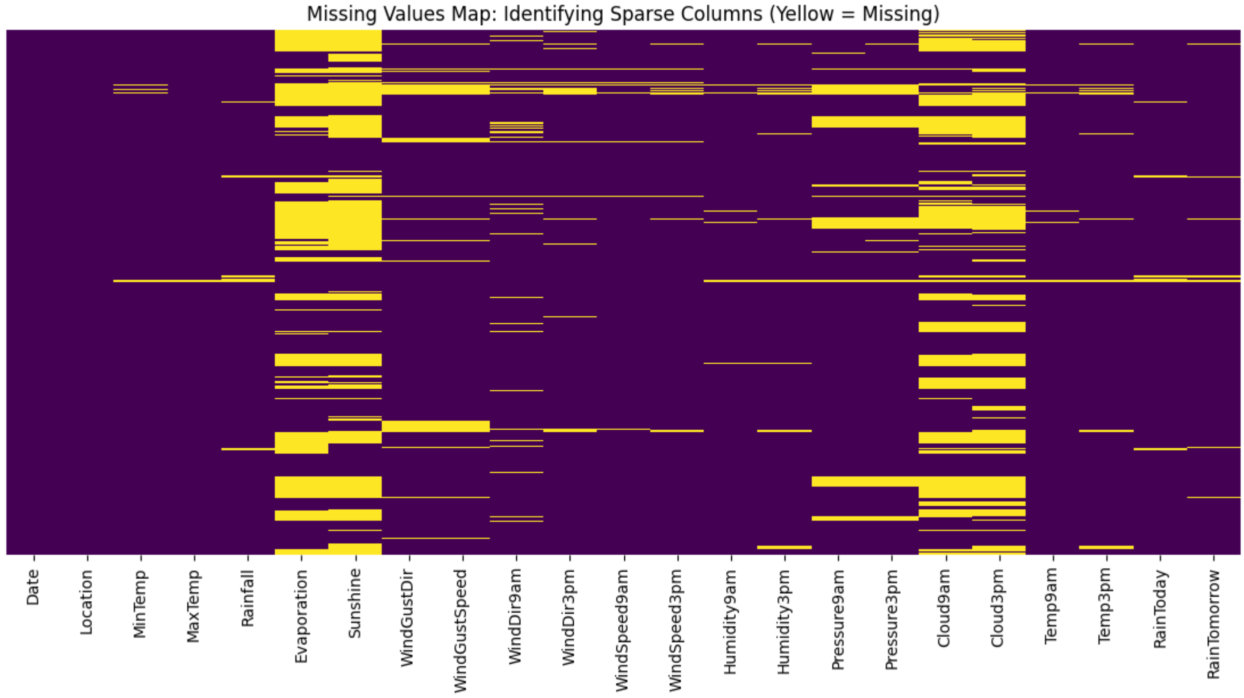
In [1]:
```
# Classification Project: Rain in Australia
# The dataset from Kaggle contains daily weather observations from variou
# Features include temperature, rainfall, sunshine, wind gusts, humidity
# The goal of this project is to build three models (Clssification Trees,
```

In [2]:
```
import pandas as pd
import os
import numpy as np
from tqdm import tqdm
import random
import csv
import statistics
import statsmodels.api as sm

import matplotlib
import matplotlib.pyplot as plt
import matplotlib.lines as mlines
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.tree import plot_tree
from sklearn import metrics
from sklearn.preprocessing import scale
from sklearn.metrics import mean_squared_error
from sklearn import tree
from sklearn.model_selection import cross_validate
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import KFold
from sklearn.metrics import recall_score, f1_score
from sklearn.metrics import roc_curve, auc
```

In [3]:
```
# Data loading and initial inspection, understanding the structure of dat

rainAUS = pd.read_csv("/Users/aleksandra/Desktop/MachineLearning2/weather
print(rainAUS.head())
print(rainAUS.dtypes.value_counts())
```

```
         Date Location  MinTemp  MaxTemp  Rainfall  Evaporation  Sunshine  
\
0  2008-12-01   Albury     13.4     22.9       0.6          NaN       NaN   
1  2008-12-02   Albury      7.4     25.1       0.0          NaN       NaN   
2  2008-12-03   Albury     12.9     25.7       0.0          NaN       NaN   
3  2008-12-04   Albury      9.2     28.0       0.0          NaN       NaN   
4  2008-12-05   Albury     17.5     32.3       1.0          NaN       NaN   

  WindGustDir  WindGustSpeed WindDir9am  ... Humidity9am  Humidity3pm  \
0           W           44.0          W  ...        71.0         22.0   
1         WNW           44.0        NNW  ...        44.0         25.0   
2         WSW           46.0          W  ...        38.0         30.0   
3          NE           24.0         SE  ...        45.0         16.0   
4           W           41.0        ENE  ...        82.0         33.0   

   Pressure9am  Pressure3pm  Cloud9am  Cloud3pm  Temp9am  Temp3pm  RainTod
ay  \
0       1007.7       1007.1       8.0       NaN     16.9     21.8           
No   
1       1010.6       1007.8       NaN       NaN     17.2     24.3           
No   
2       1007.6       1008.7       NaN       2.0     21.0     23.2           
No   
3       1017.6       1012.8       NaN       NaN     18.1     26.5           
No   
4       1010.8       1006.0       7.0       8.0     17.8     29.7           
No   

   RainTomorrow  
0            No  
1            No  
2            No  
3            No  
4            No  

[5 rows x 23 columns]
float64    16
object      7
Name: count, dtype: int64
```

In [4]:
```
#Variables with very high proportions of missing values (above 40%) are e


plt.figure(figsize=(14, 6))
# Heatmap of missing values: Yellow lines indicate missing data
sns.heatmap(rainAUS.isnull(), cbar=False, yticklabels=False, cmap='viridi
plt.title('Missing Values Map: Identifying Sparse Columns (Yellow = Missi
plt.show()
rainAUS.isna().mean() * 100
rainAUS = rainAUS.drop(columns=["Evaporation", "Sunshine", "Cloud9am", "C
print(rainAUS.head())
```



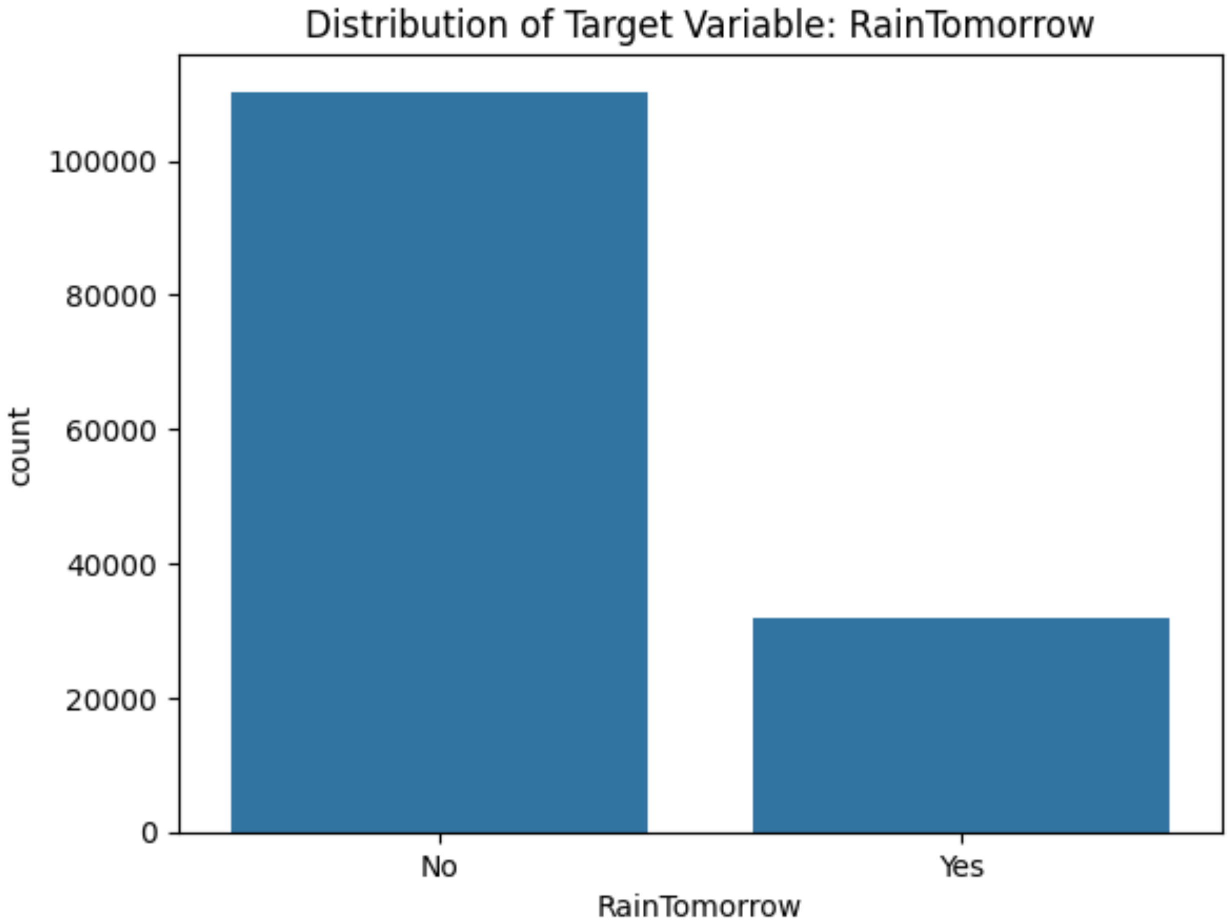

```
         Date Location  MinTemp  MaxTemp  Rainfall WindGustDir  WindGustSp
eed  \
0  2008-12-01   Albury     13.4     22.9       0.6           W            4
4.0
1  2008-12-02   Albury      7.4     25.1       0.0         WNW            4
4.0
2  2008-12-03   Albury     12.9     25.7       0.0         WSW            4
6.0
3  2008-12-04   Albury      9.2     28.0       0.0          NE            2
4.0
4  2008-12-05   Albury     17.5     32.3       1.0           W            4
1.0

  WindDir9am WindDir3pm  WindSpeed9am  WindSpeed3pm  Humidity9am  Humidity
3pm  \
0          W        WNW          20.0          24.0         71.0         2
2.0
1        NNW        WSW           4.0          22.0         44.0         2
5.0
2          W        WSW          19.0          26.0         38.0         3
0.0
3         SE          E          11.0           9.0         45.0         1
6.0
4        ENE         NW           7.0          20.0         82.0         3
3.0

   Pressure9am  Pressure3pm  Temp9am  Temp3pm RainToday RainTomorrow
0       1007.7       1007.1     16.9     21.8        No           No
1       1010.6       1007.8     17.2     24.3        No           No
2       1007.6       1008.7     21.0     23.2        No           No
3       1017.6       1012.8     18.1     26.5        No           No
4       1010.8       1006.0     17.8     29.7        No           No
```

