

Development of a Fire Weather Index Using Meteorological Observations within the Northeast United States

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ABSTRACT

A fire weather index (FWI) is developed using wildfire occurrence data and Automated Surface Observing System weather observations within a subregion of the northeastern United States (NEUS) from 1999 to 2008. Average values of several meteorological variables, including near-surface temperature, relative humidity, dewpoint, wind speed, and cumulative daily precipitation, are compared on observed wildfire days with their climatological average ("climatology") using a bootstrap resampling approach. Average daily minimum relative humidity is significantly lower than climatology on wildfire occurrence days, and average daily maximum temperature and average daily maximum wind speed are slightly higher on wildfire occurrence days. Using the potentially important weather variables (relative humidity, temperature, and wind speed) as inputs, different formulations of a binomial logistic regression model are tested to assess the potential of these atmospheric variables for diagnosing the probability of wildfire occurrence. The FWI is defined using probabilistic output from the preferred binomial logistic regression configuration. Relative humidity and temperature are the only significant predictors in the binomial logistic regression. The binomial logistic regression model is reliable and has more probabilistic skill than climatology using an independent verification dataset. Using the binomial logistic regression output probabilities, an FWI is developed ranging from 0 (minimum potential) to 3 (high potential) and is verified independently for two separate subdomains within the NEUS. The climatology of the FWI reproduces observed fire occurrence probabilities between 1999 and 2008 over a subdomain of the NEUS.

1. Introduction

a. Background

There is no universal definition for what represents a fire weather index (FWI). This is because an FWI can be developed using many different techniques depending on its intended purpose. For fire applications on very fine temporal and spatial scales (~ 1 – 10 s and ~ 1 – 10 m) an index that includes representations of combustion and

head transport processes can be employed (Sullivan 2009). For larger spatial and temporal scales, the relevant physical processes involving fire initiation are not as well understood (Potter 2012) and indices that employ representations of physical processes are often used in conjunction with statistical methods that link meteorological conditions and fire activity. In the latter case, a proliferation of meteorological reanalysis datasets (i.e., National Centers for Environmental Prediction, North American Regional Reanalysis, and Climate Forecast System Reanalysis) and abundant access to meteorological station observations allow for the examination of statistical relationships between fire activity and meteorological conditions.

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There have been several studies focusing on the importance of meteorology to wildfire activity. [Potter \(2012\)](#) discusses how weather variables are included in fire danger and fire behavior models and in research studies to explain observed fire–atmosphere interactions across a range of temporal and spatial scales. In general, [Potter \(2012\)](#) highlights the importance of temperature, moisture (such as relative humidity, absolute humidity, vapor pressure, dewpoint, and wet-bulb temperature), and wind speed, and the interactions between these three weather elements on fire initiation and behavior.

The synoptic flow pattern is important to wildfire occurrence and behavior, so conceptual models of these large-scale conditions favoring wildfires have been developed. For instance, [Schroeder et al. \(1964\)](#) examine periods of high fire danger in 14 regions of the United States and associate those periods with synoptic weather patterns. [Newark \(1975\)](#) and [Nimchuk \(1983\)](#) identify a relationship between fire danger and the magnitude of 500-hPa geopotential height ridges over western Ontario and Alberta, respectively. [Takle et al. \(1994\)](#) use the synoptic weather classification system of [Yarnal \(1993\)](#) to identify the types of surface high and low pressure patterns associated with West Virginia wildfire events. [Barbero et al. \(2015\)](#) explore the influence of interannual, subseasonal, and synoptic weather on very large fires over the eastern United States. [Pollina et al. \(2013\)](#) present a spatial and temporal climatological description of major wildfire events within the northeastern United States (NEUS) and examine the associated meteorological conditions. In general, [Pollina et al. \(2013\)](#) find that fire occurrence along the NEUS coastal plain, which maximizes during the pre-green-up period of April–May, is most commonly associated with a surface high pressure system building into the region from Canada and a dry, northwesterly surface flow. However, wildfires can occur in this region with a surface high pressure system located almost directly over the region or to the southeast of the region.

b. Operational approaches to understand wildfire threat and meteorology

Operationally, physically based fire danger rating systems include the National Fire Danger Rating System (NFDRS; [Bradshaw et al. 1983](#)) and Canadian Forest Fire Danger Rating System (CFFDRS; [Wotton et al. 2009](#)). The NFDRS consists of several modules important to fire behavior including dead fuel moisture, live fuel moisture, fire spread, vegetation greenness, drought, terrain height, and the local meteorology. The CFFDRS is similar to the NFDRS and includes an FWI component ([Taylor and Alexander 2006](#)) that considers

the effects of fuel moisture, fire behavior, and meteorological conditions. Using these physically based indices allows for the consideration of multiple different components important to fire behavior and spread. However, the complexity of the NFDRS and CFFDRS can make it difficult to isolate cause and effect, such as the relative role of the meteorological conditions versus other parameters on fire occurrence. As a result, this motivated us to develop an index that is focused solely on the meteorological component.

Meteorology-based-only FWIs have been developed, such as the Angström index ([Langholz and Schmidtmayer 1993](#)) and the Haines index ([Haines 1988](#)). The Haines index uses lower atmospheric stability and dewpoint depression and is based on a statistical analysis of proximity soundings to 74 large wildfires within the United States over a 20-yr period. The Angström index uses temperature and relative humidity to assess the favorability of fire conditions. However, it is not clear how a specific value of the Haines or Angström index relates to fire occurrence or behavior over the NEUS.

c. Motivation

The prediction of wildfire occurrence within the NEUS is important due to the region's high population density, but this is a difficult problem given the scarcity of large wildfires and the abundance of very small wildfires in the region. Although rare, larger high-impact wildfires on Long Island, New York, include the “Sunrise Fire” in August of 1995 (<http://pb.state.ny.us/1995%20wildfire%20anniversary.html>) and the 2012 Ridge–Manorville fire. In these cases, exploring the regional relationship between the meteorology and fire occurrence is critical, since the climate within the NEUS differs from regions where wildfires are more common. This motivates the development of an FWI to be used over a subdomain of the NEUS.

Operational fire weather indices are often constructed and applied over the western United States, where wildfires are most prevalent. While more physically based fire danger rating systems (e.g., NFDRS and CFFDRS) are used operationally, a statistical weather-based FWI allows for the quantitative impact of each statistical predictor to be evaluated. Because of regional differences in meteorological conditions, a flexible approach is needed so that it can be applied to different regions in order to construct a FWI. For example, [Mondal and Sukumar \(2014\)](#) use a logistic regression model trained on early dry season rainfall, daily averaged relative humidity, and temperature to predict the probability of fire occurrence over southern India. There have been no attempts to develop an FWI specifically for the NEUS.

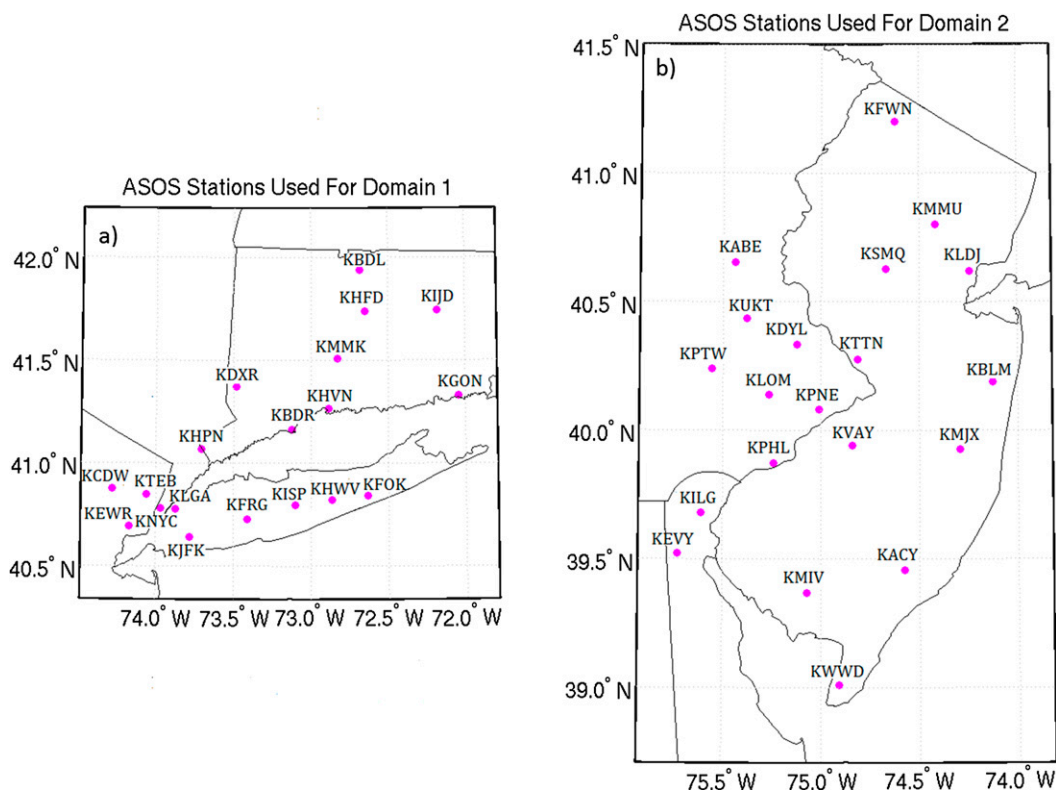


FIG. 1. ASOS stations and locations used for (a) domain 1 and (b) domain 2.

The goal of this study is to develop a meteorologically based statistical FWI for application within a subregion of the NEUS and to evaluate its skill. The FWI should be adaptable and straightforward to calculate so it can be used with different data types (i.e., point observations or gridded analyses) and incorporated into a variety of different applications (i.e., operational forecasting or conditional bias correction). This differs from other FWIs since this approach allows for the quantitative impact of each statistical predictor to be evaluated. Therefore, this study represents a statistical approach linking meteorological conditions and fire predictability within our NEUS domain. The next section describes the data and methods employed in this study, including the spatial domains used to develop and test the index. [Section 3](#) presents the results, including the characteristics of the observed wildfire climatological distribution (“climatology”), how this dataset is used differently from that in [Pollina et al. \(2013\)](#), the statistical analyses involved in developing the FWI based on Automated Surface Observing System (ASOS) station data, verification statistics that identify the most applicable and potentially informative FWI formulation, and a climatological analysis of the recommended FWI formulation.

[Section 4](#) concludes and discusses the implications of applying this FWI formulation to fire weather forecasts in the future.

2. Data and methods

a. Atmospheric variable selection

Hourly ASOS weather observations between 1999 and 2008 are compared with fire occurrence data to test different FWI configurations. Potentially important predictors of daily fire occurrence are determined by comparing the difference in near-surface weather conditions on observed wildfire days with their climatological average. Regional sensitivity to potential predictors is assessed by considering two separate domains: domain 1 (D1) includes Long Island, Connecticut, and the New York City metropolitan region, while domain 2 (D2) includes most of New Jersey, far eastern Pennsylvania, and far northeastern Delaware ([Fig. 1](#)). Domains are employed instead of single stations in order to assess the statistical probability of observed wildfire occurrence during favorable meteorological conditions. Therefore, this study assumes that fire initiations are ubiquitous and that quantifiable anomalous meteorological conditions are important predictors in their detection (in this case

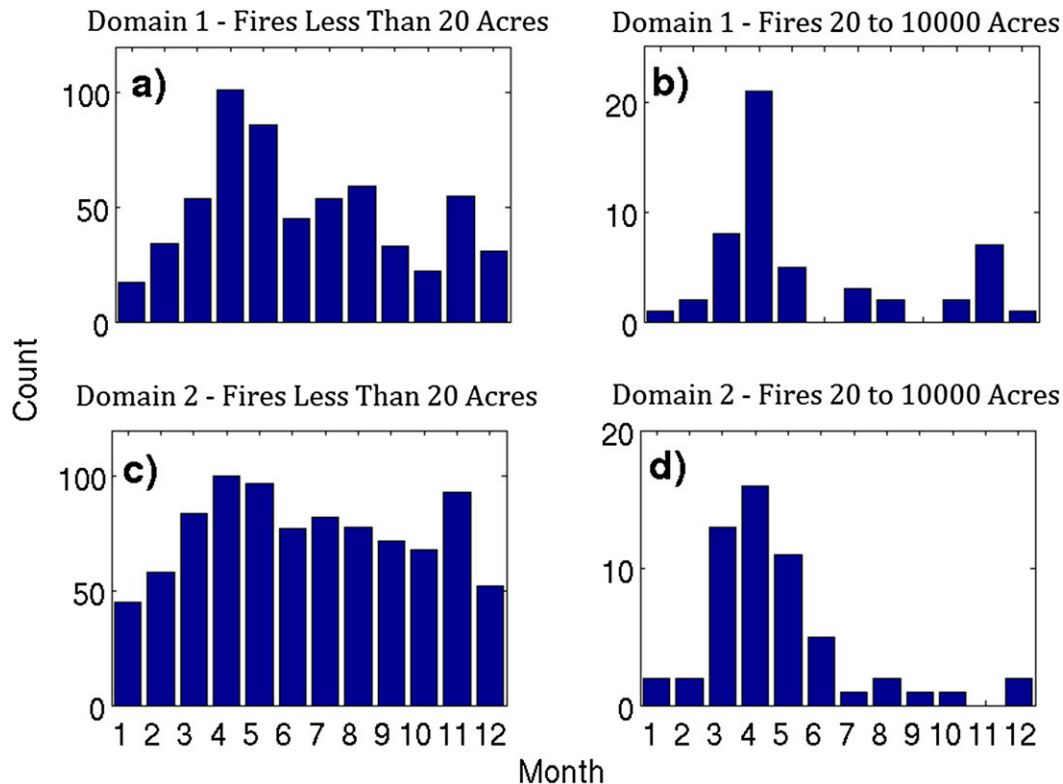


FIG. 2. Monthly frequency of observed fire size (left) <20 acres and (right) 20–10 000 acres for (a),(b) domain 1 and (c),(d) domain 2 from 1999 to 2008.

referred to as fire occurrence). The domain size encompasses both an urban population and suburban sprawl while being sufficiently small to keep daily indicators of meteorological conditions roughly homogeneous throughout the region (i.e., $\sim 30\,000\text{ km}^2$ within the NEUS).

Pollina et al. (2013) compiled the Northeast Interagency Coordination Center and the Pennsylvania Bureau of Forestry wildfire occurrence data from 1999 to 2008 to develop a NEUS climatology of wildfire events, although they only presented results for major wildfire events (i.e., wildfires that burned more than 100 acres; 1 acre $\approx 0.4\text{ ha}$). This study assesses the potential for a statistical model to predict the occurrence of all wildfire sizes within an NEUS subdomain. Therefore, the entire fire occurrence database compiled by Pollina et al. (2013) is used to quantify the effectiveness of different statistical model formulations in predicting the occurrence of small wildfires (<20 acres) and larger wildfires (20–10 000 acres).

A comparison between hourly meteorological conditions on wildfire occurrence days and the climatological average is done with the following variables: 2-m temperature (TEMP), 2-m relative humidity

(RELH), 2-m dewpoint (TMPD), 2-m specific humidity (SPHU), 2-m mixing ratio (MIXR), 10-m wind speed (WNDS), and cumulative daily precipitation (PCP). Only a single daily value for each station is used: the daily maximum value for TEMP and WNDS, and the daily minimum value for RELH and TMPD. In addition, 0–5-day lagged values of the meteorological variables are employed to assess whether days preceding the wildfire occurrence day are associated with wildfire occurrence. A single value for D1 or D2 is computed by taking the spatial median of the daily meteorological variables. The spatial mean is also tested for both D1 and D2 with similar results (not shown). In addition, the day is excluded if any station within the domain reports snow cover.

Anomalies for all variables are computed with respect to their 1) annual climatological mean with no standardization, 2) annual mean with standardization (defined as removing the mean and dividing by the standard deviation), 3) daily climatological mean with no standardization, and 4) daily mean with standardization. Note that only the anomaly is computed with PCP with no standardization. Method 2 has the largest differences between climatology and

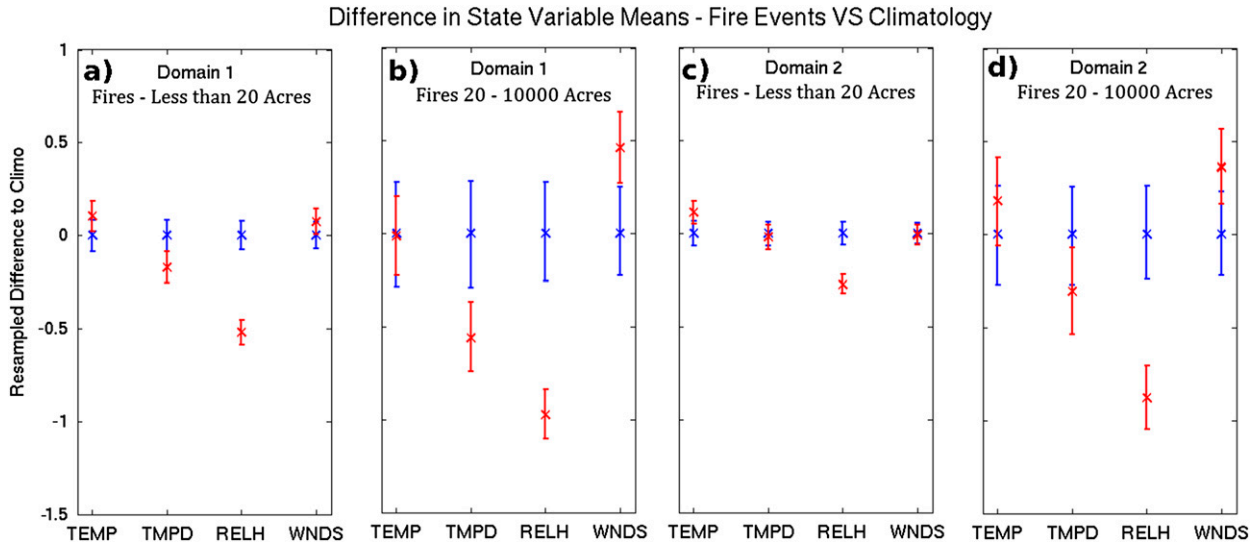


FIG. 3. Temperature (TEMP), dewpoint (TMPD), relative humidity (RELH), and wind speed (WNDS) anomalies for the climatological average (blue) and observed fire days (red) for the two domains and the two fire sizes. The tops and bottoms of the vertical lines indicate the 2.5th and 97.5th percentiles of the resampled dataset.

fire occurrence days for all variables (not shown) and is used in this study.

The statistical significance of the meteorological variable differences is assessed via bootstrapping (Wilks 2011), where both the climatology (10 yr of data) and wildfire occurrence datasets (643 days in D1 and 964 days in D2) are resampled with replacement 10 000 times. The size for each climatology or wildfire dataset is equivalent to the total number of days in the original wildfire occurrence dataset. The synoptic weather patterns controlling D1 and D2 are not likely to be independent given their spatial proximity. As a result, D1 and D2 experience 306 days where fires have been observed within both domains. In addition, multiple fires can occur on any given fire occurrence day, resulting in 1164 total fires in 643 days for D1 and 4330 fires in 964 days for D2.

b. Logistic regression model

Creating indices and warnings based on thresholds of atmospheric or other relevant variables is a common practice for fire weather [e.g., the Haines index (Haines 1988), the ventilation index (Hardy et al. 2001), and National Weather Service red-flag warnings]. However, the process of defining the thresholds is often ad hoc and poorly documented, which can contribute to subjective interpretations of what the indices mean. Using a multilinear regression with wildfire occurrence data regressed on atmospheric predictors is one methodology for documenting the index development process. However, a multilinear

regression is not necessarily appropriate for wildfire occurrence within the NEUS because the binomial distribution of daily wildfire occurrence data violates the normal distribution assumption. Furthermore, it is not obvious what useful non-probability-based output (i.e., fire size) could be generated for wildfire managers or operational forecasters by using a simple multilinear regression, since the relationship is likely to be weak.

We employ a variant of the linear regression known as a binomial logistic regression model to overcome these challenges. The binomial logistic regression model produces a probabilistic output of a binary predictand conditional on one or more predictors [Wilks 2011, his Eq. (7.29a)]. For this study, the predictand is the binary occurrence of wildfire on a given day in a region trained with near-surface weather predictors. The functional form for the logistic regression model is

$$\ln\left(\frac{p_i}{1-p_i}\right) = b_0 + b_1x_{1,i} + b_2x_{2,i} + \cdots + b_mx_{m,i}, \quad (1)$$

where p is the probability of a wildfire occurring in the domain, i is each data sample (i.e., each day), b is the regression coefficients, x is the weather predictors, and m is the number of predictors in the regression. This is similar in formulation to the logistic regression implementation in Mondal and Sukumar (2014) to predict probability of fire occurrence over southern India. Spatially averaged standardized values of the selected variables are tested in various combinations to identify

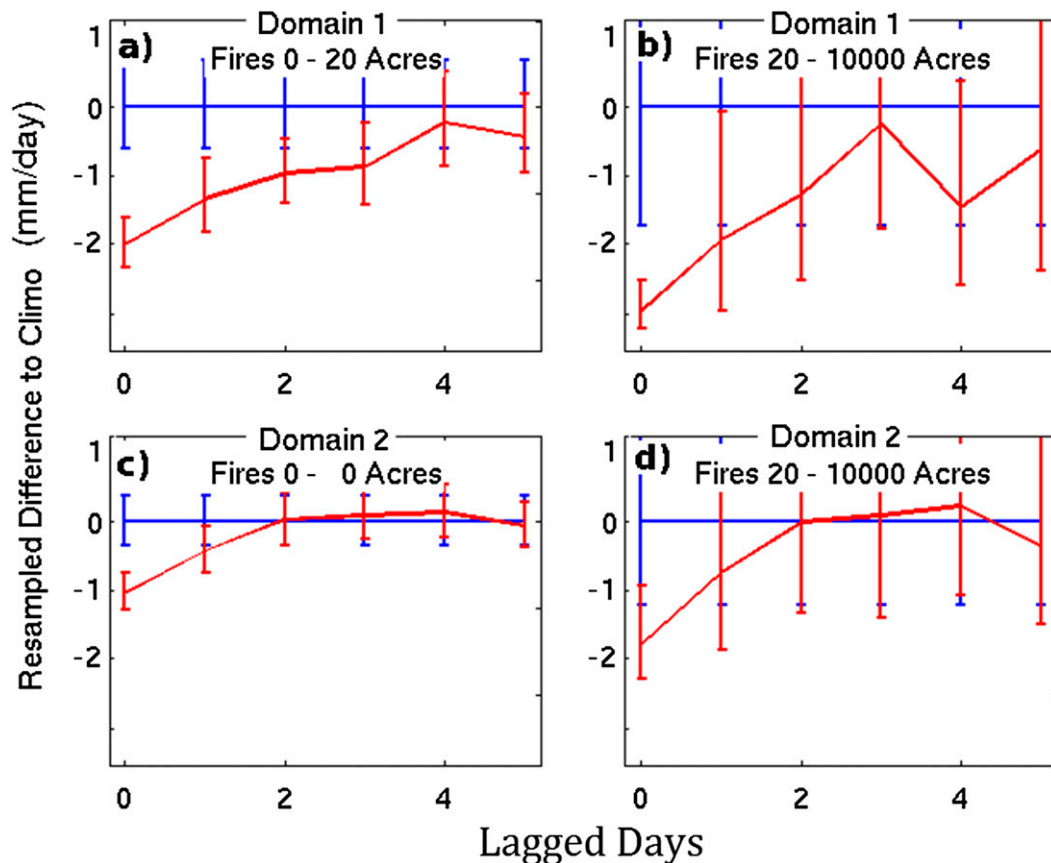


FIG. 4. As in Fig. 3, but for lagged precipitation (PCP) anomalies between 0 and 5 days.

useful predictors. Analogous to the resampling bootstrap method described in section 2a, uncertainty in the parameter estimates is determined by randomly splitting the data 10 000 times into two equally sized separate 5-yr calibration and independent verification periods. Confidence is assessed by looking at the 2.5th and 97.5th percentiles of the 10 000 resampled datasets. Once the optimal binomial logistic regression configuration is determined, the same regression is repeated using ASOS data between 1979 and 2013 to develop a climatology of the FWI.

3. Results

a. Observed wildfire weather climatology

Figure 2 shows the monthly frequency of observed wildfires from the 1999–2008 climatological dataset for small wildfires (less than 20 acres) and large wildfires (from 20 to 10 000 acres) within D1 and D2. Wildfire occurrence peaks in both D1 and D2 in April for all sizes, with a smaller secondary peak in November for D1

wildfires of all sizes and smaller D2 wildfires. The April and November peaks in wildfire occurrence are consistent with the results from Pollina et al. (2013, their Fig. 4), although their study uses a larger domain and only considers wildfire sizes greater than 100 acres. The wildfire occurrence data also suggest a stronger seasonal influence on smaller wildfire occurrence in D1 compared to D2, as indicated by the greater abundance of smaller wildfires occurring for any given month within D2.

b. Identifying relevant atmospheric variables

Anomalies with confidence intervals from the 1979–2013 surface TEMP, TMPD, RELH, and WND are shown for the climatological average (blue) and for wildfire occurrence days (red) for small and larger wildfires in the two domains (Fig. 3). RELH is significantly different than climatology (defined as the 2.5th and 97.5th percentiles of the resampled confidence intervals not overlapping) on wildfire occurrence days for D1 small wildfires [-0.53 standard deviations (SD); $>99.9\%$ confidence], D1 large wildfires

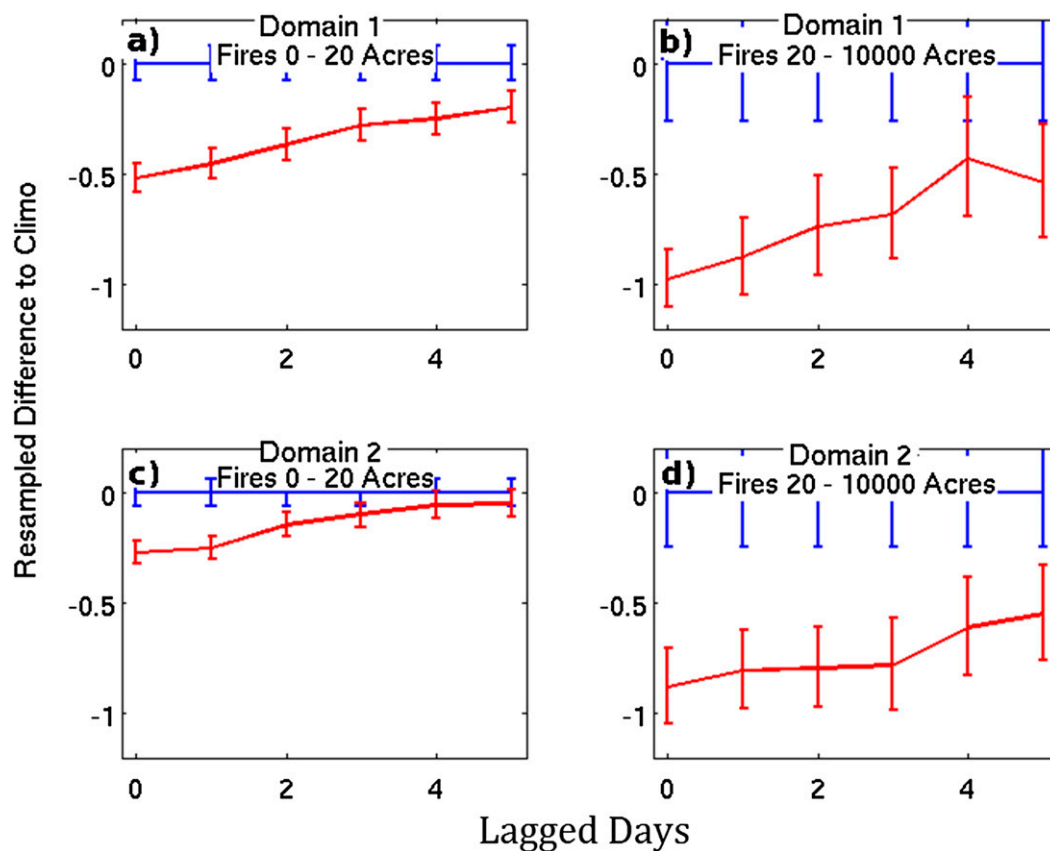


FIG. 5. As in Fig. 4, but for lagged relative humidity anomalies.

(-1.00 SD; $>99.9\%$ confidence), D2 small wildfires (-0.28 SD; $>99.9\%$ confidence), and D2 large wildfires (-0.88 SD; $>99.9\%$ confidence). TMPD differences are also statistically significant for D1 small wildfires (-0.18 K SD; $>95\%$ confidence) and large wildfires (-0.55 K SD; $>99\%$ confidence). Although not statistically significant, TEMP is slightly warmer for D1 small wildfires (0.10 K SD), D2 small wildfires (0.11 K SD), and D2 large wildfires (0.18 K SD). There is also a statistically significant WNDs difference on days with larger wildfires for D1 (0.44 m s^{-1} SD; $>95\%$ confidence) but not D2 (0.35 m s^{-1} SD). SPHU and MIXR are not significant for any domain or fire size (not shown) and are not analyzed further in this study.

These results suggest that surface RELH and TMPD are the most important meteorological predictors for wildfire occurrence days within the NEUS subdomain, while surface TEMP might help distinguish wildfire occurrence days in some cases, and WNDs might distinguish wildfire occurrence days for larger wildfires. The clear separation in RELH between fire occurrence days and climatology is consistent with the results of Simard

et al. (1987), who noted that RELH was the best discriminator in statistical tests for extreme fire environments within the NEUS.

Figure 4 shows the average 0–5-day lagged PCP anomalies with respect to the climatological average on wildfire occurrence days for D1 and D2. Day-0 lagged PCP is significantly different than climatology at the 95% confidence level on wildfire occurrence days for D1 small wildfires (-2.0 mm day^{-1} ; $>99.9\%$ confidence), D1 large wildfires (-3.0 mm day^{-1} ; $>99\%$ confidence), and D2 small wildfires (-1.0 mm day^{-1} ; $>99\%$ confidence), but not for D2 large wildfires (-1.8 mm day^{-1}). There are no statistically significant differences in lagged PCP between one and five days except for day-1 lagged average PCP for small wildfires in D1 (-1.4 mm day^{-1} ; $>95\%$ confidence).

Similar to Fig. 4, 5-day lagged RELH anomalies are shown for D1 and D2 small and large fires (Fig. 5). D1 exhibits statistically significant ($>95\%$ confidence) negative RELH anomalies for small and large fires up to 5 days before the fire occurrence, except for 4-day lagged large fires. Similarly, D2 exhibits statistically

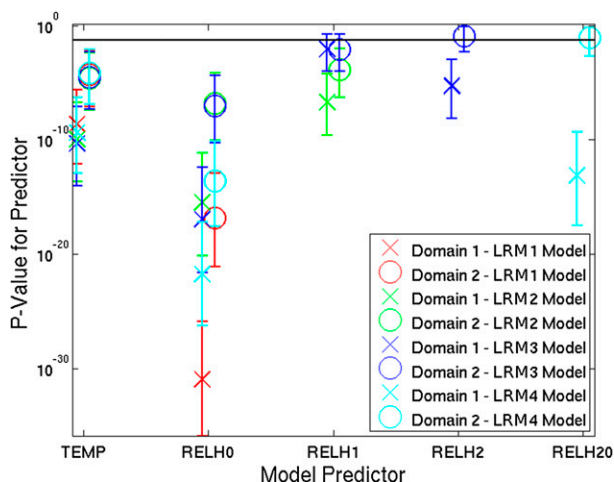


FIG. 6. The D1 and D2 p values (significance values) for the predictors in each logistic regression model formulation (LRM1—red; LRM2—green; LRM3—blue; LRM4—cyan). Values below the black horizontal line are significant at $>95\%$ confidence.

significant negative RELH anomalies except for small fires at greater than a 3-day lag. As a result, D2 small fires may be less sensitive to unlagged RELH than D1 small fires. Furthermore, the D2 day-5 lagged RELH anomaly for large fires is significantly more negative than the day-0 RELH anomaly for D2 small fires. This suggests that prolonged RELH anomalies or possibly drought indices could be used to predict fire size.

c. Evaluating logistic regression model formulations

For this study, predictors are used that were determined from section 2b to be potentially important and therefore likely to improve the statistical model skill. Since the differences between the climatological average and fire occurrence days are most robust with RELH, lagged combinations of RELH are also tested as potential predictors in the binomial logistic regression model. These additional predictors include 1-day lagged RELH (RELH1), 2-day lagged RELH (RELH2), and the 20-day averaged anomaly of lagged RELH (RELH20). The results for WNDS and TMPD are never significant in terms of the p value from the logistic regression model parameter estimate (not shown) and are not mentioned further in this study. The following logistic regression model predictor configurations are presented:

- 1) Logistic regression model 1 (LRM1) consists of two predictors—TEMP and RELH0.
- 2) Logistic regression model 2 (LRM2) consists of three predictors—TEMP, RELH0, and RELH1.

- 3) Logistic regression model 3 (LRM3) consists of four predictors—TEMP, RELH0, RELH1, and RELH2.
- 4) Logistic regression model 4 (LRM4) consists of three predictors—TEMP, RELH0, and RELH20.

To evaluate the contribution of each predictor to the logistic regression model, the significance values (p values) of b_0 and the predictor coefficients are shown for each logistic regression model formulation in the calibration period (Fig. 6). The error bars represent the 2.5th and 97.5th percentiles of the resampled parameter estimates in the calibration period's LRM1 (red), LRM2 (green), LRM3 (blue), and LRM4 (cyan) model for D1 (times signs) and D2 (open circles). Parameter estimates below the p value of 0.05 (solid black line) are statistically significant at greater than 95% confidence. For all logistic regression model formulations, TEMP and RELH0 are significant, suggesting that they would likely add skill in the verification period. RELH1 is also significant for LRM2 but not LRM3, which is an indication that including too many parameters results in overfitting for both domains. Otherwise, all logistic regression model formulations have statistically significant p values for D1. D2 parameter estimates are in all cases less significant than D1 (although most are still statistically significant), suggesting that wildfire occurrence in D2 might be less dependent upon overlying atmospheric conditions than wildfire occurrence in D1.

To test whether these results are affected by the inclusion of small wildfires in the wildfire occurrence database, LRM1 through LRM4 are repeated using different minimum wildfire size thresholds (Fig. 7). The p values associated with TEMP, RELH0, and RELH1 generally increase (i.e., become less significant) as more of the smallest fires in the database are excluded, although RELH0 remains significant for all domains and all wildfire sizes. An exception to the trend of decreasing significance occurs with the RELH0 and RELH20 predictors in D2, where parameter estimates become more statistically significant after eliminating fire sizes of less than one acre. This supports the above assertion that the occurrence of very small wildfires in D2 may not strongly depend upon overlying atmospheric conditions. However, most parameter estimates are statistically significant for all fire sizes, suggesting that meteorological conditions are a factor in the occurrence of most small and large fires within D1 and D2.

Before determining the best logistic regression model from which to develop an FWI, it is critical to analyze the performance of LRM1 through LRM4 in a randomly sampled independent verification period. This is accomplished by comparing the Brier skill scores [BSS; Wilks 2011, his Eq. (8.37)] of each logistic regression

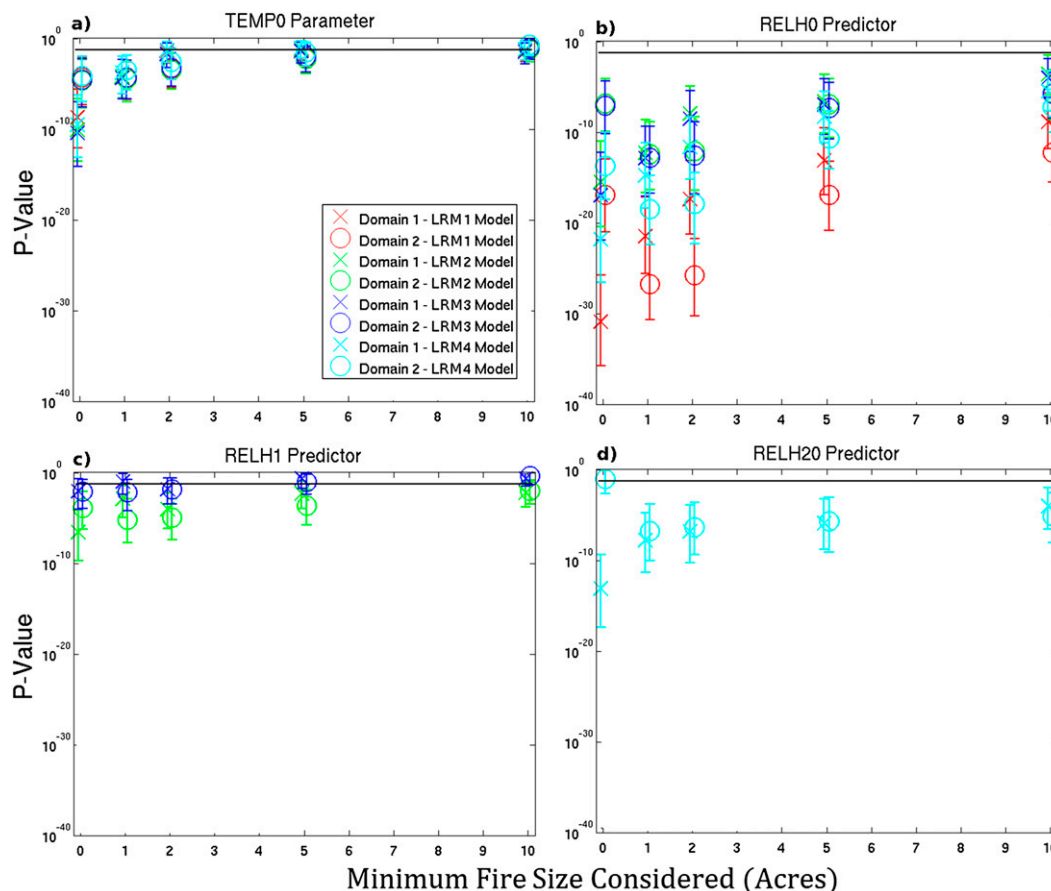


FIG. 7. Calibration-period p values in LRM 1–4 models by predictions using different minimum fire size thresholds (acres) for (a) TEMP, (b) RELH0, (c) RELH1, and (d) RELH20. Values below the black horizontal line are significant at $>95\%$ confidence.

model with climatology. In this case, climatology is defined as the twice-smoothed 30-day running mean probability of wildfire occurrence derived from the raw 10-yr climatology. This methodology gives the climatology an advantage over the model, since the climatology is computed from the full 10-yr dataset while the logistic regression model is only calibrated with 5 yr of randomly resampled data and verified with the remaining 5 yr as described in the resampling description of section 2b. The BSS of all the logistic regression models referenced against climatology are significantly greater than zero (Fig. 8), suggesting that each model formulation provides better probabilistic skill than climatology. Interestingly, even if the logistic regression model is calibrated using the wildfire climatology of a different domain, the model is still more skillful than climatology. The more complex logistic regression model formulations of LRM2–LRM4 provide more probabilistic skill than LRM1 in D1, although the differences are not statistically significant. Interestingly,

D2 does not benefit from a more complex model. The differences between models are not statistically significant; therefore, LRM1 is selected for developing an FWI since it represents the simplest formulation.

d. Verification and definition of the FWI

Before defining the FWI from the LRM1 model results, it is important to explore the LRM1 phase space and verify its ability to predict wildfire occurrence. Figure 9 shows the relationship between LRM1 fire occurrence probabilities and the size/occurrence of observed wildfires for D1 and D2. Observed wildfires for D1 and D2 tend to fall on days with lower RELH and, to a lesser extent, higher TEMP. Since there is no visible relationship between wildfire size and the fire occurrence probabilities, the FWI should be expected to predict wildfire occurrence, not wildfire size.

An important characteristic of any probabilistic model is reliability, which describes the relationship between specific values of the forecast and the average

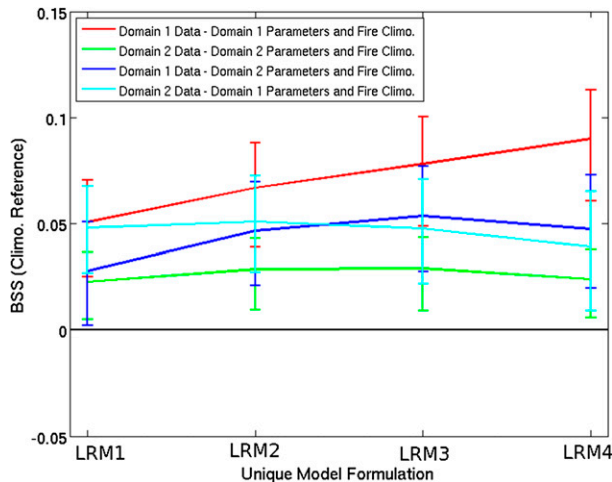


FIG. 8. Independent logistic regression model Brier skill score for LRM 1–4 models compared with climatology for D1 data calibrated with D1 parameters (red), D2 data calibrated with D2 parameters (green), D1 data calibrated with D2 parameters (blue), and D2 data calibrated with D1 parameters (cyan). Vertical bars denote 95% confidence intervals.

observation (Wilks 2011). A common methodology to display reliability is by comparing averaged model forecast probability against averaged observed relative frequency (i.e., what is actually observed) by threshold. Figure 10 shows the reliability of LRM1, where the forecasted probability of fire occurrence is binned into increments of 10% and compared to the observed relative frequency. Therefore, if the forecasted fire probability matches the observed relative frequency, the probabilities would fall perfectly on the 1:1 line and the forecast would be considered reliable on the average.

The ability of LRM1 to predict wildfire occurrence does not strongly depend upon the domain or the choice of parameter (Fig. 10), which is consistent with the BSS analysis in Fig. 8. For higher thresholds of probability, LRM1 reliability is above the 1:1 line, indicating underprediction of wildfire occurrence, although the sample sizes associated with probabilities greater than 50% are limited to 50 cases or less. These results support the conclusion that LRM1 produces a known quantitative output (i.e., probability of wildfire occurrence within a specified domain) that is on the average reliable (Fig. 10) and has greater skill than climatology (Fig. 8).

To convert the probabilistic output of the LRM1 model into an FWI, we define four potential FWI values that are categorized as 0, 1, 2, or 3. An FWI of 0 corresponds to LRM1 probabilities below 30%, 1 is between 30% and 40%, 2 is between 40% and 50%, and 3 is greater than 50%. For D1 (D2) an FWI of greater than 0, 1, or 2 consists of 10%, 4.3%, or 1.4% (26.6%, 8.4%, or 0.4%) of the total days, respectively. These thresholds are chosen based on their frequency of occurrence and their easily remembered relationship to fire occurrence within each domain. Although the difference between a 30% and 50% chance of fire occurrence may seem minor, the anthropogenic nature of fire occurrence indicates a 50% prediction to be very anomalous. Therefore, the FWI categorizes minimal, low, moderate, and high potential for wildfire occurrence as the index increases from 0 to 3, respectively.

Both the logistic regression model and climatological probabilities are converted to index values as described above to evaluate the benefit of the model using the resampled verification period. The results are presented in the form of the critical success index (CSI; Fig. 11a),

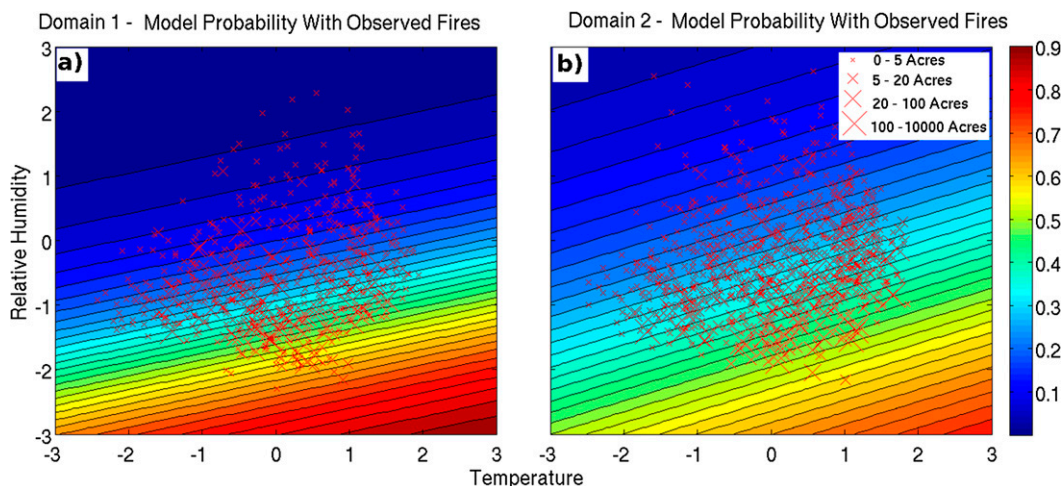


FIG. 9. LRM1 model probability of fire occurrence (color contoured) in model phase space and location of actual fire occurrence (symbols) for (a) domain 1 and (b) domain 2.

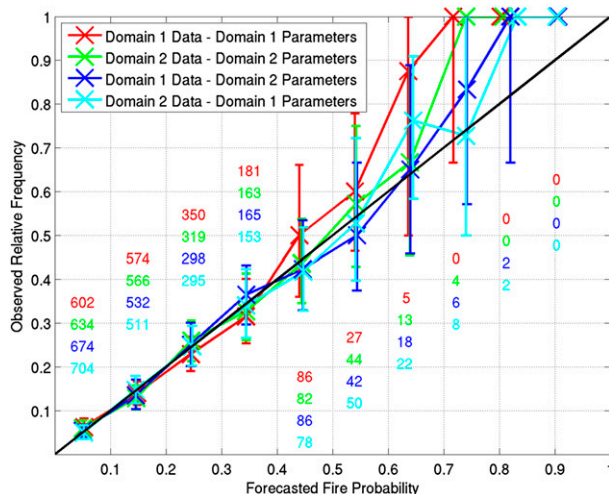


FIG. 10. LRM1 independent reliability for D1 trained with D1 parameters (red), D2 trained with D2 parameters (green), D1 trained with D2 parameters (blue), and D2 trained with D1 parameters (cyan). The numbers are the sample size for each probability bin. Error bars denote 95% confidence intervals.

false-alarm ratio (FAR; Fig. 11b) and hit rate (HIT; Fig. 11c). The climatological FWI (dashed) never produces a category greater than 1, and thus only the logistic regression model FWI produces moderate and high categories. When the FWI is 1, the logistic regression model produces better CSI and HIT and comparable FAR relative to climatology. It is not surprising that the FAR is high since almost all wildfires within the NEUS have anthropogenic sources (Northeast States Emergency Consortium 2014). For instance, on average a high FAR would arise even with a high FWI, since the anthropogenic component is not considered in the binomial logistic regression.

Figure 12 shows the relationship between FWI value and observed wildfire size and probability. For D1 and D2, both observed wildfire size and wildfire probability

increase steadily with increasing FWI with statistically significant differences for D1 (41.65%; >99% confidence) and D2 (59.4%; >99% confidence) wildfire probability between an FWI of 1 and 3. However, all changes in wildfire size with FWI are not statistically significant, emphasizing that the FWI should not be expected to predict wildfire size.

e. FWI climatology

Thus far, this study has split all LRM models into separate calibration and verification periods using a resampling technique. Since the FWI has been extensively verified, the entire 10 years of wildfire climatology (1999–2008) are used as calibration to obtain more precise parameter estimates. These parameter estimates can be used operationally in atmospheric models in a predictive sense or with historical observations to develop a climatology of wildfire potential. In this case, the latter option is chosen by using the 10-yr regressed parameter estimates on ASOS observations between 1979 and 2013.

Figure 13 shows the 1979–2013 FWI climatology using the parameters from the 1999–2008 training period stacked by FWI value for D1 and D2. The results are qualitatively similar to Fig. 2 with D2 exhibiting weaker seasonal variations and a greater number of FWI days than D1. For instance, 70.2% (56.3%) of all moderate to high FWI days occur between March and April within D1 (D2). Furthermore, FWI value has considerable variability by year (33–104 events for D1; 81–169 events for D2) for both domains (Fig. 14).

4. Discussion and conclusions

This study documents a methodology for developing a fire weather index within a smaller region of the northeast United States that predicts the probability of

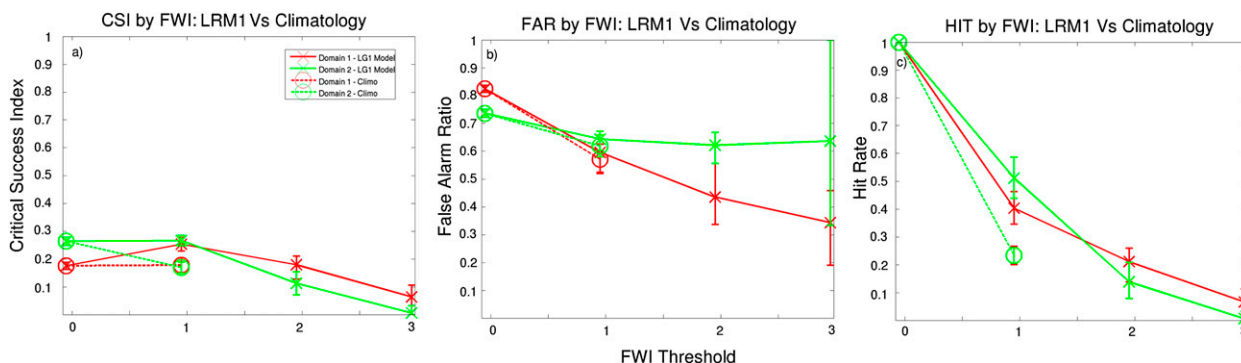


FIG. 11. Independently verified (a) CSI, (b) FAR, and (c) HIT by FWI value for domain 1 (red) and domain 2 (green) using the logistic regression model (solid) and climatology (dashed). Error bars denote 95% confidence intervals.

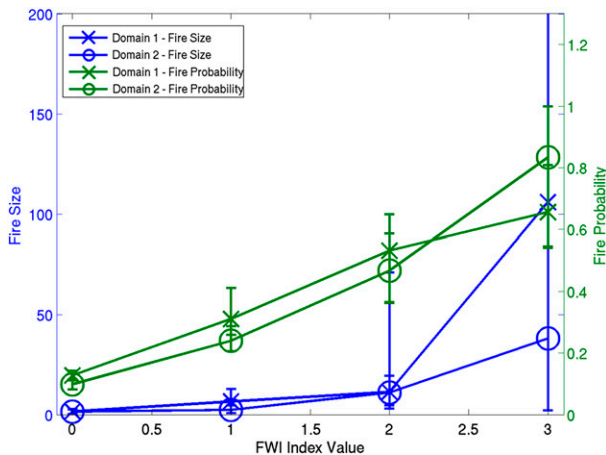


FIG. 12. Average fire size (blue) and probability (green) by FWI value for the two domains. Error bars denote 95% confidence intervals.

wildfire occurrence using only atmospheric variables. The FWI is based on a statistical model and designed to be adaptable for a variety of research, climatological, or operational uses. It is developed using atmospheric Automated Surface Observing System observations and observed wildfire occurrence days (Pollina et al. 2013) from 1999 to 2008 for two separate domains (D1 and D2).

Important weather variables for wildfires are identified by analyzing differences in weather conditions on wildfire occurrence days from the climatological average using a number of 2-m thermodynamic (TEMP, SPHU, RELH, TMPD, and MIXR; all variables are defined in section 2a) and kinematic (WNDS) variables, as well as daily accumulated precipitation (PCP). RELH (and by association TMPD) is found to be significantly lower on wildfire occurrence days. Wildfire occurrence days are generally slightly warmer and for larger wildfires (from 20 to 10 000 acres) slightly windier than climatology, although only the D1 result is statistically significant for WNDS. This suggests that TEMP and WNDS might have secondary importance in the development of wildfires within the NEUS. In addition, unlagged PCP is significantly lower on wildfire days, but this significance decays within two days of the fire event occurring.

Potentially important weather variables are tested in a binomial logistic regression model by splitting the data into separate calibration and verification periods 10 000 times via a resampling method. RELH and TEMP yield the most consistent improvement in model performance within the verification period, although including lagged RELH did improve model performance for D1. This

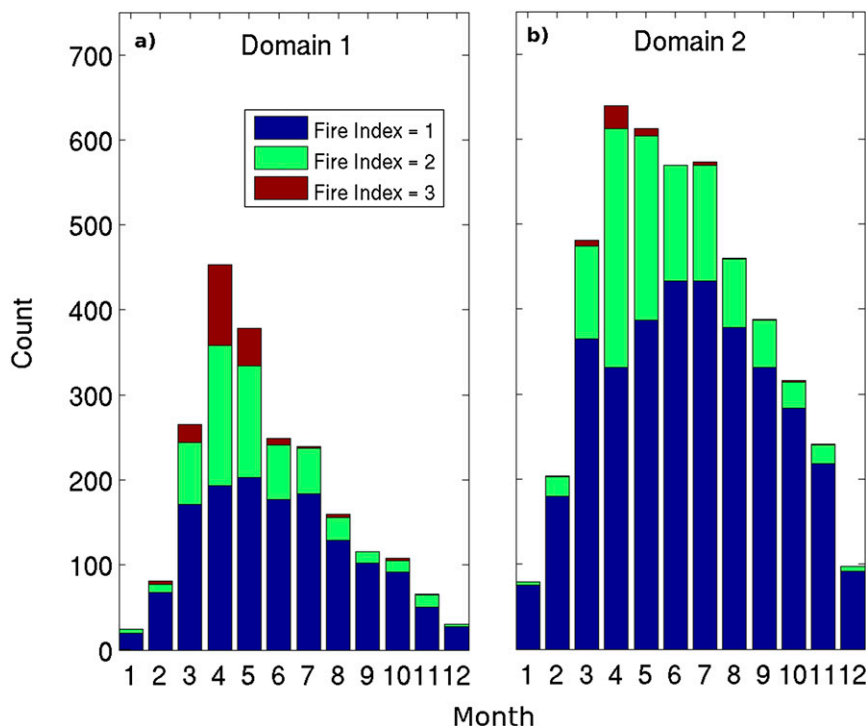


FIG. 13. Monthly FWI by index value derived from LRM1 between 1979 and 2013 for (a) domain 1 and (b) domain 2.

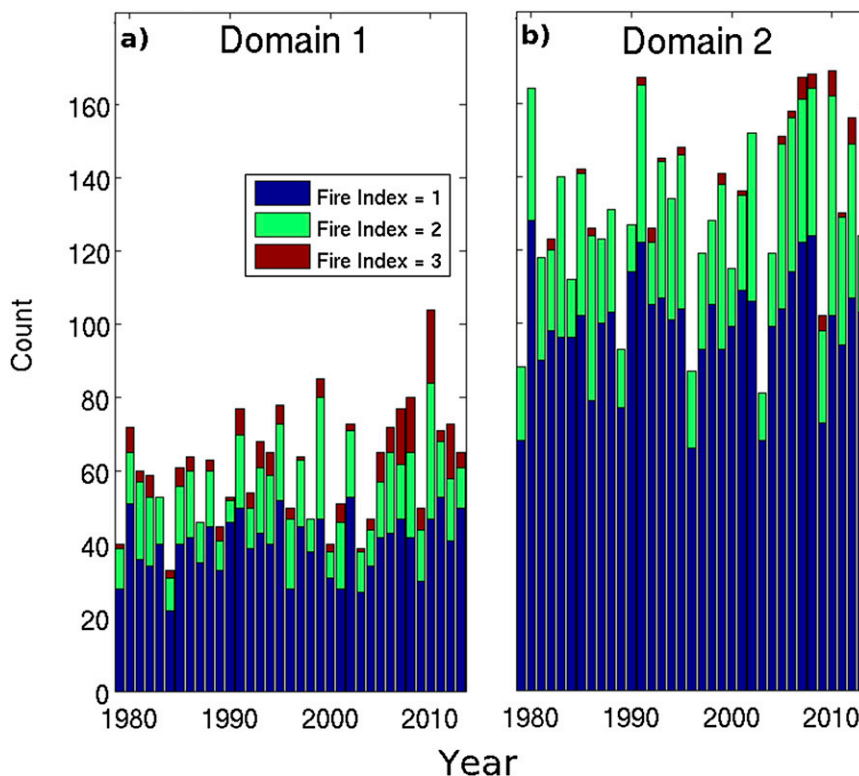


FIG. 14. As in Fig. 13, but for annual FWI frequency.

suggests that the model could potentially be improved by including a longer term slowly changing metric such as the Palmer modified drought index (Heddinghaus and Sabol 1991). For instance, Barbero et al. (2015) show that coincident long- and short-term weather variability are critical to the development of very large fires in the eastern United States, suggesting that additional parameters could be added to enhance both probability of fire occurrence and fire size.

Independent reliability plots indicate that the logistic regression model produces accurate probabilistic forecasts of wildfire occurrence, even when the model is calibrated using a different domain. In addition, the logistic regression model produces sharper and more skillful forecasts than climatology on the average. The logistic regression model output is converted to a useable index based on probability thresholds. Probabilities below 30% are given an index of 0 (i.e., minimal wildfire potential), probabilities between 30% and 40% are assigned a value of 1 (i.e., low wildfire potential), probabilities between 40% and 50% are assigned a value of 2 (i.e., moderate wildfire potential), and probabilities greater than 50% are given a value of 3 (i.e., high wildfire potential). Therefore, each category of the FWI has a useful probabilistic meaning that has been

verified using independent wildfire data for two separate domains.

As designed, applying the logistic regression model to additional data is simple and straightforward. Since the parameter estimates are generally spatially and temporally consistent within the region studied, only the standardized temperature and relative humidity for that location are needed. The model's output contains the probability of wildfire occurrence within the domain selected. For this study, the FWI is used on ASOS observation between 1979 and 2013 to develop a climatology of wildfire potential. This wildfire potential climatology is similar to the climatology of observed wildfires, with a noticeable peak in April for both domains, and a much smaller November peak. The FWI also captures the increased potential for wildfires in D2 and the weaker seasonality of wildfire occurrence in that region relative to D1.

The FWI is designed with readily available weather predictors and can be used for a variety of operational and research based applications on fire weather days (FWDs). For instance, the majority of model verification and postprocessing studies do not focus on model bias related to the synoptic flow pattern. If model biases on FWDs are different than the climatological average,

then proper bias correction of FWDs is essential when using model data to make fire forecasts.

Future work will adapt this index onto gridded re-analysis and ensemble forecast models. The purpose of this adaption is twofold: 1) An FWI can be used to create operational forecasts of weather-based wildfire potential and 2) an FWI can be used to explore and correct model biases specific to weather-based wildfire potential days. In addition, future work will focus on adapting the FWI to consider the state of dry fuels and short- and long-term drought.

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