EXTENDING ENVIRONMENTAL SURVEILLANCE TO USEFUL PUBLIC HEALTH INFORMATION

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ABSTRACT

Public Health Applications in Remote Sensing (PHAiRS) is addressing: (1) an atmospheric dust modeling system into which Earth observation (EO) data have been assimilated, and (2) a public health information system that is designed to link environmental data to aggregated health outcome data provided by the New Mexico Department of Health and other public health authorities. The objective is to provide a range of analytical, statistical, and mapping capabilities that are interoperable with syndromic surveillance systems. PHAiRS' hypothesis is that the timing and intensity of dust forecasts can be improved by assimilating satellite EO data into a dust entrainment model driven by land surface properties. Output from the model system provides dust forecasts that become part of daily weather forecasts, the reliability of which is critical to health decisions. The model outputs are portable to the public health information system, which is an n-tiered architecture of interacting services each performing specific functions. The system has a suite of application services and public services that feed map and tabular outputs to users. All of the methods and protocols used by the system are compliant with Open Geospatial Consortium (OGC) standards.

INTRODUCTION

Respiratory health is impacted by exposure to microscopic minerals, chemical particulates, by organisms bonded to air particles, and by toxic gases. These constituents may be infectious and can become contagious; others are patient-specific. For example, ozone (O_3) is linked epidemiologically to chronic asthma; viruses lead to influenza; bacteria lead to intestinal problems; and pollen leads to hay fever. Dust and smoke particles and industrial emissions in the PM_{10} to $PM_{2.5}$ micron range contribute directly to respiratory health responses and serve as carriers for respirable viruses and bacteria (Griffin, 2007). Cardiovascular and respiratory diseases typically increase in populations having frequent and/or intense exposure to airborne mineral dust.

The American Southwest is a dusty environment experiencing frequent weather-induced mineral dust storms, exacerbated by increasing amounts of human-induced dust from urban development and emissions from agriculture, combustion engines, and industry. Weather-induced dust storms are visible from space but operational weather forecasting models are not designed to measure dust concentrations. To acquire this information, dust entrainment models can be embedded into weather forecast models to simulate dust entrainment and transport in the lower troposphere. For health surveillance and applications the questions are whether model outputs are improved after assimilating Earth observation (EO) data, and whether these outputs can be delivered in a timely manner for health alerts and interventions. Clearly, the model outputs must then be integrated into health tracking and surveillance systems.

New Mexico's Environmental Public Health Tracking System (EPHTS) is part of a national Environmental Public Health Tracking Network (EPHTN) being developed by the Centers for Disease Control and Prevention (CDC). Both the system and the network aim to improve health awareness and services by linking health effects data with levels and frequency of environmental exposure. While the epidemiology connecting declining air quality and respiratory diseases in desert regions is poorly understood, patterns of rising health costs are known to be associated with rising levels of atmospheric contaminants (Pope, 2004). The goals of EPHTS are to link PM_{10} and $PM_{2.5}$ air quality data to health surveillance data; to evaluate the utility of linked data for assessing environmental exposures and health outcomes; and, to recommend adjustments to existing systems of data collection and analysis.

There is strong evidence that respirable particulates result in costly health effects (CDC, 1998; Landrigan et al., 2002; Jerrett et al., 2003; Myers, 2006). Costs are rising at alarming rates, stressing the healthcare infrastructure and adversely affecting economic productivity. The data are a compelling argument for forecasting mineral dust concentrations and movements.

The University of New Mexico and The University of Arizona have teamed to provide a dust forecasting tool for use by pubic health officials in the Southwest. The Public Health Applications in Remote Sensing (PHAiRS) project is using EO data to improve the resolution of mineral dust forecasts, which in turn are enhancing the capabilities of disease surveillance and tracking systems.

EO DATA ASSIMILATION AND MODELING

Data Assimilation

PHAiRS is focused on the coarse fraction of airborne thoracic particles ranging between $PM_{2.5}$ and PM_{10}. It uses the Dust Regional Atmospheric Model (DREAM) developed by Nickovic et al. (2001), which is a desert dust cycle model nested within the National Centers for Environmental Prediction (NCEP/eta) framework (Janjic, 1984; Georgi, 1986; Mesinger et al., 1988; Shao et al., 1993; Janjic, 1994). The combined model has two modules: an atmospheric simulator (NCEP/eta), and a dust cycle simulator (DREAM). Physical parameterization includes land surface processes, turbulent mixing, convection, large-scale precipitation, lateral diffusion, and radiation. This model system was adapted for use in the Southwest with its domain centered at 109ºW, 35ºN (Morain and Sprigg, 2005). Its performance has been tested and validated using observed weather patterns and dust events (Morain and Sprigg, 2007).

DREAM simulates dust production. In its original configuration the module has three static surface parameters: soil texture classes derived from Cosby et al. (1984) at 2x2 minute resolution; 10 minute resolution vegetation cover derived from the Olson World Ecosystems (OWE) land cover classification scheme; and 1x1 km resolution topography. The strategy of PHAiRS is to replace baseline DREAM parameters with satellite observations of the same, or closely allied, parameters that characterize the land surface and drive the physical processes of dust entrainment. Baseline DREAM parameters, and those selected for assimilation, include: (1) dust sources; (2) digital elevation (topography); (3) aerodynamic surface roughness length; and, (4) soil moisture.

Dust Sources. Dust sources are derived from the MODIS MOD12Q1 product. It has 17 classes of land cover defined by the International Geosphere-Biosphere Programme (IGBP). One of these classes is defined as "barren land." For assimilation into DREAM, MOD12Q1 is condensed to a two-class product: barren = 1; all other classes = 0 (Figure 1).

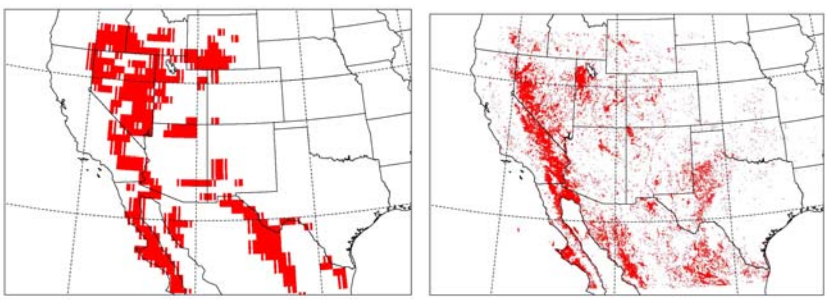

Figure 1. Comparison of Olson World Ecosystem "bare ground" category (left) with MODIS MOD12Q1 "barren land" category (right).

Digital Elevation (Topography). Topography controls land/sea breezes, mountain/valley winds, and forced airflow over and around rough terrain. Data from the Shuttle Radar Topography Mission (SRTM30) were substituted for DREAM's original design parameter. Before the data could be assimilated, however, all data voids had to be filled. Smaller "salt and pepper" voids were replaced by interpolated values using a neighborhood filter. The larger voids were filled using ancillary data (Sanchez, 2007). Figure 2 illustrates the raw and filtered SRTM data for a small part of the DREAM domain.

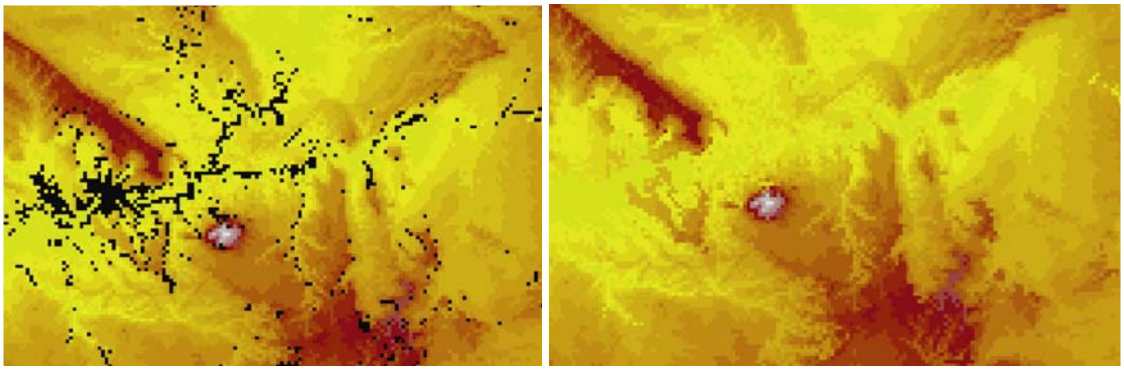

Figure 2. Pattern of voids in raw SRTM30 data (left); smoothed appearance of data assimilated into DREAM (right).

Aerodynamic Surface Roughness Length. Aerodynamic surface roughness length (z_0) is defined as the height above the ground at which wind speed is zero (that is, where air temperature is isothermal and equal to that of the surface). For z_0, the less water held in a soil, the more prone it is to wind erosion and dust entrainment. Retention of soil water consists of two factors: (a) molecular adsorption on the surface of the soil grain; and (b) inter-particle capillary forces. The latter of these determines whether dust will be lifted from a surface at a given wind speed. As soil moisture is increased, the threshold wind velocity also is increased, thus reducing the amount of dust injected into the atmosphere (van Deursen et al., 1993).

To estimate z_0, one must measure surface momentum, soil temperature, and soil water vapor among other surface properties. These properties can be measured by sensors from different satellites, but the strategy for creating a z_0 data set from different sensors that can be assimilated into DREAM does not exist yet. Consequently MOD12Q1 data were used to estimate z_0 for use in DREAM. Table 1, developed by collaborators at Stennis Space Center, is a look-up table considered to be a "best practice" estimator for z_0. Values are based on standard physiognomic cover types. The z_0 values did not replace an existing DREAM parameter and therefore represents a novel addition of data into the model system.

Table 1. Look-up values for surface roughness length (z_0). Source: Stennis Space Center.

DN	*Land Cover Category*	*Z_0 Range (m)*	*Default z_0*
8	Woody Savanna	0.10-0.20	0.15
9	Savanna	0.03-0.10	0.06
10	Grassland	0.03-0.07	0.05
12	Cropland	0.04-0.18	0.11
14	Crops/Natural Mosaic	0.10-0.30	0.20
16	Barren/Sparse	0.00-0.01	0.01
253	Fill	0.00	0.00

Soil Moisture. The Advanced Microwave Scanning Radiometer (AMSR-E) is a multi-frequency, dual-polarized sensor that detects emissions from the Earth's surface and atmosphere. Passive microwave emissions can be used to estimate soil moisture in the surface centimeters (NSIDC, 2000). However, there are several challenges to assimilating data into DREAM: (a) the effective data footprint is almost 70km, while the model outputs are aiming toward 1km resolution; (b) the data are formatted to an Equal-Area Scalable Earth Grid or EASE-Grid, which is not compatible with PHAiRS remote sensing software; (c) there are serious data voids in areas of dense vegetation (high Leaf Area Index) and under snow cover; and, (e) there are measurement errors associated with sampling depth and vegetation density. Despite formatting and resolution issues, soil moisture data from AMSR-E were assimilated into PHAiRS DREAM.

Modeling

The model system has been used to simulate dust concentrations and movements for several dust storms since December 2003. Model runs included a baseline simulation using DREAM's original design parameters and a series of runs using combinations of data assimilated into DREAM. Table 2 lists eight model runs and the EO data sets that were assimilated (marked with Y). Run-1a is the baseline (pre-assimilation) run. Mod12Q1 (barren class) was a standard replacement set in all the subsequent model runs and was the only parameter replacement in run 2a. Run 4 assimilated the barren class and digital elevation from SRTM; runs 5a and 5b added z_0; run 6 was a test of Mod12Q1 with Mod15 (FPAR) substituted for part of the domain; run 15 assimilated barren ground with soil moisture without digital elevation; and run 10a assimilated barren ground, SRTM and soil moisture.

Figure 3 shows the agreement indices for the model runs in Table 2. For PM_{10} assimilated data consistently improved DREAM's performance for simulating dust concentrations. Run 6a was slightly better than the other runs, for reasons not yet clear. The results seem to indicate most improvement is due to assimilation of MOD12Q1 data, and only small additional improvements are achieved by adding other parameters. Additional analysis is needed using more dust storms and more model runs.

For $PM_{2.5}$, the results are more variable. In contrast to its performance for PM_{10}, run 6a had the poorest performance. Note also that runs 5a and 5b performed differently. This is because of slight differences in the meteorological parameterizations of the two runs, suggesting that the model system is very sensitive to both atmospheric parameters and surface properties.

Table 2. Model runs for a December 15-17, 2003 dust storm over New Mexico and Texas.

Run #	MOD12	SRTM	Surface roughness length	FPAR	AMSR-E
Run 1a					
Run 2c	Y				
Run 4a	Y	Y			
Run 5a	Y	Y	Y		
Run 5b	Y	Y	Y		
Run 6a	Y			Y	
Run 15a	Y				Y
Run 10a	Y	Y	Y		Y

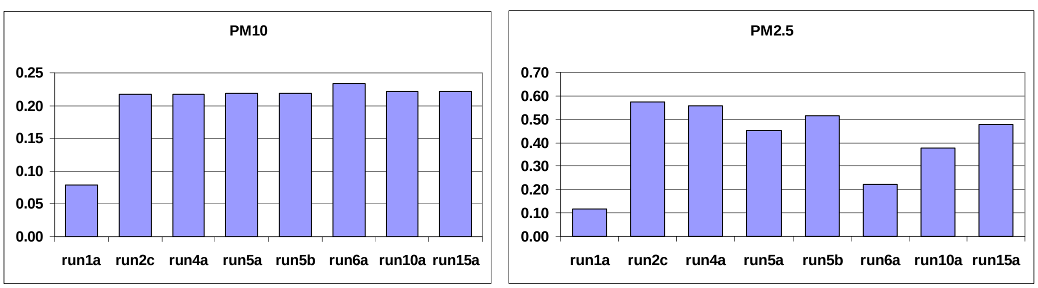

Figure 3. Agreement indices PM_{10} (left) and $PM_{2.5}$ (right) for eight model runs. Run 1a shows the baseline DREAM performance; the remaining runs include combinations of assimilated EO data.

Table 3 lists the performance statistics for modeled surface wind and temperature (Yin et al., 2005). The modeled wind, temperature, and humidity profiles were verified against sounding data. The modeled meteorological fields were compared against observational data. These comparisons showed that DREAM performed well in forecasting meteorological parameters. The agreement indices in the bottom row indicate that assimilating MOD12Q1 data had only slight impact on observed wind speed and wind direction. This is a desirable outcome since the nested model should not alter the weather forecast. On the other hand there is an important difference in the agreement indices for surface temperature. This relates directly to the ability of the model to simulate dust entrainment.

Table 3. DREAM Performance before and after EO data assimilation. Italic values are before EO data assimilation; other values are after assimilation. For the equations M = modeled; 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	$1-\frac{\sum_{i=1}^{N}(M_i - O_i)^2}{\sum_{i=1}^{N}\left(\lvert M_i-\bar{O}\rvert+\lvert O_i-\bar{O}\rvert\right)}$

After DREAM was nested within NCEP/eta, meteorological variables continued to be well simulated and predicted, even after EO data were assimilated. Comparisons showed that modeled meteorological fields, both surface and 500 millibar levels, were in agreement with measured observations. Also, vertical profiles of wind speed, wind direction, temperature, and specific humidity matched the observed profiles. As expected, the MOD12Q1 barren ground assimilation had a larger influence on modeled dust concentrations than on meteorological fields. The peak hour correlation was least affected by the change. However, major gains were made in simulating the magnitude and duration of near-surface high dust concentrations. A verification and validation program is underway to assess long-term DREAM performance over the entire model domain. Statistical measures are being used to compare surface level PM_{10} and $PM_{2.5}$ concentrations with *in-situ* particulates recorded at air quality sampling sites. Few have attempted such rigorous tests.

Figure 4 shows three generations of model improvements. The baseline model performance at left is a 2005 simulation of the December 15-17, 2003 storm; the middle image shows a refined pattern of the same storm produced in 2006 using NCEP/eta + DREAM assimilations; and the image at right shows improvements gained after switching to the non-hydrostatic NCEP/NMM/WRF model in 2007.

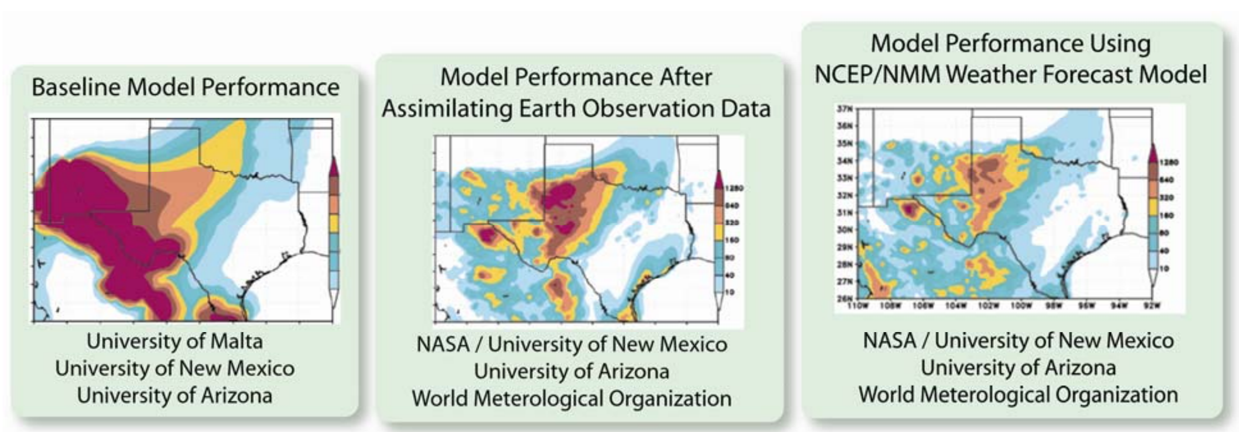

Figure 4. Three generations of DREAM model improvements.

THE EPHT SYSTEM

Research results and products from PHAiRS are being used to enhance human health surveillance and tracking systems. One of these systems is the New Mexico EPHTS which is being developed to collect, integrate, analyze, and interpret data of changing air quality conditions that can affect human health. Additionally, EPHTS will provide a conduit for rapidly disseminating these data and analytical results to a broad spectrum of users such as 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 4) 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 DREAM 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.

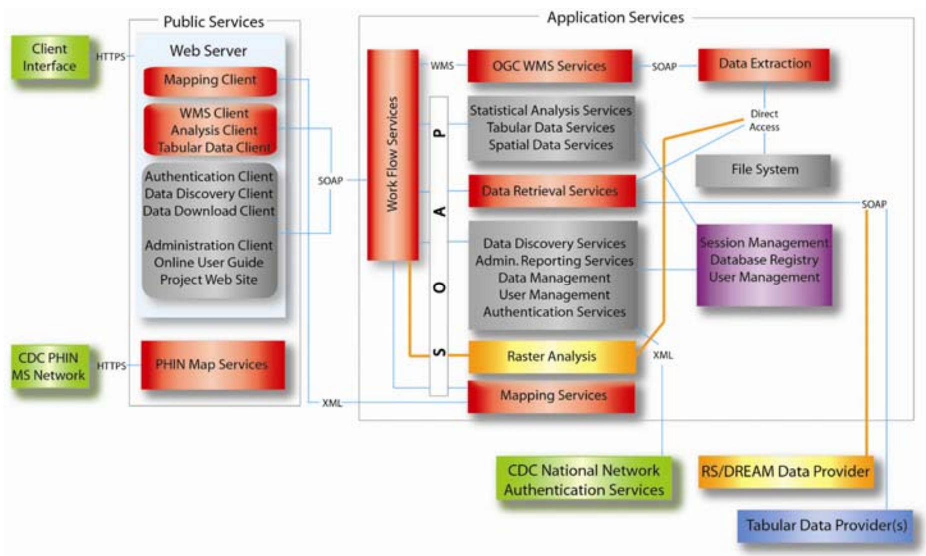

Figure 4. Components of EPHTS. Red boxes show where enhancements are expected as inputs and outcomes; yellow boxes refer to new components that are being added for archived dust episodes and 3-day dust forecasts.

Products can be integrated also into the Tabular Data Client and the Analysis Client. Specialized Simple Object Access Protocol (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, one could 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.

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