

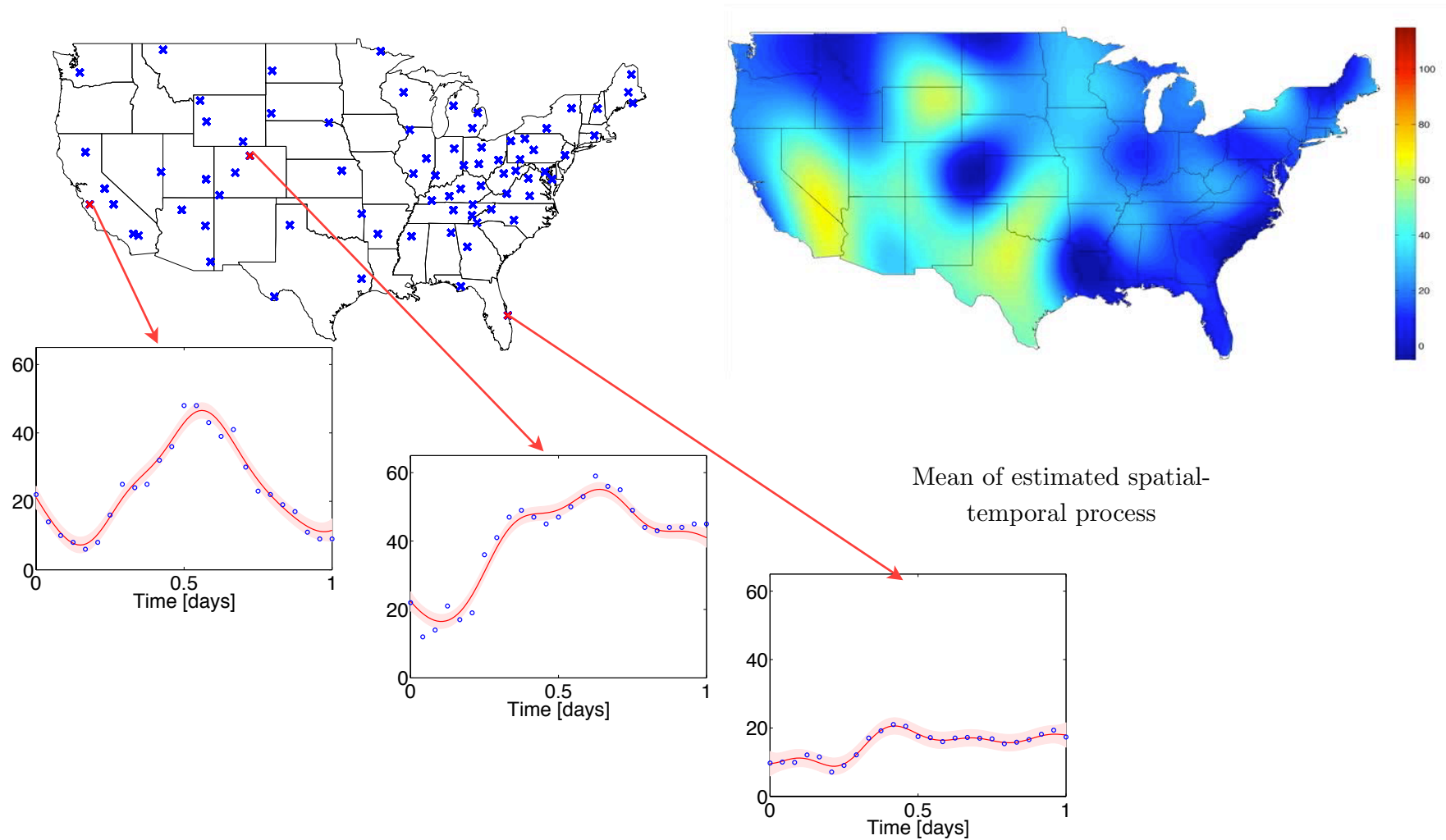
A Platform for Air Quality Forecast

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Ozone forecast



Current Approaches



Simple empirical models: fast, easy to use, but inaccurate

Advanced, physically-based approaches: accurate in specific locations, computationally expensive, not very adaptable to other environments

Statistical approaches: provides uncertainty on the predictions, learns complex spatial-temporal patterns, computationally expensive, difficult to implement

Prior belief

Likelihood function

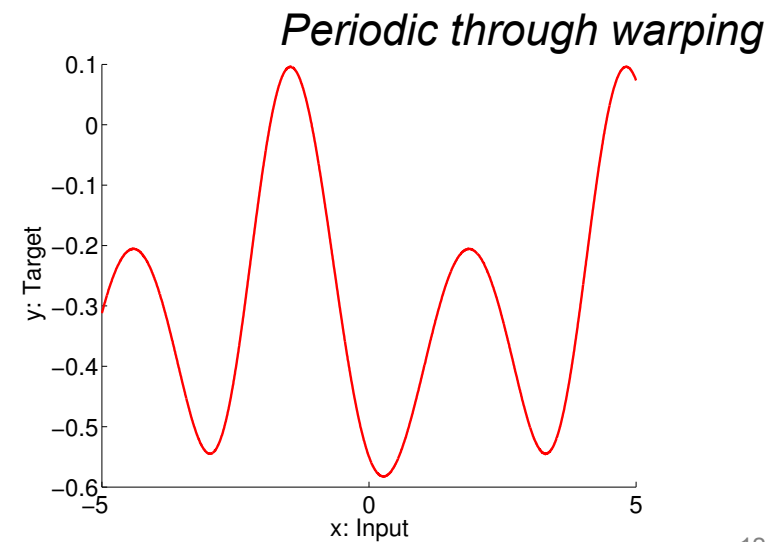
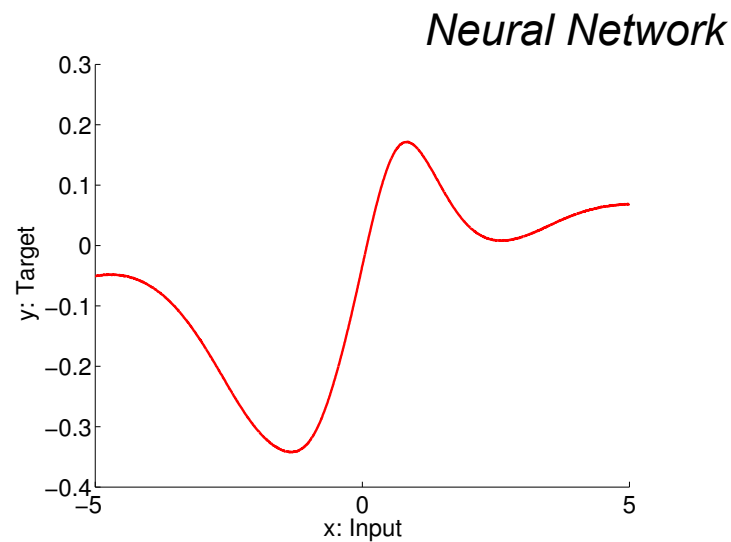
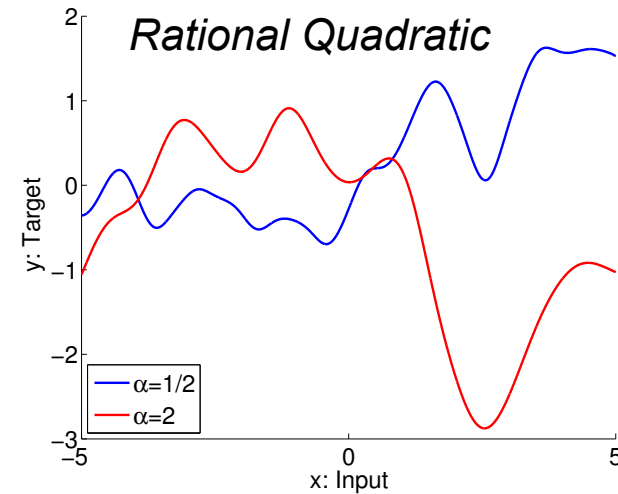
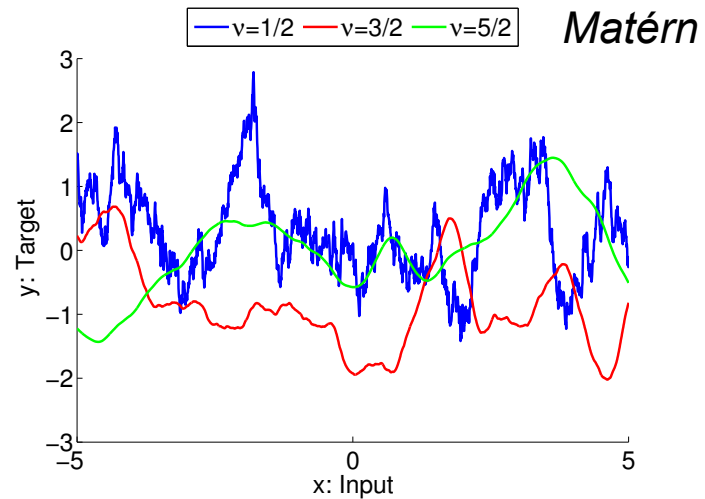
$$P(m|\mathbf{d}) = \frac{P(m)P(\mathbf{d}|m)}{\int_m P(m)P(\mathbf{d}|m)dm}$$

Posterior Belief

A Bayesian approach allows us to:

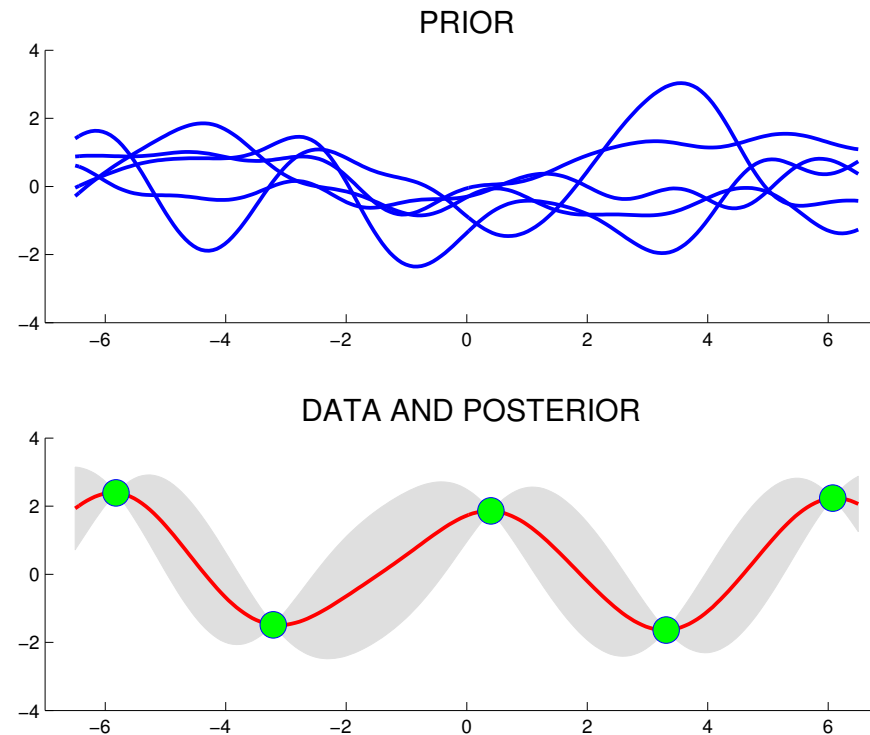
- Quantify risk – probability distribution over possible models
- Use all available data – data fusion
- Update our hypothesis with new data
- Improve decision support