In [5]:
```
# Data type distribution and missing values
```

```
print("Frequency of data type")
rainAUS.dtypes.value_counts()
print(rainAUS.head())
print(rainAUS.isna().sum())
rainAUS = rainAUS.dropna(subset=["RainTomorrow"])
```

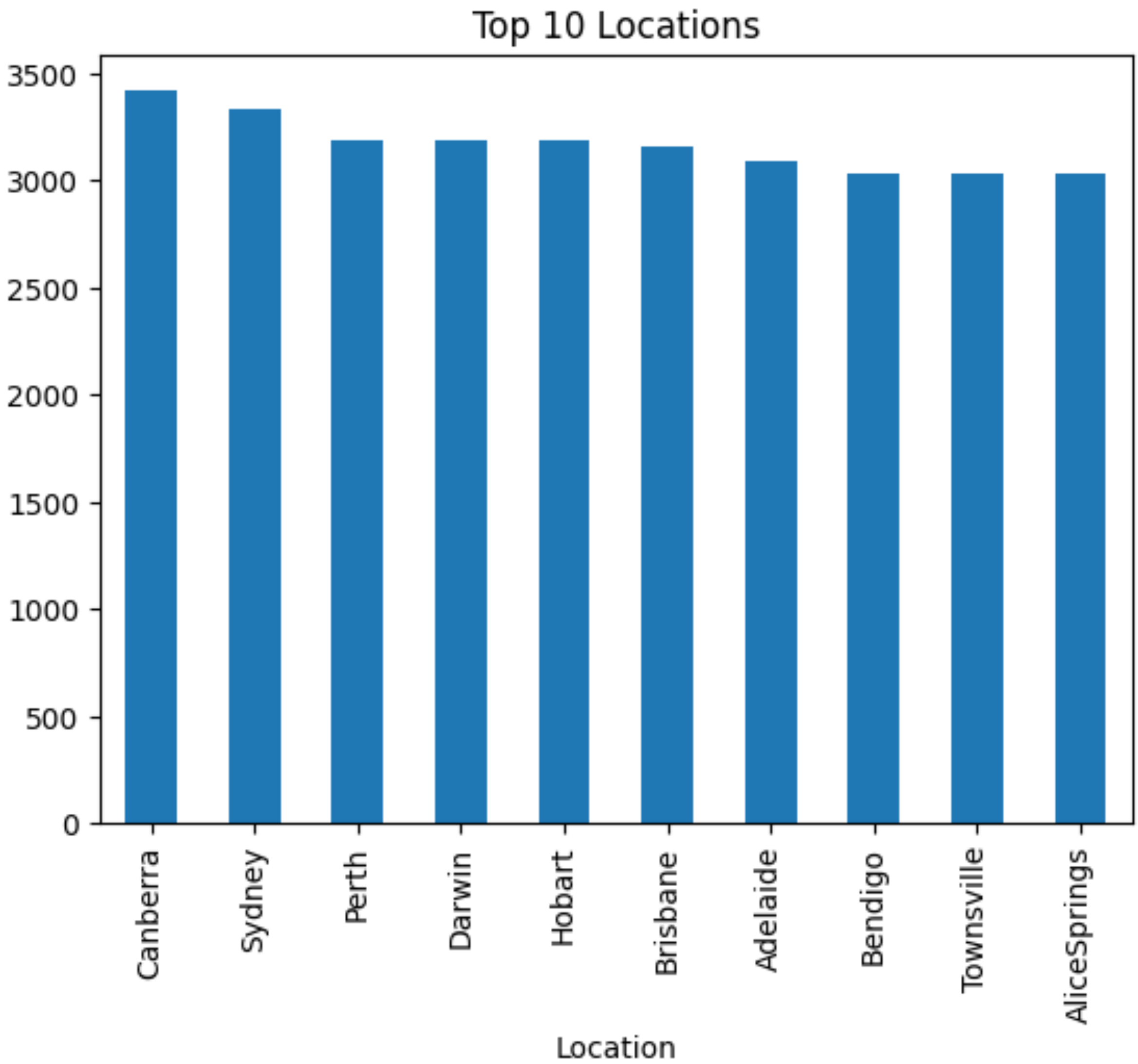
```
Frequency of data type
         Date Location  MinTemp  MaxTemp  Rainfall WindGustDir  WindGustSp
eed  \
0  2008-12-01   Albury     13.4     22.9       0.6           W            4
4.0
1  2008-12-02   Albury      7.4     25.1       0.0         WNW            4
4.0
2  2008-12-03   Albury     12.9     25.7       0.0         WSW            4
6.0
3  2008-12-04   Albury      9.2     28.0       0.0          NE            2
4.0
4  2008-12-05   Albury     17.5     32.3       1.0           W            4
1.0

  WindDir9am WindDir3pm  WindSpeed9am  WindSpeed3pm  Humidity9am  Humidity
3pm  \
0          W        WNW          20.0          24.0         71.0          2
2.0
1        NNW        WSW           4.0          22.0         44.0          2
5.0
2          W        WSW          19.0          26.0         38.0          3
0.0
3         SE          E          11.0           9.0         45.0          1
6.0
4        ENE         NW           7.0          20.0         82.0          3
3.0

   Pressure9am  Pressure3pm  Temp9am  Temp3pm RainToday RainTomorrow
0       1007.7       1007.1     16.9     21.8        No           No
1       1010.6       1007.8     17.2     24.3        No           No
2       1007.6       1008.7     21.0     23.2        No           No
3       1017.6       1012.8     18.1     26.5        No           No
4       1010.8       1006.0     17.8     29.7        No           No
Date                 0
Location             0
MinTemp           1485
MaxTemp           1261
Rainfall          3261
WindGustDir      10326
WindGustSpeed    10263
WindDir9am       10566
WindDir3pm        4228
WindSpeed9am      1767
WindSpeed3pm      3062
Humidity9am       2654
Humidity3pm       4507
Pressure9am      15065
Pressure3pm      15028
Temp9am           1767
Temp3pm           3609
RainToday         3261
RainTomorrow      3267
dtype: int64
```

