In [274…

```python
import pandas as pd # to use or generate dataframe
import seaborn as sns # for pretty plots
import numpy as np # for matrix manipulation
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
```

In [276…

```python
%cd C:\\Users\\emper\\OneDrive\\Desktop\\DSTI\\Pratical-Intro-to-Data-Science\\F
```

```
C:\Users\emper\OneDrive\Desktop\DSTI\Pratical-Intro-to-Data-Science\Final-Project
```

Let's do classification by East west

In [ ]:

```python

```

In [333…

```python
Model_Classification_data = pd.read_csv("model_classification.csv")
```

In [337…

```python
Model_Classification_data.describe()
```

Out[337…

	year	AvgTemp	af	rain	sun	
count	28154.000000	28154.000000	28154.000000	28154.000000	27880.000000	28154.000
mean	1979.320345	9.454912	3.431306	72.044807	118.450276	53.974
std	27.199292	4.509328	5.176972	48.048325	63.196272	2.542
min	1890.000000	-4.650000	0.000000	0.000000	2.800000	50.218
25%	1962.000000	5.750000	0.000000	38.400000	64.800000	51.911
50%	1982.000000	9.050000	0.000000	61.700000	111.950000	53.356
75%	2000.000000	13.300000	5.000000	94.000000	163.600000	55.846
max	2023.000000	22.450000	31.000000	568.800000	350.300000	60.139

In [335…

```python
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
```

In [340…

```python
# New function: classify based on longitude
def assign_region(lon):
    if lon >= -2.5765:  # Midpoint between max (1.727) and min (-6.880)
        return 'Eastern Half'
    else:
        return 'Western Half'

# Apply the new function
Model_Classification_data['Region_Label'] = Model_Classification_data['lon'].app
```

In [342…

```python
# Drop unneeded columns including 'region' and 'latitude'
features = Model_Classification_data.drop(columns=['station', 'year','lat', 'reg
```

```
target = Model_Classification_data['Region_Label']
Model_Classification_data
```

Out[342...

	station	year	month	AvgTemp	af	rain	sun	lat	lon	region	Re
0	aberporth	1957	Jan	6.25	2.0	80.6	55.6	52.140	-4.57	Wales	W
1	aberporth	1957	Feb	5.85	2.0	85.1	105.2	52.140	-4.57	Wales	W
2	aberporth	1957	Mar	9.80	0.0	83.1	98.3	52.140	-4.57	Wales	W
3	aberporth	1957	Apr	8.75	0.0	7.4	181.1	52.140	-4.57	Wales	W
4	aberporth	1957	May	10.50	0.0	54.1	268.7	52.140	-4.57	Wales	W
...	...	...	...	...	...	...	...	...	...	...	
28149	yeovilton	2023	Mar	7.90	2.0	113.2	55.7	51.006	-2.64	South West England	W
28150	yeovilton	2023	Apr	9.15	4.0	59.6	137.3	51.006	-2.64	South West England	W
28151	yeovilton	2023	May	13.00	0.0	68.4	231.1	51.006	-2.64	South West England	W
28152	yeovilton	2023	Jun	17.70	0.0	22.8	254.9	51.006	-2.64	South West England	W
28153	yeovilton	2023	Jul	16.80	0.0	96.0	132.5	51.006	-2.64	South West England	W

28154 rows × 11 columns

In [344...

```
Group_by_Label = Model_Classification_data.groupby('Region_Label')
Group_by_Label['station'].count()
```

Out[344...