Priors over functions



Bayesian modelling

$$\text{posterior} \propto \text{prior} \times \text{likelihood}$$



- A prior over the weights induces a prior over functions
 - e.g. smooth functions
 - Closeness in input space $\rightarrow$ closeness in output space

Automatic Parameter Estimation



Given a set of samples

$$X = [\mathbf{x}_0, \dots, \mathbf{x}_{N-1}]^T$$

$$\mathbf{y} = [y_0, \dots, y_{N-1}]^T$$

Choose a covariance function

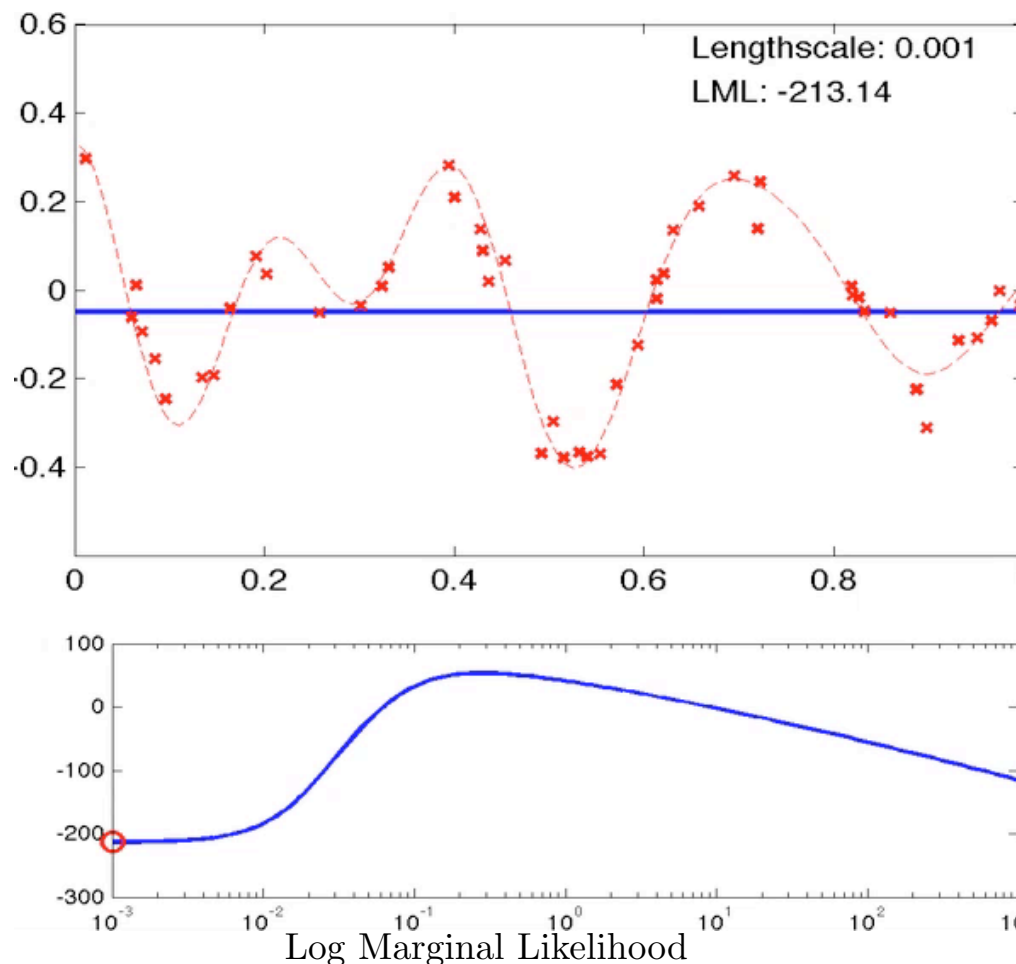
$$k(\mathbf{x}_i, \mathbf{x}_j \mid \theta)$$

