Project 3: Weather

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```
## Overview

Australia has a variety of weather stations across the country, which collect
data used for rainfall forecasting.
Although basic metrics are recorded at all stations (Max Temperature, Minimum
Temperature, Rainfall), other metrics are intermittently or never recorded at
certain stations (such as amount of Sunshine, cloudiness, Evaporation,
Pressure, etc.)

The Australian government wants to determine whether additional investment in
recording these metrics will improve rainfall forecasting in these areas.

Our models (which match state of the art accuracy) are able to predict rainfall
at stations which do not collect all metrics as well as stations which do
record all metrics.

Spending more money to collect these metrics will not improve rainfall
forecasting.
```

```
## Business Problem

Australia has a variety of weather stations across the country, which collect
data used for rainfall forecasting.
Although basic metrics are recorded at all stations (Max Temperature, Minimum
Temperature, Rainfall), other metrics are intermittently or never recorded at
certain stations (such as amount of Sunshine, cloudiness, Evaporation,
Pressure, etc.)

The Australian government wants to determine whether additional investment in
recording these metrics will improve rainfall forecasting in these areas.

Rainfall forecasting is used for a variety of purposes by the public, and
different uses are sensitive to different types of errors (false positive vs
false negative) in forecasting. We need to evaluate model performance with and
without all features on multiple types of errors.

If additional data is recommended, which data is most important?
```

Data Understanding

In [1]:
```
!pip install --quiet --upgrade --user --upgrade-strategy=eager sktime
```

In [2]:
```
import pprint
import time

import numpy as np
import pandas as pd
from code.data_preparation import fit_predict, preprocess_data, preprocess_non_ti
from code.visualization import get_all_displays

from sklearn.compose import make_column_transformer, make_column_selector
from sklearn.ensemble import AdaBoostClassifier
from sklearn.impute import KNNImputer, SimpleImputer
from sklearn.linear_model import RidgeClassifierCV
from sklearn.metrics import ConfusionMatrixDisplay
from sklearn.metrics import PrecisionRecallDisplay, RocCurveDisplay
from sklearn.metrics import confusion_matrix, classification_report
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import OneHotEncoder, FunctionTransformer, MinMaxScale
from sklearn.svm import LinearSVC
from sklearn.tree import DecisionTreeClassifier
from sktime.forecasting.model_selection import temporal_train_test_split
from sktime.transformations.panel.rocket import MiniRocket
from sktime.utils.data_processing import from_2d_array_to_nested

RANDOM_SEED = 0
```

In [3]:
```
weatherAUS = pd.read_csv('./data/weatherAUS.csv')
```

In [5]:
```
data_full = preprocess_data(weatherAUS.copy())

# Some extra pre-processing for methods which do not natively understand time ser
data_full_trad = preprocess_non_time_series(data_full.copy())
```

```
C:\Users\steve\Documents\Flatiron\project_3\code\data_preparation.py:19: Settin
gWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/sta
ble/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pyd
ata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-c
opy)
  df["RainToday"] = df["RainToday"].replace("No", 0).replace("Yes", 1).astype(f
loat)
C:\Users\steve\Documents\Flatiron\project_3\code\data_preparation.py:20: Settin
gWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/sta
ble/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pyd
ata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-c
opy)
  df["RainTomorrow"] = (
C:\Users\steve\Documents\Flatiron\project_3\code\data_preparation.py:23: Settin
gWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/sta
ble/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pyd
ata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-c
opy)
  df["WindGustDir"] = df["WindGustDir"].fillna("NaN")
C:\Users\steve\Documents\Flatiron\project_3\code\data_preparation.py:24: Settin
gWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/sta
ble/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pyd
ata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-c
opy)
  df["WindDir9am"] = df["WindDir9am"].fillna("NaN")
C:\Users\steve\Documents\Flatiron\project_3\code\data_preparation.py:25: Settin
gWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/sta
ble/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pyd
ata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-c
opy)
  df["WindDir3pm"] = df["WindDir3pm"].fillna("NaN")
C:\Users\steve\Documents\Flatiron\project_3\code\data_preparation.py:27: Settin
```

```
gWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/sta
ble/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pyd
ata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-c
opy)
  df["Date"] = pd.to_datetime(df["Date"])
C:\Users\steve\Documents\Flatiron\project_3\code\data_preparation.py:81: Settin
gWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/sta
ble/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pyd
ata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-c
opy)
  df[key] = df["Location"].map(lambda loc: latitude_longitude[loc][key])
```

In [7]:
```
# Used for Time Series prediction

data_by_location = {
    loc: preprocess_time_series(data_full[data_full["Location"]==loc].copy())
    for loc in data_full["Location"].unique()
}

na_columns_by_loc = {}
for loc, df in data_by_location.items():
    na_columns_by_loc[loc] = [
        col for col in df.columns
        if all(df[col].isna())
    ]

for loc, na_columns in na_columns_by_loc.items():
    df = data_by_location[loc]
    for col in na_columns:
        df.pop(col)

na_columns_unique = sorted(set(sum(na_columns_by_loc.values(), [])))

print("Columns which are fully NaN for at least one Location:", na_columns_unique

pprint.pprint(na_columns_by_loc)
```

```
Albury: ['Evaporation', 'Sunshine']
BadgerysCreek: ['Evaporation', 'Sunshine', 'Cloud9am', 'Cloud3pm']
Cobar: []
CoffsHarbour: []
Moree: []
Newcastle: ['Evaporation', 'Sunshine', 'WindGustSpeed', 'Pressure9am', 'Pressur
e3pm']
NorahHead: ['Evaporation', 'Sunshine', 'Cloud9am', 'Cloud3pm']
NorfolkIsland: []
Penrith: ['Evaporation', 'Sunshine', 'Pressure9am', 'Pressure3pm', 'Cloud9am',
'Cloud3pm']
Richmond: ['Sunshine']
Sydney: []
SydneyAirport: []
WaggaWagga: []
Williamtown: []
Wollongong: ['Evaporation', 'Sunshine']
Canberra: []
Tuggeranong: ['Evaporation', 'Sunshine', 'Cloud9am', 'Cloud3pm']
MountGinini: ['Evaporation', 'Sunshine', 'Pressure9am', 'Pressure3pm', 'Cloud9a
m', 'Cloud3pm']
Ballarat: ['Evaporation', 'Sunshine']
Bendigo: ['Sunshine']
Sale: []
MelbourneAirport: []
Melbourne: []
Mildura: []
Nhil: ['Evaporation', 'Sunshine', 'Cloud9am', 'Cloud3pm']
Portland: []
Watsonia: []
```

