Research Report – UCD-ITS-RR-14-08

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July 2014

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Long-term Energy Planning In California: Insights and Future Modeling Needs

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KEYWORDS: Renewable energy, global warming, model comparison, greenhouse gas emissions, California, criteria emissions

Manuscript length: 6720 words (without acknowledgements and references), 3 tables, 5 figures

Abstract (240 words) Jurisdictions throughout the world are contemplating greenhouse gas (GHG) emission mitigation strategies that will enable meeting long-term GHG targets; many jurisdictions are now focusing on the 2020-2050 timeframe. We conduct an inter-model comparison of nine California statewide energy models with GHG mitigation scenarios to 2050 to better understand common insights across models, ranges of intermediate GHG targets (i.e. for 2030), necessary technology deployment rates, and future modeling needs for the state. The models are diverse in their representation of the California economy: across scenarios with deep reductions in GHGs by 2050, annual statewide GHG emissions are 8-46% lower than 1990 levels by 2030 and 59-84% by 2050; the largest cumulative reductions occur in scenarios that favor earlier reductions; non-hydroelectric renewables account for 30%-54% of all electricity generated for the state in 2030 and 59-89% by 2050; the transportation sector is decarbonized using a mix of energy efficiency gains and alternative-fueled vehicles; and bioenergy is directed towards the transportation sector, accounting for a maximum of 40% of transportation energy by 2050. Models suggest that without new policy, emissions from other non-energy sectors and from high-global-warming-potential gases may exceed California's 2050 GHG goal. Finally, high priority areas of future model development include: implementation of uncertainty analysis, improved representation of economic impacts and logistical feasibility of given scenarios, simultaneous modeling of criteria and GHG emissions, and greater modeling of interactions between two or more specific policies.

1 Introduction

In 2006, California passed the Global Warming Solutions Act (AB32) which set the limit on greenhouse gas (GHG) emissions at 1990 levels by 2020. California Governors Schwarzenegger and Brown both passed Executive Orders providing further goals of limiting state-wide GHG emissions to *at most* 20% of 1990 levels by 2050. Like many jurisdictions throughout the world with long-term GHG targets, California is now focusing on developing post-2020 climate strategies (CARB, 2014)[1]. To assist in this process, several research groups have built integrated energy planning models[2] for California that estimate the future trajectories of technologies, fuels, infrastructure, and/or economic impacts (Roland-Holst, 2008; Williams et al., 2012; Greenblatt, 2014; Jacobson et al., 2014; Nelson et al., 2014; Wei et al., 2014; Yang et al., 2014).

However, to date no effort synthesizes the collective findings across these models. In this paper, we perform a comparison of nine statewide energy planning models with projections to 2050 that include 50 scenarios (some business-as-usual (BAU) and other GHG mitigation). Model descriptions are available in the Supplementary Information (SI)[3]. Among many benefits, inter-model comparisons can help policy makers by providing a range of conceivable technology deployment rates and GHG trajectories. These comparisons also can be useful to model developers in identifying model deficiencies and future modeling needs. A key aspect of our comparison is the solicitation of feedback from California policy makers and energy stakeholders at a two-day forum in 2013 (Morrison et al., 2014).

Past inter-model comparisons fall into two broad categories. The first category – "model discovery" – uses common scenario assumptions (or projections) at a specific point in time and compares the behaviors of the models (IPCC, WGIII, 2014). Perhaps the most well-known and enduring model discovery exercise is the Energy Modeling Forum (EMF) (e.g. Huntington, 2013; Fawcett, Clarke and Weyant, 2014). Another type of comparison – as done here – is to use *existing* model scenarios and projections to synthesize findings across models. These model

[1] Many European nations have recently set or are looking to set "mid-term" (i.e. 2030-2035) GHG targets.
[2] Below we refer to these as "energy-economic" models when discussing the class of model to which they belong and "energy planning models" when describing their function.
[3] Note that this paper makes reference to "deep reduction scenarios" which we define as scenarios that achieve one of the following: (1) greater than 75% reduction in annual GHG emissions by 2050 relative to 1990 levels, (2) have cumulatively similar reductions by 2050, or (3) 100% renewable energy penetration by 2050 (i.e. WWS).

reviews help identify common insights and deficiencies across modeling platforms (e.g. Beaver and Huntington, 1992). To our knowledge, ours is the first formal model comparison for energy-related projections for California-specific models.

The outline of this paper is as follows: Section 2 provides the methodology of the comparison. In Section 3 we examine the greenhouse gases trajectories, electricity sector, transportation sector, biofuel use, air quality, economic impacts, and non-energy emissions. We limit our analysis to these topics due to time and resource constraints and because they are often central topics in long-term energy planning in California. Other sectors and assumptions should be the focus of a future model comparison. Finally, in Section 4 we provide a discussion on future modeling needs from both the policy maker and modeler perspectives.

2 Methodology

2.1 Background on models

These nine models are scenario-based tools built to understand the merits, constraints, and timing of different mixes of policies, technologies, and energies in the future. All but the Wind, Water, Solar (WWS) model (Jacobson et al., 2014) focus on achieving the state's 2020 and 2050 climate goal. WWS examines the pathway to a 100% renewable energy system by 2050.

The exact composition of future scenarios depends significantly on the assumptions, storylines, and analytical underpinnings of the scenarios. Some scenarios in these models emphasize immature technologies such as carbon capture and sequestration (CCS), while others explore shifts in energy service demand (e.g. reduction in vehicle miles traveled), or changes to key input parameters (e.g. price elasticity of energy service demand or energy efficiency). Because most of these models have been developed over a number of years and have multiple versions, we limit this comparison to the most recent model version (Table 1) unless otherwise noted.

Table 1. Model versions used for this comparison

Model	Abbreviation	Version used in this comparison	Other related versions/resources
ARB-VISION	ARB-VISION	CARB (2012)	
Berkeley Energy and Resources	BEAR	Roland-Holst (2008)	Roland-Holst (2006;

			2008; 2010; 2011; 2012)
CA Energy Future Project	CCST	Greenblatt and Long, (2012)	Youngs (2013) (biofuels-specific report); CCST (2011)
CA-TIMES	CA-TIMES	Yang et al. (2014)	McCollum et al. (2012)
CA GHG Analysis of Policies Spreadsheet (formerly GHGIS)	CALGAPS	Greenblatt (2014)	Greenblatt (2013)
CA Long-Range Energy Alternatives Planning System	LEAP	Wei et al. (2014)	Wei et al. (2013)
SWITCH	SWITCH	Nelson et al. (2013)	Fripp et al. (2011); Nelson et al., (2012); Mileva et al. (2013)
PATHWAYS	PATHWAYS	Williams et al. (2012)	
Wind, Water, Solar (WWS)	WWS	Jacobson et al. (2014)	Jacobson et al. (2013); Hart and Jacobson (2011); www.thesolutionsproject.org

Table 2 summarizes the key characteristics of these nine models. Note that LEAP and SWITCH are two separate models run in a hybrid fashion using a consistent set of scenarios. For this paper, we also reviewed the 2008 and 2014 AB32 Scoping Plan from CARB (2008; 2014) and the CCST-Bioenergy report (Youngs, 2013).

Table 2. Comparison of nine models across multiple dimensions

	ARB-VISION	BEAR	CCST	CA-TIMES	CALGAPS	LEAP	SWITCH	PATHWAYS	WWS
Development									
Software	Excel	GAMS	Excel	GAMS	Excel	LEAP	AMPL	Excel	Excel
Structure									
Sectors modeled	Transportation, well-to-tank electricity	All	All	All	All	All but electric	Electric	All	All
Solution algorithm	Scenario-based	Computable general equilibrium (CGE)	Threshold testing	Linear program minimizing total cost or partial equilibrium	Scenario-based	"Potentials" analysis	Linear program minimizing total energy cost	Backcasting	Backcasting
Main model outputs	GHG/criteria emissions, fuel mix, technology mix, fuel economy	Employment, economic activity, GHG/criteria emissions, energy mix, technology mix	GHG emissions, energy mix, technology mix	Net present costs, GHG/criteria emissions, energy mix, technology mix	GHG/criteria emissions, energy mix, technology mix	GHG emissions, energy mix, technology mix	Power plant locations/sizes, GHG emissions, energy mix, technology mix	Economic costs, GHG/criteria emissions, energy mix, technology mix	Employment, health care costs, energy mix, technology mix
Forecast period	2000-50	2005-50	2010-50	2010-55	2010-50	2010-50	2010-50	2008-50	2010-50
Features									
Scenarios meet 2050 GHG target									*
Endogenous technology learning									
Estimates non-energy emissions									
Spatial disaggreg. within CA									
Technology stock turnover									
Greenhouse gas emissions									*
Criteria pollutant emissions and/or concentrations									
Electricity dispatch model									
Interactions with out-of-state									
Economics									
Technology costs/mitigation costs assessment									
Measures economic welfare effects of climate policy									
Other									
Documentation									
Model available online									

* WWS does not estimate GHG emissions but its mitigation scenario has an energy portfolio consistent with deep GHG reductions in 2050.

Yes/Represented	Limited	No/Not represented

2.2. Approaches to modeling California's energy and emissions

The models in this paper can be categorized into three broad model structures: optimization, equilibrium, and inventory models. A model's structure is indicative of both the types of research questions that can be addressed with the model, as well as the caveats to bear in mind when interpreting results. As others have pointed out (Beaver, 1993), while heterogeneous model structures in inter-model comparisons generally make comparison more difficult, they tend to lead to a greater number of insights. The three model structures are described in detail in the SI.

3 Model comparison

3.1 GHG emissions in Reference scenarios

Figure 1 compares the GHG emissions in the reference (or "Business as Usual") scenario. Across models, the reference scenarios demonstrate a wide range of emissions by 2050, from over 800 million metric tonnes CO_2-equivalent per year (MMT CO_2e/yr) in CCST and PATHWAYS models to under 500 MMT CO_2e/yr in CA-TIMES.

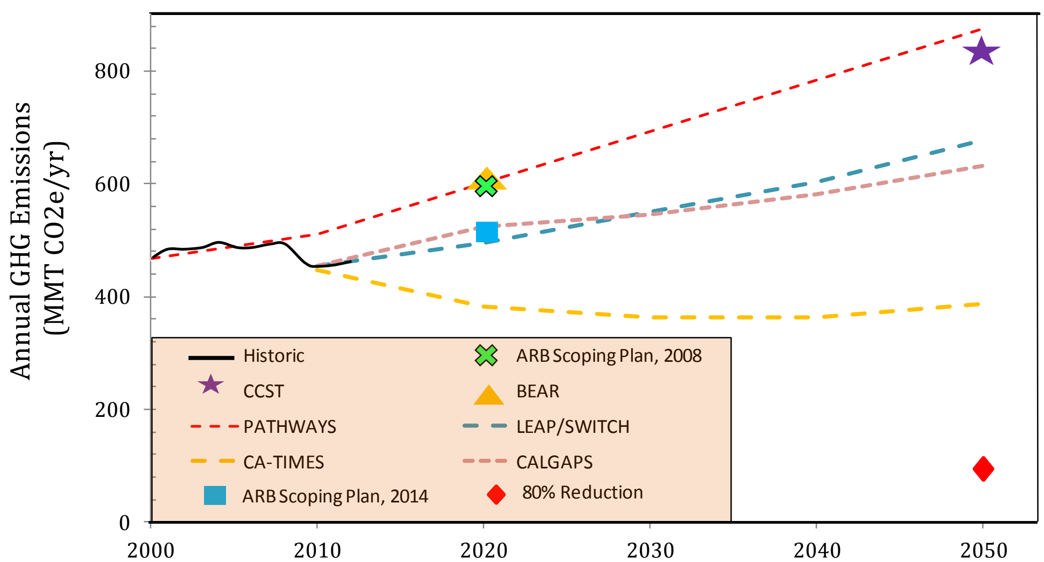

Figure 1. Business-as-usual GHG projections (MMT CO_2e/yr)[4].

[4] WWS does not count GHG emissions but Jacobson et al. (2014) Table 1 reports California end-use power demand increasing from 1805TWh in 2010 to 2453 TWh in 2050. This decreases 43.7% to 1375 TWh upon conversion to

We begin with these GHG trajectories in the BAU cases because they help capture the level of assumed growth, the necessary technology deployment, and the overall character of a model. The models with the highest GHG trajectories (PATHWAYS and CCST) are also the highest population and income assumptions (see S.I. for a comparison of population and income across models). Additionally, higher GHG trajectories in the BAU scenario means there is “more work to do” to reach the 2050 goals in terms of low-carbon technology and fuels.

Policy assumptions differ across models. For example, in CA-TIMES and SWITCH a 33% Renewable Portfolio Standard (RPS) is achieved by 2020 and maintained as the power sector grows. On the other hand, the reference scenario for LEAP and SWITCH assumes that the efficiency of end uses is frozen at today’s level. In CALGAPS, the reference scenario is generated by disabling all policies that were explicitly modeled in the “Committed Policies” (S1) scenario. Data behind all figures in this paper are available in the Supplementary Information spreadsheet. The S.I. also gives an overview of the BAU assumptions.

3.2 GHG emissions in mitigation scenarios

In scenarios that achieve deep reductions in GHGs by 2050, the GHG trajectories also vary widely (Figure 2). Annual emissions range from 230-396 $MMTCO_2e$ in 2030 (8-49% below 1990 levels) and 68-175 $MMTCO_2e$ in 2050 (59-84% below 1990 levels) (left side of Figure 2). For ease of viewing in Figure 2, we only show the highest and lowest deep reduction scenario from each model that projects GHG emissions. Also shown are the linear and constant-percent reductions between the 2020 GHG target[5] of 431 MMT CO_2e/yr to the 2050 target of 86 MMT CO_2e/yr. For models with ten-year time steps, a linear interpolation was used between steps. CCST, LEAP, and WWS explore scenarios that achieve greater than 80% reduction by 2050, but these are not presented in this paper[6].

WWS due primarily to the efficiency of electricity over combustion. Only 5-10 percentage points of this reduction are end-use energy efficiency improvements. These energy estimates are analogous to CO_2e estimates.

[5] ARB recently updated this 2020 value from 427 MMT CO_2e/yr

[6] Two LEAP-SWITCH scenarios make use of bio-power with carbon capture and sequestration (CCS) technology. WWS does not estimate GHG emissions, but has the highest deployment of renewables of any model by 2050.

As in most jurisdictions, California climate targets call for an *annual* emissions rate (i.e. GHG per year) by a given year (e.g. 2020). However, due to the long residence time of many GHGs in the atmosphere, the total heat trapped due to GHG emissions in a scenario is associated with the timing of the emissions *as well as* the cumulative emissions, not just the emissions level achieved in the end year. The right side of Figure 2 displays the cumulative emissions in deep reduction scenarios and range from 10,400 to 14,400 MMT CO_2e by 2050. Note the start year is 2010 in both figures. For perspective, the BAU emission scenarios range between 17,230 and 27,820 MMT CO_2e in 2050 (not shown in figure).

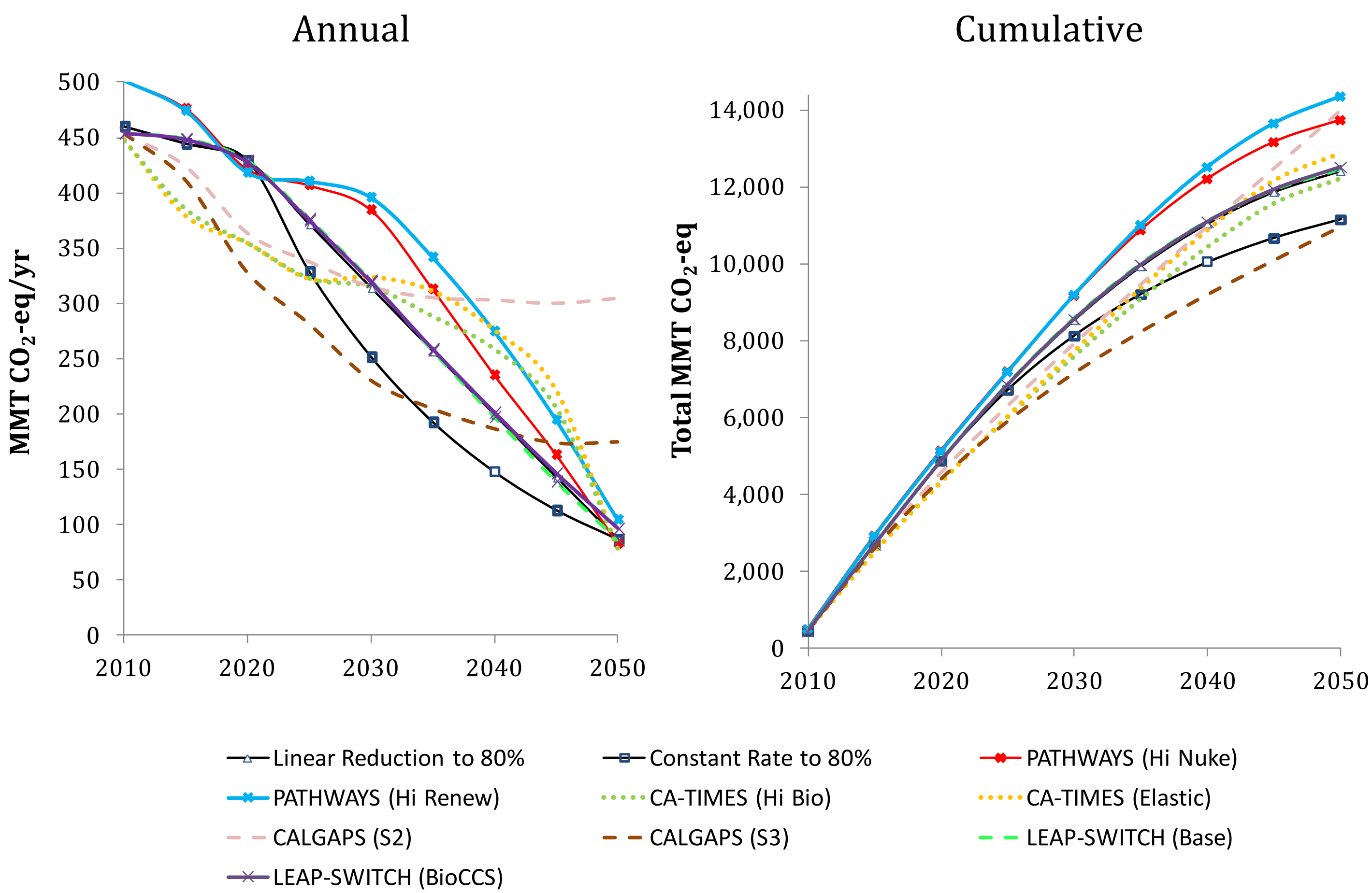

Figure 2. Annual GHG emissions (left) in MMT CO_2e /yr and cumulative emissions from 2010 onward (right) in total CO_2e for the select deep reduction scenarios (highest and lowest from each model). Trajectories and descriptions for all scenarios (including those not shown) available in supplementary spreadsheet and SI, respectively.

Figure 2 helps demonstrate the importance of early emissions reduction. For example, CALGAPS (S3) only achieves a 57% emission reduction in *annual* emissions by 2050 but has the lowest *cumulative* emissions between 2010 and 2050 due to early and aggressive emission reductions. Conversely, the PATHWAYS (Hi Renew) scenario achieves an 80% reduction by 2050 but has the highest *cumulative* emissions in 2050 due to its lagged reduction schedule. Others (Meinshausen et al., 2009) have shown that the cumulative emissions of a scenario are a robust indictor for whether that scenario achieves less than a global two degree Celsius warming. Of course, this discussion is only focused on 2050 as the end point; in some future year (e.g. to 2070) the PATHWAYS scenario will become cumulatively lower than the CALGAPS scenario (assuming annual emissions maintain 2050 levels). Driving down emissions early <u>and</u> achieving low annual emission rates are both key climate change mitigation strategies (Meinshausen et al., 2009).

3.3 Variation in GHG reduction schedules

Why do different models and scenarios achieve different GHG emission reduction schedules? Ultimately, both the modeling team and the model structure determine the trajectory of emissions. Consider electric vehicle (EV) deployment as an example. Models introduce market adoption of EVs using diverse methods: S-curves, historical trend analysis, annual constraints, relative costs with other competing technologies, and expert judgment, among others. The adoption rate is typically pegged to some underlying technology review of the literature or exogenous forecast, but which technique to use and how that technique will be employed differs between models. As Sweeney (1983, p. 6) notes: "Even if all modelers were to have the same basic perceptions of the systems being examined, they would invariably develop different models, based upon their different time constraints, goals, styles, research budgets, organizational talents, motivations, and judgments."

Optimization models like CA-TIMES and SWITCH have an additional set of factors that drive their GHG reduction schedule:

- *Relative costs of mitigation*: If technologies that mitigate GHGs cost more than technologies that do not (as is often the case), then the optimization models will delay emission reduction until absolutely necessary. The left-side of Figure 2 demonstrates
- *Discount rate*: Using a positive discount rate implies valuing present costs more than future costs; the higher the discount rate, the greater the incentive to delay high-cost investments. The impact of discount rate on energy mix can vary across models: those that use technology-specific discount rates (called hurdle rates[7]) like CA-TIMES may exhibit different sensitivity to changes in discount rates than one with a single technology-neutral discount rate. The assumed rates of financing of capital can also play a major role in the competition between technologies.
- *Endogenous learning:* The models examined here make exogenous cost assumptions as a function of time; therefore investments in a technology do not stimulate further cost reductions. With endogenous technological learning (ETL), early investments in GHG mitigation can help drive down future costs and make subsequent investment more attractive. When technology costs decline only as a function of time (as in CA-TIMES or SWITCH), rather than because of ETL, system costs are minimized when investments are delayed until technology costs decline.[8]

The design of the optimization algorithm also determines the GHG reduction schedule. SWITCH caps the GHG emissions in each modeled year (i.e. 2020, 2030, etc.), which means that a delay in emission reductions is due almost entirely by the choice of the GHG caps. In CA-TIMES, there is only a 2020 and 2050 GHG cap, giving the model freedom to choose any path between the two years. Thus, in CA-TIMES the above three factors play a much larger role than in SWITCH.

3.4. Power sector

[7] A hurdle rate is added to the discount rate for a given technology to represent factors such as risk and uncertainty in bringing a given technology to market. In CA-TIMES, hurdle rates differ by year and technology, ranging from 15-45%.

[8] Even historically modest assumptions about this kind of technological progress can dramatically affect the economics of mitigation (see e.g Roland-Holst, 2006).

Between 2001 and 2013, electricity generation in California (including both in-state and net imports) increased from 267 TWh to 296 TWh and the corresponding renewable fraction of generated energy increased from 14% to 20% (see supplementary spreadsheet for calculations). This percentage includes small hydro-electric facilities, large-scale and distributed solar and wind, geothermal, and bioelectricity and does not exactly conform to the state's definition used in its Renewable Portfolio Standard (RPS). In the same years, the capacity of the power grid (before transmission losses) expanded from 60.8 GW to 88.5 GW (CEC, 2014).

The future expansion of the electricity grid poses both spatial and temporal challenges to energy planners (Hart and Jacobson, 2011; Williams et al., 2012; Nelson et al., 2012; Wei et al., 2013). The models examined here differ widely in their geographic scope and resolution. For example, the SWITCH model includes a multi-state region (the Western Electricity Coordinating Council) which allows for optimal solutions across state boundaries. Other models assume a certain fraction of out-of-state generation is always available or, like CA-TIMES, assume all power generation after a certain year is generated in-state. SWITCH also is the only model that determines the geographic location and capacity (i.e. GW) of future power plants and transmission lines. The time dimension also differs widely between models. The models that include time-of-day dispatch models to better understand renewable intermittency problems include CA-TIMES, PATHWAYS, SWITCH, and WWS[9].

In CCST and WWS, demand for electricity is driven exogenously. SWITCH uses exogenous electricity demand values calculated by the LEAP model. PATHWAYS estimates demand using a "bottom-up" approach in which the electricity requirements of each individual end-use is first estimated then summed. CALGAPS estimates demand in a similar way as PATHWAYS, but electricity requirements are determined at the sector level rather than by end use. In CA-TIMES, electricity demand is determined endogenously based on the need to meet the 2050 GHG goal.

Across BAU scenarios, the total power generation from in-state and imported electricity ranges from 356-389 TWh by 2030 and 429-518 TWh by 2050. WWS has an increase in all-

[9] CA-TIMES disaggregates a year into 48 sub-annual time slices (every two months in a year and every three hours in a day) which is far fewer than a true dispatch model. SWITCH uses 144 per year or 576 per optimization (2020, 2030, 2040, 2050). PATHWAYS uses 12 periods per year.

purpose end-use power demand (electricity, transportation, heating/cooling, and industry) from 1804 TWh in 2010 to 2453 TWh in 2050 in its BAU case.

3.4.1 Renewables

A common result across all deep reduction scenarios is that the electricity grid shifts towards renewable generation – particularly after 2030 – and that most end-uses are electrified by 2050. Because some sectors cannot be electrified or are difficult to decarbonize (e.g. aviation, marine, heavy duty road freight, agricultural fertilizer, etc), GHG emissions from the electricity grid will likely need to be reduced beyond 80% (Williams et al., 2012; Nelson et al., 2014; Yang et al., 2014). As shown in Figure 3, across scenarios total power generation ranges from 290-410 TWh in 2030 (and up to 990 TWh for WWS) and 245-692 TWh in 2050 (and up to 1375 TWh for WWS). Across mitigation scenarios, the renewable fraction of total generation is 30%-85%[10,11] by 2030 and 38%-100%[8,12] by 2050, with the majority of new generation coming from wind and solar. In general, the lower values in these ranges reflect scenarios with greater nuclear and/or CCS deployment.

Williams et al. (2012) estimate that the maximum renewable penetration in California is 74% of in-state production[13]. Jacobson et al.'s (2014) WWS model uses the most diverse set of renewable technologies, including offshore wind and wave devices, among others. They conclude that the wind/solar variability problem can be overcome through: (1) geographically-dispersed resources with hydro power for spinning reserve, (2) demand-response, (3) oversized renewable capacity, (4) integration of weather forecasts into system operation, and (5) use of energy storage at generation sites and (6) in electric vehicles (i.e. vehicle-to-grid). They relied

[10] The ranges reported here were adjusted to be similar to the formula used for the Renewable Portfolio Standard (RPS) calculation. As such, the percentages are based on estimated retail electricity sales rather than generation (assuming a 7% transmission and distribution loss) and exclude electricity from large hydroelectric plants. Solar PV is included in the reported percentages, but because utility-scale solar PV and rooftop solar PV are not differentiated in all models, these ranges may overestimate the generation that would count towards RPS obligations. Except for CALGAPS, the models reviewed focused on achieving the 2050 emissions target. Higher proportions of renewables by 2030 might be possible given different objectives (e.g. cumulative emission targets).

[11] 85% is WWS

[12] 100% is WWS

[13] The authors of PATHWAYS (Williams et al., 2012) add that this fraction would be higher if – as subsequently happened – population and/or GSP projections decreased

largely on results from Hart and Jacobson (2011), who used a stochastic optimization model of system operation combined with a deterministic renewable portfolio planning module to simulate the impact of 100% WWS penetration for California for every hour of 2005 and 2006, including long stretches of low wind and solar. Hart and Jacobson (2011) find that 99.8% of electricity demand could be met with renewable sources (wind, solar PV, solar CSP with three hours of storage, geothermal, and existing hydroelectric) in California.

Results from SWITCH suggest a similar set of strategies as WWS, although the model does not explicitly allow for (4). Scenarios from LEAP-SWITCH (Nelson et al., 2013) include lower penetrations of wind and solar within California – the highest in 2050 is 66% of in-state generation (Expensive Transmission Scenario) – but larger fractions of wind and solar power imported into California from nearby states in most scenarios. Across western North America, the median percentage of electricity generated from wind and solar power is 67%, with scenarios reaching as high as 79%. SWITCH highlights the need to obtain sub-hourly operating reserves from low carbon sources. Under strict GHG limits, the authors find that hydroelectric generators and storage facilities provide the most cost-effective spinning reserve and that natural gas provides quickstart reserve. Natural gas with CCS is also used, but not in appreciable amounts due to an assumed low efficiency of CO_2 capture.

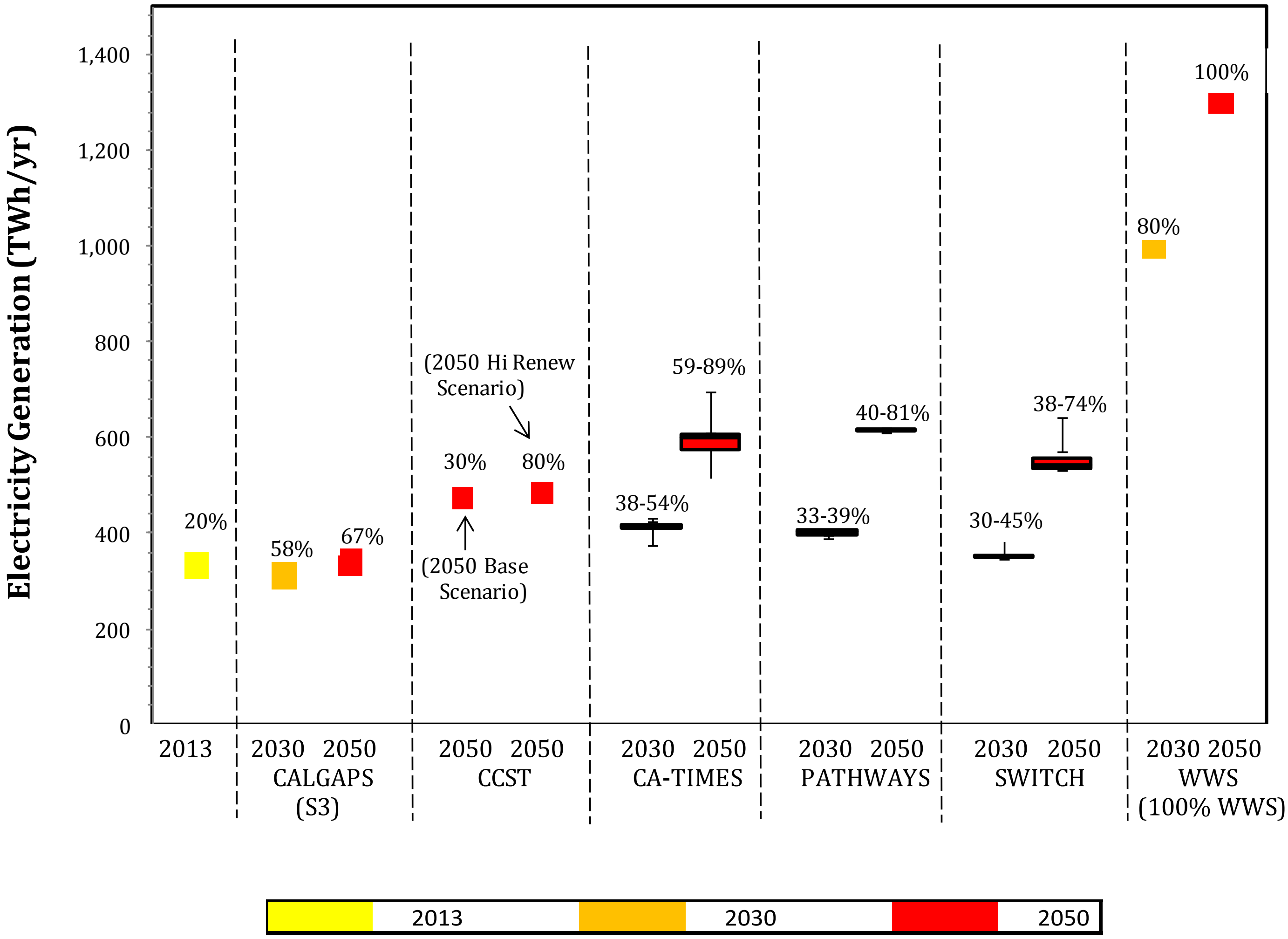

Figure 3. 2030 and 2050 electricity generation (TWh/yr) in deep reduction scenarios. Figure includes in-state production and imported generation. Box plot = quartiles (box) and max/mins (whiskers) across mitigation scenarios in the indicated year . Red squares = individual scenarios. Percentages above boxes are percent renewable (non-hydro) across mitigation scenarios

3.4.2 Nuclear and CCS

Presently, California only has one operational nuclear power plant (Diablo Canyon) providing 2.1 GW of power to the state[14]. The permit for the facility expires in 2024 but can be renewed. No new nuclear power plants are under construction or planned. Models differ in their representation of nuclear power: CA-TIMES and SWITCH include nuclear as sensitivity

[14] The San Onofre Nuclear Generating Station in Southern California is currently shutdown and owners plan to retire the plant (Songs Community, 2013).

scenarios but do not make it an available technology in the base model. On the other hand, PATHWAYS includes some nuclear generation in each of its scenarios. WWS does not allow nuclear or CCS. CALGAPS assumes a renewed permit for Diablo Canyon to 2044 and brings on additional nuclear capacity in scenario S3. Across all scenarios, the highest penetration of nuclear is 52% of total generation in 2050 in the PATHWAYS-High Nuclear scenario.

CCS also has diverse representation across models. All models have at least one scenario with natural gas CCS and some also have coal CCS. PATHWAYS is the only model that includes large quantities of coal CCS in 2050. SWITCH concludes that coal CCS is not low carbon enough to provide deep reductions by 2050 and uses natural gas CCS across mitigation scenarios and bio-power with CCS in two sensitivity scenarios. CALGAPS includes small amounts of CCS in two scenarios.

3.4.3 Growth rate of power grid

How quickly do models expand renewable electricity in deep reduction scenarios? Across scenarios, the implied build-out rate of in-state plus imported renewable electricity (mostly solar and wind) ranges between 0.2-4.2 GW per year from 2013 until 2030, with an average of 0.83 GW per year. The renewable build-out rate increases to between 1.5-10.4 GW per year from 2030 until 2050, with an average of 3.9 GW per year. Faster rates of grid expansion are assumed in the WWS model, which has an implied renewable build-out rate of 17 GW of nameplate capacity per year from 2013 to 2050 to reach 652 GW of total renewable capacity by 2050. For perspective, from 2001 to 2013 the renewable capacity used by the state (in-state and imported electricity) expanded by 0.67 GW per year while non-renewable capacity expanded by 1.6 GW per year (CEC, 2014).

3.4.4 Electricity imports

Across SWITCH's mitigation scenarios, California remains a net electricity importer, with imports ranging from 17-24% of total generation in 2030 to 19-60% in 2050. Other models either assume electricity imports are phased out (CALGAPS(S3) and WWS), make exogenous assumptions about the electricity mix out of state (PATHWAYS), or are neutral regarding the locations of electric generation plants needed to meet California's demand.

Nelson et al. (2014) note that mitigating carbon using renewables outside of California is generally cheaper than in-state mitigation because of the larger resource base, particularly for wind power. With the US EPA 111(d) proposed framework for electricity emissions (EPA, 2014), states outside of California will be pushed to develop renewables of their own. If this occurs, the WECC will need to manage an increasing quantity of out-of-California intermittent generation, and, as a result, may have less capacity to accommodate California's intermittent generation. In general, coordination with other states will become increasingly important for the cost-effective deployment of low-carbon electricity.

3.5. Passenger transportation sector

A standard practice among transportation energy models is to make exogenous assumptions about future energy service demand (e.g. statewide vehicle-miles travelled (VMT)) and then allow the model to estimate future fuel mix, vehicle/technology mix, and emissions. The models in this study all follow this practice[15]. The lower the future demand assumptions, the less the need for low-GHG emitting fuels.

For example, in deep reduction scenarios statewide VMT for light-duty vehicles[16] is assumed to change from 293 billion miles per year in 2010 (CARB, 2011) to 226-600 billion miles in 2050. Therefore, the amount of near-zero CO_2e emission energy used across these models differs widely.

The result of the various VMT assumptions is a wide variation in the projected energy mix. Figure 4 shows the light-duty vehicle energy projections (stacked columns) and the total transportation sector energy (red triangles) for the model reporting detailed LDV-specific results. Across deep reduction scenarios, total LDV energy use ranges from 8.6-25.2 billion gallons of gasoline equivalent (BGGE) in 2030 and 8.1-19.6 BGGE in 2050.

[15] The CALGAPS model exogenously assumes the total number of vehicles and changes the travel demand (Passenger-miles) by scenario. The model relies on ARB Vision's projections for: VMT per vehicle, the portion of non-electric miles travelled by gasoline and diesel PHEVs, total energy consumed by vehicle technology/fuel, and total criteria pollutants by region. From this, vehicle mix, fuel efficiency, and total VMT per vehicle type are derived in the model. CA-TIMES model has elastic demand (ED) scenarios that are not included in this review.

[16] Light-duty vehicles are typically synonymous with private cars, or passenger vehicles.

With the exception of the PATHWAYS-mitigation scenario, the total LDV energy drops from 2010-2030, and again from 2030-2050 in deep reduction scenarios. This decline results from both (1) the underlying assumptions about energy service demand decreases in future years and (2) the improved efficiency of LDV technology. Across deep reduction scenarios, petroleum consumption declines 39-59% by 2030 and 58-100% by 2050 as the light-duty-vehicle fleet moves primarily to battery electric, plug-in hybrid electric, and hydrogen fuel cell vehicles, although the composition and magnitude of change varies between scenarios. For example, in CA-TIMES the combination of battery electric and hydrogen fuel cell vehicles makes up between 50% and 96% of the LDV fleet in 2050. In the ARB VISION model's mitigation scenario, these same technologies comprise over 80% of the LDV fleet in 2050. Regardless of the exact fleet composition, hydrogen and electricity with near-zero life-cycle GHGs (e.g. from wind, solar, biomass, NG with CCS) is needed to power virtually all of the LDV fleet by 2050.

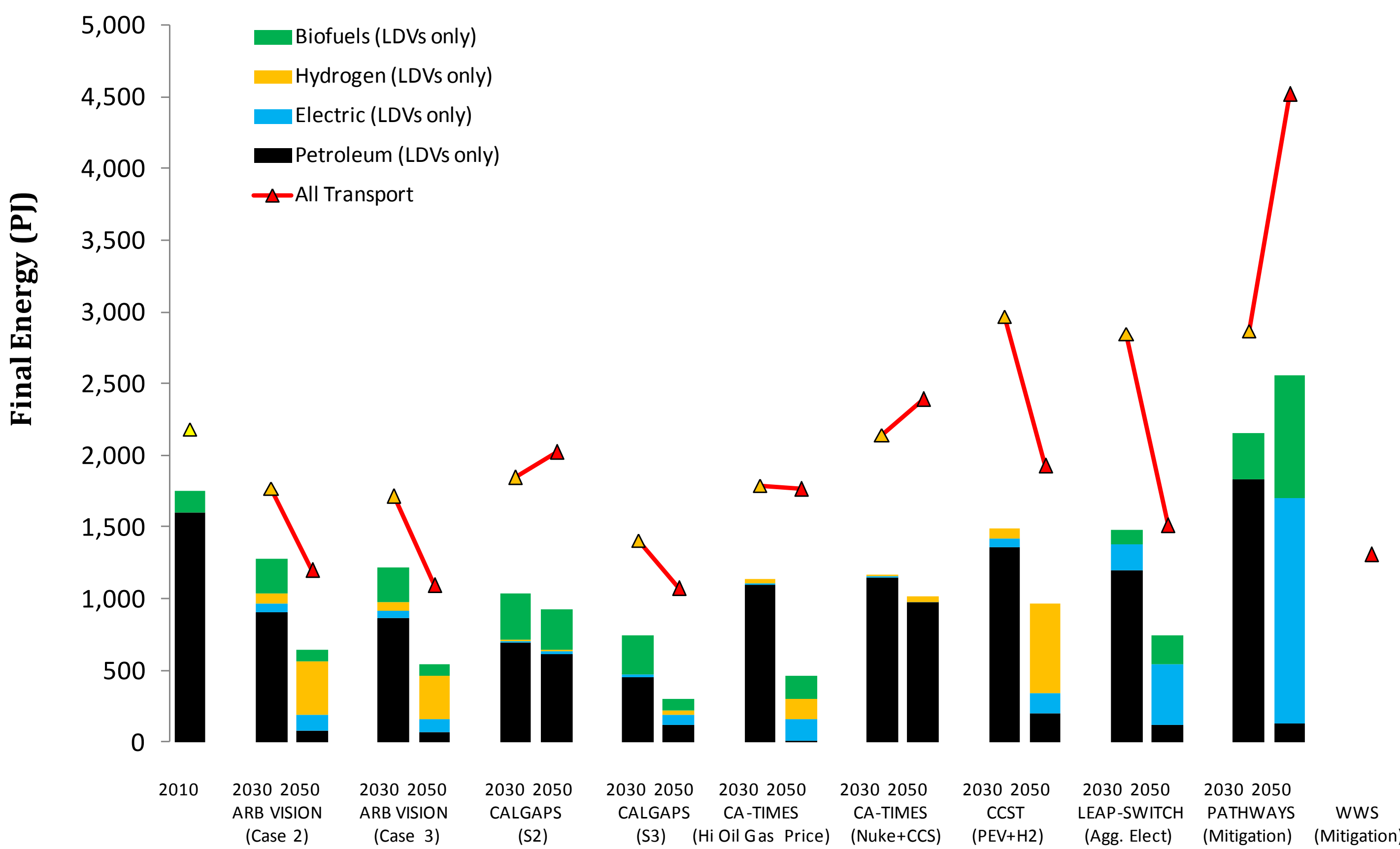

Figure 4. 2030 and 2050 light-duty vehicle final energy projections in select mitigation scenarios. Note that each fuel provides a different energy intensity of travel (e.g. electric vehicles go 2-3 times as far as a gasoline vehicle per MJ of energy).

3.6. Contribution from bioenergy

Bioenergy assumptions are important drivers in energy planning models (Rose et al., 2014; Wei et al., 2014). The more "low-carbon" bioenergy that is assumed to exist, the fewer mitigation strategies are needed in other sectors and technologies. Across models reviewed here (except for WWS), between 4-15 billion gallons of gasoline equivalent (BGGE) are available in 2050 (Figure 3) – up from about 1.0 BGGE today. These volumes are based on biomass supply curves from Parker (2011) or POLYSIS (2013). Figure 3 also includes one recent assessment of in-state biomass in 2050 (Youngs, 2013).

Most models examined here make simple assumptions regarding the carbon content of bioenergy. For example, SWITCH assumes bioenergy has 30% lower carbon intensity than petroleum-based fuels today and improves to 80% lower by 2050. PATHWAYS only includes biomass feedstocks produced in the U.S. that have a "net-zero" carbon intensity[17] on a lifecycle basis including corn stover, wheat straw, forest residues, forest thinning, and switchgrass (Williams et al., 2012). CA-TIMES assumes a carbon intensity of 75-80 gCO_2e/MJ for corn ethanol, 25-30 gCO_2e/MJ for cellulosic ethanol, and 13-30 gCO_2e/MJ for waste-based or Fischer-Tropsch bio-/renewable diesel. CALGAPS estimates net life-cycle GHG emissions for biofuels that includes offsets based on the assumed in-state portion of biofuels produced. ARB VISION assumes that the average carbon intensity of all biofuel declines from 67 to 41 gCO_2e/MJ. It should be emphasized that all models here assume point estimates rather than distributions in carbon intensity. A number of studies suggest that these carbon intensities are highly uncertain (e.g. Plevin et al., 2010) while others suggest the entire accounting system is flawed (e.g. DeCicco, 2013; Plevin et al., 2013).

Setting aside these concerns and assuming that bioenergy with low lifecycle GHG emissions will in fact exist in the future, CA-TIMES suggests these fuels are best utilized in the transportation sector (rather than in other sectors). The PATHWAYS, CCST, and CALGAPS

[17] Meaning these biofuels are assumed to exist without GHG emissions

models also make an exogenous assumption that almost all biomass goes to transportation[18]. Across scenarios, bioenergy accounts for a maximum of about 40% of transportation energy in 2050.

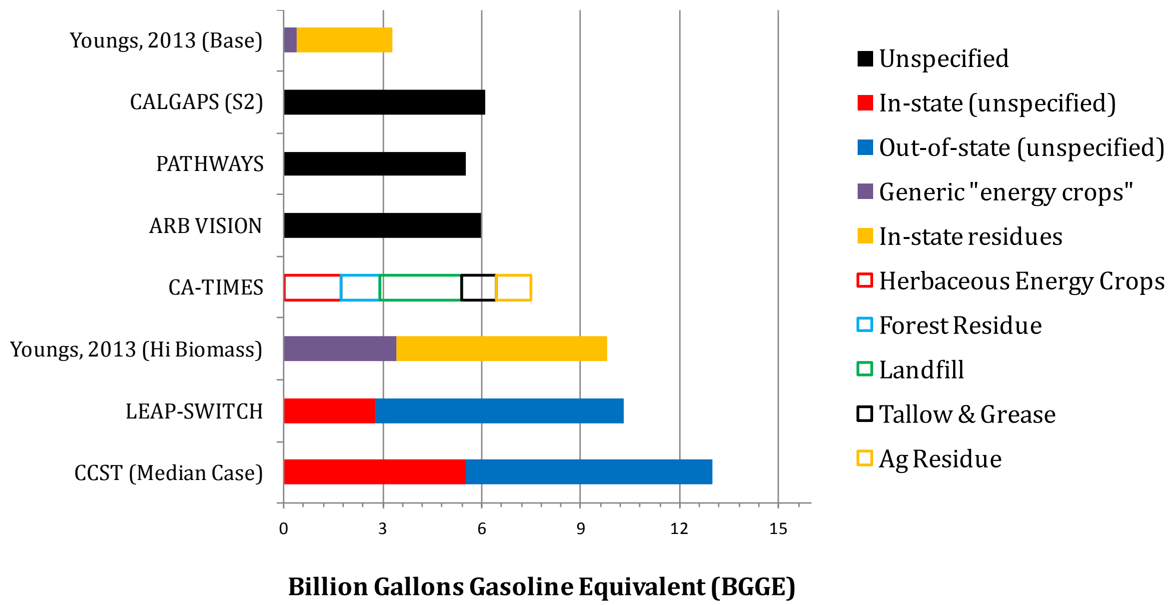

Figure 5. Maximum assumed biofuel volumes in 2050 across models/scenarios. Estimates by Youngs (2013) only includes in-state production (no imports).

Not all long-term energy modeling suggests large quantities of biofuels are needed in the transportation sector. The WWS model, presents a vision of 2050 without bioenergy, relying instead on battery electricity and hydrogen for the transportation sector.

3.8. Non-CO_2 and criteria emissions

Non-CO_2 gases are another important consideration for environmental planning in California. The relative contribution of non-energy and High Global Warming Potential (HGWP) GHGs to overall emissions levels is likely to increase in the coming decades. Greenblatt (2014) and Wei et al. (2013) find that, absent further policy, these emissions could exceed the 2050 emission goal even if all other emissions are zero.

[18] These models do assume some biomass-based electricity generation. CCST and CALGAPS (Scenario 3) also assume some biogas is incorporated into the natural gas distribution network, which supplies all sectors.

The models are at various stages of development in addressing criteria pollutant emissions. The ARB VISION, BEAR and CALGAPS models have the capability to count NO_x, ROG, and $PM_{2.5}$ emissions inventories[19]. PATHWAYS is adding Air Quality Management District resolved NO_x emissions, and the CA-TIMES group is adding a module to begin estimating changes to criteria pollutant emissions so that air quality simulations can determine $PM_{2.5}$ and ozone concentration changes from multiple energy scenarios.

Table 3. Non-GHG Emissions tracked by each model.

	Resolution	**Tracked Energy Pollutant Emissions**						**Pollutant Atmospheric Concentrations**	
		NO_x	**ROG**	**$PM_{2.5}$**	**CO**	**SO_x**	**NH_3**	**$PM_{2.5}$**	**O_3**
ARB-VISION	SC and SJV air basins, state-level								
BEAR	State-level								
CCST	N/A								
CA-TIMES	16 km^2 cells								
CALGAPS	SC and SJV air basins, state-level								
LEAP	N/A								
PATHWAYS	air quality management or control districts								
SWITCH	N/A								
WWS	County-level								

Green: represented; Yellow: currently unavailable but in progress; Red: not represented. The yellow for CA-TIMES represents an add-on feature (ex-post analysis) as opposed to being part of the integrated model. SC = South Coast; SJV=San Joaquin Valley. SO_x = sulfur oxides (primarily SO_2 and SO_3).

There is a need to pursue strategies that simultaneously reduce GHG emissions, PM, NO_x, ROG related to ozone pollution consistent with both the near-term (2023) and midterm (2032) National Ambient Air Quality Standards (NAAQS) for ozone, and long-term (2050) GHG targets (CARB, 2012). Aggressive pursuit of zero and near-zero emission transportation technologies has the potential to achieve NAAQS of 75 ppb ozone (O_3) and relevant targets in the South Coast Air Basin and many parts of the San Joaquin Valley. Accomplishing this by the

[19] NO_x = nitrogen oxides (NO and NO_2); ROG = reactive organic gases, also known as volatile organic compounds (VOC); $PM_{2.5}$ = fine (≤2.5 µm) particulate matter.

2032 legally binding deadline will be challenging given historical vehicle turnover rates and higher initial technology costs, suggesting the need for additional strategies, early action items, and more rapid development and adoption of zero-emission technologies (CARB, 2012). A better understanding and specification of spatial and temporal NO_x and ROG emissions is needed (see Table 3 for current energy model criteria pollutant spatial resolution) to guide air quality policy including the response to and relationship with GHG reduction goals and strategies. The strong relationship between proximity of emission sources to population and health impacts makes high resolution and geospatial information necessary for accurate assessment of pollution exposure impacts such as heath and fiscal benefits and costs.

3.9. Economic impacts of mitigation

Scenario costs and economics vary greatly across models in terms of both what is estimated and what is assumed. For those models that include an estimate of technology costs (BEAR, CA-TIMES, SWITCH, PATHWAYS, WWS), the results vary (as they do for any output) because of assumptions regarding technology availability, costs, learning curves, discount rates, and policy mechanisms. While initial technology and energy infrastructure investment costs are expected to increase in some sectors, the statewide investment in energy efficiency is expected to provide financial savings that can be invested back into the state economy, providing overall economic benefits (Roland-Holst, 2008). Improving energy efficiency reduces costs to the state by reducing the need to build new power plants or new refineries (Yang et al., 2014). SWITCH estimates that real electricity rates do not increase up through 2030 relative to current rates and do not vary significantly from their BAU. Electricity rates do rise, however, relative to BAU after 2030 to meet the 2050 goal, with estimates of an increase of 21-88% relative to BAU to meet a 2050 GHG emission target of 86% below 1990 levels for the entire Western Electricity Coordinating Council (Nelson et al., 2013).

Estimates of average carbon mitigation cost ($/t$CO_2$e, all converted to 2013 dollars) vary between models, across sectors, and over time. For example, in CA-TIMES mitigation costs are estimated by technology and year and range from -$75/t$CO_2$e to +$124/tCO_2e between 2010 and

2050. CA-TIMES uses a 4% discount rate[20]. Williams et al. (2012) estimate an average mitigation cost across forty years (from 2010 to 2050) of $90/tCO_2e$[21]. For perspective, in California's cap and trade program, credit prices in ARB's initial scoping plan were forecast with BEAR at $12 per ton (Roland-Holst, 2008) and, since inception of the program have ranged from $12-$24 per ton (CPI, 2014).

Policies that reduce GHG emissions, in addition to reducing the impacts from climate change, may also yield a number of valuable co-benefits (e.g., ecosystem services, improved air quality, health benefits, etc.) that are not captured in many of these estimates. For models that include macro-economic feedback (Roland-Holst, 2008), calculate net savings (Williams et al., 2012), or include full accounting of social costs (Jacobson et al., 2014), these savings have the potential to offset most or all of the increased technology costs. For example, Jacobson et al. (2014) estimates that a 100% renewable energy system would eliminate approximately 16,000 state air pollution deaths per year and avoid $131 billion per year in health care costs.

4 Discussion and Conclusions

The model results discussed here highlight how achieving deep GHG emission reductions in the state will require a coordinated effort across all sectors of the economy. The optimization models suggest that the least expensive path to achieving these reductions includes aggressive decarbonization of our electricity supply, electrification of most end-uses, increases in energy efficiency, and deployment of low-carbon transportation fuels and technologies. Models that measure monetary impacts suggest the economic and social benefits of these reductions outweigh the costs (Roland-Holst, 2008; Jacobson et al., 2014). What is clear from nearly all the deep reduction scenarios is that the rates of these transitions – such as deployment of better vehicles or renewable electricity – exceed the historical rates of change in the state. The implication: faster rates are needed to reach the 2050 target.

[20] This is the average discount

[21] This is the difference in cumulative (2010-2050) energy system cost between the mitigation scenario and BAU divided by the difference in cumulative emissions.

This model comparison and the accompanying energy stakeholder forum (Morrison et al., 2014) highlighted a number of tangible steps forward for the energy planning community in California. As a starting point, the main drivers of the models (e.g. income, population, prices, and costs) should be treated with distributions rather than point estimates (Lempert, 2010). While uncertainty analysis can be time consuming, it can also lead to insights not possible using point estimates. Policy can be designed to be more robust to uncertainty by incorporating flexible policy mechanisms (e.g. market mechanisms such as trading, banking, and borrowing) and regular review. Economic costs are another area for future focus. Yang et al. (2014) report that mitigation costs in CA-TIMES are highly sensitive to the assumed costs and availability of breakthroughs such as advanced bio-liquids, nuclear and CCS, as well as assumptions about energy demand growth.

Policy makers involved in this project expressed a desire for more modeling of: (1) individual policies (i.e. rather than generic climate policies) in order to better understand the spatial, temporal, and socio-economic effects of regulations, (2) interactive effects between two or more policies, (3) non-emission impacts like water, land-use, and economic equity, and (4) how best to sequence and prioritize policies and technologies. Lastly, policy makers requested that model output be reported in the same metrics as those used in the policy arena in order to help improve the relevance of model output[22].

Modelers at the forum requested more up-to-date information about upcoming policies and more access to the latest state-collected data to improve model calibration/validation and to strengthen analysis of existing and future policies. Modelers also emphasized the problems of attempting to incorporate multiple environmental criteria into a single model. One cogent example given was that air quality models that seek to measure human health impacts need to be highly spatially-disaggregated whereas most energy models are typically at the regional or state-level.

Standardization of input assumptions in models, such as population, income, elasticities, costs, emission factors, etc could be achieved through close coordination between modeling teams. Greater coherence/transparency of technology adoption/diffusion assumptions, and more

[22] Policy makers specifically requested greater reporting of performance metrics (such as gCO_2e/mile for vehicles, average gCO_2e/MJ for fuels, gCO_2e/kWh for electricity, % renewables by year) and economic metrics (such as $/metric ton CO_2e, % change of household expenditure on energy, and lifecycle costs of travel in $/vehicle miles traveled).

extensive data sharing, would likely improve the insights gained from model comparisons. This could include making the models open-source and increasing the interoperability between research models and government models used by the state. Similarly, having a set of standardized scenarios as done by the Intergovernmental Panel on Climate Change would help state policy makers in clarifying and simplifying the often-opaque black boxes of the modeling world. In general, more dialogue is needed between model developers and policy makers.

One of the more lucid takeaways from this exercise is the need to consider both annual *and* cumulative emissions when setting GHG targets and building climate strategies. Scenarios with aggressive and early emission reductions achieve far lower cumulative emissions by 2050. In some BAU scenarios, California has *more than twice* the cumulative emissions in 2050 as in the mitigation case. From a climate perspective, the obvious implication is that near-term reductions are preferable to delayed reductions. Of course, the preference for near-term reductions to delayed reductions must be balanced with the economic, social, and environmental impacts.

Acknowledgements

We deeply appreciate paper reviews from Joshua Cunningham (CARB), Nicole Dolney (CARB), Cody Howard (CARB), and Charanya Varadarajan (CARB). The authors also wish to thank the members of the Steering Committee of the California Climate Policy Modeling (CCPM) forum. Additionally, we received contributions and helpful insights from Mark Delucchi (UC Davis) and Mike Kleeman (UC Davis). While the content was significantly informed by the contributions of the above parties, any errors contained herein are strictly the responsibility of the authors.

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SUPPORTING INFORMATION FOR:

Comparison of California Energy Models with Scenarios to 2050: Insights and Future Modeling Needs

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1 Model descriptions

1.1 ARB-VISION

The ARB-VISION model adopts the framework from the national VISION model from Argonne National Laboratory to better understand how changes in technologies/fuels/energy patterns affect lifecycle criteria and GHG emissions from mobile and non-mobile sources to 2050. The model has three scenarios including a BAU scenario and two mitigation scenarios, and regional breakouts for the San Joaquin and South Coast air quality districts. Documentation for the model is available at (CARB, 2012). Future technology (e.g. advanced vehicle sales penetration), energy (e.g. alternative fuel supply), and energy efficiency are exogenously determined and the model estimates emissions. Technical and cost feasibility, energy production capacity, market factors, and feedbacks are not included. The scenarios are not designed to favor certain technologies and fuels over others and most of the technologies and energy sources exist in some form today (either they are already on the market, or they are in the maturation process—e.g. in demonstration programs or limited test markets).

Reference/BAU scenario: This scenario includes all current federal and state programs and those that have been adopted but not enacted. This includes the Low Carbon Fuel Standard to 2020 and the Renewable Fuel Standard. Petroleum stays as the dominant transportation fuel through 2050. As vehicle efficiency improves, diesel and natural gas increase in importance in statewide GHG emissions.

Mitigation scenarios: ARB VISION has two mitigation scenarios. In both, all the assumptions of the BAU scenario are maintained. The first includes new technologies and fuels such as electric and hydrogen passenger vehicles, hybrid heavy-duty truck technologies and a conversion to hydrogen, electricity, and natural gas to fuel the transportation sector. The second mitigation scenario builds on the BAU and the first mitigation scenario by including cleaner near-term air quality controls and greater acceleration of clean maritime technologies and reduced travel by 10-20 percent by 2050. Other assumptions are provided in (CARB, 2012).

1.2 Berkeley Energy and Resources (BEAR) Model

The Berkeley Energy and Resources (BEAR) model is a dynamic computable general equilibrium (CGE) model that estimates intertemporal economic impacts of certain policy shocks. Outputs include detailed patterns of resource/energy use, supply, demand, trade, and employment, emissions, public expenditure and revenue, prices, and incomes. Since its initial development in the early 2000s, the model has been used by the state of California and independently to answer questions about AB32 and related climate policies. The model includes up to 165 sectors (typically 50), employment by skill and other occupational categories, trade with the rest of US and abroad, federal, state, and local fiscal accounts, household income for nine tax brackets, and 14 different emission categories. The ‘BEAR’ model utilizes a nested CES (Constant Elasticity of Substitution) for energy sources, and has four components: a) core general equilibrium model, b) technology module, c) electricity module, and d) transportation module.

Reference/BAU scenario: The baseline scenario use historical trends in energy efficiency and energy use. 2020 emissions are 596 MMT CO2e/yr.

Mitigation scenario: one main mitigation scenario attempts to capture the California economy out to 2020 under the AB32 climate policy. Thus, the annual emissions in 2020 reach the year’s goal of 427 MMT CO2e.

1.3 CA-TIMES

CA-TIMES is a 4E (Energy-Engineering-Environmental-Economic) model that explores the potential of various technology and policy options for reducing GHG emissions while meeting the future energy demand for California by 2050. The model covers the entire economy, including emissions from non-energy sources. CA-TIMES can be run as a cost-optimization model or as a partial-equilibrium welfare-maximization model, and uses scenarios to help tell "what if" stories of the future. The model covers all sectors of the California energy economy, including primary energy resource extraction, fuel production/conversion, fuel imports/exports, electricity production, and the residential, commercial, industrial, transportation, and agricultural end-use sectors.

Reference/BAU scenario: Future energy service demand (e.g. passenger-km) grow at median rates projected by the state. The policies modeled include those that are currently enacted or have been adopted. This includes biofuel tax credits, biofuel import tariffs, transportation fuel taxes, low carbon fuel standard, renewable portfolio standard (33% by 2020 and remains at 33% until 2050).

Mitigation scenarios: CA-TIMES has a total of 14 mitigation scenarios which explore different sets of technology availability. The 14 scenarios include: high nuclear and CCS, high CCS, high nuclear, high renewable energy, high oil and gas use, low oil and gas use, low battery electric vehicle penetration, low fuel cell vehicle penetration, and high bioenergy consumption. Additionally, there are three scenarios which explore different levels of elasticity of demand and two that serve as the "reference mitigation" scenarios (against which other mitigation scenarios are compared).

1.4 CALGAPS

The California GHG Analysis of Policies Spreadsheet (CALGAPS; formerly GHGIS) model represents all GHG-emitting sectors within California between 2010 and 2050, as delineated by ten major modules: light-duty vehicles, heavy-duty vehicles, other transportation (rail, airplanes, marine), stationary end uses (residential, commercial, industrial, municipal, agriculture), water, hydrogen, electricity, fuels (fossil- and biomass-based), high global warming potential gases, and other non-energy emissions (petroleum extraction, cement, landfills, waste, agriculture and forestry). The model also estimates emissions of three criteria pollutants (ROG, NO_x, and $PM_{2.5}$). Input data for the model was assembled from a combination of public and proprietary data supplied by a number of state agencies. The GHG reduction impacts of each policy individually and in various combinations were also estimated in a sensitivity analysis. Monte Carlo simulation was used to provide uncertainty bounds on projected GHG emissions pathways.

Reference/BAU scenario: assumes no major GHG reduction policies are in place but demand continues to grow at historic rates.

Mitigation scenarios: The modeling team developed three mitigation scenarios: all "committed" GHG mitigation policies for the state (S1); all "uncommitted" and "committed" policy targets for the state (S2); and a number of "potential policy and technology futures" as well as policies included in the S2 scenario (S3). We consider the two most aggressive scenarios (S2 and S3) as "deep reduction scenarios" because they achieve cumulatively similar emissions reductions as many of the other models' most aggressive scenarios.

1.5 CCST

The CCST model adopts a "portraits" approach, where plausible technology combinations are constructed for 2050 (not all of which meet the GHG 80% reduction target), and the model is used to calculate the resulting demands for electricity and fuels, and the supply capacities needed to meet those demands. The model represented all energy sectors, with future demand mainly driven by inputs from an earlier study (McCarthy et al., 2006). Non-energy GHG emissions are not included.

Reference/BAU scenario: A generic BAU scenario was developed in which gaseous and liquid fuels increase from 35 bgge in 2005 to 30.5 bgge in 2050 and total electricity generation increases from 270 TWh in 2005 to 271 TWh in 2050.

Mitigation scenarios: The California Energy Futures committee developed a total of nine portraits which they use to explore the potential of electricity generation technologies: renewables, nuclear, fossil with CCS, and a mixture of the three (called the "median" case, which was the main reference case). Many other technologies were also explored; in all, about 80 portraits were constructed. A form of "back-casting" was used to construct scenarios connecting the present day (2010) to selected 2050 portraits. Energy demands were determined using a variety of literature (Yang, 2011; Greenblatt, 2012) and expert opinion. Appendix A of Greenblatt and Long (2012) give sector-level GHG emissions and energy use.

1.6 LEAP

LEAP and SWITCH are two separate models, soft-linked to run a set of consistent scenarios. The LEAP portion is a scenario-based non-economic model of the energy system that does not include substantial detail about the power grid. LEAP can provide insight into GHG and energy system impacts of policies operating outside the electricity sector, the magnitude of electrification of transportation and heating, composition of low-GHG transportation systems, the timing of technology adoption with respect to 2050 GHG compliance, and the role that non-energy/non-CO_2 emissions reductions can play.

Reference/BAU scenario: This scenario has a "frozen efficiency" in which energy conversion efficiencies stay at today's efficiency level.

Mitigation scenarios: LEAP and SWITCH include 15 mitigation scenarios which are fully described in Wei et al. (2014). Most scenarios focus on various technological, supply, policy, and demand pathways for the electricity sector. Examples include: aggressive electrification, small balancing area, limited hydro-electric production, expensive transmission, demand response, SunShot Solar prices, low natural gas prices, and high distributed photovoltaic, among others. In the electric sector, GHG emissions are reduced by 86% (or more in some cases) between 1990 and 2050. One scenarios does not allow CCS technology and two others include bio-power with CCS.

1.7 PATHWAYS

The PATHWAYS model uses a policy-centered modeling approach. The model seeks to identify the "infrastructure and technology path" that would be necessary to meet GHG reduction goals. Model outputs compare changes in electricity, fuel, GHG emissions, and cost between the baseline scenario (developed via regressions of sectoral activity measures and energy demand) and mitigation scenarios. Breaking down the state's economy into six energy demand sectors, two energy supply sectors, and a sector that covers "non-energy" CO_2 emissions and non-CO_2 emissions from all sectors, PATHWAYS uses a stock-turnover model that simulates physical infrastructure at an aggregate level. In the near-term, the model relies primarily on state policy implementation planning, given that such planning takes into account the spectrum of existing commercial technologies. In the long-term, the model simulates technological progress and rates of new technology introduction based on “physical feasibility,” resource availability, and historical uptake trends.

Reference/BAU scenario: The model’s baseline scenario uses a set of regressions and a stock-turnover model for the electricity supply to describe a future in which growth continues on a trend observed from historical data and backwards regressions going back to the 1950s.

Mitigation scenarios: PATHWAYS includes five mitigation scenarios: high renewable, high nuclear, high CCS, mixed, and mixed without energy efficiency. All scenarios achieve an 80% reduction in GHGs relative to 1990 levels.

1.8 SWITCH

Results from LEAP pertaining to electricity are input into SWITCH as exogenous assumptions. SWITCH is a spatially and temporally detailed electric sector economic optimization and investment-planning model for power systems. SWITCH identifies where electricity generation, transmission, and storage projects should be built and how these assets should be dispatched over a multi-decade time interval in a manner that minimizes cost while also meeting CO_2 reduction targets. SWITCH provides insight into electric sector capacity expansion, the economics of wind and solar power integration, electricity prices, the value of demand response, and tradeoffs between and optimization of generation, transmission, and storage infrastructure.

Reference/BAU scenario: same as LEAP scenarios

Mitigation scenarios: same as LEAP scenarios

1.9 WWS

The Wind, Water, Solar (WWS) model (Jacobson et al., 2013; 2014) identifies the technology, costs, benefits, and policies needed to achieve a 100% renewable energy system by 2050. In this regard, the WWS is different than the other eight models in this comparison that focus on GHG trajectories. WWS-California is one of 50 statewide models from the same development team that takes into account the state-specific energy resources, costs, and baseline to achieving 100%

renewable by 2050. The authors find that a 100% renewable energy system by 2050 would result in greater numbers of jobs and massive health-care savings from reduced pollution deaths.

BAU Assumptions:

Reference/BAU scenario: The model's 100% wind, water, solar scenario is the main focus of Jacobson et al. (2014). End-use power delivered (in TW of power) decrease from 0.206 TW to 0.157TW. The energy mix and technology portfolio of the state are estimate for 2010, 2030, and 2050 in a supplemental spreadsheet.

Mitigation scenario: A single reference scenario describes a future in which California's delivered power consumption increases to 0.28TW in 2050.

1.10 Description of model structures

1.10.1 Optimization models

Optimization models attempt to understand how policy measures and technology characteristics impact technology penetration in a least-cost fashion. These models minimize the net present cost of the energy system in California (CA-TIMES) or western North America (SWITCH) with respect to constraints on infrastructure capacity, policy, rates of technology change, technology availability, energy service demand, and – importantly for this exercise – GHG emissions. Both CA-TIMES and SWITCH use "perfect foresight:" rather than successively optimizing each time step, the models solve all time steps simultaneously. This leads to an elimination of "wasteful" investment[23]. CA-TIMES scenarios have a single 2050 GHG constraint, while SWITCH uses GHG constraints on each 10-year time step. The main limitations of optimization models are: (1) the models often fail to explicitly capture non-monetary drivers of energy demand such as human preferences and behavior-related variables; and (2) decisions are made solely based on exogenously-specified costs trajectories which make the model susceptible to "winner-take-all" behavior.

1.10.2. Equilibrium models

[23] i.e investment in technologies that may give an optimal outcome in one time period but not across all time periods

Computable general equilibrium (CGE) models such as BEAR and certain scenarios of CA-TIMES[24] use historical rates of substitution and transformation across sectors of the economy to help understand how a policy perturbation impacts costs, incomes, jobs, and other economic variables. BEAR uses emission intensities (e.g. CO_2e, NO_x, water, etc. per dollar of economic activity) to link the environmental burden to input-use of each sector, and to consumption expenditure in final demand. The main strengths of CGE models lie in their ability to mimic multiple markets while conserving the material balance of the economy and capturing important economic feedbacks and indirect effects (see Sue Wing, 2009 for more background). These are especially useful models for estimating economic or employment effects of proposed policies. Another advantage of equilibrium models is that prices and quantities are adjusted endogenously to capture the behavioral response to market prices/costs of mitigation costs. Key limitations of CGE models are they sometimes lack technological diversity within a given sector compared to spreadsheet or optimization models and they often can be opaque for the user. This opaqueness arises because of the complexity of the parameterizations (e.g. it may be easier to understand, interpret, and update an inventory model's technology growth rate than a CGE model's cross-sectoral elasticity) and the fact they written in non-spreadsheet language.

1.10.3 Inventory models

ARB VISION, CCST, CALGAPS, LEAP, PATHWAYS, and WWS can be loosely categorized as "inventory" or "energy-balance" models. ARB VISION projects emissions, energy use, and technology mix with user-defined inputs on technology adoption rates, fuel supply sources, and vehicle mileage activity. CCST, PATHWAYS, and WWS use "backcasting" (e.g. 80% reduction in GHGs by 2050; 100% wind-water-solar by 2050). CCST also examines a wide range of technology combinations, not all of which achieve the 2050 GHG target. CALGAPS uses four scenarios to project energy, emissions, and technology mix for sets of real-world policies. The LEAP model is an activity-based model that uses exogenous assumptions about energy service (e.g. the saturation of electric space heating in single family homes). Both CALGAPS and

[24] Some scenarios in CA-TIMES are solved using a partial equilibrium approach to maximize total social welfare.

PATHWAYS forecast sectoral growth using regressions of sectoral activity and energy demand which are, themselves, based on regressions of population and gross state product (GSP). Inventory models often provide the user with a transparent and flexible method of understanding different futures. The major limitations of such models are they often lack price feedbacks or interactions between sectors of the economy.

2 Population and income input assumptions

Income and population projections are often important drivers in energy-economic models for GHG and criteria emissions and energy service demand (Greenblatt and Long, 2012)[25]. Population has a direct link to energy use: the more people consuming energy at a given per capita consumption level, the greater the total energy service demand. For income, however, the link to emissions and energy service demand could go in either direction (i.e. positive or negative). One could argue that higher incomes would entail greater economic activity, emissions, and energy service demand. On the other hand, higher incomes could also help catalyze environmental-mindedness and lead to greater investment in low-carbon technologies. Most energy-economic models assume income and energy service demand are *positively* linked. However, there is evidence the two are becoming/have become decoupled, for example in the transportation sector (see Millard-Ball and Schipper, 2010).

Expectations of future population and income decreased in California in the last five years, meaning older models tend to use higher projections. For example, the PATHWAYS model assumes 2050 state population will be 56.6 million people while five other models assume 50.4 million based on 2013 population projections from the California Department of Finance (DOF, 2014a). Two models use U.S. Census data, which projects national-level population to 2060 and at the state-level to the year 2035. Figure SI.1 shows the population assumptions over time across the nine models as well as the input datasets.

[25] Another modeling approach is to make exogenous assumptions about future energy service demand (e.g. passenger miles traveled) and let the model endogenously solve for fuel or technology mix.

Like population, future estimates of income have shifted downward in recent years. From 1970-2012, California GSP grew at a *nominal* rate of 6.8% per year (BEA, 2014). DOF (2014b) forecasts a *nominal* growth of 5.3% in California personal income between 2014-2017. Across the nine models, *real* income and GSP growth rates range from 1.5%-3.4% per year [26]. Three models (LEAP, SWITCH, WWS) do not use income as a driver in the model. Figure SI.2 shows income production across the models.

Other input parameters are also important in model results such as assumed costs, technological efficiencies, rates of improvements, technology availability, carbon contents, and others. While some of these are discussed below, we do not conduct a detailed comparison of any due to time and resource constraints. This represents an area that would benefit both model developers and energy planners.

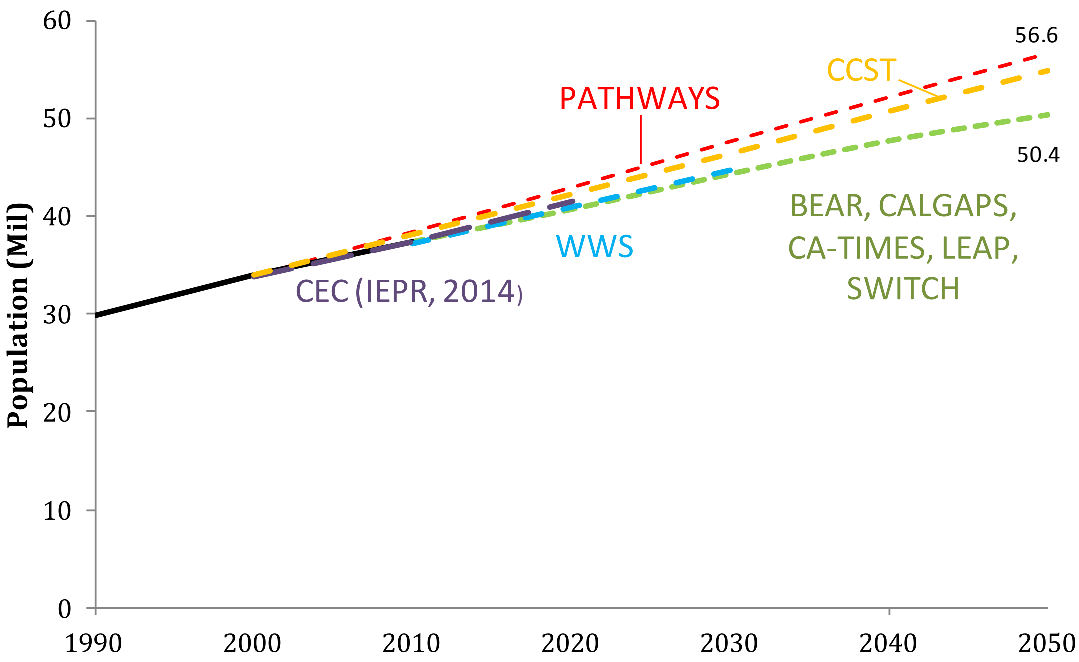

Figure SI.1. Historic and projected state population used in various energy models

Notes on data: BEAR uses DOF (2013), PATHWAYS uses U.S. Census (2005) + regressions, CA-TIMES uses DOF (2013b), CALGAPS uses DOF (2013). SWITCH uses AEO (2011), ARB VISION uses EIA (2011), WWS uses U.S. Census (2009), CCST uses DOF (2004). Also included in the figure are projections used in California's

[26] Energy-economic models typically use real growth rates (i.e. constant dollars) whereas federal or state income projections typically use nominal rates (i.e. current dollars).

Integrated Energy Policy Report (IEPR) (CEC, 2013), which uses data from IHS Global Insight for its Mid projection.

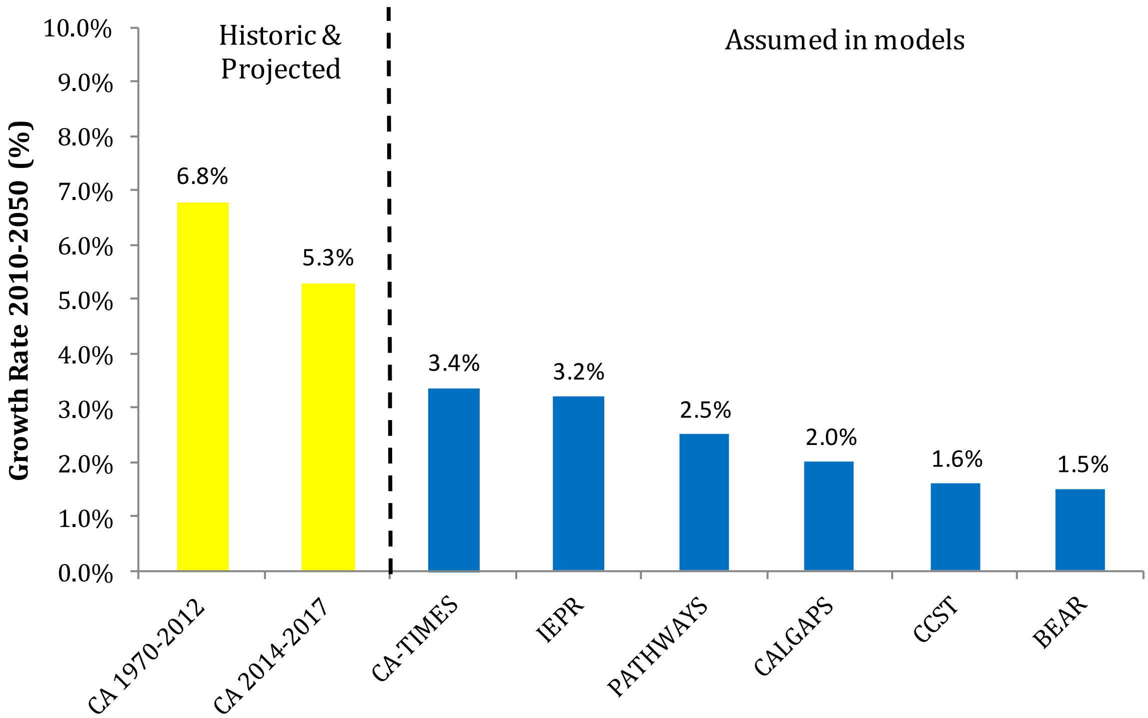

Figure SI.2 Figure SI.1. Historic and projected state income used in various energy models. Notes: historic and projected growth rates are nominal. Other growth rates are real (take into account expected inflation rate). Yang et al. (2014) based on CEC (2013), CEC (2013) based on data from Moody's and IHS Insight. Williams et al. (2012) based on equation 6.2.1 from their supplementary information. Greenblatt (2014) based on CALGAPS based on historical trend. CALGAPS conducts uncertainty analysis around GSP values, with a max and min of 1.5% and 2.7%.

3 Biofuel

Table SI-2. Notes on biofuel

Model	Volumes and Technologies	Lifecycle Emission Assumptions
ARB VISION	In all scenarios, the flex-fuel vehicle (FFV) fleet continues to grow at historic levels. In 2020, FFVs are non-consequential because of assumption that all biofuels are drop-ins. The fuel mix includes ethanol, bio-diesel, FT diesel, methanol. Fuel prices are matched to AEO to 2030 and extrapolated after. Model allows bio-diesel and FT diesel in Heavy Duty Vehicles. Carbon intensities do not change to 2050 but ratios of different biofuels do. In Scenario Two and Three, 6 and 4.8 bgge are assumed available to the market, respectively. Renewable jet enters market in 2020 and increases to 2050.	Biogenic carbon is carbon neutral. Upstream emissions counted. Static biofuel carbon intensities. Based on Argonne National Lab's GREET model, and Parker (2011). No iLUC factor.
BEAR	Model results to date assume zero biofuel use to 2020. Version under construction allows detailed analysis of biofuel technologies.	Current version allows for exogenously specified lifecycle carbon content in state imports, as well as endogenous carbon added in state distribution.
CA-TIMES	Biofuels account for ~38% of total transportation fuel demand in STEP scenarios and 42% in BAU. CA-TIMES disaggregates biomass evenly between biomass-based jet fuel, biomass-based gasoline, and biomass-based diesel. 8 billion gge maximum. Nearly all biomass goes to making biofuel. Uses California-specific supply curves. Feedstocks include forest residue, agricultural residues, municipal solid waste, energy crops, and others. Out of state and foreign biofuels allowed. Biogenic carbon assumed to be net zero. No iLUC factor used but upstream accounting incorporated.	Biogenic carbon neutral.
CALGAPS	Model produces levels of biofuels dictated by policies in its four scenarios.	Upstream and downstream GHG emission factors from ARB VISION (CARB, 2012)
CCST (2011)	CCST use a median of 7.5 bgge/yr in-state and 7.5 bgge/yr imported. Of this, 2 bgge/yr is burned for electricity. The remaining 5.5 bgge/yr of in-state biofuels requires 110 biorefineries each with 50 Mgge/yr capacity, for a build rate of 3/year between 2011-2050. 70% of feedstock comes from waste, 30% from low input (no added fertilizer or irrigation) biomass. Model uses mostly electrification of LDVs and assumes aviation, marine, and HDV sub-sectors largely rely on liquid fuels, some of which are biofuels.	LCA of liquid biofuel assumed to go from 50-70% to 20% of petroleum carbon intensity.

	Documentation discusses how biopower+CCS seems like a good option but siting of projects might be a problem because CCS resources are not necessarily located in same place as biomass resources. Greenblatt and Long (2012) find biopower+CCS is better use of biomass than bioliquids for transportation. Authors conclude that greater imports of biofuels is one way to further decarbonize the transport fuel supply.	
LEAP	By 2050, up to 2.8 billion gge of instate biofuels all going to transportation. Imports are 7.5 bgge consistent with California receiving a population-weighted share of national biomass resources in 2050. Depending on scenario, levels of biofuel use differs.	Carbon intensity of biofuel assumed to decrease from 70% to 20% of that of petroleum by 2050. Sensitivity of LCA to model results shows it's not that important of an assumption. All biofuels go to either bio-power or biofuels (not to both).
PATHWAYS	5.5 bbge total. Algae oil replaces up to 25% of diesel in freight sector. Biofuels contribute 6% to emission reduction in mitigation cases. All goes to transportation sector (only small amount of biomethane to electricity). 0.73 EJ of biofuels and biomethane by 2050 in mitigation case. Biofuel price forecasts from National Energy Technology Laboratory (NETL). Uses EIA feedstock supply forecast (from POLYSYS (De la Torre Ugarte and Ray, 2000)). Corn stover, wheat straw, forest residue, forest thinnings, and switchgrass. supply curve stationary after 2030.	Biofuels assumed carbon neutral (no biogenic or upstream emissions)
SWITCH	Same as LEAP assumptions (all goes to transportation).	n/a
WWS	Model assumes zero biofuels used in 2030 and 2050	n/a