Exercise 2.3

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1. Random Forest Model (All Stations)

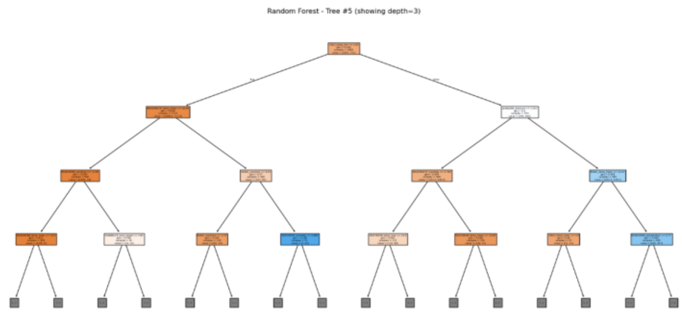
A Random Forest classifier was trained using a decade-sized subset of ClimateWins weather observations to predict whether a day would be classified as pleasant at the Basel station. All weather stations were included as input features, while all station-specific pleasant-weather labels were removed from the feature set to prevent label leakage. The model achieved strong predictive performance, demonstrating that aggregated weather patterns across stations contribute meaningfully to pleasant-day classification.

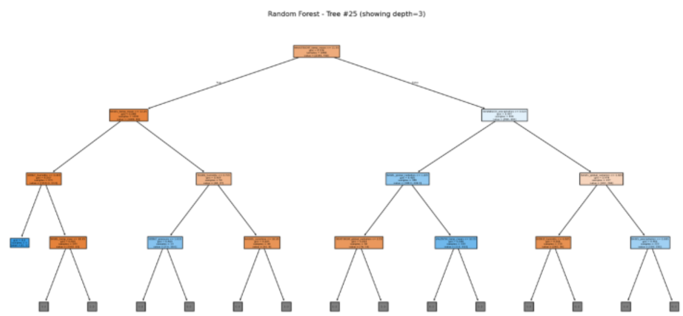
Model Accuracy

- All-station Random Forest accuracy: **0.98**

```
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn import metrics

X_train, X_test, y_train, y_test = train_test_split(
    X_decade, y_decade, test_size=0.2, random_state=42, stratify=y_decade
)

clf = RandomForestClassifier(
    n_estimators=200,
    max_depth=8,
    random_state=42,
    n_jobs=-1
)

clf.fit(X_train, y_train)

y_pred = clf.predict(X_test)
acc = metrics.accuracy_score(y_test, y_pred)

print("Random Forest Accuracy:", acc)
```

```
Random Forest Accuracy: 0.9753761969904241
```





- *Figure 1*: Random Forest — Tree #5 (depth limited for readability)
- *Figure 2*: Random Forest — Tree #25 (depth limited for readability)

2. Station Importance Analysis

To identify which weather stations most strongly influenced the Random Forest's decisions, feature importances were extracted and aggregated by station. This analysis revealed that a small subset of stations accounted for a disproportionate share of the model's decision-making influence.

The three most influential stations were:

1. Basel
2. Düsseldorf
3. München

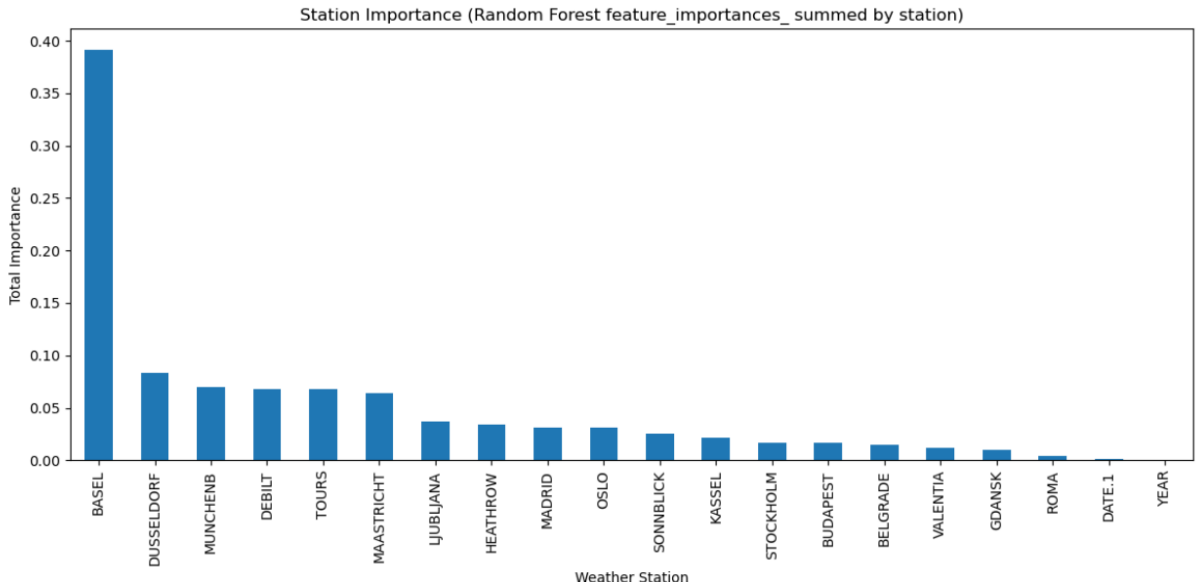


Figure 3: Bar chart showing total feature importance by weather station

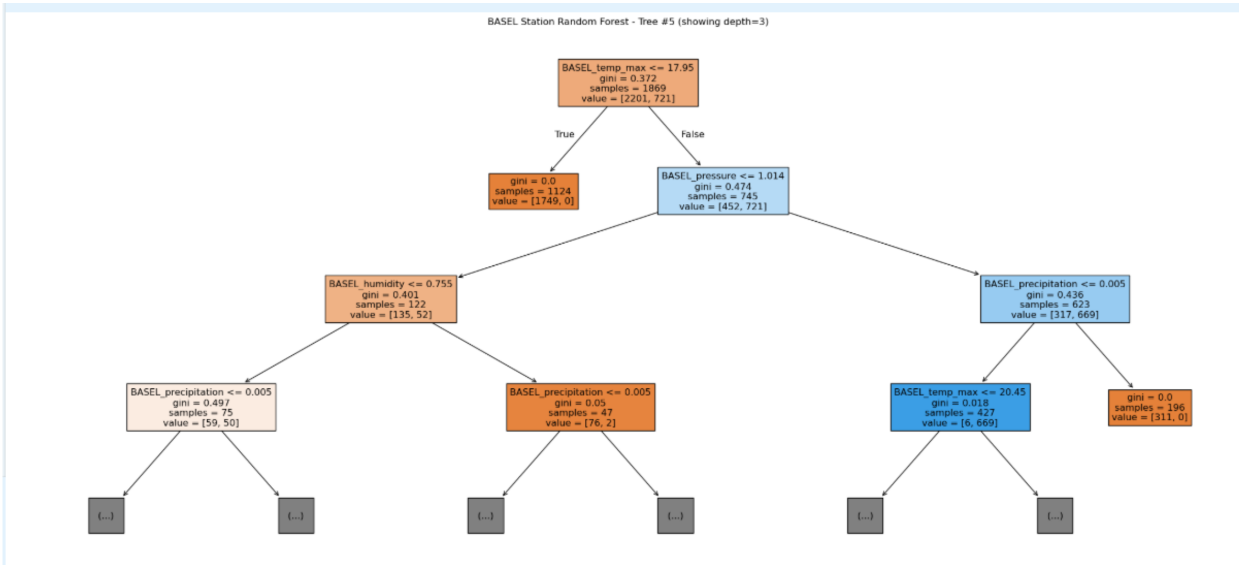
3. Station-Specific Random Forest Models

To further investigate the role of individual stations, separate Random Forest models were trained using only the observation features from each of the top three stations. Each model used the same pleasant-day target variable to allow direct comparison of predictive performance.

