Comparing CMAQ Forecasts with a Neural Network Forecast Model for $PM_{2.5}$ in New York

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1.Motivation

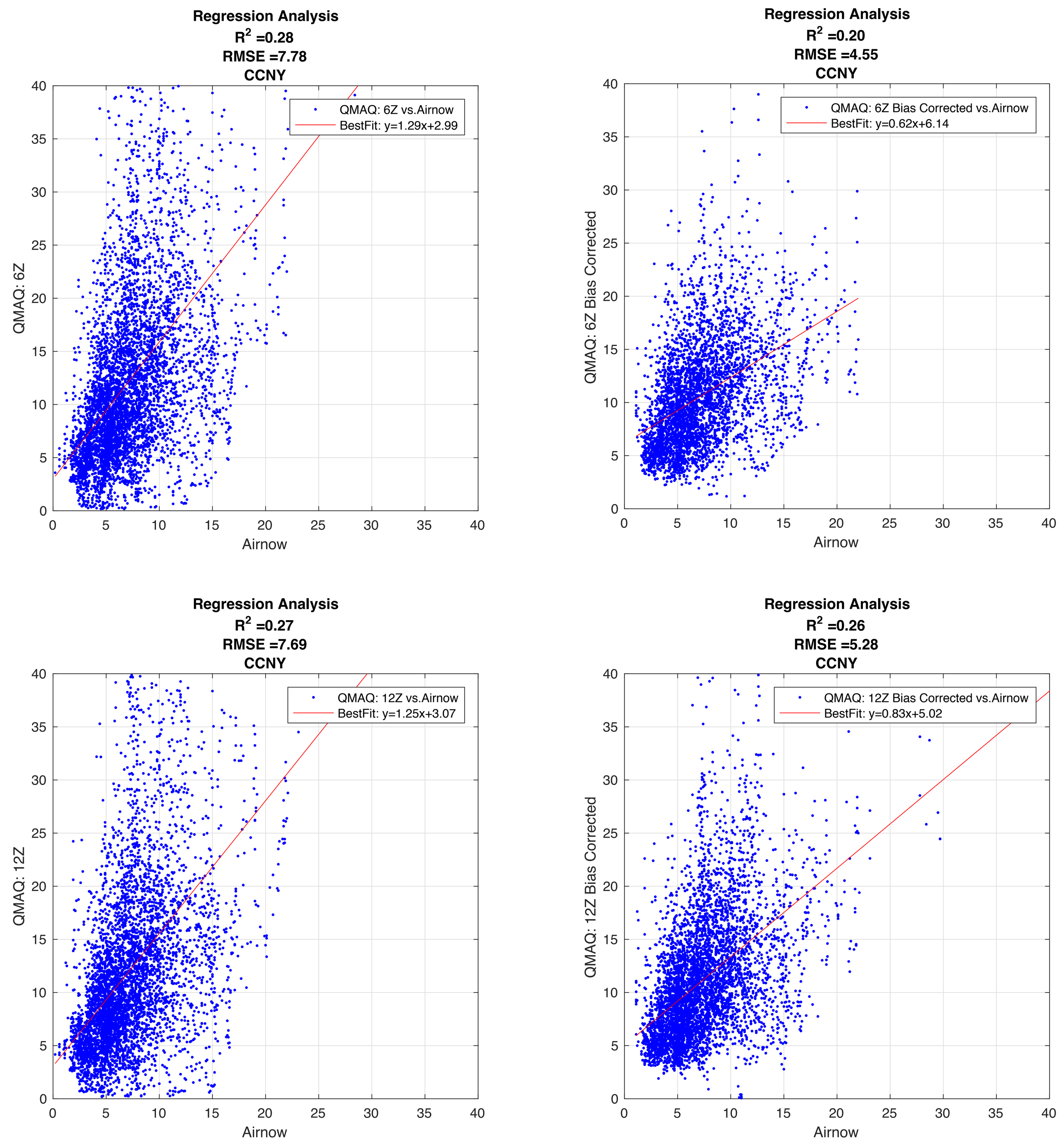
- Human Health is strongly affected by the ambient concentration of Fine Particulate Matters, PM2.5, suspended in the air including inorganic sulfates, nitrates as well as biomass products such as smoke.
- The Environmental Protection Agency (EPA) has developed 24 hour concentration guidelines for PM2.5 and has set up a network of PM2.5 monitoring stations.
- Surface sampling is quite expensive and existing networks are very limited resulting in data gaps that can affect the ability to forecast PM2.5 over a 24 hour period
- Using CMAQ PM2.5 outputs pushed to us from Jeff McQueen of NOAA-ESRL, we explore the baseline performance of both their uncompensated forecasts and bias compensated forecasts against the New York State Airnow PM2.5 monitors. (Time Period 0-8 months)
- To improve the current forecast methods, we explore the use of a Neural Network, incorporating meteorological, locational, and seasonal date into our model.
- Because of the relatively few high pollution events, standard statistical learning algorithms may at times be less effective. Therefore, it is important to identify other signatures of high pollution. Therefore, we propose the use of forward trajectories that follow air –parcel motion based on meteorological model wind fields, allowing us to track sources down wind.

