Spatiotemporal analysis of particulate matter following the WTC disaster: Initial Results using a geostatistical approach

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Abstract

Particulate matter (PM10 and PM2.5) is a criteria air pollutant providing a useful indicator to assess the impact of the WTC disaster on air quality. The objective of this initial analysis is to use a geostatistical approach to estimate particulate matter over space and time in the surroundings of the WTC site in order to assess the ability of available monitoring data to reconstruct the plume of air toxics released by the collapse of the towers and the ensuing fires. In this analysis we use the Bayesian Maximum Entropy (BME) method of modern Geostatistics, which performs a composite space/time analysis and provides the capability to account for measurement errors when that information will be available. The *implementation* of the BME method for the WTC situation resulted in the development of the BME-WTC model presented herein. Using this model we analyzed monitoring data from the US-EPA AIRS database, which contains monitoring data for the federal criteria air pollutants measured at a fixed network in the US, as well as from monitoring stations that were deployed after the 9/11 disaster to specifically monitor the air toxics coming from the WTC site. Our initial results show that the BME-WTC model provides a useful framework for the spatiotemporal exposure mapping in the WTC situation, however the data used so far in our analysis is not sufficient to reconstruct the space/time plume. Future work is focused on getting a more complete database of the monitoring data in order to obtain a better reconstruction of the plume, and combining this reconstruction of the plume with predictions from physical air transport simulations.

INTRODUCTION

The distribution of Particulate Matter (PM) concentration in the air has been monitored on a regular basis for more than 20 years at fixed stations in the New-York metropolitan area and it's surroundings. PM is a good measure of the amount of air pollution in the atmosphere, thus providing a useful indicator for assessing the effect of WTC collapse on the air quality of New York City (NYC). Typically, measurements of PM10 ('coarse' particulate matter of aero-dynamic diameter less than 10 micrometer) and more recently of PM2.5 ('fine' particulate matter of diameter less than 2.5 micrometer) are available. In response to the WTC disaster we have studied data on PM10 and PM2.5 throughout the NYC area, collected prior and after September 11, 2001. More specifically, data from two distinct groups of monitoring stations are considered in our study:

(1) The AIRS database maintained by EPA that includes various monitoring stations on the top of buildings and was operating before September 11. This database offers a reasonable assessment of pollutant distribution in the atmosphere of the New-York metropolitan area and it's surrounding at higher elevations.

(2) Since September 11, certain additional monitoring stations have been installed together with personal measuring devices on 200 individuals providing a better coverage of the area in the proximity of the WTC at lower elevation

Using these databases, we propose to use an advanced Temporal Geographic Information System (TGIS) (Christakos et al., 2002) to characterize the composite space/time distribution of PM concentrations and generate science-based spatiotemporal maps providing useful representations of air quality in NYC. The results of our analysis should be valuable tools to local and state authorities in their effort to assess population exposure and offer an adequate response, as well as to epidemiologists in their effort to understand the association between exposure and health outcome on the population. A science-based spatiotemporal analysis of the situation should account for the obvious differences between these two datasets (difference in scale, elevation level, measuring devices, etc.). The framework we have developed for this analysis relies on the Bayesian Maximum Entropy (BME) approach and it's numerical implementation (BMElib); which has been used with considerable success in the prediction of a variety of natural and epidemiologic fields exhibiting considerable fluctuations across space and time (Christakos, 1992, 2000; Christakos et al. 2001, 2002; Christakos and Serre, 2000; Serre and Christakos, 1999, 2003). BME has been integrated with spatiotemporal random field theory leading to a composite space/time view that is more accurate than the purely spatial implementation of most classical packages of Geostatistics (e.g. GSLIB, etc.). In exposure mapping and assessment, BME prediction across space and time demonstrates certain important advantages: it possesses a sound epistemic framework based on sound rules of knowledge acquisition and processing; it accounts for various sources of knowledge (scientific theories, uncertain observations, physical and biological laws, multiple-point statistics, soft data, fuzzy sets, etc.) that cannot be incorporated by traditional methods of descriptive exposure mapping; it does not require strict modelling assumptions (non-Gaussian distributions are automatically incorporated, non-linear predictors are allowed, etc.); and well-known regression techniques are derived as special cases of the BME analysis under limiting conditions (Christakos 1992, 2000; Serre and Christakos 1999; Choi *et al.,* 2003).

In the work presented in this initial report, we have developed a BME model for the WTC situation (the BME-WTC model), which performs a BME spatiotemporal analysis of air monitoring data resulting in a representation of air quality across space and time that is geostatistically consistent with the monitoring data. The BME-WTC model allows the analysis of data coming from several sources, including the US-EPA *AIRS database* with monitoring air pollution data from fixed monitoring stations in operation prior and after the September 11 event, as well as the so-called EPA *post 9/11 WTC database* that contains additional monitoring data collected at stations specially deployed after September 11 in order to capture the space/time plume of air pollutant caused by the collapse of the WTC. To date we have completed (1) the *implementation* of the BME-WTC spatiotemporal model to process WTC monitoring data coming from various source, and (2) the *analysis* using this BME model of the particulate matter (PM10 and PM2.5) monitoring data coming from the official AIRS database and from an informal version of the post 9/11 WTC database. This work has been done with the help of a collaborative effort with other groups in a NIEHS funded effort, including the Columbia group for help in getting access to the AIRS and the post 9/11 WTC databases (Dr. Diane Levy/Elsie Chettiar), and the Rutgers group for exposure assessment and air dispersion modeling (Dr. Panos Georgopoulos / Dr. Vikram Vyas), and discussions with EPA scientists (Dr. Alan Huber). These collaborative efforts are crucial in this work and for its continuation.

METHODS

We start with brief overviews of the Space/Time Random Field (S/TRF) representation of exposure fields, and we then present the BME approach for exposure mapping using the S/TRF theory.

The S/TRF representation

The distribution of a physical process varying across space and time is adequately represented in terms of a space/time random field (S/TRF), $X(\boldsymbol{p})$, which takes values at points $\boldsymbol{p}=(\boldsymbol{s},t)$ in a space/time domain, where $\boldsymbol{s}=(s_1,s_2)$ is the spatial location and t is the time. The S/TRF $X(\boldsymbol{p})$ provides a *representation* of the spatiotemporal distribution of the physical process that captures the natural space/time variability across space and time. The variability manifests itself as an ensemble of possible realizations regarding the distribution of the field values in space and time. The mean function

$$m_X(\boldsymbol{p}) = \overline{X(\boldsymbol{p})} \tag{1}$$

of the S/TRF (the bar denotes stochastic expectation) characterizes trends and systematic structures in space and time; and the covariance function

$$c_X(\boldsymbol{p},\boldsymbol{p'}) = \overline{[X(\boldsymbol{p})-\overline{X}(\boldsymbol{p})][X(\boldsymbol{p}')-\overline{X}(\boldsymbol{p}')]} \tag{2}$$

expresses relevant correlations and dependencies across space and time. In case that the S/TRF is spatially isotropic/temporally stationary, the covariance is written as $c_X(\boldsymbol{p},\boldsymbol{p'}) = c_X(r,\tau)$, where $r=||\boldsymbol{s}-\boldsymbol{s'}||$ is the spatial distance between $\boldsymbol{s}$ and $\boldsymbol{s'}$, and $\tau=|t-t'|$, denote the temporal lag. Covariance plots highlighting the composite dependence of c_X with respect to both r and τ are very useful, as they provide some insights about the spatial and temporal scales of variability across space and time that can be linked to different pollution sources and the effect of external factors such as weather, traffic, etc.. Herein, we will use capital English letter, e.g. $X(\boldsymbol{p})$ to denote random fields, small English letters, e.g. x, to denote random variables, and small Greek letters, e.g. χ, to denote their realizations. Thus, the realization vector $\chi_{\text{data}}=(\chi_1,\ldots,\chi_m)$ denotes the data values available at points $\boldsymbol{p}_i$ $(i=1,\ldots,m)$. Exposure mapping studies are generally concerned with the prediction of the values of the relevant fields at unmeasured points $\boldsymbol{p}_k$ $(k\neq i)$ given the total knowledge available.

The BME framework

The BME conceptual framework distinguishes between three main stages of physical knowledge processing and assimilation as follows:

(i) At the *structural* (or *prior*) stage, BME generates an initial probability distribution across space and time based on the general or core knowledge base denoted by $\mathcal{G}$. The base $\mathcal{G}$ includes multiple-point statistics (mean, covariance, higher order moments, etc.), and may also include physical laws describing the flow and transport of the pollutants (Serre et al., 2003).