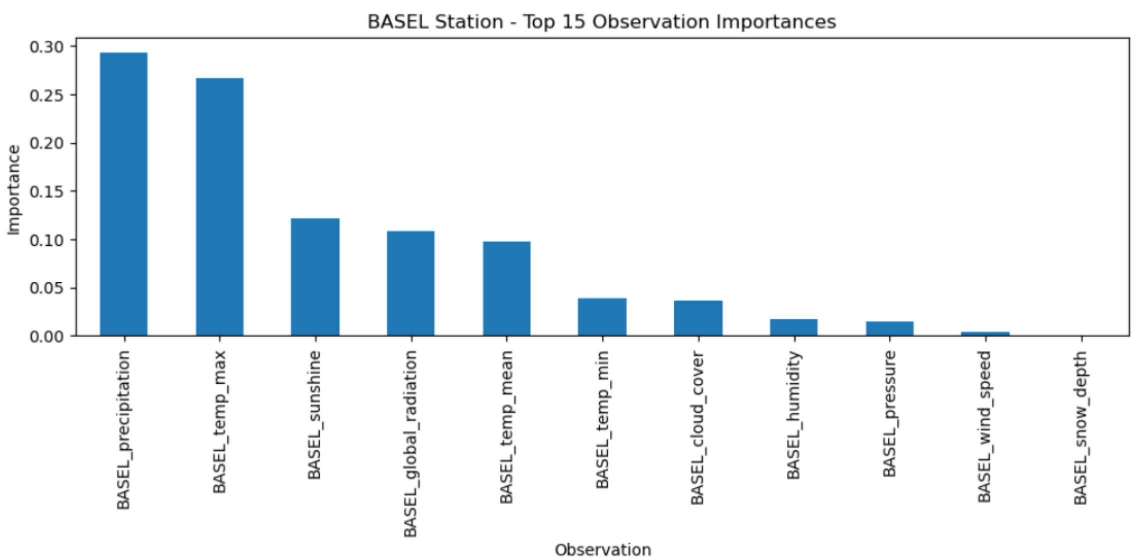
Model Accuracies

- Basel-only model accuracy: 1.00
- Düsseldorf-only model accuracy: 0.84
- München-only model accuracy: 0.86

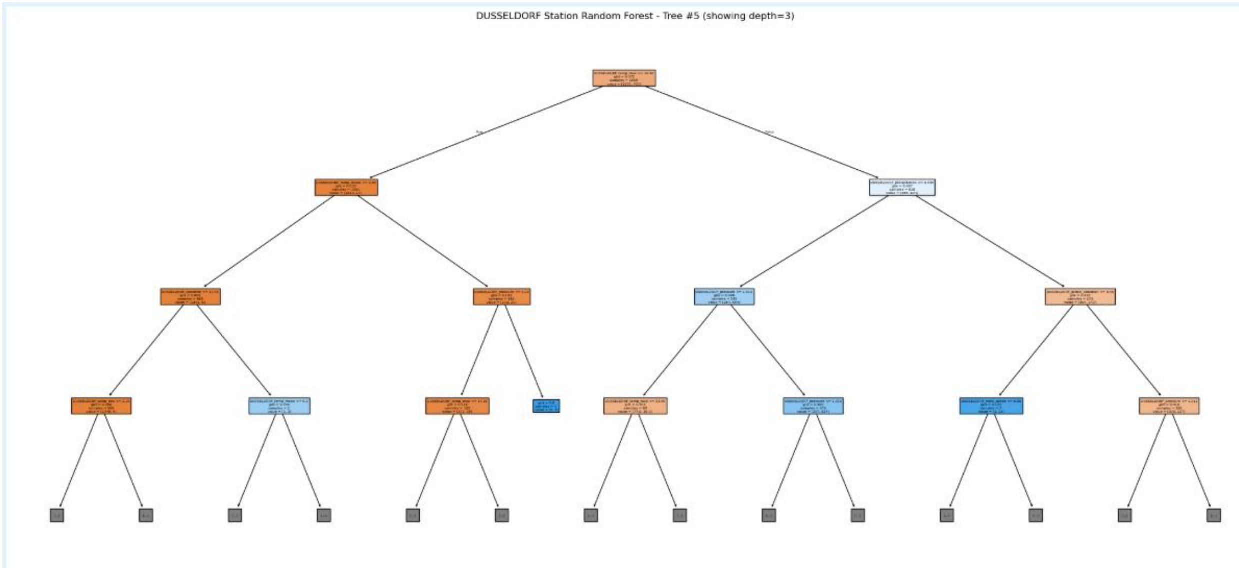
These results indicate that Basel's local observations are highly predictive of pleasant weather outcomes, while Düsseldorf and München also provide strong predictive signals when modeled independently.