2.CMAQ Assessment

Datasets

- Forecast model: CMAQ V4.6 (CB05 gas-phase chemistry)
    - 12 km horizontal resolution
    - North American Model Non-hydrostatic Multiscale Model (NAM-NMMB) meteorology driver
- Ground-based Observations: NYSDEC – Airnow
- Time period: February 2016 – October 2016 (based on availability)

Regression Analysis: Effects of Bias and Release Time



	R^2 - 6UTC	R^2 - 12UTC	RMSE - 6UTC	RMSE - 12UTC
Standard	0.28	0.27	7.78	7.69
Bias Corrected	0.20	0.26	4.55	5.28

Results

- All forecasts from the CMAQ model over CCNY have a positive correlation
- The effect on the forecast for different release times, if any, is minimal
- Standard model generally overestimates the ground
- Bias correction improves the over-prediction, the results are more dispersed
    - Bias correction decreases RMSE, but it also decreases the R^2 value for both release times

3.Neural Network

Neural Network Design Overview

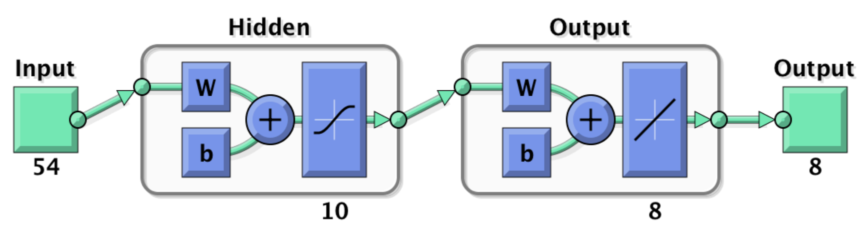
- Make a distinction between NYC and non-NYC models
- Create individual models for specific regions to account for different underlying emissions that are not quantified easily
- Explore the connections between the ground PM2.5 data and the atmospheric vertical profiles (PBL height)
- Besides aerosol-related data and environment conditions, seasonal (i.e. month) information will be added which allows for indirect inclusion of different emissions during different times of the year.