```
Dartmoor: ['Cloud9am', 'Cloud3pm']
Brisbane: []
Cairns: []
GoldCoast: ['Evaporation', 'Sunshine', 'Cloud9am', 'Cloud3pm']
Townsville: []
Adelaide: ['Cloud9am', 'Cloud3pm']
MountGambier: []
Nuriootpa: []
Woomera: []
Albany: ['WindGustSpeed']
Witchcliffe: ['Evaporation', 'Sunshine', 'Cloud9am', 'Cloud3pm']
PearceRAAF: ['Evaporation']
PerthAirport: []
Perth: []
SalmonGums: ['Evaporation', 'Sunshine', 'Pressure9am', 'Pressure3pm', 'Cloud9a
m', 'Cloud3pm']
Walpole: ['Evaporation', 'Sunshine', 'Cloud9am', 'Cloud3pm']
Hobart: []
Launceston: ['Sunshine']
AliceSprings: []
Darwin: []
Katherine: ['Sunshine']
Uluru: ['Evaporation', 'Sunshine']
Columns which are fully NaN for at least one Location: ['Cloud3pm', 'Cloud9am',
'Evaporation', 'Pressure3pm', 'Pressure9am', 'Sunshine', 'WindGustSpeed']
{'Adelaide': ['Cloud9am', 'Cloud3pm'],
 'Albany': ['WindGustSpeed'],
 'Albury': ['Evaporation', 'Sunshine'],
 'AliceSprings': [],
 'BadgerysCreek': ['Evaporation', 'Sunshine', 'Cloud9am', 'Cloud3pm'],
 'Ballarat': ['Evaporation', 'Sunshine'],
 'Bendigo': ['Sunshine'],
 'Brisbane': [],
 'Cairns': [],
 'Canberra': [],
 'Cobar': [],
 'CoffsHarbour': [],
 'Dartmoor': ['Cloud9am', 'Cloud3pm'],
 'Darwin': [],
 'GoldCoast': ['Evaporation', 'Sunshine', 'Cloud9am', 'Cloud3pm'],
 'Hobart': [],
 'Katherine': ['Sunshine'],
 'Launceston': ['Sunshine'],
 'Melbourne': [],
 'MelbourneAirport': [],
 'Mildura': [],
 'Moree': [],
 'MountGambier': [],
 'MountGinini': ['Evaporation',
                 'Sunshine',
                 'Pressure9am',
                 'Pressure3pm',
                 'Cloud9am',
                 'Cloud3pm'],
 'Newcastle': ['Evaporation',
               'Sunshine',
               'WindGustSpeed',
```

```
              'Pressure9am',
              'Pressure3pm'],
 'Nhil': ['Evaporation', 'Sunshine', 'Cloud9am', 'Cloud3pm'],
 'NorahHead': ['Evaporation', 'Sunshine', 'Cloud9am', 'Cloud3pm'],
 'NorfolkIsland': [],
 'Nuriootpa': [],
 'PearceRAAF': ['Evaporation'],
 'Penrith': ['Evaporation',
             'Sunshine',
             'Pressure9am',
             'Pressure3pm',
             'Cloud9am',
             'Cloud3pm'],
 'Perth': [],
 'PerthAirport': [],
 'Portland': [],
 'Richmond': ['Sunshine'],
 'Sale': [],
 'SalmonGums': ['Evaporation',
                'Sunshine',
                'Pressure9am',
                'Pressure3pm',
                'Cloud9am',
                'Cloud3pm'],
 'Sydney': [],
 'SydneyAirport': [],
 'Townsville': [],
 'Tuggeranong': ['Evaporation', 'Sunshine', 'Cloud9am', 'Cloud3pm'],
 'Uluru': ['Evaporation', 'Sunshine'],
 'WaggaWagga': [],
 'Walpole': ['Evaporation', 'Sunshine', 'Cloud9am', 'Cloud3pm'],
 'Watsonia': [],
 'Williamtown': [],
 'Witchcliffe': ['Evaporation', 'Sunshine', 'Cloud9am', 'Cloud3pm'],
 'Wollongong': ['Evaporation', 'Sunshine'],
 'Woomera': []}
```

In [9]:
```
# How good/bad are models trained without any Optional variables?

data_stripped_trad = data_full_trad.copy().drop(na_columns_unique, axis=1)
data_stripped_trad
```

Out[9]:

	Location	MinTemp	MaxTemp	Rainfall	WindGustDir	WindDir9am	WindDir3pm	WindSpee
0	Albury	13.4	22.9	0.6	W	W	WNW	
1	Albury	7.4	25.1	0.0	WNW	NNW	WSW	
2	Albury	12.9	25.7	0.0	WSW	W	WSW	
3	Albury	9.2	28.0	0.0	NE	SE	E	
4	Albury	17.5	32.3	1.0	W	ENE	NW	
...	...	...	...	...	...	...	...	
145454	Uluru	3.5	21.8	0.0	E	ESE	E	
145455	Uluru	2.8	23.4	0.0	E	SE	ENE	
145456	Uluru	3.6	25.3	0.0	NNW	SE	N	
145457	Uluru	5.4	26.9	0.0	N	SE	WNW	
145458	Uluru	7.8	27.0	0.0	SE	SSE	N	

140787 rows × 20 columns

In [10]:
```
# Scale all numerical features to 0-1, Convert Categorical Features to 0s or 1s
column_transformer = make_column_transformer(
    (MinMaxScaler(),
     make_column_selector(dtype_include=np.number)),
    (OneHotEncoder(handle_unknown="ignore"),
     make_column_selector(dtype_include=object)))
```

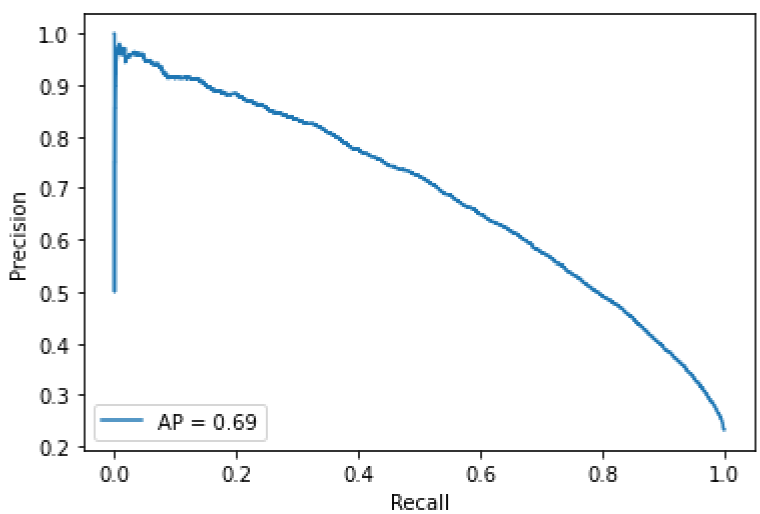
In [11]:
```
# break down for train and test
X_train_trad_full = data_full_trad[data_full_trad['Year']<2016].copy()
y_train_trad_full = X_train_trad_full.pop('RainTomorrow')
X_test_trad_full = data_full_trad[data_full_trad['Year']>=2016].copy()
y_test_trad_full = X_test_trad_full.pop('RainTomorrow')