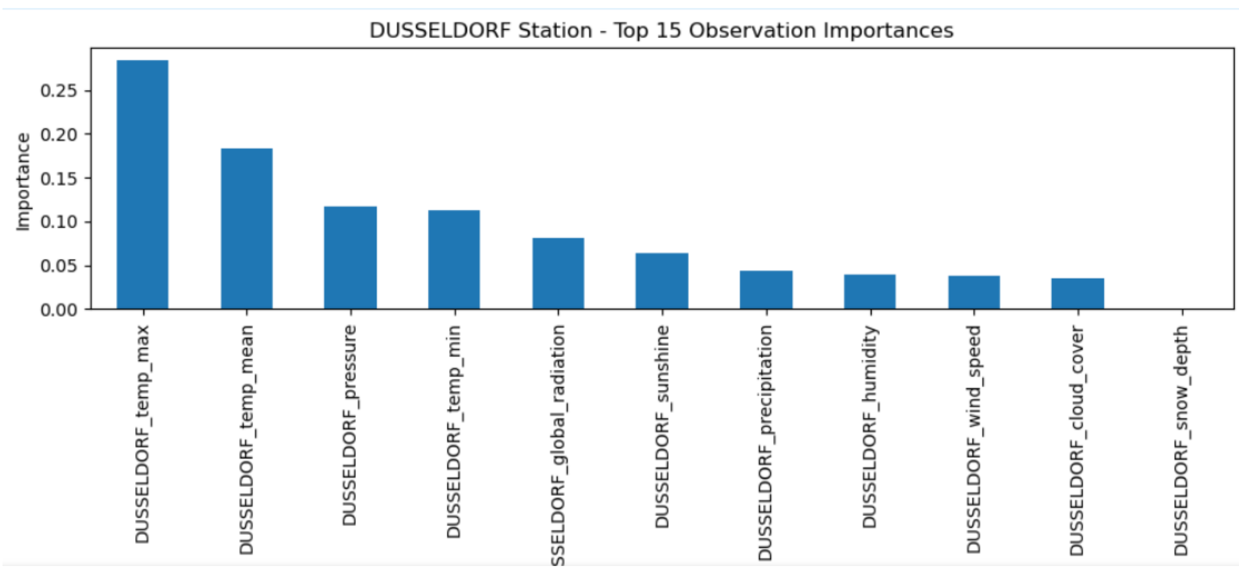
- *Figure 4*: Basel station Random Forest — Tree visualization



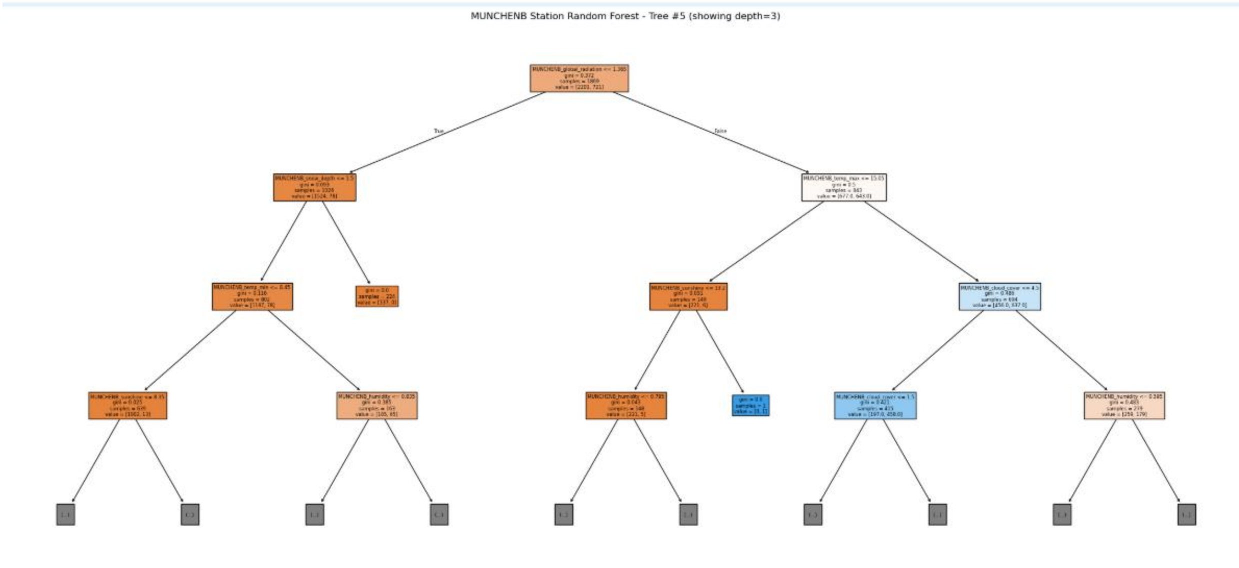
- *Figure 5*: Basel station — Observation importance bar chart