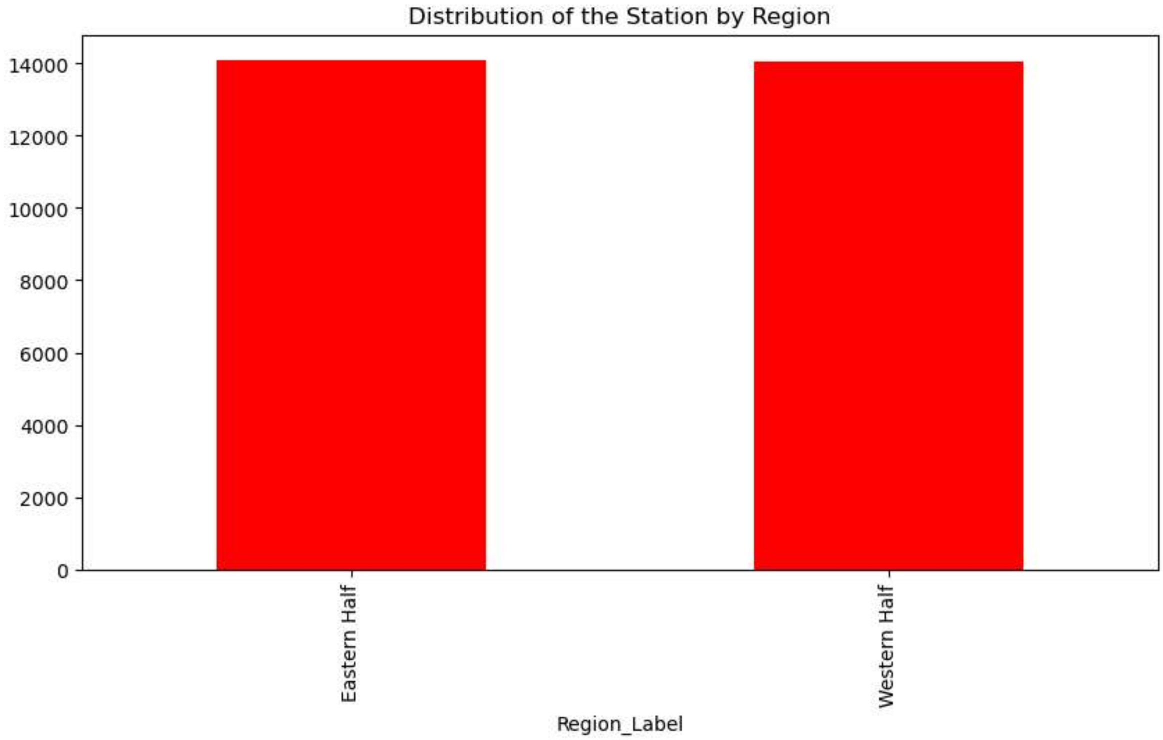
```
Region_Label
Eastern Half     14096
Western Half     14058
Name: station, dtype: int64
```

In [346...

```
Group_by_Label['station'].count().plot(kind= 'bar', title= 'Distribution of the
```

Out[346...

```
<Axes: title={'center': 'Distribution of the Station by Region'}, xlabel='Regio
n_Label'>
```



In [348…

```
# One-hot encode 'month'
categorical_features = ['month']
numeric_features = features.drop(columns=categorical_features).columns.tolist()

preprocessor = ColumnTransformer(
    transformers=[
        ('cat', OneHotEncoder(), categorical_features),
    ],
    remainder='passthrough'  # Leave numeric features unchanged
)
```

In [350…

```
# Step 1: Map each station to its most common Region_Label (usually one per stat
station_to_region = Model_Classification_data.groupby('station')['Region_Label']

# Step 2: Stratified split of station names based on their region
train_stations, test_stations = train_test_split(
    station_to_region.index,
    test_size=0.3,
    stratify=station_to_region,
    random_state=42
)

# Step 3: Split the actual data using station names
train_data = Model_Classification_data[Model_Classification_data['station'].isin
test_data = Model_Classification_data[Model_Classification_data['station'].isin(

# Step 4: Define features and target
X_train = train_data.drop(columns=['station', 'year', 'lat', 'Region_Label', 're
y_train = train_data['Region_Label']
X_test = test_data.drop(columns=['station', 'year', 'lat', 'Region_Label', 'regi
y_test = test_data['Region_Label']
```