X_train_trad_stripped = data_stripped_trad[data_full_trad['Year']<2016].copy()
y_train_trad_stripped = X_train_trad_stripped.pop('RainTomorrow')
X_test_trad_stripped = data_stripped_trad[data_full_trad['Year']>=2016].copy()
y_test_trad_stripped = X_test_trad_stripped.pop('RainTomorrow')
```

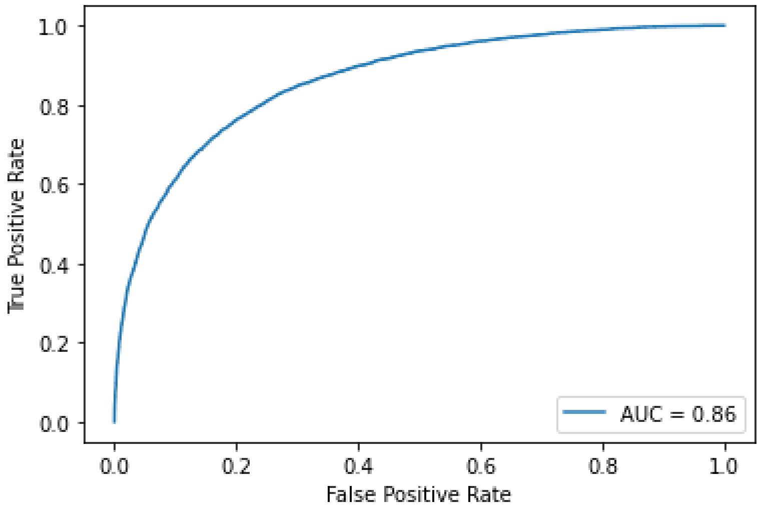
Linear Model

In [12]:
```
# Train Linear Model on Full data (all variables)

linear_clf_full = make_pipeline(
    column_transformer,
    SimpleImputer(),
    LinearSVC(
        class_weight="balanced",
        random_state=RANDOM_SEED,
    ),
)
start = time.time()
linear_summary_full = fit_predict(linear_clf_full, X_train_trad_full, y_train_tra
training_time = time.time() - start
print(f"Training time: {training_time}")

get_all_displays(linear_summary_full)
```

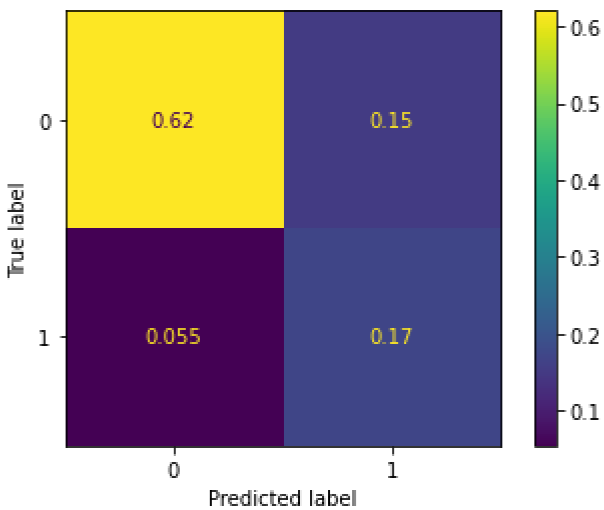
```
Training time: 11.938345432281494
```

Out[12]:
```
(<sklearn.metrics._plot.precision_recall_curve.PrecisionRecallDisplay at 0x2c3b
8481250>,
 <sklearn.metrics._plot.roc_curve.RocCurveDisplay at 0x2c3e4939a60>,
 <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x2c3e4978ee
0>)
```





1.0
0.8
0.6
0.4
0.2
0.0
True Positive Rate
AUC = 0.86
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate

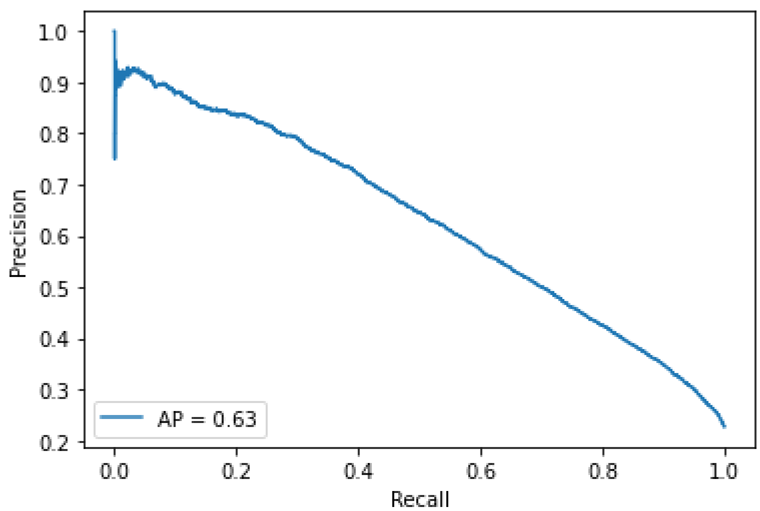


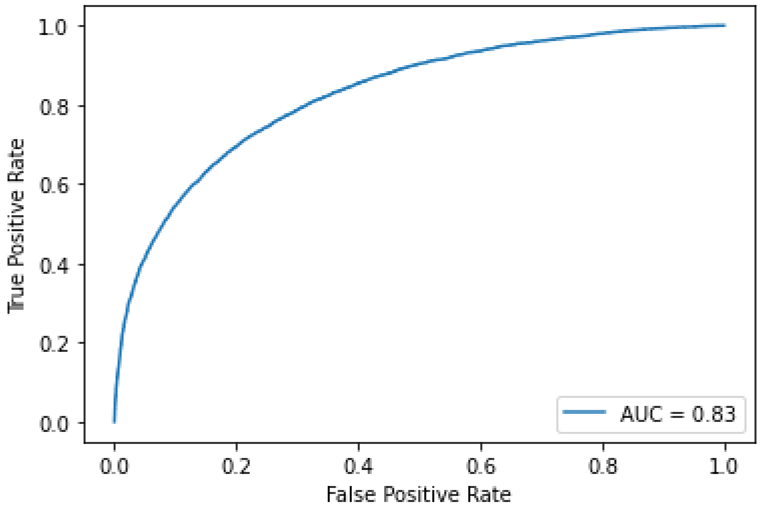
0
1
True label
0.62
0.15
0.055
0.17
0.6
0.5
0.4
0.3
0.2
0.1
0
1
Predicted label

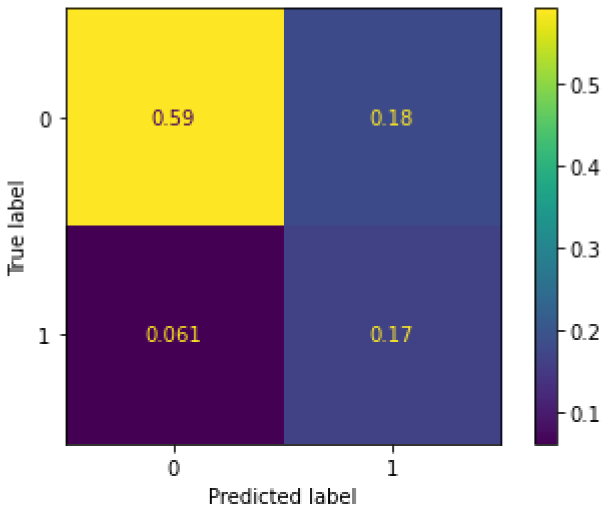
In [13]:
```
# Train Linear Model on Core/Stripped data (no optional variables)


linear_clf_stripped = make_pipeline(
    column_transformer,
    SimpleImputer(),
    LinearSVC(
        class_weight="balanced",
        random_state=RANDOM_SEED,
    ),
)
start = time.time()
linear_summary_stripped = fit_predict(linear_clf_stripped, X_train_trad_stripped,
training_time = time.time() - start
print(f"Training time: {training_time}")
#linear_summary

get_all_displays(linear_summary_stripped)
```

```
Training time: 9.251675367355347
```

Out[13]:
```
(<sklearn.metrics._plot.precision_recall_curve.PrecisionRecallDisplay at 0x2c3e
4984fd0>,
 <sklearn.metrics._plot.roc_curve.RocCurveDisplay at 0x2c3e1ee1a30>,
 <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x2c3e4b386d
0>)
```



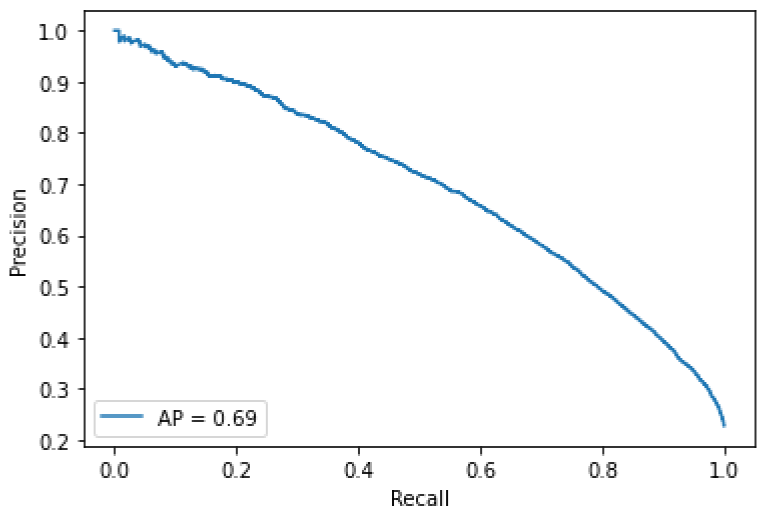


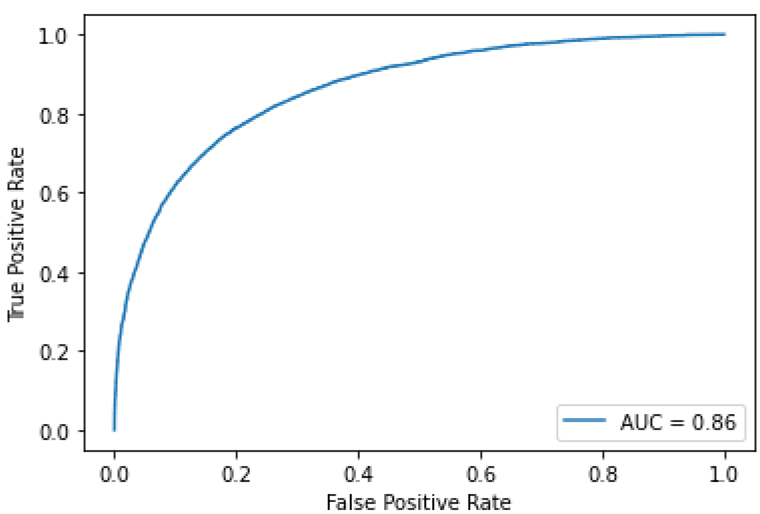


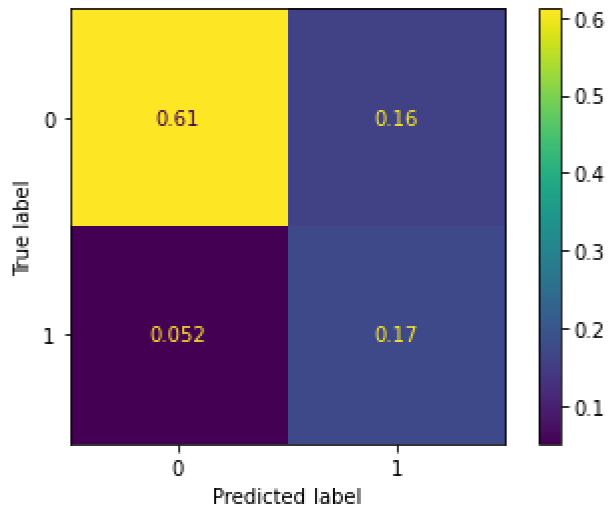
Ada Boost Model

In [14]:
```
# Train Tree based Model on Full data (all variables)


ada_clf_full = make_pipeline(column_transformer,
                    SimpleImputer(),
                    AdaBoostClassifier(n_estimators=200, base_estimator=DecisionT
                      )

ada_summary_full = fit_predict(ada_clf_full, X_train_trad_full, y_train_trad_full

get_all_displays(ada_summary_full)
```

Out[14]:
```
(<sklearn.metrics._plot.precision_recall_curve.PrecisionRecallDisplay at 0x2c3e
4bf0a00>,
 <sklearn.metrics._plot.roc_curve.RocCurveDisplay at 0x2c3e4c788b0>,
 <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x2c3e4cb513
0>)
```

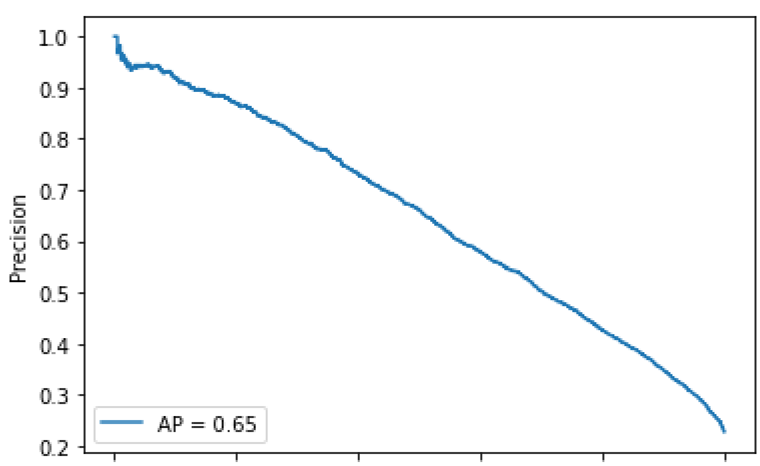






In [15]:
```
ee based Model on Core/Stripped data (no optional variables)


ripped = make_pipeline(column_transformer,
                    SimpleImputer(),
                    AdaBoostClassifier(n_estimators=200, base_estimator=DecisionTreeClassif
                      )

y_stripped = fit_predict(ada_clf_stripped, X_train_trad_stripped, y_train_trad_str

splays(ada_summary_stripped)
```

Out[15]:
```
(<sklearn.metrics._plot.precision_recall_curve.PrecisionRecallDisplay at 0x2c
3e4d72f10>,
 <sklearn.metrics._plot.roc_curve.RocCurveDisplay at 0x2c3e75dec40>,
 <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x2c3e761c
490>)
```



Interim Result

(Some of) the Optional metrics appear to be important.

- Average Precision consistently drops by ~.05 when these columns are removed, for a variety of models

- AUC_ROC consistently drops by ~.03 when these columns are removed, for a variety of models

We need to drill down to specific locations to figure out which missing columns are actually problematic...

Time Series (Location Specific) Models

In [16]:
```
# Create Test/Train data for each location

y_by_location, X_by_location = {}, {}

for loc, df in data_by_location.items():
    X_by_location[loc] = df.copy()
    y_by_location[loc] = X_by_location[loc].pop("RainTomorrow")
    X_by_location[loc].pop("Location")
    X_by_location[loc].pop("Latitude") # Constant for a single location
    X_by_location[loc].pop("Longitude") # Constant for a single location

X_train_by_loc, X_test_by_loc, y_train_by_loc, y_test_by_loc = {}, {}, {}, {}
for loc in data_by_location.keys():
    X_train_by_loc[loc], X_test_by_loc[loc], y_train_by_loc[loc], y_test_by_loc[l
```

In [17]:
```
# Same transform steps as Linear/Tree models, except "from_2d_array_to_nested" is

transform_pipeline_by_loc = {
    loc: make_pipeline(
        make_column_transformer(
            (MinMaxScaler(),
             make_column_selector(dtype_include=np.number)),
            (OneHotEncoder(handle_unknown="ignore"),
             make_column_selector(dtype_include=object)), sparse_threshold=0),
        KNNImputer(),
        FunctionTransformer(from_2d_array_to_nested),
    )
    for loc in X_train_by_loc.keys()
}
```

In [18]:
```
X_train_transformed_by_loc = {
    loc: transform_pipeline.fit_transform(X_train_by_loc[loc])
    for loc, transform_pipeline in transform_pipeline_by_loc.items()
}

X_test_transformed_by_loc = {
    loc: transform_pipeline.transform(X_test_by_loc[loc])
    for loc, transform_pipeline in transform_pipeline_by_loc.items()
}
```

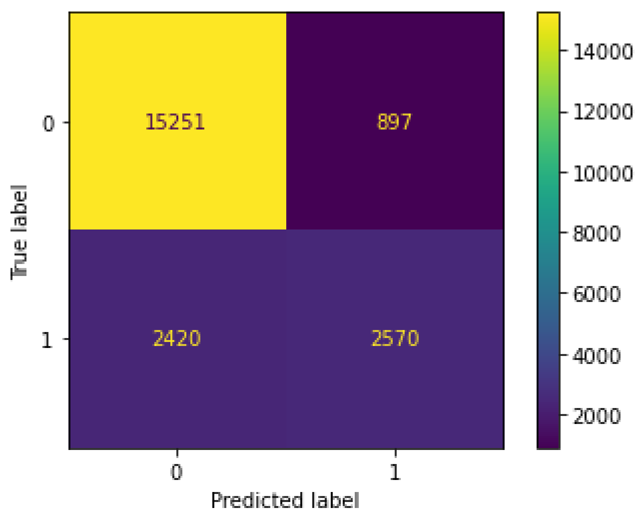
In [19]:
```
for loc, X_train_transformed in X_train_transformed_by_loc.items():
    X_train_transformed.index = X_train_by_loc[loc].index

for loc, X_test_transformed in X_test_transformed_by_loc.items():
    X_test_transformed.index = X_test_by_loc[loc].index
```

In [54]:
```
# Train for each location
# Mini Rocket is supposed to be very good, but also the only time series model th

start = time.time()

inference_pipeline_by_loc = {
    loc: make_pipeline(
        MiniRocket(random_state=RANDOM_SEED),
        RidgeClassifierCV(alphas=np.logspace(-3, 3, 10), normalize=True)
    )
    for loc in X_train_transformed_by_loc.keys()
}

summary_by_loc = {
    loc: fit_predict(inference_pipeline, X_train_transformed_by_loc[loc], y_trair
    for loc, inference_pipeline in inference_pipeline_by_loc.items()
}

training_time = time.time() - start9
print(f"Training took {training_time} seconds")
```

```
Training took 222.82181358337402 seconds
```

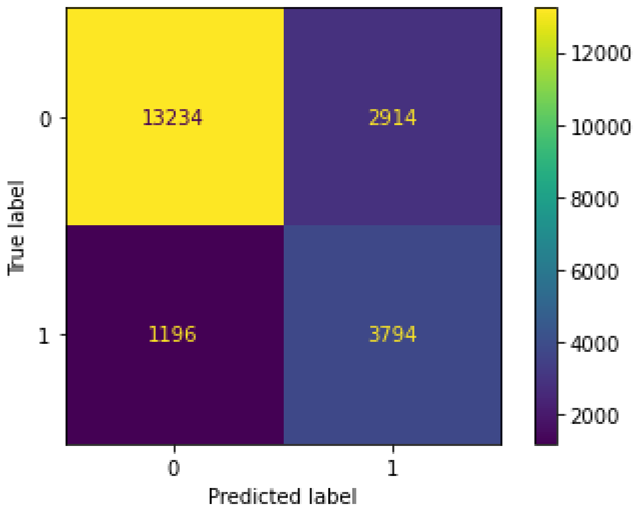
In [55]:
```
combined_y_test = sum((list(v) for v in y_test_by_loc.values()), [])
combined_y_pred = sum((list(s["y_pred"]) for s in summary_by_loc.values()), [])
combined_confusion = confusion_matrix(combined_y_test, combined_y_pred)

disp2 = ConfusionMatrixDisplay(combined_confusion)
disp2.plot()
print(classification_report(combined_y_test, combined_y_pred))
```

```
              precision    recall  f1-score   support

         0.0       0.86      0.94      0.90     16148
         1.0       0.74      0.52      0.61      4990

    accuracy                           0.84     21138
   macro avg       0.80      0.73      0.75     21138
weighted avg       0.83      0.84      0.83     21138
```



In [56]:
```
# Examine Confusion Matrix if we use different cutoff try to improve True Positiv
# This makes the confusion matrices more comparable to the models trained above

combined_y_decision = sum((list(1 if d > -.4 else 0 for d in s["decision_functior

combined_confusion = confusion_matrix(combined_y_test, combined_y_decision)

disp3 = ConfusionMatrixDisplay(combined_confusion)
disp3.plot()
```

Out[56]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x2c3ffca6ca0
>
```



In [57]:
```
print(classification_report(y_test_trad_full, linear_summary_full["y_pred"]))
print(classification_report(y_test_trad_full, ada_summary_full["y_pred"]))
print(classification_report(combined_y_test, combined_y_decision))
```

```
              precision    recall  f1-score   support

         0.0       0.92      0.80      0.86     19885
         1.0       0.53      0.76      0.62      5825

    accuracy                           0.79     25710
   macro avg       0.72      0.78      0.74     25710
weighted avg       0.83      0.79      0.80     25710

              precision    recall  f1-score   support

         0.0       0.92      0.79      0.85     19885
         1.0       0.52      0.77      0.62      5825

    accuracy                           0.79     25710
   macro avg       0.72      0.78      0.74     25710
weighted avg       0.83      0.79      0.80     25710

              precision    recall  f1-score   support

         0.0       0.92      0.82      0.87     16148
         1.0       0.57      0.76      0.65      4990

    accuracy                           0.81     21138
   macro avg       0.74      0.79      0.76     21138
weighted avg       0.83      0.81      0.81     21138
```

Note:

The Location Specific Time Series Models have combined metrics better than either the LogisticRegression or AdaBoost models in almost every aspect:

* Negative class Precision and Recall are equal or better
* Positive class Precision is better and recall is close.
* F1 scores are better
* Macro averages for precision recall and f1 score are all better.
* Weighted averages for precision, recall, and f1-score are equal or better than earlier models.

