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Developing a smartphone software package for predicting atmospheric pollutant concentrations at mobile locations

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Background

There is considerable evidence that exposure to air pollution is harmful to health. In the U.S., ambient air quality is monitored by Federal and State agencies for regulatory purposes. There are limited options, however, for people to access this data in real-time which hinders an individual's ability to manage their own risks. This paper describes a new software package that models environmental concentrations of fine particulate matter (PM_{2.5}), coarse particulate matter (PM₁₀), and ozone concentrations for the state of Oregon and calculates personal health risks at the smartphone's current location. Predicted air pollution risk levels can be displayed on mobile devices as interactive maps and graphs color-coded to coincide with EPA air quality index (AQI) categories. Users have the option of setting air quality warning levels via color-coded bars and were notified whenever warning levels were exceeded by predicted levels within 10 km. We validated the software using data from participants as well as from simulations which showed that the application was capable of identifying spatial and temporal air quality trends. This unique application provides a potential low-cost technology for reducing personal exposure to air pollution which can improve quality of life particularly for people with health conditions, such as asthma, that make them more susceptible to these hazards.

Keywords

app; air quality; community-based participatory risk assessment; modeling; ozone; particulate matter

1. Introduction

Air quality has a direct impact on pulmonary and cardiovascular health. Short term exposures to high concentrations of fine particulate matter (PM_{2.5}), coarse particulate matter (PM₁₀) and ozone are associated with increased risk of asthma attacks [1]. Long term

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exposure to lower levels of these pollutants are associated with increased risk of developing asthma [2] and decreased respiratory function [3]. It is currently estimated that 147 million Americans (41%) are exposed to elevated levels of air pollutants [4]. The United States Environmental Protection Agency (U.S. EPA) has identified ground-level ozone and PM_{2.5} as the two air pollutants that pose the greatest threat to human health [5], yet the level of concern among the general public regarding these pollutants varies widely and is largely dependent upon a person's perception of risk [6]. Efforts to communicate air quality using terminology such as "PM₁₀" and $\mu\text{g}/\text{m}^3$ are perceived as too complex for the general public [7], and air quality information that is reported at national and regional levels is not always practical for an individual [8]. Smartphones have great potential to contribute to communicating personalized information about health risks including air pollution [5, 9]. There are an estimated one billion active smartphone users worldwide [10]. For a smartphone to facilitate communication and understanding of the health risks posed from air pollution the software (app) must 1) provide pollutant information that is representative of actual pollutant conditions at the person's current location and 2) be perceived as useful and easy to use by the general public [11].

The U.S. EPA released an "AirNow" app which identifies the user's current location and lists measured air pollutant concentrations as the air quality index (AQI), at the closest U.S. EPA air monitoring station. The AQI combines the concentration of ozone, particulate matter, carbon monoxide, sulfur dioxide, and nitrogen dioxide into a single index that describes the local air quality using a scale from 1-500 with 6 color coded categories ranging from good (green, index value 1-50) to hazardous (maroon, index value 300-500) [5]. This app provides useful personal air quality information but has limited utility for users who are not located near an air monitoring station or are uncertain of the nearest air monitoring station location. AirNow is also limited to the most recent measurements of pollutant information and requires focused attention from the user, making it difficult to evaluate personal air quality conditions over time and/or during health events of interest such as an asthma attack.

To address these limitations, we developed the ParME (particulate matter estimator), app. This is a new software package that utilizes spatial pollutant distribution models to predict air pollutant levels at any smartphone location and send predicted pollutant level information to the smartphone device. The software accesses all the predicted pollutant information associated with the current location of the user's smartphone and lets users set personalized warning levels for predicted atmospheric pollutants. The software is consistent with the color warning categories employed by the the EPA AQI and presents this information in well-known formats such as Google maps and simple graphs. The complex sampling information such as predicted levels and latitude/longitude values is hidden from the user until that information is requested. ParME further minimizes user effort by collecting predicted air quality data and checking for warning levels while running in the background, which further empowers the user to collect personal information about air quality at their location.

2. Methods

A pseudocode flowchart of the ParME smartphone software program is shown in Figure 1. The app (the component of the software package that runs on smartphones) has been developed for iPhone/iPad and android devices, written in Objective C [12] and Java [13], respectively. Other components of the software package were written in Python [14] R [15], and JavaScript [16]. ParME also utilizes external libraries listed in Supplemental Materials (Supplemental List 1).

2.1 Environmental modeling

Environmental models were created for hourly $PM_{2.5}$ and PM_{10} for the state of Oregon using MODIS satellite imagery and Oregon DEQ $PM_{2.5}$, PM_{10} , temperature, and relative humidity measurements from June 2008-June 2012 following the semi-empirical method developed by Tian and Chen [17] with the following exceptions: 1) spatial maps of relative humidity were created in the statistical software program R by universal Kriging of Oregon DEQ relative humidity measurements rather than inverse distance weighing of relative humidity observations from Geostationary Operational Environmental Satellite 13; and 2) model predictions were updated hourly as $PM_{2.5}$ and PM_{10} measurements were posted on the Oregon DEQ website, approximately 10-20 minutes post-sampling. We chose Tian and Chen's semi-empirical method because it provides hourly updates based on local conditions unlike most satellite-based pollutant modeling methods that only provide daily resolution. For more details on these semi-empirical models we defer to Tian and Chen [17].

An atmospheric model of hourly ozone for the State of Oregon was also created through inverse distance weighing regression of ozone levels measured by the Oregon DEQ. Ozone predictions were restricted to the months of available data, May through September, corresponding to seasonal ozone patterns in Oregon.

2.2 App installation and data acquisition (Figure 1B,1F)

Upon initial loading of ParME, the user is asked to allow connection to a cloud storage service called Dropbox [18] using an account created for this study. The user is also asked to create a unique identification name and set warning levels for each pollutant included in the modeling database (Figure 2A). The user can establish their own warning levels for air quality by sliding bars on the smartphone screen (one bar for each predicted pollutant, color-coded to coincide with the EPA AQI categories). Once warning levels and an id name are created, ParME uses assisted global positioning system (A-GPS) technology, a combination of GPS, radio tower signals, and wi-fi signals, to determine the current location of the smartphone. ParME then sends the current location (latitude and longitude), time, and warning levels to Dropbox as a .csv file named after the user id (Table 1).

2.3 Processing smartphone data (Figure 1D)

Files sent to Dropbox from smartphones are processed by a desktop computer (Server1) connected to Dropbox and running a custom Python script. Server1 continually queries Dropbox for new .csv files. When a new file is detected, R is called to run the $PM_{2.5}$, PM_{10} , and ozone atmospheric distribution models. Models are queried for predicted pollutant

concentrations at the time and specific location provided by the device, as well as for predicted concentrations in the surrounding region within a given distance from the user. The given distance is stored in a modifiable variable, with a default value of 10 km (Figure 3). Predicted levels for each pollutant are then compared to warning levels. If predictions exceed warning levels at the current location or surrounding area, the pollutant type and direction relative to the user's location (N, SW, etc.) is added to a variable called "warning". The information in the original file along with the predicted concentrations and the warning variable are then passed into Python for further processing. Python then creates a .csv file with the location, time, predicted pollutant levels, and warning string (Table 2), and sends the file to Dropbox into a named folder that matches the smartphone user id. A second copy of the data is also added to a structured query language (SQL) database on Server1. User ids are not retained in the SQL database in order to retain participant anonymity.

2.4 Processing predictions and warnings on smartphones (Figure 1B)

ParME identifies the folder in Dropbox with the same name as the user id, and begins looking for new files in the folder 5 seconds after sending the original file described above. Files contained within the folder are downloaded and then deleted from Dropbox. Downloaded points are processed and added to a local SQLite database contained on the smartphone. Updates to the database then trigger ParME to search for a warning string. If a warning string is found, a notification with the warning string data is displayed on the smartphone screen (Figure 2B). If there is no warning string, the most recent view is refreshed with the updated smartphone data.

2.5 Displaying predicted atmospheric pollutant levels on smartphones (Figure 1G)

Predicted pollutant levels are displayed on the smartphone screen in three different forms: 1) Points on a Google map. Points are color-coded according to the EPA AQI categories, and are interactive: tapping a prediction point on the map brings up the corresponding sampling data, including latitude, longitude, sampling time, and predicted pollutant level, as shown in Figure 2C. 2) Points on a 2D graph (Figure 2D), with predicted concentrations on the y-axis and sampling time on the x-axis. Similar to the Google maps, tapping on a graph point brings up the corresponding sampling data. 3) Statistics (Figure 2E), with mean predicted levels, number of sample points, and data for the sample point with the greatest predicted level.

Predicted concentrations are displayed for only one of the modeled pollutants at a time: a touch-responsive list at the bottom of the menu allows users to select which pollutant predictions are displayed (Figure 2C). An option for a color-coded legend is also available in the menu. Pressing the legend button brings up a touch-responsive list of colors, color-coded according to the EPA AQI. Pressing a color within the list displays the EPA AQI description and pollutant concentration range for the corresponding category (Figure 2E). Pollutant queries are processed asynchronously to improve performance and keep the app responsive during query events.

2.6 Bluetooth data transfer and personal website (Figure 1E, 1A)

Smartphones with Bluetooth functionality can transfer personal predicted concentrations to a Bluetooth-enabled PC. A custom Python script must run on the target computer and instructs the computer to listen for a Bluetooth signal and send all incoming Bluetooth data to the Python script. Selecting the Bluetooth (public) option on the ParME menu begins a search for all Bluetooth compatible devices in the area, producing a touch-responsive list of computers that can accept data via Bluetooth from the smartphone. If the computer running the Python script is selected, predicted concentrations and customized warning levels will be copied from the smartphone to the PC. The PC reformats copied data to match the anonymous database format, and writes the copied data to a .geojson file that can then be linked to a personal website with interactive graph and map displays similar to the smartphone map and graphs described below (Figure 4). The website can then be viewed from any computer with an internet connection and an up to date version of Firefox, Internet Explorer, Safari, and/or Google Chrome (see http://people.oregonstate.edu/~larkinan/smartphone/website_example.html). Website menu options include sliding bars for selecting specific data points that fall within the set sliding bar ranges for pollutant concentrations, hours of the day, days of the month, and/or months. Bluetooth data file transfers are processed asynchronously to improve ParME performance and maintain app responsiveness.

2.7 Background functions

When ParME is sent to the background, all functions are turned off except for a timer that dictates when a sampling event occurs. Expiration of the sampling timer triggers an activation of the A-GPS smartphone service. A-GPS remains active until the current location is determined. Once the current location has been established, A-GPS functions turn off to prevent battery drain, and sample data is sent to Dropbox as described above. Predicted concentrations and warnings are also downloaded and checked for warnings. If ParME detects a warning, a notification is displayed on the screen (Figure 2B).

2.8 Creating 3D Predicted Pollutant Concentration Graphs (Figure 1A)

Three-dimensional graphs of predicted pollutant concentrations are created in R by reading latitude, longitude, and prediction data from a .csv file (see above). Latitude and longitude values are decreased in resolution to the nearest km, and a map covering the geographical extent of the copied data is downloaded from Open StreetMap. Predicted pollutant levels are then displayed on a 3D graph, with the x,y, and z axis corresponding to longitude, latitude, and mean predicted levels, respectively (Figure 4, 5B). Graph point size (radius) is linearly proportional to the number of sample points at each x,y coordinate pair, while color is based on AQI categories for mean predicted levels. Predicted levels are placed in geographical context by adding the downloaded map as a surface on the x,y plane, and highlighting the predicted cover area on an accompanying Oregon state map (Figure 5A).

2.9 Anonymous database queries (Figure 1A, 1C)

Anonymous data stored in the Server1 SQL database can be queried through the command line and sent to R for generating 3D graphs and maps as described above. Data can be

queried for specific times, locations, predicted pollutant levels, warning responses, or any combination of the above.

2.10 Software evaluation/validation

ParME was validated by installing the software on mobile devices of five participants that consisted of four smartphones (iPhone3, iPhone4, HTC MyTouch, and Samsung Galaxy S3) and an iPad2. To preserve the anonymity of participants this ParME validation

A sampled subset of data points collected from participant smartphones—

These data points were used to validate functions designed to handle A-GPS operations (turning on and off GPS), uploading data to Dropbox, and updating warning levels sent to Dropbox when a user updates the sliding warning level bars. Participant phones were also used to estimate user burden, measured by the amount of data plan usage and percent battery life consumed by the smartphone program.

An artificially constructed validation dataset sent to participant smartphones

—Predicted pollutant concentrations during the software validation period varied between good to moderate categories of the EPA AQI. An artificial dataset was constructed to evaluate ParME's ability to correctly categorize and display all possible AQI categories and update the visual display when a new pollutant was selected from the pollutant selection menu on the smartphone. The artificial dataset was also used to validate the Bluetooth data upload and website creation software to similarly evaluate its ability to correctly categorize and display all possible AQI categories.

A second artificial dataset to evaluate accuracy of predicted air quality information—

A second validation test was conducted using simulated data from 177 smartphones representing a population of college students at Oregon State University that operated ParME for 15 consecutive days. Smartphone locations were simulated using multinomial distributions in which the simulated population was mostly at school from 10 am-4 pm, mostly at home from 8 pm-8 am, and at school and home in equal proportions at other times. A small proportion of smartphones were simulated at random locations other than campus or home but within 20 miles of the OSU campus center (44.565N, 123.279W). Each simulated smartphone was assigned a residence location using a polar coordinate system (ρ, θ) in which the campus center corresponds to the center of the polar coordinate grid. ρ followed a 0.33 mile + exponential (2 miles) distribution, while θ followed a uniform (0,360) distribution. Predicted pollutant levels returned to smartphones were compared to predictions directly extracted from pollutant models by randomly selecting 10 of the simulated smartphone data points.

3. Results

3.1 Data points sent to Dropbox from participant smartphones

Table 1 shows an example .csv file sent from a participant smartphone to Dropbox. Time, coordinates, and warning levels in the in all of the sampled .csv files are identical to values displayed on participant smartphones.

3.2 Artificial personal data set

Comparison between initial dataset and values displayed on the smartphone screen are shown in Table 3. Latitude, longitude, and time are displayed as units of degrees instead of microdegrees, and time is expressed as a readable string instead of a Unix time stamp to improve human readability (Figure 2C shows screen display for data point 6 in Table 3). Comparison of time units using the date formatter function in Java show that time, as well as latitude, longitude and predicted pollutant levels, are identical up to the number of significant digits shown on the smartphone display. Observed and expected EPA AQI categories (good, moderate, etc.) were also identical. Statistics displayed on the smartphone screen (Figure 2E) were confirmed by calculating statistical values of the artificial data set in R. These results validate the ParME algorithms designed to download, store and retrieve data point information in the smartphone SQL database, and perform EPA AQI categorical transformations. The latitude, longitude, time, and predicted ozone concentration data in a .csv file written on a PC post-Bluetooth data transfer (data not shown) were identical to original values sent to smartphones (Table 3). Visual inspection and clicking on individual points in the website created from the Bluetooth data transfer confirm that maps and graphs on personal websites have similar functionality to those of the smartphones. Figure 2B shows the notifications produced by ParME working in the background (top) and foreground (bottom) when ParME processes the .csv file shown in Table 2. In Table 2, a warning is given for PM₁₀ at the current location (designated by HH) and ozone in the southwest direction (designated by SW). Warnings displayed on the smartphone correspond to the expected warning in both instances.

3.3 Simulated Student Populations

Table 4 compares predicted pollutant levels generated by ParME with predictions extracted directly from the environmental models for 10 simulated locations within the time interval 2-3 pm on February 25, 2013. Predictions were identical between ParME and the environmental models, validating the ParME function that interacts with pollution models to extract predicted pollutant levels at specific smartphone locations. Figure 4, 5B shows predicted PM_{2.5} concentrations for all predicted levels of the simulated student population collected from 10-11 pm and from 2-3 pm, respectively, for all 15 days of the simulation. Simulated smartphone location distributions are in agreement with the 3D exposure maps, validating ParME functions that query, process, and display anonymously collected data.

3.4 Smartphone battery life and data plan usage

Percent battery change while using the app in the background and not using the app under otherwise identical usage conditions are shown in Table 5. The battery charge is based on 3 replicates and time duration of 2 hours for each replicate. iPhone3 and iPhone4 were not included in the analysis due to frequent participant usage of batteryintensive functions such as video streaming and game playing.

A sample of 100 files sent from the smartphone to Dropbox (20 files from each of the 5 participating devices) ranged in size from 57-61 bytes (average = 58.1 bytes). A similar group of 100 files sent from Dropbox to participant smartphones ranged in size from 51-59 bytes (average = 54.5 bytes). An approximate upper bound estimation of data plan usage for

sampling every 5 minutes or 30 minutes 24 hours a day for a 31-day month would be 1.2 and 0.2 MB/month, respectively, in addition to data associated with displaying Google maps.

4. Discussion

Smartphones are very popular because of their intuitive, easy to use interface [11] and ability to incorporate real-time location information into applications [19]. We created a new smartphone app that builds upon both of these features and combined them with environmental pollutant distribution models.

We demonstrated ParMe's ability to predict pollutant levels at the users' current location and in the surrounding location and to compare predicted levels to customized warning levels for notifying users about unwanted predicted pollutant concentrations. Sensitivity and concern about air pollution varies widely within the population. When coupled with high resolution models (both spatially and temporally), the warning system has the potential to evolve and suggest optimal driving, biking, or running routes regarding air quality, or can integrate data from smartphone accelerometers to prioritize warning levels toward the general direction that the user is headed. While we did not evaluate the accuracy of air quality predictions extracted from the air pollution models, we did verify the accuracy of the smartphone software in relaying model predictions to the user. Functions within the software architecture for extracting predicted pollutant concentrations from environmental models are compatible with any pollution model output in georeferenced tiff format, facilitating use of ParME with various modeling methods and pollutants of concern. ParMe is the first app that we know of that can adapt to any combination of environmental pollutant models, regardless of the underlying methodology or the spatial and temporal extent of model predictions.

The largest sources of user burden associated with ParME were data plan usage and decreased battery life. The data plan usage was minimal and depended on the number of interactions (panning, zooming, etc.) a user had with the map display. The basic functions required by ParME for one year of service uses the data plan equivalent of one half of a high resolution photo, and amounts to less than one tenth of one percent of the smallest monthly data plans currently offered by major smartphone service carriers. Impact on battery life varied significantly between mobile devices (1%-13% average decrease in percent battery over two hours, Table 5). This was mostly due to:

1. differences in battery size and energy efficiency of internal GPS chips. We minimized the impact on battery life by taking GPS locations every 30 minutes . The popularity of location based services such as driving directions combined with continual improvements in battery size and GPS chip efficiency, however, are expected to reduce battery consumption by GPS functions to the point where battery usage related to location measurements becomes minimal.
2. Differences in smartphone hardware and memory allocation practices. Comparison of memory allocation between the HTC MyTouch, iPad2 and Samsung Galaxy S3 showed that the GalaxyS3 retained a large percentage of the ParME visual display in memory even when ParME was in running in the background. The MyTouch

and iPad2, in contrast, cleared all ParME displays from memory, greatly reducing the amount of memory and battery consumption used by ParME in the background. We believe that further optimization of ParME memory allocation can greatly reduce the amount of battery consumed by the Samsung Galaxy S3, particularly while operating in the background.

ParMe was developed using open source technology to facilitate distribution to the general public and scientific research groups for minimal or no cost. Personalized information about air quality can facilitate efforts by individuals and their health care providers to identify exposure conditions associated with adverse outcomes. People who are susceptible to air pollution, such as individuals with asthma, can benefit from advanced ParME functions, such as identifying local air quality conditions that occurred at the time of asthma attacks and sharing this information with physicians via the web. These individuals could subsequently set customized warning levels to match predicted air quality conditions which will warn them of local air quality conditions. To our knowledge, ParMe is the first app that allows for customized air pollution warning levels.

Since smartphone ownership is lower among the elderly and the very young - and these age groups are more sensitive to air pollution - we are adapting ParME to work on basic pre-paid cell phones with GPS capabilities. Preliminary results suggest that the predicted concentration display and warning capabilities can run on basic cell phones using a simple text messaging system. If past trends of smartphone technologies trickling down to basic cell phones continue [20], basic cell phones will soon have the ability to run the full ParME version.

The field of air pollution informatics is developing rapidly, and there are several alternative approaches to the smartphone software approach described in this paper. Alternative approaches include portable biomonitors and crowd source data sharing. Portable biomonitors have been developed which sample volatile organic carbons [21] and particulate matter [22] and send measurement readings to an attached smartphone in real time. Biomonitors have potential for greater accuracy and spatial and temporal resolution than the proposed environmental modeling approach. Biomonitors cannot, however, warn users about high pollution levels before an exposure occurs and are limited to individuals who have acquired the appropriate external biomonitors, a small subset of the current 1 billion smartphone users. This limitation has been partly overcome through crowd source data sharing [22], in which pollutant measurements from biomonitors are uploaded to a public participation database and are accessible through webmaps. Crowd source sharing methods can provide air quality information to most smartphone users, but are still limited in their ability to provide a history of predicted air quality conditions or customized user warnings for individuals without additional hardware. Current and future crowd source methods can benefit from implementing several of the software tools described in this paper.

In 2007, the U.S. National Research Council (NRC) called for a fundamental shift in toxicological risk assessment practices, which among other specific aims identified a need for greater biomonitoring and inclusion of inter-individual differences in exposure and susceptibility in the risk assessment process [23]. Similar visions of a 21st century

toxicology program released by the U.S. National Institutes of Health [24] and U.S. EPA [25] quickly led to support and subsequent advancements in personal biomonitoring technology, as mentioned above. Despite these recent advancements, biomonitoring of numerous chemicals of concern for the majority of the population is, at present, financially and logistically infeasible. In this paper we have demonstrated the utility of coupling open-source software with widely adopted smartphone technology for estimating both individual and population level air quality conditions. To our knowledge, ParME is the first financially feasible method for providing a modern, personalized risk assessment process to a large percentage of the population, and consequently has great potential to advance health agency visions of future risk assessment practices.

Exposure level estimates based on personal mobility, measured by geolocation, have been shown to be more accurate compared to conventional estimates based on residence location alone [26]. In this paper we demonstrated the ability to acquire geolocation data and incorporate the data into air quality measurements in an automated, open source software framework, generating 3d maps of predicted air quality for the entire sampling population (Figure 5). We therefore conclude that data anonymously collected from ParME participants have great potential utility for risk assessment and regulatory agencies as well as epidemiologists concerned with air pollution exposures.

5. Conclusions

A new software program was created that utilized smartphone technology coupled with predictive environmental air pollution models that can be used to find your personal exposure to air pollution. This information would be most useful for individuals who want to reduce their risk from the adverse effects of air pollution. Software validation was based on data collected from 5 participating smartphones, a simulated student population, and an artificial data set. Expected and realized results for all of the tested components were identical. We conclude that smartphones have the potential to integrate several aspects of community outreach and personal health into a single, user-friendly program with minimal financial cost.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Abbreviations

MODIS	Moderate Resolution Imaging Spectroradiometer
DEQ	Department of Environmental Quality
AQI	Air Quality Index
PM_{2.5}	Fine Particulate Matter
PM₁₀	Coarse particulate matter
A-GPS	Assisted Global Positioning System
SQL	Structured Query Language
OSU	Oregon State University

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Figure 1.

Flowchart of the smartphone software pseudocode. (A) Three-dimensional graphs. (B) Data transfer to and from Dropbox. (C) Anonymous database query. (D) Predicted level and warning response. (E) Bluetooth data transfer from smartphone to PC. (F) Setup and modification of user id and warning levels. (G) Smartphone display of predicted pollutant concentrations.

Figure 2. Capabilities of the smartphone program. (A) Warning levels and user id can be customized. (B) Responses to exceeded warning levels are returned when the app is running in the background (top) or foreground (bottom). (C) Google maps display the spatial distribution of predicted pollutant level history while (D) touch-responsive graphs show past predicted air quality levels as a function of time. (E) Statistics provide a quick summary of predicted pollutant concentrations.

Figure 3.

Methodology for predicting pollutant levels in the surrounding area. Predicted levels can be visualized as a grid, where each latitude, longitude coordinate pair corresponds to an x,y location (cell) on the grid. Spatial and temporal resolutions of predicted pollutant levels are equal to resolutions of the underlying models. The example above is a conceptual example for a theoretical model with a 1 km^2 spatial resolution, with ParME set to analyze pollutant levels for up to 10 km in all directions. The number of cells that must be searched to determine the pollutant levels for 10 km in all directions from the smartphone's current location is determined, and the relative direction of cells (indicated by colors) that have predicted levels above the warning level are determined and added to the warning string to be returned to the smartphone.

Figure 4.

Personal webpage created from Bluetooth upload of artificial data set. Maps and graphs in the webpage differ from those displayed on the smartphone in that highlighted points on the map are colored blue (left), and sliding bars in the menu can be used to select a subset of data points for exposure levels, hours of the day, days of the month, and months of the year that are of particular interest (bottom right).

Figure 5.

Three-dimensional graphs, legend and locator map produced by R. (A) Legend displays the EPA AQI concentrations for each color (left) and relationship between graph point size and sample size (right), while an Oregon state map shows the extent and relative location of the 3D graphs. Buttons at the top allow for turning on/off EPA AQI threshold layers and warning level in the 3d graphs. (B) 3D map of predicted concentrations from the simulated student population on February 25, 2013 from 10-11 pm and (C) from 2-3 pm. Both the range and geographical distribution of predicted levels change with respect to time.

Table 1

Sample .csv file sent from smartphone to Dropbox.

Location		Time	Warning Levels		
Latitude *	Longitude *	Unix time stamp **	PM _{2.5} (µg/m ³)	PM ₁₀ (µg/m ³)	Ozone (ppb)
44579445	-123282626	1357297323457	221.4	74.4	88.4

Data was sent from the smartphone in Figure 2A to allow for comparison between warning level display and warning level values sent to Dropbox.

* Expressed in units of microdegrees.

** The number of elapsed milliseconds since January 1st, 1970.

Table 2

Sample .csv file sent from Python to Dropbox.

Location		Time	Predicted Pollutant Levels			Warning Level Responses		
Latitude *	Longitude *	Unix time stamp ***	PM _{2.5} (µg/m ³)	PM ₁₀ (µg/m ³)	Ozone (ppb)	PM _{2.5}	PM ₁₀	Ozone
44540046	-123269458	1357297323457	10.2	38.6	NA	NA	HH	SW

Warning level responses refer to the geographical location of a warning level exceedance relative to the latitude/longitude coordinates. NA: No value for ozone prediction or no exceedance of PM_{2.5} warning level. HH: exceeded at the current location. SW: exceeded in the southwest direction.

*. Expressed in units of microdegrees.

***. The number of elapsed milliseconds since January 1, 1970.

Table 3

Comparison of artificial dataset and smartphone display

File Information		Location		Time	Predicted Levels			AQI Categories		
Point	Source	Latitude *	Longitude *	Time **	PM _{2.5} (µg/m ³)	PM ₁₀ (µg/m ³)	Ozone (ppb)	PM _{2.5}	PM ₁₀	Ozone
1	.csv	44.540046	-123.269458	1357277352553	10.9	511.4	320	Good	Hazardous	Very Unhealthy
1	phone	44.54 N	123.269 W	Jan 03, 2013 10:13PM	11	511	320	Good	Hazardous	Very Unhealthy
2	.csv	44.613945	-123.264329	1357287356552	14.9	51.8	566	Moderate	Good	Hazardous ****
2	phone	44.614 N	-123.264 W	Jan 04, 2013 9:46AM	15	52	556	Moderate	Good	Hazardous ****
3	.csv	45.543210	-123.269456	1357286356551	53.7	150.5	47	UFS ***	Moderate	Good
3	phone	45.543 N	123.269 W	Jan 04, 2013 1:00AM	54	151	47	UFS ***	Moderate	Good
4	.csv	44.754924	-123.000000	1357297356550	115.5	169.7	61	Unhealthy	UFS ***	Moderate
4	phone	44.755 N	123.0 W	Jan 04, 2013 3:46AM	116	170	61	Unhealthy	UFS ***	Moderate
5	.csv	45.125044	-122.786456	1357237356559	160.1	351.1	83	Very Unhealthy	Unhealthy	UFS ***
5	phone	45.125 N	122.786 W	Jan 03, 2013 11:06AM	160	351	83	Very Unhealthy	Unhealthy	UFS ***
6	.csv	44.096524	-123.231236	1357239356559	320.0	421.1	113	Hazardous	Very Unhealthy	Unhealthy
6	phone	44.097 N	123.231 W	Jan 03, 2013 10:55AM	320	421	113	Hazardous	Very Unhealthy	Unhealthy

Smartphone and values are in agreement up to the most significant digit on display. Color-coded categories on display are also in agreement with expected categories.

* Latitude and longitude are in units of microdegrees in the .csv file and degrees on the smartphone.

** Time is in units of milliseconds since January 1, 1970 in the .csv file and is displayed in a readable format on the smartphone.

*** UFS – Unhealthy for sensitive members of the population.

**** The AQI for 8 hr ozone exposures do not have a hazardous category. Any concentration above the highest concentration in the very unhealthy category is therefore considered hazardous for display purposes.

Table 4
Comparison of predicted pollutant levels sent to smartphones and levels directly extracted from models

Location #		Predicted levels from .csv Files				Predicted levels from models			
Latitude *	Longitude *	PM _{2.5} (µg/m ³)	PM ₁₀ (µg/m ³)	Ozone (ppb)	PM _{2.5} (µg/m ³)	PM ₁₀ (µg/m ³)	Ozone (ppb)	PM _{2.5} (µg/m ³)	Ozone (ppb)
44.51886	-123.29697	9.7	27.4	NA	9.7	27.4	NA	NA	NA
44.51429	-123.28076	9.8	29.6	NA	9.8	29.6	NA	NA	NA
44.55537	-123.27768	9.0	24.6	NA	9.0	24.6	NA	NA	NA
44.56741	-123.28738	9.3	25.7	NA	9.3	25.7	NA	NA	NA
44.56646	-123.27605	10.2	30.1	NA	10.2	30.1	NA	NA	NA
44.53038	-123.24207	10.1	33.4	NA	10.1	33.4	NA	NA	NA
44.56959	-123.27976	10.2	29.1	NA	10.2	29.1	NA	NA	NA
44.56451	-123.23441	10.1	31.0	NA	10.1	31.0	NA	NA	NA
44.56451	-123.23441	9.9	29.2	NA	9.9	29.2	NA	NA	NA
44.56362	-123.36429	11.9	37.9	NA	11.9	37.9	NA	NA	NA

Points were randomly selected from the simulated student population data corresponding to the time interval 2-3 pm on February 25, 2013.
* Expressed in units of microdegrees.

Table 5

Percent battery use with and without the app running in the background for 2 hours

		Mean percent battery $\pm$ SE (n=3)	
		Without app	With app
Device type	HTC MyTouch	92 $\pm$ 2	93 $\pm$ 2
	Samsung Galaxy S3	96 $\pm$ 1	83 $\pm$ 1
	iPad2	100 $\pm$ 0	99 $\pm$ 1