a different feature.
Y_train: This should be a 1D array or
Series containing the target variable
(the variable you want to predict)
for your training data. It corresponds to the
actual values or labels you're trying
to predict based on the features in X_train.

When you call .fit(X_train, Y_train),
the Random Forest regression model
learns the underlying patterns and
relationships in your training data
to make predictions on new, unseen data.
The model builds multiple decision trees (the "forest")
and combines their predictions to produce a regression result.
"""
```

```
rfReg = RandomForestRegressor(min_samples_leaf=40, oob_score=True)
rfReg.fit(X_train, Y_train);
dic_pred = {}
dic_pred['train'] = rfReg.predict(X_train)
dic_pred['train']
dic_pred['test'] = rfReg.predict(X_test)
dic_pred['test']
pearsonr_all = [pearsonr(dic_pred['train'],Y_train)[1],pearsonr(dic_pred['te
pearsonr_all
```

```
/var/folders/mf/0lb_7jld1p54p_x83sc_5r280000gn/T/ipykernel_75476/3946089473.
py:2: DataConversionWarning: A column-vector y was passed when a 1d array wa
s expected. Please change the shape of y to (n_samples,), for example using
ravel().
  rfReg.fit(X_train, Y_train);
```

Out[20]: [2.2947913595182273e-106, 3.6728290710318276e-59]

In [21]:

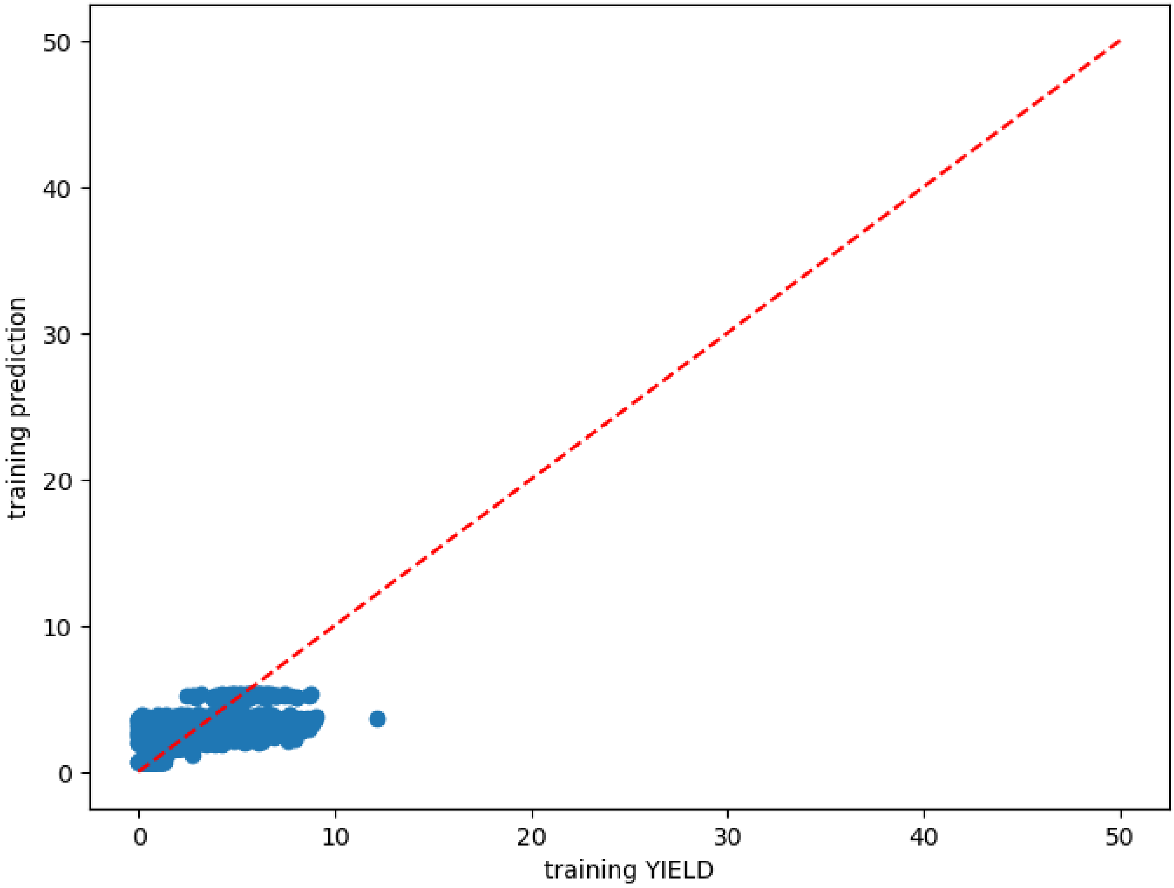
```
"""
typically refers to the out-of-bag (OOB)
score of a random forest regression model in a
programming context, often using
Python's scikit-learn library or a similar machine learning framework.