Predict the value of $f(\mathbf{x}_*)$

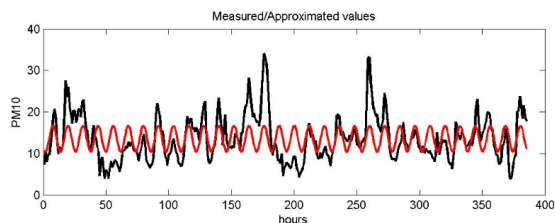
Mean $\mu(f(\mathbf{x}_*))$

Variance $\sigma(f(\mathbf{x}_*))$

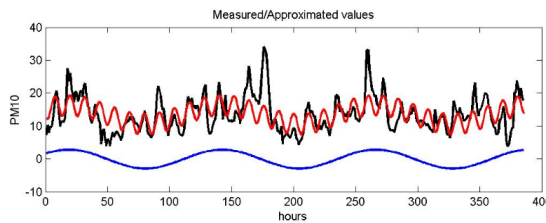
Regression



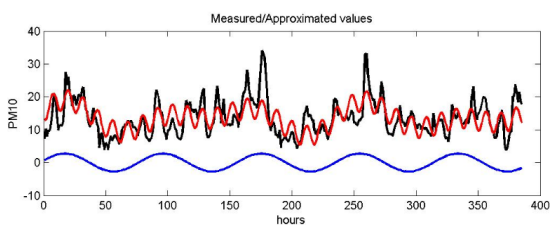
Learning Temporal Patterns



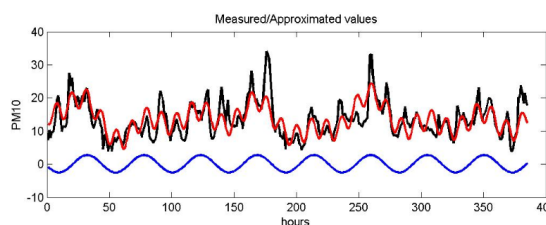
(a) Period of 12 hours



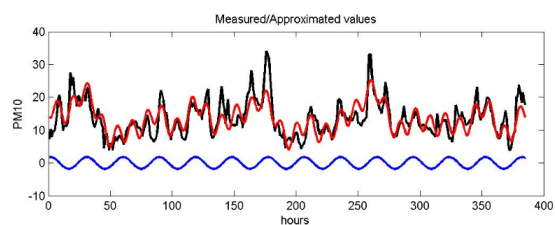
(b) Period of 123 hours



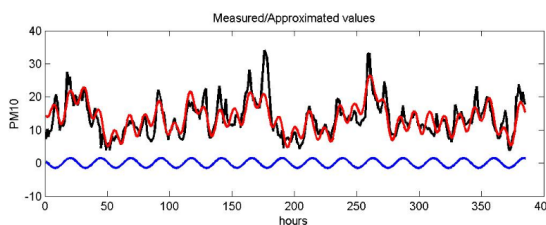
(c) Period of 79 hours



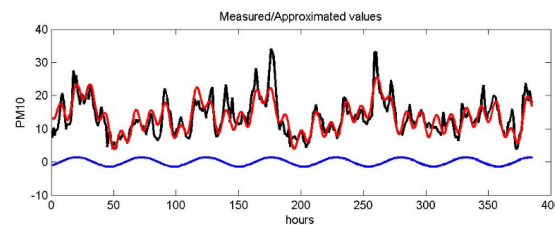
(d) Period of 45 hours



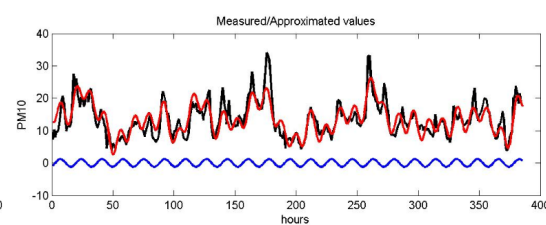
(e) Period of 29 hours



