Air Quality Prediction Using Meteorological Data

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Github Link: https://github.com/igoldin670/Air-Quality-Prediction-Using-Meteorological-Data/

1. Project Definition

a. 1.1 Project Statement

Stakeholder's Problem:

For stakeholders interested in environmental management, such as someone like city planners, public health agencies, or local governments, understanding the factors that drive changes in air quality can sometimes be really important. Accurate predictions of PM2.5 or AQI levels based on meteorological data can help show early warning signs, guide public safety advisories, and help allocate resources such as emergency response units or pollution control measures. By forecasting and reporting poor air quality conditions in advance, cities can reduce health risks for vulnerable populations, optimize traffic or industrial regulations on high pollution days, as well as make other big decisions using big data. This project addresses the need for reliable and interpretable models that clearly show how weather variables influence pollution levels in real time.

Public and Research Problem:

For individuals and communities concerned about environmental health, as well as scientists studying atmospheric trends, identifying which meteorological factors most strongly correlate with pollution levels provides important signs into how air quality evolves. By highlighting relationships between temperature, humidity, wind speed, pressure, and particulate concentration (in the data), this project helps people understand the conditions that typically worsen or improve air quality in their area. At a larger level, the analysis supports researchers seeking scalable, data driven methods to study air pollution without focusing on more complex atmospheric sims. These understandings guide community awareness and future environmental research focused on sustainability and long term air quality improvement.

b. 1.2 Connection to Course Material

This project connects directly to the concepts taught in our course, as the process requires building a complete data processing and machine learning pipeline from start to finish. I began by collecting and preparing real world environmental data (found online), which involved cleaning the data such as handling missing values, removing outliers, converting timestamps, and standardizing units, skills we learned throughout our lectures and recitation. After organizing the processed data, I manipulated the dataset by inserting and updating records, then performing feature scaling and feature engineering, and running queries to explore correlations and identify patterns relevant to air pollution trends.

This project connects to the course by building a full data pipeline: fetching real EPA AQS PM2.5/AQI data and Open-Meteo weather data, cleaning (coerce numerics, drop negatives and rows with missing modeling fields, dedupe by date), merging on date_local, and exploring with Python (NumPy/Pandas/Matplotlib/Seaborn). The modeling applies topics from class via simple linear fits and tree ensembles (RandomForest, Gradient Boosting, Extra Trees) plus evaluation with MSE and R^2, no scaling, imputation, or additional feature engineering is used, just raw data.

2. **Novelty and Importance**
    a. 2.1 Importance of the Project

As more urban populations and populations in general expand and climate conditions become increasingly unpredictable from outside variables, cities now have rising difficulty in monitoring and getting ready for harmful air quality events, like a forest fire. Poor air quality is a major link to severe health risks, including asthma, cardiovascular disease, and increased mortality, making accurate and timely prediction a must have for those people. Despite the availability of large volumes of meteorological and pollution data, many regions still lack accessible, data driven tools that can translate raw environmental records into forecasts.

By developing a predictive model that involves weather variables with PM2.5 and/or AQI measurements, this project goal is to face the challenge of transforming environmental data (big or small) into final outcomes for weather. It supports governments, researchers, and public health institutions that rely on well managed datasets to form decision making. Additionally, by focusing on interpretability through models like Linear Regression and/or Random Forrest, the project contributes to transparency in environmental data, an important issue as more institutions rely on predictive systems. Ultimately, this work aims to provide an understandable sort of framework that can improve public awareness and guide preventive health measures/support long term sustainability planning through data of air quality management.

    b. 2.2 Excitement and Relevance

I am excited about this project because it encapsulates my interest in environmental sustainability, mixed with the data science skills I've learned in class. Air quality affects daily life and public health, so applying machine learning to predict pollution levels feels both meaningful and relevant. This project gives me the chance to work with real meteorological and air quality data that could help communities better understand and prepare for poor air conditions. I am not aware of any previous class projects that combine meteorological features with machine learning models to predict PM2.5 or AQI levels in an interpretable way.

    c. 2.3 Review of Related Work

Existing environmental datasets often provide either weather data or pollution levels, but rarely integrate them into a clear predictive framework. Many forecasting systems rely on complex atmospheric models that are difficult for non-experts to interpret. Our project aims to simplify this by creating a clean, unified dataset and training regression models to show how specific weather factors influence pollution levels. This makes air quality prediction more accessible and easier to understand for students, local communities, and anyone interested in environmental health.

3. Progress and Contribution

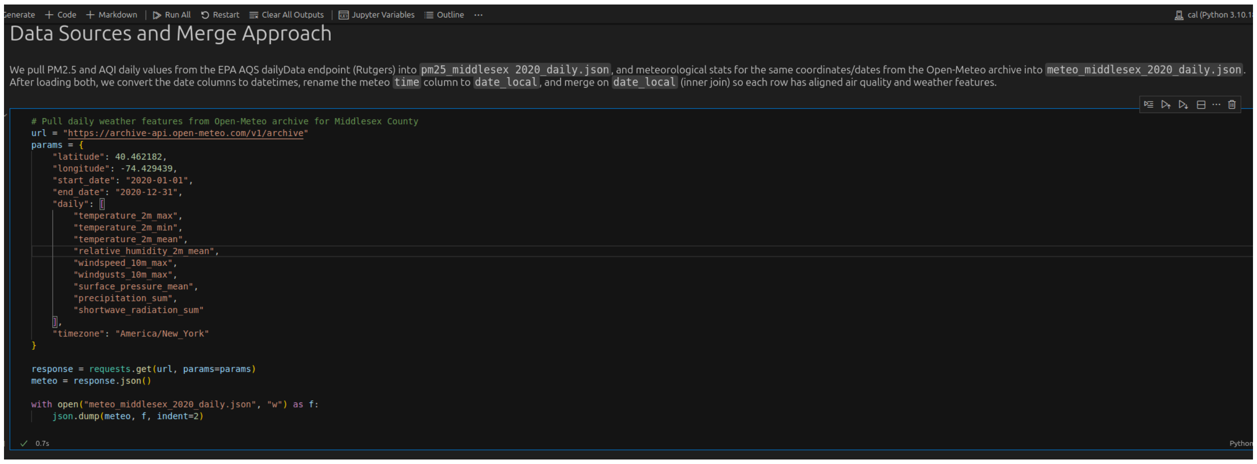
a. 3.1 Data Utilization

For this project, I worked with real environmental data instead of synthetic data. I retrieved daily PM2.5 and AQI measurements from the EPA Air Quality System (AQS) for the Rutgers/Middlesex County area and used 2020 as my main training year, with 2021 serving as an out-of-time test set. I kept all available AQS columns, PM2.5 values, AQI, sampling metadata, method codes, site coordinates, qualifiers, and more, so I could preserve any information that might later be useful for analysis or validation.

To study whether air pollution is influenced by weather, I also collected daily meteorological data for the same dates and location using the Open-Meteo Historical Weather API. This included temperature (mean/min/max), relative humidity, wind speed and gusts, surface pressure, precipitation, and shortwave radiation. I downloaded the data for the exact coordinates of the monitoring site to keep both datasets aligned in space and time, and I retained all fields for flexible exploration.

After retrieving both datasets, I merged them on the date_local field, producing a single dataframe that paired daily pollution outcomes with their corresponding weather conditions. Because real environmental data contains natural irregularities, I focused on creating a clean, model-ready dataset while preserving meaningful variation. I sorted by date, dropped duplicate days, coerced numeric fields, removed invalid negative PM2.5 values, and dropped rows with missing values in the modeling columns. I kept all extreme positive PM2.5 levels, treating them as real high-pollution events important for accurate prediction.

The result is a merged dataset covering two full years of pollution and weather data. Training on 2020 and testing on 2021 allows me to evaluate how well the model generalizes beyond the year it was trained on, forming a strong foundation for understanding and predicting daily air quality in Middlesex County.



Data Sources and Merge Approach

We pull PM2.5 and AQI daily values from the EPA AQS dailyData endpoint (Rutgers) into `pm25_middlesex_2020_daily.json`, and meteorological stats for the same coordinates/dates from the Open-Meteo archive into `meteo_middlesex_2020_daily.json`. After loading both, we convert the date columns to datetimes, rename the meteo `time` column to `date_local`, and merge on `date_local` (inner join) so each row has aligned air quality and weather features.

```
# Pull daily weather features from Open-Meteo archive for Middlesex County
url = "https://archive-api.open-meteo.com/v1/archive"
params = {
    "latitude": 40.462182,
    "longitude": -74.429439,
    "start_date": "2020-01-01",
    "end_date": "2020-12-31",
    "daily": [
        "temperature_2m_max",
        "temperature_2m_min",
        "temperature_2m_mean",
        "relative_humidity_2m_mean",
        "windspeed_10m_max",
        "windgusts_10m_max",
        "surface_pressure_mean",
        "precipitation_sum",
        "shortwave_radiation_sum"
    ],
    "timezone": "America/New_York"
}

response = requests.get(url, params=params)
meteo = response.json()

with open("meteo_middlesex_2020_daily.json", "w") as f:
    json.dump(meteo, f, indent=2)
```

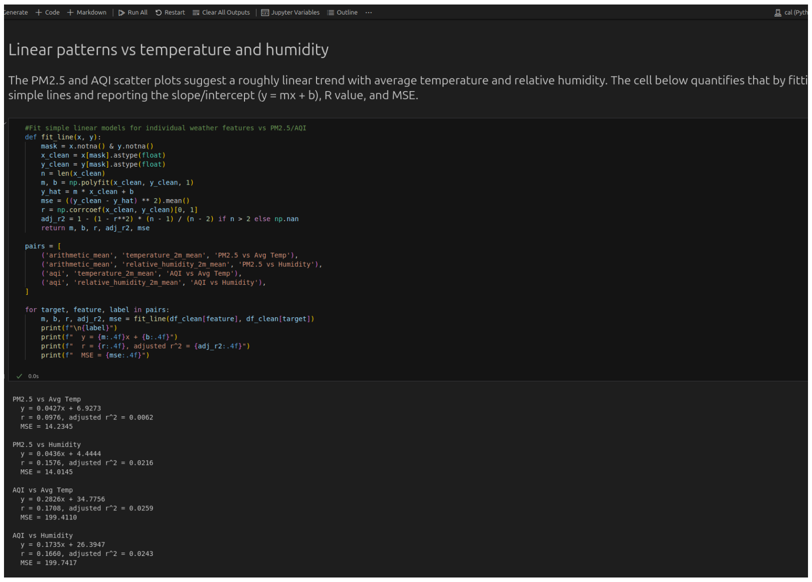
0.7s

b. 3.2 Models, Techniques, and Algorithms

Pulled daily PM2.5/AQI from EPA AQS at Rutgers and daily weather from Open-Meteo for the same dates/location. After merging,I did simple EDA, (PM2.5 vs. temperature/humidity, correlation heatmaps, residuals, feature-importance plots), to spot any patterns sticking out to me.

Cleaning: standardized types, kept one record per date, coerced modeling fields to numeric, removed negative PM2.5, and dropped rows with missing target/features. No imputation, scaling, or time-based/lag features were added, models use raw weather variables (temperature, humidity, windspeed, surface pressure, precipitation, shortwave radiation).

Models: linear fits on individual features and a small multivariate model, plus tree ensembles (RandomForest, Gradient Boosting, Extra Trees) with a random train/test split on 2020 for in year. Then separately, a RandomForest trained on all of 2020 and tested out-of-time on 2021 to check cross check for other year generalization.



Linear patterns vs temperature and humidity

The PM2.5 and AQI scatter plots suggest a roughly linear trend with average temperature and relative humidity. The cell below quantifies that by fitti
simple lines and reporting the slope/intercept (y = mx + b), R value, and MSE.

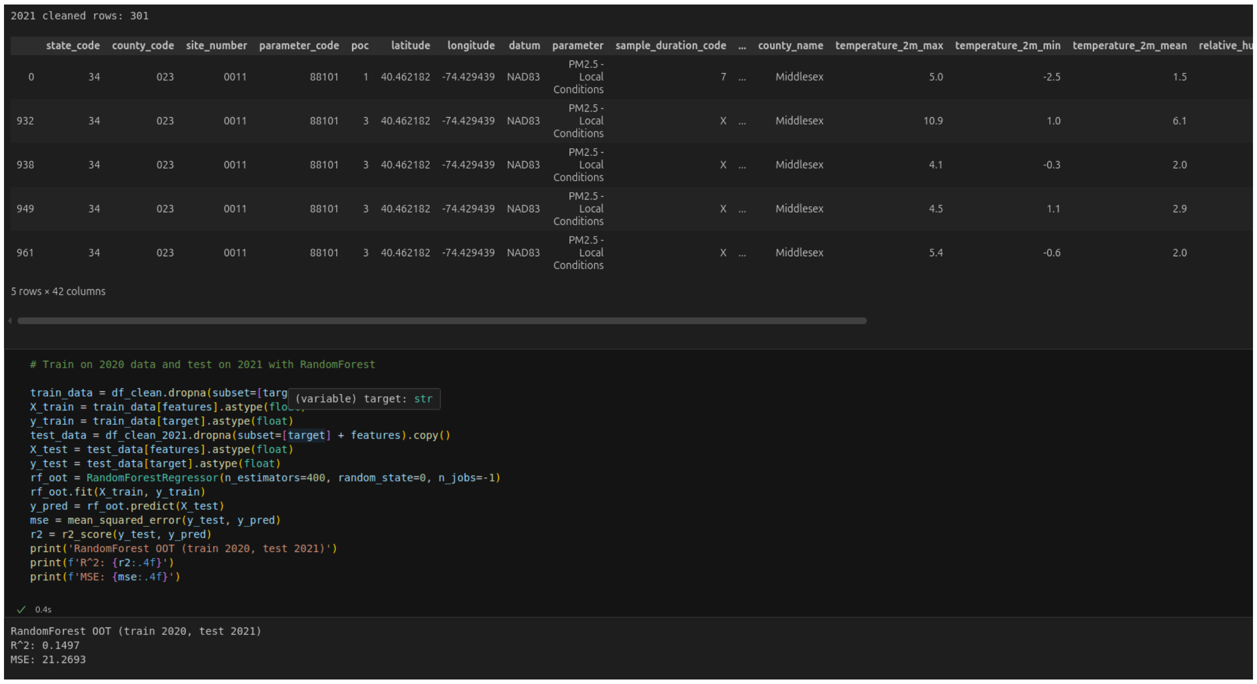
```python
#Fit simple linear models for individual weather features vs PM2.5/AQI
def fit_line(x, y):
    mask = x.notna() & y.notna()
    x_clean = x[mask].astype(float)
    y_clean = y[mask].astype(float)
    n = len(x_clean)
    m, b = np.polyfit(x_clean, y_clean, 1)
    y_hat = m * x_clean + b
    mse = ((y_clean - y_hat) ** 2).mean()
    r = np.corrcoef(x_clean, y_clean)[0, 1]
    adj_r2 = 1 - (1 - r**2) * (n - 1) / (n - 2) if n > 2 else np.nan
    return m, b, r, adj_r2, mse

pairs = [
    ('arithmetic_mean', 'temperature_2m_mean', 'PM2.5 vs Avg Temp'),
    ('arithmetic_mean', 'relative_humidity_2m_mean', 'PM2.5 vs Humidity'),
    ('aqi', 'temperature_2m_mean', 'AQI vs Avg Temp'),
    ('aqi', 'relative_humidity_2m_mean', 'AQI vs Humidity'),
]

for target, feature, label in pairs:
    m, b, r, adj_r2, mse = fit_line(df_clean[feature], df_clean[target])
    print(f"\n{label}")
    print(f"  y = {m:.4f}x + {b:.4f}")
    print(f"  r = {r:.4f}, adjusted r^2 = {adj_r2:.4f}")
    print(f"  MSE = {mse:.4f}")
```

✓ 0.0s

```
PM2.5 vs Avg Temp
  y = 0.0427x + 6.9273
  r = 0.0976, adjusted r^2 = 0.0062
  MSE = 14.2345

PM2.5 vs Humidity
  y = 0.0436x + 4.4444
  r = 0.1576, adjusted r^2 = 0.0216
  MSE = 14.0145

AQI vs Avg Temp
  y = 0.2826x + 34.7756
  r = 0.1708, adjusted r^2 = 0.0259
  MSE = 199.4110

AQI vs Humidity
  y = 0.1735x + 26.3947
  r = 0.1660, adjusted r^2 = 0.0243
  MSE = 199.7417
```

c. 3.3 Experimental Design

I expect daily PM2.5 to move with simple weather signals: warmer, calmer, and more humid days should push concentrations up, while stronger winds and higher precipitation should dilute them. My main hypothesis is that a small set of meteorological variables (temperature, humidity, wind, pressure, precipitation, shortwave radiation) will explain most of the day-to-day variation in PM2.5, with secondary effects from seasonality that aren't explicitly engineered here. The out-of-time test on 2021 checks whether relationships learned in 2020 generalize to a different year's conditions rather than just fitting one season's quirks.



```
2021 cleaned rows: 301
```

	state_code	county_code	site_number	parameter_code	poc	latitude	longitude	datum	parameter	sample_duration_code	...	county_name	temperature_2m_max	temperature_2m_min	temperature_2m_mean	relative_hu
0	34	023	0011	88101	1	40.462182	-74.429439	NAD83	PM2.5 - Local Conditions	7	...	Middlesex	5.0	-2.5	1.5	
932	34	023	0011	88101	3	40.462182	-74.429439	NAD83	PM2.5 - Local Conditions	X	...	Middlesex	10.9	1.0	6.1	
938	34	023	0011	88101	3	40.462182	-74.429439	NAD83	PM2.5 - Local Conditions	X	...	Middlesex	4.1	-0.3	2.0	
949	34	023	0011	88101	3	40.462182	-74.429439	NAD83	PM2.5 - Local Conditions	X	...	Middlesex	4.5	1.1	2.9	
961	34	023	0011	88101	3	40.462182	-74.429439	NAD83	PM2.5 - Local Conditions	X	...	Middlesex	5.4	-0.6	2.0	

5 rows × 42 columns

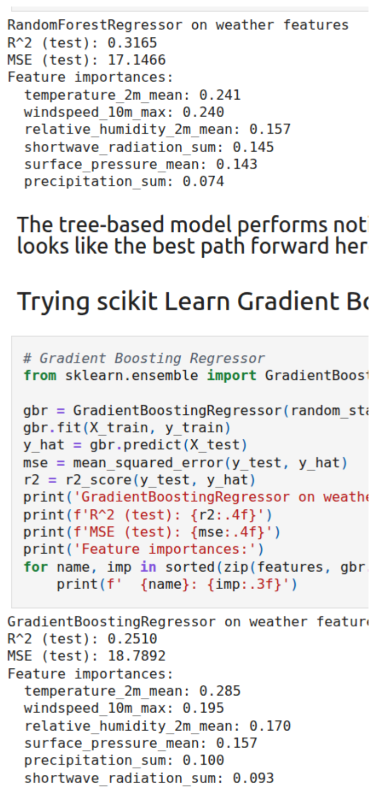
```python
# Train on 2020 data and test on 2021 with RandomForest

train_data = df_clean.dropna(subset=[targ (variable) target: str
X_train = train_data[features].astype(flo
y_train = train_data[target].astype(float)
test_data = df_clean_2021.dropna(subset=[target] + features).copy()
X_test = test_data[features].astype(float)
y_test = test_data[target].astype(float)
rf_oot = RandomForestRegressor(n_estimators=400, random_state=0, n_jobs=-1)
rf_oot.fit(X_train, y_train)
y_pred = rf_oot.predict(X_test)
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
print('RandomForest OOT (train 2020, test 2021)')
print(f'R^2: {r2:.4f}')
print(f'MSE: {mse:.4f}')
```

✓ 0.4s

```
RandomForest OOT (train 2020, test 2021)
R^2: 0.1497
MSE: 21.2693
```

d. 3.4 Key Findings and Evaluation

The analysis found that simple fits produced low r/adjusted r^2, showing weak linear relationships between PM2.5 and individual weather variables, confirming limited single variable relation. Tree-based models (RandomForest, Extra Trees, Gradient Boosting) captured a little more structure than last linear baselines but still delivered modest results. Out-of-time validation, training on 2020 and testing on 2021, R^2 stayed low for the RandomForest, suggesting the 2020 patterns don't generalize strongly across years with weather alone. The cleaning choices (dropping negatives and rows with missing modeling fields, no scaling) came out as a tidy dataset but reduced sample size (which was already small), richer features (time-based or lagged pollution) and imputation would likely be needed to improve generalization.



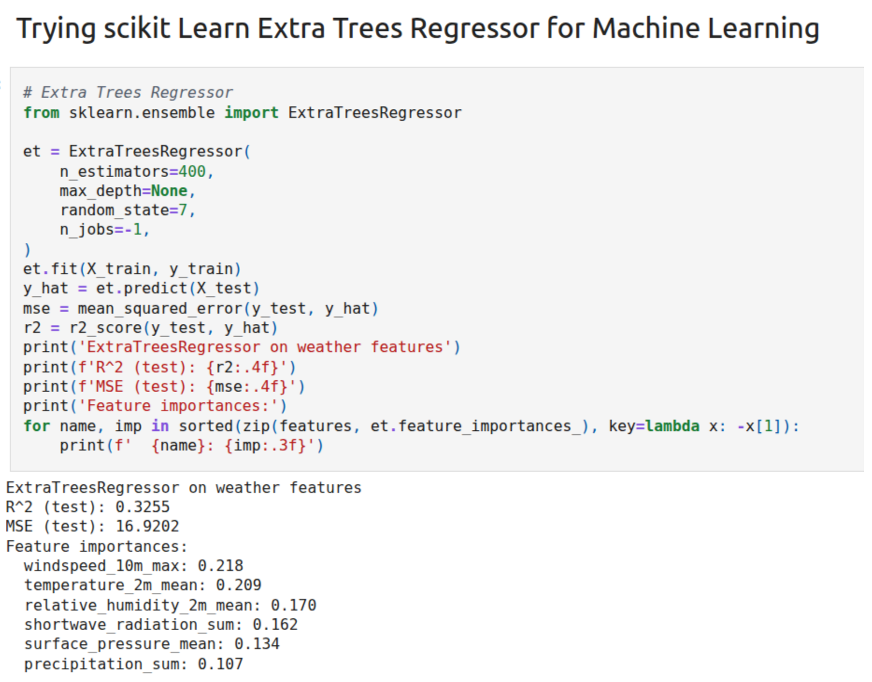
```
RandomForestRegressor on weather features
R^2 (test): 0.3165
MSE (test): 17.1466
Feature importances:
  temperature_2m_mean: 0.241
  windspeed_10m_max: 0.240
  relative_humidity_2m_mean: 0.157
  shortwave_radiation_sum: 0.145
  surface_pressure_mean: 0.143
  precipitation_sum: 0.074
```

The tree-based model performs not
looks like the best path forward her

Trying scikit Learn Gradient Bo

```
# Gradient Boosting Regressor
from sklearn.ensemble import GradientBoost

gbr = GradientBoostingRegressor(random_sta
gbr.fit(X_train, y_train)
y_hat = gbr.predict(X_test)
mse = mean_squared_error(y_test, y_hat)
r2 = r2_score(y_test, y_hat)
print('GradientBoostingRegressor on weathe
print(f'R^2 (test): {r2:.4f}')
print(f'MSE (test): {mse:.4f}')
print('Feature importances:')
for name, imp in sorted(zip(features, gbr.
    print(f'  {name}: {imp:.3f}')
```

```
GradientBoostingRegressor on weather featur
R^2 (test): 0.2510
MSE (test): 18.7892
Feature importances:
  temperature_2m_mean: 0.285
  windspeed_10m_max: 0.195
  relative_humidity_2m_mean: 0.170
  surface_pressure_mean: 0.157
  precipitation_sum: 0.100
  shortwave_radiation_sum: 0.093
```



Trying scikit Learn Extra Trees Regressor for Machine Learning

```
# Extra Trees Regressor
from sklearn.ensemble import ExtraTreesRegressor

et = ExtraTreesRegressor(
    n_estimators=400,
    max_depth=None,
    random_state=7,
    n_jobs=-1,
)
et.fit(X_train, y_train)
y_hat = et.predict(X_test)
mse = mean_squared_error(y_test, y_hat)
r2 = r2_score(y_test, y_hat)
print('ExtraTreesRegressor on weather features')
print(f'R^2 (test): {r2:.4f}')
print(f'MSE (test): {mse:.4f}')
print('Feature importances:')
for name, imp in sorted(zip(features, et.feature_importances_), key=lambda x: -x[1]):
    print(f'  {name}: {imp:.3f}')
```

```
ExtraTreesRegressor on weather features
R^2 (test): 0.3255
MSE (test): 16.9202
Feature importances:
  windspeed_10m_max: 0.218
  temperature_2m_mean: 0.209
  relative_humidity_2m_mean: 0.170
  shortwave_radiation_sum: 0.162
  surface_pressure_mean: 0.134
  precipitation_sum: 0.107
```

4. Changes After Proposal

a. 4.2 Bottlenecks and Challenges

Working with real EPA AQS and Open-Meteo data brought different hurdles than synthetic data. The public APIs limited us to day-level pulls, so we had to request year-by-year data and handle occasional missing or malformed records. Merging on date_local surfaced nulls, duplicates, and the need to coerce everything to numeric while dropping negatives without losing legitimate high pollution events. Weather-only features had weak signals for PM2.5, so even after trying multiple models (linear baselines and tree ensembles) the R^2 remained modest, especially in the out-of-time 2021 test. I also skipped imputation and time-based/lag features to keep the pipeline simple, which reduced sample size and likely hurt generalization. Overall, the main challenges were limited predictive power in the available features, careful cleaning without erasing real extremes, and ensuring the 2020-trained model didn't overfit one year's patterns when evaluated on 2021.

5. Conclusion and Future Work

a. 5.2 Future Directions

For my final model, I combined EPA AQS daily PM2.5/AQI data with daily meteorological features from Open-Meteo in order to predict daily PM2.5 levels in Middlesex County. The hope was that, by aligning real pollution measurements with weather conditions (temperature, humidity, wind, pressure, precipitation, and radiation), the model would learn a stable relationship between meteorology and air quality. In practice, however, the final model performance was relatively weak. Even after careful cleaning, merging, and feature scaling, the regression model explained only a modest portion of the day to day variation in PM2.5, and its out-of-time predictions for 2021 were poor. In other words, the combined EPA AQS and Open-Meteo dataset did not "tell" the model enough to make accurate daily predictions, especially on the days that matter most (high-pollution events).

One of the main reasons for this is that PM2.5 is driven by many factors that are not fully captured in the dataset I used. Local weather certainly influences pollution (for example, calm winds and temperature inversions can trap pollutants near the ground), but emissions themselves come from sources like traffic, industries, residential heating, construction, and long-range transport of smoke or haze from other regions. None of that source information is present in my features: there are no traffic counts, no emission inventories, no indicators for wildfires, no upwind pollution data, and no land-use or regional transport variables. As a result, the model is trying to say that it is an extremely complex process from a relatively small amount of indirect predictors. The regression model can pick up some seasonal patterns (such as higher or lower average pollution in certain months), but, with not adequate or large enough data, it struggles to predict the exact PM2.5 level on any given day just from local meteorology.

The structure of the dataset also limits what the model can learn. I am working with only two years of daily data (2020 as training and 2021 as out-of-time testing) from a single monitoring location. That means there are only a few hundred rows total, which is a very small sample size for a problem with multiple meteorological predictors and potentially complex interactions. Daily aggregation also hides sub-daily variation, pollution can change rapidly within a day, but my model only sees one average value per day. On top of that, air quality is highly autocorrelated in time (today's PM2.5 strongly depends on yesterday's), yet my final model did not include explicit lag features (like "yesterday's PM2.5") or moving averages as predictors. All of this makes it difficult for a relatively simple model, such as linear regression, to capture the true temporal structure of the pollution process.

The cleaning and preprocessing choices also affect the signal the model can use. To make the dataset strictly model-ready, I dropped rows with missing values in the target and key features, removed obviously invalid negative PM2.5 readings, and merged on dates that appeared in both the AQS and Open-Meteo data. While this produced a clean, fully numeric dataset, it also reduced the sample size further and removed some potentially informative, but messy, days. I deliberately kept extreme positive PM2.5 values (treating them as real high-pollution events rather than outliers), but these spikes are the hardest to predict from weather alone. The model tends to underestimate them because they are rare, and because the emission causes behind those spikes are not encoded in the feature set. As a result, even if the average error looks moderate, the model is not reliable on the days when air quality is worst.

Even though the final model was not particularly strong in terms of predictive accuracy, the process still revealed important insights about the limitations of using only weather and a single monitoring site to model pollution. The coefficients and correlation plots suggested some expected relationships (for example, certain wind and humidity patterns are associated with cleaner or dirtier days), but these effects were not strong enough to support high-quality forecasts on their own. In that sense, the EPA AQS and Open-Meteo data "didn't tell us much" in a predictive sense. However, they allowed me to describe patterns and build a basic regression model, but not to build a robust, operational air-quality forecasting tool.

Overall, the final model highlights that real-world environmental prediction is much more complex than just linking weather and pollution at one site. To significantly improve performance, I would likely need richer features (such as emissions data, traffic or mobility information, regional transport indicators, or more stations), more years of data, and potentially more advanced modeling approaches that explicitly handle time-series structure and nonlinear relationships. In that context, my project is best understood as a proof-of-concept. It demonstrates how to retrieve, clean, merge, and model EPA AQS and Open-Meteo data, while also showing the limits of what those data alone can explain about daily PM2.5 behavior.