Lindley, T. T., A. B. Zwink, R. R. Barnes, G. P. Murdoch, B. C. Ancell, P. C. Burke, and P. S. Skinner, 2023: Preliminary use of convection-allowing models in fire weather. *J. Operational Meteor.*, **11** (6), 72–81, doi: https://doi.org/10.15191/nwajom.2023.1106.

*Journal of Operational Meteorology*
**Short Contribution**

# Preliminary Use of Convection-allowing Models in Fire Weather

*T. TODD LINDLEY, ALEXANDER B. ZWINK, AND RYAN R. BARNES*
*NOAA/National Weather Service, Norman, Oklahoma*

*GREGORY P. MURDOCH*
*NOAA/National Weather Service, Midland, Texas (retired)*

*BRIAN C. ANCELL*
*Texas Tech University, Lubbock, Texas*

*PATRICK C. BURKE*
*NOAA/OAR/National Severe Storms Laboratory, Norman, Oklahoma*

*PATRICK S. SKINNER*
*Cooperative Institute for Severe and High-Impact Weather Research and Operations, University of Oklahoma, Norman, Oklahoma and NOAA/OAR/National Severe Storms Laboratory, Norman, Oklahoma*

(Manuscript received 11 August 2022; review completed 16 February 2023)

## ABSTRACT

**Multiple high-impact wildfire episodes on the southern Great Plains in 2021/22 provided unique opportunities to demonstrate the emerging utility of Convection-allowing Models (CAMs) in fire-weather forecasting. This short contribution article will present preliminary analyses of the deterministic Texas Tech Real Time Weather Prediction System's Red Flag Threat Index (RFTI) compared to wildfire activity observed via the *Geostationary Operational Environmental Satellite-16* during four southern Great Plains wildfire outbreaks. Visual side-by-side comparisons of model-predicted RFTI and satellite-detected wildfires will be shown in static and animated displays that demonstrate the model's prognostic signal in depicting fire-outbreak evolution. The data analyses are supplemented with preliminary information from state forestry agencies that provide context to predicted RFTI relative to size-based categorization of observed wildfires and human casualties. In addition, use of the National Severe Storm Laboratory's Warn-on-Forecast System to provide short-term updates on the evolution of fire-effective atmospheric features that promote new fire ignition, problematic spread, and extreme fire behavior is also demonstrated. The examples presented here suggest that CAMs serve an important role in the mesoscale prediction of dangerous wildfire conditions. With this novel use of CAMs in fire meteorology, the authors advocate for expanded availability of fire weather-specific fields and parameters in high-resolution numerical weather prediction systems that would improve wildfire forecasts and associated impact-based decision support.**

## 1. Introduction

Wildland fire is affected by both the biosphere and atmosphere (Pyne 2021). Although the context of fire is dependent upon the character of available combustible vegetative fuels, an ignition's propensity to propagate and spread is mostly a consequence of short-term weather (Pyne 2004). Thus, it is expected that meteorological influences on the fire environment are reflected in numerical weather prediction (NWP). In fact, short-term high-resolution meteorological model systems, particularly the High-Resolution Rapid Refresh (HRRR) model, have shown skill in predicting weather conditions associated with high-impact wildfire episodes (Nauslar et al. 2018, Mass and Ovens 2021). Yet, real-time operational use of Convection-allowing Models (CAMs, ≤4 km grid spacing) in fire prediction remains challenging in practice, largely because few CAMs output fire weather-specific fields and parameters.

This short contribution article provides preliminary observations and analyses of the Texas Tech Real Time Weather Prediction System's Weather Research and Forecasting Model (TTU WRF, Texas Tech

*Corresponding author address*: T. Todd Lindley, 120 David L. Boren Blvd., Norman, OK 73072
E-mail: todd.lindley@noaa.gov

Atmospheric Science Department 2022) deterministic Red Flag Threat Index (RFTI, Murdoch et al. 2012) relative to wildfire activity detected via *Geostationary Operational Environmental Satellite-16 (GOES-16)* shortwave infrared (SWIR) imagery. Both static and animated side-by-side comparative displays of TTU WRF RFTI and corresponding *GOES-16* satellite-detected fire hot spots are shown for four southern Great Plains wildfire outbreaks (SGPWOs, Lindley et al. 2014) that occurred between December 2021 and March 2022. These primarily visual-based comparisons demonstrate how CAM predictions of RFTI identified the general time frame and geographic location of greatest wildfire occurrence. In addition, the percentage of outbreak fires meeting defined size-based categorizations, including those that resulted in human casualties, is found for varying magnitudes of model-derived RFTI. To further demonstrate the use of CAMs in wildland fire decision support, particularly CAMs that feature rapidly cycled data assimilation, we document real-time use of the National Severe Storm Laboratory's (NSSL) Warn-on-Forecast System (WoFS; Stensrud et al. 2009, 2013, Wheatley et al. 2015, Jones et al. 2016, and Heinselman, P., and Co-authors, 2023: Warn-on-Forecast: From Vision to Reality. Wea. Forecasting, in preparation) during a subsequent 22 April 2022 SGPWO. During this event, high spatial and temporal resolution WoFS-derived projections of 500-hPa wind speed and 2-m temperature were used in short-term diagnosis and prediction of a fire-effective low-level thermal ridge (LLTR, Lindley et al. 2017), an atmospheric feature that promotes momentum transfer of strong winds aloft into a narrow zone of anomalously warm near-surface air and exacerbates wildfire ignition, spread, and behavior on the southern Great Plains. WoFS guidance relevant to the LLTR and ensemble wind gust products were used to communicate the likelihood of new problematic fire occurrence and of >26 m $s^{-1}$ (50 kt) gusts at ongoing wildfires within an interagency wildfire decision support forum. Discussion will advocate for the proliferated use of CAMs in mesoscale predictions of the fire environment and further adoption of fire weather-specific fields and parameters in such NWP systems, including ensembles.

## 2. Data and analysis

### a. *TTU WRF*

RFTI (Murdoch et al. 2012) uses quartile analyses of observed 2-m relative humidity (RH) and 6-m wind speed (WS) in excess of local red flag warning (RFW) criteria over a 10-year period to quantify the criticality of fire weather at a given site (Appendix A). The index was developed and initially employed using 2000–2009 observational data but was updated in operations for many locals in 2019. RFTI is scored 1–10 when either RH or WS exceed locally defined critical RFW thresholds. Values of 1–2 are defined as "elevated," 3–4 as "critical-low" or "near-critical" (the former adjective description was defined in literature; the latter is used in operations), 5–6 as "critical-high" or "critical," 7–8 as "extremely critical," and 9–10 as "historically critical." TTU WRF-derived RFTI was first implemented in 2015 and was previously noted in literature with respect to weather associated with megafires (≥404.7 $km^2$) on the southern Great Plains (Lindley et al. 2019). Subsequent efforts to expand the domain of TTU WRF RFTI output have occurred; however, the derived RFTI domain remains geographically limited compared to the TTU WRF model domain because of the index's dependence on analyses of observed RH and WS relative to local RFW criteria. RFTI quartile thresholds have been coordinated with National Weather Service (NWS) Weather Forecast Offices (WFOs) for many established climate/Automated Surface Observation System sites across the TTU WRF RFTI domain. Local RFW criteria, upon which the RFTI quartile scoring regime is based, varies dramatically across the country and even across WFO jurisdictions (Kimutis et al. 2018, Jakober 2023). It is not within the scope of this study to detail specific RFW criteria across the TTU WRF RFTI domain, but the basis of criterion across the region is generally RH ≤15–20% and WS ≥9 m $s^{-1}$ (17 kt). Although this paper focuses specifically on TTU WRF RFTI output in relation to observed wildfires, and not a detailed accounting of localized RFW thresholds, the authors note that RFTI's quartile analyses and two-valued range categorization helps to minimize spatial discontinuities in the output associated with discrepancies in RFW criteria across geographic boundaries. Such changes in local RH and WS thresholds can still result in unnatural RFTI gradients. RFTI, however, has been shown to be climatologically relevant to local wildland fire potential.

RFTI output is currently limited to the TTU WRF deterministic system (single-model member), which utilizes the WRF-ARW Version 3.5.1 (Skamarock et al. 2008) to create forecasts on a nested 3-km grid with 38 vertical levels over Texas, Oklahoma, Kansas, and portions of the surrounding states. The 3-km grid receives its initial and lateral boundary conditions from the Global Forecast System, and a spin-up process occurs in the first hours of the WRF forecasts to achieve high-resolution structure. Forecasts are run out to a 60-h forecast time from four initializations daily at 0000, 0600, 1200, and 1800 UTC using the NOAH land surface model (Chen and Dudhia 2001), Thompson microphysics (Thompson et al. 2004), the Yonsei University planetary boundary layer scheme (Hong 2010), and the Dudhia (1989) shortwave radiation and Rapid Radiative Transfer Model longwave radiation (Mlawer et al. 1997) schemes. No cumulus parameterization is used on the 3-km domain as it is considered convection-permitting.

The unusual frequency of high-impact wildfire episodes within the TTU WRF's RFTI domain in 2021/22 provided the unique opportunity to document spatiotemporal comparisons of this output to *GOES-16*-depicted wildfires during multiple SGPWOs in a single fire season characterized by a geographically consistent vegetative fuel environment. Analyses will focus upon four SGPWOs that occurred on 15 December 2021, 5 March 2022, 17 March 2022, and 29 March 2022. The NSSL WoFS will be used in an additional case example from the 22 April 2022 SGPWO (Table 1).

Hourly RFTI output is available in the TTU WRF from the initialization time to 60 h. For the purpose of these analyses, the 1200 UTC initialized TTU WRF RFTI is shown for a valid time of 21/2200 UTC (time shown is dependent upon the *GOES-16* observed peak burning) on the day of each respective wildfire episode in Fig. 1 (a, d, g, j). Corresponding *GOES-16* SWIR channel 7, centered near 3.9 µm, which is sensitive to subpixel heat and useful in wildland fire detection and monitoring (Dozier 1981, Weaver et al. 1995, Weaver et al. 2004), is shown to illustrate ongoing wildfire activity at approximately the same time (Fig. 1 panels b, e, h, and k). Lastly, all satellite-detected fires that occurred during the SGPWO episodes are mapped and categorized (Table 2) by burn size (National Wildfire Coordinating Group, cited 2022) based upon preliminary reports by state forestry agencies and a generalized spectrum of plains wildland fire types defined in a body of work by Lindley et al. 2015, 2018, and 2019. These summaries provide context to the cumulative magnitude and geographic scope of fire activity during each SGPWO (Fig. 1 panels c, f, i, and l) and provide the basis for rudimentary statistical analysis.

Preliminary visual comparisons of the data show that TTU WRF RFTI values corresponded in space and time to the occurrence of observed wildfires (n=138, Table 3). Nearly all (99%) initial attack fires (0–1.2 km²) were associated with TTU WRF-predicted RFTIs of elevated or greater (RFTI ≥1), with nearly two-thirds (63%) of such fires noted to occur within predicted near-critical to critical (RFTI 3–6) environments. All observed large (>1.2–20.2 km²) and significant (>20.2–404.7 km²) fires occurred in near-critical or greater (≥3) predicted TTU WRF RFTIs, and 95% of significant fires were associated with TTU WRF-predicted critical or higher (RFTI ≥5) environments. The only observed megafire in the dataset, the 15 December 2021 Four County Fire in west-central Kansas, occurred in a TTU WRF-predicted historically critical (RFTI 9) environment. In this observational dataset, extremely critical (7–8) and historically critical (9–10) RFTI values appeared to delineate particularly dangerous southern Great Plains wildfire environments that constitute a significant threat to life and property. All three fatality fires in the dataset were characterized by predicted TTU WRF RFTIs ≥7. This included the aforementioned Four County Megafire, the Cottonwood Fire in south-central Kansas on 5 March 2022, and the Eastland Complex Fire in north-central Texas on 17 March 2022. A fire that resulted in multiple injuries in Jewell County, Kansas, on 29 March 2022 also occurred within TTU WRF-predicted critical and extremely critical RFTI (6–7). The observations documented here corroborate Murdoch et al. (2012), which found that mean fire size increases with increasing RFTI.

*b. WoFS*

WoFS is an experimental 36-member analysis and 18-member forecast, rapidly cycling ensemble data assimilation and forecasting system that currently runs over a relocatable, developer-defined 900 km x 900 km region of expected high-impact weather using 3-km horizontal grid spacing. Ensemble member initial conditions are taken from the HRRR, and unique boundary conditions are created for each respective member by applying variances of Global Ensemble

**Table 1**. Impact statistics from the referenced wildfire episodes. "# of Fires" refers to the total of unique *GOES-16* hot spots identified. Burn area, damages, and casualty data are based on preliminary reports from state forestry agencies.

| Dates | Data | # of Fires | Area Burned (km$^2$) | Structures Lost | Casualties |
|---|---|---|---|---|---|
| 15 December 2021 | TTU WRF | 32 | 843 | 24 | 6 |
| 5 March 2022 | TTU WRF | 41 | 57 | 130 | 5 |
| 17 March 2022 | TTU WRF | 34 | 264 | 50 | 3 |
| 29 March 2022 | TTU WRF | 29 | 409 | 26 | 3 |
| 22 April 2022 | WoFS | 18 | 541 | 203 | 16 |

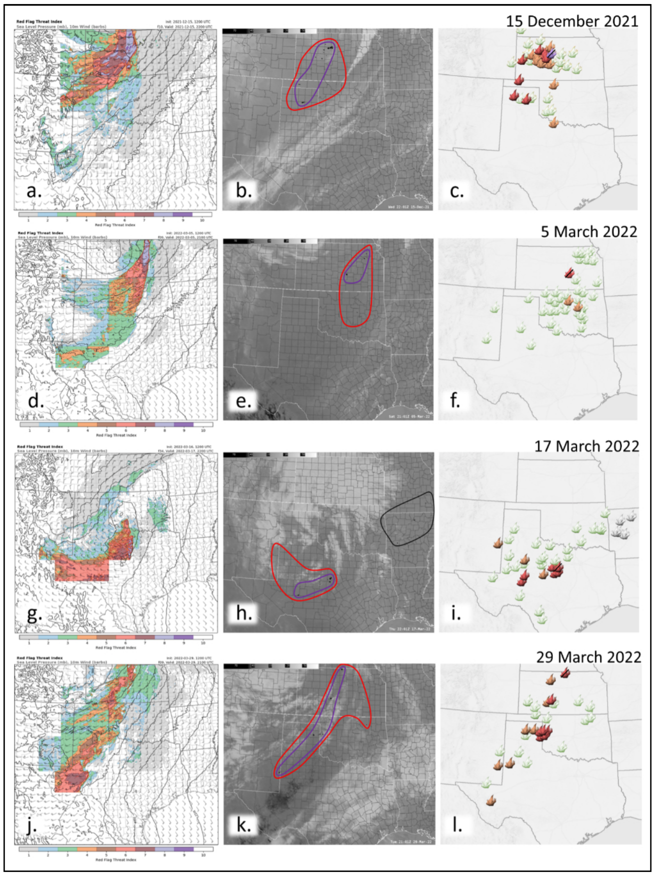



**Figure 1**. TTU WRF RFTI (a, d, g, j) initialized at 1200 UTC and valid at 2100/2200 UTC with corresponding GOES-16 SWIR imagery (b, e, h, k) showing geographic areal extent of visually large/intense fires (purple) and more subtle hot spots (red) indicated. Fires of unknown nature outside of the TTU WRF RFTI domain are indicated by black in panel h. Panels c, f, i, and l summarize cumulative and categorized SGPWO episode wildfire incidents. *Click image for an external version; this applies to all figures and animations hereafter.*

Forecast System (GEFS) members from the GEFS mean to the existing HRRR-based conditions along the boundaries. What distinguishes WoFS from other CAMs is that the system assimilates conventional radar and satellite data at 15-min intervals to continually update the model analysis and account for rapidly evolving meteorological environments. New 18-member forecasts that incorporate the latest in situ and remotely sensed observations are launched every 30 min, with forecasts out to 6 h (top-of-the-hour runs) or 3 h (bottom-of-the-hour runs). This system has proven successful in generating skillful short-term (0–3 h) probabilistic forecasts of high-impact weather in the real-time operational forecasting environment (Skinner et al. 2018, Yussouf and Knopfmeier 2019).

During a subsequent SGPWO on 22 April 2022, an NWS Incident Meteorologist (IMET; co-author Murdoch) was assigned to the Texas A&M Forest Service Operations Center at College Station, Texas, in support of ongoing wildfire response. The IMET leveraged WoFS to message the evolution of meso-β scale fire-effective atmospheric features in short-term updates to both NWS WFO forecasters and state agency fire-behavior analysists in advance of newly ignited wildfires in eastern New Mexico, eastern Colorado, and western Kansas.

Fire-effective LLTRs are atmospheric features that are known to exacerbate wildfire conditions on the southern Great Plains (Lindley et al. 2017). A fire-effective LLTR occurs when a narrow poleward-extending corridor of anomalously hot lower-tropospheric temperatures couples with an overspreading speed maximum in the wind fields aloft to create a "blow torch-like" effect of dry air and strong near-surface winds that promote wildland fire ignition, extreme fire behavior, and rapid rates of fire spread.

The SGPWO Working Group forum is an online collaborative multi-agency operations-to-research-to-operations community focused on science-based decision support for state forestry agencies in Texas, Oklahoma, and Kansas (Lindley et al. 2021). At 1923 UTC on 22 April 2022, the IMET posted to the forum that "WoFS forecast at 2100 UTC [shows that the] 500 hPa speed max and LLTR will intersect in [the] vicinity of northeastern New Mexico and southeastern Colorado" and that a new fire was "erupting in southeastern Colorado…very near [the] intersection" of

**Table 2**. Map legend for Fig. 1 panels c, f, i, and l, which map and categorize the magnitude of wildfires for each of the four documented SGPWO episodes. Reported fire sizes are based on preliminary reports from state forestry agencies.  Fig. 1 panels c, f, i, and l, which map and categorize the magnitude of wildfires for each of the four documented SGPWO episodes. Reported fire sizes are based on preliminary reports from state forestry agencies.

| Size Class | Size (km2) | Categorization | Symbol |
|---|---|---|---|
| A-D | 0-1.2 | Initial Attack Fire |  |
| E-H | >1.2-20.2 | Large Fire |  |
| I-K | >20.2-404.7 | Significant Fire |  |
| L | >404.7 | Megafire |  |
| Unknown | -- | -- |  |
| Casualty Fire | -- | -- |  |

**Table 3**. Combined percentage of fires from the four 2021/22 cases that occurred within predicted TTU WRF RFTI categories.

| Fire Categorization (Fire Size km²) | Fires Occurring Within Predicted TTU WRF RFTI by Category (%) | | | | | |
|---|---|---|---|---|---|---|
| | Nil (0) | Elevated (1–2) | Near-critical (3–4) | Critical (5–6) | Extremely Critical (7–8) | Historically Critical (9–10) |
| Initial Attack (n=94*) 0–1.2 | 1 | 11 | 33 | 31 | 19 | 5 |
| Large Fire (n=21) >1.2–20.2 | - | - | 24 | 29 | 14 | 33 |
| Significant Fire (n=22) >20.2–404.7 | - | - | 5 | 41 | 36 | 18 |
| Megafire (n=1) >404.7 | - | - | - | - | - | 100 |
| Casualty Fire (n=4) | - | - | - | - | 75 | 25 |
| Unknown (n=4) | 100 | - | - | - | - | - |
| **2 known initial attack fires were excluded because of occurrence outside of the TTU WRF RFTI Domain.* | | | | | | |

these atmospheric features (Fig. 2). At 1944 UTC, a Kansas State Forestry representative responded that fires would likely become problematic for Kansas firefighting interests and noted new fire starts occurring in eastern Colorado and western Kansas. Subsequently at 1949 UTC, the IMET relayed information derived from WoFS 30-min maximum wind gust paintball products that depicted increasing probabilities for ≥26 m s$^{-1}$ (50 kt) wind gusts near the nose of the 500-hPa jet within the windward side of the LLTR. Observed gusts of 26 m s$^{-1}$ (50 kt) in southeastern Colorado were noted shortly thereafter in proximity to the ongoing wildfires. The IMET stated at 2030 UTC that new WoFS guidance showed "excellent coupling of the 500 hPa jet nose and the windward side [of the] LLTR. Coupled intersection [is] almost directly over where the two southeastern Colorado fires are running, taking on typical elliptical shape [for wind-driven wildfires]" and that a merger of the two fires was possible. Fire activity on this day culminated with particularly damaging wildfires in northeastern New Mexico and a fatality fire with multiple injuries that burned from northwestern Kansas into southwestern Nebraska, all within proximity to the aforementioned fire effective LLTR.

These real-time communications between an NWS IMET and state forestry fire officials represent the first documented use of WoFS for direct fire-weather support. Although the same atmospheric features were evident in other NWP models and with greater forecast lead-time, in this case, the IMET applied conceptual models of a known critical fire-weather pattern toward effective mesoscale analysis informed by WoFS and its rapid update cycling and assimilation of near real-time data to convey predictions of precise locations and timing of intense fire weather conditions more confidently. This information was communicated to fire behavior analysts 1–3 h prior to the occurrence of peak burning conditions in the specified areas as observed by

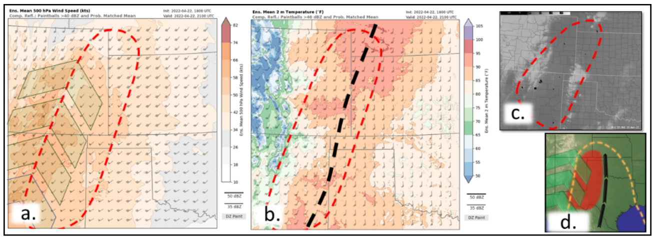



**Figure 2**. WoFS run at 1800 UTC 22 April 2022 showing a) 500 hPa wind speed with 26 m s-1 (>50 kt) speed maximum (green arrows) and b) 2-m temperature and 10-m winds (barbs) with LLTR (black dashes) valid at 2100 UTC. The conceptually favored area for problematic wildfires is indicated by the red-dash area. Panel c) is the 2236 UTC *GOES-16* SWIR with area of active wildfires indicated (red-dash area), and d) shows the conceptual model for a fire-effective LLTR with the favored area for problematic wildfires indicated (red-shaded area).

*GOES-16* SWIR imagery. Although not routinely available via WoFS at this time, a retrospective WoFS product was generated to show ensemble probabilities of exceedance for 500-hPa wind speed >26 m s$^{-1}$ (50 kt) and 2-m temperature 29°C (85°F). In this example, the overlap of exceedance probabilities in these fields serve as a proxy to identify conceptually favored areas for problematic fire associated with the fire effective LLTR (Fig. 3). This proof-of-concept demonstrates how CAMs, particularly those that frequently assimilate near real-time observations, can be used in operations to identify and predict short-term evolution of atmospheric features and their influence on the fire environment in a probabilistic sense. Similar application of WoFS and other ensemble-based CAMs (including the TTU WRF) could extend to probabilistic lightning information, downslope windstorms, and wind shifts associated with fronts, drylines, or convective outflow boundaries—all of which are common factors attributed to wildland firefighting fatalities (Wilson 1977 and National Wildfire Coordinating Group 1997).

## 3. Discussion

Pyne (1982 and 2012) described wildfires as atmospheric events that organize heat release from the surface through a climatic determinism and emphasized that particularly damaging fires synthesize anomalous environments characterized by short-lived combinations of vegetative fuel and weather. At the

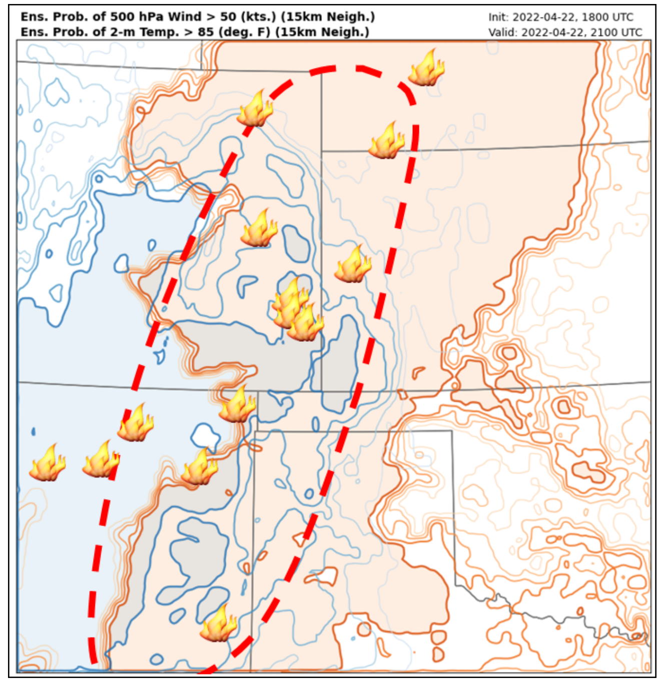



**Figure 3**. WoFS demonstration product initialized at 1800 UTC 22 April 2022 and showing ensemble probabilities of 500 hPa WS >26 m s$^{-1}$ (50 kt, blue) and 2-m temperature >29°C (85°F, orange) valid at 2100 UTC 22 April 2022. Probabilities are contoured at 10, 30, 50, 70 and 90% (10–70% indicated by increasingly thicker lines and >90% likelihood shaded. The conceptual fire-effective LLTR area favored for problematic fire identified in Fig. 2 panels a and b is annotated (red-dash area), and *GOES-16* hot spots detected between 2000–2200 UTC 22 April 2022 are denoted by flame icons.

scale of an individual wildland fire, mesoscale atmospheric processes greatly influence the potential for dangerous fire behavior and spread. The spatiotemporal resolution and projection of such atmospheric effects on the fire environment are well-suited to the domain of CAMs. It is important to note that these preliminary analyses of fire-weather relevant CAM output associated with the 2021/22 SGPWOs are focused on selective meteorological components of complex fire environments. It is beyond the scope of this short contribution article to quantifiably investigate specific fuel-based fire danger measures that contributed to these wildfire episodes. It is worth noting, however, that the fuelscape of the southern Great Plains fire regime proved supportive of intense burning across the geographic range of these fire outbreaks, all of which occurred during a single winter/

spring dormant season, the climatological peak period for wildfires on the southern Great Plains. Fuels and Fire Behavior Advisories issued for parts of Texas, Oklahoma, Kansas, and Nebraska on 11 April 2022 stated, "Above-normal to exceptional fuel loading and subsequent long-term drought persistence have promoted…dangerous fire behavior conditions," including "wildfire outbreaks with an associated increase in significant fire occurrence…for much of the region" (National Interagency Coordination Center, cited 2022).

The fact that the included preliminary analyses of a single CAM-derived fire weather parameter (RFTI) qualitatively compared favorably to observed wildfire occurrence, size, and public impacts is significant given that the results constitute NWP-based prognostication of only one variable (weather) in the fire-behavior triangle, e.g., weather, fuel, and topography (Werth et al. 2016). With 99% of all initial attack fires shown to occur in elevated or greater TTU WRF RFTI (≥1) environments, 95% of significant wildfires associated with critical or higher RFTIs (≥5), and 100% of megafire and casualty-related fires in model-predicted extremely critical or greater RFTIs (≥7), the results presented here underscore wildland fire's dependency on meteorological conditions and suggest that a role for CAMs in mesoscale wildfire prediction exists. Further, the demonstrated use of WoFS depiction of a fire-effective LLTR in identifying areas of newly evolving problematic wildfire ignition and spread potential during the 22 April 2022 SGPWO highlights the emerging capability to leverage CAMs in the provision of actionable mesoscale intelligence on the fire environment and in predicting specific fire-influencing atmospheric features.

The authors advocate for expanded availability of fire weather-specific fields and parameters in CAMs, including ensemble-based products, as well as Fire Weather Testbed activities to scientifically evaluate these and other emerging operational fire products and services. The development of high-resolution NWP systems has traditionally focused on delivery of convection-related parameters associated with severe local storms, such as ensemble-based simulated reflectivity, updraft helicity, and probability of exceedance for thresholds of wind, hail, and precipitation. Similar ensemble-based approaches to fire weather-relevant fields and composite parameters such as RFTI, Hot-Dry-Windy Index (Srock et al. 2018), Fosberg Index (Fosberg 1978), and the calibrated Grassland Fire Danger Index (Schreck et al. 2010) should be developed. In addition, exceedance probabilities of base meteorological fields like RH and WS thresholds, as well as stability and temperature anomaly parameters, would be equally important in addressing service gaps that currently exist in the prediction of dangerous wildfire environments. For instance, the development of ensemble-based smoke forecasts within both the HRRR (Ahmadov et al. 2017) and WoFS (Jones et al. 2022) are examples of how CAMs can be leveraged for fire-specific use. There will be no fire unless the state of both weather and fuels are supportive (Pyne 1982). Thus, incorporation of meteorologically derived, fuel-based fire danger indices [such as energy release component (Bradshaw et al. 1983) and total (weather and fuel) fire environment parameters such as the Severe Fire Danger Index (Jolly et al. 2019)] into CAMs would support the adoption of phenomenon-based probabilistic fire forecast and warning paradigms consistent with a Forecasting A Continuum of Environmental Threats (Rothfusz et al. 2014 and 2018) framework. Such evolution of NWS fire services could greatly enhance the provision of impact-based decision support (Uccellini and Ten Hoeve 2019) available to core fire partners and subsequently improve emergency messaging and public preparation and mitigation efforts for dangerous wildfires.

*Acknowledgments*. The authors would like to thank the following individuals who have assisted and/or supported this research: Mark Fox, Rick Smith, Scott Curl, Doug Speheger, Brian Curran, Patrick Marsh, Drew Daily, Brad Smith, Christopher Redmond, Brian Carcione, Matthew Moreland, Thomas Jones, Brian Matilla, Pam Heinselman, Paul Witsaman, and Matthew Elliot. The authors would also like to extend their gratitude and sincere appreciation to the Editor, Casey Davenport, and the two reviewers, including Dr. Timothy Juliano. Their constructive feedback and suggested edits greatly improved the quality of this manuscript. Co-author Skinner was provided support for this work by NOAA/Office of Oceanic Research under NOAA-University of Oklahoma (OU) Cooperative Agreement NA16OAR4320115, U.S. Department of Commerce.

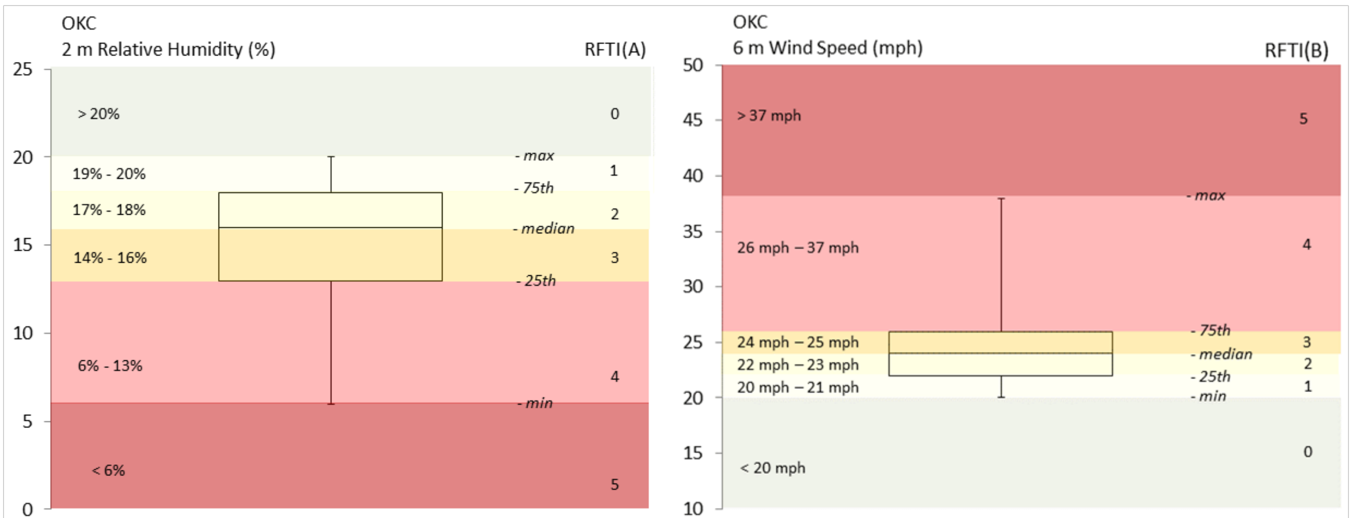
## APPENDIX A

## RFTI

RFTI is calculated as:

RFTI = *RFTI(A)* + *RFTI(B)* (1)

where *RFTI(A)* and *RFTI(B)* are assigned a value 0 through 5 corresponding to quartile rankings of observed RH and WS respectively that exceed locally defined RFW thresholds relative to a 10-year observational period. Example *RFTI(A)* and *RFTI(B)* quartile analyses for Oklahoma City (OKC) are shown below:




*Observational quartile rankings and RFTI(A) and RFTI(B) terms at Oklahoma City (OKC)*

## REFERENCES

Ahmadov, R., and Coauthors, 2017: Using VIIRS fire radiative power data to simulate biomass burning emissions, plume rise and smoke transport in a real-time air quality modeling system. *2017 IEEE Int. Geoscience and Remote Sensing Symp*., Fort Worth, TX, Institute of Electrical and Electronics Engineers, 2806–2808, Crossref.

Bradshaw, L. S., J. E. Deeming, R. E. Burgan, and J. D. Cohen, 1983: The 1978 national fire-danger rating system: Technical documentation. General Technical Report USDA Forest Service Rep. INT-169, 44 pp. [Available online at www.fs.usda.gov/rm/pubs_int/int_gtr169.pdf.]

Chen, F., and J. Dudhia, 2001: Coupling an advanced land-surface/hydrology model with the Penn State/NCAR MM5 modeling system. Part I: Model description and implementation. *Mon. Wea. Rev*., **129**, 569–585, Crossref.

Dozier, J., 1981: A method for satellite identification of surface temperature fields of subpixel resolution. *Remote Sens. Environ*., **11**, 221–229, Crossref.

Dudhia, J., 1989: Numerical study of convection observed during the winter monsoon experiment using a mesoscale two-dimensional model. *J. Atmos. Sci*., **46**, 3077–3107, Crossref.

Fosberg, M. A., 1978: Weather in wildland fire management: The fire weather index. *Proceedings of the Conference on Sierra Nevada Meteorology*, Lake Tahoe, CA, Vol. 7, 1–4. Amer. Met. Soc. and USDA Forest Service.

Hong, S.-Y., 2010: A new stable boundary-layer mixing scheme and its impact on the simulated East Asian summer monsoon. *Q. J. R. Meteorol. Soc*., **136**, 1481–1496, Crossref.

Jakober, S., T. Brown, and T. Wall, 2023: Development of a decision matrix for National Weather Service red flag warnings. *Fire*, 6, no. 4: 168. Crossref.

Jones, T. A., K. Knopfmeier, D. Wheatley, G. Creager, P. Minnis, and R. Palikonda, 2016: Storm-scale data assimilation and ensemble forecasting with the NSSL experimental warn-on-forecast system. Part II: Combined radar and satellite data experiments. *Wea. Forecasting*, **31**, 297–327, Crossref.

____, T., R. Ahmadov, E. James, G. Pereira, S. Freitas, and G. Grell, 2022: Prototype of a warn-on-forecast system for smoke (WoFS-Smoke). *Wea. Forecasting*, **37**, 1191–1209, Crossref.

Kimutis, N., T. Wall, and T. Brown, 2018: Red flag warning and fire weather watch issuance criteria. Fall Colloquium, Community College Undergraduate Research Initiative, Phoenix, AZ. [Available online here.]

Lindley, T. T., and Coauthors, 2014: Southern Great Plains wildfire outbreaks. *Electronic J. Severe Storms Meteor*., **9**, 1–43. [Available online at ejssm.org/archives/2014/vol-9-2-2014/.]

___, G. P. Murdoch, K. Schneider, N. Fenner, B. R. Smith, and C. Maxwell, 2015: A statistical analysis of energy release component for large wildland fires on the southern Great Plains. *11th Symp. Fire and Forest Meteor*., Minneapolis, MN, Amer. Meteor. Soc., 8.1. [Available online at ams.confex.com/ams/11FIRE/webprogram/Manuscript/Paper271875/8.1_Lindley.pdf.]

____, B. R. Bowers, G. P. Murdoch, B. R. Smith, and C. M. Gitro, 2017: Fire-effective low-level thermal ridges on the southern Great Plains. *J. Operational Meteor*., **5**, 146–160, Crossref.

____, G. P. Murdoch, R. Heffernan, L. Van Bussum, A. E. Gerard, and N. J. Nauslar, 2018: An impact-based decision support paradigm for National Weather Service wildfire forecast & warning services. *12th Symp. on Fire and Forest Meteorology*, Boise, ID, Amer. Meteor. Soc., P36. [Available online at ams.confex.com/ams/33AF12F4BG/mediafile/Manuscript/Paper343869/Lindley_2018.pdf.]

____, D. A. Speheger, M. A. Day, G. P. Murdoch, B. R. Smith, N. J. Nauslar, and D. C. Daily, 2019: Megafires on the southern Great Plains. *J. Operational Meteor*., **7**, 164–179, Crossref.

____, B. R. Bowers, D. Daily, and C. Gravelle, 2021: Decision support and fire warnings during the 26 November 2019 Oklahoma wildfires. *13th Fire and Forest Meteor. Virtual Symp*., Amer. Meteor. Soc. [Available online ams.confex.com/ams/13FIRE/meetingapp.cgi/Paper/374338.]

Mass, C. F., and D. Ovens, 2021: The synoptic and mesoscale evolution accompanying the 2018 Camp Fire of northern California. *Bull. Amer. Meteor. Soc*., **102**, E168–E192, Crossref.

Mlawer, E. J., S. J. Taubman, P. D. Brown, M. J. Iacono, and S. A. Clough, 1997: Radiative transfer for inhomogeneous atmospheres: RRTM, a validated correlated-k model for the longwave. *J. Geophys. Res*., **102**, 16663–16682, Crossref.

Murdoch, G. P., R. R. Barnes, C. M. Gitro, T. T. Lindley, and J. D. Vitale, 2012: Assessing critical fire weather conditions using a red flag threat index. *Electronic J. Operational Meteor*., **13**, 46−56. [Available online at nwafiles.nwas.org/ej/pdf/2012-EJ4.pdf.]

Nauslar N. J., J. T. Abatzoglou, and P. T. Marsh, 2018: The 2017 North Bay and southern California fires: A case study. *Fire*, **1**, Crossref.

National Interagency Coordination Center, cited 2022: Fuels and fire danger. [Available online at www.predictiveservices.nifc.gov/fuels_fire-danger/fuels_fire-danger.htm.]

National Wildfire Coordinating Group, 1997: Historical wildland firefighter fatalities 1910–1996. National Interagency Fire Center, PMS 822, NFES 1849. 41 pp. [Available online at www.yumpu.com/en/document/view/11660608/historical-wildland-firefighter-fatalities-1910-1996-national-]

____, cited 2022: Fire Size Class. [Available online at www.nwcg.gov/sites/default/files/data-standards/pdf/values.pdf.]

Pyne, S. J., 1982: *Fire in America*. University of Washington Press. Seattle, WA, 680 pp, [1997 Edition available at uwapress.uw.edu/book/9780295975924/fire-in-america/].

____, 2004: *Tending Fire: Coping with America's Wildland Fire*. Island Press, Washington, DC, 256 pp. [Available online at islandpress.org/books/tending-fire.]

____, 2012: *Fire: Nature and Culture*. Reaktion Books Ltd., London, UK, 208 pp. [Available online at reaktionbooks.co.uk/display.asp?K=9781780230467.]

____, 2021: *The Pyrocene: How We Created an Age of Fire and What Happens Next*. University of California Press, Oakland, CA, 192 pp. [Available online at www.ucpress.edu/book/9780520391635/the-pyrocene.]

Rothfusz, L. P., C. Karstens and D. Hilderbrand, 2014: Next-generation severe weather forecasting and communication. *Eos*, **95**, 325–326, Crossref.

____, L. P., R. Schneider, D. Novak, K. Klockow-McClain, A. E. Gerard, C. Karstens, G. J. Stumpf, and T. M. Smith, 2018: FACETs: A proposed next-generation paradigm for high-impact weather forecasting. *Bull. Amer. Meteor. Soc*., **99**, 2025–2043, Crossref.

Schreck, M-B., P. J. Howerton, and K. R. Cook, 2010: Adapting Australia's grassland fire danger index for the United States' central plains. NOAA/NWS CR Tech, Attachment, No. 10-02. [Available online at www.weather.gov/media/crh/publications/TA/TA_1002.pdf]

Skamarock, and Coauthors, 2008: A description of the advanced research WRF Version 3. NCAR Tech. Note TN-475, 113 pp., Crossref.

Skinner, P. S., and Coauthors, 2018: Object-based verification of a prototype warn-on-forecast system. *Wea. Forecasting*, **33**, 1225–1250, Crossref.

Srock, A. F., J. J. Charney, B. E. Potter, and S. L. Goodrick, 2018: The Hot-Dry-Windy Index: A new fire weather index. *Atmosphere*, **9**, 1–11. Crossref.

Stensrud, D. J., and Coauthors, 2009: Convective-scale warn-on-forecast system: A vision for 2020. *Bull. Amer. Meteor. Soc*., **90**, 1487–1500, Crossref.

____, and Coauthors, 2013: Progress and challenges with warn-on-forecast. *Atmos. Res*., **123**, 2–16, Crossref.

Texas Tech Atmospheric Science Department, cited 2022: About the Texas Tech real-time weather prediction system. [Available online at www.atmo.ttu.edu/bancell/real_time_WRF/TTUWRF-about.html.]

Thompson, G., R. M. Rasmussen, and K. Manning, 2004: Explicit forecasts of winter precipitation using an improved bulk microphysics scheme. Part I: Description and sensitivity analysis. *Mon. Weather Rev*., **132**, 519–542, Crossref.

Uccellini, L. W., and J. E. Ten Hoeve, 2019: Evolving the National Weather Service to build a weather-ready nation: Connecting observations, forecasts, and warnings to decision-makers through impact-based decision support services. *Bull. Amer. Meteor. Soc*., **100**, 1923–1942, Crossref.

Weaver, J. F., J. F. W. Purdom, and T. L. Schneider, 1995: Observing forest fires with the GOES-8, 3.9-µm imaging channel. *Wea. Forecasting*, **10**, 803–808, Crossref.

____, D. Lindsey, D. Bikos, C. C. Schmidt, and E. Prins, 2004: Fire detection using GOES rapid scan imagery. *Wea. Forecasting*, **19**, 496–510, Crossref.

Werth, P. A., and Coauthors, 2016: Synthesis of knowledge of extreme fire behavior: Volume 2 for fire behavior specialists, researchers, and meteorologists. Gen. Tech. Rep. PNW-GTR-891, USDA Forest Service, Pacific Northwest Research Station, Portland, Oregon, 258 pp. Crossref.

Wicker, L., and Coauthors, 2023: Rapid prediction of high-impact weather using the warn-on-forecast system, Part I: Background and technical description. *Wea. Forecasting*, in preparation.

Wheatley, D. M., K. H. Knopfmeier, T. A. Jones, and G. J. Creager, 2015: Storm-scale data assimilation and ensemble forecasting with the NSSL experimental warn-on-forecast system. Part I: Radar data experiments. *Wea. Forecasting*, **30**, 1795–1817, Crossref.

Wilson, C. C., 1977: Fatal and near-fatal forest fires: The common denominators. *Int. Fire Chief*, **43**, 9–15. [Available online at wildfiretoday.com/documents/CommonDenominatorsCarlWilson_1977.pdf.]

Yussouf, N., and K. H. Knopfmeier, 2019: Application of warn-on-forecast system for flash-flood producing heavy convective rainfall events. *Quart. J. Roy. Meteor. Soc*., 2385–2403, Crossref.