(ii) At the *meta-prior* stage, the site-specific knowledge available is organized into hard and soft data and expressed in terms of suitable operators. The site-specific knowledge is denoted by $\mathcal{S}$.

(iii) At the *integration* (or *posterior*) stage, the initial solution of stage *(i)* is enriched by assimilating the site-specific knowledge of stage *(ii)*. This final solution is not limited to a single estimation value but includes the complete probability law at each estimation point.

The mathematical formulation of the structural BME stage *(i)* is as follows. The general or core knowledge $\mathcal{G}$ imposes N_c+1 constraints on $X(\boldsymbol{p})$ expressed as follows

$$\left.\begin{array}{l} G_\alpha(\boldsymbol{p}_{\text{map}}) = \overline{g_\alpha(\boldsymbol{x}_{\text{map}})}, \quad \alpha = 0,1,\ldots,N_c \\ \text{with } \ \overline{g_\alpha(\boldsymbol{x}_{\text{map}})} = \int d\boldsymbol{\chi}_{\text{map}}\, g_\alpha(\boldsymbol{\chi}_{\text{map}}) f_{\mathsf{G}}(\boldsymbol{\chi}_{\text{map}};\boldsymbol{p}_{\text{map}}) \end{array}\right\}, \tag{3}$$

where the vector $\boldsymbol{x}_{\text{map}}$ represents the random variables associated with $X(\boldsymbol{p})$ at a set $\boldsymbol{p}_{\text{map}}$ of mapping points; the χ_{map} denotes a realization of $X(\boldsymbol{p})$, the g_α are functions of $\boldsymbol{x}_{\text{map}}$ chosen so that their stochastic expectation G_α can be derived from the general knowledge base $\mathcal{G}$; and $f_{\mathcal{G}}$ is the $\mathcal{G}$-based probability density function (PDF) of $X(\boldsymbol{s})$. The $f_{\mathcal{G}}$ is determined by assuming a parametric form, inserting it into Eqs. (3), and solving for the relevant parameters. A suitable $f_{\mathcal{G}}$ form with wide applicability is given by

$$f_{\mathsf{G}}(\chi_{\text{data}};\boldsymbol{s}_{\text{map}}) = \exp[\mu_0 + \textstyle\sum_{\alpha=1}^{N} \mu_\alpha(\boldsymbol{p}_{\text{map}}) g_\alpha(\chi_{\text{map}})], \tag{4}$$

where μ_α (α=0,1, …,N_c) are space/time-dependent parameters (Lagrange multipliers) the values of which are obtained by solving Eqs. (3); the constraint g_o=G_o=1 is used to normalize the PDF via parameter μ_o. Once we have solved for these multipliers, we have essentially completed the structural BME stage which yields a PDF (4) that is quite general and includes both Gaussian and non-Gaussian cases.

At the meta-prior stage we consider the decomposition of the mapping point vector $\boldsymbol{p}_{\text{map}}$ into the estimation point $\boldsymbol{p}_{\text{k}}$ (where an $X(\boldsymbol{s})$ estimate is sought), the hard data point vector $\boldsymbol{p}_{\text{hard}}$ (where exact measurements are available), and the soft data point vector $\boldsymbol{p}_{\text{soft}}$ (where soft data, e.g., intervals, are available), so that $\boldsymbol{p}_{\text{map}}=[\boldsymbol{p}_{\text{k}}, \boldsymbol{p}_{\text{hard}}, \boldsymbol{p}_{\text{soft}}]$. We then focus on the site-specific knowledge base $\mathcal{S}$: (χ_{data},χ_{soft}). More specifically, at the hard data points $\boldsymbol{p}_{\text{hard}}$ we have exact measurements χ_{hard} expressed mathematically by the probability operator

$$Prob[\boldsymbol{x}_{\text{hard}}=\chi_{\text{hard}}]=1, \tag{5}$$

where *Prob* is the probability operator. At the soft data points $\boldsymbol{p}_{\text{soft}}$ we do not have exact measurements but only partial information about the values χ_{soft} taken by $\boldsymbol{x}_{\text{soft}}$. If data intervals are available, this sort of information is mathematically expressed as $Prob[\boldsymbol{a}<\boldsymbol{x}_{\text{soft}}<\boldsymbol{b}]=1$, where $\boldsymbol{a}$ and $\boldsymbol{b}$ are vectors of the lower and upper bounds of the soft intervals. Generally, we can express the soft data using a PDF f_S by the probability operator

$$Prob[\boldsymbol{x}_{\text{soft}}<\boldsymbol{u}]= \int_{-\infty}^{\boldsymbol{u}} d\chi_{\text{soft}} f_S(\chi_{\text{soft}}). \tag{6}$$

E.g., the soft PDF corresponding to interval soft data is a PDF uniformly distributed between the lower and upper bounds of the interval.

At the integration (posterior) stage of the BME analysis we blend the general knowledge base $\mathcal{G}$ considered at the structural stage with the site-specific knowledge base $\mathcal{S}$ of stage (*ii*) to obtain the posterior PDF, f_K, describing x_{k} in light of the total knowledge base $\mathcal{K}=\mathcal{G}\cup\mathcal{S}$. A powerful knowledge-blending rule proposed by Christakos in the context of *Modern Spatiotemporal Geostatistics* (Christakos 2000, 2002) is the *operational Bayesian conditionalization*, which yields the posterior PDF as follow

$$f_K(\chi_k) = A^{-1}\int d\chi_{\text{soft}} f_S(\chi_{\text{soft}}) f_G(\chi_{\text{map}}), \qquad (7)$$

where $A = \int d\chi_{\text{soft}} f_S(\chi_{\text{soft}}) f_G(\chi_{\text{data}})$ is a normalization constant. The posterior PDF (7) provides a complete stochastic characterization of $X(\boldsymbol{s})$ at each point in space that integrates a wide variety of data (hard and soft) as well as the relevant core knowledge (physical law etc.). From the posterior PDF we obtain any estimate of interest (e.g., the *BMEmode* which provides the most likely value at the estimation point; or the *BMEmean* which minimizes the mean square estimation error).

DATA SOURCES

The air quality monitoring data in the NYC area are mainly from two sources. One source is the AIRS database with monitoring data collected from a fixed network monitoring the federal criteria air pollutants prior and after the 9/11 disaster, while the other includes all the monitoring stations that where deployed after 9/11/2001 to monitor the air quality in the vicinity of the WTC site. In the past, most criteria air pollutant monitoring stations collected PM10 data daily in New York City area. Starting in 2000, these PM10 monitoring stations were gradually discontinued, and replaced with PM2.5 monitoring stations collecting data hourly. The post-9/11 monitoring stations were gradually set up after 9/11/2001. The first few post-9/11 monitoring stations were set up around September 13 to September 18, but these stations are located in Staten Island, which is about 15 miles away from the World Trade Center (WTC) site. Most post-9/11 monitoring stations in the vicinity of WTC area were set-up after the end of September 2001. These post-9/11 monitoring stations collected data on an hourly basis. Since these data are obtained from different institutions and team efforts that may overlap, some of these data may be duplicated in our database due to duplicate reporting. In order to avoid accounting for duplicated monitoring stations in our analysis, we removed any monitoring stations if it's coordinates indicate a location that is a distance of less than 0.00001 degree from another station in the database. Figure 1 shows the locations of monitoring stations around the New York City on October 1, 2001. The data available is listed in the Table 1 by sources. Figures 2 to 4 provide temporal plots for three different monitoring stations. The monitoring data is shown with circles in these figures.