In [352…

```
#Let's define and train the model pipeline
clf_pipeline = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('classifier', RandomForestClassifier(random_state=42))
```

```
])

clf_pipeline.fit(X_train, y_train)
y_pred = clf_pipeline.predict(X_test)
```

In [354…

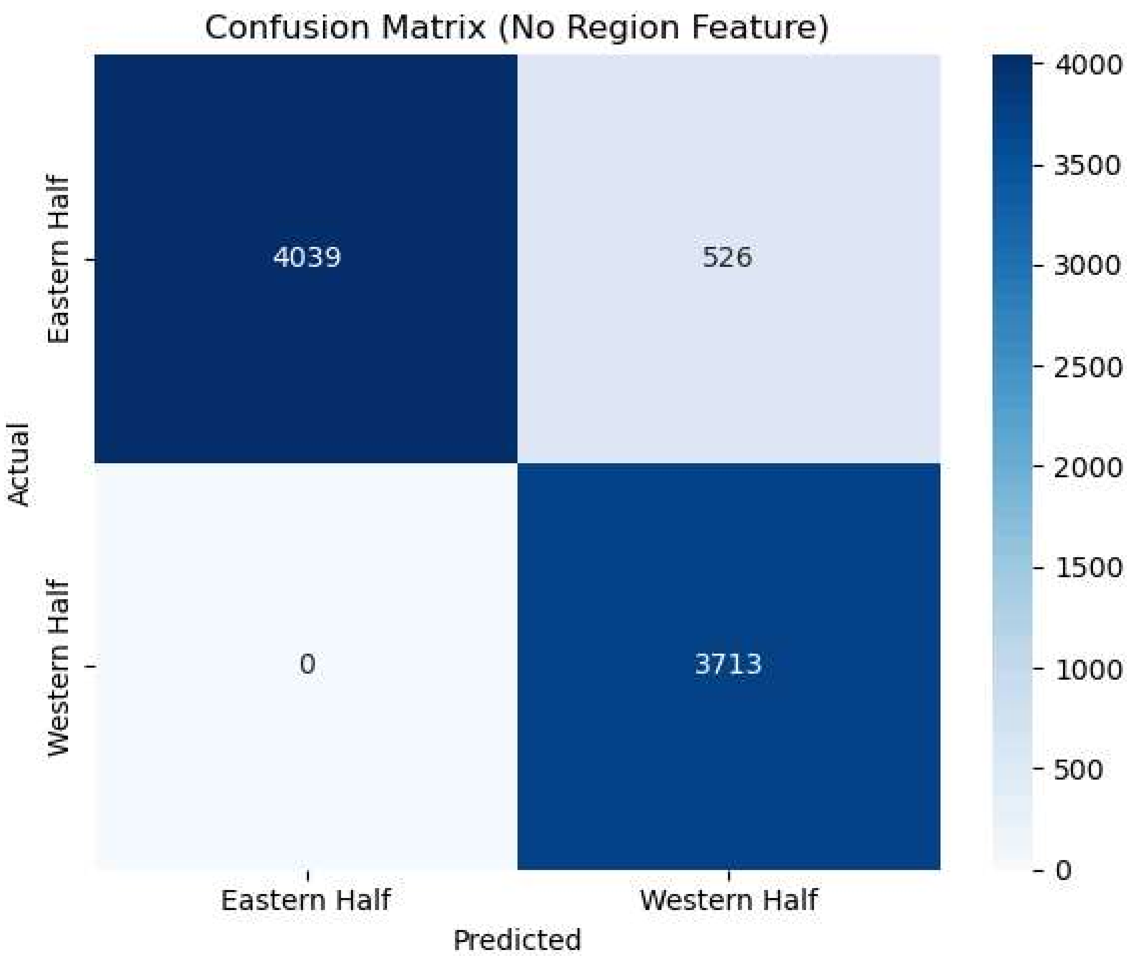
```
#Let's set the evaluation metrix
# Evaluation
report = classification_report(y_test, y_pred, output_dict=True)
conf_matrix = confusion_matrix(y_test, y_pred)
```

