Advancing Air Quality Forecasting
to Protect Human Health

Air quality and public health managers have an important task to protect the public health by alerting the population when forecasts predict the exceedance of national air quality standards, therefore, accurate prediction of the timing, location, and severity of unhealthy air quality episodes is critical.

Air quality forecasting is one of the key tools commonly used by state and local agencies to protect the public from adverse health effects of poor air quality. Exposures to air pollution caused 7 million premature deaths per year, making it the single largest environmental risk today.[1] In the United States, over one third of the population lives in areas not attaining the health-based National Ambient Air Quality Standards (NAAQS) for ozone (O_3) and fine particulate matter ($PM_{2.5}$).[2] Air quality and public health managers have an important task to protect the public health by alerting the population when forecasts predict an exceedance of the NAAQS. During exceedances, action days are issued and, depending on the levels of severity, specific sensitive groups or the entire population are advised to reduce outdoor activities or take other protective measures. Accurate prediction of the timing, location, and severity of unhealthy air quality episodes is, therefore, critical for decision-makers to protect human health.

How Is an Air Quality Warning Issued?

There are several steps involved in the decision-making to issue an air quality warning (see Figure 1). The basic principal of forecasting air quality, similar to that of weather forecasting, is "anchoring and adjustments". First, forecasters gather information of local weather forecasting and pollutant observations to understand the local and regional persistence and possible changes in air quality next day. Next, forecasters consult numerical model guidance, such as the National Air Quality Forecast Capability (NAQFC) operated by the National Oceanic and Atmospheric Administration (NOAA), or the AIRNow map, produced from monitoring and NAQFC prediction by EPA, for next-day air quality forecasts. Putting all the information together, forecasters make necessary adjustments using a variety of methods, including statistical analysis (regression and clustering) and heuristic "expert analysis," to the air quality guidance before producing the officially released air quality advisory. Within forecasters' toolbox, air quality forecasting systems, such as the NAQFC, are a central piece for many states to produce timely air quality advisories.

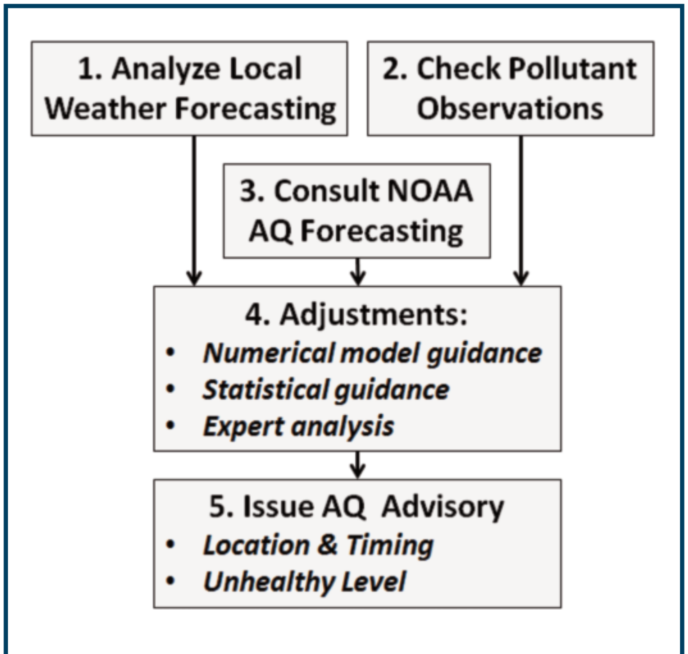

Figure 1. Decision-making process of air quality warning to protect public health.

Recent Advancements in Air Quality Forecasting

A number of advancements have been made to improve the NAQFC system, driven largely by emerging issues caused by drastic socioeconomic and environmental changes. Examples of such changes include economic recession, oil/gas production, rising dust storms and wildfires, and natural disasters such as volcanic eruptions.

