Bridging EOS Remote Sensing Measurements and Fire Emissions, Smoke Dispersion, and Air Quality DSS in the Eastern US

John J. Qu[1], Xianjun Hao, Ruixin Yang, Swarvanu Dasgupta, Sanjeeb Bhoi, and Menas Kafatos
Center for Earth Observing and Space Research (CEOSR)
School of Computational Sciences (SCS)
George Mason University (GMU), MS 5C3, Fairfax, VA22030
[1]jqu@scs.gmu.edu

Yongqiang Liu and Gary Achtemeier
Southern Research Station, USDA Forest Service

Allen R. Riebau
USDA Forest Service, Research and Development (FS R&D), Washington Office

Patrick Coronado
Code 606, NASA/GSFC

1. Introduction

Fire emissions, smoke dispersion, and air quality are very important for fire fighting and planing of prescribed burning. BlueskyRAINS (BSR) is a comprehensive and state-of-the-art Decision Support System (DSS) for fire managers and air quality managers to plan fuels treatments and support state air quality smoke regulatory actions, especially related to prescribed fires. BSR has been created by a close collaboration of land management and air quality regulator users. The primary inputs of BSR system are fuel properties (fuel moisture, fuel temperature and fuel loading) and fire characteristics (burned area, fire location and active fires). Field measurement of these parameters has limitations in spatial coverage, spatial and temporal resolution, and requires high costs. However, these parameters can be retrieved using satellite remote sensing efficiently, and a system to bridge satellite remote sensing and the BSR DSS can enhance and improve the capabilities of BSR significantly. To reach that goal, some efforts are needed to investigate how to retrieve fuel properties and fire characteristics using satellite remote sensing and how to integrate remote sensing data processing system and BSR flexibly. George Mason University (GMU) has been collaborating with partners on BSR-RS, a system to support the effort by developing a capacity to obtain necessary fuel and fire properties and monitor smoke dispersion using satellite remote sensing (RS) products (Qu et al., 2005). The USDA Forest Service and other agencies are immigrating the system to the eastern states. Our system generates real-time and composite data products of fuel properties and fire characteristics based on NASA/GSFC MODIS Direct Broadcast (DB) measurements (Dasgupta et al., 2005) and NASA RS data products, such as those from MODIS, MOPITT, TOMS, OMI and AIRS. The techniques for integrating our system and BSR are investigated so as to feed our data products to BSR efficiently and enhance BSR. The experimental implementation of the integrated system will be conduced at a couple of USDA Forest Service research stations. Detailed technical approaches for bridging EOS Remote Sensing Measurements and BSR DSS in the eastern states are discussed in this paper.

2. Methodology

BSR is composed of five components (Figure 1), that is, FIRE Characteristics to provide fuel and fire properties, Emissions to estimate heat, gases, and particles released from burning, Meteorology to provide atmospheric fields, Smoke Dispersion to simulate smoke related atmospheric chemical and physical processes, and Web Display to provide information to fire and air quality managers and other users.

We try to improve and enhance the BSR system by adding several new unique capabilities based on satellite remote sensing. Fuel property (fuel moisture, fuel type, fuel loading, and fuel temperature) and fire characteristics (fire location and area burned) can be retrieved with remote sensing technology. We develop a prototype of application server to process real-time datasets from NASA Direct Readout Portal and composite datasets from NASA DAACs and generate real-time fuel property and fire characteristic products automatically and provide data feeding and validation support to BSR. We also try to add an automated check and adjustment of modeled plume trajectories. The produced remote sensing products for fire characteristics, fuel properties, and plume trajectories will be fed into the BSR and displayed against the traditional BSR products. This allows the estimated and modeling results to be adjusted to improve system performance. Finally, in the eastern states, smoke management concerns are much different from that in the western states. Greater relative humidity and more industrial pollution, combined with large numbers of small fires confined to small geographical areas and time periods, result in much different air quality outcomes than in the west. Examples of the results of this are burning bans in some counties of metropolitan Atlanta during smog season. Incorporating the data products based on NASA missions into BSR will allow better fire emissions inventory, address eastern states fire emissions implications to National Ambient Air Quality Standards, and provide BSR with a foundation to address regional haze issues.

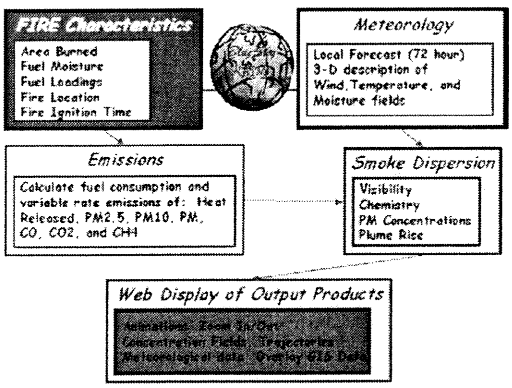

Figure 1. Components of the BlueSky smoke modeling framework, showing various types of information handled within each component (from USDA/FS BlueSky Web Page *http://www.fs.fed.us/bluesky*).

The timeliness of this project cannot be overstressed. The BSR is now being proposed for rapid national implementation. Although there has been talk of using remote sensing to improve the system, little has actually been accomplished to date. Many of the algorithms for detection from MODIS, for example, are in an advanced state and could be linked to BSR explicitly. Additionally, work with MODIS and AVHRR on plume trajectories although advanced, could be improved by linkage to BSR so that ground-level concentrations could be derived. Additionally, at present, remote sensing for small fires cannot effectively be employed to give location and burned area; by linkage to BSR field input data new insights into this problem are likely to be developed. The major expected result of this project is a RS enhanced BSR for the eastern U.S., EastFIRE BSR-RS.

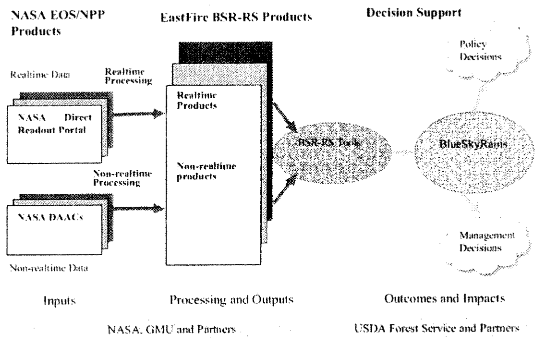

Figure 2. EastFIRE BSR-RS Architecture.

2.1 EastFIRE BSR-RS Architecture and NASA Data Needs

The proposed EastFIRE BSR-RS system architecture is shown in Figure 2. There are three major components: NASA RS inputs (real time and DAAC's RS data sources); a GMU RS data processing system; and the resulting enhanced BSR DSS system. As identified in the previous section, we believe the following data products derived from NASA RS observations will be valuable for the EastFIRE BSR-RS: live fuel moisture, fuel type, fuel loading, fuel temperature, area burned, and accurate estimation of active fire locations. We will prototype the GMU RS processing system for obtaining and disseminating the needed data products for operational use. The main steps for remote sensing data processing are: (1) Data Collection: We implement two software agents to collect datasets. One is for real-time data collection, which can check satellite overpass time and availability of new datasets, then download near real-time datasets automatically. The other is for high-level data products (MODIS, Landsat, MOPITT and AVHRR) collection from various sensors; (2) Data Generation: Once new datasets are available, the system will generate near real-time data products automatically. (3) Data Dissemination: Our system will generate datasets for BlueSkyRAINS, specially, according to the requirement of BlueSkyRAINS interface. We will integrate our system and BlueSkyRAINS together to provide near real-time decision support. In addition, we will construct a web site to publish near real-time fire danger rate, fuel moisture, and fire characteristics for general users. Detailed information and sample images for EastFIRE BSR-RS system can be obtained from EastFIRE web page (http://EastFIRE.gmu.edu). EastFIRE BSR-RS Architecture

2.2 EastFIRE Real-Time RS Data Processing System

The difficult part of the data processing system is how to handle the real-time data stream. Figure 3 shows the data flow of the proposed EastFIRE Real-Time RS data processing system, which is the main part of the GMU RS data processing system for EastFIRE BSR-RS (Qu et al., 2005, Dasgupta et al., 2005). The system is being developed with agent-based approaches for easy maintenance, flexible integration and improvements, and future transfer of technologies to interested agencies.

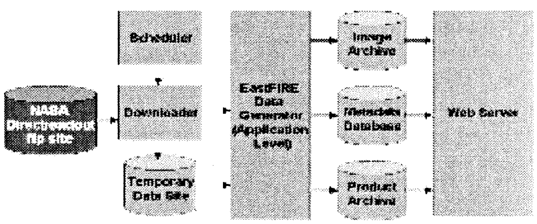

Figure 3. Data flow of the EastFIRE real time RS data processing system.

2.3 EastFIRE Products of Fuel Property and Fire Characteristics

We also generated fuel property and fire characteristics with EOS MODIS measurements. The products include; area burned, live fuel moisture, fuel loading, fire location and size, etc.

Burned area is one of the most important fire characteristics and one of the key inputs for BlueSky. Remote sensing technology can provide an efficient approach for burned area mapping. Identification of burned area with satellite remote sensing is not difficult. Currently, there are several approaches for remote sensing of burned areas (Li R. et al. 2004; Li Z. et al. 2005; Barbosa et al. 1999; Fernandez 1997; Fraser et al. 2000). Most of the existing methods are based on the NDVI (Normalized Difference Vegetation Index) change before and after fires, which work well in many cases although there are some problems because of the limitations of NDVI (Hao et al., 2005). NDVI is the most popular vegetation index. Nevertheless, it has some disadvantages, such as atmospheric influence, scaling problem, saturation problem, and high sensitivity to canopy background variations. EVI was developed to improve vegetation signal sensitivity in high biomass regions and to reduce the influences of canopy background signals and atmosphere. We will use EVI for real-time live fuel moisture retrieval following Burgan's algorithm.

Statistical approach is usually difficult for operational use because of the regressive relationships may vary with fuel types, geographic situations and meteorological conditions, and the determination of regressive relationships requires field measurements. However the statistical approach is generally more accurate and it is desirable to study the relationships between fuel moisture content and remote sensing variables to improve the retrieval of fuel moisture content. We will also use vegetation index and surface temperature to retrieval fuel moisture for comparative analysis and future improvement of live fuel moisture retrieval algorithms.

Fuel loading varies considerably with fuel type, tree density, species composition, age, etc. Fuel loading information would help improve estimates of fire emissions. Due to a lack of available spatial information on fuel loading, previous estimates of fire emissions (e.g., Cahoon et al., 1994) have assumed total fuel loading and consumption based on fire experimental data (e.g. 2.5 kg/m^2). A preliminary analysis indicates that there is a correlation between Short-Wave Vegetation Index (SWVI) and total forest biomass, and the vegetation index can explain 60-66% of the variation in post-fire forest re-growth age, an indirect measure of biomass content (Fraser and Li, 2002). For the estimation of the fuel load we will use the National Fire Danger Rating System (NFDRS) fuel model. Figure 4 shows the NFDRS fuel model map of the eastern states (data source from: http://www.fs.fed.us/land/wfas/nfdr_map.htm). The NFDRS fuel model defines parameters like the heat content, fuel particle density, total mineral content, effective mineral content, total fuel load, fuel bed depth, surface area to volume ratio and moisture of extinction for each class. The fuel load for each fuel model class is already computed by extensive field measurement, a lookup table will be used to get the 1 hour, 10 hour, 100 hour and 1000 hour dead fuel load corresponding to each fuel model class. In order to better represent the current fuel load we will take the weekly relative greenness map from MODIS NDVI data. The relative greenness will be used to assign corresponding weights while computing the 1 hour, 10 hour, 100 hour and 1000 hour dead fuel load from the fuel model map. This will reflect the current condition of the fuel load better as compared to taking a constant fuel load value.

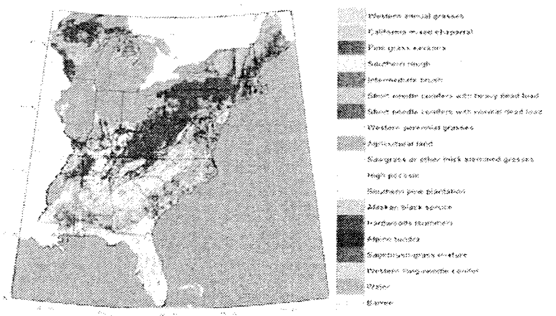

Figure 4. NFDRS fuel model map of the eastern states. (data source: http://www.fs.fed.us/land/wfas/nfdr_map.htm).

Locations of active fires are usually detected with thermal infra-red (TIR) bands because of the higher temperature in fire areas. The Active Fire Detection Product, also called the thermal anomaly product (Kaufman and Justice 1998) can be used to detect active fire locations. We will use the rapid response version of MOD14 algorithm (Giglio et al. 2003) to generate active fire product for the eastern states. This product will serve to provide fire locations input to BSR. The algorithm uses brightness temperatures derived from the MODIS 4μm channels (channels 21 and 22) and 11μm channel (channel 31). The fire detection strategy is based on absolute detection of the fire, i.e., whether the fire is strong enough to be radiating at a brightness temperature of 360K at 4 μ m. Temperatures less than that could be natural to the surface (e.g., deserts) and needs to be filtered out. To filter out naturally hot surfaces and detect weaker fires, the algorithm uses a contextual test. Contextual threshold tests are designed to look for the characteristic signature of an active fire in which brightness temperatures at 4μm, 11μm and the difference between the two 11μm brightness temperatures depart substantially from that of the non-fire background. The contextual tests thus rely on a background characterization approach in which the neighboring pixels are used to estimate the radiometric signal of the potential fire pixel in the absence of fire. Pixels with values elevated above the estimated background thermal emission are identified as fires. The algorithm incorporates further tests to eliminate false alarms caused by sun-glints, water-boundaries, desert boundaries and clouds. The 12μm channel (channel 32), the red channel at 0.65μm (channel 1), the near-infrared channel at 0.86μm (channel 2), and the 2.1μm channel (channel 7) are also used in these tests. The MODIS 1km land/sea mask is also used to mask water pixels.

2.4 Air Quality Products

The air quality products for the EastFIRE BSR-RS, such as smoke plumes, CO, aerosol index and visibility, can be used to validate BSR output results. **Smoke plumes:** Usually, visible (VIS) bands especially blue bands are very sensitive to smoke because of Rayleigh scattering, but shortwave infra-red (SWIR) bands are less sensitive to smoke. Smoke plumes can be detected with satellite remote sensing based on their spectral features in visible bands, SWIR bands and thermal infrared (TIR) bands (Li et al. 2001). We will generate real-time smoke plumes product using MODIS measurements to validate BSR (Xie 2005). **Carbon Monoxide:** Carbon Monoxide (CO) is one of BSR products. Biomass burning is an important source of global CO concentration which, when influenced by the atmospheric circulation system, can affect areas lying far from the actual source of the fire. We will monitor the regional CO concentration on daily, weekly and monthly bases for the eastern Unites States. We will get CO data from MOPITT (Measurements of Pollution in the Troposphere) measurements, re-project and re-format the datasets for the eastern states. Figure 6 shows the monthly CO concentration of May 2004 (Wang et al. 2005).

3. Conclusion and Remarks

We have been collaborating with partners on BSR-RS, a system to support the effort by developing a capacity to obtain necessary fuel and fire properties and monitor smoke dispersion using satellite remote sensing (RS) products. We also establish a prototype of real-time remote sensing processing system. The USDA Forest Service and other agencies are immigrating the system to generate products of fuel properties and fire characteristics based on NASA/GSFC MODIS Direct Broadcast (DB) measurements and NASA RS data products. We use continuous satellite measurements to: generate near real time fire related products; deliver the data products appropriately tuned to specific users; post fire related information for interested public; and provide support to federal, state and local decision makers. It is a large system, there are a lot works waiting for us, we are look for federal, state, and universities future collaborations.

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