In [356…

```
#Let's plot the confusion matrix

plt.figure(figsize=(6, 5))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues',
            xticklabels=clf_pipeline.classes_,
            yticklabels=clf_pipeline.classes_)
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix (No Region Feature)')
plt.tight_layout()
plt.savefig("confusion_matrix_no_region.png")

report_df = pd.DataFrame(report).transpose()
report_df_rounded = report_df.round(2)
```



In [358…

```
from IPython.display import display

display(report_df_rounded)
```

	precision	recall	f1-score	support
Eastern Half	1.00	0.88	0.94	4565.00
Western Half	0.88	1.00	0.93	3713.00
accuracy	0.94	0.94	0.94	0.94
macro avg	0.94	0.94	0.94	8278.00
weighted avg	0.94	0.94	0.94	8278.00

In [360…

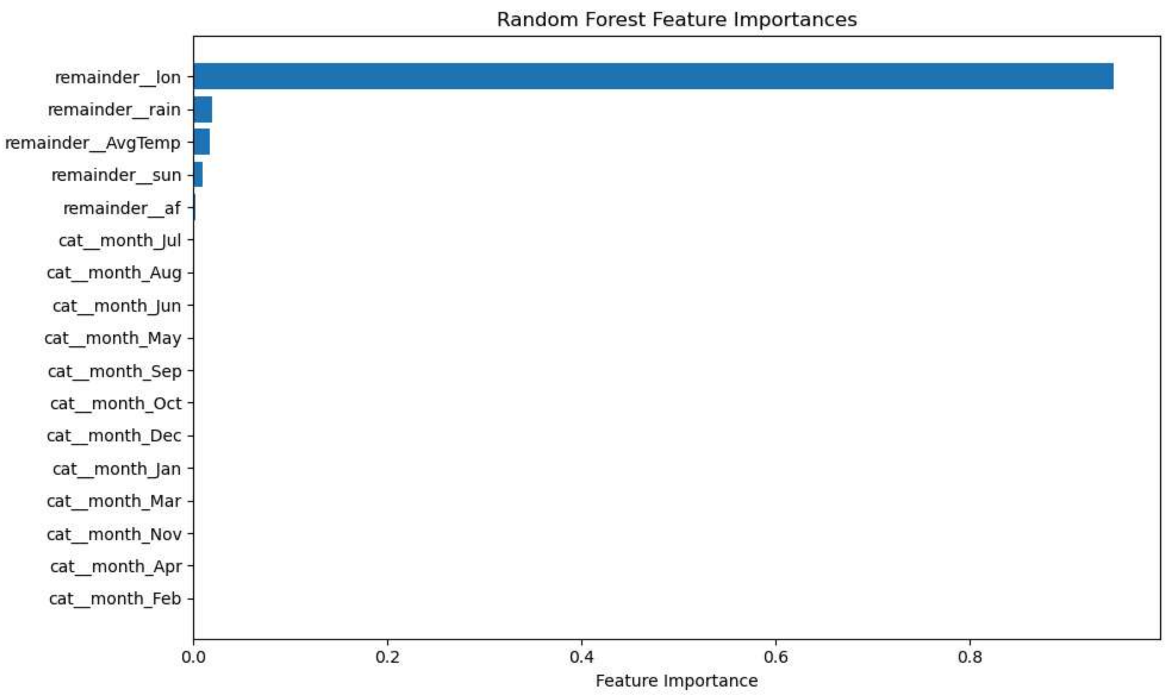
```
# Make sure your pipeline is already fitted
# clf_pipeline.fit(X_train, y_train)

# Get feature importances
importances = clf_pipeline.named_steps['classifier'].feature_importances_

# Get full feature names after preprocessing
feature_names = clf_pipeline.named_steps['preprocessor'].get_feature_names_out()

# Combine into a DataFrame
feature_importance_df = pd.DataFrame({
    'Feature': feature_names,
    'Importance': importances
}).sort_values(by='Importance', ascending=False)

# Plot
plt.figure(figsize=(10, 6))
plt.barh(feature_importance_df['Feature'], feature_importance_df['Importance'])
plt.gca().invert_yaxis()
plt.xlabel('Feature Importance')
plt.title('Random Forest Feature Importances')
plt.tight_layout()
plt.show()
```



