# NASA DEVELOP National Program
# North Carolina – NCEI

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# Vermont Wildland Fires

## Investigating the Role of Antecedent Conditions and Recent Environmental Trends in Exacerbating Fire Risk and Potential in Vermont

**DEVELOP Technical Report**

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# 1. Abstract
Under a changing climate, increases in dry conditions and extreme heat events are projected to exacerbate wildfire risk in the northeastern U.S. In recent years, Vermont has observed higher annual temperatures, more frequent heatwaves, increased annual precipitation, extreme flood events, and decreased snowfall. The mechanisms through which environmental factors contribute to increased fire risk in humid environments, such as Vermont, are poorly understood. The team partnered with the National Weather Service, the Vermont Division of Forests, and the University of Vermont to investigate phenological trends and antecedent conditions influencing wildland fire risk. For the phenological analysis, from 2001 to 2023, vegetation data, phenological dates, and snow water equivalent (SWE) values were accessed from Landsat 5 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper Plus (ETM+), Landsat 8 Operational Land Imager (OLI), Landsat 9 OLI-2, the Moderate Resolution Imaging Spectroradiometer (MODIS), and the Snow Data Assimilation System (SNODAS), respectively. For the antecedent condition analysis, from 2008 to 2023, soil moisture, Environmental Stress Index, wind speed, minimum relative humidity, and daily precipitation data were obtained from the Global Land Data Assimilation System (GLDAS), SERVIR, gridMET Wind, gridMET Humidity, and NClimGrid, respectively. The study found that green-up dates over the study period remain relatively stable, while snowmelt dates appear increasingly variable. Minimum relative humidity was the most significant environmental variable correlated with wildfire risk in Vermont. Results from this study will inform the National Weather Service's preparation of fire forecasts before prescribed burns and support community outreach by the Vermont Agency of Natural Resources.



**Key Terms**
MODIS, Landsat, Wildland Fire, Fire Potential, Vermont, NDVI, SWE


# 2. Introduction
## *2.1 Background*
Vermont is experiencing increases in annual precipitation and temperature, which are projected to continue under a changing climate (Snyder & Sinclair, 2017). Despite the increase in precipitation, higher temperatures and the influence of other environmental parameters put the state at a greater risk for flash drought conditions, resulting in increased fire risk (Snyder & Sinclair, 2017; Table A1). Between 1970 and 2000, certain springtime phenological parameter dynamics in the Northeastern United States have changed, with snow decreasing and plants blooming earlier (Hayhoe et al., 2007). Wildfire climatology literature is concentrated on the Western United States. Thus, due to dynamic environmental factors and a lack of existing research, uncertainty exists on how changing environmental conditions impact wildfire risk in the Northeastern states like Vermont.

An overall increase in precipitation could suggest a misleading narrative that fires should be less likely, but the Vermont Department of Forests predicts the opposite (Snyder & Sinclair, 2017). Increased climate variability poses a challenge to forecasting and communicating wildland fire risk to the public. Total precipitation is projected to rise 9.7% by 2100 in the region, with total annual extreme precipitation increasing 51.6% with a 109.3% increase in the winter (Picard et al., 2023). Winter will bring less snow and more rain, while less change in precipitation is expected for summers (Snyder & Sinclair, 2017). Research is ongoing concerning standardized definitions and identification of flash droughts (Lisonbee et al., 2021). This project aims to address the multiscale problem of how drought-related variables may be detected in northeastern US temperate climates and their impact on fire risk. Second, this project aims to understand how long-term snow and vegetation trends may impact fire risk in Vermont.

## *2.2 Study Area & Period*
Vermont is classified into five distinct Fire Danger Rating Areas (FDRA) per a national system reflecting similarities in topography, fuels, and climate, as shown by Schlobohm & Brain in 2002. The system was designed to be adaptable for state agencies so fire managers can make best-informed decisions on a local scale (Schlobohm & Brain, 2002). Analysis at the scale of Vermont's FDRAs is useful, as the significance of

shifting local fire risk could be underestimated by a larger-scale analysis of the broader Northeastern U.S. (Miller, 2019). To improve future management in Vermont, this study examined key environmental conditions related to drought and fire occurrence using Earth observations between 2008-2023. Long-term changes in snow and vegetation phenology were studied between 2001 and 2023.

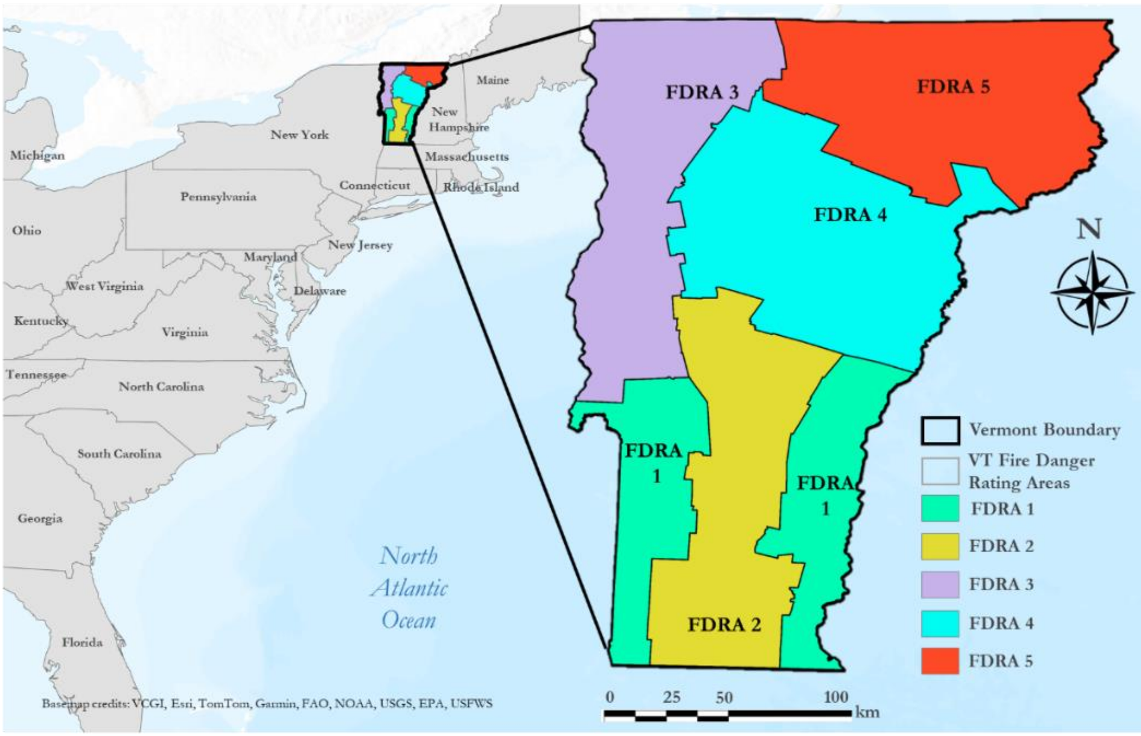

*Figure 1*. The state of Vermont, sectioned into the Five Danger Rating Areas (bordered in grey).

### *2.3 Project Partners & Objectives*

Partners for this project included federal, state, and academic institutions. The team collaborated with partners at the National Integrated Drought Information System (NIDIS) from NOAA and the University of Vermont to serve end users at the National Weather Service (NWS) Burlington, & the Vermont Division of Forests. NASA Goddard Space Flight Center contributed as a Boundary Organization Partner. The Vermont Division of Forests, housed within Vermont's Agency of Natural Resources, Department of Forests - Parks and Recreation, promotes the health of Vermont forests by implementing land management and sustainable use practices, as well as collaborates with the local NWS to monitor wildland fire range and disseminate fire observations and forecasts (State of Vermont, 2024). The NWS Burlington office provides forecasts and warning services to support fire management and control to manage fires on range and forested lands (NWS - BTV, 2024). The NWS Burlington office uses MODIS and Sentinel-2 data from the Space Science and Engineering Center (SSEC) MODIS Today website and the Sentinel Hub EO Browser to support their wildland forecasting efforts.

To quantify antecedent environmental conditions prior to fires, the team examined soil moisture, evapotranspiration, precipitation, and relative humidity at the daily, seven-day, and 30-day scales and created statistical analyses and environmental conditions maps. The statistical methods used include Pearson correlations, linear regressions and random forest (RF) modelling. The long-term phenological portion of the project used snow and vegetation data to create new datasets consisting of significant annual snowmelt and springtime dates, time series, and scatterplots with linear regression fits. These end products provide an in-depth framework of environmental conditions relevant to fire risk in Vermont. Last, a two-page flyer was compiled as a public education tool to inform communities about conditions associated with wildfire risk and potential in Vermont.  These deliverables will assist the partners in better forecasting wildland fire risk and occurrence and adapting emergency action plans to heightened fire and drought risk.

# 3. Methodology

## *3.1 Data Acquisition*

The team acquired Earth observation products and ancillary datasets for two periods: between January 1, 2008, and December 31, 2023 for antecedent condition analysis and between January 1, 2001, and December 31, 2023 for long-term phenological analysis. These environmental data were supplemented by a partner-provided historical dataset on Vermont wildfires from the Vermont Agency of Natural Resources. This supplemental dataset is populated with fire events recorded by local fire marshals and includes fire discovery date, county, cause code, fire size, township, FDRA latitude, and longitude. Since study periods were 16 and 20 years, potential datasets were often found to have an inadequate period of record. The analyses combined data from eight environmental parameters, so the team avoided datasets which were inadequate, either due to a short period of record or temporal resolution. The necessary high spatiotemporal resolution of data for this project significantly restricted the number of suitable datasets. Tables 1 and 2 provide a complete listing of Earth and surface observation data used in this study.

### *3.1.1 Antecedent Condition Study*

The team used two NASA-derived Earth observation datasets with three archival climate datasets to conduct the antecedent conditions of wildland fire analysis. Due to the short-term nature of flash droughts and the difficulty of spatially analyzing short-duration fires of less than one acre, the team opted to align dataset temporal resolution at the daily level. This allowed the team to be flexible with time periods during later analysis and significantly influenced the dataset selection for examining antecedent conditions.

The team retrieved minimum relative humidity, precipitation, soil moisture, and wind speed data using the Google Colab API. The following datasets with daily resolution were acquired: precipitation at 4.6 km resolution from NOAA's NClimGrid-Daily, minimum relative humidity and wind speed data at 4 km resolution from the University of California's GridMET, and Root Zone Soil Moisture at 24 km resolution from NASA's GLDAS Version 2.1. Additionally, the team accessed Evaporative Stress Index (ESI) data at 5 km resolution from NASA SERVIR and the Hydrology and Remote Sensing Laboratory at the USDA Agricultural Research Service (ARS). ESI represents 30 days' worth of data and is updated every seven days. For each variable—ESI, minimum relative humidity, precipitation, soil moisture, and wind speed—the retrieved dataset provided time series of spatially averaged values for each date, based on FDRA coordinates, throughout the study period.

### *3.1.2 Long-Term Phenological Study*

For long-term condition analysis, the team retrieved snow data between October 3, 2003, and December 31, 2023, and 2-band Enhanced Vegetation Index (EVI2) data between January 1, 2001, and December 31, 2022. The team retrieved daily Snow Water Equivalent (SWE) values from the Snow Data Assimilation System (SNODAS) dataset from the National Operational Hydrologic Remote Sensing Center (NOHRSC) and EVI2 data from the MODIS Land Cover Dynamics MCD12Q2 data product at 500m. This pre-processed data product uses vegetation data to provide dates per pixel, representing different green-up stages. The team sourced SWE from Climate Engine and MCD12Q2 from Google Earth Engine (GEE). Boundary coordinates of each FDRA were used to determine the spatial limits of these gridded datasets as they were accessed. For NDVI, this resulted in one spatially averaged date per year per FDRA for the study period. For snow data, this resulted in spatially averaged daily SWE values per FDRA for the study period.

### *3.1.3 Use of Landsat*

Given Landsat's long period of record and fine spatial resolution, the team initially considered using Landsat 5 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper Plus (ETM+), Landsat 8 Operational Land Imager (OLI) & Thermal Infrared Scanner (TIRS), and Landsat 9 OLI-2 & TIRS-2 for both antecedent condition studies and long-term phenological trend analysis. To investigate flash droughts, the team considered incorporating Landsat land surface temperature (LST) data from 2008 to 2023 to complement the five variables already used in the antecedent condition study. Although the 30m resolution of the optical imagers (TM, ETM+, OLI, and OLI-2) and the 100m resolution of the thermal imagers (TIRS/TIRS-2) could be used to spatially pinpoint flash droughts and fires, the temporal resolution of Landsat made it very difficult to reconcile this dataset with others temporally. Since flash droughts can occur in days or weeks, the 8- or 16-day resolution of Landsat LST was insufficient to capture this phenomenon. For the long-term condition analysis, the team retrieved Landsat 5, 7, 8, and 9 NDVI per FDRA between March, 1984, and December, 2023. The team used the Landsat data to create time series visualizations, however the spatiotemporal resolutions of these preliminary visualizations later led them to switch away from Landsat for LST and NDVI (Section 3.2.3).

Table 1
*List of NASA sensors and data products utilized for this project*

| Platform and Sensor | Data Product | Dates Retrieved | Acquisition Method |
|---|---|---|---|
| Terra/Aqua MODIS | MCD12Q2 Land Cover Dynamics, Version 2.1 500 m | 2001 – 2022 | Google Earth Engine & Google Colab |
| Landsat 5 TM | Landsat 5 TM Collection 2 Tier 1 Level-2 NDVI | March 1984 - May 2012 | Climate Engine API & Google Colab |
| Landsat 7 ETM+ | Landsat 7 ETM+ Collection 2 Tier 1 Level-2 NDVI | May 1999 - April 2022 | Climate Engine API & Google Colab |
| Landsat 8 OLI/TIRS | Landsat 8 OLI/TIRS Collection 2 Tier 1 Level-2 NDVI | April 2013 - Dec. 2023 | Climate Engine API & Google Colab |
| Landsat 9 OLI-2/TIRS-2 | Landsat 9 OLI-2/TIRS-2 Collection 2 Tier 1 Level-2 NDVI | Oct. 2021 - Dec. 2023 | Climate Engine API & Google Colab |

Table 2
*List of ancillary datasets utilized for this project*

| Source | Data Product | Dates Retrieved | Acquisition Method |
|---|---|---|---|
| NOAA – NCEI | NClimGrid-Daily Precipitation | Dec. 1, 2007 – Dec. 31, 2023 | Climate Engine API & Google Colab |
| NASA | Global Land Data Assimilation System (GLDAS) Surface soil moisture: Daily/24 km | Dec. 1, 2007 – Dec. 31, 2023 | Google Earth Engine API & Google Colab |
| NASA – USDA | Evaporative Stress Index (ESI): 4-week Daily Global 5km | Dec. 1, 2007 – Dec. 31, 2023 | Climate Engine API & Google Colab |
| University of California Merced | GridMET Minimum relative humidity and Wind Speed Daily/4km | Dec. 1, 2007 – Dec. 31, 2023 | Google Earth Engine API & Google Colab |
| National Operational Hydrologic Remote Sensing Center (NOHRSC)/NOAA | SNODAS: Snow Water Equivalent Daily/1 km | Oct. 1, 2003 – Dec. 31, 2023 | Climate Engine API & Google Colab |
| Vermont Agency of Natural Resources, Department of Forests, Parks and Recreation - Division of Forests | Historical Fires Database | Jan. 1, 1999 – Dec. 31, 2023 | Provided by Dan Dillner, State Forest Fire Supervisor, with permission |

| | | | |
|---|---|---|---|
| Vermont Agency of Natural Resources, Department of Forests, Parks and Recreation - Division of Forests | Vermont<br>Fire Danger Rating Areas | n/a | Provided by Vermont Division of Forests, with permission |

### *3.2 Data Processing*

*3.2.1 Antecedent Conditions Study*

For the antecedent condition analysis (covering January 1, 2008, to December 31, 2023), the team retrieved time series data on daily precipitation amounts (P), minimum daily relative humidity (RH), wind speed (W), and soil moisture (SM) to compare environmental trends among the five FDRA (spatially- averaged per FDRA) before fire events. Then, the team calculated daily 7-day and 30-day moving averages for soil moisture, wind speed, and relative humidity, as well as daily 7-day and 30-day cumulative values for precipitation. The resulting datasets for each variable include daily values from the same day, the previous week, and the previous month, accounting for the lag effect these variables have on fire occurrence. Next, the team divided the previous datasets into five seasonal datasets based on classifications of earlier studies in Vermont (Evenson & Jean, 2003). The seasonal periods evaluated were as follows: the **Winter** period spans from November through March; the **Pre-Green-up** period covers April and May; the **Summer and early Fall** months extend from June through October; the **Fall** period includes September through November; and there is an **additional Fall** period specifically for October and November.

The team summed the number of fires per day throughout the antecedent condition study period, assigning a value of zero for days without fires. This data was then incorporated into the processed seasonal datasets. From these datasets, the team created sub-datasets that were ready for further analysis. The sub-datasets were created by filtering as follows:

- 7-day values of all variables (P, RH, SM, W) by FDRA during Spring, dataset called **spring_fdra7**
- Same-day, 7-day, and 30-day values of all variables (P, RH, SM, W) for all FDRA, grouped by season, dataset called **seasons_var**
- Same-day, 7-day, and 30-day values of all variables (P, RH, SM, W) for all dates, grouped by FDRA, dataset called **fdra_var**

ESI shows potential for detecting flash droughts and assessing soil moisture before fires (NIDIS, 2024). However, since ESI values are reported weekly as monthly averages, the team retrieved time series data of ESI by FDRA and aligned 30-day averages of environmental variables (P, RH, SM, W) with ESI dates, extracted every seven days. To correlate fire events with ESI data, the team calculated 30-day moving averages of fires for each FDRA and extracted values every seven days. These values were incorporated into the dataset, named **var_fdra30**, for further analysis.

*3.2.2 Long-Term Phenological Study*

SWE and vegetation data were processed at the FDRA level. To process SWE data, the team determined the melt timing date, which is the date upon which the SWE value reaches half the maximum SWE value for the previous winter (Clow, 2010). The formula from Clow was selected as a repeatable, objective process for arriving at a single date per year that indicates decreasing snowpack and the onset of spring fire season in Vermont.

The team wrote a function which iteratively calculated the twenty spring melt timing dates of the study period per FDRA, resulting in 100 computed melt timing dates. To assess the quality of this algorithm, the team plotted SWE values per FDRA for the entire study period with overlaid marks denoting the maximum SWE date and melt timing date for each FDRA. This provided an accessible format to visually check that the melt timing date for a given year occurs after the date of maximum SWE, and that the SWE value at the melt timing date appears to be approximately half the maximum SWE value for the winter.

The team validated FDRA-level SWE values at the melt timing date calculated within Google Colab against daily snow depth point data from selected Cooperative Observer Program (COOP) sites from each FDRA. Measurements at COOP sites are taken by NWS-trained volunteers who report measurements daily (National Weather Service). Due to variations in snow depth from freshly fallen snow, differences in snow ratios of falling snow, the settling of snow throughout the season, and missing data points, this comparison of the snow depth to SWE made precise validation of the SWE magnitude very difficult, and so the team used this validation to verify the existence of snowpack. Overall, this exercise showed that when the areal average SWE values at the FDRA level indicated snowpack, point data from COOP stations did as well.

Dates of the green-up season were identified using the MODIS MCD12Q2 version 6.1 Land Cover Dynamics data product (Friedl et al., 2020). Mean day-of-year values for the variables of green-up, mid-green-up, and peak from 2001 to 2022 were processed and retrieved through Google Colab. Dates of phenology are identified from a time series of EVI2 values. At a resolution of 500 meters, vegetation phenology is calculated as the date at which the EVI2 time series reaches a threshold percentage of the annual EVI2 amplitude per pixel. Green-up dates are defined by the date at which 15% of the amplitude was crossed. Mid-green-up and peak dates occur when 50% and 100% of the amplitude were reached, respectively (Friedl et al., 2020).

#### *3.2.3 Landsat NDVI*

The team attempted to determine an accurate start-of-season (SOS) date according to the methodology in Kern et al. (2020), which is similar to the early green-up date from MCD12Q2. The method to determine SOS entails applying a fractional value to the difference between a season's minimum and maximum Normalized Difference Vegetation Index (NDVI) values. The team applied this equation to NDVI data from Landsat Imagery between 1984 and 2023 per FDRA and found that the SOS dates returned occurred in January and February of each year. Examination of individual annual springtime NDVI curves revealed that the equation used to determine SOS date from Landsat data relied on a very small number of data points due to coarse temporal resolution. Sparse data along with considerable noise in NDVI curves inhibited the team's ability to extract phenological trends and conclusions of NDVI with confidence. These factors led to the team switching from using Landsat to MODIS data for assessing vegetation phenology.

### ***3.3 Data Analysis***

#### *3.3.1 Antecedent Conditions*

Using Python in Google Colab, the team applied different statistical analyses to understand the relationships between fire occurrence and antecedent environmental conditions (P, RH, SM, W, ESI) using the processed datasets described in the previous section. The analysis was conducted as follows:

*Linear Regression Analysis:* The team conducted a linear regression analysis to explore correlations between fire occurrences and antecedent environmental variables during the Spring seasons from 2008 to 2023 in Vermont. This analysis, conducted on a seasonal (Spring each year- fire season in Vermont) and regional (by FDRA) scale, used the **spring_fdra7** dataset to examine the relationship between aggregated fire occurrences and 7-day moving averages of environmental variables (RH, P, SM, and W).

*Pearson Correlation Analysis:* The team performed a Pearson correlation analysis to investigate the relationships between fire occurrences and antecedent variables across different FDRA regions using the **var_fdra30** dataset. This analysis covered all dates from 2008 to 2023 to capture sufficient variation and understand fire behavior over time on a spatial scale (by FDRA). The analysis assessed the correlation between 30-day moving averages of fire occurrences and variables such as RH, P, SM, W, and ESI, with calculations done every seven days to align with ESI data retrieval. This approach detailed how changes in these variables relate to fire activity variations across FDRA regions.

*Random Forest:* The team employed RF, a machine learning algorithm, to evaluate the importance of environmental variables in predicting fire occurrences at different scales. The analysis focused on determining feature importance to understand how each environmental variable—such as P, W, SM, and RH—contributes to the model's predictive performance. The team conducted two separate analyses:

- **Spatial Scale (FDRA Level):** The team used the **fdra_var** dataset to analyze how environmental variables influence fire predictions at the FDRA scale, examining feature importance across different FDRA regions.
- **Temporal Scale (Seasonal Level):** The team analyzed the **seasons_var** dataset to assess the impact of environmental variables on fire occurrences seasonally, aggregating data from all FDRAs to capture seasonal patterns and variations in feature importance.

*Maps of environmental anomalies:* The team developed a series of maps to visualize the spatial patterns of ecological anomalies and their relationship with fire occurrences. Specifically, these maps illustrate the distribution of minimum relative humidity during the Spring season and its association with fire activity for each year from 2008 to 2023.

*3.3.2 Long-Term Phenology*

Using Python in Google Colab, the team analyzed the new distributions of 100 melt timing and three sets of 110 green-up dates using histograms and boxplots per FDRA (Figures B1 through B8 in Appendix B). Since these dates are not normally distributed, the team extracted median dates and days-of-year per FDRA for melt timing and early, mid, and peak green-up as representative dates.

Next, the team created scatterplots per FDRA for melt timing and green-up dates (Figure B1 through Figure B8 in Appendix B). These scatterplots allowed the team to discern visually potential trends over the study period. To assess such changes, the team calculated linear regression fits for each scatterplot for the 20 years of melt timing dates and 22 years of green-up dates. This produced a total of 20 $R^2$ values, each representing the significance of a linear fit that aims to characterize phenological trends at a regional level (FDRA) in Vermont. The team also analyzed melt timing dates by breaking each FDRA 20-year dataset into two sets representing 10 years each: one set contains melt timing dates from 2004 to 2013, and the other from 2014 to 2023. The team then created boxplots of these new data subsets and performed the Wilcoxon Rank Sum test between each subset per FDRA. This test ranks the values in each 10-year dataset in a common pool and compares the rankings to determine if there is a statistically significant difference between the datasets.

## 4. Results & Discussion

### *4.1 Analysis of Results*

*4.1.1 Antecedent Conditions*

The team performed a linear regression analysis to explore potential correlations between fire occurrences and antecedent environmental variables during the spring seasons of 2008 to 2023, given that spring is the fire season in Vermont. This analysis was conducted on a temporal scale (each spring) and a spatial scale (by FDRA). The analysis used 7-day moving averages for P, SM, W, and RH.

The results (Figure C1 in appendix C) showed that across all FDRAs, the maximum R-squared value for any variable was below 0.4 (an R-squared value of 1 indicates a perfect correlation between the variable and fire occurrences, while a value of 0 indicates no correlation), indicating weak correlations between antecedent climatological variables (SM, P, W, RH) and fire occurrences during spring. Specifically, FDRAs 1-3 had R-squared values generally below 0.2, reflecting very weak correlations, while FDRAs 4 and 5 had slightly higher R-squared values, still under 0.4. In these areas, relative humidity and precipitation had marginally higher importance, but correlations were not significant enough to be predictive.

Given the weak results from the linear correlation analysis and the limited sample size of fire occurrences outside spring, the team combined data from 2008 to 2023 to explore correlations between fire occurrences and climatological variables at the FDRA level. The team calculated correlation coefficients, where 1 indicates a perfect positive correlation, -1 denotes a perfect negative correlation, and 0 signifies no linear relationship, using 30-day moving averages of environmental variables (P, RH, W, SM, and ESI), computed every seven days. The results, displayed in Figure 2, revealed that ESI showed a negligible correlation with fire occurrences across most FDRAs. Minimum RH, however, exhibited the strongest negative correlation with fire occurrences, suggesting that lower RH values are associated with increased fire activity. This finding supports the understanding that lower relative humidity conditions contribute to higher wildfire risk, similar to patterns observed in the Western US. Soil moisture and precipitation showed weak negative correlations with fire occurrences, although less pronounced than RH, indicating that drier conditions are related to increased fire occurrences. Wind speed exhibited a negligible correlation across all FDRAs.

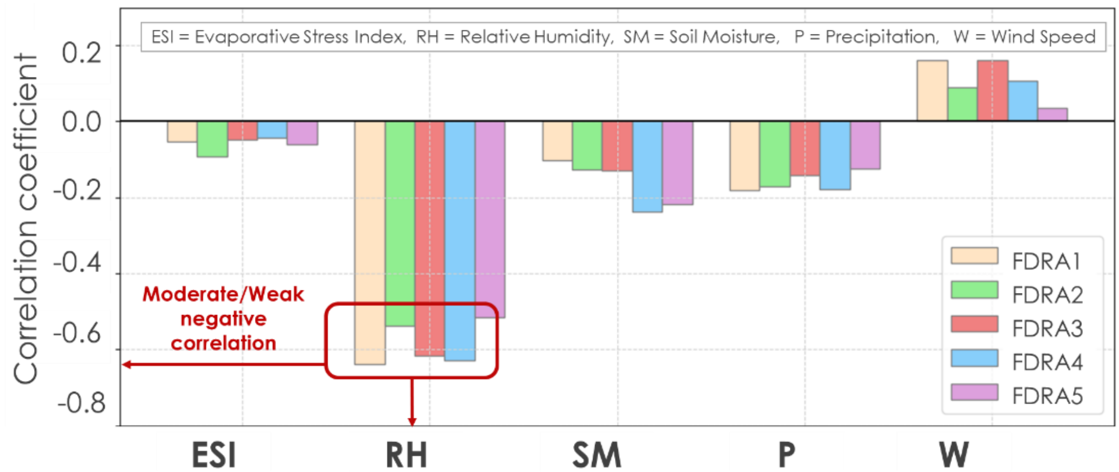


*Figure 2*. Linear Correlation Between Fire Occurrence and Climatological Variables (30-Day Moving Average) by FDRA (2008-2023)

Given that the results from the regression models and Pearson correlations were inconclusive for variables other than minimum RH, the team turned to more advanced methods, such as the RF Model, to better understand the influence of antecedent conditions on fire occurrences. In Figure 3, the team presents the feature importance analysis from the RF models, which were used to predict fire occurrences at the FDRA level across all dates from 2008 to 2023. The analysis shows that variables related to minimum relative humidity—specifically, RH on the same day, the antecedent 7-day average, and the 30-day average—are consistently identified as the most influential factors across all FDRAs.

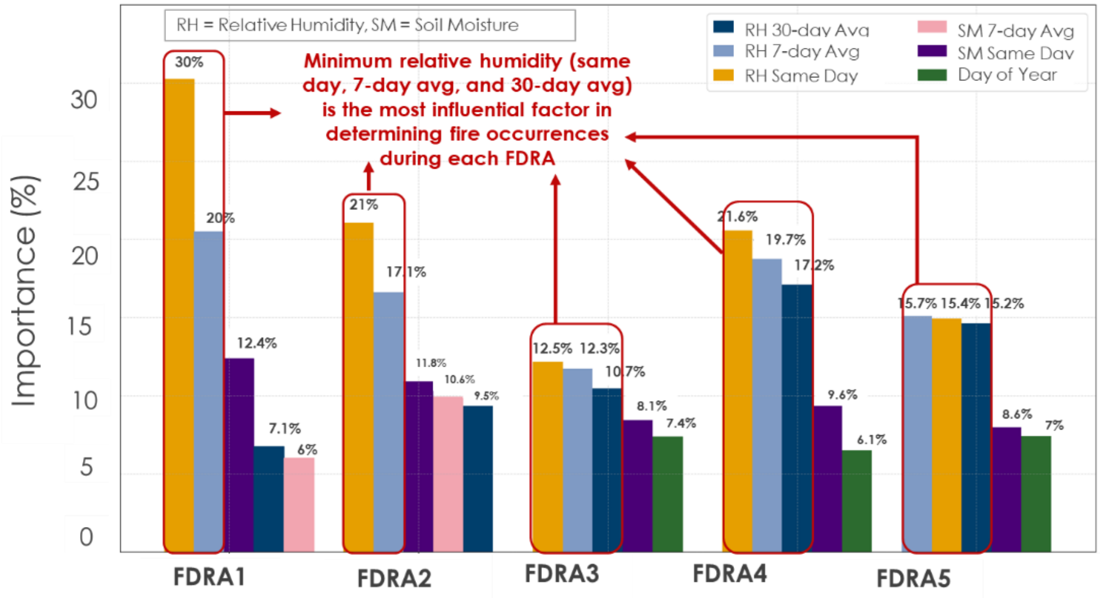


*Figure 3*. Feature Importance Analysis of RF Models for Fire Occurrence Prediction by FDRA (2008-2023)

The team created a series of maps (Figure 4) to analyze the spatial relationship between anomalies in minimum RH —identified as a key factor influencing fire occurrence in Vermont—and spring fire events from 2008 to 2023. The analysis revealed several key patterns: between 2008 and 2010, maps indicated red areas with lower-than-average RH, where fires were more frequent. Conversely, 2011 and 2012 maps showed blue areas with higher RH and fewer fires. In 2013, red areas with frequent fires reappeared, similar to earlier years. From 2014 to 2016, maps displayed a balanced mix of red and blue areas with no clear fire patterns. From 2017 to 2019, predominantly blue areas suggested higher RH and fewer fires, particularly in 2019. In 2020, lower RH was linked to increased fires. From 2021 to 2023, maps returned to a balanced mix of red and blue areas, with no clear fire patterns.

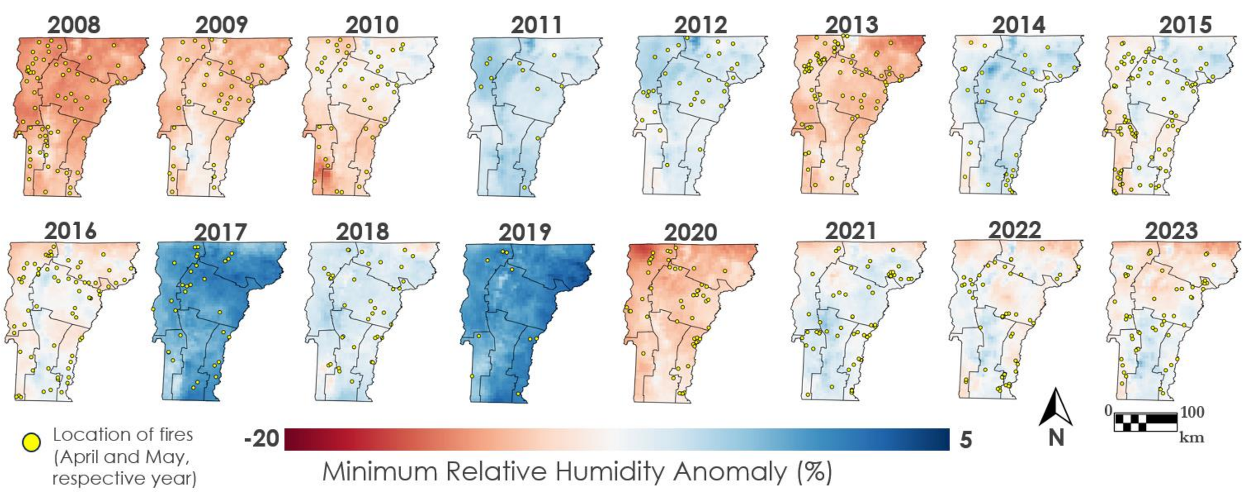


*Figure 4*. Minimum RH departure from average and fire occurrence (April 1- May 30) with respect to a 2001-2023 base period. Red indicated lower-than-average RH, white represented near-normal conditions, and blue denoted higher-than-average RH.

*4.1.2 Long-Term Phenology*

For snow, the team found that median dates of melt timing dates ranged from March 7 to April 2 amongst FDRAs. Given Vermont's range of elevations, it is plausible that the earliest melt timing date is nearly a month before the latest. FDRAs with higher elevations correspond with later melt timing dates, despite being at the same latitude as other FDRA's with lower elevations, such as with FDRA 2 and FDRA 1 (Figure 1). The highest $R^2$ value from linear regression fits of melt timing dates was 0.042 for FDRA 2 and the remaining $R^2$ values were all less than 0.01, indicating that no statistical trend is detected over the 20-year study period. Although the inter-quartile range of the of second ten years of melt timing dates shows a visual increase from the first ten years (Figure 5), the Wilcoxon Rank Sum tests revealed no significant difference between these two datasets with *p*-values falling outside of rejection zones (Table B1 in Appendix B). From this analysis, no statistical change is detected in regional melt timing dates between 2004 and 2023.

Table 3
*Median melt timing dates and early, mid, and peak green-up dates per FDRA and accompanying day of year.*

| **Median Melt Timing and Green-Up Dates per FDRA** | | | | |
|---|---|---|---|---|
| FDRA | Melt Timing Date/Day of Year | Early Green-Up Date/Day of Year | Mid Green-Up Date/Day of Year | Peak Green-Up Date/Day of Year |
| FDRA 1 | March 10/69 | April 17/107 | May 13/133 | July 7/188 |
| FDRA 2 | April 5/95 | April 21/111 | May 18/138.5 | July 8/189.5 |
| FDRA 3 | March 7/66 | April 16/106 | May 13/133.5 | July 14/195.5 |
| FDRA 4 | March 29/88 | April 21/111 | May 17/137 | July 8/189.5 |
| FDRA 5 | April 2/92 | April 24/114 | May 20/140.5 | July 12/193.5 |

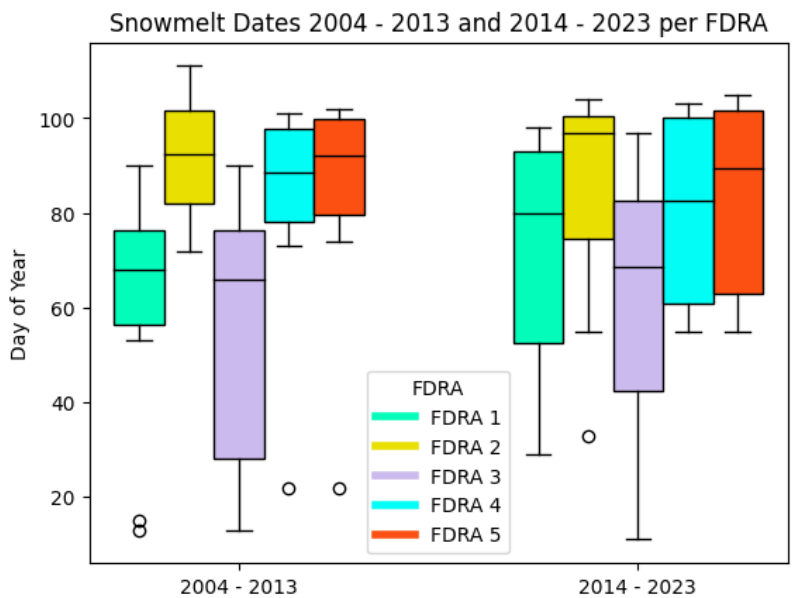


*Figure 5*. The first ten years of melt timing dates per FDRA and the second ten years of snowmelt dates per FDRA show an increase in the inter-quartile range.

For stages of green-up, three distinct sets of dates were found for all of Vermont: early green-up occurs in April, mid green-up in May, and peak green-up in July. During the study period of 2001 – 2022, green-up periods amongst FDRAs span eight days: early from April 16 to April 24, mid green-up between May 13 and May 20, and peak between July 7 to July 14 (Table 3). Relative to melt timing dates, whose median dates span 26 days amongst FDRAs, green-up dates show less variability. The highest $R^2$ value of the fifteen linear regression fits for green-up dates per FDRA was 0.068 and the lowest 0.001. From these linear fits, no statistically significant trend in early, mid, or peak green-up dates was detected over the 22-year study period.

***4.2 Errors & Uncertainties***

The limited accuracy of point locations of fires in this partner-provided dataset pre-2008 imposed restrictions on the antecedent condition study period. A larger and longer record of fire events would increase the types of analysis that can be conducted on environmental variables. Also, the inclusion of all possible fire events could not be validated due to a low average fire area size and the possibility of underreporting at certain fire stations. The project would benefit from validation and accuracy assessments of example fire events and precise locations, which would allow for more precise analysis outside of the April-May fire season. Furthermore, an understanding of the ignition classification of the known fires (e.g., natural v. anthropogenic) would add value to the analysis.

Limitations in this project stem from combining variables with differing resolutions and periods of record. The datasets range from 500 m to 24 km spatial resolution and one to eight-day temporal resolution. Due to the large number of datasets to be statistically combined, the team opted to include datasets whose period of record spanned the entire study period rather than splice together multiple sources. Because of this, more recent datasets offering higher spatiotemporal resolution, such as SMAP for soil moisture, were not included. Last, for the antecedent portion, this study did not include two major factors that affect fire occurrence in Vermont: human influence and fuels. For the phenological study, since trends in melt timing and green-up dates were assessed per FDRA, these correlations came from datasets with only 20 (melt timing) or 22 (green-up) data points due to the existing period of record from both MODIS and SNODAS. A more extensive dataset may allow for more significant relationships to be extracted.

Although the calculation from Clow (2010) is used in the western US to quantify snowpack (USGS, 2019), the relevance of this particular calculation to fire risk in the northeastern US remains undetermined. The melt timing date may be a straightforward computation in high snow years. However, the arrival at a single 'melt date' becomes more complex for low snow years. For instance, in a year with low SWE and high temperatures, the snowpack may melt or decrease below half its maximum value multiple times throughout the winter season. This increases the necessary complexity of the algorithm used to compute a single date, indicating decreasing snowpack and raising broader questions at the intersection of low-snow years and fire risk.

### *4.3 Feasibility & Partner Implementation*

*Applicability of Earth Observations to Partners:* The team found that using Earth observations is feasible to examine environmental conditions and trends related to Vermont fire risk, given a willingness to operate within the abovementioned methodology. The team recognizes that Earth observations are best analyzed in conjunction with *in situ* data. The end products of time series, maps, and statistical results address partner interest in providing a better understanding of variables which drive fire risk and may be useful at an operational daily level.

*Feasibility of Landsat:* Low temporal resolution combined with the exclusion of high cloud cover imagery rendered the use of Landsat incompatible with the project goals. Following discussions with partners and advisors, the use of Landsat was discontinued, which shifted the study period from 1984 to 2001 for the long-term phenological study.

*Feasibility for Studying Drought:*
Flash droughts were a notable element of the work plan that was not feasible to incorporate into analysis this term. The Landsat datasets initially prescribed in the workplan were not feasible for examining flash drought conditions before and after fire events as the fire events were too small to analyze the data precisely. Additionally, the spatiotemporal resolution of variables related to drought were not sufficient to study this element fully. Increased climate variability mean that conditions can shift rapidly from droughts to floods. As such, Resources were focused on examining other environmental variables and phenology. The methodology and datasets for studying this phenomenon should be revisited in future projects.

## 5. Conclusions

Minimum relative humidity was the most significant environmental variable leading to wildfire risk in Vermont at the daily, seven-day, and 30-day timescale from 2008-2023. Soil moisture, precipitation, and evapotranspiration represent less significant negative correlations, while wind speed demonstrated a less significant positive correlation. Random forest models indicate that minimum relative humidity and precipitation are consistently significant in predicting fire occurrence by season. Green-up dates across all FDRAs over the study period remain relatively stable and consistently fluctuating (Figures B6-B8), while snowmelt dates appear to be becoming increasingly variable. This may indicate the influence of increased climate variability on the transition from the winter to spring seasons.

The antecedent condition study within this project provides a framework for incorporating many data streams. The team focused on daily data and expanded to larger timeframes for analyzing disparate variables simultaneously while maintaining data fidelity. A distinctive methodology was established for aligning data with different resolutions and conducting parallel analyses. While analysis of imagery from the Landsat suite was unsuccessful due to the large temporal resolution, statistical techniques such as machine learning were critical in analyzing antecedent conditions.

From the long-term phenological methodology, extracting dates from the MODIS MCD12Q2 data product to arrive at areal averages of different stages of green-up and calculating single melt timing dates per year per FDRA was successful. For snow, however, issues persist regarding how to most accurately pinpoint snowpack melt dates relevant to wildfire risk in Vermont. Assuming the complexities of quantifying snowpack may be overcome with method relevant to fire risk, then green-up and snowmelt dates could be used to examine the length of fire season and fire occurrence alongside total SWE accumulated over the winter.

Using this methodology, partners can enhance their fire forecasting and hazard mitigation strategies by monitoring environmental variables identified and confirmed as key drivers of wildfires during fire seasons, such as minimum relative humidity. By understanding the phenological patterns and antecedent conditions leading to wildfire risk, the National Weather Service may be able to increase the accuracy of their fire forecasts by combining the results from the project with Fire Family Plus-sourced data. Accordingly, the Vermont Agency of Natural Resources can use end products from the project to develop evidence-based mitigation plans to protect Vermont's ecosystems and communities from future wildfire threats.

## 6. Acknowledgements

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## 7. Glossary

**Earth observations** – Satellites and sensors that collect information about the Earth's physical, chemical, and biological systems over space and time

**Evaporative Stress Index** – An index used to estimate vegetation stress based on temperature measurements

**EVI2** – 2-Band Enhanced Vegetation Index

**Feature importance in RF** – Measures the impact of each variable on the model's predictions, highlighting which factors most significantly influence the outcome

**Fire Danger Rating Area (FDRA)** – Operational areal delineation for managing fire resources based upon similarity in topography, fuels and climate; analysis conducted at this regional level throughout this study.

**Google Earth Engine and Climate Engine** – Platforms for acquiring and processing Earth observations and ancillary data.

**Google Colab** – Platform that allows users to write, execute, and share Python code in a Jupyter notebook environment.

**Green-up** – In Northeast US, period in springtime when tree canopies leaf out and NDVI increases.

**Melt Timing** – Date in late winter/early spring at which SWE value reaches half its maximum value from the previous winter.

**MODIS** – Moderate Resolution Imaging Spectroradiometer

**NDVI** – Normalized Difference Vegetation Index

**Random Forest (RF)** – Machine learning algorithm that builds and aggregates multiple decision trees to improve prediction accuracy.

**SOS** – Start-of-season

**Vermont fire season** – Unless otherwise specified, typically defined as the months of April and May; frequently synonymous with "pre green-up"

**Wilcoxon Rank Sum test** – Ranks the values in a common pool and compares the rankings to determine if there is a statistically significant difference between the datasets

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# 9. Appendices

**Appendix A: Climate Table**

Table A1

*A summary of selected observed Vermont climate trends, adapted from Vermont Snyder & Sinclair (2017)*

| Parameter | Trend | Projection |
|---|---|---|
| Annual Temperature | Increase | 3.7-5.8°F higher by 2050 |
| Temperature Variability | Increase | Less stable; seasonal variability |
| **Annual Precipitation** | **Increase** | **10% increase by 2100** |
| Snow | Decrease | Fewer days with snowpack; earlier snowmelt |
| Soil Moisture | Decrease | Higher summer evapotranspiration |
| **Short-Term Droughts** | **Increase** | **Potential for annual recurrence in areas** |
| **Fire** | **Increase** | **Fire events more likely** |

## Appendix B: Statistical Results from Long-Term Phenological Analysis

Table B1

*Statistical results from linear fits of melt timing and green-up dates and Wilcoxon Rank Sum Test for melt timing dates.*

| **$R^2$ Values of Linear Regression Fits for Melt Timing and Green-up per FDRA** | | | | | |
|---|---|---|---|---|---|
| FDRA | Melt Timing $R^2$ | Wilcoxon Rank Sum *p*-value (Melt Timing) | (Early) Green-Up $R^2$ | Mid Green-Up $R^2$ | Peak Green-Up $R^2$ |
| FDRA 1 | 0.008 | 0.308 | 0.001 | 0.028 | 0.007 |
| FDRA 2 | 0.042 | 0.571 | 0.001 | 0.048 | 0.026 |
| FDRA 3 | 0.006 | 0.880 | 0.008 | 0.002 | 0.068 |
| FDRA 4 | 0.001 | 0.880 | 0.001 | 0.000 | 0.002 |
| FDRA 5 | 0.000 | 0.910 | 0.011 | 0.004 | 0.001 |

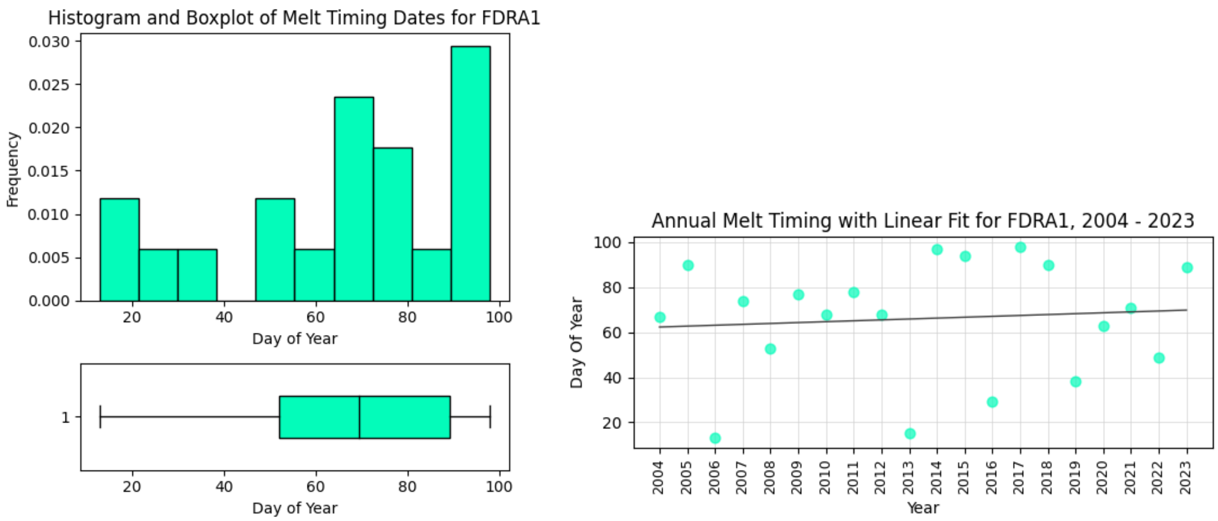



*Figure B1*. Histogram, boxplot, and scatterplot with linear regression for melt timing dates within FDRA 1, 2004 – 2023.

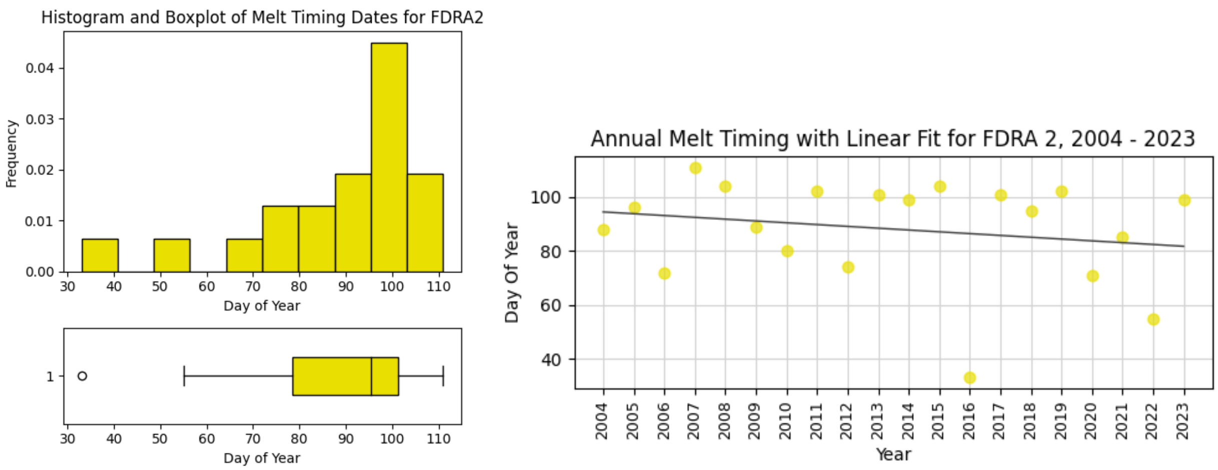



*Figure B2*. Histogram, boxplot, and scatterplot with linear regression for melt timing dates within FDRA 2, 2004 – 2023.

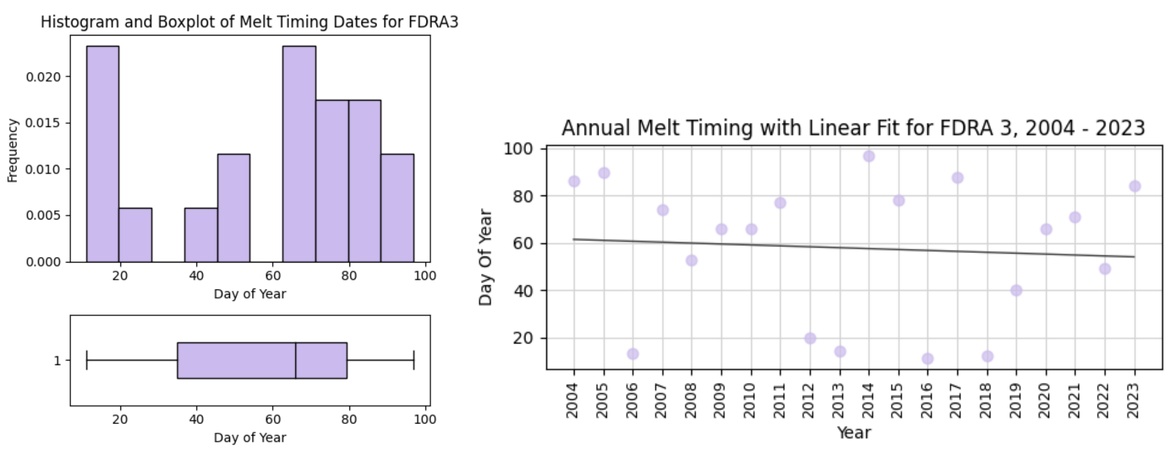



*Figure B3*. Histogram, boxplot, and scatterplot with linear regression for melt timing dates within FDRA 3, 2004 – 2023.

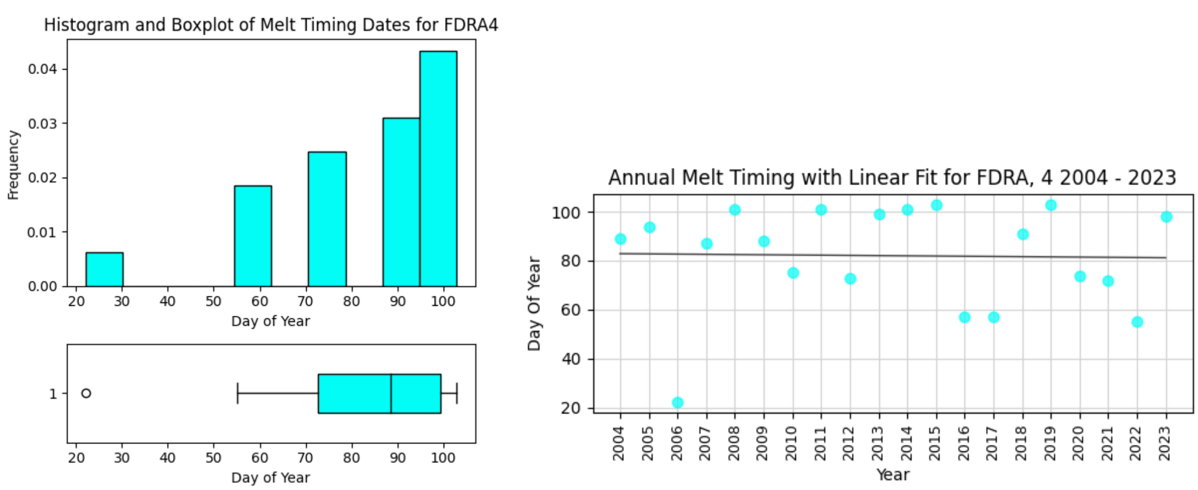
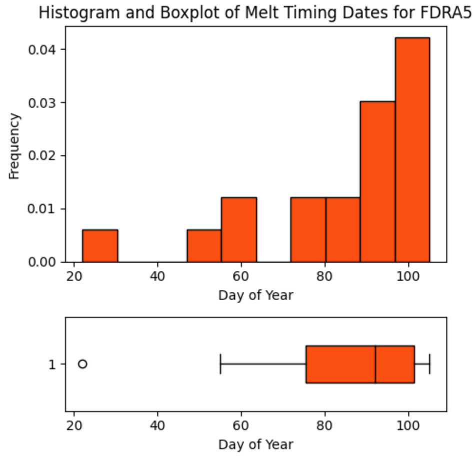



*Figure B4*. Histogram, boxplot, and scatterplot with linear regression for melt timing dates within FDRA 4, 2004 – 2023.



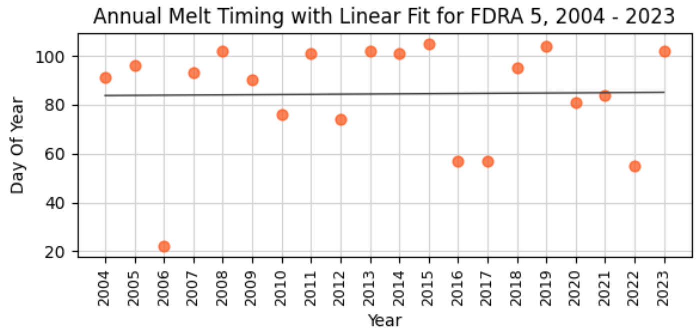




*Figure B5*. Histogram, boxplot, and scatterplot with linear regression for melt timing dates within FDRA 4, 2004 – 2023.

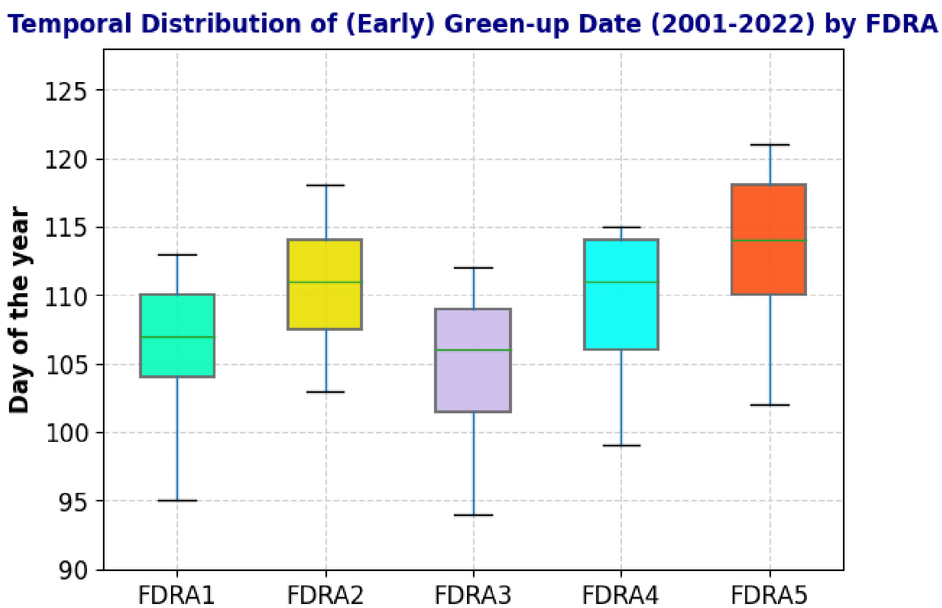



*Figure B6*. Boxplot for the distribution of early green-up dates from 2001-2022 in each FDRA.

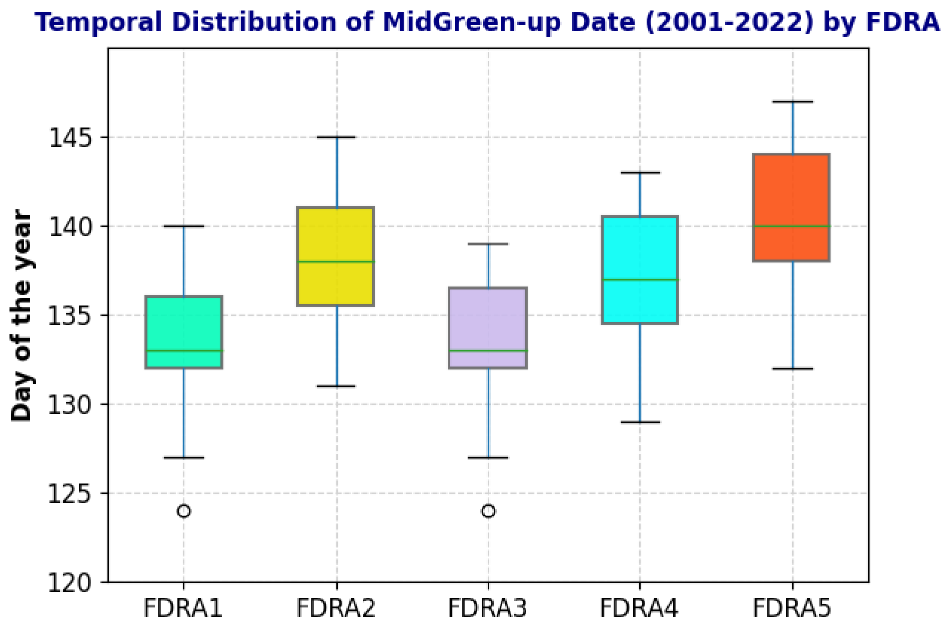



*Figure B7*. Boxplot for the distribution of midgreen-up dates from 2001-2022 in each FDRA.

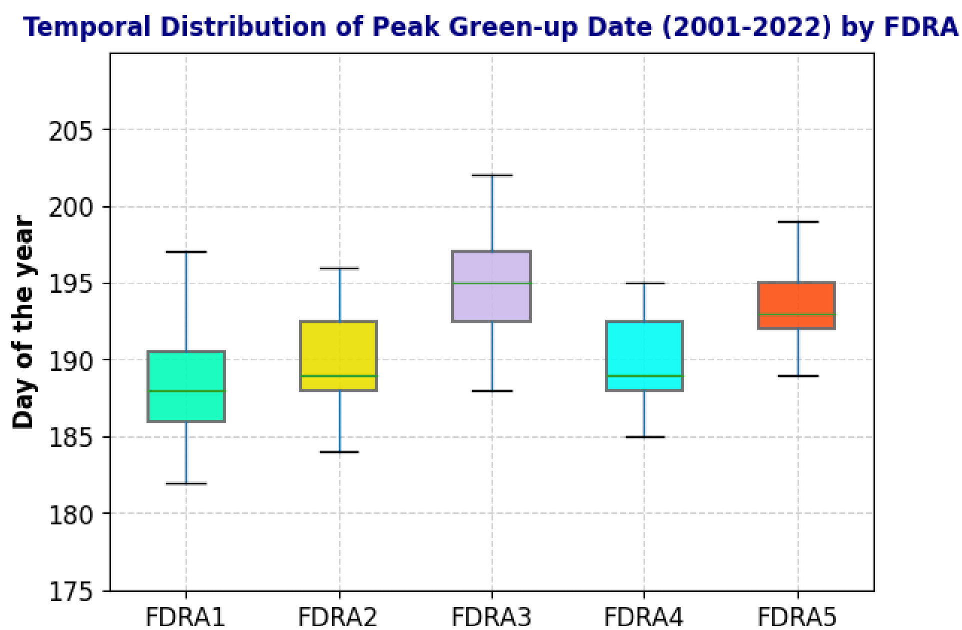



*Figure B8*. Boxplot for the distribution of peak green-up dates from 2001-2022 in each FDRA.

**Appendix C: Statistical Results from Antecedent condition Analysis**

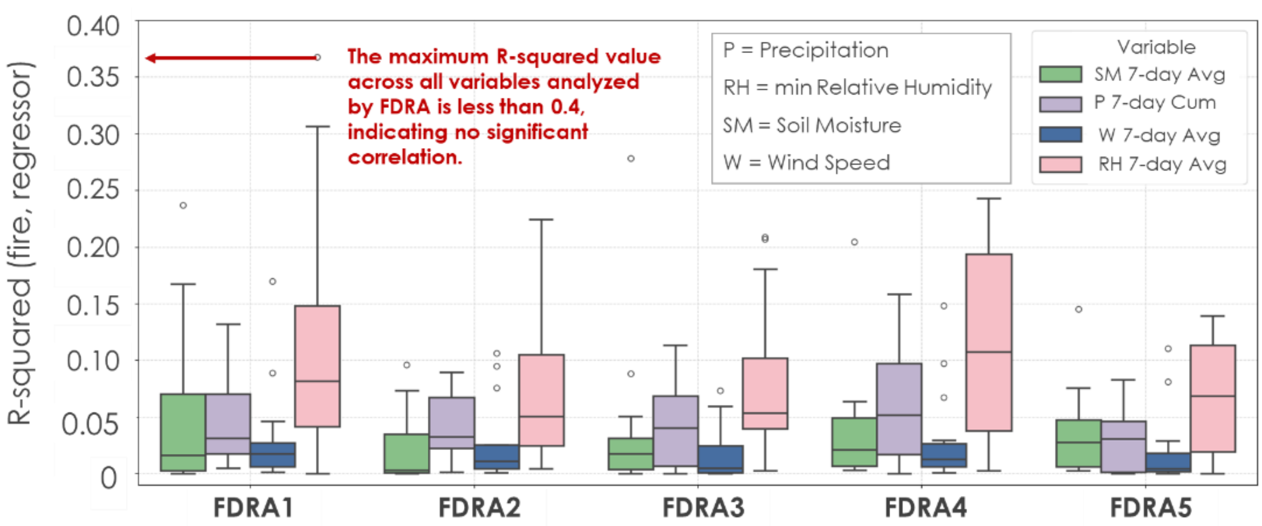



*Figure C1*. R-squared Values for Climatological Variables (7-day Avg) and Fire Occurrence by FDRA in Spring (2008-2023)