In [6]:
```
# Target variable analysis - distribution
import seaborn as sns
import matplotlib.pyplot as plt

sns.countplot(x="RainTomorrow", data=rainAUS)
plt.title("Distribution of Target Variable: RainTomorrow")
plt.show()

# Percantage distribution

rainAUS["RainTomorrow"].value_counts(normalize=True) * 100
```

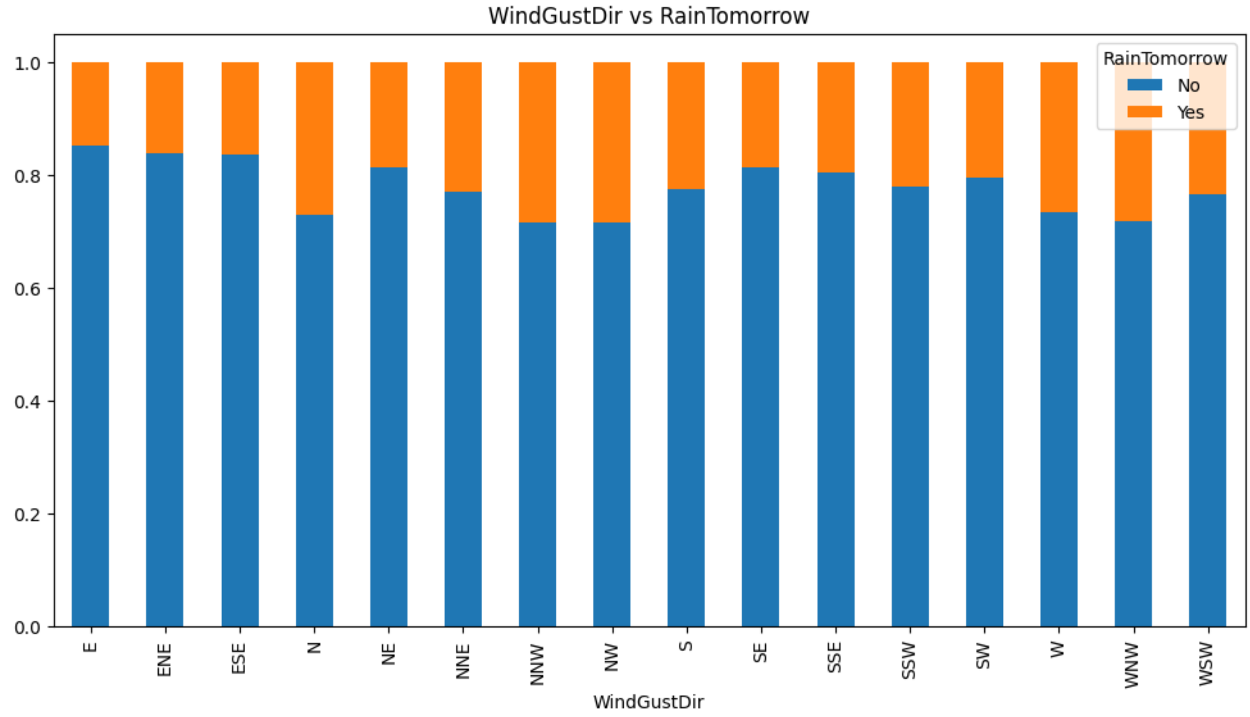


Out[6]:
```
RainTomorrow
No     77.581878
Yes    22.418122
Name: proportion, dtype: float64
```

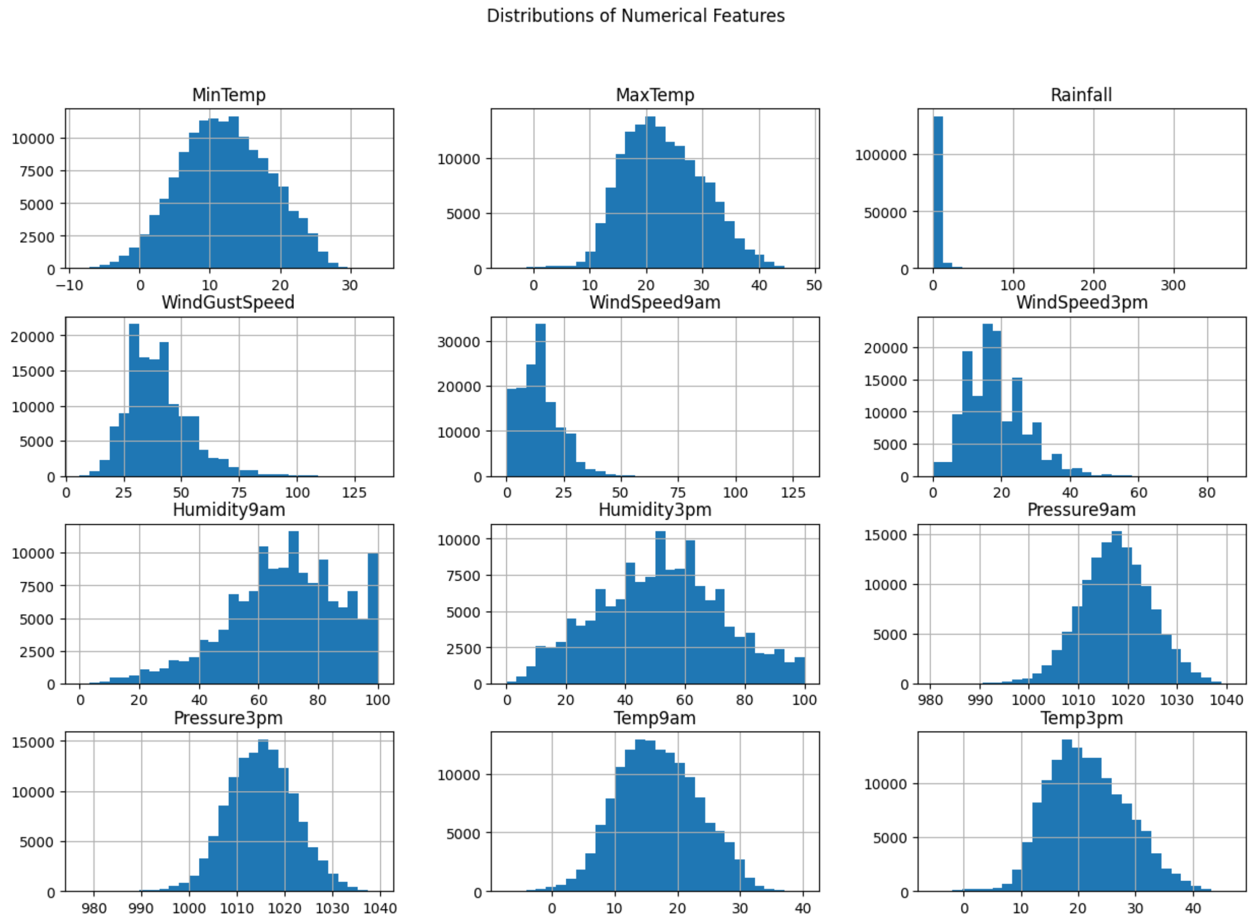
In [7]:
```
rainAUS["Location"].value_counts().head(10).plot(kind="bar")
plt.title("Top 10 Locations")
plt.show()
```



