Energy Policy and Economics 021

"Dynamics of the Oil Transition: Modeling Capacity, Costs, and Emissions"

Adam R. Brandt and Alexander E. Farrell
Energy and Resources Group, University of California, Berkeley

January 2008

This paper is part of the University of California Energy Institute's (UCEI) Energy Development and Technology Working Paper Series. UCEI is a multi-campus research unit of the University of California located on the Berkeley campus.

UC Energy Institute
2547 Channing Way
Berkeley, California 94720-5180
www.ucei.org

Dynamics of the oil transition: modeling capacity, costs, and emissions*

Adam R. Brandt† and Alexander E. Farrell‡
Energy and Resources Group, University of California, Berkeley

January 15th, 2008

Abstract

The global petroleum system is undergoing an "oil transition," shifting from conventionally produced petroleum to a suite of substitutes for conventional petroleum (SCPs). This paper describes the Regional Optimization Model for Emissions from Oil Substitutes, or ROMEO, which models this oil transition. ROMEO models the dynamics of the transition to substitutes for oil and the environmental impacts (greenhouse gas (GHG) intensity) of such a transition. It models the global liquid fuel market in an optimization framework. The ROMEO market mechanism operates differently than "perfect foresight" models: it solves each year sequentially, with each year optimized under uncertainty about future prevailing prices or resource quantities.

ROMEO includes more fuel types than models designed for integrated assessments of climate change. ROMEO also includes the differing carbon intensities and costs of production of these fuel types. We use ROMEO to calculate the uncertainty of future costs, emissions, and total fuel production under a number scenarios. We first explore the effects of altering three key input parameters. We then use this flexibility to more formally explore two uncertainties simultaneously: the endowment of conventional petroleum, and future carbon taxes. Results indicate that emissions penalties from production of oil substitutes are on the order of 5-20 GtC over the next 50 years, and that these results are highly sensitive to the endowment of conventional oil and less sensitive to the values of a carbon tax.

*Preparation of this report was supported in part by a competitive grant from UCEI.
†Contact: abrandt@berkeley.edu
‡Contact: aef@berkeley.edu

1 Introduction: vast uncertainties, few guideposts

Liquid fuels are incredibly useful for powering automobiles, airplanes and other forms of transport. Where will we get these fuels in twenty years? In fifty years? What affect will production, refining, and consumption of these fuels have on the future environment? Or, perhaps more fundamentally, will we need liquid fuels at all? And, if there is to be a transition to replacements for conventional petroleum, will it be a benign transition induced by the development of a superior technology such as advanced biofuels? Or, will it be a unfavorable and panicked response to high oil prices and geopolitical threats to conventional oil supply?

The answer to the first of these questions is likely as follows: approximately where we get them today. The time required for capacity expansion in such an enormous and inertial industrial system suggests that twenty years is not sufficient time for large changes to occur. The answers to the other questions are not nearly so certain. All that can be said, whether qualitatively (e.g. via informed discussion or scenario planning), or quantitatively (e.g. through models) is at least somewhat speculative. In short, these questions are important and their answers are clouded by uncertainties.

It is useful to outline some of these uncertainties. First, the future of global petroleum supply is uncertain. This uncertainty is due to poor knowledge of petroleum resources, data that are unavailable for political or economic reasons, and varying definitions of resources. There is also uncertainty about the potential to produce oil-like hydrocarbon fuels from non-conventional petroleum resources or other fossil fuels. Just as importantly, future hydrocarbon demand is uncertain: some predict a transition to non-hydrocarbon fuels, such as biofuels, hydrogen, or electricity, while others see steadily increasing demand for hydrocarbons. Because the environmental impacts of fuels differ, all of these uncertainties translate into significant uncertainty about future environmental impacts from liquid fuel production and consumption.

Despite this uncertainty, one aspect of the problem is clear: a transition to substitutes for oil is underway. Petroleum producers currently exploit a variety of hydrocarbon deposits of differing composition and quality, with a trend over time toward increased exploitation of high-cost, low-quality, non-conventional petroleum. In addition, synthetic liquid fuels from non-petroleum feedstocks (coal and natural gas) are currently produced in small quantities, plug-in hybrid electric cars are nearing commercial production, and biofuels production is increasing rapidly.

For simplicity, this paper focuses on the transition to hydrocarbon-based substitutes for conventional petroleum. As stated above, this transition is already underway and these fuels are already produced in significant quantities. Enhanced oil recovery represented about 10% of total US oil production in 2004, almost entirely from steam-induced heavy oil production in California [30]. Production of oil from Canada's tar sands passed 1 Mbbl/d in 2004 [31]. Production from Venezuela's extra-heavy oil reached about 0.6 Mbbl/d in 2000 [39]. In addition, approximately 150,000 bbl/d of synthetic fuels are produced, primarily from coal [16]. Oil shale is only produced in minor quantities around the world in small facilities, with total world output estimated at 10,000 to 15,000 bbl/d [2]. Total SCP production, as defined above, is somewhere above 2 Mbbl per day, depending on the definition used, and is growing rapidly.

These resources have two properties that cause them to differ from conventional oil and result in necessarily higher GHG emissions: 1) they tend to be more difficult to extract than conventional oil, and 2) they tend to be hydrogen deficient compared to the approximately 2:1 H to C ratio present in liquid fuels. Heavy and extra-heavy oil are very viscous and require the injection of thermal energy to allow flow out of the reservoir. Tar sands are currently produced by either mining or steam stimulation, with the former being more common [31]. Both of these types of fuels must also be chemically upgraded (H must be added or C rejected) and often cleaned of impurities such as heavy metals and sulfur before use.

Oil shale is sedimentary rock that contains a significant percentage of organic matter. It is thought be the same material from which oil is naturally created [13]. Oil shale must be heated in the absence of oxygen to 300 to 500 °C in order to produce usable hydrocarbons. This requires energy and therefore adds cost and carbon emissions. Retorting of oil shale can also release inorganic CO_2 from carbonate minerals present in the shale, possibly resulting in very high emissions [35, 37].

In contrast to synthetic crude oils produced from the above processes, finished synthetic liquid fuels can also be produced, typically either from natural gas or coal. These fuels are currently manufactured in two steps: a syngas comprised mainly of CO and H_2 is created from the hydrocarbon feedstock, then the syngas is converted into liquid fuel using the Fischer-Tropsch (FT) process, a catalytic process that "chains together" the carbon atoms from the CO to produce a variety of hydrocarbon products. The much higher C to H ratio of coal causes more emissions of carbon from CTL production than GTL production.

Previous modeling efforts Because of this uncertainty about oil resources, many modelers have attempted to forecast the future of liquid fuel production. Current models come from three communities: petroleum geologists, energy and climate modelers, and resource economists. Petroleum geologists' predictions of conventional petroleum production often assume that production follows a Gaussian curve (the Hubbert methodology) and therefore that production increases until resources are half consumed, at which point production decreases [3, 9, 11, 12]. Some assessments are similar but different models for depletion, such as exponential models [5, 41]. These predictions are typically based on bottom-up assessments of global oil endowment and have historically tended to be conservative with respect to available resources and future technologies.

Energy modelers and climate analysts are also interested in petroleum production because of carbon dioxide (CO_2) emissions from oil use. These models typically employ a "top-down" perspective. They simulate the extraction of oil by calling upon a simplified non-specific petroleum resource base. Examples of these types of models include the six modeling efforts represented in the Intergovernmental Panel on Climate Change (IPCC) Special Report on Emissions Scenarios (SRES) [23, 24]. These top-down models generally assume larger amounts of petroleum resources than do the typical Hubbert-type projections. They also allow for a variety of petroleum resources of varying quality [6, 34].[1] Unfortunately, these top down models typically do not include detailed characteristics of individual SCPs: in some SRES models all oil types have identical emissions, while in others the emissions are modeled using only two resource categorizations. This is problematic because of the fundamental differences between resource types described above. For a detailed analysis of this problem, see Brandt and Farrell [6].

In contrast to energy/climate modeling efforts, economists have produced models of depletable resources for decades. These models are typically termed "optimal depletion" models, and they attempt to determine the level of production, and therefore speed of depletion, of a resource that results in the maximum net present value of the resource [15, 22]. Oftentimes these models describe a transition to "backstop" resources, such as Nordhaus' classic model of long-term transitions to nuclear power and synthetic fuels [32]. Economic optimal depletion models typically do not have

[1] The justification for inclusion of a wide spectrum of resources is valid: there is little hope of guessing today the technologies that might be developed over the coming century to exploit low-quality resources, and resources that seem uneconomic today will likely become economic in the future.

detailed characterization of different resources and lack detail with regard to production techniques [40].[2] These models also generally lack phenomena such as exogenous increasing energy efficiency or technological learning (see Slade [36] for an exception), features that are common in energy-climate models.

The important model of Green et al. [20, 21] models much the same phenomenon as ROMEO. This model looks at many of the same questions as ROMEO, but with less of a focus on greenhouse gas (GHG) emissions consequences of the transition. One ROMEO module (the depletion module) was directly inspired by this model, and other inspiration was found in their work as well.

A role for ROMEO ROMEO fills a gap in the current literature - it explores the emissions consequences of depletion of conventional oil by modeling the transition to substitutes for conventional petroleum. ROMEO models the transition from conventionally produced petroleum to fossil-fuel-based petroleum substitutes and forecasts the greenhouse gas emissions (as carbon equivalent, or Ceq.) consequences of this transition. The four substitutes for petroleum included in ROMEO are tar sands and extra-heavy oil, gas-to-liquid synfuels (GTL synfuels), coal-to-liquid synfuels (CTL synfuels), and oil shale.

For the purposes of this documentation, this suite of four liquid fuels produced from low-quality petroleum resources or non-petroleum fossil-fuel feedstocks will be called *substitutes for conventional petroleum* (SCPs). We omit biofuels and electricity from this definition, and from the current incarnation of ROMEO, simply to limit problem scope.

2 Methods: ROMEO in brief

2.1 ROMEO's goals and scope

ROMEO works from a set of exogenous demand functions for liquid hydrocarbons from the IPCC SRES. The SRES documents the results of 6 international modeling teams who forecast future energy use under a variety of scenarios. Specifically, the demand functions come from the IMAGE implementation of the SRES scenarios [23]. The IMAGE (Integrated model

[2] Withagen discusses this problem in detail, stating that "considerable further work is needed to understand the micro-foundations of the industry cost function" [40]. A lack of available data on the oil industry is the culprit, with no public data available for specification or design of improved production cost models.

to assess the global environment) model is produced by the Netherlands Institute for Public Health and the Environment (RIVM).[3] These projections, as extracted from the IMAGE model, already account for biofuels production and non-liquid fuels penetration into the transportation market, allowing our model to focus on the supply of crude oil and crude-oil-like hydrocarbon fuels.

ROMEO compares these demand projections to forecasts of conventional oil resource availability. Estimates of ultimate recovery of conventional oil (estimated ultimate recovery, or EUR), are between 1800 to 4000 gigabarrels (Gbbl) [1], while consumption to date is approximately 1000 Gbbl. This suggests that roughly 1000 to 3000 Gbbl of conventional oil remain. However, consumption of oil in the SRES scenarios is as high as 5200 Gbbl over the next century. This means that unconventional oil *must* be produced if these demand projections are to be fulfilled [6].

Thus, ROMEO can answer a two-part question: 1) "given modeled demand for petroleum products, and a range of estimates of conventional petroleum supply, what is the difference between supply and demand, and how is it optimally filled with substitutes for conventional oil?" and 2) "what are the emissions consequences of filling this gap with the modeled suite of oil substitutes?" ROMEO is therefore not a full featured emissions model: it models a specific portion of the energy system in more detail than was included in the IPCC SRES models, and should be considered complementary to those efforts. The system boundaries of ROMEO, including the features that are implicitly and explicitly included in ROMEO, are shown in Figure 1.

