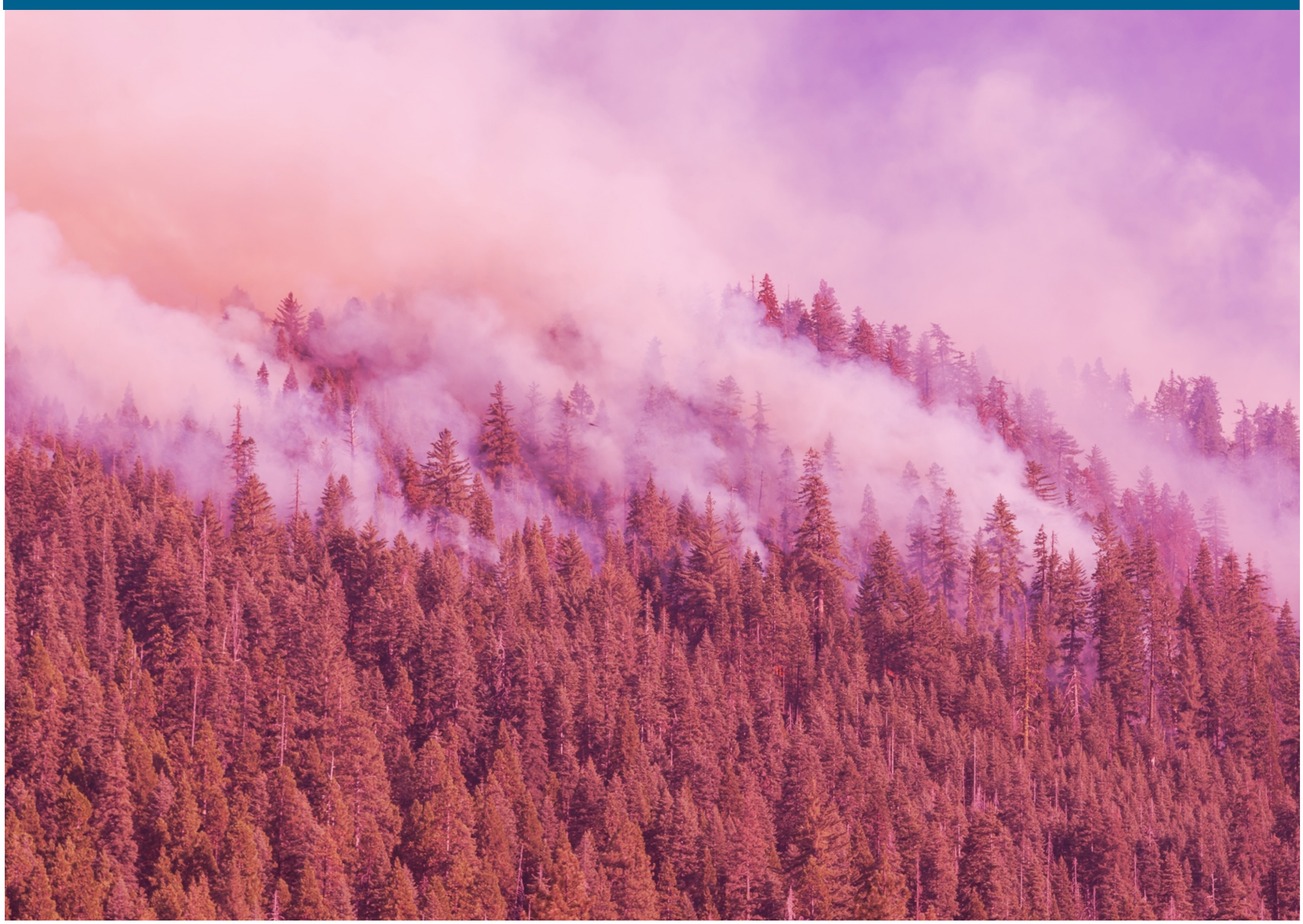
Potential Impacts of Climate Change on U.S. Wildfire Risk by Mid Century

Catastrophe and Climate



September 2021

Potential Impacts of Climate Change on U.S. Wildfire Risk by Mid Century

AUTHORS
Peter Sousounis, PhD
Vice President/Director of Climate Change Research
AIR Worldwide
Boston, MA 02111

Alastair Clarke, PhD
Senior Research Associate
AIR Worldwide
London, UK

Doug Fullam
Director, Life and Health Modeling
AIR Worldwide
Boston, MA 02111

SPONSOR
Catastrophe and Climate Strategic Research Program Steering Committee

Give us your feedback!
Take a short survey on this report.
Click Here

Caveat and Disclaimer
The opinions expressed and conclusions reached by the authors are their own and do not represent any official position or opinion of the Society of Actuaries Research Institute, the Society of Actuaries or its members. The Society of Actuaries Research Institute makes no representation or warranty to the accuracy of the information.

Copyright © 2021 by the Society of Actuaries Research Institute. All rights reserved.

CONTENTS

Copyright © 2021 Society of Actuaries Research Institute

Potential Impacts of Climate Change on U.S. Wildfire Risk by Mid Century

Executive Summary

Impacts to U.S. Property losses from future climate change influences on U.S. Wildfire Risk are evaluated using the AIR Wildfire Model for the United States (AIR 2018) for the year 2050 under an assumed Representative Concentration Pathway (RCP) 8.5. The AIR Model captures the current risk for the western half of the U.S. across the thirteen U.S. states where property losses are generally largest (AZ, CA, CO, ID, MT, NM, NV, OK, OR, TX, UT, WA, WY). The RCP 8.5 greenhouse gas concentration-based climate scenario is a business-as-usual (Fossil-fueled development) scenario and one that society have been following since 2005. The period through 2050 is relevant for practice of Society of Actuaries members. The basic approach for this study involves first defining targets of how climate change is expected to alter the wildfire hazard risk and then creating 50,000-year climate change catalogs by subsampling the 100,000-year catalog in the AIR Model according to the defined targets. The latter is a file that contains information on stochastically generated wildfire events defined in terms of burned area, flame length, time of year, stochastic year, etc. which the loss-component of the AIR Model uses to generate losses by location. Each years-worth of stochastic events is generated using a historical seed year where the events are influenced by the climate of that seed year. Any one of the events in the 100,000-year catalog can occur today. Thus, AIR's 100,000-year catalog reflects the current climate, while the 50,000-year climate change conditioned catalog reflects the climate at RCP 8.5 2050.

The recent literature of wildfire (wildland fire) dependence on climate is reviewed. The latest studies show a strong dependence of burned forest area to a quantity of atmospheric aridity called vapor pressure deficit (VPD), which is a measure of how far the atmosphere is from being saturated. A high VPD (drier air) means that the atmosphere can more quickly, and more thoroughly, dry the land surface, including the fuel (e.g., vegetation) on and in the surface. A drier fuel load (i.e., the total amount of combustible material in a defined space) in turn increases flammability of a forest or other ecosystem leading to the generally positive relationship between fire and VPD. VPD has been increasing in the recent historical past and burned area has increased at the same time. Climate change modeling studies show that VPD will continue to increase because the saturated vapor pressure will increase more than the actual vapor pressure in the western US. Saturated vapor pressure is principally determined by the temperature while actual vapor pressure is determined by the available precipitation. Increasing temperature increases the amount of moisture needed for saturation, so even no change in precipitation yields an increase in VPD. Because high VPD reflects a combination of low relative humidity and high temperature it is typically a better predictor of fire incidence than either factor alone.

Annual totals on wildfire burn area from the Fire Occurrence Database (FOD) from 1992–2015 are used in conjunction with VPD calculations from summertime (June–August) reanalysis data over the same period to develop annual burned area-VPD relationships for each of the 30 ecoprovinces in the AIR Model. Ecoprovinces are geographic units intended to represent groupings of uniform climate and physical geography landforms that are typically characterized by similar or related ecosystems across the unit. The fitted Generalized Linear Models (GLMs) show that burned area tends to increase with summertime VPD, but the degree of sensitivity varies considerably between ecoprovinces. Some ecoprovinces are highly responsive to increasing summertime VPD; others show a weak to no response; while the rest are mildly responsive with high uncertainty associated with their behavior.

Several general circulation models (GCMs) were reviewed (eighteen were available from the fifth phase of the Coupled Model Intercomparison Project (CMIP5)). Two were selected that represent low and high dryness

Copyright © 2021 Society of Actuaries Research Institute

projections for 2050 relative to 2018, the representative or "base" year of the AIR model.) A mean VPD projection, taken as the average of low and high projections, was combined with the historical annual burned area-VPD relationships to create an annual burned area target for each ecoprovince for 2050. The targets are redefined as the relative change in burned area from the present-day burned area distributions before being used for subsampling.

Significant increases in area burned were projected by 2050. Changes in California are among the smallest percentage wise at 100% by 2050 whereas changes in Colorado are over 600% by 2050. The extreme increases in Colorado punctuate the expected largest increases in area burned over the intermountain west (area between Sierra Nevada and Cascade Range on the west and Rocky Mountains on the east). The projected several-fold increases in annual area burned are consistent with results from a prior study done independently and published earlier by the National Research Council (2011).

Climate change conditioned catalogs were created using the 2050 burn area targets for each ecoprovince. Entire years-worth of stochastic events in each ecoprovince were swapped to achieve the target. Each swapped years-worth of events has the same historic seed year as the one it replaced, in order to retain the climate information baked into each stochastic year. All targets were achieved in the subsampling procedure. No explicit provision was made for the possibility for the exact same area to be burned twice in the same or consecutive years. However, the likelihood is very small given that the total amount of burnable area is typically three orders of magnitude larger than what is projected to burn, even for ecoprovinces that are projected to have significant increases in annual burned area.

The climate change conditioned catalogs were used to evaluate climate change impacts (relative change in losses) to the AIR Worldwide U.S. Industry Exposure Database, with all factors other than area burned held constant. The database contains information on all property considered insurable from a structural and use standpoint including buildings for residence, commerce, and industry and includes mobile homes, automobiles, and contents within structures. Estimates of average annual loss across the AIR Model domain increases 125% by 2050. Loss increases in California are relatively modest at 50% but for some states like Colorado the average annual loss triples. For most states the losses double. Percent changes in return period losses are also high: higher than those for average annual loss (AAL) at low return periods but less at high return periods. More granular results show that the biggest increases in risk do not coincide with areas that currently have the highest exposure and suggest areas where mitigation efforts should be focused.

The results of this study yield useful information about how wildfire risk and loss may change in the western U.S. in the future because of climate change under the assumptions of a particular RCP scenario, which is a subset of climate projection information from GCMs. No changes in ecoprovince vegetation, industry exposure, fire management practices, other ignition sources, and climate-wildfire relationships (other than VPD) were considered in this study. Future studies are recommended to address some, or all of the limitations noted above.

Give us your feedback!
Take a short survey on this report.
Click Here
SOA Research INSTITUTE

Copyright © 2021 Society of Actuaries Research Institute

Section 1. Introduction

Wildfire activity has increased during the last several decades with very extreme activity punctuating the last few years across many parts of the western United States. Several studies indicate a connection to climate variability and change and a big concern therefore is that as climate change continues the wildfire risk will worsen. This report provides results from a recently conducted study using the AIR Wildfire Model for the United States and available climate and climate change information to estimate how climate change may influence wildfire losses to U.S. property by mid-century. Losses here refer to the costs incurred to the insurer to replace and repair damaged buildings and contents, and to remunerate businesses for loss of revenue stemming from damaged property. The exposure at risk is all property in the western U.S. considered insurable from a structural and use standpoint including buildings for residence, commerce, and industry and includes mobile homes, automobiles, and contents within structures.

In this study we examine how climate change will affect the average annual burned area from wildfires. Other factors that may vary over time, such as how vegetation types may change, exposure changes, or mitigation strategies may evolve, are held constant and are based on present-day. A new catalog representing the possible wildfire risk by 2050 is created by sub-sampling wildfire events from the AIR Model. Comparing the loss probability distributions between the current and future climates allows us to quantify the possible impact of climate change on wildfire risk by 2050.

We begin with a discussion of the relevant literature, some of the recent extreme fires, and the connection between climate and wildfire.

1.1 SOME HISTORICAL PERSPECTIVE

Fires are a natural process in most terrestrial ecosystems and probably have been occurring for several hundred million years (Scott & Glasspool, 2006). While wildland fires occur naturally, they do cause significant damage to properties, with losses becoming increasingly large in western U.S. in recent years. Several factors have contributed to this. One of the most important is the fact that many wildlands are considered desirable places to live and construction of properties in fire-prone wildlands, namely the wildland-urban interface (WUI), occurred at rapid rates in recent decades (Radeloff et al., 2018), with little indication that this activity will be curtailed in the near future (Mann et al., 2014). This has been a major factor driving property losses in recent decades.

A second factor is the policy for many decades of fighting as many forest fires as possible in the western states. This has resulted in the buildup of plant biomass (the fuel for wildfires) and altered forest structure in ways that can promote more devastating wildfires (Keane et al., 2002). Because it is widely recognized by the wildfire science community that forest fire suppression can lead to worse fires in the future, the U.S. Forest Service is changing its strategies for forest management, including the use of prescribed fires[1], to reduce future risk of damaging wildfires.

A third factor is the introduction, intentionally or unintentionally by human actions, of invasive plant species that significantly affect fire behavior from the perspective of risk to properties[2].

Causes of wildfire are varied, but in the western states, humans are responsible for most fires by number in recent decades (Balch et al., 2017). Lightning caused the most burned area in the western states (but not California) since 2001 (Statistics | National Interagency Fire Center (nifc.gov)) and during 2020 lightning was a major cause of wildfire

[1] https://www.fs.usda.gov/science-technology/fire; https://smokeybear.com/en/about-wildland-fire/benefits-of-fire/prescribed-fires
[2] e.g.: https://www.usgs.gov/centers/werc/science/invasive-plants-and-fire-0?qt-science_center_objects=0#qt-science_center_objects; https://theconversation.com/invasive-grasses-are-fueling-wildfires-across-the-us-126574

Copyright © 2021 Society of Actuaries Research Institute

ignitions throughout the west. In California, AIR estimates that area burned in 2020 in lightning-caused fires was more than 10 times the annual average during the previous 19 years. Another cause can be structural failure of the electricity utility distribution network, especially in California[3] but other states as well[4].

Practices both during construction of new properties (for California see, e.g., https://www.hcd.ca.gov/building-standards/state-housing-law/wildland-urban-interface.shtml) and during maintenance of existing properties may have quantitatively important effects on property damage sustained in the event of a nearby wildfire[5]. For new construction (and retrofits), structures can be hardened against embers (flying pieces of burning plant biomass), which are reportedly the main cause of structural damage caused by wildland fires. For property maintenance, the 'defensible space' surrounding structures can be an important barrier against wildfires and an aid to firefighting actions[6].

New terminology is being used to describe the largest of recent wildfires. The term 'gigafire' is now used to refer to fires burning more than a million acres (Gabbert, 2020). (The term megafire was already being used to denote 100,000-acre fires, even though the prefix 'mega' means million in scientific usage.) Much of the media coverage implies that gigafires are a new phenomenon, but we know of several million-acre wildfires from the late 1800s and early 1900s in the United States, and there may be lessons to be learned from that history about the potential for even larger fires today. For example, within the period 100 to 150 years ago, episodes of very dry and very windy conditions (related to past climate variability) were associated with what would now be called gigafires. Examples are the Great Fire of 1910 in Idaho and Montana that burned 3 million acres (Peterson, 1994/95); the Peshtigo Fire of 1871 in northeastern Wisconsin the burned 1.2 million acres in a day (Brown, 2004); the Great Michigan Fire, also in 1871, that burned 2.5 million acres (Brown, 2004); the Thumb Fire in Michigan in 1881 that burned over a million acres in less than a day; and in 1898, the 3 million acres burned in South & North Carolina in two days (Hairr, 2002). These examples are for fire complexes composed of multiple fires burning (nearly) simultaneously in close proximity, which is also the case for today's gigafires. This raises the issue of whether labeling today's largest wildfire complexes as 'record' is a result of recency bias and possibly reducing an awareness of the probabilities of even larger individual wildfires and wildfire complexes in the near future.

A similar consideration may be needed in terms of assessing changes in total annual area burned in the United States. One analysis of historical wildfire data (Littell et al., 2009) indicates recent wildfire activity, in terms of fire size in the western United States in recent years, is not new. Rather, area burned at least 100 years ago may have been like the area burned in recent years, with a long-term downward trend in annual area burned, bottoming out in the 1960s, and since then increasing to areas burned 100 years ago. Are we, therefore, moving through a normal centennial cycle for wildfire area burned, and if so, are we reaching the peak or can we expect a continuation of increasing area burned, and for how long?

On an even longer time scale (the last 3000 years), there is good evidence of cycles of fire activity (biomass burned in this case) with periodicity on the scale of multiple hundreds of years (Marlon et al., 2012). There are many factors underlying these longer-term historic cycles, but one question especially relevant for this project is: will a new, future climate disrupt the older cycles of wildfire activity, perhaps increasing the amplitude of the area burned, or altering the frequency of the cycle, or both. And as a possible specific 'warning' about the future, it appears that biomass burned in the western U.S. was extensive during the Medieval Warm Period—from 1000 to 800 years

[3] https://www.fire.ca.gov/stats-events/; https://www.levinsimes.com/electrical-power-3rd-most-common-cause-of-wildfire/
[4] https://wildfiremitigation.tees.tamus.edu/faqs/how-power-lines-cause-wildfires
[5] e.g.: https://www.sacbee.com/news/california/fires/article227665284.html; https://www.mdpi.com/2571-6255/2/3/49/pdf; https://firesafesanmateo.org/resources/california-wildland-urban-interface-code-information; https://www.denverpost.com/2019/04/11/california-building-code-wildfires/
[6] https://www.ready.gov/sites/default/files/2020-03/home-builder-guide-construction-defensible-space.pdf

Copyright © 2021 Society of Actuaries Research Institute

ago—while biomass burned was low during the Little Ice Age—about 400 years ago (Marlon et al., 2012). In that context, and from a western U.S. wildfire-caused property damage perspective, a warmer future, akin to the Medieval Warm Period contrasted with the Little Ice Age, may be undesirable.

Finally, ongoing and expected future climate changes (and increased climate variability) have the potential to increase the frequency, intensity, and/or areal extent of wildfires in the western states. Among many factors, we already see a lengthening of the 'fire season' in parts of the west due to changes in temperature and precipitation amount and timing (Schweizer, 2019). Any increase in the frequency or severity of drought—either past, present, or future—might also play a key role in wildfire activity, as could any changes in local or regional climatologies of winds. Importantly, climate change will almost certainly not be uniform across the western states, and different ecosystems (ecoprovinces—see Appendix B) will respond differently to climate change, so regional perspectives will be important to considerations of future changes in wildfire risk due to climate change.

1.2 RECENT EVENTS

The period 2017 to 2020 is thus far the most destructive wildfire period in recent U.S. history. The California wildfires of 2017 collectively burned over 1.5 million acres and caused the most property damage in the state ever at the time. It was a record setting year for the state. Damages of US$18 billion exceeded by a factor of three the previous record set in 1991. Five of the 20 most destructive wildfires in the state's history burned between October and December: #1 Tubbs, #6 Nuns, #7 Thomas, #11 Atlas, and #17 Redwood Valley Complex.

Then, it happened again in 2018—and even worse, with nearly 2 million acres burned. Total damages exceeded US$26 billion. The Carr Fire in July and August 2018 caused more than US$1.5 billion in property damage. The Mendocino Complex Fire burned more than 459,000 acres (186,000 ha), becoming the largest fire complex in the state's history at the time, with the complex's Ranch Fire surpassing the Thomas Fire and the Santiago Canyon Fire of 1889 to become California's single-largest recorded wildfire.

Although there was a reprieve in 2019, the U.S. Wildfire season returned with a vengeance in 2020. A combination of factors including moisture from the remnants of tropical cyclone Fausto that energized a cold front that generated numerous lightning strikes, were responsible for inducing the fires in mid-August across California, Oregon, and Washington. Other factors including a large scale-pressure ridge over the western U.S. that contributed to strong down-sloping winds during the 2020 fire season as well as to record setting heat that primed the fuel early on, ultimately contributed to wildfires that burned more than 8.2 million acres (33,000 square kilometers) of land. In September 2020, the August Complex (composed of 38 individual fires) surpassed the Mendocino Complex to become California's single-largest recorded wildfire complex.

The wildfires in California, and to a lesser degree the western U.S. contribute the majority of the damage and loss in the U.S. and also contribute significantly to acres burned. Figure 1 indicates the number of fires and acres burned annually across the U.S. since 1992. Two points are noteworthy. One is that the number of fires has been decreasing. The second is that the total number of acres burned has been increasing. The two points together indicate that the average fire size has been increasing.

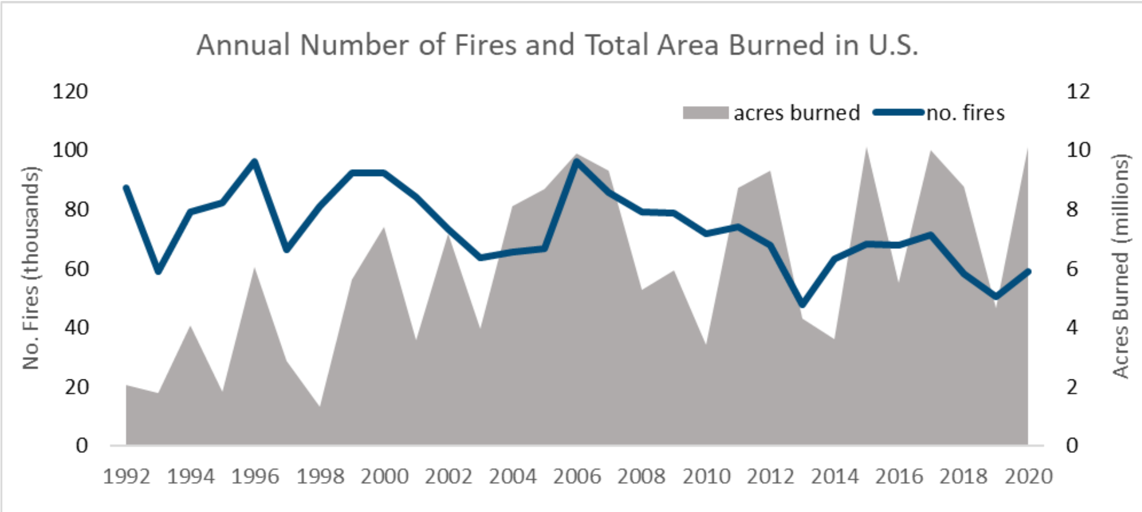
1.3 WILDFIRE DEPENDENCE ON WEATHER AND CLIMATE

There is a definite connection between climate, weather and wildfire. However, it is not as simple as saying dry areas are at high risk. Collins et al. (2006) note the importance of an oscillation between wet and dry periods for growing vegetation and then drying it to create the fuel for wildfires. That study provides an excellent overview of the connection between wildfire and climate, and we have excerpted below for convenience some key comments from that paper. As one extreme example of this phenomenon, following two years of exceptionally heavy rain in

Copyright © 2021 Society of Actuaries Research Institute

Figure 1

ANNUAL TOTAL NUMBER OF WILDFIRES (BLUE LINE) AND ACRES BURNED EACH YEAR IN THE UNITED STATES DURING THE PERIOD 1991–2020.



Source: Data from National Interagency Fire Center (NIFC).

Australia, which produced ample fuel, 15% of the continent burned in the 1974/75 summer – almost three times the area of California.

Several fire scar dendrochronological studies of multi-century fire patterns, and studies of recently recorded fire area and weather in the western United States, have shown that an antecedent increase in moisture, followed by drought, leads to extensive synchrony in fires (Swetnam and Betancourt 1998; Brown and Shepperd 2001; Westerling et al., 2003; Stephens and Collins 2004). The effect of this wet-dry sequence is a net increase in fuel readily available for burning. The connection between moisture availability and fire varies across vegetation types, depending on the fuel dynamics. In areas where fine fuels (grasses, forbs, light shrubs, etc., found in grasslands and shrublands) are prevalent, fuel accumulation is responsive to antecedent climatic conditions (1– 2 years previously). In forest systems, which typically carry a significant fuel load, drought during the current fire season is often positively related to area burned, which is thought to be due to drying of fuels increasing flammability. In those systems, precipitation amount in the previous 1– 4 years may be relatively unrelated to area burned.

In addition to linking fire directly with moisture availability, several studies have shown that synoptic-scale climatic processes relate to increased fire activity. In the southern and to a lesser extent the central Interior West, the El Nino-Southern Oscillation (ENSO) has been shown to relate to both yearly burned area and historically reconstructed fire events (Swetnam and Betancourt 1990; Swetnam and Betancourt 1998; Veblen et al. 2000). Additionally, recent work has shown that the Pacific Decadal Oscillation (PDO) can enhance the connection between widespread fire and ENSO in these regions (Westerling and Swetnam 2003). Both ENSO and PDO influence moisture availability by altering precipitation and temperature patterns throughout the Interior West (Cayan 1996; Mantua et al. 2001; Dettinger et al. 1998; McCabe and Dettinger 1999). Thus, the connection between these processes and fuel is driven by fluctuations in moisture availability, which ultimately affect fuel moisture and fuel quantity.

Both the ENSO and the PDO cycle back and forth between warm (positive) and cool (negative) phases caused by episodic fluctuations in Pacific Ocean sea-surface temperatures (SSTs). In the Interior West the climatic effects of these warm and cool phases are reversed between the southern and northern regions. During warm-phase ENSO, or El Nino conditions, and warm phase PDO, the southern Interior West experiences substantially wetter and slightly cooler winters, while in the northern Interior West, winters tend to be warmer and drier than usual (Cayan 1996; Western Regional Climate Center 1998). The effects of cool-phase ENSO, or La Nina conditions, and cool-phase PDO

Copyright © 2021 Society of Actuaries Research Institute

are opposite to those associated with the warm phases. The strength of ENSO-related climatic effects can depend on the PDO phase, which shifts at 20- to 30-year intervals (Brown and Comrie 2004). As a result, the effects of ENSO and PDO vary at annual to decadal time scales, but in general the effect of ENSO on climate is more consistent in the southern Interior West, while the effect of PDO is more consistent in the northern Interior West (Mantua et al. 1997).

The Atlantic Multidecadal Oscillation (AMO) is yet another influence on moisture availability that could be used to further elucidate our understanding of climate-fire relationships. Like ENSO and PDO, AMO alternates between warm and cool phases (based on SST anomalies in the North Atlantic Ocean) that differentially affect precipitation patterns. During warm-phase AMO much of the Interior West is drier, mainly because of below-average summer precipitation (Enfield et al. 2001). This warm-phase AMO may also create a synergistic effect when it coincides with cool-phase PDO, resulting in extensive long-term drought (Gray et al. values were as low as −4.6). The PDO and AMO indices are based on SSTs in the North Pacific Ocean and North Atlantic Ocean, respectively. However, they differ in that the PDO index is constructed from the leading principal component of monthly SST (Mantua et al. 1997), while the AMO index is the 10-year running mean of SST anomalies (Enfield et al. 2001). Monthly values of the PDO and AMO indices typically range from −3 to 3 and from −0.5 to 0.5, respectively. For both indices, positive values correspond to warm phases of oscillation, while negative values correspond to cool phases.

1.4 UNDERSTANDING TRENDS IN WILDFIRE ACTIVITY

A number of studies have looked at quantifying relationships between climate and wildfire risk (e.g., burn area) either for improving the forecast-ability of large (>1000 acres) or very large fires (>5000 acres); and/or for understanding the climate change connection to them. For the current study we are interested in the latter and thus cite some of the more relevant and recent publications.

Abatzoglou and Kolden (2013) examined macroscale climate–fire relationships in forested and non-forested lands for eight Geographic Area Coordination Centers in the western United States. They found strong correlations between fire and climate earlier in the same year for forested areas and strong correlations between fire and climate in the preceding year for non-forested lands. However, despite differences in the role of antecedent climate in preconditioning fuels, synchronous regional fire activity in forested and non-forested lands suggests that atmospheric conditions during the fire season unify fire activity and can compound or supersede antecedent climatic stressors.

Barbero et al. (2014) used Generalized Linear Modeling to develop separate regression relationships between various atmospheric parameters/indices and very large fires (> 5000 acres) by ecoprovince. It is important to note that their definitions of ecoprovinces are different than what are in the AIR Model. The relationships included indices such as Burning Index, Composite Water Deficit, Energy Release Component, Fosberg Fire Weather Index, Initial Spread Index, Effective Precipitation Index, as well as more familiar ones like Palmer Drought Severity Index, etc. While the correlations were good, it was difficult to justify physically the different relationships in different locations.

Ficklin and Novick (2017) examined historic and projected changes in atmospheric moisture over the entire US. The study used 4 km Gridded Surface Meteorological Data (METDATA) and output from general circulation models to examine how vapor pressure deficit (VPD) has been changing and is expected to change. Vapor pressure deficit (VPD) is defined as the amount of moisture that is missing from the atmosphere that would lead to saturation. It is expressed in terms of pressure units since water vapor is a gas (just like dry air) and so it exerts a pressure. Mathematically, it is simply:

$$VPD = e_s(T_a) - e_a \tag{1}$$

Copyright © 2021 Society of Actuaries Research Institute

And the saturation vapor pressure is a function only of air temperature T_a. As air temperature increases, the amount of water vapor that can be in the atmosphere (e.g., in vapor form) increases exponentially. The relationship between air temperature T_a and saturation vapor pressure e_s is known as the Clausius Clapeyron relationship. Furthermore, the ratio of actual vapor pressure e_a to saturation vapor pressure e_s is basically the relative humidity RH as:

$$RH = 100 \times \frac{e_a}{e_s(T_a)} \qquad (2)$$

Vapor pressure deficit VPD can increase simply by an increase in air temperature. A decrease in the amount of atmospheric moisture (e.g., through prolonged reduction in precipitation and/or less evaporation from plants) does not have to occur but if it does the VPD will further increase. Ficklin and Novick (2017) showed that the seasons where VPD has been increasing most since 1979 are spring and summer across the west and southwestern portions of the U.S. And, although the actual reason for it is a combination of increases in saturation vapor pressure e_s and decreases in actual vapor pressure e_a, the primary driver is from increases in e_s (see their Figure 1). The increases in e_s are the result of increasing temperatures associated with climate change. The decreases in e_a may be related to changes in atmospheric circulation patterns (e.g., increasing positive PNA pattern, more frequent/severe La Ninas) and may also be related to climate change.

Williams et al. (2019) also examined historical trends but focused on burned area for California as it correlated to several aridity metrics. The study found a five-fold increase in burned area since the early 1970s (see their Figure 1). They also examined correlations of burned area with six different aridity metrics: standard precipitation index (SPI), antecedent SPI defined as SPI from March of 2 years prior to the fire year through October of the year prior to the fire year, number of wet days with precipitation > 2.54 mm, maximum temperature (Tmax), 1000-hr dead fuel moisture (FM1000), and vapor pressure deficit (VPD). We do not provide all the detailed definitions here save for VPD since it showed the highest correlation (see their Figure 2) with burn area in forested regions. The foundations for relationships between VPD and area burned by wildfires are reviewed by Seager et al. (2015). The regressions performed by Williams et al. (2019) were with the log of burn area vs VPD. owing to their finding that actual burn area is very sensitive to changes in VPD. Figure 3 in Williams et al. (2019) provides a good example of the sensitivity.

1.5 EXPECTED IMPACTS FROM CLIMATE CHANGE

More recent literature has focused on understanding the connection between climate change and wildfire risk. Numerous studies have developed regression relationships between burn area and derived aridity metrics that can be calculated using historical reanalysis data as well as output from general circulation models. Some of the studies have already been mentioned in this section. We note here a subset of available literature and only then going back several years. The studies, on the whole, are essentially ingredients-based. That is, the aforementioned connections between changes in climate (e.g., over the historical record) affecting available fuel and the assumption is that increased fuel correlates with increased wildfire either in terms of frequency or area or both.

Also, especially because of the time in which the study was conducted, different vintages of climate models were used. Early studies used a suite of GCMs called CMIP3 and later ones use CMIP5 (Coupled Model Intercomparison Project Phase 3 or Phase 5, respectively).

The latest suite is called CMIP6 (Phase 6) and is just now becoming widely available for study. The CMIP6 models generally have higher resolution in the atmosphere and ocean, improved representation of physics, and improved

Copyright © 2021 Society of Actuaries Research Institute

representation of aerosols and for the most part are the ones informing the latest Intergovernmental Panel on Climate Change (IPCC) Report (IPCC 2021). The types of climate change experiments are also more involved, using a number of new and updated atmospheric greenhouse gas concentration pathways that explore a wider range of possible future outcomes than were included in CMIP5 (Eyring et al. 2016). Published reports available at the time of this study (e.g., Li et al., 2021) comparing some precipitation and dryness metric between CMIP5 and CMIP6 s, although not the ones used in this study, showed comparable results across the U.S. Despite higher resolution it is likely that because wildfire-climate change studies typically focus on large-scale ingredients that results will not differ markedly from CMIP5 based ones.

A study by Liu et al. (2010) used CMIP3 models to identify that wildfire risk would increase because of climate change. Increase in the western U.S. would be particularly severe. A lengthening of the wildfire season primarily because of warmer but also drier conditions would exacerbate the effect. Barbero et al. (2015) used the relationships they derived in a companion paper (Barbero et al. 2014) applied to output from 17 GCMs to evaluate how climate change would impact wildfire risk in the U.S. by mid-21st century. A key finding from that study was the significant increases in the number of wildfire days on the order of hundreds of percent—especially over the inter-mountain western region of the US. Ficklin and Novick (2017) evaluated VPD output from a suite of CMIP5 GCMs for late 21st century changes and found increases across all of the U.S. that were driven primarily from increases in saturation vapor pressure (e_s) rather than decreases in actual vapor pressure (e_a). Moreover, the biggest changes they found were for the Midwest – just west of the Mississippi River but still outside the eastern boundary of the AIR Model (see their Figure 5). Littel et al. (2018) noted recently that ecosystems that are fuel-limited would not necessarily realize the drier conditions from climate change. They looked at 70 different sub-ecoregions in the western U.S. and found that flammability-limited regions would more likely achieve the hundreds of percent increases in burn area calculated from increased aridity in the GCM projections.

Section 2: Defining the Climate Change Target

In this section we describe the methodology for defining the climate change target that is used to guide the sub-sampling. The targets reflect the time horizon 2050 under the RCP 8.5 scenario. The RCP 8.5 greenhouse gas concentration scenario was chosen to explore the consequences of a world with limited action taken to address climate change. Although Hausfather & Peters (2020) suggested that greenhouse gas concentrations already departed to the low side from RCP 8.5, Schwalm et al. (2020) showed that RCP 8.5 is in close agreement with historic emissions and that RCP 8.5 is the best match of the four available RCPs "out to midcentury under current and stated [national energy] policies." Even though greenhouse gas emission rates declined modestly because of the COVID-19 pandemic, they may recover quickly post-pandemic. On balance, RCP 8.5 remains a plausible upper bound and a useful analytical reference point.

2.1 HISTORICAL DATA ANALYSIS

First, we identified the relationship between fire size (e.g., area burned) and VPD in summer (June to August) in each ecoprovince within the AIR Model domain which consists of 30 ecoprovinces. A map detailing the ecoprovinces along with labels and descriptions are provided in Appendix A. Fifteen of them are dominated by forest (7, 10, 13, 16, 21, 32, 33, 34, 35, 36, 37, 40, 45, 46, 47), and the rest are considered as non-forest (5, 12, 14, 16, 18, 20, 24, 25, 26, 28, 29, 31, 41, 42, 48). The fire size data comes from the Fire Occurrence Database (FOD) (Short,

Copyright © 2021 Society of Actuaries Research Institute

2017). It includes every reported fire, no matter how small, during the period 1992– 2015[7] in all the United States. Prescribed/planned fires are included in the FOD.

The summer VPD values are derived from University of Idaho Gridded Surface Meteorological Data daily values. This is a high-resolution (4-km) gridded dataset of daily VPD that spans the continental U.S. for the period 1979–2019. This observational dataset, known as METDATA, blends spatial attributes of climate data from PRISM[8] with desirable temporal attributes from regional reanalysis (NLDAS-2) (Abatzoglou, 2011).

VPD can of course vary throughout the day, so it is important to state the definition of daily VPD in the present study. Here the daily VPD is defined as the difference between Saturation Vapor Pressure (SVP) and Actual Vapor Pressure (AVP) where SVP is the mean of the SVP at minimum and maximum daily temperatures and AVP the product of relative humidity and SVP. Expressions for SVP and AVP are provided earlier in (1) and (2) in Section 1.4.

We first temporally aggregate the daily VPD data to give monthly mean VPD grids. An example of the September 1986 VPD grid from the METDATA is shown in Figure 2. The monthly VPD grids are then spatially averaged across each ecoprovince and the average VPD over the summer months (June, July and August) is calculated to give annual summer VPD timeseries for each ecoprovince. Summer VPD is a measure of sustained dryness during the height of the wildfire season in western US. Fire sizes from FOD were aggregated by year for each ecoprovince and then calculated by the following equation:

$$\text{per mil (‰) area burned} = \text{fire size}/\text{ecoprovince size} \times 1000.$$

The VPD summer average for a specific year was defined as the mean of VPD values over the period June, July and August. The scaled VPD was defined as below:

$$\text{Scaled VPD} = \text{VPD summer average of a specific year} \; / \; \text{VPD summer average of 1992 to 2015.}$$

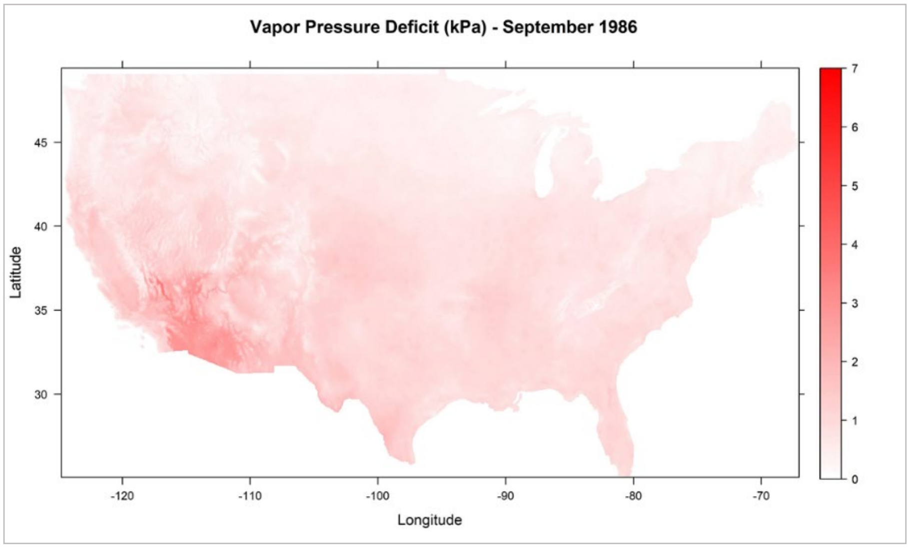
The upper bound for the conterminous United States is 16.8‰ (Ecoprovince 23), while the lower bound is 0.03‰ (Ecoprovince 1). Within our 13-states model domain, the highest burned area fraction is 11.8‰ (Ecoprovince 13), while the lowest is 0.07‰ (Ecoprovince 40). In the southeastern U.S., most fires were prescribed fires, which did not cause large losses.

[7] An updated FOD database for 1992-2018 became available during this study (Short, 2021) but time constraints precluded a full re-calculation of VBD-burned area relationships with it. Some analysis however was done and showed that the relationships by ecoprovince effectively remained unchanged.
[8] Parameter-elevation Regressions on Independent Slopes Model (PRISM)

Copyright © 2021 Society of Actuaries Research Institute

Figure 2

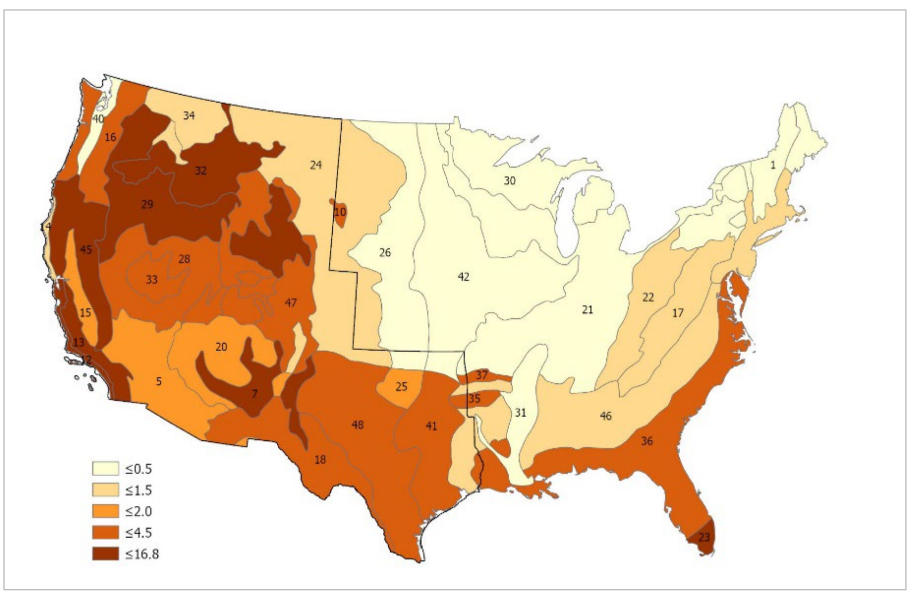
VAPOR PRESSURE DEFICIT (KPA) OVER THE CONTINENTAL UNITED STATES FOR SEPTEMBER 1986 CALCULATED FROM DAILY 4-KM METDATA.



GLM modeling results are illustrated below for six ecoprovinces. Four of them are mostly in California and the other two are mostly in Texas.

Figure 3

PER MIL (‰) AREA BURNED PER YEAR IN EACH ECOPROVINCE. THE ECOPROVINCE LEVEL ID WERE LABELED. THE BLACK BOUNDARY DELINEATED OUR MODEL DOMAIN.



Ecoprovince 45 (Figure 4), Sierran Steppe-Mixed Forest-Coniferous Forest-Alpine Meadow, is located in Northern and Northeastern California and Southern Oregon. This is where most of the fires in California happened in 2020. It is mountainous with steep slope, and glaciated mountain ranges from 2,000–14,000 feet. Temperature and precipitation vary by elevation, but in general this is a cool province with 80+% of the moisture falling as snow in winter. Vegetation across the lower slopes and foothills is dominated by shrubs and conifers. Middle elevations are

Copyright © 2021 Society of Actuaries Research Institute

dominated by pines and subalpine species. Fires are infrequent. High intensity ground or stand-replacing fires kill all or most of the living overstory trees in a forest and initiate forest succession or regrowth. The burned area in this ecoprovince is 6.9‰, which is in the highest category.

Ecoprovince 13 (Figure 5), California Coastal Range Open Woodland-Shrub-Coniferous Forest-Meadow, is located in southwestern California. The terrain is mountainous with steep slopes. Summers are hot and dry; winters are mild and wet. Vegetation is primarily evergreen shrubland, with lesser areas of woodland, consisting of broadleaf species, some of which are drought-deciduous (which may lose their leaves during dry seasons, rather than winter-deciduous plants that lose their leaves in autumn). The burned area of this ecoprovince is 11.8‰, which is among the highest of the six discussed ecoprovinces. Compared to Ecoprovince 45, burned area size is less sensitive to the VPD change.

Ecoprovince 12 (Figure 6), California Coastal Chaparral Forest and Shrub, is located in the coastal area of southwestern California. It has coastal plains, low mountains and a Mediterranean-like climate of mild wet winters and hot, dry summers, with a brief period of drought. Vegetation is a mosaic of woodland, dwarf-woodland, and shrubland species that are evergreen and drought deciduous. Fires are common, usually set by lightning during the summer dry season. Many species are adapted to fire and regenerate readily after fire. However, in chaparral environments of southern California, fires now occur more frequently, and most are human caused. The burned area of this ecoprovince is 5.8‰, which is also in the highest category.

Ecoprovince 14 (Figure 7), Redwood forests, is located in the coastal area of northwestern California. The prevailing climate is maritime, which is a Mediterranean type consisting of mild winters and cool summers. Winters are wet, with short periods of summer drought. Forests consist of very tall needleleaf, and evergreen trees with smaller areas of broadleaf woodlands. Species are adapted to fire and regenerate readily afterward. For example, the redwoods here are incredibly resilient trees. They live to over two thousand years old and one of the characteristics of identifying old-growth redwoods are signs of fire scarring. The data points are very scattered, which is analyzed as a slightly decreasing trend, but it is not strong. The burned area of this ecoprovince is 1.1‰, which is in the second lowest category.

Ecoprovince 48 (Figure 8), Southwest Plateau and Plains Dry Steppe and Shrub, is located in central Texas. It contains flat to rolling plains and plateaus. The climate is semi-arid. It is covered mainly by herbaceous plants and shrubland with increasing woodland on steeper slopes. Fires vary in frequency and intensity, depending on fuel load and moisture. Fire and drought have probably been the principal historical disturbances. Most precipitation falls during the growing season but is less than potential evaporation. The burned area of this ecoprovince is 3.1‰, which is in the second highest category.

Ecoprovince 41 (Figure 9), Prairie Parkland (Subtropical), is located in eastern Texas. The landforms are plains with low hills, and many of them are part of the Gulf Coastal Plain. The climate is modified maritime subtropical, which is a humid climate consisting of relatively warm winters and hot summers. Moderate amounts of precipitation occur during summer. The vegetation is dominated by various short and medium-to-tall grasses, which is due to the aridity and probably also to fires and grazing. Herbaceous vegetation with areas of deciduous broadleaf woodland is typically found along floodplains. The burned area of this ecoprovince is 2.1‰, which is in the middle level.

In summary, there is a wide variation of burned area size in response to VPD in different ecosystems. Therefore, ecoprovinces need to be and are treated separately.

Copyright © 2021 Society of Actuaries Research Institute

Figure 4

GLM RESULT (UPPER) AND PER MIL (‰) AREA BURNED PER YEAR (LOWER) IN ECOPROVINCE 45: SIERRAN STEPPE-MIXED FOREST-CONIFEROUS FOREST-ALPINE MEADOW.

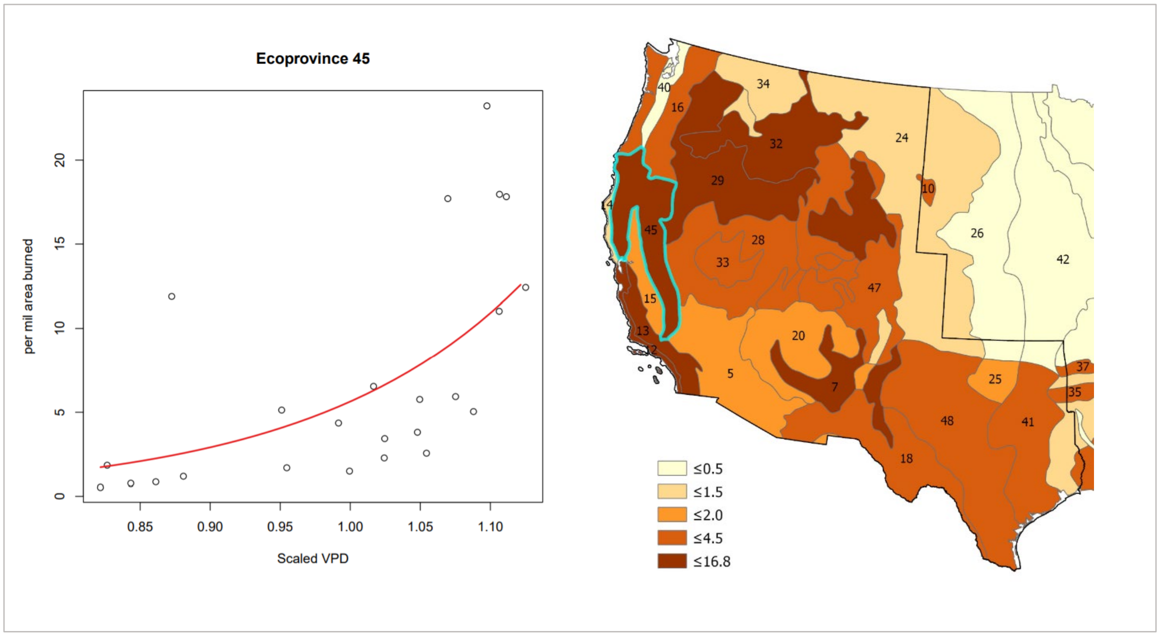
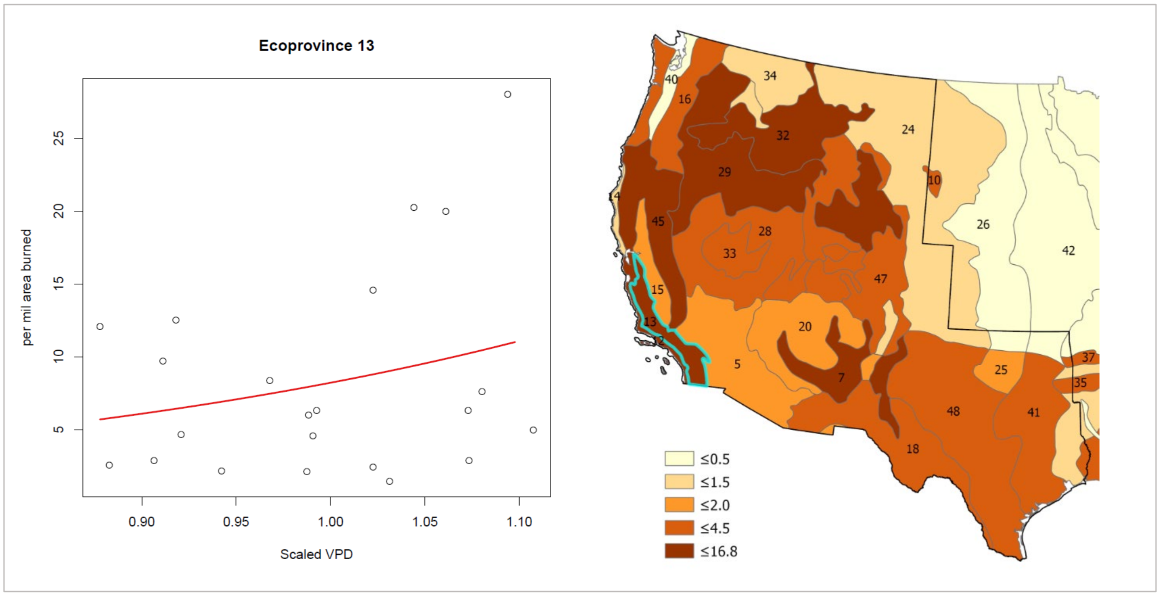


Figure 5

GLM RESULT (UPPER) AND PER MIL (‰) AREA BURNED PER YEAR (LOWER) IN ECOPROVINCE 13: CALIFORNIA COASTAL RANGE OPEN WOODLAND-SHRUB-CONIFEROUS FOREST-MEADOW.



Copyright © 2021 Society of Actuaries Research Institute

Figure 6

GLM RESULT (UPPER) AND PER MIL (‰) AREA BURNED PER YEAR (LOWER) IN ECOPROVINCE 12: CALIFORNIA COASTAL CHAPARRAL FOREST AND SHRUB.

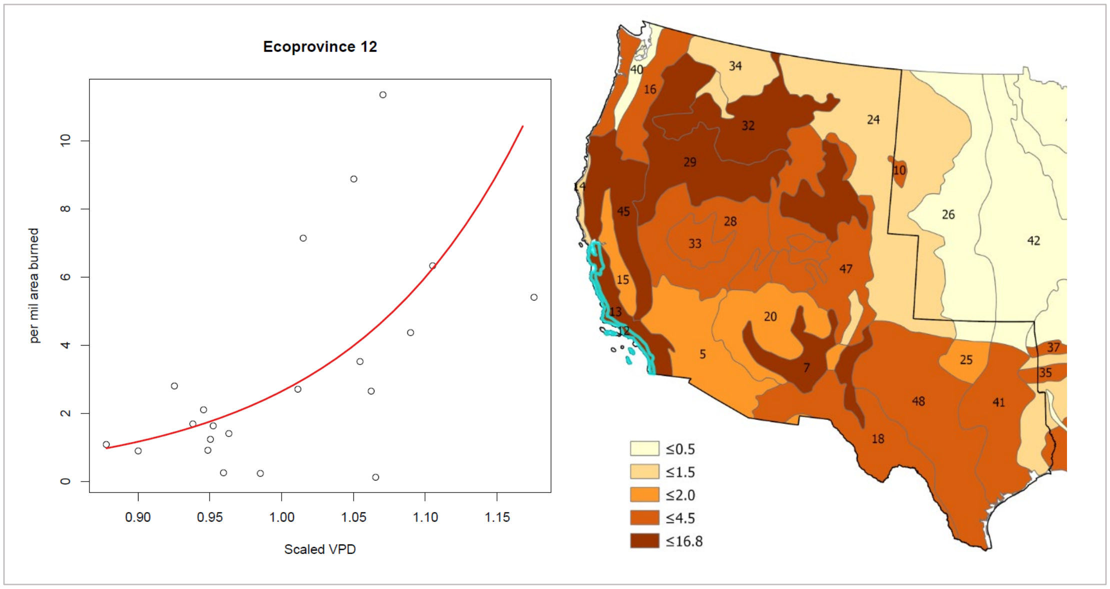
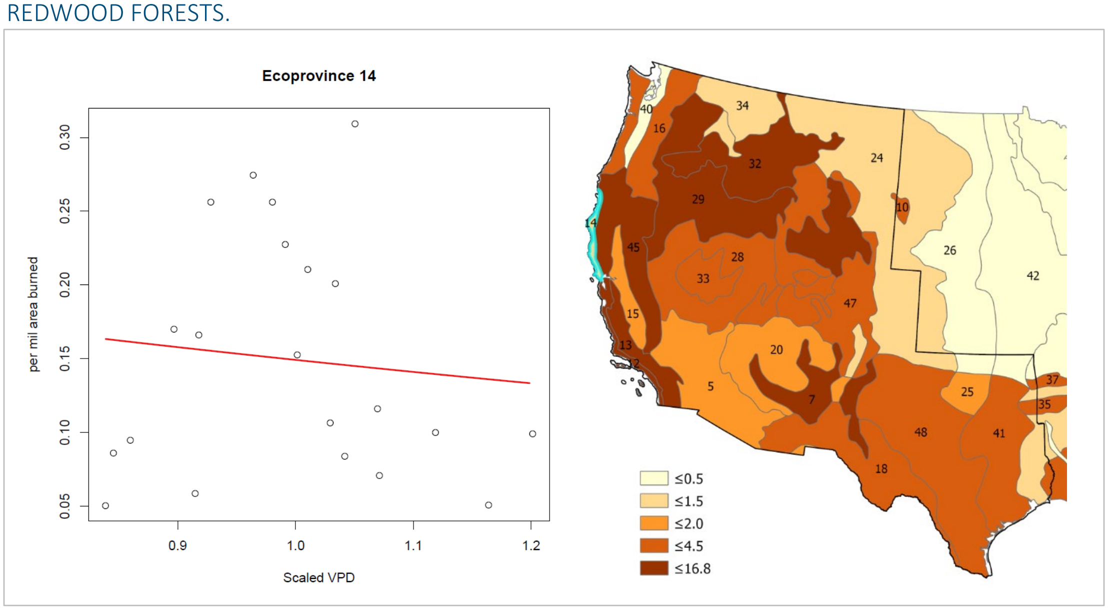


Figure 7

GLM RESULT (UPPER) AND PER MIL (‰) AREA BURNED PER YEAR (LOWER) IN ECOPROVINCE 14: REDWOOD FORESTS.



Copyright © 2021 Society of Actuaries Research Institute

Figure 8

GLM RESULT (UPPER) AND PER MIL (‰) AREA BURNED PER YEAR (LOWER) IN ECOPROVINCE 48: SOUTHWEST PLATEAU AND PLAINS DRY STEPPE AND SHRUB.

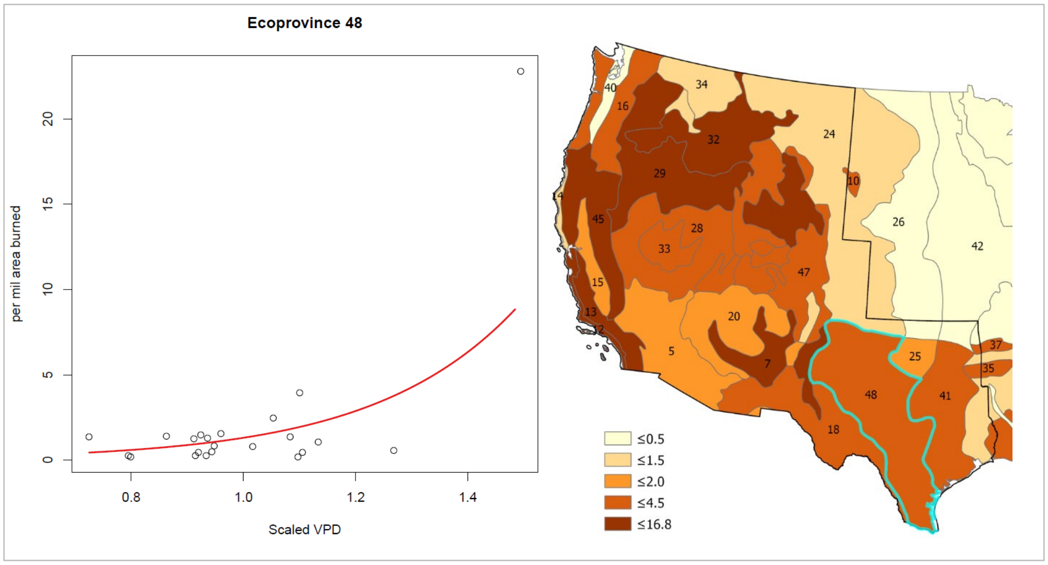
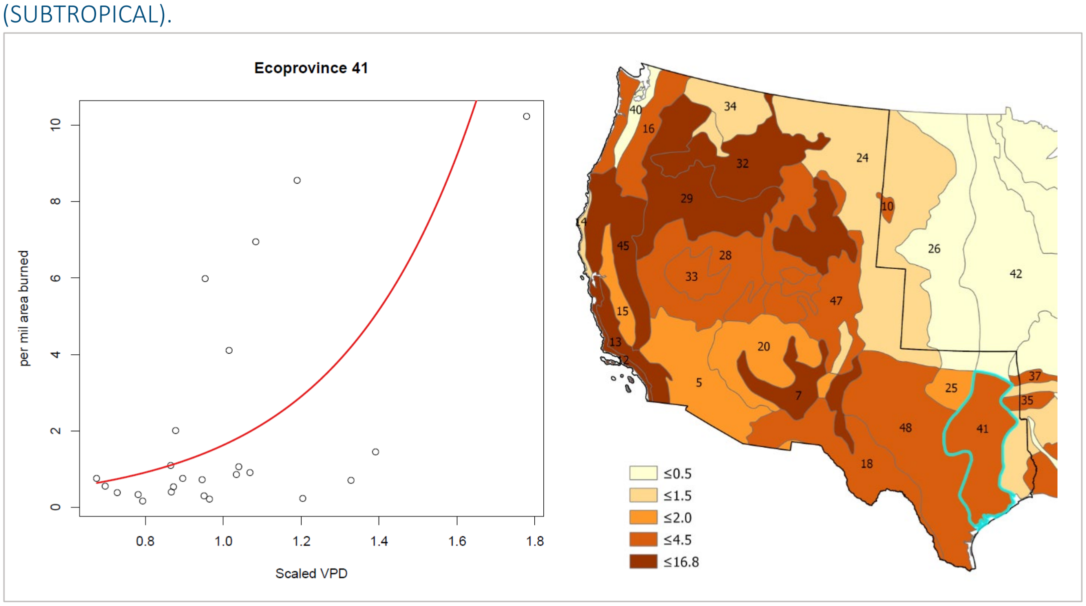


Figure 9

GLM RESULT (UPPER) AND PER MIL (‰) AREA BURNED PER YEAR (LOWER) IN ECOPROVINCE 41: PRAIRIE PARKLAND (SUBTROPICAL).



2.2 CLIMATE MODEL ANALYSIS

The statistical model described in 2.1 Historical Data Analysis that relates summer VPD to annual burn area requires summer VPD values by ecoprovince for the present (2018) and 2050 time-horizon. Here we describe how these values are derived.

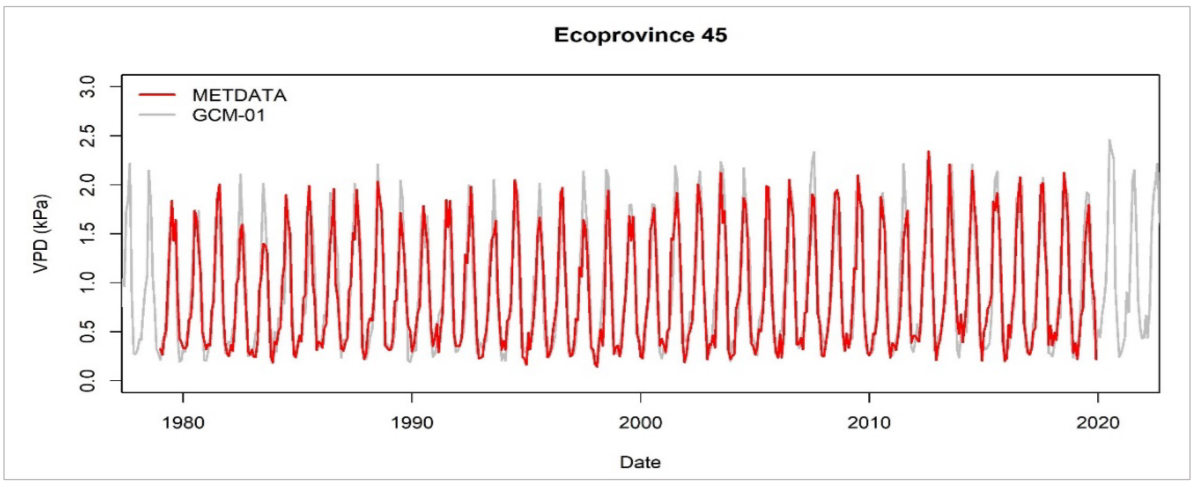
Copyright © 2021 Society of Actuaries Research Institute

The present summer VPD is derived from METDATA as described in 2.1 Historical Data Analysis. Future VPD projections are derived from a complementary dataset known as MACAv2-METDATA that draws climate forcings from a statistical downscaling of GCM data from the Coupled Model Intercomparison Project 5 (CMIP5) (Taylor et al. 2012). This dataset uses a modification of the Multivariate Adaptive Constructed Analogs (MACA) method with the METDATA acting as a training set (Abatzoglou and Brown, 2012). MACAv2-METDATA contains downscaled, bias-corrected historical (1950–2005) and projected RCP 8.5 (2006–2099) data for up to 18 GCMs. For the present study we use the data from two GCMs to compute a mean view: (1) HadGEM2-ES365 and (2) MRI-CGCM3. These two GCMs provide the upper and lower bounds of the projected VPD increases (Ficklin and Novick, 2017).

Figure 10 shows a comparison of monthly VPD timeseries for ecoprovince 45 (Northern California) from the METDATA and HadGEM2-ES365. It shows how VPD peaks in the summer and troughs in the winter and it demonstrates that the MACAv2-METDATA for this particular GCM in this particular ecoprovince adequately captures the summer peaks. In general, both GCMs used in this study capture the summer peaks well in most of the model domain but tend to overestimate in eastern U.S. (outside the domain). A slight overestimation is observed in ecoprovinces 35, 37, 41 and 48, all in Texas.

Figure 10

COMPARISON OF THE MONTHLY VPD TIMESERIES IN ECOPROVINCE 45 (NORTHERN CALIFORNIA) CALCULATED FROM THE OBSERVATIONAL METDATA (RED) AND SIMULATED DATA FROM GCM-01 (HADGEM2-ES365, GREY).



The 1979–2019 summer VPD METDATA is used to calculate a summer VPD that is representative of that in the AIR U.S. Wildfire 100,000-year catalog. Normal linear models are fitted to the summer VPD timeseries for each ecoprovince and the interpolated 2018 value is read. These are the base VPD values. The summer VPD MACAv2-METDATA is used to calculate the change in summer VPD at 2050 relative to 2018. An 11-year averaging filter is applied to the 1975–2070 data for both GCMs, and the rolling mean is read at 2018 and 2050. An 11-year filter is deemed long enough to smooth out interannual variability but short enough to capture interdecadal variability. Figure 11 presents an example for ecoprovince 45 showing the observed summer VPD fitted with a linear trend line plus the projected rolling mean trends from the two GCMs. The 2018 base value is read from the red line while the 2018 and 2050 simulated values are read from blue, dark blue and purple lines.

The change in VPD at 2050 relative to 2018 is calculated. The HadGEM2-ES365 provides the upper estimate and MRI-CGCM3 provides the lower estimate. Since the MACAv2-METDATA is bias-corrected relative to METDATA, these relative changes in VPD can be used to scale the base VPD values and project forward for 2050.

Figure 11
SUMMER VPD METDATA (CIRCLES) WITH A LINEAR FIT (RED LINE) AND THE 11-YEAR ROLLING MEAN OF THE SUMMER VPD FROM GCM1 (HADGEM2-ES365, DARK BLUE), GCM2 (MRI-CGCM3, LIGHT BLUE) AND MEAN OF BOTH GCMS.

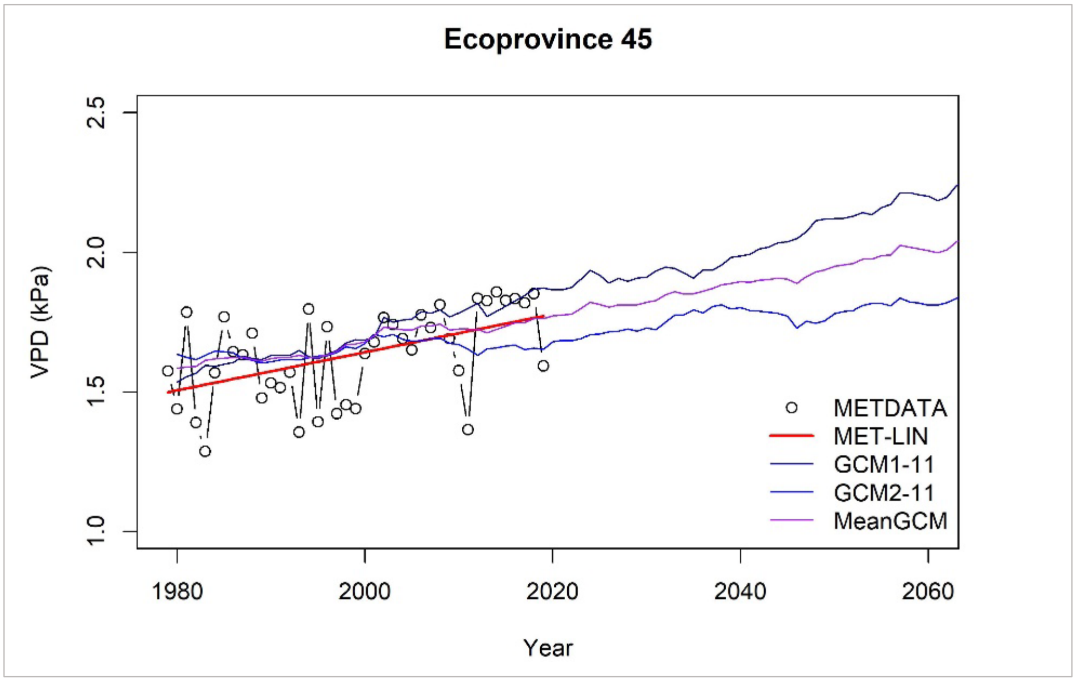
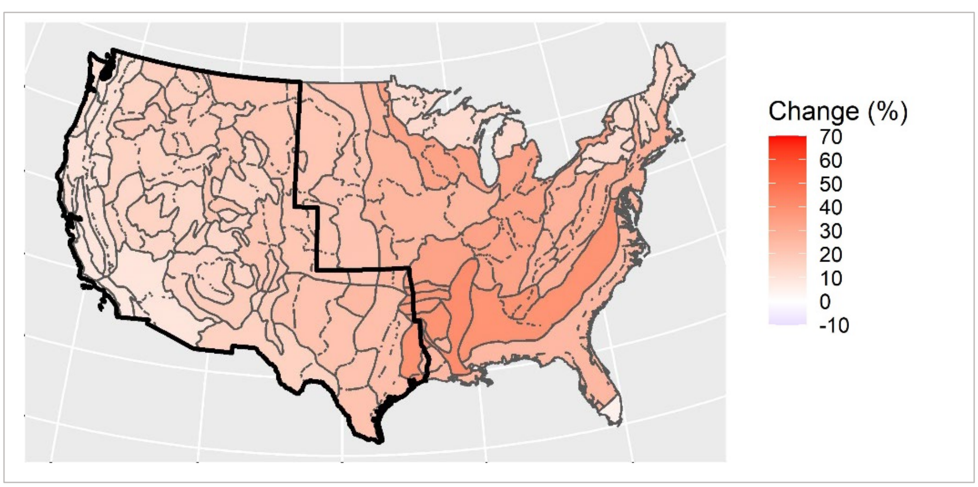


Figure 12 presents the VPD projections in 2050 based on the mean ensemble. Note that all of the U.S. is shown even though the AIR Model currently covers only the western half. The 2050 projections range from 6% to 41% with the lowest in ecoprovince 14 and highest in ecoprovince 31. Ecoprovinces 21, 37, 35 and 46 also have projections higher than 30%. These five ecoprovinces in eastern Texas occupy a small part of the model domain. Ecoprovinces 41, 47 and 48 occupy a larger part of the domain and have projections of 20–23%. The VPD in ecoprovinces 29, 34, 32 and 24 are projected to increase by 15–20% by 2050. The lower GCM projects a 3–18% increase by 2050 across the model domain, while the upper GCM projects 8–68%.

Figure 12
PROJECTED CHANGE IN SUMMER VPD FOR 2050 RELATIVE TO 2018 BASED ON THE MEAN GCM ENSEMBLE. THE BOUNDARY OF THE MODEL DOMAIN IS REPRESENTED BY THE BOLD BLACK LINE.



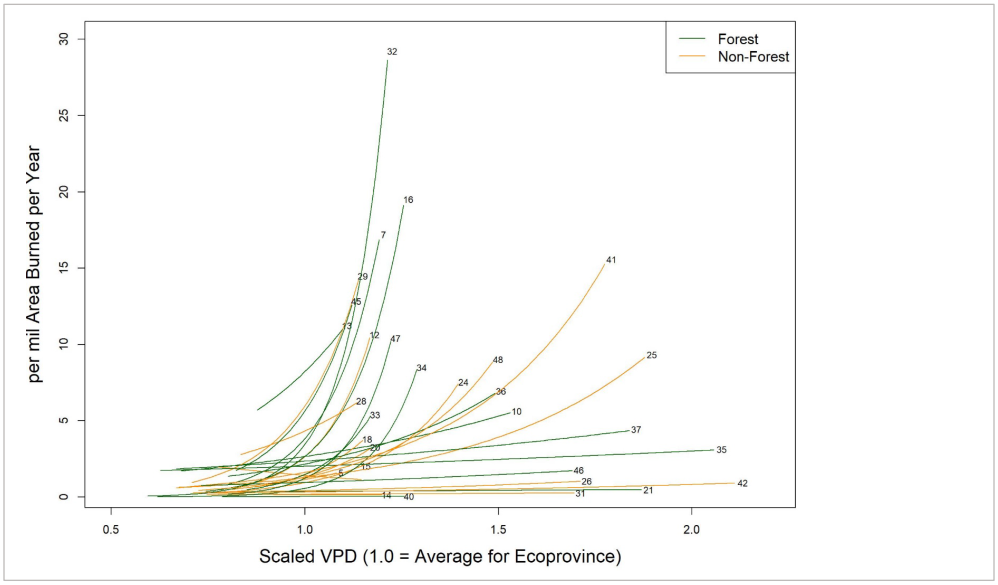
Copyright © 2021 Society of Actuaries Research Institute

2.3 BURNED AREA TARGETS FOR 2050

Figure 13 presents all the 30 GLMs together. It is important to note that, in different ecoprovinces, the area burned responds differently to the VPD change. Some are quite sensitive, such as ecoprovince 32, while some are much less sensitive, such as ecoprovinces 14, 40, 31 and 21. Forest ecoprovinces and non-forest ecoprovinces are not statistically significantly different in the response of fire size. Finally, the projected VPD values at 2050 were used to determine per million changes in burned area targets. Also, we defined 2018 as our base year, so the fire size estimation of 2018 was derived from the model as a baseline for burned area targets at 2050.

Figure 13

RELATIONSHIP BETWEEN AREA BURNED AND VPD FOR ALL 30 ECOPROVINCES FROM GLM.



The summer VPD values calculated in the 2.2 Climate Model Analysis section for the present (2018) and future (2050) under an RCP 8.5 scenario represent the dryness of the air during wildfire season. They in-turn represent the fuel aridity and as demonstrated through the statistical model described in the 2.1 Historical Data Analysis section the annual burned area in some ecoprovinces is highly sensitive to this variable. In this section, the average annual burned area for each ecoprovince in 2018 and 2050 is calculated using the summer VPD value and statistical model for each ecoprovince. The change in average annual burned area for 2050 relative to 2018 provides a burned area target, which is used to create the climate change conditioned catalogs, as described in the Section 3: Subsampling Methodology section.

The method is illustrated here using ecoprovince 45. The upper panel of Figure 4 is replotted in Figure 14 with tie-lines that show how the statistical model is used to read-off the expected annual burned area from the summer VPDs in 2018 and 2050. The results are summarized in Table 1. In 2018, the current climate, the average annual burned area is 0.9% of the ecoprovince area. In 2050, this is projected to increase by 112% to 1.9%.

Copyright © 2021 Society of Actuaries Research Institute

Figure 14

RELATIONSHIP BETWEEN SCALED VPD AND SCALED ANNUAL BURNED AREA FOR ECOPROVINCE 45. THE GENERALIZED LINEAR MODEL (BLUE LINE) IS FITTED TO OBSERVATIONS (CIRCLES). TIE-LINES RELATE THE VPD TO THE BURNED AREA IN 2018 (GREY) AND IN 2050 (RED) TAKEN FROM THE MEAN GCM.

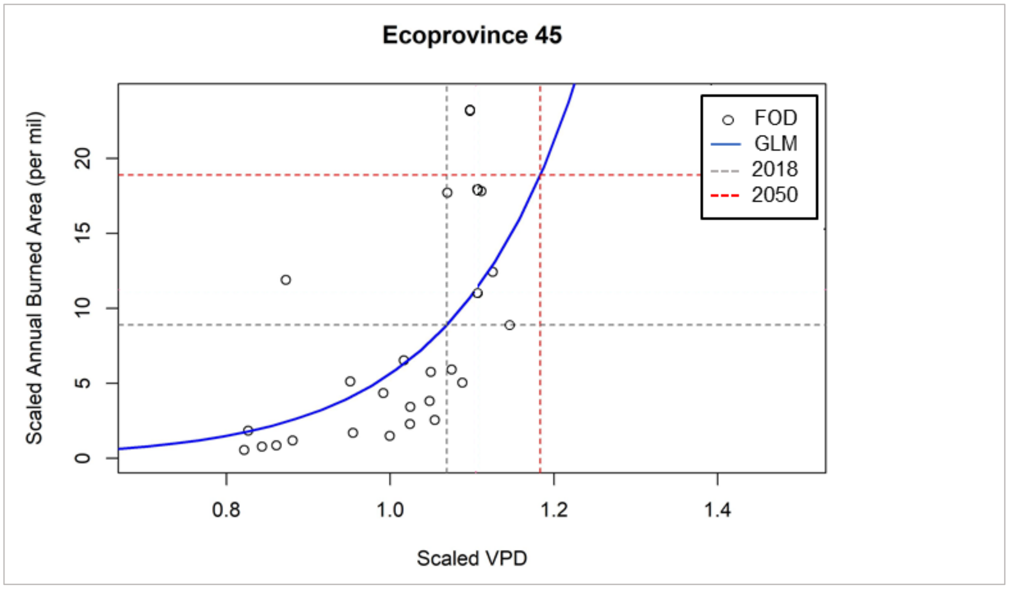


Table 1

SUMMARY OF THE SUMMER VPD AND BURNED AREA ESTIMATES FOR ECOPROVINCE 45 IN 2018 AND 2050 USING THE MEAN-GCM.

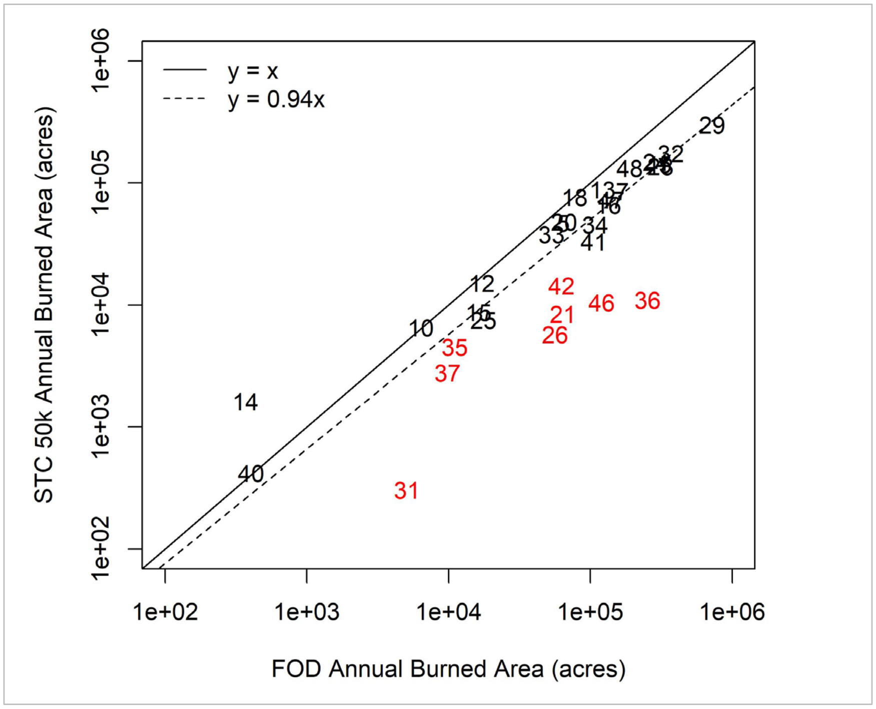
Time-Horizon	VPD (kPa)	VPD Change	Scaled VPD	Scaled Burned Area (‰)	Area Change
2018	1.77	0%	1.07	8.9	0%
2050	1.95	11%	1.18	18.9	112%

Burned area changes are derived from the FOD but it is assumed that they extend to the AIR catalog. This assumption is validated by Table 1, which shows that across almost all ecoprovinces in the model domain, the observed average annual burned area in the FOD is directly proportional to the modelled variable in the AIR U.S. Wildfire 50,000-year catalog. A relative change predicted by the statistical model can therefore be extended to predictions for the AIR catalog. Most ecoprovinces do not lie on the perfect 1:1 line because FOD includes fires of all sizes whereas AIR's catalog contains fires above a minimum size. Some ecoprovinces, colored red in Figure 15 are outliers because they are only partially in the model domain. These ecoprovinces are on the eastern sides of Oklahoma and Texas.

Copyright © 2021 Society of Actuaries Research Institute

Figure 15

AVERAGE ANNUAL BURNED AREA BY ECOPROVINCE FROM THE FOD (1992–2015) AND THE AIR 50,000-YEAR STOCHASTIC CATALOG. ECOPROVINCES PARTIALLY IN THE MODEL DOMAIN ARE IN RED, WHILE THOSE FULLY IN THE DOMAIN ARE IN BLACK. LINE OF BEST FIT (DASHED) IS FITTED TO ECOPROVINCES FULLY IN DOMAIN.



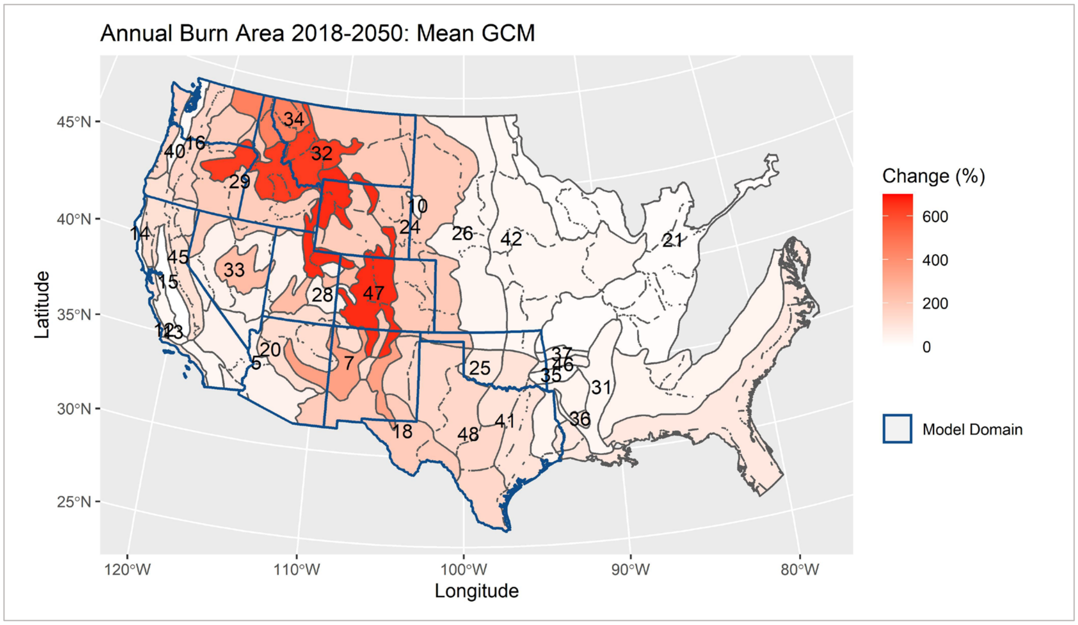
The above method for ecoprovince 45 is applied to all but two ecoprovinces in the model domain using the VPD values from the low, mean and high GCMs. The exceptions were ecoprovince 14 and 15 (which is the California Central Valley, now dominated by agriculture rather than native vegetation) in western and central California. For those ecoprovinces, burned area-increase targets are set to zero (no change) for 2050 for all three GCMs. Historically, the relationship between burned area and VPD in these two ecoprovinces was nonexistent (statistically insignificant) to slightly negative and AIR's opinion is that without a better understanding of why the relationship might be negative it was judicious to assume no change in burned area with climate change, even though the summer VPD is projected to increase in both ecoprovinces.

The mean-GCM results for 2050 are presented in Figure 16. The burned area target ranges are an order-of-magnitude larger than the VPD ranges presented in the 2.2 Climate Model Analysis section (see Figure 12) due to the sensitive response of some ecoprovinces to VPD changes. In 2050, burned area targets range from 0 to 635% and 661% in ecoprovince 32 and 47 respectively. Ecoprovince 34 has a target of 447% and ecoprovince 7 has a target of 339%. The targets of 13 ecoprovinces exceed 100%, and the median of all ecoprovinces is 80%.

Ecoprovinces with the highest targets tend to be northern and inland. Ecoprovince 32 spans eastern Idaho and western Montana and belongs to the Temperate Steppe division with ecoprovince 47. As described in 2.2 Climate Model Analysis, ecoprovince 32 is projected to see a significant VPD increase of 19% in 2050. Annual burned area increases exponentially with summer VPD in ecoprovince 32, which consequently leads to an average annual burned area target of 635% in 2050. During the historic period 1992–2015, the maximum summer VPD experienced in ecoprovince 32 was 1.51 kPa, which occurred in both 2003 and 2007 (which were associated with burned areas of 0.8% and 3.2%, respectively). That value was smaller than the 2050 mean GCM value (target) of 1.56 kPa, meaning that the 2050 target VPD was outside the range of VPD seen in history and that extrapolation beyond historical experience was required. A similar situation arose for ecoprovince 47.

Copyright © 2021 Society of Actuaries Research Institute

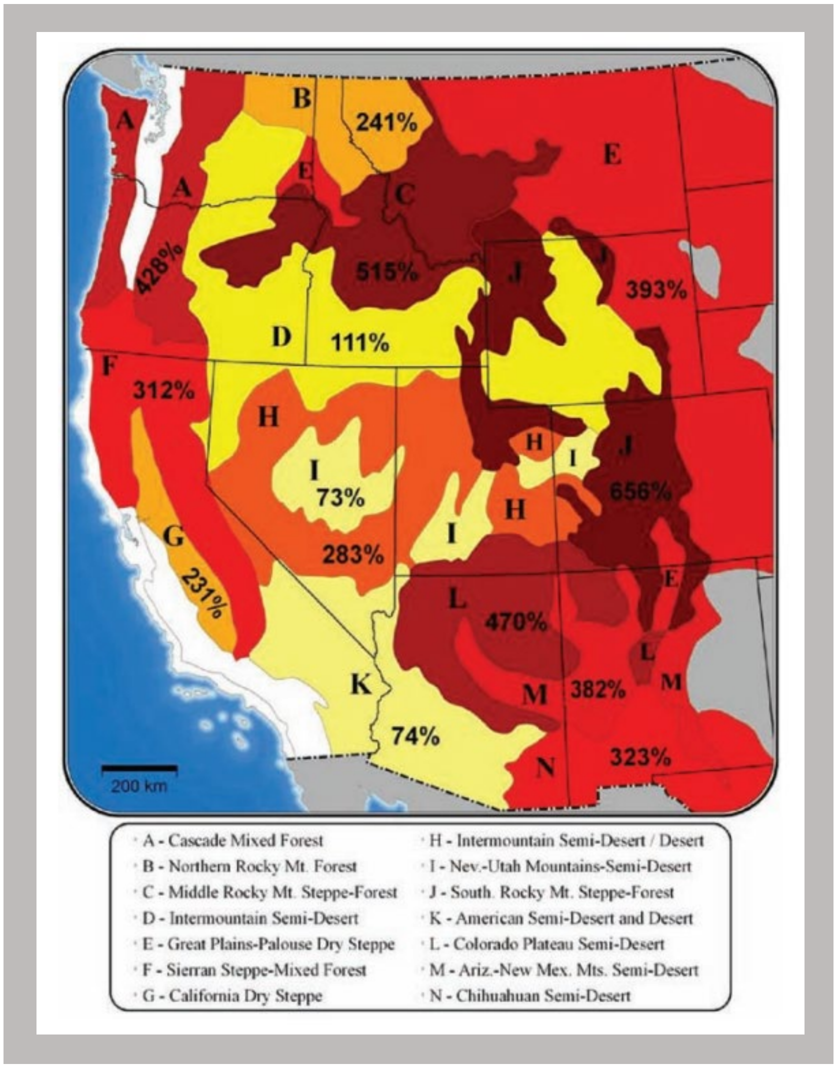
Figure 16
PROJECTED CHANGE IN AVERAGE ANNUAL BURNED AREA BY 2050 RELATIVE TO 2018 BASED ON THE MEAN GCM. ECOPROVINCES ARE LABELLED AND THE STATES OF THE MODEL DOMAIN ARE OUTLINED.



The percent changes in burn area we have computed may seem extreme, but we note that not only can they be justified in terms of the available data and the methods we have used, but that more importantly, the general magnitudes of the changes agree with those found in a previous study (National Research Council, 2011). In that study, a graphic was shown for expected changes in burn area for a one-degree Celsius increase in global atmospheric temperature. For that study, a base period of late 1900s was used but that is not as relevant as the fact that under RCP 8.5, global atmospheric temperatures are expected to increase by about another one-degree Celsius by 2050. The agreement between that study and our results is in fact remarkable, given the earlier date for the study, less fire data was available, and that different methods were used to obtain the result. The graphic is reproduced as Figure 17 here as for convenience. While some features may not agree with our result (e.g., the relative maximum in ecoprovince 33 in our result does not agree with the relative minimum in that area from the NRC 2011 study), the entire intermountain region is an area of expected high increase in both studies and the extreme increase of 656% across the mountain range of Colorado agrees remarkably to our estimated increase of 661% for that same area (ecoprovince 47). A summary of the Climate Change Targets for all ecoprovinces from our analysis can be found in Table B.1 of Appendix B.

Copyright © 2021 Society of Actuaries Research Institute

Figure 17
PERCENT INCREASE (RELATIVE TO 1950-2003) IN MEDIAN ANNUAL AREA BURNED FOR ECOPROVINCES OF THE WEST WITH A 1°C INCREASE IN GLOBAL AVERAGE TEMPERATURE. CHANGES IN TEMPERATURE AND PRECIPITATION WERE AGGREGATED TO THE ECOPROVINCE LEVEL USING THE SUITE OF MODELS IN THE CMIP3 ARCHIVE. CLIMATE-FIRE MODELS WERE DERIVED FROM NATIONAL CLIMATIC DATA CENTER (NCDC) CLIMATE DIVISION RECORDS AND OBSERVED AREA BURNED DATA FOLLOWING METHODS DISCUSSED IN LITTELL ET AL. (2009).



Source: National Research Council 2011, reprinted with permission.

Section 3: Subsampling Methodology

3.1 BASIC STRATEGY

The AIR U.S. Wildfire 100,000-year catalog contains a pool of years of events from which to create new catalogs that have the average annual burned areas projected for 2050. This task is performed using a sampling algorithm developed by AIR.

Copyright © 2021 Society of Actuaries Research Institute

The algorithm works by swapping events between the current 50,000-year catalog and the 100,000-year pool until all the ecoprovince-specific targets are achieved. Some events can occur in multiple ecoprovinces, as many as three, which suggests the need to sample on multiple ecoprovinces simultaneously. However, most events only affect one ecoprovince, so to simplify the algorithm, events that occur in more than one ecoprovince are tagged with the ecoprovince that most of their burned area occurs in. If an equal proportion of area occurs in more than one ecoprovince, the assigned ecoprovince is randomly selected. The result is a list of events each tagged with a single ecoprovince. This allows the algorithm to work sequentially through each ecoprovince to achieve the targets.

Individual events are not swapped but instead whole years-worth of events are swapped to achieve each annual-based target. The same years-worth of events can be sampled multiple times, which is needed to reach the larger targets. To retain the information in the 100,000-year catalog that relates historical seed years to stochastic years, sampling is constrained so that years can only be replaced by years that share the same historical seed year. This historical-to-stochastic mapping also allows us to assign each years-worth of events in each ecoprovince to the original stochastic year they replaced. The final selected catalog is then a table of stochastic year and event IDs where the years range from to 1 to 50,000 and the event IDs belong to any events in the 100,000-year catalog. The event IDs in the final catalog are not unique.

3.2 PROCEDURE

The following contains a brief description of the steps taken by the sampling algorithm. The procedure is analogous to dealing a hand from a deck of cards. The initial hand that is dealt is the current 50,000-year catalog. The deck in this case is the 100,000-year catalog but unlike in normal card games, the same “card” in the deck can be sampled many times, technically known as sampling with replacement.

1. Starting with the initial hand, move to ecoprovince 5. If the target average annual burned area is different to the average annual burned area in the current catalog, then sampling must occur.
2. Select a year at random from the hand and attempt to swap it with a random year from the deck that has the same historical seed year as the year selected from the hand. If the swap gets the ecoprovince closer to the target burned area, the swap is made, otherwise another year is picked from the hand.
3. Step 2 is repeated until the ecoprovince’s target is achieved within a tolerance of 0.1%. The algorithm then moves on to the next ecoprovince, e.g., ecoprovince 12.
4. Steps 2 and 3 are repeated until all ecoprovince targets are achieved.

The final hand, the 50,000-year climate change conditioned catalog, tells us which years of events occur in each ecoprovince. These events are brought into the catalog and are assigned the original stochastic year of the events they replaced because both sets of events share the same historical seed year.

A maximum limit is set on the number of times that a year can be sampled from the 100,000-year catalog in a given ecoprovince. If this limit is too low, the larger targets will not be reached, but if it is too high, there will be not be enough variability in the catalog for that ecoprovince. A limit of 600 is used because this allowed the algorithm to comfortably achieve the mean-GCM 2050 target in ecoprovince 47 but still retain enough variability. Ecoprovinces 34 and 32 require about 50–100 samples of the same year to reach the mean-GCM 2050 target. The rest of the ecoprovinces require 30 or less. No explicit provision is made for the possibility for the exact same area to be burned twice in the same or consecutive years. However, the likelihood is very small given that the total amount of burnable area is typically three orders of magnitude larger than what is projected to burn, even for ecoprovinces that are projected to have significant increases in annual burned area.

Copyright © 2021 Society of Actuaries Research Institute

3.3 CLIMATE CHANGE CONDITIONED CATALOGS

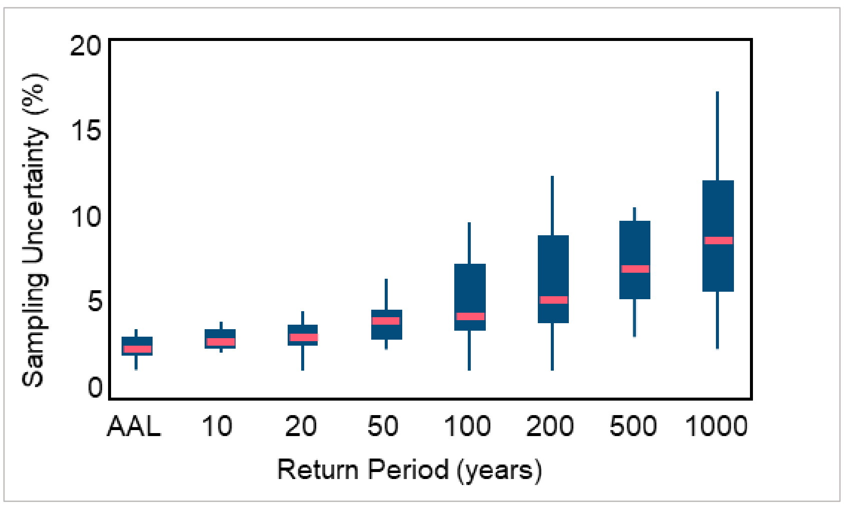
The stochastic nature of sampling means that multiple climate change conditioned catalogs can achieve the same set of burned area targets. The sampling procedure therefore adds some uncertainty to the projected losses. This sampling uncertainty is quantified for key loss metrics from an ensemble of catalogs for each scenario. We define sampling uncertainty as the ratio of the 95% confidence interval to the median loss of each ensemble.

An ensemble of 20 catalogs was created for the 2050 climate scenario and the loss impacts were calculated using the AIR U.S. Exposure Database. An example of the sampling uncertainty calculated in the 13 states for aggregate loss metrics is shown in Figure 18. Loss metrics at higher return periods tend to have higher sampling uncertainty and a larger range of state-level uncertainty. This shows that the higher frequency metrics are more robust across the catalog ensemble whereas the low frequency metrics are more sensitive to the addition or removal of severe events in high exposure.

Loss metrics at higher resolution tend to have higher sampling uncertainty too. At the portfolio-level, the uncertainty is smallest and varies from 0.5–1% up to the 50-year return period, 3-5% up to the 500-year, and up to 10% at the 1000-year. At the state-level, the uncertainty varies typically from 2-15% across these return periods and at the county-level, it varies typically from 5-30% but can be much higher in certain counties. These findings do not vary much between GCMs or time-horizons (as demonstrated in Figure 18.

Figure 18

LOSS SAMPLING UNCERTAINTY (%) FOR 13 STATES AT KEY AGGREGATE LOSS METRICS CALCULATED FROM A 20-MEMBER ENSEMBLE OF CATALOGS FOR THE 2050-8.5 MEAN-GCM SCENARIO. HORIZONTAL LINES INSIDE BOXES REPRESENT MEDIAN VALUES, BOXES REPRESENT 25-75% CONFIDENCE INTERVALS, AND WHISKERS INDICATE 5-95% CONFIDENCE INTERVALS. SAMPLING UNCERTAINTY IS THE RATIO OF 95% CONFIDENCE INTERVAL TO MEDIAN VALUE. LOSSES ARE CALCULATED FROM AIR'S INDUSTRY EXPOSURE.



Sampling uncertainty is now compared to the uncertainty from the GCMs. GCM uncertainty is defined as the range of losses from the low and high GCMs relative to the loss from the mean GCM. For all three losses (low, mean and high), the median loss from the 20-member ensemble is used.

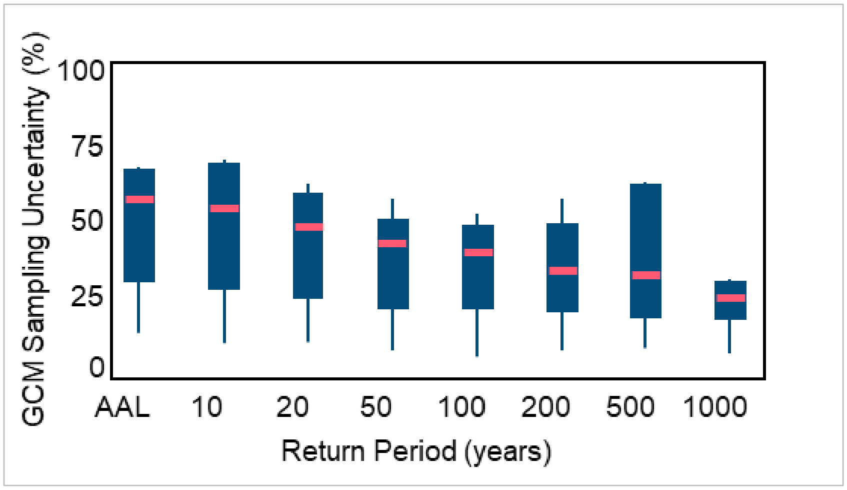
Figure 19 shows the GCM uncertainty for 13 states at key aggregate loss metrics for the 2050-8.5 scenario. GCM uncertainty varies by return period and the exact value varies considerably between states. In contrast to sampling uncertainty, GCM uncertainty is highest at the lower return periods and decreases with higher return periods. Across most return periods GCM uncertainty is an order-of-magnitude higher than sampling uncertainty, but the

Copyright © 2021 Society of Actuaries Research Institute

two uncertainties converge to having similar magnitudes at higher return periods. This suggests that lower return periods are more sensitive to different GCM projections than high return periods. This could be because high return period losses are constrained by the limited number of high exposure areas near to wildfire fuel, but it could also be due to the limited number of high burned area years to sample from. As with sampling uncertainty, GCM uncertainty is higher for loss metrics at higher resolution, e.g., county-level.

Figure 19

GLOBAL CLIMATE MODEL (GCM) UNCERTAINTY (%) FOR 13 STATES AT KEY AGGREGATE LOSS METRICS CALCULATED USING THE MEDIAN LOSSES FOR THE 2030-8.5 (RED) AND 2050-8.5 (BLUE) SCENARIOS. GCM UNCERTAINTY IS THE RANGE OF LOSSES FROM THE LOW AND HIGH GCMS RELATIVE TO THE LOSS FROM THE MEAN GCM. LOSSES ARE CALCULATED FROM AIR'S INDUSTRY EXPOSURE.



Because sampling uncertainty is small compared to GCM uncertainty (for most return periods), we can select one catalog for each scenario which is representative of the ensemble. The selected catalogs are those whose county-level AALs deviate least from the median county-level AALs calculated from the 20-member ensemble. The selection is based on AIR's Industry Exposure.

Section 4: Results

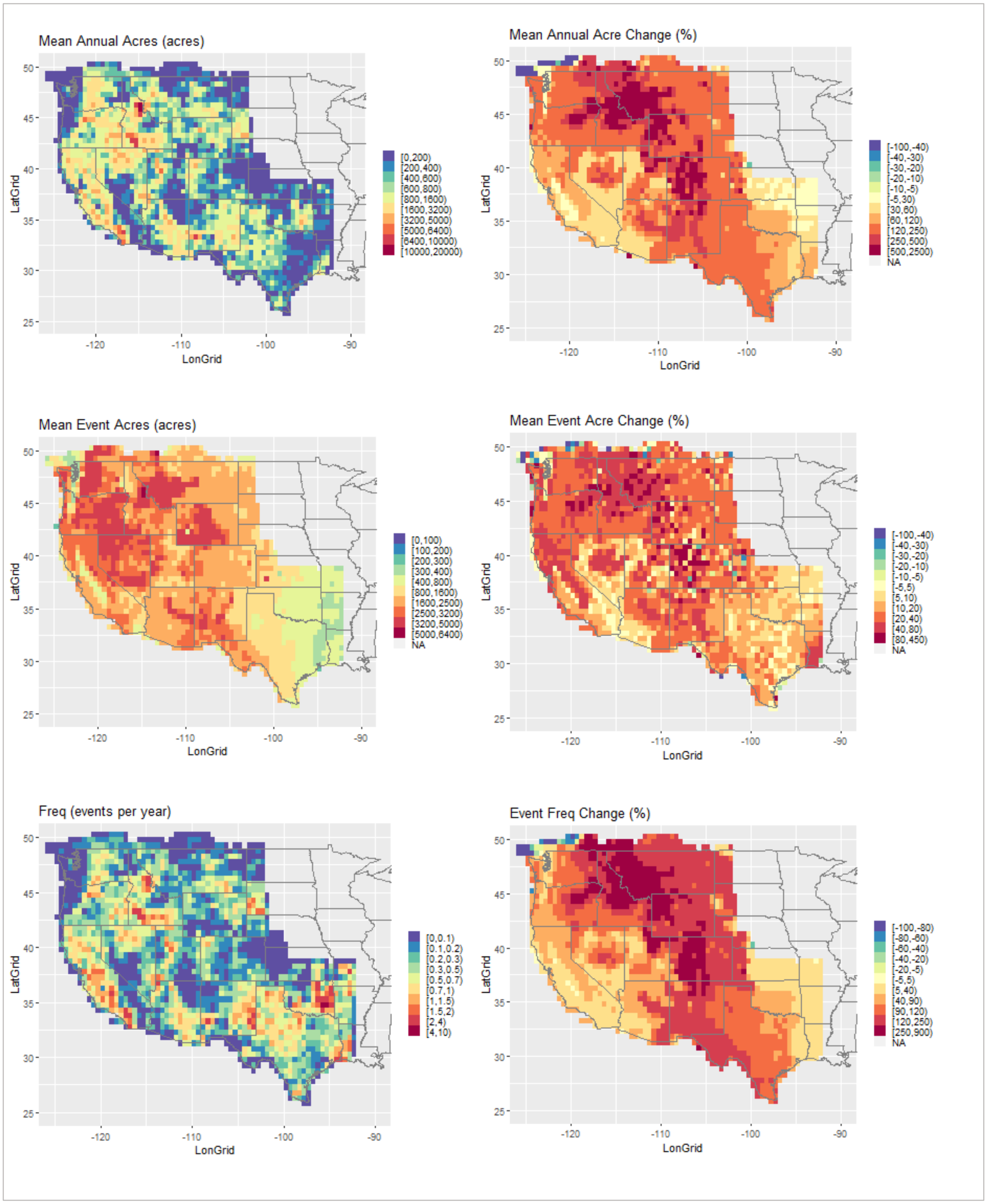
4.1 CLIMATE CHANGE IMPACTS ON HAZARD

Figure 20 illustrates the changes in burn area and frequency that resulted from the mean catalogs generated for the 2050 scenario as compared to that in the base 100,000-year catalog. The upper left panel represents the mean current climate burn area per year by 0.5° × 0.5° grid cell, the upper right panel indicates the mean annual change in the burn area. The middle row is somewhat similar, but the left panel indicates mean burn area per event and the right panel is the mean change in event burn area. The lower row shows current climate event frequency (fires/year) on the left and changes in event frequency on the right.

Average annual burned area shows moderate to high values (e.g., yellow-red shading) across the eastern two-thirds of Washington and Oregon, much of Idaho, much of California, northern Nevada, and much of Arizona. Other smaller areas exist in many other states. The annual area burned is a reflection of the product of mean event burn area and mean event frequency. The above-mentioned areas for the most part show both moderate to large event

Figure 20

LEFT COLUMN SHOWS CURRENT CLIMATE AVERAGE ANNUAL BURN AREA (UPPER PANEL IN ACRES/YEAR), AVERAGE EVENT BURN AREA (MIDDLE PANEL IN ACRES/EVENT), AND ANNUAL FREQUENCY (LOWER PANEL IN EVENTS/YEAR). RIGHT COLUMN SHOWS CORRESPONDING CHANGES FOR 2050 CLIMATE CHANGE SCENARIO.



Copyright © 2021 Society of Actuaries Research Institute

size and moderate to high event frequency. Some additional areas not mentioned above experience very large infrequent fires such as much of Wyoming and western Montana. The opposite situation also appears: eastern Oklahoma experiences a high frequency of relatively small fires. The area and frequency patterns for the Current Climate are consistent with the ecoprovince characteristics. For example, mean burned area per event shows highest values in the eastern Oregon-western Montana-western Wyoming area, corresponding to ecoprovinces 28 (Intermountain Semi-Desert and Desert Province), 29 (Intermountain Semi-Desert), and 32 (Middle Rocky Mountain Steppe-Coniferous Forest-Alpine Meadow Province). Ecoprovinces 29 and 32 account for the large event burn areas in Oregon, Montana, and Wyoming while ecoprovince 28 contributes to the ring-like region of high event burn area in Nevada. It is noteworthy that the ecoprovince type does not always explain (correlate) to event burn area or frequency. For example, in between the high burn areas of Oregon and Montana there is a low burn area across southern Idaho that is also labeled as 29 and 32. A possible reason for this may be the lower elevation because of its location in-between the Bitterroot Mountains (e.g., part of the Rockies) to the east and the Columbia Plateau to the west. Also, because the climate change targets did not include sub-ecoprovince specificity that the increases in burn area for a given ecoprovince are not necessarily uniformly distributed within the ecoprovince.

The right-hand column in Figure 20 indicates that annual burn area changes are accomplished by changes in both mean event area and mean frequency. The result makes sense from the standpoint of the methodology because in order to increase the annual burn area as specified by the climate change target, similar years with more annual burn area had to replace years that were initially part of the current climate catalog. Because there was no restriction on how that should occur, a mix of year types was drawn so that the distribution of individual fire size did not change. The strong relationships between VPD (as well as other metrics of aridity in fact) are between extent of dryness and area burned. Additionally, because the real focus is on the loss that may occur, it is somewhat immaterial whether that happens because ten fires each with a size of 1000 acres burn, or whether twenty fires each with a size of 500 acres burn.

Finally, the difference in the changes of burn area and frequency from 2030 to 2050 reflect a continued northward expansion of increasing fire risk. The northward expansion is consistent with the expected continued northward migration of the jet stream and storm tracks that would otherwise supply more abundant precipitation further south (Tamarin-Brodsky and Kaspi, 2017).

4.2 CLIMATE CHANGE IMPACTS ON LOSS

Losses for the AIR industry exposure database were run at the country, state, and county level for the base case and the future climate scenario. Losses were analyzed by sub-region. A discussion of the analyses and different crosscuts is provided here.

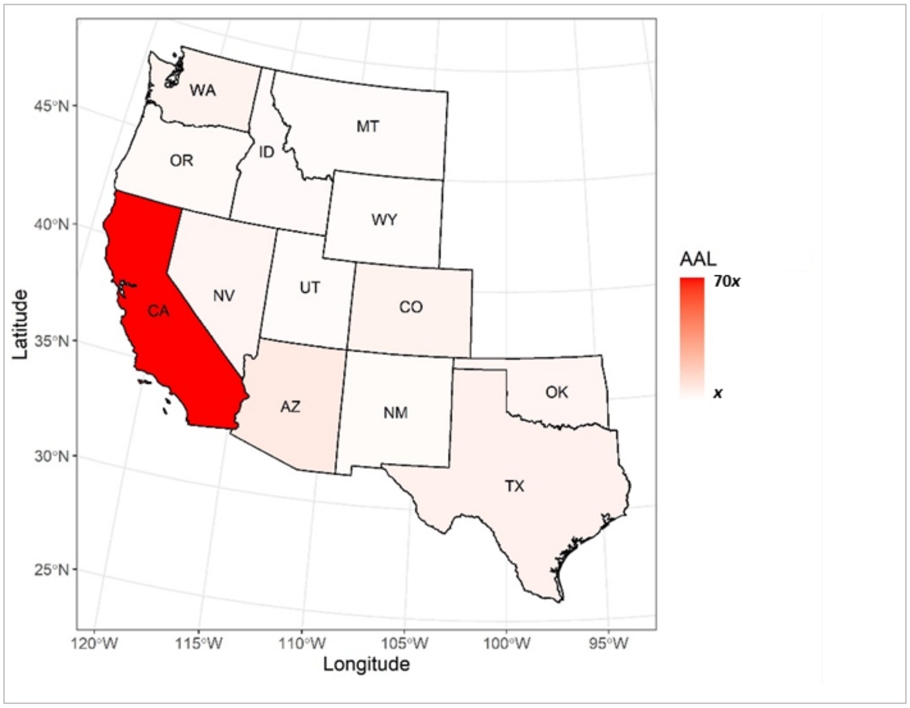
4.1.1 CURRENT CLIMATE LOSSES

Figure 21 shows the Average Annual Loss (AAL) for Ground Up (GU) Aggregate Losses for each state in the AIR Model for the current climate. California by far has the highest AAL – more than four times the sum of the next three highest contributing states, which are Arizona, Texas, and Colorado in decreasing order. Altogether, the top four states contribute about 81% to the AAL. The same is true for the individual state return periods. The ground up aggregate return period losses for AZ, CA, CO, and TX are shown in Figure 22. The differences in the values and the shapes of the RP curves are related to the amount of available fuel, which is a result of the native plant species that characterize those regions, which itself is constrained by the climate and soil (climate is a function of many things as well). For example, Texas can certainly be wetter than Colorado and Arizona because of its proximity to the Gulf of Mexico and its exposure to hurricanes. Even though California contributes to industry loss more than any other individual state, we note that it is a very small subset of counties – Los Angeles, Riverside, San Bernadino, and San Diego—that account for that loss, as shown in Figure 23.

Copyright © 2021 Society of Actuaries Research Institute

Figure 21

AVERAGE ANNUAL GROUND UP LOSS RELATIVITIES BY STATE USING AIR INDUSTRY EXPOSURE FOR CURRENT CLIMATE. DARKEST (IN CA) TO LIGHTEST (IN WY) SHADES OF RED SPAN A FACTOR OF ~70 IN LOSS.



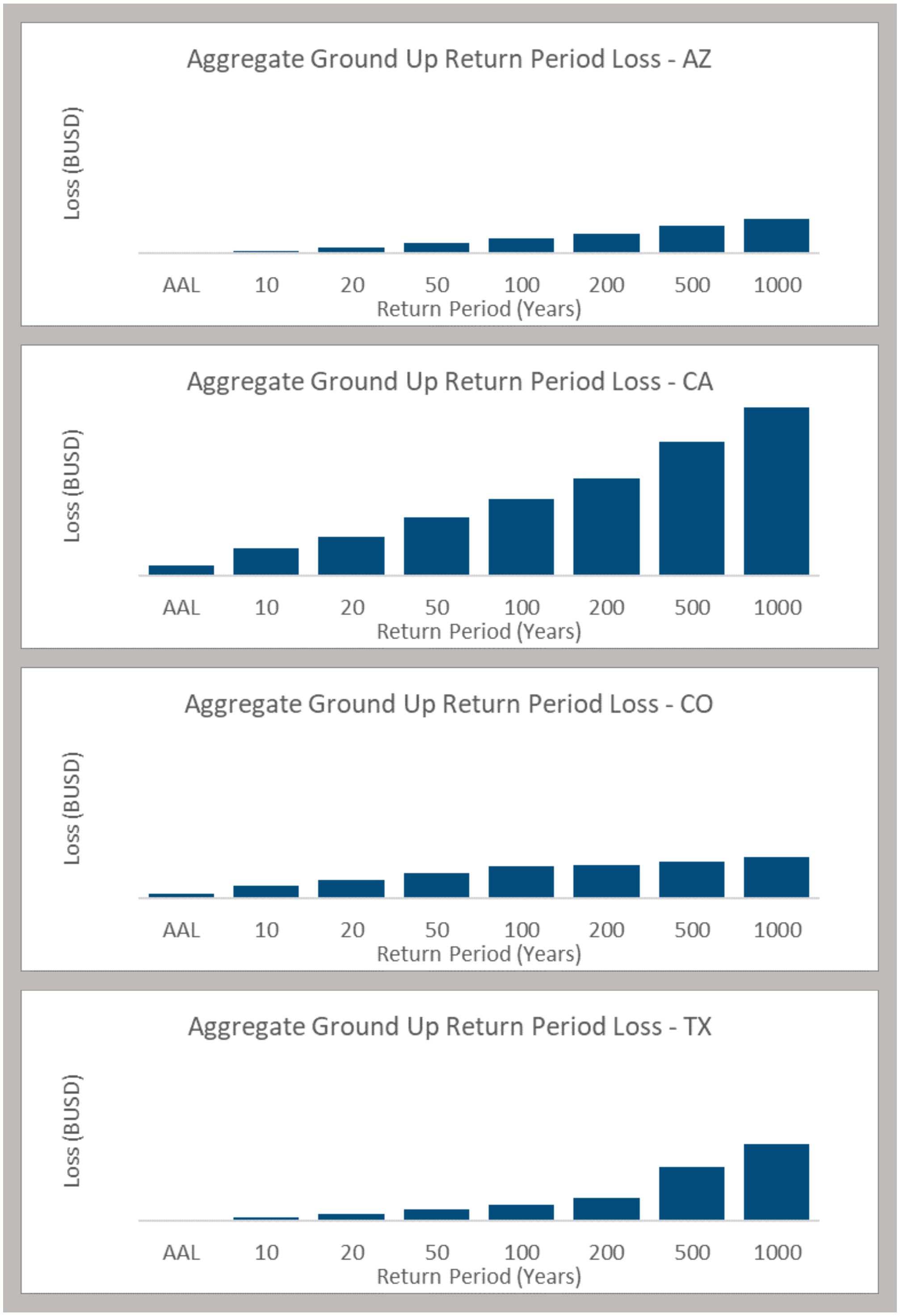
The losses from these counties reflect a combination of high density, high value of exposure, climatic factors that can periodically grow and dry the necessary fuel, and influence from Santa Ana Winds that can dramatically and quickly spread a fire to the coast.

A large majority of the number of fires and area burned in Arizona occurs in the mostly coniferous high-elevation forests stretched across the state (the average elevation in the state is 4,249 ft). There is little insured exposure threatened by those fires. Although a large majority of the number of Arizona wildfires are caused by humans, area burned in lightning-caused (generally dry lightning) fires can rival that of human-caused fires, with the main fire season spanning May to September. Maricopa County, home to most of the Phoenix metropolitan area in southcentral Arizona, accounts for a significant fraction of the state's exposure. Pima county, which borders on Mexico and Maricopa county and which contains most of the Tucson metropolitan area and the southernmost ski destination in the continental United States, is next in terms of exposure. When combined with Pinal county, which borders with Pima and Maricopa counties, the three account for more than 65% of the loss in the AIR Industry Exposure Database for Arizona.

In Texas the greatest contribution comes from Travis County in which Austin (state capital) is located. The fire risk itself is low to moderate and somewhat the opposite situation to El Paso County in Colorado. The contributing counties are at the southeastern edge of a large area covering roughly the northwest quadrant of Texas that experiences a moderately high frequency of wildfires although the mean fire size is low because of fuel type and availability. Basically, there is a lot of grassland with some trees. The fuel grows quickly, and it burns off quickly.

Copyright © 2021 Society of Actuaries Research Institute

Figure 22
GROUND UP AGGREGATE RETURN PERIOD LOSSES BY STATE FOR TOP FOUR LOSS CAUSING STATES USING AIR INDUSTRY EXPOSURE FOR CURRENT CLIMATE. VERTICAL AXIS RANGE OF VALUES IS SAME FOR ALL FOUR PANELS.

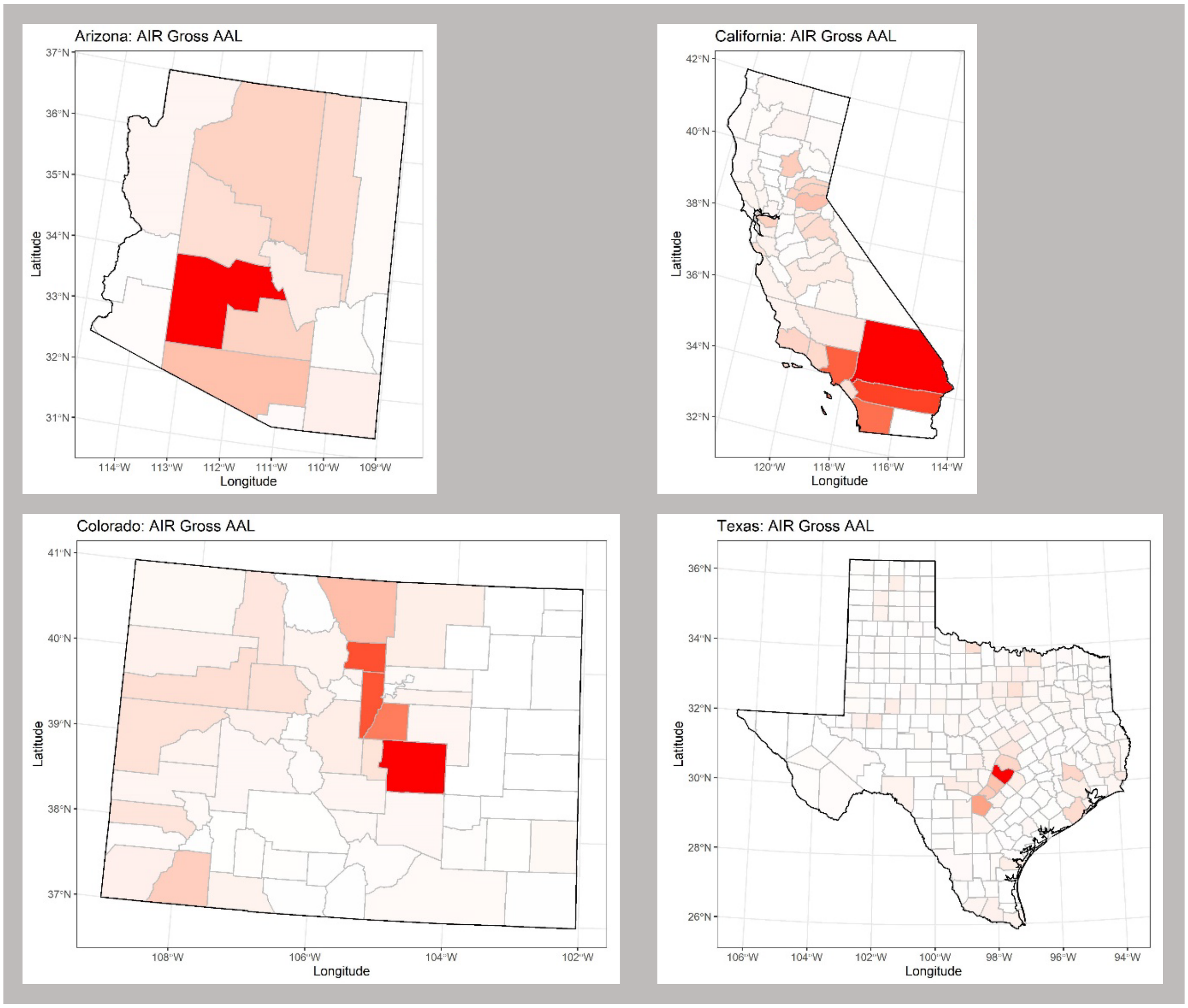


The most significantly contributing county for Colorado is El Paso, where Colorado Springs is located. The county is not the most populated and does not have the most exposure or fuel, but it is where the U.S. Air Force Academy is

Copyright © 2021 Society of Actuaries Research Institute

located (just to the north of Colorado Springs). In terms of fire risk, fires are relatively infrequent (every two to three years) although the median fire size tends to be large – on the order of 1600–2500 acres.

Figure 23
AVERAGE ANNUAL LOSS BY COUNTY FROM THE AIR MODEL FOR THE CURRENT CLIMATE FOR THE TOP FOUR LOSS CONTRIBUTING STATES.



The concept of only a few counties contributing in any significant way to the state-wide loss holds true for most states with a few exceptions. New Mexico shows a slightly more widespread perspective with about half the counties contributing. Obviously, the pattern is related to the locations or urban locations as well as climate and ecological factors.

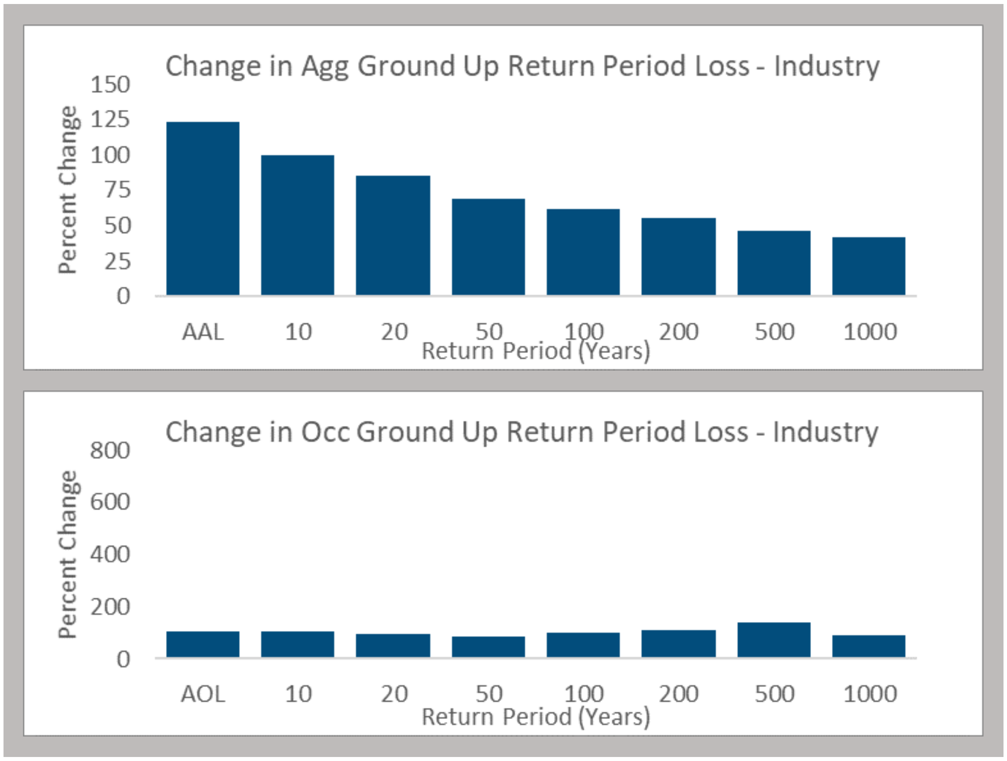
4.1.2 FUTURE CLIMATE LOSSES

In this portion of the report, we present changes to industry losses at the portfolio, state and county levels for the 2050 climate change scenario. Changes in the average annual loss as well as selected return periods are included. Figure 24shows the RP loss changes in percent for the entire AIR Model domain for the AIR industry exposure for occurrence and aggregate losses.

Copyright © 2021 Society of Actuaries Research Institute

Figure 24

CHANGES IN AVERAGE ANNUAL LOSS OVER THE AIR U.S. WILDFIRE DOMAIN USING AIR INDUSTRY EXPOSURE FROM 2018 TO 2050 FOR AGGREGATE (UPPER) AND OCCURRENCE (LOWER) LOSSES.



At the portfolio level, changes in the average occurrence loss almost double from the current value by 2050. Changes to the RP occurrence losses are also significant although less percentagewise compared to that of the Average Occurrence Loss (AOL). The greater impact to AOL is to be expected as the AOL event may be the result of a multi-state wildfire whereas the RP occurrence wildfires may be from single-state events. The lower impact at this high RP is likely an influence of the sub-sampling technique. Because of the rather large increases in loss there may not be an adequate supply of sufficiently large fires to adequately represent this high RP impact. Thus, it is quite possible that even the change at the AOL may be slightly under-represented.

For aggregate losses, the impacts are larger than those for occurrence losses although the behavior across the RPs is identical. While the domain level results may seem large, they are simply an industry-exposure-weighted reflection of the climate change targets in burn area.

Figure 25 shows that at a state level, changes in AAL that reflect the burned area targets by ecoprovince can be seen more clearly. Specifically, largest percent changes are located across the intermountain region: NM, CO, WY, MT, and ID. By 2050, the top four states still contribute to nearly 80% of the total, although the relative risk has changed. Loss increases in California are relatively modest at 50% but for some states like Colorado the average annual loss triples. For most states the losses double.

Copyright © 2021 Society of Actuaries Research Institute

Figure 25

CHANGES IN AVERAGE ANNUAL LOSS BY STATE USING AIR INDUSTRY EXPOSURE FROM 2018 TO 2050.

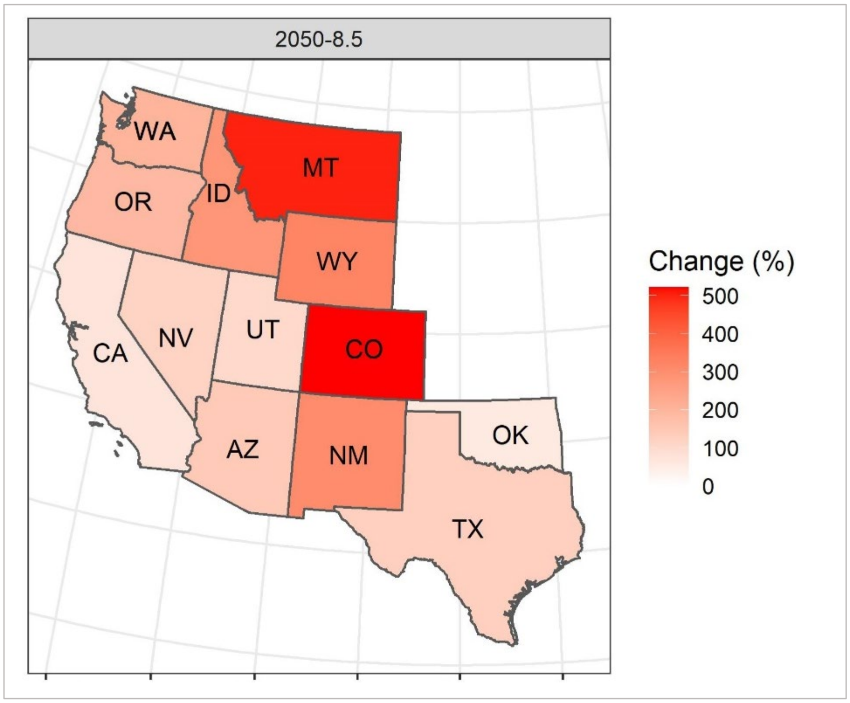
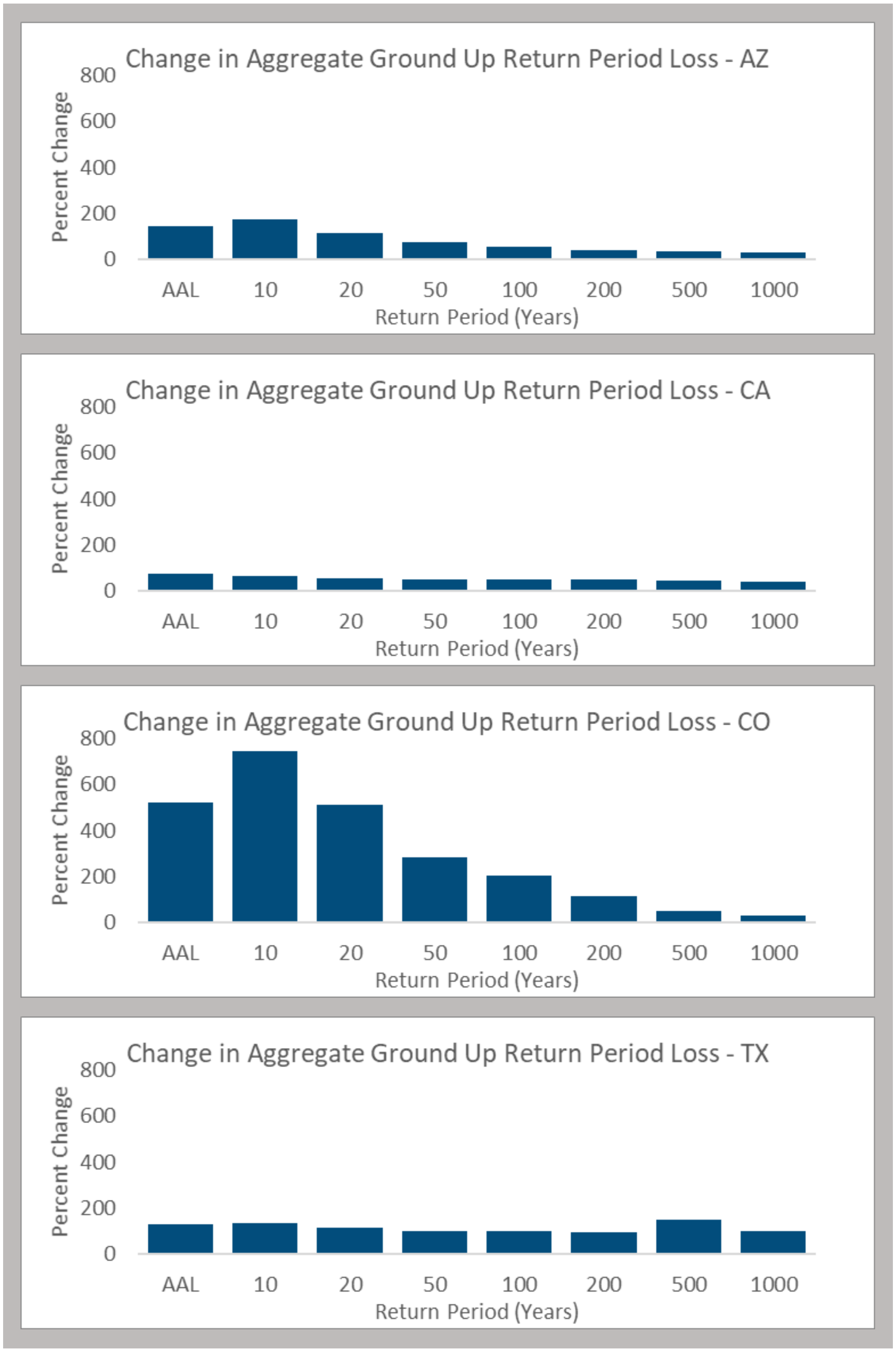


Figure 26 shows the percent changes in the AAL and selected return periods for aggregate losses (the shapes of the occurrence loss change curves are similar and not included). Percent changes for California are less than those for the other three states, across the return periods. Some other noteworthy features include the fact that changes in low RP losses exceed those of the AAL in all three states besides California. This result is likely related to the climate variability impact on wildfire risk – specifically how the periods of wet and dry years align to create a year with relatively high wildfire risk. The fact that California as a state likely receives rainfall more regularly than the other three states because of its proximity to the Pacific Ocean and because of the Sierra Nevada Mountains that not only enhance precipitation, but which also cause winter precipitation to fall as snow, may be the reason this effect is suppressed. In fact, the effect is most evident in Arizona and in Colorado, which on the whole receive less precipitation annually than California or Texas, which is adjacent to the Gulf of Mexico. The last and perhaps the most noteworthy feature occurs in Colorado and other states intercepted by ecoprovince 47. We note the extremely high percent increase in the AAL for Colorado, especially by 2050. The magnitude of this increase can be traced back to the climate change target for ecoprovince 47, which used the FOD, historical reanalysis data, and forward-looking GCM output for VPD to determine how changes in VPD would translate to changes in annual burn area. The climate change target for 2050 for ecoprovince 47 was 652% and was a combination of relatively large increases in VPD for that region, as well as an already sensitive relationship between VPD and burn area from the historical record.

Copyright © 2021 Society of Actuaries Research Institute

Figure 26

PERCENTAGE CHANGE FROM 2018 TO 2050 IN AGGREGATE GROUND UP RETURN PERIOD LOSSES FOR TOP FOUR LOSS CONTRIBUTING STATES (ALPHABETICAL ORDER).



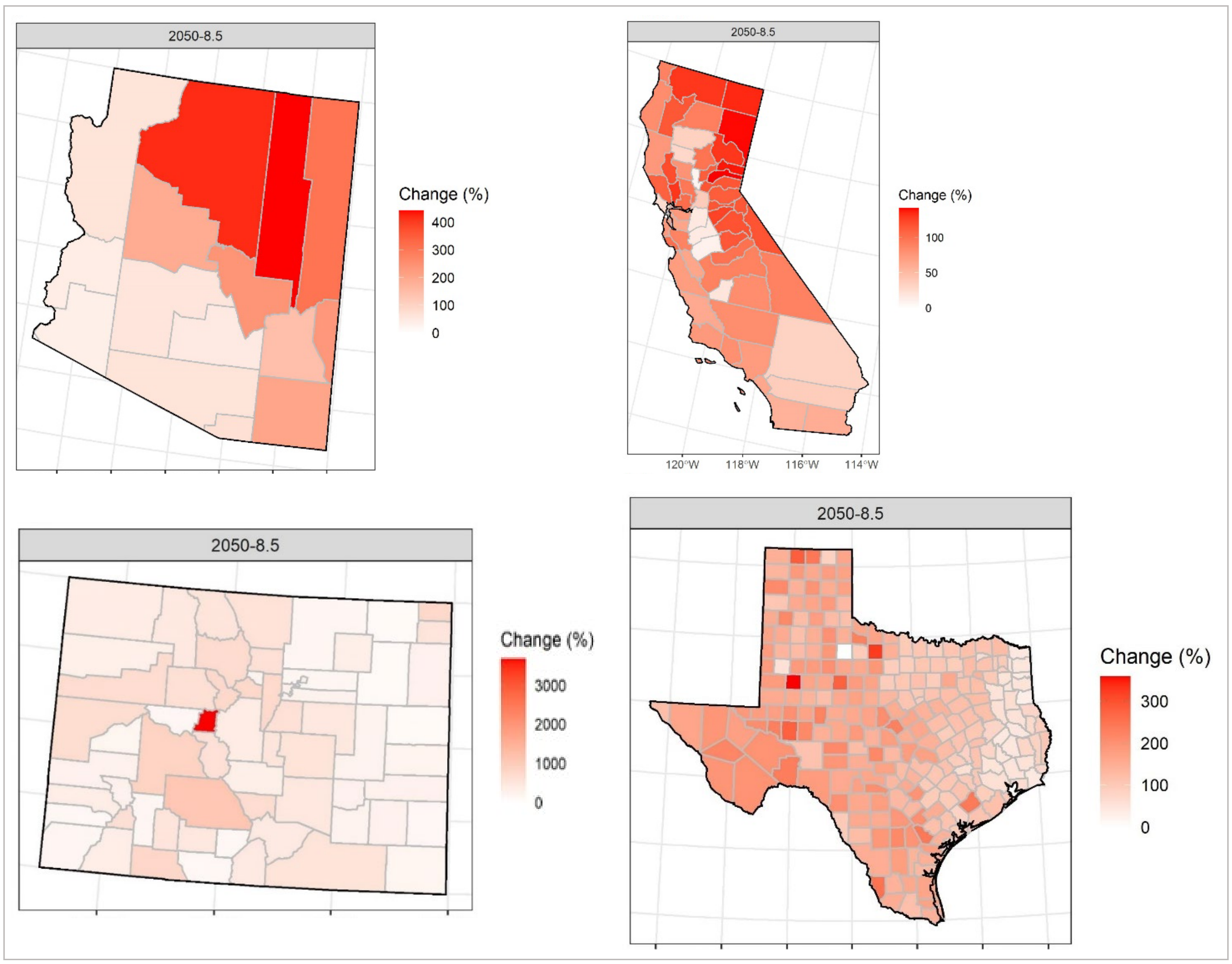
Copyright © 2021 Society of Actuaries Research Institute

At the county level, the changes in industry loss at 2050 are a reflection of the amount of exposure in each county, as well as the number of ecoprovinces within a state, as well as how different their climate change targets are. It is an important result that, despite the very large percent increases in burned area for some ecoprovinces, that they do not coincide with areas of very high exposure.

Figure 27 shows the percent change in AAL at the county level for the top four loss-causing states. The loss results can be explained with the help of Figure 26, which shows the hazard impacts and where we can see similar patterns. For example, in southern California, the biggest contributions to loss by area come from ecoprovinces 5 and 13 although ecoprovince 12 contributes significantly to loss because of its location. The climate change targets for these ecoprovinces are only slightly less than those for ecoprovince 45, which exhibits some of the largest percent changes in loss – especially for 2050. Thus, the top contributing counties in the current climate remain the top contributing ones in 2050 but by lesser margins.

Figure 27

PERCENT CHANGE IN AAL BY COUNTY FROM 2018 TO 2050.



For Arizona, loss increases are highest in the northern tier of counties. The central and northern parts of the state are characterized by ecoprovinces 7 and 20 which have burned area targets of 339% and 124% respectively. The impact of these targets is reflected in wildfire frequency and burned area for those regions and results in the highest losses occurring in central and northern Arizona. The shapes and county level granularity limit more precise identification of where largest changes in loss are projected to occur.

In Colorado, a similar inspection-based analysis shows that the western part of the state is expected to have the biggest increases in wildfire activity which is related to the fact that much of that portion of the state is characterized by ecoprovince 47 with a burned area target of 661. The county-level distribution of losses does reflect that with slightly higher (i.e., darker shades) loss changes in the west than in the east. Note that because the legend (e.g., range of colors) is capturing the dramatic increases in one small county in Colorado (Lake County) in Figure 27 that the changes in loss in the other counties do not appear to be as large or as different from some of the others in the state. Largest changes in loss in the western part of the state do show hundreds of percent increase in loss.

Finally, for the three ecoprovinces that cover Texas, we see that south-west Texas experiences the most change, followed by central Texas, with Eastern Texas experiencing the least change. This hazard change pattern is reflected in the loss change pattern with higher percentage changes in the southwest part of Texas and lower ones in the northeast.

The results presented in this section represent the mean view from our evaluation of the climate change results in the GCMs. Recall a range of GCMs was considered but output from only two were actually used for this study. The two represent the smallest (low) and the largest (high) increases in VPD for the entire United States by 2050. Our mean view was thus an average of these two projections. An extension of the methodology used here could be applied to create additional targets, to create additional sub-sampled catalogs, and to evaluate changes in loss based on those targets, and to at least at some level, quantify the uncertainty of how climate change will impact wildfire risk.

Section 5: Considerations for Actuaries

Wildfires have the potential to cause immediate and longer-term elevated risk profiles across many sectors of the economy and health of our society. In the short term, their impact may be more acute and localized. Given the findings in this paper, the potential for these risks to grow and the resulting downstream affects should be considered by actuaries across nearly all business practices: Life, Health, Property, and Casualty. This risk is especially problematic for long duration liabilities or assets. This paper is intended to provide more color to our fundamental understanding of the physical forces at play, which undoubtedly will have impacts on our general society, and more specifically, the actuarial community.

Climate impacts and changes will not have a uniform impact across markets, but likely have amplified or depressed impacts in specific locales. These impacts may have compounding negative impacts on both the assets and liabilities projections. These risks are likely to affect the general building blocks approach to assumption setting but may also have special correlations which may need to be address. It may be helpful to think of the risk in three dimensions – general impact to risks, specific / localized impact, and trend changes between now and 2050. For some actuarial practices, it may be hard to implement spatial correlations, while others may be challenged by the temporal risk assessment.

Copyright © 2021 Society of Actuaries Research Institute

For the actuary, the impact will vary by product and risk. A select set of the areas we think actuaries should take a hard look at their ultimate assumptions would include:

1. Property insurance – Direct loss to buildings and time element
    a. Risk assessment and adjustments may be able to handle this risk due to the short contract length, though the risk is likely to be similar to extreme weather in which loss is hit or miss with high spatial correlation
2. Morbidity and Mortality – Acute impacts from the direct loss of life / injury with long term impacts on respiratory illness and cancer because of excess particulates in the air
    a. Current underwriting and risk measurement practices are not adept enough to account for this risk
3. Investment – Acute and macro impacts given overall impact from fires.

As we think about these risks, it is important to think about the risk at the enterprise level. Especially for companies which operate in several domains and have exposure on both asset and liability sections of the balance sheet. Developing integrated sensitivity projections or correlated stochastic systems would be warranted. It is likely, the combined risk profile is greater than the sum of the individual.

We encourage actuaries to use these projections and assessments to help them derive, validate, or question their ultimate assumptions across product lines and balance sheets.

Section 6: Closing Remarks

The study uses historical wildfire data (FOD) from the period 1992-2015 and environmental conditions to quantify ecoprovince-specific relationships between vapor pressure deficit (VPD) and area burned in a given year. For most ecoprovinces, the Generalized Linear Models (GLMs) show nonlinear relationships such that small changes in VPD yield very large changes (e.g., increases) in burn area. The GLM based relationships are used in conjunction with CMIP5 climate model output to understand how vapor pressure deficit will change in the different regions by 2050 because of climate change and how those changes will affect wildfire risk. Although climate change is expected to have a steady increase in the summer dryness for the region, considerable interannual variability will also be present. Thus, the VPD values used for 2050 were obtained from an 11-year time average centered on the time horizons in question. And the mean values were obtained from looking at high- and low- projections of VPD in the GCMs and then creating an average (mean) view. The GCM-based uncertainty discussed in the last section and the sub-sampling-based uncertainty discussed earlier are two kinds of uncertainty. But there are a couple of others worth mentioning as well as some other limitations of what this study shows.

One type of uncertainty is that in the GLMs developed for each ecoprovince. With a total of only 24 data points for each ecoprovince (one datum for each year in the 1992-2015 FOD period per ecoprovince) it is possible that one or two additional data points could change the VPD-burn area relationship. AIR believes the effect is relatively small – even for ecoprovinces in California with very active years in 2017, 2018, and 2020.[9] While record breaking burned areas have occurred recently, the VPD-burned area relationships are effectively robust. Additional confidence that the relationships are accurate can be instilled by the fact that 2050 burn area targets agree in key ecoprovinces between our results and those in NRC 2011.

[9] In fact, a partial re-analysis conducted as this report was being completed with FOD data that became available through 2018 (Short, 2021) showed little change even by ecoregion and over the entire domain the impact was essentially zero.

Copyright © 2021 Society of Actuaries Research Institute

Another type of uncertainty is associated with the RCP scenarios themselves. It is important to recognize that these scenarios are not forecasts per se and because of that, it is not appropriate to assign probabilities to them – at least not preferentially. From that standpoint they are all equally probable. Although the RCP 8.5 scenario is on the high end of the group of 4 RCP scenarios (RCP 2.6 reflects the smallest impact from climate change because of assumed changes in emissions) it is a scenario that society have been following over the last 15 years. Related to the uncertainty of the RCP scenario is the spread of climate change. For example, an RCP 8.5 is expected to yield a 2.0 ^{o}C temperature increase +/- 0.5 ^{o}C by 2055. However, the selection of high and low GCM projections mostly accounts for this aspect of uncertainty.

One other type of uncertainty worth noting is that associated with changes in conditions to enhance or prohibit the realization of wildfire. The underlying premise of the VPD-burn area relationships is that the climate conditions provide an environment (e.g., fuel supply) and that fires will ignite at the same frequency and from the same causes they do now (e.g., lightning, downed power lines, human carelessness). But that could certainly change. We do not address how lightning frequency, intensity, or geographic and altitudinal distribution may change in this study. It is hopeful that power lines can become more resilient to high winds, and ice and snow accretion. We also can only hope that humans will be more careful, but we cannot say for certain.

Also, while not sources of uncertainty, there are factors which were held constant, primarily in the interest of isolating the impact of climate change. For example, we did not change exposure. Thus, on one hand the study may underestimate future loss as there is a low chance that exposure will decline. But on the other hand, we also did not change any damage functions and used existing losses in the 100,000-year catalog to reflect changes in building codes and hopefully improved resiliency. In the future we (AIR) fully expect that new construction will be hardened against embers (the main cause of house ignition) and that mitigation measures such as defensible space will be taken more seriously. We expect future damages for 'the same' fire might be lower in the future, partly offsetting increased exposure. Without better (more wildfire-proof) construction and implementation of defensible space, the future looks like significantly more risk. The insurance industry can now support policy and policymakers that will reduce risk via better construction codes and their enforcement, for example.

One other feature we did not account for was changes in vegetation. As the climate changes, it may very well be the case that vegetation will acclimate, adapt, or change location – e.g., change its period of leaf display or migrate northward. While many studies have addressed the climate change induced migration of species and GCMs even attempt to model it, it is hard to say if or how it will keep pace with climate change itself. Also, following a fire, the succeeding plant community could differ from the pre-fire community and produce different amounts or types of fuels available for future fires.

In closing, it is important to emphasize that despite the uncertainties and limitations, the study provides useful guidance for how climate change likely will affect wildfire risk in the future. As disturbingly large as some of the numbers are, we note that at least from a hazard perspective, we have agreement with prior results using different methods from different researchers based on different data. And, especially with what a potentially damaging future may bring, it is better to have quantitative information on what the changes in hazard mean for U.S. wildfire losses now in order to give time to react and protect against the projected losses.

Give us your feedback!
Take a short survey on this report.
Click Here
SOA Research INSTITUTE

Copyright © 2021 Society of Actuaries Research Institute

Section 7: Acknowledgments

The authors wish to acknowledge help from a larger team at AIR-Worldwide for assisting with development of the VPD-burned area relationships and with evaluating hazard results (Jeff Amthor, Baijing (Betty) Cao, Phil Cunningham, and Les Muir).

The authors also wish to extend their gratitude to the POG members and SOA members for their guidance throughout the project and for their careful review of this report.

Project Oversight Group members:

Joan Barrett, FSA, MAAA; Consultant, Axene Health Partners

Laura Bass, FSA, MAAA

Sam Gutterman, FSA, MAAA, FCAS, FCA, HONFIA, CERA; Director, PricewaterhouseCoopers

Steve Kolk, ACAS, MAAA; Climate Data Scientist, Kolkulations LLC

Julie Meadows, FSA, MAAA, CERA; Associate Director, Actuarial Services at UnitedHealth Group

Shone Mousseiri, ASA, ACIA, PRM, GradStat; Analyst, Manulife

Brad Paulis, ASA, MAAA, FCA; Partner, Continuing Care Actuaries

Didier Serre, FSA; Head of Climate Risk Modeling and Research; Clearsum

Manyu Wong, FSA, CERA; Business Steering Specialist, Vice President, Swiss Re

Cathy (Cici) Zhang, FSA, MAAA; Consulting Actuary, Milliman

At the Society of Actuaries:

Rob Montgomery, ASA, MAAA; Independent Consultant, Project Manager

Erika Schulty, Research Associate, Society of Actuaries

Copyright © 2021 Society of Actuaries Research Institute

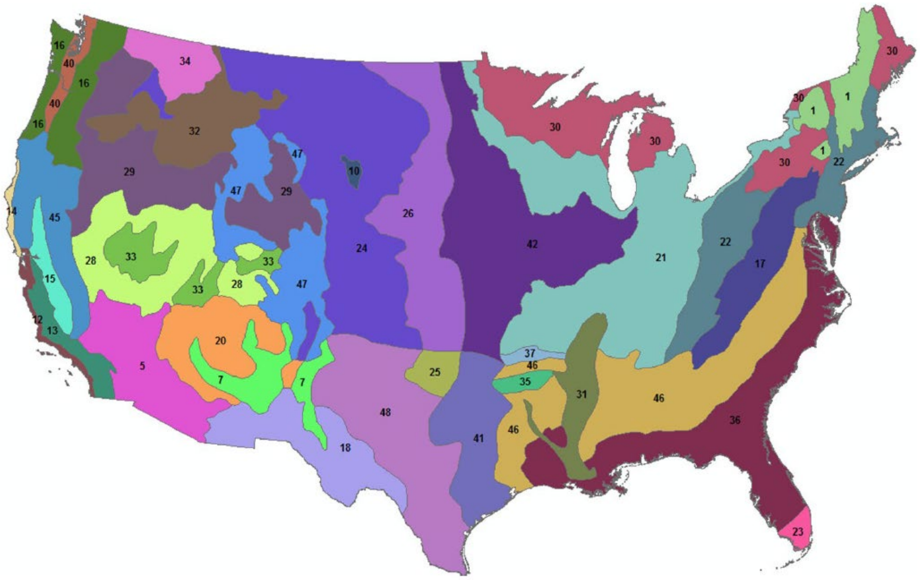
Appendix A – AIR Wildfire Model Ecoprovinces in the United States

Table A.1
LIST OF ECOPROVINCES IN THE AIR WILDFIRE MODEL FOR THE UNITED STATES

ID	Name
5	American Semi-Desert and Desert Province
7	Arizona-New Mexico Mountains Semi-Desert-Open Woodland-Coniferous Forest-Alpine Meadow Province
10	Black Hills Coniferous Forest Province
12	California Coastal Chaparral Forest and Shrub Province
13	California Coastal Range Open Woodland-Shrub-Coniferous Forest-Meadow Province
14	California Coastal Steppe-Mixed Forest-Redwood Forest Province
15	California Dry Steppe Province
16	Cascade Mixed Forest-Coniferous Forest-Alpine Meadow Province
18	Chihuahuan Semi-Desert Province
20	Colorado Plateau Semi-Desert Province
21	Eastern Broadleaf Forest (Continental) Province
24	Great Plains-Palouse Dry Steppe Province
25	Great Plains Steppe and Shrub Province
26	Great Plains Steppe Province
28	Intermountain Semi-Desert and Desert Province
29	Intermountain Semi-Desert Province
31	Lower Mississippi Riverine Forest Province
32	Middle Rocky Mountain Steppe-Coniferous Forest-Alpine Meadow Province
33	Nevada-Utah Mountains-Semi-Desert-Coniferous Forest-Alpine Meadow Province
34	Northern Rocky Mountain Forest-Steppe-Coniferous Forest-Alpine Meadow Province
35	Ouachita Mixed Forest - Meadow Province
36	Outer Coastal Plain Mixed Forest Province
37	Ozark Broadleaf Forest - Meadow Province
40	Pacific Lowland Mixed Forest Province
41	Prairie Parkland (Subtropical) Province
42	Prairie Parkland (Temperate) Province
45	Sierran Steppe-Mixed Forest-Coniferous Forest-Alpine Meadow Province
46	Southeastern Mixed Forest Province
47	Southern Rocky Mountain Steppe-Open Woodland-Coniferous Forest-Alpine Meadow Province
48	Southwest Plateau and Plains Dry Steppe and Shrub Province

Copyright © 2021 Society of Actuaries Research Institute

Figure A.1
MAP OF ECOPROVINCES IN THE AIR WILDFIRE MODEL IN THE UNITED STATES



Copyright © 2021 Society of Actuaries Research Institute

Appendix B – Hazard Target Summary

Table B.1

PERCENT CHANGE IN VAPOR PRESSURE DEFICIT (VPD) AND AVERAGE ANNUAL BURNED AREA (AREA) FOR EACH ECOPROVINCE IN 2050 RELATIVE TO 2018 UNDER RCP 8.5.

Eco-ID	VPD 2050	Area 2050
5	10	47
7	18	339
10	22	36
12	8	94
13	9	31
14	6	0
15	10	0
16	11	153
18	17	189
20	15	124
21	33	12
24	20	195
25	25	77
26	21	32
28	14	49
29	16	182
31	41	29
32	19	635
33	16	240
34	17	447
35	36	16
36	26	84
37	36	30
40	9	18
41	23	102
42	26	29
45	11	112
46	39	41
47	20	661
48	21	143

Copyright © 2021 Society of Actuaries Research Institute

References

Abatzoglou, J. T., 2011: Development of gridded surface meteorological data for ecological applications and modelling. *International Journal of Climatology* **33**, 121-131.

Abatzoglou, J.T., and T. J. Brown, 2012: A comparison of statistical downscaling methods suited for wildfire applications. *Int. J. Climatology,* **32**, 772-780.

Abatzoglou John T., Kolden Crystal A., 2013: Relationships between climate and macroscale area burned in the western United States. *International Journal of Wildland Fire,* **22**, 1003-1020.

AIR, 2018: The AIR Wildfire Model for the United States, AIR-Worldwide, Boston, MA, 6 pp. The AIR Wildfire Model for the United States (wa.gov)

Balch J.K., Bradley B.A., Abatzoglou J.T., Nagy C., Fusco E.J., Mahood A.L., 2017: Human-started wildfires expand the fire niche across the United States. *Proceedings of the National Academy of Sciences* **114,** 2946-2951.

Barbero R., Abatzoglou J.T., Steel E.A., 2014: Modeling very large fire occurrences over the continental United States from weather and climate forcing. *Environmental Research Letters*, **9**, doi:10.1088/1748-9326/9/12/124009.

Barbero, R., J. T. Abatzoglou, N. K. Larkin, C. A. Kolden, and B. Stocks, 2015: Climate change presents increased potential for very large fires in the contiguous United States. *International Journal of Wildland Fire*, **24(7)**, 892–899. https://doi.org/10.1071/WF15083.

Brown, H., 2004: "The air was fire": fire behavior at Peshtigo in 1871. *Fire Management,* 64(4), 20-30.

Brown, P. and W. Shepperd, 2001: Fire history and fire climatology along a 5° gradient in latitude in Colorado and Wyoming, USA. *Paleobotanist*, **50**, 133-140.

Cayan, D. R., 1996: Interannual climate variability and snowpack in the western United States. *J. Climatol*., **9**, 928–948.

Collins, B. M. P. N. Omi, P. L. Chapman, 2006: Regional relationships between climate and wildfire-burned area in the interior West, USA. *Can. J. For. Res*., **36**, 699-709.

Dettinger, M. D. D. R. Cayan, H. F. Diaz, D. M. Meko, 1998: North–South Precipitation Patterns in Western North America on Interannual-to-Decadal Timescales. *J. Clim*., **11**, 17.

Eyring, V., S. Bony, G. A. Meehl, C. A. Senior, B. Stevens, R. J. Stouffer, and K. E. Taylor, 2016: Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) experimental design and organization, *Geosci. Model Dev*., **9**, 1937-1958, doi:10.5194/gmd-9-1937-2016, 2016.

Enfield, D. B., A. M. Mestas-Nuñez, P. J. Trimble, 2001: The Atlantic multidecadal oscillation and its relation to rainfall and river flows in the continental U.S. *Geophys. Res. Lett*. **28**, 2077–2080.

Ficklin D. L., K. A. Novick, 2017: Historic and projected changes in vapor pressure deficit suggest a continental-scale drying of the United States atmosphere. *J. Geophys. Res. Atmos.,* **122**, 2061-2079.

Gabbert, B., 2020: Where did the term "gigafire" originate. *Wildfire Today*. Online: https://wildfiretoday.com/2020/10/07/where-did-the-term-gigafire-originate/.

Hairr, J., 2002: The Great Fire of 1898. *Our State*, **70(5)**: 24–25.

Copyright © 2021 Society of Actuaries Research Institute

Hausfather Z., G. P. Peters, Comment: Emissions—the 'business as usual' story is misleading. *Nature,* **577**: 618–620.

IPCC, 2021: Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Masson-Delmotte, V., P. Zhai, A. Pirani, S.L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M.I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J.B.R. Matthews, T.K. Maycock, T. Waterfield, O. Yelekçi, R. Yu, and B. Zhou (eds.)]. Cambridge University Press. In Press.

Keane, R. E., K. C. Ryan, T. T. Veblen, C. D. Allen, J. Logan, B. Hawkes, 2002: Cascading effects of fire exclusion in Rocky Mountain ecosystems: a literature review. *USDA Forest Service General Technical Report*, **RMRS-GTR-91**, 24 p.

Li, Jingjing, Huo Ran, Chen Hua, Zhao Ying, Zhao Tianhui, 2021: Comparative Assessment and Future Prediction Using CMIP6 and CMIP5 for Annual Precipitation and Extreme Precipitation Simulation. *Frontiers in Earth Sci.*, **9**, 20pp.

Littell, J. S., D. McKenzie, H. Y. Wan, and S. A. Cushman, 2018: Climate change and future wildfire in the western United States: An ecological approach to nonstationarity. *Earth's Future,* **6**, 1097– 1111.

Littell, J. S., D. McKenzie, D. L. Peterson, and A. L. Westerling, 2009: Climate and wildfire area burned in western U.S. ecoprovinces, 1916–2003. *Ecological Applications*, **19**, 1003–1021.

Liu, Y., J. Stanturf, and S. Goodrick, 2010: Trends in global wildfire potential in a changing climate. Forest Ecology and Management, **259**, 685–697.

Michael L. Mann, P. Berck, M. A. Moritz, E. Batllori, J. G. Baldwin, C. K. Gately, D. R. Cameron, 2014: Modeling residential development in California from 2000 to 2050: Integrating wildfire risk, wildland and agricultural encroachment, *Land Use Policy*, **41**, 438-452.

Mantua, N.J., 2001: The Pacific Decadal Oscillation. *In: Encyclopedia of Global Environmental Change*, John Wiley & Sons, Inc.

Marlon, J. R., P. J. Bartlein, D. G. Gavin, C. J. Long, R. S. Anderson, C. E. Briles, K. J. Brown, D. Colombaroli, D. J. Hallett, M. J. Power, E. A. Scharf, M. K. Walsh, 2012: Long-term perspective on wildfires in the western USA. *Proceedings of the National Academy of Sciences*, **109 (9)**, E535-E543; DOI: 10.1073/pnas.1112839109

Mccabe, G., 1999: Decadal variations in the strength of ENSO teleconnections with precipitation in the western United States. International *J. Climatol*., **19**, 1399-1410.

National Research Council, 2011: Climate Stabilization Targets: Emissions, Concentrations, and Impacts over Decades to Millennia. Washington, DC: *The National Academies Press*. https://doi.org/10.17226/12877.

Petersen J., 1994/95: The 1910 Fire. *Evergreen Magazine,* **7(7)**, 8-13.

Radeloff, V. C., D. P. Helmers, H. A. Kramer, M. H. Mockrin, P. M. Alexandre, A. Bar-Massada, V. Butsic, T. J. Hawbaker, S. Martinuzzi, A. D. Syphard, S. I. Stewart, 2018: Rapid growth of the U.S. wildland-urban interface raises wildfire risk. *Proc. Natl. Acad. Sci.*, **115 (13)**, 3314-3319; DOI: 10.1073/pnas.1718850115.

Scott A. C. and I. J. Glasspool, 2006: The diversification of Paleozoic fire systems and fluctuations in atmospheric oxygen concentration. *Proc. Natl. Acad. Sci*., **103**, 10861.

Copyright © 2021 Society of Actuaries Research Institute

Schwalm, C. R., S. Glendon, and P.B. Duffy, 2020: RCP8.5 tracks cumulative CO_2 emissions. *Proceedings of the National Academy of Sciences* **117,** 19656–19657.

Schweizer D., 2019: Wildfires in all seasons? https://www.fs.usda.gov/features/wildfires-all-seasons.

Seager, R., A. Hooks, A. P. Williams, B. Cook, J. Nakamura and N. Henderson. 2015: Climatology, variability, and trends in the U.S. vapor pressure deficit, an important fire-related meteorological quantity. *J. Appl. Meteorol*. **54,** 1121-1141.

Short, K. C. 2017: Spatial wildfire occurrence data for the United States, 1992-2015 [FPA_FOD_20170508]. 4th Edition. Fort Collins, CO: I. https://doi.org/10.2737/RDS-2013-0009.4

Short, K. C. 2021. Spatial wildfire occurrence data for the United States, 1992-2018 [FPA_FOD_20210617]. 5th Edition. Fort Collins, CO: Forest Service Research Data Archive. https://doi.org/10.2737/RDS-2013-0009.5

Stephens, S. L., and B. M. Collins, 2004: Fire regimes of mixed conifer forests in the north-central Sierra Nevada at multiple spatial scales. *Northwest Sci.*, **78**, 12-23.

Swetnan, T. W., and J. L. Betancourt, 1998: Mesoscale disturbance and ecological response to decadal climatic variability in the American Southwest. *J. Clim*., **11**, 3128-3147.

Swetnan, T. W., and J. L. Betancourt, 1990. Fire - Southern Oscillation relations in the southwestern United States. *Science* (Washington, D.C.), **249**, 1017-1020.

Tamarin-Brodsky, T., Y. Kaspi, Y., 2017: Enhanced poleward propagation of storms under climate change. *Nature Geosci* **10,** 908–913. https://doi.org/10.1038/s41561-017-0001-8

Taylor, K. E., R. J. Stouffer, G. A. Meehl, 2012: An Overview of CMIP5 and the experiment design. *Bull. Amer. Meteor. Soc.,* **93**, 485-498.

Tymstra, C., 2015: The Chinchaga Firestorm: When the Moon and Sun Turned Blue. University of Alberta Press.

Veblen, T. T., T. Kitzberger, and J. Donnegan, 2000: Climatic and human influences on fire regimes in ponderosa pine forests in the Colorado Front Range. *Ecol. Appl.*, **10**, 1178-1195.

Westerling, A. L., and T. W. Swetnam, 2003: Interannual to decadal drought and wildfire in the western United States. *Eos*, **M**, 545- 560.

Westerling, A. L., A. Gershunov, T. J. Brown, D. R. Cayan, and M. D. Dettinger, 2003: Climate and wildfire in the western United States. *Bull. Amer. Meteor. Soc*., **84**: 595-604.

Western Regional Climate Center. 1998: El Nino, La Nina, and the western U.S., Alaska and Hawaii [online]. *Western Regional Climate Center, Desert Research Institute*. Available from www.wrcc.dri.edu/enso/ensofaq.html [updated June 1998; cited February 2M].

Williams, A. P., J. T. Abatzoglou, A. Gershunov, J. Guzman-Morales, D. A. Bishop, J. K. Balch, and D. P. Lettenmaier, 2019: Observed impacts of anthropogenic climate change on wildfire in California. *Earth's Future,* **7***,* 892-910*.* https://doi.org/10.1029/2019EF001210.

Give us your feedback!
Take a short survey on this report.
Click Here
SOA Research INSTITUTE

About The Society of Actuaries Research Institute

Serving as the research arm of the Society of Actuaries (SOA), the SOA Research Institute provides objective, data-driven research bringing together tried and true practices and future-focused approaches to address societal challenges and your business needs. The Institute provides trusted knowledge, extensive experience and new technologies to help effectively identify, predict and manage risks.

Representing the thousands of actuaries who help conduct critical research, the SOA Research Institute provides clarity and solutions on risks and societal challenges. The Institute connects actuaries, academics, employers, the insurance industry, regulators, research partners, foundations and research institutions, sponsors and non-governmental organizations, building an effective network which provides support, knowledge and expertise regarding the management of risk to benefit the industry and the public.

Managed by experienced actuaries and research experts from a broad range of industries, the SOA Research Institute creates, funds, develops and distributes research to elevate actuaries as leaders in measuring and managing risk. These efforts include studies, essay collections, webcasts, research papers, survey reports, and original research on topics impacting society.

Harnessing its peer-reviewed research, leading-edge technologies, new data tools and innovative practices, the Institute seeks to understand the underlying causes of risk and the possible outcomes. The Institute develops objective research spanning a variety of topics with its strategic research programs: aging and retirement; actuarial innovation and technology; mortality and longevity; diversity, equity and inclusion; health care cost trends; and catastrophe and climate risk. The Institute has a large volume of topical research available, including an expanding collection of international and market-specific research, experience studies, models and timely research.

Society of Actuaries Research Institute
475 N. Martingale Road, Suite 600
Schaumburg, Illinois 60173
www.SOA.org

Copyright © 2021 Society of Actuaries Research Institute