(f) Period of 24 hours

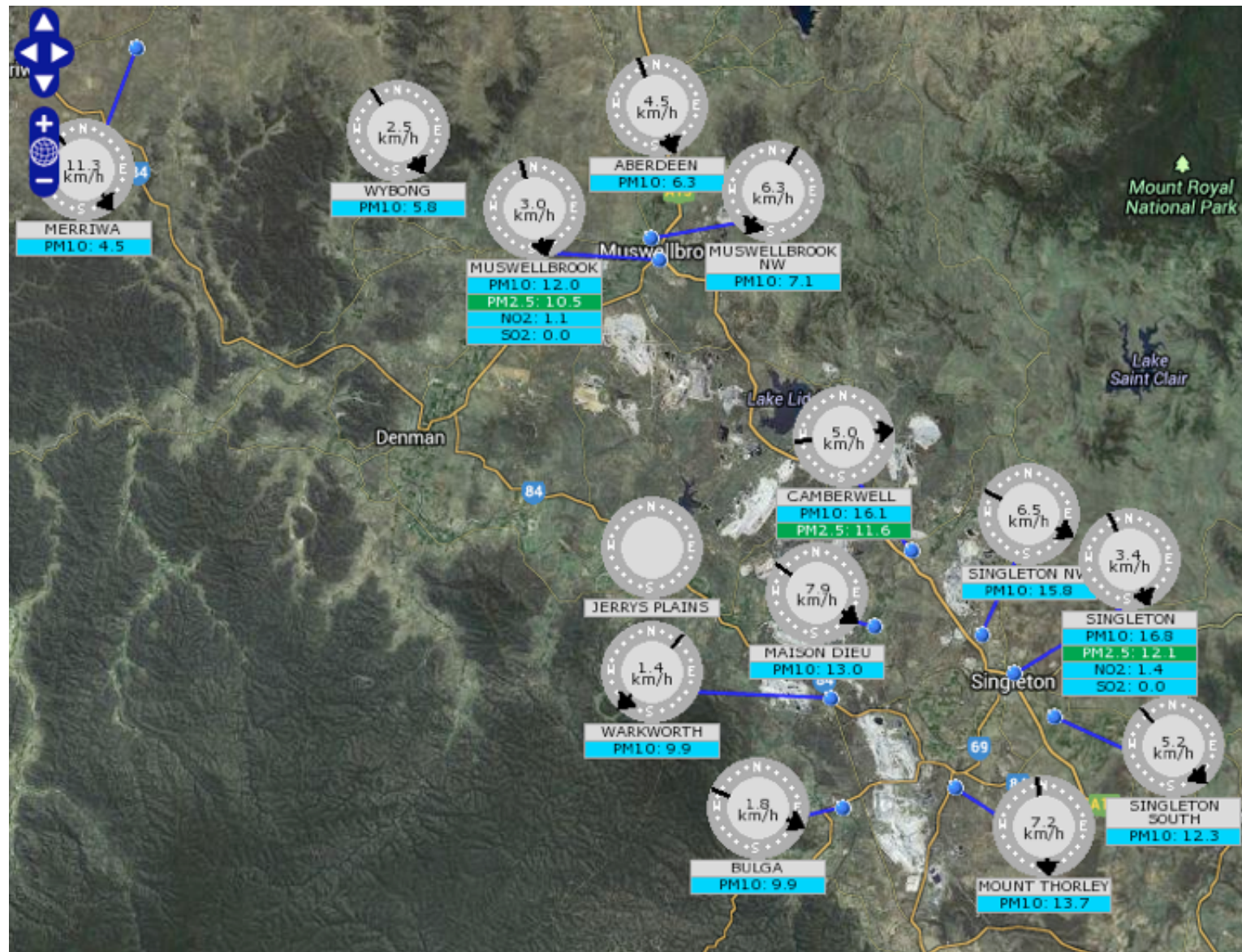


(g) Period of 52 hours



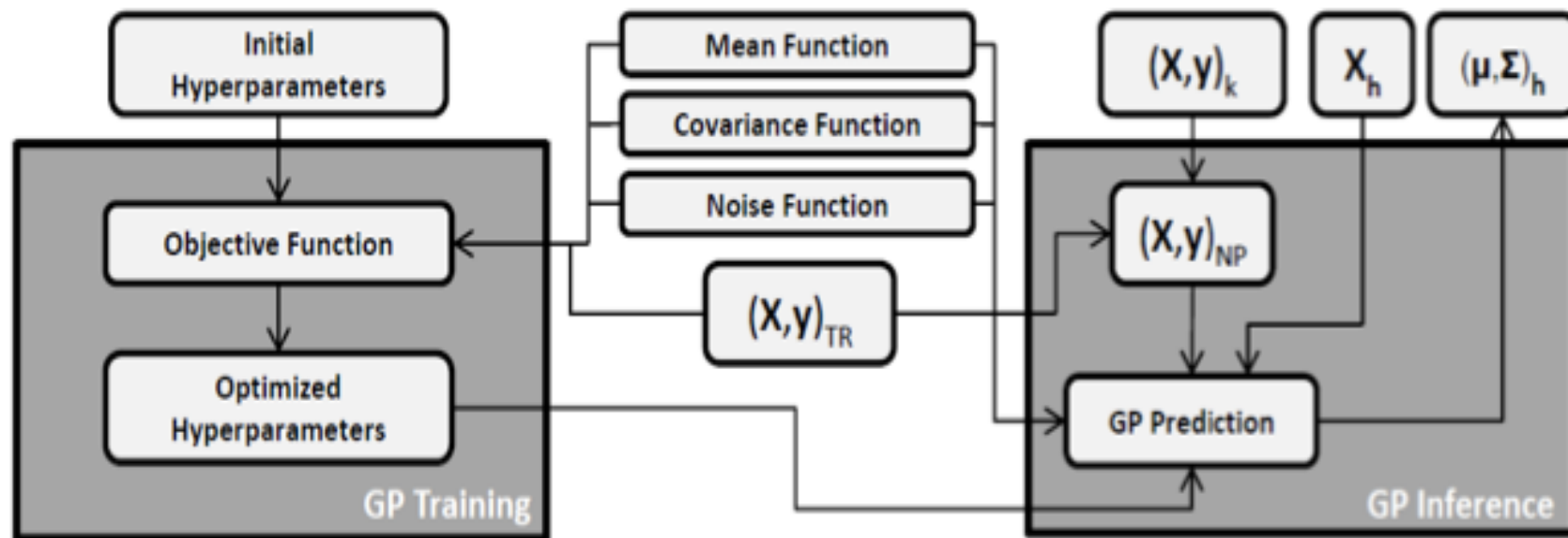
(h) Period of 17 hours

Case Study - Hunter Valley



First Approach: Separate Models

Body Level One

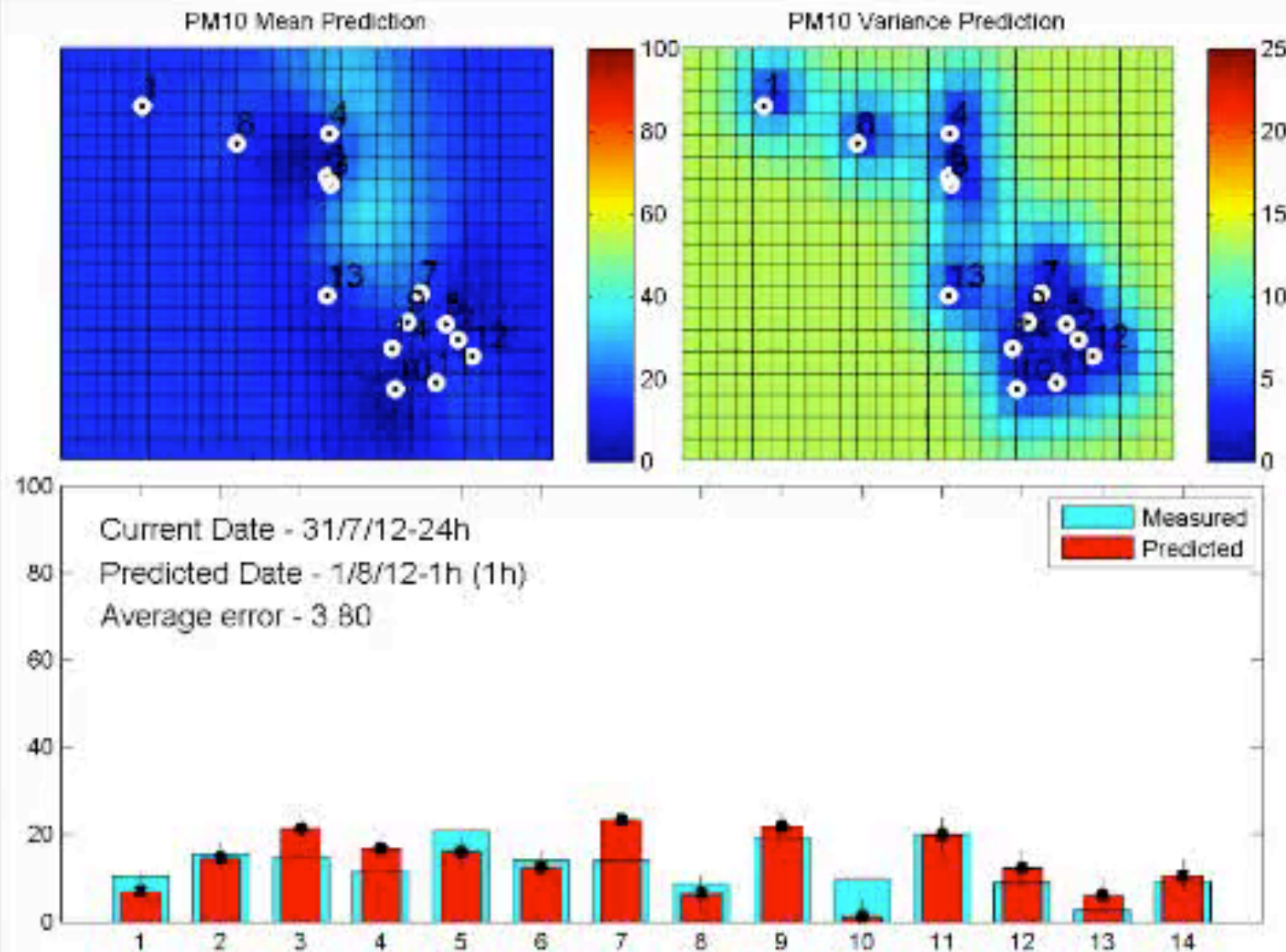


From space and time to PM10

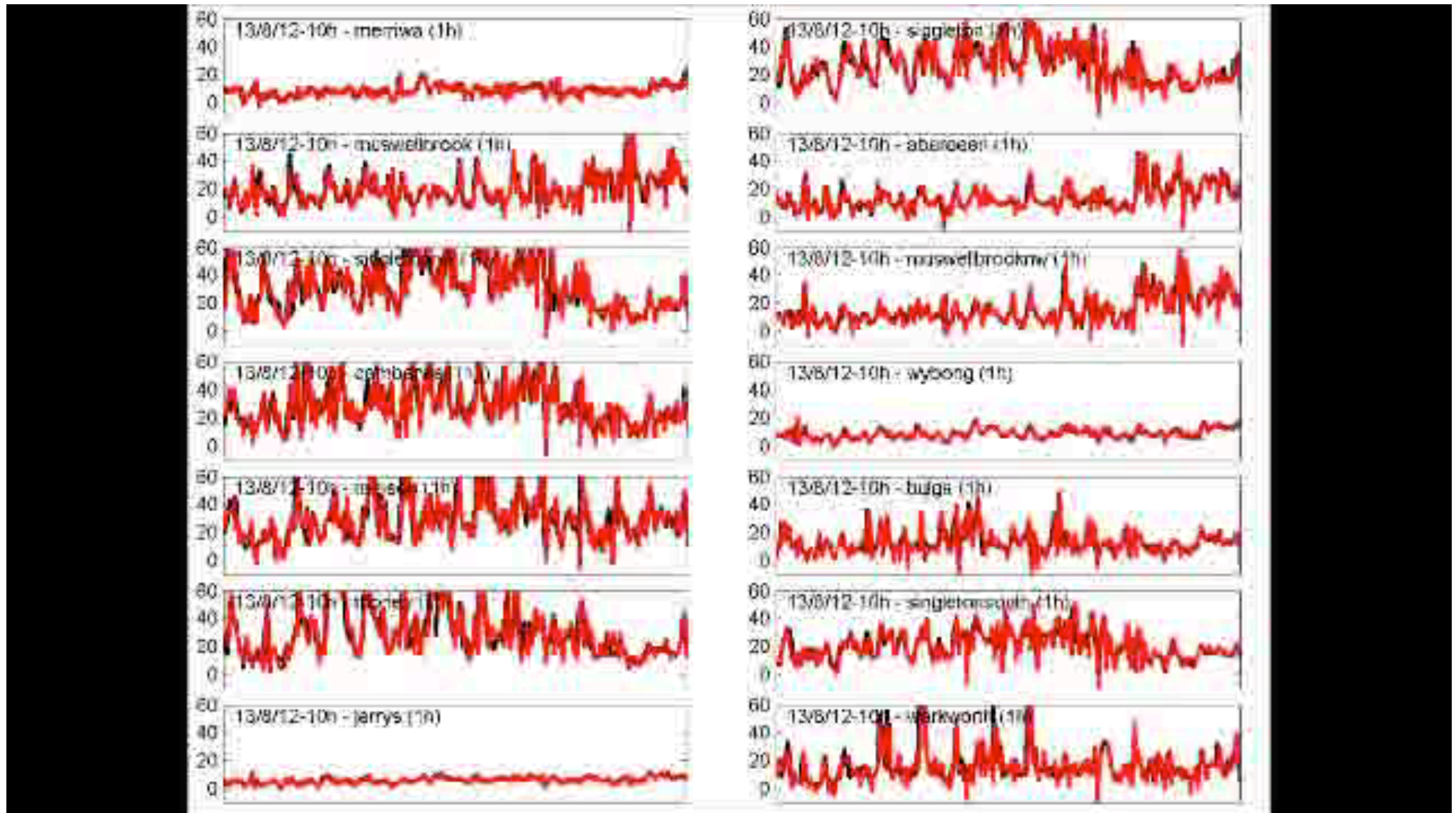
From space and time to PM2.5

From space, time, and PM10 to PM2.5

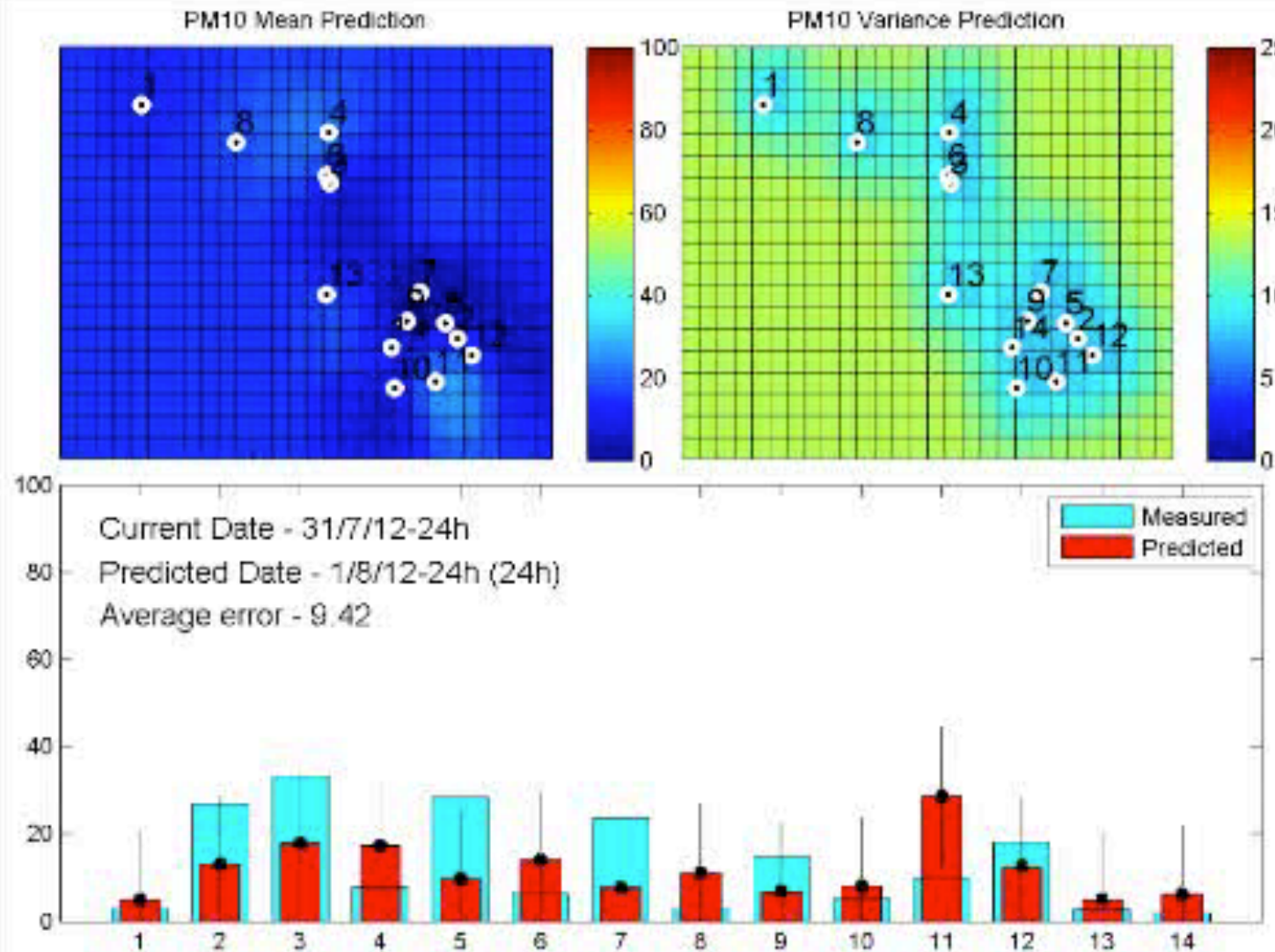
PM10 1-hour prediction



PM10 1-hour prediction

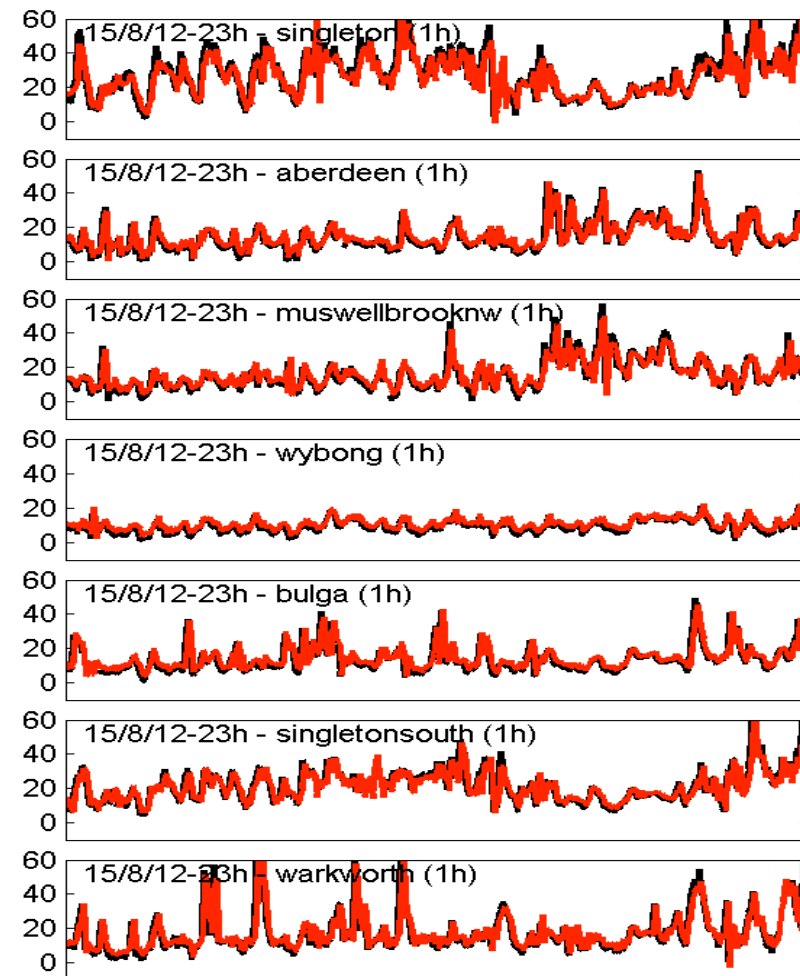
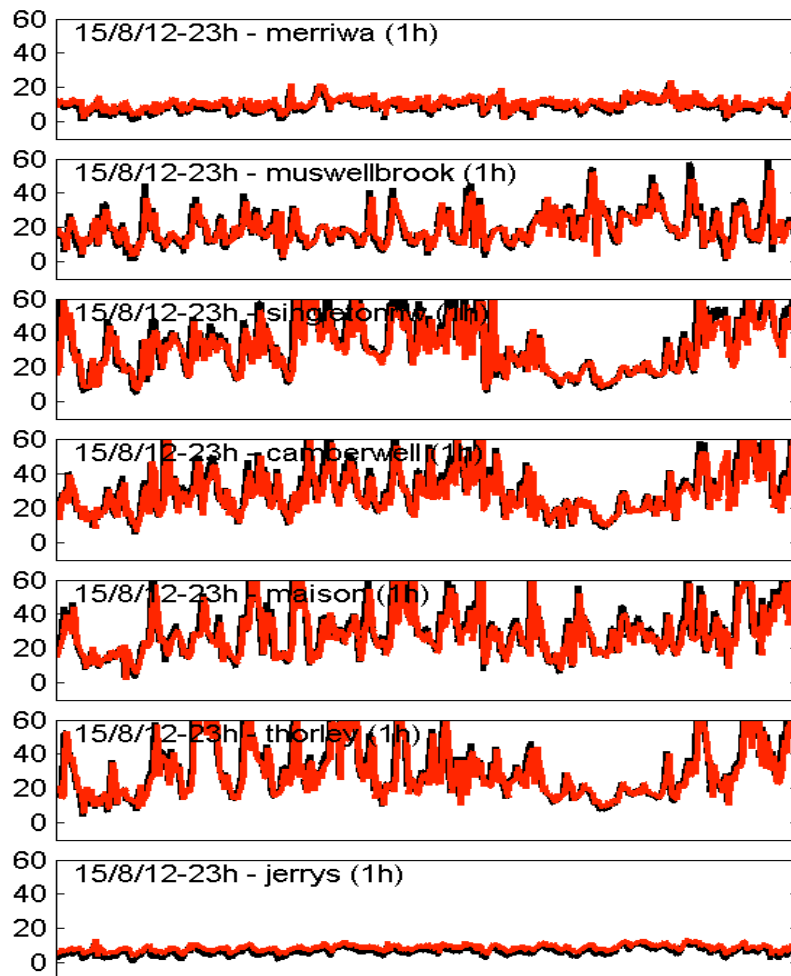


