A regression model for smoke plume height of prescribed fire using meteorological conditions

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Submitted to

Journal of Applied Meteorology and Climatology

Revised on July 15, 2013

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Abstract. Smoke plume height is an important factor for smoke transport and air quality impact modeling. This study provides a practical tool for simulating plume height of prescribed fires. A regression model was developed based on the measured smoke plume height for 20 prescribed fires in the southeastern United States. The independent variables include surface wind, fuel temperature, fuel moisture, and atmospheric planetary boundary layer (PBL) height. The first three variables were obtained from the Remote Automatic Weather Stations (RWAS), most of which are installed in locations where they can monitor local fire danger and are easily accessed by fire managers. The PBL height was estimated based on WRF simulations. The regression model appears in two forms to simulate hourly or average smoke plume height during a burn, respectively. A suite of alternative regression models were also provided that could be used in case that one of the independent variables is not available. The regression model as well as the alternatives is found to be statistically significant at the 99% confidence level. The model is more capable of explaining the variance of the average than hourly series of the observed smoke plume height. Model skill is improved remarkably by adding PBL height to the RAWS variables. The regression model also shows improved skill over two extensively used empirical models for the prescribed burn cases, suggesting that it may have the potential in improving air quality modeling.

Keywords: Smoke plume height, prescribed fire, regression modeling, RAWS measurement.

1. Introduction

Prescribed fire (Rx fire) is a forest management tool to reduce the buildup of hazardous fuels and the risk of destructive wildfire. Any fire is ignited by management actions under a pre-determined "window" of very specific conditions including winds, temperatures, humidity, and other factors specified in a written and approved burn plan. Rx fire has been widely used. In the southern United States, for example, about 2~3 million ha (6~8 million acres) of forest and agricultural lands are burned by Rx fire each year (Wade et al., 2000). Emissions from Rx fire, however, can impact air quality. Biomass burning is a primary source of ambient $PM_{2.5}$ in less populated areas in the southeastern U.S. (Lee et al., 2007). For example, smoke plumes from two Rx fires in central Georgia led to ground $PM_{2.5}$ concentrations much higher than the daily U.S. National Ambient Air Quality Standard (Hu et al., 2008; Liu et al., 2009).

Smoke plume height, also called smoke plume rise, is the elevation above the ground of the top of a smoke plume. A typical plume height is about 1 kilometer for Rx fire and several kilometers for wildfire. Smoke plume height is an important factor for local and regional air quality modeling. Particles emitted from Rx fire with a higher plume height are more likely to be transported out of the rural burn site and may affect air quality in downwind remote populated areas. Plume height is required by many regional air quality models. The Community Multiscale Air Quality (CMAQ) model (Byun and Ching, 1999; Byun and Schere, 2006), for example, uses the Sparse Matrix Operator Kernel Emissions Modeling System (SMOKE) (Houyoux et al., 2002) to provide plume height as part of initial and boundary conditions for elevated emission sources, including fire emission.

Various smoke plume height models have been developed using dynamical (e.g., Latham, 1994; Freitas, 2007; Freitas et al., 2009), empirical (e.g., Briggs, 1975; Harrison and Hardy, 2002; Pouliot et al., 2005), and hybrid (Achtemeier et al., 2011) approaches. One of the differences among various approaches is the degree of complexity. Dynamical models consist of differential equations governing fluxes of mass, momentum and energy that often require time and space integration. Details of fire behavior and ambient conditions at high tempo-spatial resolutions (e.g. seconds and meters) are needed. Empirical models, on the other hand, are based on field and laboratory measurements using statistical or similarity theory. They usually appear as algebraic expressions that require burn and ambient conditions at a lower time frequency (e.g., one hour) without spatial resolution. The simplicity with empirical models makes them a more practical tool for forest managers. Empirical models have been included in many fire and air quality management systems such as the Fire Emission Production Simulator (Anderson et al., 2004), the Western Regional Air Partnership's Fire Emission Inventory (WRAP, 2005), and the BlueSky smoke modeling system (Larkin et. al 2009).

Empirical models often use parameters related to fire behavior and atmospheric conditions. The modified Briggs model used in FEPS (Anderson et al., 2004), for example, calculates smoke plume height using heat release from fire, transport wind (averaged wind within the atmospheric planetary boundary layer or PBL), and atmospheric stability. Heat release is determined by fuel and fire properties include total consumption rate, combustion efficiency, buoyant efficiency, and entrainment efficiency. The uncertainty in the related burn properties such as burned area, burn phase (flaming or smoldering) partition, and empirical parameters is one of the error sources.

Based on the statistics of plume height measurements of Rx fires in the southeastern United States, Liu et al. (2012) developed a guideline for forest managers to estimate smoke plume height without using any burn and meteorological information. The averaged smoke plume height over 20 Rx fires, approximately 1 km, was suggested to be a first-order approximation. A second-order approximation was suggested by making seasonal adjustments, that is, using the average value for spring and fall, decreasing by 0.2 km from the average for winter, and increasing by 0.2 km for summer. The guideline may avoid the uncertainty related to the burn property specification with the empirical models such as the one used in FEPS, but is unable to describe the variability in smoke plume height related to fire behavior and meteorological conditions.

This study was to develop empirical regression models for smoke plume height of Rx fire, which have a complexity level in between the FEPS approach (Anderson et al., 2004) and the guideline (Liu et al., 2012). Similar to Liu et al. (2012), this study was based on plume height measurements of Rx fires in the southeastern United States. However, only meteorological conditions, which include both forest understory fuel conditions (temperature and moisture) and weather conditions (wind and PBL height) in this study, were taken into account; however, a buoyancy factor determined by heat release from burn, which is used in many existing empirical models such as FEPS (Anderson et al., 2004), was not used. The major source for the meteorological conditions was the Remote Automated Weather Stations (RAWS) (http://raws.fam.nwcg.gov/). RAWS is run by the U.S. Forest Service and the U.S. Bureau of Land Management and monitored by the National Interagency Fire Center. There are more than

2000 stations across the U.S., most of which are placed in locations where they can monitor fire danger. Thus, the empirical models have the potential to be a practical tool for fire managers and researchers to obtain smoke plume height information needed for assessing the air quality impacts of smoke from Rx fire.

The rest of this paper is arranged as follows. The methods are described in Section 2. The meteorological conditions and relationships with smoke plume height variations are described in Section 3. The models and evaluation are presented in Section 4. And discussion and conclusions are provided in the last two sections.

2. Methods

a. Smoke plume height measurement

The smoke plume heights for 20 Rx fires in the southeastern U.S. were measured during 2009-2011 using a Vaisala CL31 ceilometer (a Light Detection and Ranging or LIDAR device) with a frequency of 2 s and vertical resolution of 20 m. The results were analyzed in Liu et al. (2012). A summary of the fires is provided in Table 1. Six burns (denoted as F1-F6) occurred at the Ft. Benning Army Base (32.33N, 84.79W, near Columbus in southwestern Georgia), five (O1-O5) at the Oconee National Forest (33.54N, 83.46W, in central Georgia), one (P1) at the Piedmont National Wildlife Refuge (33.15N, 83.42W, in central Georgia), and eight (E1-E8) at the Eglin Air Force Base (30.15N, 86.55W, near Niceville in northwestern Florida). The burns were typical Rx fires for the southeastern U.S., with the fuel types of mainly pine understory dead fuels and little live fuels. The burns had varied sizes (about half of the burns between 500~1000 acres and half over 1000 acres), occurred in three seasons (five in winter, 13 in spring, and two in summer), and applied aerial (11 burns) and ground (nine burns) ignition techniques. Burning lasted between 1 – 6 hours, mostly during afternoon hours. Cloudy conditions appeared for a few burn cases.

b. Data

The RAWS observation data at four stations were used. The Ft Benning station has the same location as the corresponding burn site. The Brender station is located near the southwestern side of the Piedmont and Oconee burn sites. Two other stations are Naval Live Oaks by the Florida coast and Open Pond at the Florida-Alabama border, about 60 km west and north to the burn site at Eglin, respectively. The averaged meteorological conditions over the two stations were used for Eglin. The automated measurements include solar radiation, wind speed and direction, wind gusts, air temperature, fuel temperature, fuel moisture, relative humidity, dew point, wet bulb, and precipitation. Only wind, air temperature, fuel temperature, fuel moisture (10-hour), and relative humidity were used in this study.

In addition, the vertical meteorological profiles at the grid points near the RAWS stations simulated with the Weather Research and Forecast (WRF) model (Skamarock et al., 2008) were used to estimate PBL height, transport wind, and the stability factor. The WRF model domain covered the southeastern U.S. with a resolution of 4 km and 27 vertical layers. The Yonsei University scheme for PBL processes was selected, which uses non-local-K scheme with explicit entrainment layer and parabolic K profile in unstable mixed layer. The PBL height was defined as the geometric height of a model level where potential temperature starts to increase upwards.

The stability factor used in this study was defined as the difference in air temperature between the model levels near the ground and at the PBL height (multiplying gravity acceleration and divided by temperature).

Fig. 1 shows hourly variations of smoke plume height and meteorological conditions for each of 19 fires (The fire F2 is not shown because it was only one hour long). The hourly trends of smoke plume height are classified into increase, decrease and flat groups (Table 2). For the increase group, hourly smoke plume height either increases constantly or fluctuates with time but with an overall increasing trend over the burn period.

Three out of the four variables show consistent trends for the increase group. Fuel moisture reduces with time for all 11 burns, PBL height increases or is flat for 10 burns, and surface wind increases or stays steady for 9 burns. Fuel temperature, however, has mixed trends for these burns. Drying fuel or active PBL is in favor to the development of smoke plume, while increasing wind suppresses the development of smoke plume to a larger degree.

Inconsistence is found mainly for two other trend groups. For the 5 burns in the decrease group, there are no consistent trends in various variables except for fuel temperature, which decreases with time for 4 burns. For the 3 burns in the flat group, there are no dominant trends in all variables.

c. Regression model

We here use index notation in the following way: i is used to represent an individual meteorological variable; j is used to represent an individual element in a smoke measurement series; and, k is used to represent individual resampled series for cross validation. A multiple linear regression equation for smoke plume height, H, can be written as:

$$H = b_0 + \sum_{i=1}^{M} b_i X_i \qquad (1)$$

where b_0 is regression interception, b_i is regression coefficients, X_i is meteorological variable, and M is the number of all meteorological variables used. An F-distribution test (Blackwell, 2008) was used to determine whether or not to reject a null hypothesis (that is, all the regression coefficients are zero). The critical value is dependent on the number of independent variables, the sample number of variable series, and the confidence level. A confidence level of 99% was used in this test (as well as the correlation analysis and the cross validation). This confidence level means that there is a probability of one out of 100 cases that the conclusion is incorrect.

Denote the observed smoke plume height series as $H_{obs}(j)$ and the corresponding meteorological variable series as $X_i(j)$ ($j=1, N$), *where* N *is* the sample number of the series. We use a cross-validation technique (Barnett and Preisendorfer, 1987) to examine the sensitivity of the regression models to individual observations by:

(1) Creating new series of smoke plume height and meteorological variables with a total series sample number of N for each, $H'_{obs}(j, k)$ and $X'_i(j, k)$, by resampling the original series. Here $j=1, N-1$ is an individual series element and $k=1, N$ *is an individual* series. The kth series did not include the element $j = k$ in $H_{obs}(j)$ and $X_i(j)$.

(2) Building regression equations $H'(k) = b_0'(k) + \sum_{i=1}^{M} b_i'(k) X_i'(k)$, $k=1, N$.

(3) Simulating smoke plume height $H_{simu}(j)$ $(j=1, N)$ using the equation for $H'(k)$ and $X_i'(j)$, where $j=1, N$, and $k=j$.

(4) Estimating systematic error using mean error (ME), random error using root mean square error (RMSE), and their normalized errors by dividing the standard deviation of observed plume height, SD_{obs}:

$$ME = \frac{1}{N} \sum_{j=1}^{N} [H_{simu}(j) - H_{obs}(j)] \qquad (2)$$

$$RMSE = \{ \frac{1}{N} \sum_{j=1}^{N} [H_{simu}(j) - H_{obs}(j)]^2 \}^{0.5} \qquad (3)$$

$$ME_{norm} = ME / SD_{obs} \qquad (4)$$

$$RMSE_{norm} = RMSE / SD_{obs} \qquad (5)$$

$H_{obs}(j)$ $(j=1, N)$ was categorized into the group of positive anomaly if $\geq 0.5\ SD_{obs}$, negative anomaly if $\leq -0.5\ SD_{obs}$, or normal if otherwise. Same categorization was made for $H_{simu}(j)$. The series elements had a binomial distribution. There was a probability of $p=1/3$ for $H_{obs}(j)$ *and* $H_{simu}(j)$ to be in a same group and a probability of $q=2/3$ to be in different groups. The modeling skill of a regression model is $S = \frac{N_c}{N}$, where N_c is the number of same group occurrence (correct number) (Barnett and Preisendorfer, 1987). Assuming that the binomial distribution could be approximated by normal distribution, a z-score (Blackwell, 2008) defined as

$$z = (S - p)/\sqrt{pq/N} \qquad (6)$$

was used to test the statistical significance of the regression model, together with p-score. The z-score is a statistical significance indicator that determine whether or not to reject a null hypothesis, that is, the analyzed pattern (the simulated plume height falls into a same group of positive anomaly, negative anomaly, or normal as the observed plume height) is likely randomly generated. For a critical value, z_{cri}, which is 2.56 at the 99% confidence level, the hypothesis is rejected if z-score > + z_{cri} (z-score > 0) or z-score < - z_{cri} (z-score < 0). In addition, a p-value smaller than the corresponding significance level (0.01) was used as another criteria. The p-value is the probability that the null hypothesis has been falsely rejected.

3. Meteorological conditions

a. Hourly series

RAWS observation data were available hourly. WRF simulation outputs at each hour were used accordingly. Hourly smoke plume heights were obtained by averaging the measured values over each of the individual hours during a burn period. Smoke measurement during the first or final hour of a burn period was usually less than 60 minutes. The average for the hour was not included in the smoke plume height series if the measurement length was less than 25 minutes. One exception was the first hour for E5, which had a smoke measurement length of about 50 minutes, but heavy clouds were on top of the smoke layer and therefore the detected heights by the ceilometer were likely those of the clouds rather smoke plume. The number of hours, $I(j)$, ranged between 1 and 6, where j represents a burn (Table 1). An hourly smoke plume height series, $H_{hour}(i, j)$, was formed, where $i=1,I(j)$ and $j=1,20$ (burn) with change in i first followed by change in j. The hourly series of smoke plume height had 58 elements. The corresponding hourly series was formed for each of the meteorological variables.

Fig.2 shows the variations of hourly smoke plume height series vs. each of the four meteorological variable series. The series elements were normalized by departing from series average and divided by series standard deviation. The entire smoke plume height series are composed of five portions, including the negative 1st (F1 to F4), 3rd (late hours of E1 to early hours of E2), and 5th (late hours of E6 to early hours of E8) portions, and positive 2nd and 4th portions covering the elements in between two adjacent negative portions. There is an exception with the 2nd portion which has small negative values at a few hours for O1, O3, and O5.

Wind and fuel moisture vary in an opposite direction to smoke plume height. Fuel temperature, on the other hand, follows smoke plume height closely, despite the difference occurring in the 3nd portion where plume height is negative while temperature is positive, and from the 1st portion to the first half of the 2nd portion where both have an increasing trend, but temperature remains negative while plume height has turned to be positive. PBL height also generally follows plume height except for the first half of the 2nd portion.

The statistics of the hourly series are provided in Table 3. Besides the meteorological variables described above, four other variables (air temperature, air relative humidity, transport wind, and stability factor) are also analyzed for comparison. As indicated below, air relative humidity and transport wind have low correlations with smoke plume height, while surface air temperature and stability have similar relationships with smoke plume height to fuel temperature and PBL height, respectively.

Fuel temperature and surface air temperature have the averages of 30^oC and 22.4^oC and SDs of 8.6^oC and 7.4^oC, respectively. The correlation coefficients with smoke plume height are +0.434 and 0.464, which are statistically significant (at the 99% confidence level, same hereafter). The critical value is 0.33. Fuel and air temperature are related to sensible heat energy for smoke plume lifting. PBL height and stability factor have the averages of 1320 m and 0.3 m/s^2 and SDs of 385 m and 0.1 m/s^2, respectively. The correlation coefficients are around +0.40 and are significant. Similar to smoke plume, the development of PBL and status of atmospheric stability depend on sensible heat from the ground. The surface and transport winds have the averages of 3.0 m/s and 5.7 m/s and SDs of 0.83 m/s and 2.5 m/s, respectively. The correlation coefficients of -0.22 for the surface wind and -0.15 for transport wind are insignificant. Winds make smoke plume moving horizontally and therefore reduce the buoyancy in the smoke area for vertical lifting of smoke plume. Fuel moisture and air relative humidity have the averages of 8.69% and 43.2%, and SDs of 2.13% and 13.2%, respectively. Both are negatively correlated to smoke plume height with a magnitude of 0.53 for fuel moisture (significant), but only 0.02 for relative humidity (insignificant). Evaporation of water within fuels during burning consumes latent heat, which reduces the sensible heat energy used to lift smoke plume.

b. Average series

An average series of smoke plume height, $H_{ave}(j)$ $(j=1,20)$， was formed, where the jth element was the average of $H_{hour}(i, j)$ over $i=1, I(j)$. The corresponding average series was formed for each of the meteorological variables. The average series shows the same feature as the hourly series, but the relationships between average meteorological variables and smoke plume height are closer (Fig.3). The correlation coefficients have the same signs for each of the meteorological variables between the average and hourly series. The magnitude, however, is larger for the average series. The coefficients are 0.683 and 0.874 for air and fuel temperature and -0.583 and 0.582 for fuel moisture and PBL height (all significant; the critical value is 0.56), 0.538 for the stability factor (close to the significant level), -0.422 for surface wind, and -0.234 and 0.201 for transport wind and air relative humidity (insignificant).

4. Regression models

a. Regression model

The regression model, denoted as *RxPH* (prescribed fire plume height), was formed using four meteorological variables (surface wind speed, temperature, fuel moisture, and PBL height). It appears in two forms, depending on the series type (hourly or average). The regression coefficients and some model properties are listed in Table 4. The model for hourly smoke plume height has an interception (b_0) of 1112 m, which is 64 m more than the observed average of smoke plume heights of all 20 burns. The regression coefficients (b_1-b_4) are - 63.85, 3.849, - 25.78, and 0.163. The standardized regression coefficients, which are the coefficients for a regression model built using normalized independent and dependent variables and measure the relative contributions of independent variables to the variance of the dependent variable, are - 0.374, 0.167, - 0.279, and 0.335. They are comparable in magnitude, suggesting that all the four variables are important to smoke plume height modeling. The squared correlation coefficient, which measures the total contribution of all independent variables to the variance of the observed dependent variable, is 44%, meaning the simulated smoke plume height series explains less than half of the observed smoke plume height variance.

The model has a small systematic modeling error with an ME value of 4.6 m, which is only about 2.5% of the SD value (i.e., ME_{norm} = 2.5%). Fig.4 is the scatter plot of the simulated vs. observed smoke plume height values. The model overestimates, exactly estimates, or underestimates an observed plume height, respectively, if the corresponding point is located above, on, or below the line with a unit slope. There are comparable numbers of points located above and below the line. The overestimated values largely offset the underestimated ones, leading to the small modeling systematic error as seen above. The RMSE and $RMSE_{norm}$, however, are large at 141 m and 76%.

It can be seen from the simulated smoke plume series (Fig.5) that the model is able to produce the observed high plume heights (peak values) for F5, O1, O3, P1, E2, E5 and the low heights (valley values) for F1, F5, O1, O3, O4, and E3. However, it misses the high heights for O2, E1 and the low heights for F3, F4, F6, and O2, and falsely produces high height for E5 and low heights for E1 and E6. The cross-validation results are provided in Table 5. The simulated series has 20, 18, and 20 elements in the positive anomaly, negative anomaly and normal groups, respectively. The corresponding numbers for the observed series are 16, 19, and 23. The correct number is 33 out of total 58 elements, leading to a modeling skill of 56%. The corresponding z-score is 3.81, which is greater than the critical value at the 99% confidence level. The p-score is 0.0001, which is smaller than the critical value of 0.01. Thus, the model is statistically significant.

The model for the average smoke plume series is different from the one for the hourly series in several ways. First, the average model contributes about 78% to the variance of the measured smoke plume height series, which is an absolute increase by 35% from the hourly model. Thus, the average model has a much improved modeling capacity. Second, the average model has the ME of 10.5 m and ME_{norm} of 6.7%, increasing by 5.9 m and 4.2% from the hourly model; the RMSE of 63 m and $RMSE_{norm}$ of 40%, however, are reduced by 78 m and 36%. This indicates an increased systematic error but decreased random error. Third, the magnitude of the standardized regression coefficient for fuel moisture is much smaller than that for other variables, indicating a very small contribution from fuel moisture to the variance of the simulated average smoke plume height**.**

The simulated average smoke plume height series follows the observed one very well (Fig.6). The average model is able to produce all the high and low plume heights except the low height for F3. It procures falsely the high heights for F6 and E1, but only by small margins. The simulated average series has 8, 6, and 6 elements in the positive anomaly, negative anomaly, and normal groups, in comparison with the numbers for the observed series of 7, 5, and 8. The correct number is 14 out of total 20 elements, leading to a modeling skill of 67%. The corresponding z-score is 3.48, which is greater than the critical value. The p-value is 0.0005, which is smaller than the critical value of 0.01.

b. Alternatives

(1) Model without using PBL height

Several alternative regression models (Table 6), which are statistically significant, were also formed in case that one of the variables used in the regression model described above (called reference model hereafter) is not available. One of them, denoted as *RxPH-RAWS*, is an alternate to the regression model *RxPH* if PBL height is not available. For the hourly series, the alternative model has the following major changes from the reference model. First, the simulated variance explains only about 34% of variance of observed smoke plume height, an absolute reduction by 10%. Second, the RMSE and $RMSE_{norm}$ of 153 m and 82% become slightly larger, meaning a larger random error. The model produces larger differences with the observed series for F6, O3, and E2, though smaller for O4 and E5. Finally, the correct number is only 29 out of 58 elements, leading to a lower skill of 49% with a z-score of 2.69. The p-score is 0.0069, smaller than the critical value of 0.01.

Similar differences between the hourly and average series for the reference model are found for the alternative model. For the average series, the alternative model, however, produces larger differences from the observed plume height than the general regression model for most burns (Fig.6). The skill is 62%, and the z-score is 3.00. The p-score is 0.0027, smaller than the critical value of 0.01.

Besides the fact that a regression model will increase the contribution to total variance of the simulated series with an additional variable, PBL height is a good indicator for PBL development; after smoke particles are released from fire, the rise of smoke plume largely depends on PBL conditions.

(2) Other alternatives

The alternative model using air temperature instead of fuel temperature, denoted as *RxPH-Ta*, is used if no fuel temperature and moisture are available (Fuel moisture can be obtained using weather conditions). The performance of the alternative model is close to that of the reference regression model. The alternative model using stability factor instead of PBL height, denoted as *RxPH-SF*, simulated hourly and average series that explain smaller variances of the corresponding observed series (0.35 vs. 0.43 for hourly series and 0.68 vs. 0.78 for average series). The alternative model using transport wind instead of surface wind, denoted as *RxPH-Vt*, simulated an hourly series that explains slightly larger variance of the observed series (0.46 vs. 0.43) but smaller variance for average series (0.7 vs. 0.78) than the reference model.

5. Discussion

a. A regression model as well as its alternatives with statistical significance has been formulated to provide a practical tool for fire managers to estimate plume height of prescribed burns. To further understand the value of the regression model, the results from the model were compared with the preliminary results from Daysmoke and the FEPS plume height scheme (the modified Briggs scheme) in simulating the average plume height series of the 20 prescribed burns. The results from the two empirical models will be described in detail in Liu et al. (2013).

the ME and RMSE are -5.6 m and 94 m for the regression model, 19 m and 281 m for Daysmoke, and 184 m and 765 m for the FEPS scheme. Thus, the regression model has much smaller errors for the specific burn cases. The FEPS scheme was found to overestimate plume height for most burn cases. The reasons are yet to be investigated. One possible reason is that the scheme does not distinct between wildfires and prescribed fires, but some model parameters may be more appropriate to wildfires than prescribed fires. For example, the heat release rate in the scheme is 8000 BTU/lb, which is about 20% higher than the average value suggested for prescribed burns in the South (SFES, 1976).

b. The role of fire behavior, another primary factor often used in empirical smoke plume height models, could have been indirectly included in the regression models because the meteorological conditions used in this study can impact fire behavior. It is expected that skills of the regression models would be improved by directly incorporating heat release, updraft core number (Liu et al. 2010, Achtemeier et al. 2011), and other important information provided from fire behavior simulation and measurement. Topography is another factor for smoke plume height. For the prescribed fires conducted in the northwestern U.S. (Harrison and Hardy, 2002), for example, the burn sites were predominantly located on the lateral slopes of alpine river valleys. The up-valley thermal winds were locally amplified by heat release from the fires. The plumes did not rise solely from thermal buoyancy, but were significantly accelerated by up-valley convergence of horizontal winds.

The approach of not directly using fire-related factors in the regression model does not mean that these factors are less important for smoke plume height prediction. They were not used because the primary purpose of the regression model was to provide a practical tool for fire manages. This type of approach has been widely used in statistical weather forecast. For example, precipitation is determined by dynamic lifting mechanism (vertical velocity), thermal instability, and water vapor supply. Some statistical precipitation forecast models only use the last two factors. This does not mean that the first one is less important; it is not used often due to the difficulty in obtaining a quality value for the factor. This way makes the models only using the last two factors a more practical tool for meteorological managers and users.

c. Empirical smoke plume height models are easy to use and computation effective. With measured or predicted fire and meteorological conditions, the models are able to provide speedy plume height information for air quality models (AQM). One of the issues with the models for prescribed burning is the possible low accuracy. For the FEPS scheme, which is one of the two plume height schemes used by the EPA community multiple-scale air quality (CMAQ) model, may sometimes lead to large errors for prescribed burns, as shown above.

Other techniques for plume height also have both advantages and disadvantages. Dynamic plume height models are more complete description of physics and have been used in some AQMs such as WRF-Chem. The models, however, usually include many parameters that need to be empirically specified or parameterized. The models themselves need temporal integration and therefore present a speed disadvantage in comparison with empirical models. The complexity and time costing present an issue for fire managers.

Plume height measurements are needed for model development and evaluation. They, however, have a timing issue for AQM. They only provide information while the measurements are taking, but not at later times, which is also needed by AQM. Satellite measurements have limited frequency and specific time of passing over a specific location and therefore often miss a large number of prescribed burns which often have very short burning periods. Also, satellite is difficult to detect small prescribed burns, especially if they occur understory, while ground measurements are too expensive to be installed at every burn site across a region.

Thus, any specific model or technique, including the model developed in this study, could provide more useful plume height information than other models or techniques for AQM only under certain specific circumstances. The regression model developed in this study is expected to be a practical tool for fire managers and also a useful tool for AQM with improved skill in plume height prediction for prescribed burning.

6. Conclusions

A regression model for smoke plume height as well as alternatives has been developed and evaluated using the measured smoke plume heights of 20 prescribed fires in the southeastern United States, together with the measured and simulated meteorological conditions near the burn sites. The model was found statistically significant. The model can be used to simulate plume heights for individual hours during a prescribed fire or averaged height over the burn period. The model showed more capable of explaining the observed variance of the average than hourly smoke plume height series. The model skill was found to be improved by adding PBL height information to RAWS varaibles.

The RAWS measurements used in the model are easily obtained by forest managers. Thus, the regression model could be a practical tool for them. The regression model also showed improved skill over some existing empirical models for the measured prescribed burn cases. This suggests that it may have the potential in improving air quality modeling. Further evaluation for other regions, however, should be conducted to understand how robust the model's performance is.

Acknowledgement

The author would like to thank Sanjeeb Bhoi for conducting WRF simulations, the colleagues and field managers for collecting the ceilometer measurements, and three reviewers for the constructive comments and suggestions. This study was supported by the Joint Fire Science Program of US Department of Agriculture and Department of Interior under Agreement No. JFSP 081606. The National Center for Atmospheric Research (NCAR) Command Language (NCL) was used for the regression analysis.

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Tables

Table 1 Prescribed fire information.

Site	Fire	Date	Acre	Period	Length (hr)	Element #	
						hour	ave
Ft. Benning	F1	2009/1/14	364	13-14	2	1-2	1
	F2	2009/1/15	583	13	1	3	2
	F3	2009/4/8	236	13-14	2	4-5	3
	F4	2009/4/9	343	13-14	2	6-7	4
	F5	2010/4/28	1000	14-15	2	8-9	5
	F6	2010/4/29	447	11-13	3	10-12	6
Oconee	O1	2009/3/24	1580	13-15	3	13-15	7
	O2	2010/3/25	2500	11-14	4	16-19	8
	O3	2010/4/1	725	12-15	4	20-23	9
	O4	2010/4/2	1069	12-14	3	24-26	10
	O5	2010/4/7	996	1-15	6	27-32	11
Piedmont	P1	2009/4/27	1195	12-14	3	33-35	12
Eglin	E1	2009/5/6	500	14-15	2	36-37	13
	E2	2009/5/7	641	12-16	5	38-42	14
	E3	2009/5/8	1058	15-16	2	43-44	15
	E4	2009/6/6	1500	14-15	2	45-46	16
	E5	2009/6/7	1600	12-16	4	47-50	17
	E6	2011/2/6	1650	14-15	2	51-52	18
	E7	2011/2/8	2046	13-15	3	53-55	19
	E8	2011/2/12	500	12-14	3	56-58	20

Table 2 Trends of hourly smoke plume height and meteorological variables. The signs represent increase (/), decrease (\), and flat with or without fluctuation (−).

Plume trend	Fire	Meteorological variable trends			
		Wind	Fuel temp	Fuel moist	PBL height
Increase	F1,F3,O3,P1,E1,E8	/, /, \, /, /, −	/, \, /, /, \, −	\, \, \, \, \, \	/, /,−, /, \, /
	O2,O4,O5, E2,E5	\, −, −, /, /	\, /, /, −, \	\, \, \, \, \	−, /, /, /, /
Decrease	F4,O1,E3, E4,E6	/, \, /, \, −	\, \, \, −, \	\, −, /, /, \	\, −, −, −, −
Flat	F5, F6, E7	\, \, −	−, /, \	\, \, −	/, −, −

Table 3 Statistics of smoke plume height and meteorological variables. The notations of Ave, SD, and r represent average, standard deviation, and correlation coefficient between plume height and a meteorological variable.

Plume height / meteorological variable		Unit	Hourly series			Average series		
			Ave	SD	r (%)	Ave	SD	r (%)
H_{obs}	Plume height	m	1048	187	(-)	1023	158	(-)
V_{sfc}	Surface wind	m/s	2.9	0.8	-21.6	3.0	0.8	-42.2
T_a	Air temperature	^oC	23.6	6.8	46.4	22.4	7.4	67.4
T_f	Fuel temperature	^oC	31.5	8.1	43.4	30.2	8.5	68.3
M_f	Fuel moisture	%	8.4	2.0	-52.6	8.7	2.1	-58.5
R_h	Air humidity	%	43.2	13.2	2.4	42.0	12.8	20.1
H_{PBL}	PBL height	m	1320	385	44.8	1289	365	58.2
V_t	Transport wind	m/s	5.7	2.5	-15.2	5.5	2.4	-23.4
SF	Stability factor	m/s^2	0.3	0.1	39.5	0.3	0.1	53.8

Table 4 Regression model. b_0 is interceptor. b_1-b_4 are regression coefficients for surface wind, fuel temperature, fuel moisture, and PBL height. ME and RMSE are mean error and root mean squared error. r^2 is squared correlation coefficient.

Model		Regression coefficient					Error		r^2
		b_0	b_1	b_2	b_3	b_4	ME	RMSE	
RxPH	Hourly	1112	-63.85	3.849	-25.78	0.163	4.6	141	0.43
	Average	711	-83.58	11.26	3.60	0.150	10.5	63	0.78

Table 5 The z-score and p-score of regression model. G1, G2, and G3 are the numbers of smoke plume height series elements occurring in positive anomaly, negative anomaly, and normal groups. N_c is the correct number and S is correct percent.

Model		Simulation			Observation			N_c (S, %)	z-score	p-score
		G1	G2	G3	G1	G2	G2			
RxPH	Hourly	20	18	20	16	19	23	33 (56)	3.81	0.0001
	Average	8	6	6	7	5	8	14 (67)	3.48	0.0005

Table 6 Same as Table 4 except for alternative regression models. b_1-b_4 are regression coefficients for surface wind (V_{sfc}), fuel temperature (T_f), and fuel moisture (M_f) for RxPH-RAWS (b_4 is not used), V_{sfc}, air temperature, M_f, and PBL height (H_{PBL}) for RxPH-Ta, V_{sfc}, T_f, M_f, and stability factor for RxPH-Sf, and transport wind, T_f, M_f, and H_{PBL} for RxPH-Vt.

Model		Regression coefficient					Error		r^2
		b_0	b_1	b_2	b_3	b_4	ME	RMSE	
RxPH-RAWS	Hourly	1350	-53.70	4.544	-34.66		4.1	153	0.33
	Average	971	-85.79	12.03	-5.980		6.9	79	0.69
RxPH-Ta	Hourly	1111	-64.95	5.425	-24.64	0.153	4.6	141	0.43
	Average	885	-82.56	11.19	-4.06	0.133	9.6	69	0.75
RxPH-SF	Hourly	1031	-38.89	6.246	-27.75	688.4	3.9	151	0.35
	Average	575	-58.42	13.48	5.434	731.9	6.0	81	0.68
RxPH-Vt	Hourly	1008	-15.73	5.330	-27.85	0.198	1.9	152	0.46
	Average	572	-20.74	12.05	1.500	0.204	14.7	85	0.70

Figure captions

Figure 1 Variation trends of hourly plume height (blue) and meteorological variables. One panel is for one fire. The x-axis is hours during a fire. The y-axis is smoke plume height. The value ranges for meteorological variables (not shown) are between 1-5 m/s for surface wind speed (red), 10-50^{o}C for fuel temperature (brown), 5-15% for fuel moisture (green), and 600-2200 m for PBL height (pink).

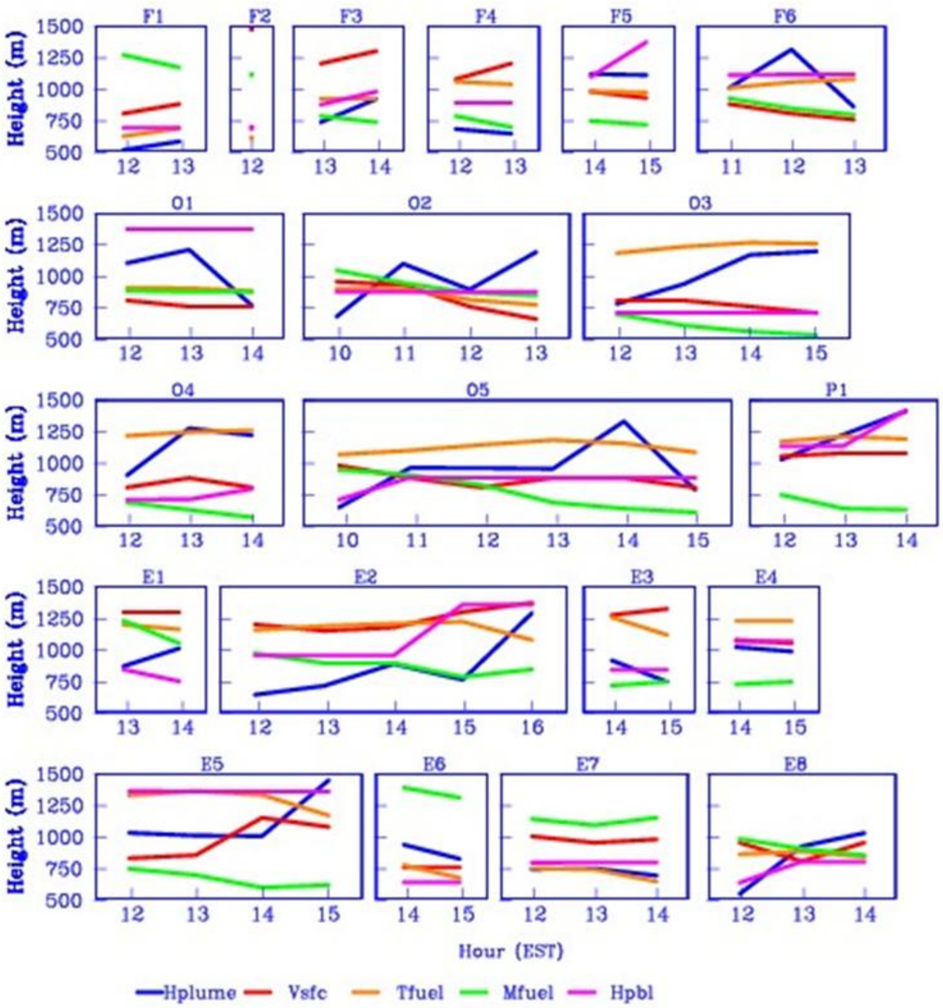
Figure 2 Variations of normalized hourly smoke plume height (blue) and meteorological variables (red). The panels from top to bottom are for wind, fuel temperature, fuel moisture, and PBL height. The minor ticks in the x-axis are different hours during a fire. The vertical lines separate various series portions.

Figure 3 Same as Figure 2 except for average series.

Figure 4 Scatter plots of the observed (x-axis) vs. simulated (y-axis) smoke plume height. RxPH is the reference regression model. RxPH-RAWS is the alternative regression model without using PBL height. r^2 is squared correlation coefficient.

Figure 5 Normalized observed (blue), and simulated hourly smoke plume height with RxPH (the reference regression model) in red and RxPH-RAWS (the alternative regression model without using PBL height) in green. The minor ticks in the x-axis are different hours during a fire.

Figure 6 Same as Figure 5 except for average smoke plume height.



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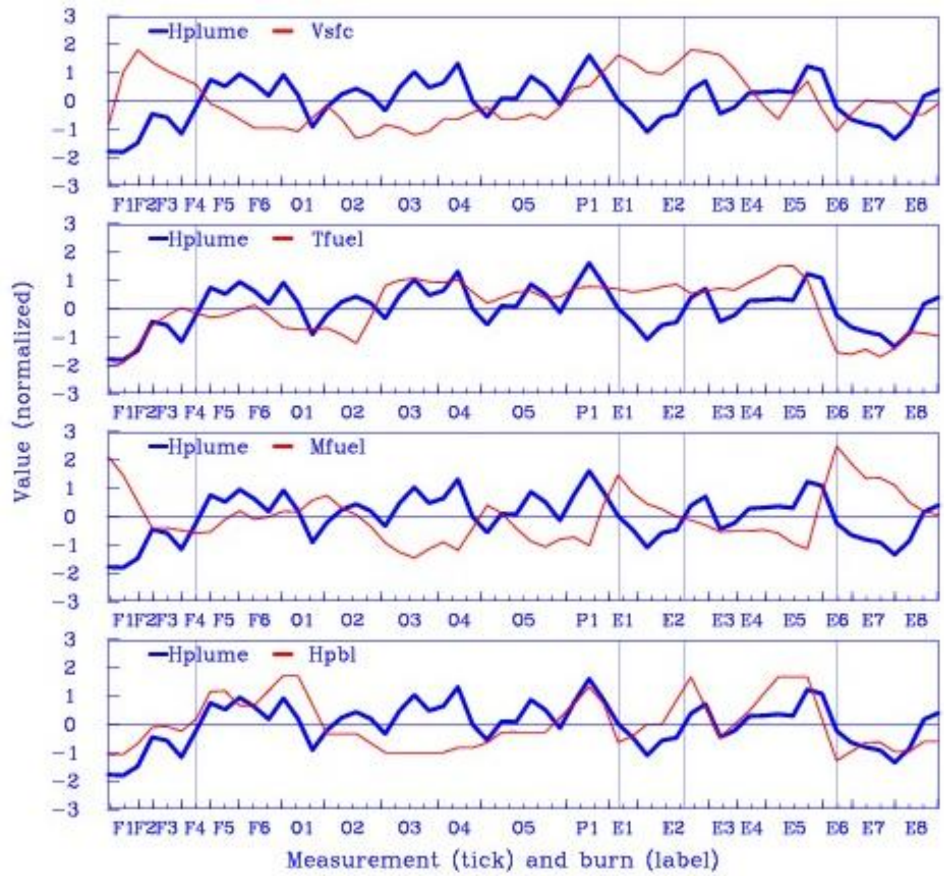

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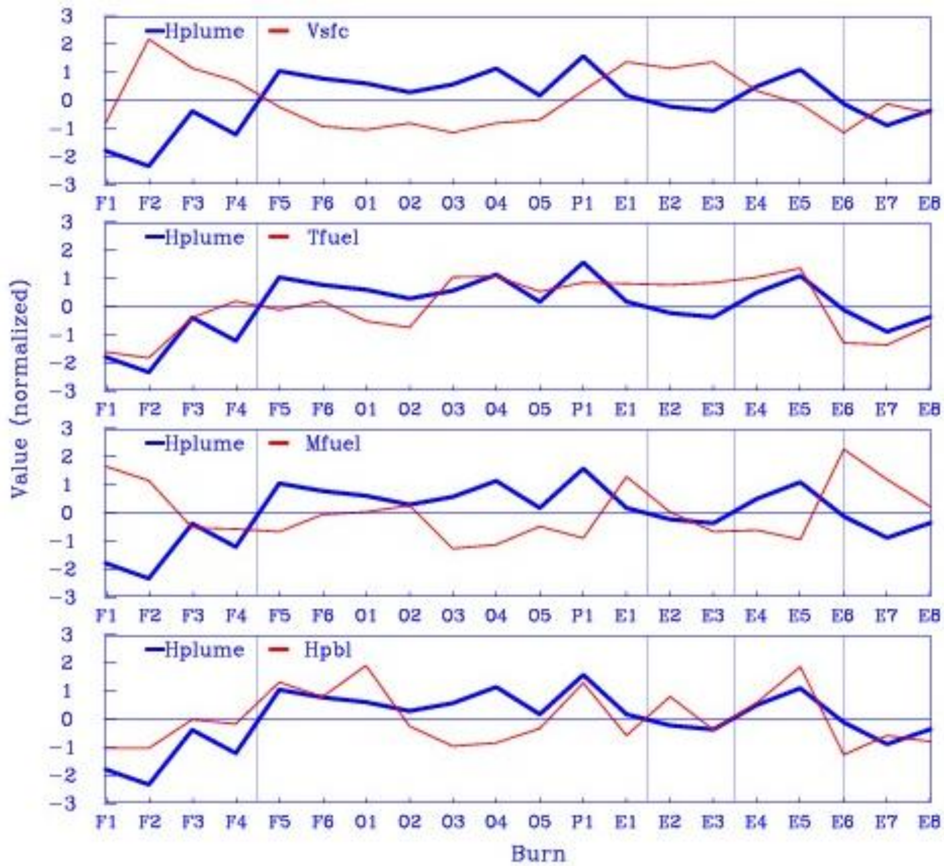
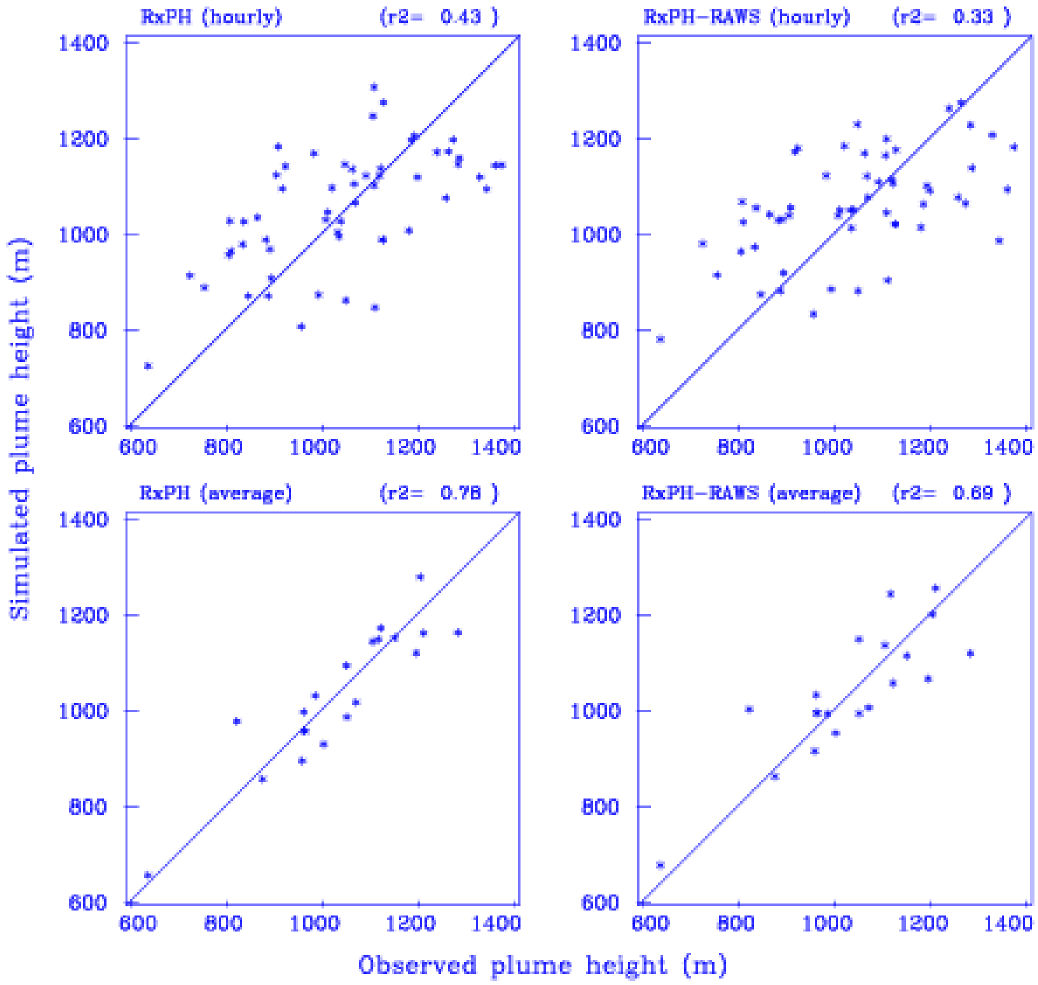


Figure 3 Same as Figure 2 except for average series.



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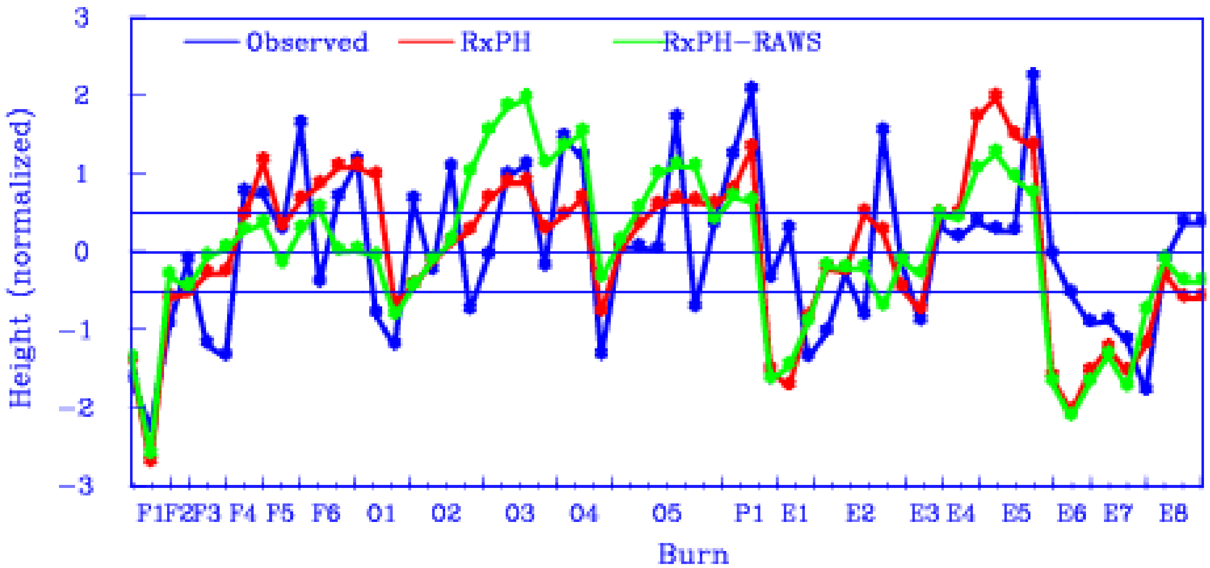

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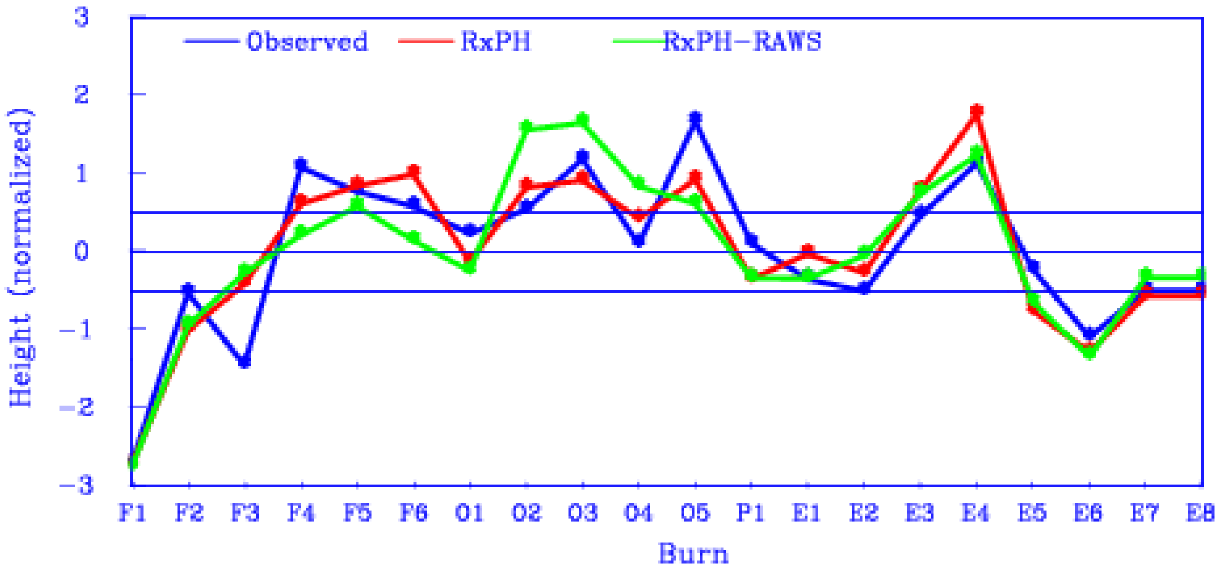

Figure 6 Same as Figure 5 except for average smoke plume height.