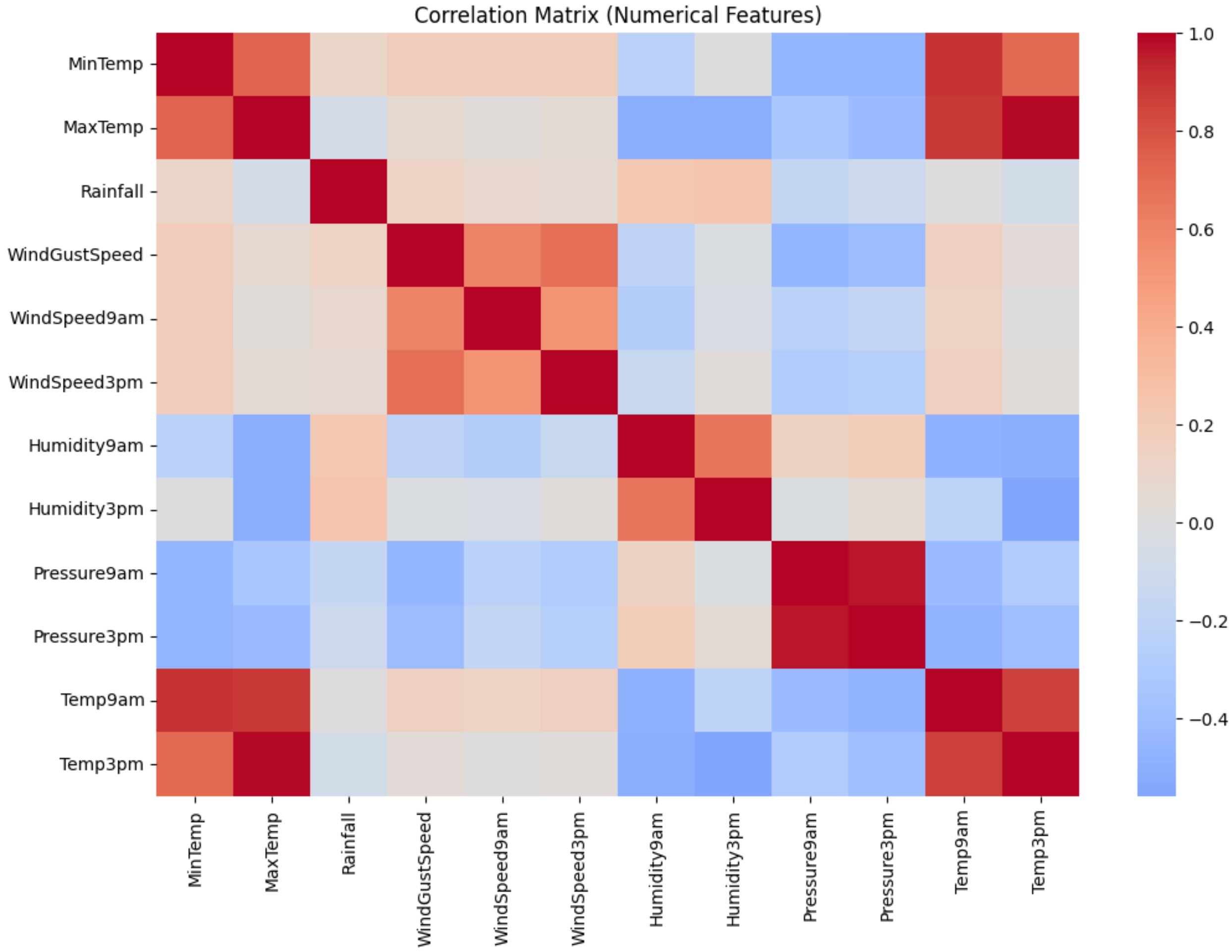
In [8]:
```
pd.crosstab(rainAUS["WindGustDir"], rainAUS["RainTomorrow"], normalize="i
    kind="bar", stacked=True, figsize=(12,6)
)
plt.title("WindGustDir vs RainTomorrow")
plt.show()
```



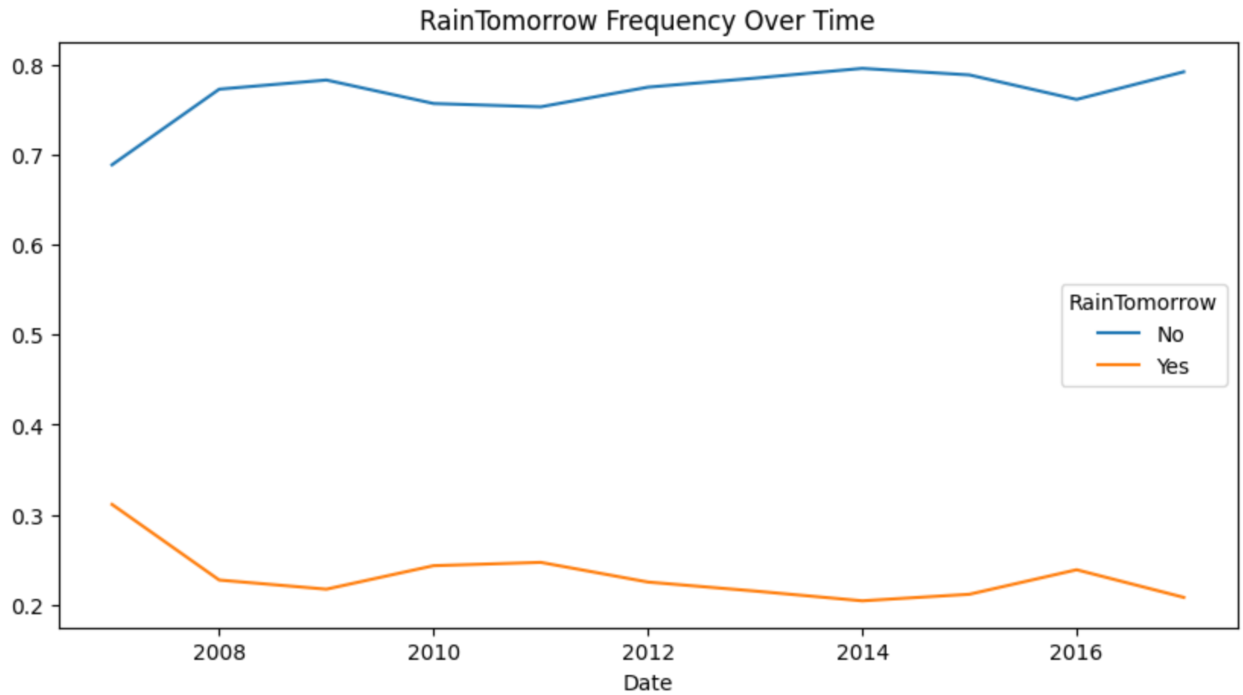
In [9]:
```
num_cols = rainAUS.select_dtypes(include="number").columns

rainAUS[num_cols].hist(bins=30, figsize=(15,10))
plt.suptitle("Distributions of Numerical Features")
plt.show()

# Temperature and pressure variables exhibit approximately normal distrib
# strongly right-skewed, reflecting the presence of rare extreme events.
# indicating potential predictive relevance for rainfall occurrence. The
#skewness motivate the use of tree-based classification models, which are
```



In [10]:
```
num_cols = rainAUS.select_dtypes(include="number").columns

plt.figure(figsize=(12,8))
sns.heatmap(
    rainAUS[num_cols].corr(),
    cmap="coolwarm",
    center=0
)
plt.title("Correlation Matrix (Numerical Features)")
plt.show()

# Temperature and Humidity – negative correlations (expected meteorologic
```

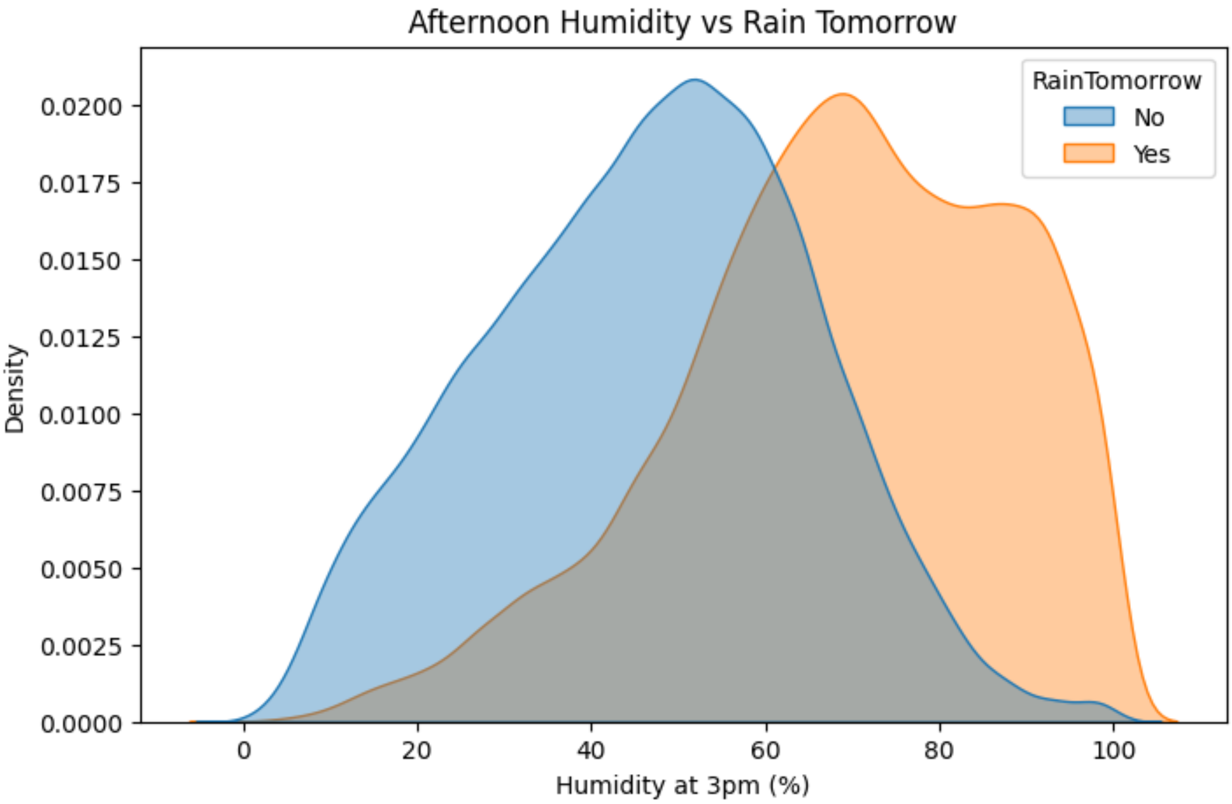


In [11]:
```
rainAUS["Date"] = pd.to_datetime(rainAUS["Date"])
rainAUS.groupby(rainAUS["Date"].dt.year)["RainTomorrow"].value_counts(nor
  .unstack().plot(figsize=(10,5))
plt.title("RainTomorrow Frequency Over Time")
plt.show()
```



