Future Climate Projections
Umatilla County

October 2020

A Report to the Oregon Department of Land Conservation and Development

Prepared by
The Oregon Climate Change Research Institute

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OCCRI DLCD

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A report to the Oregon Department of Land Conservation and Development

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Executive Summary

Climate change is expected to increase the occurrence of most climate-related natural hazards. This report addresses how climate change is expected to influence eleven climate-related natural hazards or risks categorized with very high, high, medium, and low confidence levels.

The risks of heat waves are projected to increase with very high confidence due to strong evidence in published literature, model consensus, and robust theoretical principles for continued increasing temperatures. The majority of risks expected to increase with climate change have high or medium confidence due to moderate to strong evidence and consensus, yet they are influenced by multiple secondary factors in addition to increasing temperatures. Risks with low confidence, while important, show relatively little to no changes due to climate change or the level of evidence is limited. The projected direction of change, along with the level of confidence in the direction of change for each climate change-related natural hazard or risk, is summarized in Table 1. The full report describes the projected changes for each climate metric representing the natural hazard (see Table 2).

Table 1 Summary of projected direction of change along with the level of confidence in climate change-related risk of natural hazard occurrence. Very high confidence means all models agree on the direction of change and there is strong evidence in the published literature. High confidence means most models agree on the direction of change and there is strong to medium evidence in the published literature. Medium confidence means that there is medium evidence and consensus on the direction of change with some caveats. Low confidence means the direction of change is small compared to the range of model responses or there is limited evidence in the published literature.

	Low Confidence	Medium Confidence	High Confidence	Very High Confidence
Risk Increasing ↑	Poor Air Quality	Drought Increased Invasive Species Risk	Heavy Rains Flooding Wildfire Loss of Wetland Ecosystems	Heat Waves
Risk Unchanging =	Windstorms			
Risk Decreasing ↓	Dust Storms			Cold Waves

This report presents future climate projections for Umatilla County relevant to specific natural hazards for the 2020s (2010–2039 average) and 2050s (2040–2069 average) relative to the 1971–2000 average historical baseline. The projections were analyzed for a lower greenhouse gas emissions scenario as well as a higher greenhouse gas emissions scenario, using multiple global climate models. This Executive Summary lists only the projections for the 2050s under the higher emissions scenario. Projections for both time periods and both emissions scenarios can be found within relevant sections of the main report.

Heat Waves

Extreme heat events are expected to increase in frequency, duration, and intensity due to continued warming temperatures.

In Umatilla County, the frequency of hot days per year with temperatures at or above 90°F is projected to increase on average by 29 days, with a range of about 11 to 41 days, by the 2050s under the higher emissions scenario relative to the historical baselines. This average increase represents a more than doubling of hot days relative to the average historical baseline.

In Umatilla County, the temperature of the hottest day of the year is projected to increase on average by nearly 8°F, with a range of about 3 to 11°F, by the 2050s under the higher emissions scenario relative to the historical baselines.

Cold Waves

Cold extremes are still expected to occur from time to time, but with much less frequency and intensity as the climate warms.

In Umatilla County, the frequency of cold days per year at or below freezing is projected to decrease on average by 11 days, with a range of about 5 to 17 days, by the 2050s under the higher emissions scenario relative to the historical baselines. This average decrease represents a future with a little more than half as many cold days per year as in the average historical baseline.

In Umatilla County, the temperature of the coldest night of the year is projected to increase on average by about 9°F, with a range of about 0 to 17°F, by the 2050s under the higher emissions scenario relative to the historical baselines.

Heavy Rains

The intensity of extreme precipitation events is expected to increase in the future as the atmosphere warms and is able to hold more water vapor.

In Umatilla County, the frequency of days with at least ¾" of precipitation is not projected to change substantially. However, the magnitude of precipitation on the wettest day and wettest consecutive five days per year is projected to increase on average by about 19% (with a range of 7% to 39%) and 14% (with a range of -1% to 32%), respectively, by the 2050s under the higher emissions scenario relative to the historical baselines.

In Umatilla County, the frequency of days exceeding a threshold for landslide risk, based on 3-day and 15-day precipitation accumulation, is not projected to change substantially. However, landslide risk depends on a variety of factors and this metric may not reflect all aspects of the hazard.

River Flooding

Mid- to low-elevation areas in Umatilla County's Blue Mountains that are near the freezing level in winter, receiving a mix of rain and snow, are projected to experience an increase in winter flood risk due to warmer winter temperatures causing precipitation to fall more as rain and less as snow.

Drought

Drought conditions, as represented by low summer soil moisture, low spring snowpack, low summer runoff, and low summer precipitation are projected to become more frequent in Umatilla County by the 2050s relative to the historical baseline.

By the end of the 21st century, summer low flows are projected to decrease in the Blue Mountains region putting some sub-basins at high risk for summer water shortage associated with low streamflow.

Wildfire

Wildfire risk, as expressed through the frequency of very high fire danger days, is projected to increase under future climate change. In Umatilla County, the frequency of very high fire danger days per year is projected to increase on average by about 40% (with a range of -14 to +101%) by the 2050s under the higher emissions scenario compared to the historical baseline.

Air Quality

Under future climate change, the risk of wildfire smoke exposure is projected to increase in Umatilla County. The number of "smoke wave" days—days with high concentrations of wildfire-specific particulate matter—is projected to increase by 141% and the intensity of "smoke waves" is projected to increase by 82% by 2046–2051 under a medium emissions scenario compared with 2004–2009.

Windstorms

Limited research suggests very little, if any, change in the frequency and intensity of windstorms in the Pacific Northwest as a result of climate change.

Dust Storms

Limited research suggests that the risk of dust storms in summer would decrease in eastern Oregon under climate change in areas that experience an increase in vegetation cover from the carbon dioxide fertilization effect.

Increased Invasive Species Risk

Warming temperatures, altered precipitation patterns, and increasing atmospheric carbon dioxide levels increase the risk for invasive species, insect and plant pests for forest and rangeland vegetation, and cropping systems.

Loss of Wetland Ecosystems

Freshwater wetland ecosystems are sensitive to warming temperatures and altered hydrological patterns, such as changes in precipitation seasonality and reduction of snowpack.

Introduction

Industrialization has given rise to increasing amounts of greenhouse gas emissions worldwide, which is causing the Earth's climate to warm (IPCC, 2013). The effects of which are already apparent here in Oregon (Dalton *et al.*, 2017; Mote *et al.*, 2019). Climate change is expected to influence the likelihood of occurrence of existing natural hazard events such as heavy rains, river flooding, drought, heat waves, cold waves, wildfire, air quality, and coastal erosion and flooding.

Oregon's Department of Land Conservation and Development (DLCD) contracted with the Oregon Climate Change Research Institute (OCCRI) to perform and provide analysis of the influence of climate change on natural hazards. The geographic scope of this analysis is Umatilla County. This report is funded through the Hazard Mitigation Grant Program (HMGP) grant that DLCD received from FEMA. Outcomes of this analysis include county-specific data, graphics, and text summarizing climate change projections for climate metrics related to each of the natural hazards listed in Table 2. This information will be integrated into the Natural Hazards Mitigation Plan (NHMP) updates for Umatilla County, and can be used in other county plans, policies, and programs. In addition to the county reports, sharing of data, and other technical assistance will be provided to the counties. This report covers climate change projections related to natural hazards within Umatilla County.

Table 2 Natural hazards and related climate metrics evaluated in this project.

Heavy Rains Wettest Day ⬩Wettest Five Days Landslide Threshold Exceedance	**Heat Waves** Hottest Day ⬩Warmest Night "Hot" Days ⬩"Warm" Nights
River Flooding Annual maximum daily flows Atmospheric Rivers Rain-on-Snow Events	**Cold Waves** Coldest Day ⬩Coldest Night "Cold" Days ⬩"Cold" Nights
Drought Summer Flow ⬩Spring Snow Summer Soil Moisture Summer Precipitation	**Air Quality** Unhealthy Smoke Days
Wildfire Fire Danger Days	**Dust Storms**
Windstorms	**Loss of Wetland Ecosystems**
Increased Invasive Species Risk	

Future Climate Projections Background

Introduction

The county-specific future climate projections prepared by OCCRI are derived from 10–20 global climate models (GCM) and two scenarios of future global greenhouse gas emissions. Future climate projections have been "downscaled"—that is, made locally relevant—and summaries of projected changes in the climate metrics in Table 2 are presented for an early 21st century period and a mid 21st century period relative to a historical baseline. (Read more about the data sources in the Appendix.)

Global Climate Models

Global climate models are sophisticated computer models of the Earth's atmosphere, water, and land and how these components interact over time and space according to the fundamental laws of physics (Figure 1). GCMs are the most sophisticated tools for understanding the climate system, but while highly complex and built on solid physical principles, they are still simplifications of the actual climate system. There are several ways to implement such simplifications into a GCM, which results in each one giving a slightly different answer. As such, it is best practice to use at least ten GCMs and look at the average and range of projections across all of them. (Read more about GCMs and uncertainty in the Appendix.)

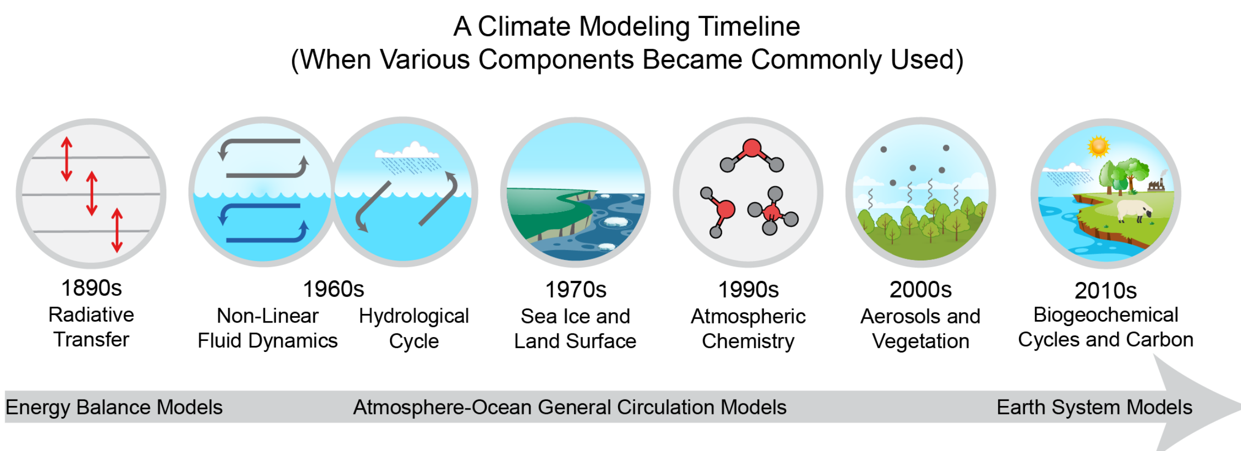

Figure 1 As scientific understanding of climate has evolved over the last 120 years, increasing amounts of physics, chemistry, and biology have been incorporated into calculations and, eventually, models. This figure shows when various processes and components of the climate system became regularly included in scientific understanding of global climate calculations and, over the second half of the century as computing resources became available, formalized in global climate models. (Source: science2017.globalchange.gov)

Greenhouse Gas Emissions

When used to project future climate, scientists give the GCMs information about the quantity of greenhouse gases that the world would emit, then the GCMs run simulations of what would happen to the air, water, and land over the next century. Since the precise amount of greenhouse gases the world will emit over the next century is unknown, scientists use several scenarios of different amounts of greenhouse gas emissions based on plausible societal trajectories. The future climate projections prepared by OCCRI uses emissions pathways called Representative

Concentration Pathways (RCPs). There are several RCPs and the higher global emissions are, the greater the expected increase in global temperature (Figure 2). OCCRI considers a lower emissions scenario (RCP 4.5) and a higher emissions scenario (RCP 8.5) because they are the most commonly used scenarios in published literature and the downscaled data is available for these scenarios. (Read more about emissions scenarios in the Appendix.)

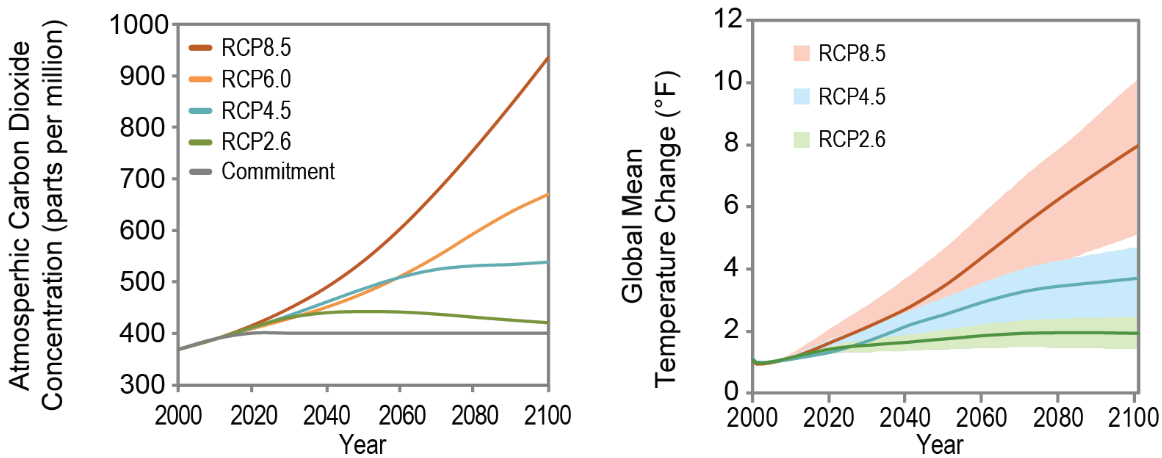

Figure 2 Future scenarios of atmospheric carbon dioxide concentrations (left) and global temperature change (right) resulting from several different emissions pathways, called Representative Concentration Pathways (RCPs), which are considered in the fourth and most recent National Climate Assessment. (Source: science2017.globalchange.gov)

Downscaling

Global climate models simulate the climate across adjacent grid boxes the size of about 60 by 60 miles. To make this coarse resolution information locally relevant, GCM outputs have been combined with historical observations to translate large-scale patterns into high-resolution projections. This process is called statistical downscaling. The future climate projections produced by OCCRI were statistically downscaled to a resolution with grid boxes the size of about 2.5 by 2.5 miles (Abatzoglou and Brown, 2012). (Read more about downscaling in the Appendix.)

Future Time Periods

When analyzing global climate model projections of future climate, it is best practice to compare the average across at least a 30-year period in the future simulations to an average across at least a 30-year period in the historical simulations. The average over a 30-year period in the historical simulations is called the *historical baseline*. For the future climate projections in this report, two 30-year future periods are analyzed in comparison with a 30-year historical baseline (Table 3).

Each of the twenty global climate models simulates historical and future climate slightly differently. Thus, each global climate model has a different historical baseline from which future projections are compared. Because each climate model's historical baseline is slightly different, this report presents the average and range of projected *changes* in the variables relative to each model's own historical baseline (rather than the average and range of future projected absolute values). The average of the twenty historical baselines, called the *average historical baseline*, is also presented to aid in understanding the relative magnitude of projected changes. The average historical baseline can be combined with the average projected future change to infer the average projected future absolute value of a given variable.

Table 3 Historical and future time periods for presentation of future climate projections

Historical Baseline	Early 21st Century "2020s"	Mid 21st Century "2050s"
1971–2000	2010–2039	2040–2069

How to Use the Information in this Report

Climate change may bring novel conditions that have not been encountered in communities in the recent past. Thus, anticipating future outcomes by considering only past trends and variability may become increasingly unreliable. Future projections from GCMs provide an opportunity to explore a range of plausible outcomes taking into consideration the climate system's complex response to increasing concentrations of greenhouse gases. Considering future projections alongside past trends or hazard events may provide additional insight when updating natural hazard mitigation plans and mitigation actions. It is important to be aware that GCM projections should not be thought of as predictions of what the weather will be like at some specified date in the future, but rather viewed as projections of the long-term statistical aggregate of weather, in other words, "climate", if greenhouse gas concentrations follow some specified trajectory.[1]

The projections of climate variables in this report, both in the direction and magnitude of change, are best used in reference to the historical climate conditions under which a particular asset or system is designed to operate. For this reason, considering the projected changes between the historical and future periods allows one to envision how current systems of interest would respond to climate conditions that are different from what they have been. In some cases, the projected change may be small enough to be accommodated within the existing system. In other cases, the projected change may be large enough to require adjustments, or adaptations, to the existing system. However, engineering or design projects would require a more detailed analysis than what is available in this report.

The information in this report can be used to:

- Explore a range of plausible future outcomes taking into considering the climate system's complex response to increasing greenhouse gases
- Envision how current systems may respond under climate conditions different from those the systems were designed to operate under
- Evaluate potential mitigation actions to accommodate future conditions
- Influence the risk assessment in terms of the likelihood of a particular climate-related hazard occurring.

[1] Read more: https://nca2014.globalchange.gov/report/appendices/faqs#narrative-page-38784

Average Temperature

Oregon's average temperature warmed at a rate of 2.2°F per century during 1895–2019 (National Centers for Environmental Information (NCEI), 2020). Average temperature is expected to continue warming during the 21st century under scenarios of continued global greenhouse gas emissions; the rate of warming depends on the particular emissions scenario (Dalton *et al.*, 2017). By the 2050s (2040–2069) relative to the 1970–1999 historical baseline, Oregon's average temperature is projected to increase by 3.6 °F with a range of 1.8°–5.4°F under a lower emissions scenario (RCP 4.5) and by 5.0°F with a range of 2.9°F–6.9°F under a higher emissions scenario (RCP 8.5) (Dalton *et al.*, 2017). Furthermore, summers are projected to warm more than other seasons (Dalton *et al.*, 2017).

Average temperature in Umatilla County is projected to warm during the 21st century at a similar rate to Oregon as a whole (Figure 3). Projected increases in average temperature in Umatilla County relative to each global climate model's 1971–2000 historical baseline range from 1.2–4.1°F by the 2020s (2010–2039) and 2.1–7.9°F by the 2050s (2040–2069), depending on emissions scenario and climate model (Table 4).

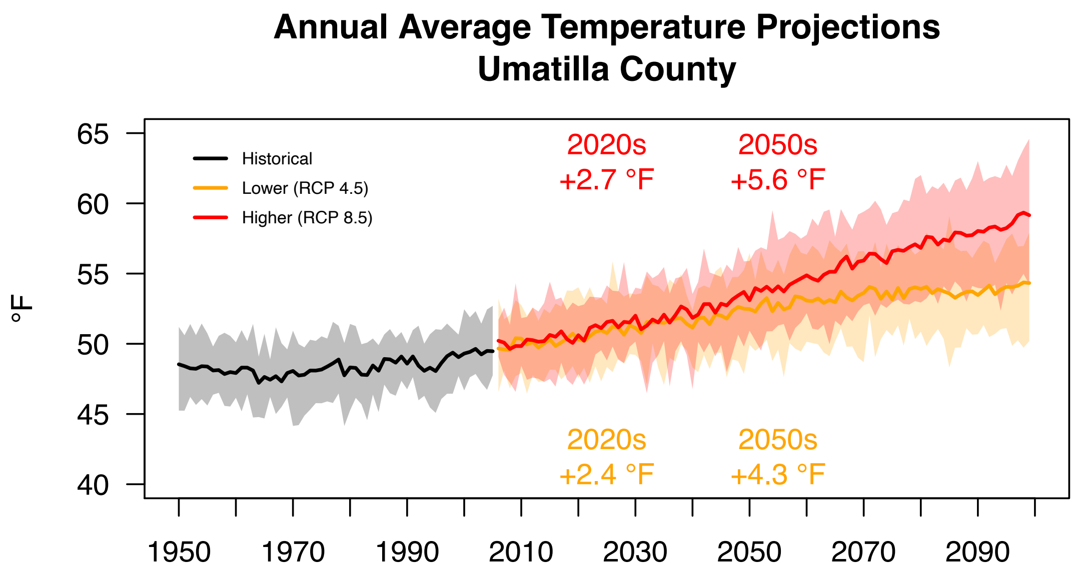

Figure 3 Annual average temperature projections for Umatilla County as simulated by 20 downscaled global climate models under a lower (RCP 4.5) and a higher (RCP 8.5) greenhouse gas emissions scenario. Solid line and shading depicts the 20-model mean and range, respectively. The multi-model mean differences for the 2020s (2010–2039 average) and the 2050s (2040–2069 average) relative to the average historical baseline (1971–2000 average) are shown.

Table 4 Average and range of projected future changes in Umatilla County's average temperature relative to each global climate model's (GCM) historical baseline (1971–2000 average) for the 2020s (2010–2039 average) and 2050s (2040–2069 average) under a lower (RCP 4.5) and higher (RCP 8.5) emissions scenario based on 20 GCMs.

	Change by Early 21st Century "2020s"	Change by Mid 21st Century "2050s"
Higher (RCP 8.5)	+2.7°F (1.6 to 3.9)	+5.6°F (3.0 to 7.5)
Lower (RCP 4.5)	+2.4°F (1.1 to 3.9)	+4.3°F (2.0 to 5.9)

Heat Waves

Extreme heat events are expected to increase in frequency, duration, and intensity in Oregon due to continued warming temperatures. In fact, the hottest days in summer are projected to warm more than the change in mean temperature over the Pacific Northwest (Dalton *et al.*, 2017). This report presents projected changes for three metrics of heat extremes for both daytime (maximum temperature) and nighttime (minimum temperature) (Table 5).

Table 5 Heat extreme metrics and definitions

Metric	Definition
Hot Days	Number of days per year maximum temperature is greater than or equal to 90°F
Warm Nights	Number of days per year minimum temperature is greater than or equal to 65°F
Hottest Day	Annual maximum of maximum temperature
Warmest Night	Annual maximum of minimum temperature
Daytime Heat Waves	Number of events per year with at least 3 consecutive days with maximum temperature greater than or equal to 90°F
Nighttime Heat Waves	Number of events per year with at least 3 consecutive days with minimum temperature greater than or equal to 65°F

In Umatilla County, all the extreme heat metrics in Table 5 are projected to increase by the 2020s (2010–2039) and 2050s (2040–2069) under both the lower (RCP 4.5) and higher (RCP 8.5) emissions scenarios (Table 6). For example, for the 2050s under the higher emissions scenario climate models project that the number of hot days greater than or equal to 90°F per year, relative to each model's 1971–2000 historical baseline, would increase by as little as 11 days to as much as 41 days. The average projected increase in the number of hot days per year is 29 days above the average historical baseline of 19 days. This represents a projected more than doubling in the frequency of hot days by the 2050s under the higher emissions scenario.

Likewise, the temperature of the hottest day of the year is projected to increase by as little as 2.9°F to as much as 11.3°F by the 2050s under the higher emissions scenario relative to the models' historical baselines. The average projected increase is 7.9°F above the average historical baseline of 96.8°F. The frequency of daytime heat waves is projected to double on average relative to the average historical baseline of nearly three events. In other words, hot days are projected to become more frequent and the hottest days are projected to become even hotter.

Projected changes in the frequency of extreme heat days (i.e., Hot Days and Warm Nights) are shown in Figure 4. Projected changes in the magnitude of heat records (i.e., Hottest Day and Warmest Night) are shown in Figure 5. Projected changes in the frequency of extreme heat events (i.e., Daytime Heat Waves and Nighttime Heat Waves) are shown in Figure 6.

Table 6 Mean and range of projected future changes in extreme heat metrics for Umatilla County relative to each global climate model's (GCM) historical baseline (1971–2000 average) for the 2020s (2010–2039 average) and 2050s (2040–2069 average) under a lower (RCP 4.5) and higher (RCP 8.5) emissions scenario based on 20 GCMs. The average historical baseline across the 20 GCMs is also presented and can be combined with the average projected future change to infer the average projected future absolute value of a given variable. However, the average historical baseline cannot be combined with the range of projected future changes to infer the range of projected future absolute values.

		Change by Early 21st Century "2020s"		Change by Mid 21st Century "2050s"	
	Average Historical Baseline	Lower	Higher	Lower	Higher
Hot Days	18.8 days	+10.7 days (3.5–17.1)	+12.6 days (4.4–17.6)	+20.6 days (7.4–30.8)	+29.2 days (10.8–40.7)
Warm Nights	3.2 days	+3.7 days (0.9–8.4)	+4.3 days (2.1–8.1)	+8.3 days (1.3–18.0)	+14.0 days (3.8–28.7)
Hottest Day	96.8°F	+3.3°F (0.7–5.0)	+3.8°F (1.1–5.4)	+5.9°F (2.2–8.4)	+7.9°F (2.9–11.3)
Warmest Night	65.2°F	+2.5°F (0.9–4.1)	+2.8°F (1.2–3.7)	+4.4°F (1.3–7.0)	+6.4°F (3.3–9.5)
Daytime Heat Waves	2.6 events	+1.1 events (0.5–1.7)	+1.3 events (0.7–1.8)	+1.9 events (1.1–3.1)	+2.3 events (1.3–3.8)
Nighttime Heat Waves	0.4 events	+0.5 events (0.1–1.0)	+0.6 events (0.3–0.9)	+1.1 events (0.1–2.3)	+1.7 events (0.3–3.2)

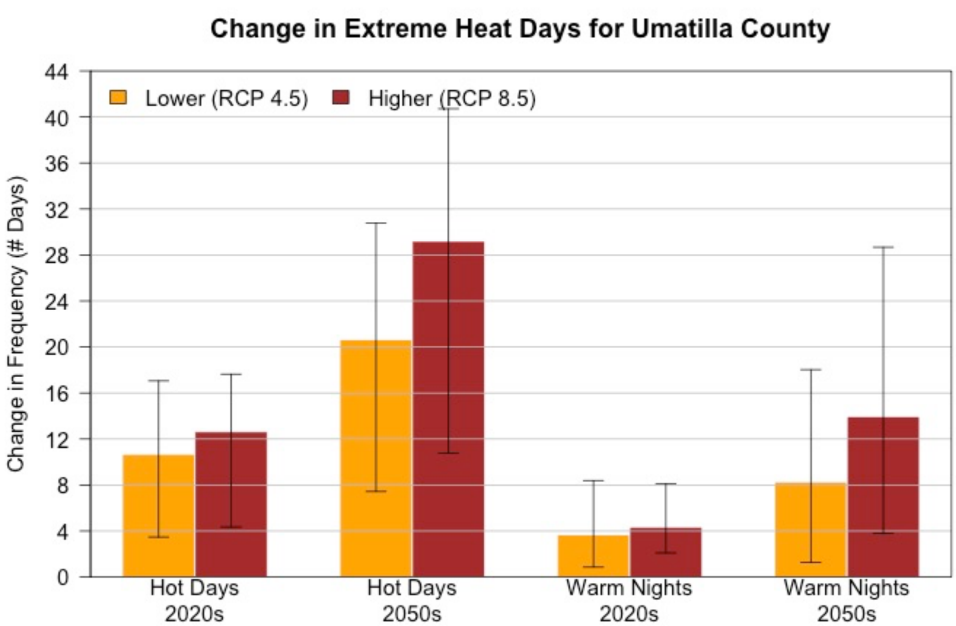

Figure 4 Projected future changes in the number of hot days (left two sets of bars) and number of warm nights (right two sets of bars) for Umatilla County relative to the historical baseline (1971–2000 average) for the 2020s (2010–2039 average) and 2050s (2040–2069 average) under a lower (RCP 4.5) and higher (RCP 8.5) emissions scenario based on 20 global climate models (GCMs). The bars and whiskers display the mean and range, respectively, of changes across the 20 GCMs relative to each GCM's historical baseline. Hot days are defined as days with maximum temperature of at least 90°F; warm nights are defined as days with minimum temperature of at least 65°F.

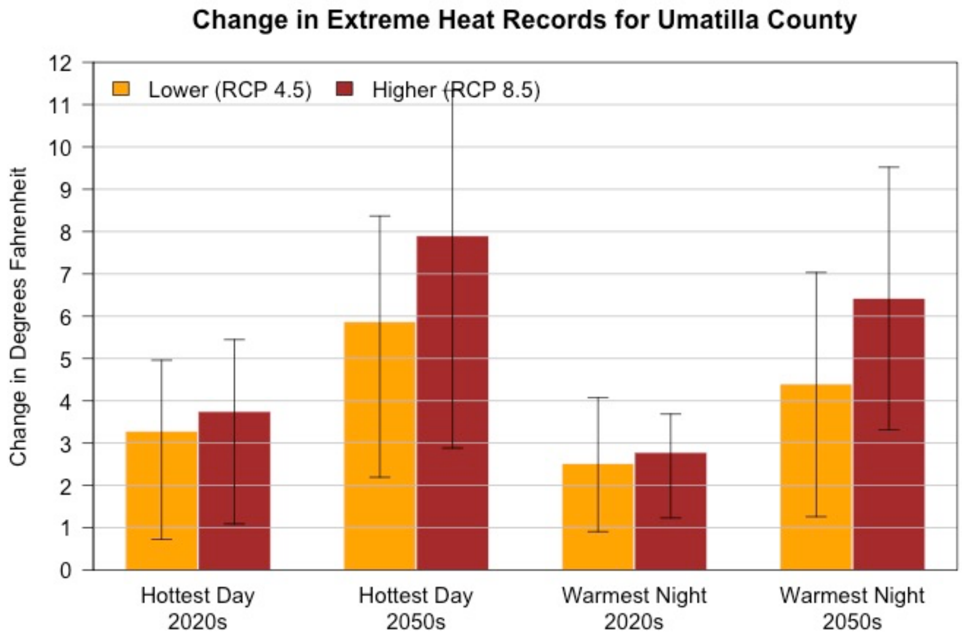

Figure 5 Projected future changes in the hottest day of the year (left two sets of bars) and warmest night of the year (right two sets of bars) for Umatilla County relative to the historical baseline (1971–2000 average) for the 2020s (2010–2039 average) and 2050s (2040–2069 average) under a lower (RCP 4.5) and higher (RCP 8.5) emissions scenario based on 20 global climate models (GCMs). The bars and whiskers display the mean and range, respectively, of changes across the 20 GCMs relative to each GCM's historical baseline.

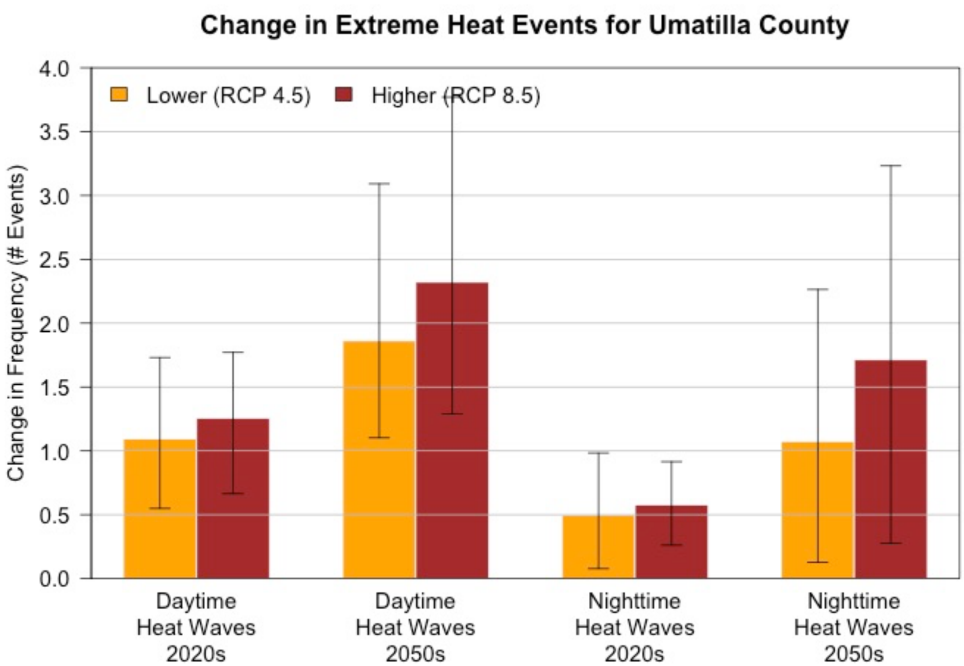

Figure 6 Projected future changes in the number of daytime heat waves (left two sets of bars) and number of nighttime heat waves (right two sets of bars) for Umatilla County relative to the historical baseline (1971–2000 average) for the 2020s (2010–2039 average) and 2050s (2040–2069 average) under a lower (RCP 4.5) and higher (RCP 8.5) emissions scenario based on 20 global climate models (GCMs). The bars and whiskers display the mean and range, respectively, of changes across the 20 GCMs relative to each GCM's historical baseline. Daytime heat waves are defined as events with three or more consecutive days with maximum temperature of at least 90°F; nighttime heat waves are defined as events with three or more consecutive days with minimum temperature of at least 65°F.

Key Messages:

⇒ Extreme heat events are expected to increase in frequency, duration, and intensity due to continued warming temperatures.

⇒ In Umatilla County, all the extreme heat metrics in Table 5 are projected to increase by the 2020s and 2050s under both the lower (RCP 4.5) and higher (RCP 8.5) emissions scenarios (Table 6).

⇒ In Umatilla County, the frequency of hot days per year with temperatures at or above 90°F is projected to increase on average by 29 days, with a range of about 11 to 41 days, by the 2050s under the higher emissions scenario relative to the historical baselines. This average increase represents a more than doubling of hot days relative to the average historical baseline.

⇒ In Umatilla County, the temperature of the hottest day of the year is projected to increase on average by nearly 8°F, with a range of about 3 to 11°F, by the 2050s under the higher emissions scenario relative to the historical baselines.

Cold Waves

Over the past century, cold extremes have become less frequent and severe in the Northwest; this trend is expected to continue under future global warming of the climate system (Vose *et al.*, 2017). This report presents projected changes for three metrics of cold extremes for both daytime (maximum temperature) and nighttime (minimum temperature) (Table 7).

Table 7 Cold extreme metrics and definitions

Metric	Definition
Cold Days	Number of days per year maximum temperature is less than or equal to 32°F
Cold Nights	Number of days per year minimum temperature is less than or equal to 0°F
Coldest Day	Annual minimum of maximum temperature
Coldest Night	Annual minimum of minimum temperature
Daytime Cold Waves	Number of events per year with at least 3 consecutive days with maximum temperature less than or equal to 32°F
Nighttime Cold Waves	Number of events per year with at least 3 consecutive days with minimum temperature less than or equal to 0°F

In Umatilla County, the extreme cold metrics in Table 7 are projected to become less frequent or less cold by the 2020s (2010–2039) and 2050s (2040–2069) under both the lower (RCP 4.5) and higher (RCP 8.5) emissions scenarios (Table 8). For example, for the 2050s under the higher emissions scenario climate models project that the number of cold days less than or equal to 32°F per year, relative to each model's 1971–2000 historical baseline, would decrease by at least 5 days to as much as 17 days. The average projected decrease in the number of cold days per year is 11 days relative to the average historical baseline of 18 days. This represents a future with a little more than half as many cold days as before by the 2050s under the higher emissions scenario.

Likewise, the temperature of the coldest night of the year is projected to increase by at most 16.9°F relative to the models' historical baselines. The average projected increase is 9.4°F above the average historical baseline of 0.0°F. The frequency of daytime cold waves is projected to decrease by one event per year on average relative to the average historical baseline of about two events. In other words, cold days are projected to become less frequent and the coldest nights are projected to become warmer.

Projected changes in the frequency of extreme cold days (i.e., Cold Days and Cold Nights) are shown in Figure 7. Projected changes in the magnitude of cold records (i.e., Coldest Day and Coldest Night) are shown in Figure 8. Projected changes in the frequency of extreme cold events (i.e., Daytime Cold Waves and Nighttime Cold Waves) are shown in Figure 9.

Table 8 Mean and range of projected future changes in extreme cold metrics for Umatilla County relative to each global climate model's (GCM) historical baseline (1971–2000 average) for the 2020s (2010–2039 average) and 2050s (2040–2069 average) under a lower (RCP 4.5) and higher (RCP 8.5) emissions scenario based on 20 GCMs. The average historical baseline across the 20 GCMs is also presented and can be combined with the average projected future change to infer the average projected future absolute value of a given variable. However, the average historical baseline cannot be combined with the range of projected future changes to infer the range of projected future absolute values.

		Change by Early 21st Century "2020s"		Change by Mid 21st Century "2050s"	
	Average Historical Baseline	**Lower**	**Higher**	**Lower**	**Higher**
Cold Days	17.8 days	-5.5 days (-9.4 to 0.5)	-7.0 days (-11.6 to -1.6)	-9.4 days (-12.9 to -3.7)	-10.9 days (-16.5 to -5.2)
Cold Nights	1.6 days	-0.5 days (-1.3 to 0.6)	-0.8 days (-1.5 to 0.0)	-1.0 days (-1.9 to -0.1)	-1.1 days (-1.8 to -0.0)
Coldest Day	17.1°F	+2.1°F (-1.3 to 5.3)	+3.7°F (-0.1 to 8.5)	+5.7°F (0.2 to 9.8)	+6.8°F (-0.1 to 12.8)
Coldest Night	0.0°F	+3.3°F (-1.6 to 9.4)	+5.3°F (0.8 to 12.2)	+7.7°F (1.2 to 13.7)	+9.4°F (0.0 to 16.9)
Daytime Cold Waves	2.4 events	-0.7 events (-1.3 to 0.3)	-0.9 events (-1.7 to -0.2)	-1.2 events (-1.9 to -0.6)	-1.4 events (-2.2 to -0.6)
Nighttime Cold Waves	0.2 events	-0.0 events (-0.2 to 0.1)	-0.1 events (-0.2 to 0.1)	-0.1 events (-0.3 to 0.0)	-0.1 events (-0.3 to -0.0)

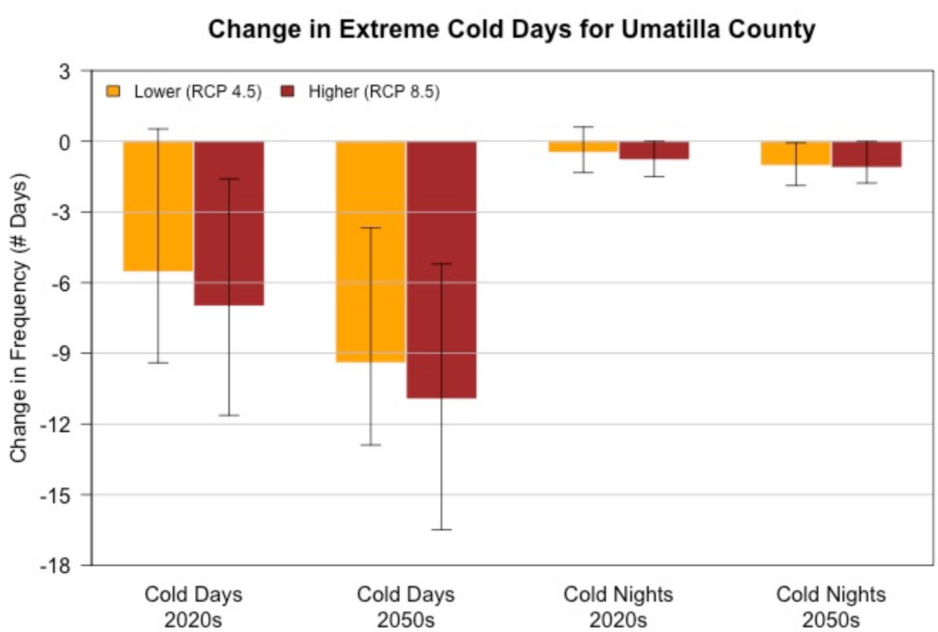

Figure 7 Projected future changes in the number of cold days (left two sets of bars) and number of cold nights (right two sets of bars) for Umatilla County relative to the historical baseline (1971–2000 average) for the 2020s (2010–2039 average) and 2050s (2040–2069 average) under a lower (RCP 4.5) and higher (RCP 8.5) emissions scenario based on 20 global climate models (GCMs). The bars and whiskers display the mean and range, respectively, of changes across the 20 GCMs relative to each GCM's historical baseline. Cold days are defined as days with maximum temperature at or below 32°F; cold nights are defined as days with minimum temperature at or below 0°F.

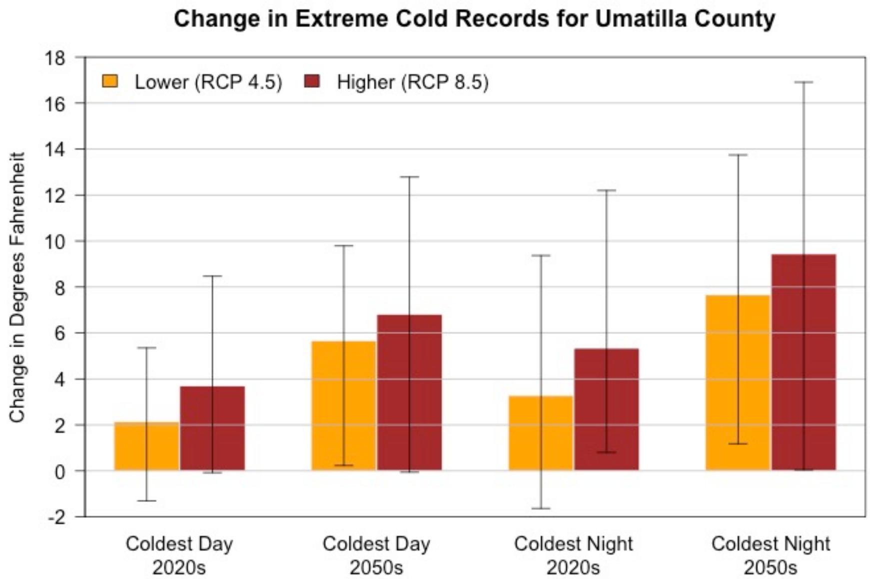

Figure 8 Projected future changes in the coldest day of the year (left two sets of bars) and coldest night of the year (right two sets of bars) for Umatilla County relative to the historical baseline (1971–2000 average) for the 2020s (2010–2039 average) and 2050s (2040–2069 average) under a lower (RCP 4.5) and higher (RCP 8.5) emissions scenario based on 20 global climate models (GCMs). The bars and whiskers display the mean and range, respectively, of changes across the 20 GCMs relative to each GCM's historical baseline.

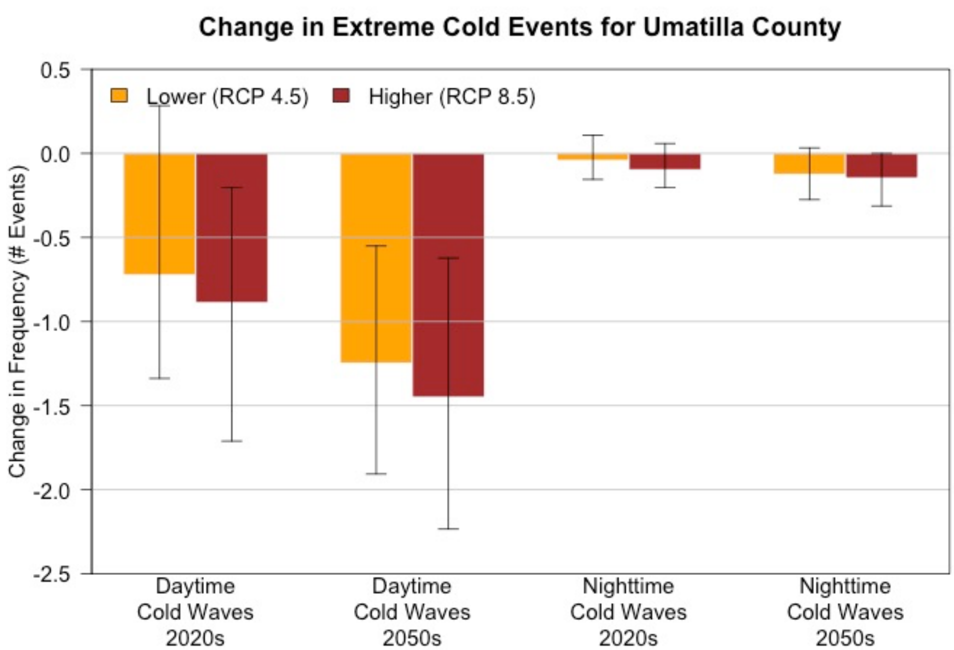

Figure 9 Projected future changes in the number of daytime cold waves (left two sets of bars) and number of nighttime cold waves (right two sets of bars) for Umatilla County relative to the historical baseline (1971–2000 average) for the 2020s (2010–2039 average) and 2050s (2040–2069 average) under a lower (RCP 4.5) and higher (RCP 8.5) emissions scenario based on 20 global climate models (GCMs). The bars and whiskers display the mean and range, respectively, of changes across the 20 GCMs relative to each GCM's historical baseline. Daytime cold waves are defined as events with three or more consecutive days with maximum temperature at or below 32°F; nighttime cold waves are defined as events with three or more consecutive days with minimum temperature at or below 0°F.

Key Messages:

⇒ Cold extremes are still expected to occur from time to time, but with much less frequency and intensity as the climate warms.

⇒ In Umatilla County, the extreme cold metrics in Table 7 are projected to become less frequent or less cold by the 2020s and 2050s under both the lower (RCP 4.5) and higher (RCP 8.5) emissions scenarios (Table 8).

⇒ In Umatilla County, the frequency of cold days per year at or below freezing is projected to decrease on average by 11 days, with a range of about 5 to 17 days, by the 2050s under the higher emissions scenario relative to the historical baselines. This average decrease represents a future with a little more than half as many cold days per year as in the average historical baseline.

⇒ In Umatilla County, the temperature of the coldest night of the year is projected to increase on average by about 9°F, with a range of about 0 to 17°F, by the 2050s under the higher emissions scenario relative to the historical baselines.

Heavy Rains

There is greater uncertainty in future projections of precipitation-related metrics than temperature-related metrics. This is because of the large natural variability in precipitation patterns and the fact that the atmospheric patterns that influence precipitation are manifested differently across GCMs. From a global perspective, mean precipitation is likely to decrease in many dry regions in the sub-tropics and mid-latitudes and increase in many mid-latitude wet regions (IPCC, 2013). That boundary between mid-latitude increases and decreases in precipitation is positioned a little differently for each GCM, which results in some models projecting increases and others decreases in Oregon (Mote *et al.*, 2013).

In Oregon, observed precipitation is characterized by high year-to-year variability and future precipitation trends are expected to continue to be dominated by this large natural variability. On average, summers in Oregon are projected to become drier and other seasons to become wetter resulting in a slight increase in annual precipitation by the 2050s (2040–2069). However, some models project increases and others decreases in each season (Dalton *et al.*, 2017).

Extreme precipitation events in the Pacific Northwest are governed both by atmospheric circulation and by how it interacts with complex topography (Parker and Abatzoglou, 2016). Atmospheric rivers—long, narrow swaths of warm, moist air that carry large amounts of water vapor from the tropics to mid-latitudes—generally result in coherent extreme precipitation events west of the Cascade Range, while closed low pressure systems often lead to isolated precipitation extremes east of the Cascade Range (Parker and Abatzoglou, 2016).[2]

Observed trends in the frequency of extreme precipitation events across Oregon have depended on the location, time frame, and metric considered, but overall the frequency has not changed substantially. As the atmosphere warms, it is able to hold more water vapor that is available for precipitation. As a result, the frequency and intensity of extreme precipitation events are expected to increase in the future (Dalton *et al.*, 2017), including atmospheric river events (Kossin *et al.*, 2017). In addition, regional climate modeling results suggest a weakened rain shadow effect in winter projecting relatively larger increases in precipitation east of the Cascades and smaller increases west of the Cascades in terms of both seasonal precipitation totals and precipitation extremes (Mote *et al.*, 2019).

This report presents projected changes for four metrics of precipitation extremes (Table 9).

[2] Verbatim from the Third Oregon Climate Assessment Report (Dalton *et al.*, 2017)

Table 9 Precipitation extreme metrics and definitions

Metric	Definition
Wettest Day	Annual maximum 1-day precipitation per water year
Wettest Five-Days	Annual maximum 5-day precipitation total per water year
Wet Days	Number of days per year with precipitation greater than 0.75 inches
Landslide Risk Days	Number of days per water year exceeding the USGS landslide threshold[3]: https://pubs.er.usgs.gov/publication/ofr20061064 o P3/(3.5-.67*P15)>1, where: ▪ P3 = Previous 3-day precipitation accumulation ▪ P15 = 15-day precipitation accumulation prior to P3

In Umatilla County, the magnitude of precipitation on the wettest day and wettest consecutive five days is projected to increase on average by the 2020s (2010–2039) and 2050s (2040–2069) under both the lower and higher emissions scenarios (Table 10). However, some models project decreases in the wettest consecutive five days in all time periods and scenarios.

For the 2050s under the higher emissions scenario, climate models project that the magnitude, or amount, of precipitation on the wettest day of the year, relative to each model's 1971–2000 historical baseline, would increase by as little as 7.0% to as much as 38.8%. The average projected percent increase in the amount of precipitation on the wettest day of the year is 19.0% above the average historical baseline of 0.88 inches.

For the magnitude of precipitation on the wettest consecutive five days of the year, some models project decreases by as much as 1.4% while other models project increases by as much as 32.1% for the 2050s under the higher emissions scenario. The average projected percent change in the amount of precipitation on the wettest consecutive five days is an increase of 13.7% above the average historical baseline of 2.07 inches.

The average number of days per year with precipitation greater than ¾" is projected to increase only by about one day per year by the 2050s under the higher emissions scenario relative to the average historical baseline of about two days per year.

Landslides are often triggered by rainfall when the soil becomes saturated. This report analyzes a cumulative rainfall threshold based on the previous 3-day and 15-day precipitation accumulation as a surrogate for landslide risk. For Umatilla County, the average number of days per year exceeding the landslide risk threshold is projected to increase on average by one day per year by the 2050s under the higher emissions scenario relative to the average historical baseline of three days per year. Landslide risk depends on a variety of site-specific factors and this metric may not reflect all aspects of the hazard. It is important to note that this particular landslide threshold was developed for Seattle, Washington and may or may not have similar applicability to other locations.

[3] This threshold was developed for Seattle, Washington and may or may not have similar applicability to other locations.

Projected changes in the magnitude of extreme precipitation events (i.e., Wettest Day and Wettest Five-Days) are shown in Figure 10. Projected changes in the frequency of extreme precipitation events (i.e., Wet Days and Landslide Risk Days) are shown in Figure 11.

Table 10 Mean and range of projected future changes in extreme precipitation metrics for Umatilla County relative to each global climate model's (GCM) historical baseline (1971–2000 average) for the 2020s (2010–2039 average) and 2050s (2040–2069 average) under a lower (RCP 4.5) and higher (RCP 8.5) emissions scenario based on 20 GCMs. The average historical baseline across the 20 GCMs is also presented and can be combined with the average projected future change to infer the average projected future absolute value of a given variable. However, the average historical baseline cannot be combined with the range of projected future changes to infer the range of projected future absolute values.

		Change by Early 21st Century "2020s"		Change by Mid 21st Century "2050s"	
	Average Historical Baseline	**Lower**	**Higher**	**Lower**	**Higher**
Wettest Day	0.88"	+13.5% (6.9 to 23.6)	+11.7% (-1.7 to 23.2)	+15.6% (3.6 to 26.0)	+19.0% (7.0 to 38.8)
Wettest Five-Days	2.07"	+9.6% (-1.4 to 25.4)	+7.5% (-1.9 to 20.5)	+11.2% (-1.2 to 26.3)	+13.7% (-1.4 to 32.1)
Wet Days	2.4 days	+0.4 days (-0.2 to 0.8)	+0.2 days (-0.2 to 0.8)	+0.6 days (0.0 to 0.9)	+0.7 days (0.1 to 1.5)
Landslide Risk Days	3.2 days	0.5 days (-0.2 to 1.4)	0.4 days (-0.7 to 1.8)	0.7 days (-0.3 to 1.5)	1.0 days (-0.2 to 2.6)

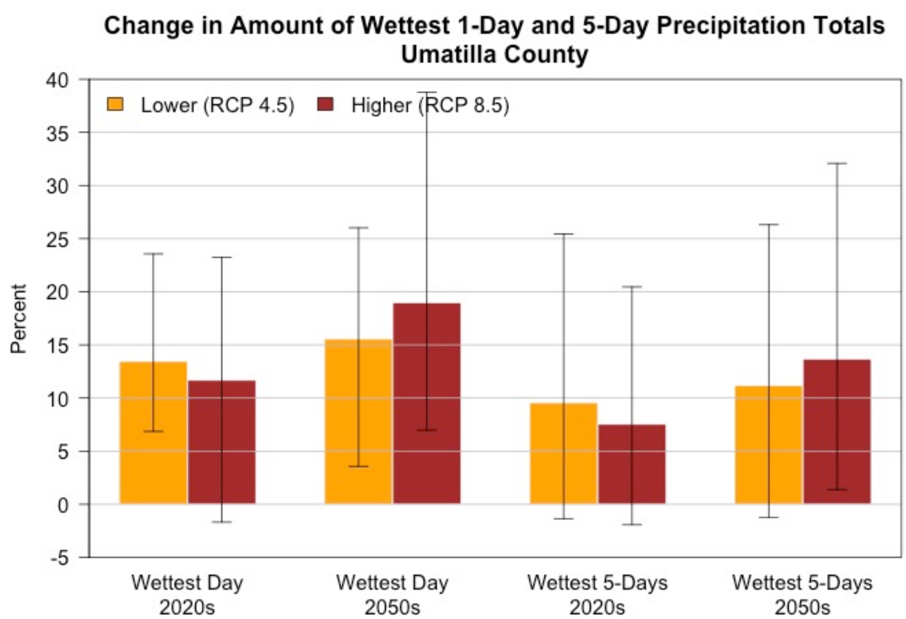

Figure 10 Projected future changes in the wettest day of the year (left two sets of bars) and wettest consecutive five days of the year (right two sets of bars) for Umatilla County relative to the historical baseline (1971–2000 average) for the 2020s (2010–2039 average) and 2050s (2040–2069 average) under a lower (RCP 4.5) and higher (RCP 8.5) emissions scenario based on 20 global climate models (GCMs). The bars and whiskers display the mean and range, respectively, of changes across the 20 GCMs relative to each GCM's historical baseline.

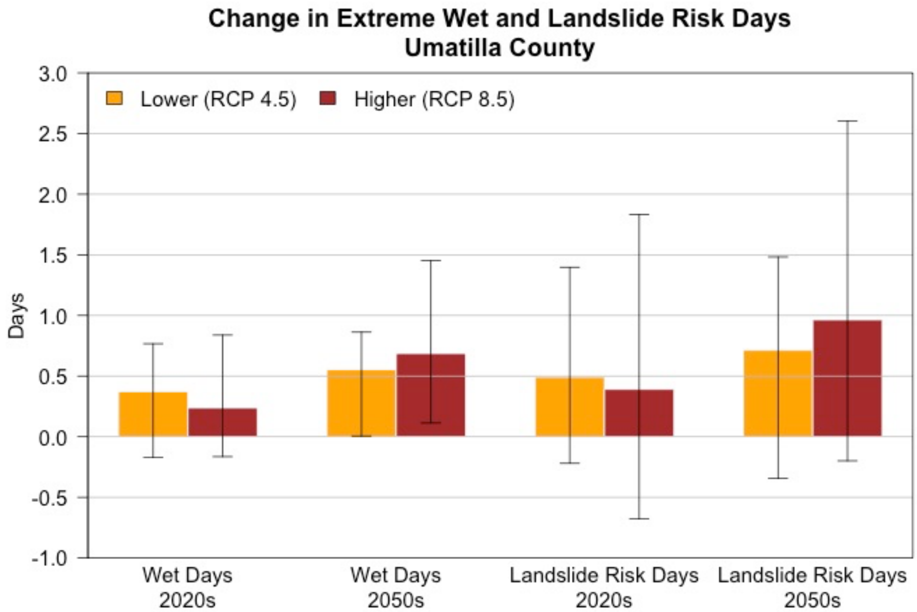

Figure 11 Projected future changes in the frequency of wet days (left two sets of bars) and landslide risk days (right two sets of bars) for Umatilla County relative to the historical baseline (1971–2000 average) for the 2020s (2010–2039 average) and 2050s (2040–2069 average) under a lower (RCP 4.5) and higher (RCP 8.5) emissions scenario based on 20 global climate models (GCMs). The bars and whiskers display the mean and range, respectively, of changes across the 20 GCMs relative to each GCM's historical baseline.

Key Messages:

⇒ The intensity of extreme precipitation events is expected to increase in the future as the atmosphere warms and is able to hold more water vapor.

⇒ In Umatilla County, the frequency of days with at least ¾" of precipitation is not projected to change substantially. However, the magnitude of precipitation on the wettest day and wettest consecutive five days per year is projected to increase on average by about 19% (with a range of 7% to 39%) and 14% (with a range of -1% to 32%), respectively, by the 2050s under the higher emissions scenario relative to the historical baselines.

⇒ In Umatilla County, the frequency of days exceeding a threshold for landslide risk, based on 3-day and 15-day precipitation accumulation, is not projected to change substantially. However, landslide risk depends on a variety of factors and this metric may not reflect all aspects of the hazard.

River Flooding

Future streamflow magnitude and timing in the Pacific Northwest is projected to shift toward higher winter runoff, lower summer and fall runoff, and an earlier peak runoff, particularly in snow-dominated regions (Raymondi *et al.*, 2013; Naz *et al.*, 2016).[4] These changes are expected to result from warmer temperatures causing precipitation to fall more as rain and less as snow, in turn causing snow to melt earlier in the spring; and in combination with increasing winter precipitation and decreasing summer precipitation (Dalton *et al.*, 2017; Mote *et al.*, 2019).

The projected change in the mean monthly hydrograph of the Columbia River at McNary is shown in Figure 12 and of the Umatilla River at Pendleton is shown in Figure 13. On the Columbia River at Brownlee Dam, the monthly hydrograph is characteristic of a snow-dominated basin with peak flows during the late spring snowmelt season (Figure 12). On the Umatilla River at McNary, the monthly hydrograph is characteristic of a mixed rain-snow basin with peak flows during the early to mid-spring snowmelt season and a smaller peak in late fall to early winter reflecting rainfall contributions early in the water year (Figure 13). By the 2050s (2040–2069), under both emissions scenarios, the peak streamflow in both rivers is projected to shift earlier in the spring as warmer temperatures cause the snowpack to melt earlier. In addition, winter streamflow is projected to increase due to increased winter precipitation and that precipitation falling more as rain than snow.

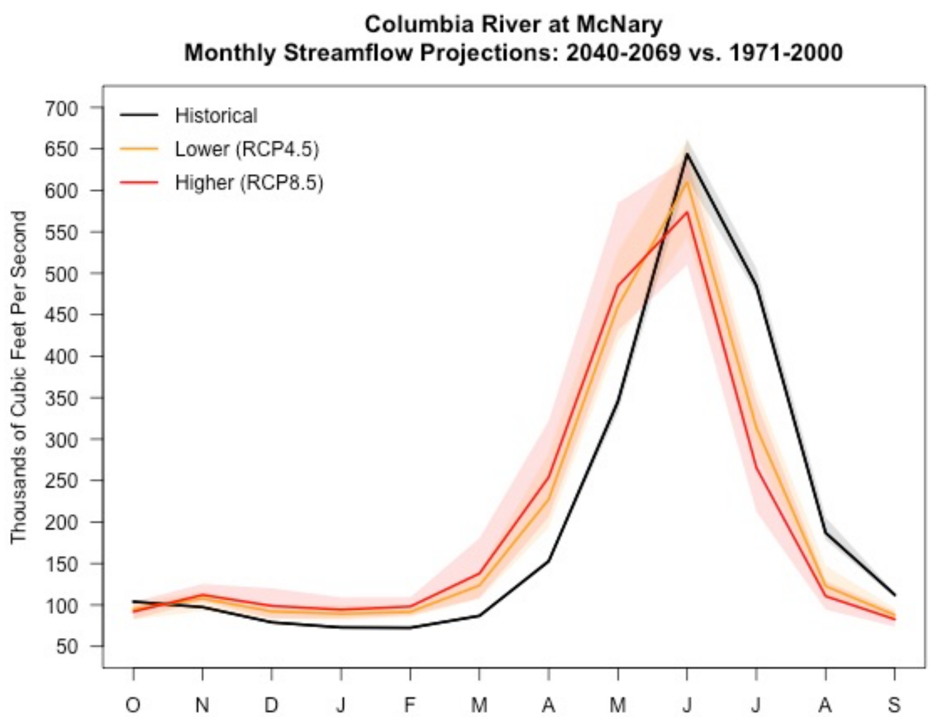

Figure 12 Simulated historical and future bias-corrected mean monthly non-regulated streamflow at the Columbia River at McNary for 2040–2069 compared to 1971–2000. Solid lines and shading depict the mean and range across ten global climate models. (Data source: Integrated Scenarios of the Future Northwest Environment, https://climatetoolbox.org/tool/future-streamflows)

[4] Verbatim from the Third Oregon Climate Assessment Report (Dalton *et al.*, 2017)

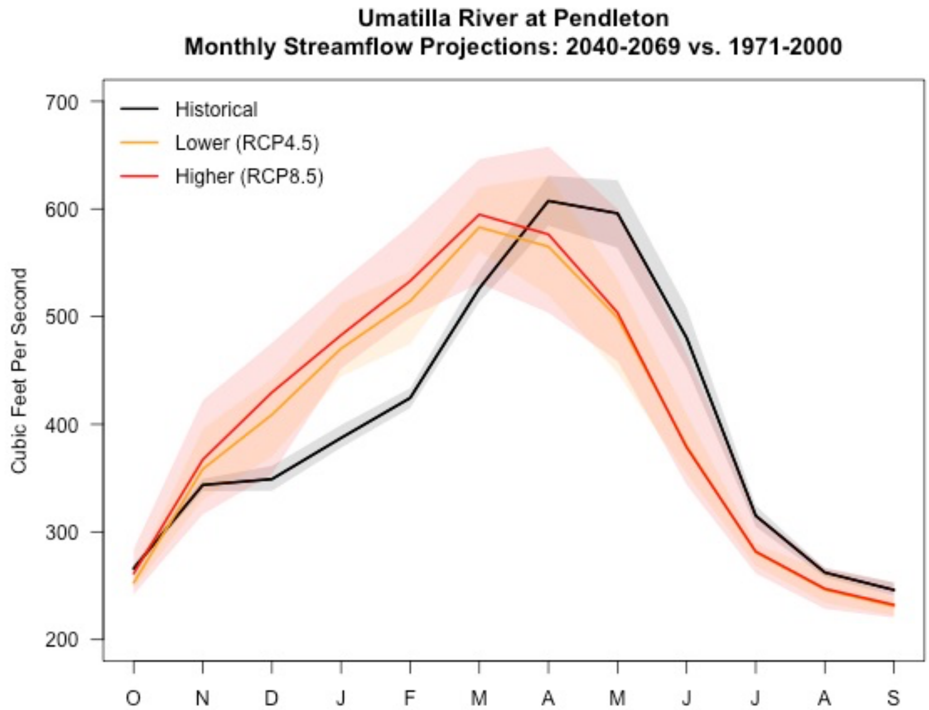

Figure 13 Simulated historical and future bias-corrected mean monthly non-regulated streamflow at the Umatilla River at Pendleton for 2040–2069 compared to 1971–2000. Solid lines and shading depict the mean and range across ten global climate models. (Data source: Integrated Scenarios of the Future Northwest Environment, https://climatetoolbox.org/tool/future-streamflows)

Warming temperatures and increased winter precipitation are expected to increase flood risk for many basins in the Pacific Northwest, particularly mid- to low-elevation mixed rain-snow basins with near freezing winter temperatures (Tohver *et al.*, 2014). The greatest changes in peak streamflow magnitudes are projected to occur at intermediate elevations in the Cascade Range and the Blue Mountains (Safeeq *et al.*, 2015). Recent advances in regional hydro-climate modeling support this expectation, projecting increases in extreme high flows for most of the Pacific Northwest, especially west of the Cascade Crest (Salathé *et al.*, 2014; Najafi and Moradkhani, 2015; Naz *et al.*, 2016). One study, using a single climate model, projects flood risk to increase in the fall due to earlier, more extreme storms, including atmospheric river events, and to a shift of precipitation from snow to rain (Salathé *et al.*, 2014).[5] Across the western US, the 100-year and 25-year peak flow magnitudes—major flooding events—are projected to increase at a majority of streamflow sites by the 2070–2099 period compared to the 1971–2000 historical baseline under the higher emissions scenario (RCP 8.5) (Maurer *et al.*, 2018).

In parts of the Blue Mountains (the Wallowa Mountains, Hells Canyon Wilderness Area, and northeast Wallowa-Whitman National Forest), flood magnitude for the 1.5-year return period event is expected to increase by the end of the 21st century under a medium emission scenario (SRES-A1B)[6], particularly in mid-elevation areas, as precipitation falls more as rain and less as snow (Clifton *et al.*, 2018) (Figure 14). The 1.5-year return period event has a 67% probability of occurrence in a given year and is indicative of flooding levels that can begin to cause damage to

[5] Verbatim from the Third Oregon Climate Assessment Report (Dalton *et al.*, 2017)
[6] The medium emissions pathway (SRES-A1B) is from an earlier generation of emissions scenarios and it is most similar to RCP 6.0 from Figure 2.

roads. An increase in flood magnitude for a specified flood frequency implies an increase in flood frequency for a given flood magnitude. Figure 14 shows projections of flood magnitude change for the 1.5-year return period event for the 2080s compared to a historical baseline. Unfortunately, this study does not project changes in flood magnitude for the Blue Mountains region for the 2020s and 2050s; projected changes can be expected to be of a similar direction but a smaller magnitude.

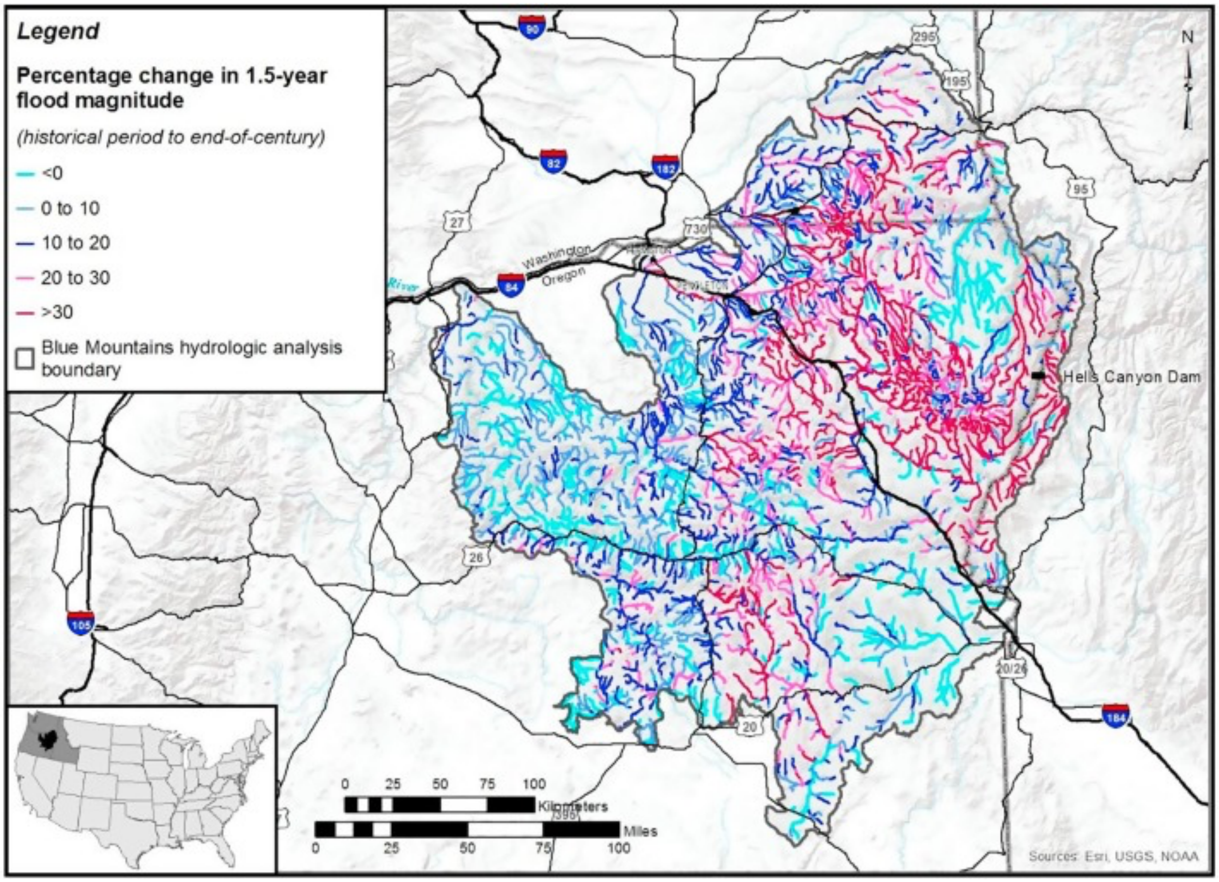

Figure 14 Projected change in the 1.5-year return interval daily flow magnitude between the historical period (1970–1999) and the 2080s (2070–2099) under a medium emissions scenario (SRES-A1B)[7] for the Blue Mountains region. (Source: Clifton et al., 2018)

Some of the Pacific Northwest's largest floods occur when copious warm rainfall from atmospheric rivers combine with a strong snowpack, resulting in rain-on-snow flooding events (Safeeq *et al.*, 2015). [8] The frequency and intensity—amount of transported moisture—of atmospheric river events is projected to increase along the West Coast in response to rising atmospheric temperatures (Kossin *et al.*, 2017). This larger moisture transport of atmospheric rivers would lead to greater likelihoods of flooding along the West Coast (Konrad and Dettinger, 2017).

Future changes in rain-on-snow events as a result of climate warming depend on elevation. At lower elevations, the frequency of rain-on-snow events is projected to decrease due to decreasing snowpack, whereas at high elevations the frequency of rain-on-snow events is projected to

[7] The medium emissions pathway (SRES-A1B) is from an earlier generation of emissions scenarios and it is most similar to RCP 6.0 from Figure 2.

[8] Verbatim from the Third Oregon Climate Assessment Report (Dalton *et al.*, 2017)

increase due to the shift from snowy to rainy days (Surfleet and Tullos, 2013; Safeeq *et al.*, 2015; Musselman *et al.*, 2018). How such changes in rain-on-snow frequency would affect high streamflow events is varied. For example, projections for the Santiam River, OR, show an increase in annual peak daily flows with moderate return intervals (<10 years) but a decrease at higher (> 10-year) return intervals (Surfleet and Tullos, 2013).

Key Messages:

⇒ Mid- to low-elevation areas in Umatilla County's Blue Mountains that are near the freezing level in winter, receiving a mix of rain and snow, are projected to experience an increase in winter flood risk due to warmer winter temperatures causing precipitation to fall more as rain and less as snow.

Drought

Across the western US, mountain snowpack is projected to decline leading to reduced summer soil moisture in mountainous environments (Gergel *et al.*, 2017). Climate change is expected to result in lower summer streamflows in historically snow-dominated basins across the Pacific Northwest as snowpack melts off earlier due to warmer temperatures and summer precipitation decreases (Dalton *et al.*, 2017; Mote *et al.*, 2019). See, for example, the decrease in summer flows expected for the Columbia River at McNary (Figure 12) and the Umatilla River at Pendleton (Figure 13) by the 2050s (2040–2069) under both lower and higher emissions scenarios.

This report presents future changes in five variables indicative of drought conditions—low spring snowpack, low summer soil moisture[9], low summer runoff, low summer precipitation, and high summer evaporation—in terms of a change in the frequency of the historical baseline 1-in-5 year event (that is, an event having a 20% chance of occurrence in any given year). The future projections, displayed in the orange and brown bars of Figure 15, are the frequency in the future period of the magnitude of the event that has a 20% frequency in the historical period.

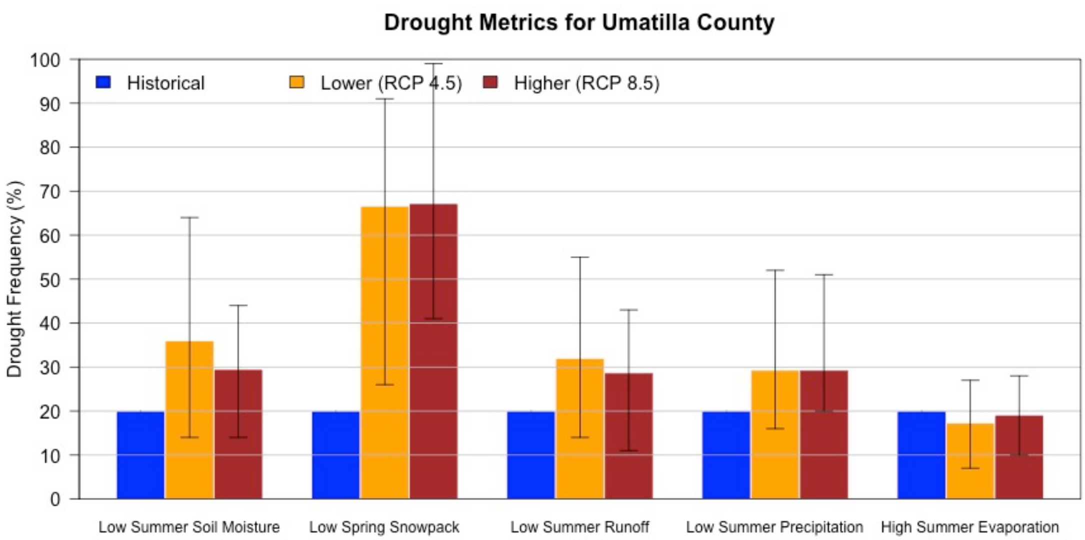

Figure 15 Frequency of the historical baseline (1971–2000) 1-in-5 year event (by definition 20% frequency) of low summer soil moisture (average of June-July-August), low spring snowpack (April 1 snow water equivalent), low summer runoff (total of June-July-August), low summer precipitation (total for June-July-August), high summer evaporation (total for June-July-August) for the future period 2040–2069 for lower (RCP 4.5) and higher (RCP 8.5) emissions scenarios. The bar and whiskers depict the mean and range across ten global climate models. (Data Source: Integrated Scenarios of the Future Northwest Environment, https://climate.northwestknowledge.net/IntegratedScenarios/)

In Umatilla County, spring snowpack (that is, the snow water equivalent on April 1), summer runoff, summer soil moisture, and summer precipitation are projected to decline under both lower (RCP 4.5) and higher (RCP 8.5) emissions scenarios by the 2050s (2040–2069). This leads to the magnitude of low summer soil moisture, low spring snow pack, low summer runoff, and low summer precipitation expected with a 20% chance in any given year of the historical period being projected to occur more frequently by the 2050s under both emissions scenarios (Figure 15). Of the five metrics, climate change shows the strongest impact on spring snowpack in Umatilla County. By the 2050s under the higher emissions scenario, the 1-in-5 year event for

[9] Soil moisture projections are for the total moisture in the soil column from the surface to 140 cm below the surface.

low spring snowpack is projected to become roughly a 1-in-1.5 year event. The projected changes in the 1-in-5 year events for the other variables are smaller and less certain given that some models project an increase and others a decrease. On average, the 1-in-5 year event for low summer precipitation, runoff, and soil moisture is projected to become roughly a 1-in-3.5 year event by the 2050s under the higher emissions scenario. The 2020s (2010–2039) were not evaluated in this drought analysis due to data limitations, but can be expected to be similar but of smaller magnitude to the changes for the 2050s.

Some areas in northeast Oregon are more sensitive to changes in spring snowpack and summer streamflow than others. A climate vulnerability analysis for the Blue Mountains region indicates that declines in spring snowpack are projected to be largest in low to mid-elevation locations, but even some locally higher elevation ranges, such as mid-elevations in the North Fork John Day Wilderness, North Fork Umatilla Wilderness, and Wenaha-Tucannon Wilderness would have relatively high sensitivity to snow losses (Clifton *et al.*, 2018). Summer streamflow in about half of the perennial streams in the Blue Mountains are projected to decrease by less than 10%, while areas more sensitive to changing low flows, such as the Wallowa Mountains, Elkhorn Mountains, and Wenaha-Tucannon Wilderness, are projected to see decreases in summer streamflow of more than 30% by the late 21st century (Clifton *et al.*, 2018) (Figure 16). Sub-basins with high risk for summer water shortage associated with low streamflow include the Upper Grande Ronde, Upper John Day, and Wallowa sub-basins (Figure 17) (Clifton *et al.*, 2018).

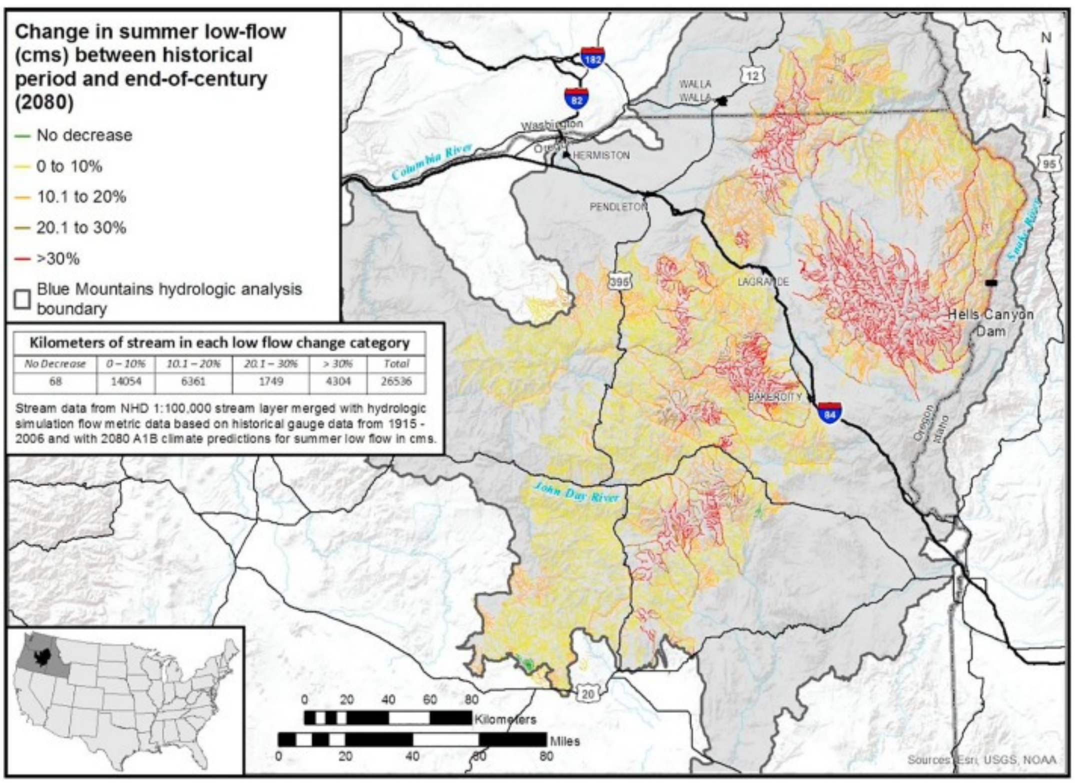

Figure 16 Projected change in mean summer streamflow from the historic time period (1970–1999) to the 2080s (2070–2099) under a medium emissions scenario[10] for streams in the Blue Mountains region. Note, the 0 to 10%, 10.1 to 20%, etc. all indicate decreases in flow. (Source: Clifton et al., 2018)

[10] The medium emissions pathway (SRES-A1B) is from an earlier generation of emissions scenarios and it is most similar to RCP 6.0 from Figure 2.

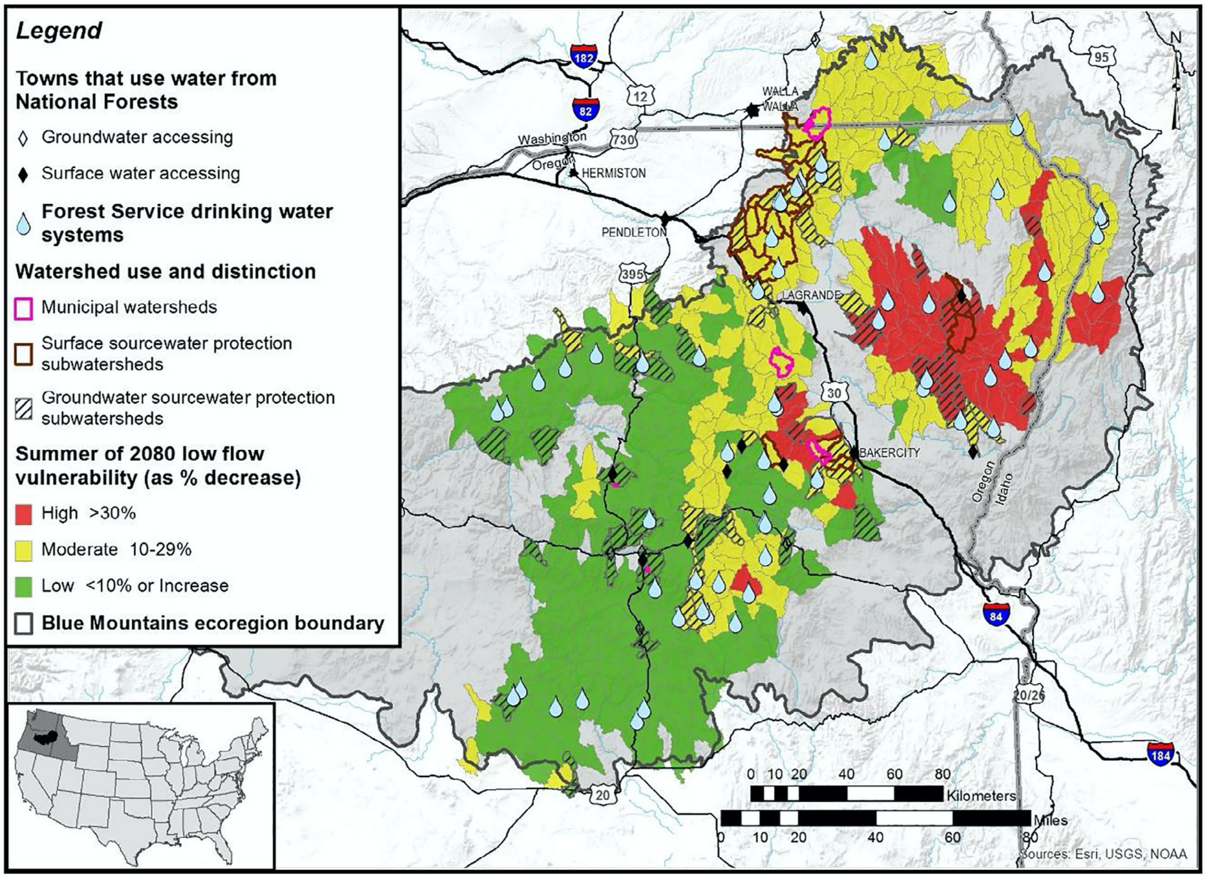

Figure 17 Projected risk of summer water shortage in the Blue Mountains region, based on low streamflows for 2080s (2070–2099) under a medium emissions scenario[11]. (Source: Clifton et al., 2018)

Key Messages:

⇒ Drought conditions, as represented by low summer soil moisture, low spring snowpack, low summer runoff, and low summer precipitation are projected to become more frequent in Umatilla County by the 2050s relative to the historical baseline.

⇒ By the end of the 21st century, summer low flows are projected to decrease in the Blue Mountains region putting some sub-basins at high risk for summer water shortage associated with low streamflow.

[11] The medium emissions pathway (SRES-A1B) is from an earlier generation of emissions scenarios and it is most similar to RCP 6.0 from Figure 2.

Wildfire

Over the last several decades, warmer and drier conditions during the summer months have contributed to an increase in fuel aridity and enabled more frequent large fires, an increase in the total area burned, and a longer fire season across the western United States, particularly in forested ecosystems (Dennison *et al.*, 2014; Jolly *et al.*, 2015; Westerling, 2016; Williams and Abatzoglou, 2016). The lengthening of the fire season is largely due to declining mountain snowpack and earlier spring snowmelt (Westerling, 2016). Recent wildfire activity in forested ecosystems is partially attributed to human-caused climate change: during the period 1984–2015, about half of the observed increase in fuel aridity and 4.2 million hectares (or more than 16,000 square miles) of burned area in the western United States were due to human-caused climate change (Abatzoglou and Williams, 2016).[12]

With climate change, warmer and drier conditions are expected to become more frequent leading to lower fuel moisture and longer fire seasons, which would increase the frequency and area burned of wildfires in the Pacific Northwest (Halofsky *et al.*, 2020). In dry coniferous forests on the east side of the Cascades, there is high likelihood (>66% probability) and high confidence for large increases in wildfire frequency, extent, and severity as well as fire-drought-insect stress interactions by the mid- to late-21st century (Halofsky *et al.*, 2020). Because climate is such a strong driver of factors that lead to total area burned, resource managers are unlikely to have a great influence on total area burned. However, strategic fuel treatments may be able to decrease fire intensity and severity as well as increase forest resilience (Halofsky *et al.*, 2020).

As a proxy for wildfire risk, this report considers a fire danger index called 100-hour fuel moisture (FM100), which is a measure of the amount of moisture in dead vegetation in the 1–3 inch diameter class available to a fire. It is expressed as a percent of the dry weight of that specific fuel. FM100 is a common index used by the Northwest Interagency Coordination Center to predict fire danger. A majority of climate models project that FM100 would decline across Oregon by the 2050s (2040–2069) under the higher (RCP 8.5) emissions scenario (Gergel *et al.*, 2017). This drying of vegetation would lead to greater wildfire risk, especially when coupled with projected decreases in summer soil moisture. This report defines a "very high" fire danger day to be a day in which FM100 is lower (i.e., drier) than the historical baseline 10th percentile value. By definition, the historical baseline has 36.5 very high fire danger days annually. The future change in wildfire risk is expressed as the average annual number of additional "very high" fire danger days for two future periods under two emissions scenarios compared with the historical baseline (Figure 18). The impacts of wildfire on air quality are discussed in the following section on Air Quality.

[12] Verbatim from the Third Oregon Climate Assessment Report (Dalton *et al.*, 2017)

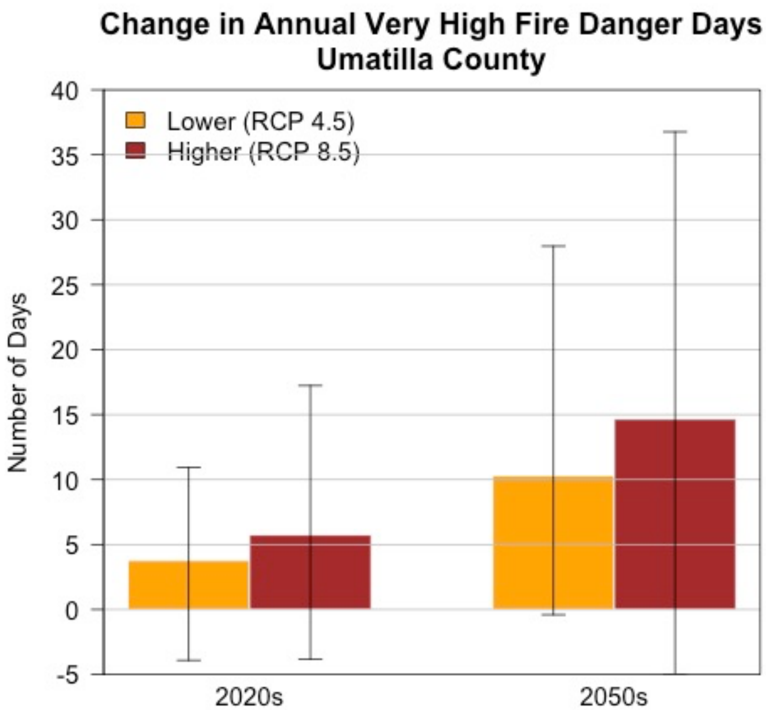

Figure 18 Projected future changes in the frequency of very high fire danger days for Umatilla County from the historical baseline (1971–2000 average) for the 2020s (2010–2039 average) and 2050s (2040–2069 average) under a lower (RCP 4.5) and higher (RCP 8.5) emissions scenario based on 18 global climate models. The bars and whiskers display the mean and range, respectively, of changes across the 18 GCMs. (Data Source: Northwest Climate Toolbox, climatetoolbox.org/tool/Climate-Mapper)

Key Messages:

⇒ Wildfire risk, as expressed through the frequency of very high fire danger days, is projected to increase under future climate change in Umatilla County.

⇒ In Umatilla County, the frequency of very high fire danger days per year is projected to increase on average by about 15 days (with a range of -5 to +37 days) by the 2050s under the higher emissions scenario compared to the historical baseline.

⇒ In Umatilla County, the frequency of very high fire danger days per year is projected to increase on average by about 40% (with a range of -14 to +101%) by the 2050s under the higher emissions scenario compared to the historical baseline.

Air Quality

Climate change is expected to worsen outdoor air quality. Warmer temperatures may increase ground level ozone pollution, more wildfires may increase smoke and particulate matter, and longer, more potent pollen seasons may increase aeroallergens. Such poor air quality is expected to exacerbate allergy and asthma conditions and increase respiratory and cardiovascular illnesses and death (Fann *et al.*, 2016).[13] In addition to increasing health risks, wildfire smoke impairs visibility and disrupts outdoor recreational activities (Nolte *et al.*, 2018). This report presents quantitative projections of future air quality measures related to fine particulate matter (PM2.5) from wildfire smoke.

Climate change is expected to result in a longer wildfire season with more frequent wildfires and greater area burned (Sheehan *et al.*, 2015). Wildfires are primarily responsible for days when air quality standards for PM2.5 are exceeded in western Oregon and parts of eastern Oregon (Liu *et al.*, 2016), although woodstove smoke and diesel emissions are also main contributors (Oregon DEQ, 2016). Across the western United States, PM2.5 levels from wildfires are projected to increase 160% by mid-century under a medium emissions pathway[11] (SRES A1B) (Liu *et al.*, 2016). This translates to a greater risk of wildfire smoke exposure through increasing frequency, length, and intensity of "smoke waves"—that is, two or more consecutive days with high levels of PM2.5 from wildfires (Liu *et al.*, 2016).[14]

The change in risk of poor air quality due to wildfire-specific PM2.5 is expressed as the number of "smoke wave" days within a six-year period and the average intensity—concentration of particulate matter—of smoke wave days in the present (2004–2009) and mid-century (2046–2051) under a medium emissions pathway[15] (Figure 19). See Appendix for description of methodology and access to the Smoke Wave data.

In Umatilla County the frequency of "smoke wave" days is expected to more than double and the intensity—the concentration of particulate matter—of "smoke wave" days is expected to increase.

[13] Verbatim from the Third Oregon Climate Assessment Report (Dalton *et al.*, 2017)
[14] Verbatim from the Third Oregon Climate Assessment Report (Dalton *et al.*, 2017)
[15] The medium emissions pathway used is from an earlier generation of emissions scenarios. Liu et al. (2016) used SRES-A1B, which is most similar to RCP 6.0 from Figure 2.

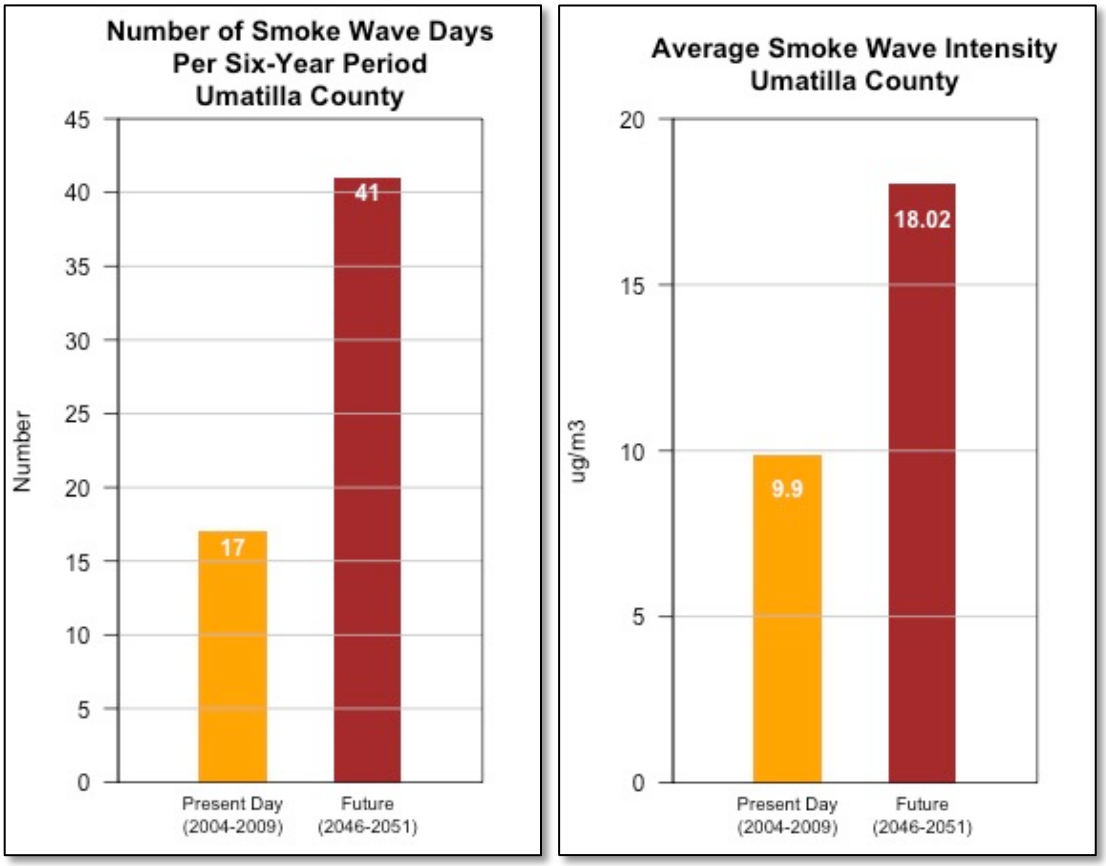

Figure 19 Simulated present day (2004–2009) and future (2046–2051) frequency (left) and intensity (right) of "smoke wave" days for Umatilla County under a medium emissions scenario[11]. The bars display the mean across 15 GCMs. (Data source: Liu et al. 2016, https://khanotations.github.io/smoke-map/)

Key Messages:

⇒ Under future climate change, the risk of wildfire smoke exposure is projected to increase in Umatilla County.

⇒ In Umatilla County, the number of "smoke wave" days is projected to increase by 141% and the intensity of "smoke waves" is projected to increase by 82% by 2046–2051 under a medium emissions scenario compared with 2004–2009.

Windstorms

Climate change has the potential to alter surface winds through changes in the large-scale free atmospheric circulation and storm systems, and through changes in the connection between the free atmosphere and the surface. West of the Cascade Mountains in the Pacific Northwest, changes in surface wind speeds tend to follow changes in upper atmosphere winds associated with extratropical cyclones (Salathé *et al.*, 2015). East of the Cascades, cool air pooling is common which can impede the transport of wind energy from the free atmosphere to the surface. Changes in this factor are likely important for understanding future changes in windstorms (Salathé *et al.*, 2015). However, this is not yet well studied.

Winter extratropical storm frequency in the northeast Pacific exhibited a positive, though statistically not significant, trend since 1950 (Vose *et al.*, 2014). However, there is a high degree of uncertainty in future projections of extratropical cyclone frequency (IPCC, 2013). Future projections indicate a slight northward shift in the jet stream and extratropical cyclone activity, but there is as yet no consensus on whether or not extratropical storms (Vose *et al.*, 2014; Seiler and Zwiers, 2016; Chang, 2018) and associated extreme winds (Kumar *et al.*, 2015) will intensify or become more frequent along the Northwest coast under a warmer climate. Therefore, no descriptions of future changing conditions are included in this report.

Key Messages:

⇒ Limited research suggests very little, if any, change in the frequency and intensity of windstorms in the Pacific Northwest as a result of climate change.

Dust Storms

Climate, through precipitation and winds, and vegetation coverage can influence the frequency and magnitude of dust events, or dust storms, which primarily concern parts of eastern Oregon. Periods of low precipitation can dry out the soils increasing the amount of soil particulate matter available to be entrained in high winds. In addition, the amount of vegetation cover can influence the amount of soil susceptible to high winds.

One study found that in eastern Oregon, precipitation is the dominant factor affecting dust event frequency in the spring whereas vegetation cover is the dominant factor in the summer (Pu and Ginoux, 2017). The same study projected that in the summertime in eastern Oregon, dust event frequency would decrease largely due to a decrease in bareness (or an increase in vegetation cover) (Pu and Ginoux, 2017). There were no clear projected changes in other seasons or locations in Oregon. These projections compare the 2051–2100 average under a higher emissions scenario (RCP 8.5) with the 1861–2005 average.

Another study found that wind erosion in Columbia Plateau agricultural areas is projected to decrease by mid-century under a lower emissions scenario (RCP 4.5) largely due to increases in biomass production, which retain the soil (Sharratt *et al.*, 2015). The increase in vegetation cover in both studies is likely due to the fertilization effect of increased amounts of carbon dioxide in the atmosphere and warmer temperatures. Tillage practices may also influence the amount of soil available to winds. Therefore, no descriptions of future changing conditions are included in this report.

Key Messages:

⇒ Limited research suggests that the risk of dust storms in summer would decrease in eastern Oregon under climate change in areas that experience an increase in vegetation cover from the carbon dioxide fertilization effect.

Increased Invasive Species Risk

Warming temperatures, altered precipitation patterns, and increasing atmospheric carbon dioxide levels increase the risk for invasive species, insect and plant pests for forest and rangeland vegetation, and cropping systems.

Warming and more frequent drought will likely lead to a greater susceptibility among trees to insects and pathogens, a greater risk of exotic species establishment, more frequent and severe forest insect outbreaks (Halofsky and Peterson, 2016), and increased damage by a number of forest pathogens (Vose *et al.*, 2016). In Oregon and Washington, mountain pine beetle (*Dendroctonus ponderosae*) and western spruce budworm (*Choristoneura freemani*) are the most common native forest insect pests, and both have caused substantial tree mortality and defoliation over the past several decades (Meigs *et al.*, 2015).[16]

Climatic warming has facilitated the expansion and survival of mountain pine beetles, particularly in areas that have historically been too cold for the insect (Littell *et al.*, 2013). Across the western United States, the time between generations among different populations of mountain pine beetles is similar; however, the amount of thermal units required to complete a generation cycle was significantly less for beetles at cooler sites (Bentz *et al.*, 2014). Winter survival and faster generation cycles could be favored under future projections of decreases in the number of freeze days (Rawlins *et al.*, 2016).[17] Bark beetle outbreaks can interact with drought stress to influence fire hazard in forests in the years after the outbreak. Within the first four years after an outbreak when trees retain drying needles, "fire hazard has been found to increase as the proportion of the stand killed by bark beetles increases" (Halofsky *et al.*, 2020). About five to ten years after an outbreak when snags remain standing, surface fire potential increases while crown fire potential decreases. However, one to several decades after an outbreak when snags have fallen and understory vegetation grows, fire hazard is generally lower (Halofsky *et al.*, 2020).

Western spruce budworm is a destructive defoliator that sporadically breaks out in interior Oregon Douglas-fir (*Pseudotsuga menziesii*) forests (Flower *et al.*, 2014). An analysis of three hundred years of tree ring data reveals that outbreaks tended to occur near the end of a drought, when trees' physiological thresholds had likely been reached. This analysis suggests that such outbreaks would likely intensify under the more frequent drought conditions that are projected for the future (Flower *et al.*, 2014), unless increasing atmospheric carbon dioxide, which may enhance water use efficiency, mitigates drought stress.[18]

More frequent rangeland droughts could facilitate invasion of non-native weeds as native vegetation succumbs to drought or wildfire cycles, leaving bare ground (Vose *et al.*, 2016). Cheatgrass (*Bromus tectorum L.*), a lower nutritional quality forage grass, facilitates more frequent fires, which reduces the capacity of shrub steppe ecosystem to provide livestock forage and critical wildlife habitat (Boyte *et al.*, 2016). Cheatgrass is a highly invasive species in the rangelands in the West that is projected to expand northward (Creighton *et al.*, 2015) and remain stable or increase in cover in most parts of the Great Basin (Boyte *et al.*, 2016) under climate change.[19]

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[16] Verbatim from the Third Oregon Climate Assessment Report (Dalton *et al.*, 2017), p. 49

[17] Verbatim from the Third Oregon Climate Assessment Report (Dalton *et al.*, 2017), p. 49

[18] Verbatim from the Third Oregon Climate Assessment Report (Dalton *et al.*, 2017), p. 49–50

[19] Verbatim from the Third Oregon Climate Assessment Report (Dalton *et al.*, 2017), p. 70

Crop pests and pathogens may continue to migrate poleward under global warming as has been observed globally for several types since the 1960s (Bebber *et al.*, 2013). Much remains to be learned about which pests and pathogens are most likely to affect certain crops as the climate changes, and about which management strategies will be most effective.[20]

Key Messages:

⇒ Warming temperatures, altered precipitation patterns, and increasing atmospheric carbon dioxide levels increase the risk for invasive species, insect and plant pests for forest and rangeland vegetation, and cropping systems.

[20] Verbatim from the Third Oregon Climate Assessment Report (Dalton *et al.*, 2017), p. 67

Loss of Wetland Ecosystems

Wetlands play key roles in major ecological processes and provide a number of essential ecosystem services: flood reduction, groundwater recharge, pollution control, recreational opportunities, and fish and wildlife habitat, including for endangered species.[21] Climate change stands to affect freshwater wetlands in Oregon through changes in the duration, frequency, and seasonality of precipitation and runoff; decreased groundwater recharge; and higher rates of evapotranspiration (Raymondi *et al.*, 2013).

Reduced snowpack and altered runoff timing may contribute to the drying of many ponds and wetland habitats across the Northwest.[22] The absence of water or declining water levels in permanent or ephemeral wetlands would affect resident and migratory birds, amphibians, and other animals that rely on the wetlands (Dello and Mote, 2010). However, potential future increases in winter precipitation may lead to the expansion of some wetland systems, such as wetland prairies.[23]

In Oregon's western Great Basin, changes in climate would alter the water chemistry of fresh and saline wetlands affecting the migratory water birds that depend on them. Hotter summer temperatures would cause freshwater sites to become more saline making them less useful to raise young birds that haven't yet developed the ability to process salt. At the same time, increased precipitation would cause saline sites to become fresher thereby decreasing the abundance of invertebrate food supply for adult water birds (Dello and Mote, 2010).

Key Messages:

⇒ Freshwater wetland ecosystems are sensitive to warming temperatures and altered hydrological patterns, such as changes in precipitation seasonality and reduction of snowpack.

[21] Verbatim from the Oregon Climate Change Adaptation Framework, p. 62
[22] Verbatim from the Climate Change in the Northwest (Dalton *et al.*, 2013), p. 53
[23] Verbatim from the Climate Change in the Northwest (Dalton *et al.*, 2013), p. 53

Appendix

Future Climate Projections Background

Read more about emissions scenarios, global climate models, and uncertainty in the Climate Science Special Report, Volume 1 of the Fourth National Climate Assessment (https://science2017.globalchange.gov).

Emissions Scenarios: https://science2017.globalchange.gov/chapter/4#section-2

Global Climate Models & Downscaling:
https://science2017.globalchange.gov/chapter/4#section-3

Uncertainty: https://science2017.globalchange.gov/chapter/4#section-4

Climate & Hydrological Data

Statistically downscaled GCM output from the Fifth phase of the Coupled Model Intercomparison Project (CMIP5) served as the basis for future projections of temperature, precipitation, and hydrology variables. The coarse resolution of GCMs output (100–300 km) was downscaled to a resolution of about 6 km using the Multivariate Adaptive Constructed Analogs (MACA) method, which has demonstrated skill in complex topographic terrain (Abatzoglou and Brown, 2012). The MACA approach utilizes a gridded training observation dataset to accomplish the downscaling by applying bias-corrections and spatial pattern matching of observed large-scale to small-scale statistical relationships. (For a detailed description of the MACA method see: https://climate.northwestknowledge.net/MACA/MACAmethod.php.)

This downscaled gridded meteorological data (i.e., MACA data) is used as the climate inputs to an integrated climate-hydrology-vegetation modeling project called Integrated Scenarios of the Future Northwest Environment (https://climate.northwestknowledge.net/IntegratedScenarios/). Snow dynamics were simulated using the Variable Infiltration Capacity hydrological model (VIC version 4.1.2.l; (Liang *et al.*, 1994) and updates) run on a 1/16th x 1/16th (6 km) grid.

Simulations of historical and future climate for the variables maximum temperature (*tasmax*), minimum temperature (*tasmin*), and precipitation (*pr*) are available at the daily time step from 1950 to 2099 for 20 GCMs and 2 RCPs (i.e., RCP4.5 and RCP8.5). Hydrological simulations of snow water equivalent (*SWE*) are only available for the 10 GCMs used as input to VIC. Table 11 lists all 20 CMIP5 GCMs and indicates the subset of 10 used for hydrological simulations. Data for all the models available was obtained for each variable from the Integrated Scenarios data archives in order to get the best uncertainty estimates.

All simulated climate data and the streamflow data have been bias-corrected using quantile-mapping techniques. Only SWE is presented without bias correction. Quantile mapping adjusts simulated values by creating a one-to-one mapping between the cumulative probability distribution of simulated values and the cumulative probability distribution of observed values. In practice, both the simulated and observed values of a variable (e.g., daily streamflow) over the some historical time period are separately sorted and ranked and the values are assigned their respective probabilities of exceedence. The bias corrected value of a given simulated value is assigned the observed value that has the same probability of exceedence as the simulated value.

Table 11 The 20 CMIP5 GCMs used in this project. The subset of 10 CMIP5 GCMs used in the Integrated Scenarios: Hydrology dataset are noted with asterisks.

Model Name	Modeling Center
BCC-CSM1-1 BCC-CSM1-1-M*	Beijing Climate Center, China Meteorological Administration
BNU-ESM	College of Global Change and Earth System Science, Beijing Normal University, China
CanESM2*	Canadian Centre for Climate Modeling and Analysis
CCSM4*	National Center for Atmospheric Research, USA
CNRM-CM5*	National Centre of Meteorological Research, France
CSIRO-Mk3-6-0*	Commonwealth Scientific and Industrial Research Organization/Queensland Climate Change Centre of Excellence, Australia
GFDL-ESM2G GFDL-ESM2M	NOAA Geophysical Fluid Dynamics Laboratory, USA
HadGEM2-CC* HadGEM2-ES*	Met Office Hadley Center, UK
INMCM4	Institute for Numerical Mathematics, Russia
IPSL-CM5A-LR IPSL-CM5A-MR* IPSL-CM5B-LR	Institut Pierre Simon Laplace, France
MIROC5* MIROC-ESM MIROC-ESM-CHEM	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies
MRI-CGCM3	Meteorological Research Institute, Japan
NorESM1-M*	Norwegian Climate Center, Norway

The historical bias in the simulations is assumed to stay constant into the future; therefore the same mapping relationship developed from the historical period was applied to the future scenarios. For MACA, a separate quantile mapping relationship was made for each non-overlapping 15-day window in the calendar year. For streamflow, a separate quantile mapping relationship was made for each calendar month.

Hydrology was simulated using the Variable Infiltration Capacity hydrological model (VIC; Liang et al. 1994) run on a $1/16^{th}$ x $1/16^{th}$ (6 km) grid. To generate daily streamflow estimates, runoff from VIC grid cells was then routed to selected locations along the stream network using a daily-time-step routing model. Where records of naturalized flow were available, the daily streamflow estimates were then bias-corrected so that their statistical distributions matched those of the naturalized streamflows.

The wildfire danger day metric was computed using the same MACA climate variables to compute the 100-hour fuel moisture content according to the equations in the National Fire Danger Rating System.

Smoke Wave Data

Abstract from Liu et al. (2016):
Wildfire can impose a direct impact on human health under climate change. While the potential impacts of climate change on wildfires and resulting air pollution have been studied, it is not known who will be most affected by the growing threat of wildfires. Identifying communities that will be most affected will inform development of fire manage- ment strategies and disaster preparedness programs. We estimate levels of fine particulate matter ($PM_{2.5}$) directly attributable to wildfires in 561 western US counties during fire seasons for the present-day (2004–2009) and future (2046–2051), using a fire prediction model and GEOS-Chem, a 3-D global chemical transport model. Future estimates are obtained under a scenario of moderately increasing greenhouse gases by mid-century. We create a new term "Smoke Wave," defined as ≥2 consecutive days with high wildfire-specific $PM_{2.5}$, to describe episodes of high air pollution from wildfires. We develop an interactive map to demonstrate the counties likely to suffer from future high wildfire pollution events. For 2004–2009, on days exceeding regulatory $PM_{2.5}$ standards, wildfires contributed an average of 71.3 % of total $PM_{2.5}$. Under future climate change, we estimate that more than 82 million individuals will experience a 57 % and 31 % increase in the frequency and intensity, respectively, of Smoke Waves. Northern California, Western Oregon and the Great Plains are likely to suffer the highest exposure to wildfire smoke in the future. Results point to the potential health impacts of increasing wildfire activity on large numbers of people in a warming climate and the need to establish or modify US wildfire management and evacuation programs in high-risk regions. The study also adds to the growing literature arguing that extreme events in a changing climate could have significant consequences for human health.

Data can be accessed here: https://khanotations.github.io/smoke-map/
For the DLCD project, we looked at the variables "Total # of SW days in 6 yrs" and "Average SW Intensity". The first variable tallies all the days within each time period in which the fine particulate matter exceeded the threshold defined as the 98th quantile of the distribution of daily wildfire-specific $PM_{2.5}$ values in the modeled present-day years, on average across the study area. The second variable computes the average concentration of fine particulate matter across identified "smoke wave" days within each time period. Liu et al. (2016) used 15 GCMs from the Third Phase of the Coupled Model Intercomparison Project (CMIP3) under a medium emissions scenario (SRES-A1B). The data site only offers the multi-model mean value (not the range), which should be understood as the aggregate direction of projected change rather than the actual number expected.

References

Abatzoglou JT, Brown TJ. 2012. A comparison of statistical downscaling methods suited for wildfire applications. *International Journal of Climatology*, 32(5): 772–780. https://doi.org/10.1002/joc.2312.

Abatzoglou JT, Williams AP. 2016. Impact of anthropogenic climate change on wildfire across western US forests. *Proceedings of the National Academy of Sciences*, 113(42): 11770–11775. https://doi.org/10.1073/pnas.1607171113.

Bebber DP, Ramotowski MAT, Gurr SJ. 2013. Crop pests and pathogens move polewards in a warming world. *Nature Climate Change*, 3(11): 985–988. https://doi.org/10.1038/nclimate1990.

Bentz B, Vandygriff J, Jensen C, Coleman T, Maloney P, Smith S, Grady A, Schen-Langenheim G. 2014. *Mountain Pine Beetle Voltinism and Life History Characteristics across Latitudinal and Elevational Gradients in the Western United States*. Text. .

Boyte SP, Wylie BK, Major DJ. 2016. Cheatgrass Percent Cover Change: Comparing Recent Estimates to Climate Change — Driven Predictions in the Northern Great Basin,. *Rangeland Ecology & Management*, 69(4): 265–279. https://doi.org/10.1016/j.rama.2016.03.002.

Chang E. 2018. CMIP5 Projected Change in Northern Hemisphere Winter Cyclones with Associated Extreme Winds. *Journal of Climate*, 31(16): 6527–6542. https://doi.org/10.1175/JCLI-D-17-0899.1.

Clifton CF, Day KT, Luce CH, Grant GE, Safeeq M, Halofsky JE, Staab BP. 2018. Effects of climate change on hydrology and water resources in the Blue Mountains, Oregon, USA. *Climate Services*, 10: 9–19. https://doi.org/10.1016/j.cliser.2018.03.001.

Creighton J, Strobel M, Hardegree S, Steele R, Van Horne B, Gravenmier B, Owen W, Peterson D, Hoang L, Little N, Bochicchio J, Hall W, Cole M, Hestvik S, Olson J. 2015. *Northwest Regional Climate Hub Assessment of Climate Change Vulnerability and Adaptation and Mitigation Strategies*. United States Department of Agriculture, 52.

Dalton MM, Dello KD, Hawkins L, Mote PW, Rupp DE. 2017. *The Third Oregon Climate Assessment Report*. Oregon Climate Change Research Institute, College of Earth, Ocean and Atmospheric Sciences, Oregon State University: Corvallis, OR, 99.

Dalton MM, Mote PW, Snover AK. 2013. *Climate Change in the Northwest: Implications for Our Landscapes, Waters, and Communities*. Island Press: Washington, DC.

Dello KD, Mote PW. 2010. *Oregon Climate Assessment Report*. Oregon Climate Change Research Institute, College of Oceanic and Atmospheric Sciences, Oregon State University: Corvallis, OR.

Dennison PE, Brewer SC, Arnold JD, Moritz MA. 2014. Large wildfire trends in the western United States, 1984–2011. *Geophysical Research Letters*, 41(8): 2014GL059576. https://doi.org/10.1002/2014GL059576.

Fann N, Brennan T, Dolwick P, Gamble JL, Ilacqua V, Kolb L, Nolte CG, Spero TL, Ziska L. 2016. Ch. 3: Air Quality Impacts. *The Impacts of Climate Change on Human Health in the United States: A Scientific Assessment*. US Global Change Research Program: Washington, DC, 69–98.

Flower A, Gavin DG, Heyerdahl EK, Parsons RA, Cohn GM; 2014. Drought-triggered western spruce budworm outbreaks in the Interior Pacific Northwest: A multi-century dendrochronological record. *Forest Ecology and Management*, 324: 16–27.

Gergel DR, Nijssen B, Abatzoglou JT, Lettenmaier DP, Stumbaugh MR. 2017. Effects of climate change on snowpack and fire potential in the western USA. *Climatic Change*, 141(2): 287–299. https://doi.org/10.1007/s10584-017-1899-y.

Halofsky JE, Peterson DL. 2016. Climate Change Vulnerabilities and Adaptation Options for Forest Vegetation Management in the Northwestern USA. *Atmosphere*, 7(3): 46. https://doi.org/10.3390/atmos7030046.

Halofsky JE, Peterson DL, Harvey BJ. 2020. Changing wildfire, changing forests: the effects of climate change on fire regimes and vegetation in the Pacific Northwest, USA. *Fire Ecology*, 16(1): 4. https://doi.org/10.1186/s42408-019-0062-8.

IPCC. 2013. Summary for Policymakers. *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press: Cambridge, United Kingdom and New York, NY, USA.

Jolly WM, Cochrane MA, Freeborn PH, Holden ZA, Brown TJ, Williamson GJ, Bowman DMJS. 2015. Climate-induced variations in global wildfire danger from 1979 to 2013. *Nature Communications*, 6: 7537. https://doi.org/10.1038/ncomms8537.

Konrad CP, Dettinger MD. 2017. Flood Runoff in Relation to Water Vapor Transport by Atmospheric Rivers Over the Western United States, 1949–2015. *Geophysical Research Letters*, 44(22): 11,456-11,462. https://doi.org/10.1002/2017GL075399.

Kossin JP, Hall T, Knutson T, Kunkel KE, Trapp RJ, Waliser DE, Wehner MF. 2017. Chapter 9: Extreme Storms. *Climate Science Special Report: Fourth National Climate Assessment Volume I [Wuebbles, D.J., D.W. Fahey, K.A. Hibbard, D.J. Dokken, B.C. Stewart, and T.K. Maycock (eds.)]*. US Global Change Research Program: Washington, DC, USA, 257–276.

Kumar D, Mishra V, Ganguly AR. 2015. Evaluating wind extremes in CMIP5 climate models. *Climate Dynamics*, 45(1): 441–453. https://doi.org/10.1007/s00382-014-2306-2.

Liang X, Lettenmaier DP, Wood EF, Burges SJ. 1994. A simple hydrologically based model of land surface water and energy fluxes for general circulation models. *Journal of Geophysical Research*, 99(D7): 14415–14428.

Littell JS, Hicke JA, Shafer SL, Capalbo SM, Houston LL, Glick P. 2013. Forest ecosystems: Vegetation, disturbance, and economics: Chapter 5. In: Dalton MM, Mote PW and Snover AK (eds) *Climate Change in the Northwest: Implications for Our Landscapes, Waters, and Communities*. Island Press: Washington, DC, 110–148.

Liu JC, Mickley LJ, Sulprizio MP, Dominici F, Yue X, Ebisu K, Anderson GB, Khan RFA, Bravo MA, Bell ML. 2016. Particulate air pollution from wildfires in the Western US under climate change. *Climatic Change*, 138(3–4): 655–666. https://doi.org/10.1007/s10584-016-1762-6.

Maurer EP, Kayser G, Gabel L, Wood AW. 2018. Adjusting Flood Peak Frequency Changes to Account for Climate Change Impacts in the Western United States. *Journal of Water Resources Planning and Management*, 144(3): 05017025. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000903.

Meigs GW, Kennedy RE, Gray AN, Gregory MJ. 2015. Spatiotemporal dynamics of recent mountain pine beetle and western spruce budworm outbreaks across the Pacific Northwest Region, USA. *Forest Ecology and Management*, 339: 71–86. https://doi.org/10.1016/j.foreco.2014.11.030.

Mote PW, Abatzoglou JT, Dello KD, Hegewisch K, Rupp DE. 2019. *Fourth Oregon Climate Assessment Report*. Oregon Climate Change Research Institute: Corvallis, OR.

Mote PW, Abatzoglou JT, Kunkel KE. 2013. Climate: Variability and Change in the Past and the Future: Chapter 2. In: Dalton MM, Mote PW and Snover AK (eds) *Climate Change in the Northwest: Implications for Our Landscapes, Waters, and Communities*. Island Press: Washington, DC, 25–40.

Musselman KN, Lehner F, Ikeda K, Clark MP, Prein AF, Liu C, Barlage M, Rasmussen R. 2018. Projected increases and shifts in rain-on-snow flood risk over western North America. *Nature Climate Change*, 8(9): 808–812. https://doi.org/10.1038/s41558-018-0236-4.

Najafi MR, Moradkhani H. 2015. Multi-model ensemble analysis of runoff extremes for climate change impact assessments. *Journal of Hydrology*, 525: 352–361. https://doi.org/10.1016/j.jhydrol.2015.03.045.

National Centers for Environmental Information (NCEI). 2020. *National Centers for Environmental Information, Climate at a Glance: Statewide Time Series*. .

Naz BS, Kao S-C, Ashfaq M, Rastogi D, Mei R, Bowling LC. 2016. Regional hydrologic response to climate change in the conterminous United States using high-resolution hydroclimate simulations. *Global and Planetary Change*, 143: 100–117. https://doi.org/10.1016/j.gloplacha.2016.06.003.

Nolte CG, Dolwick PD, Fann N, Horowitz LW, Naik V, Pinder RW, Spero TL, Winner DA, Ziska LH. 2018. Air Quality. In: Reidmiller DR, Avery CW, Easterling DR, Kunkel KE, Lewis KLM, Maycock TK and Stewart BC (eds) *Impacts, Risks, and Adaptation in the United States: Fourth National Climate Assessment, Volume II*. U.S. Global Change Research Program: Washington, DC, USA, 512–538.

Oregon DEQ. 2016. *2015 Oregon Air Quality Data Summaries*. Oregon Department of Environmental Quality: Portland, OR.

Parker LE, Abatzoglou JT. 2016. Spatial coherence of extreme precipitation events in the Northwestern United States. *International Journal of Climatology*, 36(6): 2451–2460. https://doi.org/10.1002/joc.4504.

Pu B, Ginoux P. 2017. Projection of American dustiness in the late 21 st century due to climate change. *Scientific Reports*, 7(1): 5553. https://doi.org/10.1038/s41598-017-05431-9.

Rawlins MA, Bradley RS, Diaz HF, Kimball JS, Robinson DA. 2016. Future Decreases in Freezing Days across North America. *Journal of Climate*, 29(19): 6923–6935. https://doi.org/10.1175/JCLI-D-15-0802.1.

Raymondi RR, Cuhaciyan JE, Glick P, Capalbo SM, Houston LL, Shafer SL, Grah O. 2013. Water Resources: Implications of Changes in Temperature and Precipiptation: Chapter 3. In: Dalton MM, Mote PW and Snover AK (eds) *Climate Change in the Northwest: Implications for Our Landscapes, Waters, and Communities*. Island Press: Washington, DC, 41–66.

Safeeq M, Grant GE, Lewis SL, Staab B. 2015. Predicting landscape sensitivity to present and future floods in the Pacific Northwest, USA. *Hydrological Processes*, 29(26): 5337–5353. https://doi.org/10.1002/hyp.10553.

Salathé E, Mauger G, Steed R, Dotson B. 2015. *Final Project Report: Regional Modeling for Windstorms and Lightning. Prepared for Seattle City Light.* Climate Impacts Group, University of Washington: Seattle, WA.

Salathé EP, Hamlet AF, Mass CF, Lee S-Y, Stumbaugh M, Steed R. 2014. Estimates of Twenty-First-Century Flood Risk in the Pacific Northwest Based on Regional Climate Model Simulations. *Journal of Hydrometeorology*, 15(5): 1881–1899. https://doi.org/10.1175/JHM-D-13-0137.1.

Seiler C, Zwiers FW. 2016. How will climate change affect explosive cyclones in the extratropics of the Northern Hemisphere? *Climate Dynamics*, 46(11): 3633–3644. https://doi.org/10.1007/s00382-015-2791-y.

Sharratt BS, Tatarko J, Abatzoglou JT, Fox FA, Huggins D. 2015. Implications of climate change on wind erosion of agricultural lands in the Columbia plateau. *Weather and Climate Extremes*, 10, Part A: 20–31. https://doi.org/10.1016/j.wace.2015.06.001.

Sheehan T, Bachelet D, Ferschweiler K. 2015. Projected major fire and vegetation changes in the Pacific Northwest of the conterminous United States under selected CMIP5 climate futures. *Ecological Modelling*, 317: 16–29. https://doi.org/10.1016/j.ecolmodel.2015.08.023.

Surfleet CG, Tullos D. 2013. Variability in effect of climate change on rain-on-snow peak flow events in a temperate climate. *Journal of Hydrology*, 479: 24–34. https://doi.org/10.1016/j.jhydrol.2012.11.021.

Tohver IM, Hamlet AF, Lee S-Y. 2014. Impacts of 21st-Century Climate Change on Hydrologic Extremes in the Pacific Northwest Region of North America. *JAWRA Journal of the American Water Resources Association*, 50(6): 1461–1476. https://doi.org/10.1111/jawr.12199.

Vose JM, Clark JS, Luce CH, Patel-Weynand T. 2016. Executive Summary. In: Vose JM, Clark JS, Luce CH and Patel-Weynand T (eds) *Effects of drought on forests and rangelands in the United States: a comprehensive science synthesis. Gen. Tech. Rep. WO-93b*. U.S. Department of Agriculture, Forest Service, Washington Office: Washington, D.C., 289.

Vose RS, Applequist S, Bourassa MA, Pryor SC, Barthelmie RJ, Blanton B, Bromirski PD, Brooks HE, DeGaetano AT, Dole RM, Easterling DR, Jensen RE, Karl TR, Katz RW, Klink K, Kruk MC, Kunkel KE, MacCracken MC, Peterson TC, Shein K, Thomas BR, Walsh JE, Wang XL, Wehner MF, Wuebbles DJ, Young RS. 2014. Monitoring and Understanding Changes in Extremes: Extratropical Storms, Winds, and Waves. *Bulletin of the American Meteorological Society*, 95(3): 377–386. https://doi.org/10.1175/BAMS-D-12-00162.1.

Vose RS, Easterling DR, Kunkel KE, LeGrande AN, Wehner MF. 2017. Temperature changes in the United States. In: Wuebbles DJ, Fahey DW, Hibbard KA, Dokken DJ, Stewart BC and Maycock TK (eds) *Climate Science Special Report: Fourth National Climate Assessment, Volume 1*. U.S. Global Change Research Program: Washington, DC, USA, 185–206.

Westerling AL. 2016. Increasing western US forest wildfire activity: sensitivity to changes in the timing of spring. *Phil. Trans. R. Soc. B*, 371(1696): 20150178. https://doi.org/10.1098/rstb.2015.0178.

Williams AP, Abatzoglou JT. 2016. Recent Advances and Remaining Uncertainties in Resolving Past and Future Climate Effects on Global Fire Activity. *Current Climate Change Reports*, 2(1): 1–14. https://doi.org/10.1007/s40641-016-0031-0.