PM10 24-hour prediction



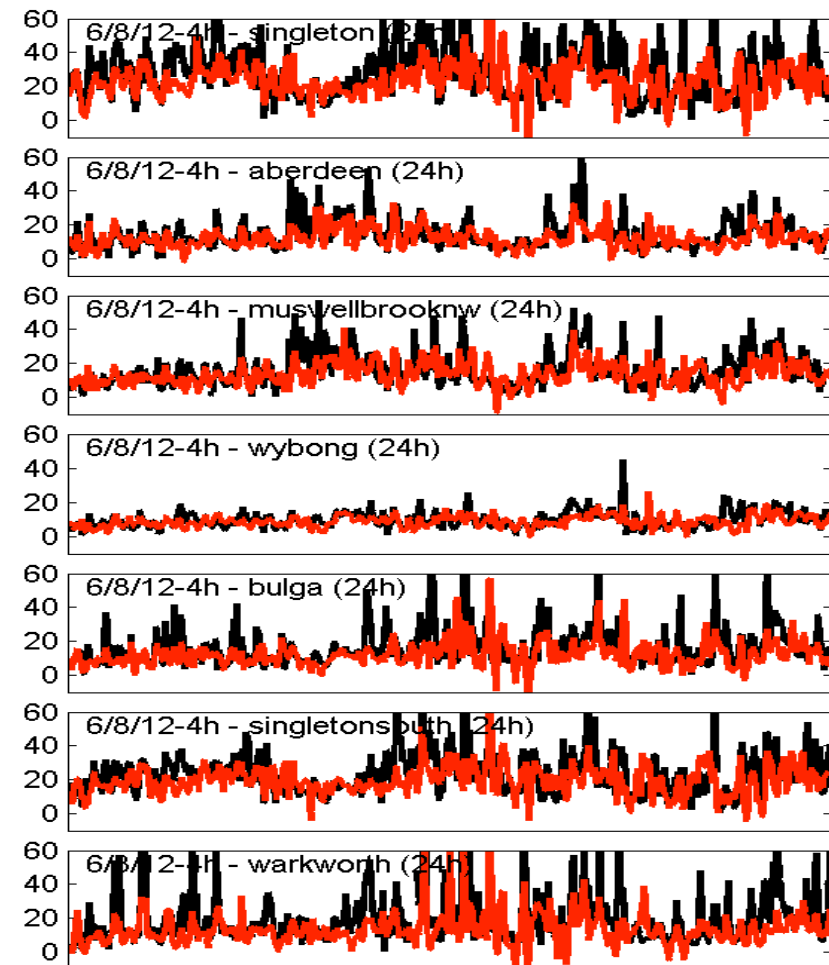
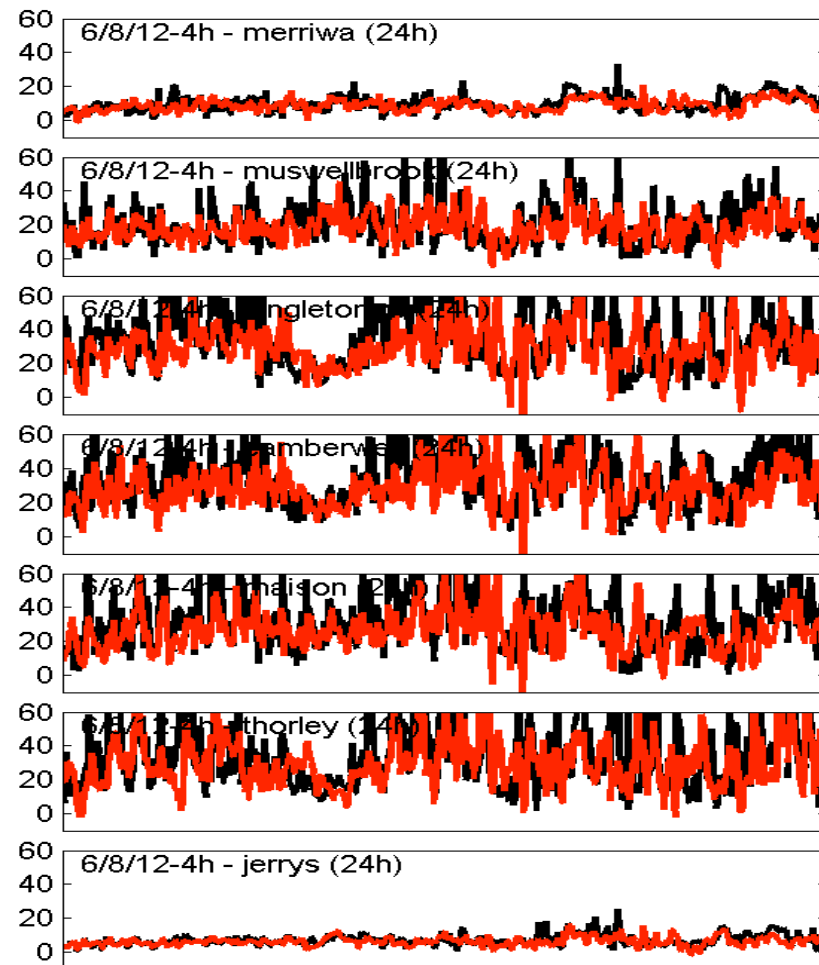
Experimental Results

• PM10 – 1h individual sensor prediction



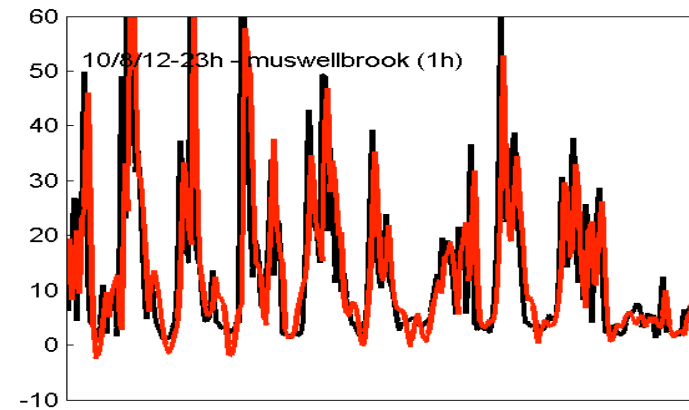
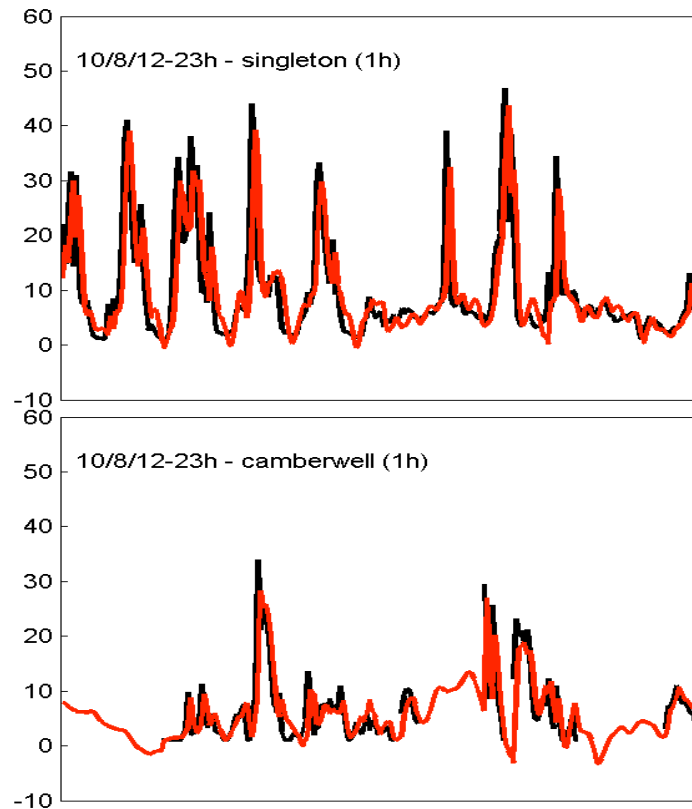
Experimental Results