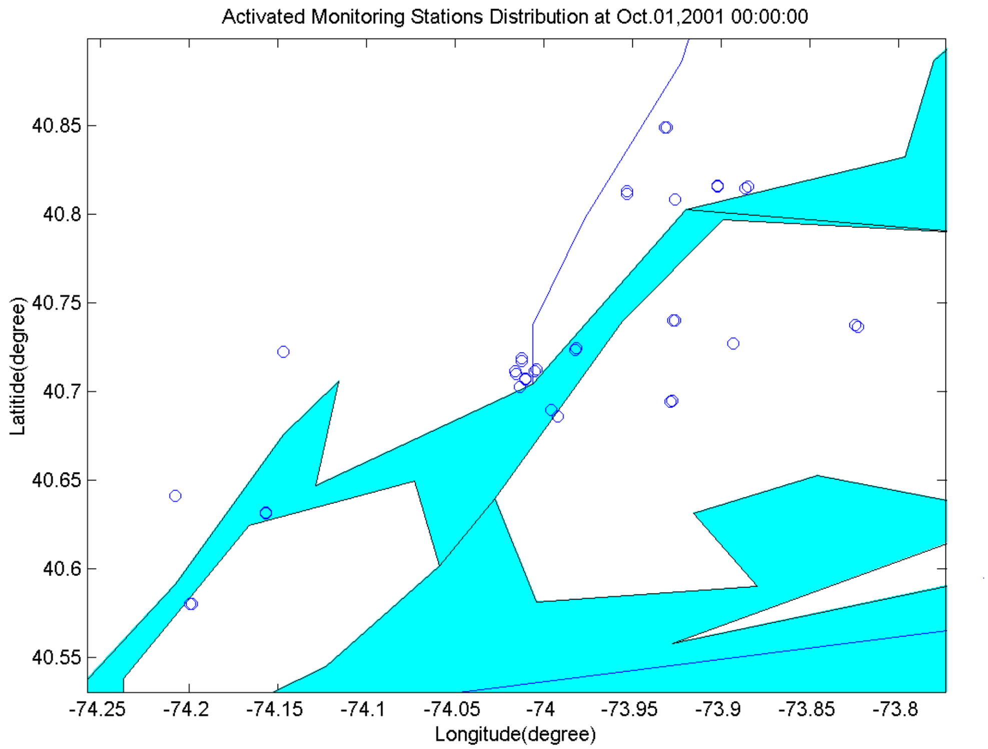

Figure 1: Spatial distribution of monitoring stations in New York City on 00:00 Oct 1.

Table 1: data category

Source		Data Type			Collection period
Category	Institution	Pollution Type	hourly	daily	
AIRS		PM10		X	1982-2002
AIRS		PM2.5	X		2000-2002
Post-9/11	NYSDEC	PM10	X	X	09/2001-05/2002
Post-9/11	NYSDEC	PM2.5	X		09/2001-05/2003
Post-9/11	EPA Website	PM10		X	09/2001-05/2004
Post-9/11	EPA Website	PM2.5		X	09/2001-05/2005
Post-9/11	JHU	PM10			only few periods

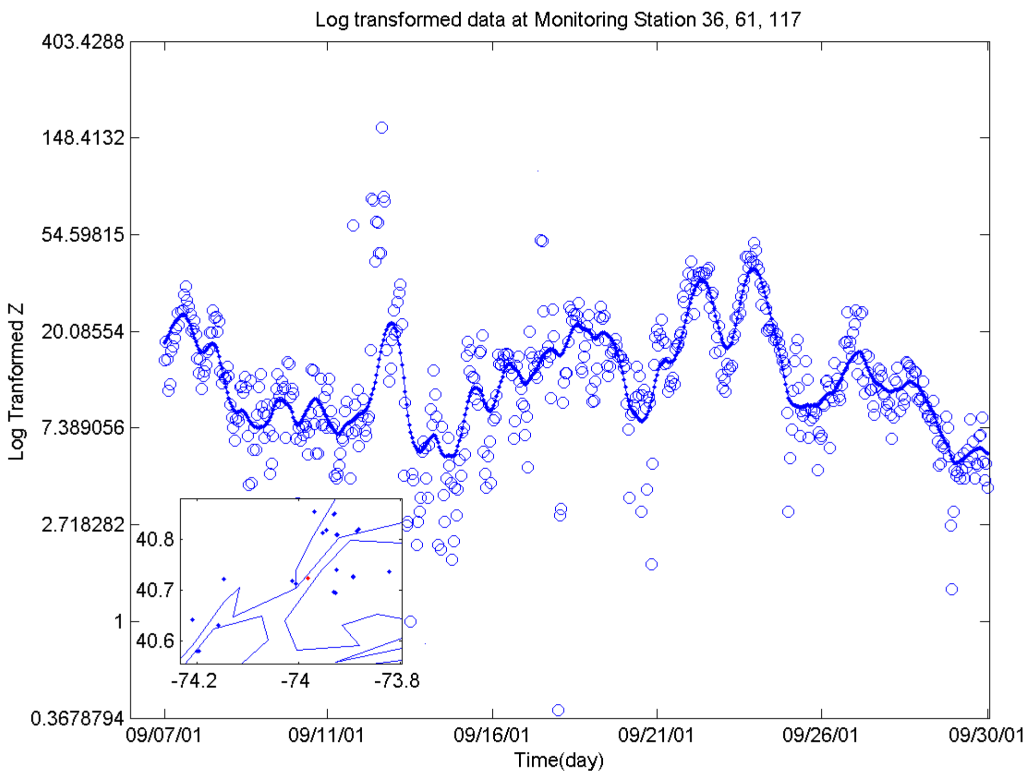

Figure 2. Plot of log-transformed PM2.5 monitoring data (circles) and mean trend (line) at station 36,61,117

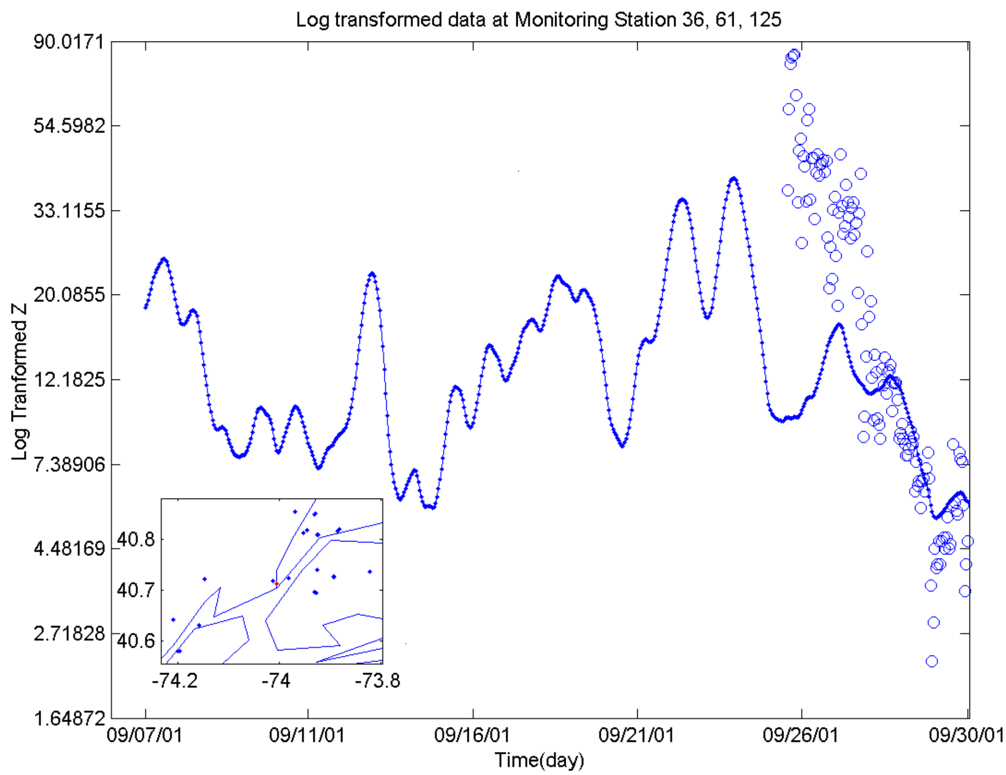

Figure 3. Plot of log-transformed PM2.5 monitoring data (circles) and mean trend (line) at station 36,61,125