In random forest regression, the OOB score is a measure of the model's
performance on unseen data. It is computed using the data points that
were not included in the bootstrapped training sets
for individual decision trees within the random forest. These OOB data
points can be seen as a form of cross-validation within the ensemble model.

The OOB score provides an estimate of
how well the random forest model is
likely to perform on new, unseen data.
It is a useful metric for assessing
the model's generalization ability
without the need for a separate validation dataset.

In this case, an OOB score of approximately
0.188 suggests that the random forest
regression model has a relatively low
level of accuracy when making predictions on unseen data.
OOB scores typically range from 0 to 1,
with higher values indicating better predictive performance.
Therefore, a lower OOB score implies
that the model may not be fitting the data well or may require
further optimization.

"""

rfReg.oob_score_
```

Out[21]: 0.1879241617456956

In [22]:

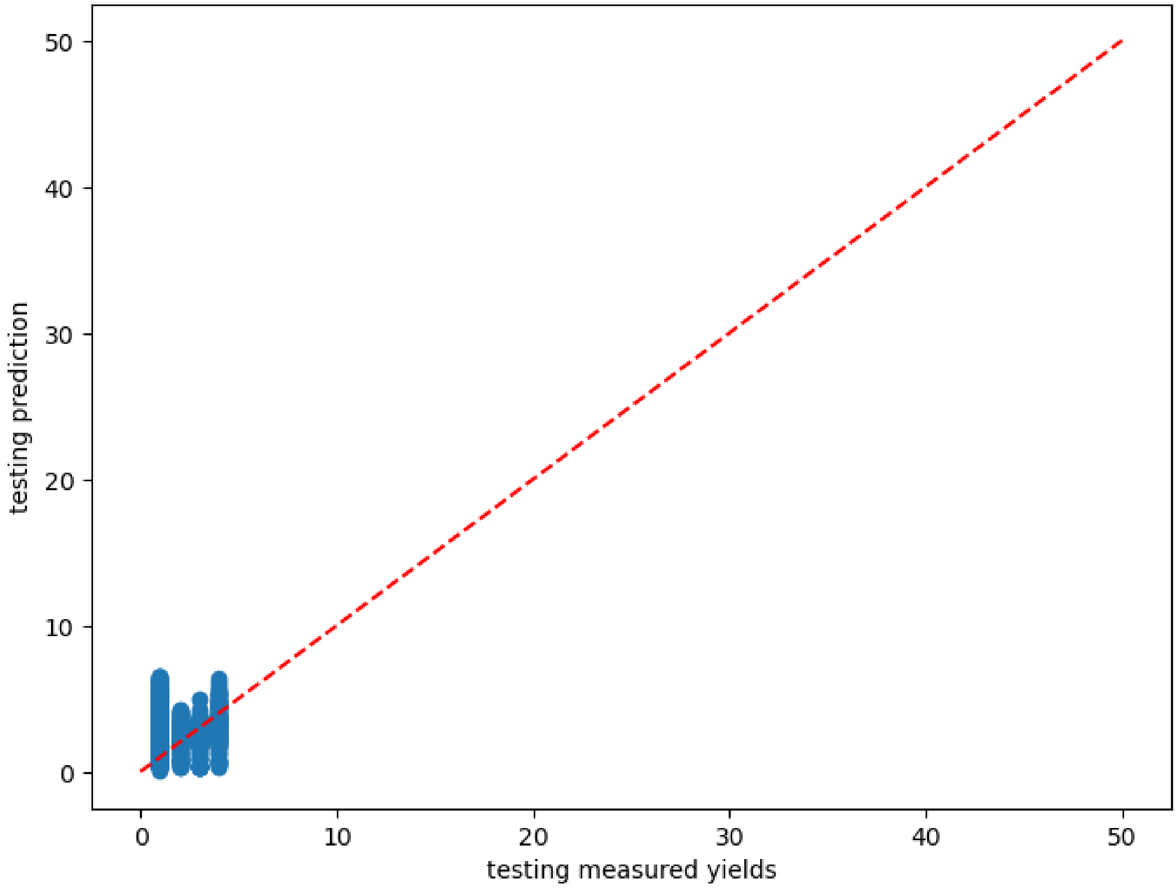
```
plt.rcParams["figure.figsize"] = (8,6)
plt.scatter(y_train,dic_pred['train'])
plt.xlabel('training YIELD')
plt.ylabel('training prediction')
ident = [0, 50]
plt.plot(ident,ident,'r--')
```

Out[22]: [<matplotlib.lines.Line2D at 0x7ff516debbe0>]



In [56]:
```
plt.rcParams["figure.figsize"] = (8,6)
plt.scatter(y_test,dic_pred['test'])
plt.xlabel('testing measured yields')
plt.ylabel('testing prediction')
ident = [0, 50]
plt.plot(ident,ident,'r--')
```

Out[56]:
```
[<matplotlib.lines.Line2D at 0x7ff4bae6c8e0>]
```



In [24]:

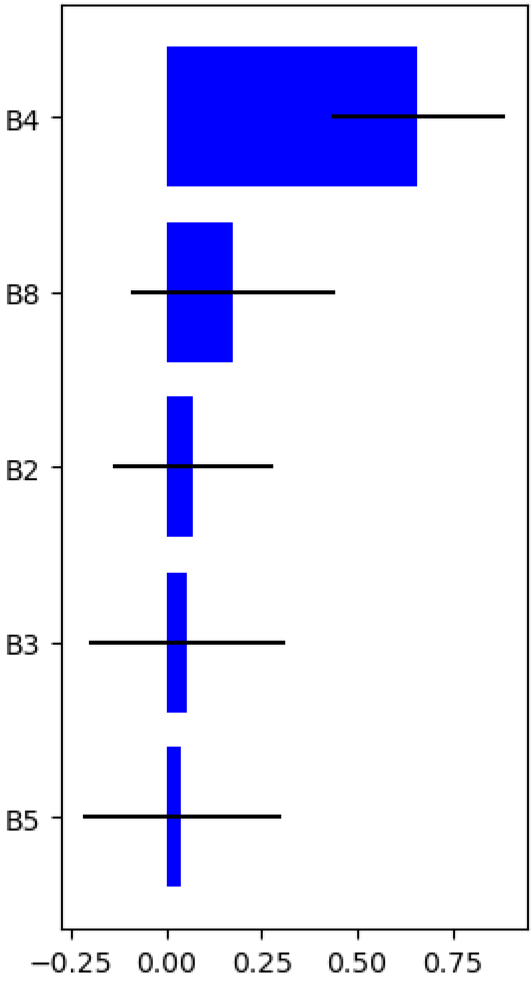
```
"""
A model outputting model parameters importance,
this assists in eliminating redundancy in the input datasets
A visual plot follows below
"""

