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Fire Potential in Arkansas through the Lens of the Keetch-Byram Drought Index

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Abstract

Vegetation fires are a complicated phenomenon to predict both the occurrence and intensity. In the United States, fire behavior has been widely studied in high-risk regions such as in the American West, but fires also occur regularly in states that receive greater levels of precipitation, such as Arkansas. Fires are an expensive and dangerous environmental problem. As climate trends caused by global warming continue to progress, quantifying the extent to which climate factors influence their occurrence in Arkansas would be useful for land management, public safety, public health, agriculture, urban development, and to advance the science of fire-climate dynamics in the American South. In this study, fires are evaluated using the Visible Infrared Imaging Radiometer (VIIRS) monthly active fires dataset, which is used to determine fire season peak. Land use/land cover (LULC) classifications in the state of Arkansas are analyzed to determine whether the climate-fire relationship varies according to predominant land covers. Finally, this study will explore the relationships between fire occurrence and climate variables using the Keetch-Byram Drought Index (KBDI) that incorporates temperature and precipitation to provide an outlook of fire risk. KBDI is commonly used for fire risk assessment in the US, but it's unclear if the index can be relied on to assess fire risk in Arkansas or whether it provides different levels of reliability according to predominant landscape. KBDI in this study was calculated using Google Earth Engine in JavaScript, which facilitates consultation of daily KBDI estimates for Arkansas to the public.

Acknowledgements

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Chapter 1: Introduction

1.1 Trends in Fire and Impacts

Fire occurrence is expected to increase over portions of North America and change regionally in the coming century due to increasing temperature and fuel aridity, consequences of land management policies, and expanding human development leading to a growing wildfire urban interface (Abatzoglou et al., 2021; Bowman et al., 2020; Krawchuk et al., 2009; Liu et al., 2010a). Wildfire suppression cost the U.S. government around 3 billion USD annually in recent years and has been increasing at roughly $60 million per year since the mid-1980s (Burke et al., 2021).

The greatest number of major wildfires occur in the Western U.S. which threaten human settlements, destroy wildlife habitats, affect tourism industries, risk human health, and further feedback loops that worsen climate change trends (Bowman et al., 2020; Burke et al., 2021). However, wildfires also occur in the eastern half of North America. The 2023 wildfires in eastern Canada are an example of increasing, and devastating, wildfires in eastern North American ecosystems and may well be exacerbated in the future (Wang et al., 2022). At times, wildfires greater than 1,000 acres do occur in mountainous regions of Arkansas and in nearby Oklahoma and Missouri according to Monitoring Trends in Burn Severity (MTBS) data (Kurtis Nelson, 2023).

Agricultural fires, although purposefully created, are another important factor of overall fire behavior. Agricultural burning is a practice in which farmers will burn fields and refuse in order to clear debris or prepare for the next harvest. Some states and regions in the U.S. consistently contribute more to overall agricultural burning than others. The Mississippi Delta (comprised of parts of Arkansas, Louisiana, and Mississippi), the Blackbelt (comprised of parts of Georgia and Alabama), and pockets in the Great Plains (parts in Kansas, North Dakota, Oklahoma, South Dakota, and Texas for example) contribute disproportionately to the amount of agricultural burning in the U.S. (McCarty et al., 2009). Arkansas, particularly the eastern agricultural areas, experiences a significant amount of agricultural burning which should be considered when analyzing fire behavior in the state.

As fires and fire weather are projected to increase in North America throughout the coming century due to increased temperatures and drought (Liu et al., 2010a), it is important to study fire behavior not only in western regions of North America but also in regions where fires do occur but have historically not played a major ecological role. Better understanding climatic impacts on fire in Arkansas will better prepare communities for potential hazards in the future in regard to fire suppression, land management, tourism, human health, and development.

1.2 Keetch-Byram Drought Index

The Keetch-Byram Drought Index (KBDI) was created in the American southeast by the U.S. Forest Service to use the coupling effects of temperature and precipitation to estimate soil and duff moisture content and, therefore, fire potential of forest fires (Keetch & Byram, 1968). The index was originally created to prevent wildfire damage. In 1955 and 1956, four fires burned over 1,000 acres in the southeast where typically moist lands that served as barriers against fire had become excessively dry and fostered large, damaging, and costly fires.

Since fire occurrences are expected to increase globally due to rising temperatures and drought, the KBDI is used in this study to measure fire potential in Arkansas. The KBDI is a commonly used drought index in research and operationally to estimate fire potential. Much literature exploring fire potential globally and regionally commonly uses the KBDI to measure fire potential (Dimitrakopoulos & Bemmerzouk, 2003; Dolling et al., 2005; Gannon & Steinberg, 2021; Liu et al., 2010a; Morton et al., 2013), making it an established index in this realm of study. Several states and organizations have historically used and currently implement KBDI. States such as North Carolina and Texas use the KBDI to estimate fire potential state and nation-wide daily (*Keetch-Byram Drought Index (KBDI) – North Carolina State Climate Office | Drought.Gov*, n.d.; *TWC | Keetch-Byram Drought Index (KBDI)*, n.d.) and forest agencies also use the KBDI, among other indices and climate/meteorologic variables, to estimate forest conditions (Brown et al., 2021).

Other drought indices, such as the SPEI (Standardized Precipitation Evapotranspiration Index) and the PDSI (Palmer Drought Severity Index), are more commonly used (Balbo et al., 2019) and are at times implemented for estimating fire potential (particularly the PDSI (Office of Environmental Health Hazard Assessment (OEHHA), 2022)). However, these indices focus on the balance between precipitation and temperature based on average precipitation. These indices provide a more general idea of drought, which can be used to understand climatic fluctuations or climate impacts on crop production. Whereas the KBDI was specifically developed to focus on soil conditions in relation to fire potential and how the coupling effect of temperature and precipitation impact these conditions and potential for fire.

The KBDI has experienced success and significance in fire behavior research. KBDI values are supposed to estimate soil and duff layer moisture and the index successfully estimates herbaceous moisture content (Dimitrakopoulos & Bemmerzouk, 2003). KBDI and modified KBDI indices have successfully correlated index values with fire occurrences in places such as Hawaii (Dolling et al., 2005), Lebanon (Hamadeh et al., 2017), and the continental United States (Brown et al., 2021). Since the original formula for the KBDI was developed to be implemented in the U.S. southeast, modified KBDI indices have been created to adjust for climates of specific study areas outside of the U.S. southeast by adjusting the coefficients that factor in for annual precipitation and estimate total evapotranspiration. This makes the index a flexible tool that can be tailored for study areas outside of the U.S. southeast as well.

However, there have also been some studies that found that KBDI was not a good indicator of fire occurrence (Chan et al., 2004; Morris, 2007). Chan et al. (2004) discusses how KBDI in the state of Georgia can sometimes inversely correspond to fire occurrences and Morris (2007) discusses their results of poor correlation between fire and KBDI values. This study aims to shed light on why a discrepancy in KBDI success in measuring fire potential is experienced between studies. In fact, section 6.1 may help to explain the results of Chan et al. (2004) and Morris (2007) as relevant similarities between Arkansas, Georgia, and Mississippi exist.

The KBDI's success and its current use operationally and in research prove its potential usefulness. The KBDI is the most widely used fire potential index that strictly uses climate variables and since it was developed to be specifically used in the U.S. southeast (the U.S. southeast was determined by U.S. forest service regional administrative boundaries), it is the most logical index to begin measuring climate impacts on fire occurrences in Arkansas. The KBDI is used for daily decision-making regarding fire potential, but this study will help to determine its effectiveness for evaluating seasonal fire occurrence. Temperature and precipitation are the two variables most relevant to fire occurrence at the seasonal timescale and projected changes in their behavior are expected to exacerbate fire occurrence in the future (Liu et al., 2010a, 2010b), making the KBDI a simple yet powerful index to calculate fire potential. The original KBDI formula is used in this study as it was developed for the U.S. southeast, and Arkansas can be classified as being a part of that region. Through personal communications with professionals working with fire in Arkansas, ecologically (Dr. Douglas Zollner at The Nature

Conservancy) and in natural hazards (Mr. Marcus Reed at the Arkansas Department of Agriculture – Division of Forestry Dispatch Center), the standard KBDI is an implemented index in the region. The KBDI scale ranges from 0 (complete soil saturation, no drought present), to 800 (extremely dry soil, maximum drought). An example of a common daily decision making this index helps to inform is when burn bans should be put into place. For example, if the KBDI exceeds a threshold, decision makers may decide to implement a burn ban until KBDI reaches a lower level. This hypothetical threshold would of course vary from location to location depending on other factors such as topography, fuel load, human activity, etc.

1.3 Fire Behavior in Arkansas

There is a relatively small body of literature regarding fire behavior in Arkansas being most of them within the scopes of crop burning impacts on human health (McCarty et al., 2009; Rutlen et al., 2021; Zamanialaei et al., 2023), historic human-fire regime relationship changes via dendrochronological examination (Flatley et al., 2023; Guyette et al., 2006; Stambaugh & Guyette, 2006), and as part of larger research exploring nationwide fire trends in the U.S (Lin et al., 2014; Mitchell et al., 2014).

The literature focusing on crop burning regarding human health does acknowledge that fires, agricultural, prescribed, and wildfires, exist in Arkansas and can affect human health (McCarty et al., 2009; Rutlen et al., 2021; Zamanialaei et al., 2023) . However, the focus of these studies prioritizes particulate matter (PM) from smoke that intersects with human establishments, rather than on fire behavior itself. What is important is that these studies, such as Zamanialaei et al. (2023), suggest that a significant amount of crop burning occurs in Arkansas. These crop residue burning fires, while intentionally created, should be considered when examining statewide fire behavior as this study is examining fire wholly, not only examining wildfire or otherwise accidental fire.

Literature on historic human-fire regime relationship changes via dendrochronological examination in Arkansas and nearby regions are usually very spatially smaller in scope than this study's statewide assessment. The study areas of this literature, focusing on the Boston and Ouachita Mountains in Arkansas and in the Ozarks of neighboring Missouri, are a key piece of this study's hypotheses as these regions contribute largely to the naturally vegetated LULC in Arkansas. This literature examines historical fire behavior in regions such as the Boston and Ouachita Mountains in Arkansas and the Ozarks in Missouri from pre-European settler times through the 20^{th} century (Flatley et al., 2023; Guyette et al., 2002, 2006; Stambaugh & Dey, 2021; Stambaugh & Guyette, 2006). These studies discuss how fire regimes in these regions have changed and how fire in these forested and mountainous regions has largely been used as a tool, or greatly suppressed, by human inhabitants at different points in the region's previous 500 years. However, humans in the 21^{st} century are largely introducing a new fire regime, one that incorporates a significant prescribed burn practice for environmental and economic benefit (Guyette et al., 2002).

These studies focus on the history of fire behavior, rather than historic climatic drivers of fire in Arkansas. As human population and development expands in the region, the risk of wildland fire occurrence and damage to human life and settlement increases. These are other reasons why it is important to understand how wildfire can impact Arkansas ecosystems in the future.

1.4 Climate and Fires in Arkansas

The literature regarding climatic drivers on fire in Arkansas or the southeastern U.S. are usually only briefly mentioned within the scope of larger studies examining fire trends in the continental U.S. (CONUS), North America, or worldwide. For example, Lui et al. 2010 suggests that the southeastern U.S. will see increased fire potential per the Keetch-Byram Drought Index (KBDI) by the end of the 21st century, to approximately an annual average increase of 100 KBDI (the KBDI scale ranges from 0 (complete soil saturation, no drought present), to 800 (extremely dry soil, maximum drought).

Many other studies link higher drought with higher fire potential and, thus theoretically, with higher fire occurrence (Morton et al., 2013; Riley et al., 2013). These studies discuss such intuitive relationships. If sharp decreases in precipitation and higher temperatures are experienced, fuel load will dry and facilitate a higher likelihood of fostering fire. Other proven factors that exacerbate fire potential include, but not limited to, wind, relative humidity, and fuel load and moisture (Keeley & Syphard, 2019; Liu et al., 2014). However, some of these variables are meteorologic in nature or ecosystem specific. Temperature and precipitation are climatic variables that locally may trend differently in the long term and affect regions or states in specific ways regarding fire behavior. Drought, driven largely by temperature and precipitation, should be examined to understand climatic impacts on fire potential in Arkansas. Specifically regarding Arkansas as a study area, the importance of examining drought is reinforced by a study on wildfire in Arkansas that found that soil moisture and the Palmer drought severity index were among the leading factors out of 15 variables that contributed to wildfires greater than 500 acres (Saim & Aly, 2022). However, it is important to keep in mind that while drought can drive fire potential, it will not drive fire potential uniformly. LULC, regional forest management, fuel conditions, and ignition can impact drought's influence on fire potential (Littell et al., 2016).

There remain some disagreements on climate trends and their impacts on fire behavior in the southeastern U.S. Mitchell et al. 2014 discusses differences in climate projections. While commonly used climate projections, such as the Community Climate System Model (CCMS) and the Hadley Centre Coupled Model, version 3 (HadCM3), disagree on the severity of temperature change, they both project rising summertime temperatures in the southeast U.S., including Arkansas. Other factors are also important such as the southeast's varied topography, land use/land cover (LULC), fire size, and fire ignition type, which make it difficult to generalize fire behavior and thus fire behavior drivers in the region (Mitchell et al., 2014; Morton et al., 2013). Arkansas is no exception as topography and LULC in the state can range from rugged, dense forests to flat wetlands, to the agriculturally dominant Delta. However, research does suggest that drier conditions do impact fire size and that fires have statistically increased in the southeast generally over the past 25 years (Morton et al., 2013).

To fill in the gaps of our understanding of fire behavior in Arkansas, this study explores relationships between fire occurrences in Arkansas and climate as expressed by KBDI. The analyses are further interpreted according to Arkansas main LULC.

Chapter 2: Goals and Motivation

The KBDI, while widely used publicly and in research, is not readily accessible for analytical use in a gridded spatial format for the public. KBDI maps online can provide an idea of visual drought patterns, but downloadable values across specified areas for specified timescales are needed for manipulation and analysis. This study provides code that can be implemented for any region and timescale, provided climate data is available in gridded format. While Google Earth Engine, which is used to generate KBDI values in this study, does have computational limitations (specifically calculating an index formula daily for rasters over a longer time period (over ~3 months)) that can make KBDI data generation tedious, the code can be used by anyone. This code can be used for free in Google Earth Engine or to transfer the code to another platform with improved computational capacity to generate their own KBDI data.

As the climate changes, our understanding of how the climate impacts fire behavior in different regions becomes more important. This not only applies to already fire prone areas of the American west but to less fire prone regions such as the American southeast. Fires can pose several risks such as danger to human settlement and health and damage to infrastructure and natural areas due to increased wildfire behavior. Fire is an expensive hazard, and these dangers are coupled with financial costs (Burke et al., 2021). It is of great interest to understand how fire behavior responds to temperature and varied precipitation patterns in current times and throughout the 21st century (Gannon & Steinberg, 2021).

Another aspect to consider is the varied LULC in Arkansas, ranging from topographically rough forests of the Boston and Ouachita mountains to wetlands in the south, and to the agriculturally dominant Mississippi Delta in the east. These differences in LULC can easily impact fire behavior as reviewed in the literature in section 1.3 and 1.4. These differences in fire behavior per LULC may vary in intensity, spatially, and seasonally across the state. The forested areas for example may exhibit more intense fire behavior in the warmer and drier months whereas agriculturally dominant LULC may exhibit stronger fire behavior according to harvest schedules in the state. These examples of the study's results would mean that Arkansas exhibits different fire behaviors in the state dependent on LULC. This would not only be useful for understanding fire behavior in the state but also in neighboring states.

With these considerations in mind, the stated goals and/or questions of this study are:

1) provide workable code to generate KDBI that will be easily accessible to the public.

2) determine if the KBDI is a viable index to measure seasonal fire potential in Arkansas at the seasonal timescale.

3) determine whether fires and KBDI relationships differ according to LULC in Arkansas.

The hypothesis tested linked to goal #2 is: increased fire occurrence will correspond positively with increased drought (expressed as higher KBDI values – see section 1.2) and lower fire occurrence will correspond with lower KBDI values. The hypothesis tested in relation to goal #3 is: the relationship between fire occurrence and KBDI will be stronger for native vegetation (e.g. forest, herbaceous, and shrub), especially in a fire-prone ecosystem; and weaker in managed (e.g. human development and agriculture) land covers. This hypothesis assumes that more developed areas are more human-controlled, and therefore more fire suppressed, whereas naturally vegetated LULC is more prone to fluctuations in climate and weather.

Chapter 3: Data and Methods

3.1 Datasets Used

The datasets to be examined in this study are PRISM climate data (PRISM Climate Group, 2014) to calculate KBDI values, VIIRS 375m active fire product (Hillger et al., 2013; Schroeder & Land Atmosphere Near Real-Time Capability For EOS Fire Information For Resource Management System, 2020), Monitoring Trends in Burn Severity (MTBS) (Kurtis Nelson, 2023), and the National Land Cover Database (NLCD) 2021 (Dewitz, 2023).

3.2 Visible Infrared Imaging Radiometer Suite (VIIRS) Active Fire Product 375m

Obtaining acceptably accurate and moderately comprehensive fire data is now feasible thanks to satellite datasets available through Fire Information for Resources Management System (FIRMS) (such as MODIS Active Fire Products (Giglio, 2000) and VIIRS 375m Active Fire Product (Hillger et al., 2013; Schroeder & Land Atmosphere Near Real-Time Capability For EOS Fire Information For Resource Management System, 2020). Other satellite-based fire datasets exist, however, with disadvantages. Studying fires from satellite estimates often requires the researcher to make a choice between high spatial resolution or high temporal resolution and/or short timeseries. The Landsat active fire dataset (Schroeder et al., 2016) would be a preferred dataset to use to measure fire behavior due to its fine spatial resolution of 30 meters. However, it has only been available since 2022 which makes aggregating monthly data for a reasonable study period unfeasible. The MODIS active fire dataset (Land Atmosphere Near Real-Time Capability For EOS Fire Information For Resource Management System, 2021) collects data daily and has been around since the year 2000 but is spatially coarser 1,000 meters than the VIIRS dataset at 375 meters. Due to the VIIRS dataset being spatially finer, it can provide a more nuanced picture of fire behavior. The VIIRS active fire product was chosen for this study for its balance between time series length and spatial resolution. The VIIRS data is downloaded from the NASA FIRMS (Fire Information for Research Management System) website as a shapefile of point data. ArcGIS Pro (ESRI Inc., 2023), is used to clip the data to retain the points within the Arkansas border. Each active fire point is flagged for quality of observation and low confidence fire occurrences are removed from the dataset, while nominal and high confidence level fire occurrences are retained.

3.3 PRISM Climate Data

The KBDI data is calculated from the PRISM (Parameter-elevation Regressions on Independent Slopes Model) available for the continental United States at 4km spatial resolution, at daily timesteps from 1991 to current (PRISM Climate Group, 2014). This study uses PRISM data from February 2012 through January 2024. The variables necessary to calculate KBDI are maximum daily temperature, daily precipitation, and annual climatological precipitation as described in section 4.1.

3.4 MTBS Data

The Monitoring Trends in Burn Severity (MTBS) (Kurtis Nelson, 2023) dataset will also be used in a visual capacity to determine where large fires generally occur throughout Arkansas and what kind of fires they are (wildfire vs. prescribed fire). The MTBS dataset collects fire data for fires greater than 500 acres in the eastern half of the CONUS (including Arkansas) and fires greater than 1,000 acres in the western half of CONUS. Because this is not a comprehensive dataset of all fires, and fires smaller than 500 acres are also of importance for determining fire behavior in the state, this dataset will not be examined statistically.

The MTBS provides shapefiles of the burn area for these large fires. Fires from 2012 through 2023 are mapped onto the state of Arkansas and are compared to fire season, LULC, and climate/fire relationship patterns across counties in Arkansas.

3.5 LULC Impacts

Given the LULC diversity in the state of Arkansas, the significance of VIIRS-KBDI correlation coefficients are examined by counties' dominant LULC per the National Land Cover Database 2021 (Dewitz, 2023). The NLCD is available from 1992, new LULC data being made available in updated datasets, and it is comprised of land cover classes over the continental United States. There are 20 classes describing the various native vegetation types of the US, bodies of water, level of development and agricultural use. Generally, the western portions of Arkansas are topographically rougher and more forested while the eastern portions are flatter and dominated by agricultural LULC. It is hypothesized that due to these differences in LULC and human activity (or lack thereof), variations in fire behavior will be observed.

Chapter 4: Methods

4.1 KBDI Formulation

The KBDI is not a straightforward index to calculate. Despite the original paper introducing the index's calculation, there is not a concise, cohesive explanation of how to precisely implement the index. Part of this study's goal is to provide KBDI calculation readily available to the public, so it is rational to include a concise, cohesive set of directions to calculate the index.

The KBDI uses maximum daily temperature, daily precipitation, and annual average total precipitation (or "climatological precipitation") to estimate the soil and duff layer moisture of a given area. Ultimately, the formula can be represented as $KBDI = Q + dQ \times 10^{-3}$ where Q represents the previous day's KBDI value adjusted for daily precipitation and dQ represents the effects of daily maximum temperature and climatological precipitation. The final KBDI value will range between 0 (complete soil saturation, minimum drought present) and 800 (extremely dry soil and duff layer, maximum drought possible). The units for which to use the KBDI formula will be described in imperial units as per the original paper introducing the formula. However, metric units can be used if temperature and precipitation units agree, but the formula coefficients must be adjusted and are not covered in this document.

Q is the previous day's KBDI adjusted for precipitation and can be represented as $Q = (KBDI_{t-1}) - (NETP_t \times 100)$. The *t* variable represents time, so $KBDI_{t-1}$ is the previous KBDI value recorded. In this study, $KBDI_{t-1}$ is the previous day's KBDI value since daily data is being used. *NETP* represents net daily precipitation. If net daily precipitation does not exceed 0.2 inches, *NETP* precipitation is equal to zero. If precipitation does exceed 0.2 inches, *NETP* equals daily precipitation minus 0.2 inches. In the case of consecutive days of precipitation, if

$NETP_{t-1}$ exceeds zero, $NETP_t$ is equal to total net daily precipitation and ignores the step to subtract 0.2 inches.

For the variable dQ, maximum daily precipitation and annual precipitation are taken into account and is represented as $dQ = \frac{\left((Q-800)\cdot\left(0.968\cdot e^{0.0486T}-8.3\right)\cdot\Delta t\right)}{1+(10.88\cdot e^{-0.0441P})} \times 10^{-3}$. Q is the variable calculated in the previous paragraph, T represents maximum daily temperature in Fahrenheit, Δt represents amount of time passed, and P represents climatological precipitation. Climatological precipitation is the average annual total amount of precipitation over a 30-year period. Δt for the use of this study is 1 because daily data is being used and iterating this function for each day. However, this may increase from 1 if using coarser climate data that, for example, collected data weekly or if the function is not iterated every day for daily climate data.

4.2 Calculating KBDI using PRISM and Google Earth Engine (GEE)

The KBDI data must be manually generated as gridded KBDI values are not readily available for Arkansas. The index formula is coded into Google Earth Engine (GEE) (Gorelick et al., 2017) using PRISM maximum daily temperature, daily precipitation, and annual climatological variables at 4km resolution to produce a daily output of KBDI values. For comparison with fires, KBDI data is needed starting in February 2012, but calculations need ‘spin-up’ time to calibrate. To do so, Arkansas KBDI was calculated beginning in January 2008, with the first image having a KBDI value of 0 across Arkansas. By the time KBDI values are collected for this study in February 2012, four years after spin-up was initialized, the values should be close, if not exact, to what the true KBDI values estimate for soil and duff moisture.

The ‘spin up’ time for the KBDI index, the time it takes for index values to normalize to accurate values, is recommended to be only several years for areas that experience a wetter climate but potentially over five years for drier climates (Brown et al., 2021). Figure 1 shows where 7-day precipitation accumulated to a minimum of six inches at least once during the calendar year for 2008, 2009, and 2010. If an area receives six inches or more of precipitation in a 7-day window, the top eight inches of soil should reach complete saturation where KBDI would reset to zero (Keetch & Byram, 1968), a necessary condition to start the daily sequential

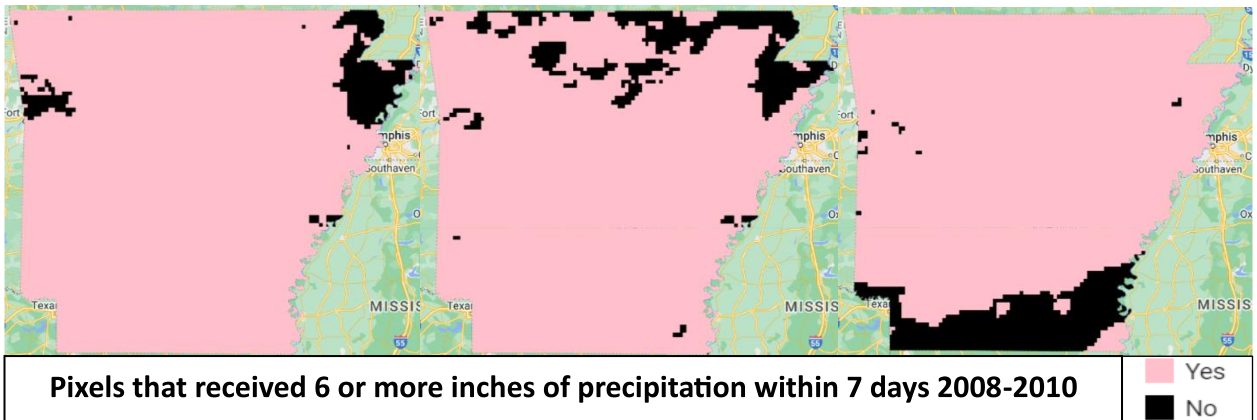

Figure 1: The black pixels represent areas that did not accumulate at least six inches of precipitation during any 7-day period of the years 2008, 2009, and 2010 (left to right).

KBDI calculations.

Given that there is only a small number of pixels where the 7-day precipitation did not add up to six inches between 2008 and 2010, 2008 was determined to be an acceptable year to begin the KBDI spin-up for an analysis beginning in 2012. After beginning to generate KBDI values, it became clear that most pixel areas in Arkansas, according to PRISM climate data, reach a KBDI value of zero naturally at some point nearly every winter. Not only would values normalize to their true value given a four-year spin-up, but most pixels in Arkansas naturally drop to zero at some point during the winter due to the coupling effect of precipitation and low temperatures, which effectively resets the index. It is safe to assume that the remaining pixels that did not receive at least six inches of precipitation in these years normalized to proper values in the four years of index spin-up.

Using the PRISM climate data, images of KBDI values across Arkansas can be produced daily for the duration of the study period. To match the resolution of the VIIRS data, the KBDI pixel values are averaged monthly and then averaged spatially by county. This results in a dataset that provides the monthly average KBDI value for each Arkansas county.

Using PRISM climate data, Google Earth Engine, and the formula above, gridded KBDI values can be calculated daily at 4.6 km (the spatial resolution of PRISM Climate Data). By using PRISM climate data inputs and Google Earth Engine in conjunction, every pixel of PRISM-provided data undergoes the calculations described above and produces a KBDI value. These KBDI formula calculations are coded into Google Earth Engine using the JavaScript language.

4.3 Spatial Aggregation

The modifiable areal unit problem (MAUP) (Openshaw, 1984) and the modifiable temporal unit problem (MTUP) (Cöltekin et al., 2011) (the latter, as it relates to this project, is discussed in section 4.4) are two considerations when deciding how to aggregate data. How data is aggregated spatially and temporally may affect the results of the analysis and potentially lead to inaccurate conclusions. Spatial data is provided in pixels and shapes of varying areal sizes and at temporal scales of varying intervals. The spatial and temporal resolution of data may not reflect the nuance of reality. Additionally, further manipulation and aggregation of data will affect the results of analysis. How the aggregation may affect the results should be considered. However, these spatial and temporal problems are inherent in all spatial analysis.

The KBDI and VIIRS datasets are aggregated to a common spatial aggregation at the level of counties in Arkansas. The decision to use Arkansas counties as the spatial unit is threefold. 1) Conventional weather and climate systems often use counties as spatial units for data aggregation (*NOAA Offers Climate Data for Counties*, 2019). 2) Policy and decision making occur frequently at administrative levels, such as at the county and state level, not at the pixel level. 3) Fires at the 375-meter resolution (VIIRS active fire product resolution) may not repeat year to year due to fuel levels not recovering (Roccaforte et al., 2012) limiting an analysis of interannual variability at the pixel level.

It is important to avoid ecological fallacy regarding results produced in this study. Fire behavior is not uniformly distributed throughout each county and therefore it is important to avoid assuming that fires occurred in a particular area or LULC on the intra-county scale. Due to the decision to aggregate data by county lines, these intra-county variations are not observed and are a result of the MAUP. However, given that data must be aggregated spatially, this problem would exist to some degree in any case.

4.3.1 VIIRS Active Fire Product

The VIIRS data is downloaded from the NASA FIRMS (Fire Information for Research Management System) website (*NASA-FIRMS*, n.d.) as a shapefile of point data, using latitude and longitude coordinates to overlap the Arkansas border. Using ArcGIS Pro, the data are clipped using the Arkansas border. The daily VIIRS active fires point data is first filtered to retain the nominal and high confidence values. The point data are spatially joined to a shapefile of Arkansas county borders, assigning each fire occurrence to the county it occurred in. Then, active fires are counted within the borders of each county in Arkansas using the GroupStats tool in QGIS. A monthly time series of active fires count is then produced for all 75 counties in Arkansas from February 2012 through January 2024.

4.3.2 KBDI

The daily gridded KBDI generated using GEE is also aggregated to county level in GEE. Due to computational limitations of GEE, the script code was adjusted and run for every month of the time series. In GEE, the KBDI pixel values were averaged for the entire month and then spatially averaged according to Arkansas county borders. These county averages were exported out of GEE and compiled to create a final timeseries of monthly average KBDI values for all 75 Arkansas counties from February 2012 through January 2024.

4.3.3 NLCD

Fire potential describes how prone or resilient an environment is to fire provided a source of ignition. Fire may occur in circumstances of high fire potentiality, but it may also occur in circumstances of low fire risk. Fire during times of low fire risk may be caused by ill-managed prescribed burning or otherwise neglectful fire practices and is dependent upon factors such as moisture content, live vegetation, dead vegetation, ignition source, ignition strength, wind, etc. (Keeley & Syphard, 2019; Liu et al., 2014). Thus, in this study the relationship between fire and KBDI is evaluated according to predominant land cover in Arkansas to assess whether patterns of certain LULC impact positively, or negatively, the fire/drought relationship. The gridded 2021 NLCD layer is used to extract the dominant LULC of each county by first creating a NLCD simplified classification. The original NLCD classes: "deciduous", "evergreen", and "mixed forests" are combined into a single “forest” classification; open, low, medium, and high intensity developed areas are combined into a single “developed” classification; dwarf-shrub and shrub/scrub are combined into a single “shrubland” classification; grassland herbaceous, sedge/herbaceous, lichens, and moss are combined into a single “herbaceous” classification; pasture/hay and cultivated crops are combined into a single “agriculture” classification; woody wetlands and emergent herbaceous wetlands are combined into a single "wetland" classification. This makes a final LULC classification list of 1) water, 2) developed, 3) barren, 4) forest, 5) shrubland, 6) herbaceous, 7) agriculture, and 8) wetland. This re-classification characterizes LULC that falls under two main umbrellas: developed (urban and agriculture) and non-developed (forests, shrub, herbaceous, and wetland). By using the 2021 layer, as opposed to an earlier NLCD product (e.g. 2011 or 2019), the most common change (non-developed to developed) should be well represented. In addition, it is not expected that the dominant land cover and percentage of total land cover changed drastically from 2011 to 2021.

The proportion of each county's land cover is calculated in ArcGIS Pro using the spatial statistics tool. The dominant three land cover of each county and their respective percentages are recorded. This provides a metric of each county's developed vs. non-developed LULC.

4.4 Temporal Aggregation

Regarding the MTUP (referred in section 4.3), how data will be aggregated and how that aggregation may affect the results of the project should be considered. This study will aggregate data monthly to determine the season when each county experiences the most fires. Fires are caused due to ignition sources, not drought. Drought may provide conditions favorable to fire given an ignition source, but fire will not propagate without a source of ignition regardless of moisture levels. This study aims to determine whether fire and drought relationships exist in Arkansas by determining maximum fire season for each county and observe if drought conditions correlate with fire season.

Monthly fire counts calculated at the county level (Section 4.3.1), were used to derive a monthly climatology throughout the study period (i.e. averaging all January fire counts, February fire counts, etc.). Then, an overlapping 3-month climatology (i.e. January-February-March

(JFM), February-March-April (FMA), etc.) was calculated. Seasonal climatology was used to determine the season with the highest monthly average fire count in each county and spatial patterns of maximum fire season in Arkansas which facilitates comparison with LULC coverage across the state.

The KBDI values for each county's fire season are calculated in the same way, but dependent on maximum fire season. Given each county's maximum fire season, the KBDI values for these respective months are averaged. By doing so, the hypothesis of greater fire occurrence corresponds with higher fire potential can be tested. If a greater average fire occurrence during maximum fire season corresponds to a higher average KBDI value, a climate/fire relationship can be exhibited. If a greater average fire occurrence during maximum fire season does not correspond to a higher average KBDI value, a climate/fire relationship is not exhibited. The correlation analysis (see section 4.5) is then conducted at each county for the maximum climatological fire season.

4.5 Correlation Analysis

The average 3-month VIIRS fire count during maximum fire season for each county is correlated with average 3-month KBDI values during each county's respective fire season. Table 1 is an example of this correlation being performed on Lonoke County (located in the east central region of Arkansas) using the Pearson's correlation coefficient. If the correlation coefficient (r-value) is above 0.5 (which means the relationship is positively correlated), the p-value is calculated. For this study, r-values above 0.5 and p-values below 0.1 are significant and have a low likelihood to have randomly occurred.

KBDI Avg Monthly	Sep	Oct	Nov	SON Avg		**VIIRS**	Sep	Oct	Nov	SON Avg	R	P
2012	267.4	288.1	269.1	274.8		2012	13	44	23	26.66667	0.868867	0.000244
2013	572.1	330.9	209.3	370.8		2013	103	66	6	58.33333		
2014	531.0	450.9	320.6	434.2		2014	118	90	8	72		
2015	661.0	654.4	172.3	495.9		2015	152	122	2	92		
2016	461.0	541.4	558.5	520.3		2016	91	151	85	109		
2017	394.1	584.1	590.9	523.1		2017	64	111	18	64.33333		
2018	247.9	66.3	12.7	108.9		2018	31	13	0	14.66667		
2019	485.4	437.8	45.1	322.7		2019	75	23	1	33		
2020	228.4	190.9	112.6	177.3		2020	24	48	30	34		
2021	667.0	430.4	363.2	486.9		2021	105	55	12	57.33333		
2022	626.8	668.1	445.3	580.1		2022	155	127	15	99		
2023	687.0	595.7	217.3	500.0		2023	205	103	13	107		
2024						2024						

Table 1: Correlation calculation for Lonoke County. Average Sep-Oct-Nov KBDI values are averaged each year, and average Sep-Oct-Nov VIIRS fire occurrences are averaged each year. The SON averages for each dataset are then correlated, producing R- and P-values for the county.

Chapter 5: Results

5.1 Maximum Fire Seasons in Arkansas

The maximum 3-month fire period was calculated for Arkansas county-wide. The mapped results can be seen in Figure 2.

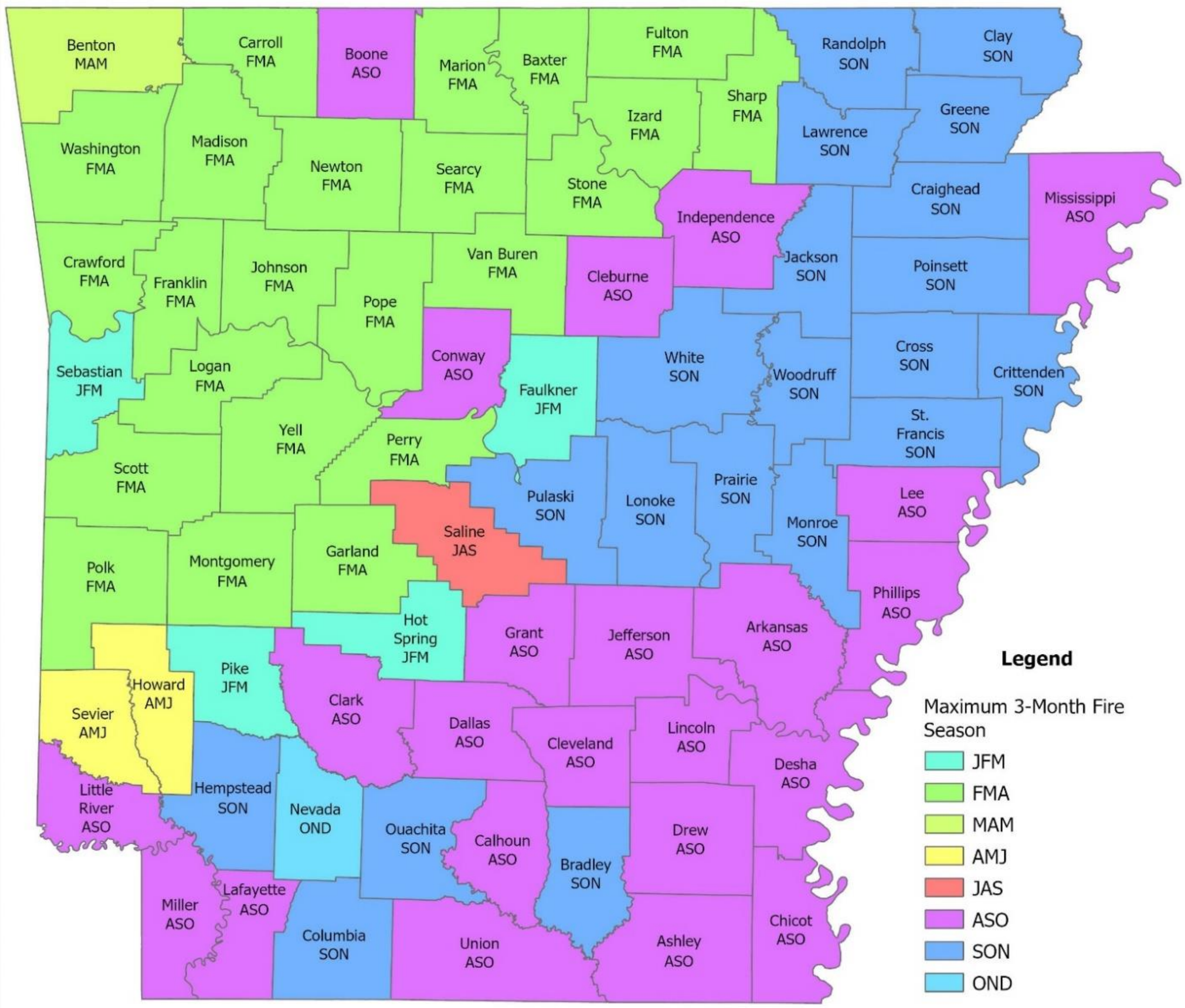

Figure 2: The dominant maximum fire season for northwest Arkansas is Feb-Mar-Apr and in the south and east it is dominantly later in the year, Aug-Sep-Oct and Sep-Oct-Nov.

The northwestern third of Arkansas exhibits a similar maximum fire season early in the year. The dominant season in this third of the state is February-March-April, but some counties exhibit January-February-March, March-April-May, and April-May-June seasons as well.

The southern region and the eastern region exhibit maximum fire seasons later in the year yet are slightly varied. The southern third exhibits a dominant maximum fire season of August-September-October but also exhibits maximum fire seasons of September-October-November and October-November-December. Whereas the eastern third exhibits a dominant maximum fire season of September-October-November.

The lines separating these regions of maximum fire season dominance are similar, but not exact, to the lines separating LULC differences in the state (Figure 7, Section 5.3). The northwest third, containing the heavily forested regions of the Ouachita and Boston Mountains and surrounding areas, exhibits a common maximum fire season. The southern Arkansans region of mosaiced LULC of forest, agriculture, and wetlands shares a common maximum fire season and the eastern Arkansans region agricultural dominance shares a common fire season.

The spatial patterns of LULC (Figure 7, Section 5.3) and maximum fire season are similar. However, the maximum fire season separations are not quite as sharp as the LULC separations. When considering this, it is important to keep in mind that the maximum fire season map is an aggregation of fires by county lines. This will not capture intra-county variations in fire behavior where fires may occur dominantly in a certain area within the county or upon certain LULC in the county (see Section 4.3 discussing importance of MAUP and ecological fallacy).

Maximum fire season only reveals which 3-month period each county experiences most of its fire, not how much fire is experienced within the county. Figure 3 reveals the average monthly number of fires during each county's respective maximum fire season. The patterns of average monthly fires during maximum fire season share much less in common with the patterns of the simplified LULC or the maximum fire season. However, there are spatial patterns where fire behavior is significantly more intense than in other parts of the state.

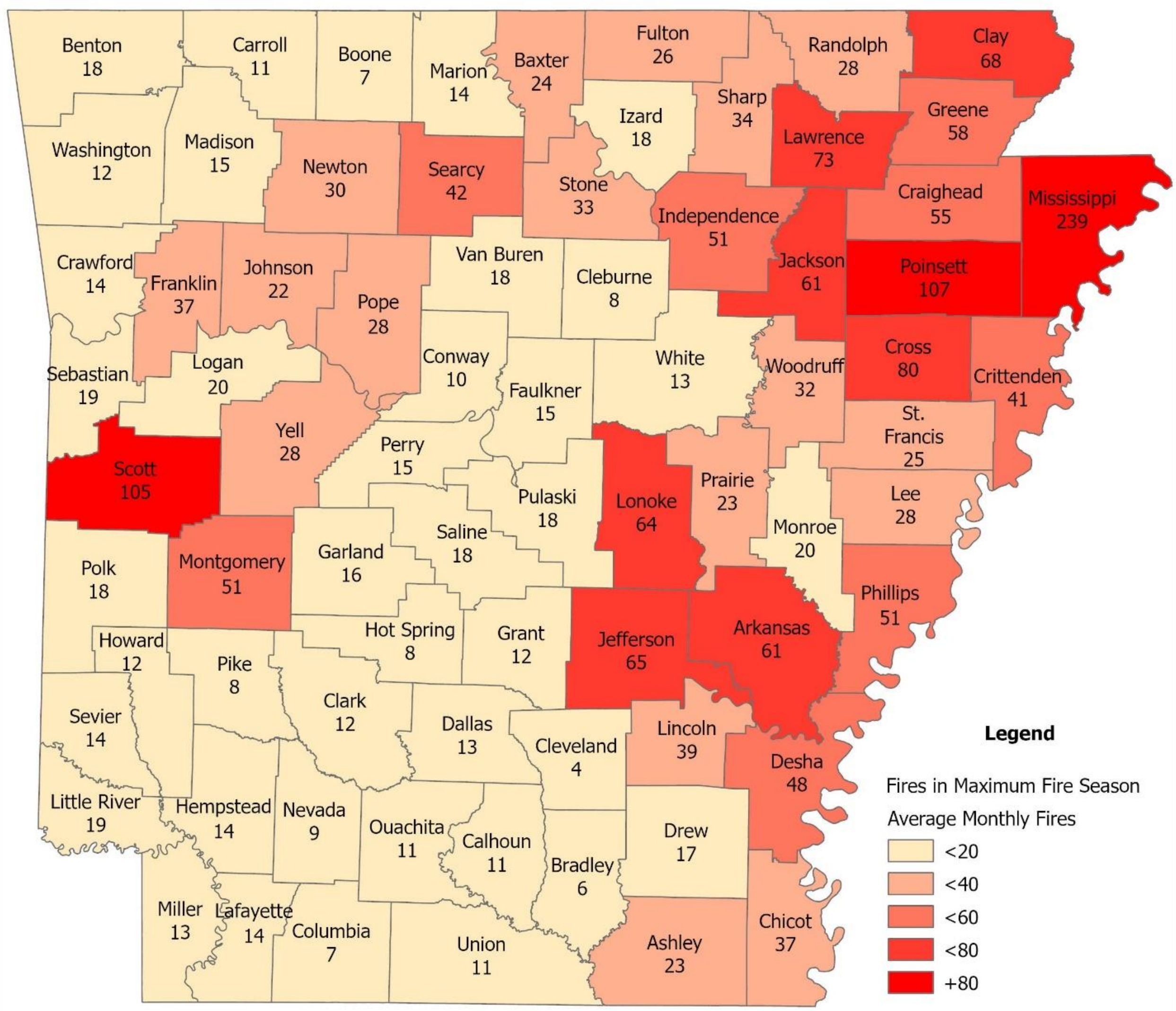

Figure 3: Pockets of more intense fire seasons in Arkansas are in the northeast and east central. West central counties such as Scott and Montgomery exhibit noticeably higher fire counts in maximum fire season than their neighbors.

The east central and northeastern regions of Arkansas experience much more intense fire seasons than the rest of Arkansas. Mississippi county particularly, the eastern most county in Arkansas, exhibits over double the number of average monthly fires during maximum fire season than the second highest county, which is neighboring Poinsett County.

The west central counties of Scott and Montgomery comprise the only pocket of intense fire season outside of the east central and northeastern parts of the state. These counties are largely comprised of Ouachita National Forest lands and exhibit a significantly higher number fires than any other county in the Ouachita or Boston Mountains. Searcy County experiences the most fire during fire season than any county in the Boston Mountains but still exhibits a relatively lower number of monthly fires at 42 occurrences in comparison to eastern counties.

5.2 KBDI in Google Earth Engine

The finalized KBDI dataset was completed to provide average monthly KBDI values per county from February 2012 through December 2023. In this period, daily KBDI images were averaged monthly and spatially by each county. Figure 4 is an example of daily KBDI images from October 1st, 15th, and 31st of 2023. The KBDI is measured from a 0 (no drought) to 800 (maximum drought) scale. Here, blue represents low drought, yellow represents medium

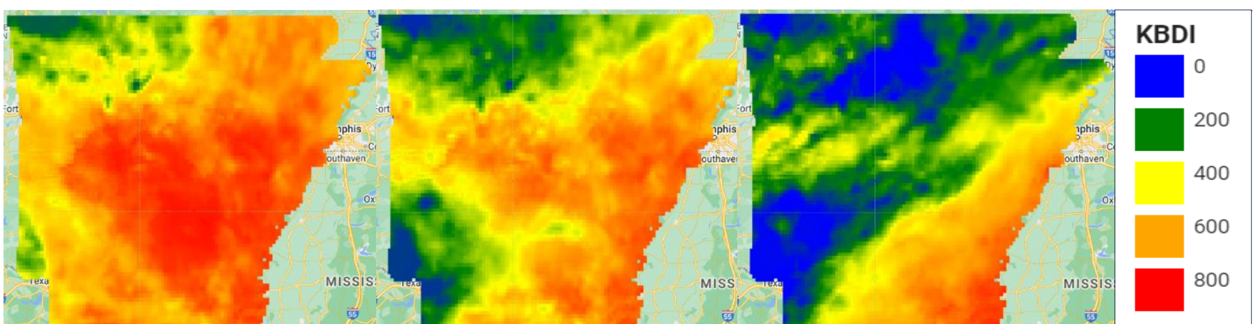

Figure 4: An example of KBDI value progression throughout the month of October 2023. October 1st, 15th, and 30th (left to right).

Figure 5: An example of KBDI value progression and statewide uniformity throughout the month of February 2023. February 1st, 15th, and 28th (left to right).

drought, and red represents high drought conditions. The variation in drought conditions throughout the state can vary considerably at times as seen in Figure 4 where at some point during the month there was always an area of very low drought and an area of very high drought. Figure 5 (KBDI images from February 1st, 15th, and 28th of 2023) also reveals that KBDI values during winter can be very low throughout the state, due to low temperatures and winter precipitation. The code and images for KBDI in Arkansas can be found using this link (https://code.earthengine.google.com/ec6bba3a0cfcab21e9750a6ed33cdf03), however, a free GEE account will be needed to access and run the code.

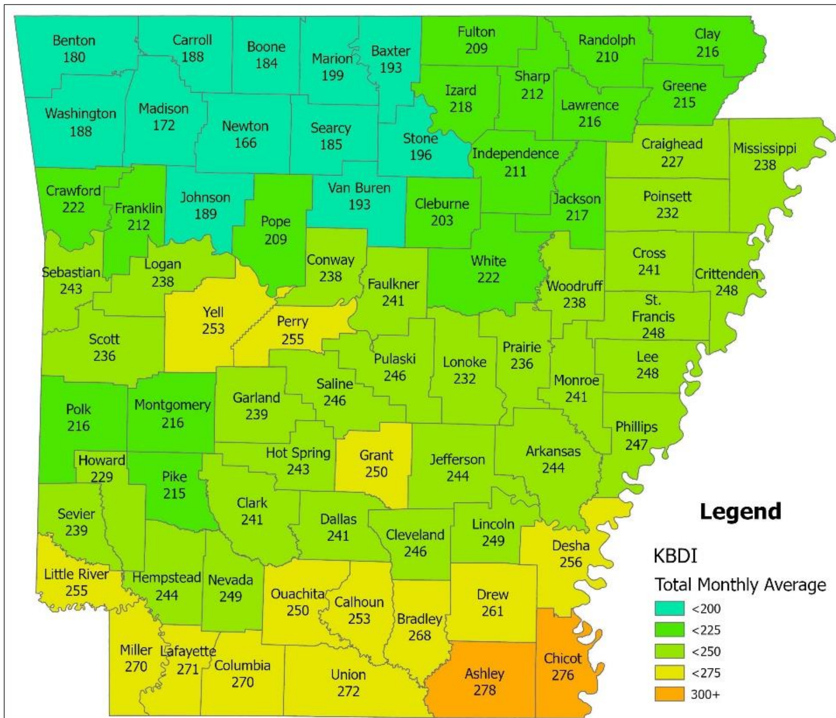

Figure 6: Average monthly KBDI value 2012-2023. The average KBDI value is within a score of 100 which is a noticeable, but not significant, difference in usual drought levels.

Figure 6 shows mean monthly KBDI values by county, averaged throughout the entire timeline, independent of maximum fire season. Even though the total monthly averages mostly fall within a narrow range of values (most counties exhibiting an average between 200 to 300 on the KBDI scale), the spatial variations that do exist do not share similar spatial variation with maximum fire season. Comparing the counties that experience the most fires in maximum fire season (Figure 3, Section 5.1) and which counties experience the more average drought (Figure 6), these datasets do not share similar spatial patterns and thus no obvious relationship between fires and KBDI exist.

5.3 NLCD 2021

The LULC of Arkansas was simplified into broad categories of developed, forest, shrub, herbaceous, wetland, and agricultural LULC. The mapped results can be seen in Figure 7. The spatial patterns of these LULC are evident. The thicker forested areas are in the Ouachita Mountains and the Boston Mountains (west central and northwest respectively). There is a

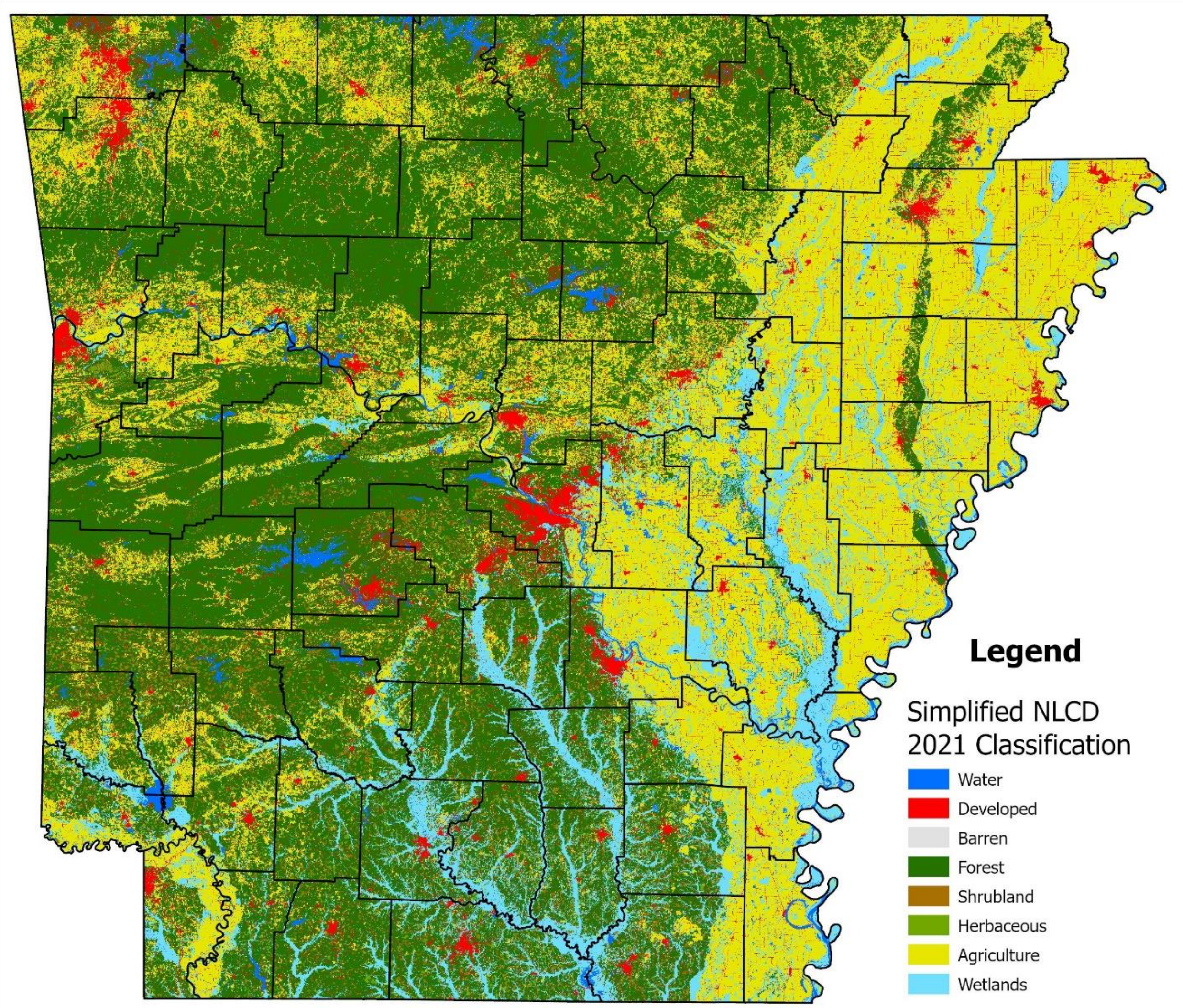

Figure 7: Spatial patterns to consider are dominant agriculture LULC in the east, presence of thick forests in the northeast, and a mosaic of wetlands and forest in the south-central region.

mosaic of agricultural, forested, and developed LULC north and south of both the Boston and Ouachita Mountains. A mixture of agricultural, forested, and wetland LULC in the southern portion of Arkansas is exhibited. The eastern half of Arkansas is clearly dominated by agricultural LULC except for a narrow stretch of each forested and wetland LULC. The visual interpretation of predominant land cover is supported by the analysis of percentage cover of the three classes with highest incidence (Table 2).

NAME	Dominant LULC	2nd LULC	3rd LULC	NAME	Dominant LULC	2nd LULC	3rd LULC
Arkansas	Agriculture 55%	Wetland 33%	Developed 4%	Lee	Agriculture 72%	Wetland 17%	Forest 4%
Ashley	Forest 35%	Wetland 25%	Agriculture 24%	Lincoln	Agriculture 48%	Forest 23%	Wetland 18%
Baxter	Forest 67%	Agriculture 15%	Developed 8%	Little River	Forest 33%	Agriculture 31%	Wetland 18%
Benton	Forest 42%	Agriculture 35%	Developed 16%	Logan	Forest 57%	Agriculture 29%	Developed 5%
Boone	Forest 48%	Agriculture 39%	Developed 7%	Lonoke	Agriculture 65%	Wetland 15%	Forest 9%
Bradley	Forest 46%	Wetland 35%	Shrub 5%	Madison	Forest 67%	Agriculture 25%	Developed 5%
Calhoun	Forest 48%	Wetland 33%	Herb 5%	Marion	Forest 65%	Agriculture 19%	Developed 5%
Carroll	Forest 52%	Agriculture 37%	Developed 6%	Miller	Agriculture 38%	Forest 29%	Wetland 17%
Chicot	Agriculture 68%	Wetland 19%	Developed 3%	Mississippi	Agriculture 83%	Wetland 7%	Developed 7%
Clark	Forest 58%	Wetland 13%	Agriculture 11%	Monroe	Agriculture 55%	Wetland 38%	Developed 3%
Clay	Agriculture 73%	Wetland 11%	Forest 10%	Montgomer	Forest 80%	Agriculture 10%	Developed 4%
Cleburne	Forest 60%	Agriculture 20%	Developed 6%	Nevada	Forest 56%	Wetland 15%	Agriculture 11%
Cleveland	Forest 50%	Wetland 33%	Developed 4%	Newton	Forest 85%	Agriculture 9%	Developed 4%
Columbia	Forest 66%	Wetland 13%	Herb 6%	Ouachita	Forest 50%	Wetland 31%	Developed 6%
Conway	Forest 44%	Agriculture 36%	Developed 6%	Perry	Forest 68%	Agriculture 14%	Herb 5%
Craighead	Agriculture 75%	Developed 10%	Wetland 7%	Phillips	Agriculture 72%	Wetland 16%	Developed 4%
Crawford	Forest 60%	Agriculture 27%	Developed 8%	Pike	Forest 63%	Agriculture 11%	Shrub 8%
Crittenden	Agriculture 77%	Wetland 12%	Developed 7%	Poinsett	Agriculture 79%	Wetland 11%	Developed 5%
Cross	Agriculture 77%	Forest 10%	Wetland 8%	Polk	Forest 71%	Agriculture 13%	Shrub 5%
Dallas	Forest 63%	Wetland 19%	Herb 5%	Pope	Forest 64%	Agriculture 21%	Developed 7%
Desha	Agriculture 57%	Wetland 31%	Developed 3%	Prairie	Agriculture 61%	Wetland 21%	Forest 8%
Drew	Forest 40%	Wetland 26%	Agriculture 19%	Pulaski	Forest 37%	Developed 24%	Agriculture 21%
Faulkner	Agriculture 41%	Forest 39%	Developed 11%	Randolph	Forest 45%	Agriculture 42%	Wetland 5%
Franklin	Forest 54%	Agriculture 35%	Developed 5%	Saline	Forest 62%	Developed 12%	Agriculture 8%
Fulton	Forest 54%	Agriculture 34%	Developed 5%	Scott	Forest 79%	Agriculture 12%	Developed 4%
Garland	Forest 67%	Developed 12%	Agriculture 7%	Searcy	Forest 70%	Agriculture 22%	Developed 4%
Grant	Forest 49%	Wetland 28%	Herb 6%	Sebastian	Forest 46%	Agriculture 26%	Developed 14%
Greene	Agriculture 67%	Forest 19%	Developed 7%	Sevier	Forest 46%	Agriculture 20%	Wetland 14%
Hempstead	Forest 46%	Agriculture 26%	Wetland 11%	Sharp	Forest 68%	Agriculture 22%	Developed 5%
Hot Spring	Forest 64%	Agriculture 13%	Developed 7%	St. Francis	Agriculture 70%	Wetland 15%	Forest 8%
Howard	Forest 51%	Agriculture 22%	Shrub 8%	Stone	Forest 76%	Agriculture 15%	Developed 4%
Independe	Forest 47%	Agriculture 40%	Developed 6%	Union	Forest 51%	Wetland 27%	Herb 6%
Izard	Forest 63%	Agriculture 26%	Developed 5%	Van Buren	Forest 73%	Agriculture 15%	Developed 5%
Jackson	Agriculture 76%	Wetland 11%	Forest 6%	Washingto	Forest 52%	Agriculture 34%	Developed 12%
Jefferson	Agriculture 49%	Forest 20%	Wetland 15%	White	Agriculture 47%	Forest 29%	Wetland 12%
Johnson	Forest 66%	Agriculture 21%	Developed 6%	Woodruff	Agriculture 73%	Wetland 22%	Developed 3%
Lafayette	Forest 49%	Agriculture 25%	Wetland 11%	Yell	Forest 64%	Agriculture 21%	Wetland 5%
Lawrence	Agriculture 64%	Forest 23%	Wetland 6%				

Table 2: The top three dominant LULC per county in Arkansas. The percentage refers to how much total land cover the classification comprises of the county.

There is a sharp line cutting through the state, separating where agriculture is clearly the dominant LULC for counties in the eastern region of the state and where counties' LULC turns into largely forested or a mosaic of forested, developed, and agriculture. However, this sharp line dividing dominant LULC runs through the middle of many counties and is an example of the MAUP in terms of analysis. Under the assumption that LULC impacts fire behavior, this major divide of LULC should be kept in mind. The following results of this study will be observed with the spatiality LULC differences in Arkansas.

5.4 VIIRS-KBDI Relationship

The results of the Pearson correlation coefficient between average fire occurrence in maximum fire season and average KBDI in maximum fire season per county can be seen in Figure 8.

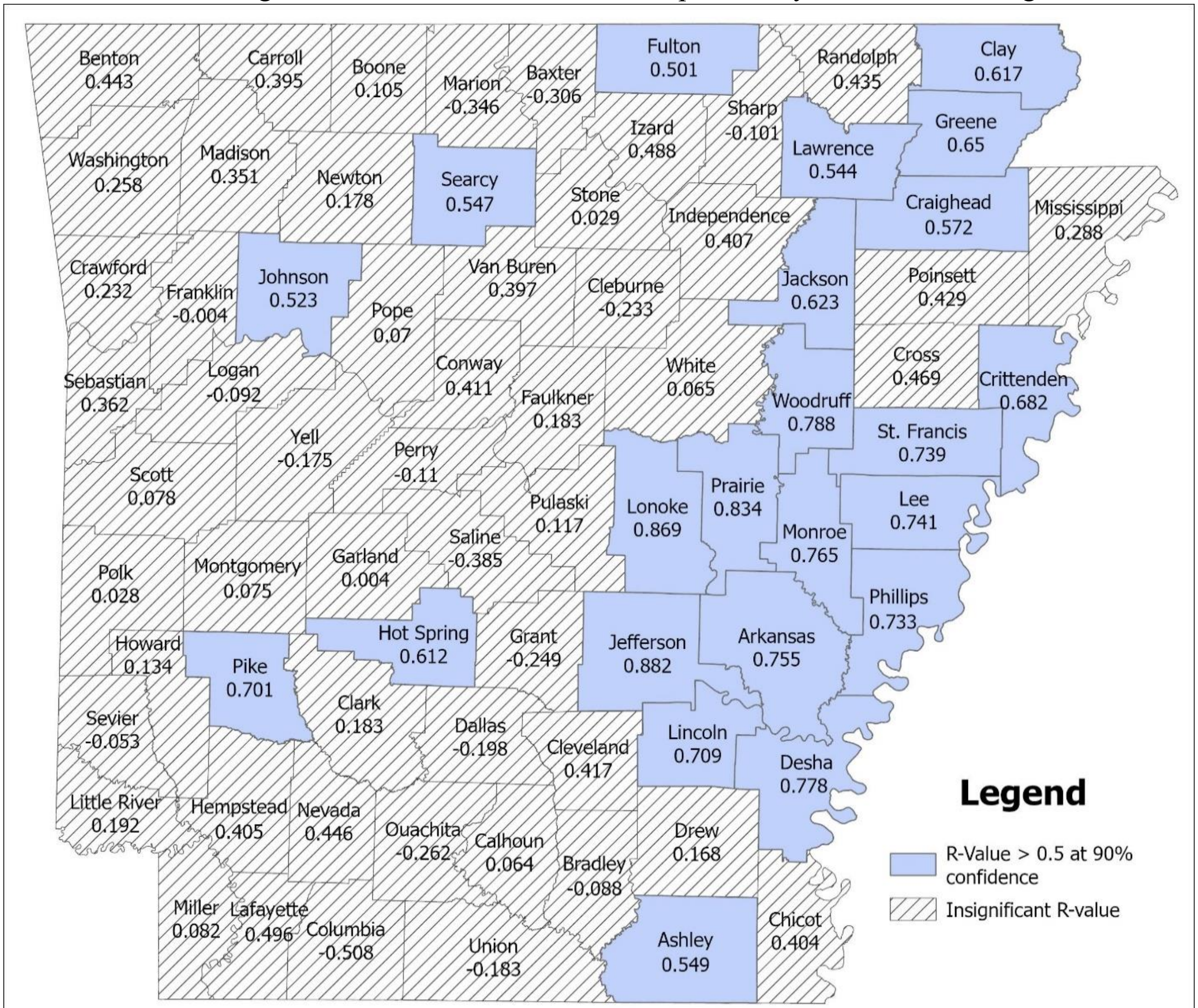

Figure 8: Counties that exhibit a significant VIIRS-KBDI correlation are dominantly in the eastern region of Arkansas.

Counties that exhibit a significant correlation coefficient (*r*-value > 0.5) at 90% confidence (*p*-value < 0.05, two-tailed test) are highlighted in the figure. Most counties that exhibit significant relationships between drought and fire occurrence are in the eastern half of Arkansas. Specifically, the central eastern region of Arkansas is an evident concentration of counties where the VIIRS-KBDI relationship is significant. Pike, Hot Spring, Searcy, and Johnson counties are the only counties with significant VIIRS-KBDI relationship in the western half of Arkansas.

The spatial distribution of statistically significant correlation (Fig. 8) and land cover (Fig. 7, Sec. 5.3) indicate a pattern following the boundary separating agriculturally dominant LULC and forest dominant LULC. In fact, 17 of the 23 eastern agricultural counties express at least some degree of VIIRS-KBDI relationship. Only six forest-dominant counties express a VIIRS-KBDI statistically significant relationship, most exhibiting a noticeably lower R-value than agricultural counties exhibiting a VIIRS-KBDI relationship.

The top counties that experience the greatest number of fire occurrences during maximum fire season, however, did not express a VIIRS-KBDI relationship. Mississippi County (agriculturally dominant), Poinsett County (agriculturally dominant), Scott County (forest dominant) all lack a VIIRS-KBDI relationship. These counties experience the highest number of fire occurrences during maximum fire season (all counties average over 100 monthly fires in maximum fire season).

These findings are contrary to the initial hypothesis which stated that forest-dominant counties were expected to exhibit stronger VIIRS-KBDI relationships than developed (e.g. agricultural) counties. During this timeframe, the agricultural areas of Arkansas are where higher drought appreciably corresponds with higher fire occurrence.

Counties where forests predominate (Fig. 7, Sec. 5.3) and fires occur regularly (Fig. 3, Sec. 5.1) do not seem to be greatly affected by fluctuations in KBDI, as demonstrated by poorer correlations between KBDI and fires (example: Scott and Montgomery counties) also contrary to the initial hypothesis. To further investigate the types of fires that occur in some of these landscapes, an analysis of prescribed versus wildfires is presented next and will serve as evidence to support the arguments presented in the Discussion section.

5.5 Prescribed vs. Wildfires

Figure 9 below overlays all fires greater than 500 acres in Arkansas from 2012 through 2023 as per the MTBS dataset. As can be observed, most of these largest fires in Arkansas are in the northwest third of Arkansas. Prescribed fires are the dominant classification of these large fires while wildfires greater than 500 acres are scarce. Johnson and Searcy Counties experience a few of these large, prescribed fires but most of them occur in counties where a VIIRS-KBDI relationship is absent.

In comparing Figure 9 with Figure 3, Section 5.1 (monthly frequency of fire occurrences during maximum fire season), many of the counties that experience a higher number of fires during maximum fire season than their neighbors are these counties where large, prescribed burns occur. Scott and Montgomery Counties in particular exhibit much higher fire counts during maximum fire season and are shown to experience more large, prescribed fires than other counties in the northwest. Wildfires of greater than 500 acres are rare and are often located adjacent to large, prescribed burns. Since the fire data is provided by a satellite active fire product, the dataset collects all fire occurrences and does not discern wildfires from prescribed fire.

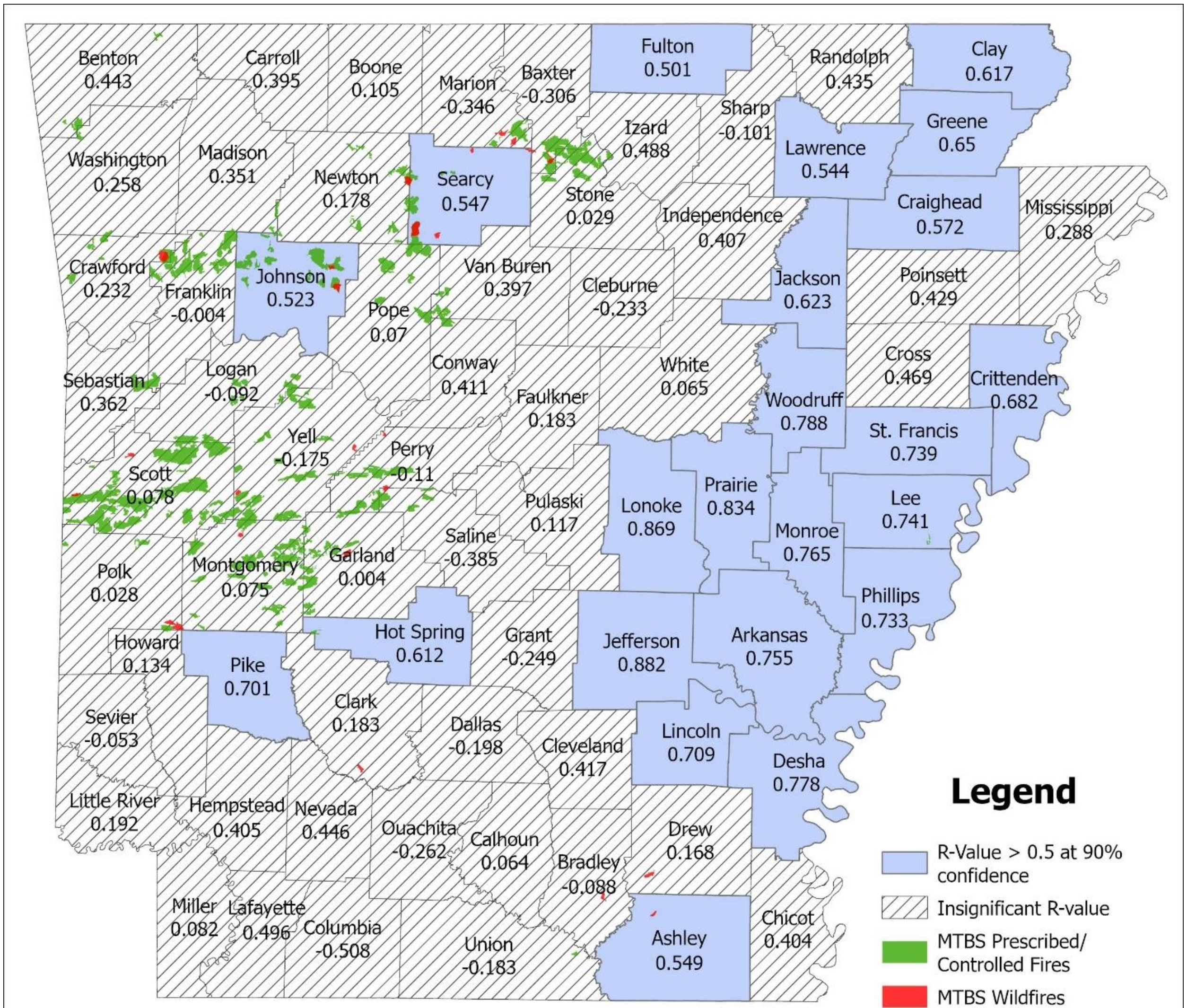

Figure 9: MTBS fires larger than 500 acres overlayed on the R-values of VIIRS-KBDI correlation for all Arkansas counties.

5.6 Comparative Analysis for Northern California

A conclusion of this study in Arkansas is that the KBDI is not an effective indicator of fire season variability in naturally vegetated LULC in Arkansas, but it is an effective indicator in agriculturally dominant LULC in Arkansas. This is because, in this region, fire is often not a climate-driven phenomenon but a human-driven phenomenon. Northern California, infamous for its extreme wildfire behavior, was thought to be a study area where the KBDI may perform more effectively as an indicator of fire season variability.

A comparative analysis was run in the northern half of California between the years February 2012 and January 2023, a similar 11 seasons of data and the same methodologies were used. Figure 10 shows the maximum fire season per county. Most counties exhibit mid-year fire season such as MJJ and ASO. Figure 11 shows which counties experienced the most fires in this timeframe. The counties that experienced the most intense fire behavior are generally along the Sierra Nevada Mountains on the eastern side of the state and in the northern most counties. Figure 12 shows the

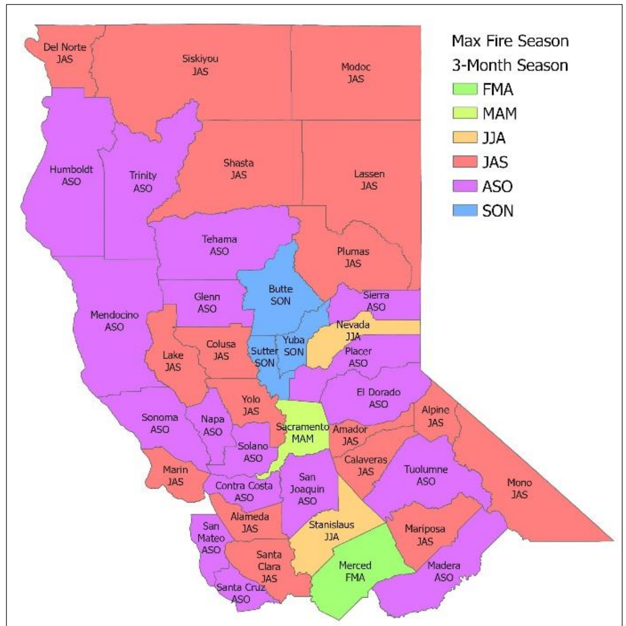

Figure 10: Maximum fire season of north California counties. Most counties exhibit a late summer/early fall maximum fire season.

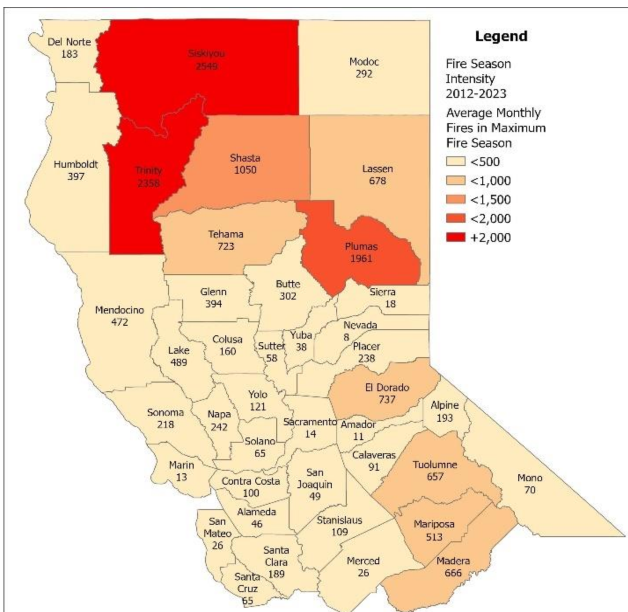

Figure 11: The range of fire behavior among counties in northern CA is significant. Some northern counties experience thousands of fires during maximum fire season while most counties experience under 500.

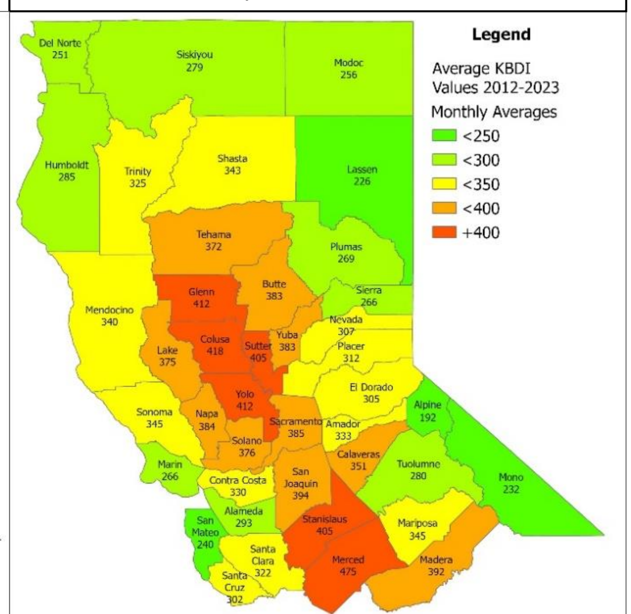

Figure 12: Average monthly KBDI value 2012-2023. The average KBDI value ranges from just below 200 to almost 500, exhibiting significant difference in drought spatiality in northern CA.

average monthly KBDI value independent of maximum fire season.

Figure 13 shows which counties exhibit significant VIIRS-KBDI relationships (r-value > 0.5) at 90% confidence (p-value < 0.05) with MTBS fires of greater than 1,000 acres (MTBS only collects fires of 1,000 acres or greater in the Western U.S.). The counties that exhibit the

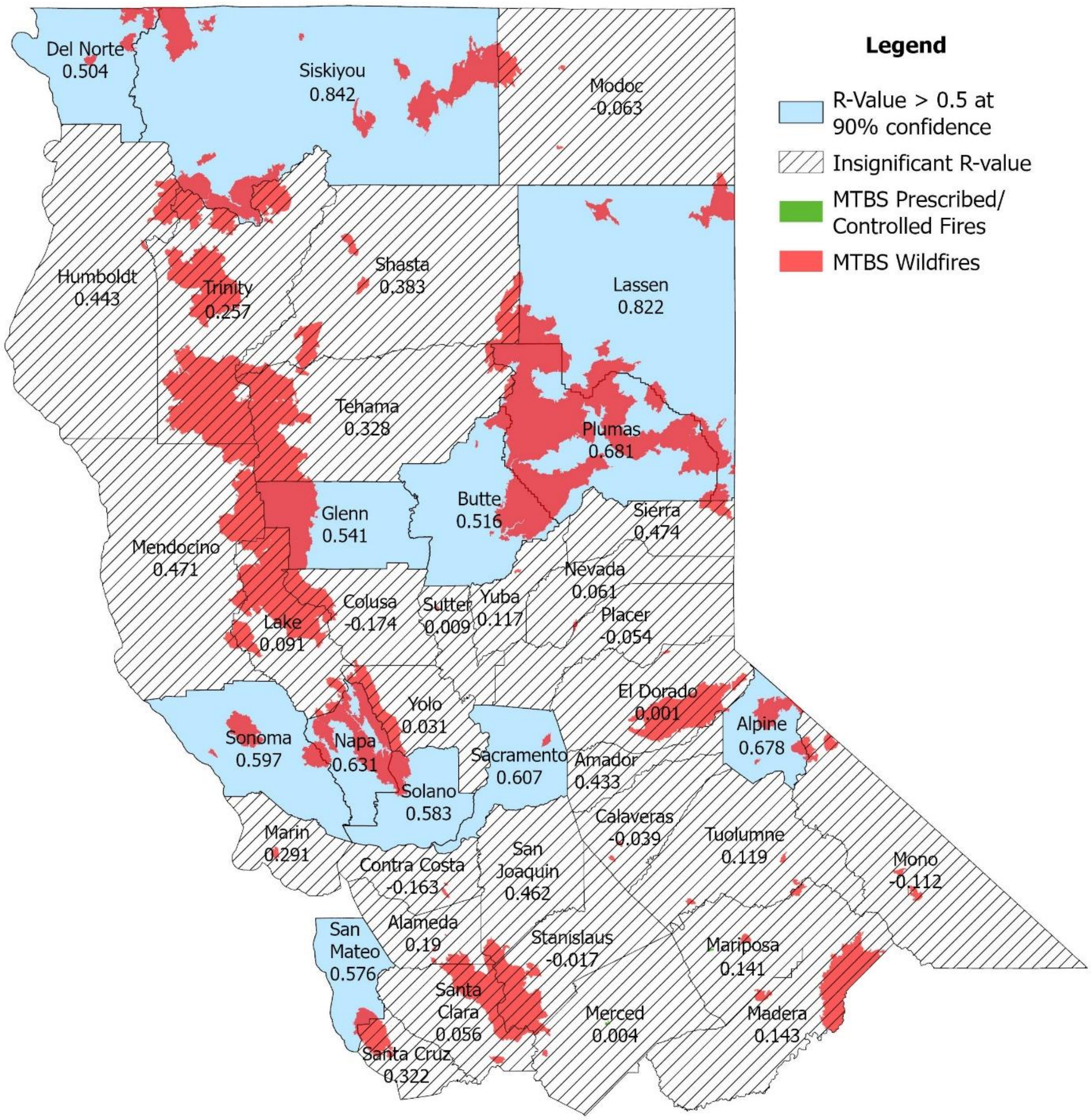

Figure 13: MTBS fires greater than 1,000 acres overlayed on the R-values of VIIRS-KBDI correlation for northern California counties 2012-2023 (excluding San Francisco County).

most significant VIIRS-KBDI relationships are Siskiyou and Lassen Counties. The other counties that exhibit VIIRS-KBDI relationships exhibit *r*-values below 0.7 and most *r*-values are slightly above 0.5. In comparison to Arkansas, northern California's large fires are dominantly wildfires, whereas Arkansas's large fires are dominantly prescribed fires.

Again, these results are not what was hypothesized to be exhibited in a region where wildfires are more climate-driven than a region such as Arkansas. However, northern California experienced several historic wildfire events during this time according to MTBS data, such as the August Complex fire of 2020 or the Dixie fire of 2021 that burned 1,068,802 and 979,795 acres respectively. The size of these fires, providing such a huge number of VIIRS fire occurrences, and provided the relatively short temporal scale of this study (11 seasons), it is possible that these historic fire events skewed the true maximum fire seasons of some key counties by occurring outside of maximum drought season or obscured average fire behavior in some parts of the state.

Still, the counties that exhibited positive VIIRS-KBDI relationships are mostly forested, shrub, or herbaceous LULC as shown in Figure 14. A few counties such as San Matero and Solano exhibit positive relationships although these are not counties of intense fire behavior in comparison to other counties. These results are not strong enough to determine if the KBDI is a good indicator of fire season variability and VIIRS-KBDI analysis at the county scale for California is not advised due to the large differences in total area county to county. To determine whether KBDI is a positive indicator of fire season variability, it is recommended that a similar analysis take place but with 1) a longer temporal range and 2) a way to limit fire occurrence frequency for historic fire events where drought impacts are secondary to factors that perpetuate large wildfire such as wind and fuel load (Keeley & Syphard, 2019) and 3) a more appropriate spatial unit to correlate relationships than the county scale. Additionally, since fire behavior in northern California is difficult to generalize, it may be worth considering to include a fuel aridity index (as such used by Abatzoglou et al., 2021) alongside the KBDI to further explore soil vs. fuel moisture impacts on fire behavior.

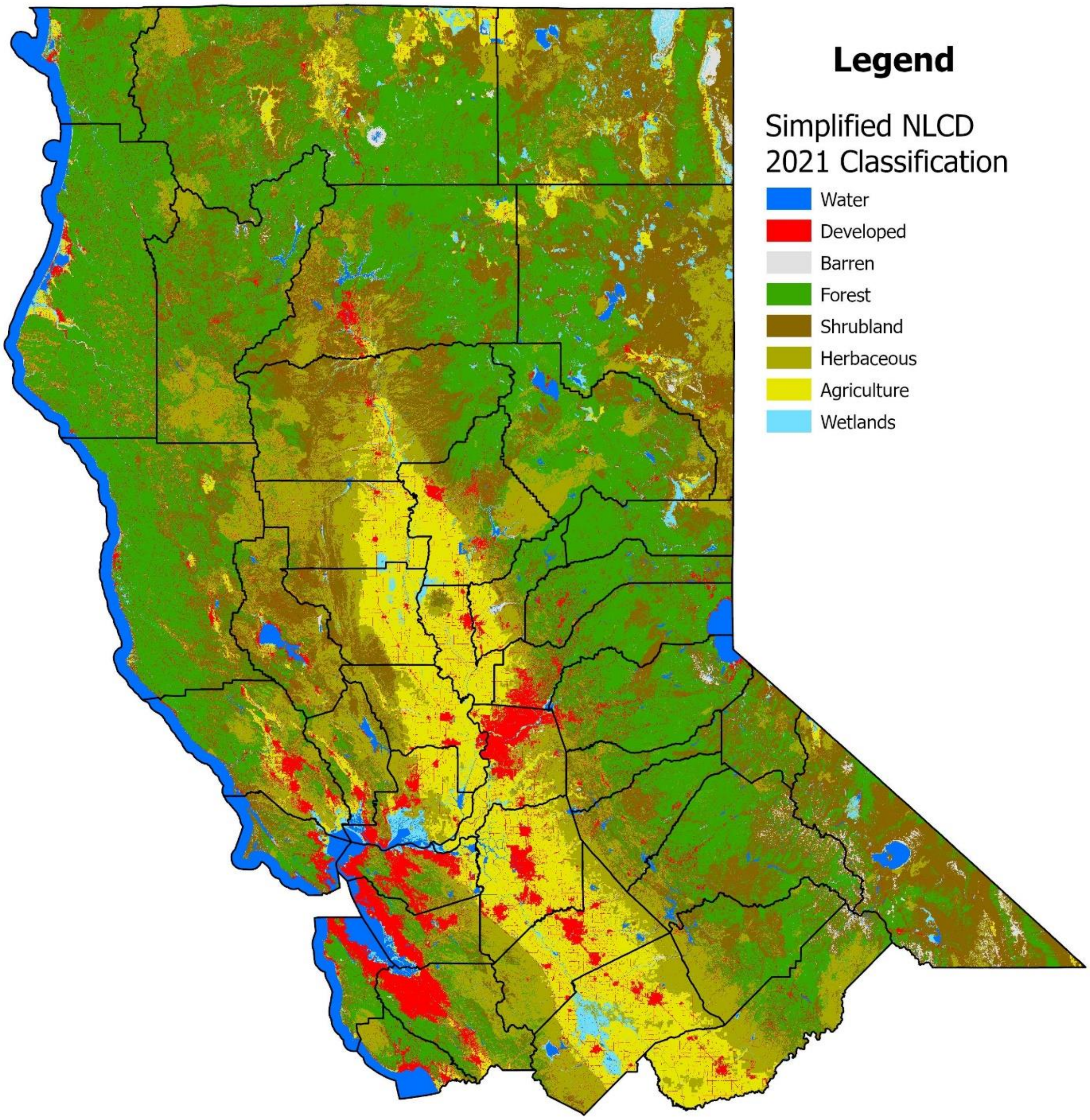

Figure 14: A concentrated agricultural area in central northern California and most developed areas are in the south central and southwestern part of northern California. Naturally vegetated LULC, such as forest, shrubland, and herbaceous, dominate the other regions of northern California.

Chapter 6: Discussion

6.1 KBDI as a viable indicator for fire season variability

The results of this project show that KBDI can be a reliable indicator of fire variability as assessed by the correlation analyses, though not similarly in all landscapes. The initial assumption that VIIRS and KBDI relationships in Arkansas would be stronger in native vegetation versus agricultural land was proved the opposite.

In Arkansas, agricultural land generally exhibits a strong VIIRS-KBDI relationship and forested landscapes mostly do not. The methods and results of this study were shared with an experienced Arkansan ecologist working with the Little Rock chapter of The Nature Conservancy and with a professional at the Arkansas Forestry Commission Fire Dispatch Center in Malvern, Arkansas. A review of literature and the interactions with these professionals offered insights into some of the reasons behind this study's results.

There are two major human-controlled phenomena that drive these VIIRS-KBDI relationships, or lack-thereof. First off, there are great efforts of prescribed and controlled burns implemented in the naturally vegetated, forested LULC in Arkansas. This can be seen in Figure 9, Section 5.5. While forest fires do occur in Arkansas, the prescribed burn practices in Arkansas limit the severity and number of natural fires. Most of the prescribed and controlled burns in the forested LULC occur earlier in the year to ensure that fire is easily controllable, which agrees with this study’s finding that the northwest third of Arkansas exhibits a February-March-April maximum fire season. These fires are intentionally created when drought values are low in order to better control the prescribed fire. This effectively skews most fire occurrences in these regions to take place when KBDI is low, which would mean that using the methodology for this study, fire occurrence would not correspond with higher KBDI values. However, the professionals did discuss that the KBDI is used when determining safe and unsafe dates to burn. When the KBDI value of an area to undergo a prescribed burn exceeds a certain threshold, the prescribed burn is postponed. When KBDI values are low, prescribed fire can be implemented more controllably and confidently.

Wildfire Cause	Frequency	Proportion
Debris Burning	15314	36%
Incendiary	12341	29%
Miscellaneous	6764	16%
Equipment	3108	7%
Lightning	2146	5%
Unknown	804	2%
Smokers	651	2%
Children	540	1%
Railroad	487	1%
Camp Fire	408	1%
Under Investigati	181	0%

Table 3: Frequency and proportion of wildfires on non-federal lands in Arkansas 1997-2022 from Arkansas Forest Service.

Secondly, farms in Arkansas, dominantly in the eastern part of the state where positive VIIRS-KBDI relationships exist, burn refuse after harvest and before winter. Literature on human health and agriculture in Arkansas backs up these claims. Human health literature focusing on COPD cites the increase in PM due to agricultural burns, in and outside of Arkansas (McCarty et al., 2009; Rutlen et al., 2021; Zamanialaei et al., 2023). A crop that is a significant contributor to total PM caused by agricultural burning is rice (Zamanialaei et al., 2023) and parts of eastern Arkansas produce an extremely high proportion of the United States' rice output. Rice fields are often burned post-harvest to clear stubble to make way for planting the next crop.

Arkansas farmers, according to the professionals that were advised, may burn precisely when KBDI is high to ensure that their fires effectively burn refuse after the harvest. This increases the number of fire occurrences in these regions at the end of the year after harvest which this study found to be true. Most agriculturally dominant counties exhibit a maximum fire season August and after, during autumn when KBDI values are still high.

The Division of Forestry Dispatch Center of Arkansas shared a dataset detailing every fire dispatched through their office that includes all wildfires that occurred on non-federal lands in Arkansas from 1997-2022. Table 3, created from the provided dataset, shows the proportional causes of wildfire. Most fires were caused by humans and very few were created by natural phenomena such as lightning. Most of these wildfires were caused by ill managed debris burning or were incendiary in nature. While wildfire does exist, the major culprits of wildfire in Arkansas are controlled burning and fires that are intentionally ignited illegally (e.g. debris burning and incendiary) breaking into wildfire. Most wildfires often occur accidentally because of intentionally created fire by humans, most often at the end of the year after harvest, rather than by natural causes such as lightning. Thus, the maximum fire seasons exhibited in Arkansas (early year in forested regions and later in the year for agricultural regions) reflect human activity, rather than natural phenomena.

These explanations also may be the reason why there exists literature citing KBDI as a poor indicator of fire occurrences. The study areas of the literature citing KBDI as a poor indicator of fire occurrence are in the southeast U.S., where, as this study found, most of the fire in agriculturally dominant areas is intentionally created by humans, minimizing the natural effect of drought on fire occurrence. States such as Arkansas, Florida, and Louisiana contribute to a disproportionally large amount of crop burning in the continental U.S. The dominant source of Arkansas crop burnings are from the eastern portion of the state (McCarty et al., 2009). When all fire is treated equally in the southeast U.S., it should now be expected that KBDI would be an extremely poor indicator of fire occurrence due to the inverse KBDI-fire relationship described above. Specifically regarding KBDI/fire relation studies in the southeast U.S. (Chan et al., 2004;

Morris, 2007), wildfire must be made distinct from prescribed and controlled burns to draw conclusions of climate impacts on fire behavior.

To separate agricultural burns to fires in naturally vegetated areas, the spatial resolution differences between the VIIRS active fire product (375 meters) and NLCD 2021 (30 meters) is too great to produce reliable results. In all regions of Arkansas except for the agriculturally dominant east, there is often too much variation in LULC at 375 meters to reliably assume which LULC classification the VIIRS fire occurrence took place. Assuming that the center of the 375 meter VIIRS fire occurrence is where the fire occurred in reality, and on the LULC classification it would land on in Arkansas, would be an unreliable assumption due to the ecological fallacy (Cöltekin et al., 2011). The ecological fallacy is a problem in which the entirety of a pixel is assumed to be uniform and is analyzed as such. Additionally, to create 375-meter aggregations of dominant LULC is unreliable because the VIIRS Suomi-NPP satellite collects fire occurrences at 375 meters at difference swathes across the surface of the earth. Due to this, creating a coarser 375-meter LULC dataset to consistently match the VIIRS dataset would be unfeasible.

Because of the inability to determine on which LULC each fire occurred, the fire data must be aggregated to a spatial unit (in this case, Arkansas counties). This introduces issues of MAUP (Section 4.3). However, provided that the fire data must be aggregated to a spatial unit, this MAUP is inherent regardless of chosen spatial unit. Although, it should be noted that the spatial unit should be chosen deliberately and with consideration to how this spatial unit may alter analysis results. For reasons discussed in section 4.3, the county level was chosen because conventional weather and climate systems often use counties as spatial units for data aggregation (*NOAA Offers Climate Data for Counties*, 2019), policy and decision making occur frequently at administrative levels, such as at the county and state level, and fires at the 375-meter resolution may not repeat year to year due to fuel levels not recovering (Roccaforte et al., 2012).

Provided these results, in Arkansas and other places where fire is a dominantly human-controlled phenomenon, the KBDI is not a viable indicator for fire season variability for naturally vegetated LULC. That is not to say that the KBDI is a useless index, but because fires are a human-driven phenomenon in the state and not a climate-driven phenomenon, the index does not actual reflect fire behavior in contemporary Arkansas. The index is currently used as one of the parameters in the state to determine when prescribed and controlled burns should be taken place and when recreationists should exercise caution when starting fires. This is an appropriate use of the index, but the KBDI should not be used as a reference to understand natural fire behavior where fire is dominantly an intentionally human-created phenomenon.

6.2 Margins of Error and Future Studies

The VIIRS fire product cannot gather comprehensive data. Main limitations to this dataset are cloud cover and canopy cover. The Suomi NPP satellite, or any satellite for that matter, cannot record fire occurrences through cloud cover, which would most likely obscure fires that are ignited via lightning. Satellites can neither record fire occurrences through thick canopy or cloud cover. Small fire occurrences in thickly vegetated parts of Arkansas forests may be obscured by canopy cover. These limitations which exist in the forested, natural areas of interest to this study can obscure some fire behavior. Future studies may be interested in compiling fire data from state and federal fire dispatch centers which would narrow the fire data to include only wildfires but may risk losing some comprehensiveness.

Comparing the analysis using different satellite fire products may be a worthwhile endeavor. The Landsat Active Fire and Thermal Anomalies product (Schroeder et al., 2016), with a spatial resolution of 30m, will be of great interest to future studies analyzing fire behavior. Using the Landsat Active Fire and Thermal Anomalies product would help to analyze at finer scales and to help estimate on which LULC the fire occurrence took place. Implementing similar studies to this project with the Landsat product may yield different, and potentially more relevant, results.

While this study analyzed climate-fire relationships at the county level, it would be worthwhile to conduct these climate-fire relationships at the grid level instead of using political boundaries as spatial units. Analyzing at a grid level, finer spatial resolutions can be implemented to determine more accurate climate-fire relationships. Many of the counties in Arkansas exhibit a significant variation in LULC which has been shown to impact fire behavior greatly. Analyzing at a grid level of finer resolution would negate the variation in intra-county fire behavior impacting analysis and therefore improve issues related to the MAUP. For example, half of a county may exhibit agricultural LULC and the other half may exhibit a mixture of forested and developed LULC. Fire dominating in one part of the county skews and negates the climate-fire results for the entire state. Analysis at the grid level, there may be still exhibit LULC variation within a grid unit but this variation will be much less intense than the LULC variation at the county level.

For potentially more complex fire regimes, such as in northern California, or as an alternative method of analysis, the use of a bivariate LISA (local indicators of spatial association) analysis may be useful to examine the spatial relationships of two variables. A bivariate LISA analysis would be another way to determine KBDI-fire relationships and other important factors in complex fire regimes such as KBDI-fuel moisture relationships. This analysis determines how two variables may influence one another across space (*How Local Bivariate Relationships*

Works—ArcGIS Pro | Documentation, n.d.). If using this approach, an alternative to county-level data aggregation would be needed.

Another tactic may be to not analyze an entire region, but to strategically hand pick certain study areas within a region. Using this method would, for example, entail choosing a select few counties or study areas that are naturally vegetated and are known to experience relatively low levels of human activity. Although, it may be difficult to find suitably large, forested areas where no prescribed burns take place or would be significantly affected by previous prescribed burns. Consultation with forest services or other organizations may be necessary to determine such study areas. This tactic would help to answer the question of how climate impacts fires at the intra-county scale where LULC is relatively homogeneous.

6.3 Conclusions

The KBDI is not a good indicator of contemporary fire behavior in Arkansas in naturally vegetated LULC, but it is in agricultural LULC. This is because most fire occurrences in Arkansas are intentionally created by humans. To determine climatological effects on fire behavior in Arkansas and regions that share similar fire behavior to this state, LULC should be considered as a major driving force of fire behavior.

The comparative study in northern California does show some naturally vegetated dominated counties exhibit a noticeably significant VIIRS-KBDI relationship, but extremely large fires may skew the relationship of VIIRS fire occurrence and KBDI values. Afterall, the KBDI does not consider fuel availability, fuel aridity, vapor pressure deficit, or wind, which are important factors for major wildfire growth (Abatzoglou et al., 2021; Keeley & Syphard, 2019) which would undermine the role of drought in the cases of these extreme fire events. The analysis of northern California at the county scale is also less desirable than an analysis at a grid level would be for this study area due to significant variations in total area county to county. Wildland fires, and their size, in northern California pose too great of complexity for an analysis of this methodology or for generalizing fire behavior in this region.

Literature discussing an increase in the southeast U.S., including Arkansas, should exercise caution when assuming higher drought will cause an increase in fire occurrences. Drought can very well influence fire occurrences, however, the general increase in fire occurrence in Arkansas seems to be an indirect, rather than direct, result of general increase in drought due to human activity. In Arkansas (and possibly other southeastern U.S. states where agricultural burning is prevalent), climate can exacerbate fire behavior through increasing human-caused fires due to more favorable conditions for agricultural burning and accidentally occurring fires associated with these burnings, not predominantly through naturally occurring fires.

Chapter 7: References

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