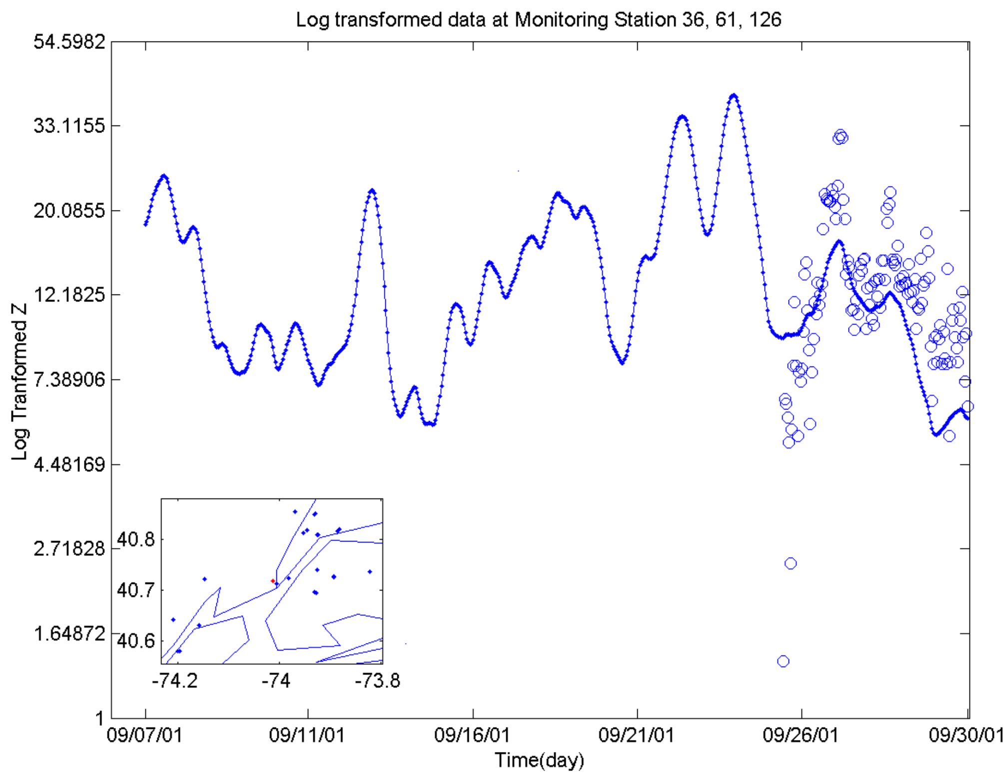

Figure 4. Plot of log-transformed PM2.5 monitoring data (circles) and mean trend (line) at station 36,61,126

ANALYSIS AND RESULTS

Implementation of BME for the WTC situation

Our main goal is to obtain spatiotemporal maps of the air quality in NYC after the 9/11 disaster. The BME framework and it's numerical library, BMElib, were used to implement the BME-WTC model, as follow

1) PM2.5 is the indicator used to assess the impact of the WTC collapse on air quality. The distribution of log-transformed PM2.5 across space $\boldsymbol{s}$ and time t is conceptualized as a Space/Time Random Field (S/TRF) $Y(\boldsymbol{s},t)$ that is the sum of a mean trend function $m_Y(\boldsymbol{s},t)=E[Y(\boldsymbol{s},t)]$ and a homogeneous/stationary random field $X(\boldsymbol{s},t)$, so that $Y(\boldsymbol{s},t)=m_Y(\boldsymbol{s},t)+X(\boldsymbol{s},t)$.

2) The mean trend function was obtained by applying a space/time moving average algorithm on several years of data in the greater WTC area. This mean trend is shown

for a 3 month period in Figures 2 to 4, and for a six year period in Figure 16. A clear yearly pattern was found in the years prior to the 9/11/2001 event. The pattern shows an expected decrease of pollution every year in the 3-month period of September till November.

3) The space/time covariance function is modeled using three space/time separable exponential covariance functions. The component of this model explaining most of the variability has a spatial range of about 0.09 degrees (1 degree is approximately equal to 111 Km) and a temporal range of about 7 hours. The experimental covariance values and the covariance model are shown in Figure 5. The covariance model selected is given by the following equations

$$c(r,t) = 0.119\exp(\frac{-3r}{0.09})\exp(\frac{-3t}{7}) + 0.0175\exp(\frac{-3r}{150})\exp(\frac{-3t}{7}) + 0.0175\exp(\frac{-3r}{150})\exp(\frac{-3t}{365})$$

4) Using the mean trend and covariance models as general knowledge, and the monitoring data as hard data, we obtain with BMElib maps describing the distribution of PM2.5 over the NYC area for any time after 9/11/2001.

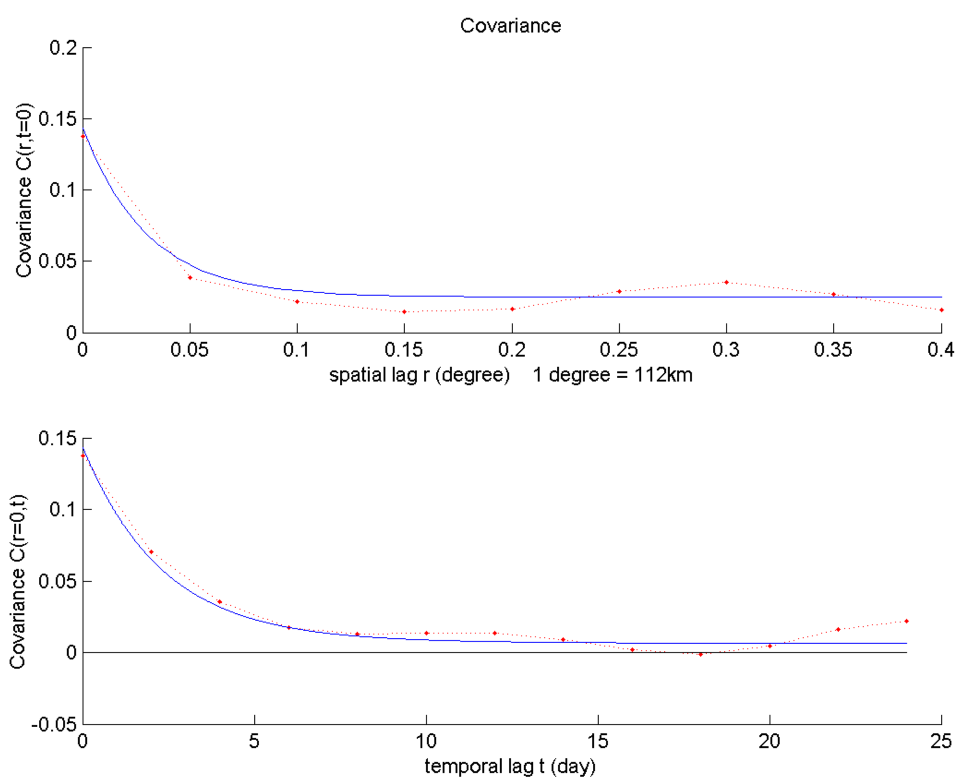

Figure 5. Covariance $c(r,\tau)$ of log-PM2.5 as a function of spatial lag r (top) and

temporal lag τ (bottom). The dotted line shows the experimental covariance, while the line shows the covariance model.

Results and Discussion

Using the BME-WTC model described above, we produced the maps of hourly average of PM2.5 concentration shown in figure 6 to figure 9. The maps show PM2.5 concentration in the NYC area at 10am for each day from September 11 till September 14. Figures 6 to 9 provide representative snapshots of the information available from the PM2.5 monitoring data in the days following 9/11/2001 (for movies of these maps go to www.unc.edu/~hlyu/WTC/WTCFrame.htm). The general knowledge base considered here consists *only* of the covariance of PM2.5 obtained from data (i.e. it did not include any physical law for the atmospheric transport of PM). We say that these maps provide a representation of PM2.5 across space and time that is consistent in a *Geostatistical* sense with the monitoring data, so that they tell us how much information there is in the monitoring data alone. As can be seen from these figures, the pollution plume cannot be seen clearly and consistently from the monitoring data alone in the few days immediately following 9/11/2001. This is because most of the data available for this period are coming from the AIRS monitoring stations that are too sparse and too far from the WTC site to properly delineate the space time plume of air toxics. As the number of monitoring stations deployed around the WTC site increased in the months following 9/11/2001, the corresponding information content of monitoring data increased, resulting in maps where the plume can be better delineated. Additionally we note that on September 13, the values of monitoring stations are very high. These high values come from samples collected by different teams after the WTC collapse and may be of questionable data quality. We will be able to resolve this problem when we work with a data quality controlled version of the database, which is work under progress.

