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Supplement of

Low-carbon energy generates public health savings in California

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Supplementary Information

Table S1: Integrated GHG and co-benefit assessments that encompass California and examines criteria pollutant emissions, air pollution simulations, health benefits, and valued health savings for 2050.

Author	Region, resolution	Time-frame	Energy model, scenario, policy, economics, sectors	Emission Estimation	Climate/ Atmospheric Model	Short-lived Pollu-tant(s)	Additional Impacts analyzed
This study	California, 4 km x 4 km (~0.05° x 0.05°)	2050	2 scenarios from CA-TIMES: BAU, GHG-Step. System-wide cost minimization optimization. (Yang, Yeh et al. 2014, Yang, Yeh et al. 2015)	$16km^2$ spatial emissions scaling for each sector/mode/technology/fuel (fossil and alterative) based on literature, and existing current emission inventories	UCD/CIT Airshed (Kleeman, Cass et al. 1997, Kleeman and Cass 2001, Ying, Fraser et al. 2007)	$PM_{2.5}$ (speciation and size re-solved), O_3	Mortality (deaths, death rate), cost (US$)
(Jacobson, Delucchi et al. 2014)	California, 0.6º x 0.5º	2020, 2030, 2050	2 scenarios: reference, 100% Wind, Water, Sunlight (WWS) by 2050	Measured California county 2010-2012 PM2.5 concentration and 8-hour ozone level	GATOR-GCMOM, Gas, Aerosol, Transport, Radiation, General Circulation, Mesoscale, and Ocean Model (Jacobson, Kaufman et al. 2007)	$PM_{2.5}$, O_3	Mortality (deaths), costs ($US), job loss (jobs, earnings)
Garcia-Menendez, Saari et al. (2015)	US contiguous, 1.9° × 2.5°	2050, 2100	3 scenarios: reference, 4.5 W m^{-2} and 3.7 W m^{-2} stabilization to 2100	Emissions Prediction and Policy Analysis (EPPA) Model (Paltsev, Reilly et al. 2005)	CAM-Chem (Lamarque, Emmons et al. 2012)	O_3, $PM_{2.5}$	Years of life saved, Cost/Benefit (% GDP), % ton^{-1}

Table S2 ***(cont.)*****:**

Author	Region, resolution	Time-frame	Energy model, scenario, policy, economics, sectors	Emission Estimation	Climate/ Atmospheric Model	Short-lived Pollu-tant(s)	Additional Impacts analyzed
Shindell, Kuylenstierna et al. (2012)	Global, 4° x 5°	2050	manually selected policy measures based on GAINS	Greenhouse Gas and Air Pollution Interactions and Synergies (GAINS) model used for reductions (GAINS Development Team. International Institute for Applied Systems Analysis (IIASA) 2009)	ECHAM5-HAMMOZ (Pozzoli, Bey et al. 2008) and GISS PUCCINI (Shindell, Faluvegi et al. 2006)	CH_4, BC	mortality, crop loss, Cost ($ $tonne^{-1}$), temperature, RF (W m^{-2}),
Smith, West et al. (2011) West, Smith et al. (2013)	Global, 2° x 2.5°/1000km^2	2030, 2050, 2100	2 scenarios from Global Change Assessment Model (GCAM) : RCP4.5 scenario (Thomson, Calvin et al. 2011), global carbon price	ERB module in Mini Climate Assessment (MiniCAM) model (Brenkert, Smith et al. 2003)	MAGICC6 (Model for the Assessment of Greenhouse-gas Induced Climate Change) module in MiniCAM model (Brenkert, Smith et al. 2003, Meinshausen, Raper et al. 2011)	$PM_{2.5}$, O_3	Mortality, cost ($/tonne)
van Aardenne, Dentener et al. (2010)	Global, 1x1 North America, Europe, India, China, 3x2 remaining Northern Hemisphere, 6x 4 Southern Hemisphere	2050	6 scenarios: climate/air policy alone or together with various country adoption from Prospective Outlook for the Long term Energy System (POLES) model (Russ, Wiesenthal et al. 2007)	Emission Database for Global Atmospheric Research (EDGAR) v4 and GAINS	TM5 (Tracer Model ver. 5) (Krol, Houweling et al. 2005)	PM, O_3	Crop loss reduction (%), years life lost/ life expectancy (years/person), radiative forcing (W/m^{-2})

Numerous regional and worldwide studies have examined how climate policies and energy scenarios impact air quality, health, and costs as far as 2050 (Table S1). However, the approach and assumptions associated with each study's energy/climate policy scenarios produce very different outcomes and insights. For instance, some studies produced future energy/climate policy scenarios that are heavily user defined, often on the basis that both pollutants be mitigated. Shindell, Kuylenstierna et al. (2012), used only measures that were "assumed to improve air quality" and mitigate both long-lived GHGs and short-lived criteria pollutants after ranking them by climate impact. The scenario by Jacobson, Delucchi et al. (2014) is defined by 100% wind, water, sunlight (100%WWS) renewable supply (and no fossil fuels and biofuels) versus one that is constrained to achieve 80% GHG emissions reduction such as CA-TIMES GHG-Step. These user-defined measures and energy constraints not only produce different energy projections, but air pollution/health outcomes as well. By permitting only low polluting or zero-emission technologies and policy measures, these scenarios are more heavily defined by the authors/modelers to be somewhat biased to be much cleaner and highly advantageous to human health. The extensive study by van Aardenne, Dentener et al. (2010) explores 6 scenarios with wider levels of air and/or climate policy, as well as the option of biofuel consumption, however, technology adoption is again largely dependent on user specified assumptions on shares of existing technologies. In comparison, this study did not predefine scenario conditions that ensured both criteria pollutants and GHGs would reduce.

In contrast, CA-TIMES (1) permits dirtier energy resources (such as biofuels) and measures that don't necessary reduce air pollution, enabling a more conservative pollution outcome, (2) reveals sectors/technology investments and fuel/energy that are most cost-effective rather than user defined choices (3) has more complex new/alternative technology choices, deployment costs, that simpler scenarios ignore. Additional differences exist in the development of the criteria emissions in CA-REMARQUE such as spatial (12 electric utility regions) resource mix growth projections based on SWITCH (Fripp 2012, Johnston, Mileva et al. 2013, Nelson, Mileva et al. 2013) 2050 electricity generation projections, optimal biofacility siting locations that comply with potential air quality permitting restrictions (Tittmann, Parker et al. 2010, Parker 2012), and alternative fuel and regenerative braking emission rates based on alternative fuel emission literature.

Table S3: Population growth rate between 2050 and 2010.

County	2050:2010 Population	County	2050:2010 Population
Alameda	1.113	Orange	1.102
Alpine	0.985	Placer	1.562
Amador	1.184	Plumas	0.983
Butte	1.515	Riverside	1.747
Calaveras	1.321	Sacramento	1.452
Colusa	1.711	San Benito	1.479
Contra Costa	1.415	San Bernardino	1.594
Del Norte	1.127	San Diego	1.279
El Dorado	1.565	San Francisco	1.126
Fresno	1.619	San Joaquin	2.009
Glenn	1.351	San Luis Obispo	1.256
Humboldt	1.099	San Mateo	1.244
Imperial	1.863	Santa Barbara	1.194
Inyo	1.244	Santa Clara	1.205
Kern	2.209	Santa Cruz	1.153
Kings	1.706	Shasta	1.46
Lake	1.636	Sierra	1.125
Lassen	1.183	Siskiyou	1.161
Los Angeles	1.164	Solano	1.435
Madera	2.138	Sonoma	1.237
Marin	1.048	Stanislaus	1.673
Mariposa	1.264	Sutter	2.241
Mendocino	1.136	Tehama	1.551
Merced	1.941	Trinity	1.325
Modoc	1.119	Tulare	1.77
Mono	1.335	Tuolumne	1.118
Monterey	1.304	Ventura	1.207
Napa	1.354	Yolo	1.476
Nevada	1.425	Yuba	1.991

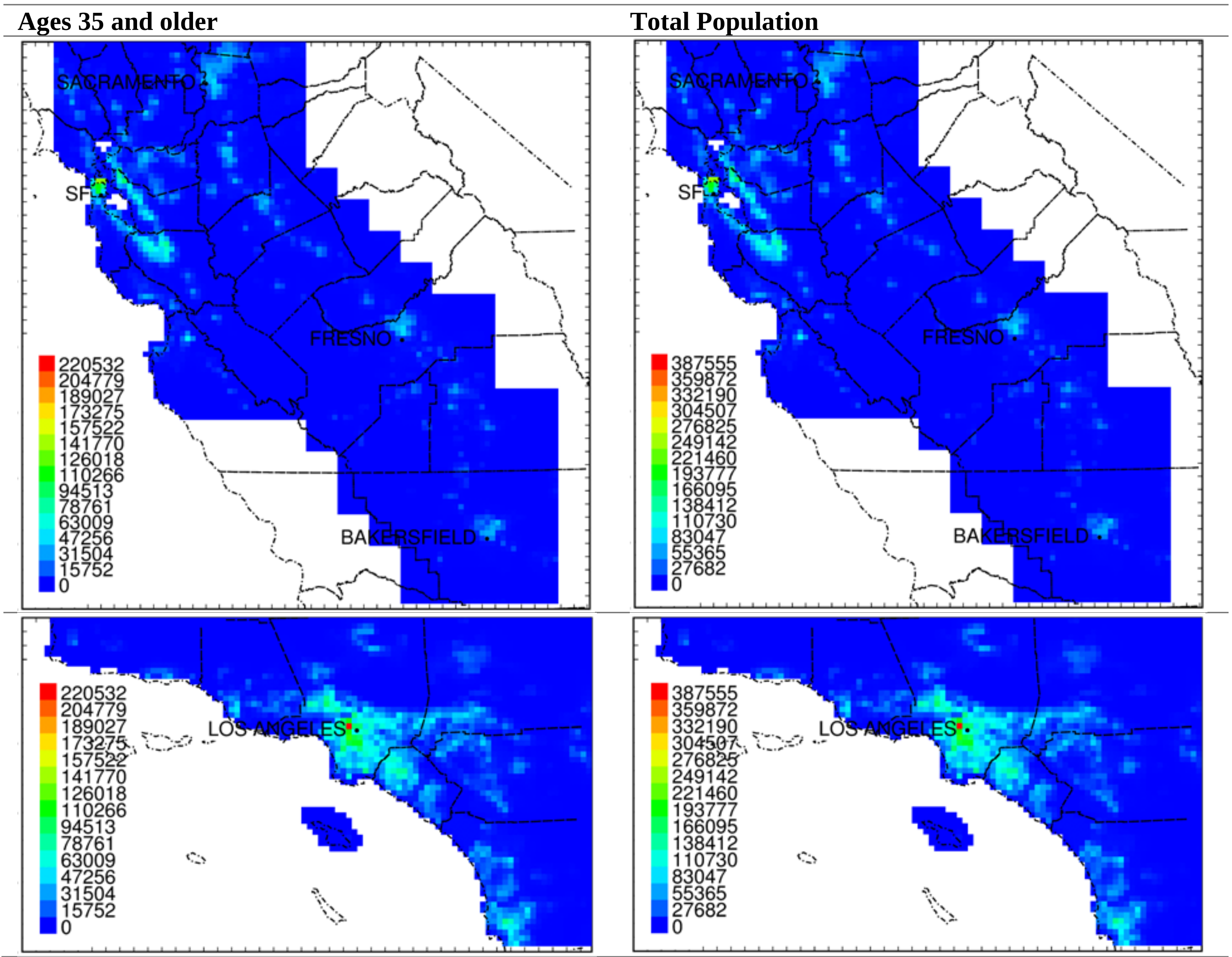


Figure S1: 2050 population projection. The population is projected using 2010 census block group population interpolated 16km^2 information, and projected for each age group within each county projections (California Department of Finance. Demographic Research Unit 2014).

Both 4km domains combined constitute about 93 % of the state's projected population. The maximum population density occurs in areas surrounding downtown Los Angeles and the San Francisco Financial District. The population ages 35 and older represent roughly 57 % of the total all age group population for either domain.

Table S4: 2050 population summary.

Region Type	Region	Area (km^2)	Population (persons)	Percentage of the CA Population (%)
Domain Total	CA statewide	162912.0	57,952,084	92.6 %
Domain	Northern/ Central CA	94464.00	22,946,980	36.7 %
Basin	San Francisco (SF)	14422.26	11,611,289	18.5 %
Basin	San Joaquin Valley (SJV)	46881.20	6,426,141	10.3 %
Domain	Southern CA	68448.00	35,005,104	55.9 %
Basin	South Coast (SC)	16773.50	26,069,030	41.6 %
Basin	San Diego (SD)	7756.350	4,825,970	7.7 %

Table S5: California 8-hour O3 nonattainment areas and attainment dates as of June 16, 2016. Design values are listed from designation in 2008-2010.

Area Name	Design Values (ppm)	Classification	Expected Attainment Date	Number of Counties	2010 Population	Percent of Population
Los Angeles-South Coast Air Basin	0.112	Extreme	2031	4	15,719,485	45.4 %
San Joaquin Valley	0.104	Extreme	2031	8	3,842,365	11.1 %
Riverside Co, (Coachella Valley)	0.095	Extreme	2026	1	425,806	1.2 %
Los Angeles-San Bernardino Counties (West Mojave Desert)	0.099	Severe 15	2026	2	868,380	2.5 %
Sacramento Metro	0.095	Severe 15	2026	6	2,241,057	6.5 %
Ventura County	0.086	Serious	2020	1	823,262	2.4 %
Kern Co (Eastern Kern)	0.083	Moderate	2017	1	95,176	0.3 %
San Diego County	0.082	Moderate	2017	1	3,095,199	8.9 %
Nevada Co. (Western part)	0.079	Moderate	2017	1	82,107	0.2 %
Imperial County	0.078	Moderate	2017	1	174,528	0.5 %
Mariposa County	0.077	Moderate	2017	1	18,251	0.1 %
San Francisco Bay Area	0.080	Marginal	2015	9	6,973,020	20.1 %
Chico (Butte County)	0.079	Marginal	2015	1	220,000	0.6 %
San Luis Obispo (Eastern San Luis Obispo)	0.078	Marginal	2015	1	1,649	0.0 %
Calaveras County	0.077	Marginal	2015	1	45,578	0.1 %
Tuscan Buttes	0.076	Marginal	2015	1	0	0.0 %

S1 PM2.5 Species Concentration Results

S1.1 $PM_{2.5}$ Nitrogen containing species

Table S3 summarizes population-weighted BAU $PM_{2.5}$ concentrations and changes induced by the GHG-Step scenario across different locations in California. The results in Table S3 are broken down by chemical species for an improved understanding of the different sources and atmospheric processes involved in the total particulate matter reductions. Nitrate (NO_3^-) accounts for 17 % of the statewide population-weighted $PM_{2.5}$ mass concentrations in the BAU scenario (2nd most dominant chemical species) with contributions as high as 19 % for SD and as low as 15 % for the SJV. Population-weighted nitrate concentrations decrease by 49 %-50 % in SD and the SJV in the GHG-Step scenario, with more modest reductions in San Francisco (-45 %) and Los Angeles (-34 %). Most of this nitrate reduction is associated with lower NO_x emissions from avoided combustion through the adoption of electric power generated from solar or wind energy. Net NO_x emissions from all land sources (excluding marine and aviation) are lower in the GHG-Step scenario. This trend is also reflected in atmospheric concentrations. Population-weighted gas-phase NO and NO_x ($NO+NO_2$) concentrations fall by 71 % and 46 % in the GHG-Step scenario (Table S5).

$PM_{2.5}$ ammonium (NH_4^+) concentrations also decrease in the GHG-Step scenario which contributes strongly to overall $PM_{2.5}$ reductions, but this trend is not driven by the same source changes that affected nitrate. Ammonium (NH_4^+) accounts for 0.57 µg m^{-3} (6 %) of the population weighted mass in the BAU scenario with concentrations decreasing by 33 % - 50 % in the GHG-Step scenario. These reductions mainly stemmed from the improved management of animal waste in agricultural operations to produce biogas as a renewable energy source which had the added benefit of reducing ammonia emissions.

S1.2 $PM_{2.5}$ Carbonaceous Species

Elemental carbon (EC), primary and secondary organic aerosol (POA and SOA) contribute to 43 % of the statewide population-weighted $PM_{2.5}$ concentration in the BAU scenario making any changes to these species under the GHG-Step scenario extremely important for public health. Statewide average concentrations of $PM_{2.5}$ EC, POA, and SOA are predicted to decrease in the GHG-Step scenario but the effects are mixed, with both increases and decreases depending on location. There is a significant EC increase of 1.0 µg m^{-3} in the GHG-Step scenario in the shipping lanes over the Pacific Ocean near southern California cities of Malibu, Santa Monica and south towards Manhattan Beach due to higher emissions from marine vessels but there is little population exposure associated with this change. All inland locations experience a significant decrease in EC concentrations with the largest reductions around the San Francisco Bay Area where population weighted EC concentration decreases by 38 % from a BAU value of 0.88 µg m^{-3}. Statewide, population weighted EC concentrations decrease by 22 % accounting for a 10 % reduction in total population-weighted $PM_{2.5}$ mass.

Primary organic aerosol (POA) accounts for approximately 1/3 of $PM_{2.5}$ mass across all of California including large population centers in the 2050 BAU scenario, but the modest 12 % POA reductions under the GHG-Step scenario yield only a 13.9 % reduction in population-weighted $PM_{2.5}$ mass concentrations (3rd highest). POA reductions occur around emissions sources that are affected by GHG mitigation strategies such as natural gas reduction in the residential and commercial sectors. The population-weighted POA reductions for each basin in order of highest to lowest are SD, SJV, SC, and SF at 19 %, 16 %, 14 %, and 10 % respectively.

Secondary organic aerosol (SOA) contributes to 1.10 μg m^{-3} (14 %) of population-weighted $PM_{2.5}$ mass in the 2050 BAU scenario. Changes to population-weighted $PM_{2.5}$ SOA concentrations caused by the adoption of the GHG-Step scenario were not statistically significant over the majority of California and their individual contributions to $PM_{2.5}$ mass reduction were not analyzed further in the current study. Updated models of SOA production could change this finding but an exploration of this research topic is outside the scope of the current study.

S1.3 $PM_{2.5}$ Sulfate

California adopted low sulfur fuels in the decades after 1980, which greatly reduced $PM_{2.5}$ sulfate concentrations. Not surprisingly then, statewide population-weighted $PM_{2.5}$ sulfate (SO_4^{2-}) concentrations are only 0.39 μg m^{-3} in the 2050 BAU scenario, which represents 5 % of $PM_{2.5}$ mass. Some point sources and marine vessels switch to low sulfur biofuels in the GHG-Step scenario, leading to significant decreases in sulfate concentrations in the immediate vicinity around those sources but much smaller changes across other areas. Overall, statewide population-weighted $PM_{2.5}$ sulfate concentrations decrease by 23 % yielding a 7 % reduction in population-weighted $PM_{2.5}$ mass in the GHG-Step scenario.

S1.4 $PM_{2.5}$ Metals

In the BAU scenario, copper (Cu), iron (Fe), and manganese (Mn) contribute to a relatively smaller percentage of $PM_{2.5}$ mass. Cu, Fe, and Mn concentrations align strongly with freeways and roads as well as some off-road areas. Population-weighted concentrations of Cu, Fe, and Mg have large relative reductions in the GHG-Step scenario (51 % decrease) but still account for modest reductions in total $PM_{2.5}$ mass (9 % of the total decrease). Reductions occurred mainly along transportation corridors due to the widespread adoption of regenerative breaking in electric vehicles and hybrid electric vehicles. Regenerative breaking reduces brake wear emissions rich in Cu and Fe by approximately 59 %. Both of these metals are considered to be toxic in airborne particulate matter due to their contribution to oxidative stress.

Table S5: Annual average population-weighted Business-as-Usual (BAU) concentration and percent change between BAU and GHG-Step scenario for each species and air basin jurisdiction. SJV, SD, SF, SC are the San Joaquin Valley, San Diego, San Francisco, and South Coast air basins, respectively. The statewide or CA value represents roughly 93 % of the population represented by both 4km high resolution northern and southern CA modeling domains. All annual average concentration differences between BAU and GHG-Step scenarios were found to have p-values less than 0.1 for all pollutants listed except for those in bold italics mainly SD and SC SOA and SD's 1-hour O_3.

Pollutant	Units	Avg.	BAU Concentration					GHG-Step Scenario Percentage Change				
			Air Basin				State	Air Basin				State
			SJV	SD	SF	SC	CA	SJV	SD	SF	SC	CA
Ozone (O_3)	ppb	1-hr max.	55.9	56.8	50.1	55.2	54.1	-4.3 %	**+0.5 %**	+6.5 %	+5.1 %	+2.8 %
		8-hr max.	52.0	51.0	45.0	50.2	49.5	-3.5 %	+2.8 %	+9.5 %	+5.5 %	+3.9 %
Nitrogen Oxide (NO)	ppb	24-hr avg.	0.77	2.77	8.62	2.00	3.15	-50 %	-81 %	-82 %	-53 %	-71 %
Nitrogen Dioxide (NO_2)	ppb	24-hr avg.	6.62	13.8	20.2	10.7	12.1	-35 %	-56 %	-46 %	-32 %	-39 %
Nitrogen Oxides (NO_x)	ppb	24-hr avg.	7.38	16.5	28.8	12.7	15.3	-36 %	-60 %	-57 %	-35 %	-46 %
Sulfur Dioxide (SO_2)	ppm	24-hr avg.	0.88	0.25	0.85	0.47	0.55	-6 %	-30 %	-20 %	-17 %	-16 %
$PM_{0.1}$ mass ($PM_{0.1}$)	µg m^{-3}	24-hr avg.	2.06	2.97	3.59	2.94	2.88	-35 %	-46 %	-35 %	-31 %	-34 %
$PM_{2.5}$ mass ($PM_{2.5}$)	µg m^{-3}	24-hr avg.	5.98	8.37	9.54	7.63	7.63	-20 %	-25 %	-19 %	-15 %	-18 %
$PM_{2.5}$ elemental carbon (EC)	µg m^{-3}	24-hr avg.	0.38	0.70	0.88	0.59	0.59	-29 %	-34 %	-38 %	-8.0 %	-22 %
$PM_{2.5}$ primary organic aerosol (POA)	µg m^{-3}	24-hr avg.	1.15	1.53	2.01	1.82	1.56	-16 %	-19 %	-10 %	-14 %	-12 %
$PM_{2.5}$ secondary organic aerosol (SOA)	µg m^{-3}	24-hr avg.	1.03	1.18	0.85	1.19	1.10	-8.0 %	**+0.7 %**	-2.9 %	**+0.1 %**	-2.2 %
$PM_{2.5}$ nitrate (NO_3^-)	µg m^{-3}	24-hr avg.	0.88	1.81	1.47	1.47	1.31	-50 %	-49 %	-45 %	-34 %	-39 %
$PM_{2.5}$ sulfate (SO_4^{2-})	µg m^{-3}	24-hr avg.	0.36	0.55	0.51	0.47	0.39	-13 %	-61 %	-23 %	-25 %	-23 %
$PM_{2.5}$ ammonium (NH_4^+)	µg m^{-3}	24-hr avg.	0.44	0.76	0.67	0.63	0.57	-36 %	-50 %	-36 %	-30 %	-33 %
$PM_{2.5}$ copper, iron, magnesium (Cu, Fe, Mg)	µg m^{-3}	24-hr avg.	0.16	0.35	0.23	0.28	0.25	-52 %	-53 %	-52 %	-51 %	-51 %
$PM_{2.5}$ metals	µg m^{-3}	24-hr avg.	0.14	0.33	0.29	0.26	0.25	-19 %	-23 %	-17 %	-16 %	-17 %
$PM_{2.5}$ other	µg m^{-3}	24-hr avg.	0.80	0.97	0.81	0.64	0.67	-2.5 %	-20 %	-1.9 %	-4.7 %	-3.1 %
$PM_{2.5}$ unknown	µg m^{-3}	24-hr avg.	0.47	0.68	1.57	0.61	0.75	0.5 %	+2.6 %	+2.3 %	+1.4 %	+2.3 %
PM10 mass (PM_{10})	µg m^{-3}	24-hr avg.	7.85	10.9	12.4	9.04	9.60	-19 %	-21 %	-16 %	-14 %	-16 %

S2 PM Size Distribution Results

Figure S2 summarizes predicted changes to the airborne particle size distribution in the GHG-Step scenario relative to the BAU scenario. Size distribution shifts are caused by changes to emissions sources (which each emit different particle size distributions) and changes to the rate of secondary PM formation (which condense on particles and change the size distribution).

S2.1 Ultrafine particles (Dp<0.1 µm)

$PM_{0.1}$ mass (mass of particles with diameter D_p < 0.1 µg m^{-3}) is substantially reduced in the GHG-Step scenario; $PM_{0.1}$ decreases are greater than any other size fraction. BAU $PM_{0.1}$ concentrations are highest around large combustion sources associated with urban centers and many of these combustion sources are controlled through GHG mitigation measures. Peak $PM_{0.1}$ concentrations over California in the BAU scenario are predicted to be 5.8 µg m^{-3} -7.2 µg m^{-3} with GHG-Step reductions of about 2.76 µg m^{-3} in SF, 3.2 µg m^{-3} in SF and in San Bernardino. $PM_{0.1}$ decreases from a statewide population-weighted average of 2.9 µg m^{-3}in the BAU scenario to 1.9 µg m^{-3} (-34 %) in the GHG-Step scenario. Regionally, population-weighted $PM_{0.1}$ declines from 31 %-46 %, with minimal decline in SC and the highest decline in SD. The $PM_{0.1}$ mass fraction of PM_{10} drops from 30 % to 23 % statewide.

S2.2 Accumulation mode (0.1<Dp<2.5 µm)

As expected, the accumulation mode has the highest BAU PM mass with a statewide population-weighted average of 4.8 µg m^{-3} and regional concentrations ranging from 3.9-5.9 µg m^{-3}. Most regions have accumulation mode population-weighted concentrations that are roughly double the ultrafine and coarse mode concentrations. GHG mitigation strategies have less effect on the accumulation mode than on the ultrafine mode. Population-weighted concentrations of accumulation model mass decrease by 0.35 µg m^{-3} (-7.4 %) but their contribution to $PM_{2.5}$ mass increases from 50 % in the BAU scenario to 54 % in the GHG-Step scenario. This statewide trend is reflected in all regions of California.

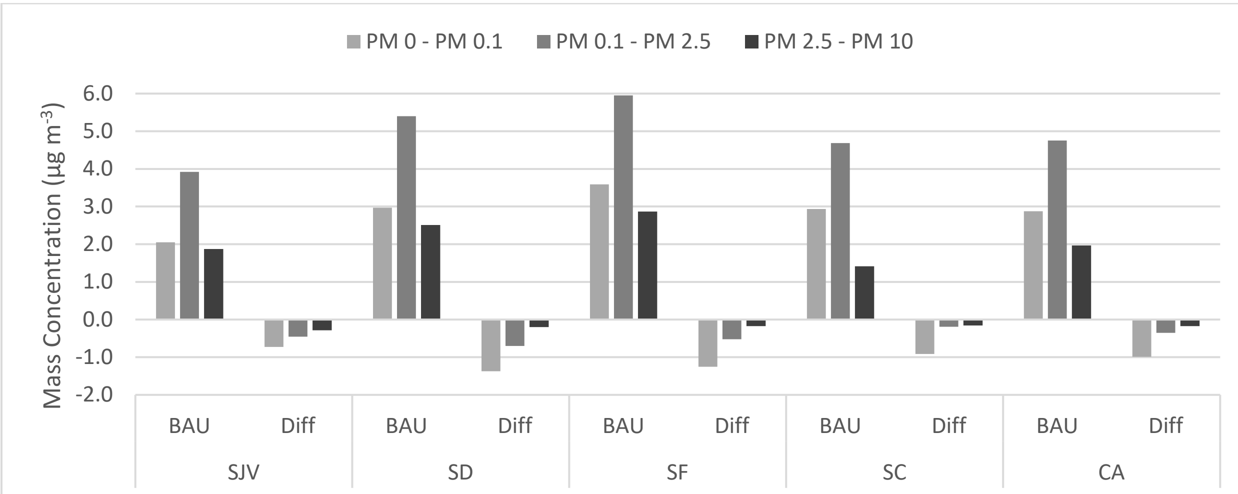
S2.3 Coarse mode (Dp>2.5 µm)

Particles in the coarse mode (Dp>2.5 µm) are predicted to contribute to 20.5 % of the population-weighted PM_{10} mass across California in the BAU scenario. The GHG-Step scenario is predicted to decrease concentrations of coarse mode particles by 0.17 µg m^{-3} (-8.7 %), which is the smallest amount for any of the size ranges considered.

S2.4 Particulate size distribution shift

As the chemical composition of PM changes from fuel and energy consumption changes, the size distribution will also change. Smaller ultrafine particles of $PM_{0-0.1}$ drop steeper than fine $PM_{2.5-10}$ and coarse $\geq PM_{10}$. Since primary emissions from combustion have a size distribution profile that skews towards ultrafine PM, it explains why the ultrafine mode would reduce substantially. Reductions in the accumulation mode $PM_{2.5-1}$largely attributes to the sulfate and nitrate particles that are largely caused gas-to-particle partitioning of NO_x and SO_x into the aqueous phase. The coarse ≥ PM_{10} decline likely attributes to the reduction of brake wear metals such as Cu, Mg, and Fe.

Figure S1: Particulate size mode concentration for BAU scenario and GHG-Step−BAU scenario difference.



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