Inputs

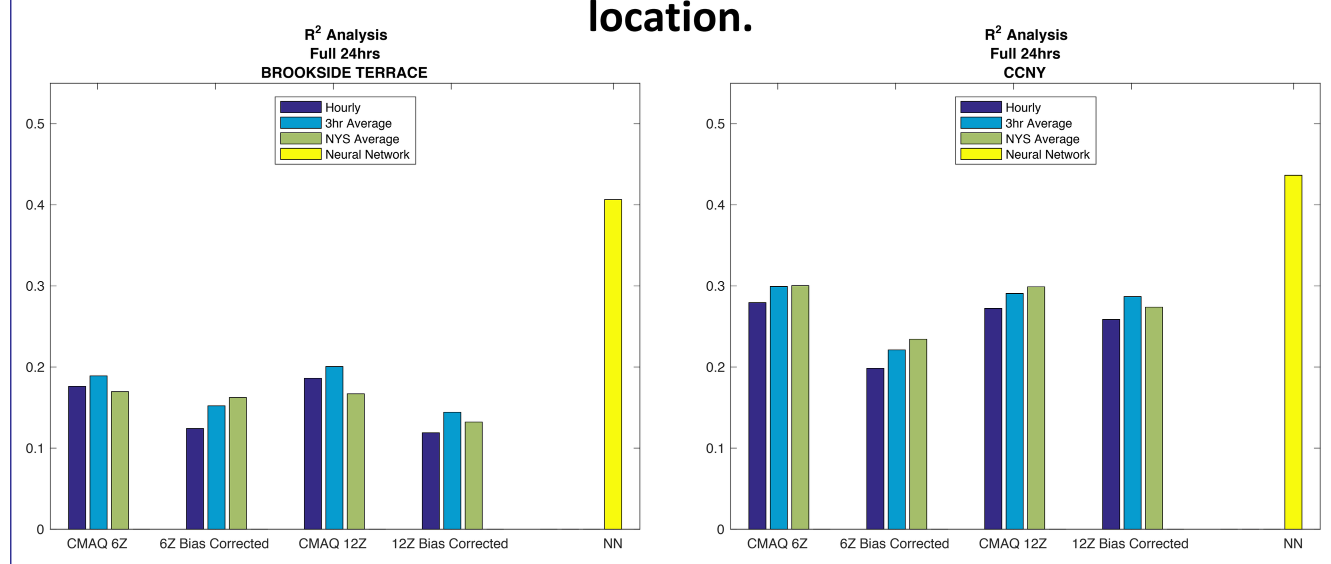
Month	PM2.5 from observations	Forecast/Observed Meteorological
1 input	5 inputs	Temp, PBL, P, RH, U+V Wind 6x8 =48 inputs

Targets

PM2.5
8 outputs



Regression Analysis: The R2 value for CMAQ and the NN, both compared to AirNow observations, is computed for each forecast model and for each location.



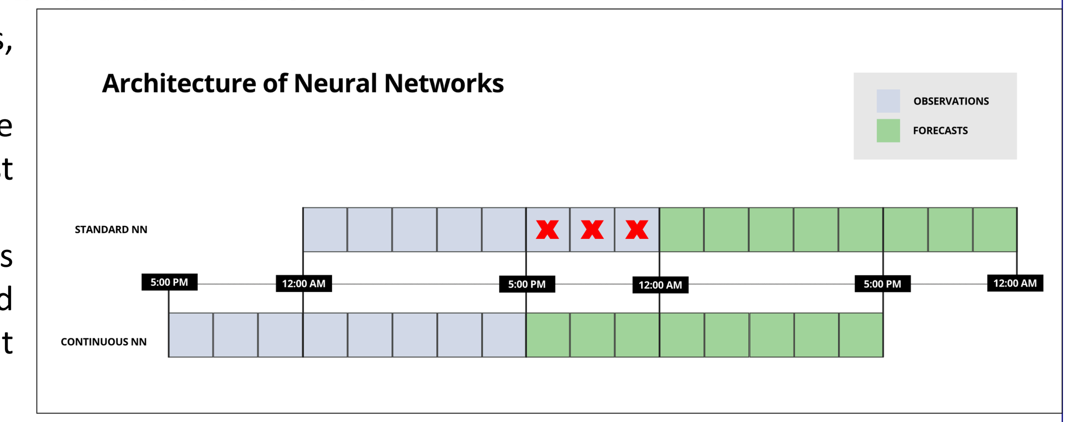
Results

- Most accurate forecast model is the the NN for both NYS and NYC
- New York City vs. New York State
    - CMAQ shows better performance in NYC
    - NN shows little contrast between urban and non-urban
        - Locational inputs in the model, such as the surface pressure, improves forecasting skill
- Time averaging improves CMAQ results
- Release time has minimal effect
- Spatial averaging over NYS shows more improvement in most NYC cases and some non-NYC cases as well
- Possibility best use of CMAQ is on a regional level
- NN approach generally results in a more accurate prediction of future pollution levels, as compared to CMAQ, for a single grid cell