• PM10 – 24h individual sensor prediction



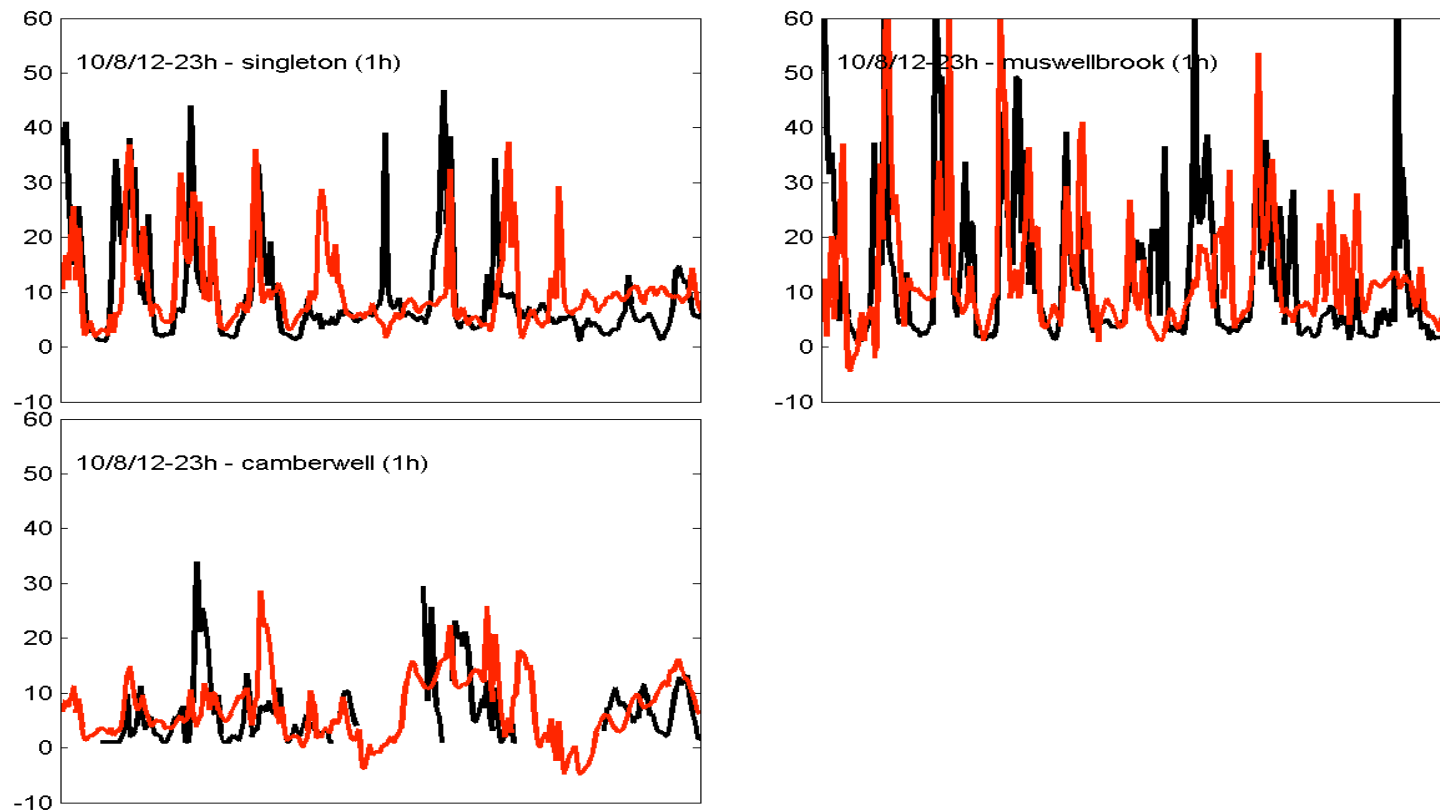
Experimental Results

- **PM2.5 – 1h individual sensor prediction**

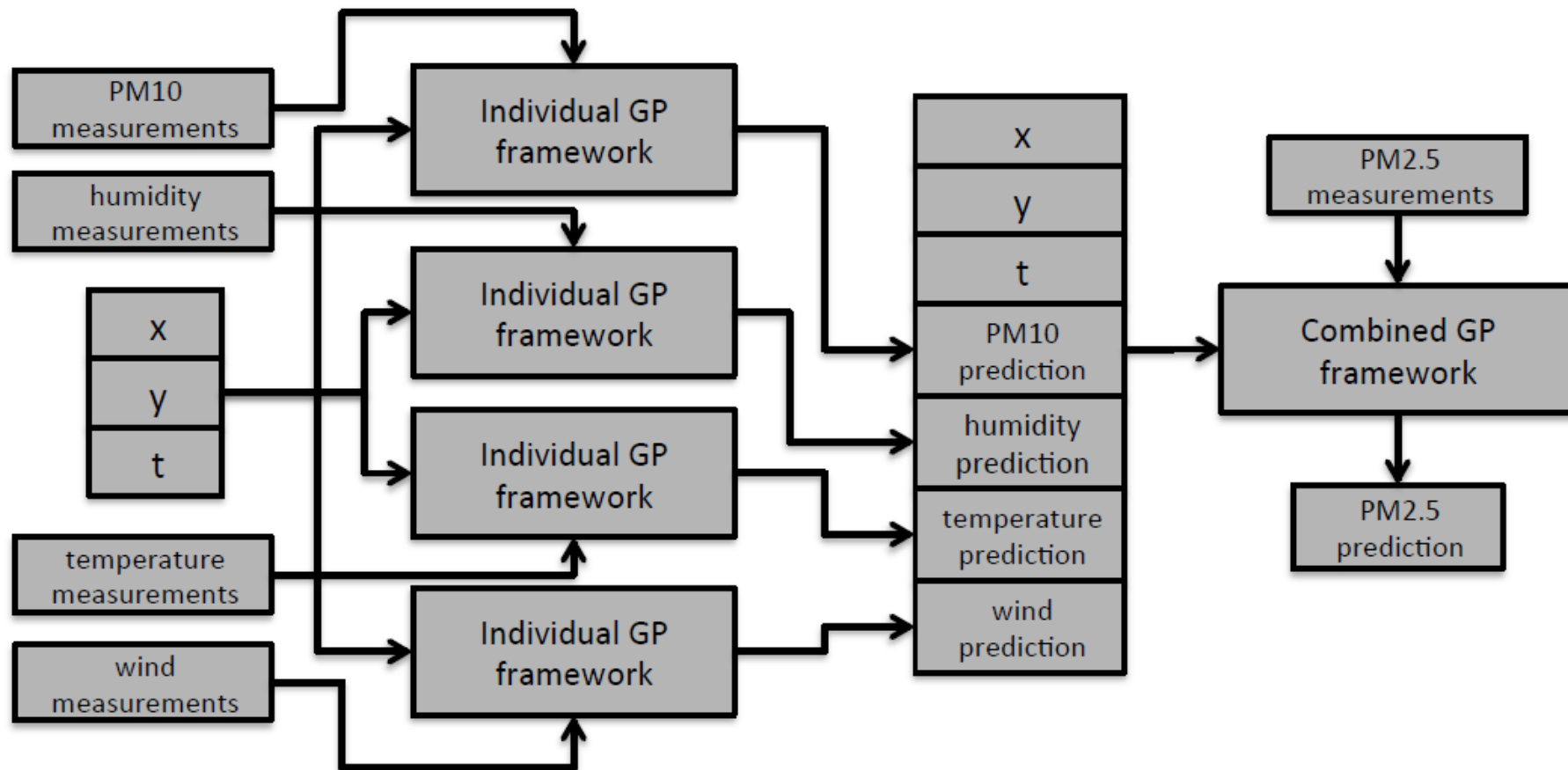


Experimental Results

● PM2.5 – 24h individual sensor prediction

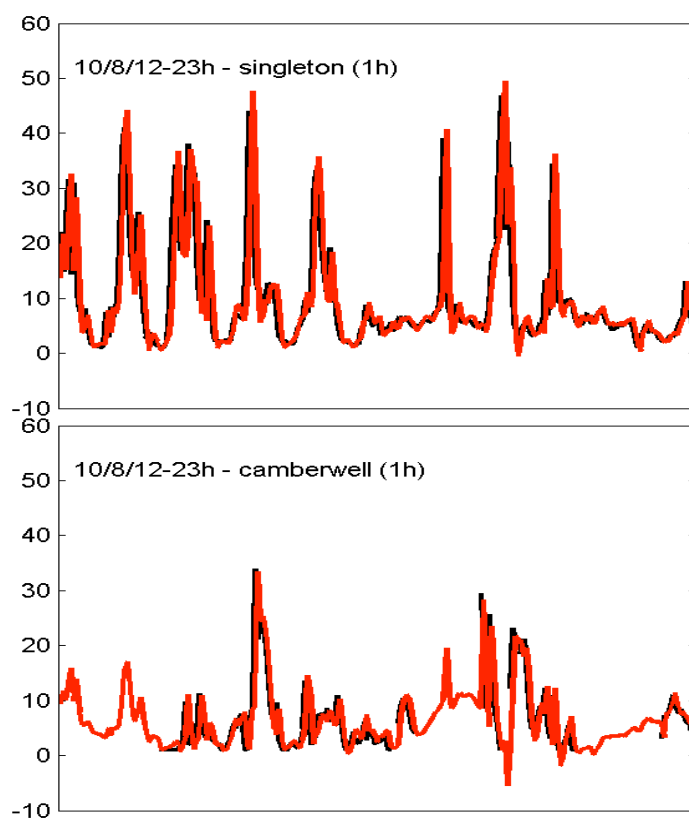


Second Approach: All Together



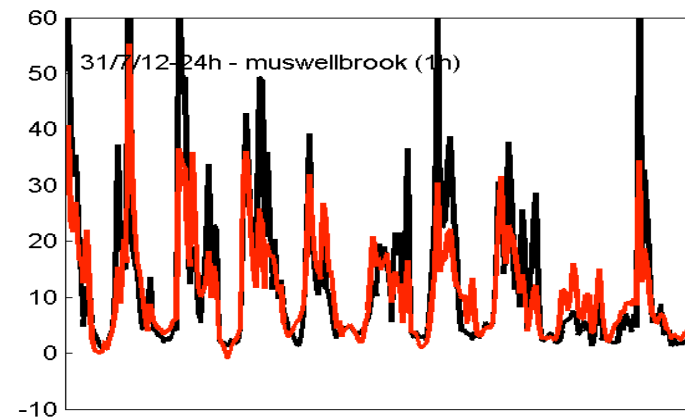
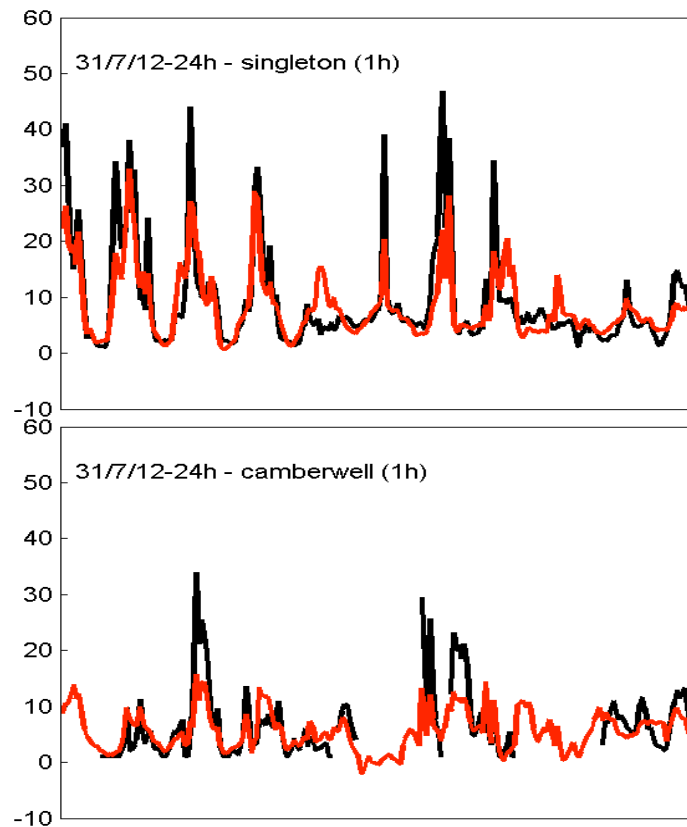
Experimental Results