In [66]:
```
avg_precision_by_loc = {loc: s["average_precision_score"] for loc, s in summary_b

roc_auc_score_by_loc = {loc: s["roc_auc_score"] for loc, s in summary_by_loc.iter

print("Average Precision by location:\n", pd.Series(avg_precision_by_loc.values()
print("\nROC AUC by location:\n", pd.Series(roc_auc_score_by_loc.values()).descri
```

```
Average Precision by location:
 count    49.000000
mean      0.701341
std       0.091339
min       0.482133
25%       0.650952
50%       0.705508
75%       0.756792
max       0.877215
dtype: float64

ROC AUC by location:
 count    49.000000
mean      0.862254
std       0.041353
min       0.705093
25%       0.835185
50%       0.867109
75%       0.885991
max       0.944724
dtype: float64
```

In [67]:
```
avg_precision_by_loc_na_columns = {loc: s["average_precision_score"] for loc, s i
roc_auc_score_by_loc_na_columns = {loc: s["roc_auc_score"] for loc, s in summary_
avg_precision_by_loc_no_na_columns = {loc: s["average_precision_score"] for loc,
roc_auc_score_by_loc_no_na_columns = {loc: s["roc_auc_score"] for loc, s in summa
```

In [68]:
```
pd.DataFrame({
    "Avg Precision w/NAs": pd.Series(avg_precision_by_loc_na_columns.values()).de
    "Avg Precision w/o NAs": pd.Series(avg_precision_by_loc_no_na_columns.values(
})
```

Out[68]:

	Avg Precision w/NAs	Avg Precision w/o NAs
count	23.000000	26.000000
mean	0.717355	0.687174
std	0.086763	0.094599
min	0.482133	0.498253
25%	0.681913	0.628387
50%	0.714233	0.701733
75%	0.772585	0.742530
max	0.877215	0.832416

In [69]:
```
pd.DataFrame({
    "ROC AUC w/NAs": pd.Series(roc_auc_score_by_loc_na_columns.values()).describe
    "ROC AUC w/o NAs": pd.Series(roc_auc_score_by_loc_no_na_columns.values()).des
})
```

Out[69]:

	ROC AUC w/NAs	ROC AUC w/o NAs
count	23.000000	26.000000
mean	0.863457	0.861190
std	0.048863	0.034349
min	0.705093	0.799104
25%	0.834912	0.836227
50%	0.867109	0.862786
75%	0.893077	0.883871
max	0.944724	0.929656

Surprising Result

The Location Specific Time Series models are better for locations which do not record at least one Optional metric:
* Mean, min, 25%, 75% and max avg_precision are all better
* 50% avg_precision is nearly identical
* mean, 25%, 50%, 75%, and max ROC AUC are all better

The minimum ROC AUC is much lower however (.70 vs .79).

Looking at this outlier gives us a key insight:

In [70]:
```
print("Three worst ROC AUC scores in locations which do not record at least one (
pprint.pprint(sorted((roc_auc_score, loc, na_columns_by_loc[loc]) for loc, roc_au
```

```
Three worst ROC AUC scores in locations which do not record at least one Option
al metric:

[(0.7050934862147447,
  'Newcastle',
  ['Evaporation', 'Sunshine', 'WindGustSpeed', 'Pressure9am', 'Pressure3pm']),
 (0.8126399095534201, 'Albany', ['WindGustSpeed'])]
```

In [71]:
```
print([loc for loc, na_columns in na_columns_by_loc.items() if "WindGustSpeed" ir
```

```
['Newcastle', 'Albany']
```

Key Insight
* Newcastle is by far the worst ROC AUC score of any location specific classifier.
* Albany is the second worst out of all sites missing a column. It would be <25% in either group of locations

* These are the only two sites which do not record the WindGustSpeed Optional metric

In [72]:
```
avg_precision_by_loc_na_wind_columns = {loc: s["average_precision_score"] for loc

roc_auc_score_by_loc_na_wind_columns = {loc: s["roc_auc_score"] for loc, s in sum

print("Average Precision by location non-Wind NAs:\n", pd.Series(avg_precision_by
print("\nROC AUC by location non-Wind NAs:\n", pd.Series(roc_auc_score_by_loc_na_
```

```
Average Precision by location non-Wind NAs:
 count    21.000000
mean      0.728565
std       0.073364
min       0.605664
25%       0.681929
50%       0.714233
75%       0.772980
max       0.877215
dtype: float64

ROC AUC by location non-Wind NAs:
 count    21.000000
mean      0.873418
std       0.033750
min       0.823143
25%       0.852611
50%       0.872085
75%       0.894222
max       0.944724
dtype: float64
```

In [73]:
```
pd.DataFrame({
    "Avg Precision w/NAs  (excluding wind)": pd.Series(avg_precision_by_loc_na_wi
    "Avg Precision w/o NAs": pd.Series(avg_precision_by_loc_no_na_columns.values(
})
```

Out[73]:

	Avg Precision w/NAs (excluding wind)	Avg Precision w/o NAs
count	21.000000	26.000000
mean	0.728565	0.687174
std	0.073364	0.094599
min	0.605664	0.498253
25%	0.681929	0.628387
50%	0.714233	0.701733
75%	0.772980	0.742530
max	0.877215	0.832416

In [74]:
```
pd.DataFrame({
    "ROC AUC w/NAs (excluding wind)": pd.Series(roc_auc_score_by_loc_na_wind_colu
    "ROC AUC w/o NAs": pd.Series(roc_auc_score_by_loc_no_na_columns.values()).des
})
```

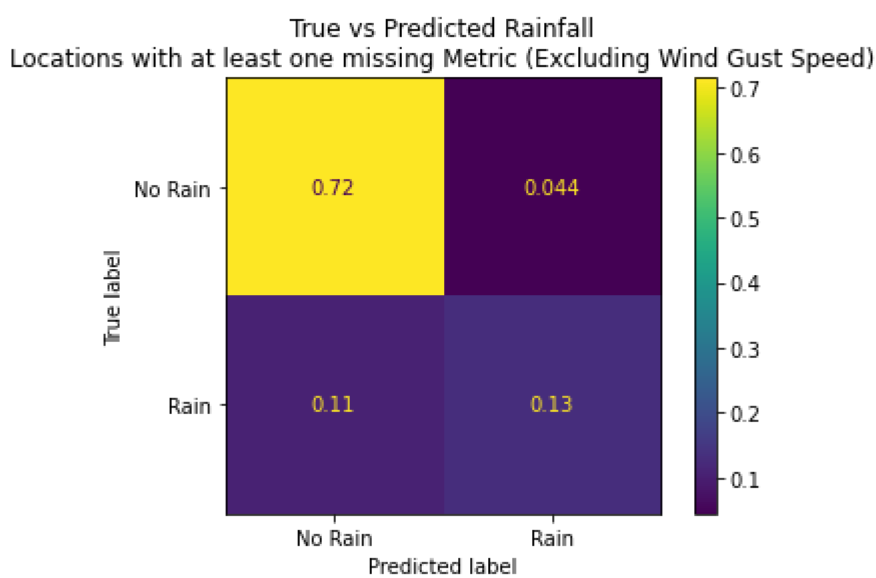
Out[74]:

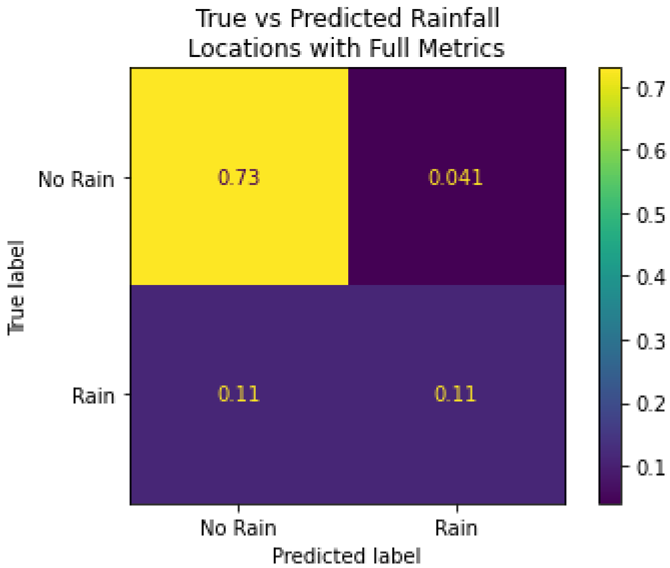
	ROC AUC w/NAs (excluding wind)	ROC AUC w/o NAs
count	21.000000	26.000000
mean	0.873418	0.861190
std	0.033750	0.034349
min	0.823143	0.799104
25%	0.852611	0.836227
50%	0.872085	0.862786
75%	0.894222	0.883871
max	0.944724	0.929656