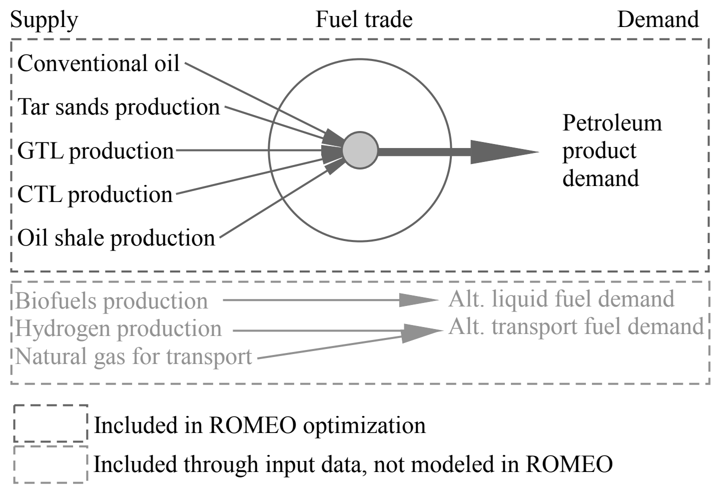
2.2 A brief outline of ROMEO model structure

What follows is a brief outline of the structure of ROMEO. For more details, see Appendix A and the full ROMEO model documentation [7]. Within this working paper, names of model elements (functions, parameters, data inputs) are presented in sans serif font. Indexed elements are presented as coded in the model. For example, fuel production, an element indexed over regions (r), fuels (f) and years (y), is written FuelProduction[r,f,y].

ROMEO is a nonlinear optimization model, coded in the AMPL mathematical programming language [17] and solved using the SNOPT solver [19]. It models the adoption of substitutes for conventional petroleum (SCPs) over

[3] IMAGE has undergone a number of model versions. ROMEO is based on output from IMAGE version 2.2 and the current model version is 2.4 (as of November 2007).

Figure 1: ROMEO model scope. Elements in light gray are included implicitly through IMAGE input data, but are not explicitly included in ROMEO.



the years 2000 to 2050 based on the demand for liquid hydrocarbons, availability of conventional oil, the prices of SCPs, and the SCP resource base in each of 17 model regions. ROMEO does not solve for all fifty years of production simultaneously, but instead solves each year sequentially, ensuring that supply equals demand in each year. A "run script" is used to load the model in each year, save results, and transfer information between model years.

Objective function The objective function of ROMEO, which is minimized by the solver, is equal to the total cost of capital investment in fuel production infrastructure, fuel production, and fuel trade:

$$(1)\quad \min \sum_y \mathsf{TotalCapacityCost[y]} + \sum_y \mathsf{TotalProductionCost[y]} + \sum_y \mathsf{TotalShippingCost[y]}.$$

By constructing ROMEO in a cost-minimization framework, we are assuming that the global fuels market seeks to supply fuels at the lowest cost (or, equivalently, that at a given market price, producers will act to maximize profits).

Decision variables The solver minimizes the objective function by choosing optimal values of the decision variables. These decision variables include: $\mathsf{NewCapacity[r,f,y]}$, the amount of new production capacity added in a given region r and year y for each fuel f; $\mathsf{FuelProduction[r,f,y]}$, the amount of a given fuel f produced in each region r in a given year y; and $\mathsf{FuelShipped[r1,r2,f,y]}$, the amount of fuel f traded from a given region $\mathsf{r1}$ to another region $\mathsf{r2}$ in year y. There are ≈75,000 decision variables over all years, mostly in the fuel trading module.

Constraints The values of decision variables chosen by the solver are subject to a number of constraints. Some constraints prevent non-physical solutions, such as limiting the solver to positive values of $\mathsf{FuelProduction}$ so that "negative fuel" is not be produced. Also, the cumulative extraction of a resource over time cannot be larger than the original resource base in each region. A second type of constraint guarantees that the fuel market functions. For example, supply of all fuels in each region must be greater than or equal to the adjusted demand (the demand that remains after accounting for the effect of the oil price through the price elasticity of petroleum demand). Still other constraints attempt to reproduce more subtle aspects of the global oil market. One such constraint limits the rate at which production capacity can be built in each region:

$$(2)\quad \mathsf{NewCapacity}[\mathsf{r},\mathsf{f},\mathsf{y}] \leq \mathsf{MaxCapacityGrowth}.$$

Another constraint is important enough to deserve description here. Production of fuels is not dictated by externally generated functional forms (e.g. Gaussian-based Hubbert curves). Instead the shape of production is governed by a constraint that limits production in a given year to a defined fraction of the remaining resource base. This assumes that production can increase freely until the reserve-to-production ratio (or, more accurately, a "resource-to-production ratio") hits a specified level:

$$\begin{aligned}(3)\quad & \mathsf{FuelProduction}[\mathsf{r},\mathsf{f},\mathsf{y}] \leq \\ & \mathsf{MaxAnnualPercentage} \times (\mathsf{AvailableResource}[\mathsf{r},\mathsf{f}] \\ & \qquad - \mathsf{CumulativeFuelProductionResourceConsumption}[\mathsf{r},\mathsf{f},\mathsf{y}]).\end{aligned}$$

Each of these terms is defined in detail in the full ROMEO documentation [7]. The result of this constraint is exponential decay of production once the minimum reserve-to-production ratio is met. A similar model was used by Wood et al. in projecting future production and an equivalent exponential formulation was found to fit historical oil production profiles slightly better than a Gaussian model in a comprehensive study of 139 historical oil production curves [5, 41]. All constraints are defined mathematically below in Appendix A.

Three important modules ROMEO has a three important modules that govern model functioning in significant ways: the short- and long-term price elasticity of fuel demand, technological learning which lowers production costs, and resource depletion, which increases production costs. Each of these modules are described briefly below and in more detail in Appendix A.

First, ROMEO accounts for the price elasticity of fuel demand. Along with demand projections, corresponding oil price series are extracted from IMAGE and input to ROMEO. This provides a baseline price and level of fuel demand for each year. If the cost of production of the most expensive barrel of fuel (the marginal cost, equal to the oil price in a competitive market) rises above the price of oil from the IMAGE model, then the demand for fuels is reduced. This is performed on a yearly basis, using the marginal cost of the current year's production (short-term elasticity of demand, modeled with elasticities found by Krichene and Cooper [27, 10]). Additionally, a weighted average of historical marginal production costs is compared to the IMAGE input oil price to account for the long-term elasticity in demand allowed by changes in fuel consuming capital (e.g. automobile efficiency), consumption patterns, and long-term economic growth. This long-term elasticity module is adapted from Gately and Huntington's econometric model, which weights previous years' prices with decaying importance. We also use their elasticities as found for OECD and non-OECD nations [18]. These modules are somewhat complex, especially the calculation of the marginal cost, which involves a non-linear threshold value that prevents very small quantities of fuel from affecting the marginal cost. See Appendix A for a full specification.

ROMEO also models the declining cost of production that occurs due to experience gained over time, commonly called "learning by doing" [29]: $Y = aX^{-b}$, where Y represents cost of production, a is the cost of the first unit of output, X represents cumulated output, and b represents the learning elasticity [29]. Because of poor data availability, each fuel in ROMEO is subject to the same learning rate. Also, the learning module affects capital costs only. As an example of this effect, see Figure 9 for tar sands capacity costs in the baseline scenario.

Lastly, ROMEO accounts for the fact that the last barrel of fuel produced from a given resource base is invariably more costly to produce than the first barrel produced. To do this, ROMEO utilizes the depletion module developed by Greene et al. for their model of oil depletion and transition [20]. This module is adapted somewhat from Greene et al.'s formulation and is parameterized using ROMEO-specific data. It is defined as follows:

$$(4)\quad \mathsf{DepMultiplier}[\mathsf{r},\mathsf{f},\mathsf{y}] = \frac{\ln\left(\frac{1}{\mathsf{DepletionRatio}[\mathsf{r},\mathsf{f},\mathsf{y}]} - 1\right) - \mathsf{Alpha}[\mathsf{r},\mathsf{f}]}{\mathsf{InitialCostDepletion}[\mathsf{r},\mathsf{f}] \times \mathsf{Beta}[\mathsf{r}]},$$

where DepMultiplier is a multiplicative factor that increases the cost of production as depletion progresses. An example of this module is shown in Figure 10 which plots DepMultiplier for tar sands resources by region. This module aids smooth model functioning because regions with a small resource base experience production cost increases as they deplete their meager resources, providing a "soft" constraint that gradually makes their resources uneconomic.

Of these modules, only the price elasticity of demand modules are implemented in a truly non-linear, current-year fashion. The other two modules act "between years." That is, they utilize the previous year's data within the run script to calculate new, static factors for input as fixed data into the current year's solution of the model. Thus, to the solver these modules are seen as linear, while across years they act in a pseudo-nonlinear fashion. This choice was made to minimize the non-linearity of the model, improving model stability and solvability.

3 Results: the baseline scenario, and its sensitivity to model parameters

The results of ROMEO, and the sensitivity of those results to parameter inputs, are easiest to illustrate by first showing a suite of results from a "baseline" scenario and then showing summary figures resulting from perturbations to the model parameters.

3.1 Baseline results - scenario s2

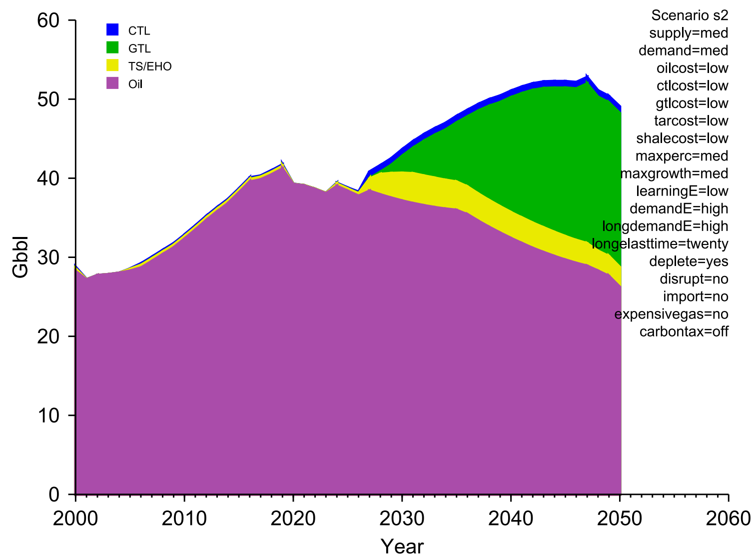
The standard ROMEO model runs include 8 scenarios, s1-s8, as described below in Appendix A (See Table 3) and further described in the full ROMEO model documentation [7]. Of these scenarios, scenario s2 is chosen as the baseline scenario for this report. It is a very "central" or "normal" scenario, with demand and conventional oil endowment set to their medium (med) levels, and technological learning, price elasticity of demand, fuel input prices, and depletion impacts all set to moderate levels. To illustrate the suite of graphical outputs from the model, a number of plots from scenario s2 are presented below.

First, overall fuel supply over time is shown in Figure 2. We see that as conventional oil production is forced down by resource constraints, unconventional production increases, but fitfully and with some lag, creating an "undulating plateau" of the kind described by Yergin and others (a good summary of differing views of peak oil, including Yergin's, is provided by Kerr [26]). We see that tar sands production increases first, followed quickly by GTL synfuels and small amounts of CTL synfuels. The magnitude of total fuel production can be compared to the original exogenous demand projection from IMAGE, as shown in figure 3. Note that ROMEO modeled demand is lower than the IMAGE input demand data because the prices modeled in ROMEO are higher than the prices modeled in IMAGE. These relative price levels are shown in Figure 4. The top curve is the modeled oil price path from ROMEO, while the bottom curve is the exogenous oil price path associated with the IMAGE demand projection utilized in the model run. In this figure the result of the peak and decline in conventional oil production is clear: the price rises consistently to levels that will support production of substitutes for conventional petroleum so as to meet demand.

The production profiles for the various modeled fuels are also of interest. Figure 5 shows oil production by region and year, Figure 6 shows tar sands production, Figure 7 shows GTL production, and Figure 8 shows CTL production, all in units of Gbbl/y. This fuel production over the model run results in a decline in capacity costs through the learning-by-doing module, as shown in Figure 9 for tar sands and heavy oil. But, because of the depletion module, this fuel production also results in a depletion-induced increase in variable costs. DepMultiplier, defined above, is plotted by model region for the tar sands and heavy oil resource in Figure 10. Note that regions with small tar sands and heavy oil endowment use their resources up quickly, increasing their depletion multiplier and making further production of their resources uneconomic.

The end result of the modeled fuel production on carbon emissions is plotted in Figure 11 as an "emissions penalty." This is the difference in emissions between the model results and what emissions would have been had the same modeled demand been met with conventional oil. Since the alternatives to oil included in the model are all more carbon intensive than conventional oil, the emissions penalty is positive. The results shown here

Figure 2: FuelProduction[r,f,y] - supply of fuels over time, scenario s2. Values summed over all regions for each fuel.



suggest that emissions penalties from SCPs may approach 1 GtC per year by mid-century. This result is of a consistent order of magnitude across all scenarios.

These results from scenario s2 are indicative of the overall results from the eight ROMEO scenarios. In general, altering the parameters produces straightforward and predictable changes: tightening constraints results in a less smooth transition, a generally higher oil price and generally higher emissions. This is because there is a correlation between fuel price and fuel carbon emissions across the fuels studied here.

Figure 3: Global fuel supply, exogenous input demand from IMAGE, and adjusted demand, summed over all regions.

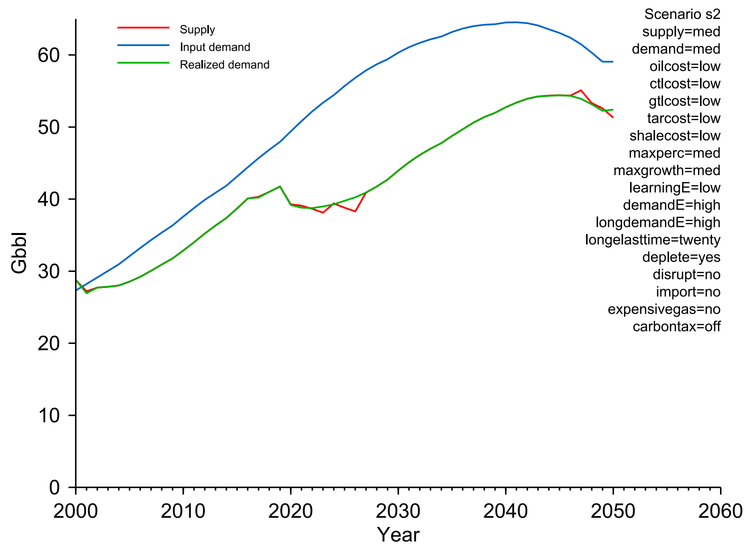


Figure 4: IMAGE input oil price, ImageOilPrice[y], bottom curve, and modeled oil price from ROMEO, MarginalCost[y], top curve.

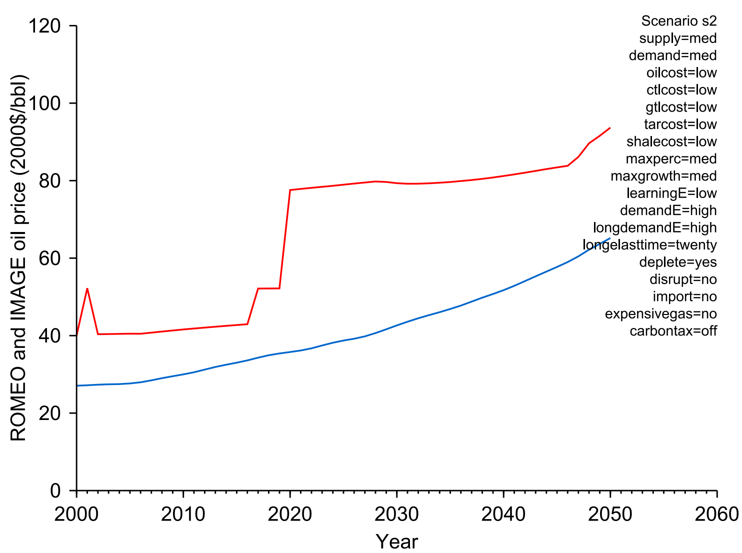


Figure 5: FuelProduction[r,oil,y] - oil production by region and year.

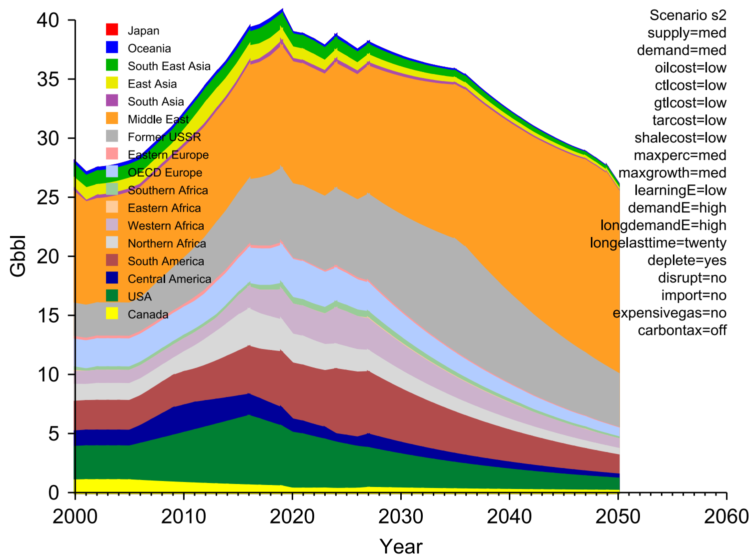


Figure 6: FuelProduction[r,tar,y] - tar sands production by region and year.

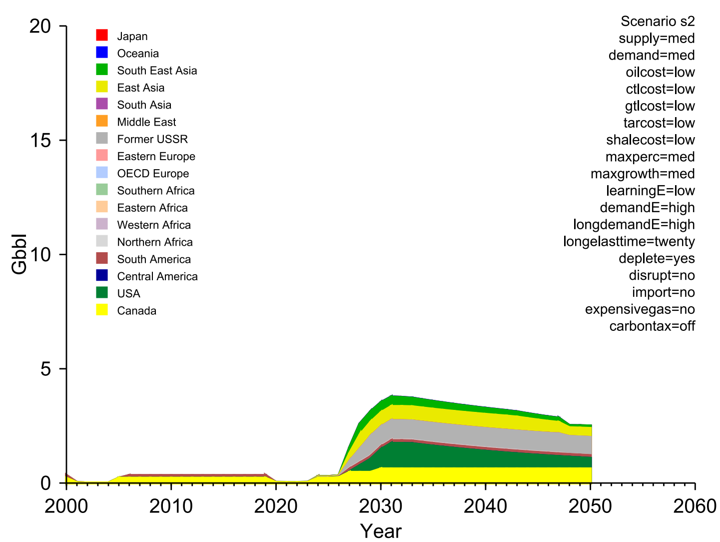


Figure 7: FuelProduction[r,gtl,y] - GTL production by region and year.

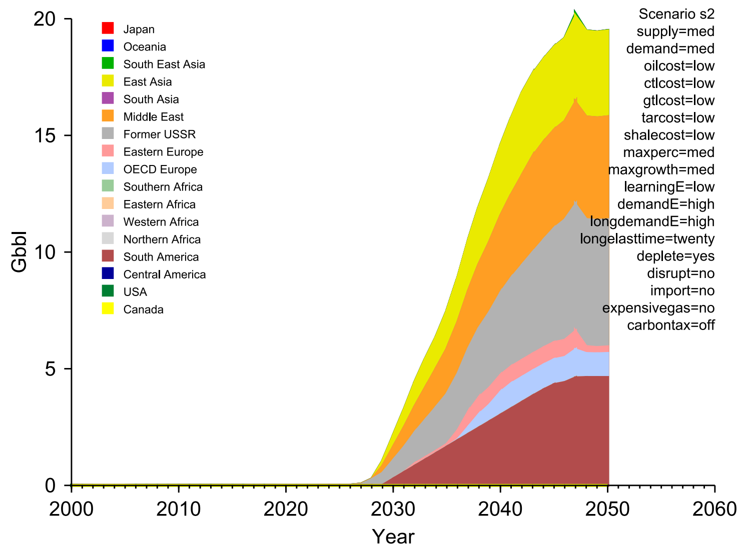


Figure 8: FuelProduction[r,ctl,y] - CTL production by region and year.

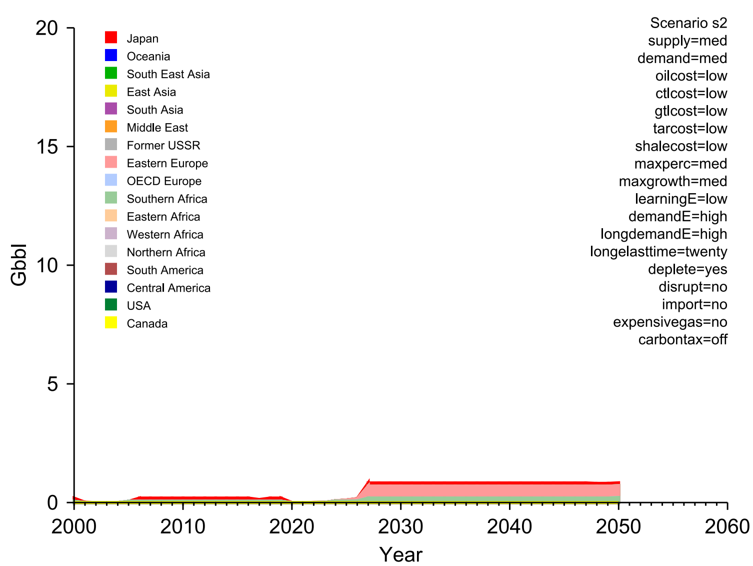


Figure 9: Tar sands capacity costs by year, InitialCapactiyCost[tar] × LearningMultiplier[r,y].

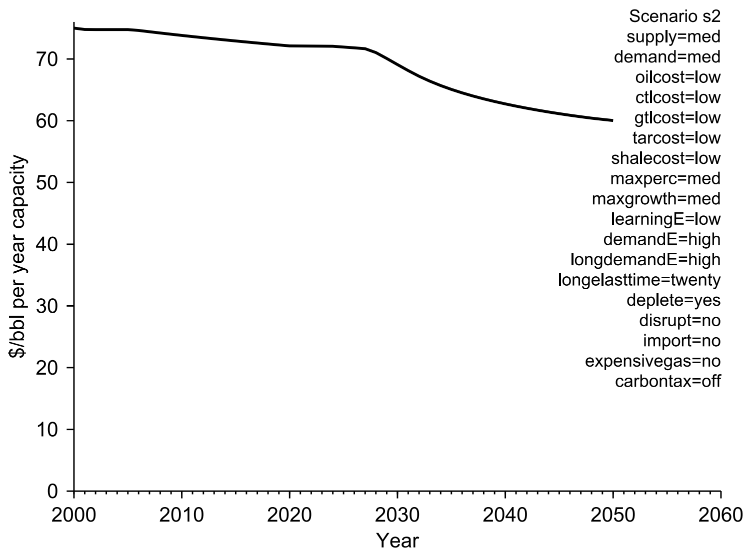


Figure 10: DepletionMultiplier[r,tar,y] - tar sands/extra heavy oil depletion multipliers by year.

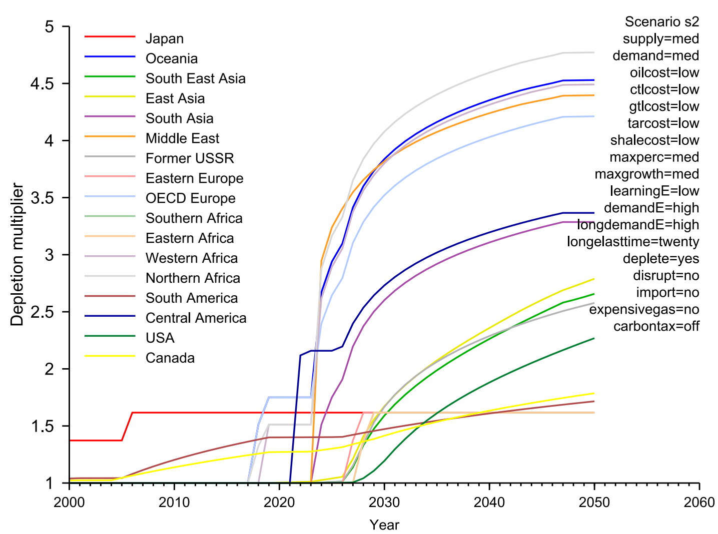
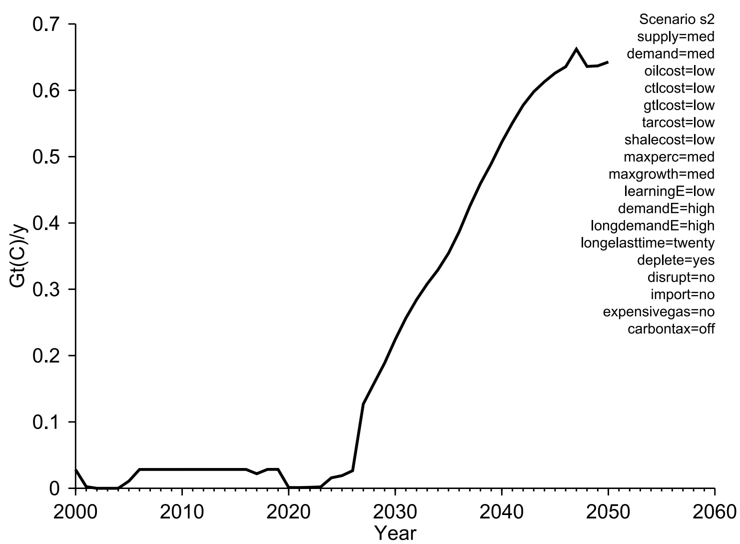


Figure 11: Emissions increment from the adoption of SCPs.



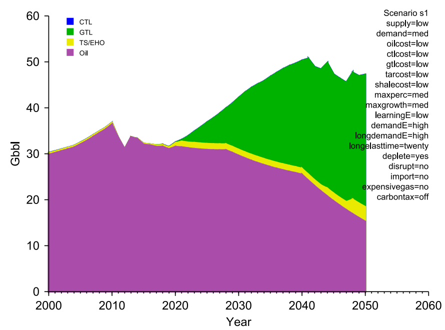
3.2 Effects of varying model parameters

What happens when ROMEO model parameters are varied? This depends on the sensitivity of the model to the input parameter. For data inputs, this sensitivity varies depending on how fundamental the varied data are (e.g. a change in total global oil endowment is more important than a change in the initial regional cumulated production used to calibrate the learning module). When altering constraint parameters, such as the maximum amount of capacity that can be added in a given year, the impact depends on whether or not the constraint is binding. And lastly, some model parameters have effects of greater importance than might be expected because of non-linear model behavior. These non-linearities cause minor variations of certain parameters to affect the overall functioning of the model. We will illustrate the impacts of these three types of parameter changes with three examples below.

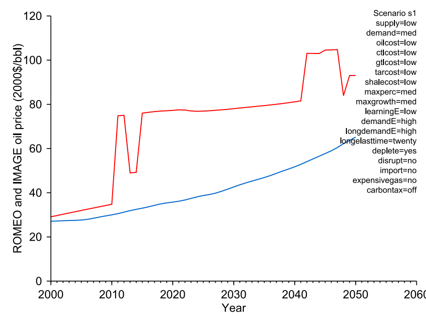
Altering key data inputs First, we can plot the results of altering a key data input: the conventional oil endowment. As discussed elsewhere [6, 14], the endowment of conventional oil is quite uncertain, with USGS uncertainty bounds (95% to 5%) ranging from about 2000 to 4000 Gbbl of conventional oil [38]. The amount of conventional oil available will affect the speed and extent of a transition to substitutes for conventional oil.

In scenario s2, the global oil endowment parameter is set to its med level. We can alter this to the low and high values and plot the results. The results of altering the global oil endowment are shown in Figure 12. The impact on the overall fuel production (corresponding to Figure 2 above) is shown in the left-hand figures and on the modeled oil price (corresponding to Figure 4) in the right-hand figures. The middle results correspond to scenario s2 as shown above and their captions are highlighted in bold.

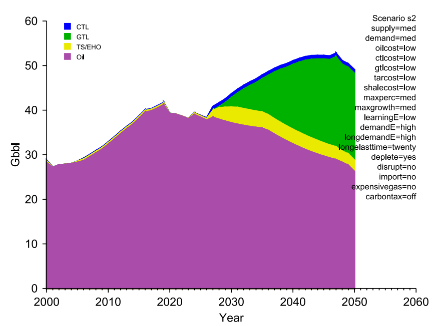
From these results we can see that lower conventional crude oil availability has the following results: less overall fuel consumption, the transition to substitutes for oil occurs sooner, and more SCPs are produced overall. We also see that the highest price achieved (>$100/bbl) is seen in the low conventional oil endowment scenario These results are congruent with what one would expect.



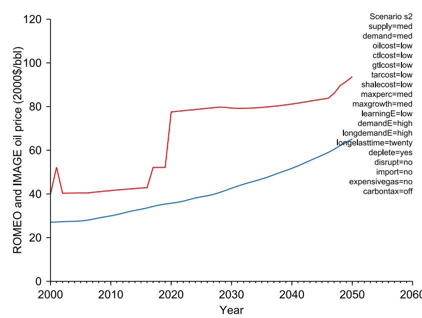
(a) Low oil endowment - production



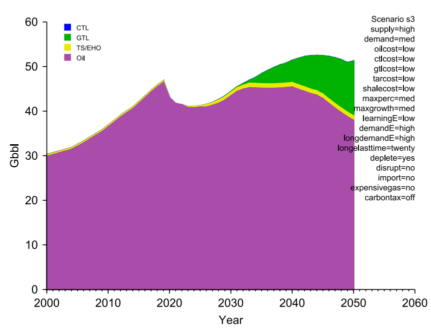
(b) Low oil endowment - price



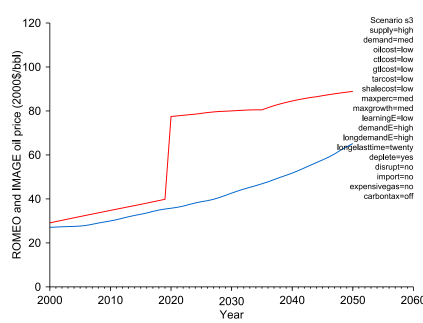
(c) **Med oil endowment - production**



(d) **Med oil endowment - price**



(e) High oil endowment - production



(f) High oil endowment - price

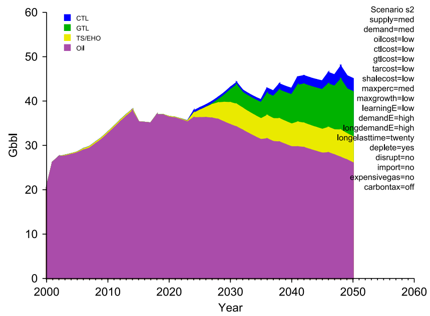
Figure 12: Change in total fuel production (left) and modeled oil price (right) with variations in assumed conventional oil endowment.

Altering a binding constraint A key binding constraint in the model is the maximum level of capacity expansion per fuel per region per year. This is an important model parameter because it strongly governs the adoption of particular fuels and overall model behavior. Unfortunately, this model parameter is uncertain.

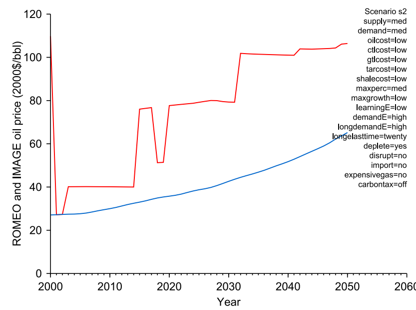
Historical data on production capacity additions are difficult to obtain, so production data from BP Statistical Review are used instead [4]. We sort and aggregate national production data from 1965 to 2004 into the 17 IMAGE regions. We then find the largest year-to-year production growth across the 17 model regions, excluding Russian Federation and Middle East data because of politically-induced swings in production. The largest increase over the time period for the remaining regions was 1.084 Mbbl/d between 1976 and 1977 for region 9, OECD Europe, a result of increased production from significant discoveries in the North Sea.

Can SCP technologies expand at this rate of 1 mbbl/d over a one year period? Could this rate of expansion go on across multiple regions at the same time? Arguments could be made in either direction regarding this historical analogue. One could argue that production from SCPs will not be able to grow this fast, because they are more capital intensive, are difficult to extract, and do not exist in high-flow deposits. As an example, Canadian tar sands production grew to 1 Mbbl/d over three decades, not one year. One could also argue that the urgency created by oil price increases that could accompany a peak in conventional oil production would spur development of SCPs as fast as has been seen historically for crude oil.

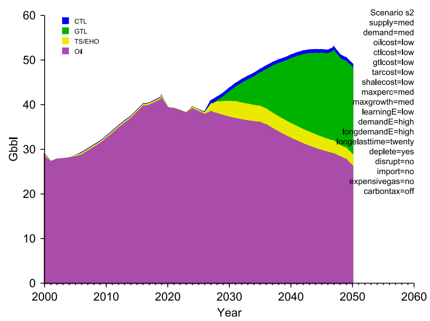
To account for this uncertainty, we choose values for maximum capacity growth of 0.5, 0.75, and 1 Mbbl/d capacity increase (maxgrowth = low, med, high, respectively). The default value for baseline scenario s2 is maxgrowth = med. We discuss potential improvements to this constraint below in *Conclusions*. The impact of changing this model value is shown below in Figure 13. In this figure, the captions are bold for the settings corresponding to the baseline s2 scenario. Note that the low capacity expansion setting results in more erratic expansion of SCPs and a higher oil price. This, again, is consistent with expectations.



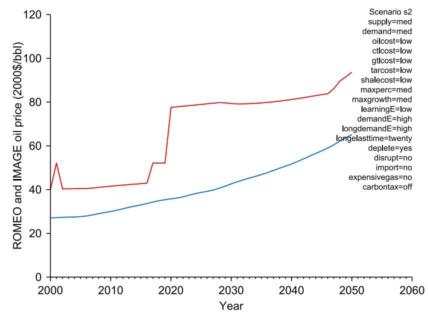
(a) Low cap expansion - production



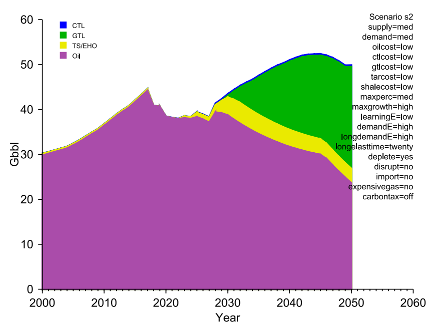
(b) Low cap expansion - price



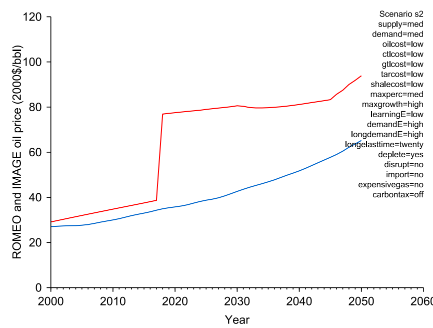
(c) **Med cap expansion - production**



(d) **Med cap expansion - price**



(e) High cap expansion - production



(f) High cap expansion - price

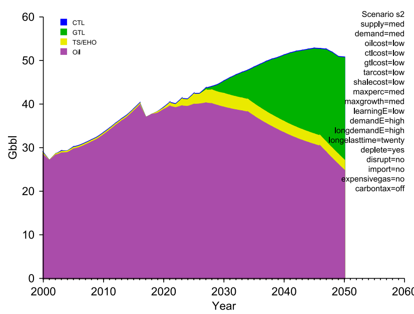
Figure 13: Change in total fuel production (left) and modeled oil price (right) with variations in maximum capacity expansion. MaxGrowth = low, med, high in top, middle and bottom figures respectively.

Altering a non-linear model feature It is most difficult to predict the impact of varying a parameter related to non-linear aspects of the model. The key non-linearities in the current version of ROMEO involve the operation of the oil market. As an example, here we explore the impact of altering the parameter EconomicLimit from its baseline value (see Appendix A and the ROMEO documentation for how EconomicLimit is defined in terms of the model equations [7]).

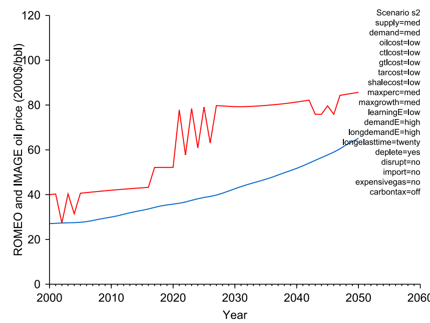
The oil market in ROMEO does not include in its oil-price-setting mechanism the production cost of all fuels that *could* be produced, but only those that *are* produced. This is because the model sets the price to the cost of the marginal (most expensive) barrel produced. Unfortunately, if the oil market mechanism is set to include all fuels with values of FuelProduction[r,f,y] $\geq$ 0, all fuels effectively end up being included in the oil market calculation. This is because the precision of the numerical solver is set such that small quantities (below 1×10^{-6}) are "ignored" for the purposes of determining model feasibility. (If the feasibility tolerance is decreased, errors occur, such as tiny amounts of negative production, e.g. -1×10^{-19} bbl of fuel, causing the violation of positivity constraints.)

To solve this problem, fuels only "enter the market," or are included in the calculation of the marginal cost of production, if they are produced in quantities greater than the parameter EconomicLimit. If fuels are produced in quantities less than EconomicLimit it is assumed that these are experimental fuels that producers do not expect to be economic under current market conditions. In the baseline settings that produced all of the above results, EconomicLimit is set to 0.0001825 Gbbl, or 500 barrels of fuel produced per day. Although this is a highly uncertain number, there is some justification for the order of magnitude used. For example, OSEC Inc., an oil shale development company, is planning a 3-phase scale-up process for testing their above-ground shale oil retorting technology. Phase 2 of their plan is still clearly experimental, with 6000 bbl to be produced over the course of one year, or roughly 20 bbl/d [33, pp. 28-29]. Phase 3 of their operation will involve a 250 ton/hr retort and will produce on average 2500 bbl/d over the two year time period [33, pp. 33-36]. While the Phase 2 operation is clearly still experimental, and is likely not expected to be economic, Phase 3 is clearly of the scale that should be approaching economic viability (producing 2500 bbl/d, with each barrel produced at an economic loss, seems unrealistic for long periods of time).

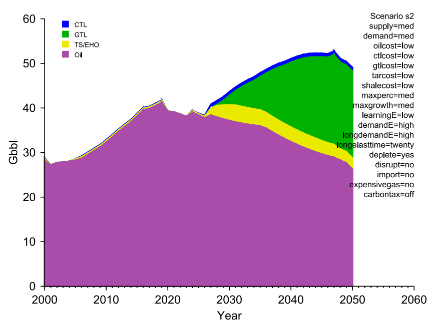
To study the impact of varying this aspect of the ROMEO fuel market, we adjust the EconomicLimit parameter from its baseline setting by one order of magnitude in each direction. The resulting range clearly includes projects that any industry would consider experimental (50 bbl/d), as well as projects that seem likely to be of economic scale (5000 bbl/d). The results of varying this value are shown in Figure 14, with the baseline result (from scenario s2 above) presented with a bold caption. These results show that altering this parameter significantly changes the dynamics of the transition: if EconomicLimit is set to a low value, the transition happens suddenly, while if it is set to a higher value the market is less responsive and takes more time to transition to SCPs.



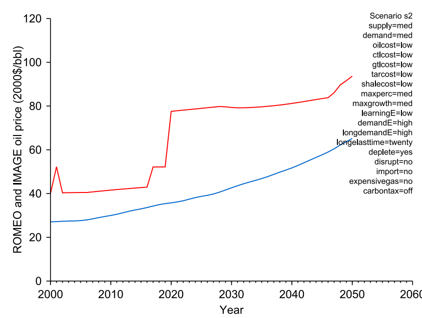
(a) Low economic limit - production



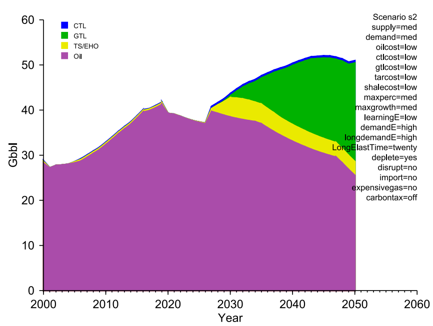
(b) Low economic limit - price



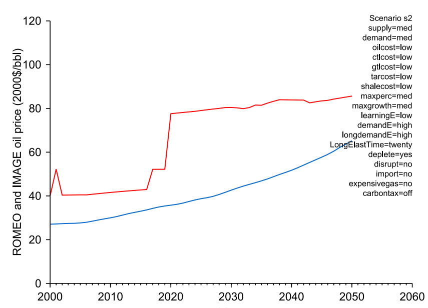
(c) **Med economic limit - production**



(d) **Med economic limit - price**



(e) High economic limit - production



(f) High economic limit - price

Figure 14: Change in fuel production and oil price with variations in the parameter EconomicLimit from 50 bbl/d (top) to 500 bbl/d (middle, as modeled in baseline s2 scenario) to 5000 bbl/d (bottom).

3.3 A more formal uncertainty analysis: the case of conventional oil endowment and a carbon tax

The ROMEO run script allows for simple specification of group scenario runs for uncertainty analysis. To illustrate the possibilities therein, we show an example where we vary two parameters simultaneously and tabulate the results of this two-dimensional exploration. In this example we vary the conventional oil endowment and the carbon tax.[4] We first set the conventional oil endowment to four values: VeryLow, Low, Med, and High. The actual input values and sources for these conventional oil estimates are given in Table 1. In addition, we vary the time path of the carbon tax to four different settings. In the off setting, there is no carbon tax. In the low setting the tax increases to \$7 per metric tonne of carbon in 2010 and remains constant thereafter. In the med and high settings the tax starts at \$7 as above, but increases linearly to \$20 and \$50 per tonne, respectively, by 2050. These two parameters with four settings each produce a matrix of sixteen scenarios.

Four summary statistics from each of the sixteen scenarios are presented in Table 2. Also, these summary statistics are plotted in Figure 15 as functions of the two variables. The summary statistics include: the total cumulative cost of meeting fuel demand plus the carbon tax paid (in trillions of 2000\$), the total cumulative amount of fuel consumed (in trillions of bbl of crude-oil-equivalent fuels), the "emissions penalty" (in gigatonnes of carbon equivalent), and the total emissions from fuel production and consumption (in gigatonnes of carbon equivalent). Recall that the "emissions penalty" is the difference between the total emissions as modeled and the total emissions as they would be *if* demand were the same, but conventional oil was able the meet all demand (see Figure 11). The results from this two-dimensional uncertainty analysis are congruent with what intuition would suggest:

1. Total cost of fuel consumption increases as the carbon tax increases and as the endowment of conventional oil decreases, simply because our assumed "backstop" resources are more expensive than conventional oil;

2. The total amount of fuel consumed increases with increasing conventional oil endowment and decreases with an increasing carbon tax;

3. The "emissions penalty" increases with decreasing conventional fuel availability, since all backstop resources considered are more carbon

[4] The carbon tax is an optional setting in ROMEO and is set to zero for the purposes of the baseline scenario s2 described above.

intensive than conventional oil;

4. Total emissions increase with increasing conventional oil availability and with decreasing carbon tax, because the price elasticity impact of the more expensive fuels outweighs the increased carbon intensity of the fuels produced.

Two phenomena of interest are illustrated by Figure 15. First, in Figure 15(c) we see that the emissions penalty increases as the conventional oil endowment decreases. This is because we have to produce more carbon-intensive fuels to fill the gap between conventional oil supply and demand. But, interestingly, Figure 15(d) shows that the *total emissions* decline with less conventional oil availability. This, as stated above, is due to the price elasticity of demand, which causes overall demand to drop by a sufficient amount to counteract the impact of using more carbon intensive fuels. Thus, whether or not this transition to oil substitutes is seen as more carbon intensive depends on one's perspective (i.e. the baseline against which emissions are being compared).

Also of interest is the generally weak response, across all four plots in Figure 15, of the oil market to the magnitude of the applied carbon tax. The potential for this type of behavior has been noted in numerous places, and the reason is straightforward: a carbon tax affects the price of liquid fuels less than other energy types because liquid fuels are already more expensive when measured by energy or embodied carbon content as compared to other fuels (e.g. applying a carbon tax to coal-fired electric power will raise the price proportionately much more than applying the same tax to oil, because coal is very carbon intensive and its conversion to electricity is inefficient, resulting in greater embodied carbon content per unit of electricity).

The potential for a more complete, multidimensional uncertainty analysis is described below in *Conclusions.*

Table 1: Resource[r,'oil'] - Conventional oil resource endowments as set by supply parameter (Gbbl)[a]

Regional total	VeryLow[b]	Low[c]	Med[c]	High[c]
Canada	50.0[d]	42.5	44.5	48.2
USA	67.2[e]	345.0	362.0	383.0
Central America	31.5	80.1	94.6	121.9
South America	64.6	196.2	274.1	419.2
Northern Africa	70.2	113.9	127.8	153.3
Western Africa	46.7	88.0	123.5	169.5
Eastern Africa	3.6	0.6	1.6	2.8
Southern Africa	6.2	14.4	24.6	40.4
OECD Europe	44.5	88.4	155.1	249.3
Eastern Europe	4.3	14.8	15.7	17.3
Former USSR	200.7	433.2	512.3	648.2
Middle East	549.2	969.2	1108.9	1323.5
South Asia	7.7	17.7	19.7	22.6
East Asia	31.9	76.3	84.9	100.8
South East Asia	34.4	63.5	73.2	89.2
Oceania	7.4	13.7	17.2	23.3
Japan	1×10^{-3}	1×10^{-3}	1×10^{-3}	1×10^{-3}
Total	**1220**	**2557**	**3039**	**3812**

a - Values of 1×10^{-3} are entered for regions with no appreciable resources so as to prevent errors from dividing by zero in the depletion module.

b - Campbell's estimates [8]. To achieve congruence with USGS estimates, natural gas liquids are added using the USGS low estimates (highest likelihood of being found). See full ROMEO documentation for more details [7].

c - US Geological Survey estimates used [38]. For low setting their 95% likely to be found estimate is used, for med their mean or 50% probability estimate is used, and for high the 5% probability estimate is used. In each case, already consumed oil and known oil reserves [38, Table AR-9] are added to the appropriate estimate of undiscovered oil. Natural gas liquids are added as well in the same fashion. See full ROMEO documentation for more details [7].

d - Campbell includes 40 Gbbl to be found in "unforseen" location. We add this to Canada because Campbell has a skeptical view of Canadian low-quality oil, thus, this brings his estimate somewhat closer to other resource assessments.

e - 50 Gbbl is added to the US endowment because Campbell's US endowment is sufficiently low that the ROMEO runs into immediate infeasiblities if his endowment is used.

Table 2: Two-dimensional analysis results. Each value results from a ROMEO model run with the carbon tax setting specified by the top legend and the conventional oil endowment specified by the left legend.

Total Cost (T$)

	Carbon tax			
Conv. oil	Off	Low	Med	High
Very low	50	56	54	65
Low	45	46	51	61
Med	43	47	50	62
High	39	44	52	58

Total fuel production (Tbbl)

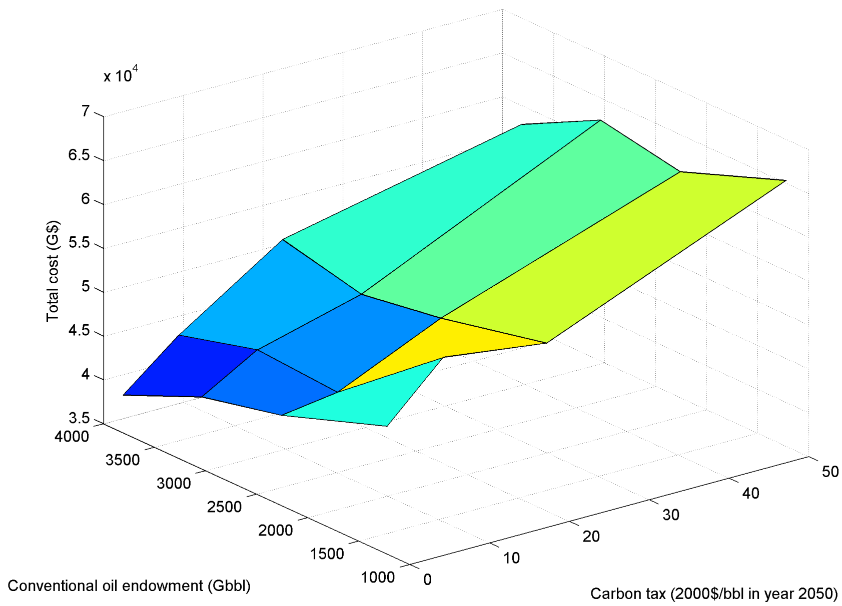
	Carbon tax			
Conv. oil	Off	Low	Med	High
Very low	2.7	2.7	2.6	2.6
Low	2.8	2.8	2.8	2.7
Med	3.0	2.9	2.9	2.9
High	3.0	3.1	3.1	3.0

Carbon emissions penalty (Gtonne C)

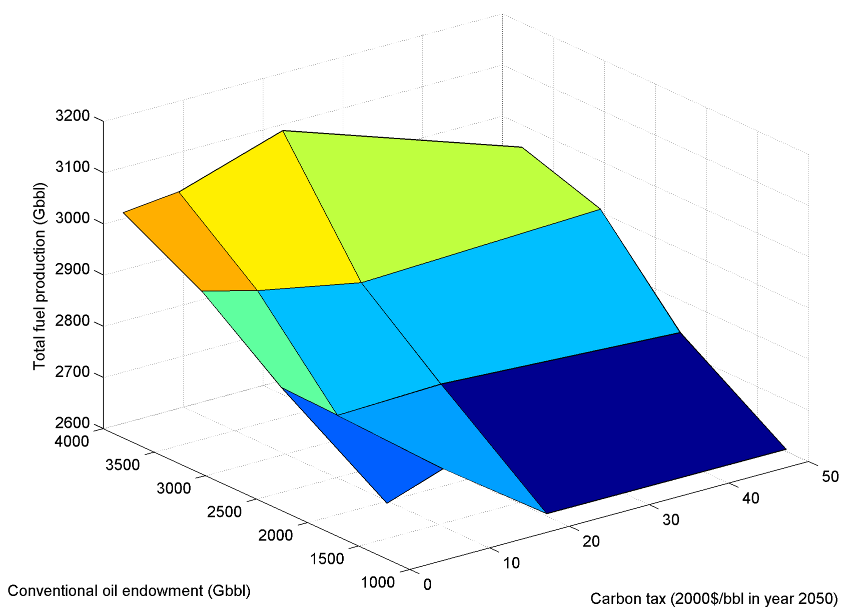
	Carbon tax			
Conv. oil	Off	Low	Med	High
Very low	20	21	18	17
Low	14	12	12	12
Med	10	9	8	9
High	4	4	4	3

Total emissions (Gtonne C)

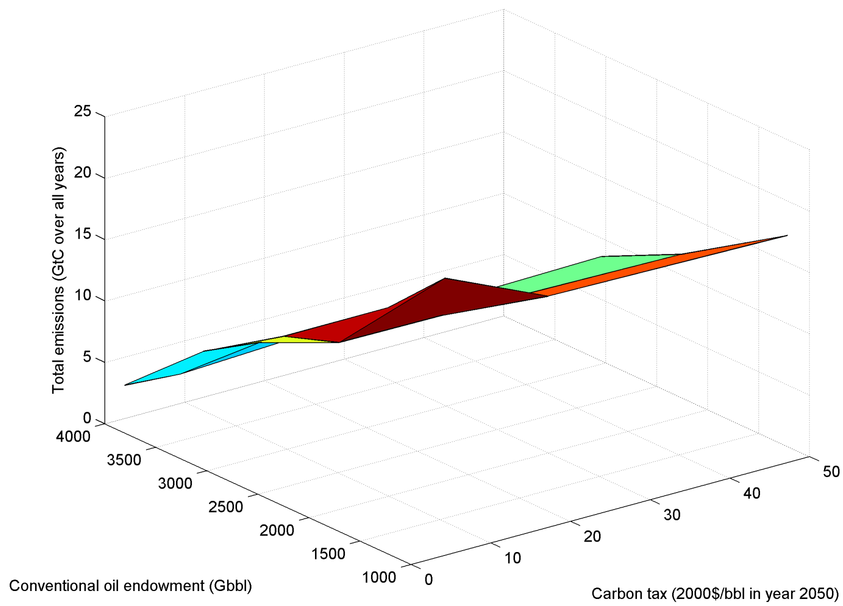
	Carbon tax			
Conv. oil	Off	Low	Med	High
Very low	286	293	269	269
Low	299	285	286	282
Med	311	307	300	303
High	317	318	328	305



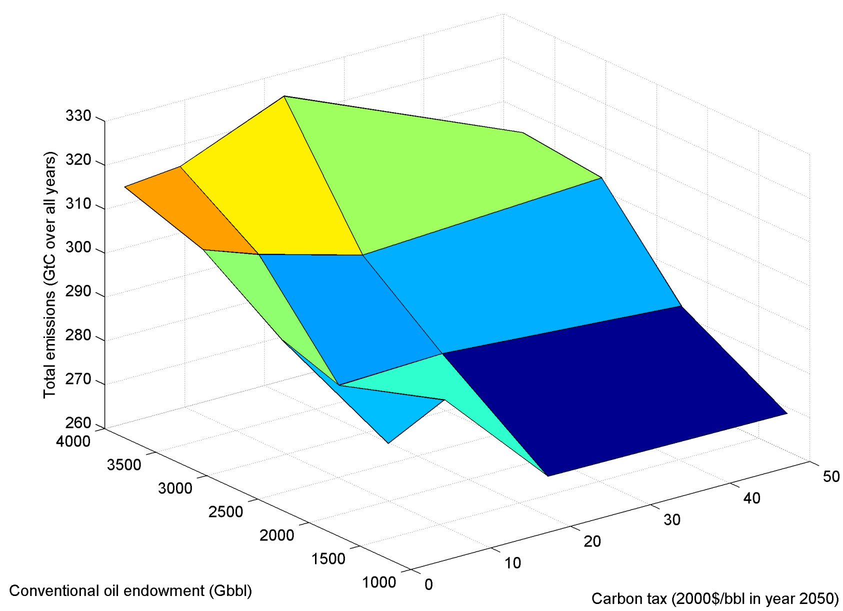
(a) Total cost



(b) Fuel production



(c) Emissions penalty



(d) Total emissions

Figure 15: Variation in summary parameters with variation in endowment of conventional oil and carbon tax. These plot use the data of Table 2.

4 Conclusions

4.1 Concluding thoughts and preliminary numerical conclusions

ROMEO allows increased understanding of the transition to oil substitutes and illustrates a number of important phenomena:

1. The rate of capacity addition possible in a given region or fuel may be a critical determinant for the fuels we produce in the future (indeed, such constraints are currently limiting production of conventional petroleum);

2. The environmental impacts of a transition to substitutes for conventional petroleum are somewhat uncertain because of the impact of the demand elasticity on total fuel consumption; and

3. The transition to substitutes for petroleum may be relatively smooth or may be jarring, depending on the responsiveness and functioning of the world oil market.

Additionally, some tentative quantitative results are suggested by ROMEO. First, consistent price behavior is seen across all scenarios modeled: a "floor" appears under the oil price, varying by scenario, generally from \$60 to \$80 year-2000 dollars per barrel of crude oil or synthetic-crude-oil. This floor is required to support the production of fuels that replace conventional oil, and if the price were to drop below this floor, production capacity would be taken offline until the price rises again. This sort of behavior has been long predicted by energy economists, and may be beginning in the current oil market as tar sands and other marginal, expensive fuels become increasingly important. As modeled in ROMEO, if the oil price were to drop below the level at which these fuels are profitable, they would not be produced and the price would then increase.

Secondly, the impact of a carbon tax can be seen to be fairly muted in this model. The change in cumulated total emissions with year-2050 carbon tax rate ranges from 0.15 to 0.3 GtC per dollar of carbon tax applied in the year (see Table 2). The drop by 2050, in cumulated emissions, due to the carbon tax ranges from 8 to 17 GtC depending on the conventional oil endowment. This is not an insignificant quantity of avoided emissions (current global emissions are $\approx$7 GtC per year), but it does not seem as large when compared to cumulated total emissions from the sector (on order 300 GtC). As noted above, this effect can be compared to the electricity generation sector, where carbon taxes of $50 per tonne are predicted to result in significant mitigation efforts, including carbon capture and sequestration [25].

These conclusions, although preliminary, illustrate the potential for future understanding that could be gained from an expanded version of this model.

4.2 Possible improvements to ROMEO

There seem to be a number of ways to improve ROMEO, and some of these improvements may be implemented in a future version of ROMEO.

A number of "small" changes will likely be implemented in ROMEO before final publication of these results. One such change would be to improve the capacity addition constraints in a number of ways. First, each region could have an individual capacity addition constraint, based on historical production capacity increases. This would account for the historical fact, and likely continuing reality, of slower possible capacity additions in underdeveloped regions of the world, such as East Africa. Alternatively, capacity constraints could be represented in terms of capital flow, such that total capacity investment could not increase above a given level. This, of course would be more realistic, as it is easier to add cheap capacity than expensive capacity. Another change might be to disaggregate the learning rate by fuel: because the SCPs modeled by ROMEO are quite different (tar sands are much like heavy oil production, while GTL synfuel processes are more akin to refining), there may be benefit to disaggregating the learning module by fuel. See the full ROMEO documentation for the sources of learning rates across the range of applicable industries [7].

Furthermore, a number of additions call out for inclusion in a longer-term ROMEO project. First, the capacity addition process is not modeled realistically in ROMEO. Because ROMEO is myopic, each model year is solved separately, and the model cannot add capacity for future years because it does not know that those future years exist. ROMEO avoids this problem by assuming that capacity addition can occur within one year (that is, production can occur in the same year that capacity construction begins). Given that large capital projects commonly take 3 to 7 years to construct, this assumption needs to be reworked. The solution to this problem will likely require modeling a more sophisticated "agency" for the model equations that govern capacity addition. This would require equations that add capacity based on projections of future prices and future demand. Thus, the model would look at previous years' demand and prices, commit to adding capacity based on the projected profitability of that capacity, and wait multiple years for the capacity to become available.

Another future improvement would be to treat uncertainty in a much more sophisticated and comprehensive manner. One potential way to do this would be to model a large number of scenarios with ROMEO, possibly using the "robustness" framework of Lempert et al. [28]. This framework is based on exploring a wide subset of the parameter space and by varying multiple parameters over wide ranges. A summary statistic from each run (e.g. total carbon emissions) can then be compared to a target value, illustrating potential "danger" regions, or could be plotted as surfaces such as in Figure 15. This method would require partitioning the input parameter space into a number finely graduated segments, and running the model many times (hundreds to thousands), varying the input parameters and recording the output. Each outcome can then be evaluated and rated based on defined criteria.

A third possible extension to ROMEO would be to model more than just the liquid hydrocarbon/petroleum system. The input data extracted from IMAGE and used in the current version of ROMEO represent petroleum demand after accounting for increased efficiency, fuel substitution (biofuels, hydrogen, etc.), and economic growth. By using these input data we assume that the IMAGE projections for alternative fuels penetration are correct. A more broad and interesting version of ROMEO would model some or all parts of the broader fuel substitution question. This problem is of indeterminate size: adding biofuels to the current model could be seen as a relatively minor addition, while modeling systemic changes (e.g. large-scale electrification of transport) would require substantial reworking of the model structure.

5 Appendix A: Simplified ROMEO documentation

This appendix is a shortened version of the complete ROMEO documentation, which is available at http://abrandt.berkeley.edu. The full model documentation includes a glossary of model terms and additional supporting information (e.g. all data inputs and data sources in tabular or graphical form).

5.1 Modeling methodology

ROMEO is a nonlinear optimization model, coded in the AMPL mathematical programming language [17] and solved using the SNOPT solver [19]. It models the adoption of substitutes for conventional petroleum (SCPs) over the years 2000 to 2050 based on the demand for liquid hydrocarbons, availability of conventional oil, the prices of SCPs, and the SCP resource base in each of 17 model regions.

ROMEO does not solve for all fifty years of production simultaneously, but instead solves each year sequentially, ensuring that supply equals demand in each year. A "run script" is used to call the model each year, save results, and transfer information between model years. Some complex model elements are included explicitly in the model, while others are implemented through the run script (more on this in *Important model features*).

Within this documentation, names of model elements (functions, parameters, data inputs) are presented in sans serif font. Indexed elements are presented as coded in AMPL. For example, fuel production, an element indexed over regions (r), synfuels (s) and years (y), is written FuelProduction[r,s,y]. File names are presented in `typewriter` font.

5.2 Objective function and constraints

Objective function

The objective function (the function minimized by the solver) is the cost of filling the conventional petroleum shortfall in each region by either trade or production of SCPs. By constructing ROMEO within an optimization framework, we assume that the world petroleum market supplies fuels at the lowest cost (or equivalently, at the highest profit for producers at a given price). The objective function is defined as follows:

$$(5)\quad \min \sum_{y} \mathsf{TotalCapacityCost[y]} + \sum_{y} \mathsf{TotalProductionCost[y]} + \sum_{y} \mathsf{TotalShippingCost[y]}.$$

The objective function is minimized in each year y. These terms can be expanded:

$$(6)\quad \mathsf{TotalCapacityCost[y]} = \sum_{r,f} \mathsf{NewCapacity[r,f,y]} \times \mathsf{InitialCapacityCost[f]} \times \mathsf{LearningMultiplier[f,y]};$$

$$(7)\quad \mathsf{TotalProductionCost[y]} = \sum_{r,f} \mathsf{FuelProduction[r,f,y]} \times [\mathsf{OtherVariableCost[f]} + \mathsf{ResourceCost[r,f]}] \times \mathsf{DepMultiplier[r,f,y]};$$

and

$$(8)\quad \mathsf{TotalShippingCost[y]} = \sum_{r1,r2,f} \mathsf{FuelShipped[r1,r2,f,y]} \times \mathsf{Distance[r1,r2]} \times \mathsf{ShippingCost}.$$

In these equations NewCapacity, FuelProduction, and FuelShipped are the decision variables. LearningMultiplier and DepMultiplier are described below in *Important model features.*

Decision variables

Decision variables are variables whose values are chosen by the solver so as to minimize the objective function. In ROMEO, the decision variables include: NewCapacity[r,f,y], the amount of new production capacity added in a given region and year for each fuel f; FuelProduction[r,f,y], the amount of a given fuel f produced in each region r in a given year y; and FuelShipped[r1,r2,f,y], the amount of fuel f shipped from a given region r1 to another region r2 in year y.

Constraints

Constraints limit the ranges of values chosen for decision variables, ensuring that the values are logically consistent and realistic. The constraints are:

1. Positivity Decision variables must be positive (e.g. negative fuel cannot be created):

$$\mathsf{FuelProduction}[\mathsf{r},\mathsf{s},\mathsf{y}] \geq 0, \tag{9}$$

$$\mathsf{NewCapacity}[\mathsf{r},\mathsf{s},\mathsf{y}] \geq 0, \tag{10}$$

$$\mathsf{FuelShipped}[\mathsf{r1},\mathsf{r2},\mathsf{f},\mathsf{y}] \geq 0. \tag{11}$$

2. Demand constraint Demand must be met. Thus in each region r1 the supply of all liquid fuels[5] (conventional oil, SCPs and net imports of all liquid fuels) must be greater than or equal to demand for liquid fuels in that region:

$$\begin{aligned}\sum_{f} \mathsf{FuelProduction}[\mathsf{r1},\mathsf{f},\mathsf{y}] + \sum_{r1,r2,f} \mathsf{FuelShipped}[\mathsf{r2},\mathsf{r1},\mathsf{f},\mathsf{y}] \\ - \sum_{r1,r2,f} \mathsf{FuelShipped}[\mathsf{r1},\mathsf{r2},\mathsf{f},\mathsf{y}] \geq \mathsf{AdjustedDemand}[\mathsf{r1},\mathsf{y}].\end{aligned} \tag{12}$$

for each time period y and region r1. AdjustedDemand is the demand for crude-oil-equivalent fuels, adjusted using the price elasticity of petroleum demand. It is described in detail in *Important model features*.

3. Availability of resources More resources cannot be extracted from any region than exist in that region. For each region r, fuel f, and year y:

$$\sum_{t=2000}^{y} \mathsf{FuelProduction}[\mathsf{r},\mathsf{f},\mathsf{y}] \leq \mathsf{AvailableResource}[\mathsf{r},\mathsf{f}], \tag{13}$$

where AvailableResource[r,f] equals TotalResourceNotConsumedByImage[r,f] multiplied by ConversionFactor[f]. ConversionFactor[f] accounts for losses in converting fuels from their primary energy type to modeled fuel production (it is equal to 1 except for CTL and GTL, as other resources are measured in units of crude oil volume). TotalResourceNotConsumedByImage[r,f] is the total available resource from which ROMEO draws. See Appendix A for more details.

[5] Although omitted here for simplicity, the model equation multiplies each fuel by a factor called CrudeOilEquivalence[f]. This corrects for the fact that the model accounts for volumes of crude oils produced, but CTL and GTL produced finished fuels, thus displacing more than 1 unit of crude for each unit produced. See discussion in Appendix A.

4. Speed of resource extraction This constraint limits the percentage of remaining resource that can be extracted in a given year:

$$(14)\quad \mathsf{FuelProduction}[\mathsf{r},\mathsf{f},\mathsf{y}] \leq \mathsf{MaxAnnualPercentage} \times (\mathsf{AvailableResource}[\mathsf{r},\mathsf{f}] - \mathsf{CumulativeFuelProductionResourceConsumption}[\mathsf{r},\mathsf{f},\mathsf{y}]).$$

In this constraint MaxAnnualPercentage is the percentage of the total resource that can be extracted in each year (See full ROMEO documentation for values [7]). This constraint stabilizes model output. Without this constraint, regions can increase production sharply and deplete their resources in only a few years. Also, this constraint governs the overall shape of increasing and decreasing production of a resource, being, in effect, an exponential model of resource extinction.[6] CumulativeFuelProductionResourceConsumption is the amount of resource consumed producing fuel since the model began. See equation in Appendix A.

5. Production is constrained by capacity This constraint limits the production of fuels in each region to less than or equal to the fuel production capacity. For all regions r, fuels f, and years y:

$$(15)\quad \mathsf{FuelProduction}[\mathsf{r},\mathsf{f},\mathsf{y}] \leq \mathsf{NewCapacity}[\mathsf{r},\mathsf{f},\mathsf{y}] + \mathsf{FunctionalCapacity}[\mathsf{r},\mathsf{f},\mathsf{y}].$$

Note that because NewCapacity[r,f,y] is included in the constraint, we assume that new capacity can come online within a one year time period (This does not cohere with actual practice, but significantly improves model functioning. See discussion below in *Potential for future improvements to ROMEO*).

6. Trade is constrained by production The amount of fuel f shipped out of a region r1 must be less or equal to production of that fuel in that region. So, for all regions r1, fuels f, and years y:

$$(16)\quad \sum_{r2} \mathsf{FuelShipped}[\mathsf{r1},\mathsf{r2},\mathsf{f},\mathsf{y}] \leq \mathsf{FuelProduction}[\mathsf{r1},\mathsf{f},\mathsf{y}].$$

[6] Exponential models of oil depletion have been explored by Wood et al. [41], and were found to be as good as or superior to the Hubbert (Gaussian) model in a systematic comparison of 139 oil producing regions [6].

7. Capacity does not grow too quickly Capacity additions in each year y and region r for fuel f are limited. This constraint models the limitations on the ability of the market to access capital and construct production capacity. Without this constraint, unrealistic solutions are found by the solver (e.g. replicating one-third of the existing global oil infrastructure in a single region in a single year). Thus:

(17) $\mathsf{NewCapacity}[\mathsf{r}, \mathsf{f}, \mathsf{y}] \leq \mathsf{MaxCapacityGrowth}.$

5.3 Important model features

There are three complex model functions that are key to model functioning. These include adjusting demand given the price of fuels prevalent in a given year, the effect of resource depletion on the cost of production, and the technical learning associated with growth of industries.

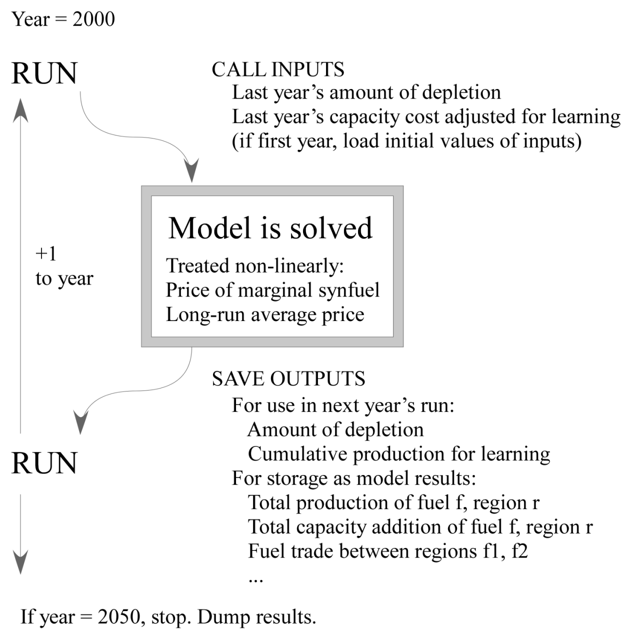
These features are implemented in two ways. First, the effect of price on demand is explicitly written into the model structure. Therefore it affects the model as seen by the solver and makes the model non-linear. The other two features of the model described above are defined "outside" the model. They operate within the run script that carries the model from year to year, saves results, and updates cumulated parameters. Therefore, these features of the model are seen as linear from the point of view of the solver (they are dependent on unvarying parameters), although they are dynamic across years. This layered model structure is illustrated in Figure 16. Ideally all model features would be included explicitly in the model structure. Unfortunately, this would make the model significantly more non-linear and thus more difficult to solve.