Rapid Emission Refresh

An air quality forecasting system has two key inputs: meteorology and emissions. Emissions are often provided by the National Emission Inventories (NEIs). It often takes several years to come up with new NEIs, which become outdated quickly due to rapid changes in emission sources. Consequently, outdated emission data impose large uncertainties on air quality forecasting. To reduce emission time lag, a new technique, called rapid emission refresh, recently emerged to improve time-sensitive modeling applications, such as air quality forecasting. Rapid emission refresh utilizes near-real-time observations from satellites and ground monitors to update either emission data directly, or the parameters used to calculate emissions.

One of the successful stories is to apply this technique to study the air quality impact of the 2008 Great Recession.[3] The Great Recession, kicked off by the bursting of an US$8 trillion housing bubble, was blamed for a loss of 8.4 million jobs, as well as a substantial decrease in air pollutant emissions in the United States.[4,5] The impact is quantified by comparing O_3 concentrations under two model scenarios: business-as-usual (BAU) and recession.

Under the BAU scenario, the emission projection from the Cross-State Air Pollution Rule (CSAPR) is used to estimate the "would-be" NOx emissions level in 2011. In the recession case, the actual NOx trends observed from ground monitors and the Ozone Monitoring Instrument (OMI) on the Aura satellite are used to obtain "realistic" changes in NOx emissions. The Great Recession was shown to cause a1–2 parts per billion by volume (ppbv) decrease in surface O_3 concentration over the eastern United States, a slight increase (0.5–1 ppbv) over the Rocky Mountain region, and mixed changes in the Pacific West.

Oil and Gas Emissions

Recent rapid increase in unconventional oil and gas production raised concerns about health impacts. For instance, emissions in an oil/gas basin elevated wintertime surface O_3 well above national air quality standards.[6] As the O_3 standards are tightened and oil/gas production continues to increase, it is therefore important to account for the fast changing emissions from oil and gas production. A new method has been developed to project emission inventories using annual energy production data. Model simulations with an NAQFC experimental system suggest that oil/gas emissions could have considerable impacts on air quality with active oil/gas production.

Windblown Dust and Wildfires

As many western states see more frequent droughts, windblown dust storms and wildfires become an increasing concern. In the past three decades, wildfires have increased in number and size across western North America, and the trend will continue in response to further warming.[7] This will, inevitably, lead to substantially higher risk of fire damages to human health and properties. Meanwhile, the frequency of dust storms has increased by 240 percent from the 1990s to 2000s.[8] Rising dust activity imposes myriad effects on the environment and society, including poor air quality, infectious diseases, highway and aviation safety, cropland erosion, and reduced solar energy productivity.

Unlike traditional emission sources, wildfires and dust storms are more difficult to predict. Sophisticated emission models and satellites are often needed to forecast these intermittent events. Over North America there is an interesting phenomenon, called "Tax Day dust storm". Each year, on the day when Americans file their tax returns, one or more large dust storms often sweep across the Southwest.