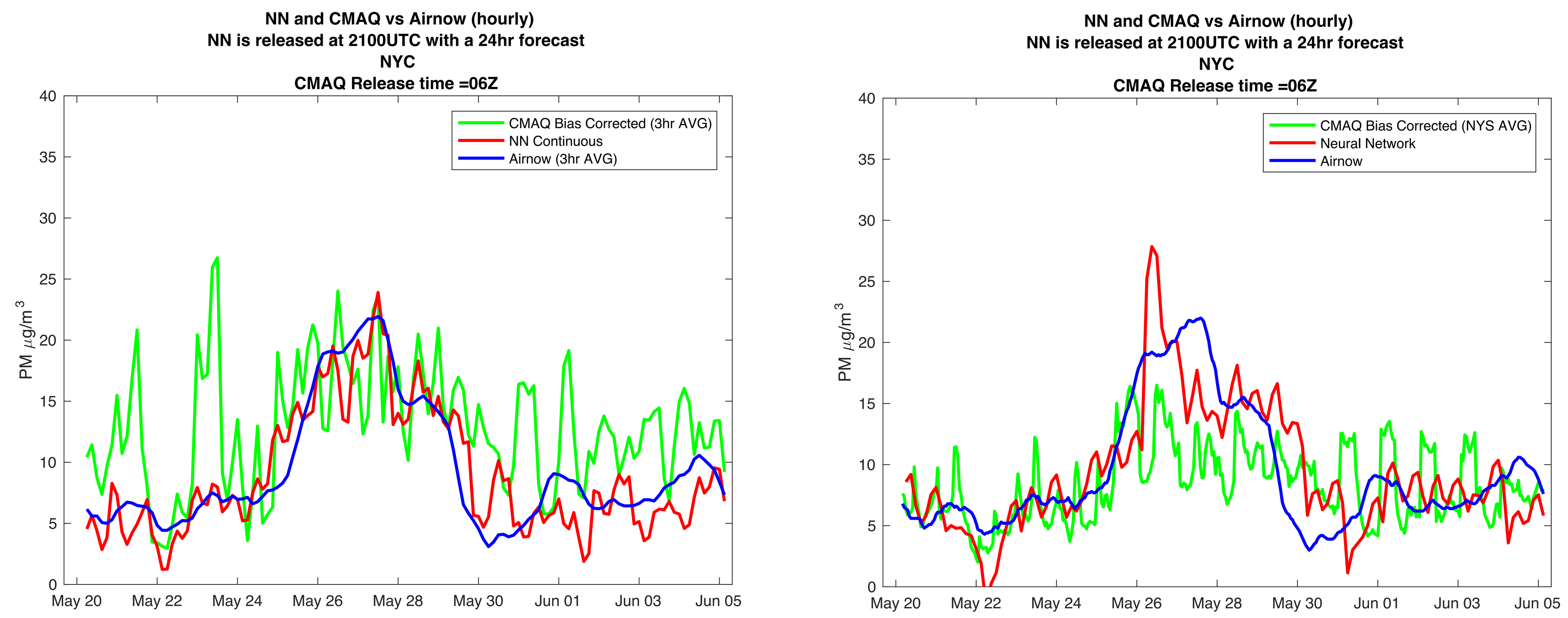
4.Heavy Pollution Transport Events

Design of Continuous Neural Network

- In the training of the NN, there were very few extreme event cases, PM2.5 >25µg/m3
- The lack of suitable training statistics for these events causes the NN approach to have difficultly in adjusting to the sharp contrast with the onset of the event
- The Continuous Neural Network: a second neural network was trained with the same design as the neural network illustrated above; however, this neural network produces a 24-hour forecast at 5PM for the time period, 5PM – 5PM



