CUMULATIVE GLOBAL CO₂ EMISSIONS AND THEIR CLIMATE IMPACT FROM LOCAL THROUGH REGIONAL SCALES

A Report for:

California's Fourth Climate Change Assessment

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DISCLAIMER

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Edmund G. Brown, Jr., Governor

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PREFACE

California's Climate Change Assessments provide a scientific foundation for understanding climate-related vulnerability at the local scale and informing resilience actions. These Assessments contribute to the advancement of science-based policies, plans, and programs to promote effective climate leadership in California. In 2006, California released its First Climate Change Assessment, which shed light on the impacts of climate change on specific sectors in California and was instrumental in supporting the passage of the landmark legislation Assembly Bill 32 (Núñez, Chapter 488, Statutes of 2006), California's Global Warming Solutions Act. The Second Assessment concluded that adaptation is a crucial complement to reducing greenhouse gas emissions (2009), given that some changes to the climate are ongoing and inevitable, motivating and informing California's first Climate Adaptation Strategy released the same year. In 2012, California's Third Climate Change Assessment made substantial progress in projecting local impacts of climate change, investigating consequences to human and natural systems, and exploring barriers to adaptation.

Under the leadership of Governor Edmund G. Brown, Jr., a trio of state agencies jointly managed and supported California's Fourth Climate Change Assessment: California's Natural Resources Agency (CNRA), the Governor's Office of Planning and Research (OPR), and the California Energy Commission (Energy Commission). The Climate Action Team Research Working Group, through which more than 20 state agencies coordinate climate-related research, served as the steering committee, providing input for a multisector call for proposals, participating in selection of research teams, and offering technical guidance throughout the process.

California's Fourth Climate Change Assessment (Fourth Assessment) advances actionable science that serves the growing needs of state and local-level decision-makers from a variety of sectors. It includes research to develop rigorous, comprehensive climate change scenarios at a scale suitable for illuminating regional vulnerabilities and localized adaptation strategies in California; datasets and tools that improve integration of observed and projected knowledge about climate change into decision-making; and recommendations and information to directly inform vulnerability assessments and adaptation strategies for California's energy sector, water resources and management, oceans and coasts, forests, wildfires, agriculture, biodiversity and habitat, and public health.

The Fourth Assessment includes 44 technical reports to advance the scientific foundation for understanding climate-related risks and resilience options, nine regional reports plus an oceans and coast report to outline climate risks and adaptation options, reports on tribal and indigenous issues as well as climate justice, and a comprehensive statewide summary report. All research contributing to the Fourth Assessment was peer-reviewed to ensure scientific rigor and relevance to practitioners and stakeholders.

For the full suite of Fourth Assessment research products, please visit <u>www.climateassessment.ca.gov</u>. This report contributes to our understanding of the relationship between global greenhouse gas emissions and regional climate impacts in California that allows the estimation of potential impacts with the Paris Agreement.

ABSTRACT

Previous work has shown that analyzing climate change as a linear function of cumulative CO_2 emissions is a useful approach when assessing climate change projections over global and large regional scales in response to different emissions scenarios. Here we demonstrate that this approach holds true for regionally confined projections over California using downscaled CMIP5 and CMIP3 GCM simulations. Measures that exhibited consistent well-behaved responses include local and regional temperature, spring snow water content over the California region, and early summer soil moisture. The response of temperature and temperature-related measures are roughly linear, with +1.4°C to +2.8°C warming for each additional 1000 GtC. Precipitation changes over the period of projected climate changes show little relationship to cumulative CO_2 , being dominated by the noise due to natural variations. Modeled area burned by wildfire and area of potential vegetation conversion increase substantially with cumulative CO_2 , illustrating how this approach may provide a way to evaluate implications of emissions on the impacts of climate change on ecosystems. Projected sea level rises are time dependent and therefore exhibit trajectories whose shapes differ between emissions scenarios.

Keywords: California climate impacts, Cumulative CO2 emissions, climate scenarios, global CO2 emissions and local impacts

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HIGHLIGHTS

- Changes in temperature, snowpack conditions, and soil moisture at the local, regional, and California statewide level depends almost linearly upon global cumulative carbon dioxide emissions since 1870, independent of global emissions pathways. This not only applies to the current suite of global emission scenarios known as RCPs but also for the prior suite of global emission scenarios known as SRES. This correlation potentially provides a unifying way to interpret studies that have used different assumptions about global emission pathways.
- Impact of extreme temperature events, wildfires, and some measures of potential ecological impacts are also a function of global cumulative carbon dioxide emissions.
- Sea level rise in California can be explained, but require a time dependent measure in addition to global cumulative carbon dioxide emissions.
- The strong relationship of some important climate variables to cumulative CO₂ emissions can be used to estimate the potential physical impacts to California of global compliance with the United Nations Framework Agreement on Climate Change Paris Agreement, which has a goal of limiting global average temperature to less than 2 °C and, if possible, to 1.5 °C.