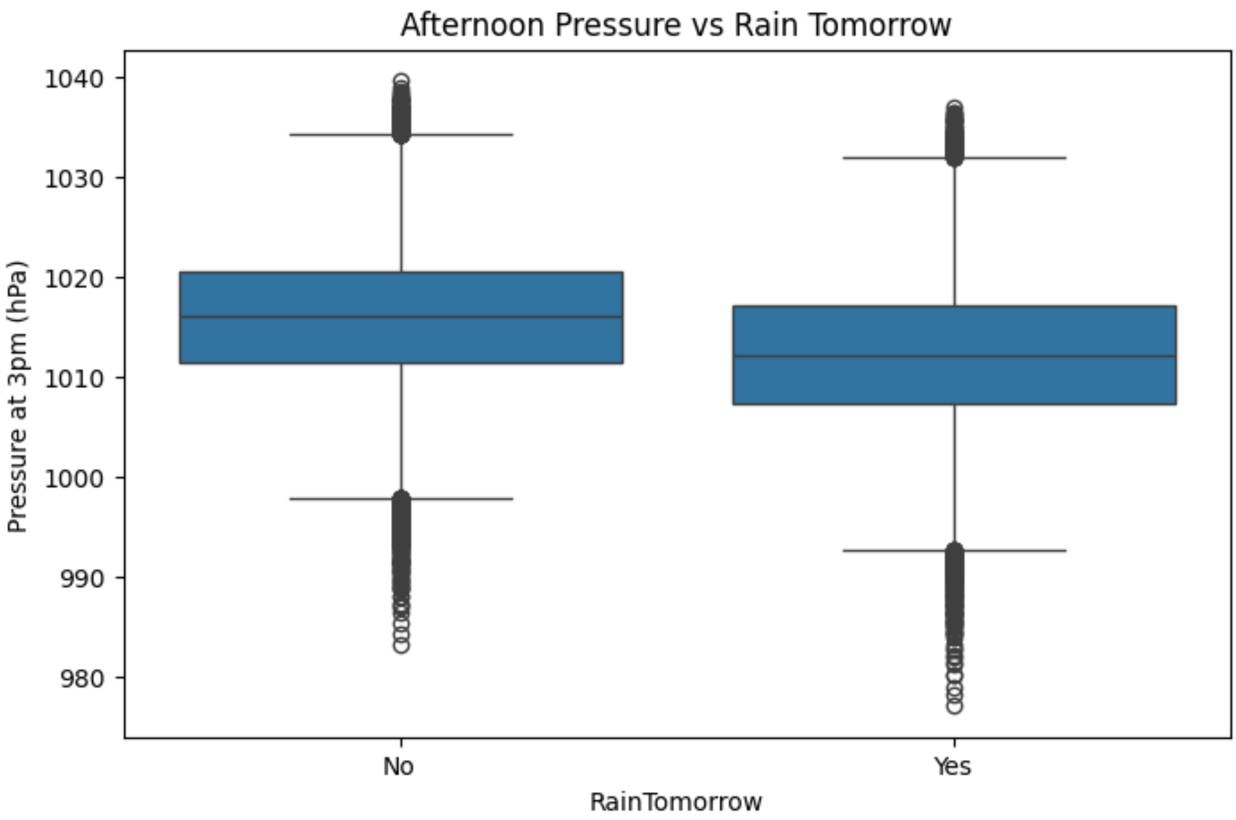
In [12]:

```
plt.figure(figsize=(8,5))
sns.kdeplot(
    data=rainAUS,
    x="Humidity3pm",
    hue="RainTomorrow",
    common_norm=False,
    fill=True,
    alpha=0.4
)
plt.title("Afternoon Humidity vs Rain Tomorrow")
plt.xlabel("Humidity at 3pm (%)")
plt.show()

#Rain rarely comes suddenly — the atmosphere is already saturated the day
```

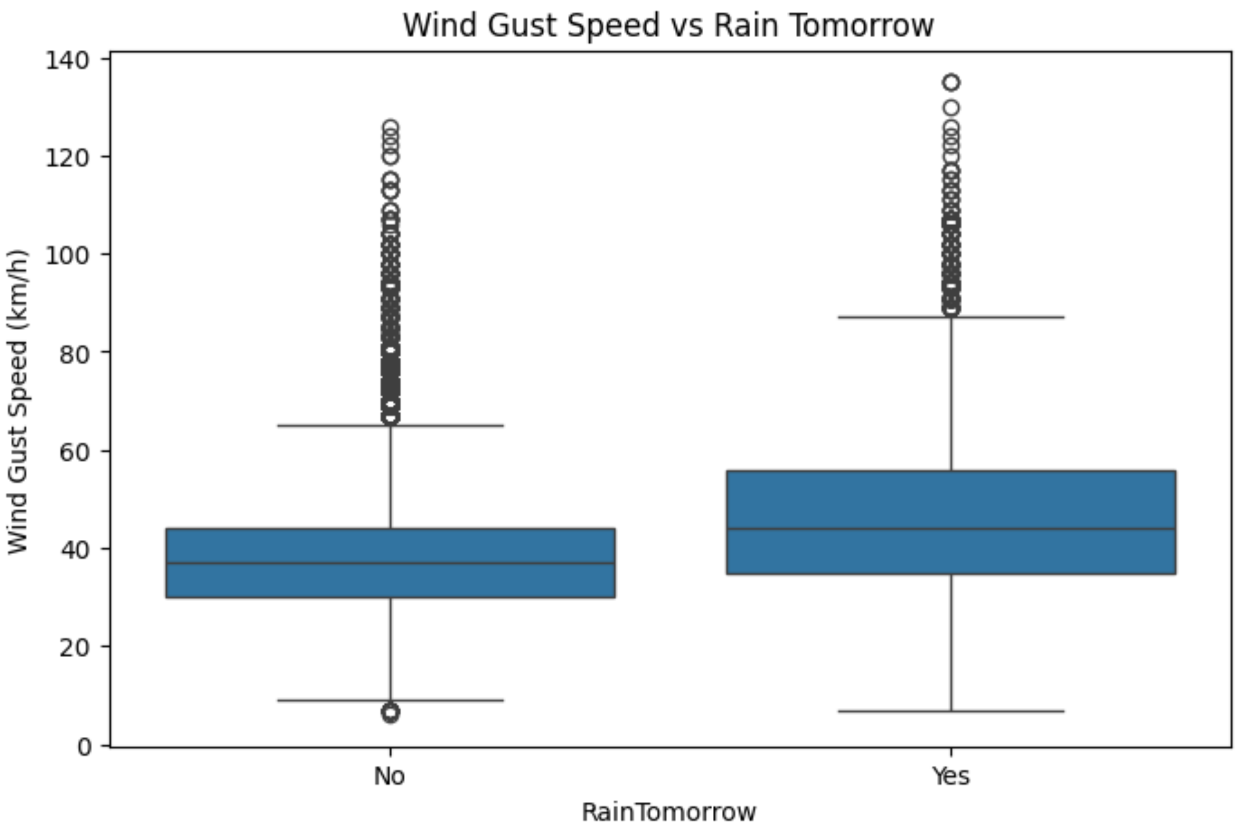


In [13]:

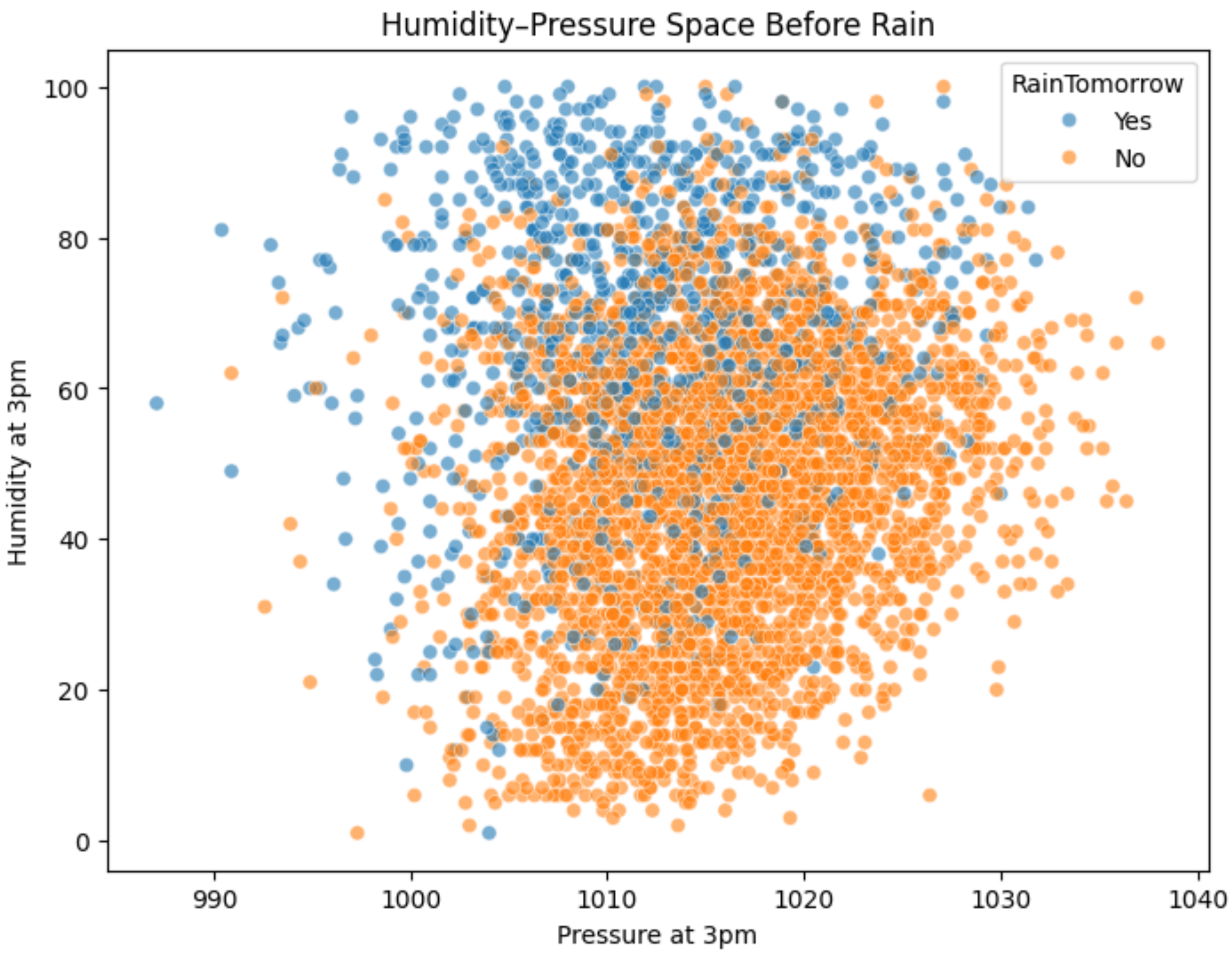
```
plt.figure(figsize=(8,5))
sns.boxplot(
    data=rainAUS,
    x="RainTomorrow",
    y="Pressure3pm"
)
plt.title("Afternoon Pressure vs Rain Tomorrow")
plt.ylabel("Pressure at 3pm (hPa)")
plt.show()

# Rainy days tomorrow are preceded by lower pressure. This matches meteor
# Falling pressure is an early sign of incoming rain.
```



In [14]:
```
plt.figure(figsize=(8,5))
sns.boxplot(
    data=rainAUS,
    x="RainTomorrow",
    y="WindGustSpeed"
)
plt.title("Wind Gust Speed vs Rain Tomorrow")
plt.ylabel("Wind Gust Speed (km/h)")
plt.show()

# Wind strenghtens before rain. Extreme values are more frequent.
```



In [15]:
```
plt.figure(figsize=(8,6))
sns.scatterplot(
    data=rainAUS.sample(5000, random_state=42),
    x="Pressure3pm",
    y="Humidity3pm",
    hue="RainTomorrow",
    alpha=0.6
)
plt.title("Humidity–Pressure Space Before Rain")
plt.xlabel("Pressure at 3pm")
plt.ylabel("Humidity at 3pm")
plt.show()
```



In [16]:
```
# Dataset is divided into input features ('X') and the target variable ('
# All explanatory variables are ssigned to X, while 'RainTomorrow' is iso

X = rainAUS.drop(columns="RainTomorrow")
y = rainAUS["RainTomorrow"]
```

In [17]:
```
# Target variable encoding - 'RainTomorrow' is converted into binary nume
# The labels *No* and *Yes* are mapped to 0 and 1 - where 1 indicates the

y = y.map({"No": 0, "Yes": 1})
```

In [18]:
```
# New features representing the year, month, and day are derived from the
# potential seasonal and time-related patterns in rainfall occurrence. Th

X["Date"] = pd.to_datetime(X["Date"])
X["Year"] = X["Date"].dt.year
X["Month"] = X["Date"].dt.month
X["Day"] = X["Date"].dt.day

X = X.drop(columns="Date")
```

In [19]:
```
# Separating numerical and categorical variables

from sklearn.impute import SimpleImputer
num_cols = X.select_dtypes(include="number").columns
```

```
cat_cols = X.select_dtypes(include="object").columns
```

In [20]:
```
# Handling missing values - categorical variables are imputed usnig the m
# No missing values - suitable for model training.

cat_imputer = SimpleImputer(strategy="most_frequent")
X[cat_cols] = cat_imputer.fit_transform(X[cat_cols])

num_imputer = SimpleImputer(strategy="median")
X[num_cols] = num_imputer.fit_transform(X[num_cols])
```

In [21]:
```
#One-hot encoding
# cateogorical features are transformed into numerical format using one-h
# allowing machine learning algorithms to process categorical information


X = pd.get_dummies(X, columns=cat_cols, drop_first=True)
print(X.head())
```

```
   MinTemp  MaxTemp  Rainfall  WindGustSpeed  WindSpeed9am  WindSpeed3pm
\
0     13.4     22.9       0.6           44.0          20.0          24.0
1      7.4     25.1       0.0           44.0           4.0          22.0
2     12.9     25.7       0.0           46.0          19.0          26.0
3      9.2     28.0       0.0           24.0          11.0           9.0
4     17.5     32.3       1.0           41.0           7.0          20.0

   Humidity9am  Humidity3pm  Pressure9am  Pressure3pm  ...  WindDir3pm_NW
\
0         71.0         22.0       1007.7       1007.1  ...          False
1         44.0         25.0       1010.6       1007.8  ...          False
2         38.0         30.0       1007.6       1008.7  ...          False
3         45.0         16.0       1017.6       1012.8  ...          False
4         82.0         33.0       1010.8       1006.0  ...           True

   WindDir3pm_S  WindDir3pm_SE  WindDir3pm_SSE  WindDir3pm_SSW  WindDir3pm
_SW  \
0         False          False           False           False          Fa
lse
1         False          False           False           False          Fa
lse
2         False          False           False           False          Fa
lse
3         False          False           False           False          Fa
lse
4         False          False           False           False          Fa
lse

   WindDir3pm_W  WindDir3pm_WNW  WindDir3pm_WSW  RainToday_Yes
0         False            True           False          False
1         False           False            True          False
2         False           False            True          False
3         False           False           False          False
4         False           False           False          False

[5 rows x 109 columns]
```

In [22]:

```
# All variables are now bool or float64 type. There are no missing values

print("Frequency of data type")
print(X.dtypes.value_counts())

print(y.isna().sum())
```

```
Frequency of data type
bool       94
float64    15
Name: count, dtype: int64
0
```

In [23]:

```
# TRAIN-TEST SPLIT and DECISION TREE MODEL TRAINING
# Data is split into training and test set (80% of the observations used
```

```
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, shuffle=True
)


# A Decision Tree classifier is then initialized with constraints on tree


tree = DecisionTreeClassifier(
    max_depth=5,
    min_samples_leaf=50,
    random_state=42
)

tree.fit(X_train, y_train)
```

Out[23]:

DecisionTreeClassifier

```
DecisionTreeClassifier(max_depth=5, min_samples_leaf=50, random_s
tate=42)
```