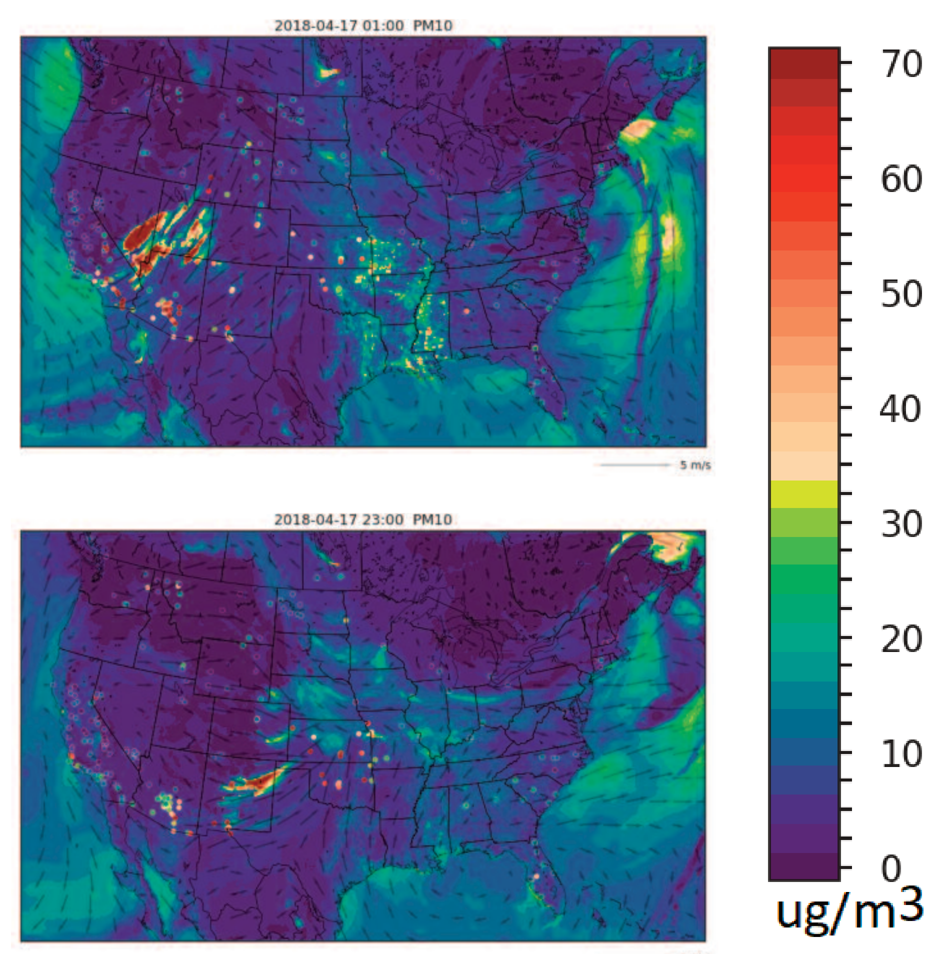

Figure 2. Forecasts of two dust storms (shown in red with high PM_{10} concentrations) during the 2018 Tax Day (April 17, 2018). Courtesy of Barry Baker.

Figure 2 shows the forecast of the "Tax Day" dust storms in 2018. On April 17, 2018–the extended income tax return deadline due to a computer failure at the Internal Revenue Service–two dust storms swept over Nevada, Arizona, Utah, and New Mexico. The forecasts of high winds and reduced visibility caused by dust storms led the Utah Department of Transportation to prohibit high-profile trucks to enter Highway I-80, a precautionary action to prevent fatal accidents during a 2015 dust storm in this region.