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1: Introduction

Climate change has profound ramifications on diverse sectors at local to regional scales. In particular, anthropogenic climate change alters the hydrologic cycle in ways that may dramatically disturb ecosystems, agriculture, human-built infrastructure, and economies. The myriad impacts and the continuing, rapid evolution in our scientific understanding of them pose significant challenges to managing and coordinating responses to climate change at all scales.

One challenge regional (town, cities, counties, states) decision makers face is that climate projections change in both their assumptions and outcomes over time, prompting stakeholders to question whether previously agreed upon mitigation or adaptation efforts should be altered in light of new knowledge. This is exacerbated by the fact that structures, roads, building codes, and other similar aspects of policy and the human-built environment have multi-decadal lifespans and require significant expense and agreement to change (Milly et al 2008). Another challenge is that new global greenhouse gas emission scenarios (e.g., scenarios compatible with the Paris Agreement) may become available after the spatially downscaled climate scenarios have become available for a specific region. It may be difficult or impractical for such efforts to keep up with changing future climate scenario assumptions or newer generations of climate model projections that show different local climate outcomes in association with ongoing rounds of the IPCC climate assessment process. Since running global and regional climate models can take years, it is hard to estimate the potential implications of the new global emission scenarios to a specific region.

Previous work considering global and large-scale regional impacts has shown that analyzing climate change as a function of cumulative CO₂ emission is a useful approach that can unify expected climate change in the face of different emissions scenarios (e.g., Matthews et al. 2009; Gillett et al. 2009; Allen et al. 2009; IPCC, 2013). Theoretical and model-based investigations (Goodwin et al. 2015; Williams et al. 2016) indicate that the nearly linear relationship of warming to cumulative CO₂ emissions may arise when radiative forcing, which varies as the log of atmospheric CO₂ concentration, is modified by carbon uptake by terrestrial and ocean systems as the planet warms. As CO₂ emissions grow, there is an increase in carbon uptake that diminishes the role of CO₂ emissions on radiative forcing while, simultaneously, a decrease of heat uptake by the oceans approximately compensates for the smaller increase in radiative forcing due to CO₂ emissions (Williams et al., 2016). This behavior is valid up to a cumulative CO₂ emissions threshold of approximately 1500 gigatons of carbon (GtC), beyond which the global temperature response may be less pronounced (Herrington and Zickfeld, 2014). This value is reached at about year 2067 in the RCP 8.5 scenario while RCP 4.5 never reaches this level of global cumulative emissions in this century.

The relationship between global average annual temperature increases and cumulative global CO_2 emissions can be quantified by the transient climate response to cumulative carbon emissions (TCRE). The TCRE is model-dependent since different models have different climate sensitivities, with values ranging from about 0.7 to 2.5 °C per 1,000 GtC (IPCC, 2013; Gillete et al. 2013). Recent studies have also investigated how TCRE may be affected by the rate of increasing CO_2 emissions (Krasting et al., 2014) and short-lived atmospheric aerosols or non- CO_2 greenhouse gases (Rogelj, et al., 2015). Importantly, the latter may alter the relationship

between global average temperatures and cumulative CO₂ emissions (see Figure 2.3 in IPCC, 2014). This effect becomes important when considering a "budget" for cumulative CO₂ emissions needed to contain global warming below a given threshold. For example, with a target global warming threshold of 2°C, Roelj et al., 2015 found that the CO₂ budget is 25% larger if stringent methane mitigation is implemented, since methane is a more potent greenhouse gas than CO₂. Conversely, the CO₂ budget is reduced if sulfate aerosols are decreased via a reduction in sulfur oxide emissions, since sulfate aerosols cool the planet by reflecting sunlight (Rogelj et al., 2015). In reality, CO₂ emissions are not independent of emissions of other short-lived climate pollutants (such as black carbon, methane, and reflective agents such as sulfate), so the RCPs already implicitly include assumptions about future trajectories of short-lived climate pollutants.

Cumulative carbon emissions have been linked to physical manifestations of a changing climate other than annual mean temperature. Observed Artic sea-ice loss has followed an approximate linear relationship with cumulative emissions (Notz and Stroeve, 2016). Projected regional climate extremes such as the hottest and coldest day per year and the annual maximum consecutive 5-day precipitation total were found to be approximately linearly associated with cumulative carbon emissions at large regional levels, such as the conterminous U.S. (Senevitratne et al, 2016). Projected changes in precipitation over the oceans also seems to scale linearly with emissions, but over land, where precipitation is complicated by phenomena such as the interaction of atmospheric circulation and orographic features, this relationship can break down. The studies referenced in this paragraph used a myriad of Earth System Models (ESMs) but a more detailed study exercising a single ESM, the third Hadley Center Climate Model (HadCM3; Gordon et al., 2000), indicates that at levels exceeding 1,000 GtC of cumulative emissions, precipitation over land may actually decrease; this is mostly due to changes in precipitation in the tropics and, more specifically, in the Amazon region (Liddicoat et al., 2016).

Research has also investigated relationships between physical impacts and cumulative carbon emissions at large regional scales including Northern Europe, the Western USA, and Eastern Africa, indicating that nearly linear regional TCREs (RTCREs) are present, but with regional differences. For example, the average RTCRE for the Western USA was found to be about 2.4 °C per 1,000 GtC, and for the Arctic about 5 °C per 1,000 GtC (Leduc et al., 2016; Seneviratne et al., 2016). A recent study investigated the relationship between cumulative CO₂ emissions and seasonal climate at regional scales (Partanen et al., 2017). The authors used results from 12 ESMs from the Coupled Model Intercomparison Project Phase 5 (CMIP5) involving numerical experiments with CO₂ concentrations increasing at 1% per year. Seasonal regional temperature and precipitation changes scale almost linearly with cumulative CO₂ emissions, but natural variability tends to make results for precipitation less robust (Partanen et al., 2017). Importantly, the existence of a defined RTCRE suggests that cumulative carbon emissions can be used to quantify physical impacts at regional levels and sheds light on regional implications of global targets, such the Paris Agreement global warming targets of less than 2°C or, more optimistically, less than 1.5°C (Sanderson et al 2016).

Although the work cited above shows that projected global and large-scale regional temperature changes, are largely independent of emission pathways if presented as a function of cumulative CO_2 emissions, there may be other important physical, ecological, or economic impacts that are time- or path-dependent. Key factors driving this behavior include local feedbacks and processes that change slowly compared to changing atmospheric CO_2

concentrations. For example, a notable departure from the linear relationship between cumulative CO₂ emissions and regional temperature projections was identified in the Barents Sea and ascribed to ice albedo feedbacks and reduced oceanic meridional overturning circulation (Leduc et al., 2016). Other climate impacts that may depend on emissions history include sea level rise, changes of flora and fauna (LoPresti, et al., 2015), and changes of longlived human infrastructure.

For purposes of the present study, time dependent impacts are defined as those impacts that differ depending on the time required to reach a given cumulative CO₂ emission level (e.g., 2050 vs 2100), even if the same final warming is attained. For example, Leemans and Eickhout (2004) estimated that a warming of 0.1°C per decade may allow 50% of ecosystems to keep pace with warming and migrate to suitable regions, but 0.3°C per decade may allow only 30% of ecosystems to keep pace. In essence, slower warming may lessen ecological impacts of climate change. Turning to sea level, the substantial thermal inertia of Antarctica's cryosphere means there could be a delay in the contribution of Antarctica to sea level rise due to warming.

Here we consider whether linear CO₂ relationships exist for downscaled climate projections throughout and within California, which has a large economy (equivalent to the fifth largest in the world, were it a county (Business Insider 2018). The California region is a particularly challenging case for this analysis since it has considerable spatial variation that accords with its highly varied landscape ranging from coastal plains, inland valleys, rugged mountains and desert basins. If this approach yields results that are consistent with the body of global and larger regional studies described above, it would allow, in an approximate way, the interpretation of an extensive body of ongoing (e.g. the Fourth California Climate Change Assessment: <u>http://resources.ca.gov/climate/safeguarding/research/</u>) and prior studies of climate impacts and adaptation options in the California region.

We explore various measures of projected climate change to cumulative CO₂ emissions in our domain of interest (California), using spatially downscaled climate model data from two generations of global climate models, as collected in the Coupled Model Intercomparison Project versions 3 (CMIP3) and 5 (CMIP5). In Section 2 we describe the data and methods used in this work, including those for global and spatially downscaled temperature, precipitation, and related hydrologic and land processes. Section 3 shows the results, and Section 4 presents discussions and conclusions.

2: Data Sets and Methods

Because of our interest in hydrologic and other land processes, which are poorly represented in the relatively coarse-resolution global climate models (GCMs), we used existing archives of spatially downscaled climate data for this study rather than data from the original GCMs. Additionally, part of our objective is to see how results from different generations of climate models can be sensibly compared and used together, so we used downscaled data from two generations of climate models, CMIP3 and CMIP5.

From the CMIP3 GCMs, we use a subset of six global climate models selected for California's Second Climate Assessment (Franco, et al, 2011). These models were selected based on their ability to represent large-scale climate impacts of importance to California and on the

availability of monthly and daily data. The CMIP3 data were downscaled using the Bias Corrected Spatially Downscaled (BCSD) methodology (Maurer and Hidalgo 2008) with CMIP3 IPCC greenhouse gas and aerosol emissions scenarios A2 and B1 that were part of the IPCC Special Report Emission Scenarios (SRES) (IPCC, 2000).

From the CMIP5 GCMs, we used statistically downscaled data using the Localized Constructed Analogues (LOCA) technique (Pierce et al. 2014). The data are first bias corrected using methods that attempt to retain the original GCM-predicted future change, multiplicatively for precipitation and additively for temperature, and then frequency-dependent bias correction is applied to better reproduce the observed spectrum of variability (Pierce et al. 2015). The data were then spatially downscaled using a constructed analogues method, whereby the best-matching days from historical observations (Livneh et al., 2015) were identified, first in the wider region around the point being downscaled, and then in the local region around the point (a 1°x1° box; see Pierce et al. 2014 for details). The best-matching observed days are used to construct the final result on a 1/16th degree latitude-longitude grid, each grid cell containing an area of about 38 km². The data cover 1950-2005 for the historical period, and include two future climate projections for the period 2006-2100, one using medium (RCP 4.5) and one high (RCP 8.5) greenhouse gas and aerosol emissions scenarios.

The LOCA data set includes 32 GCMs, all which had the required daily minimum temperature (Tmin), daily maximum temperature (Tmax), and daily precipitation available when the downscaling project was undertaken. From this, the subset used in this study are the downscaled data from 10 of the CMIP5 GCMs, which were selected for their superior ability to realistically represent large scale and regional climatic features of importance to California (DWR, 2015). The 10 models also approximately cover the range of temperature and precipitation projections from the full set of GCMs that participated in CMIP5. From those 10 GCMs, a smaller subset that we use are downscaled data from 4 of the CMIP5 GCMs, selected to effectively cover the climate changes exhibited in the 10 GCM set (Pierce et al. 2018).

The LOCA-downscaled meteorological data (Tmin, Tmax, and precipitation) were used to drive the Variable Infiltration Capacity (VIC) hydrological model (Liang et al. 1994; Hamlet et al. 2005; Das et al. 2009) to estimate land surface impacts of interest in this work, such as soil moisture and snowpack.

Cumulative CO₂ emissions for RCP4.5 and RCP8.5 were obtained from the central data repository hosted by IIASA for the IPCC as described in the IPCC Data Distribution Center (http://sedac.ipcc-data.org/ddc/ar5_scenario_process/RCPs.html).

To evaluate impacts on spring snowpack and other related variables, locations in California, Oregon, and Nevada that are presently affected directly by snow were identified using an historical (1950-1999) VIC simulation. VIC grid cells were included if they received, as an average over the historical period, at least 1cm of April 1 snow water equivalent (SWE) and that amount of SWE comprised at least 25% of their annual precipitation.

Hydro-meteorological data from LOCA/VIC came from Cal-Adapt¹ and from a website² maintained by Lawrence Livermore National Laboratory which hosts downscaled CMIP3 and CMIP5 climate and hydrological projections for the United States (Maurer et al., 2017).

The SRES emissions data came for the data repository maintained by the IPCC (<u>http://sres.ciesin.org/final_data.html</u>).

3: Results

3.1 Temperature Projections and Cumulative CO₂ Emissions

LOCA annual average temperature projections for California suggest about equal warming in the RCP 4.5 and 8.5 data sets until mid-21st Century, with a divergence thereafter. Ultimately, the state is projected to experience a 2 °C warming over the 21st century for RCP 4.5, and a 4 °C warming for RCP 8.5 (See Figure A1 in the Appendix). Figure 1 presents annual average temperatures as a function of global CO₂ emissions for 10 global climate models. The blue and red "spaghettis" present results for RCP4.5 and RCP8.5, respectively. The almost perfect agreement of the results for RCP4.5 and RCP8.5, when temperature is plotted as a function of global cumulative emissions, is reassuring because it means that it is possible to estimate future changes in temperatures for other emissions scenarios by simply using its cumulative CO₂ emissions with time. The correlation coefficient R is 0.995 with a very high level of confidence (p < 0.001). The correlation is estimated here and in the rest of the figure in this paper, between the average values for RCP4.5 (tick blue line) and RCP8.5 (tick red line).

¹ http://cal-adapt.org/

² https://gdo-dcp.ucllnl.org/downscaled_cmip_projections/dcpInterface.html#About



Figure 1: Annual average California temperatures for historical simulations (1950 to 2005) and projections after 2005 for RCP4.5 and RCP8.5 using outputs from LOCA. Each line represents results from one of 10 GCMs. The mean of the 10 models is emphasized with darker lines. Blue and red represent results for RCP4.5, and RCP8.5, respectively.

The same results are observed at the individual grid levels. As an illustration, Figure 2 compares annual average temperatures downscaled using LOCA from a specific GCM (HadGEM2-ES) for a grid point in Sacramento (R = 0.886; p < 0.001).



Figure 2: Annual average temperatures for historical simulations (1950 to 2005) and projections after 2005 for RCP4.5 and RCP8.5 using outputs from LOCA for a grid point in Sacramento, CA. In 2005 cumulative CO₂ emissions were 441.7 GtC.

Annualy and seasonally averaged temperatures show a close-to linear relationship with cumulative CO_2 emissions. For example, Figure 3 presents average temperature from July to September, which is dry season in California (R=0.993; p<0.001). The median values of the 10 GCMs closely follow a linear relationship. The spread for different years is expected due to natural variability and also to variability in GCM climate sensitivity as demonstrated by differences in their TCRE and RTCRE as reported by others (e.g. Gillette et al. 2013).



Figure 3: Cumulative global CO₂ emissions versus average temperature from October to March for the selected 10 GCMs for simulations of historical and projected periods for California.

The number of temperature extremes, defined here as temperatures equal to or above the 98th percentile of summer maximum daily temperature³ from 1950 to 2005, exhibits an increasing relationship with cumulative CO_2 emissions (Figure 4). The average number of extreme events for RCP4.5 and RCP8.5 are very similar ((R= 0.845; p<0.001). Figure 4 shows the projected extremes for a grid point near Sacramento, California, but similar results were found for other locations

³ We used 98th percentile to be in agreement with Cal-Adapt.org, which is one of the repositories of climate projections for California used by state agencies and local governments in California.



Figure 4: Number of summer temperature extremes per year where extremes are daily maximum temperatures equal to or higher than the 98th percentile in the historical period for Sacramento, California.

For multiple individual grid points in different climatic zones in California, we plotted annual and seasonal averaged temperatures with cumulative CO₂ emissions for the SRES and RCP global emission scenarios. To reduce the differences resulting from the use of different GCMs, we used an earlier and a more recent version of the same GCM (e.g., CCSM3 and CCSM4 in Figure 4), but similar behavior was found for other GCMs. Even at the local level we found a close to functional relationship of temperature with cumulative CO₂ emissions, as shown in Figure 5.



Figure 5: Annual average temperature for a local point in Sacramento, California for the A2, B1, scenario using BCSD downscaling results and RCP 4.5 and RCP 8.5 using LOCA and BCSD for CCSM3 and CCSM4 models.

We also created sample temperature maps for California for decades with similar cumulative CO_2 emissions from both RCP4.5 and RCP8.5 (See supplementary Figure A2). The maps, as expected, are very similar (R= 0.99; p<0.001), confirming our results at grid scale and at broader geographical resolution and coverage.

Finally, we performed an analysis of temperature using available results from dynamic regional climate models provided via NA-CORDEX (North America Coordinated Regional Climate Downscaling Experiment). The temperatures generated by NA-CORDEX follow the same behavior as with LOCA in the sense that the temperatures are mostly a function of cumulative CO₂ emissions independent of the RCPs (see Figures A5 to A8 in the Appendix).

3.2 Precipitation and other Climate Parameters and Cumulative CO₂ Emissions

Natural climate variability for precipitation is very high in California (Dettinger et al., 2011), which is expected to obscure the relationship between precipitation and cumulative emissions. As shown in Figure 6, this is indeed the case. Nevertheless, Figure 6 shows that for both RCP4.5 and RCP8.5 there is little dependence upon cumulative CO₂ emissions, although there may be a



slight increase in precipitation as cumulative CO_2 increases. The correlation (R) between the blue (RCP4.5) and red (RCP8.5) lines is 0.46 (p<0.001).

Figure 6: Precipitation changes with climate change in California as a function of global cumulative CO₂ emissions.

Mountain snowpack in the California region is of great importance because it provides water for agricultural, industrial, and domestic users as well as natural ecosystems. California's Mediterranean climate is characterized by dry summers with about 90% of the precipitation taking place from October to March (e.g. Dettinger et al. 2011; Cayan et al. 2016). Water managers carefully survey the amount of water stored in mountain catchments on April 1st to determine the allocation of water for different uses such as irrigation in the spring and summer of the same year. Figure 7 shows that the VIC modeled snow water content totaled over the region contributing to California's water supply on April 1st is projected to decrease markedly with a warming climate. The loss of snow water equivalent continues until Cumulative CO_2 emissions rise to about 1500 GtC, beyond which April 1 SWE decline is not as steep because over much of the region it has already fallen to a very low amount and there is little remaining to lose. The correlation coefficient showing the association of between the average values for RCP4.5 (dark blue line) and RCP8.5 (dark red line) is 0.86 at a very high confidence level (p < 0.0001).



Figure 7: April 1st snow water equivalent (SWE) exhibits a clear connection to cumulative CO₂ emissions. SWE was calculated for the dark region in the map.

Soil moisture conditions at the beginning of the summer are important because they have strong influence on natural ecosystems and they condition wildfire hazards (Westerling et al., 2006, Westerling 2016). Soil moisture conditions in the agricultural areas of California likely serve as an index for the amount of irrigation that is needed for annual and perennial crops. Figure 8 shows that VIC modeled June 1st soil moisture declines steadily with cumulative CO₂ emissions (R=0.71; p<0.0001), falling about 16 mm per 1,000 GtC cumulative CO₂ (p <0.0001). This decline reflects the region's increase in temperature because, as shown in Figure 6, precipitation is essentially unchanged with cumulative CO₂ emissions.



Figure 8: Soil moisture near to the surface declines with cumulative CO₂ emissions in California.

3.3 Wildfire and Vegetation as a Function of Cumulative CO₂ Emissions

Projected changes in wildfire may also be a function of time because wildfire activity is not only a function of temperature and aridity but depends also on the type of vegetation available as a fuel, which may respond to changes in climate at different time scales. We use here a recent set of wildfire projections available for California (Westerling et al., 2018) and focus on Sierra Nevada forests, which contain most of the biomass vulnerable to climate change-altered disturbance regimes in the state. Figure 9 shows the outputs for four GCMs for which results are available. There are, as expected, large natural fluctuations from year to year but averaging across all the GSMs suggests that for this particular set of projections, a close to linear relationship exists.



Figure 9: Wildfire projections (areas burned) for the Sierra Nevada for the averages of four global climate models.

Figure 10 presents the average of areas burned in California for the 4 models used by Westerling, 2018 for time periods of the RCP 4.5 and RCP 8.5 simulations when cumulative CO_2 emissions are nearly the same (0.1% difference). The mean acres burned for RCP 4.5 and RCP 8.5 are 24.4 and 24.6 hectares, respectively, with a correlation coefficient of 0.985 (p < 0.0001), which means that the two maps are identical from a statistical perspective.

30-yr mean area burned: 2039-2068 RCP 8.5

30-yr mean area burned: 2070-2099 RCP 4.5



Figure 10: Mean area burned for two 30-year periods for RCP 4.5 and RCP 8.5 with similar average cumulative CO₂ emissions.

The rather surprising similarity of the area burned in the two prior figures may reflect the fact that the method used to generate the wildfire projections does not include potential changes in vegetation patterns. On-going work will consider changes in vegetation patterns and explore the usefulness of using time as a second explanatory variable.

Another assessment of the California landscape uses a climate exposure model to examine potential stress to natural vegetation using bracketed futures for California that vary between 1.9 and 4.5 °C or +22.9 and -24.8% precipitation by 2100 (Thorne et al. 2017). This approach classifies the frequency with which different vegetation types occupy current climate conditions, identifies marginal (high stressful) conditions, and tracks how much area of each vegetation type becomes highly climatically exposed under different emission pathways through time. Based upon 270 m spatial units, cumulative area increases in climate risk were determined over 99% of California's natural vegetated area (353,719 km²). Using a cutoff of the most marginal 5% of climate conditions in current time as the conditions under which vegetation is likely to be at higher climatic risk, the increase in the area under climate risk was determined. We found that there is a non-linear increase in the area-at-risk in association with cumulative CO₂ emissions (Figure 11). While the non-linear relationship differs from one GCM to another (not-shown), the results for RCP 4.5 and RCP 8.5 follow each other very closely when the same GCM is used, as shown in Figure 11 for the MIROC GCM. Also, the geographical distribution of heightened risk looks similar for periods with similar cumulative CO₂ emissions for the same GCMs (See supplementary Figure A3).



Figure 11: Areas at risk for California's natural vegetation entering climatically stressful conditions using the MIROC ESM GCM.

3.4 Sea Level Rise Depends on Cumulative CO₂ Emissions and Time

Sea level rise will result in large challenges to California coastal residents, infrastructure, and natural systems (Griggs et al 2017). The large inertia of some natural and human systems, including the volume occupied by ocean waters, may result in a delayed response to atmospheric temperature and, therefore to cumulative CO₂ emissions. For example, we found that sea level rise projections for San Francisco (Pierce et al., 2018) do not scale linearly with cumulative CO_2 emissions as shown in Figure 12. For the same cumulative CO_2 emissions, the response of RCP4.5 is stronger than for RCP8.5. This is because the same cumulative CO_2 emissions are reached later in RCP4.5 than in the RCP8.5. Giving delayed grounded ice loss processes, more time would be required to manifest in the sea level record. Remarkably, the addition of a simple function depending also on time with the following mathematical function $[\ln (SLR) = a - b/(cumulative emissions) - c/(time)^2]$ has a strong explanatory power ($R^2 > 0.99$) (see supplementary Figure A4), where a, b, and c are derived constants estimated using a curve fitting tool available in MATLAB® (see Figure A4). This suggests that this approach can be used to estimate sea level rise using both time and cumulative CO₂ emissions for other global emission scenarios. This first order approximation should be corroborated with sea level rise projections covering a wider range than the three RCPs represented in Figure 12.



Figure 12: Sea level rise projections for San Francisco as a function of cumulative CO₂ emissions. This figure shows the 50th percentile of the projections in Pierce et al., 2018. Sea level rise [cm] is relative to mean sea level in the year 2000.

3.5 California Climate and Impacts under a Stabilized Global Climate Scenario

Downscaled global climate model projections indicate that California faces elevated temperature wherein under moderate (RCP4.5) to high (RCP8.5) emissions, statewide mean annual temperature increases would range from 2°C and 6°C by 2100. To avoid dangerous impacts, future CO₂ emissions will need to be reduced dramatically. There are several estimates about additional CO₂ emissions that can be emitted to stabilize global average temperatures between 2°C and 1.5°C from pre-industrial temperature levels (e.g., see Table 2 in Rogelij et al., 2016). The nearly-linear relationships between impacts and cumulative CO₂ emissions can be used to estimate the potential impacts of the Paris Agreement on California. For Table 1 we use the range between 652 GtC and 790 GtC of total cumulative CO₂ emissions as the range that gives a reasonable chance of limiting warming in the Paris range. We estimate this range from Millar et al., 2017 and Rogelij et al., 2016, respectively

Table 1 shows the range of outcomes for the cumulative CO_2 scenarios reported above. California statewide temperature increases that would occur under this scenario would range between roughly 0.67 °C (1.2 °F) and 0.9 °C (1.6°F) compared to 1976-2005 average temperatures (corresponding to global temperatures being stabilized at 1.5 °C and 2 °C, respectively). This would be on top of the warming of about 1.1 °C (2 °F) already experienced in California from 1895 to the present (California Climate Tracker <u>https://wrcc.dri.edu/monitor/cal-mon/frames_version.html</u>).

Case	Baseline:	RCP 8.5	Stabilization	Stabilization
	1976 - 2005	End of Century	1.5°C	2°C
Annual Average Temperature	14°C	19°C	15.2°C	15.6°C
Number of extreme hot days: Sacramento	1.6	14.3	2.37	2.9
April 1 st Snow Water Equivalent (mm)	477	- 74 %	- 22 %	- 22.8 %
Soil Moisture (mm)	298 mm	- 10%	- 1.3 %	- 2.5 %
Wildfires: area burned (Hectares)	169,084	+ 63 %	+ 20 %	+ 20 %
Sea Level Rise (cm) increase in 2100 from year 2000: mean values	NA	137	28	41

Table 1: Summary of potential climatic impacts to California under different cases

The changes estimated in Table 1 demonstrate that meeting the Paris target would make a significant difference with respect to what is expected for the RCP8.5 scenario by the end of the century. Since sea level rise is also a function of time, we compute sea level rise by the end of this century using both cumulative CO_2 emissions and time since year 2000. The values for the 1.5 °C and 2 °C stabilization compare well with estimates reported by Bittermann et al., 2017 (their table 2) for global sea levels. According to Bittermann et al. 2017, the trajectory to stabilization to the Paris goals has little long-term influence on global mean sea levels, in agreement with the idea that sea level rise is a strong function of cumulative CO_2 and time.

4: Conclusions and Future Directions

Downscaled CMIP5 and CMIP3 GCM results over the California region demonstrate that global cumulative CO₂ (CumCO₂) emissions can be used to estimate some important measures of physical change at the local and regional levels in the state. We find the response of temperature and temperature-related measures to be roughly linear, with +0.7°C to +1.4°C warming for each additional 500GtC. Measures we have investigated that appeared to exhibit well-behaved responses with cumulative CO₂ include spring snowpack over the California region and summer soil moisture. In addition, to the extent that can be determined from recent model results, there was a quasi-linear relationship between cumulative CO₂ and the acres in California burned by wildfires and the amount of vegetated area in California under high risk of being converted to other vegetation types, as driven by climate changes.

Other changes due to warming and other global climate change drivers are time dependent, so they register a non-linear relationship with cumulative CO₂, and the projected results from different scenarios follow different trajectories. Notable is the magnitude of regional sea level rise and by extension the magnitude of coastal impacts.

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APPENDIX A: Supplmentary Figures



Figure A1: Annual Average Temperature for California



Figure A2: Spatial distribution of Tmax when CumCO₂ with similar for RCP 4.5 (top left) and RCP 8.5 (top right). Projections for the same model: MIROC5. The average cumulative CO₂ emissions are 1162 GtC and 1208 GtC for the RCP4.5 and RCP8.5, respectively. The correlation between the two maps is R = 0.99 (p<0.001). The map in the middle shows the diffrences between RCP4.5 and RCP8.5 with the time series showing correlations for the points with the maximum positive and negative differences.



Source: The map comes from Thorne, J. H., H. Choe, R. M. Boynton, J. Bjorkman, W. Albright, K. Nydick, A. L. Flint, L. E. Flint, M. W. Schwartz. 2017. The impact of climate change uncertainty on California's vegetation and adaptation management. *Ecosphere* 8(12):e02021. <u>http://onlinelibrary.wiley.com/doi/10.1002/ecs2.2021/full</u>

Figure A3: The extent of California's natural vegetation entering climatically stressful conditions using the MIROC GCM. The left panel shows end-century climate stress in orange and red (the most marginal 5 % of current climates for each vegetation type) under RCP4.5. The right hand panel shows the mid-century level of stress under the current level of emissions, the business as usual RCP8.5 scenario. The spatial patterns of stress are similar (R = 0.96), in part because the underlying circulation assumptions are held constant while CO₂ concentrations increase. Grey areas representing agriculture and urban extents were not analyzed.



Data Source: Cayan et al, 2018. Climate Scenarios for the California 4th Climate Change Assessment: Model Selection, Downscaling, Drought Scenario and Sea Level Rise. Under Review

Figure A4: Curve fitting of the 50th percentile projections in Cayan et al., 2018 for RCP 2.6, RCP 4.5, and RCP 8.5 using MATLAB®.



Figure A5. Annual Average Temperature for California from the available NA-CORDEX outputs. The dynamic regional climate models inherit the substantial biases present for the California region from the parent Global Climate Model.



Figure A6. Annual Average Temperature for California from the available NA-CORDEX outputs shown as anomalies with respect to 1950-2005 average temperatures for each coupled regional and global climate model available via CORDEX.



Figure A7. Same as in Figure A6 but as function of cumulative CO₂ emissions.



Figure A8. Typical NA-CORDEX results for California for annual average temperatures for a regional climate model downscaling the results of a global climate model. In this case CanRCM4 is the regional climate model driven by the CanESM2 global model. The correlation coefficient is R = 0.946 with a very high level of confidence (p<0.0001)