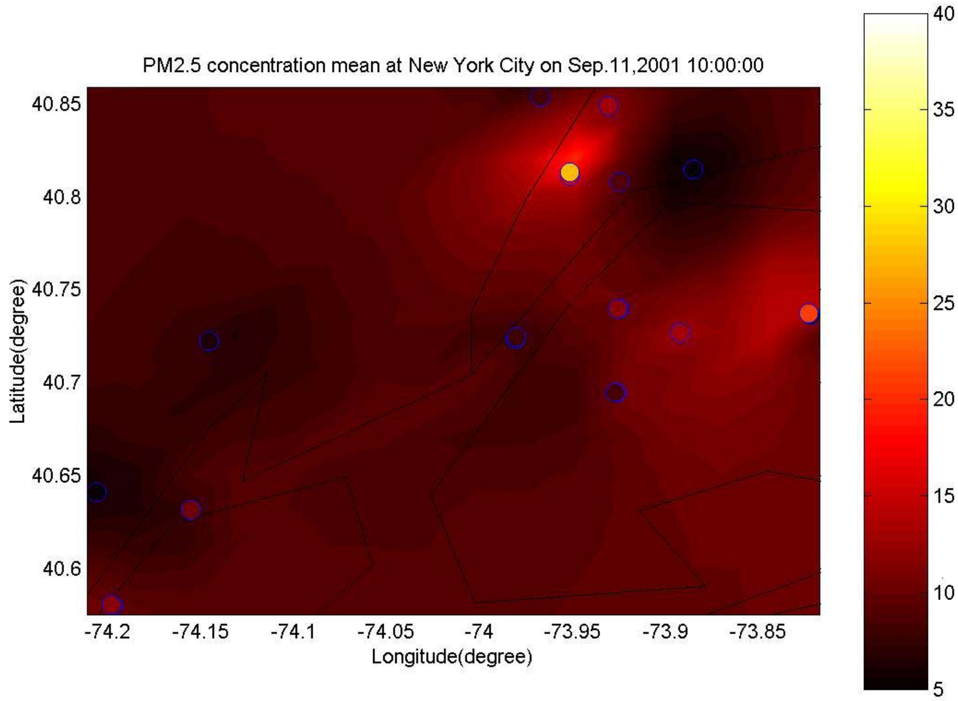
PM2.5 concentration mean at New York City on Sep.11,2001 10:00:00
Latitude(degree)
Longitude(degree)
40.85
40.8
40.75
40.7
40.65
40.6
-74.2
-74.15
-74.1
-74.05
-74
-73.95
-73.9
-73.85
40
35
30
25
20
15
10
5

Figure 6

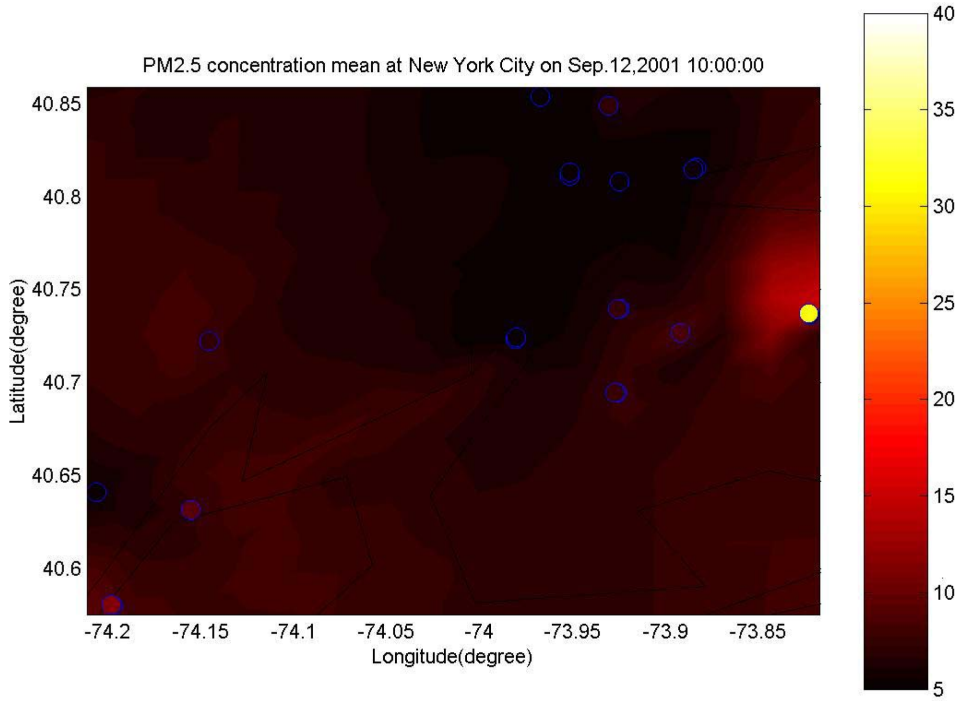
PM2.5 concentration mean at New York City on Sep.12,2001 10:00:00
Latitude(degree)
Longitude(degree)
40.85
40.8
40.75
40.7
40.65
40.6
-74.2
-74.15
-74.1
-74.05
-74
-73.95
-73.9
-73.85
40
35
30
25
20
15
10
5

Figure 7

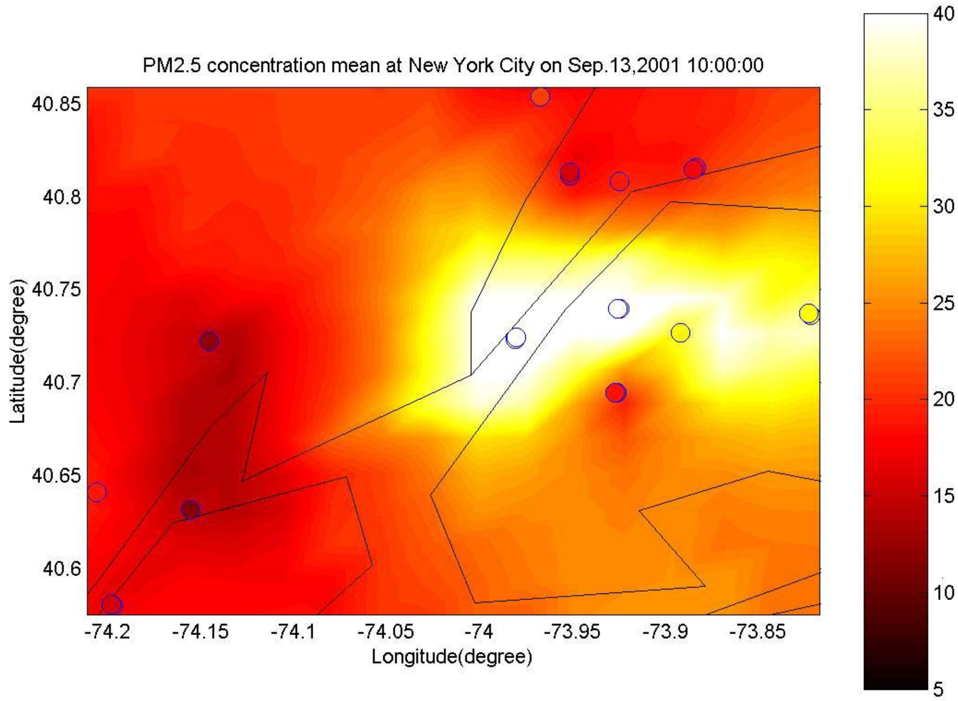
PM2.5 concentration mean at New York City on Sep.13,2001 10:00:00
Latitude(degree)
Longitude(degree)
40.85
40.8
40.75
40.7
40.65
40.6
-74.2
-74.15
-74.1
-74.05
-74
-73.95
-73.9
-73.85
40
35
30
25
20
15
10
5