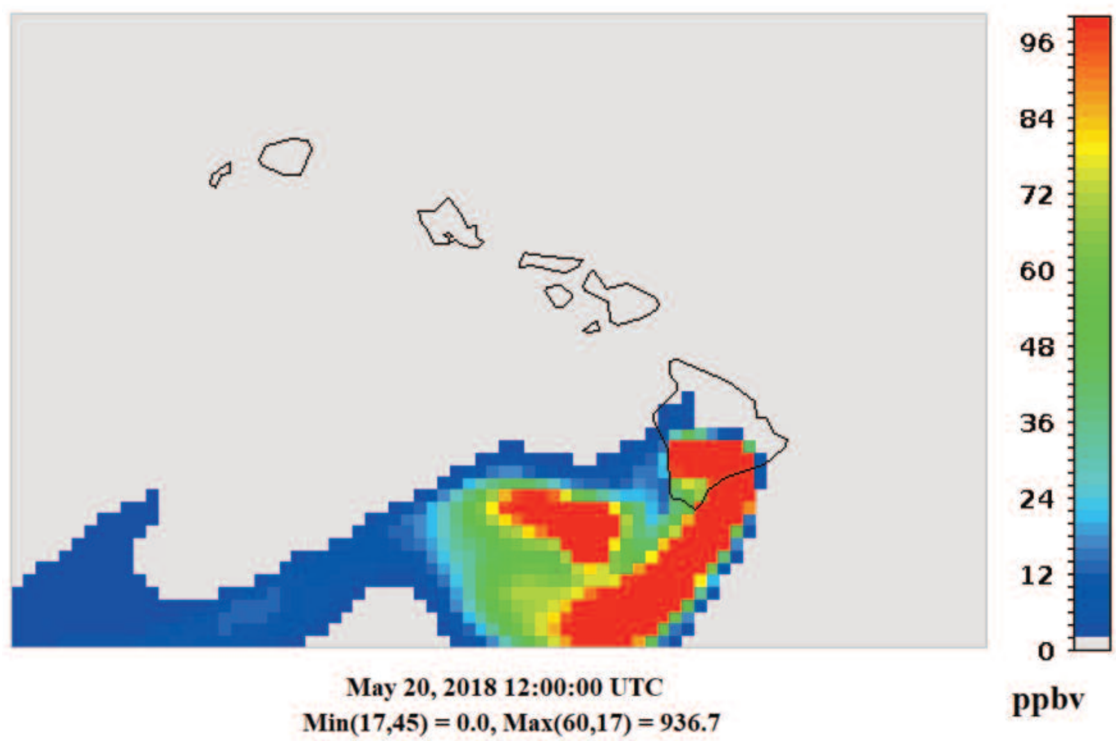

Figure 3. Predicted surface SO_2 concentration over Hawaii from Kilauea volcanic emissions, May 2018.

Volcanic Eruption

The recent eruption of the Kilauea volcano in Hawaii highlights another need for air quality forecasting: providing predictive air quality data for emergency response. At times of natural disasters such as volcanic eruptions, elevated levels of toxic gases and particles can result in severe health stress among the people living in the impacted areas and further downwind. Advanced air quality forecasting systems can be equipped with near-real-time emission estimates to provide critical air quality data to assess population exposure to volcanic smog (vog) and to assist in developing effective evacuation plans, if necessary.

Near-real-time estimates of volcanic emissions can be made from sulfur dioxide (SO_2) and aerosol vertical column density by satellite sensors, such as OMI and Ozone Mapping Profiling Suite (OMPS). The health-based air quality standard for SO_2 is 75 ppbv, which has been frequently exceeded in the areas downwind to the Kilauea volcano during the eruption on May 17, 2018 (see Figure 3).

Chemical Data Assimilation

Similar to weather forecasting, air quality forecasting benefits greatly from assimilating near-real-time observations from ground monitors and satellites. Chemical data assimilation techniques have been developed to improve initial conditions of chemical transport models and yield better prediction by blending the information from a model estimate (referred to as prior or background) and from observations in certain methods.[9] The purpose is to eliminate the accumulated biases in the model system.

One method is direct blending, for instance, using observed chemical mass concentrations to correct the modeled mass concentrations. This approach is relatively straightforward, as they are directly comparable. Since most monitoring data are captured near the surface, this method is usually applied to near-surface field. Another method is indirect guessing, such as comparing satellite retrieved aerosol optical depth (AOD) with modeled AOD to estimate the biases of modeled column mass concentrations and make the corresponding adjustment. Depending on the quality of observations used in data assimilation, the overall effect of this technique is to reduce the difference between the modeling field and the true field as represented by the observations.

Challenges and Future Directions

Advancements in air quality forecasting allow improved early warning to protect human health. Innovative approaches have been developed to address emerging air quality issues. As emissions from traditional sources decrease, unconventional and intermittent sources become increasingly important at regional and national scales. Assimilating near-real-time data, such as satellite observations, proves an effective measure to improve forecasting performance, calling for further development of emission rapid refresh and chemical data assimilation techniques. **em**

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