impt = [rfReg.feature_importances_, np.std([tree.feature_importances_ for tr
ind = np.argsort(impt[0])
ind
```

Out[24]:

```
array([3, 1, 2, 4, 0])
```

In [25]:

```
plt.rcParams["figure.figsize"] = (3,6)
plt.barh(range(len(feat)),impt[0][ind],color="b", xerr=impt[1][ind], align="
plt.yticks(range(len(feat)),feat[ind]);
```



In [26]:

```
"""
This functio tried to aid in picking the
best parameters for a random forest model to be
used in estimation, and typically to be
fed in the training model as model parameters.
Please notice the out put print format
"""


pipeline = Pipeline([('rf',RandomForestRegressor())])

parameters = {
        'rf__max_features':(3,4,5),
        'rf__max_samples':(0.5,0.6,0.7),
        'rf__n_estimators':(500,1000),
        'rf__max_depth':(50,100,200,300)}

grid_search = GridSearchCV(pipeline,parameters,n_jobs=6,cv=5,scoring='r2',ve
grid_search.fit(X_train,y_train)


rfReg = RandomForestRegressor(n_estimators=500,max_features=0.33,max_depth=5
rfReg.fit(X_train, y_train);
dic_pred = {}
dic_pred['train'] = rfReg.predict(X_train)
dic_pred['test'] = rfReg.predict(X_test)
pearsonr_all_tune = [pearsonr(dic_pred['train'],y_train)[0],pearsonr(dic_pre
pearsonr_all_tune

grid_search.best_score_
```

```
print ('Best Training score: %0.3f' % grid_search.best_score_)
print ('Optimal parameters:')
best_par = grid_search.best_estimator_.get_params()
for par_name in sorted(parameters.keys()):
    print ('\t%s: %r' % (par_name, best_par[par_name]))
```

```
Fitting 5 folds for each of 72 candidates, totalling 360 fits
Best Training score: 0.177
Optimal parameters:
        rf__max_depth: 100
        rf__max_features: 4
        rf__max_samples: 0.5
        rf__n_estimators: 1000
```

In [27]:

```
"""

"""

impt = [rfReg.feature_importances_, np.std([tree.feature_importances_ for tr
ind = np.argsort(impt[0])
ind
```

Out[27]:

```
array([1, 2, 3, 4, 0])
```

In [28]:

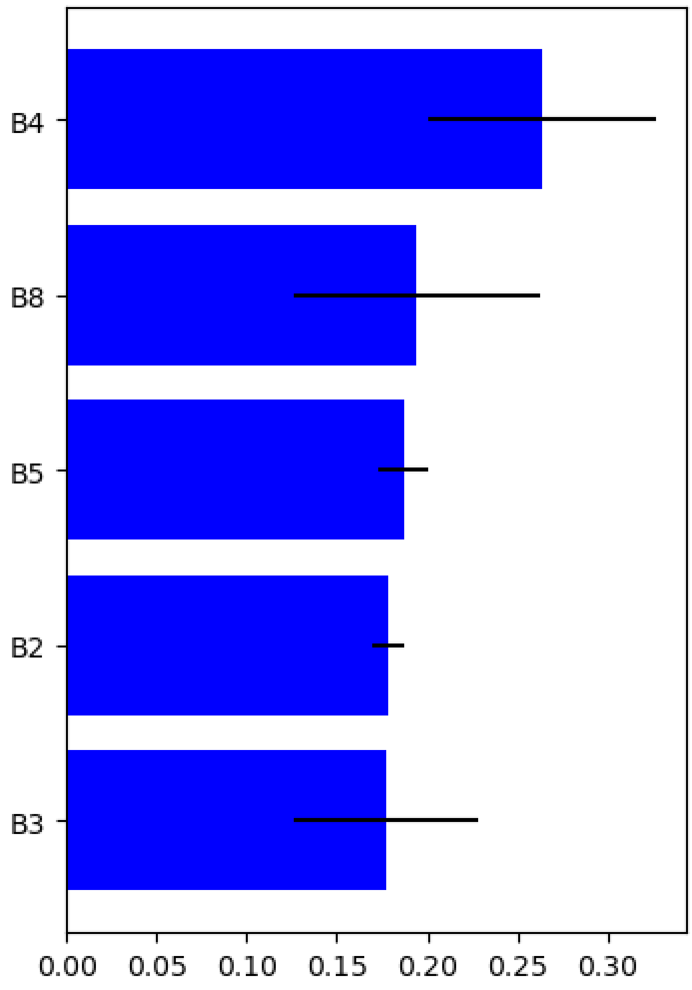
```
rfReg.oob_score_
```

Out[28]:

```
0.12570995536022378
```

In [29]:

```
plt.rcParams["figure.figsize"] = (4,6)
plt.barh(range(len(feat)),impt[0][ind],color="b", xerr=impt[1][ind], align="
plt.yticks(range(len(feat)),feat[ind]);
```



In [30]:
```
"""
Calling rasters/geotiffs using the pyspatial library/model

"""
yield1 = "Zim_final_image_100.tif"
yield2 = "Zim_final_image_200.tif"

yield2
```

Out[30]:
```
'Zim_final_image_200.tif'
```

In [32]:
```
"""
This is the main ML model. You need to
insert the values as generated by the tuning function

rf__max_depth: 100
        rf__max_features: 4
        rf__max_samples: 0.5
        rf__n_estimators: 1000
"""


rfReg = RandomForestRegressor(n_estimators=1000,max_features=4,max_depth=100
rfReg.fit(X_train, y_train);
```

In [35]:
```
"""
Calling RF model to check the outputs
"""

rfReg
```

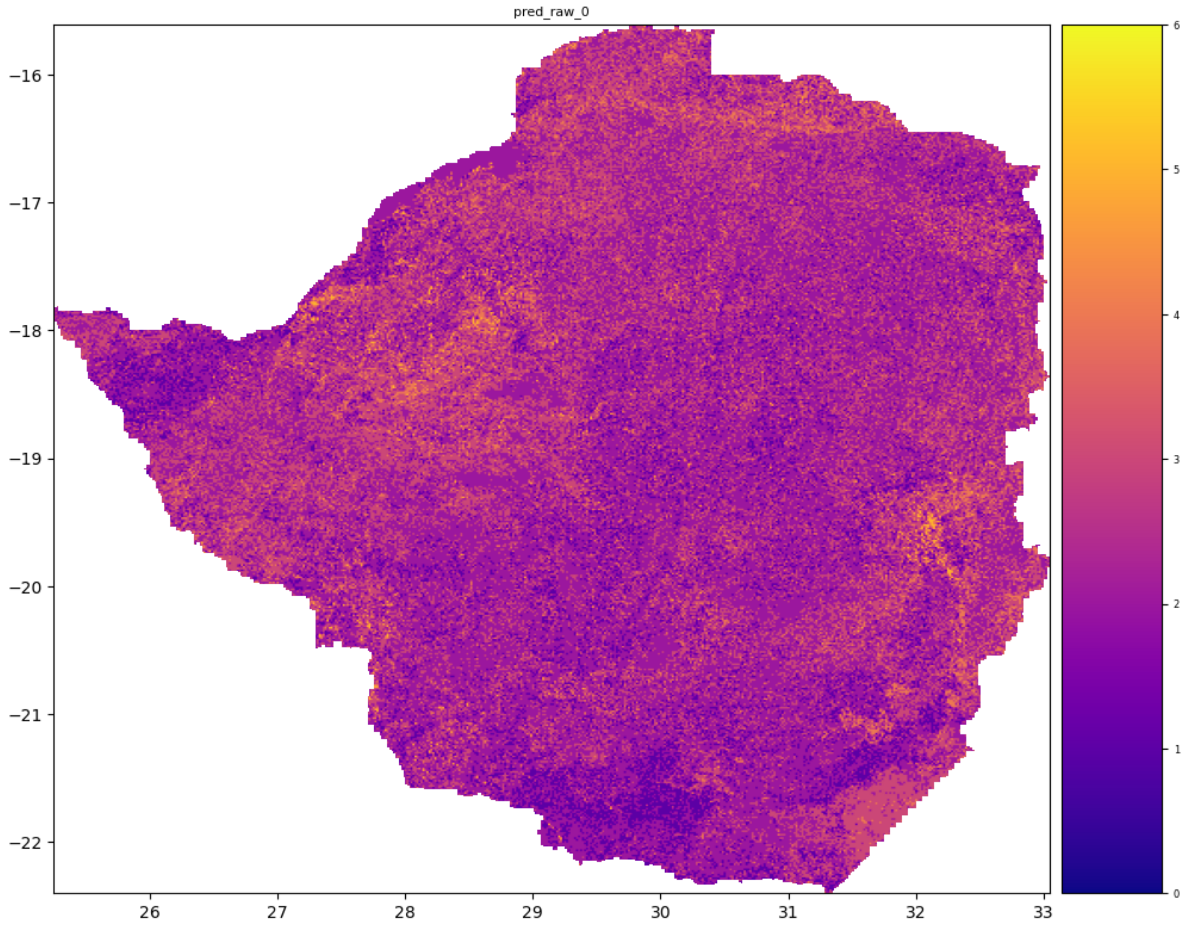
Out[35]:
```
▾                           RandomForestRegressor
RandomForestRegressor(max_depth=1000, max_features=4, max_samples=
0.5,
                      n_estimators=1000, n_jobs=-1, oob_score=True,
                      random_state=24)
```

In [36]:
```
"""
Predicting the trained model on the geotiffs i.e multi spectral image and sa
"""

predictors_rasters = [yield1]

stack = Raster(predictors_rasters)

result = stack.predict(estimator=rfReg, dtype='int16', nodata=-1)

result.write("Yield_Prediction_VERSION_2_OCT.tif")
```

```
Raster Object Containing 1 Layers
    attribute                                          values
0       names                                    [pred_raw_0]
1       files            [Yield_Prediction_VERSION_2_OCT.tif]
2        rows                                            7561
3        cols                                            8684
4         res  (0.0008983152841195215, 0.0008983152841195215)
5   nodatavals                                     [-32768.0]
```

Out[36]:

In [37]:
```
"""
Plotting the yield predcition output
"""

plt.rcParams["figure.figsize"] = (12,12)
result.iloc[0].cmap = "plasma"
result.plot()
plt.show()
```



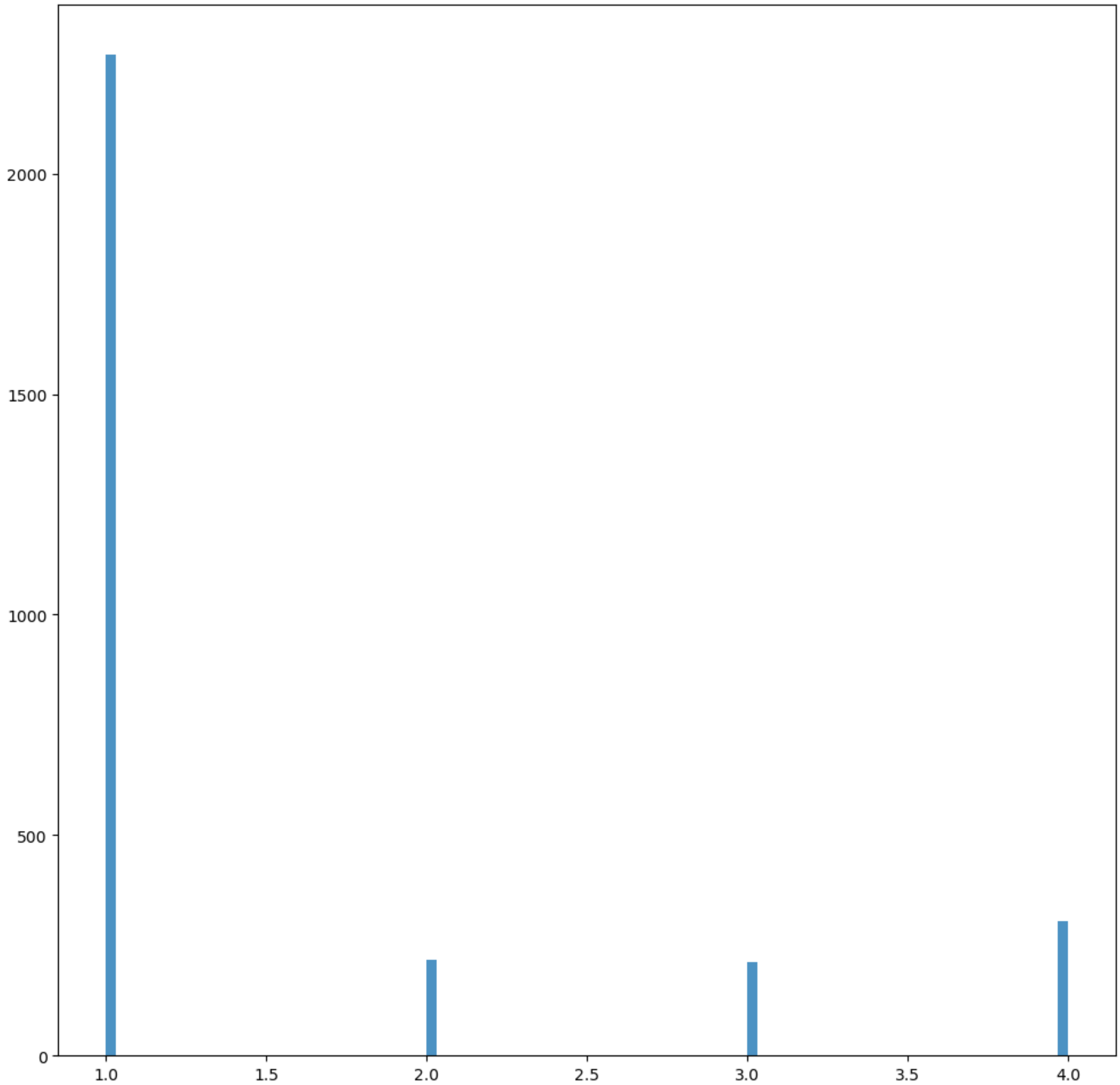
The first implementation estimates the yield of different crops based on the band values, while this one predicts/maps out the crop mask areas based on a column for different crops identified. The main difference, is while yield prediction uses Random forest regressor(Rreg), crop mask method uses random forest classifier(Rclas) method. Both models end up providing different outputs. ML engineer should understand what they want to achieve.

In [41]:
```
import geopandas as gpd

# Read the shapefile
# gdf = gpd.read_file("AUS_GEDI_UPDATED.shp")
gdf_2 = pd.read_csv("predicted_crop_type_data_extacted_2.csv")

# Print the first few rows of the GeoDataFrame
# print(gdf_2.tail())
```

```
gdf_2['yield'].unique()
```

Out[41]:
```
array([4, 1, 2, 3])
```

In [44]:
```
df2 = gdf_2
df2.head()
predictors2 =  df2
bins = np.linspace(min(predictors2['yield']),max(predictors2['yield']),100)
plt.hist((predictors2['yield']),bins,alpha=0.8);
```



In [45]:
```
X = predictors2.iloc[:,[0,1,2,3,4]].values
# Y = predictors['yield'].values
Y = predictors2.iloc[:,5:6].values
feat = predictors2.iloc[:,[0,1,2,3,4]].columns.values
feat
Y
```

Out[45]:
```
array([[4],
       [4],
       [4],
       ...,
       [1],
       [1],
       [1]])
```

In [46]:
```
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.5, ran
y_train = np.ravel(Y_train)
y_test = np.ravel(Y_test)
y_test
```

Out[46]:
```
array([1, 1, 1, ..., 2, 1, 1])
```

In [47]:
```
cf = RandomForestClassifier(random_state = 42)
cf.get_params()
```

Out[47]:
```
{'bootstrap': True,
 'ccp_alpha': 0.0,
 'class_weight': None,
 'criterion': 'gini',
 'max_depth': None,
 'max_features': 'sqrt',
 'max_leaf_nodes': None,
 'max_samples': None,
 'min_impurity_decrease': 0.0,
 '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': 42,
 'verbose': 0,
 'warm_start': False}
```

In [48]:
```
rfclas = RandomForestClassifier(min_samples_leaf=40, oob_score=True)
rfclas.fit(X_train, Y_train);
dic_pred = {}
# dic_pred = {}
dic_pred['train'] = rfReg.predict(X_train)
dic_pred['train']
dic_pred['test'] = rfReg.predict(X_test)
dic_pred['test']
pearsonr_all = [pearsonr(dic_pred['train'],Y_train)[1],pearsonr(dic_pred['te
pearsonr_all
```

```
/var/folders/mf/0lb_7jld1p54p_x83sc_5r280000gn/T/ipykernel_75476/2524072168.
py:2: DataConversionWarning: A column-vector y was passed when a 1d array wa
s expected. Please change the shape of y to (n_samples,), for example using
ravel().
  rfclas.fit(X_train, Y_train);
```

Out[48]:
```
[1.6479275493445155e-13, 0.0011638087543276944]
```

In [49]:
```
rfclas.oob_score_
```

Out[49]:
```
0.7568287808127915
```

In [ ]:
```
pipeline = Pipeline([('rf',RandomForestClassifier())])

parameters = {
        'rf__max_features':(3,4,5),
        'rf__max_samples':(0.5,0.6,0.7),
        'rf__n_estimators':(500,1000),
        'rf__max_depth':(50,100,200,300)}

grid_search = GridSearchCV(pipeline,parameters,n_jobs=6,cv=5,scoring='r2',ve
grid_search.fit(X_train,y_train)
```

```
# rfReg = RandomForestClassifier(n_estimators=500,max_features=0.33,max_dept
# rfReg.fit(X_train, y_train);
rfReg = RandomForestClassifier(n_estimators=500,max_features=0.33,max_depth=
rfReg
dic_pred = {}
dic_pred['train'] = rfReg.predict(X_train)
dic_pred['test'] = rfReg.predict(X_test)
pearsonr_all_tune = [pearsonr(dic_pred['train'],y_train)[0],pearsonr(dic_pre
pearsonr_all_tune

grid_search.best_score_


print ('Best Training score: %0.3f' % grid_search.best_score_)
print ('Optimal parameters:')
best_par = grid_search.best_estimator_.get_params()
for par_name in sorted(parameters.keys()):
    print ('\t%s: %r' % (par_name, best_par[par_name]))
```

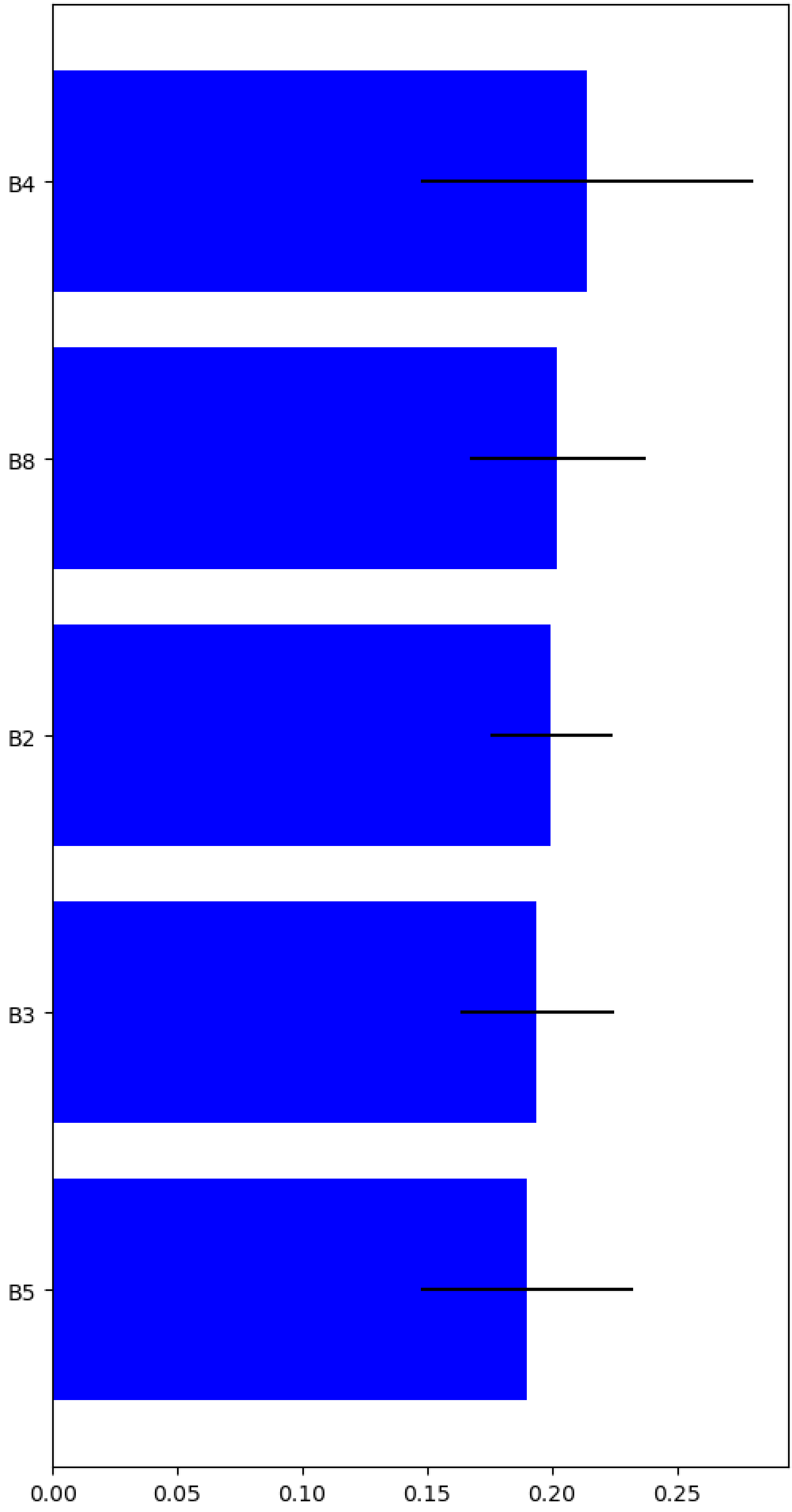
In [50]:
```
rfclas = RandomForestClassifier(n_estimators=500,max_features=0.33,max_depth
rfclas.fit(X_train, y_train);
rfclas
```

Out[50]:
```
▾                    RandomForestClassifier
RandomForestClassifier(max_depth=50, max_features=0.33, max_samples
=0.5,
                       n_estimators=500, n_jobs=-1, oob_score=True,
                       random_state=24)
```

In [51]:
```
impt = [rfclas.feature_importances_, np.std([tree.feature_importances_ for t