Figure 8

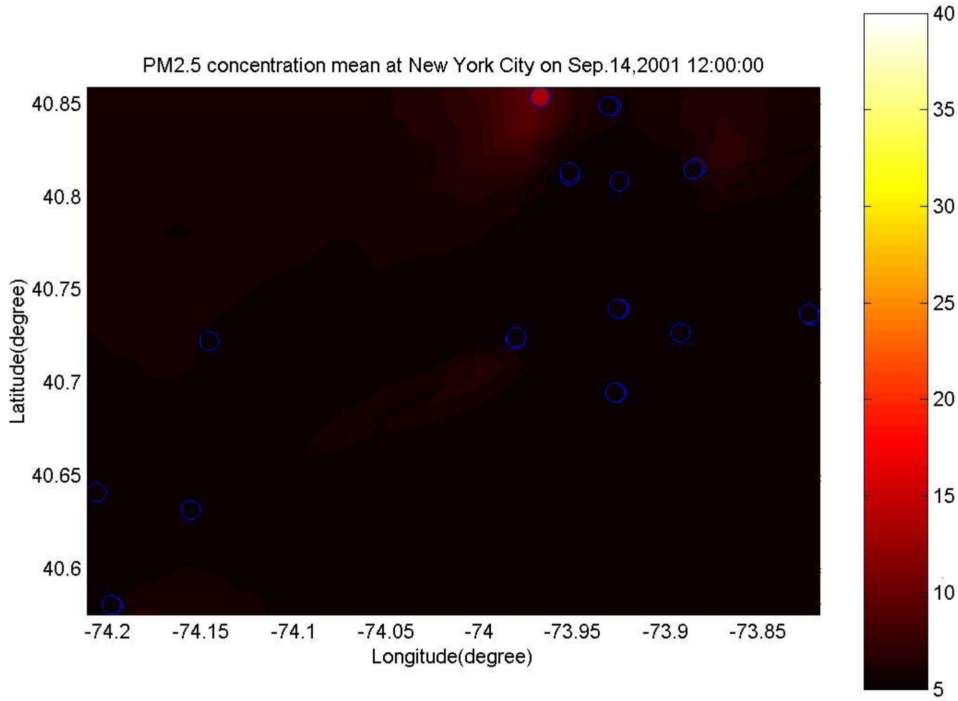

Figure 9

Including the monitoring data in this version of the database adds a few monitoring stations that are closer to the WTC, but does not seem in general to provide a sufficient coverage to re-construct the space time plume in the vicinity of the WTC based only on monitoring data. It will therefore be necessary to combine the present monitoring data with output from dispersion plume modeling in order to obtain a more accurate representation of the air pollution plume. A few high air pollution episodes have been identified in the monitoring data for the 3-month period following 9/11/2001. These episodes will be extremely useful in order to calibrate the dispersion model. Due to the fact that additional monitoring stations were added only several weeks after 9/11, the episodes identified in the monitoring data are mainly in October 2001, with one of the main episode centered on Oct 3. Figure 10 to Figure 15 provide snapshots of hourly PM2.5 at different times on October 3, 2001. We can see from these figures that even with the addition of the post 9/11 monitoring stations at the WTC site, the plume cannot be clearly delineated on the basis of the monitoring data alone.

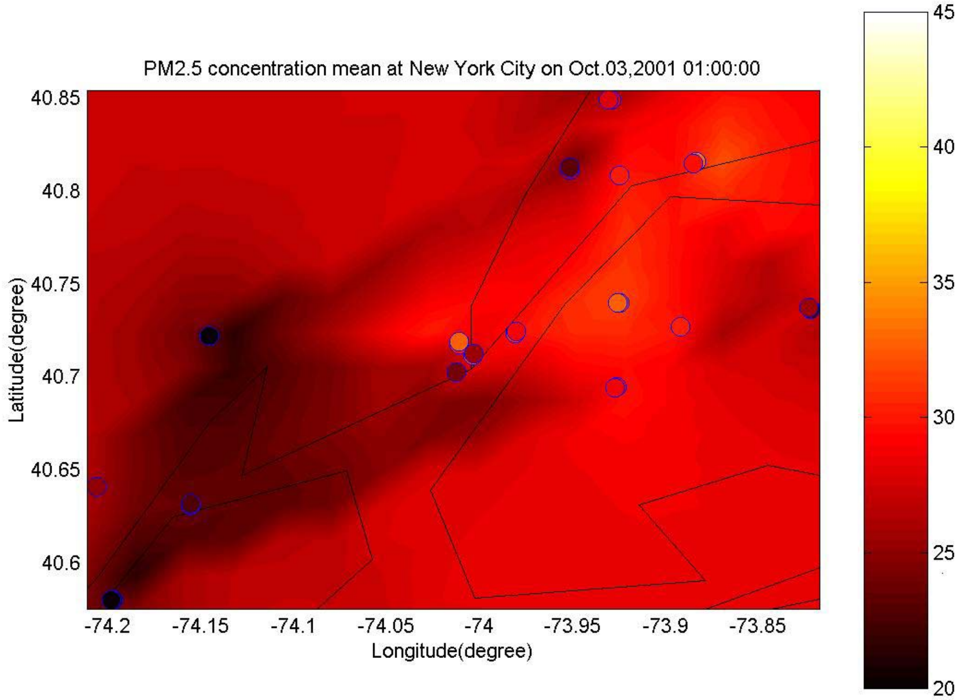
PM2.5 concentration mean at New York City on Oct.03,2001 01:00:00
Latitude(degree)
Longitude(degree)
40.85
40.8
40.75
40.7
40.65
40.6
-74.2
-74.15
-74.1
-74.05
-74
-73.95
-73.9
-73.85
45
40
35
30
25
20

Figure 10

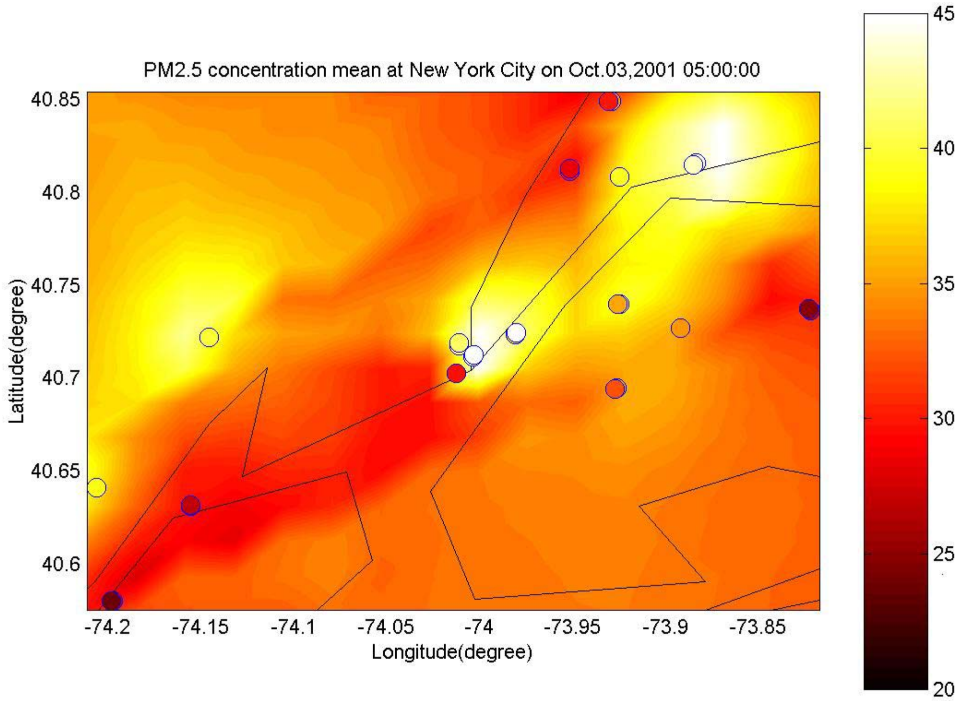
PM2.5 concentration mean at New York City on Oct.03,2001 05:00:00
Latitude(degree)
Longitude(degree)
40.85
40.8
40.75
40.7
40.65
40.6
-74.2
-74.15
-74.1
-74.05
-74
-73.95
-73.9
-73.85
45
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Figure 11

