Catastrophe and Climate

Tipping Points in Climate-Related Insurance Modeling

AUGUST | 2024

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Executive Summary

This report provides actuaries and other professionals working on climate-related risk with a methodology to identify climate regime shifts in different climate scenarios that could represent a "new normal" for insurers. As climate change occurs, insurers need new techniques to identify regime shifts: large sudden changes in systems that indicate a transition from one steady state in a system to another. By incorporating these new techniques and datasets into existing risk management, underwriting, pricing and investment management processes, insurers can prepare and adapt to a changing climate.

As defined by the United Nations Intergovernmental Panel on Climate Change (IPCC), climate tipping points are "critical thresholds in a system, that, when exceeded, can lead to a significant change in the state of the system, often with an understanding that the change is irreversible" (Hoegh-Guldberg et al., 2018). While climate tipping points are usually understood to take place over geologic time scales (millions of years) and have worldwide impacts, this research delineates more narrow physical regimes or systems to evaluate for significant and rapid change. The focus is on two systems that are meaningful to insurers in North America and regime shifts that occur on near-term (business-relevant) time scales: wildfires in California and heat stress in the Pacific Northwest.

This report outlines the above concepts of tipping points and regime shifts. It then lays out a methodology to evaluate physical regime shifts, including data and statistical tools actuaries can use to understand where systems have entered "new normal" states. This is followed by a qualitative discussion of climate-related impacts to insurers in the event of regime shifts, and where insurers may need to reevaluate and adapt current business practices. The report highlights the following key insights:

- Actuaries can utilize climate projections to identify regime shifts under different emissions scenarios. This will enable them to understand the changing frequency and severity of extreme weather events and chronic climate changes, and implications for their business.
- Wildfire conditions in California are expected to worsen over the next hundred years, with impacts to the residential insurance market. A wildfire regime shift can lead to a potential collapse, indicated by increased exposed housing value, decreased admitted market share, higher rates of non-renewal, rising average premiums, a decrease in the coverage-to-values ratio, and an increased number of policies covered by the state-provided FAIR plan.
- Heat stress is also expected to worsen, and insurers can consider indicators like hospitalization rates, mortality rates, morbidity rates, outdoor work accidents, low rates of air conditioning usage, and potential grid failure to better understand the impacts of heatwaves on health and safety. Evaluating these leading indicators can help develop strategies to manage risks and mitigate heat-induced morbidity.
- While this work qualitatively discusses financial impacts to insurers, it has revealed avenues for future research, including the opportunity to more explicitly model the impacts of physical regime shifts to insurers' key financial metrics.

Section 1: Introduction and Relevance to Insurers

1.1 OVERVIEW

Climate change represents one of the most pressing challenges of our time, with implications for ecosystems, societies, and economies worldwide. Insurers play a critical role in society for risk mitigation and management, and actuaries are well-positioned to evaluate climate-related risks with their expertise in risk assessment, modeling, and scenario analysis. However, traditional actuarial methods and models used by insurers do not typically incorporate climate change. Recent attempts to do so rarely represent the potential impacts of climate change fully, and they are thus likely underestimated (Lenton et al., 2023). Financial market actors, including insurers, have been seeking new data and models to better understand climate-related risks. This paper aims to bridge the gap between climate science and actuarial practice by identifying regime shifts in climate scenarios and assessing their implications for the insurance sector.

Understanding tipping points and their implications is essential for effective risk management, particularly for the insurance sector, as climate-related risks increase. While tipping points are often understood as critical thresholds within the physical climate system, this understanding can extend beyond the physical realm to socio-economic systems (political, economic, demographic, etc.), known as socio-economic tipping points (SETPs). In this broader context, tipping points are similarly described as abrupt and drastic shifts from one stable state to another, reflecting the complex interplay between human activities and the environment. To depict this interplay more accurately, traditional actuarial modeling may incorporate modern climate science to gain valuable insights.

Modern climate science can be leveraged by actuaries through climate projections under multiple scenarios. The Intergovernmental Panel on Climate Change (IPCC) defines future climate scenarios, defined mainly by the level of greenhouse gas emissions, which dictate how the physical climate system may evolve (Mason-Delmotte et al., 2021). These scenarios may be used to determine the future likelihood and severity of extreme weather events, like heatwaves or hurricanes, or chronic changes in the climate, like heat stress and drought. This study will explore the extent to which tipping points, including changing weather and climate patterns, may be identified in IPCC scenarios.

Historically, of the actuarial models that incorporate climate data, climate tipping points have not been incorporated for several reasons, including a lack of representation of tipping points in existing data (McPherson et al., 2023; Trust et al., 2023). For example, positive feedback loops that may contribute to climate tipping points are not explicitly captured in some projections of climate and remain an area of active scientific research (Masson-Delmotte et al., 2021; Trust et al., 2023). Critical thresholds, metrics defining the point at which a given tipping point has been surpassed, are difficult to pinpoint due to the complexity of feedback loops, and the intricacy of capturing multiple tipping point dynamics (Masson-Delmotte, 2021; McPherson et al., 2023).

While significant uncertainty exists in identifying tipping point critical thresholds, more narrow systems of analysis can be defined to evaluate significant changes that may represent a climate regime shift, which has relevant implications for insurers' decision-making. Regime shifts are significant, often abrupt, and long-lasting changes to complex systems, like climate or financial systems. These shifts often lead to the establishment of new stable states (i.e., regimes) (Scheffer, 2009). This report addresses the extent to which these regime shifts can be identified in existing climate scenarios with straightforward statistical methods and publicly available data. Also discussed is the value of incorporating new sources of data to evaluate climate regime shifts and associated downstream impacts to insurers and the societies in which they operate. A replicable methodology to evaluate climate regime shifts under multiple, publicly available climate scenarios and straightforward statistical techniques is introduced.

1.2 PHYSICAL TIPPING POINTS IN THE CLIMATE SYSTEM

The Intergovernmental Panel on Climate Change (IPCC) defines physical tipping points as "critical thresholds in a system, that, when exceeded, can lead to a significant change in the state of the system, often with an understanding that the change is irreversible" (Hoegh-Guldberg et al., 2018). Examples of classic tipping points in the climate system include the melting of the Greenland ice sheet, thawing of Arctic-tundra permafrost, the collapse of the Atlantic Meridional Overturning Circulation (AMOC), and the loss of Arctic Sea ice. These tipping points can contribute to further warming through positive feedback loops, reinforcing changes in the system until it reaches an irreversible state (Hoegh-Guldberg et al., 2018). Classic tipping points may have downstream impacts that affect society locally. For example, a tipping point in land ice melt may lead to exponential sea level rise of coastal areas, resulting in migration away from coastlines. Understanding and identifying tipping points like these will be crucial for developing effective climate mitigation and adaptation strategies.

Historically, politicians and economists have assumed that physical tipping points are unlikely and lack empirical evidence (Lenton et al., 2019). As evidence grows in terms of both their likelihood and widespread impacts across physical and socioeconomic systems, tipping points have attracted global interest in debates surrounding national and sectoral carbon budgets. In 2023, temperatures reached unprecedented levels, making it the hottest year on record (Hawkins, 2024), and the conversation at COP28 in Dubai placed the precipice of tipping points at odds with the fate of the fossil fuel industry (Dalton, 2023). Many global physical tipping points are expected to be reached when certain critical thresholds, most commonly global warming levels, are exceeded. Under a warming scenario of 1.5°C compared to the between 1.5°C and 2°C scenario (in line with the Paris agreement), the likelihood of reaching many of these tipping points is reduced. For example, Arctic summer sea ice is likely to be maintained if warming is kept to 1.5°C or less, whereas the risk of an ice-free Arctic summer is 50% or greater under a 1.5°C to 2°C scenario (Hoegh-Guldberg et al., 2018). The continual rise of global temperatures brings the issue of tipping points to the forefront, due to both their anthropogenic causes and impacts on society.

1.3 SOCIO-ECONOMIC TIPPING POINTS IN THE INSURANCE INDUSTRY

In addition to physical tipping points, climate change can induce SETPs, wherein socio-economic systems undergo abrupt and fundamental changes. Whereas physical tipping points described in Section 1.2 are typically focused on physical dynamics of Earth systems, the study of SETPs involves defining a connection of those physical processes to social and economic systems. Rapid, cascading tipping points in socio-economic systems are more likely to cause impactful shocks than predictable gradual change (Rye, 2023). A SETP can refer to changes in various defined systems, such as declines in home prices due to the threat of sea level rise-related flooding, or even so-called “positive tipping points” related to technological or behavioral change that would lead to further beneficial changes in the global climate (van Ginkel et al., 2022).

Insurability tipping points are an illustrative example of SETPs and may arise from both physical and transitional risks. They can lead to insurers withdrawing from markets due to challenges in accurately assessing changes in consumer preferences, policies, and technological advancements (Khoo, 2023). On a small scale, insurability tipping points might destabilize local insurance and financial markets. On a larger scale, individuals, businesses, and communities may find themselves exposed to significant financial risks without adequate protection, leading to potential economic destabilization and inequalities in insurance coverage. Furthermore, the inability to secure insurance coverage can hinder recovery efforts in the aftermath of climate-related disasters, exacerbating the long-term socio-economic impacts on affected regions. As such, insurability tipping points underscore the urgent need for proactive measures to enhance resilience, mitigate climate risks, and ensure the continued availability of affordable insurance coverage for all stakeholders.

1.4 CLIMATE REGIME SHIFTS

This paper seeks to bring together analysis of physical tipping points and downstream SETPs relevant to the insurance industry. There are three criteria that may be leveraged to locate tipping points (van Ginkel et al., 2022):

1. A point or critical threshold in the system indicating an abrupt transition,
2. The states before and after the abrupt transition are fundamentally different,
3. The final state is stable or irreversible.

The degree to which these three criteria are met depends on several factors. Classic tipping points often operate on global spatial scales and geologic timescales, making it difficult to determine the degree of reversibility (criterion 3; see Appendix A for more details). Projections of physical climate change vary from model to model, and some tipping point dynamics may not be fully represented in models, leading to uncertainty in critical thresholds or even the existence of a tipping point at all (McPherson et al., 2023) (criterion 1). As a result, significant uncertainty exists when identifying tipping point critical thresholds and this remains an area of active research (Masson-Delmotte, 2021). For example, there is still uncertainty surrounding the timing and extent of a critical threshold in Greenland ice sheet melt, beyond which it cannot recover (Robinson et al., 2012; Gregory et al., 2020; Noel et al., 2021).

In the interest of focusing on near-term time horizons and impacts to the insurance industry, this study instead defines a narrower scope of climate regimes to evaluate. **Regime shifts are large sudden changes in systems and may precede or indicate a tipping point, or otherwise indicate oscillations between two steady states**. While not all regime shifts are associated with tipping points (Dakos et al., 2015), a regime shift may still result in significant and disruptive changes to the system that are relevant to the insurance industry. Data from climate models can help insurers identify new climate regimes, where impacts may be felt before critical tipping point thresholds are passed. Within our more narrowly defined temporal and spatial scope, considerations of "reversibility" differ from those of classic tipping points on long geological time scales and large global spatial scales (van Ginkel et al., 2022). Instead, emphasis is placed on developing statistical methods and metrics to pinpoint significant changes in a system's stable state which may impact how actuaries evaluate and manage risks and opportunities for their business.

These statistical methods provide a replicable methodology for insurers to understand large changes in the magnitude and trend of the physical climate in relevant regions where they operate, and which may impact their underwriting, pricing, and risk management decisions. This report provides quantitative techniques for identifying metrics which indicate regime shifts in the physical climate system that impact the insurance sector. It then provides a qualitative discussion of impact pathways and SETPs in the insurance sector resulting from physical regime shifts but leaves quantitative modeling of these impacts as a proposed area for future research. Throughout the remainder of the paper, the discussion of the physical climate system will refer to regime shifts rather than tipping points, and the discussion of the socio-economic realm will center on SETPs.

The structure of the paper is as follows:

- Section 2 delves into the methodology. It begins with an introduction of a replicable framework to quantitatively identify climate regime shifts and qualitatively assess their implications on the insurance sector as SETPs. Next is a definition of the system, metrics, data sources, and regime shifts of interest to be quantitatively analyzed in Section 3.

- Section 3 showcases the results of the statistical methods outlined in Section 2 for two regime shifts of interest: (1) increasing incidence of wildfires in California, and (2) increasing extreme heat that may lead to heat-related illness.
- Section 4 transitions to a qualitative discussion of the socio-economic implications for insurers, with a focus on the SETPs resulting from the case studies analyzed in Section 2: (1) a new normal in the residential insurance market, and (2) implications for the health and life insurance market.
- Section 5 concludes by presenting final remarks, the limitations of this report, and suggested areas for future research.

Section 2: Methods

2.1 REGIME SHIFT IDENTIFICATION FRAMEWORK

Figure 2.1 presents the seven-step framework (adapted from van Ginkel et al., 2022) to guide insurers in identifying regime shifts in climate scenarios which are applied in this report. This technique connects quantitative analysis of the physical climate to the qualitative implications for the socio-economic realm.

Figure 2.1
FRAMEWORK TO IDENTIFY AND UNDERSTAND REGIME SHIFTS

1	System Definition:	Delineate the system boundaries by defining spatial and temporal borders, as well as system aspects (physical, ecological, social, economic, etc.) to be considered.
2	System Description:	Describe the system considering uncertainties and performance metrics.
3	Regime Shift Operationalization:	Operationalize the regime shift in terms of system metrics' relationship to the IPCC definition of 'tipping points.'
4	Regime Shift Identification:	Identify conditions under which regime shifts occur in existing and available climate datasets and scenarios.
5	Impact Analysis:	Assess regime shift impact within the system and in the wider system context. In this case, the insurance industry in North America.
6	Action Identification:	Identify actions to prevent or adapt to regime shifts, and indicators to detect approaching regime shifts.
7	Decision Support:	Formulate advice for regime shift risk measurement and management.

Adapted from van Ginkel et al. (2022).

Step 1 has been performed by first narrowing the temporal and spatial scales to those relevant to insurers, as described in Section 1.4. Step 2 is outlined below but is demonstrated in more detail in Section 3 as regime shifts using various system metrics are identified. Steps 3 and 4 describe the data and statistics used and are described below but are further illustrated in Section 3. Steps 5—7 are demonstrated in Section 4 with a discussion of the implications for the insurance industry through impact pathways.

2.2 SYSTEM DEFINITION AND SYSTEM DESCRIPTION

Defining the system in which a regime shift occurs is important for its identification. Global climatic regime shifts, like those listed in Section 1.2, have numerous drivers in the physical system and cascading impacts in society and the insurance sector. This study develops quantitative metrics to detect signals of regime shifts and further leverages the use of qualitative impact pathways to define causal links between physical climate drivers and resulting regime shifts, or new normal states, in the insurance sector. Illustrated in this report are two insurance-related regime shifts with case studies: (1) increasing incidence of wildfires in California may lead to a new normal in the residential insurance market, and (2) increasing extreme heat and associated heat-related illness may have implications for the health and life insurance market. Following step 2 above, these systems will be described in further detail in Section 3: Results.

2.3 REGIME SHIFT OPERATIONALIZATION: SYSTEM METRICS AND DATA

In the systems described above, metrics are defined based on the future changes in the physical climate system using publicly available climate model data under multiple emissions scenarios. This study tries to locate regime shifts in historical data and projections of various climate metrics in order to identify new normal states under potentially different futures. The data analyzed in this study will be taken from two public climate model data repositories and consider multiple climate scenarios.

In this study, low, moderate, and high emissions scenarios are used to create a cone of uncertainty regarding future greenhouse gas emissions levels (see Appendix B for more details). Evaluating multiple climate scenarios will highlight how greenhouse gas emissions may affect the range of potential changes expected and the degree of severity of the regime shift.

Metrics are developed using physical climate model output from various Global Climate Models (GCM). Data is collected from two suites of climate model data: Cal-Adapt (Cal-Adapt, 2018) for assessing regime shifts in California wildfires, and Intersectoral Impact Model Intercomparison Project (ISIMIP) for assessing shifts in heat causing heat-related illness (Hempel et al., 2013; Warszawski et al., 2014). Both suites of climate model data leverage simulations from international climate institutions that participate in the Climate Model Intercomparison Project (CMIP), which informs analysis in the IPCC report. The differences between the two suites of climate projections are related to resolution and methods for "bias-correction." Bias correction is a process of statistically correcting projections to match historical observations of the climate more accurately, including temperature, precipitation, and atmospheric circulation variables.

1. Cal-Adapt: Cal-Adapt is a large modeling effort to provide stakeholders with historical data and climate model projections used in California's Climate Change Assessments. This data leverages bias-corrected CMIP models but additionally downscales the horizontal resolution to one sixteenth of a degree (approximately 3 km x 3 km at the equator), allowing users to consider climate impacts at the local level. The data provided prioritizes variables relevant for climate impacts to California, including drought and wildfires. In addition to bias-corrected and downscaled CMIP model output, wildfire simulations were run as part of the modeling effort and downloaded for use in this study.
2. ISIMIP data: The goal of ISIMIP is to provide sector-relevant projections to the wider community for direct application. International climate modeling institutions submit climate simulations to ISIMIP after following a set of protocols, including bias-correcting climate model projections. ISIMIP projections are provided at a horizontal resolution of about half of a degree (approximately 50 km x 50 km at the equator).

2.4 REGIME SHIFT IDENTIFICATION

This study applies a variety of parametric and non-parametric analytical statistical methods for detecting regime shifts described in Table 2.1. The four climate metrics (three indicative of wildfire and one indicative of heat-related morbidity) described in Section 3 are represented as annual timeseries under two climate scenarios, and some will be assessed for multiple climate models. Statistical analysis following the three criteria of regime shifts from Section 1.4 will be used to identify potential regime shifts between two distinct states in the system.

Table 2.1
A DESCRIPTION OF THE STATISTICS USED TO IDENTIFY A REGIME SHIFT

Statistic	Relation to Regime Shift
Change in lag-1 autocorrelation	The first criterion to identify regime shifts is a rapid, abrupt change in the system (van Ginkel et al., 2022). To detect a rapid change in the system, autocorrelation is used to determine a "critical slowing down" of the system, which occurs before an abrupt transition to another stable state (Dakos et al., 2012; Dakos et al., 2015). Specifically, a critical transition is determined by a positive trend in the autocorrelation or slowing down of the system during a predetermined time period, followed by a negative trend in the correlation, or a speeding up of the system. This shift in autocorrelation indicates that an abrupt shift has occurred.
Change in variance	The second criterion is that a regime shift is characterized by a stable state moving into another stable state (van Ginkel et al., 2022). A significant change in variance of the state is determined using Levene's test, which compares the variance between two consecutive time periods. This test does not require the underlying data to be normal. If the change in variance corresponds to a p-value of < 0.05, the change is considered significant.
Change in mean	The third criterion of a regime shift is that the two states before and after a regime shift are fundamentally different states (van Ginkel et al., 2022). This is determined by a significant change in the mean of the variable between the two time periods before and after the critical transition. A significant change is determined by comparing the t-statistic calculated between the two consecutive time periods and a bootstrapped t-statistic calculated using the same time periods. A significant change is detected if <5% of the bootstrapped t-statistics are greater than the actual t-statistic. This corresponds to a p-value < 0.05. This is also referred to as a moving t-test (Li et al., 1996; Xiu et al., 2007; Rodionov, 2004).

A wide variety of statistics have been employed in order to detect regime shifts, but these three statistics are chosen due to their straightforward implementation, their correspondence to the three criteria of tipping points outlined in the IPCC and van Ginkel et al. (2022), as well as their widespread use across regime shift literature. A change in the variance and a change in the mean, corresponding to the second and third criterion, respectively, are straightforward, extensively used statistics to identify regime shifts (Li et al., 1996; Rodionov, 2004; Xiu et al., 2007; Liu et al., 2016; Dakos et al., 2012; Dakos et al., 2015; van Ginkel et al., 2022). The representation of criterion 1, a rapid, abrupt change in the system (van Ginkel et al., 2022), required more consideration. Studies identifying "rapid" changes in timeseries vary in their choice of statistical methods. For example, van Ginkel et al. (2022) use a first-order derivative to identify a rapid change in the system. These authors define a threshold using models, and the criteria is met when the first-order derivative surpasses this threshold. In line with extensive work performed by Dakos et al. (2012, 2015), this study uses a positive-to-negative trend shift in lag-1 autocorrelation. Increasing lag-1 autocorrelation is an indicator of a "critical slowing down" of the system and is considered an "early warning signal" of an abrupt change to a new, stable state (Dakos et al., 2012; 2015; Liu et al., 2016). This analysis does not require a predetermined threshold. More information about a change in lag-1 autocorrelation may be found in Appendix C.

A significant change in each statistic is evaluated by comparing two consecutive, non-overlapping windows of a certain size. If a significant change in the statistic is detected between the two windows, then the year separating the two windows is documented as a potential regime shift. If all three criteria locate a regime shift at the same time, it can be concluded that a significant regime shift occurred (in the case of historical observations) or will occur (in climate model projections). Taken separately, a significant change detected for each statistical metric can still provide insights on expected changes in the system. In fact, across the many studies cited above that employ statistics to identify regime shifts, most utilize one statistic to identify regime shifts. This study is interested in regime shifts that may precede a tipping point, and so follows the IPCC and van Ginkel et al. (2022) definition of a tipping point in order to identify *significant* regime shifts.

Window sizes are chosen to correspond to certain period lengths and are based on the variability of the system and the length of the timeseries. Since moisture-related metrics are highly variable and thus, many points are needed to detect statistical significance, wildfire metrics are evaluated over the course of 150 years and the window size is 50 years. A smaller window may misrepresent the overall state of the system since moisture varies tremendously from year-to-year. The length of the observational period for heat stress is 85 years. Because temperature tends to be more coherent, i.e., temperature tends to change more slowly, a window size of 30 years is used to detect regime shifts. The size of the window may affect the results. A smaller window size ($n<30$) is less likely to detect significant regime shifts because statistically significant changes are harder to detect. Likewise, a larger window size more easily detects statistically significant changes. This presents a challenge with physical climate data because the length of climate datasets is often short (<200 years).

Section 3: Results

3.1 REGIME SHIFTS IN WILDFIRE IN SAN DIEGO COUNTY

Losses, including insurance, economic, and ecological, due to increased frequency of wildfires and burnt areas in California are at an all-time high (Struzik, 2020). The increased frequency and severity of wildfires in California have been linked to climate change, population growth, and values of exposed housing. (Bryant and Westerling, 2014). Challenges to the insurance market in high wildfire-risk areas highlight the urgent need for adaptation strategies to reduce vulnerability to wildfires (Dixon et al., 2018). This study's methodology looks at the dynamics of wildfire regime shifts to provide insights into implications for the insurance sector and to inform strategies for risk management and adaptation. Below are descriptions of the wildfire system along with metrics and data used to analyze the system with results in Sections 3.1.1, 3.1.2, and 3.1.3.

This study evaluates physical climate metrics associated with wildfires in San Diego County, where risk exposure is greatest (FEMA, 2023), and a potential regime shift in the residential insurance market may be detected. Physical climate metrics are analyzed from 1950 through 2100 under moderate- and high-emissions scenarios (Note: low-emissions was not analyzed due to data availability. Please see Appendix B for more details). The following physical climate metrics are collected from climate model data compiled and downscaled as part of the Cal-Adapt effort (Pierce et al., 2018; Westerling, 2018):

- The average number of days per year across San Diego County in which the Keetch-Byram Drought Index (KBDI) exceeds 600, which is often associated with severe drought and increased wildfire occurrence (Keetch and Byram, 1968; Gannon and Steinberg, 2021). This index considers latitude, rainfall, mean annual precipitation, maximum dry bulb temperature, and indicates the cumulative moisture deficiency in an environment and soil. This index is taken as an average across four climate model projections.
- The average number of days per year across San Diego County in which the standardized precipitation-evaporation index (SPEI) is less than -1, which is an alternative indicator for severe drought. This wildfire indicator does not consider relative humidity or solar radiation, which could miss the rapid onset of drought that could exacerbate fire weather. This index is taken as an average across four climate model projections.
- Historical and projected total area burned by wildfire across San Diego County represented by four different climate models.

Total area burned by wildfire across San Diego County is a direct indicator of wildfire but may miss the frequency or severity of individual wildfires. Precipitation, evapotranspiration, and relative humidity, or a lack thereof, represent the aridity of the soil and environment and contributes to wildfire occurrence. Taken together, these metrics represent a system of wildfire potential in San Diego County, California.

CALLOUT BOX 3.1: FIGURE INTERPRETATION GUIDE

The order in which criteria are evaluated

For all figures, the three criteria are evaluated in the following order: criterion 3 (change in mean), criterion 2 (change in variance), and criterion 1 (change in the trend of autocorrelation), due to the frequency in which each criterion indicate a potentially significant shift.

- **Criterion 3**, identifying a move to a fundamentally different state, is met the most frequently, because global warming causes the mean state of the climate system to change steadily throughout the period of observation. Until greenhouse gas emissions stop and global warming stabilizes, this steady change is expected to continue. Criterion 3 is indicated by gray shading in the background of each plot.
- **Criterion 2**, a move from one stable to another stable state, is met less frequently than criterion 1, because it not only depends on global warming, but may also depend on other factors in the system. Criterion 2 is indicated by pink shading in a low emissions scenario and blue shading in a high emissions scenario. Because criterion 3 is met so frequently, years meeting criterion 2 almost always coincide with years meeting criterion 3. Therefore, in the figures, pink and blue shading indicating criterion 2 almost always overlay gray shading indicating criterion 3.
- **Criterion 1**, an abrupt change in the system, is the hardest criterion to meet since a change in the autocorrelation, or "memory" of the system, depends on many factors in the system. This criterion is indicated by dotted vertical lines in either scenario.

Interpretation of single timeseries versus multi-model timeseries

Single timeseries, or multi-model average timeseries, are shown in Figures 3.1 and 3.2. These figures should have one layer of shaded gray (corresponding to criterion 3) and one layer of shaded pink or blue (corresponding to criterion 2) overlaid. Since criterion 3 is expected to be met throughout the period of observation, one may assume that pink or blue shading is always overlaid gray shading, and thus, criterion 3 always coincides with criterion 2. This can be confirmed by Tables 3.1 and 3.2.

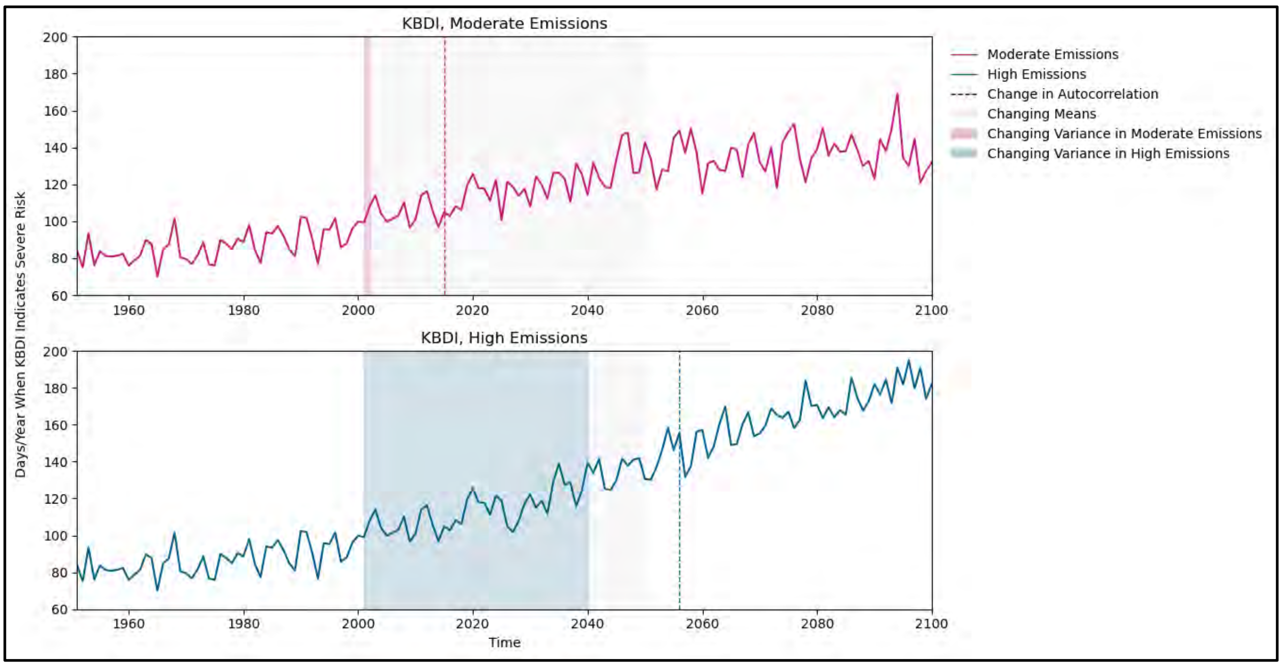
- Multi-model timeseries are shown in Figures 3.3 and 3.4. These figures have multiple, slightly transparent layers of shaded gray, pink, or blue. If multiple models identify the same period as a potential regime shift, then the shading will appear darker. Criterion 3 is also expected to be met throughout the period of observation, but is not always the case (for example, changes in the mean are not as obvious for the Area Burned by Wildfire, shown in Figure 3.3). Tables 3.3 and 3.4 should confirm whether years where criterion 3 is met coincide with years meeting other criteria.

3.1.1 EXTREME DROUGHT CONDITIONS VIA KBDI

The KBDI produced by Cal-Adapt (Cal-Adapt, 2018; Pierce et al., 2018) represents an average across climate models under moderate- and high-emissions scenarios, which represents the mean response of drought to greenhouse gas emissions across various climate models (Figure 3.1). The timeseries shows that severe drought is projected to become more likely across San Diego County under either greenhouse gas emissions scenario. In a moderate emissions scenario, the number of days per year in which severe drought conditions are projected to occur increases from approximately 100 days per year, or a little over three months per year in 2020, to 130 days per year, or over four months per year by the end of the century. By the end of the century in a high emissions scenario, the amount of time that San Diego County is projected to face severe drought conditions will be around 180 days per year, or around six months per year. One may draw two conclusions at this point: (1) increasing greenhouse gas emissions are expected to exacerbate severe drought conditions in San Diego County, and (2) the average time spent in severe drought by the end of the century is projected to be longer than today.

Figure 3.1

DAYS PER YEAR THAT KBDI INDICATES SEVERE DROUGHT IN SAN DIEGO COUNTY



Timeseries showing the number of days per year in which the KBDI > 600 or shows severe drought. The top and bottom panels show the likelihood of severe drought under moderate and high emissions scenarios, respectively. Shifts in criterion statistics are marked in shading and vertical lines.

Table 3.1

SUMMARY OF CHANGE POINTS FOUND IN KBDI METRIC

Metric	Emissions Scenario	Model	Criterion 1 (Pos. → Neg. trend in autocorrelation)	Criterion 2 (Change in variance)	Criterion 3 (Change in the mean)	Critical Change Points
No. days per year where KBDI > 600	Moderate	Ensemble Average	2015	2001-2002	2001-2050	None found within model average
	High		2056	2001-2040	2001-2050	

Critical transition points are identified, any year where all three statistical tests identify a change, to indicate a regime shift. As summarized in Table 3.1 the results of the statistical analysis confirm that a significant change in drought conditions is expected over the next century, though the precise timing of the regime cannot be identified. The three criteria separately identified significant shifts in the KBDI index, but the shifts occur at different times across the three criteria. Instead, one may conclude generally that, by the end of the century, a new, stable state of severe drought will likely occur, and severe drought will be fundamentally more frequent from that of today.

As shown in the years shaded grey (roughly 2000-2050 in moderate emissions and 2040-2050 in high emissions), there is a significant change in the mean, indicating the steady increase in the time spent in severe drought (criterion 3, change in mean). In other words, drought conditions are changing; one can expect a fundamentally different state of drought between now and in the future.

Meanwhile, the timing of a change in stability of severe drought (criterion 2, change in variance) depends on the emissions scenario. The pink shading in a moderate emission scenario shows a shift to a new, stable state of drought in 2002. Because no other shifts in the variability are identified under a moderate emissions scenario, the stability of this new drought state is expected to last to the end of the century. In a high emissions scenario, the blue shading indicates a critical change in variance starting in 2040 will occur, and based on the window size chosen, that this change in variance will sustain over the next 50 years. This result is consistent with the idea that a large increase in greenhouse gas emissions increases the likelihood that a given year will experience prolonged, severe drought in San Diego County.

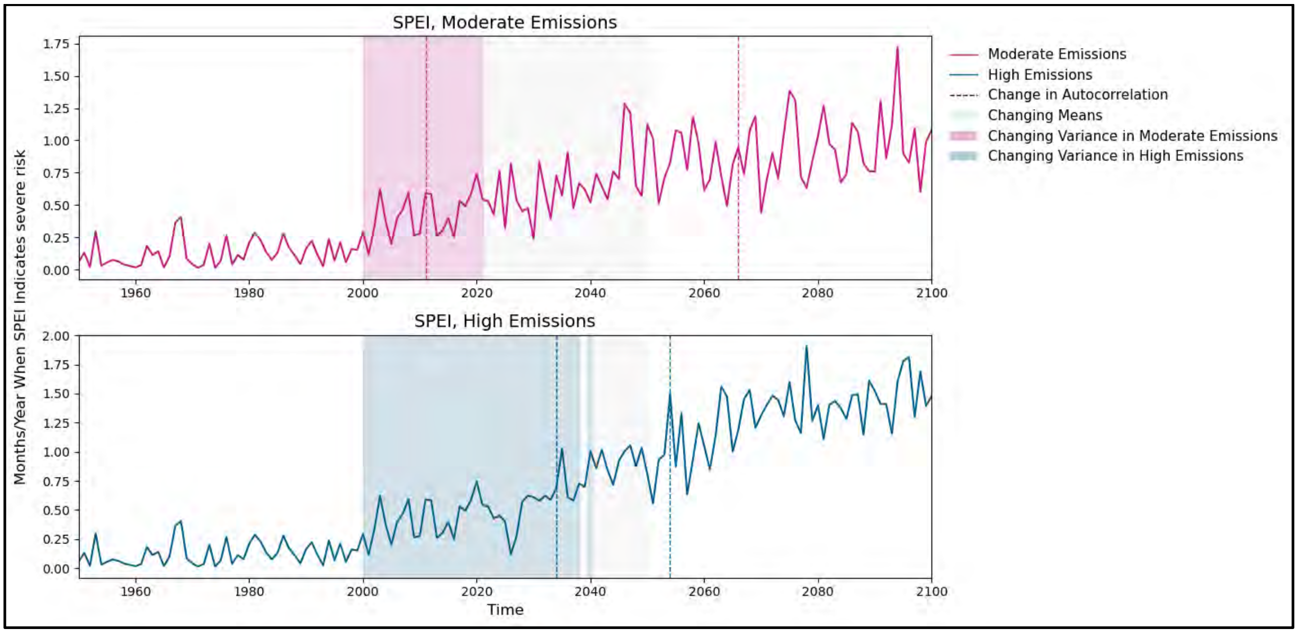
As indicated by the dotted vertical lines, criterion 1 (a negative to positive change in the trend of lag-1 autocorrelation) the timing of a single abrupt change, depends on the emissions scenario. An abrupt shift system is indicated by an increase of persistence in the system, indicated by a positive correlation from year to year, followed by a sudden decrease in persistence of the system, or a negative correlation from year to year. Under a moderate emissions scenario, fluctuations in severe drought become less coherent until 2015. Between 2015 and 2065, the timing and severity of drought events become more coherent, and remain coherent for the remainder of the century, so no other abrupt changes in drought are identified. In a high emissions scenario, an abrupt shift in the persistence of the system is not identified until 2056.

3.1.2 EXTREME DROUGHT CONDITIONS VIA SPEI

The SPEI provided by Cal-Adapt (Cal-Adapt, 2018; Pierce et al., 2018) provides high-level insight into drought based purely on precipitation and evapotranspiration. Taken in conjunction with the KBDI, one can develop a holistic view of projected changes in drought under different greenhouse gas emissions scenarios. Like the KBDI, an increase in drought severity and frequency is expected under both scenarios. Unlike the KBDI, the statistics corresponding to each regime shift criterion point to a significant, abrupt regime shift to a fundamentally different and stable state in each of the greenhouse gas emissions scenarios.

Figure 3.2

MONTHS PER YEAR THAT SPEI INDICATES SEVERE DROUGHT IN SAN DIEGO COUNTY



Timeseries showing the number of months per year in which the SPEI < -1 or indicates severe drought. The top and bottom panels show the likelihood of severe drought under moderate and high emissions scenarios, respectively. Shifts in criterion statistics are marked in shading and vertical lines.

Table 3.2

SUMMARY OF CHANGE POINTS FOUND IN SPEI METRIC

Metric	Emissions Scenario	Model	Criterion 1 (Pos. → Neg. trend in autocorrelation)	Criterion 2 (Change in variance)	Criterion 3 (Change in the mean)	Critical Change Points
No. months per year where SPEI < -1	Moderate	Ensemble Average	2011, 2066	2000 - 2021	2000-2050	2011
	High		2034, 2054	2000 - 2038, 2040	2000-2050	2034

Figure 3.2 displays the results of statistical tests for each of the criteria in the same manner as Figure 3.1. In both scenarios, an overlap among all three criteria is found. The grey shading on this figure indicates a significant shift in the mean is detected throughout the timeseries in both scenarios, indicating a continual shift to a fundamentally different state of drought (criterion 3). Pink shading indicates a significant shift in the variance is detected earlier in the period of the observation in a moderate emissions scenario, and blue shading indicates a continual shift in variance is detected throughout the middle of the timeseries under a high emissions scenario. The difference between shifts in drought conditions represented by the SPEI and the KBDI lies in the abruptness of the shift. Pink dotted lines indicate abrupt shifts (criterion 1) are detected in 2011 and in 2066 in a moderate emissions scenario and blue dotted lines in 2034 and 2054 in a high emissions scenario. The fact that the abrupt shift in 2011 overlaps shifts in the mean in variance in the moderate scenario suggests that a significant, abrupt regime shift to new drought conditions is expected (top panel in Figure 3.2). The same conclusion can be drawn about the shift detected in 2034 in a high emissions scenario (bottom panel in Figure 3.2).

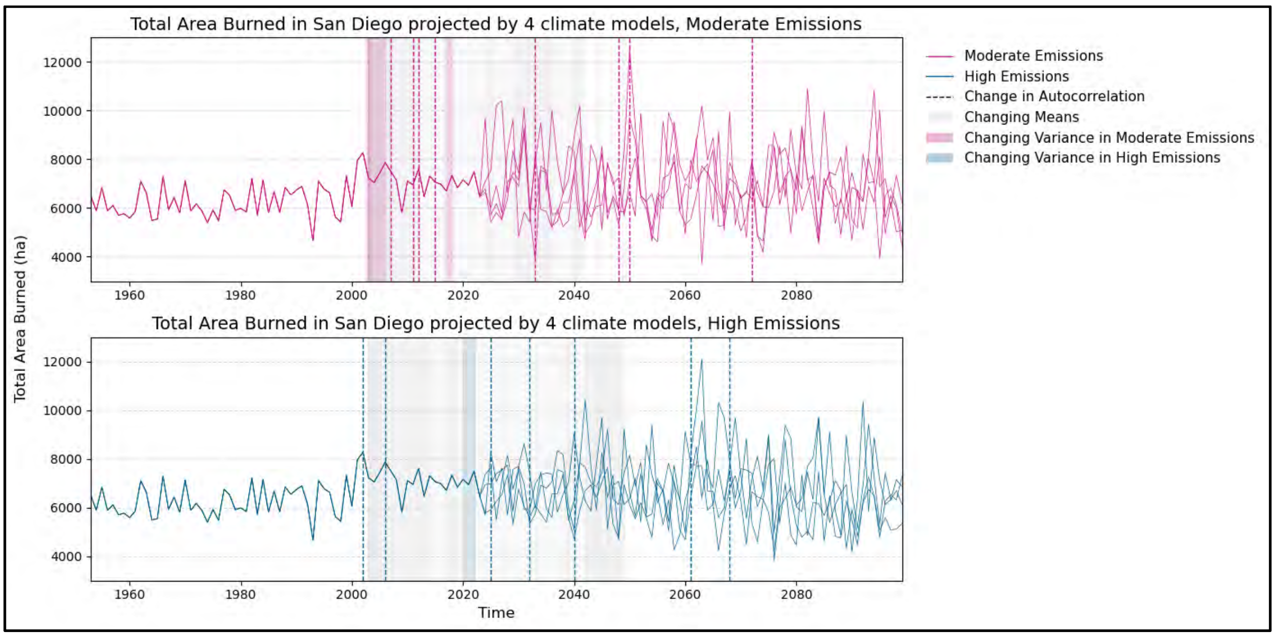
Considering both drought indicators (KBDI and SPEI) in tandem, it can be concluded that a significant and abrupt transition to a fundamentally different state in precipitation and evapotranspiration will occur in either the moderate- or high-emissions scenario, while changes in environmental aridity may occur, but slowly and gradually over time.

3.1.3 AREA BURNED BY WILDFIRE

Projections of total area burned by wildfire are provided by Cal-Adapt (Cal-Adapt, 2018; Westerling et al., 2018) for multiple climate models under moderate and high emissions scenarios. This enables the user to establish confidence around when a regime shift will occur. Here, the statistical analysis corresponding to the three criteria is performed separately for each climate model, and then overlapped visually, and allows for a comprehensive view of regime shifts in expected damages due to wildfire. Abrupt regime shifts may not arise in a single climate model, but analyzing multiple climate models at once may reveal potential regime shifts otherwise missed in a single model.

Figure 3.3

HECTARES OF AREA BURNED PER YEAR ACROSS SAN DIEGO COUNTY PROJECTED BY FOUR CLIMATE MODELS



Timeseries showing the hectares of area burned per year. The top and bottom panels show the likelihood of severe drought under moderate and high emissions scenarios, respectively. Shifts in criterion statistics are marked in shading and vertical lines.

Table 3.3

SUMMARY OF CHANGE POINTS IDENTIFIED ACROSS FOUR MODEL PROJECTIONS FOR AREA BURNED BY WILDFIRE

Metric	Emissions Scenario	Model	Criterion 1 (Pos. → Neg. trend in autocorrelation)	Criterion 2 (Change in variance)	Criterion 3 (Change in the mean)	Critical Change Points
Area burned by wildfire	Moderate	CanESM2	2012, 2050	None	2003 - 2007	None found across models
		CNRM-CM5	2007, 2033	2003	2003 - 2005, 2025, 2029, 2030 - 2036	
		HadGEM2-ES	2011, 2048	None	2003 - 2012, 2017, 2040 - 2042, 2044, 2045, 2047, 2049	
		MIROC5	2015, 2072	2003 - 2006, 2017, 2018	2003 - 2041	
	High	CanESM2	2040, 2068	2020 - 2022	2039, 2044, 2046 - 2049	None found across models
		CNRM-CM5	2006, 2025	None	2003 - 2005, 2042 - 2049	
		HadGEM2-ES	2002	None	2003 - 2014, 2017 - 2019	
		MIROC5	2032, 2061	None	2003- 2046	

The statistical analysis of the moderate emissions scenario shows that an abrupt shift to a new wildfire regime has occurred before 2020. Like the drought indices, the grey shading on both panels of Figure 3.3 indicates a shift in the mean state of wildfire is apparent between 2003 and 2010 in at least three models (criterion 3), as greenhouse gas emissions heighten warming and drought. The pink shading indicates the variance in wildfire occurrence also increases by the middle of the period of observation (criterion 2). Pink shaded lines show individual model simulations all indicate a sudden increase in area burned by wildfire, punctuated with years with less area burned, by around 2025. Last, pink dotted lines showing abrupt shifts in area burned were identified across individual model simulations in 2007, 2011, 2012, and 2015 (criterion 1). All three criteria are highlighting the period between 2007 and 2015 as a significant, abrupt shift to a fundamentally different, stable state in area burned by wildfire under a moderate emissions scenario.

In a high emissions scenario, the model ensemble points to the middle of the observation period for the timing of a significant regime shift, though with less certainty. Grey shading indicates most models in the ensemble identified significant changes in the mean in the middle of the period of observation (criterion 3), though there is some disagreement about when this shift will occur. Likewise, blue shading indicates years 2020-2022 as a period when significant changes in variance will occur (criterion 2). Blue dotted lines show that each model captured different years of abrupt shifts (criterion 1): 2025, 2032, 2040. None of these years overlap with the change in variance identified by criterion 2.

This analysis identifies potential regime shifts in the area burned by wildfire by considering significant changes in mean, variance, and autocorrelation under moderate- and high-emissions scenarios. The area burned by wildfire is projected to change more quickly in a moderate emissions scenario than in a high emissions scenario. In a moderate emissions scenario, many years were identified between 2000 and 2020 as potential change points in the mean, variance, and autocorrelation. In a high emissions scenario, the area burned by wildfire is projected to change more slowly. A few years were identified as potential change points in the mean, variance, and autocorrelation between 2020 and 2050. In either scenario, no significant regime shifts were identified since the criteria did not align on years for potential change points.

3.2. REGIME SHIFTS IN HEAT-RELATED MORBIDITY IN SEATTLE

A regime shift in the occurrence of heatwaves is expected to cause increased heat-related morbidity, with implications for public health and insurance. Heatwaves have the potential to exacerbate health risks and strain healthcare systems. The IPCC has highlighted that these heat-related impacts may represent a regime shift, especially for local communities that are unable to adapt (Hoegh-Guldberg et al., 2018). The rise in morbidity has implications for insurance markets, as health insurance may see higher frequency of claims or the emergence of new markets for heat-related coverage (Kelly, 2023). Our methods examine the existence of regime shifts in heat-related morbidity in existing climate scenarios. Below is a description of the metrics and data used to analyze shifts in heat-related morbidity with results in Section 3.2.1.

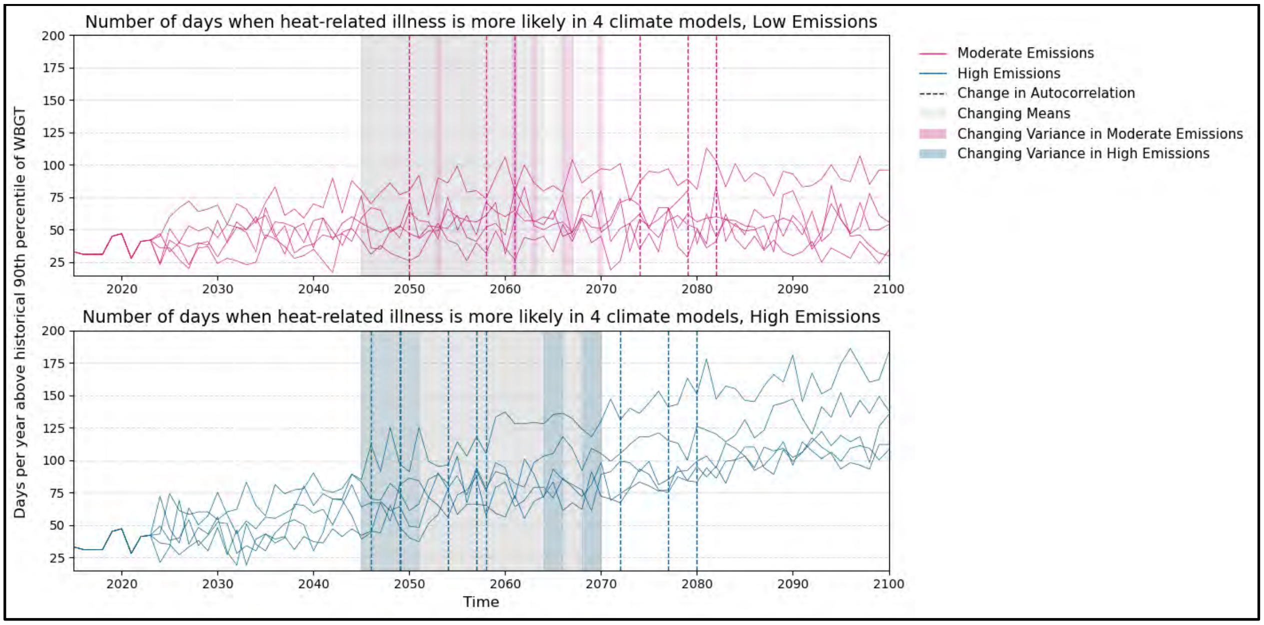
The focus of this study is Seattle, where the likelihood of dangerous temperatures is expected to increase, and there are low AC usage rates (Hubbard, 2021). When temperatures exceed the local historical 90th percentile, temperatures which people in a region are not acclimatized to, incidences of heat-related illness can increase (Puvvula, 2022). Temperatures related to heat stress and heat-related morbidity are often expressed as daily maximum wet-bulb globe temperature (WBGT) (Coffel et al., 2017). WBGT is calculated from temperature, relative humidity, wind speed, and solar radiation to convey a “real feel” temperature and is often used in early warning systems of dangerous temperatures (National Weather Service; Budd, 2008). WBGT in Seattle was analyzed across another set of climate models and in low emissions scenario and high emissions scenarios. Regime shifts in extremes in heat stress are detected from 2015 to 2100 from multiple model projections of WBGT under low- and high-emissions scenarios. The WBGT is derived using data from the ISIMIP modeling repository. The number of days per year is used in which the daily maximum WBGT is greater than the local 90th percentile of temperatures of historical temperatures (2015 – 2023) as a proxy for heat-related illness.

Similar to the analysis of the area burned by wildfire, analyzing a suite of climate model simulations can provide confidence in determining when a regime shift will occur. Generally, the number of days in which WBGT will surpass the local historical 90th percentile will increase with higher greenhouse gas emissions. The goal of this analysis is to detect a critical change point, indicating an abrupt regime shift to a fundamentally different state.

3.2.1 HEAT STRESS VIA WET BULB GLOBE TEMPERATURES

Figure 3.4

DAYS PER YEAR THAT WBGT INCREASES LIKELIHOOD OF HEAT-RELATED ILLNESS IN SEATTLE



Timeseries showing the number of days in which the maximum wet bulb globe temperature exceeds the 90th percentile of historical daily maximum temperatures per year. The top and bottom panels show the likelihood of severe drought under moderate and high emissions scenarios, respectively. Shifts in criterion statistics are marked in shading and vertical lines.

Table 3.4

SUMMARY TABLE OF CHANGE POINTS IDENTIFIED ACROSS FIVE MODELS FOR HEAT STRESS METRIC

Metric	Emissions Scenario	Model	Criterion 1 (Pos. → Neg. trend in autocorrelation)	Criterion 2 (Change in variance)	Criterion 3 (Change in the mean)	Critical Change Points
No. of days per year where WBGT > 90^{th} percentile of historical temperatures	Low	gfdl-esm4	2061	None found within single model	2045 - 2064, 2066	None found across models
		ipsl-cm6a-lr	None found within single model	None found within single model	2045 - 2062, 2065, 2066	
		mpi-esm1-2-hr	2050	None found within single model	2045 - 2064, 2066	
		mri-esm2-0	2058, 2082	2053, 2066, 2067, 2070	2045 - 2057	
		ukesm1-0-ll	2074, 2079	2061, 2063	2045 - 2070	
	High	gfdl-esm4	2054	None found within single model	2045 - 2070	2049
		ipsl-cm6a-lr	2049, 2077, 2080	None found within single model	2045 - 2070	
		mpi-esm1-2-hr	2057	2045 - 2051	2045 - 2070	
		mri-esm2-0	2049	None found within single model	2045 - 2070	
		ukesm1-0-ll	2046, 2058, 2072	2064 - 2066, 2068 - 2070	2045 - 2070	

Overall, no individual climate model identifies a significant, abrupt shift to a different state. Instead, potential regime shifts are identified using the combination of model simulations. Like other physical climate variables that change with greenhouse gas emissions, grey shading in Figure 3.4 shows a significant shift in the mean (criterion 3) in the middle of the timeseries in both greenhouse gas emission scenarios. Table 3.4 confirms that all models consistently show the period between 2045 and 2070, a period where the mean changes significantly. In a low emissions scenario, pink shading shows that a significant change in variance occurs between 2055 and 2066 (criterion 2). Two models locate a significant change in the variance during this period, but the models do not agree on the year in which the shift in variance occurs (Table 3.4). In a high emissions scenario, blue shading indicates a significant change in variance across the models is detected between 2045 and 2051, and between 2065 and 2070 (criterion 2). The detection of a regime shift depends on the identification of abrupt shifts. Under the moderate emissions scenario, abrupt shifts detected by one model coincide with mean and variance changes in 2058 and 2061 detected by another model. It may be concluded that heat stress, and thus heat related morbidity, may experience a new, stable, regime abruptly within this period. Under the high emissions scenario, abrupt shifts detected coincide with mean and variance changes earlier—in 2046 and 2049. Due to rapid warming from high greenhouse gas emissions, an abrupt change to a new stable state in heat-related morbidity may occur in the late 2040s.

3.3 RESULTS TAKEAWAYS

The analysis above shows how one may apply regime shift statistics to locate an abrupt transition to a new, fundamentally different state in the physical climate system. First, regime shift is defined based on three criteria defined in Section 1.4. By the definition used in this paper, all three criteria must point to the same transition point in order to conclude that a significant regime shift will occur. However, individual statistics associated with each criterion can still offer valuable insight to insurers. For example, a significant shift in variance may shed light on the likelihood of extremes. Second, by incorporating multiple emissions scenarios, insurers may develop a better idea of how and when to prepare for a potential regime shift. For example, generally, a regime shift due to increased greenhouse gases may be felt as early as the late 2030s, or, depending on the physical system of interest, a significant regime shift may already be underway. Finally, data from a single climate model can offer some insight into potentially significant changes in the climate system, but the use of multiple climate models can provide a more nuanced understanding of the likelihood of a significant change occurring.

Section 4: Impact Pathways to Identifying Socio-Economic Tipping Points

The results in Section 3 illustrate how regimes of wildfire and heat stress are shifting under various emissions scenarios. In anticipation of such profound changes and informed by the most current and advanced climate modeling techniques, financial sector actors have a role to play in understanding the socio-economic implications. Such due diligence may ensure responsible management of climate regime shifts and their associated risks. This section discusses potential socio-economic tipping points (SETPs) resulting under a regime of wildfires in San Diego County and a regime of heat-related morbidity in Seattle. While these SETPs are not a full representation of the potential impacts of regime shifts on the insurance sector, they are significant impact pathways to regime shifts as they manifest from *rate-induced tipping*, as opposed to gradual change occurring in the absence of regime shifts. In this section, these exemplary impact pathways are explored qualitatively.

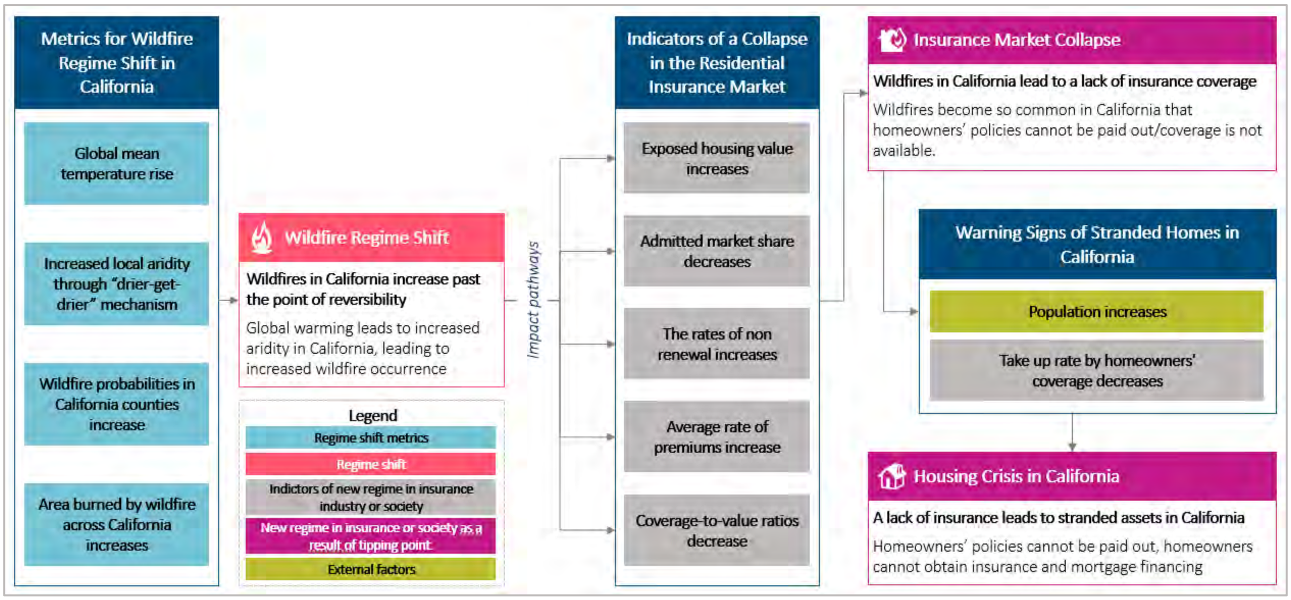
Mechanisms of rate-induced tipping in socio-economic systems are more likely to cause shocks in socio-economic systems than the gradual crossing of bifurcation points. Rate-induced tipping occurs when rapid rates of change in a variable, such as climate-related risk, trigger sudden shocks in socio-economic systems (Rye, 2023). The cascading nature of SETPs, in which a small change in underlying indicators triggers a large, non-linear response in the social system, are of heightened importance under climate change. SETPs may be either positive or negative as a new normal is entered in the system of interest. Examples range from the 2008 financial crisis driven by liquidity risk, to human migration from areas of intense sea-level rise driven by physical climate risk. In the case of insurance, climate-induced new normals occur when climate risks become so geographically concentrated that the risk of underwriting those areas is no longer economical.

Gradual adaptation efforts are insufficient for wide-scale systemic change associated with rate-induced SETPs. If alternative adaptation options are unavailable, individuals confront adaptive limits or maladaptation. Adaptive limits are thresholds within socio-economic systems at which assets or objectives are no longer attainable through adaptive action (Dow et al., 2013). For instance, in scenarios where traditional flood mitigation measures encounter socio-economic barriers (e.g., social resistance or financial constraints), communities, whether residents or entire businesses, may opt for migration from vulnerable regions. Insurance markets are vulnerable to rate-induced SETPs, where rapid changes can result in market dislocation and pose challenges for insurers. Incorporating rates of change and socio-economic adaptation limits into insurance decision-making processes can enhance climate change risk management (Rye, 2023).

4.1 WILDFIRES LEAD TO A COLLAPSE IN RESIDENTIAL INSURANCE IN CALIFORNIA

The results in Section 3.1 imply that indicators of wildfire—specifically environmental aridity, precipitation and evapotranspiration, and area burned by wildfire—may increase in severity over the next century. It is anticipated that there will be several implications for the California insurance market. The deadliest wildfire in Californian history, the 2018 Camp Fire, resulted in over $12 billion in claims from homeowners and businesses (CA Department of Insurance, 2019). A collapse in the insurance market for wildfires in California could occur if wildfires become so prevalent that insurers become insolvent, coverage becomes unavailable or unaffordable through the private market, and/or the California FAIR plan becomes overwhelmed while population continues to increase. Key indicators of a SETP in the residential insurance market due to wildfires include increased exposed housing value, decreased the amount of state-licensed carriers operating (i.e., admitted market share), rising average premiums, and a decrease in the coverage-to-values ratio (Dixon et al., 2018). While these indicators may still occur without a new wildfire regime, the industry's ability to adapt to the sudden rate of physical change heightens the likelihood of rate-induced SETPs.

Figure 4.1
WILDFIRE REGIME SHIFT AND RESULTING IMPACT PATHWAY



(Williams et al., 2020), (Cook et al., 2009), (Guan et al., 2024), (L. Dixon et al., 2018), and (Bryant and Westerling, 2014).

4.1.1 Identifying an Insurability Regime Shift

Increased Exposed Housing Value

As wildfire regimes intensify, the increased frequency and severity of fires pose a significant threat to residential properties, thereby escalating the value of exposed housing (Dixon et al., 2018). This indicator highlights the escalation of financial exposure within the residential insurance market, signaling a greater potential for substantial losses in the event of a catastrophe. Currently, an estimated 1.2 million homes with a reconstruction value of over $760 billion are at moderate or high risk of wildfire damage (CoreLogic, 2023). As the value of insured properties rises, insurers face heightened liability and must prepare to cover larger claims, thereby impacting their financial stability and risk management strategies.

Decreased Admitted Market Share

Heightened competition among insurers coupled with the increasing unpredictability of wildfire events may lead to a decline in admitted market share (Dixon et al., 2018). Additionally, as insurers reassess their risk appetites and underwriting criteria in the face of evolving wildfire regimes, some may opt to reduce their exposure to high-risk areas, thereby diminishing their presence in the market. Dixon and coauthors found that, by 2055, the market share of admitted insurers will decrease by an average of five percentage points in the ZIP codes with the most elevated fire risk (2018). This trend may stem from several factors, including the inability to retain required premium increases, changing consumer preferences, or unfavorable market conditions.

Higher Rates of Non-Renewal

Increasing rates of non-renewal suggest a growing reluctance among insurers to continue coverage for existing policies within wildfire prone areas. This may result from heightened risk perceptions, adverse loss experiences, or shifts in underwriting criteria. Currently, areas of high wildfire risk in California are facing elevated rates of policy nonrenewal (Dixon et al., 2018). Non-renewals can disrupt policyholders' continuity of coverage and indicate challenges in managing risk accumulation within certain geographic areas or property types.

Rising Average Premiums
The upward trend in average premiums for residential properties following increasing frequency and severity of wildfire events impacts the affordability and accessibility for policyholders, particularly those residing in wildfire-prone regions. In ZIP codes with the highest wildfire exposure, the rate per $1,000 of the rate in the admitted market is projected to rise by 18% from 2017 to 2055 (Dixon et al., 2018). Insurers may adjust premiums in response to evolving risk exposures, regulatory requirements, or market dynamics, potentially leading to financial strain for homeowners and reduced demand for insurance products.

Decrease in Coverage-to-Values Ratio
A reduction in the coverage-to-values ratio in wildfire prone regions of California signifies a diminishing level of insurance protection relative to the value of insured properties. In these areas, the ratio of coverage to property value is projected to decrease by 6.5%, while the deductible is anticipated to rise by $121 (Dixon et al., 2018). This may result from inadequate coverage limits, policy exclusions, or underinsurance, leaving policyholders vulnerable to significant financial losses in a disaster. A lower coverage-to-values ratio underscores the importance of ensuring adequate insurance coverage to mitigate the potential impact of property damage or loss.

4.1.2 Identifying a Residential Housing Collapse

A lack of insurance leading to stranded assets in California could trigger a housing crisis, where homeowners' policies cannot be paid out due to insolvencies, and obtaining insurance or mortgage financing becomes challenging. Key indicators of such a scenario include population increases coupled with the inability for residual insurance market to cover losses.

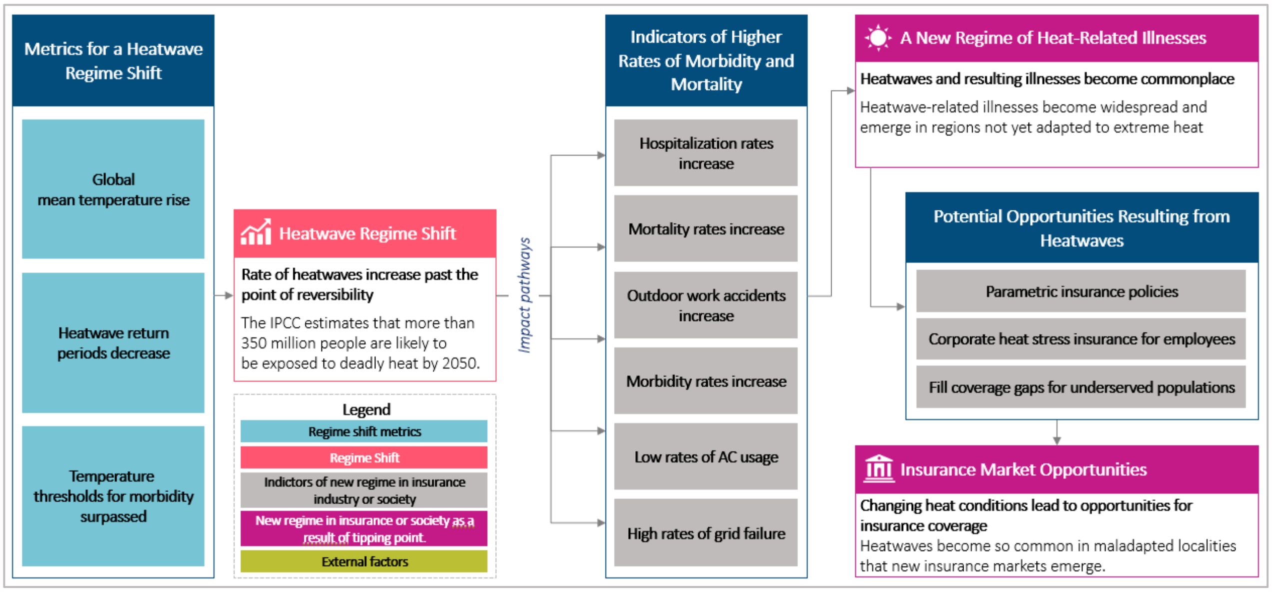
Population Increases
Population increases in wildfire-prone areas serve as a warning sign for asset stranding of residential properties in California. As the population grows in these high-risk zones, there is a corresponding expansion of urban development into wildfire-vulnerable areas, increasing the exposure of residential properties to wildfire hazards. The influx of residents amplifies the demand for housing, leading to the construction of homes in previously uninhabited or underdeveloped regions, often characterized by dense vegetation and proximity to forested areas. Consequently, the heightened human presence in these wildfire-prone landscapes exacerbates the risk of property damage and loss in the event of wildfires, potentially resulting in asset stranding as homes become increasingly vulnerable to destruction.

California's Residual Insurance Market (FAIR plan) Becomes Overwhelmed
When the private insurance market becomes unavailable, residents may lean on California's residual insurance market, otherwise known as the FAIR plan. The FAIR plan offers insurance in areas that are highly exposed to wildfires or earthquakes. It is considered a "last resort" option and requires residents to apply for private insurance first if it is available. Even still, the number of policies issued by the FAIR plan have more than doubled, and premiums have increased more than 145% from 2017 to 2024 (Sumagaysay, 2024). If areas of California enter a riskier wildfire regime, California may place the burden of increased losses on the taxpayer, or worse, residents may choose to be uninsured or move away. A new wildfire regime could lead to properties being so risky that they become uninsurable stranded assets.

4.2 HEATWAVES RESULT IN AN UNPRECEDENTED REGIME OF HEAT-RELATED ILLNESS

Our findings in Section 3.2 suggest that, under a high emissions scenario, an abrupt change to a new stable state in heat-related morbidity may occur in the late 2040s. With more than 350 million people globally likely to be exposed to deadly heat by 2050 (Hoegh-Guldberg et al., 2018), the impacts of heatwaves on morbidity and mortality are expected to be widespread. Insurers may be faced with a unique opportunity to provide innovative solutions for coverage to populations without previous exposure to high heat. Monitoring indicators of higher rates of morbidity and mortality is a prudential risk management practice. Key indicators include increased hospitalization rates, mortality rates, outdoor work accidents, morbidity rates, low rates of air conditioning usage, and high rates of grid failure (Bunker et al., 2016; Kelly, 2023; Gao et al., 2017; Stone et al., 2021).

Figure 4.2
HEATWAVE REGIME SHIFT AND RESULTING IMPACT PATHWAY



(Hoegh-Guldberg, 2018), (Chen et al., 2024), (Khan, 2024), (Bunker et al., 2016), (Stone et al., 2021), and (Kelly, 2023).

4.2.1 Identifying a Regime of Heat-Induced Morbidity

Increased Hospitalization Rates
Rising hospitalization rates due to heat-related illnesses serve as a critical indicator of the escalating health impacts of heatwaves (EPA, 2023). As more individuals require medical treatment for heat-related conditions, healthcare systems face increased strain and healthcare costs surge (Wondmaggen et al., 2019). Insurers monitoring hospitalization rates can better assess the severity of heatwave impacts and anticipate potential spikes in insurance claims, allowing for proactive risk management and resource allocation.

Mortality Rates
Elevated mortality rates during heatwaves signify the severity of heat-related health risks and the potential for loss of life within affected populations. Insurers tracking mortality rates can gauge the magnitude of heatwave impacts on population health and mortality risk, informing underwriting decisions and pricing strategies for life and health insurance products. Additionally, insurers can collaborate with public health authorities to implement preventive measures and interventions aimed at reducing heat-related mortality and enhancing community resilience to extreme heat events.

Outdoor Work Accidents
An increase in outdoor work accidents during heatwaves underscores the occupational hazards posed by extreme heat conditions. Insurers monitoring trends in outdoor work accidents can assess the impact of heatwaves on workforce health and safety, particularly in sectors with high outdoor activity levels such as construction, agriculture, and transportation. By identifying hotspots of occupational risk and implementing

risk mitigation measures, insurers can support policyholders in reducing workplace injuries and liabilities associated with heat-related accidents.

Morbidity Rates
Elevated heat-related morbidity rates, indicating a rise in non-fatal heat-related illnesses, reflect the broader health burden imposed by heatwaves on affected populations. Insurers tracking morbidity rates can gain insights into the prevalence and severity of heat-related health conditions, informing the design of insurance products and services that address emerging healthcare needs. By collaborating with healthcare providers and offering innovative health insurance solutions, insurers can help mitigate the financial impact of heat-related morbidity on individuals and healthcare systems.

Low Rates of Air Conditioning Usage
Low rates of air conditioning (AC) usage during heatwaves highlight disparities in access to cooling technologies and the potential for heat-related health risks among vulnerable populations (Romitti et al., 2022). Insurers monitoring AC usage patterns can identify areas with inadequate cooling infrastructure and populations at heightened risk of heat-related illnesses, facilitating targeted interventions to improve access to cooling solutions and enhance community resilience. By incentivizing investments in energy-efficient AC systems and promoting climate adaptation measures, insurers can contribute to reducing heat-related health disparities and strengthening societal preparedness for extreme heat events.

High Rates of Grid Failure
High rates of grid failure during heatwaves signify challenges in maintaining reliable electricity supply and infrastructure resilience under extreme weather conditions. Insurers monitoring grid failure incidents can assess the susceptibility of power systems to heat-induced disruptions and evaluate the associated risks to insured properties and businesses. By incorporating grid resilience considerations into risk assessment models and insurance coverage options, insurers can help policyholders mitigate the financial impact of power outages and support investments in grid modernization and climate adaptation measures aimed at enhancing energy system reliability and resilience.

4.2.2 Identifying Heat-Related Opportunities for Insurers

Parametric Insurance
Under changing heat conditions, insurers can introduce parametric insurance policies tailored to mitigate the financial impact of heatwaves on various stakeholders. Parametric insurance, based on predefined triggers such as temperature thresholds, allows for swift claims processing without the need for lengthy loss assessments, providing policyholders with timely payouts to cover heat-related losses. For example, in 2022, a life insurance company in Japan started offering heatstroke insurance that covers hospitalizations and medical costs (Kohyama, 2022). By 2023, the company had sold over 60,000 policies (Clark and Uranaka, 2023). By offering parametric insurance solutions, insurers can enhance their capacity to respond effectively to the increasing frequency and severity of heatwaves, thereby improving risk transfer mechanisms and bolstering resilience against climate-related risks.

New Markets
Insurers can explore the development of corporate heat stress insurance tailored to address the occupational health risks posed by extreme heat exposure in the workplace. Corporate heat stress insurance offers coverage for medical expenses, income protection, and rehabilitation services for employees affected by heat-related illnesses or injuries. Additionally, future markets in corporate heat stress insurance may include parametric insurance, which could offer payouts to companies in the face of a disruption due to a heatwave. For example, parametric insurance could cover the losses faced by a construction company due to delays from extreme heat. By partnering with employers to implement heat

stress prevention measures and provide comprehensive insurance coverage, insurers can mitigate liability risks, safeguard workforce well-being, and promote sustainable business practices in the face of rising temperatures and heatwave hazards.

Coverage Gaps

There is also opportunity to address coverage gaps and expand access to insurance protection for underserved populations vulnerable to heat-related risks. By designing innovative insurance products tailored to the specific needs and vulnerabilities of marginalized communities, insurers can contribute to reducing disparities in insurance coverage and enhancing social equity in climate resilience. Though addressing coverage gaps may present challenges to the insurance industry. First, heatwaves are volatile and can be unexpected, which means losses could be significant if modeled incorrectly. Pricing policies for the uninsured can also be challenging, because uninsured populations may present a different set of risk factors and current claims data used for pricing does not include uninsured populations. Nonetheless, initiatives such as microinsurance schemes, community-based risk pooling, and targeted outreach programs can empower underserved populations to manage heatwave risks effectively and build resilience against climate-induced shocks, fostering inclusive and sustainable insurance markets in the context of evolving heat conditions.

Section 5: Conclusion

5.1 CONCLUDING REMARKS

The goal of this study was to provide a framework for identifying regime shifts in the climate system that are relevant to traditional actuarial modeling and discuss the qualitative impacts of regime shifts on the insurance industry. Regime shifts, or on longer timescales, “tipping points,” result from an abrupt change in a system to a new, stable, fundamentally different state. Global warming may cause regime shifts in the physical and socioeconomic system that are impactful to insurers. This study outlined a methodology and examples of identifying regime shifts in the physical climate system that may be relevant to insurers. By using publicly available data and straightforward statistics, insurers may replicate a similar analysis for their own business purposes to prepare for a potentially impactful regime shift.

This study also highlighted the challenge in identifying potential regime shifts. Regime shifts that may be impactful to insurers can occur in a variety of domains, both physical and socioeconomic, and isolating their timing is contingent on data availability. Depending on the system, the timing of a regime shift may be easily identifiable or may require a multi-model ensemble to confidently identify. Defining the scope of the system involved in the regime shift is paramount in the decision-making in extracting actionable insights from data.

5.2 LIMITATIONS

There are some limitations to the techniques proposed in this study. First, the availability of publicly available data that is useful for insurers may be limited. The data from physical climate models used in this study were accessed through public websites but required pre-processing and some coding expertise to conduct analysis. The scenarios analyzed were chosen based on data availability. Other physical climate data may be large and require substantial computational resources to analyze. Likewise, socioeconomic data can be sparse. For regime-shift analysis, extensive data is required to detect statistically significant changes. If the data used in this study had more temporal coverage, the results may change.

Additionally, the use of model projection data comes with its own uncertainties. Projections of socioeconomic data, from Integrated Assessment Models, for example, are made with a diverse set of assumptions that should be considered before developing actionable insights. Similarly, physical climate models are often biased, show spread in projections, or have unresolved dynamical processes that could impact representations of the future climate. At the very least, climate models’ projections should be bias-corrected to match historical climate observations. It is recommend analyzing multiple climate models to build a distribution of potential regime shifts before interpreting results.

Last, the identification of regime shifts in climate data through statistical analysis has been widely studied, but the identification of tipping points through statistical analysis is an emerging field of research. The assumptions presented in this study are novel. This study followed the approach of van Ginkel et al. (2022) to locate tipping points statistically, though like other tipping point identification studies, these authors additionally employ models to validate their results. Thus, validation of the methods used in this study requires future research.

5.3 FUTURE RESEARCH

5.3.1 MODELING TO LINK THE PHYSICAL CLIMATE TO IMPACTS TO INSURERS

This study quantitatively identified the timing of potential regime shifts in the physical climate system, and then qualitatively drew links to potential regime shifts relevant to the insurance industry through impact pathways. Instead, insurers may choose to quantify the impact of the regime shift on the insurance industry by modeling the link between the physical climate system and the societal or insurance impact. For example, one may quantify the link between a change in each of the statistical criterion in Table 2.1 in Section 2.4 and a change in an insurance-related metric using historical observations. For example, as part of California's Fourth Climate Change Assessment, Dixon et al. (2018) quantified the impact of wildfires on residential insurance policies by building a model that included demographic data. Modeling the link between the physical climate system and the impact to insurers is the next natural step in applying the methods laid out in this study.

5.3.2 KEY OPPORTUNITIES: NEW PRODUCTS AND MARKETS

SETPs present insurers with an opportunity to innovate and develop new products. Parametric insurance policies tailored to emerging climate risks are a prime example. Parametric insurance, which pays out based on predefined triggers such as temperature thresholds or precipitation levels, can provide rapid and transparent compensation to policyholders affected by climate-related events. By leveraging parametric insurance, insurers can enhance their responsiveness to changing risk landscapes and offer innovative solutions that meet the evolving needs of businesses and individuals facing climate-induced challenges.

There is also the opportunity for insurers to expand into new markets. As traditional risk profiles shift and previously uninsurable assets become vulnerable to climate-related risks, insurers can capitalize on this growing demand for coverage. By diversifying their portfolios and exploring opportunities in regions susceptible to climate impacts, insurers can tap into new revenue streams and broaden their market reach. Additionally, by offering specialized products tailored to the unique needs of emerging markets, insurers can strengthen their competitive position and establish themselves as leaders in climate risk management.

Innovative risk transfer mechanisms provide another opportunity for effective risk management. Insurers can play a pivotal role in developing and implementing novel risk transfer solutions, such as resilience bonds or catastrophe bonds, which enable governments, businesses, and communities to transfer climate-related risks to the financial markets. By facilitating the transfer of risk from vulnerable entities to investors willing to assume it, insurers can foster resilience-building efforts and contribute to the sustainable management of climate risks at both local and global scales. Such risk transfer mechanisms not only provide financial protection but also incentivize investments in climate adaptation and mitigation measures, enhancing resilience to climate-induced shocks.

Section 6: Acknowledgments

The researchers' deepest gratitude goes to those without whose efforts this project could not have come to fruition: the Project Oversight Group for their diligent work overseeing, reviewing and editing this report for accuracy and relevance.

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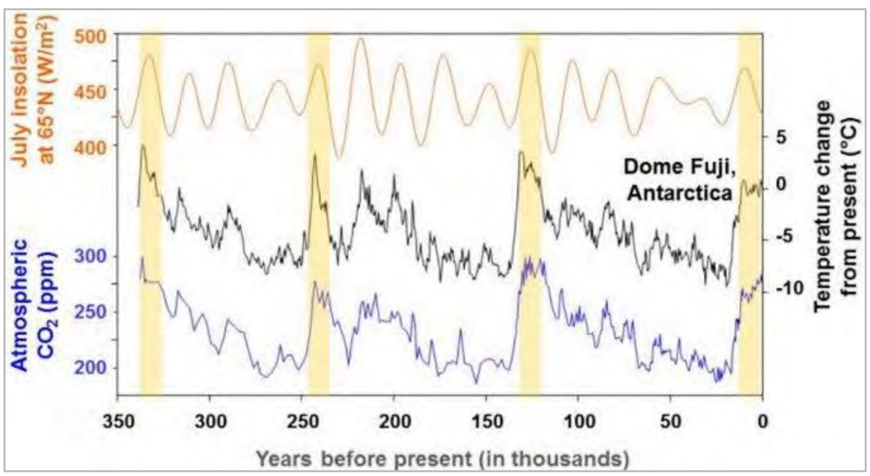
Appendix A: Regime Shifts in the Climate System

Regime shifts and tipping points represent distinct yet interconnected concepts within the context of complex systems dynamics. Regime shifts are large sudden changes in systems and may precede or indicate a tipping point, or otherwise indicate oscillations between two steady-states, or regimes. These shifts can occur within the broader framework of a system's dynamics, encompassing a range of interacting components and feedback mechanisms. In contrast, tipping points often involve uncertainties regarding system boundaries, as the precise thresholds for triggering irreversible changes may be challenging to define with certainty. Moreover, the dynamics leading to tipping points can be influenced by several factors, including external forcings, feedback loops, and system resilience. Therefore, understanding the interplay between regime shifts and tipping points requires careful consideration of system boundaries and uncertainties inherent in complex systems dynamics.

Deglaciation events are tipping points identifiable on a relatively small timescale (~10,000 years). When observed on a longer timescale (~100,000 years), these deglaciation events are a small piece of larger glacial-interglacial cycles. While the system enters a new steady state within a shorter reference frame, the state reverses on a longer timescale.

Figure A.1

REGIME SHIFTS AND TIPPING POINTS



Tipping points are identified by analyzing the cycle of regime shifts on a smaller reference frame, highlighted in yellow (NOAA NCEI, 2021).

Appendix B: Physical Climate Scenarios Used in this Study

Physical IPCC scenarios used in this study include RCP4.5, RCP8.5, SSP1-2.6, and SSP5-8.5.

Representative Concentration Pathways, or RCP scenarios, describe futures with various levels of radiative forcing from greenhouse gas emissions concentrations, including carbon dioxide. For example, the RCP4.5 scenario is used as a “middle-of-the-road” or moderate emissions scenario, when the total amount of radiative imbalance (i.e., “forcing”) from greenhouse gases is 4.5 watts/meters squared, leading to a moderate amount of trapped heat and resulting warming. Likewise, RCP8.5 is considered the “business-as-usual” or high emissions scenario, where no concerted effort is made to lower anthropogenic greenhouse gas emissions, and the resulting global radiative forcing is 8.5 watts/meters squared, and global mean warming increases by at least 4°C. The Cal-Adapt research initiative utilized moderate and high emissions RCP forcing scenarios for their projections of wildfire-related metrics over California.

Shared Socioeconomic Pathways, or SSP scenarios, on the other hand, assume both changes in emissions levels as well as socioeconomic drivers, such as changes in climate policy, population growth, land use, and economic disparity (Mason-Delmotte et al., 2021). In this case, SSP1-2.6 is considered a future with low emissions/”Taking the Green Road,” while SSP5-8.5 is considered high emissions/”Taking the Highway.” Most global, publicly available climate model data, including the data used to derive the heat-related morbidity metric used in this study, is provided under the SSP scenarios.

Appendix C: Using Lag-1 Autocorrelation to Identify Abrupt Shifts

Lag-1 autocorrelation is the correlation between values within each selected window that are one time step apart. Mathematically, the lag-1 autocorrelation is defined as

$$\rho_{X_{w1},X_{w2}} = corr(X_{w1}, X_{w2}) = \frac{cov(X_{w1}, X_{w2})}{std(X_{w1}) * std(X_{w2})}$$

Where

$$cov(X_{w1}, X_{w2}) = \frac{\sum_{i=0}^{n}(X_{w1,i} - \overline{X_{w1}})(X_{w2,i} - \overline{X_{w2}})}{n-1}$$

and

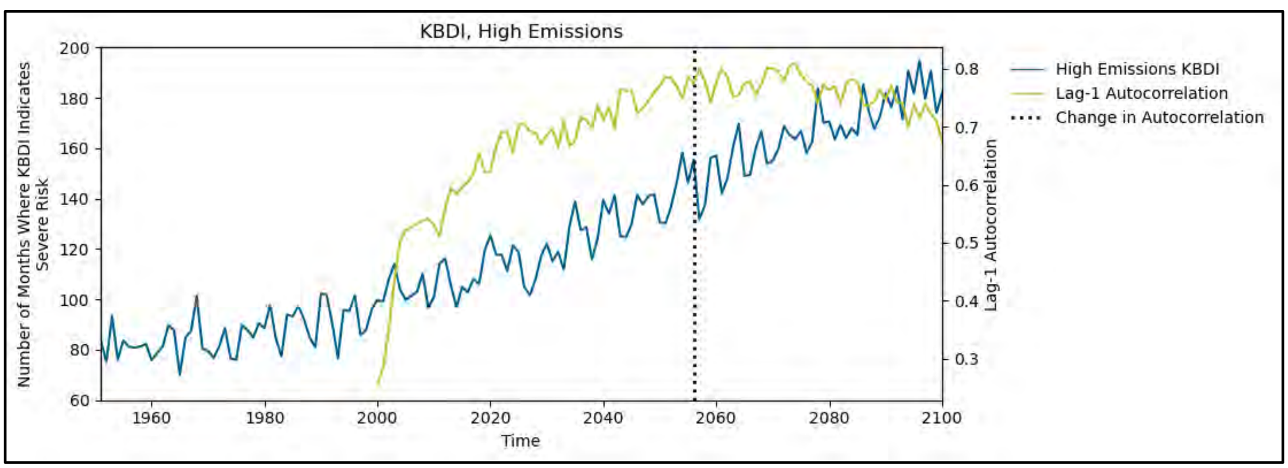
$$std(X) = \sigma_X = \sqrt{\frac{\sum_{i=0}^{n}(X_i - \bar{X})^2}{n-1}}$$

The size of the window is represented by n. $w1$ and $w2$ refers to windows 1 and windows 2, respectively. For example, the first two windows over which the lag-1 autocorrelation is calculated cover the following indices: $w1_{\mathrm{i}} = 1,\ \mathrm{n}$ and $w2_i = 2,\ \mathrm{n}+1$.

The lag-1 autocorrelation is often used to describe the persistence of the timeseries, the "memory" of the system, or how much correlation exists across time. If two periods of time have a high correlation, then the timing and magnitude of fluctuations are very similar between the two periods. In the case of autocorrelation, one may think of a timeseries slowing down and starting to follow a very regular cadence.

Following the theory by Dakos et al. (2012, 2015), this study leverages a positive-to-negative change in the trend of lag-1 autocorrelation to look for abrupt changes in timeseries (criterion 1 listed in section 2.4; van Ginkel et al., 2022). Dakos et al. (2015) state that a "critical slowing down" of the system, equivalent to an increase in persistence, or an increase in autocorrelation, occurs prior to an abrupt change in the system. The example below, illustrates the identification of a positive-to-negative change in the trend of autocorrelation in the projections of KBDI under a high emissions scenario.

Figure C.1
KBDI AUTOCORRELATION TREND PROJECTIONS



Timeseries showing the number of days in which the KBDI indicates severe drought risk under a high emissions scenario (blue line) with the lag-1 autocorrelation (green line) evaluated over the previous 50 years. A change from a positive trend in autocorrelation to a negative trend in autocorrelation is indicated by the black, vertical dotted line.

A positive-to-negative change in the trend of the autocorrelation is detected at year 2056, indicated by the black dotted vertical line in Figure C.1. This is noticeable by the steady increase in lag-1 autocorrelation followed by a steady decrease in autocorrelation illustrated in the solid green line. A closer look at the underlying KBDI timeseries shows regular, slow fluctuations, corresponding to an increase in autocorrelation, followed by more frequent, random fluctuations, corresponding to a decrease in autocorrelation.

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