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Improving Public Health Services through Space Technology and Spatial Information Systems

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ABSTRACT

Every day there are natural and human caused disasters that impact public health and that have adverse impacts on the affected societies and their economic productivity. In addition, there are very subtle, evolutionary forces of global change with profound impacts on human health and well being. Satellites have long been used to illustrate and measure global and regional Earth system processes by observing circulation patterns in the atmosphere and hydrosphere; but, the direct impacts of these patterns on human health have only recently been thrust into "prime time" awareness of the scientific, economic, and policy arenas. Public health infrastructures and mechanisms that link less dramatic environmental events to public health outcomes are just beginning to emerge. Earth system science requirements needed to integrate environmental monitoring with health services rest on (a) verifying, validating, and benchmarking the medical value of spectral and spatial observations for health; and (b), developing decision-support tools that enhance and streamline disease surveillance and information dissemination. This paper describes an effort to link air quality to respiratory health, reviews initiatives that address how data and information can be accessed to improve health services and explain how these services can assist in developing the etiology of air quality factors in health.

AIR QUALITY AND PUBLIC HEALTH

Public health is defined as *the science and art of preventing disease, prolonging life, and promoting health through organized efforts of society* (Eisenberg et al., 2001, p.230). It is concerned with populations rather than individuals. Its chief responsibilities are to monitor population health, identify societal health needs, foster policies that promote health, and evaluate health services. A broader definition includes domesticated animal and plant species that are the foundation of food supplies and that also serve as disease transmission pathways. Medical and health communities recognize five broad categories of diseases: (1) *infectious and zoonotic*, e.g. AIDS, TB, influenza, gastroenteritis, plague; (2) *degenerative*, e.g. arteriosclerosis; (3) *environmental*, e.g. asthma, cholera, meningitis, malaria, yellow fever; (4) *neoplastic*, e.g. cancer; and (5), *metabolic*, e.g. diabetes. This paper concentrates on environmental and selected zoonotic diseases whose origins or transmission pathways depend on airborne mechanisms.

Public health officials are only partly concerned with the effects of air quality on populations, and these must be considered in context of other risk factors that link demographics, life style, socioeconomic status and nutrition, access to health care, exposure rates, and genetic heritage (Dearry, 2005; Brilliant, 2007). Doctors and public health officials are aware of environmental factors in health, but the day-to-day pace of data and information-gathering procedures in hospital admissions and emergency room visits seldom leave time for referencing factors that might have triggered a respiratory or cardiovascular outcome. Finding the smoking guns requires working at the interface between two communities of practice: environmental health and public health. This is precisely where there is too little infrastructure, too few trained personnel, and too little time to fully assess causes and effects (etiology). Physicians, school nurses, emergency responders, clinicians, and others in healthcare professions have been trained to diagnose their patient's "chief complaints," not necessarily to inquire about that person's physical whereabouts or duration of a possible exposure. There is also a need to integrate geospectral and geospatial data into digital systems that allow health professionals to access reliable environmental data for more in-depth diagnoses, and that enable issuance of public health alerts (Lang, 2000; Morain and Budge, 2006; Griffin, 2007; Morain and Budge, 2008).

Relating air quality to human health

There is a rich literature linking airborne contaminants to health outcomes (see, for example: Bar-Ziv and Goldberg, 1974; Policard and Collet, 1952; Norboo et al., 1991; Gloster and Alexandersen 2004; Vineis 2004; Wu et al., 2004; Yu et al. 2004; Becker et al., 2005; Cringoli et al. 2005; Grattan et al. 2005; Park et al., 2005a; Sulaiman et al. 2005; Selinus et al. 2005; Kuehn, 2006; and, Schlesinger et al. 2006). Public health is impacted by exposures to airborne toxic gasses, microscopic mineral and chemical substances, and by organisms bound onto air particles (Kellogg et al., 2004; Stetzenbach et al., 2004; Kaiser, 2005; Griffin, 2007; Griffin et al., 2007). An individual's health is determined by complex interactions between genetic factors and environmental factors. Many of the latter represent the pathways for transmitting infectious or contagious diseases throughout whole populations. Moreover, prolonged exposures to injurious air quality events such as dust storms, high-levels of smoke and industrial emissions, and toxic gas emissions exacerbate chronic obstructive pulmonary diseases (COPD aka COL[ung]D), allergic reactions, and a host of respiratory conditions affecting particular age groups within a population (Pope, 2004; Zanobetti and Schwartz, 2005). The annual toll of these air quality impacts on public health directly affects every nation's health care facilities, GDP, and quality of life (Schmidt, 2005). Moreover, there is ample evidence that the toll is rising because of global changes in climate variability, land-use, economic development, population dynamics, and technological advances (Sultan et al., 2005; Park et al., 2005b). Consequently, air quality and public health are highly intertwined and complex, especially in context of global change (Varmus et al, 2004; Park et al., 2005b). Figure 1 shows avenues that airborne biological contaminants use to spread across environments. Clearly, air quality is a critical environmental variable for health officials because atmospheric circulation patterns and modern commercial jet aircraft can expose populations to chronic, and sometimes lethal, contaminants anywhere and anytime.

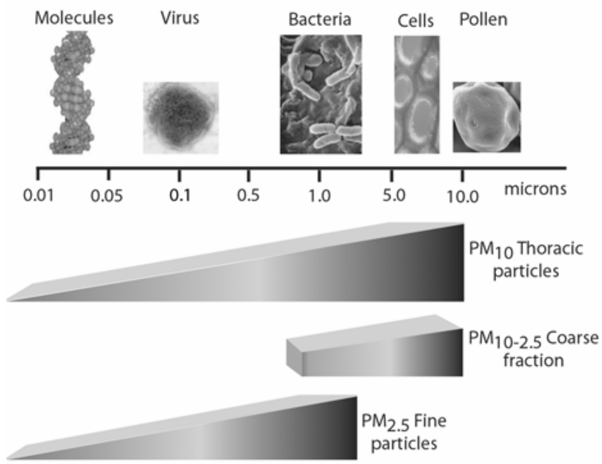

Figure 1. Particulate size distribution and related biophysical impacts. Modified from Kaiser (2005).