In [24]:

```
# Model evaluation and generating predictions on the test set. Model perf
#

from sklearn.metrics import classification_report, confusion_matrix

y_pred = tree.predict(X_test)

print(confusion_matrix(y_test, y_pred))
print(classification_report(y_test, y_pred))
```

```
[[21090   928]
 [ 3730  2691]]
              precision    recall  f1-score   support

           0       0.85      0.96      0.90     22018
           1       0.74      0.42      0.54      6421

    accuracy                           0.84     28439
   macro avg       0.80      0.69      0.72     28439
weighted avg       0.83      0.84      0.82     28439
```

In [25]:

```
# Re-trained with class weights set to balances in order to adress th imb
# Re-evaluating on the test set using same metrics.

tree = DecisionTreeClassifier(
    max_depth=5,
    min_samples_leaf=50,
```

```
    class_weight="balanced",
    random_state=42
)
tree.fit(X_train, y_train)

from sklearn.metrics import classification_report, confusion_matrix

y_pred = tree.predict(X_test)

print(confusion_matrix(y_test, y_pred))
print(classification_report(y_test, y_pred))

# This model misses far fewer rainy days, which is the main objective of
# The balanced Decision Tree provides a more appropriate model for rainfa
```

```
[[17266  4752]
 [ 1774  4647]]
              precision    recall  f1-score   support

           0       0.91      0.78      0.84     22018
           1       0.49      0.72      0.59      6421

    accuracy                           0.77     28439
   macro avg       0.70      0.75      0.71     28439
weighted avg       0.81      0.77      0.78     28439
```

In [26]:

```
# RANDOM FOREST MODEL TRAINING AND EVALUATION

# Class weights are set to balanced to address the class imbalance and to
# prioritise correct identification of rainy days. Hyperparameters such a
# and minimum leaf size are chosen to control model complexity and reduce
# The trained model is evaluated on the test set using a confusion matrix

from sklearn.ensemble import RandomForestClassifier

rf = RandomForestClassifier(
    n_estimators=300,
    max_depth=10,
    min_samples_leaf=50,
    class_weight="balanced",
    random_state=42,
    n_jobs=-1
)

rf.fit(X_train, y_train)

from sklearn.metrics import classification_report, confusion_matrix

y_pred_rf = rf.predict(X_test)

print(confusion_matrix(y_test, y_pred_rf))
print(classification_report(y_test, y_pred_rf))
```

```
[[17557  4461]
 [ 1685  4736]]
              precision    recall  f1-score   support

           0       0.91      0.80      0.85     22018
           1       0.51      0.74      0.61      6421

    accuracy                           0.78     28439
   macro avg       0.71      0.77      0.73     28439
weighted avg       0.82      0.78      0.80     28439
```

In [27]:

```
# GRADIENT BOOSTING MODEL TRAINING AND EVALUATION
# Model performance is first evaluated using the default classification t
# probabilities are used to adjust the decision threshold to 0.3 in order
# improve recall for the rainfall class. The impact of this threshold adj


from sklearn.ensemble import GradientBoostingClassifier

gb = GradientBoostingClassifier(
    n_estimators=200,
    learning_rate=0.05,
    max_depth=3,
    random_state=42
)

gb.fit(X_train, y_train)

from sklearn.utils.class_weight import compute_sample_weight

sample_weights = compute_sample_weight(
    class_weight="balanced",
    y=y_train
)

gb.fit(X_train, y_train, sample_weight=sample_weights)

y_pred_gb = gb.predict(X_test)

print(confusion_matrix(y_test, y_pred_gb))
print(classification_report(y_test, y_pred_gb))

y_prob_gb = gb.predict_proba(X_test)[:, 1]
y_pred_gb = (y_prob_gb > 0.3).astype(int)

print(classification_report(y_test, y_pred_gb))
```

```
[[17674  4344]
 [ 1619  4802]]
              precision    recall  f1-score   support

           0       0.92      0.80      0.86     22018
           1       0.53      0.75      0.62      6421

    accuracy                           0.79     28439
   macro avg       0.72      0.78      0.74     28439
weighted avg       0.83      0.79      0.80     28439

              precision    recall  f1-score   support

           0       0.95      0.59      0.73     22018
           1       0.39      0.90      0.54      6421

    accuracy                           0.66     28439
   macro avg       0.67      0.74      0.64     28439
weighted avg       0.82      0.66      0.69     28439
```

In [28]:

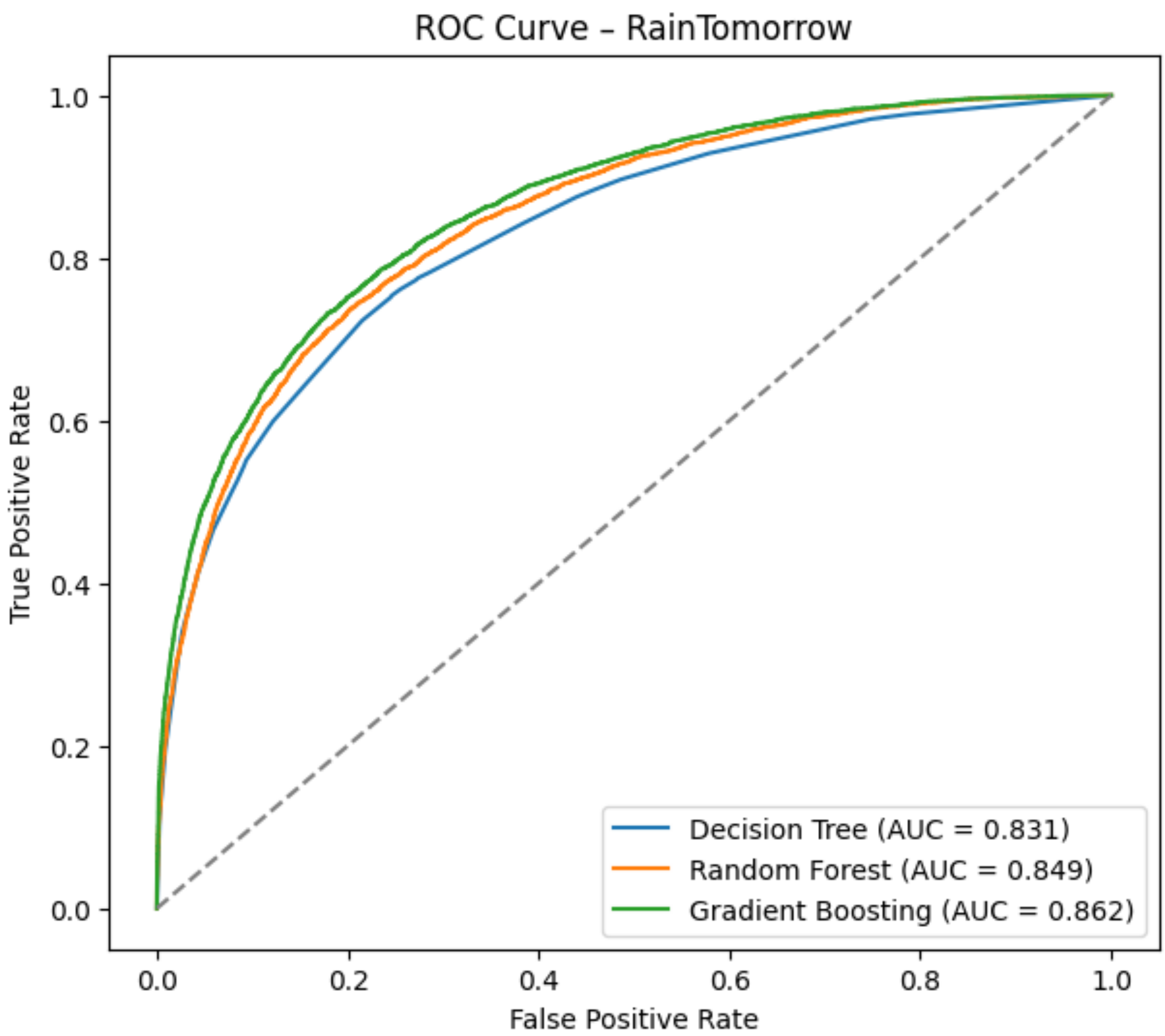
```
# COMPARISON


models = {
    "Decision Tree": tree,
    "Random Forest": rf,
    "Gradient Boosting": gb
}

for name, model in models.items():
    y_pred = model.predict(X_test)
    print(
        name,
        "Recall (rain):", recall_score(y_test, y_pred),
        "F1 (rain):", f1_score(y_test, y_pred)
    )
```

```
Decision Tree Recall (rain): 0.7237190468774334 F1 (rain): 0.5874841972187
105
Random Forest Recall (rain): 0.7375798162280018 F1 (rain): 0.6064797029069
023
Gradient Boosting Recall (rain): 0.7478585890048279 F1 (rain): 0.616946103
9378171
```

