Sonoma Technology, Inc.
Air Quality Research and Innovative Solutions

October 2, 2009

To: Rich Mason and Venkatesh Rao, U.S. EPA STI-905517-3714

From: Dana Sullivan, Yuan Du, and Sean Raffuse

Re: SMARTFIRE- and BlueSky-enabled Methodology for Developing Wildland Fire Emission Inventories for 2006-2008

This memorandum provides specific technical details of the methods used by STI for inventory development under a contract with the U.S. Environmental Protection Agency (EPA) for Preparation of Wildland and Agricultural Fire Emissions Inventory for 2006, 2007, and 2008 (Contract No. EP-D-05-004, Work Assignment 5-17). Information provided in this memorandum is intended to be sufficient for a third party to independently reproduce the inventories developed for this work assignment.

DATA SOURCES

The following sources of activity data were used:

- Inputs to SMARTFIRE (update to data source of 2006–2008)
  - *Hazard Mapping System (HMS)* data were acquired daily from the NOAA HMS system via FTP as part of a routine process. Data were acquired in Shapefile format available at http://satepsanone.nesdis.noaa.gov/FIRE/fire.html.
  - *ICS-209 Reports* in BlueSky input format (a .csv-style format) were acquired nightly via FTP.from USFS servers (ftp2.fs.fed.us).
  - *MODIS* satellite data were downloaded via the USFS Remote Sensing Applications Center website (http://activefiremaps.fs.fed.us/fireptdata.php). Data were converted from exchange files to Shapefiles (if necessary) and reprojected to the SMARTFIRE projection (Albers Equal Area).
- *Fuel Moistures* – Fire weather observation files (fdr_obs.dat) were acquired for each analysis day from http://72.32.186.224/archive/www.fs.fed.us/land/wfas/archive. Files were acquired and combined for database ingest using Python scripts.
- *Fuel Loading* – Fuel Characteristic Classification System (FCCS) 1-km fuels Shapefile and lookup table were provided by the AirFire Team.

PREPARATION OF ACTIVITY DATA

SMARTFIRE was used to process and reconcile HMS data and ICS-209 Reports. In addition, SMARTFIRE was used to generate daily input files for emissions processing through the BlueSky Framework for wildland fires. SMARTFIRE was configured and operated as described by Raffuse and Sullivan (2008) and in the attachments, “SMARTFIRE Algorithm Description” and “Development and Analysis of Wildland Fire Emission Inventories for 2006–2008”.

MODIS data were used to gap-fill on dates when data were missing from the HMS: March 27, April 1, July 14, and November 14, 2006.

Satellite fire data were categorized as “wildland” or “agricultural” fires by intersecting the fire data with FCCS gridcode <> 0 (wildland) and FCCS gridcode = 0 (agricultural) (see **Figure 1**). This fire-typing process was accomplished by using the FCCS module in the Bluesky Framework. After fire-typing, wildland and agricultural fires were processed separately.

FCCS does not include Alaska or Hawaii; therefore, these states were excluded from the emission inventories.

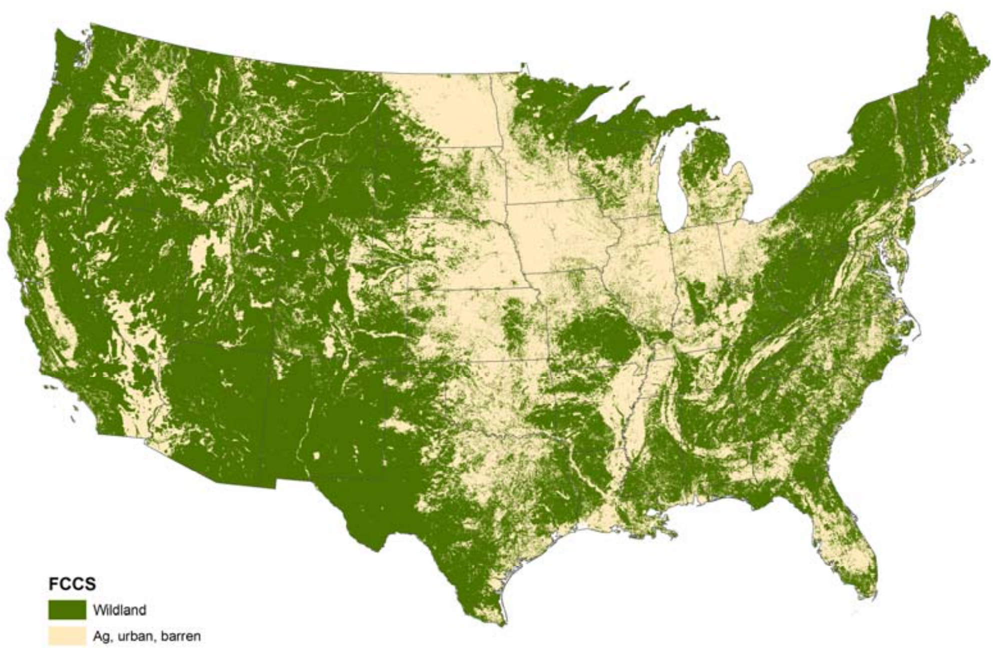


Figure 1. Distribution of wildlands in the FCCS database.

ACTIVITY DATA QC

SMARTFIRE outputs were quality-controlled manually by reviewing maps and summary graphs of the data set as a whole and by individually examining the largest fires in each year.

PROCESS STREAM

The BlueSky Framework provides several choices of models at each step of the smoke modeling process. The model chain used for this project is summarized in **Table 1**.

Table 1. Model chain for Wildland Fire Emission Inventory Development (2006–2008).

Process	Model Used	Version No.
Activity data	SMARTFIRE	Version 1.0, Build 812
Fuel loading	Fuel Characteristic Classification System (FCCS)	As implemented in Bluesky Framework 3.1.0 revision 6700
Fuel consumption	Consume 3.0	
Emissions	Fire Emission Production Simulator (FEPS)	

EMISSIONS PROCESSING

The following steps were applied to process activity data and estimate emissions:

1. *Assign fuel moistures* – Individual fire locations from SMARTFIRE prediction points were assigned to the nearest fire weather station reporting on that day using VBA code in AssignFuelMoisture06_08.mxd. This code produced a lookup table (yyyy_Join.csv) of fire IDs, station IDs, dates, and distances.
2. *Append latitude/longitude* – The SMARTFIRE prediction points table does not include latitude and longitude as attributes. (They are inherent in the shape field). They were added using a GIS application before exporting the attribute table to a text file called SF_PredictionPoints_yyyy_LatLon.txt.
3. *Create BlueSky input file* – The daily input files for the BlueSky Framework (fire_locations_yyyymmdd.csv) were created using VBA code in CreateFireLocations.xls. Input tables are stored in the Microsoft Access database CreateFireLocInput.mdb, including the tables SF_PredictionPoints_yyyy_LatLon and yyyy_JOIN. If the distance between the fire and the nearest fire weather station was greater than 300 km, default values were assigned (fuel_moisture_10hr = 9; fuel_moisture_1khr = 12). Outputs were created in .csv format and saved directly to the BlueSky Framework install.
4. *Process through BlueSky Framework* – A module was customized for the BlueSky Framework to calculate hazardous air pollutant (HAP) emissions using emission factors provided by EPA. The Framework is currently designed to process one day at a time. A shell script (batchEmissions) was used to process emissions one year at a time. The resulting files are daily BlueSky outputs.
5. *Post-process emissions* – The BlueSky Framework produces three output files for each day. For this project, we only required fire_locations_yyyymmdd.csv, which is the same as the input file, but with additional calculated fields (fuel loading, emissions, and

consumption) appended to each fire record. The daily files were concatenated using a Python script, ConcatEmissions.py, into yearly files (fire_locations_yyyy.csv) for ingest into the emissions.mdb database and analysis.

6. *Prepare agricultural data* – Agricultural fires are now designated through the FCCS module in the BlueSky Framework. Fire locations from SMARTFIRE with geographic information (latitude-longitude and county Federal Information Processing Standard [FIPS] code) in .csv format are read in the FCCS module and intersected with the FCCS fuel-loading file in network Common Data Form (NetCDF) format which was rasterized from the FCCS 1-km Shapefile. The module assigned an FCCS code to each fire record. Satellite fires with FCCS code = 0 were extracted from the yearly file (fire_locations_yyyy.csv) to make a yearly agricultural fire table (AgActivityClean_yyyy) in the emissions.mdb database.
7. *Preparing wildland fire data* – Fire_Locations_yyyy tables in the emissions.mdb database were merged into one table (WF_locations_All) after filtering out the agricultural data.

EMISSIONS QC

Numerous tabular, graphic, and geographic views of the results were created and examined by an analyst.

GRAPHIC ILLUSTRATIONS OF RESULTS

Figures 2 through 5 graphically illustrate the annual average and total $PM_{2.5}$ emission inventories for wildland fires. Further graphic summaries of emissions and results are available in the attachment, “Development and Analysis of Wildland Fire Emission Inventories for 2006–2008”.

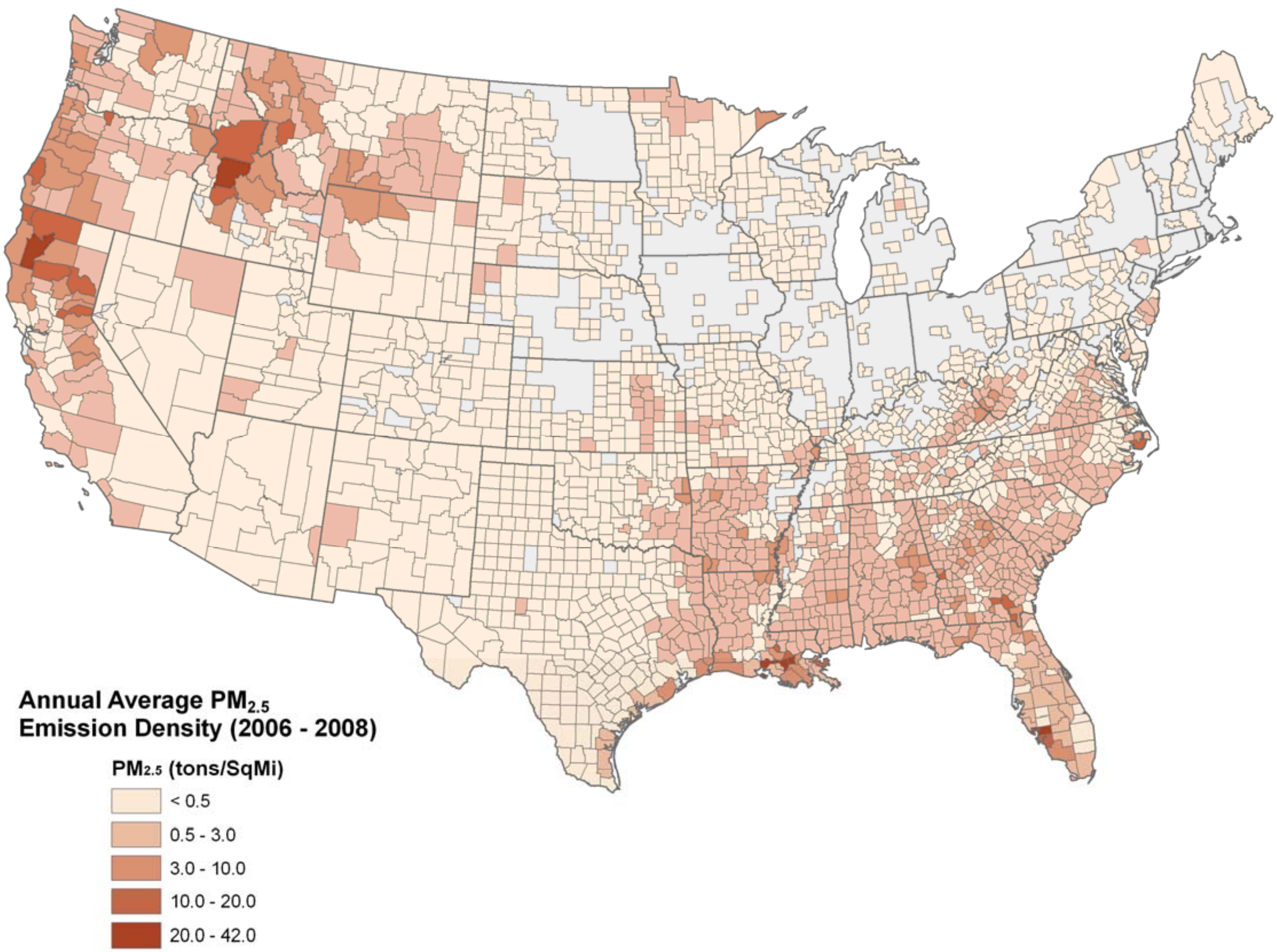


Figure 2. County-level annual average emissions density of $PM_{2.5}$ for the period from 2006 through 2008.

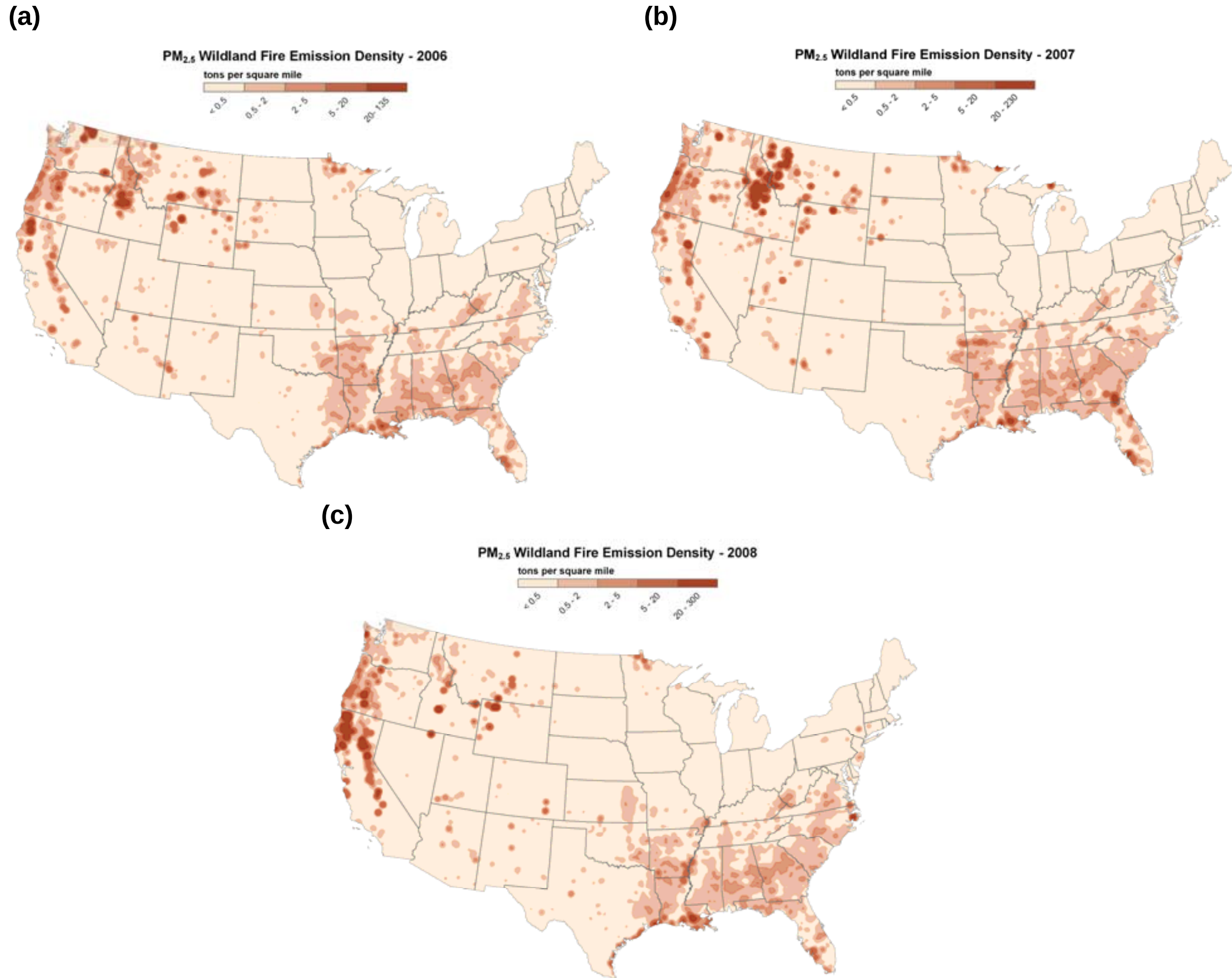


Figure 3. Annual $PM_{2.5}$ emissions density estimated for year (a) 2006, (b) 2007, and (c) 2008.

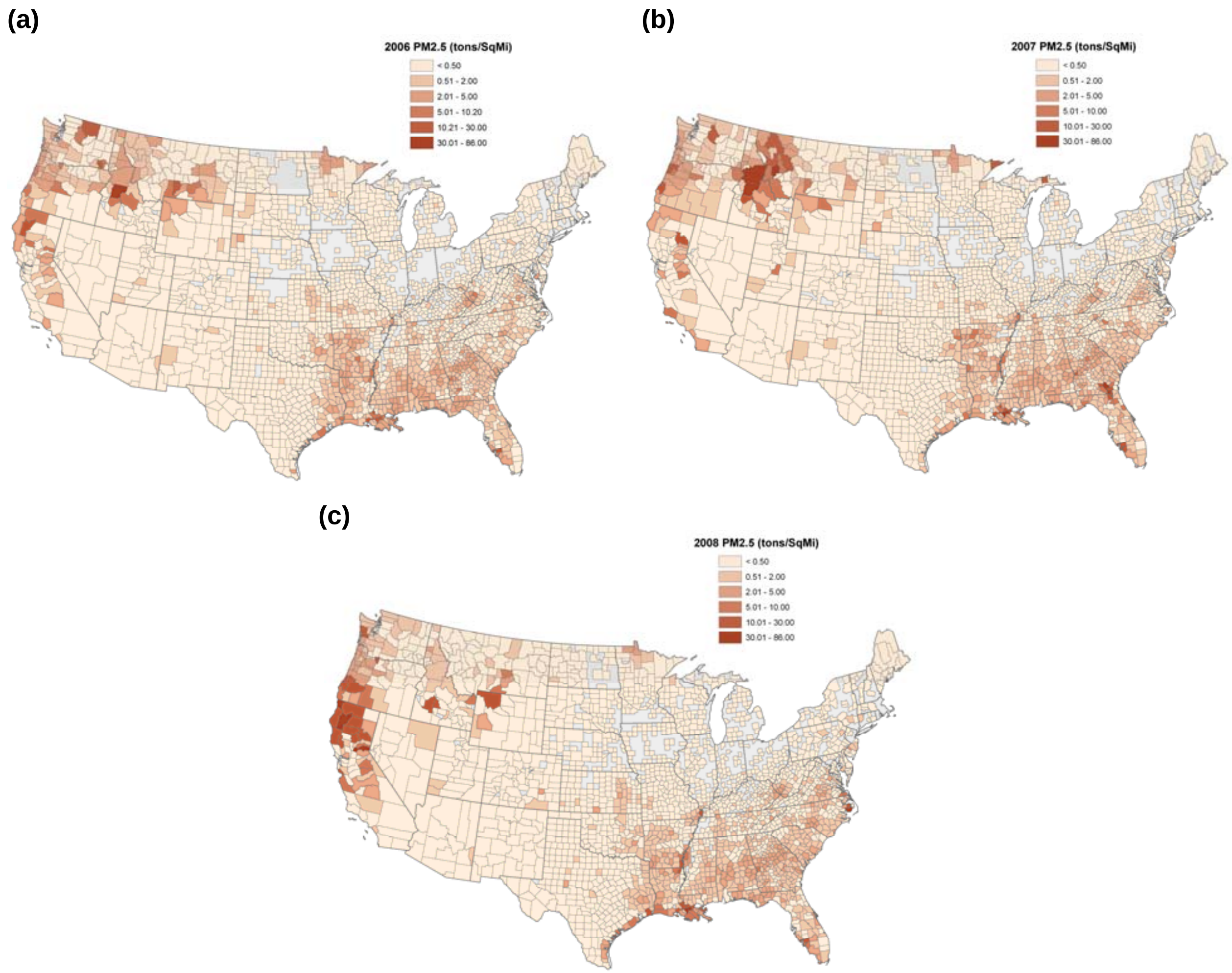


Figure 4. County-level annual $PM_{2.5}$ emission density for year (a) 2006, (b) 2007, and (c) 2008.

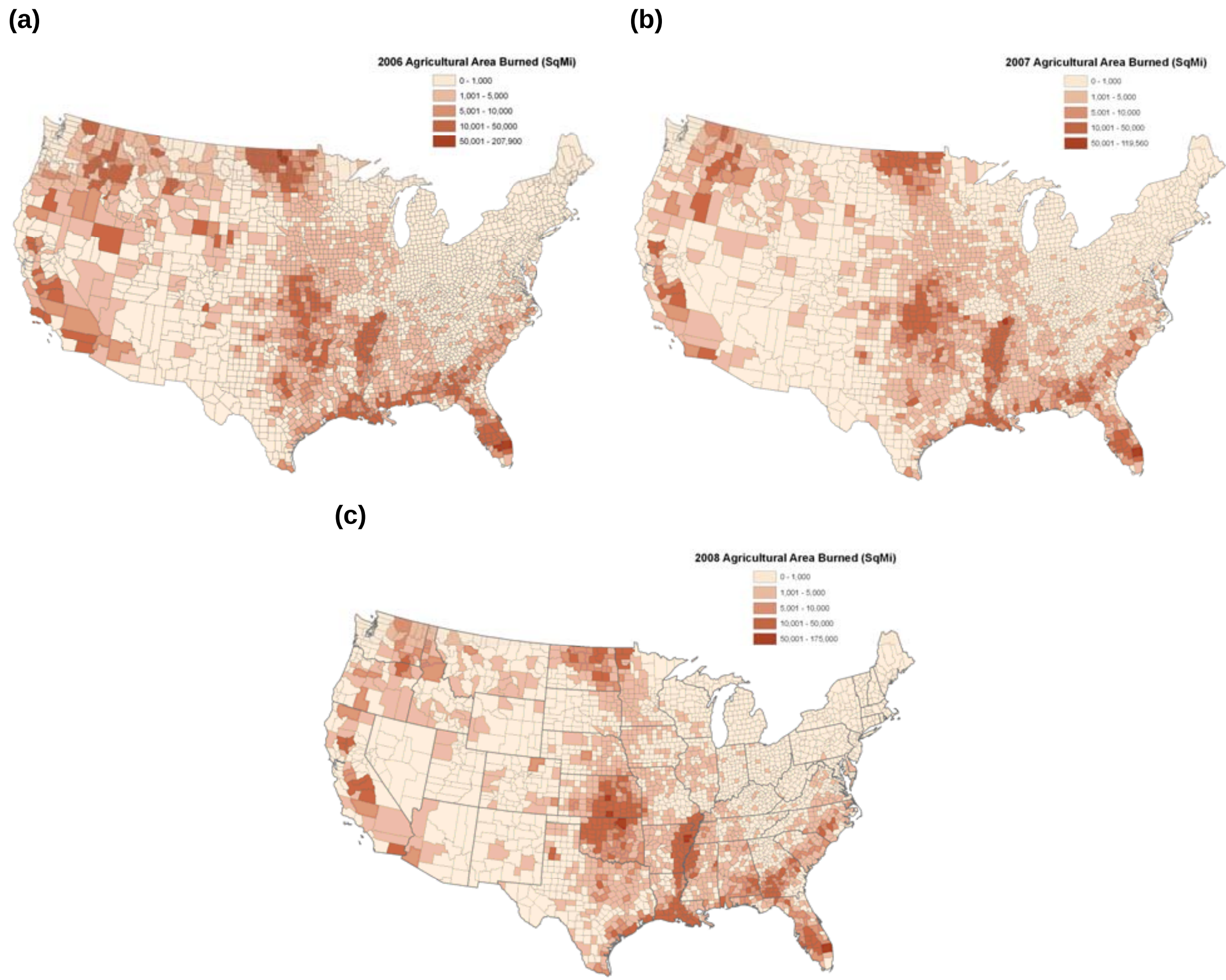


Figure 5. County-level areas burned in agricultural fires for year (a) 2006, (b) 2007, and (c) 2008.

COMPARISON TO PRIOR INVENTORY DEVELOPMENT EFFORTS

Several updates to the emissions models were implemented since the EPA's last emission inventory development effort in 2007-2008 (Raffuse et al., 2008). These updates included the following changes:

- *Corrections to the FEPS model operating in the BlueSky Framework*: Units-conversion calculations were found to be formed incorrectly in a prior version of FEPS and/or the BlueSky Framework. These calculations were corrected.
- *Two major updates to FCCS modeling*: (1) For the previous effort, the spatial reference for FCCS fuel loading files in NEFCDF format (fccs_fuelloading.ncf) were denoted as conforming to Lambert Conformal Conic projection. The data were actually projected inLambert Azimuthal Equal Area projection, but were correctly converted to Lambert Conformal Conic projection for this inventory. Additionally, the geodetic datum (fccs_fuelloading.ncf) was transformed from a spherical coordinate system to the North America Datum 1983 (NAD83) to be consistent with the geodetic datum of fire locations latitude/longitude. (2) For the previous effort, fuel loading was not available for the "urban" land use category. However, for the current effort, the fuel loading for "scrub oak - chaparral shrubland" was applied as a rough approximation for urban lands. (This approximation is admittedly very coarse; however, we considered it to be at least a minimal improvement over the previous *de facto* value of zero.) This alteration produced non-zero fuel consumptions and emissions for wildland fires in urban-classified areas.
- *Changes to canopy involvement modeling*: For the current inventory development effort, the involvement of the forest canopy was assumed to be a fractional value of 0.4 for fires detected solely with satellites (i.e., with no corresponding ICS-209 reports) and with daily burn areas of at least 150 acres. For the previous effort, no canopy involvement was assumed for such fires.

In order to evaluate the effects of these changes, we directly compared the current 2006 wildland fire emission inventory to the analogous inventory previously prepared for EPA by Raffuse, et al. (2008). Our findings were as follows:

- On a national scale, the effects of these changes on the 2006 emission inventory were less than 20% for all pollutants (from -6% to +17%) as shown in Table 2.
- We compared previous and current estimates of area burned and emissions for individual fire events (see **Figures 6a and 6b**). Current estimates of wildland areas burned were virtually identical to previous estimates (plotting tightly to a 1:1 line on the scatter plot shown in Figure 6a). Current estimates of emissions varied from previous estimates with predictable consistency (plotting closely to a regression line with an r-squared of 0.99).
- Fire events that were identical in their daily fuel consumption estimates (when the previous and current 2006 inventories) were selected. Daily emissions from such selected fires were examined to isolate the changes attributable solely to the FEPS model update (see **Figure 7**). Current estimates of emissions varied from previous estimates

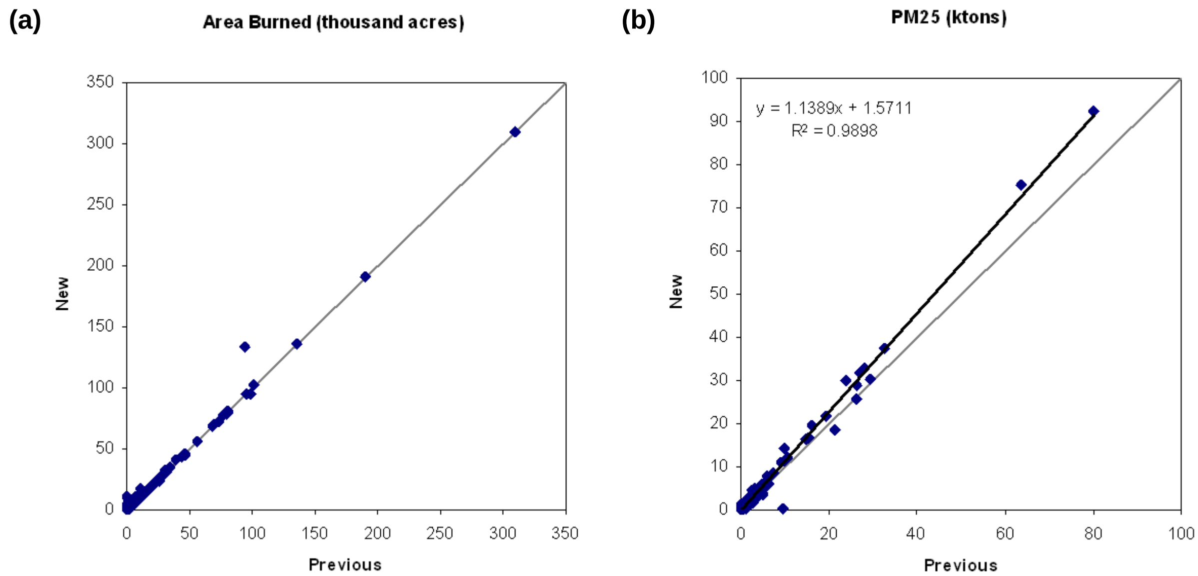
with predictable consistency (either plotting closely to a regression line with or plotting closely to a 1:1 line).

- The two versions of the 2006 emission inventory were temporally consistent. **Figure 8** shows that the daily estimates of area burned and $PM_{2.5}$ emissions for 2006 were very similar.
- The two versions of the 2006 emission inventory were spatially consistent. Figures 9 and 10 plot the emissions densities for the two versions of the inventory for the lower 48 United States.

Table 2. Effects of updated emissions modeling techniques on the 2006 wildland fire emission inventory.

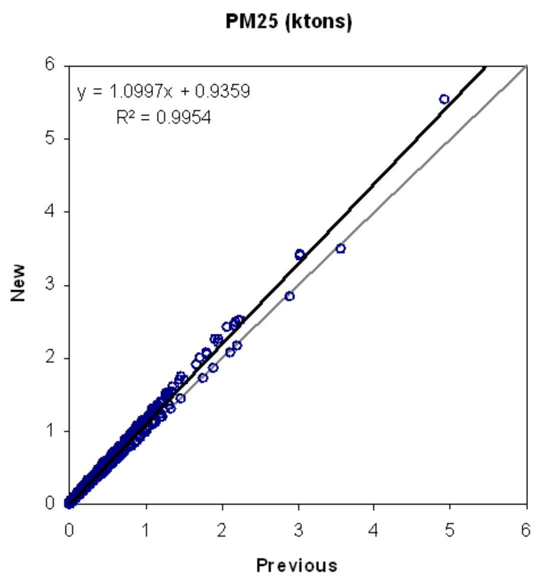
2006	Difference (%)
Consumption	3.33
Area	-0.51
$PM_{2.5}$	14.37
PM_{10}	14.37
CO	17.43
CH_4	15.91
NO_x	-6.36
NH_3	17.01
SO_2	3.75
VOC	17.01
CO_2	1.72
HAPs	3.33

Note: Difference (%) = (New - Previous) /Previous *100%



Note: Each point represents a cumulative fire event in 2006, each of which may have been a multi-day event.

Figure 6. Comparisons of the results of EPA's current and previous wildland fire emission inventory development efforts, including (a) estimates of area burned and (b) estimates of $PM_{2.5}$ emissions for inventory year 2006.



Note: Each point represents daily emissions for selected fire events in 2006.

Figure 7. $PM_{2.5}$ emissions comparison between new and previous modeling of year 2006 for fire with same fuel consumptions.

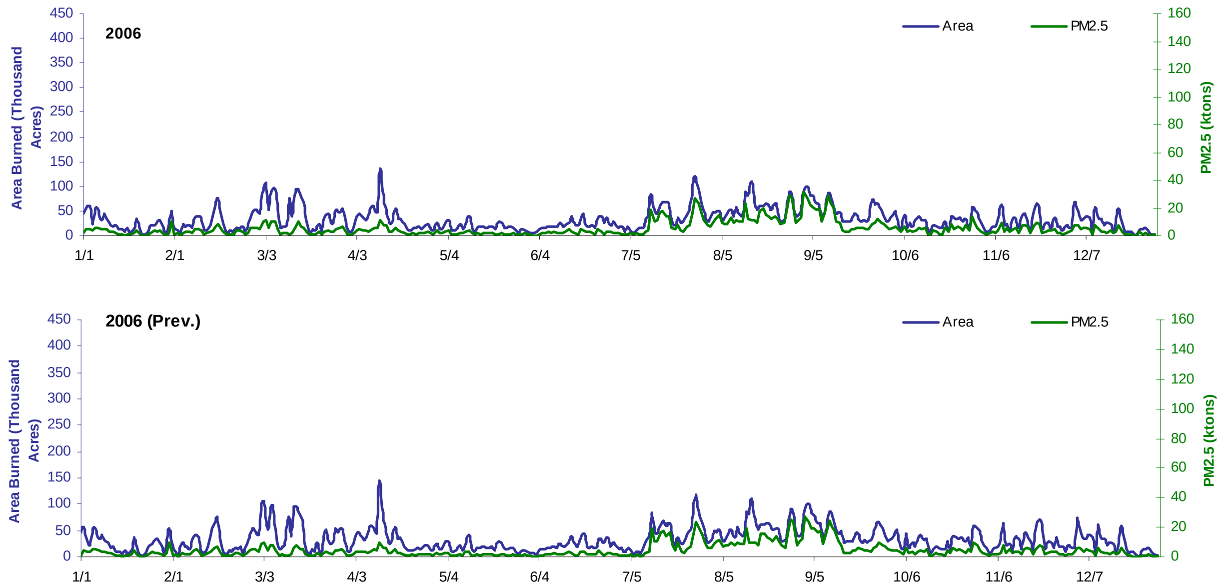


Figure 8. Daily area burned and $PM_{2.5}$ emissions in 2006 as estimated for the current EPA wildland fire emission inventory (top) and the previous EPA inventory (bottom).

(a) (b)

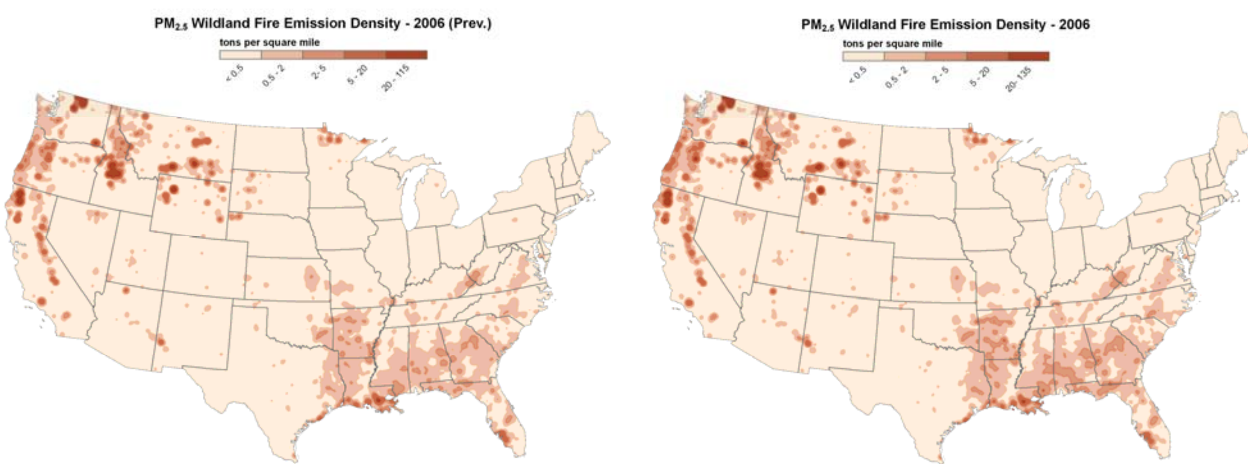


Figure 9. Annual $PM_{2.5}$ emissions density estimated for (a) the prior version of the 2006 inventory (Raffuse et al., 2008), and (b) the current version of the 2006 inventory.

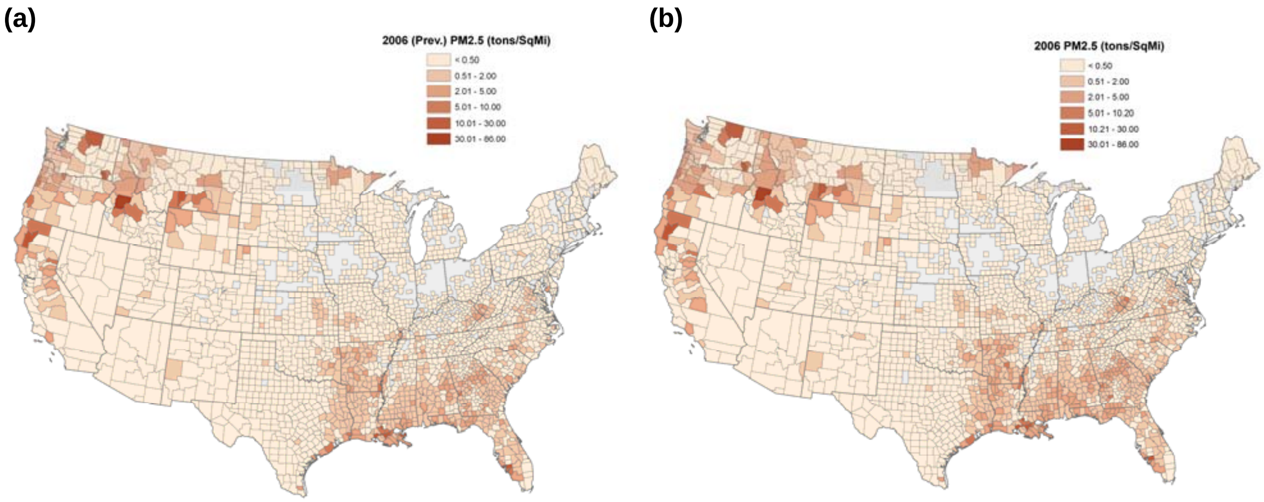


Figure 10. County-level annual $PM_{2.5}$ emission density for (a) the prior version of the 2006 inventory (Raffuse et al., 2008), and (b) the current version of the 2006 inventory.

REFERENCES

Raffuse S.M. and Sullivan D.C. (2008) SMARTFIRE- and BlueSky-enabled methodology for developing wildland fire emission inventories for 2002-2006. Technical memorandum prepared for the U.S. Environmental Protection Agency, Research Triangle Park, NC, by Sonoma Technology, Inc., Petaluma, CA, STI-905409-3395, June.

Raffuse S.M., Sullivan D.C., Gilliland E.K., Chinkin L.R., Larkin S., Solomon R., and Pace T. (2008) Development of wildland fire emission inventories for 2003-2006 and sensitivity analyses. Presentation made at the *U.S. Environmental Protection Agency's 17th International Emission Inventory Conference, Portland, OR,, June 5,* by Sonoma Technology, Inc., Petaluma, CA; U.S. Forest Service AirFire Team, Seattle, WA; and U.S. Environmental Protection Agency Office of Air Quality Planning and Standards, Research Triangle Park, NC (STI-905028-3377).

SMARTFIRE Algorithm Description

Sean M. Raffuse, Daniel A. Pryden, Dana Coe Sullivan
Sonoma Technology, Inc., 1455 N. McDowell Blvd., Suite D, Petaluma, CA 94954

Narasimhan K. Larkin, Tara Strand, and Robert Solomon
US Forest Service, AirFire Team, Pacific Northwest Research Laboratory
400 N. 34th St #201, Seattle, WA 98103

INTRODUCTION

For large wildfires and wildland fire use (WFU) fires for which there is a federal response, Incident Command Summary reports (known as ICS-209 reports) are created on a near-daily basis. ICS-209 reports contain useful information about particular fires or fire complexes from the incident command team on the ground, such as descriptions of the fuel loading, growth potential, and type of fire. However, ICS-209 reports also have several limitations. Daily estimates of actively burning areas are required, but ICS-209 reports provide only the ignition point of the fire and an estimate of the total area burned over the lifetime of the fire. For large fires, active flame fronts can move dozens of kilometers from the original ignition point of the burn. More importantly, ICS-209 reports are only created for a small subset of fires. Fires that are not tracked with ICS-209 reports include prescribed burns, agricultural burns, and wildfires for which there is no federal response. Taken together, these missing fires represent a large fraction of the total area burned and resulting smoke emissions. The National Interagency Fire Center (NIFC) reports that at least 9000 km^2 of prescribed burning has been accomplished each year since 2001 in the US, representing up to 40% of the total area burned (http://www.nifc.gov/fire_info/fire_stats.htm).

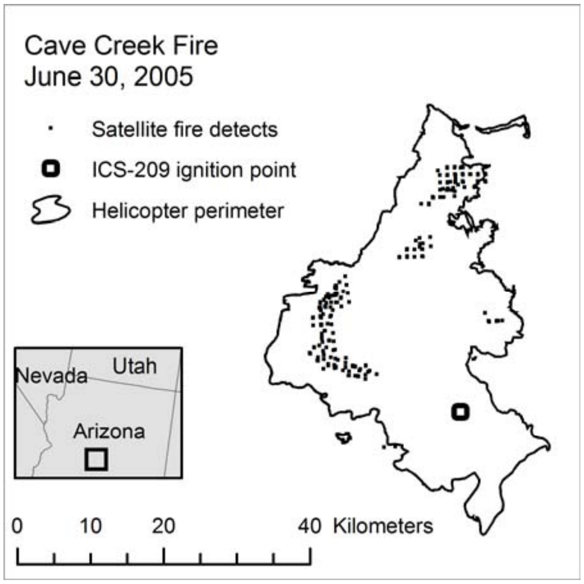
Numerous jurisdictions have burn authorization and reporting systems that provide information on prescribed fires. These data systems are the primary source of information for prescribed fires. Unfortunately, these individual systems were not developed to be interoperable which introduces difficulty in synthesizing their information in a regional- or national-scale system. For example, formats are inconsistent, contain different burn information, are difficult to acquire, and include information on potential prescribed burns that may never occur. Some of these issues are currently being addressed with the Fire Emissions Tracking System (FETS), which will provide a unified burn reporting system for the western United States (http://www.wrapfets.org/).

Near real-time fire information is also available from satellite-derived measurements (e.g., Dozier, 1981; Justice et al., 2002; Prins and Menzel, 1994; Li et al., 2000). Fire information from current space-borne instruments provides many advantages over ground-based reporting systems, including daily or better temporal resolution, the ability to detect relatively small fires, and consistency across jurisdictions. However, satellite-derived fire observations are limited by false positive detections, interference from clouds, and limited information about the total area burned. Total area burned can be derived from analysis of burn scars from satellite data (Li et al., 2004), but satellite burn scar data are not currently available in near real-time (i.e., data available on the day of detection). In the absence of burn scar data, other studies have used the sensor's nominal resolution (e.g., 1 km^2 for MODIS) as an upper limit of the total area burned by the fire (Wiedinmyer et al., 2006), sensor-based calculations of Fire Radiative Power to estimate the instantaneous burning area (Wooster et al., 2005), or used regression tree analysis to develop area-per-pixel relationships dependant on forest cover, region, and pixel cluster size (Giglio et al., 2006).

The Satellite Services Division (SSD) of NOAA's National Satellite and Data Information Service (NESDIS) produces a daily quality controlled fire and smoke analysis for the United States using the Hazard Mapping System (HMS) (Ruminski et al., 2006). The HMS integrates satellite data from three instrument types (Geostationary Operation Environmental Satellite (GOES), Moderate Resolution Imaging Spectroradiometer (MODIS), Advanced High Resolution Radiometer (AVHRR)) onboard seven different satellite platforms. Trained NOAA satellite analysts use the output from automated fire detection algorithms as well as various ancillary data layers. The automated fire detection algorithms produce false detections, especially in areas of high surface reflectance, sun glint, or high surface temperature (Hoelzemann et al., 2004; Giglio, 2005). The analysts review fire detects from the algorithms to reduce false detects and scan the satellite imagery and add fires that the algorithms have not detected (i.e., if a smoke plume detected in visible imagery has no associated fire detect, it will be added). The analysis is updated at http://www.ssd.noaa.gov/PS/FIRE/hms.html several times a day. The HMS is described by Ruminski et al. (2006),

Ideally, a daily, operational fire reporting system would take advantage of all available data sets to produce the most complete picture of daily area burned; however, simple summation of all data sets will result in double counting of some fires due to information overlaps. Multiple data sets can be combined if the data overlaps can be identified and rectified. Identifying data overlaps is difficult due to both the differences in the data sources and the fact that a fire can move many kilometers from its original ignition point over the course of its lifetime. For example, Figure 1 shows a June 30, 2005 snapshot of information for the Cave Creek wildfire, which burned over 800 km^2 of Arizona wildland in 2005. This fire ignited on June 22, 2005. The reported burn perimeter derived from a helicopter overflight shows the approximate final shape of the Cave Creek fire. Hot-spot points detected by satellite show the actively burning flame fronts for the June 30, 2005. From the helicopter perimeter, (which we do not have reliable access to in an operational time frame), it is obvious that all of the clusters of satellite fire points are actively burning sections of the same wildfire event. The ground-reported (ICS-209) fire ignition point is 50 km from some of the satellite points. To use multiple overlapping data sets, an algorithm for reconciliation must be developed. In this manuscript, we describe the SMARTFIRE algorithm and database system that combines disparate data on fires into a unified datasets. SMARTFIRE was developed specifically for use in the BlueSky smoke modeling framework (Larkin et al., 2009)) although, in principle, it should be portable to other modeling and emission inventory applications.

Figure 1. An illustration of the single-day satellite fire detection pixels for the day of June 30, 2005, the ICS-209 helicopter-flown final burn area perimeter, and ICS-209 ignition point for the Cave Creek Fire in Arizona.



METHODS

Data Sources

SMARTFIRE is an algorithm and database system developed and built within a geographic information system (GIS) framework that combines multiple sources of fire information and reconciles them into a unified data set. It was developed to take advantage of multiple data sources while avoiding double counting. The BlueSky system, developed by the US Forest Service, is a framework that attempts to serve these needs by connecting several submodels to produce predictions of emissions and resulting concentrations of smoke pollution from fires, both in near-real-time and retrospectively (Larkin et al., 2009).

SMARTFIRE was built with the capability to ingest multiple disparate fire reporting data sets to produce a single unified data set. Currently, two input data sources have been implemented within SMARTFIRE: (1) ICS-209 reports and (2) satellite data from the NOAA Hazard Mapping System (HMS).

Development of the SMARTFIRE Algorithm

The SMARTFIRE algorithm consists of four general steps, outlined for a small area in Figure 2 a-d:

a. Daily input data are loaded into the geodatabase.
b. Individual data points are associated together by proximity into Fire Perimeters representing contiguous burning regions.

c. Fire Perimeters are associated to Fire Events by proximity in time and space. Fire Events grow over time as long as the fire continues to be detected and represent the history and progression of the fire.

d. Fire Perimeter polygons are converted to point data for modeling by calculating centroids. For each model point, an area burned is estimated.

(a) Input Data

Daily input data are loaded into a geographic information system database (geodatabase). The currently implemented data sets, ICS-209 ignition points and HMS fire pixels, are both point data sets (i.e., they have a coordinate location but no associated shape); however, the algorithm could also incorporate line or polygon sources. The data for a small area on a single day are shown in panel (a). The region shown contains a single ICS-209 reported fire and many HMS fire pixels.

(b) Create Fire Perimeters

Data are converted from points to polygons by drawing circles of a specific radius centered on each point and then dissolving all intersecting circles into a set of disjoint polygons called Fire Perimeters (b). This is done to associate nearby data into contiguous burning areas (clusters) and to minimize double counting from multiple data sources detecting the same burning area. The radius varies by data source. For HMS, the value is an adjustable parameter set at 750 m, which assures that adjacent pixels are associated (HMS data are on a 1-km resolution grid). ICS-209 reports provide cumulative instead of daily area burned. To create a Fire Perimeter for an ICS-209 report, an estimate of the daily area burned is made by subtracting the cumulative area of the current report from the cumulative area of the previous report of the same name.

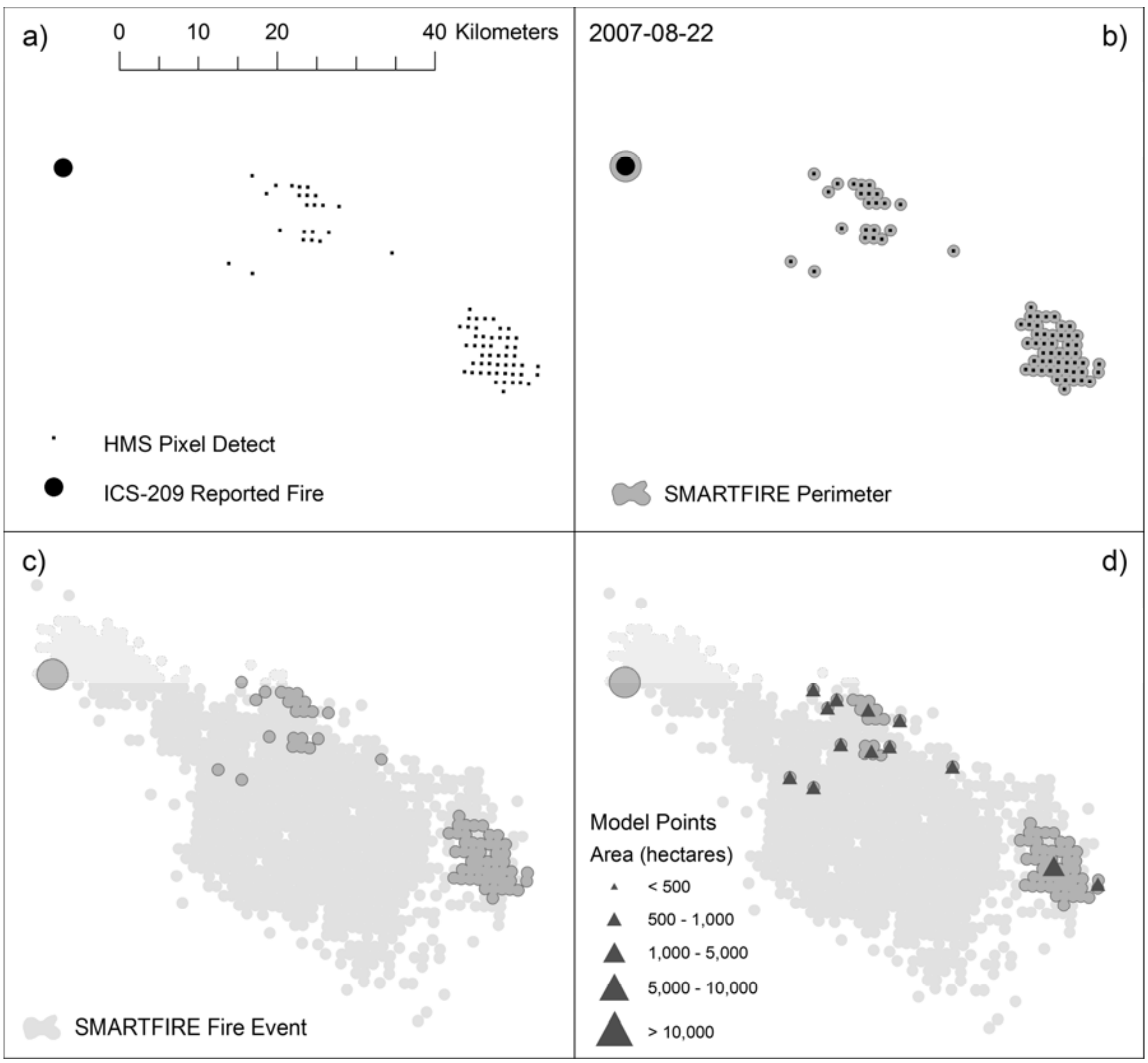
(c) Associate Fire Perimeters to Fire Events

The next step in the algorithm is to associate Fire Perimeters to active Fire Events in the SMARTFIRE geodatabase by proximity. A Fire Event is a collection of fire information that has been associated together. The Fire Event groups information into collections that resemble the way fires are understood in the fire management community. For example, all detection information from a single named fire should be associated into a single Fire Event. Fire Events can span multiple days. Fire Perimeters are associated with Fire Events by drawing a buffer around the Perimeters and intersecting them with active Fire Events. Buffer distance is a function of the Perimeter area (500 m for Perimeters less than 1.77 km^2; 1500 m for larger Perimeters). Buffer distances were selected by examining several wildfires and wildfire complexes and determining the distances which minimized false associations while maximizing positive associations. If no active Fire Event is found within the buffer distance, one is created. After four days without new data, Fire Events become inactive and are no longer considered in the algorithm (i.e., additional Fire Perimeters will be assigned to new Fire Events). Four days was chosen to account for gaps in the data stream, such as when clouds obscure satellite detections or no ICS-209 reports are produced.

(d) Create Model Points

The SMARTFIRE geodatabase provides activity data for predictive and historical modeling of air quality impacts from fires, such as the BlueSky smoke modeling framework. BlueSky requires burning point locations identified as latitude/longitude pairs and an associated estimate of area burned. Fire Perimeter polygons cannot be used as inputs for BlueSky and must be converted into point locations with area estimates. Points are created by calculating centroids from HMS Fire Perimeters (d). ICS-209 based perimeters are used if no HMS perimeters are available for the Fire Event on the specific date. Area burned estimates for each model point are not equal to their parent Fire Perimeter areas, but are scaled to them. The development of area estimates for model points is detailed below.

Figure 2. SMARTFIRE reconciliation algorithm illustration. (a) One day of input data (ICS-209 report and HMS pixels for the Zaca Fire on 2007-08-22, (b) SMARTFIRE Perimeters added to each data source, (c) the Perimeters overlaid on the active SMARTFIRE FireEvent from the previous day, (d) The SMARTFIRE Model Points at the centroid of each HMS-based Perimeter.



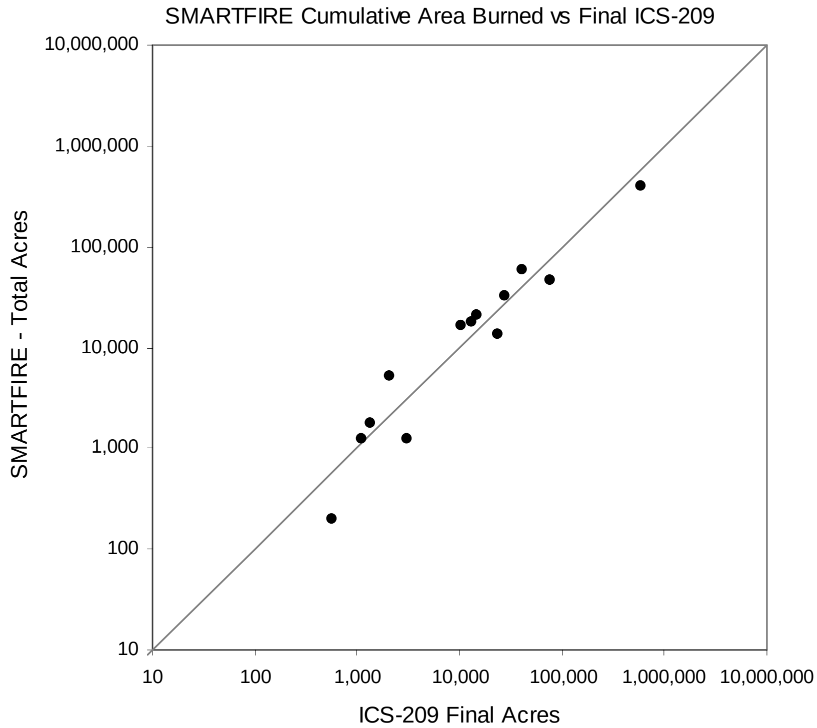
(e) Area Estimation

Satellite-derived hot-spots from HMS do not provide information about the area burned. SMARTFIRE area burned estimates for HMS data are estimated using one technique for large, multi-pixel fires and a second technique for small, single-pixel fires.

Large wildfire burn area estimates were derived by comparing HMS pixel perimeters to ICS-209 burned area polygons. For large wildfires, the responsible incident command team produces burned area polygons produced by helicopters equipped with GPS data loggers flying around the perimeter of the fire. The area within the last flown perimeter represents an estimate of the total area burned. The area per pixel in SMARTFIRE was determined by correlating final helicopter perimeter areas to total cumulative HMS pixel perimeters for 14 large fires (Figure 3). The fires ranged from about 2 to 2500 km^2 in size over various parts of the United States. The resulting area per pixel is 0.6 km^2. However, not all of the area encompassed by a helicopter-flown perimeter will have burned in a typical wildfire. Thus the actual burned area (sometimes called the blackened area) will be some fraction of the perimeter area. Based on past research, we estimated this fraction as 0.8 (Tom Pace, EPA, personal communication). Accounting for the estimate of only 80% of the helicopter perimeter area burned results in a per pixel area of 0.49 km^2.

Small single-pixel fire burn area estimates were derived by a comparison of a silvicultural prescribed burns database with HMS fire detects. The multi-pixel burn area estimate does not apply to small fires, which may be detected by only a single satellite pixel. To estimate the per pixel area burned by these fires, we used a silviculture database provided by the state of Georgia. The database provides information on the number and total acreage of fires by month and county for the year 2002. According to the database, about 20,000 prescribed fires burned a total of over 3100 km^2 in 2002. Unfortunately, HMS data do not exist for the full year in 2002. The prescribed fire count and total area were compared to HMS pixel counts for Georgia for 2004, 2005, and 2006. Pixel counts for these years ranged from 6,700 to 8,700 and averaged 7,723. The fires in the Georgia database were mostly small in size (< 0.4 km^2) so the vast majority of fires were detected by a single HMS pixel. Thus, HMS detects approximately 40% of the small fires in Georgia. Many fires are either too small to be detected or obscured by cloud cover or canopy. To account for the total reported acreage, we divide the annual average HMS pixel count by the total reported acreage in the database. The resulting area per pixel for single pixel fires is 0.4 km^2. Note that this value is much smaller than the nominal pixel resolutions for any of the instruments that HMS uses.

Figure 3. Scatter plot of SMARTFIRE total burn area estimates with ICS-209 helicopter burn perimeter areas.



Limitations

Four years (2003-2006) of daily area estimates across the continental US have been processed. Robust validation of the SMARTFIRE algorithm and its parameters is currently underway. The data used to tune the algorithm parameters were limited, especially for small fires. For example, area estimates for fires detected by a single HMS pixel are based on a prescribed fire database from the state of Georgia. This estimate needs to be corroborated with other data sources in other regions. The buffer distance parameters that dictate which ICS-209 reports and satellite pixels get reconciled have not been rigorously tested. False associations and non-associations sometimes occur.

Because SMARTFIRE was originally designed primarily to support predictions on a near-real-time basis, the possible input sources are limited. ICS-209 data are created by hand input and sometimes contain typographical errors. The most common errors are incorrect cumulative area burned from adding an extra zero to the value and transposed latitude and longitude. HMS data are currently produced on a 1-km grid that is lower resolution than some of the satellite input sources. Also, HMS does not report potentially useful values such as the fire radiative power, which could be used to calculate total emissions (Jordan et al., 2008). More refined and potentially more accurate data sources, such as satellite-derived burn scars, are available for retrospective studies. Future work will explore the incorporation of these high quality but time lagged data sets for retrospective analyses such as emission inventories.

REFERENCES

Dozier J. (1981) A method for satellite identification of surface temperature fields of subpixel resolution. *Remote Sens. Environ.* **11** (3), 221-229.

Giglio L. (2005) MODIS collection 4 active fire product user's guide: version 2.2. Prepared by Science Systems and Applications, Inc., Lanham, MD, November.

Giglio L., van der Werf G.R., Randerson J.T., Collatz G.J., and Kasibhatla P. (2006) Global estimation of burned area using MODIS active fire observations. *Atmos. Chem. Phys* **6**, 957-974.

Hoelzemann J.J., Schultz M.G., Brasseur G.P., Granier C., and Simon M. (2004) Global Wildland Fire Emission Model (GWEM): Evaluating the use of global area burnt satellite data. *J. Geophys. Res* **109** (D14S04).

Jordan N.S., Ichoku C., and Hoff R.M. (2008) Estimating smoke emissions over the US Southern Great Plains using MODIS fire radiative power and aerosol observations. *Atmos. Environ.* **42** (9), 2007-2022.

Justice C.O., Giglio L., Korontzi S., Owens J., Morisette J.T., Roy D.P., Descloitres J., Alleaume S., Petitcolin F., and Kaufman Y. (2002) The MODIS fire products. *Remote Sens. Environ.* **83**, 244-262.

Larkin N.K., O'Neill S.M., Solomon R., Raffuse S., Strand T.M., Sullivan D.C., Krull C., Rorig M., Peterson J., and Ferguson S.A. (2009) The BlueSky smoke modeling framework. *Int. J. Wildland Fire* (accepted).

Li R., Kaufman Y., Hao W., Salmon M., and Gao B. (2004) A technique for detecting burn scars using MODIS data. *ITGRS* **42** (6), 1300-1308.

Li Z., Nadon S., and Cihlar J. (2000) Satellite-based detection of Canadian boreal forest fires: development and application of the algorithm. *Int. J. Remote Sensing* **21** (16), 3057–3069.

Prins E.M. and Menzel W.P. (1994) Trends in South American biomass burning detected with the GOES visible infrared spin scan radiometer atmospheric sounder from 1983 to 1991. *J. Geophys. Res.* **99**, 16719-16735.

Ruminski M., Kondragunta S., Draxler R.R., and Zeng J. (2006) Recent changes to the Hazard Mapping System. *15th International Emission Inventory Conference, New Orleans, LA.* Available on the Internet at <http://www.epa.gov/ttn/chief/conferences.html>.

Wiedinmyer C., Quayle B., Geron C., Belote A., McKenzie D., Zhang X., O'Neill S.M., and Wynne K. (2006) Estimating emissions from fires in North America. *Atmos. Environ.* **40**, 3419-3432.

Wooster M.J., Roberts G., Perry G.L.W., and Kaufman Y.J. (2005) Retrieval of biomass combustion rates and totals from fire radiative power observations: FRP derivation and calibration relationships between biomass consumption and fire radiative energy release. *J. Geophys. Res.* **110**, D24311 (doi:10.1029/2005JD006318).

Development of Wildland Fire Emission Inventories for 2006-2008

Sean M. Raffuse, Yuan Du, and Dana Coe Sullivan
Sonoma Technology, Inc., 1455 N. McDowell Blvd., Suite D, Petaluma, CA 94954

ABSTRACT

The BlueSky smoke modeling framework and the Satellite Mapping Automatic Reanalysis Tool for Fire Incident Reconciliation (SMARTFIRE) were applied to facilitate the development of day-specific wildland fire emission inventories for the continental United States. SMARTFIRE was used to generate activity data (acres burned). The latest updated versions of the FCCS, CONSUME 3.0, and FEPS models were used within the BlueSky Framework to model vegetation distribution, fuel consumption, and emission rates, respectively. Emission inventories were compared to analogous inventories previously prepared under a prior U.S. Environmental Protection Agency (EPA) inventory development effort for comparison. We found that the latest updates to the available emissions models produced modest changes to the emission inventories.

INTRODUCTION

Globally, wildland fire (wildfire and prescribed burning of forests and rangelands) contributes significantly to atmospheric pollution. Pollutants emitted from fires include particulate matter (PM), carbon monoxide (CO), nitrogen oxides (NO_x), and acrolein (a regulated hazardous air pollutant [HAP]) (Andreae and Merlet, 2001). In the United States, the U.S. Environmental Protection Agency (EPA) estimates that 22% of the primary emissions of non-dust particulate matter less than 2.5 microns in aerodynamic diameter ($PM_{2.5}$) came from non-residential fires in 2001 (970,000 tons, source: AirData web site, http://www.epa.gov/air/data/). Exposure to wildfire smoke has been associated with increased eye and respiratory symptoms, medication use, physician visits, and exacerbated asthma (Kuenzli et al., 2006). Emissions of carbon monoxide and nitrogen oxides from fires contribute ozone formation in the troposphere (the key component of photochemical smog). Estimates of the magnitude of tropospheric ozone from biomass burning range from less than 15% to 40% of the global total (Levine et al., 1995; Galanter et al., 2000). Carbon particles from fires also contribute to climate forcing, both directly by increasing atmospheric reflectance, and indirectly by influencing the formation of clouds (Kaufman and Fraser, 1997).

Accurately modeling wildland fire emissions requires many pieces of information, including fire location, ignition time and growth rate, fire intensity, and final size. This information is needed at a daily or more frequent temporal resolution to be useful for air quality modeling of smoke impacts. Emissions from wildland fires can be modeled using the formula in Equation 1.

Equation (1) $E_s = A * F * c * EF_s$

where

E_s = emissions of species s
A = area burned
F = fuel available for consumption
C = fraction of available fuel consumed
EF_s = emission factor (mass of species s emitted per mass of fuel consumed)

Each of the variables (A, F, c, EF_5) used to predict emissions are uncertain. The area burned is one of the most important areas of uncertainty that can be constrained using available observations.

Historically, for national-scale emission inventories in the United States, estimates of area burned have come from compilations of fire reporting systems from federal, state, tribal, and local agencies. Given that data are originally collected in a variety of formats, compilation is costly. Some fire reporting systems do not track individual fires, keeping only monthly statistics. To create a fire emission inventory with daily resolution in a timely matter requires a different data source.

Satellites have been used to detect fires globally for several decades (Dozier, 1981). The global climate community routinely uses satellite-based data to derive estimates of area burned (van der Werf et al., 2006). Satellite data offer several advantages over ground reporting systems for estimating area burned over a large area (such as nationally). Satellite data sets are available with global coverage in a single format, making them easy to work with. Also, satellites detect fires that are often too small or too remote to be reported by human observation.

There are, however, limitations in the use of satellite data for emission inventories. Satellite instruments that provide global daily coverage of fires do not yet routinely provide an estimate of area burned for each fire. Instead, a thermal anomaly or “hot spot” is detected and reported. The smallest fire that can be detected is instrument-, algorithm-, and condition-specific. Large fires will be detected as a cluster of several “hot spot” pixels. To use these types of data in Equation 1, one must estimate the area burned per pixel. Though algorithms exist for estimating total burned area (Li et al., 2004) directly from satellite observations of burn scars, these algorithms are not routinely available. Also, burn-scar algorithms may have trouble detecting burns that occur below the forest canopy (understory burns). Understory burns are very common in the southeastern United States, where millions of acres of prescribed burning occur annually.

Though satellites are able to detect many fires, they do not detect all fires. Fires that are too small or too cold, are not burning during the satellite overpass, or are obscured by clouds go undetected. Satellite fire detections have not been used previously to estimate area burned for the National Emission Inventory.

Using data from ground reporting systems in concert with satellite fire detects can help improve fire area-burned estimates. The Satellite Mapping Automatic Reanalysis Tool for Fire Incident Reconciliation (SMARTFIRE) is an algorithm and database system designed to reconcile these disparate fire information sources to produce daily fire location and size information while minimizing double-counting (Sullivan et al., 2008).

Using SMARTFIRE as the fire activity source, we prepared three years (2006–2008) of daily emission estimates for wildland fires for the lower 48 United States, including wildfire, wildland fire use (WFU), and prescribed burns. (We also prepared activity data for fires in agricultural areas for EPA's use in estimating emissions.) The 2006 wildland fire inventory was then directly compared to the EPA's analogous 2006 inventory prepared previously by Raffuse, et al (Raffuse et al., 2008).

BODY

Methods

Fire Information Sources via SMARTFIRE

SMARTFIRE uses both satellite-detected and ground-reported fires to produce daily fire information (locations and area burned). SMARTFIRE currently reconciles ICS-209 ground reports and hot spots from the National Oceanic and Atmospheric Administration (NOAA) Hazard Mapping System (HMS) (Ruminski et al., 2006).

- For large wildfires and WFU fires for which there is a federal response, ICS-209 reports are created on a near-daily basis. ICS-209 reports contain useful information about particular fires or fire complexes from the incident command team on the ground, such as descriptions of the fuel loading, growth potential, and type of fire.
- HMS data consist of compiled fire detection information from three different instruments onboard seven satellite platforms enhanced by human quality control. Individual detections are inspected by a trained analyst for false detects and inaccurate geolocation. The HMS product relies on data from the MODIS, Advanced Very High Resolution Radiometer (AVHRR), and Geostationary Earth Observing Satellite (GOES) instruments.

Emissions Modeling Pathway

The emissions were processed using models embedded in the BlueSky smoke modeling framework (Larkin et al., 2009). The BlueSky Framework is designed to facilitate the operation of predictive models that simulate cumulative smoke impacts, air quality, and emissions from forest, agricultural, and range fires. The BlueSky Framework allows users to combine state-of-the-science emissions and meteorological and dispersion models to generate results based on the best available models. In other words, the BlueSky Framework connects models that provide values for the terms in Equation 1. The BlueSky Framework allows the user to choose one of several models at each step in the smoke modeling process. The models used for this study are shown in Table 1.

Table 1. Model chain within the BlueSky Framework used to estimate emissions.

Process	Model Used	Version No.
Activity data	SMARTFIRE	Version 1.0, Build 812
Fuel loading	Fuel Characteristic Classification System (FCCS)	As implemented in Bluesky Framework 3.1.0 revision 6700
Fuel consumption	Consume 3.0	As implemented in Bluesky Framework 3.1.0 revision 6700
Emissions	Fire Emission Production Simulator (FEPS)	As implemented in Bluesky Framework 3.1.0 revision 6700

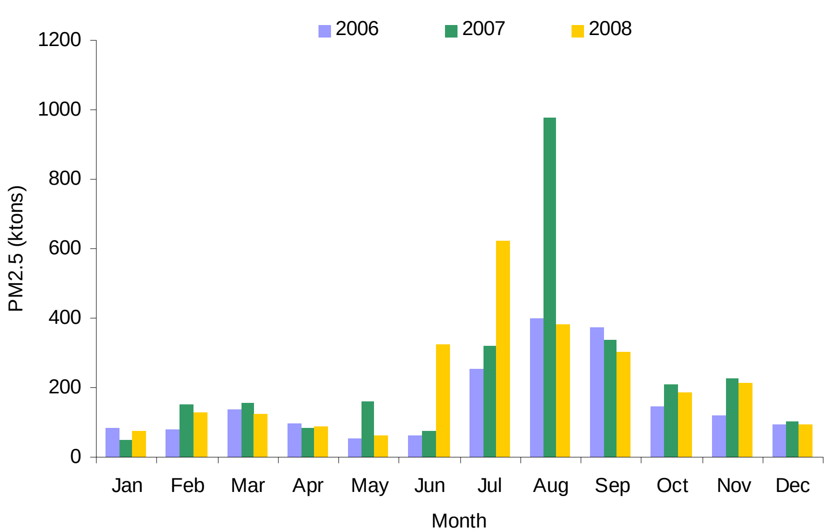
In addition to the standard emission products produced by FEPS ($PM_{2.5}$, CO, etc.), emissions for 29 HAP species were estimated based on emission factors provided by Tom Pace of EPA (U.S. Environmental Protection Agency, 2007). Fires were assigned fuel moisture values based on the nearest weather station from the U.S. Department of Agriculture Forest Service (USDA-FS) Wildland Fire Assessment System.

Results

Emissions from SMARTFIRE

Though emission estimates were calculated for many species, this paper focuses on $PM_{2.5}$ emissions. (Atmospheric formation of secondary aerosols was not considered.) All other pollutants were modeled with similar spatiotemporal patterns. Figure 1 shows the estimated primary $PM_{2.5}$ emissions by month for each modeled year. Wildland fire emissions in the lower 48 states exhibit a bimodal yearly pattern, with a modest peak in the spring and a prominent peak in the late summer/early fall.

Figure 1. Modeled yearly primary $PM_{2.5}$ wildland fire emissions by month for the lower 48 states.

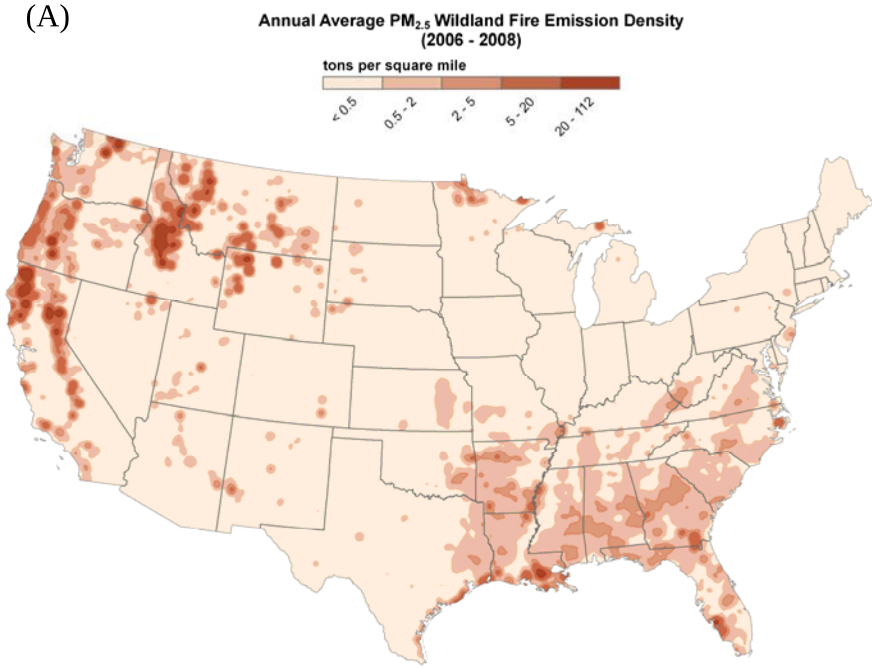


The bulk of emissions comes from two regions: the West and the Southeast. This concentration can be seen in the emissions density plot shown in Figure 2A, which shows the average annual tons of $PM_{2.5}$ emitted per square mile, smoothed for display clarity. The national spatiotemporal pattern is shown in more detail in Figure 2B, which depicts the monthly average $PM_{2.5}$ emissions for each state. The springtime emissions are mostly from the southeastern states, where prescribed burning is a common land management practice in spring. The summer/fall emissions occur primarily in the West, particularly the Northwest and California.

Figure 3 shows the modeled daily area burned and $PM_{2.5}$ emitted for the entire modeled time period (2006 through 2008). Note that the area burned in the spring is large relative to the associated emissions when compared to the summer/fall pattern. The summer/fall burning is dominated by large wildfires in the West, while the spring burning is largely due to prescribed burning in the Southeast, which produces fewer $PM_{2.5}$ emissions per acre than western wildfires. Also note that 2006 was considered a relatively active year for wildfires, while 2007–2008 were exceptionally active years.

Figure 2. (A) Annual average $PM_{2.5}$ emission density (2006–2008). (B) Average monthly $PM_{2.5}$ emissions by state (2006–2008).

(A)



(B)

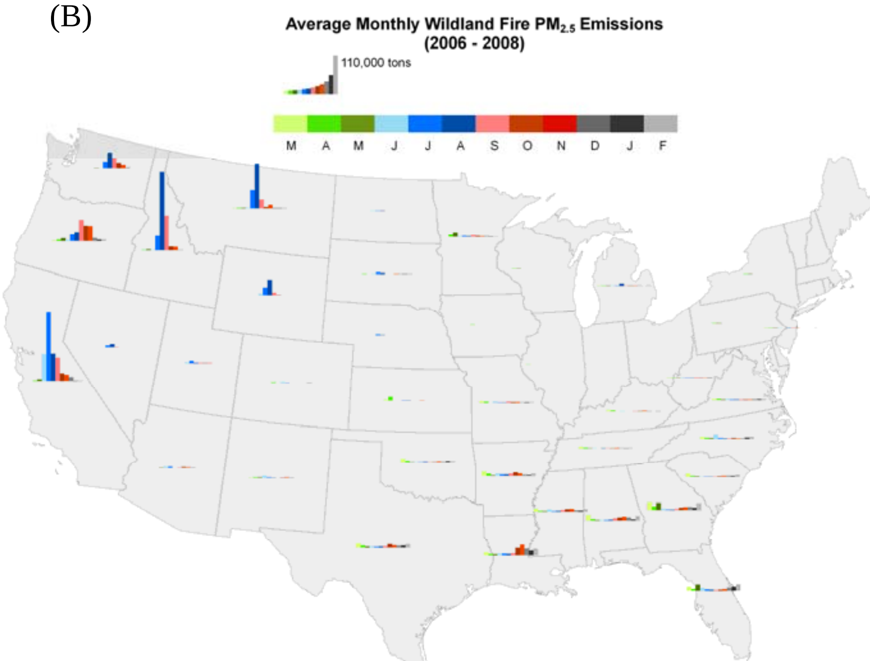
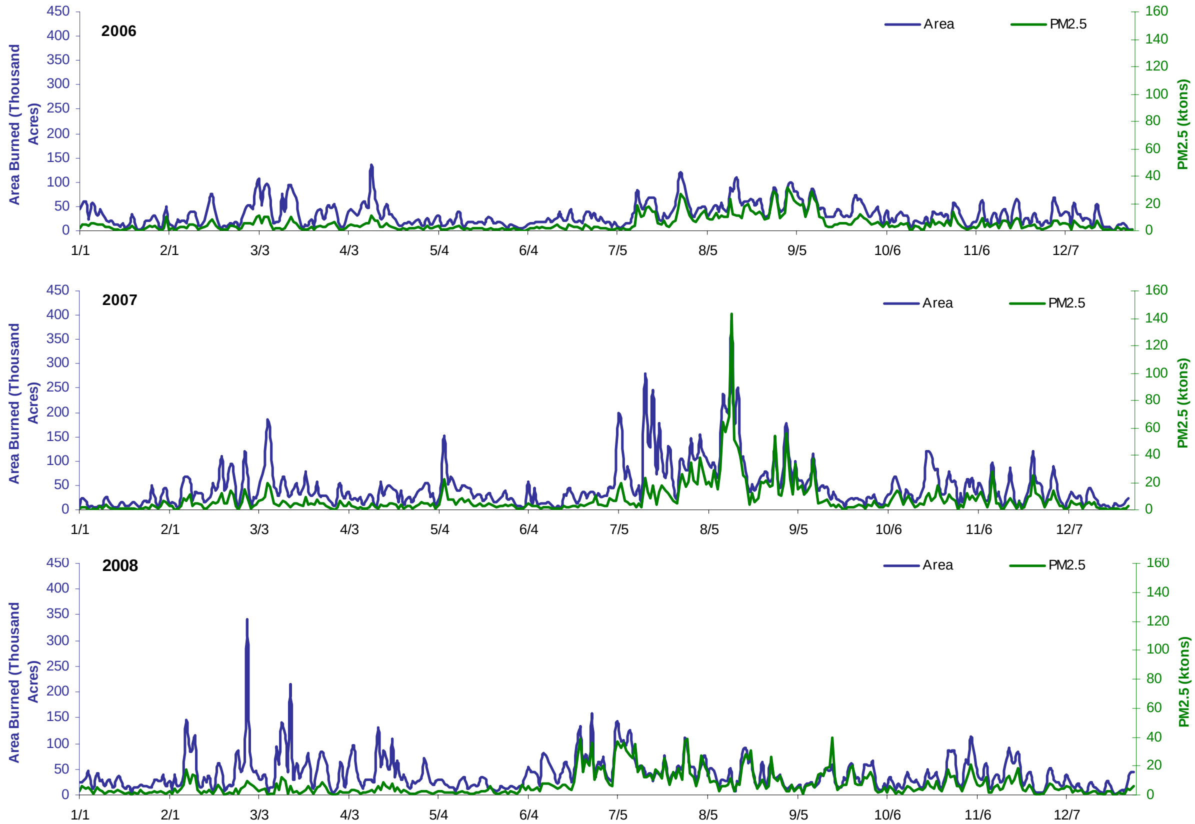


Figure 3. Daily area burned and $PM_{2.5}$ emitted (2006–2008).



Comparison with Previous Emission Inventories

Several updates to the emissions models were implemented since the EPA's last emission inventory development effort in 2007–2008 (Raffuse et al., 2008). These updates included the following changes.

- *Corrections to the FEPS model operating in the BlueSky Framework*: Units-conversion calculations were found to be formed incorrectly in a prior version of FEPS and/or the BlueSky Framework. These calculations were corrected.
- *Two major updates to FCCS modeling*: (1) For the previous effort, the spatial reference for FCCS fuel loading files were denoted as conforming to Lambert Conformal Conic projection. The fuel loading data (projected in Lambert Azimuthal Equal Area projection) were correctly converted to Lambert Conformal Conic projection for this inventory. Additionally, the geodetic datum was transformed from a spherical coordinate system to the North America Datum 1983 (NAD83) to be consistent with the geodetic datum of fire locations latitude/longitude. (2) For the previous effort, fuel loading was not available for the "urban" land use category. However, for the current effort, the fuel loading for "scrub oak - chaparral shrubland" was applied as a rough approximation for urban lands. (This approximation is admittedly very coarse; however, we considered it to be at least a minimal improvement over the previous *de facto* value of zero.) This

alteration produced non-zero fuel consumptions and emissions for wildland fires in urban-classified areas.

- *Changes to canopy involvement modeling*: For the current inventory development effort, the involvement of the forest canopy was assumed to be a fractional value of 0.4 for fires detected solely with satellites (i.e., with no corresponding ICS-209 reports) and with daily burn areas of at least 150 acres. For the previous effort, no canopy involvement was assumed for such fires.

In order to evaluate the effects of these changes, we directly compared the current 2006 wildland fire emission inventory to the analogous inventory previously prepared for EPA by Raffuse, et al. (2008). Our findings follow:

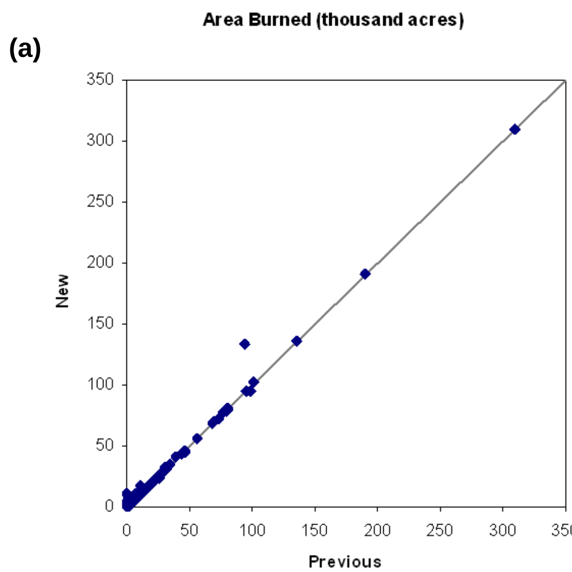
- On a national scale, the effects of these changes on the 2006 emission inventory were less than 20% for all pollutants (from -6% to +17%) as shown in Table 2.
- We compared previous and current estimates of area burned and emissions for individual fire events (see Figures 4a and 4b). Current estimates of wildland areas burned were virtually identical to previous estimates (plotting tightly to a 1:1 line on the scatter plot shown in Figure 4a). Current estimates of emissions varied from previous estimates with predictable consistency (plotting closely to a regression line with an r^2 of 0.99).
- Fire events that were identical in their daily fuel consumption estimates (when the previous and current 2006 inventories) were selected. Daily emissions from such selected fires were examined to isolate the changes attributable solely to the FEPS model update (see Figure 5). Current estimates of emissions varied from previous estimates with predictable consistency (either plotting closely to a regression line with or plotting closely to a 1:1 line).
- The two versions of the 2006 emission inventory were temporally consistent. Figure 6 shows that the daily estimates of area burned and $PM_{2.5}$ emissions for 2006 were very similar.

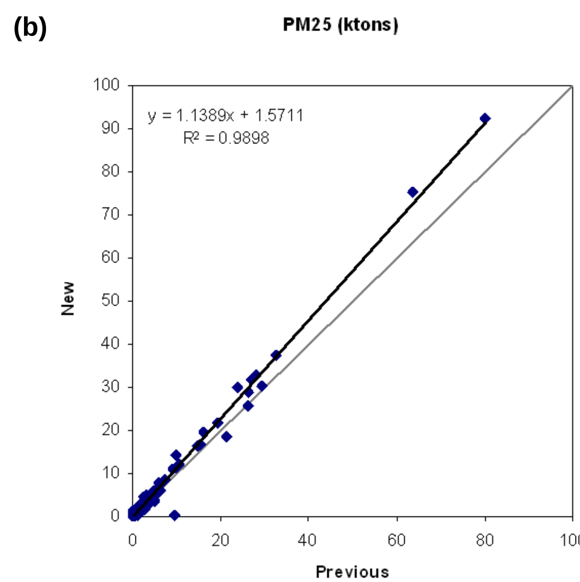
Table 2. Effects of updated emissions modeling techniques on the 2006 wildland fire emission inventory.

2006	Difference (%)
Consumption	3.33
Area	-0.51
$PM_{2.5}$	14.37
PM_{10}	14.37
CO	17.43
CH_4	15.91
NO_x	-6.36
NH_3	17.01
SO_2	3.75
VOC	17.01
CO_2	1.72
HAPs	3.33

Note: Difference (%) = (New - Previous) /Previous *100%

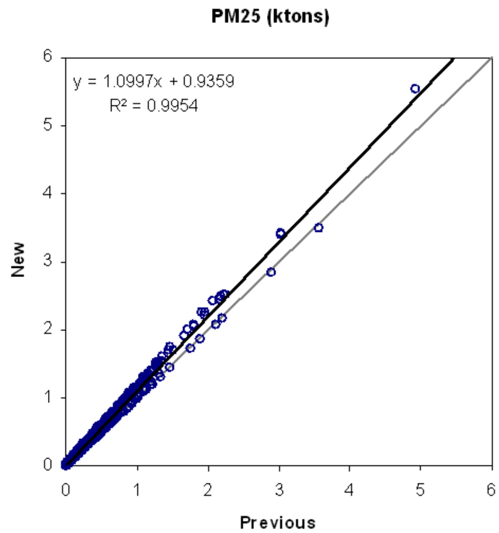
Figure 4. Comparisons of the results of EPA's current and previous wildland fire emission inventory development efforts, including (a) estimates of area burned and (b) estimates of $PM_{2.5}$ emissions for inventory year 2006.





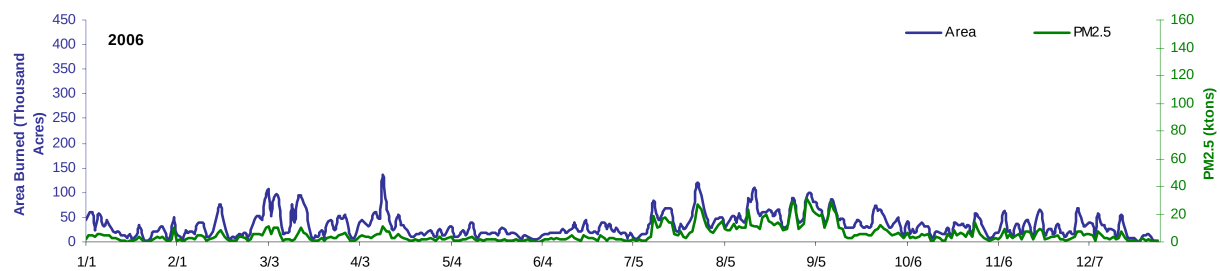
Note: Each point represents a cumulative fire event in 2006, each of which may have been a multi-day event.

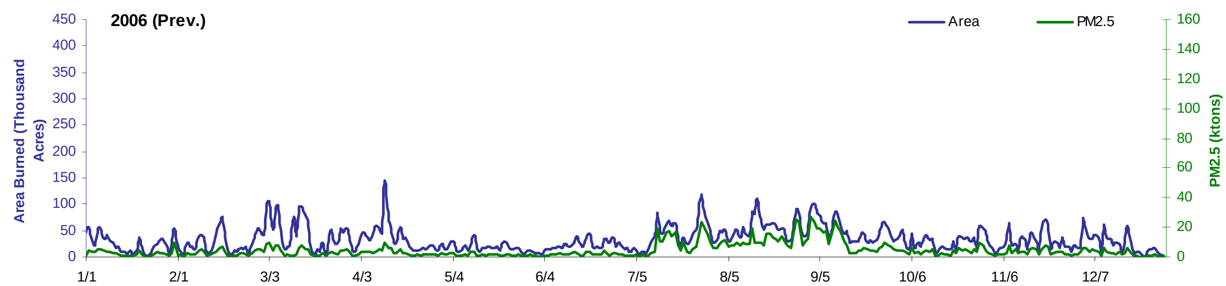
Figure 5. $PM_{2.5}$ emissions comparison between new and previous modeling of year 2006 for fire with same fuel consumptions.



Note: Each point represents daily emissions for selected fire events in 2006.

Figure 6. Daily area burned and $PM_{2.5}$ emissions in 2006 as estimated for the current EPA wildland fire emission inventory (top) and the previous EPA inventory (bottom).





CONCLUSIONS

The BlueSky Framework was used to produce wildland fire emission inventories for the lower 48 United States for 2006 through 2008 using SMARTFIRE as the fire information source and the most recently updated models for emission processing (FCCS, Consume 3.0, and FEPS). Comparison to previous emission inventory efforts showed that recent updates to the emissions models produced modest changes to the emission inventories.

There is significant spatio-temporal variability in wildland fires, and especially wildfires. An annual emission inventory needs to be year-, day-, and location-specific to accurately account for these emissions. Using one year's emissions data to estimate or project emissions for another year may result in poor emission estimates for modeling purposes.

REFERENCES

Andreae M.O. and Merlet P. (2001) Emission of trace gases and aerosols from biomass burning. *Global Biogeochemistry Cycles* **15** (4), 955-966.

Dozier J. (1981) A method for satellite identification of surface temperature fields of subpixel resolution. *Remote Sens. Environ.* **11** (3), 221-229.

Galanter M., Levy H., and Carmichael G.R. (2000) Impacts of biomass burning on tropospheric CO, NO_x, and O_3. *JGR* **105**, 6633-6654 (D5).

Kaufman Y.J. and Fraser R.S. (1997) The effect of smoke particles on clouds and climate forcing. *Sci* **277**, 1636 (5332).

Kuenzli N., Avol E., Wu J., Gauderman W.J., Rappaport E., Millstein J., Bennion J., McConnell R., Gilliland F.D., and Berhane K. (2006) Health effects of the 2003 southern California wildfire on children. *Am. J. Respir. Crit. Care Med.*, 200604.

Larkin N.K., O'Neill S.M., Solomon R., Raffuse S., Strand T.M., Sullivan D.C., Krull C., Rorig M., Peterson J., and Ferguson S.A. (2009) The BlueSky smoke modeling framework. *Int. J. Wildland Fire* (accepted).

Levine J.S., Cofer W.R., Cahoon D.R., and Winstead E.L. (1995) Biomass burning: a driver for global change. *Environ. Sci. Technol.* **29**, 120A-125A (3).

Li R., Kaufman Y., Hao W., Salmon M., and Gao B. (2004) A technique for detecting burn scars using MODIS data. *ITGRS* **42** (6), 1300-1308.

Raffuse S.M., Sullivan D.C., Gilliland E.K., Chinkin L.R., Larkin S., Solomon R., and Pace T. (2008) Development of wildland fire emission inventories for 2003-2006 and sensitivity analyses. Presentation made at the *U.S. Environmental Protection Agency's 17th International Emission Inventory Conference, Portland, OR,, June 5,* by Sonoma Technology, Inc., Petaluma, CA; U.S. Forest Service AirFire Team, Seattle, WA; and U.S. Environmental Protection Agency Office of Air Quality Planning and Standards, Research Triangle Park, NC (STI-905028-3377).

Ruminski M., Kondragunta S., Draxler R.R., and Zeng J. (2006) Recent changes to the Hazard Mapping System. *15th International Emission Inventory Conference, New Orleans, LA.* Available on the Internet at <http://www.epa.gov/ttn/chief/conferences.html>.

Sullivan D.C., Raffuse S.M., Pryden D.A., Craig K.J., Reid S.B., Wheeler N.J.M., Chinkin L.R., Larkin N.K., Solomon R., and Strand T. (2008) Development and applications of systems for modeling emissions and smoke from fires: the BlueSky smoke modeling framework and SMARTFIRE. Paper presented at the *17th International Emissions Inventory Conference, Portland, OR, June 5,* by Sonoma Technology, Inc., Petaluma, CA, and the U.S. Forest Service, Seattle, WA (STI-3378).

U.S. Environmental Protection Agency (2007) Wildland fires EI for 2003-2006. Work assignment for Sonoma Technology, Inc., Petaluma, CA, prepared by Thompson G. Pace, OAQPS/AQAD/EIAG, Research Triangle Park, NC, EP-D-05-004, WA 3-18, June.

van der Werf G.R., Randerson J.T., Giglio L., Collatz G.J., Kasibhatla P.S., and Arellano Jr A.F. (2006) Interannual variability in global biomass burning emissions from 1997 to 2004. *Atmos. Chem. Phys* **6**, 3423–3441.