<u>Connecting satellite data to human health</u>

Public health cannot be monitored directly from environmental sensors because disease transmission pathways are seldom direct. However, environments that harbor potential health threats *can* be observed by sophisticated sensors operating in space. Through the accumulated literature, it is clear that long term, systematic air quality monitoring from integrated sensor systems is needed by medical and health professionals to determine the etiology and epidemiology of respiratory diseases. Air quality data for dust, aerosols, volcanic ash, and smoke from fires have been collected for over four decades by progressive generations of space sensors. It is apparent now that the northern mid-latitudes are home to growing numbers of emerging and re-emerging infectious diseases (Epstein, 1997; Binder et al., 1999; Gauderman et al., 2004; Morens et al., 2004; Fauci et al. 2005; Gyan et al., 2005; WMO, 2005; Kuske, 2006), and that an integrated global observing strategy is required to monitor these changing patterns (Kennel et al., 1997; Morain and Budge, 2008). The most heavily populated areas of North America, Western Europe, and Japan represent a triple threat because they have the highest concentration of air travelers to global destinations; are home to societies adding the highest concentrations of industrial emissions and biological contaminants into the air; and comprise the hemisphere over which there is measureable evidence for global change. Satellite data confirm the existence of a persistent ring of hemispheric aerosols around the northern mid-latitudes contributed by industrialized societies. The Earth's wind and ocean circulation systems also play a role in raising the rates of respiratory diseases like chronic asthma, myocardial infarction (MI), tuberculosis, severe acute respiratory syndrome (SARS), and influenza.

Dust storms so large that they can be animated using time-series satellite imagery can be seen to move across Asia toward North America. Similarly, dust entrained by winds over North Africa can be carried to the Caribbean. These phenomena have captured the attention of the World Health Organization (WHO), the International Council for Science (ICSU), and the Group on Earth Observations (GEO). While the medical community recognizes the adverse effects that dust, smoke, and ash can have on a population, they have lacked timely and reliable information for issuing warnings or implementing mitigation programs. WMO is proceeding to develop an *International Sand and Dust Storm Warning and Assessment System (ISDSWAS)* to alert governments and health officials of pending environmental episodes through a network of interactive and interoperable data centers. For its part, members of GEO are implementing *GeoNetCAST* as an element of the Global Earth Observing System of Systems (GEOSS) to broadcast and communicate weather information to authorities at the local level.

Technologies for making air quality measurements continue to improve, but the data and observations themselves are not systematically stored for retrieval and medical research. Science, technology, and policy communities face huge challenges in capturing and storing air quality data, of modelling complex biological, chemical, and physical processes that impair health, and in helping to find reliable measures for tracking health outcomes in populations (ICSU Scoping Group, 2007). Biogeochemical and dynamical processes of airborne pathogens and pollutants must be vigorously researched so that epidemiologists can begin to understand the medical consequences of air masses traversing regions and continents. What is needed, moreover, are long term archives of global air quality data and information for use in longitudinal studies of sentinel populations. Another equally challenging research area is to translate findings into actionable human health mitigations and policies that protect populations at risk. The grand challenge is to add health professionals into efforts that merge environmental surveillance with human health syndromes.

Health surveillance systems

Health decisions are always based on the best available information. One challenge for integrating air quality data and information into routine public health practices is to develop systems that constantly monitor conditions that trigger health responses. Environmentally induced risks having either $PM_{2.5}$ (respirable) or PM_{10} (inhalable) respiratory outcomes are a growing international concern. In some cases authorities rely on reports received at clinics, hospitals, and other care facilities. Others access databases having information on syndromes and outbreaks in local areas and across regions. Only a few assess environmental conditions at the global scale (Westphal et al., 1987 and 1988; Goudie et al., 2001). Decision support systems that provide early detection and analysis of environmental events enhance the ability of officials to warn populations at risk. In future, solutions to health surveillance systems will need to integrate environmental data that characterize complex physical and biogeochemical processes thought to have health consequences. The next generation of modellers may well be required to form teams of collaborating partners from the biogeophysical sciences with those from the medical sciences to assess changing and highly variable situations.

Several pioneering surveillance systems are being developed that provide electronic access to spatial and environmental data and information on diseases and syndromes. Two of these are the Syndrome Reporting Information System (SYRIS) by ARES Corporation, and the Environmental Public Health Tracking Network (EPHTN) by the Centers for Disease Control and Prevention in the USA. Both have enhanced their system's utility by incorporating mapping, visualization, and analytical tools. However, the use of these tools is only slowly evolving because public health communities do not routinely use spectral or spatial data and information in their daily work flows. There are two reasons for this. Users need assurance that: (a) these new and (to them) exotic inputs are accurate and reliable for use in health decisions; and, (b) data and information can be provided in timely electronic form without demanding additional processing for a work environment that is already overloaded. To address these issues, the *Public Health Applications in Remote Sensing (PHAiRS)* project[1] is developing an application framework to enhance existing public health decision support systems.

[1] Jointly executed by the University of New Mexico's Earth Data Analysis Center, the University of Arizona's Institute for Atmospheric Physics, and the University of Malta's DREAM modeling team.

ENVIROMENTAL/HEALTH MONITORING:
A Description of PHAiRS

Objectives

PHAiRS has three objectives. The first focuses on nesting a regional dust model within a global weather forecasting model to simulate regional dust storms, and then: (a) verifying that advanced satellite data can be assimilated to replace the regional model's design parameters; and, (b) validating that parameter replacements lead to more reliable dust model forecasts. The purpose of this effort is to enhance both the spatial and temporal resolution of the regional model by incorporating daily satellite observations. This is a necessary step because global weather models forecast weather but not dust.

The second objective focuses on optimizing dust model outputs by iterating inputs with a variety of satellite products and assessing incremental improvements. Interest has been concentrated on respiratory diseases that are known clinically to be triggered by air quality episodes. The questions of greatest interest are: (a) can the modeling system forecast dust entrainment?; (b) can the system predict the speed and direction of moving dust clouds?; (c) can areas affected by dust clouds be forecast in a timely fashion to alert health officials and populations at risk?; and, (d) can medically sound evidence be generated that couples dust episodes to documented respiratory health responses at the population level?

The third objective involves working with public health authorities to address objective 2(d); that is, to determine whether there are statistically valid relationships between dust episodes and records for increased respiratory complaints. This is a difficult effort in the United States because public health authorities are distributed throughout all levels of government and because public health reporting is not mandatory for all types of records within or between these levels.

The modeling system

PHAiRS employs an operational weather forecasting model developed by the National Centers for Environmental Prediction, eta version (NCEP/eta). It simulates large-scale numerical solutions controlled by conservation of integral properties. It uses a non-linear horizontal advection numerical scheme that preserves energy and squared vorticity and controls non-linear energy cascade. With the eta vertical coordinate, which generates quasi-horizontal model levels, topography is represented by step-like elements. Physical parameterization includes land surface processes, turbulent mixing, convection, large-scale precipitation, lateral diffusion, and radiation. Its parameters include lat/lon, 32 pressure levels from the surface to 100 hPa, geopotential height, wind components, specific humidity, and soil temperature, moisture, and albedo. Resolution of these inputs range from 0.1° to 1.0° lat/lon.

For simulating dust events, the Dust Regional Atmospheric Model (DREAM) has been nested within the NCEP/eta simulator to form the model system described here (Janjic, 1984; Mesinger et al., 1988; Janjic, 1994; Nickovic et al., 2001). DREAM was originally developed for use in the Mediterranean region and was run as a European Center for Medium-Range Weather Forecast (ECMWF) system using initial and boundary conditions of one degree. Verification and validation of this system's outputs are reported by Nickovic et al. (2004), and Perez et al. (2006). The DREAM/eta system is also undergoing extensive V&V analyses. Preliminary results are given in (Morain and Sprigg, 2007). DREAM is a desert dust cycle model consisting of two simulators: (a) an atmospheric simulator; and (b) a dust cycle simulator. The dust cycle simulator models dust production, advection and turbulent diffusion, and dry and wet deposition (Nickovic et al., 2001; Shao et al., 1993; Georgi, 1986). It relies on three static surface parameters: (1) soil texture classes at 2 minute x 2 minute resolution (Cosby et al., (1984); (2) vegetation cover at 10 minute resolution from the Olson World Ecosystems (OWE) map; and, (3) topography at 1x1 km resolution.

The health surveillance system adopted by PHAiRS is SYRIS. It has been designed for epidemiologists, school nurses, doctors, and veterinarians, among others. Its objective is to augment traditional medical data and information (health questions) with web-based services that provide a geographical and environmental context for the broader implications of reported cases that might otherwise be static, individual case records. The web-based service system not only provides doctors and clinicians with a *rapid* response capability at the case level, but provides public health authorities with longer range forecast capabilities that protect the public at large.

<u>Baseline DREAM/eta model run</u>

The baseline version of DREAM/eta was run for a dust-storm event on December 15-17, 2003 (Figure 2, left) to assess whether critical meteorological variables could be predicted. A Pacific cold front swept across eastern Arizona, New Mexico, and west Texas bringing gale force winds and dry conditions. It generated one of the worst dust storms in recent years. A *Continuous Air Monitoring Station (CAMS)* located in Lubbock, Texas measured its highest $PM_{2.5}$ one-hour average (485.6 μg/m^3) between 1300-1400 hrs Central Standard Time. It also measured a daily average $PM_{2.5}$ of 76.7 μg/m^3. The PM_{10} daily average concentration of 84 μg/m^3 was estimated to be five times higher than is considered “healthy” by the US/EPA. A comparison was made between the observed pattern (Figure 2,middle) and modelled pattern (Figure 2, right) to assess how well DREAM/eta could forecast Southwest meteorology.

Figure 2. (Left) Terra MODIS image of the December 15, 2003 dust storm that swept into the panhandle of Texas. Both siliceous and calcareous dust, and their points of origin are seen clearly in the cloud-free areas; (Middle image), a geostatistically generated map of visibility classes based on a network of six $PM_{2.5}$ CAMS at 12:00pm CST (yellow = < 7 miles, orange = < 3 miles, and red = < 1 mile visibility); (right image), baseline DREAM/eta model output of dust concentrations (white/pale blue = lowest, purple/ brown = highest). Baseline means before environmental data were assimilated.

The DREAM/eta meteorological fields were compared with measurements and analysis products from 95 surface synoptic sites, 663 surface Meteorological Aerodrome Reports (METAR sites), and 77 upper-air radiosondes. The modeled dust field patterns and dust concentrations were compared with satellite images, measured visibility distributions, and surface $PM_{2.5}$ and PM_{10} observations made by the Texas Commission on Environmental Quality and the US/EPA’s Air Quality System (AQS). Graphical measures, such as pattern comparison, site against site time-series, vertical profile comparison, and statistical metrics were used.

DREAM/eta predicted the meteorological patterns quite well (Figure 3). Performance of the baseline DREAM model is mixed but encouraging (Morain and Sprigg., 2005). This suggests that DREAM/eta outputs might be improved by replacing DREAM baseline parameters with temporally adjusted satellite terrain data. Considering that DREAM was used to model hundreds of weather reporting stations across more than 10° of latitude and 20° of longitude, the output is encouraging.

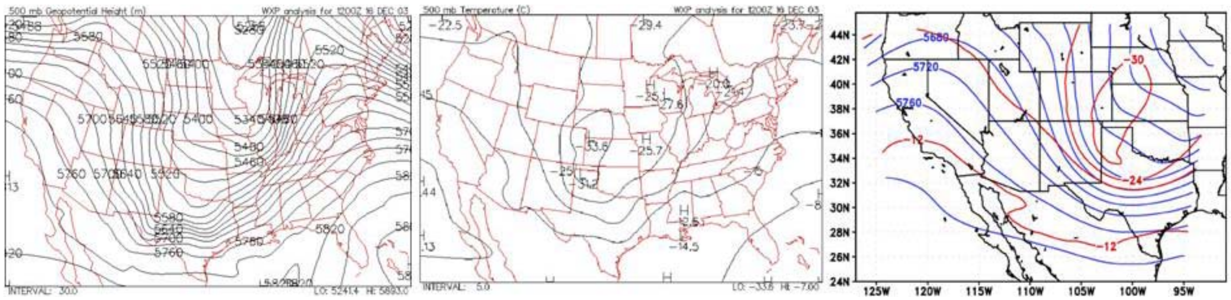

Figure 3. Observed vs. modeled synoptic patterns at 12Z 16 Dec 03. Top, left is observed temperature; bottom, left is observed geopotential height; and right is the DREAM simulation of both geopotential height (blue isolines) and temperature (red isolines).

<u>Data assimilation and sample model runs</u>

Data assimilation is a multifaceted process, hampered by the general absence of metadata. Attributes of baseline DREAM/eta parameters and of possible replacement replacements must be compatible in terms of: (a) measurement units, (b) x,y,z resolution, (c) map projection, (e) file formats, (f) error and error propagation, and (g) subsequent validation that the replacement parameters enhance or improve the simulation. Table 1 includes satellite data products that were used as replacements for baseline data sets.

Table 1: Data sets assimilated into DREAM/eta (see Morain and Sprigg, 2005 for detailed descriptions).

Model parameter	Baseline data source	Satellite data source
Land cover	OWE 10-min. (19km) res.	MOD-12 1km res.
Topography, Elevation	USGS 1km terrain data	SRTM-3 arcsec terrain data resampled to 30 arcsec 1km res.
Aerodynamic roughness length	Predicted using 12 SSiB land cover types	Look-up table linked to MOD-12 land cover
Dust source areas	Not a baseline parameter	FPAR “Fill” class 254-255
Soil Moisture	Simulated using a land surface model	AMSR-E

The sequence of sample model runs with assimilated satellite data is given in Table 2. MOD12 land cover data have been converted into a binary map of barren vs. vegetated surfaces. It has been a consistent parameter replacement, followed by Shuttle Radar Terrain Mission (SRTM-90) data and aerodynamic surface roughness estimates (z_0) derived from a table look-up. In addition, two other parameters have been assimilated but not systematically used. These are the Fractional Photosynthetically Active Radiation (FPAR) “fill” class, which is another MODIS terrain product called MOD15; and, soil moisture data from the Advanced Microwave Sounding Radiometer-E (AMSR-E). Enhanced DREAM/eta has simulated dust storms over a five year period from 2003-2008 and has created an archive of rolling 3-day forecasts across the Southwest. Statistical analyses are made on the model's performance under day-to-day conditions. Yet a third version of the model has been configured to run with NCEP/NMM[2], called enhanced DREAM/NMM. Figure 4 shows the incremental improvements in these three model configurations, but no verification or validation analyses have been performed on the third configuration.

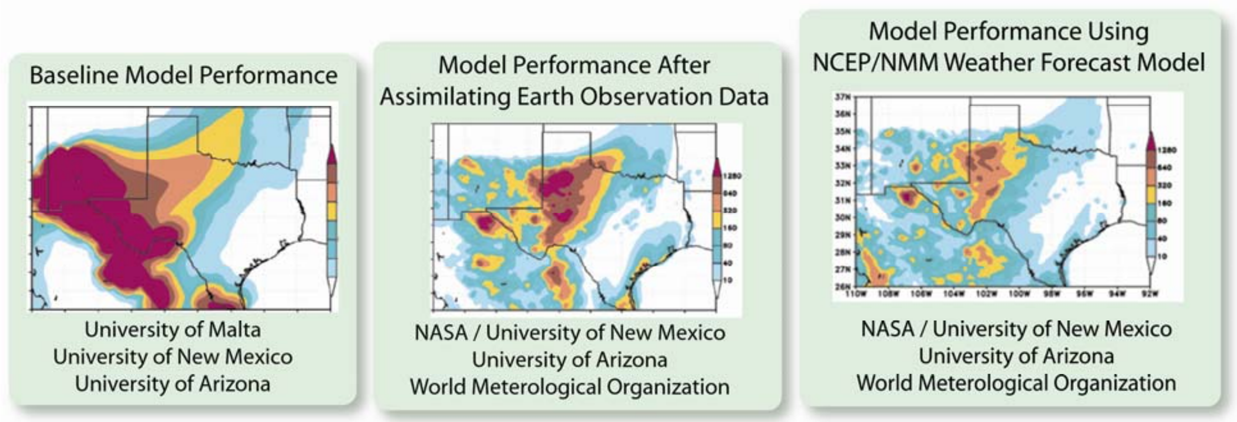

Figure 4. Three generations of DREAM model improvements. (left) the baseline model performance without satellite-acquired data included; (middle) the same dust storm with assimilated satellite data replacing baseline model parameters; (right) the same dust storm as modeled by the latest version of NCEP/NMM replacing NCEP/eta.

Table 2: DREAM data set replacements in various model runs

Run #	MOD-12	SRTM-30	z_0 (m)	FPAR	AMSR-E
Baseline	No assimilated satellite terrain data				
Run 2c	✓				
Run 4a	✓	✓			
Run 5a	✓	✓	✓		
Run 5b	✓	✓	✓		
Run 6a	✓			✓	
Run 10a	✓	✓	✓		✓
Run 15a	✓				✓

Model results before and after data assimilation, show that *surface* weather patterns (sea level pressure, 500 hPa potential height, and temperature) match well with the observed weather patterns. As hoped, this indicates that finer resolution land cover data have little effect on the overall performance of the NCEP/eta atmospheric simulator. The primary difference between the two sets of model results is seen in sea level pressure fields, although these differences do not affect the overall patterns. Similarly, the upper-air fields were not affected by the model data set replacements. Among the vertical profiles for wind, temperature, and specific humidity, only slight differences were seen after data assimilation, except for differences in the near-ground wind speed.

[2] In June 2006, the eta version of NCEP was superseded by a non-hydrostatic version, NCEP/NMM

The performance statistics of the modeled surface meteorological variables using MOD12 data showed that enhanced DREAM/eta performance in 2m (height above surface) temperature improved by comparison to baseline DREAM/eta results. The model performance for 10m wind speed and direction showed slight improvement using assimilated data. This seems reasonable since the OWE land cover data used for the "before" model run had much coarser spatial resolution than the run after assimilating MOD12 data. Both OWE and MOD12 data sets performed well, but the finer resolution MOD12 data, when combined with SRTM topography and surface roughness length (z_0) data, provided a better simulation of surface wind speeds. This improvement led to better dust entrainment simulations. Table 3 lists performance statistics for modelled surface wind speed, wind direction and temperature. The biggest differences between results from before and after MOD-12 data assimilation are for 2m temperature. The agreement index after data assimilation was 0.95, compared with 0.71. This is a significant model improvement. The mean bias and mean error after parameter replacement are less than those for the baseline parameters. The agreement index for 10m wind direction and speed was slightly better after MOD-12 data were assimilated, but the mean bias and mean error were actually slightly higher than those obtained using the original DREAM parameters.

Table 3: DREAM performance for model run 10A before and after satellite data assimilation. DREAM/eta values are in italic font; enhanced DREAM/eta values are in bold font. For the equations M = modelled; O = observed

Metrics	***Wind Speed (m/s)***	***Wind Direction (°)***	***Temp (K)***	***Definition***
Mean Obs.	5.53	231.40	276.74	$\frac{1}{N}\sum_{i=1}^{N} O_i$
Mean Mod.	*4.65* **4.37**	*226.60* **230.38**	*275.56* **277.48**	$\frac{1}{N}\sum_{i=1}^{N} M_i$
Mean Bias	*-0.88* **-1.16**	*-4.80* **-1.02**	*-1.20* **0.72**	$\frac{1}{N}\sum_{i=1}^{N} (M_i - O_i)$
Mean Error	*1.97* **2.03**	*51.76* **47.85**	*4.09* **2.67**	$\frac{1}{N}\sum_{i=1}^{N} \lvert M_i - O_i \rvert$
Agreement Index	*0.74* **0.75**	*0.74* **0.76**	*0.71* **0.95**	$1-\frac{\sum_{i=1}^{N}(M_i - O_i)^2}{\sum_{i=1}^{N}\left(\lvert M_i - \overline{O}\rvert + \lvert O_i - \overline{O}\rvert\right)}$

Verification and Validation

PHAiRS has developed a verification and validation subsystem intended to provide needed confidence by users that enhanced DREAM/eta outputs are reliable, that research and development data are accessible for testing and analysis, and that data can be integrated into routine applications for health surveillance. Development efforts have focused on three tasks: (1) defining statistical measures; (2) creating a model output archive; and (3), creating an interoperable, open-source data management system for web services.

The first task was to create statistical measures and indices to assess how well enhanced DREAM/eta performs in comparison to *in-situ* dust concentrations reported by ground-based networks. In order to verify and validate the performance of consecutive versions of the model, the system has been designed to calculate *measures of central tendency* and *measures of variability* for both observed and modelled dust concentration values. These measures include the mean and standard deviation. Another set of statistics provides *measures of association* between these two variables. These include: mean observed value at each site; mean bias (0 if perfect); mean error (0 if perfect); normalized mean bias (0% if perfect); normalized mean error (0% if perfect); fractional bias (0% if perfect); fractional error (0% if perfect); and index of agreement (1 if perfect); the correlation coefficient (R); and the centered root mean square (RMS). The performance statistics are defined in Yin et al. (2005). These statistics can be obtained for a single station for a date range specified by the user.

For these comparisons (modelled and observed), *in-situ* data for hourly $PM_{2.5}$ and PM_{10} are available from the US/EPA AIRNow network for 2006 to present. These data are acquired for all EPA stations within the DREAM/eta domain; that is 94 $PM_{2.5}$ and 41 PM_{10} sites. Many sites have missing data for lengthy periods, especially for days of known dust events. It is suspected that *in-situ* sensors fail under extreme conditions and/or that reporting of these events is delayed. It is unclear how many sites within the *in-situ* network have this problem, but it happens often that dust events of interest have missing data at many sites. Most AIRNow sites are located in cities, making validation over rural areas difficult. It has been shown also that the MOD12 data for northern Mexico (included in the DREAM/eta modelling domain) improve validation statistics at US stations (Yin et al., 2007). At present, there are no *in-situ* measurements from Mexico for use in V&V.

The second task was to create an archive of model outputs. This includes a daily model run for the 48-hour period beginning at 00:00:00 hours of the previous day. It also includes twice daily model runs beginning January 1, 2006. The archiving system is designed to execute three model runs per day and an animated rolling 72-hour forecast for the current day. The model runs represent a true forecast of pending air quality episodes. However, because PHAiRS seeks to build user confidence with statistical V&V comparisons to the AIRNow data stream, confirmation of an episode may take two or three days. As the archive and user confidence grow, the archive will serve two purposes: (1) to provide advance warning of episodes for public health alerts and interventions; and (2) to provide a lengthening historical record of dust storm frequencies and intensities for use in longitudinal respiratory health research.

The third task was to create a web-based data management system permitting users to search for, access, and download dust storm frequency and intensity data, together with data collected by *in-situ* networks. Both the historical and daily forecasts are part of this system to deliver public health decision support through Simple Object Access Protocols (SOAP) and web mapping service (WMS) interfaces (Budge et al., 2006). The web service architecture allows users to find and download $PM_{2.5}$ and PM_{10} data from *in-situ* monitors and model output values for areas or specific locations. They can download $PM_{2.5}$ or PM_{10} data for a defined date range, or for a single day. Similarly, SOAP service functions allow users to download both *in-situ* and enhanced DREAM/eta dust concentration values for a single station, or for all stations within the modelling domain. Animations of air quality episodes can be downloaded for a specific day, a 48-hour period corresponding to a model run, or a date range specified by the user.

Dust cloud detection and movement

For dust cloud detection and movement, V&V analyses use the growing archive of model runs. The 72-hour rolling dust forecast alerts team members to impending dust events, but receipt of the AIRNow data needed for statistical comparison typically lag a few days behind the model runs. When the *in-situ* data become available, model outputs are compared to observed PM_{10} and $PM_{2.5}$ in a hindcast mode. The measures of greatest interest for monitoring human exposures to dust are: dust concentration; dust episode duration; and, hour of peak concentration. One dust episode occurred in January 2007. A severe wind and dust storm near Barstow, California caused traffic accidents killing two and leaving others with severe injuries. Wind continued to interrupt traffic, freeways were congested, and several large trucks toppled or jack-knifed. High winds spread across the southwest eventually including parts of Texas. This dust event was investigated using DREAM model hindcasting.

Data from seven AIRNow monitoring stations were used for the analysis. Four were located in Southern California (Burbank, Riverside, Palm Springs, and Indio) and three in Texas (El Paso, Mission, and Selma). Figure 5 shows a 72-hour plot for each station (Jan 4-6, 2007) and illustrates the dust event that occurred around 2300 UTC on January 5th at most stations. The stations are plotted geographically west (on the left) to east (on the right). Southern California was affected most by this event. Both the observed and modelled data show a strong dust gradient from mild in the east to more severe in the west, with the exception of Riverside, where virtually no significant dust was recorded by the ground station data. Of particular note in the figure is the difference in dust concentrations between model run 15a and 20a. Dust concentration is estimated in the model by partitioning particle sizes into four bins. PM_{10} is extracted from parts of 2 bins. Therefore the modelled dust concentration can be higher or lower depending on how highly refined the extraction process is. Comparison between run 15a and 20a shows a slight decrease in dust concentration at several stations (Burbank, Riverside, and Palm Springs). This difference was obtained by refining the bin size algorithm in run 20a to use a narrower bin size.

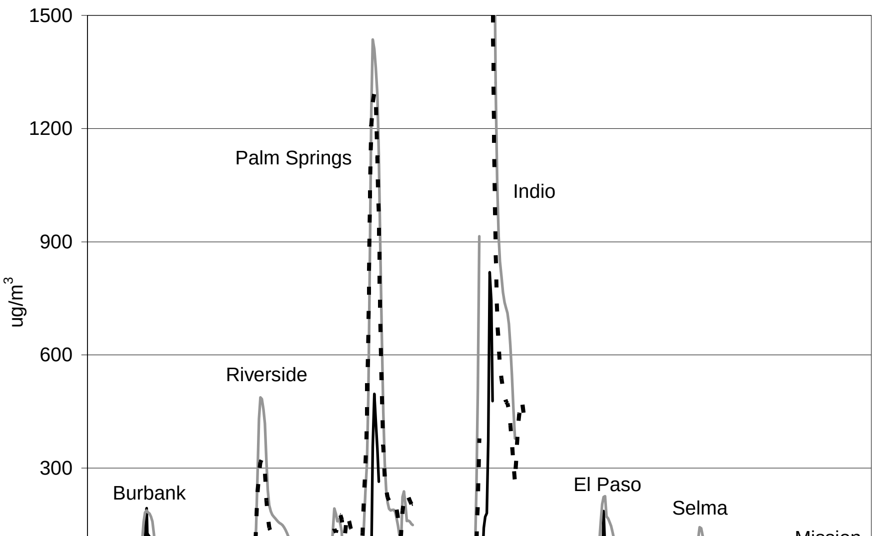

Figure 5. Modelled and observed PM_{10} concentrations at seven AIRNow stations across the southwest for January 4-6, 2007.

Figure 6 shows the correlation between modelled and observed dust concentrations for the January 4–6 event. Correlation lines are skewed toward the modelled data axis, illustrating the model's tendency to over-predict dust event concentrations. However, model improvements are indicated in the higher correlation from run 15a to 20a (R^2=0.67 vs. R^2=0.59, respectively).

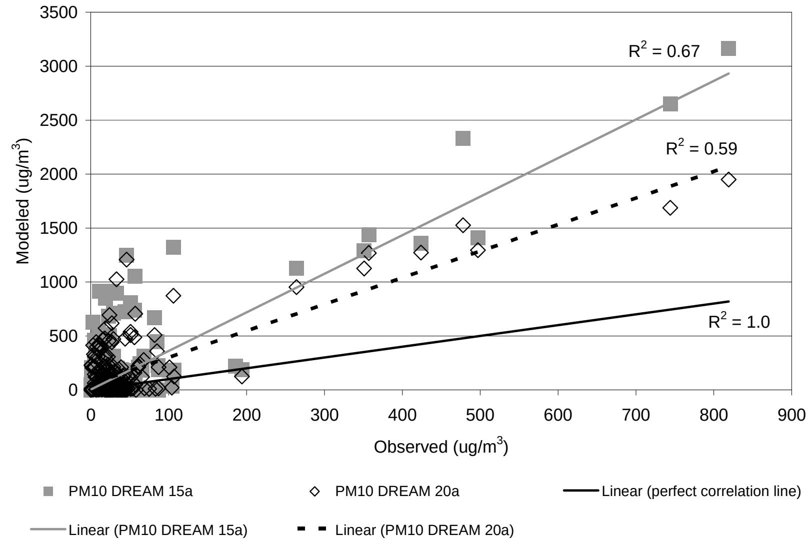

Figure 6. Magnitude correlation for seven sites during the Jan 4-6, 2007 event (N = 443).

A statistical analysis that included the seven sites using the latest version of the model (20A) is shown in Table 5.

Table 5. Statistical analysis of seven test sites, Jan 4-6, 2007.

N (seven sites)	443 obs / 443 mod
Mean	29.2 obs / 26.3 mod
Mean bias	2.8
Mean error	26.0
Normalized mean bias	10.8
Normalized mean error	76.2
Fractional bias	12.1
Fractional error	88.1
Index of agreement	0.63

The timing correlation for the January 4-7 dust event is shown in Figure 7. The X-axis is a 72-hour event clock showing the observed peak hour concentration. The Y-axis shows the modelled peak hour concentrations during the event. Several sites had more than one peak hour during the three-day event. A plot of daily peak hours for each of the seven sites would yield 21 data points. Occasionally, however, no peak hour was evident, particularly on January 4. These results (R^2 = 0.95) for model version 20a show an improvement over previous versions of the model published in earlier work (R^2 = 0.76, Yin et al., 2005).

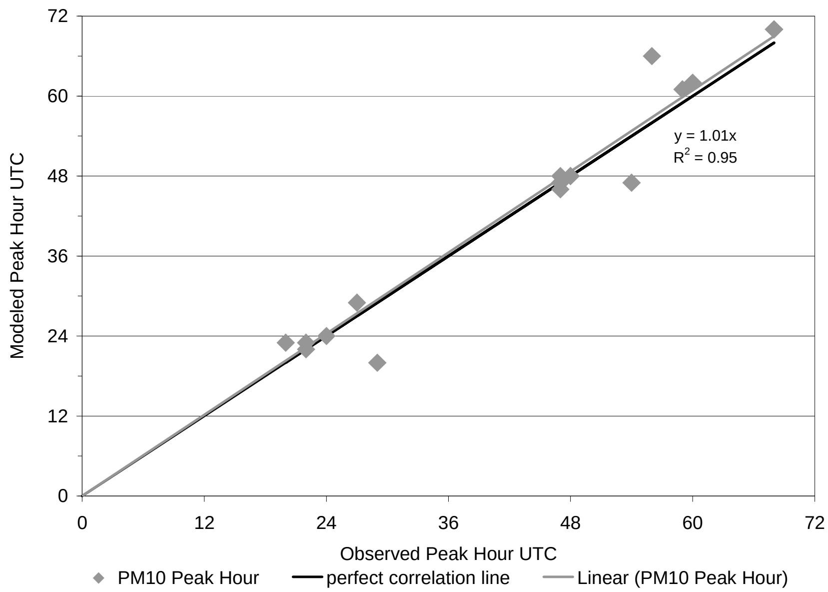

Figure 7. Timing Correlation (N=18 peak hours, seven sites) for the Jan 4-6, 2007 dust event.

Sample health surveillance system

Research results and products from PHAiRS are being used to enhance human health surveillance and tracking systems. One of these systems is the Environmental Public Health Tracking System (EPHTS), which in New Mexico is being developed to collect, integrate, analyze, and interpret data of changing air quality conditions (Figure 8). Additionally, EPHTS provides a conduit for rapidly disseminating these data and analytical results to epidemiologists, public health officials, and other qualified persons. One of its functions is to link data from the Statewide Asthma Surveillance System and other respiratory and cardiovascular diseases that are tracked by the Hospital Inpatient Discharge Database to $PM_{2.5}$ and PM_{10} air quality data. A key goal of EPHTS implementation is to develop an information architecture that facilitates the performance of epidemiological analyses and the delivery of results and products to the public and to state health professionals.

The EPHTS architecture is a system of interacting services each providing a specific function. Products are integrated into several clients in a Service Oriented Architecture (SOA). Enhancements to this system will be in the Public Services area (left side of Figure 8) where new datasets are integrated into client interfaces that include the Mapping Client, Web Mapping Services (WMS) Client, Analysis Client, and Tabular Data Client. Both the Mapping Client and the WMS Client allow users to visualize raster images derived from the enhanced DREAM/eta modeling system. While the WMS Client acts as an image viewer for routine GIS operations (e.g., zoom, pan, and overlay with user-selected vector data), the Mapping Client is capable of performing advanced GIS functions. Users have access to ArcGIS functions like buffering, distance measurements, layer attribute extraction, and querying. Moreover, users can access customized raster processing models that are built on the server.

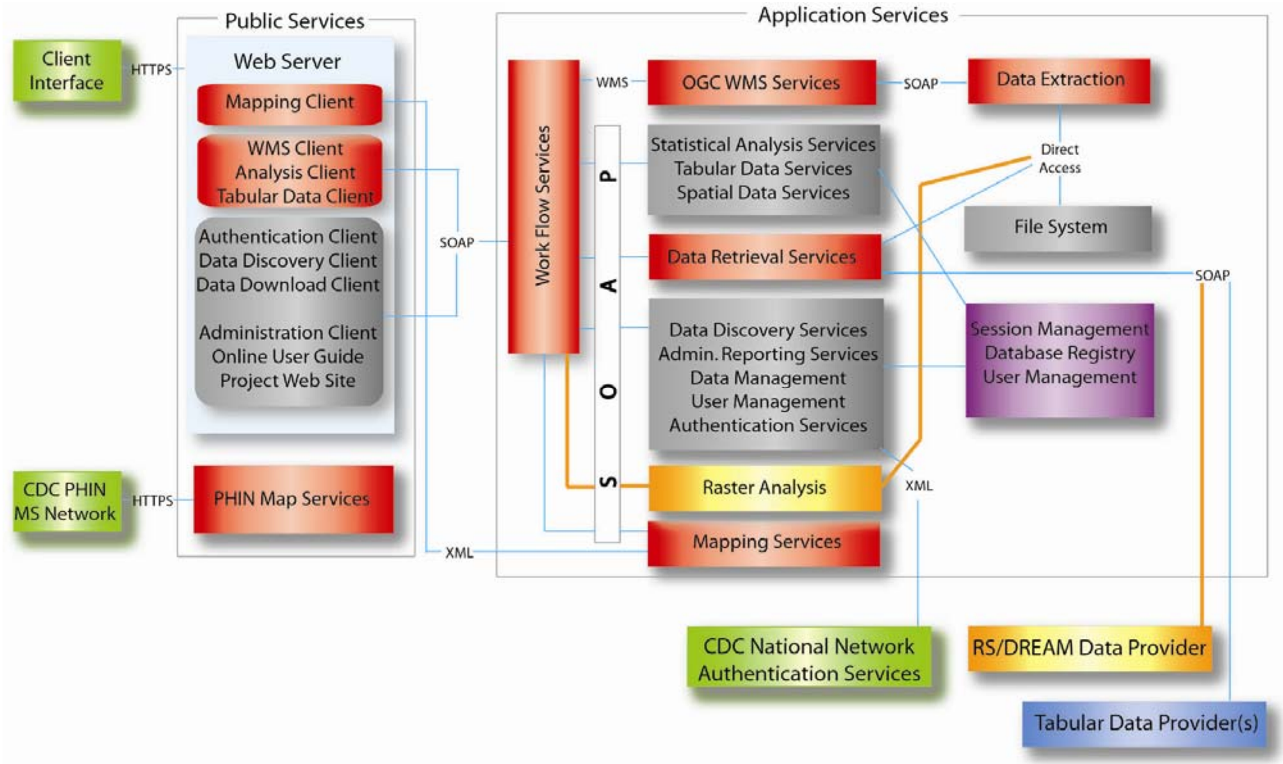

Figure 8. Components of EPHTS. Red boxes show where enhancements are expected as inputs and outcomes; yellow boxes refer to new components that are being added for archived dust episodes and 3-day dust forecasts.

Products can be integrated also into the Tabular Data Client and the Analysis Client. SOAP functions enable users to extract and analyze specific characteristics or attributes from raster-formatted data. Examples include extracting summarized data from raster coverages that fall within political or administrative boundaries (e.g., counties, census tracts). Therefore, users can generate both the distribution of ozone values and the average values for each county, census tract, or zip-code in a state. SOAP requests can return such data in tabular formats as charts and graphs, or as images. Similarly, products generated from the dust forecasts could be presented. Another application provides time-series data for environmental parameters. It is possible to generate time series of dust concentrations derived from DREAM for particular points on the landscape. In this way, users can analyze how environmental parameters vary through both time and space.

FINDINGS AND CHALLENGES

Remote sensing of the environment is critical in advanced systems to warn of imminent, life-threatening sand and dust storms and to reduce risk of exposure to mineral dust concentrations that contribute to respiratory and cardiovascular diseases. MODIS data improve identification of active mineral dust sources, and thus, numerical model simulations and forecasts of dust generation, entrainment, and downwind dispersal and deposition.

Enhanced DREAMeta can forecast the timing of an advancing dust storm verifiably to meet the needs of public health decision makers. While the dust forecast system simulates and predicts the three-dimensional size-concentration characteristics of the dust cloud, verification of model output requires on-going verification and validation.

V&V of airborne particulate concentrations rely primarily on a regionally sparse network of *in-situ* sampling stations for statistical comparison with DREAM-generated PM_{10} and $PM_{2.5}$ concentrations. These sampling networks are concentrated in large, densely-populated urban areas that include PM_{10} and $PM_{2.5}$ anthropogenic as well as atmospherically generated concentrations.

Products designed specifically with end users in mind are being evaluated in state health offices with operational health and air quality responsibilities. These products are being modified as needed, and further V&V will play a large role in adapting/adopting the new technology developed under PHAiRS for public health services.

Air quality and public health are highly intertwined and complex, especially in context of global change. It is apparent now that the northern mid-latitudes are home to growing numbers of emerging and re-emerging infectious diseases, and that an integrated global observing strategy is required to monitor these changing patterns (Kennel et al., 1997; Morain and Budge, 2008). Satellite data confirm the existence of a persistent ring of hemispheric aerosols around the northern mid-latitudes contributed by industrialized societies.

Technologies for making air quality measurements continue to improve, but the data and observations themselves are not systematically stored for retrieval and medical research. Science, technology, and policy communities face huge challenges in capturing and storing air quality data, of modelling complex biological, chemical, and physical processes that impair health, and in helping to find reliable measures for tracking health outcomes in populations. Biogeochemical and dynamical processes of airborne pathogens and pollutants must be vigorously researched so that epidemiologists can begin to understand the medical consequences of air masses traversing regions and continents. Long term archives of global air quality data and information are needed for longitudinal studies of sentinel populations. Challenging research areas remain in integrating air quality and health datasets and for translating the results into actionable human health mitigations and policies that protect populations at risk. The grand challenge is to add health professionals into efforts that merge environmental surveillance with human health syndromes.

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