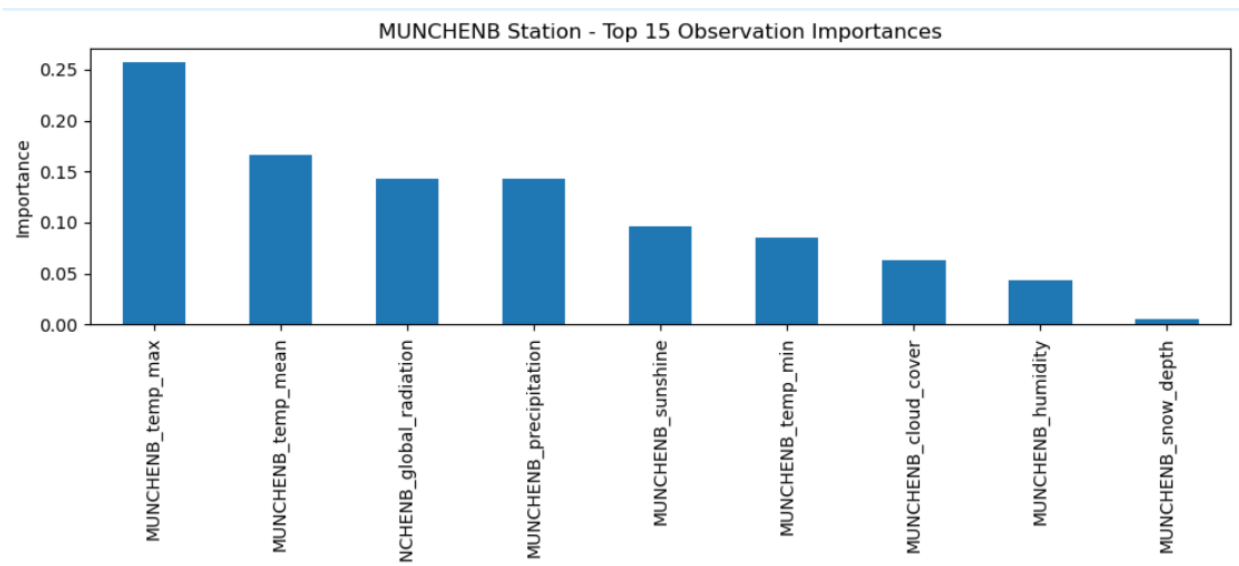
- *Figure 6*: Düsseldorf station Random Forest — Tree visualization



- *Figure 7*: Düsseldorf station — Observation importance bar chart



- *Figure 8*: München station Random Forest — Tree visualization



- *Figure 9*: München station — Observation importance bar chart

4. Interpretation and Implications

The results suggest that both station location and specific weather indicators play a critical role in determining whether a day is classified as pleasant. Stations such as Basel, Düsseldorf, and München consistently contributed the most to model performance, indicating that investments in high-quality data collection and instrumentation at these locations are likely to yield the greatest predictive benefit. Observation-level analyses further suggest that temperature-related and radiation-related variables are especially influential, which may help guide future climate-tracking and infrastructure investment decisions.