In [29]:

```
models = {
    "Decision Tree": tree,
    "Random Forest": rf,
    "Gradient Boosting": gb
}

plt.figure(figsize=(7,6))

for name, model in models.items():
```

```
    y_prob = model.predict_proba(X_test)[:, 1]
    fpr, tpr, _ = roc_curve(y_test, y_prob)
    roc_auc = auc(fpr, tpr)
    plt.plot(fpr, tpr, label=f"{name} (AUC = {roc_auc:.3f})")

plt.plot([0,1], [0,1], linestyle="--", color="gray")
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC Curve – RainTomorrow")
plt.legend()
plt.show()

# the ROC analysis confirms that ensemble methods outperform a single tre
# reliable model for rainfall prediction, particularly when probability-b
```



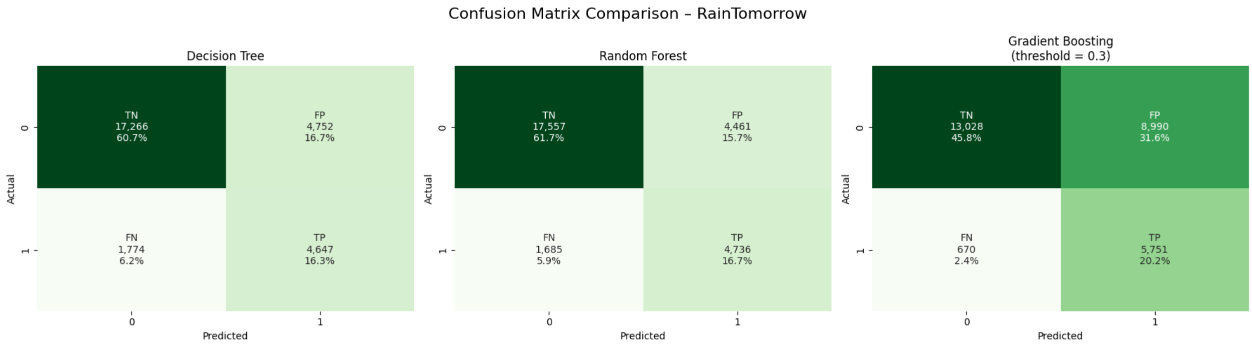
In [30]:
```
# Comparing the classification performance of a Decision Tree, Random For

# Decision Tree
y_pred_dt = tree.predict(X_test)

# Random Forest
y_pred_rf = rf.predict(X_test)
```

```
# Gradient Boosting (threshold = 0.3)
y_prob_gb = gb.predict_proba(X_test)[:, 1]
y_pred_gb = (y_prob_gb > 0.3).astype(int)
```

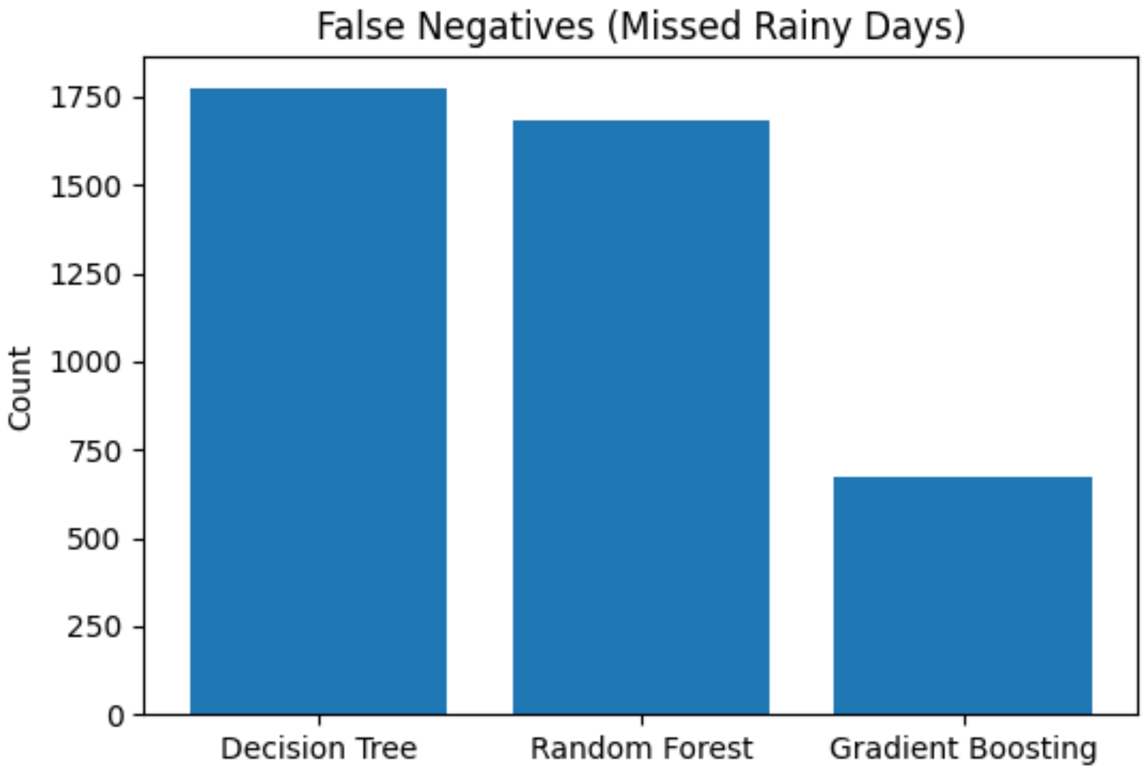
In [31]:
```
def plot_confusion(ax, y_true, y_pred, title):
    cm = confusion_matrix(y_true, y_pred)
    cm_pct = cm / cm.sum() * 100

    labels = np.array([
        [f"TN\n{cm[0,0]:,}\n{cm_pct[0,0]:.1f}%",
         f"FP\n{cm[0,1]:,}\n{cm_pct[0,1]:.1f}%"],
        [f"FN\n{cm[1,0]:,}\n{cm_pct[1,0]:.1f}%",
         f"TP\n{cm[1,1]:,}\n{cm_pct[1,1]:.1f}%"]
    ])

    sns.heatmap(
        cm,
        annot=labels,
        fmt="",
        cmap="Greens",
        cbar=False,
        ax=ax
    )
    ax.set_title(title)
    ax.set_xlabel("Predicted")
    ax.set_ylabel("Actual")
```

In [32]:
```
fig, axes = plt.subplots(1, 3, figsize=(18, 5))

plot_confusion(
    axes[0],
    y_test,
    y_pred_dt,
    "Decision Tree"
)

plot_confusion(
    axes[1],
    y_test,
    y_pred_rf,
    "Random Forest"
)

plot_confusion(
    axes[2],
    y_test,
    y_pred_gb,
    "Gradient Boosting\n(threshold = 0.3)"
)

plt.suptitle("Confusion Matrix Comparison — RainTomorrow", fontsize=16)
plt.tight_layout()
```

```
plt.show()
```



In [33]:
```
# FN comparison bar chart

fn_counts = {
    "Decision Tree": confusion_matrix(y_test, y_pred_dt)[1,0],
    "Random Forest": confusion_matrix(y_test, y_pred_rf)[1,0],
    "Gradient Boosting": confusion_matrix(y_test, y_pred_gb)[1,0]
}

plt.figure(figsize=(6,4))
plt.bar(fn_counts.keys(), fn_counts.values())
plt.title("False Negatives (Missed Rainy Days)")
plt.ylabel("Count")
plt.show()

# visually says that Gradient Boosting is the best
# why?
# False Negatives = model is predicting "No Rain", but in reality it rain
# Missing rain is far more costly than prediciting the rain that does not
# In rainfall prediction, false negatives are the most critical error bec
# to predict rain leads to higher real–world costs and risks than issuing
```



In [ ]:
```
# CONCLUSIONS
# The ROC curves show that ensemble methods (Random Forest and Gradient B
# False Negative analysis highlights that Gradient Boosting produces the
# The Gradient Boosting model achieves the best trade-off between precisi

# The Gradient Boosting Classifier is the most suitable model for rainfal
#It provides:

#The best overall predictive performance (highest ROC-AUC and F1-score).
#The best recall for rain predictions (fewest missed rainy days).
#Robustness against class imbalance when threshold tuning and sample weig
#Thus, it is the recommended model for deployment in a rainfall predictio
```