- **PM2.5 + PM10 – 1h individual sensor prediction**



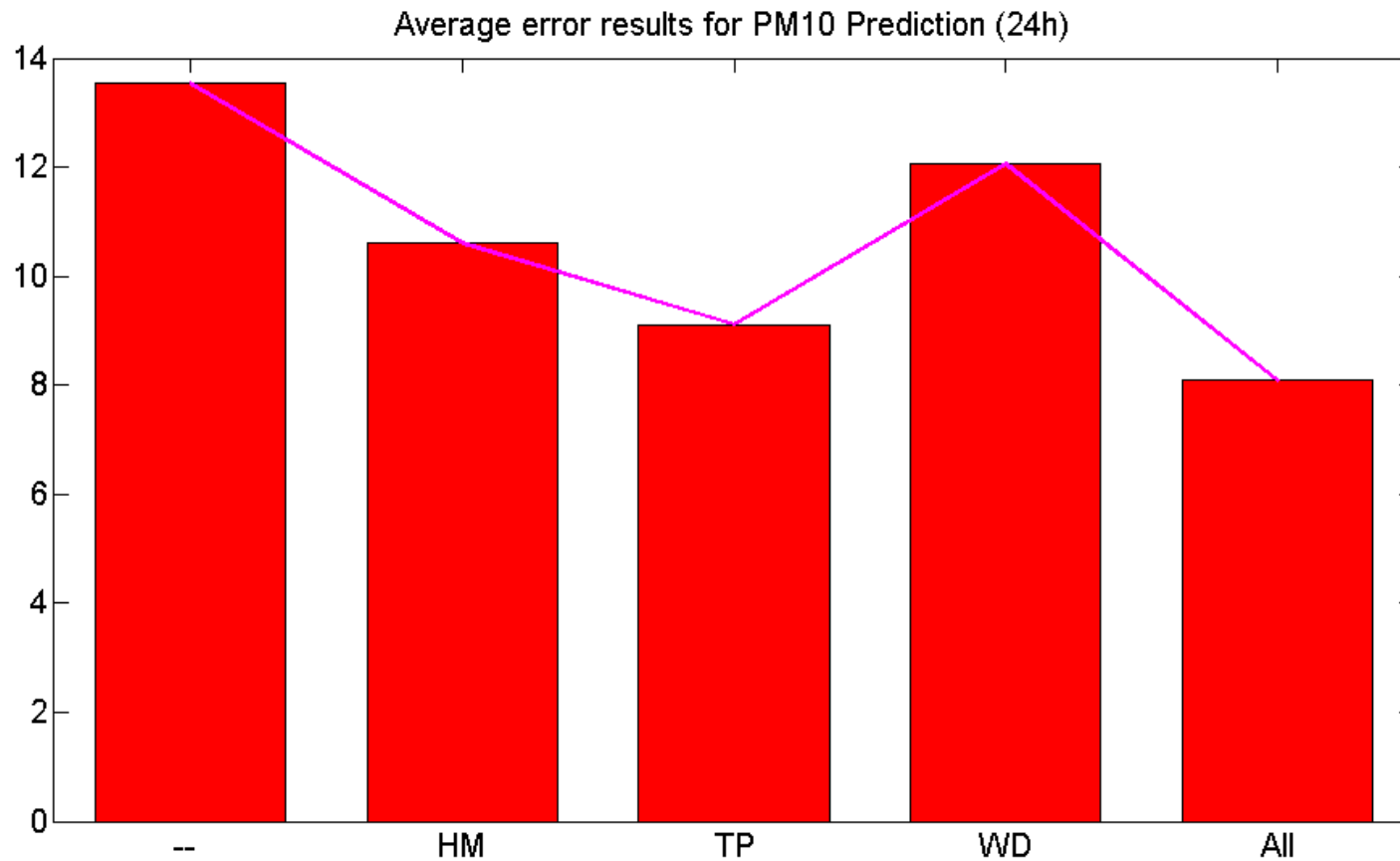
Experimental Results

- **PM2.5 + PM10 – 24h individual sensor prediction**



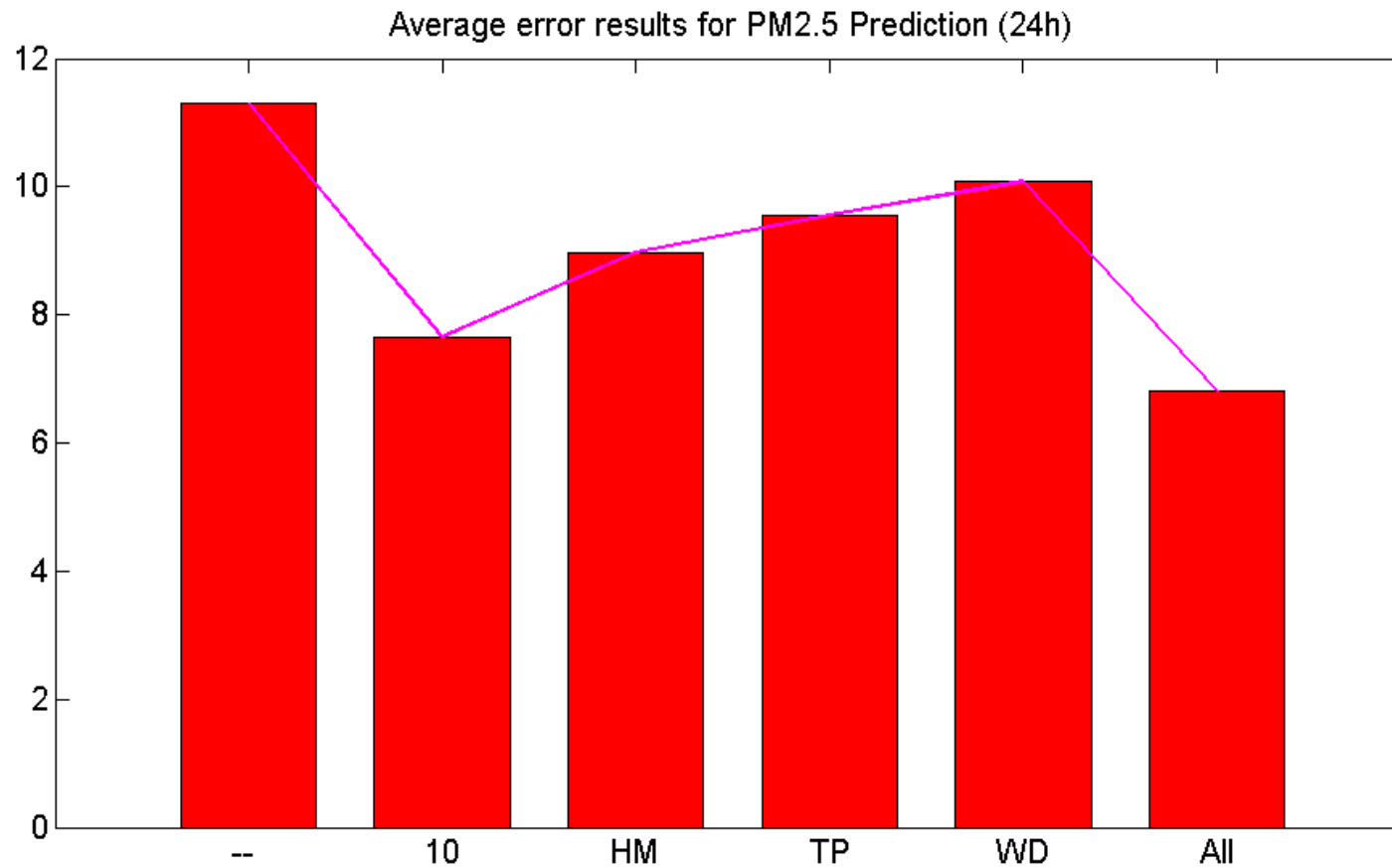
Experimental Results

► Average Errors (**PM10 – 24h**)

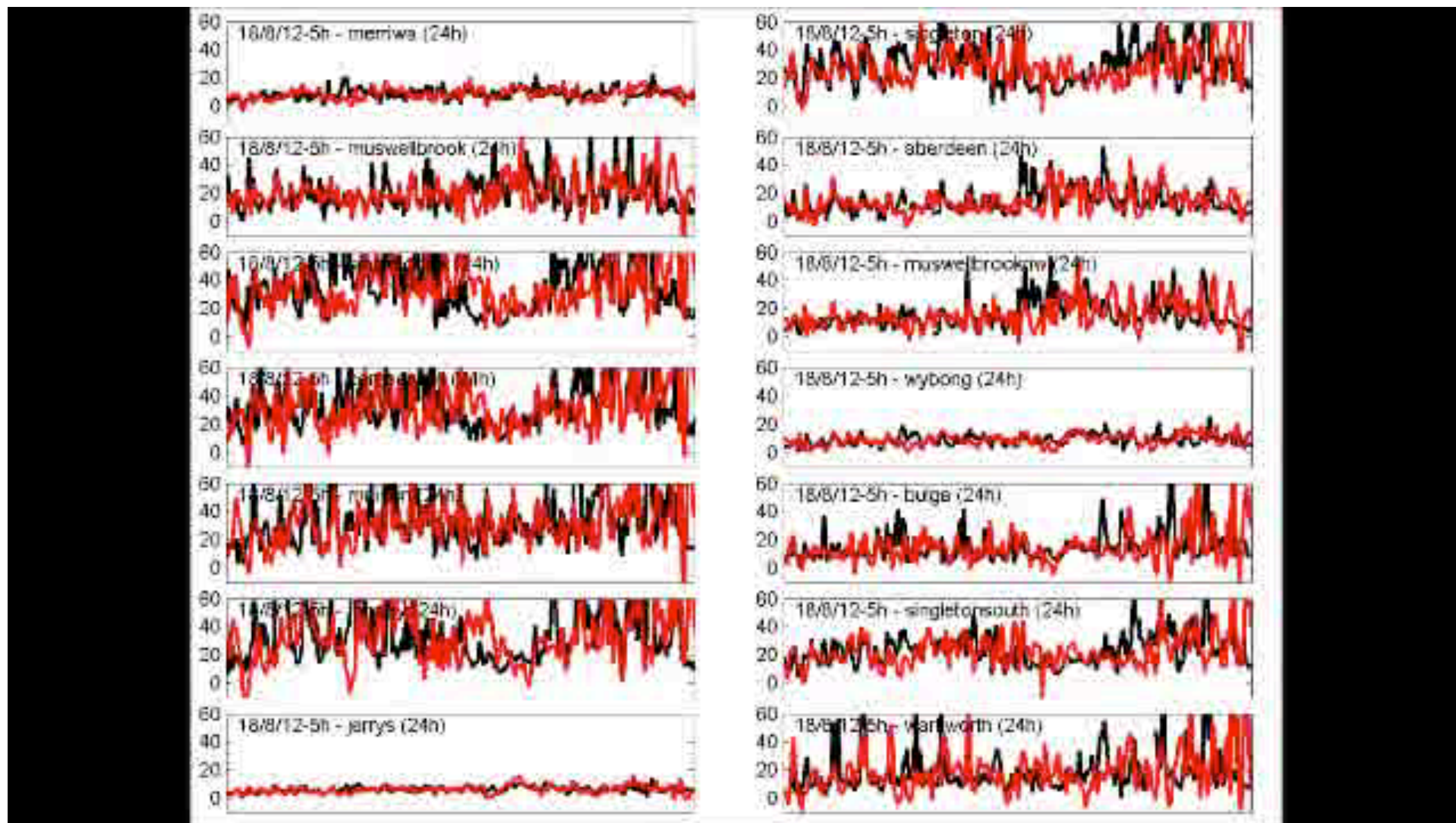


Experimental Results

► Average Errors (**PM25 – 24h**)

