Wildfire smoke forecasts using HYSPLIT-based emission inverse modeling system and GOES observations

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Motivation

Wildfire smoke forecasts have been challenged by high uncertainty in fire emission estimates, such as the BlueSky emission used in the current NOAA smoke forecasts (Fig. 1). We develop an inverse modeling system, the HYSPLIT-based Emissions Inverse Modeling System for wildfires (or HEIMS-fire) to estimate wildfire emissions from the smoke plumes measured by satellite observations.

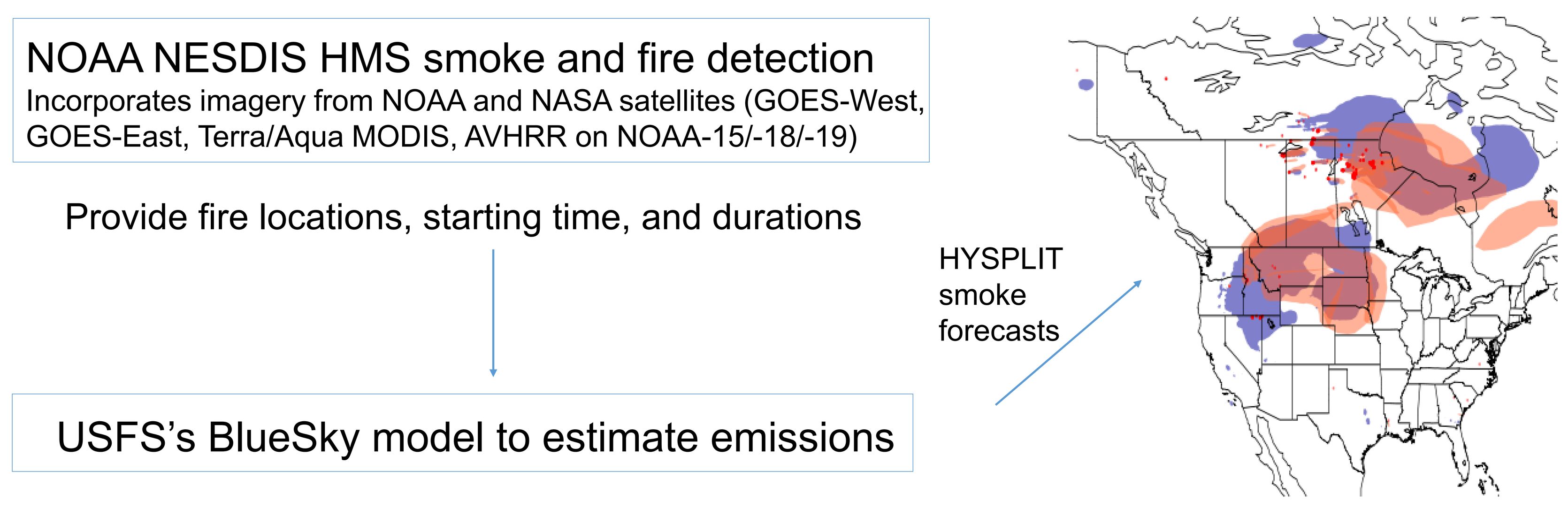

Figure 1. Current NOAA HYSPLIT wildfire smoke forecast system and comparison between HYSPLIT smoke forecasts (blue) and NESDIS HMS smoke (orange).

Methodology

In this top-down approach, the unknown emission terms are obtained by searching the emissions that would provide the best model predictions closely matching the observations. The wildfire emission locations are identified by HMS, the unknown emission rates and the release heights are left to be determined. The emission rates may vary significantly with time. Thus, the unknowns of the inverse problem are the emission rates q_{ikt} at each location *i*, at different height *k* and period *t*. The cost function *F* is defined as,

$$\mathcal{F} = \frac{1}{2}\sum_{t=1}^{T}\sum_{k=1}^{K}\sum_{i=1}^{I}\frac{(q_{ikt}-q_{ikt}^{b})^2}{\sigma_{ikt}^2} + \frac{1}{2}\sum_{n=1}^{N}\sum_{m=1}^{M}\frac{(c_{nm}^{h}-c_{nm}^{o})^2}{\epsilon_{nm}^2} + \mathcal{F}_{other}$$

where c^o_{nm} is the *m-th* observed concentration or mass loading at time period *n* and c^h_{nm} is the HYSPLIT counterpart. As shown in Equation (1), a background term is included to measure the deviation of the emission estimation from its first guess q^b_{ikt}. The background terms ensures that the problem is well-posed even when there are not enough observations available in certain circumstances. The background error variances σ^2_{ikt} measure the uncertainties of q^b_{ikt}. The observational error variances ε^2_{nm} represent the uncertainties from both the model and observations as well as the representative errors. F_{other} refers to the other regularization terms that can be included in the cost function. The optimization problem can be solved using many minimization tools, such as L-BFGS-B package, to get the final optimal emission estimates.

HEIMS-fire system

The HEIMS-fire system is shown in Fig. 2. The extensive fires in the southeastern U.S. region in November 2016 is studied here. (Fig.3).

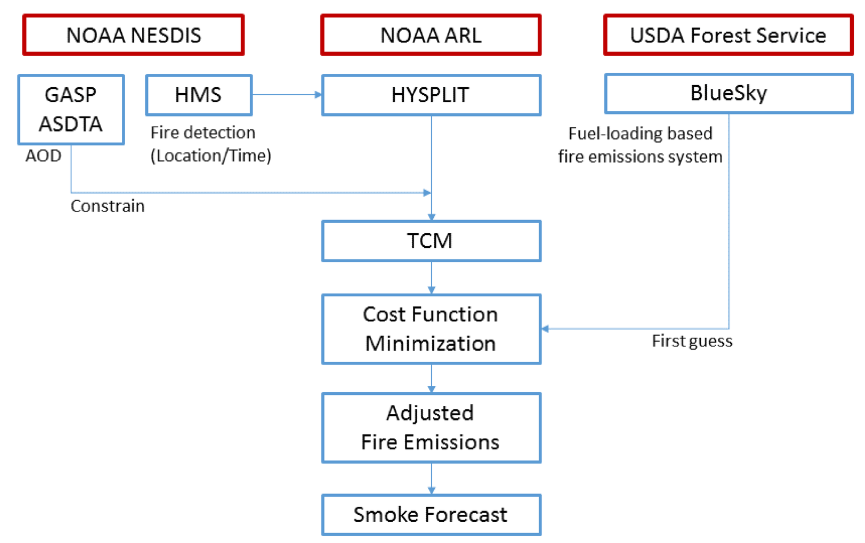

Figure 2. Schematic diagram of HYSPLIT based fire emission inverse modeling system.

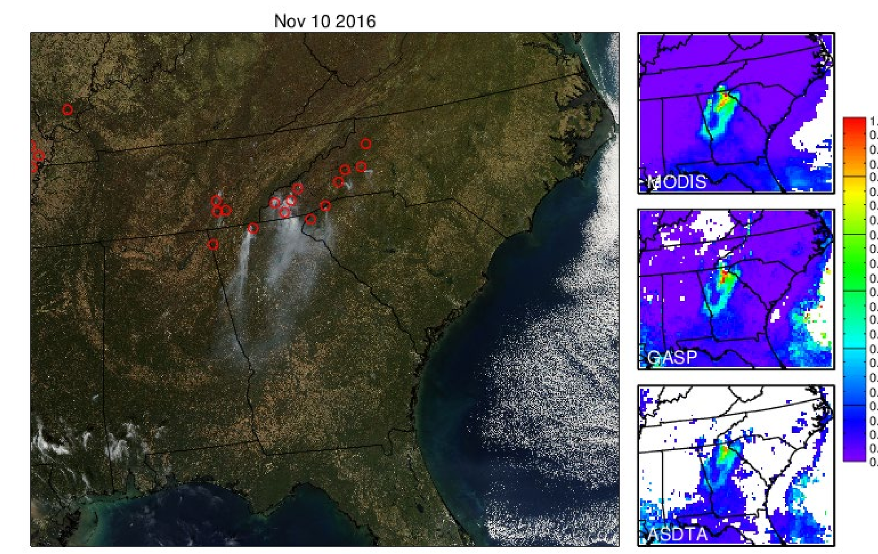

Figure 3 True-color image from MODIS (left), MODIS AOD (top right), GOES GASP AOD (middle right), and GOES ASDTA AOD (bottom right) on Nov. 10, 2016

Reconstructed smoke results

As smoke may come from distant sources, four domains of fire source inputs are considered (Fig.4). Sensitivity tests show that only including the domain 1 would generate comparable results. Using the HEIMS estimated emissions, the smoke plume predicted match the observation pretty well (Fig.5).

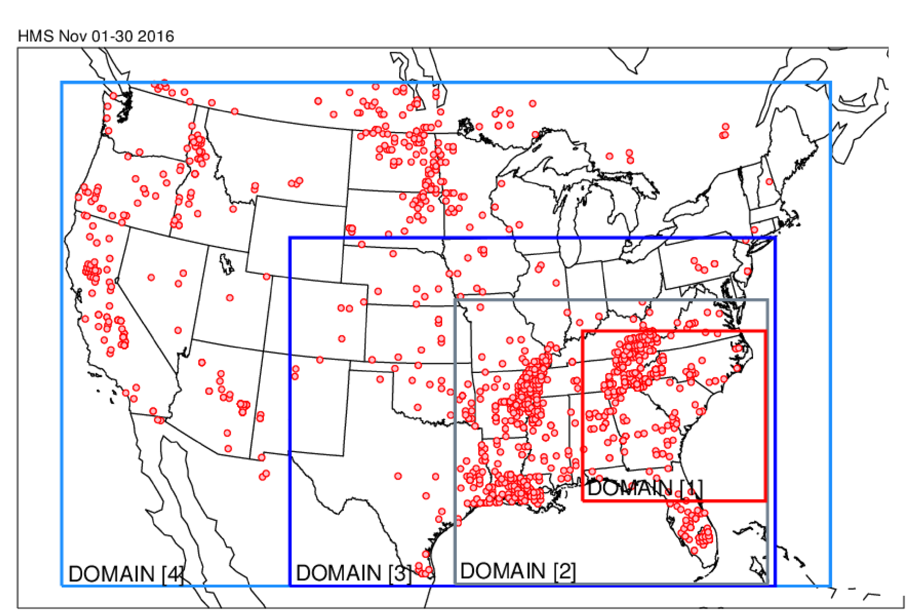

Figure 4 Four domains for fire source inputs in sensitivity tests. Red dots indicate HMS detected fire locations in November, 2016.

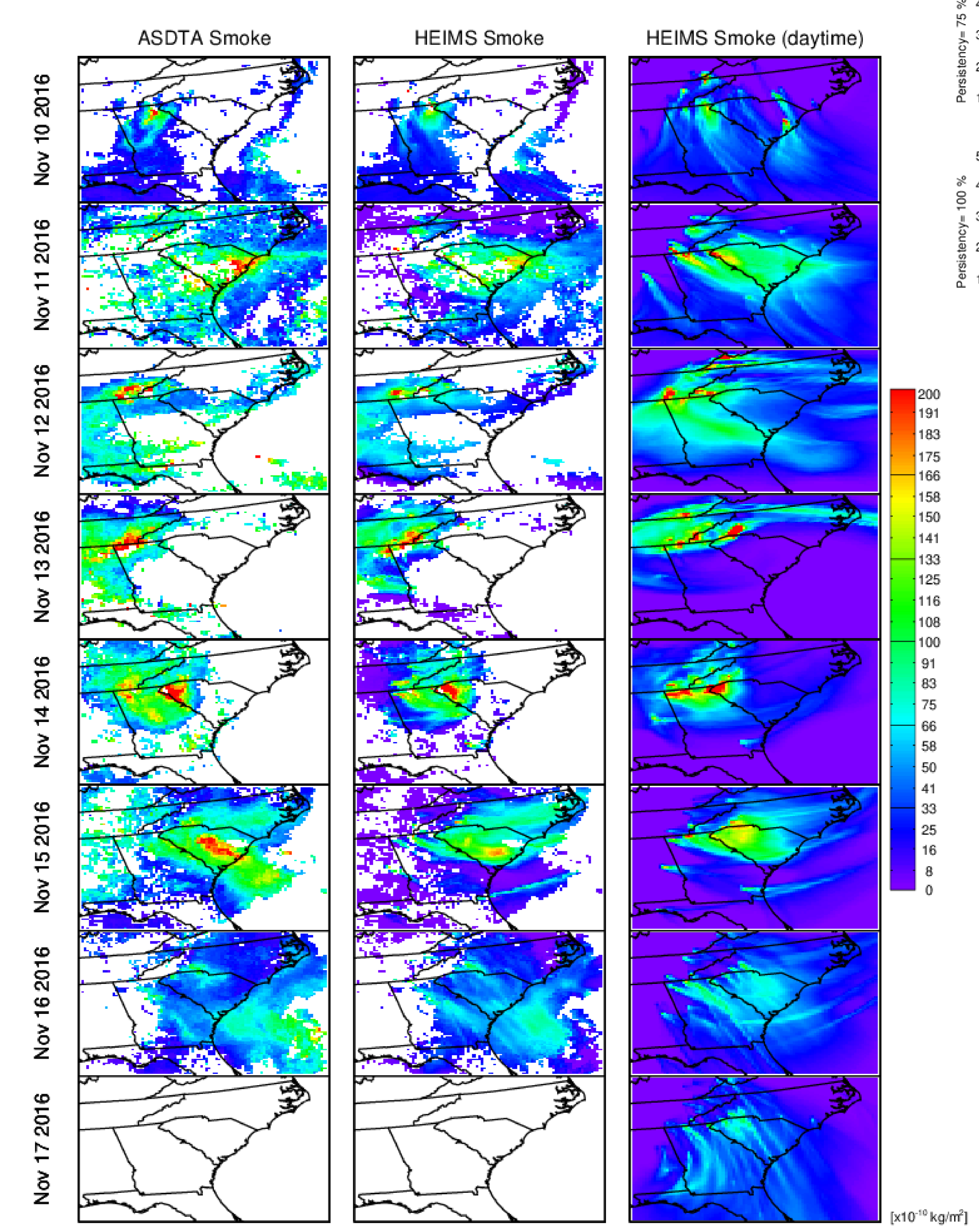

Figure 5. GOES observations (left) and HYSPLIT smoke counterparts (center). Right column shows daytime smoke predictions for the entire domain.

Hindcast

Figure 7 demonstrate the simulated fire smoke by operational NOAA HYSPLIT Smoke Forecast System (SFS) and HEIMS hindcast results on Nov. 11 and two-day forecasts for Nov. 12 and 13. Both systems reproduced well the smoke in their general patterns and intensity, as shown in ASDTA AOD and MODIS true color image. Note that the SFS assumes 75% of emissions still happen at the same location the next day, but the HEIMS uses 50% persistence assumption after sensitivity tests (Fig. 6)

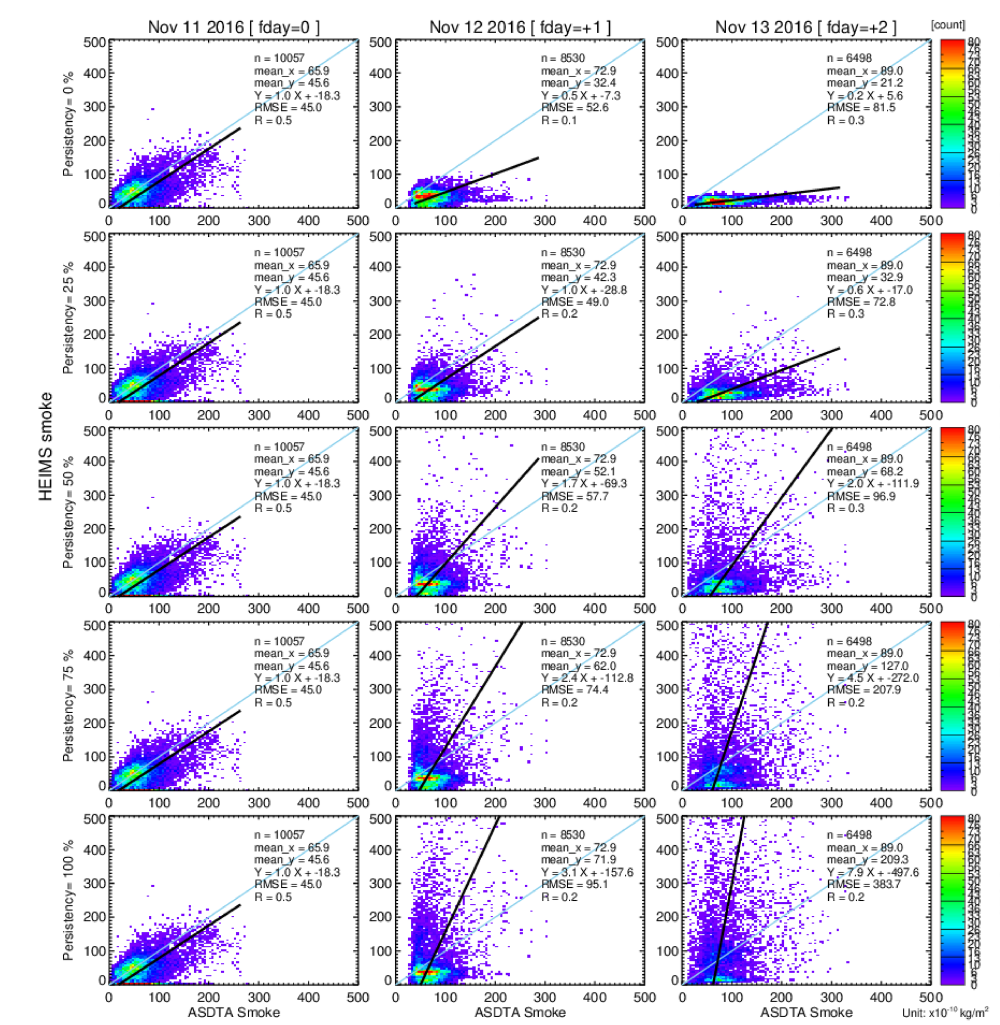

Figure 6. Effect of varying persistent rates for 2 forecast days.

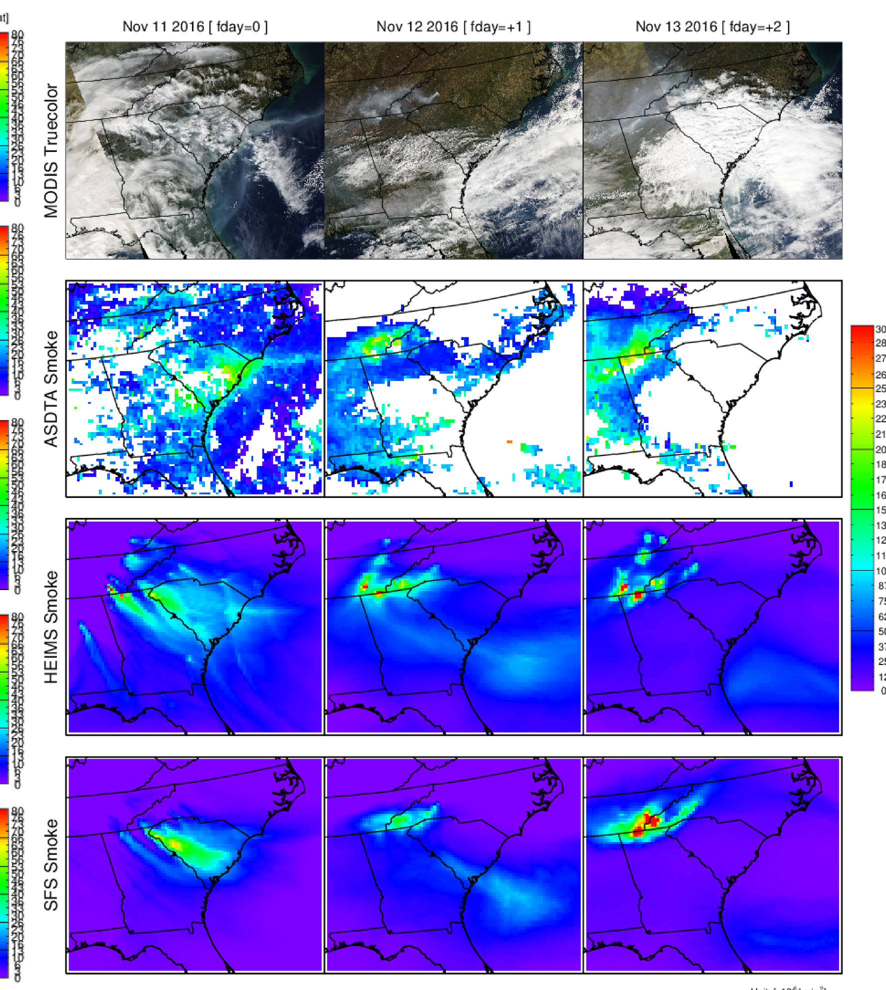

Figure 7. Observed and forecasted smoke on November 11-13. Rows 1-4: True color image from MODIS, ASDTA smoke, HEIMS smoke hindcast, and SFS smoke forecasts (from operation).

Summary and future work

Wildfire emission inversion system HEIMS-fire has been built based on HYSPLIT model, its TCM, and a cost function;

A case study using real GOES data has been performed;

High resolution GOES-16/17 data will be tested;

More evaluation will be performed using VIIRS AOD and surface PM2.5 observations;

Estimated emissions will be tested in other models, such as CMAQ and HRRR-smoke.

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