Wildfires of Fort McMurray in Alberta, Canada

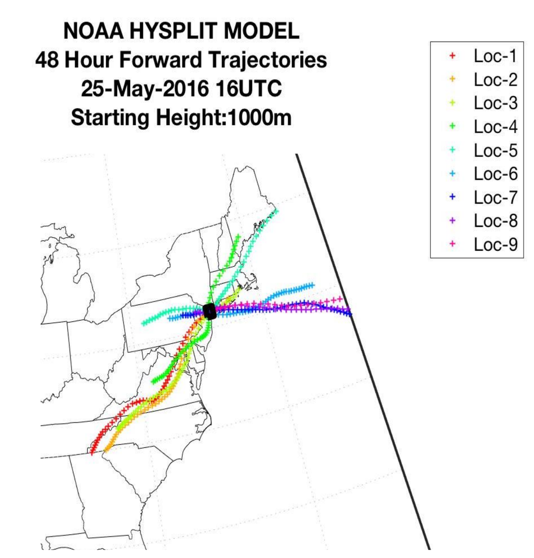


- Oscillations in the CMAQ smooth with time and spatial averaging
- It is logical that for heavy transport cases, domain averaging helps decrease oscillations; however, we still see significant underestimation of the event
- The continuous neural network is able to respond to the trend of the high pollution event faster, and more accurately, then the standard neural network.

5.Future Work

Applying satellite AOD and meteorological transport to forecast significant pollution events

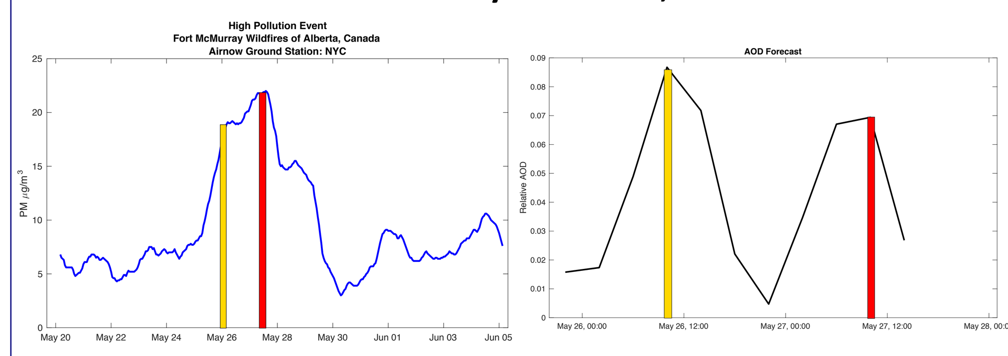
- Determine from Polar and Geostationary Satellites (including the newly launched GOES-R) and overlay AOD onto trajectories
- Quantify the cumulative pollution that the air parcel intercepts as a potential measure of transported pollution and indicator of high event conditions.
- Qualitatively assess usefulness of AOD into high pollution events
- Use ensemble forward trajectories to perform real time future forecasts



- Method: Run ensemble forward trajectories for different vertical heights and determine which trajectories lie within +0.25/- 0.25 degree of NYC and bin into transport time.
- Calculate the weighted average of the AOD bins, and project the AOD forecast onto the PM forecast.
- Relative AOD: This formula assigns an averaged AOD value for each time interval from all trajectories whose time delay is within the same time interval $\frac{1}{N_j}\sum_i AOD_{i,j}$

6.Preliminary Results

Wildfires of Fort McMurray in Alberta, Canada Revisited



- Dominant peaks of the heavy pollution event are forecasted in the AOD trajectory model
- Unfortunately, we also see some AOD valleys when PM2.5 is high
- Cloud contamination issues or poor AOD retrievals GOES-R AOD retrievals, which are superior due to high data latency and multispectral inversion capabilities

7.Conclusion

Assessment of CMAQ

- Significant dispersion as well as a tendency for the model to over estimate the ground truth field measurements
- Residuals error in the model was found to have significant bias patterns, indicating that there are predictors not included in the model that could significantly improve the results

Head to Head Comparisons

- Neural Network showed better forecasting skill for all cases, including transport events
- CMAQ improvement was found with spatial and time averaging

When GOES-R AOD retrievals, with high data latency and multispectral inversion capabilities, become available, we plan to incorporate the Relative AOD metrics as predictors in the NN.