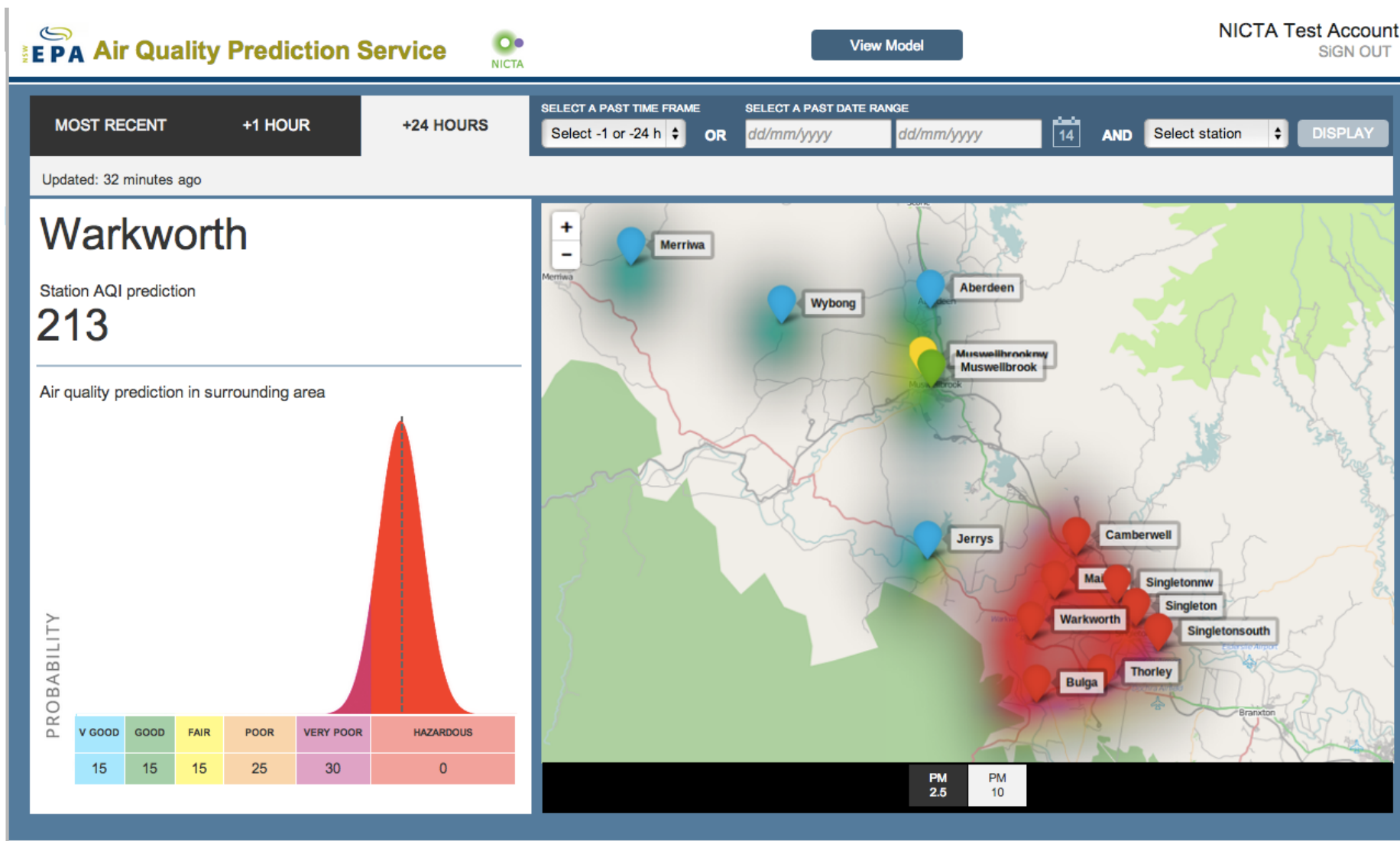


PM10 24-hour prediction

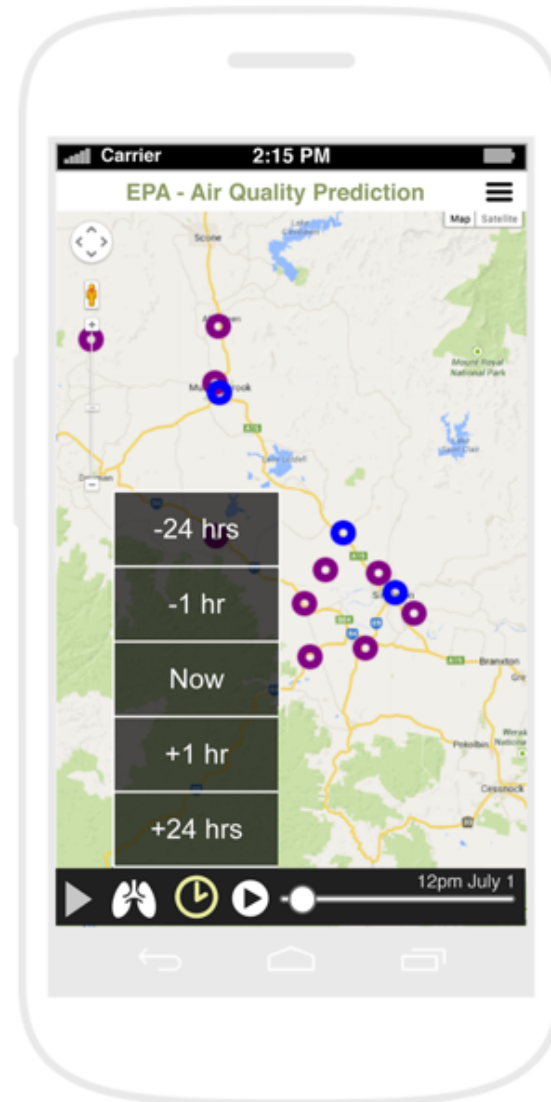
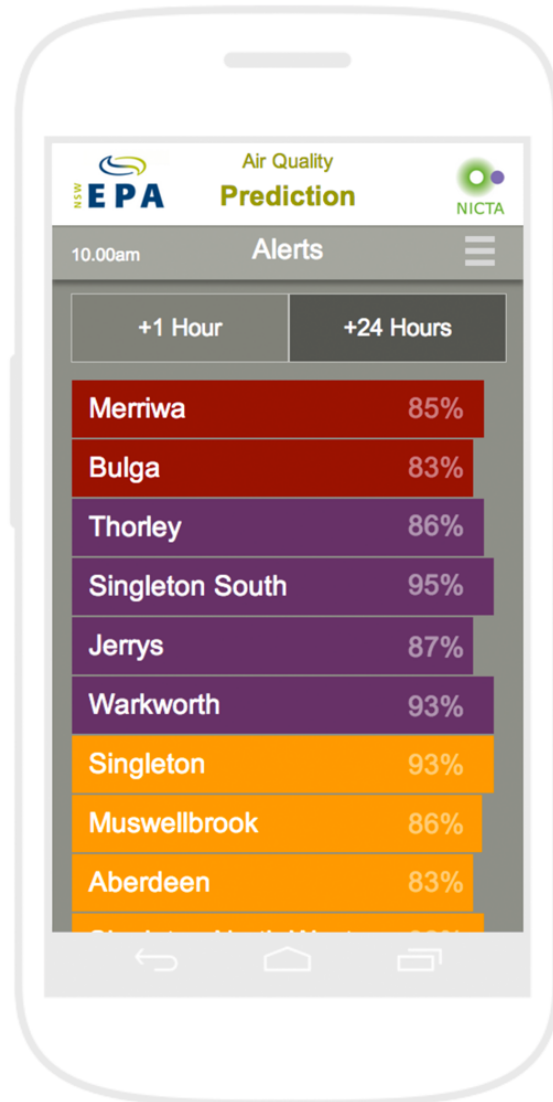


How do we make these complex algorithms easily accessible to EPAs?

Web Interface



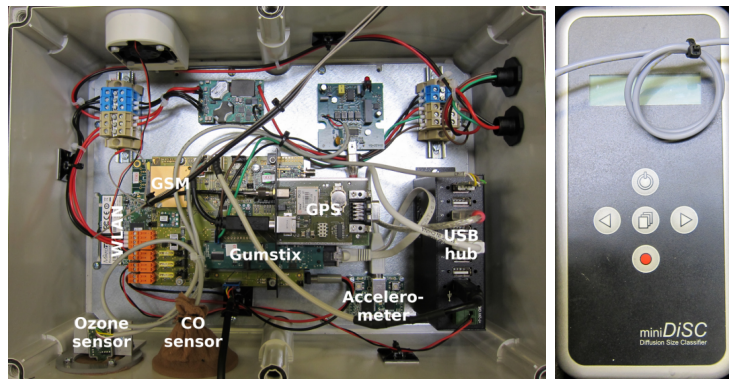
Mobile Phone Apps



What's next in air pollution forecast?

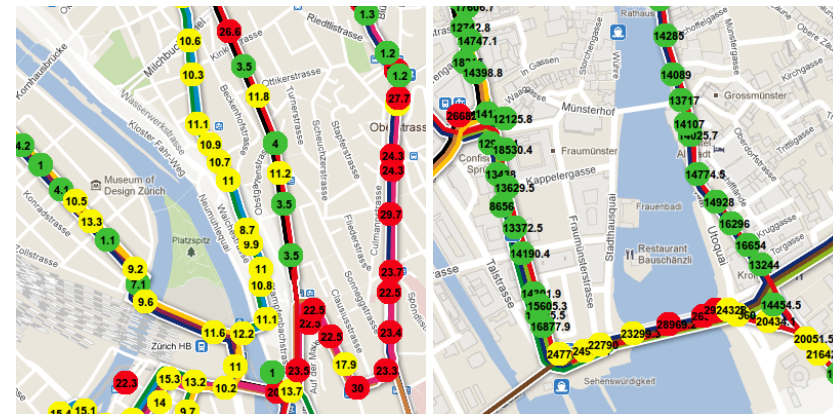
Dynamic Monitoring: Where and When to Monitor

OpenSense Zurich Monitoring System



(a) Sensor box

(b) DiSCmini



(a) Ozone

(b) PM

Figure 4: Web-based interactive data browsing through the datasets of ozone and PM measurements in Zurich.



(a) Tram deployment

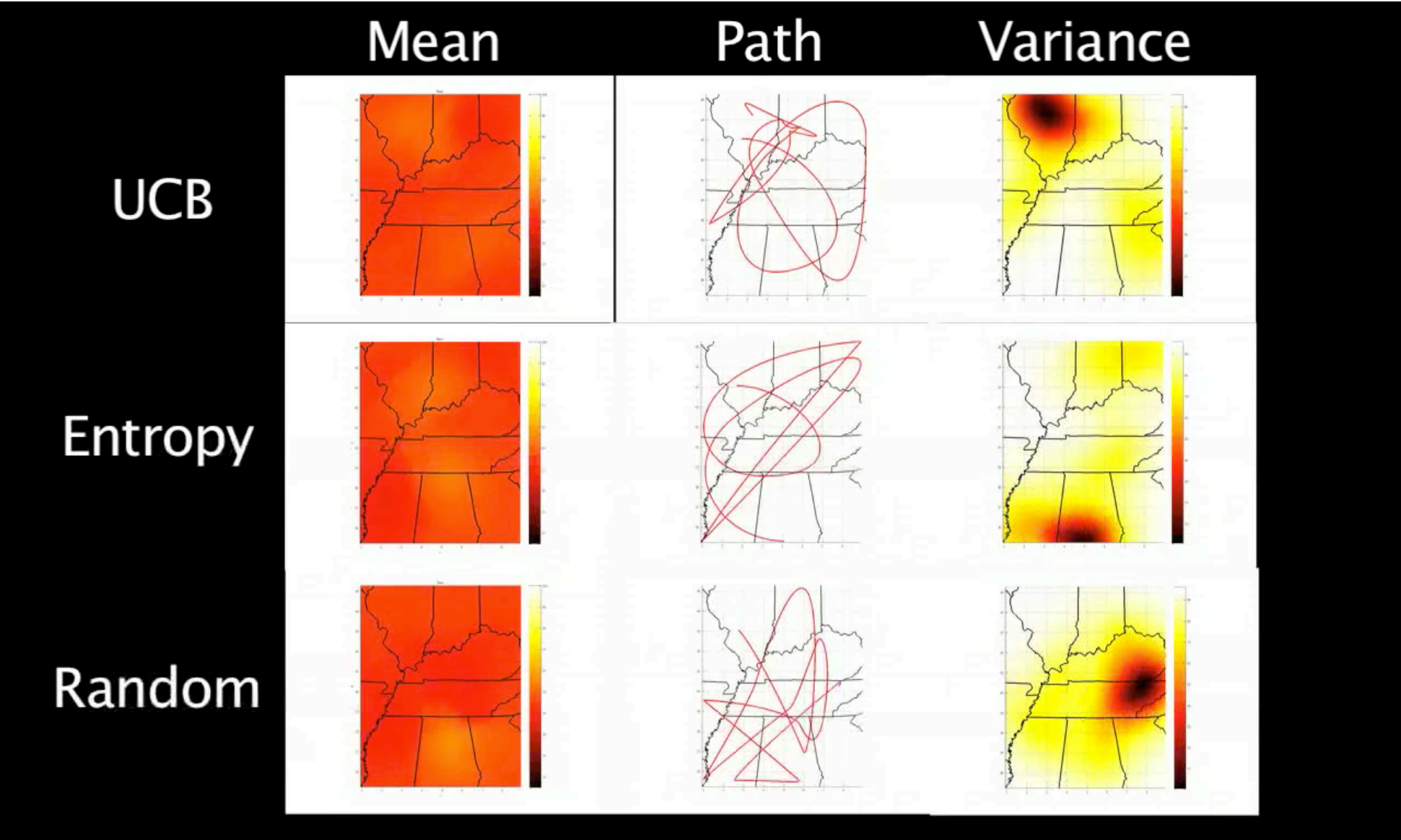
(b) Fixed station deployment



UAVs

USVs

Path Planning for Smart Monitoring



Summary



- Immense opportunities for statistical machine learning in air pollution forecast
- Assessing uncertainties is crucial
- Complex algorithms and computer systems are easily accessible through web services
- Where and when to monitor is as important as the quality of the measurements

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