In [ ]:

Let's Look at Happiness Vs Earnings

In [278…
```
# Step 1: Load both files
happiness = pd.read_csv('Happiness_only.csv')
earnings = pd.read_csv('Weekly earning by boroughs.csv')
```

In [280…
```
# Step 2: Inspect columns (quick check)
print(happiness.columns)
print(earnings.columns)
```

```
Index(['Area Codes', 'Area names', 'Borough', 'Unnamed: 3',
       'Per cent in each category on 11 point scale3:', 'Medium', 'High',
       'Very High', 'Means', 'Unnamed: 9', 'Unnamed: 10', 'Unnamed: 11',
       'Unnamed: 12', 'Unnamed: 13', 'Unnamed: 14', 'Unnamed: 15',
       'Unnamed: 16', 'Unnamed: 17', 'Unnamed: 18', 'Unnamed: 19',
       'Unnamed: 20', 'Unnamed: 21', 'Unnamed: 22', 'Unnamed: 23',
       'Unnamed: 24'],
      dtype='object')
Index(['Borough', 'Code', 'N of jobs (thousands)', 'Median',
       'Annual percent change', 'Mean', 'Unnamed: 6', 'Unnamed: 7',
       'Unnamed: 8', 'Unnamed: 9', 'Unnamed: 10', 'Unnamed: 11', 'Unnamed: 12',
       'Unnamed: 13', 'Unnamed: 14', 'Unnamed: 15', 'Unnamed: 16',
       'Unnamed: 17', 'Unnamed: 18', 'Unnamed: 19'],
      dtype='object')
```

In [282…
```
# Step 3: Rename important columns correctly
# Adjust depending on the new actual names
happiness = happiness.rename(columns={
    'Borough': 'borough',  # if it's already 'borough', no change needed
    'Means': 'average_happiness'
})

earnings = earnings.rename(columns={
    'Borough': 'borough',  # if it's already 'borough', no change needed
    'Median': 'median_earnings'
})
```

In [284…
```
# Step 4: Clean borough names to avoid merge issues (remove spaces, lowercase)
happiness['borough'] = happiness['borough'].str.strip().str.lower()
earnings['borough'] = earnings['borough'].str.strip().str.lower()
```

In [286…
```
#Keep only earnings where borough is in happiness list
earnings = earnings[earnings['borough'].isin(happiness['borough'])]
```

In [288…
```
#Now select and merge
happiness_clean = happiness[['borough', 'average_happiness']]
earnings_clean = earnings[['borough', 'median_earnings']]
```

In [290…
```
# Step 6: Merge the datasets on 'borough'
happiness_vs_earnings = pd.merge(happiness_clean, earnings_clean, on='borough',
```

In [292…
```
happiness_vs_earnings.head(50)
```

Out[292…

	borough	average_happiness	median_earnings
0	NaN	7.46	NaN
1	NaN	7.46	NaN
2	NaN	7.46	NaN
3	NaN	7.46	NaN
4	NaN	7.45	NaN
5	NaN	7.45	NaN
6	NaN	7.45	NaN
7	NaN	7.45	NaN
8	NaN	7.34	NaN
9	NaN	7.34	NaN
10	NaN	7.34	NaN
11	NaN	7.34	NaN
12	county durham ua	7.37	555.7
13	darlington ua	7.46	558.8
14	hartlepool ua	7.48	566.9
15	middlesbrough ua	7.28	543.6
16	northumberland ua	7.44	575.6
17	redcar and cleveland ua	7.46	544.3
18	stockton-on-tees ua	7.56	544.6
19	gateshead	7.25	562.8
20	newcastle upon tyne	7.2	593.8
21	north tyneside	7.26	604.4
22	south tyneside	7.2	546.3
23	sunderland	7.27	547.5
24	NaN	7.39	NaN
25	NaN	7.39	NaN
26	NaN	7.39	NaN
27	NaN	7.39	NaN
28	blackburn with darwen ua	7.34	528.1
29	blackpool ua	7.3	523
30	cheshire east ua	7.77	648
31	cheshire west and chester ua	7.49	605.6
32	halton ua	7.31	585.5