ind = np.argsort(impt[0])
ind
```

Out[51]:
```
array([3, 1, 2, 4, 0])
```

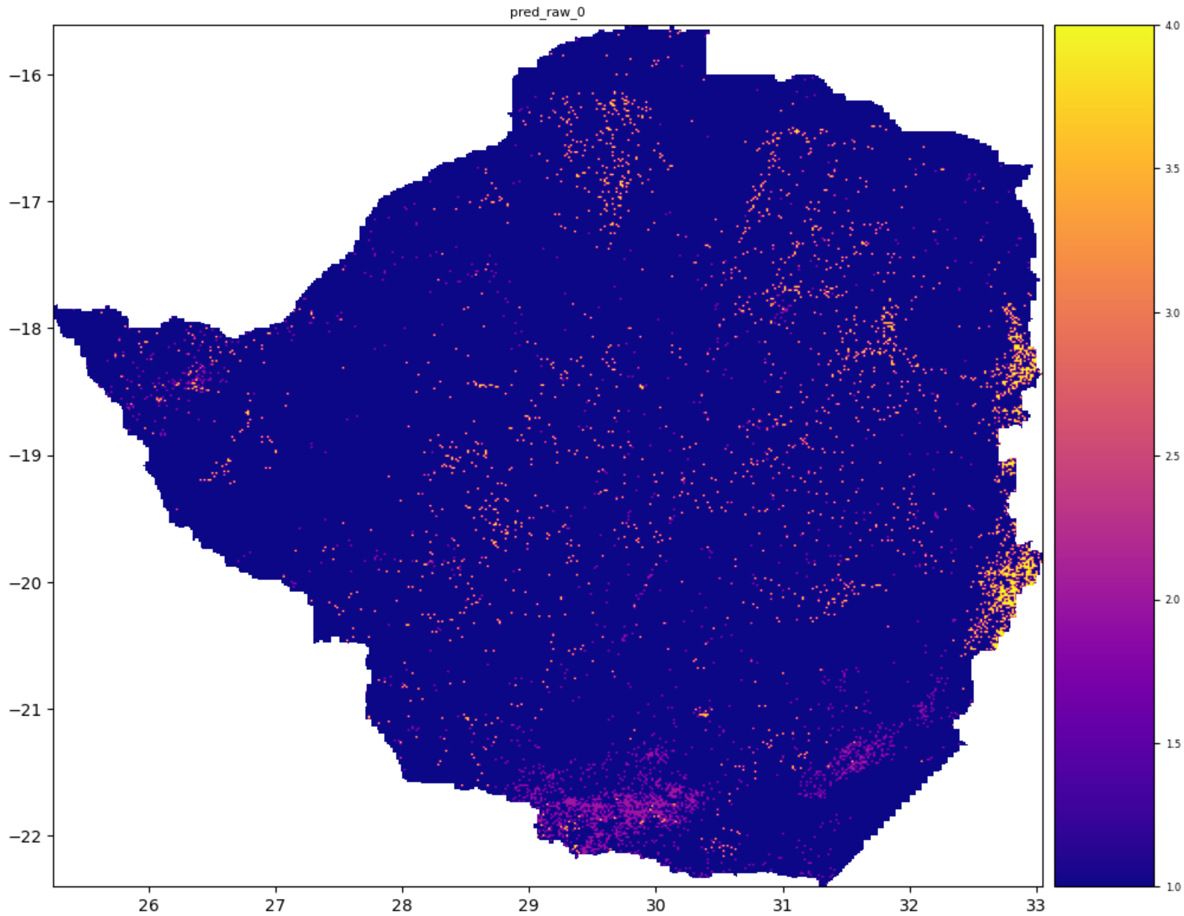
In [52]:
```
plt.rcParams["figure.figsize"] = (6,12)
plt.barh(range(len(feat)),impt[0][ind],color="b", xerr=impt[1][ind], align="
plt.yticks(range(len(feat)),feat[ind]);
```



In [53]:

```
predictors_rasters = [yield1]

stack = Raster(predictors_rasters)
```

```
result2 = stack.predict(estimator=rfclas, dtype='int16', nodata=-1)


plt.rcParams["figure.figsize"] = (12,12)
result2.iloc[0].cmap = "plasma"
result2.plot()
plt.show()
```



In [54]:

```
type(result)
result.write("Crop_Mask_trial_2.tif",nodatavals=-1)
```

```
Raster Object Containing 1 Layers
    attribute                                              values
0       names                                          [pred_raw_0]
1       files                                [Crop_Mask_trial_2.tif]
2        rows                                                  7561
3        cols                                                  8684
4         res  (0.0008983152841195215, 0.0008983152841195215)
5  nodatavals                                            [-32768.0]
```

Out[54]: