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A modeling comparison of deep greenhouse gas emissions reduction scenarios by 2030 in California

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ABSTRACT

California aims to reduce greenhouse gas (GHG) emissions to 40% below 1990 levels by 2030. We compare six energy models that have played various roles in informing the state policymakers in setting climate policy goals and targets. These models adopt a range of modeling structures, including stock-turnover back-casting models, a least-cost optimization model, macroeconomic/macro-econometric models, and an electricity dispatch model. Results from these models provide useful insights in terms of the transformations in the energy system required, including efficiency improvements in cars, trucks, and buildings, electrification of end-uses, low- or zero-carbon electricity and fuels, aggressive adoptions of zero-emission vehicles (ZEVs), demand reduction, and large reductions of non-energy GHG emissions. Some of these studies also suggest that the direct economic costs can be fairly modest or even generate net savings, while the indirect macroeconomic benefits are large, as shifts in employment and capital investments could have higher economic returns than conventional energy expenditures. These models, however, often assume perfect markets, perfect competition, and zero transaction costs. They also do not provide specific policy guidance on how these transformative changes can be achieved. Greater emphasis on modeling uncertainty, consumer behaviors, heterogeneity of impacts, and spatial modeling would further enhance policymakers' ability to design more effective and targeted policies. This paper presents an example of how policymakers, energy system modelers and stakeholders interact and work together to develop and evaluate long-term state climate policy targets. Even though this paper focuses on California, the process of dialogue and interactions, modeling results, and lessons learned can be generally adopted across different regions and scales.

1. Introduction

The passage of the California Global Warming Solutions Act of 2006 (AB32) and the adoptions of wide-ranging implementation plans [1,2] make California a leader in developing and implementing policies that reduce greenhouse gas (GHG) emissions, improve air quality, and promote efficient use of energy and other resources [3–6]. The current climate law, AB 32, required the state to reach 1990 levels by 2020. In August 2016, California passed SB32 requiring the California Air Resources Board (ARB) to ensure that statewide GHG emissions are reduced to 40% below 1990 levels by 2030 [7].

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Policymakers should rely on transparent and high-quality technical and economic models to help evaluate plausible future emission scenarios and assess environmental and economic impacts of current or proposed emission targets and policy instruments. There is a rich modeling comparison literature focused on understanding the range of mitigation options for abating climate change [8–13] by comparing input assumptions and the results across a range of relevant models and exploring the underlying causes contributing to the observed differences [14]. These differences can result from: (1) assumptions about activity drivers and technologies and mitigation costs and options available between now and 2050; (2) structure and level of detail of the models (e.g. macroeconomic vs. sectoral-specific vs. technology-detailed model); (3) the model solution method (equilibrium vs. optimization vs. scenarios-based); and (4) scope and system boundaries of the models (multi-state vs. California-only, single-sector vs. economy-wide), etc.

This paper is a summary of the California Climate Policy Modeling (CCPM) workshop, held on February 23, 2015 (https://policyinstitute.ucdavis.edu/initiatives/ccpm/). It brought together energy economic modelers, academics, policymakers (including the senior advisor in the governor's office and the Executive Officer of ARB), lawmakers and stakeholders (including industry representatives, environmental non-governmental organizations NGOs, and environmental justice communities) reviewing the current status of energy models and examining pathways to meet long-term climate abatement objectives in California. Our paper focuses on the following metrics highlighted by both modelers and policymakers in the first CCPM workshop [13]: (1) common insights and divergence across models; (2) the implied technical/socioeconomic hurdles of given scenarios and economic costs; (3) performance metrics (e.g. gCO_2e/mile for vehicles, carbon intensity of fuels and electricity, share of renewable electricity generation) and economic metrics (e.g. \$/metric ton CO_2e, percent change of household expenditure on energy, costs of travel); and (4) the limitations of the modeling approaches and the issue of uncertainty. These models can inform policy by elucidating scenarios of specific sets of technology and resource options for GHG mitigation and their timing. The workshop also highlighted the caveats of the models and levels of uncertainties. We steer away from the discussion of policy needs and needs for specific policy instruments, as this will be the focus of future workshops.

In Section 2, we introduce the different modeling types included in this modeling comparison workshop, the pros and cons of each model, and the key findings from each study. We compare the key results of deep GHG mitigation scenarios in 2030 by sector in Section 3. In Section 4, we summarize the key findings consistent across models, and the opportunities as well as challenges in using models to inform policymakers when setting long-term policy goals and targets.

2. Methods

We briefly describe the models examined in this paper, focusing on the structure of the model (as opposed to different assumptions used in the models) and the key insights from each model. We limit our review of the results to 2030 as it is the target year for the next major policy discussion [2,15]. Almost all of the models reviewed here analyze emissions to 2050 and many achieve the 80% GHG reduction target for 2050. All the models reviewed here have conducted extensive sensitivity analysis or uncertainty analysis to explore a wide range of scenarios that are published elsewhere. For simplicity, our review here only focuses on the "main" scenarios. Not all scenarios reviewed in this paper achieve 40% reduction below 1990 level by 2030. As we have shown previously, models that meet the 2050 target do not necessarily meet the newly proposed 2030 target: 40% reduction below 1990 level by 2030. We will show later in the article that setting the 2030 target clearly influences the trajectory of how the 2050 target is achieved.

The structure and methods of a model determine the types of questions that the models are suitable to answer. The modeling types included in this review range from scenario-based stock-turnover model (PATHWAYS [16] and CALGAPS [17]), bottom-up optimization (CA-TIMES [18]), computable general equilibrium model (BEAR [19]), macro-econometric (REMI PI+ [20,21]) model, and economic-dispatch model for the electricity sector (LCGS [22]) (Table 1).

In a *scenario-based stock-turnover model* (which can be forecast-based or backcast-based), the rate and type of technology adoptions and resources use are determined based on modelers' judgments. These models calculate the portfolio of technology stock (and sometimes, but not always, costs) over time based on the lifetime of technology and their retirement rates. They are suited to answer "what if" questions (i.e. *what* is the impact *if* these technologies are adopted), as it has a high degree of transparency and traceability with regards to the assumptions and the impacts of the assumptions on the results. A limitation of these models is that they may rely too much on experts' assumptions with regards to technology penetration rates.

A *bottom-up optimization model* optimizes technology investment decisions based on the overall costs of the system. The model minimizes total system costs when demands for energy services are fixed or maximizes social welfare if demands for energy services are responsive to price changes. The model assumes perfect foresight and makes investment decisions solely based on the costs of technology, and resources from the perspective of a single decision-maker. It is therefore suited to ask the question: "What are the socially optimal (i.e. least-cost) technology and resource options to achieve a policy target, especially those that exhibit tradeoffs across sectors. One of the downsides of this type of model is that real-world decisions often involve markets, which are not represented in these models and consumer choices are rarely made solely on costs alone; significant heterogeneity exists in consumer demand and consumer preferences [23]. Factors such as convenience, familiarity with technologies, risk attitude, or market barriers (e.g. lack of awareness) often dominate consumers' decisions [24], which are not usually included in the optimization framework.

A macro-econometric model is usually constructed using statistical estimation methods based on pooled time series and regional (panel) data. Its forecasting strengths are to relate the role of government, capital markets, and other trading partners to account for economy-wide resource allocation, production, and income determination. While the other models focus primarily on the quantities of low-carbon technologies and resources and their direct costs, macroeconomic models such as *macro-econometric model or computable general equilibrium (CGE) models* accounts for economy-wide impacts (both direct and indirect) of these technology/resource shifts on consumption, employment, and income, brought about by the adoption of alternative technologies and resources. A typical drawback of these types of models is that most of these models make relatively simple assumptions about technology types, costs and operation decisions. Thus they are suitable for asking high-level, macro economy questions pertaining to income growth, labor markets, GDP impacts, economy feedback at the sectoral level, etc. even though they are typically vague about the impacts of specific technology pathways or choices.

An *economic-dispatch production simulation model* for the electric sector optimizes operating decisions at very high temporal resolutions to supply electricity demand at the lowest cost,