	borough	average_happiness	median_earnings
33	warrington ua	7.47	636
34	bolton	7.41	550.2
35	bury	7.53	626.8
36	manchester	7.31	565
37	oldham	7.19	579.3
38	rochdale	7.31	579.7
39	salford	7.23	611
40	stockport	7.41	633.2
41	tameside	7.26	579
42	trafford	7.4	664.7
43	wigan	7.31	586.4
44	lancashire	7.55	580.9
45	burnley	7.52	567.4
46	chorley	7.79	624.7
47	fylde	7.78	549.3
48	hyndburn	7.64	574.6
49	lancaster	7.58	551.4

In [294…

```
happiness_vs_earnings.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 494 entries, 0 to 493
Data columns (total 3 columns):
 #   Column             Non-Null Count  Dtype 
---  ------             --------------  ----- 
 0   borough            354 non-null    object
 1   average_happiness  410 non-null    object
 2   median_earnings    354 non-null    object
dtypes: object(3)
memory usage: 11.7+ KB
```

In [296…

```
happiness_vs_earnings.to_csv('happiness_vs_earnings.csv', index=False)
```

In [298…

```
happiness_vs_earnings = pd.read_csv('happiness_vs_earnings.csv')
```

In [300…

```
happiness_vs_earnings.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 494 entries, 0 to 493
Data columns (total 3 columns):
 #   Column             Non-Null Count  Dtype 
---  ------             --------------  ----- 
 0   borough            354 non-null    object
 1   average_happiness  410 non-null    object
 2   median_earnings    354 non-null    object
dtypes: object(3)
memory usage: 11.7+ KB
```

In [304…

```
happiness_vs_earnings['average_happiness'] = pd.to_numeric(happiness_vs_earnings
```

In [306…

```
happiness_vs_earnings['median_earnings'] = pd.to_numeric(happiness_vs_earnings['
```

In [308…

```
happiness_vs_earnings.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 494 entries, 0 to 493
Data columns (total 3 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   borough            354 non-null    object 
 1   average_happiness  409 non-null    float64
 2   median_earnings    353 non-null    float64
dtypes: float64(2), object(1)
memory usage: 11.7+ KB
```

In [310…

```
happiness_vs_earnings.describe()
```

Out[310…

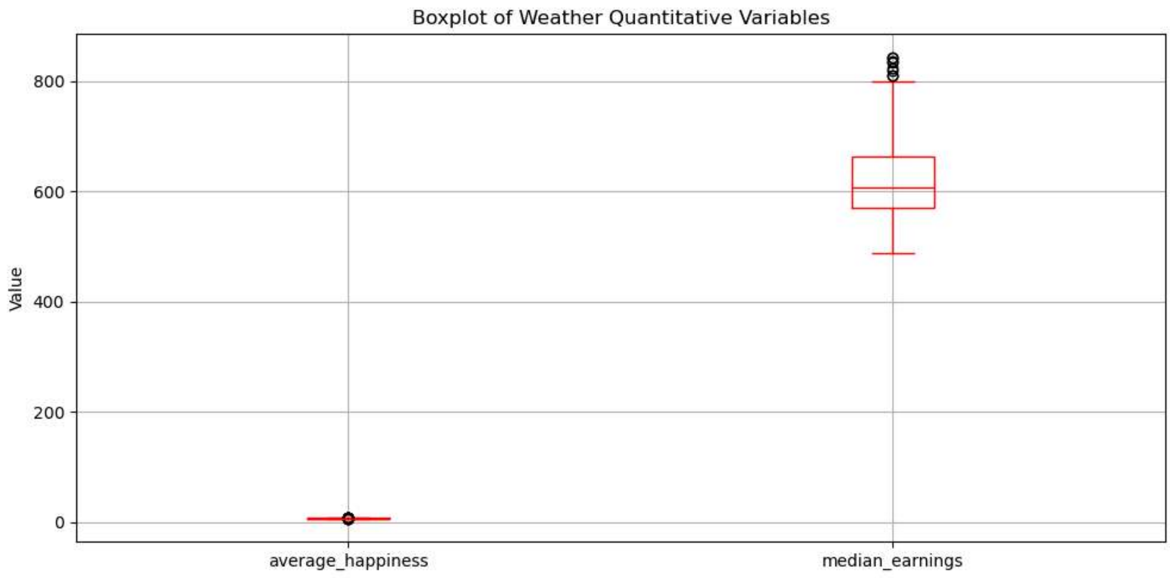
	average_happiness	median_earnings
count	409.000000	353.000000
mean	7.482421	624.545892
std	0.197820	72.884827
min	6.890000	488.700000
25%	7.370000	571.300000
50%	7.460000	607.400000
75%	7.600000	663.700000
max	8.210000	843.300000

In [314…

```
key_columns = ['average_happiness', 'median_earnings']
```

In [320…

```
plt.figure(figsize=(10, 5))
happiness_vs_earnings.boxplot(column=key_columns, color='red')
plt.title("Boxplot of Weather Quantitative Variables")
plt.ylabel("Value")
plt.grid(True)
plt.tight_layout()
plt.show()
```

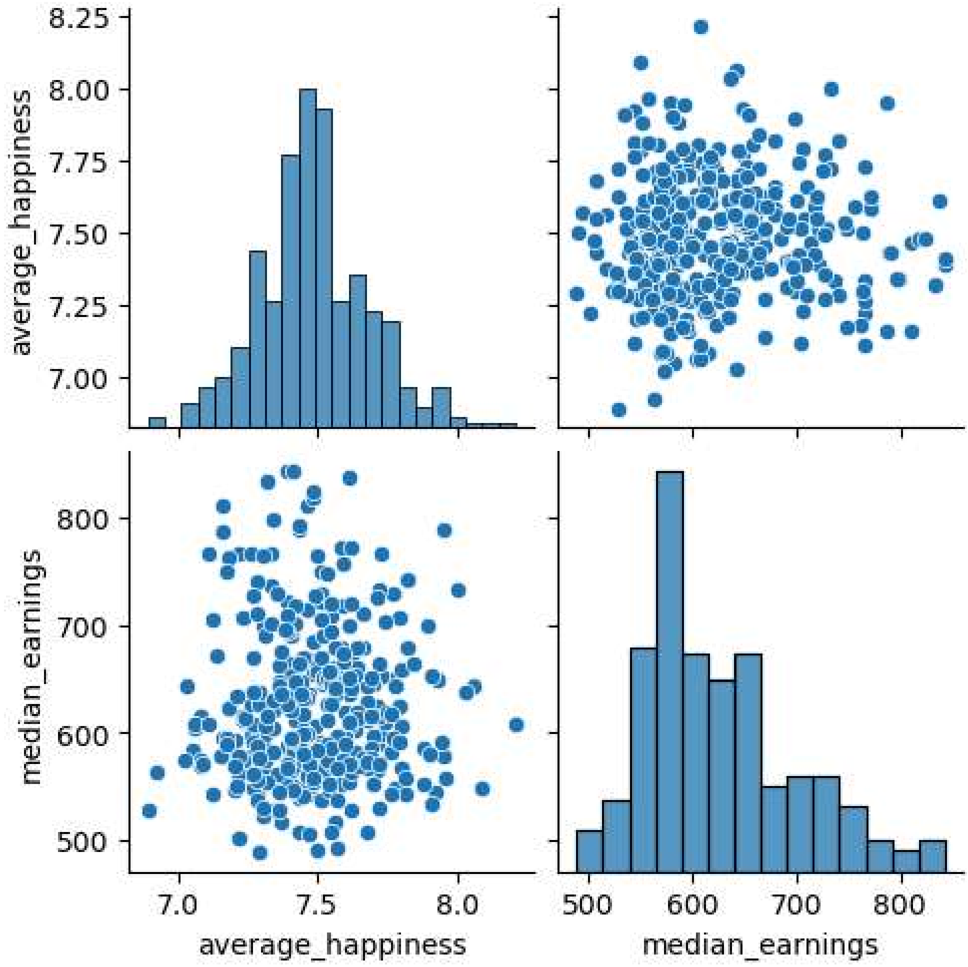


In [322…

```
sns.pairplot(happiness_vs_earnings[key_columns])
```

Out[322…

```
<seaborn.axisgrid.PairGrid at 0x1ceaedd59a0>
```

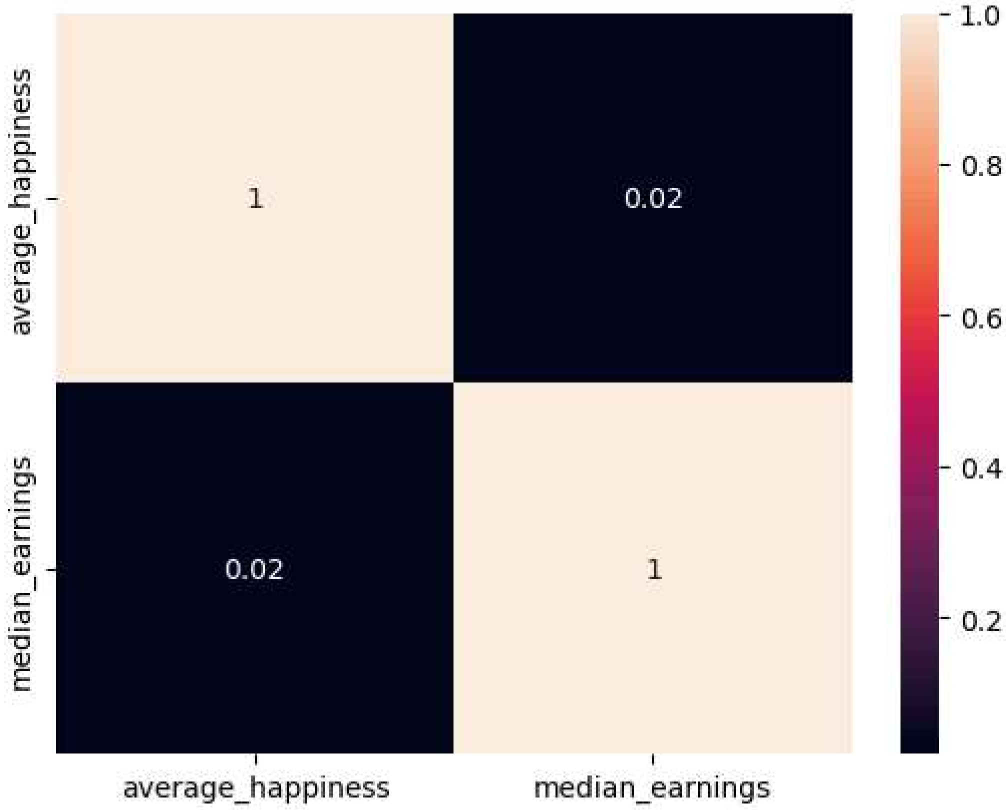


In [324…

```
#Let's use Scatter Plot Heatmap to see the correlation index between the variabl
correlation = happiness_vs_earnings[key_columns].corr().round(2)
sns.heatmap(correlation, annot = True)
```

Out[324…

```
<Axes: >
```



average_happiness
median_earnings
1
0.02
0.02
1
average_happiness
median_earnings
1.0
0.8
0.6
0.4
0.2

In [ ]:

In [ ]: