Evaluation of Fire Weather Forecasts Using PM_{2.5} Sensitivity Analysis

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Abstract

Fire weather forecasts are used by land and wildlife managers to determine when meteorological and fuel conditions are suitable to conduct prescribed burning. In this work, we investigate the sensitivity of ambient PM_{2.5} to various fire and meteorological variables in a spatial setting that is typical for the southeastern US, where prescribed fires are the single largest source of fine particulate matter. We use the method of principle components regression to estimate sensitivity of PM_{2.5}, measured at a monitoring site in Jacksonville, NC (JVL), to fire data and observed and forecast meteorological variables. Fire data were gathered from prescribed fire activity used for ecological management at Marine Corps Base Camp Lejeune, extending 10-50 km south from the PM_{2.5} monitor. Principal components analysis (PCA) was run on 10 data sets that included acres of prescribed burning activity (*PB*) along with meteorological forecast data alone or in combination with observations. For each data set,

observed $\text{PM}_{2.5}$ (unitless) was regressed against PCA scores from the first seven principal components (explaining at least 80% of total variance). $\text{PM}_{2.5}$ showed significant sensitivity to *PB*: $3.6 \pm 2.2 \mu\text{g m}^{-3}$ per 1000 acres burned at the investigated distance scale of ~10-50 km. Applying this sensitivity to the available activity data revealed a prescribed burning source contribution to measured $\text{PM}_{2.5}$ of up to 25% on a given day. $\text{PM}_{2.5}$ showed a positive sensitivity to relative humidity and temperature, and was also sensitive to wind direction, indicating the capture of more regional aerosol processing and transport effects. As expected, $\text{PM}_{2.5}$ had a negative sensitivity to dispersive variables but only showed a statistically significant negative sensitivity to ventilation rate, highlighting the importance of this parameter to fire managers. A positive sensitivity to forecast precipitation was found, consistent with the practice of conducting prescribed burning on days when rain can naturally extinguish fires. Perhaps most importantly for land managers, our analysis suggests that instead of relying on the forecasts from a day before, prescribed burning decisions should be based on the forecasts released the morning of the burn when possible, since these data were more stable and yielded more statistically robust results.

Introduction

Fire plays an important role in the management of forest ecosystems of the Southeastern United States (Southeast), where prescribed burning is employed to manage more than 8 million acres of land every year [1]. Over the last few decades, the Southeast has experienced substantial population growth [2], causing significant urban sprawl in an otherwise heavily forested region, and making the wildland urban interface (WUI) especially susceptible to air quality impacts from prescribed burning. Prescribed burning is the largest single source of directly emitted primary (filterable and condensable) $\text{PM}_{2.5}$ in the Southeast (EPA region 4), emitting 20.6 % of the total

primary PM_{2.5} emissions from all 54 inventoried sectors [3]; unpaved road dust and wildfires follow with 13.6 and 12.4 %, respectively. In addition, source apportionment modeling of PM_{2.5} mass concentrations from 23 Speciation Trend Network sites suggests prescribed burning may contribute more than 30% of the annual PM_{2.5} mass in the Southeast during winter [4]. Further, individual prescribed burning plume events can significantly impact air quality in neighboring communities, and can lead to short-term increases of ambient PM_{2.5} and contribute to increases in secondary air pollutants, such as ozone [5, 6].

Meeting Clean Air Act (CAA) rules mandated by the U.S. Environmental Protection Agency (EPA) can be in conflict with the Endangered Species Act, which recommends the use of prescribed burning to re-create the natural fire regimes needed to protect the habitat of threatened and endangered species by maintaining the health of its native forest ecosystems [7]. This conflict is especially severe at the WUI where ambient concentrations of PM_{2.5} can be elevated due to increasing mobile source and domestic emissions associated with the continuous population growth and urban sprawl into managed lands. There is also increasing evidence of anthropogenic emissions enhancing PM_{2.5} from biogenic emissions [8, 9]. EPA recently lowered the annual PM_{2.5} standard from 15 $\mu\text{g m}^{-3}$ to 12 $\mu\text{g m}^{-3}$ and retained the 24-hour standard at 35 $\mu\text{g m}^{-3}$ [10]. Further, EPA has recently tightened the ozone standard from previously 0.075 ppm to now 0.070 ppm effective October 1, 2015 [11]. Prescribed burning was observed to increase ozone levels in Atlanta by up to 30 ppb [5]. Thus, emissions from prescribed burning makes local community compliance with federal air quality standards more difficult. Therefore, land managers across the Southeast consult the fire weather forecast released twice daily by the National Weather Service (NWS) before conducting prescribed burning on any particular day. Understanding the NWS fire weather forecast and its individual variables' relationship to

ambient $PM_{2.5}$ as well as further improving how land managers utilize forecasts based on this understanding is of critical importance for both sides of the conflict.

In this work, we investigate the sensitivity of ambient $PM_{2.5}$ to various fire weather forecast variables in a spatial setting that is typical for the WUI in the Southeast. Military installations are ideal locations to study such sensitivities because Department of Defense (DoD) lands are intensely managed and neighbored by relatively large civilian communities that are mandated through the CAA to monitor air quality. The prescribed burning activity on the installations is well tracked and recorded, whereas it is poorly tracked in the surrounding region with little or no records available. The importance of fire weather forecasts for land management in the WUI is evident when comparing the largest installations in the Southeast in terms of managed forested land area with the size of the adjacent metropolitan statistical area (MSA) mandated to monitor $PM_{2.5}$ (Table S1).

Land managers consult fire weather forecasts, released twice daily by the NWS, to determine if conditions are favorable to conduct prescribed burning. The AM version of the fire weather forecast (released early mornings) provides a 24 hour forecast, while the PM version (released late afternoon) provides a 48 hour forecast. Each posting provides forecast variables that are considered in the final preparations and decision process of whether or not to conduct a prescribed burn. Among the issued variables, an area-specific ventilation rate (*VR*) (i.e. the product of wind speed and mixing height), the probability of precipitation (*POP*), min/max temperature and relative humidity (*RH*), inversion burn-off temperature (*IBT*), boundary layer mixing height (*BLH*), transport wind speed and direction (*TWS*, *TWD*), and Haines Index (*HAI*) (a lower atmospheric stability index used to forecast the potential for large fire growth and/or erratic fire behavior) are considered more important in the decision making process (Table 1). In

many areas of the Southeast, forest managers keep records of the Keetch-Byram Drought Index (*KBDI*), a continuous reference scale for estimating dryness of soil and duff layers presenting wildfire risks, which is not part of the routine NWS fire weather forecast but has been included in our analysis.

This work builds on an earlier study in a similar setting investigating sensitivities of ambient $PM_{2.5}$ measured in Columbus, GA to burn activities at Fort Benning (expressed in acres burned) relative to fire forecast data [12]. The method bypasses individual atmospheric processes and looks at statistical links between the source (prescribed fires) and receptor ($PM_{2.5}$ monitoring station) by ranking the relevance and importance of forecast variables and fire data (i.e. acres burned and *KBDI*) on the receptor's $PM_{2.5}$ concentration. Such a ranking can inform fire managers of the most important forecast variables that may influence the fire's impact on $PM_{2.5}$ in their district. In other words, the ranking allows a quantitative assessment of local $PM_{2.5}$ concentration sensitivity to each forecast and fire data parameter. Note that all available *PB* records used here are in units of acres that were subject to prescribed burning, whereby the amount of fuel actually consumed remains unknown because post-burn inventories do not exist.

Methods

This study utilizes prescribed burning data, observed and forecast meteorological data, and $PM_{2.5}$ data from December 2002 to March 2007 (Table 1, Figure S1). Acres burned in a prescribed fashion (*PB*) and *KBDI* were gathered at the Marine Corps Base Camp Lejeune (MCBCL), located south from the city of Jacksonville, NC (Figure S2). Of its total land area of 125,000 acres, MCBCL manages 95,000 acres of forested land, employing prescribed burning in a 3-year rotation with an annual treatment target of approximately 30,000 acres. MCBCL is surrounded by managed forests outside its borders; including the Hofmann Forest to the north,

Croatan National Forest to the north-east and game lands to the west and south-west. Foresters managing these lands apply similar tools and rely on the same fire weather forecasts as the MCBCL foresters.

The Marine Corps Air Station (“MCAS New River” in Figure S2) operates a suite of meteorological sensors that are typical for most airports in the U.S.; i.e. cloud ceiling and visibility in addition to barometric pressure, temperature, humidity, precipitation, wind speed and direction. Observational data are reported to the NWS and are available through the MesoWest Web site (<http://mesowest.utah.edu/index.html>) run by the University of Utah’s Department of Meteorology. Since these data represent different averaging intervals and different reporting frequencies, we homogenized the data to represent consistent hourly averages, allowing the determination of daily minimum humidity and visibility, and daily max-min temperature difference (see Table 1). Historical fire weather forecast data were extracted from the National Climate Data Center (NCDC) archive in Ashville, NC [13].

In compliance with the CAA, Jacksonville (population 179,487 per 2010 Census) began the required regulatory monitoring of ambient $PM_{2.5}$ in 1999, since which time the state’s environmental agency (NCDENR-DAQ) collected 24 h integrated $PM_{2.5}$ filter samples to report average 24 h (midnight to midnight) $PM_{2.5}$ mass concentration every third day. Most prescribed burning activities occur in winter and spring, addressing both dormant and growing season management objectives. We collected $PM_{2.5}$ data several days after and prior to when prescribed burning activity was documented.

Sensitivity Analysis using Principal Components Regression (PCR)

PCR is a statistical analysis technique that combines principal components analysis (PCA) with multivariate regression [14-16]. PCA is often used to remove multi-collinear effects

of the original data (input variables), and to reduce dimensionality of large data sets. The former is of particular importance in our case, since collinearities potentially exist between many of the meteorological and fire input variables. Details of PCA are widely available in the literature but briefly, the first step in PCA is to standardize a given data matrix, X_{org} , so that all variables have a mean of 0 and standard deviation of 1 (called X_{std} , or just X for simplicity). Next, singular value decomposition is used to determine the principal components, which are the eigenvectors, V , of the dispersion matrix, $X^T * X$. The relative strength, or scores, Z , of each component, for each day are therefore, a rotation of the data matrix X (Eq. 1).

$$Z = X * V \quad \text{(Equation 1)}$$

PCA results in the same number of eigenvectors as variables in the data matrix, X . The eigenvectors, V , are orthonormal, and the resulting scores, Z are orthogonal, which has the net effect of removing collinearity within the data matrix, X . Also, the components are ordered by their eigenvalues. The higher the eigenvalue for a particular component, the more variability in X that component explains. Typically, PCA is used for exploratory analysis of a data set and is often used to identify variables that vary together and qualitatively to identify components which explain most of the total variability of the data set. There are several different ways of determining the most important components. Two often-used methods include choosing components that explain a certain percentage of the total variability or only choosing components with eigenvalues greater than 1. In this work, we use the method of choosing the fewest components possible that together explain at least 80% of variability.

PCR combines PCA with multivariate regression. In standard multivariate regression, the dependent variable, Y , is regressed against the independent variable matrix, X (Eq. 2). In PCR,

the dependent variable is regressed against the scores, Z , from the PCA analysis (Eq. 3). Note that Y in both equations represents standardized, unitless $PM_{2.5}$ and that the scores are only from the components determined to be most important via the manner explained above.

$$Y = X * \alpha + \varepsilon \quad (\text{Equation 2})$$

$$Y = Z * \beta + \varepsilon \quad (\text{Equation 3})$$

Since $V^T V = V V^T = I$, the identity matrix, due to orthonormality, we can also derive Eq. 3 from Eq. 2 via the following:

$$\begin{aligned} Y &= X * \alpha + \varepsilon \\ &= X * V * V^T * \alpha + \varepsilon \\ &= Z * V^T * \alpha + \varepsilon \\ &= Z * \beta + \varepsilon \end{aligned}$$

Thus, we can derive the relationship between α and β (Eq. 4).

$$\alpha = V * \beta \quad (\text{Equation 4})$$

where α represents the unitless sensitivity of $PM_{2.5}$ to the standardized variables, and β is the vector of regression coefficients from the PCR analysis. Further, only the coefficients in β that are less than a predetermined p-value are used. As explained later, we used a p-value of 0.08 (92% confidence). Coefficients in β with a p-value greater than 0.08 are forced to a value of zero when applying Equation 4. Physical units can be applied back to the unitless sensitivities by applying Eq. 5, where $\delta_{t,k}$ is the unit-based sensitivity of $PM_{2.5}$ to parameter k , $s_{PM_{2.5}}$ is the standard deviation of $PM_{2.5}$, s_k is the standard deviation of parameter k , and α_k is the unitless sensitivity of $PM_{2.5}$ to parameter k .

$$\delta_{i,k} = \frac{s_{PM_{2.5}}}{s_k} \alpha_k \quad (\text{Equation 5})$$

The full data set contained 635 days of observed and forecast meteorological variables and fire data (i.e. acres burned (*PB*), and *KBDI*). $PM_{2.5}$ data were not included in determining PCs as $PM_{2.5}$ was the dependent variable in the PCR. The 635 days spanned a period from December 1, 2002 to March 15, 2007, largely determined by the occurrence of prescribed burning days, and thus was limited to days during the burn season (winter and spring) with a few occasions in early summer (see Fig. S1). During this 4.5 year period, prescribed burning was conducted on 201 occasions (days) with areas burnt between 2 and 3800 acres, the daily average being 269 ± 3.7 acres (geometric mean and geometric std. dev.) and median being 323 acres. The main criterion for selection into the data matrix was no more than 2 days before and 5 days after a single burn day. The 2 days before would capture the $PM_{2.5}$ conditions prior to the burn, and the 5 days after would allow the capture of potential effects from smoldering and regional signature of prescribed fires that may have taken place around the same time as those on MCBCL. Figure S1 illustrates the prescribed burning occurrences with total daily acres burned relative to the daily average $PM_{2.5}$ data measured at JVL that were available for this analysis. The available number of daily $PM_{2.5}$ records is 209, averaging at $11.0 \pm 5.1 \mu\text{g m}^{-3}$.

PCA was applied to several data sets that represented a combination of exploratory variables. PCA was initially run on two data sets that combined fire data with: i) observed meteorological conditions with AM-reported meteorological forecast (PC-AM) and ii) observed meteorological conditions with PM-reported meteorological forecast (PC-PM). Here, AM means the forecast in the morning of the performed prescribed burn and PM refers to the forecast in the evening prior to the prescribed burn (performed next day). Subsequently, three more data sets were analyzed using PCA. They included meteorological observations with fire data (OBS only),

AM forecast with fire data (AM ONLY) and PM forecast with fire data (PM ONLY).

Due to the proximity (10-50 km) of the source (MCBCL) relative to the receptor (Jacksonville proper - see Figure S2), the PCR analysis is expected to be particularly sensitive to wind direction. Wind direction is reported in degrees for only the observed data and in main sectors (e.g. N, NNE, NE etc.) for the forecasted data, which were converted into degrees for the PCR analysis. We tested the sensitivity of the method to this parameter by running PCA on all five data sets with both observed and forecast wind direction in degrees as well as split into its north-south and east-west vector components (Table S2), with the mathematical convention of southerly and westerly component flows being positive, respectively. Thus, there were a total of 10 data sets, each with 635 days of data, analyzed by PCA.

Observed $PM_{2.5}$ (unitless) was regressed against scores from the principal components which explained ~80% of the variance (the first seven components) on days that met two conditions: (1) there was both measured $PM_{2.5}$ data (JVL PM in Table 1) and PB activity at MCBCL and (2), there was no prescribed burning activity the previous two days. This allowed us to quantify same day effects (lag 0) of *PB* on $PM_{2.5}$. 32 days met the lag 0 condition. The importance of one and two-day lag on sensitivities was also examined. Understanding lag is important because the smoldering stages of a prescribed fire can last for days, and in effect turn it into a continuous source. Also, potentially long transport times (e.g. under stagnant conditions) may result in impacts at a receptor location days after the actual prescribed burning conduct. We reduced the data set so that days with multiple lag effects were removed in order to evaluate lag 0, 1 and 2 effects individually since some work has suggested that lag 1 and 2 effects from prescribed fires are minimal [17]. While multiple lag effects could be evaluated using other methods, such as distributed lag models, here such models would add complexity in

interpretation of and introduce more uncertainty into model results. For lag 1, regression was conducted only for days for which there was *PB* on day n and $PM_{2.5}$ measurement on day $n+1$ and no *PB* on days $n-1$ and $n+1$. Similarly for lag 2, regression was conducted only for days for which there was *PB* on day n and $PM_{2.5}$ measurement on day $n+2$ and no *PB* on days $n+1$ and $n+2$. 16 and 32 days met the lag 1 and lag 2 conditions, respectively. The regression yielded a standardized coefficient vector β , which was converted to unitless sensitivities, α , via Equation 4, and to unit-based sensitivities, $\delta_{t,k}$, via Equation 5. Only the components that had regression coefficients significant at $p < 0.08$ were used to calculate unitless sensitivities. A p-value of 0.08 was chosen because at 0.05, sensitivities for the cases using fire data with observed meteorology with (PCA Obs Only) and fire data with observed meteorology with wind direction split into components (PCA Obs Only WD) decreased by several orders of magnitude due to two prescribed burning-based components that had p-values slightly higher than 0.05, and were found to be influential (Table S3). However, at a p-value of 0.08, $PM_{2.5}$ sensitivities are consistent across all cases, indicating that the PCR method employed in this work is robust.

Results

Principal Components Analysis

For all 10 PCA runs, the first seven principal components (V in Eq. 1) cumulatively explained at least 80 % of the total variance of the PCA data set, with PC1 explaining the largest amount of variability and PC7 the smallest for each PCA run. Each of the seven PCs, is dominated by a few variables (Tables S4 and Excel File SI-File1). While there are differences between these 10 cases, several of the principal components have similarities. For example, the first principal component is dominated by relative humidity and temperature, indicating their importance to the overall variability of $PM_{2.5}$. The second component is typically loaded by a

combination of temperature and dispersive variables, including wind (WS, WD) and atmospheric stability (*HAI*). Prescribed burning is not prominent until the fourth PC or later; this is to be expected because its sample size (i.e. 201 occurrences with values greater than zero of total 635 records) is far smaller than any meteorological parameter.

Principal Components Regression

Lag 0 Unitless sensitivities

Unitless sensitivities calculated via PCR are used for direct comparison of the relative importance of different forecast variables on the local PM_{2.5} burden (Table S5). Reducing the data so that they contained no days with multiple lag effects resulted in a regression data set of 32 days for lag 0. Of the ten cases evaluated, nine cases had at least one PC with a statistically significant regression coefficient at lag 0, suggesting that there are day-of-prescribed burning impacts to the JVL monitoring site. Although the coefficient(s) of determination (COD) were low ($R^2 = 0.28$ to 0.37 in Table S3), the regression analysis of the lag 0 data set identified some empirical relationships of potential use to land managers. Positive unitless sensitivities indicate these particular variables contribute to an increase in PM_{2.5}, while negative values point to a decreasing effect on PM_{2.5}. Our input variables' association with PM_{2.5} is investigated for the five sets where wind direction is used in degrees (Figure 1) and when it is split in to N-S and E-W components (Figure 2). In both wind cases, forecast variables characterizing atmospheric stability (e.g. Haines Index, ventilation rate, wind speed and mixing height) have similar responses to ambient PM_{2.5} levels, and contribute to a decrease in PM_{2.5}, thus exhibiting a negative sensitivity. In contrast, *PB* and *KBDI* are important when PM_{2.5} concentration increases. Sensitivity to *PB* is positive and consistently appears to be an important contributor to PM_{2.5}, and is similar in seven cases where forecast meteorology is used (the 8th case, PCA-PM

only WD, yielded no statistically significant sensitivities). However, $PM_{2.5}$ has a lower unitless sensitivity to PB when only observational data is used. $KBDI$, on the other hand, impacts $PM_{2.5}$ more when only observations are used. The forecast variables IBT and $dayT$ are consistently positive, indicating clear sky conditions under which a preceding strong nocturnal inversion allows $PM_{2.5}$ emissions to accumulate. Dispersive variables TWS and VR and measured WS are consistently negative, pointing to their diluting effects on $PM_{2.5}$ concentrations.

Splitting the wind direction into N-S and E-W vector components led to notable differences in unitless sensitivities. First, using only the PM forecast with wind directions split (case PM Only WD dark blue in Figure 2) resulted in no statistically significant regression coefficients. For the other cases, splitting caused $PM_{2.5}$ sensitivity to be largest to measured precipitation, indicative of managers' decisions to start fires on days where precipitation, especially later in the day, can naturally extinguish the fires, which is further discussed later. A similar effect can be seen for the forecasted temperature difference parameter. In addition, wind direction had an association with $PM_{2.5}$, suggesting that continental air masses carry more $PM_{2.5}$ than maritime air from easterly directions. When wind direction is split into components, $PM_{2.5}$ shows a slight positive sensitivity to the E-W component when both observed and forecast variables are used and negative for N-S component, indicating additional $PM_{2.5}$ being transported to our receptor location from westerly and northerly directions, respectively, both of which can be considered continental air masses and in line with the result when wind direction is entered in degrees.

A number of $PM_{2.5}$ sensitivities changed from positive to negative, depending on if only observations, forecast variables, or both were used. For example, in the case with wind direction in degrees, the forecast wind direction, TWD , exhibits a large positive sensitivity (higher $PM_{2.5}$ in

continental air masses) when only forecast variables are used, whereas it appears to have a small negative sensitivity when observations and forecast variables are used together (slightly higher $PM_{2.5}$ loadings in maritime air or sea breeze). To a lesser extent, measured precipitation has a positive association with $PM_{2.5}$ when observations and AM forecast are used, but more plausible negative otherwise (a reason for this apparently implausible connection is discussed below). The forecast temperature difference (the indicator for clear sky conditions causing large difference between daytime high and nighttime low temperatures prone for shallow nocturnal inversion layers near the ground) has the expected positive impact when only the AM forecast is used, but negative with the PM forecast, possibly reflecting the greater uncertainty of predicting the temperature difference in the earlier forecast.

The wind direction split has similar effects only for the forecast variables *BLH*, *TWS*, and E-W wind component, such that the *BLH* and E-W wind component positively impact $PM_{2.5}$ when observations are used combined with forecasts. However, *BLH* yields negative impact (pointing to $PM_{2.5}$ accumulation in a shrinking boundary layer) when only the AM forecast is used, being physically in line with the temperature difference. When observations are used combined with forecasts, $PM_{2.5}$ has a negative sensitivity to *TWS* due to its diluting effect on the boundary layer, while a small positive effect is obtained when only the AM forecast is used, indicating the transport wind speed's diminishing diluting effects in a shrinking boundary layer.

The averages of the unitless sensitivities across all applicable runs, with two standard deviations taken as an estimate of uncertainty, indicate which variables have the most influence on $PM_{2.5}$ (Figure 3). That is, unitless sensitivities whose standard deviation crosses the x-axis, can be viewed as statistically not significant at ~95% confidence (ie. $\pm 2\sigma$). Thus, for the fire data variables, sensitivity of $PM_{2.5}$ to *PB* is significant, but not *KBDI*. For the measured meteorology,

relative humidity and wind direction splits are significant. Positive $PM_{2.5}$ sensitivities to E-W winds indicate importance of winds coming from the west while negative $PM_{2.5}$ sensitivities to N-S winds indicate importance of winds coming from the north, the origin of both can be considered continental. For the forecast variables *POP*, *dayT*, *IBT*, and *RH* have significant positive sensitivities while *HAI* and *VR* have significant negative sensitivities. The positive sensitivity associated with *POP* was not expected but reflects the fire managers' actual positive consideration of *POP* in their decision to start prescribed burning on days when precipitation might be expected in late afternoons because it acts as a natural fire break preventing uncontrolled fire spread (see discussion of unit-based sensitivities below). Similar to measurements, although not significant at 95% CI, the forecast southerly wind component carried by the sea breeze leads to a decrease in $PM_{2.5}$.

AM vs. PM Forecasts

Being able to rely on PM weather forecasts to determine if a particular day will have ideal conditions for prescribed burning would bear significant advantages for land managers in their preparation efforts. Therefore, it is of interest to evaluate if there are salient differences between AM and PM forecasts. While lag 0 sensitivity means and standard deviations between cases using AM versus PM forecasts are quite similar, suggesting that both AM and PM forecasts are equally applicable to PCR (Figure S3), AM forecasts yield more variables with statistically significant influence on $PM_{2.5}$ (eight versus five).

In addition, we assessed how the inclusion of observations and treatment of wind affects PCR results. When observations are included in the PCA data set, COD between PCR results using AM versus PM forecasts are higher (Figures S4 and S5). Further, splitting the wind direction into N-S and E-W components leads to a higher COD of unitless sensitivities (Figure

S4) between the use of AM or PM forecast data. This suggests that as long as the WD is split into components and observations are included, AM and PM forecasts yield similar sensitivity results. When the PCA data sets exclude observations (i.e. the PCA data set contains only fire data and forecasts), splitting the wind direction into N-S and E-W components leads to statistically significant unitless sensitivities for the AM forecast only (Figure S5), indicating that PM forecasts bear greater uncertainty in predicting immediate (lag 0) PM_{2.5} impacts.

Similarly for the lag 2 case, results suggest that the PM forecasts are more unstable to PCA treatment than using AM forecasts. The high variability of lag 2 PM_{2.5} sensitivity results suggest that lag 2 effects estimated in this study are highly uncertain. This high variability, especially of PM_{2.5} to PB is driven by two cases, PCA AM only and PCA PM WD, which had relatively high lag 2 unitless sensitivities of 0.24 and 0.13, respectively. Second, one other case, PCA-PM only WD, exclusively produced lag 2 sensitivities, implying that *PB* affects monitored PM_{2.5} not on the same day but two days after the prescribed burning conduct. Although there is a very real potential of emissions from residual smoldering combustion impacting monitored PM_{2.5} [18-20], this single PM forecast result of lag 2 impacts without generating any lag 0 or 1 impacts is highly coincidental. Based on the different uncertainties in lag 0 and lag 2 results, we conclude that the AM forecasts yield overall more reliable results in predicting direct impacts on PM_{2.5} than the PM forecasts.

Unit-based Sensitivities

From an air quality perspective, it is of interest to land managers to know the unit-based sensitivity of PM_{2.5} to certain variables, especially *PB*. Across the nine out of 10 cases that had statistically significant results at a p-value of 0.08 (92% confidence) or stronger, there is consistency, resulting in an average sensitivity of $3.6 \pm 2.2 \mu\text{g m}^{-3}$ (two standard deviation) per

1000 acres burned (Table 2, Table S8). This value is comparable to the $2 \mu\text{g m}^{-3}$ per 1,000 acres found in a similar analysis for a 3-year study period at Columbus, GA next to Fort Benning [12]. The reason for our *PB* sensitivity being higher lies in the longer study period and lower burn intensity. Not knowing the amounts of acres burned in the surrounding forests (Figure S2) makes our *PB* sensitivity more uncertain and likely an upper estimate.

The observed daily average and minimum *RH* correlated positively and statistically significantly with $\text{PM}_{2.5}$ (Figure 3). When transformed back to the unit-based relationship, an increase in daily average *RH* of 10% would result in a $0.27 \mu\text{g m}^{-3}$ increase in $\text{PM}_{2.5}$; the relationship with daily minimum *RH* is very similar at $0.23 \mu\text{g m}^{-3}$ per 10% (Table 2). *RH* governs the liquid water content (LWC) in $\text{PM}_{2.5}$, which plays an important role in secondary aerosol formation by providing a large aqueous surface for increased gas uptake and chemical reactions resulting in products of lower vapor pressures than the absorbed gases [21]. In the Southeast, it has been suggested that more water-soluble organic carbon (WSOC) partitions into the particle phase as *RH*, and with it LWC increases [22]. Thus, LWC enhances particle scattering effects and promotes secondary aerosol formation [23, 24]. It has also been suggested that even though organics are less hygroscopic than inorganics, they can contribute to water uptake due to their large mass fraction; however, the dissociation of organic acids under low-pH conditions is minimal compared to inorganic acids [25]. Given the low, year-round pH (0.5 to 3.0) conditions in the Southeast, the observed increase in gravimetrically determined (at 35% *RH*) ambient $\text{PM}_{2.5}$ mass of $0.27 \mu\text{g m}^{-3}$ per 10% increase in ambient *RH* calculated in this work must be interpreted as mostly attributable to inorganic salts dominated by sulfate with a minor contribution from organic salts.

For temperature-related variables, statistically significant relationships were found only

for the forecast daytime high temperature (day_T , 0.024 ± 0.015), and the forecast inversion burnoff temperature (IBT , 0.021 ± 0.012), and not for the forecast temperature difference ($diffT$), the observed daily average temperature (T_{avg}) and the observed temperature difference (T_{diff}). Therefore, an increase in the forecast daily maximum temperature of 20 °F (NOTE: that forecast temperature variables have units of degrees Fahrenheit) would add $0.48 \mu\text{g m}^{-3}$ of $\text{PM}_{2.5}$ at Jacksonville, suggesting an important contribution from atmospheric secondary organic aerosol. Although SOA is more dominant in the summer, and largely influenced by isoprene, in the Southeast's winter, there is still significant VOC production from terpenes emitted by coniferous trees. In addition, PB activity can extend well into summer and represents 27% of all PB days here (Fig S1). During PB activities, it has been suggested that significant isoprene emissions occur primarily during the hot flaming phase of the fuel combustion (e.g. [26] and references therein). Together with other biogenic VOC emissions, mainly monoterpenes, O_3 and SOA may be formed from such emissions as the PB plume disperses and ages under favorable ambient conditions typically encountered in late spring and early summer [27]. Our results also suggest the influence of IBT may be more important than daily max temperature to $\text{PM}_{2.5}$. For example, in our data set, the largest day-to-day increase in forecast IBT was 33 F, which would result in an increase of $\text{PM}_{2.5}$ of $0.7 \mu\text{g m}^{-3}$.

Since rain is a main sink for $\text{PM}_{2.5}$ in the atmosphere, it is plausible to assume that an increase in measured precipitation, (PCP), or in forecast probability of precipitation (POP) would reduce $\text{PM}_{2.5}$ mass concentration. However, we find that there is a slightly positive association of $\text{PM}_{2.5}$ of $0.12 \pm 0.33 \mu\text{g m}^{-3}$ per mm measured rainfall albeit the high standard deviation indicates that there is significant variability across the different cases. The $\text{PM}_{2.5}$ sensitivity to forecast POP , $0.011 \pm 0.011 \mu\text{g m}^{-3}$ for every percent increase in probability of

precipitation, is less variable than measured precipitation. This significantly positive sensitivity is most likely due to fire managers' decision to start fires on days that have precipitation in the forecast for periods after the fires have been completed (personal communication with Danny Becker, Environmental Management Division at MCBCL). This is common practice because afternoon rain is considered welcome, preventing unwanted spread of fires and naturally extinguishing smoldering fires.

$PM_{2.5}$ is not as sensitive to BLH and wind speed as compared to VR . However, the observed wind speed (WS), has a more significant influence on $PM_{2.5}$ than the modeled transport wind speed (TWS), which may be due to the greater uncertainty of TWS , but $PM_{2.5}$ levels would benefit from both due to dilution. Hence, an increase of 1 m s^{-1} measured near the surface will reduce the $PM_{2.5}$ level by $\sim 0.42 \pm 1.01 \text{ } \mu\text{g m}^{-3}$. Splitting the wind direction into N-S and E-W components showed that directionality is important. Our analysis shows that $PM_{2.5}$ is most sensitive to winds coming from the west (positive E-W sensitivity) and north (negative N-S sensitivity) (Table 2). This is most likely due to the 201 days of prescribed burning activity in our data set having winds with predominantly northerly and westerly components for both observed and forecasted winds (Figure 4). Southerly winds are mainly from the SW, and for the lag 0 days used in the regression, have lower $PM_{2.5}$ than from other directions (Figure 5c). This ostensibly leads to positive sensitivity for E-W winds (i.e. sensitivity to westerly winds) and negative for N-S winds (i.e. sensitivity to northerly winds).

Although the $PM_{2.5}$ monitor is located north from the MCBCL, forested lands ca. 20 km to the north-northeast (Hoffman Forest), 40-50 km to the east (Croatan National Forest) and 40-50 km to the west/southwest (Holly Shelter and Angola Bay game lands) are being managed similarly to MCBCL; i.e. foresters there employ similar criteria in their prescribed burning

decision process. Wind rose plots of the lag 0 data (32 days) reveal that the highest $PM_{2.5}$ occurs when winds blow from the south/southeast (SSE) (Figure 5c). When the winds are from other directions, including from the north, WSW, WNW and NNE, $PM_{2.5}$, although not as high as from SSE, is moderate and greater than $8 \mu g m^{-3}$. The wind frequency plot (Figure 5a) for the 32 lag 0 days is similar to the wind frequency for the larger data set (Figure 5b) in that easterly component winds are rare and potentially influencing the directional sensitivity of $PM_{2.5}$.

The wind rose of $PM_{2.5}$ corroborates our analysis that $PM_{2.5}$ at the monitoring site is impacted by *PB* at MCBCL, even though winds are predominantly from the west. Impacts from *PB* in other forest areas is evident from the NNE sector of the $PM_{2.5}$ rose pointing to Hofmann Forest, which is a bit smaller than MCBCL and only a little farther away, but for which no *PB* activity data are available. It should be noted that we used only MCBCL's *PB* activity records, providing the most readily available and reliable *PB* data. However, all forested land in the greater area surrounding MCBCL proper is managed utilizing prescribed burning. Therefore, the MCBCL records are potentially a surrogate measure for more wide spread *PB* activity in the region. Nevertheless, the $PM_{2.5}$ monitor in Jacksonville is directly adjacent to the northern border of MCBCL, making this specific setting the most direct source-receptor relationship, followed by the southern part of Hofmann Forest to the north. Even if there was significant amounts of acres burned in regional forests, impact from those prescribed burning activities would not be as direct and far more dilute. Thus, the PCR method employed in this work provides insight into local impacts from *PB*, and makes our unit-based $PM_{2.5}$ sensitivity an upper limit estimate for local to sub-regional settings.

Finally, we applied the sensitivity result of $3.6 \mu g m^{-3}$ per 1000 acres burned to the 32 lag 0 days ($PM_{2.5}$ measured on same day with *PB* but no *PB* 1 and 2 days prior) to estimate a source

contribution from prescribed burning on the JVL monitor. As illustrated in the Figure 5c wind rose, *PB*-based $PM_{2.5}$ has a clear source from the SSE and the ENE, and contributes up to 25% to the total $PM_{2.5}$ load. This is consistent with other studies in the Southeast estimating prescribed burning emissions contribution to $PM_{2.5}$ to be ~8-30% from different source apportionment approaches calculating biomass burning impacts [4, 6, 28-34]. For receptor locations in the fast expanding wildland urban interface of the Southeastern US that are impacted by biomass burning but do not have speciated $PM_{2.5}$ data, the PCR method used in this work could be an alternative, fast and relatively simple way to estimate prescribed burning source impacts.

Conclusions

Fire weather forecasts are used by land and wildlife managers in determining when prescribed burning activities should occur. In this work, we explored potential prescribed burning impacts on air quality in light of differences in early morning (AM) and previous evening (PM) forecasts by using PCR to estimate sensitivity of $PM_{2.5}$ to prescribed burning activity and meteorological variables. We ran PCA on 10 data sets that included prescribed burning activity data from the managed forest area at MCBCL located closest to the $PM_{2.5}$ monitor, along with meteorological variables of interest; the meteorological variables included either observational data only, forecast data only or a combination of both. Prescribed burning activity data from MCBCL were the only data available and are considered surrogate for all other managed forests in the surrounding area. Regardless of how the data were treated for PCR analysis, $PM_{2.5}$ showed significant sensitivity to *PB*, with a unit-based sensitivity of $3.6 \pm 2.2 \mu g m^{-3}$ per 1000 acres burned, indicating that prescribed burning conducted in the local surroundings consistently affects air quality in Jacksonville, NC. Since prescribed burning activity data are limited to MCBCL, this sensitivity has to be regarded an upper limit estimate. $PM_{2.5}$ had a

negative sensitivity to dispersive variables like wind speed, *BLH*, *Haines Index*, and especially ventilation rate (*VR*). When looking at all cases, the forecast variables positively associated with $PM_{2.5}$ were *dayT* (daytime temperature), *diffT* (daily max-min temperature difference), *IBT* (inversion burnoff temperature), relative humidity, and winds coming from the west and north. These relationships point to our analysis picking up more regional signatures of secondary atmospheric $PM_{2.5}$ formation and transport in more polluted continental air masses. The PCR method also showed positive sensitivity to forecast precipitation (*POP*), which likely reflects fire managers' decision to conduct prescribed burning on days where rainfall potentially helps extinguish fires in the evening. Perhaps most importantly for land managers, our PCR analysis suggests that instead of relying on the forecasts from a day before, prescribed burning decisions should be based on the forecasts released the morning of the potential burn since the AM forecasts were more stable to PCR treatment and produced less uncertain results. Therefore, fire managers should continue to use forecast precipitation but also focus on temperature, relative humidity, boundary layer stability and ventilation rate as the most important factors in making decisions about prescribed burning.

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Figures

Figure 1: Unitless $PM_{2.5}$ sensitivities for the five cases with wind direction in degrees.

Figure 2: Unitless $PM_{2.5}$ sensitivities for the four cases with wind direction in N-S (negative for N) and E-W (positive for W) components. NOTE: PCA PM Only WD analysis did not yield any PC with regression p value < 0.08 .

Figure 3: Average unitless sensitivities. Error bars indicate two standard deviations over all cases where the variable was used in the analysis. Statistically significant averages (at 95%CI) are in red.

Figure 4: Wind rose plots of (a) observed wind frequency for the full data set (red), days with PM_{2.5} observations (black) and days with PB (green) and (b) wind frequency on PB days for observed winds (green, same as a), AM forecast winds (blue) and PM forecast winds (red).

CHN is at 34.374167 N, -77.843333 W ca. 100 km SW from JVL at 34.776667 N, -77.435556 W

Figure 5: 24 hour average wind rose plots for lag 0 days of a) wind frequency, b) wind speed, c) $PM_{2.5}$ (overlain on vicinity map), and d) maximum PB contribution based on computed $PM_{2.5}$ sensitivity of $3.6 \mu g m^{-3}$ per 1000 acres burned; magnified from red trace in c).

Tables

Table 1: Measured and modeled (from NWS forecast) input variables.

Parameter Type	Variable Name	Units	Description
PM	<i>JVL PM</i>	µg/m3	24 h average PM2.5 measured every 3 rd day at JVL monitoring site
Fire Data	<i>PB</i>	acr	Acres of prescribed burning
	<i>KBDI</i>	0-800	Keetch Byram Drought Index continuous reference scale for estimating wildfire risks.
Observations	<i>T_avg</i>	degC	Daily average temperature
	<i>T_diff</i>	degC	Daytime maximum – Nighttime minimum temperature difference
	<i>RH_avg</i>	%	Daily average relative humidity
	<i>RH_min</i>	%	Daily minimum RH
	<i>PCP</i>	mm	Daily total precipitation
	<i>VIS_min</i>	km	Daily minimum visibility
	<i>WS</i>	m/s	Daily average wind speed
	<i>WD_NS</i>	-1 to 1	N-S wind component (1 is from the south)
	<i>WD_EW</i>	-1 to 1	E-W wind component (1 is from the west)
Forecast*	<i>WD</i>	degN	Vector averaged daily wind direction (0 degrees is from the north)
	<i>POP</i>	%	Probability/chance of precipitation
	<i>dayT</i>	F	Daily maximum air temperature
	<i>diffT</i>	F	Difference in daily max-min air temperature
	<i>IBT</i>	F	Inversion burnoff temperature. Temperature required to dissipate nocturnal inversion
	<i>dayRH</i>	%	Daytime average humidity
	<i>HAI</i>	-	Haines Stability Index. Atmospheric stability index for large fire growth.
	<i>BLH</i>	ft	Top of the atmospheric boundary layer that is well mixed and in which smoke disperses best during midday.
	<i>TWS</i>	mph	Transport wind speed as average wind speed between ground and BLH
	<i>TWD_NS</i>	-1 to 1	N-S wind component (1 is from the south)
	<i>TWD_EW_am</i>	-1 to 1	E-W wind component (1 is from the west)
	<i>TWD</i>	23-360	Transport wind direction as average wind direction between ground and BLH
	<i>VR</i>	ftmph	Ventilation Rate = BLH*TWS

Table 2: Unit-based sensitivities of PM_{2.5} to various variables. NOTE: “Number” refers to the number of cases that a particular parameter is included in a PCA run (see Table S2). Also, of the 10 data sets, PCA PM Only WD did not yield a statistically robust solution. Therefore, the maximum number of statistically significant cases is 9, 7 for AM and PM forecasts combined. *NOTE: AM and PM forecast variables entered individual PCA runs separately.

	Parameter	Units ($\mu\text{g m}^{-3}$ PM _{2.5} per unit change of parameter. Parameter units noted below)	Average Unit-based Sensitivities ($\delta_{t,k}$)	2 x St. Dev	Number of Cases
Fire Data	<i>PB</i>	acr	0.0036	0.0022	9
	<i>KBDI</i>	0-800	0.0064	0.0138	9
Observations	<i>T_avg</i>	degC	0.0233	0.0726	6
	<i>T_diff</i>	degC	-0.1559	0.2184	6
	<i>RH_avg</i>	%	0.0265	0.0166	6
	<i>RH_min</i>	%	0.0232	0.0154	6
	<i>PCP</i>	mm	0.1185	0.3307	6
	<i>VIS_min</i>	km	-0.1469	0.3604	6
	<i>WS</i>	m/s	-0.4208	1.0127	6
	<i>WD</i>	-1 to 1	-0.0081	0.0336	4
	<i>WD_NS</i>	-1 to 1	-0.4054	0.2903	3
	<i>WD_EW</i>	degN	0.5184	0.3574	2
Forecast*	<i>POP</i>	%	0.0112	0.0109	7
	<i>dayT</i>	F	0.0243	0.0148	7
	<i>diffT</i>	F	0.0373	0.2346	7
	<i>IBT</i>	F	0.0213	0.0118	7
	<i>dayRH</i>	%	0.0188	0.0259	7
	<i>HAI</i>	-	-0.4995	0.6505	7
	<i>BLH</i>	ft	-0.0001	0.0005	7
	<i>TWS</i>	mph	-0.0244	0.0706	7
	<i>TWD</i>	-1 to 1	0.0066	0.0166	4
	<i>TWD_NS</i>	-1 to 1	-0.8246	1.5063	3
	<i>TWD_EW</i>	23-360	-0.1024	1.8209	3
	<i>VR</i>	ftmph	-7.474E-06	6.62 E-06	7