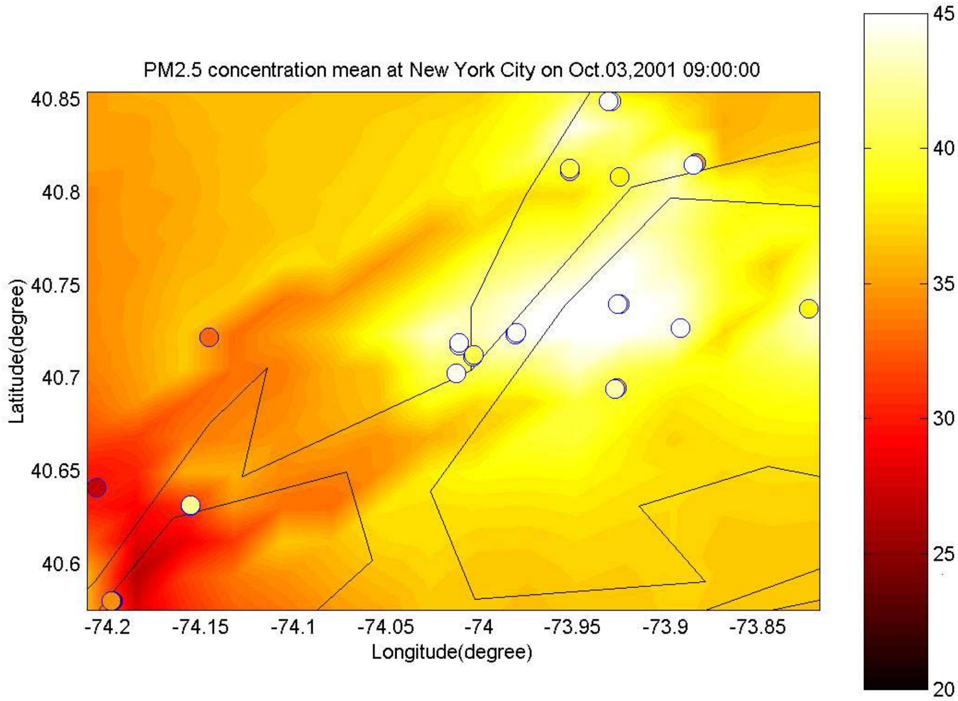
PM2.5 concentration mean at New York City on Oct.03,2001 09:00:00
Latitude(degree)
Longitude(degree)
40.85
40.8
40.75
40.7
40.65
40.6
-74.2
-74.15
-74.1
-74.05
-74
-73.95
-73.9
-73.85
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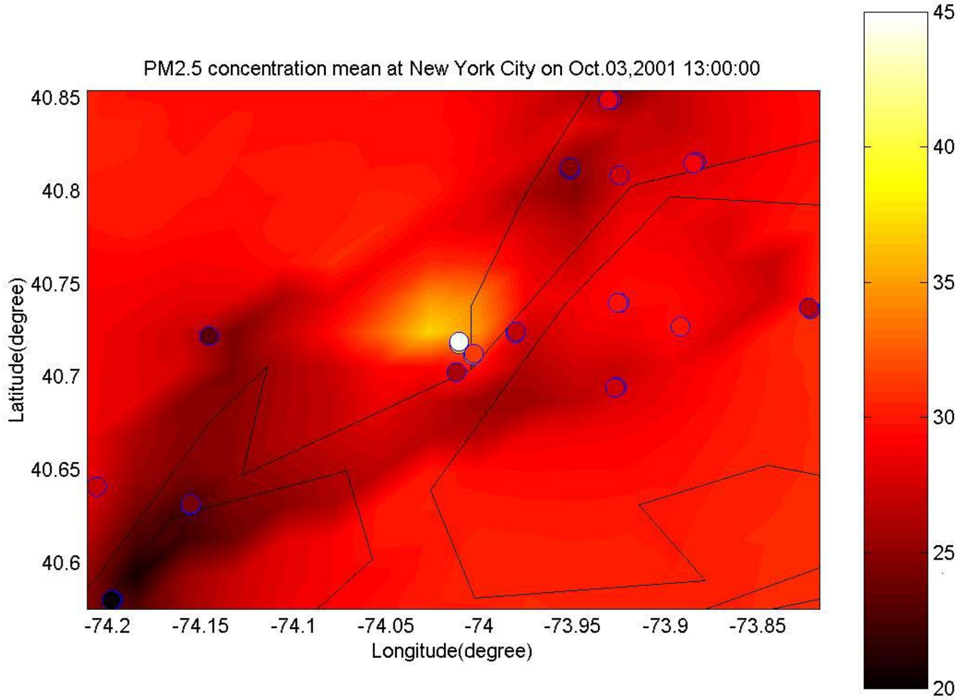
Figure 12



PM2.5 concentration mean at New York City on Oct.03,2001 13:00:00
Latitude(degree)
Longitude(degree)
40.85
40.8
40.75
40.7
40.65
40.6
-74.2
-74.15
-74.1
-74.05
-74
-73.95
-73.9
-73.85
45
40
35
30
25
20

Figure 13

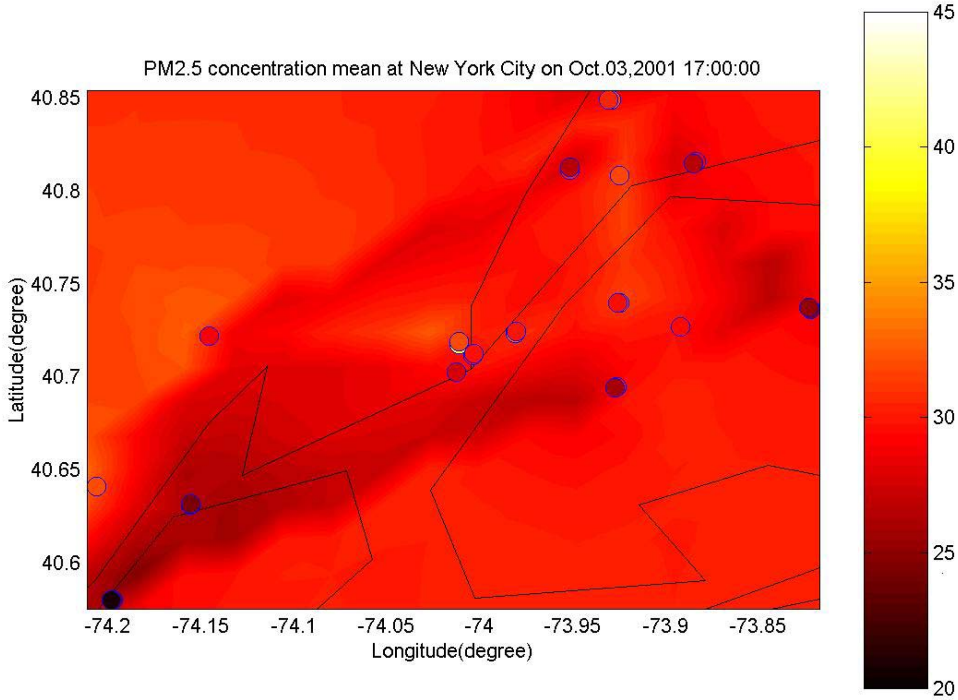

PM2.5 concentration mean at New York City on Oct.03,2001 17:00:00
Latitude(degree)
Longitude(degree)
40.85
40.8
40.75
40.7
40.65
40.6
-74.2
-74.15
-74.1
-74.05
-74
-73.95
-73.9
-73.85
45
40
35
30
25
20

Figure 14

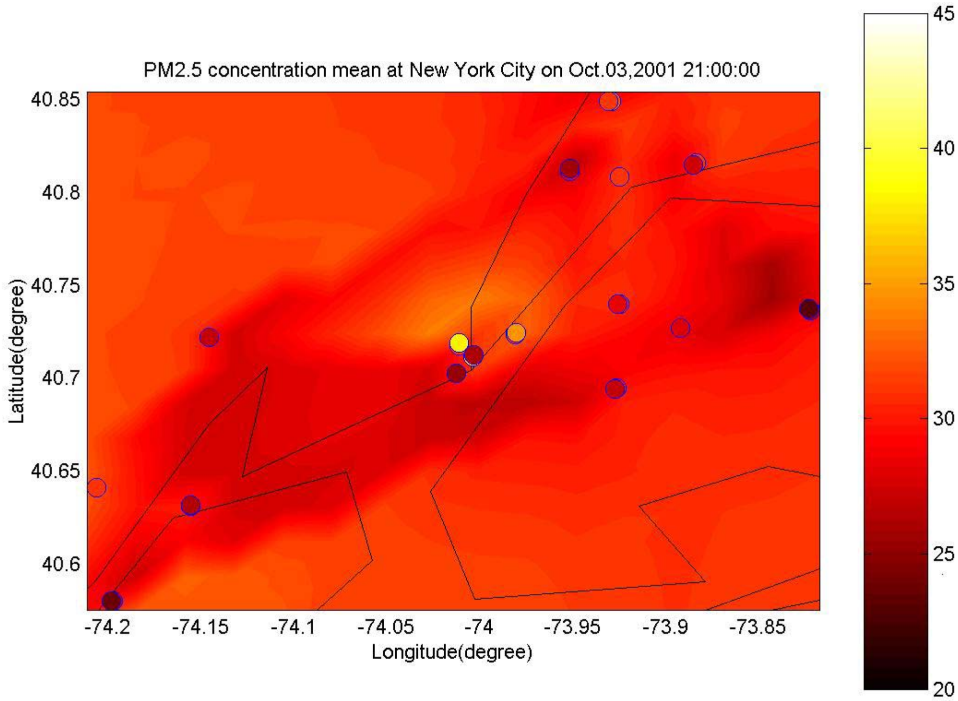


Figure 15

In order to assess the long-term effect of the WTC collapse onto air quality, we performed a time-series analysis of the mean over the NYC area of PM10 24-hour concentration. The measured PM10 mean for the NYC area is shown with a blue line in Figure 16. This measured PM10 mean was obtained by taking an average of measured PM10 24-hour concentrations at all the stations in the NYC area. As can be seen from the figure, there is a clear annual pattern of PM10, with high values in the summer and lower values in the winter. Using the four years prior to 9/11/2001 we modeled this annual pattern, and we predicted the mean PM10 level after 9/11/2001 using the model calibrated only on data prior to 9/11/2001. The predicted mean PM10 is shown in green in Figure 16, together with the corresponding lower and upper bound 95% confidence interval shown as dotted lines. The measured PM10 mean did clearly raise above the predicted mean after September 2001. This change in PM10 mean concentration over the NYC area is a clear indication that WTC crash increased the background concentration in the NYC Area, though no clear plume evidence is found on the basis of monitoring data alone.

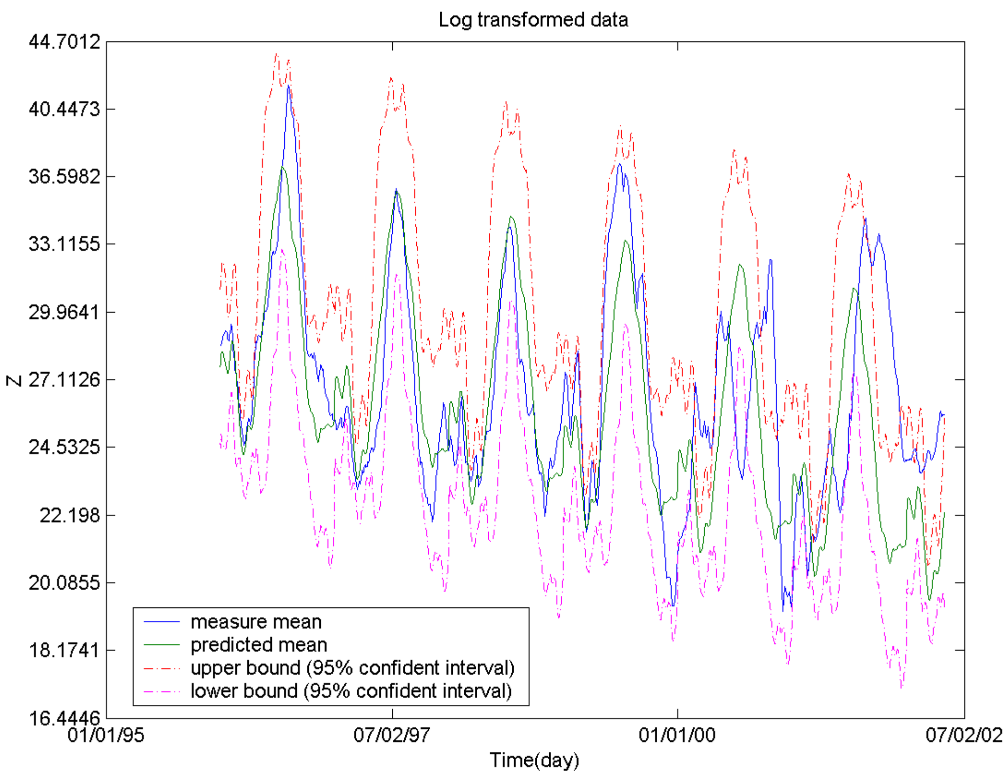


Figure 16

From the movies (www.unc.edu/~hlyu/WTC/WTCFrame.htm), we can tell that there is usually at least one monitoring station in the vicinity of the WTC with higher concentration than in the surrounding areas. Though the monitoring data are too sparse to clearly delineate the plume, they provide some evidence that the pollution from WTC was constricted in a localized space around the WTC site. Future work under way will focus on combining estimates of an atmospheric transport model of air quality with hard monitoring data to obtain the best assessment of the air quality in the WTC area after 9/11/2001.

CONCLUSIONS

1) PM2.5 is a criteria air pollutant providing a useful indicator to assess the impact of the WTC collapse on air quality. The distribution of log-transformed PM2.5 across space $\boldsymbol{s}$ and time t may be conceptualized for the WTC event as a Space/Time Random Field (S/TRF) $Y(\boldsymbol{s},t)$ that is the sum of a mean trend function $m_Y(\boldsymbol{s},t)$=E[$Y(\boldsymbol{s},t)$], where E[.] is the expectation operator,

and a homogeneous/stationary random field $X(\boldsymbol{s},t)$, so that $Y(\boldsymbol{s},t)=m_Y(\boldsymbol{s},t)+X(\boldsymbol{s},t)$. The mean trend function $m_Y(\boldsymbol{s},t)$ of $Y(\boldsymbol{s},t)$ represent systematic trends in air pollution, while the covariance function $c_Y(\boldsymbol{s},t;\boldsymbol{s'},t')=\mathrm{E}[(Y(\boldsymbol{s},t)-m_Y(\boldsymbol{s},t))(Y(\boldsymbol{s'},t')-m_Y(\boldsymbol{s'},t'))]$ describes it's variability over space and time.

2) The mean trend function was obtained applying a space/time moving average algorithm on several years of data in the greater WTC. A clear yearly pattern was found in the years prior to the 9/11/2001 event. The pattern shows an expected decrease of pollution every year in the 3-month period of September - November. The impact of the WTC collapse on air quality is modeled by using a discontinuous mean trend function with a source starting on 9/11/2001 at the WTC site.
3) The space/time covariance function is modeled using three space/time separable exponential covariance functions. The component of this model explaining most of the variability has a spatial range of about 0.09 degrees (1 degree is approximately equal to 111 Km) and a temporal range of about 7 hours.
4) The space/time maps obtained for the 3-month period after 9/11/2001 show that in general the AIRS monitoring data provide information about the background air pollution away from the WTC source, however this data is too sparse and too far from the WTC source to provide a coverage that would allow the reconstruction of the space/time plume in the vicinity of the WTC.
5) The informal version of the post 9/11 WTC database seems to have some data point with questionable data quality, and may be incomplete. Including the monitoring data in this version of the database adds a few monitoring stations that are closer to the WTC, but does not seem in general to provide a sufficient coverage to re-construct the space time plume in the vicinity of the WTC. It will therefore be necessary to combine the present monitoring data with output from dispersion plume modeling in order to obtain a more accurate representation of the air pollution plume.
6) A few high air pollution episodes have been identified in the monitoring data for the 3-month period following 9/11/2001. These episodes will be extremely useful in order to calibrate the dispersion model. Due to the fact that additional monitoring stations were added only several weeks after 9/11, the episodes identified in the monitoring data are mainly in October 2001, with one of the main episode centered on Oct 3.

Acknowledgments

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References:

Choi, K, M.L. Serre and G. Christakos, "Spatiotemporal BME mapping of health fields at different spatial scales", Journal of Exposure Analysis and Environmental Epidemiology, 13 (2), (2002).

Christakos, G., 1992, Random Field Models in Earth Sciences, Academic Press, San Diego, CA, USA, 474 p.

Christakos, G., 2000, Modern Spatiotemporal Geostatistics, Oxford University Press, New York, NY, 304 p. (3rd Reprint, 2001).

Christakos, G., P. Bogaert, and M.L. Serre, Temporal GIS: Advanced Functions for Field-Based Applications, Springer-Verlag, New York, N.Y., 217 p., CD ROM included, 2002

Christakos, G. and M L. Serre, "BME analysis of particulate matter distributions in North Carolina", Atmospheric Environment, 34, 3393-3406, (2000).

Christakos, G., M.L. Serre and J. Kovitz, "BME representation of particulate matter distributions in the state of California on the basis of uncertain measurements", Journal of Geophysical Research-D, 106 (D9), 9717-9731, (2001).

Serre, M. L., and G. Christakos, "Modern geostatistics: Computational BME in the light of uncertain physical knowledge--The Equus Beds Study", Stochastic Environmental Research and Risk Assessment, 13(1), 1-26, (1999).

Serre, M.L., G. Christakos, H. Li, C.T. Miller, "A BME solution to the inverse problem for saturated groundwater flow", Stochastic Environmental Research and Risk Assessment, in press, (2003)

Serre, M.L. and G. Christakos, "Efficient BME estimation of subsurface hydraulic properties using measurements of water table elevation in unidirectional flow", in K. Kovar and Z. Hrkal, editors, Calibration and Reliability in Groundwater Modelling: A

Few Steps Closer to Reality (Proc. ModelCARE'2002, Prague, June 2002). IAHS Publ. no. 277, in press, (2003)