In [77]:
```
# Let's look at the Confusion Matrix for predictions in these categories: "Full"

combined_y_test_wind_nas = sum((list(v)
                                for loc, v in y_test_by_loc.items()
                                if na_columns_by_loc[loc] and "WindGustSpeed" not
combined_y_pred_wind_nas = sum((list(s["y_pred"])
                                for loc, s in summary_by_loc.items()
                                if na_columns_by_loc[loc] and "WindGustSpeed" not
combined_confusion_wind_nas = confusion_matrix(combined_y_test_wind_nas, combined

disp_wind_nas = ConfusionMatrixDisplay(combined_confusion_wind_nas, display_label

print(disp_wind_nas.__dir__())
plt_wind_nas = disp_wind_nas.plot(values_format=".3g")
plt_wind_nas.ax_.set_title("True vs Predicted Rainfall\nLocations with at least o


combined_y_test_no_nas = sum((list(v)
                                for loc, v in y_test_by_loc.items()
                                if not na_columns_by_loc[loc]), [])
combined_y_pred_no_nas = sum((list(s["y_pred"])
                              for loc, s in summary_by_loc.items()
                              if not na_columns_by_loc[loc]), [])
combined_confusion_no_nas = confusion_matrix(combined_y_test_no_nas, combined_y_p

disp_no_nas = ConfusionMatrixDisplay(combined_confusion_no_nas, display_labels=['
plt_no_nas = disp_no_nas.plot(values_format=".2g")
plt_no_nas.ax_.set_title("True vs Predicted Rainfall\nLocations with Full Metrics
```

```
['confusion_matrix', 'display_labels', '__module__', '__doc__', '__init__', 'pl
ot', '__dict__', '__weakref__', '__repr__', '__hash__', '__str__', '__getattrib
ute__', '__setattr__', '__delattr__', '__lt__', '__le__', '__eq__', '__ne__',
'__gt__', '__ge__', '__new__', '__reduce_ex__', '__reduce__', '__subclasshook_
_', '__init_subclass__', '__format__', '__sizeof__', '__dir__', '__class__']
```

Out[77]:
```
Text(0.5, 1.0, 'True vs Predicted Rainfall\nLocations with Full Metrics')
```






```
# Final Time Series Results

WindGustSpeed is the only Optional metric that seriously improved the Location
Specific Time Series Models (or made them worse when it was missing).

Rainfall predictions for locations missing one or more of the other metrics
actually did *better* than predictions for locations with full Optional metrics
(this is a good subject for future investigation).

We don't want to assume the Australian government will only ever use Location
Specific Time Series models, so we'll check our earlier models. We want to see
if "Core+WindGustSpeed" models (trained on all Core features + WindGustSpeed)
does better than the Core models (trained on Core features with no Optional
features) and is close to the "Full" models (trained on all Core + Optional
features)
```

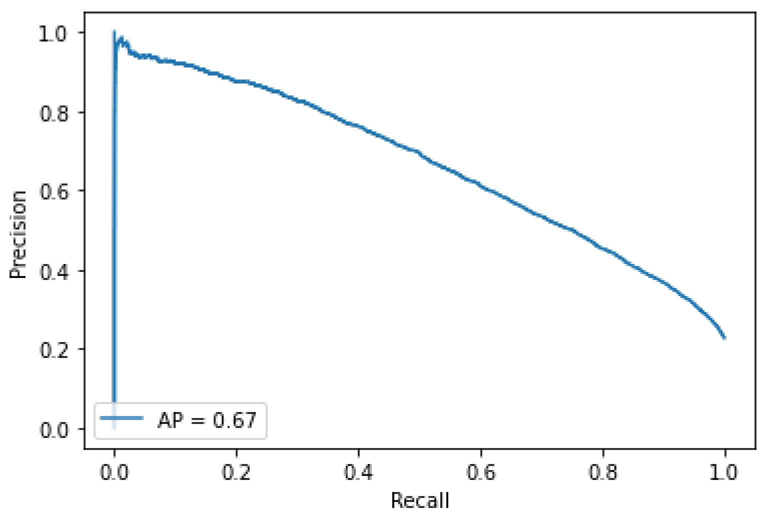
Adding Back in WindGustSpeed

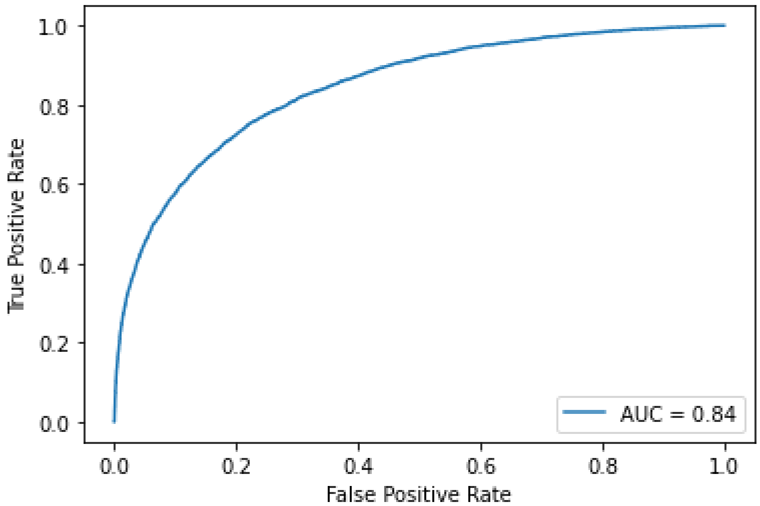
In [34]:
```
X_train_trad_wind = X_train_trad_stripped.copy()
X_test_trad_wind = X_test_trad_stripped.copy()
y_train_trad_wind = y_train_trad_stripped.copy()
y_test_trad_wind = y_test_trad_stripped.copy()

X_train_trad_wind["WindGustSpeed"] = X_train_trad_full["WindGustSpeed"].copy()
X_test_trad_wind["WindGustSpeed"] = X_test_trad_full["WindGustSpeed"].copy()
```

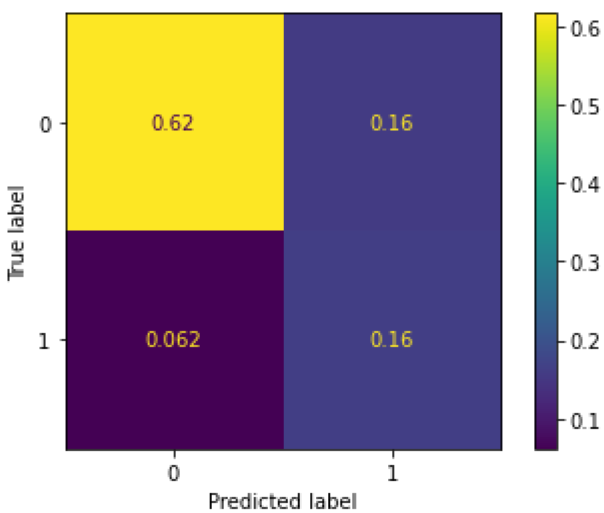
In [35]:
```
# Train Linear classifier on Core  variables + WindGustSpeed
linear_clf_wind = make_pipeline(
    column_transformer,
    SimpleImputer(),
    LinearSVC(
        class_weight="balanced",
        random_state=RANDOM_SEED,
    ),
)
start = time.time()
linear_summary_wind = fit_predict(linear_clf_wind, X_train_trad_wind, y_train_tra
training_time = time.time() - start
print(f"Training time: {training_time}")

get_all_displays(linear_summary_wind)
```

```
Training time: 9.203127145767212
```

Out[35]:
```
(<sklearn.metrics._plot.precision_recall_curve.PrecisionRecallDisplay at 0x2c3e
4d528e0>,
 <sklearn.metrics._plot.roc_curve.RocCurveDisplay at 0x2c3fde4e880>,
 <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x2c3fe26076
0>)
```

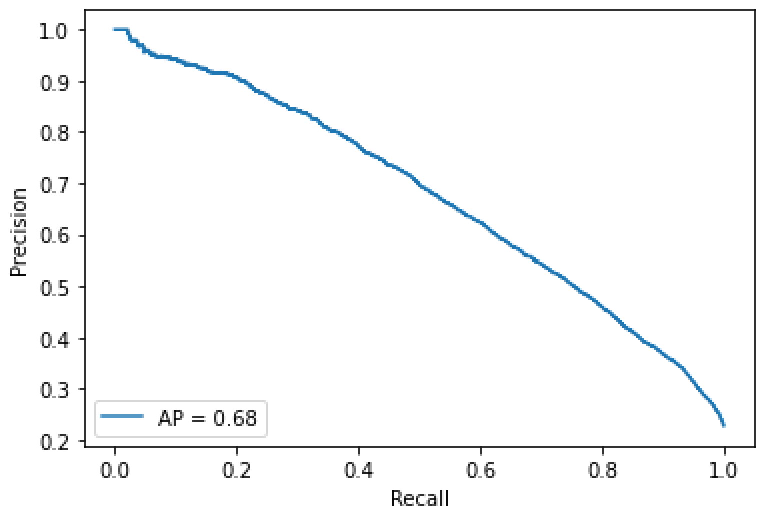


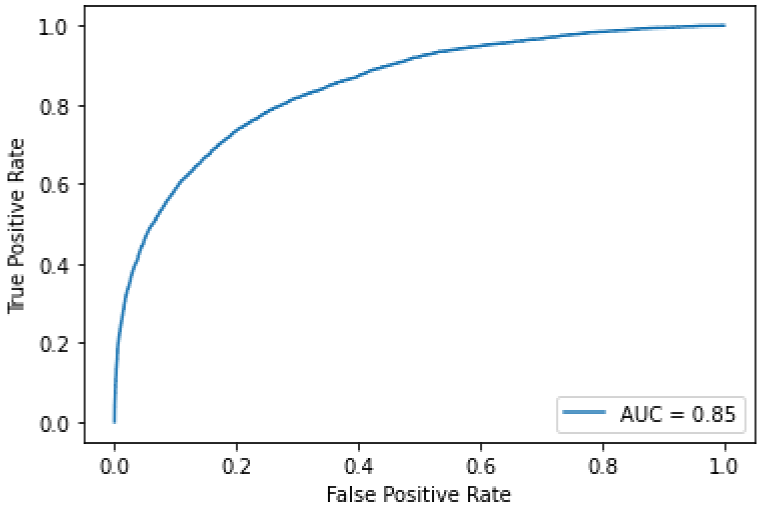

True Positive Rate
False Positive Rate
AUC = 0.84
0.0
0.2
0.4
0.6
0.8
1.0

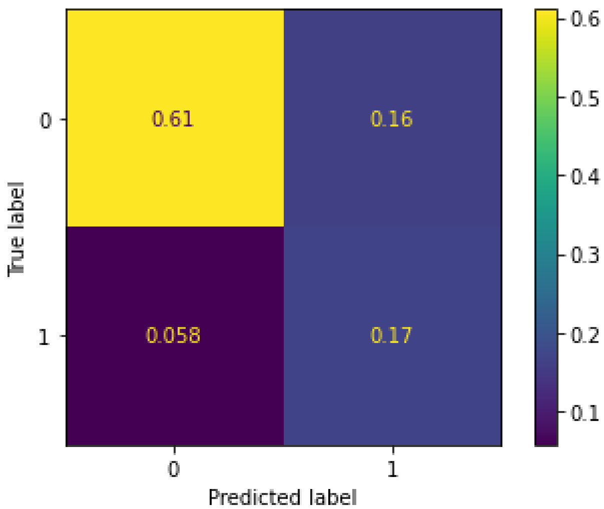

True label
Predicted label
0.62
0.16
0.062
0.16
0
1
0.1
0.2
0.3
0.4
0.5
0.6

In [36]:
```
# Train Tree Based classifier on Core  variables + WindGustSpeed

ada_clf_wind = make_pipeline(column_transformer,
                    SimpleImputer(),
                    AdaBoostClassifier(n_estimators=200, base_estimator=DecisionT
                      )

ada_summary_wind = fit_predict(ada_clf_wind, X_train_trad_wind, y_train_trad_winc

get_all_displays(ada_summary_wind)
```

Out[36]:
```
(<sklearn.metrics._plot.precision_recall_curve.PrecisionRecallDisplay at 0x2c3f
e3215b0>,
 <sklearn.metrics._plot.roc_curve.RocCurveDisplay at 0x2c3fe39b220>,
 <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x2c3fe3c8a3
0>)
```




1.0
0.8
0.6
0.4
0.2
0.0
True Positive Rate
AUC = 0.85
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate


0
1
True label
0.61
0.16
0.058
0.17
0
1
Predicted label
0.6
0.5
0.4
0.3
0.2
0.1

In [37]:
```
# Compare Linear models using Core, Core + Wind, or Full data


print("Linear Model:")
pd.DataFrame({
    "Core": {
        "ROC_AUC": linear_summary_stripped["roc_auc_score"],
        "Average_Precision": linear_summary_stripped["average_precision_score"]},
    "Core+Wind": {
        "ROC_AUC": linear_summary_wind["roc_auc_score"],
        "Average_Precision": linear_summary_wind["average_precision_score"]},
    "Full": {
        "ROC_AUC": linear_summary_full["roc_auc_score"],
        "Average_Precision": linear_summary_full["average_precision_score"]},
        },
)
```

```
Linear Model:
```

Out[37]:

	Core	Core+Wind	Full
ROC_AUC	0.827815	0.844643	0.862450
Average_Precision	0.630241	0.665506	0.686304

In [38]:
```
# Compare Tree based models using Core, Core + Wind, or Full data


print("AdaBoost Model:")
pd.DataFrame({
    "Core": {
        "ROC_AUC": ada_summary_stripped["roc_auc_score"],
        "Average_Precision": ada_summary_stripped["average_precision_score"]},
    "Core+Wind": {
        "ROC_AUC": ada_summary_wind["roc_auc_score"],
        "Average_Precision": ada_summary_wind["average_precision_score"]},
    "Full": {
        "ROC_AUC": ada_summary_full["roc_auc_score"],
        "Average_Precision": ada_summary_full["average_precision_score"]},
        },
)
```

```
AdaBoost Model:
```

Out[38]:

	Core	Core+Wind	Full
ROC_AUC	0.830956	0.847496	0.862973
Average_Precision	0.645311	0.677190	0.693929

Final Final Result

```
The Linear model improves from .63 to .67
```