In [131]:
```
## EDA libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns


## feature engineering libraries
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split

## model preparation libraries
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.tree import DecisionTreeRegressor
from xgboost import XGBRegressor
from sklearn.neighbors import KNeighborsRegressor
from sklearn.ensemble import RandomForestRegressor

## model evaluation libraries
from sklearn.metrics import mean_absolute_error, r2_score, mean_squared_error
from sklearn import metrics

## model hyperparameter tuning
from sklearn.model_selection i

from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import RandomizedSearchCV


import joblib
%matplotlib inline
```

In [132]:
```
df=pd.read_csv("WildBlueberryPollinationSimulationData.csv")
```

In [133]:
```
df.head()
```

Out[133]:

	Row#	clonesize	honeybee	bumbles	andrena	osmia	MaxOfUpperTRange	MinOfUpperTRange
0	0	37.5	0.75	0.25	0.25	0.25	86.0	52.0
1	1	37.5	0.75	0.25	0.25	0.25	86.0	52.0
2	2	37.5	0.75	0.25	0.25	0.25	94.6	57.2
3	3	37.5	0.75	0.25	0.25	0.25	94.6	57.2
4	4	37.5	0.75	0.25	0.25	0.25	86.0	52.0

In [134]:
```
#drop Row#
df.drop(columns=['Row#'])
```

Out[134]:

	clonesize	honeybee	bumbles	andrena	osmia	MaxOfUpperTRange	MinOfUpperTRange	Ave
0	37.5	0.750	0.250	0.250	0.250	86.0	52.0	
1	37.5	0.750	0.250	0.250	0.250	86.0	52.0	
2	37.5	0.750	0.250	0.250	0.250	94.6	57.2	
3	37.5	0.750	0.250	0.250	0.250	94.6	57.2	
4	37.5	0.750	0.250	0.250	0.250	86.0	52.0	
...	...	...	...	...	...	...	...	
772	10.0	0.537	0.117	0.409	0.058	86.0	52.0	
773	40.0	0.537	0.117	0.409	0.058	86.0	52.0	
774	20.0	0.537	0.117	0.409	0.058	86.0	52.0	
775	20.0	0.537	0.117	0.409	0.058	89.0	39.0	
776	20.0	0.537	0.117	0.409	0.058	89.0	39.0	

777 rows × 17 columns

In [135]:
```
df.drop('Row#',axis=1,inplace=True)
```

In [136]:
```
df.shape
```

Out[136]:
```
(777, 17)
```

In [137]:
```
##Finding null values in the dataset
percent_missing = df.isnull().sum() * 100 / len(df)
percent_missing
```

Out[137]:
```
clonesize               0.0
honeybee                0.0
bumbles                 0.0
andrena                 0.0
osmia                   0.0
MaxOfUpperTRange        0.0
MinOfUpperTRange        0.0
AverageOfUpperTRange    0.0
MaxOfLowerTRange        0.0
MinOfLowerTRange        0.0
AverageOfLowerTRange    0.0
RainingDays             0.0
AverageRainingDays      0.0
fruitset                0.0
fruitmass               0.0
seeds                   0.0
yield                   0.0
dtype: float64
```

In [138]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 777 entries, 0 to 776
Data columns (total 17 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   clonesize             777 non-null    float64
 1   honeybee              777 non-null    float64
 2   bumbles               777 non-null    float64
 3   andrena               777 non-null    float64
 4   osmia                 777 non-null    float64
 5   MaxOfUpperTRange      777 non-null    float64
 6   MinOfUpperTRange      777 non-null    float64
 7   AverageOfUpperTRange  777 non-null    float64
 8   MaxOfLowerTRange      777 non-null    float64
 9   MinOfLowerTRange      777 non-null    float64
 10  AverageOfLowerTRange  777 non-null    float64
 11  RainingDays           777 non-null    float64
 12  AverageRainingDays    777 non-null    float64
 13  fruitset              777 non-null    float64
 14  fruitmass             777 non-null    float64
 15  seeds                 777 non-null    float64
 16  yield                 777 non-null    float64
dtypes: float64(17)
memory usage: 103.3 KB
```

In [139]:
```
df.describe()
```

Out[139]:

	clonesize	honeybee	bumbles	andrena	osmia	MaxOfUpperTRange	MinOfUppe
count	777.000000	777.000000	777.000000	777.000000	777.000000	777.000000	77
mean	18.767696	0.417133	0.282389	0.468817	0.562062	82.277091	4
std	6.999063	0.978904	0.066343	0.161052	0.169119	9.193745	
min	10.000000	0.000000	0.000000	0.000000	0.000000	69.700000	3
25%	12.500000	0.250000	0.250000	0.380000	0.500000	77.400000	4
50%	12.500000	0.250000	0.250000	0.500000	0.630000	86.000000	5
75%	25.000000	0.500000	0.380000	0.630000	0.750000	89.000000	5
max	40.000000	18.430000	0.585000	0.750000	0.750000	94.600000	5

In [140]:
```
df.nunique()
# Print the number of unique values in each column here
```

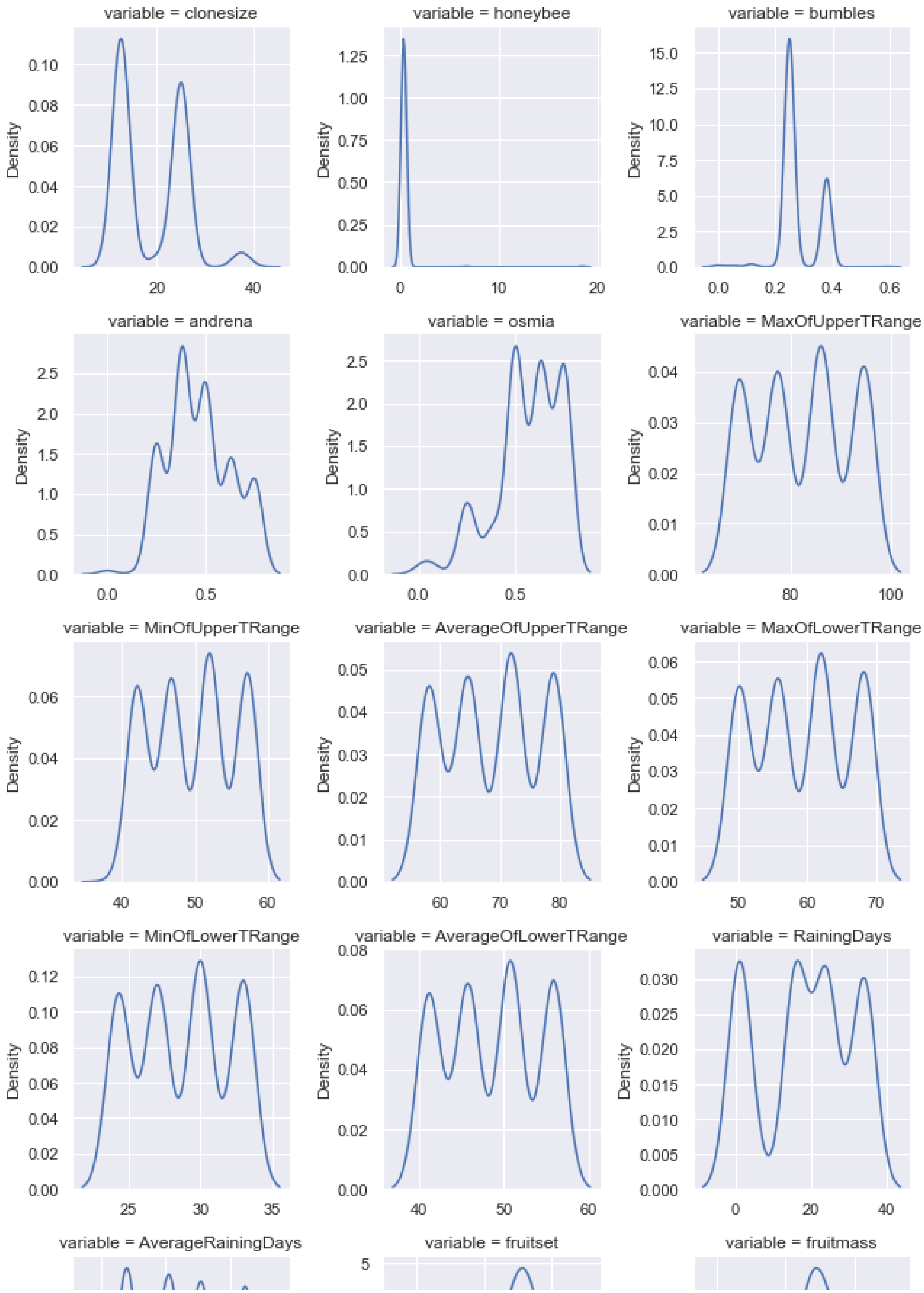
Out[140]:
```
clonesize                6
honeybee                 7
bumbles                 10
andrena                 12
osmia                   12
MaxOfUpperTRange         5
MinOfUpperTRange         5
AverageOfUpperTRange     5
MaxOfLowerTRange         5
MinOfLowerTRange         5
AverageOfLowerTRange     5
RainingDays              5
AverageRainingDays       5
fruitset               777
fruitmass              777
seeds                  777
yield                  777
dtype: int64
```

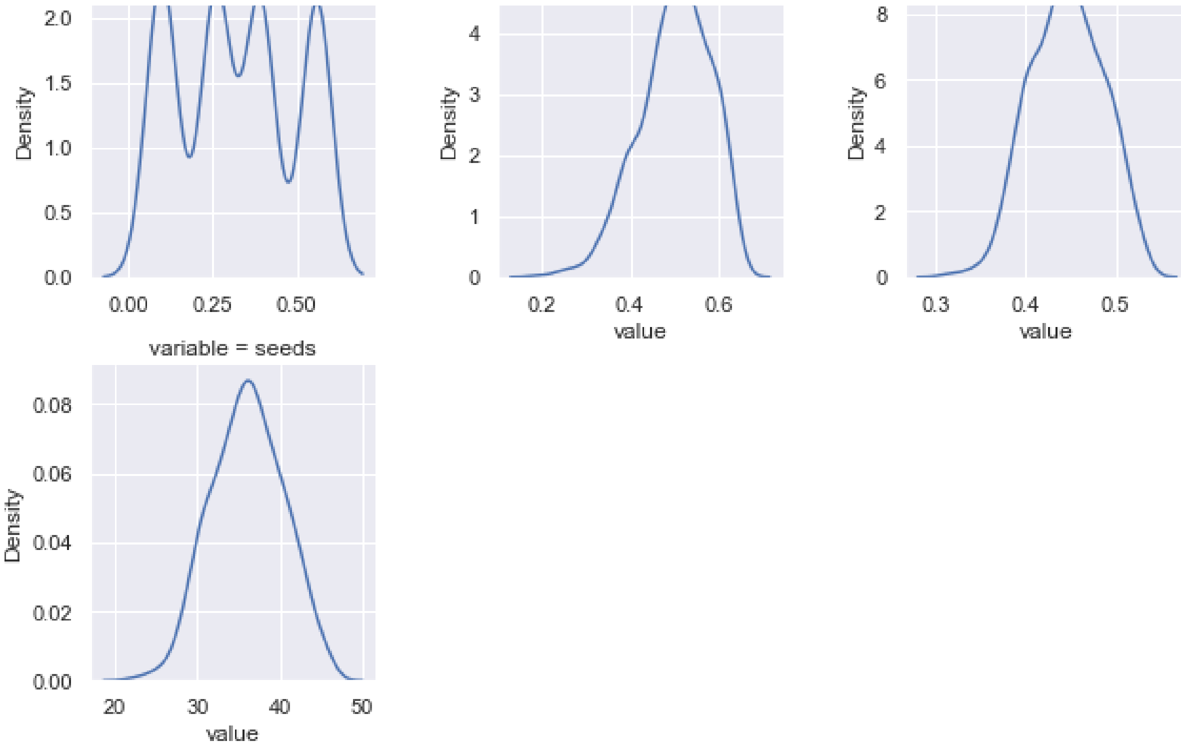
Univariate Analysis

In [141]:
```
unpivot = pd.melt(df, df.describe().columns[-1], df.describe().columns[:-1])

g = sns.FacetGrid(unpivot, col="variable", col_wrap=3, sharex=False, sharey=False
g.map(sns.kdeplot, "value")

plt.show()
```





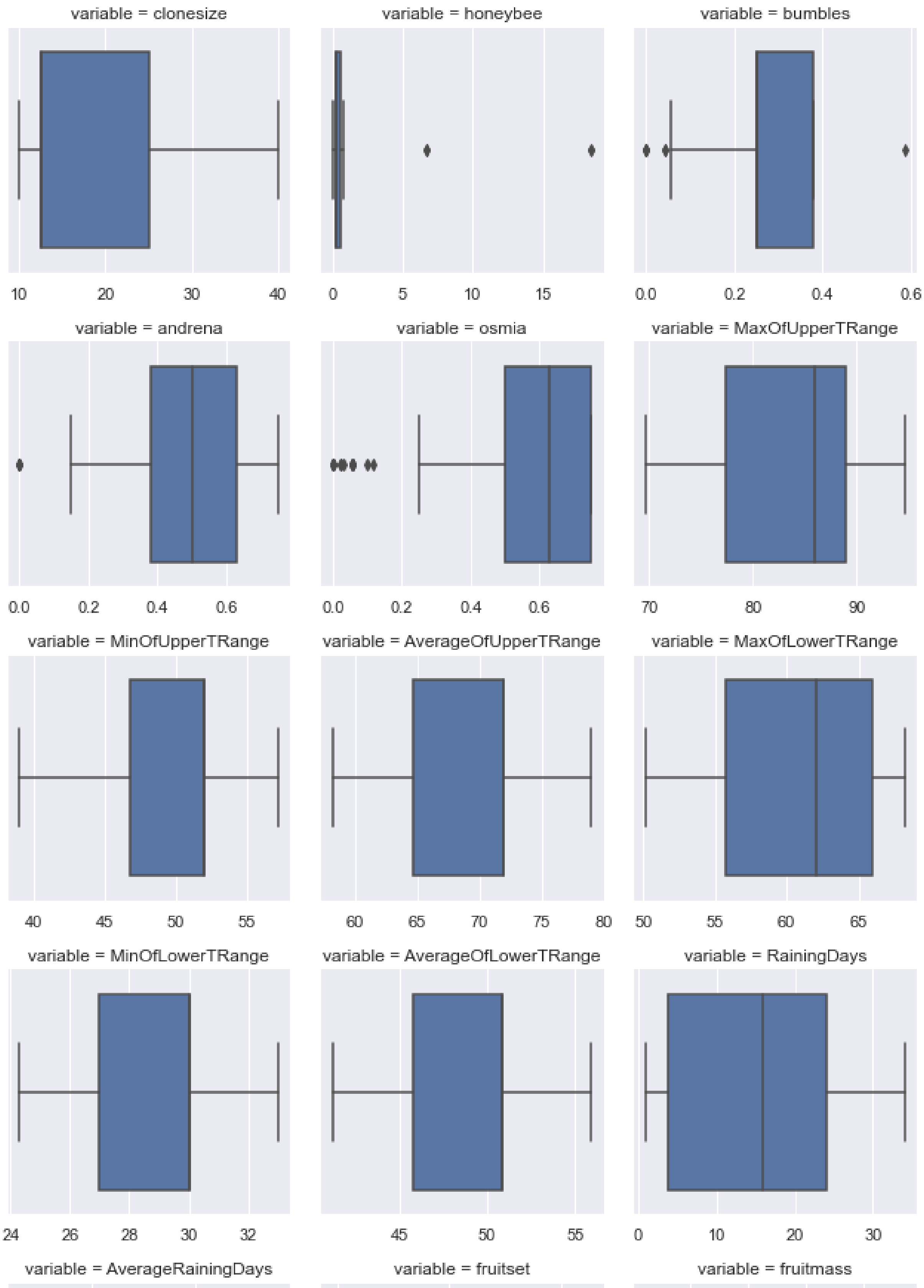
Through this analysis we determine that the columns such as Honeybee has very less variability to be considered for prediction

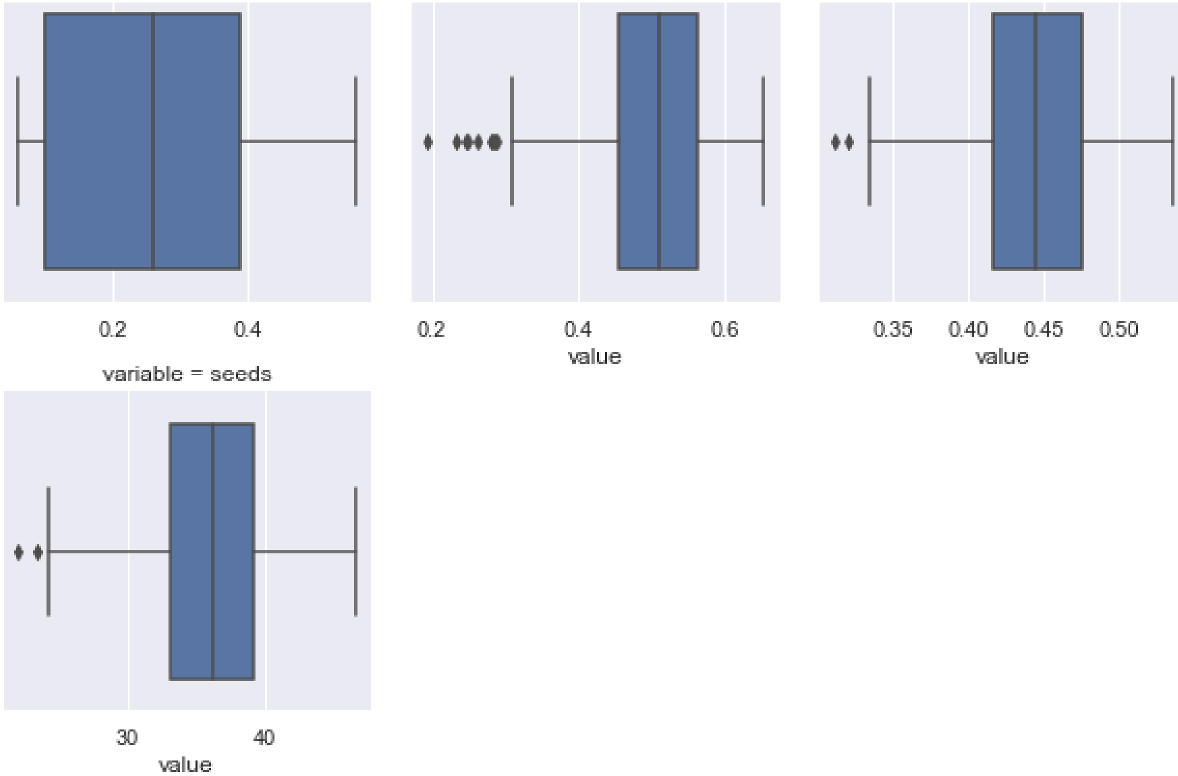
Finding out the Outliers

In [142]:
```
unpivot = pd.melt(df, df.describe().columns[-1], df.describe().columns[:-1])

g = sns.FacetGrid(unpivot, col="variable", col_wrap=3, sharex=False, sharey=False
g.map(sns.boxplot, "value")

plt.show()
```





Interquartile range

In [143]:
```python
q1 = df.quantile(0.25)
q2 = df.quantile(0.75)
iqr = q2 -q1
print(iqr)
```

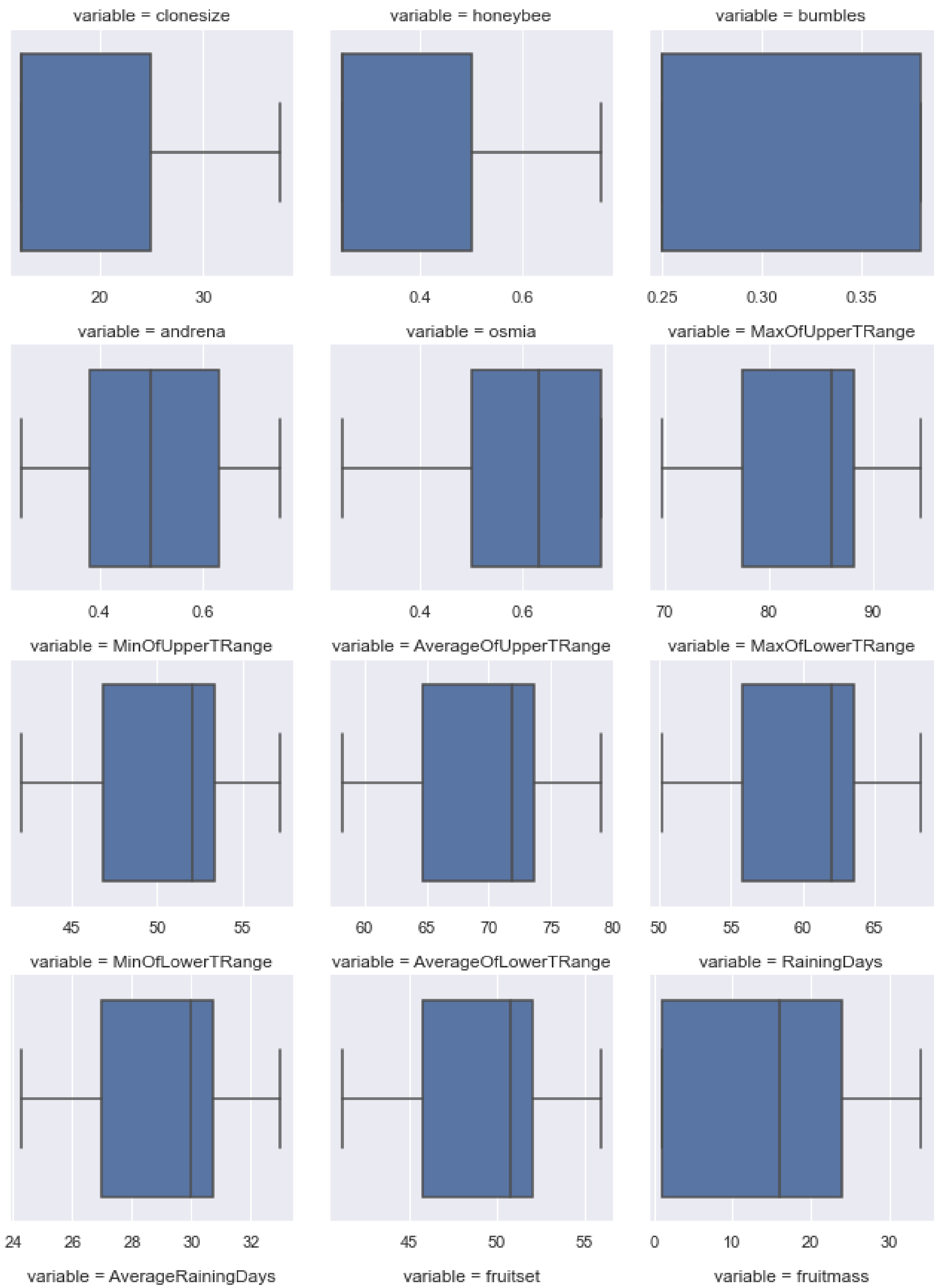
```
clonesize                 12.500000
honeybee                   0.250000
bumbles                    0.130000
andrena                    0.250000
osmia                      0.250000
MaxOfUpperTRange          11.600000
MinOfUpperTRange           5.200000
AverageOfUpperTRange       7.200000
MaxOfLowerTRange          10.200000
MinOfLowerTRange           3.000000
AverageOfLowerTRange       5.000000
RainingDays               20.230000
AverageRainingDays         0.290000
fruitset                   0.106571
fruitmass                  0.059869
seeds                      6.123577
yield                   1897.334830
dtype: float64
```

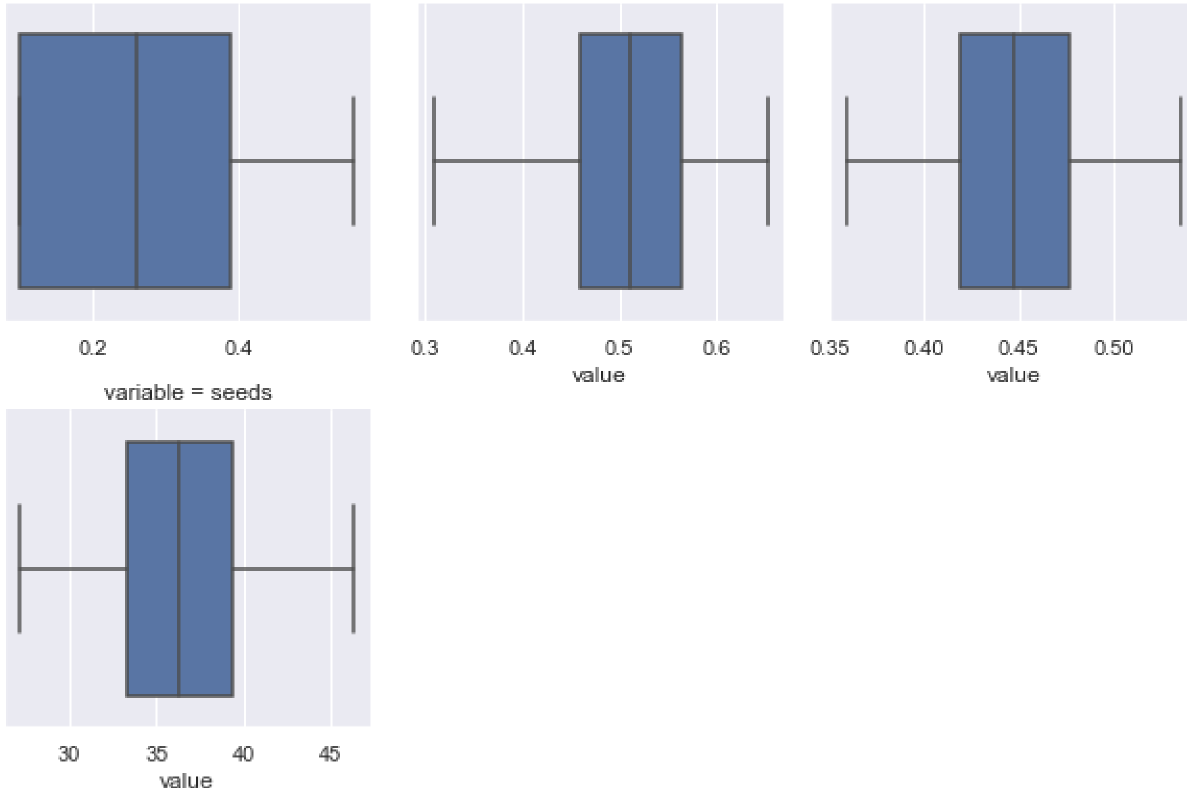
Removing the Outliers

In [144]:
```
df_new = df[~((df < (q1 - 1.5 * iqr)) |(df > (q2 + 1.5 * iqr))).any(axis=1)]
unpivot = pd.melt(df_new, df_new.describe().columns[-1], df_new.describe().columr

g = sns.FacetGrid(unpivot, col="variable", col_wrap=3, sharex=False, sharey=False
g.map(sns.boxplot, "value")

plt.show()
```



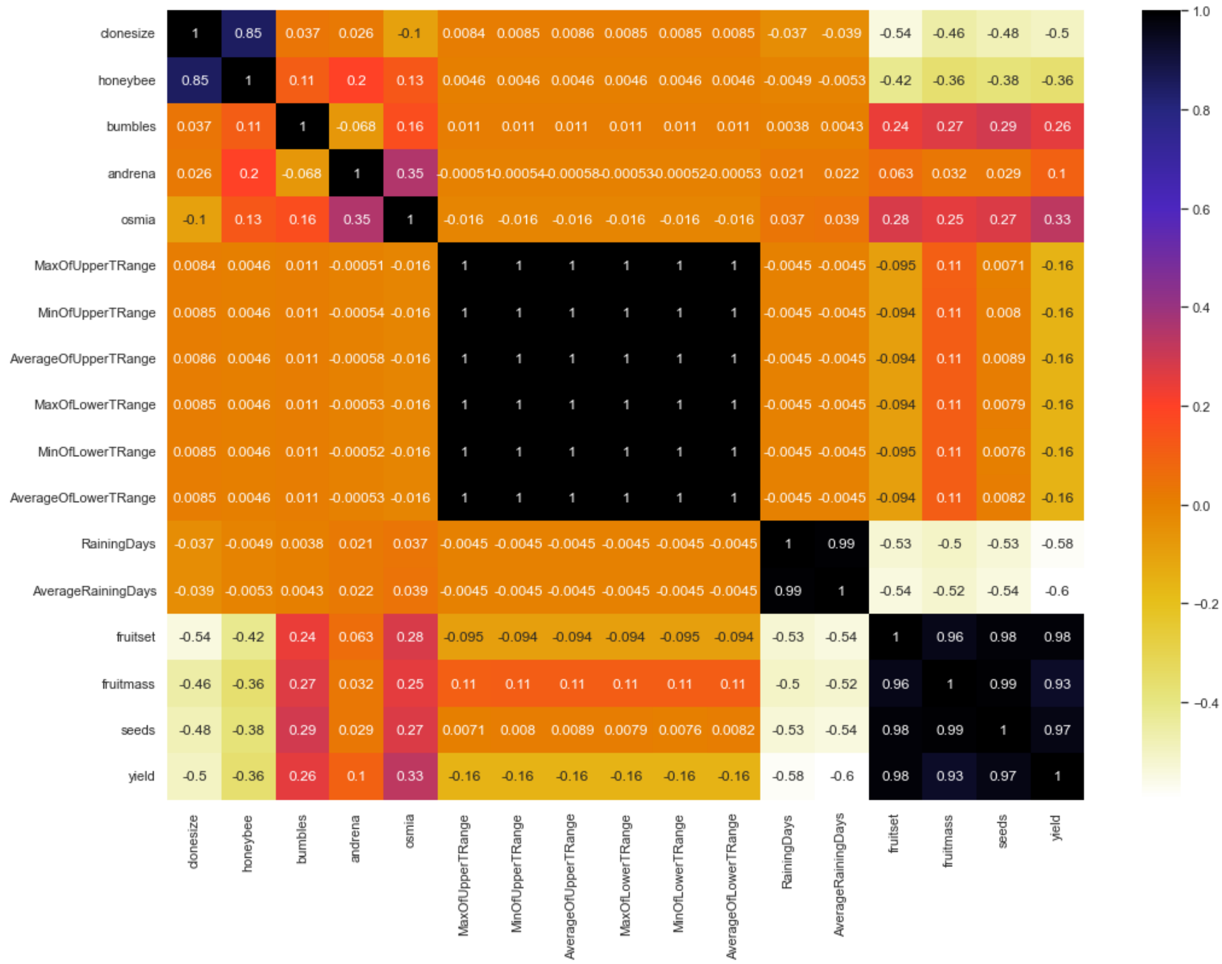


Outliers skew the data so it's important to remove them

Multivariate Analysis

In [145]:
```
plt.figure(figsize=(17,12))
sns.set()
sns.heatmap(df_new.corr(), annot=True, cmap=plt.cm.CMRmap_r)
```

Out[145]: <AxesSubplot:>



Removing the multi-collinearity

Preprocessing

Removing the irrelevant columns

In [146]:
```
UpperTRange', 'MinOfUpperTRange', 'MaxOfLowerTRange', 'MinOfLowerTRange', 'Rainin
```

In [147]:
```
df_new.columns
```

Out[147]:
```
Index(['clonesize', 'bumbles', 'andrena', 'osmia', 'AverageOfUpperTRange',
       'AverageOfLowerTRange', 'AverageRainingDays', 'seeds', 'yield'],
      dtype='object')
```

Standardization

In [148]:
```
X=df_new.drop('yield', axis=1)
Y=df_new['yield']
```

In [149]:
```
from sklearn.preprocessing import MinMaxScaler
```

In [150]:
```
scaler=MinMaxScaler()
```

In [151]:
```
X=scaler.fit_transform(X)
```

Implementation of models

In [152]:
```
from sklearn.model_selection import train_test_split
```

In [153]:
```
X_train,X_test,Y_train,Y_test=train_test_split(X,Y, test_size=0.2)
```

Linear Regression

In [155]:
```
lreg = LinearRegression()

lreg.fit(X_train, Y_train)

ypred = lreg.predict(X_test)
```

In [156]:
```
mae_linear = mean_absolute_error(Y_test, ypred)
mse_linear = mean_squared_error(Y_test, ypred)
rmse_linear = np.sqrt(mse_linear)
rsq_linear = r2_score(Y_test, ypred)

print('MAE: %.3f' % mae_linear)
print('MSE: %.3f' % mse_linear)
print('RMSE: %.3f' % rmse_linear)
print('R-Square: %.3f' % rsq_linear)
```

```
MAE: 109.194
MSE: 20348.817
RMSE: 142.649
R-Square: 0.987
```

Knearest Neighbor

In [158]:
```
knn=KNeighborsRegressor()
```

In [159]:
```
knn.fit(X_train, Y_train)

ypred = knn.predict(X_test)
```

In [160]:
```
mae_knn = mean_absolute_error(Y_test, ypred)
mse_knn = mean_squared_error(Y_test, ypred)
rmse_knn = np.sqrt(mse_linear)
rsq_knn = r2_score(Y_test, ypred)

print('MAE: %.3f' % mae_linear)
print('MSE: %.3f' % mse_linear)
print('RMSE: %.3f' % rmse_linear)
print('R-Square: %.3f' % rsq_linear)
```

```
MAE: 109.194
MSE: 20348.817
RMSE: 142.649
R-Square: 0.987
```

Decision Tree

In [162]:
```
dtree = DecisionTreeRegressor()

dtree.fit(X_train, Y_train)

ypred = dtree.predict(X_test)
```

In [163]:
```
mae_dt = mean_absolute_error(Y_test, ypred)
mse_dt = mean_squared_error(Y_test, ypred)
rmse_dt = np.sqrt(mse_linear)
rsq_dt = r2_score(Y_test, ypred)

print('MAE: %.3f' % mae_linear)
print('MSE: %.3f' % mse_linear)
print('RMSE: %.3f' % rmse_linear)
print('R-Square: %.3f' % rsq_linear)
```

```
MAE: 109.194
MSE: 20348.817
RMSE: 142.649
R-Square: 0.987
```

Random Forest Regressor

Randomized search cv

In [165]:
```
# Number of trees in random forest
n_estimators = [int(x) for x in np.linspace(start = 200, stop = 2000, num = 10)]
# Number of features to consider at every split
max_features = ['auto', 'sqrt','log2']
# Maximum number of levels in tree
max_depth = [int(x) for x in np.linspace(10, 1000,10)]
# Minimum number of samples required to split a node
min_samples_split = [2, 5, 10,14]
# Minimum number of samples required at each leaf node
min_samples_leaf = [1, 2, 4,6,8]
# Create the random grid
random_grid = {'n_estimators': n_estimators,
               'max_features': max_features,
               'max_depth': max_depth,
               'min_samples_split': min_samples_split,
               'min_samples_leaf': min_samples_leaf}
print(random_grid)
```

```
{'n_estimators': [200, 400, 600, 800, 1000, 1200, 1400, 1600, 1800, 2000], 'max
_features': ['auto', 'sqrt', 'log2'], 'max_depth': [10, 120, 230, 340, 450, 56
0, 670, 780, 890, 1000], 'min_samples_split': [2, 5, 10, 14], 'min_samples_lea
f': [1, 2, 4, 6, 8]}
```

In [166]:
```
rf=RandomForestRegressor()
rf_randomcv=RandomizedSearchCV(estimator=rf,param_distributions=random_grid,n_ite
                               random_state=100,n_jobs=-1)
```

In [167]:
```
### fit the randomized model
rf_randomcv.fit(X_train,Y_train)
```

```
Fitting 3 folds for each of 100 candidates, totalling 300 fits
```

Out[167]:
```
RandomizedSearchCV(cv=3, estimator=RandomForestRegressor(), n_iter=100,
                   n_jobs=-1,
                   param_distributions={'max_depth': [10, 120, 230, 340, 450,
                                                      560, 670, 780, 890,
                                                      1000],
                                        'max_features': ['auto', 'sqrt',
                                                         'log2'],
                                        'min_samples_leaf': [1, 2, 4, 6, 8],
                                        'min_samples_split': [2, 5, 10, 14],
                                        'n_estimators': [200, 400, 600, 800,
                                                         1000, 1200, 1400, 160
0,
                                                         1800, 2000]},
                   random_state=100, verbose=2)
```

In [168]:
```
rf_randomcv.best_params_
```

Out[168]:
```
{'n_estimators': 1400,
 'min_samples_split': 2,
 'min_samples_leaf': 1,
 'max_features': 'log2',
 'max_depth': 230}
```

In [169]:
```
ypred=rf_randomcv.predict(X_test)
```

In [170]:
```
mae_rsv = mean_absolute_error(Y_test, ypred)
mse_rsv = mean_squared_error(Y_test, ypred)
rmse_rsv = np.sqrt(mse_linear)
rsq_rsv = r2_score(Y_test, ypred)

print('MAE: %.3f' % mae_linear)
print('MSE: %.3f' % mse_linear)
print('RMSE: %.3f' % rmse_linear)
print('R-Square: %.3f' % rsq_linear)
```

```
MAE: 109.194
MSE: 20348.817
RMSE: 142.649
R-Square: 0.987
```

GridSearch CV

In [171]:
```
param_grid = {
    'max_depth': [rf_randomcv.best_params_['max_depth']],
    'max_features': [rf_randomcv.best_params_['max_features']],
    'min_samples_leaf': [rf_randomcv.best_params_['min_samples_leaf'],
                         rf_randomcv.best_params_['min_samples_leaf']+2,
                         rf_randomcv.best_params_['min_samples_leaf'] + 4],
    'min_samples_split': [rf_randomcv.best_params_['min_samples_split'] - 2,
                          rf_randomcv.best_params_['min_samples_split'] - 1,
                          rf_randomcv.best_params_['min_samples_split'],
                          rf_randomcv.best_params_['min_samples_split'] +1,
                          rf_randomcv.best_params_['min_samples_split'] + 2],
    'n_estimators': [rf_randomcv.best_params_['n_estimators'] - 200, rf_randomcv.
                     rf_randomcv.best_params_['n_estimators'],
                     rf_randomcv.best_params_['n_estimators'] + 100, rf_randomcv.
}

print(param_grid)
```

```
{'max_depth': [230], 'max_features': ['log2'], 'min_samples_leaf': [1, 3, 5],
'min_samples_split': [0, 1, 2, 3, 4], 'n_estimators': [1200, 1300, 1400, 1500,
1600]}
```

In [172]:
```
#### Fit the grid_search to the data
rf=RandomForestRegressor()
grid_search=GridSearchCV(estimator=rf,param_grid=param_grid,cv=10,n_jobs=-1,verbo
grid_search.fit(X_train,Y_train)
```

```
Fitting 10 folds for each of 75 candidates, totalling 750 fits
```

Out[172]:
```
GridSearchCV(cv=10, estimator=RandomForestRegressor(), n_jobs=-1,
             param_grid={'max_depth': [230], 'max_features': ['log2'],
                         'min_samples_leaf': [1, 3, 5],
                         'min_samples_split': [0, 1, 2, 3, 4],
                         'n_estimators': [1200, 1300, 1400, 1500, 1600]},
             verbose=2)
```

In [173]:
```
grid_search.best_estimator_
```

Out[173]:
```
RandomForestRegressor(max_depth=230, max_features='log2', n_estimators=1500)
```

In [174]:
```
ypred=rf_randomcv.predict(X_test)
```

In [175]:
```
ypred=rf_randomcv.predict(X_test)

mae_gsv = mean_absolute_error(Y_test, ypred)
mse_gsv = mean_squared_error(Y_test, ypred)
rmse_gsv = np.sqrt(mse_linear)
rsq_gsv = r2_score(Y_test, ypred)

print('MAE: %.3f' % mae_linear)
print('MSE: %.3f' % mse_linear)
print('RMSE: %.3f' % rmse_linear)
print('R-Square: %.3f' % rsq_linear)
```

```
MAE: 109.194
MSE: 20348.817
RMSE: 142.649
R-Square: 0.987
```

XGBoost

In [176]:
```
from xgboost import XGBRegressor
```

In [177]:
```
xgb = XGBRegressor()

xgb.fit(X_train, Y_train)

ypred = xgb.predict(X_test)
```

In [178]:
```
mae_xg = mean_absolute_error(Y_test, ypred)
mse_xg = mean_squared_error(Y_test, ypred)
rmse_xg = np.sqrt(mse_linear)
rsq_xg = r2_score(Y_test, ypred)

print('MAE: %.3f' % mae_linear)
print('MSE: %.3f' % mse_linear)
print('RMSE: %.3f' % rmse_linear)
print('R-Square: %.3f' % rsq_linear)
```

```
MAE: 109.194
MSE: 20348.817
RMSE: 142.649
R-Square: 0.987
```

Model Performance Evaluation

In [182]:
```
error_rec = {
    "linearreg": {
        "mae": mae_linear,
        "rmse": rmse_linear,
        'r2': rsq_linear*100
    },
    "randomforest_random": {
        "mae": mae_rsv,
        "rmse": rmse_rsv,
        'r2': rsq_rsv*100
    },
    "randomforest_grid": {
        "mae": mae_gsv,
        "rmse": rmse_gsv,
        'r2': rsq_gsv*100
    },
    "decisiontree": {
        "mae": mae_dt,
        "rmse": rmse_dt,
        'r2': rsq_dt*100
    },"xgboost": {
        "mae": mae_xg,
        "rmse": rmse_xg,
        'r2': rsq_xg*100},"knn": {
        "mae": mae_knn,
        "rmse": rmse_knn,
        'r2': rsq_knn*100}}
pd.DataFrame(error_rec).plot(kind="bar",
             color=[
                 sns.color_palette("pastel")[0],
                 sns.color_palette("pastel")[1],
                 sns.color_palette("pastel")[2],
                 sns.color_palette("pastel")[3],sns.color_palette("pastel")[4],sr
```

In [ ]:

In [ ]:

In [ ]:

In [ ]: