DEVELOPMENT OF WILDLAND FIRE EMISSION INVENTORIES WITH THE BLUESKY SMOKE MODELING FRAMEWORK

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1. INTRODUCTION

Globally, wildland fire (wildfire and prescribed burning of forests and rangelands) contributes significantly to atmospheric pollution. Pollutants emitted from fires include particulate matter, carbon monoxide, nitrogen oxides, 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 to 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 better temporal resolution to be useful for air quality modeling of smoke impacts.

*Corresponding author: Sean Raffuse, Sonoma Technology, Inc., 1455 N. McDowell Blvd., Suite D, Petaluma, CA, USA 94954-6503; e-mail: sraffuse@sonomatech.com Historically, for national scale emission inventories in the United States, area burned estimates 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 (e.g., 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 "hotspot" 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 "hotspot" pixels. To use this type of data, one must estimate the area burned per pixel. Though algorithms exist for estimating total burned area directly from satellite observations of burn scars (Li et al., 2004) 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 (Sullivan et al., 2008).

2. METHODOLOGY

2.1 Fire Information Sources

2.1.1 ICS-209 reports

ICS-209 reports are created on a near-daily basis for large wildfires and wildland fire use (WFU) fires for which there is a federal response. 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 have several limitations as a data source for predicting daily emissions. 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. Also, 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.

To estimate daily area burned from ICS-209 cumulative area burned, we subtracted the previous day's reported area from the current day. Fires were modeled as a single point source located at the reported ignition point of the fire. Historical ICS-209 reports are available at the Fire and Aviation Management Web Applications (FAMWEB) web site (http://fam.nwcg.gov/famweb/).

2.1.2 Moderate Resolution Imaging Spectroradiometer (MODIS)

The MODIS instrument is onboard both the National Aeronautics and Space Administration's (NASA) Terra and Aqua satellites. Each

instrument provides daily global coverage, with Terra passing over the conterminous United States in the late morning and Aqua passing over in the mid-afternoon. One of the products available from MODIS is thermal anomalies, or "hotspots" (Justice et al., 2002). MODIS hot spots are widely used to track actively burning fires on a global level. Historical MODIS hotspot data are available from the United States Department of Agriculture Forest Service's (USDAFS) Remote Sensing Applications Center.

MODIS hotspots are detected when a given area is actively burning, but they do not directly provide an estimate of the area burned. The MODIS hotspot product (also known as MOD14) has a nominal pixel resolution of 1 square kilometer (about 450 acres). However, MODIS can detect fires that are much smaller. To estimate daily area burned using MODIS requires an estimate of the area burned that each hotspot pixel represents. We compared MODIS total pixel counts with final area burned for 30 fires ranging from 2,000 to 300,000 acres in size (Figure 1). The area burned was derived from final helicopterflown burn scar perimeters. Total pixel count includes all hotspot pixels within the burn scar over the entire life of the fire. We used a final value of 100 acres per MODIS pixel.

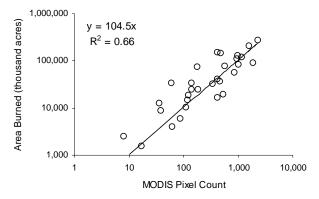


Fig. 1. Relationship between total MODIS pixel count and final burn perimeter.

2.1.3 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). HMS data consist of compiled fire detection information from three different instruments onboard seven satellite platforms coupled with

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.

2.2 Emissions Modeling Pathway

The emissions for all three fire information cases were processed in the same way using the BlueSky smoke modeling framework (Larkin et al., 2008). 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 needed to estimate fire emissions. BlueSky allows the user to choose one of several models at each step in the smoke modeling process. The models used for this study were the Fuel Characteristic Classification System (FCCS), Consume 3.0, and the Fire Emission Production Simulator (FEPS): the BlueSky pathway is shown in Figure 2.

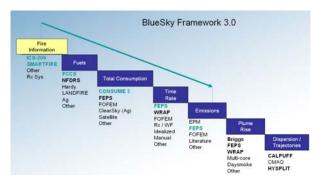


Fig. 2. The BlueSky pathway used in this study.

In addition to the standard emission products produced by FEPS ($PM_{2.5}$, CO, etc.), 29 HAP species emissions were estimated based on emission factors provided by the EPA. Fires were assigned fuel moisture values based on the nearest weather station from the USDAFS Wildland Fire Assessment System.

3. RESULTS

3.1 Emissions from SMARTFIRE

Though emission estimates were calculated for many species, this paper focuses on the primary PM_{2.5} results. All other pollutants were modeled with similar spatiotemporal patterns. Aerosol that formed secondarily in the atmosphere was not estimated. Figure 3 shows the estimated primary PM_{2.5} emissions by month for each modeled year. Wildland fire emissions in the contiguous United States exhibit a bimodal yearly pattern, with peaks in the spring and late summer/early fall. Over the four years modeled, emissions in the spring season were fairly consistent year to year. The summer/fall season, however, showed much more variability.

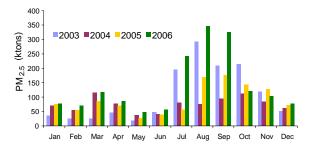


Fig. 3. Modeled yearly primary $PM_{2.5}$ wildland fire emissions by month for the contiguous United States.

The bulk of emissions come from two regions: the west and the southeast. This concentration can be seen in the emissions density plot shown in Figure 4, which shows the average annual tons of $PM_{2.5}$ emitted per square mile, smoothed for display clarity.

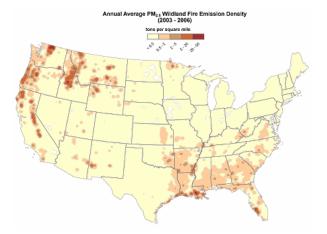


Fig. 4. Average yearly PM_{2.5} emission density by state.

The national spatiotemporal pattern is shown in more detail in Figure 5, 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 management practice in spring. The summer/fall emissions are higher in the west, particularly the northwest and California. The largest single state monthly contribution is Idaho in August.

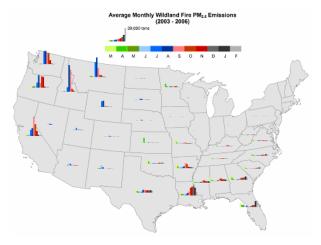


Fig. 5. Average monthly PM_{2,5} emissions by state.

In reviewing the modeled daily area burned and PM_{2.5} emitted for the entire modeled time period (August 2002 through December 2006), it was noted that the area burned in the spring is similar in quantity to the area burned in the summer/fall, but the PM_{2.5} emitted is greater in the summer/fall. The summer/fall burning is dominated by large wildfires in the west, while the spring burning largely reflects prescribed burning in the southeast, which results in less PM_{2.5} per area burned than the western wildfires. Note also the relatively calm wildfire season in 2004.

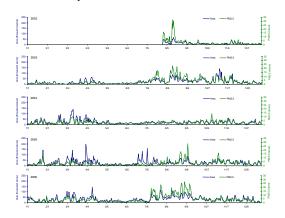


Fig. 6. Daily area burned and $PM_{2.5}$ emitted (August 2002 through December 2006).

3.2 Fire Information Source Comparison

Emissions for 2003-2006 were modeled using two other information sources to compare with SMARTFIRE, ICS-209 reports, and MODIS fire detects. Neither of these data sets is independent from SMARTFIRE because both are used as inputs to the SMARTFIRE algorithm, so this is not a validation. Rather, it is an intercomparison.

Figure 7 shows the annual average area burned by state for the three fire information sources. In the west, the totals are similar for all three data sources, with the exception of Nevada, where the ICS-209 value is much larger than the others. The large ICS-209 value is caused by a typographical error in a single daily report: an extra zero was added to the area of a large wildfire. The error was corrected on subsequent daily reports, but highlights the type of errors that occur in the ICS-209 data, which are created by human data entry.

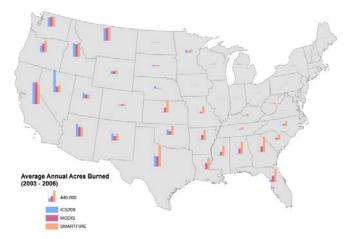


Fig. 7. Annual average area burned by state for ICS-209 reports, MODIS fire detects, and SMARTFIRE.

Note that total burned area in the west is dominated by wildfires, which is captured well both by ground reports (ICS-209s) and satellite (MODIS). SMARTFIRE combines both ground reports and satellite data, but seems to successfully avoid double-counting. The fires in the southeastern United States are largely prescribed burning. ICS-209 reports are not created for the vast majority of prescribed burns, so that data set reports little acreage in the southeastern states. Both MODIS and SMARTFIRE report area burned for the southeast, but SMARTFIRE estimates over twice the total area throughout the region.

The primary reason for the differences between MODIS and SMARTFIRE in the southeast is shown in Figure 8. SMARTFIRE uses NOAA HMS as its source of satellite-derived fire detects. HMS gathers fire detects from several instruments, including MODIS. Although MODIS is the most sensitive and sophisticated instrument that HMS relies on for fire information, MODIS data are typically only available twice per day over the lower 48 states. Thus, small, shortlived fires, burning during cloudy conditions (such as many prescribed fires in the southeastern United States.) are easily missed by the MODIS instrument. HMS incorporates fire detects from GOES and AVHRR in addition to MODIS. GOES in particular is useful for detecting short-lived fires because, as a geostationary instrument, it detects fire every 30 minutes. Figure 8 shows the density of fire hotspot pixels detected by MODIS and HMS for 2004 in the southeast.

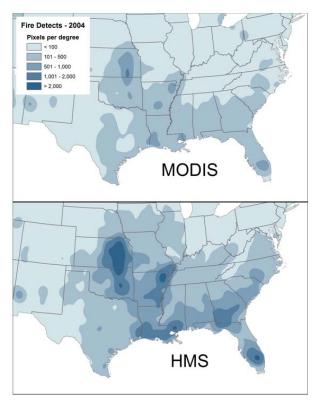


Fig. 8. Fire pixel hotspot density for MODIS and HMS for 2004.

Another key advantage of HMS over other satellite-derived data products is the human quality control that is applied to the data set. Certain industrial sources that operate at very hot temperatures often cause false positives in fire detection algorithms. The standard MODIS

product, for example, often shows fires in Detroit, Michigan; Cleveland, Ohio; and the northern tip of West Virginia, which are known industrial sources. These false fires are not as common in the HMS data.

4. SUMMARY AND CONCLUSIONS

The BlueSky framework was used to produce wildland fire emission inventories for the conterminous United States for August 2002 to December 2006 using SMARTFIRE as the fire information source and the most recent models for emission processing (FCCS, Consume 3.0, and FEPS). The emission inventory processing for 2003-2006 was repeated using ICS-209 reports as the fire information source and repeated again using MODIS fire detection hotspots.

All fire information sources produce similar estimates of area burned in the western United States where larger wildfires are dominant. In the southeastern United States, which has significant prescribed burning, ICS-209 reports provide little information on area burned. SMARTFIRE reports more burning than MODIS because it incorporates information from more satellite instruments, particularly the GOES satellites, which are able to detect many short-lived fires that MODIS may miss.

For specific fires, emission estimates may be very different between the various fire information sources even if the area burned estimates are similar. This is because ICS-209 reports only report the ignition point of the fire; the fuel loading at that point may be very different from the areas that the fire eventually burns into. Individual fire burned area estimates are still difficult to pin down, but SMARTFIRE appears better than ICS-209 reports or MODIS fire detects alone.

There is significant spatiotemporal variability in wildland fire emissions 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 for another year may result in poor emission estimates for modeling purposes.

5. ACKNOWLEGEMENTS

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