Price elasticity of petroleum demand

The elasticity of petroleum demand with respect to price is modeled in ROMEO. As the price of the marginal barrel of liquid fuel in ROMEO increases above the price at which the IMAGE demand was modeled, demand is reduced below the level modeled in IMAGE. This is implemented as follows:

$$(18)\quad \begin{aligned} &\mathsf{AdjustedDemand}[\mathsf{r}, \mathsf{y}] = \mathsf{Demand}[\mathsf{r}, \mathsf{y}] \\ &\quad \times (1 + [(\mathsf{PriceRatio}[\mathsf{y}] - 1) \times \mathsf{DemandElasticity}]) \\ &\quad\quad \times (1 + [(\mathsf{LongPriceRatio}[\mathsf{y}] - 1) \times \mathsf{RegionalLongDemandElasticity}[\mathsf{r}]]), \end{aligned}$$

Figure 16: ROMEO model structure, interaction between run script and model.



where DemandElasticity is the short-run price elasticity of liquid fuel demand, and RegionalLongDemandElasticity[r] is the region-specific long-run price elasticity of petroleum demand. Demand[r,y] is the exogenous baseline demand from IMAGE (again, see full ROMEO documentation for more details [7]).

The parameter PriceRatio[y] is the ratio of the current year's cost of production for the marginal barrel of fuel produced (or the price in a competitive market) to the current year's input oil price from IMAGE. LongPriceRatio[y] is the ratio of a long-run weighted price to the current year's price from IMAGE. Since the IMAGE oil prices are the prices at which our exogenous input demand was forecast, these ratios show how much higher our modeled prices are than the prices that generated the input demand. These ratios are defined as follows:

(19) $\mathsf{PriceRatio[y]} = \frac{\mathsf{MarginalCost[y]}}{\mathsf{ImageOilPrice[y]}},$

and

(20) $\mathsf{LongPriceRatio[y]} = \frac{\mathsf{AverageMarginalCost}X\mathsf{YearHistorical[y]}}{\mathsf{ImageOilPrice[y]}}$.

In the LongPriceRatio equation "X" represents the string 'five', 'ten', or 'twenty' depending on the number of years over which the long-run price is averaged (i.e. the long-run price is computed over the last 5, 10 or 20 years). This parameter is controlled through the LongElastTime parameter, and the default value is twenty years. As an example, AverageMarginalCostThreeYearHistorical[y], if it were to be used, would be defined as follows:

(21) $\mathsf{AverageMarginalCostThreeYearHistorical[y]} =$

$$\frac{\left(\mathsf{MarginalCost[y]} + \theta \cdot \mathsf{MarginalCost[y-1]} + \theta^2 \cdot \mathsf{MarginalCost[y-2]}\right)}{1 + \theta + \theta^2}.$$

In this equation, MarginalCost[y] is the current year's marginal cost of production, MarginalCost[y-1][7] is the marginal cost from the previous year's model run, etc. The parameter θ, named ThetaElasticity in the model, is the decay rate of the influence of prior year's prices. This formulation is adapted from Gately and Huntington [18, Table 6], and we use their value of θ, 0.84 derived from non-OECD regions.[8]

The effect of this equation is to have previous years' prices affect demand in the current model year, with decaying impact over time. Gately and Huntington, when calculating their estimates for long-run demand elasticity, did not truncate the effect of any year's price, but included all of their data (there is little effect from including more data: given the decay implied by θ, prices occurring 20 years previous to the modeled year are multiplied by θ^{19} (0.84^{19}, or 0.0002), and so have little effect on model results).

In these equations, MarginalCost[y] is defined as the cost of production of the highest-priced barrel of fuel produced in the model. It is calculated as follows:

(22) $\mathsf{MarginalCost[y]} =$

$$\text{if } \max_{r,f} \mathsf{BreakEvenPrice[r, f, y]} \geq \mathsf{ImageOilPrice[y]},$$

$$\text{then } \max_{r,f} \mathsf{BreakEvenPrice[r, f, y]}, \text{ else } \mathsf{ImageOilPrice[y]}.$$

[7]The model actually uses AnnualMarginalCost[y-1] etc. in this equation, because MarginalCost[y] does not store previous year's model results.

[8]It is unclear whether this non-OECD value of θ or the OECD value would be more accurate to use over the time period of the model, so this value is chosen because of the likely future increase in non-OECD demand.

Where $\mathsf{BreakEvenPrice}$ is defined as follows:

$$(23)\quad \mathsf{BreakEvenPrice[r,f,y]} = \text{ if } \mathsf{FuelProduction[r,f]} \geq \mathsf{EconomicLimit} \text{ then } \\ \mathsf{LearningMultiplier[f]} \times (\mathsf{CapitalRecoveryFactor} \times \mathsf{InitialCapacityCost[f]}) \\ + \mathsf{DepMultiplier[r,f]} \times (\mathsf{OtherVariableCost[f]} + \mathsf{ResourceCost[r,f]}).$$

$\mathsf{BreakEvenPrice}$ is only defined for fuels that meet a minimum economic level of production, which helps to eliminate the "knife-edge" behavior that occurs when tiny amounts of an expensive fuel are produced and drive up the cost of the marginal barrel of fuel. $\mathsf{EconomicLimit}$ is the minimum amount of production above which we can assume that fuels will need to be economic. That is, if fuels are produced in less than this quantity, they can be seen as "experimental" or in the scale-up stage, and not be expected to be traditionally profitable. Therefore the cost of producing these fuels does not affect the going price of fuels.

The learning effect

ROMEO models the declining cost of production that occurs due to experience gained over time. This effect is commonly called "learning by doing." This effect is calculated using the Wright learning model [29]:

$$(24)\quad Y = aX^{-b}$$

where Y represents cost of production, a is the cost of the first unit of output, X represents cumulated output, and b represents the learning elasticity [29].

Since the initial cost of production for the first unit is not available, we require X in multiples of the initial cumulative production ($\mathsf{InitialCumulativeProduction}$). We call parameter b the $\mathsf{LearningRate[f]}$ and a the $\mathsf{InitialCapicityCost}$. Thus, $\mathsf{InitialCapacityCost[f]}$ is multiplied by a learning multiplier:

$$(25)\quad \mathsf{LearningMultiplier[f,y]} = \left(\frac{\mathsf{CumulativeGlobalProduction[f,y]}}{\mathsf{InitialCumulativeGlobalProduction[f]}}\right)^{\mathsf{LearningRate[f]}}.$$

We use cumulative output rather than cumulative capacity additions because "cumulated industry output is the best single proxy for learning" [29]. Because of poor data availability, each fuel in ROMEO is subject to the same learning rate. As a further simplification, learning affects capital costs only. The full ROMEO documentation includes more discussion of the learning rate [7].

Resource depletion

The depletion cost multiplier, DepMultiplier[r,s,y], increases the cost of production as a resource is depleted. Our model is based on the oil depletion model of Greene et al. [20]. DepMultiplier[r,s,y] affects the variable cost of production of synfuels. Thus it acts in opposition to the learning effect: as production increases, learning lowers the capital costs, but depletion increases the variable costs.[9] The depletion multiplier is equal to:

$$(26)\ \mathsf{DepMultiplier}[\mathsf{r},\mathsf{f},\mathsf{y}] = \frac{\ln\left(\frac{1}{\mathsf{DepletionRatio}[\mathsf{r,f,y}]} - 1\right) - \mathsf{Alpha}[\mathsf{r,f}]}{\mathsf{InitialCostDepletion}[\mathsf{r,f}] \times \mathsf{Beta}[\mathsf{r}]},$$

where DepletionRatio[r,f,y] is the fraction of total resource endowment depleted (See Appendix A). InitialCostDepletion[r,f] is the total variable cost of resource f at time y = 2000. This functional form results in variable costs that rise rapidly at first, then level off, and begin to finally rise rapidly again once depletion reaches a significant level. The parameters Alpha[r,f] are tuning parameters that fit the curve to each region. Due to lack of data we assume a value of 0.15 for Beta[r] for all regions, as did Greene et al. [20]. Alpha[r,f] are obtained using the initial state of depletion and initial cost.

Because the depletion multiplier is nonlinear (logarithmic), we simplify its implementation. First, it is evaluated between years, not within each model year. That is, the depletion multiplier is calculated using the depletion level from the previous year (CumulativeResourceConsumption [r,f,y] is defined as the cumulative consumption up to that year, not including the consumption in the year currently being modeled). This makes depletion linear from the viewpoint of the solver, allowing more reliable solutions.[10] Second, each region needs an endowment of each resource because the depletion multiplier is undefined if there is zero resource. Small amounts of each resource (1×10^{-3}) are added to each region where data on the resource endowment could not be found. Third, when the depletion ratio is zero, i.e., when none of the resource has been exploited, the function is also undefined. Thus, all regions with no production to date (InitialCumulativeResourceConsumption [r,f]) are given a nominal production-to-date of 1×10^{-4}. Lastly, the function

[9] In the case of tar and shale, DepMultiplier modifies only the OtherVariableCost term in the objective function (because tar sands/ extra-heavy oil and shale have zero ResourceCost), while in GTL and CTL production, it modifies OtherVariableCost as well as ResourceCost, the cost of feedstock natural gas and coal.

[10] For reliable solutions, nonlinear aspects of large models such as ROMEO should be linearized as much as possible [17].

approaches ∞ as depletion approaches 100%. Thus, the depletion multiplier is only defined for DepletionRatio[r,s,y] between 0.001 and 0.999.

There are shortcomings with this implementation. It is not clear that the effects of depletion will be solely to increase the variable cost of production. Indeed, it is easy to argue that depletion could affect the capital costs of production as well as the variable costs. But, in order to simplify the model, depletion only acts on the variable costs of production in this version of ROMEO.

5.4 Scenarios in ROMEO

ROMEO is run over a number of base-case scenarios. Possibilities for optional exploratory scenarios are also described.

Base-case scenarios

Base-case scenarios provide an illustration of model functioning. These base-case scenarios are "economic" scenarios. In them the supply and trade of fuels is governed only by cost, and restrictions due to non-economic factors are not included. The settings for the baseline scenarios are shown in Table 3.

There are eight base-case scenarios modeled. Scenarios 1-6 are grouped into two categories: low cost (scenarios 1-3) and high cost (scenarios 4-6). In scenarios 1-3, demand is set to medium, while supply of conventional oil varies from low (scenario 1), to medium (scenario 2), to high (scenario 3). In all of these scenarios the cost of fuels is low (e.g. oilcost = low). The cost parameter adjusts the variable costs, capital costs, conversion efficiencies, and emissions in unison (i.e. "cost" is broadly defined), so this set of scenarios can be seen representing a smoother, easier transition to low-polluting fuels. In scenarios 4-6, the settings are the same as scenarios 1-3, except all fuel cost parameters are set to high (e.g. tarcost = high) and the maximum rate at which capacity can be added is set to low (maxgrowth = low). These scenarios therefore represent a more difficult transition to more costly, environmentally damaging fuels.

Scenario 7 is a "best case" scenario: supply of conventional oil is high, while demand remains low. Costs are low, emissions are low, and the limit on capacity growth is high, ensuring a more smooth transition. Scenario 8 is a "worst case" scenario: supply of conventional oil is low, demand is high, costs and emissions of substitutes are high, and the rate of capacity addition is slow. In addition, the short- and long-run elasticities of petrol-

Table 3: Parameter settings for studied baseline scenarios[a,b]

Scenario	Demand	Supply	Fuel Costs[c]	Conv. Eff.	Emiss.	Demand Elast.[d]	Max. growth
1	M	L	L	H	L	H	M
2	M	M	L	H	L	H	M
3	M	H	L	H	L	H	M
4	M	L	H	L	H	H	M
5	M	M	H	L	H	H	M
6	M	H	H	L	H	H	M
7	L	H	L	H	L	H	H
8	H	L	L	H	L	L	L

a - L = low, M = medium, H = high

b - A number of the parameters remain constant across all eight baseline scenarios: deplete = yes, longelasttime = twenty, maxperc = med, disrupt = no, import = no, and expensivegas = no.

c - SCP costs are varied in unison with efficiency and emissions. That is, high cost is always paired with low efficiency and high emissions, while low cost is paired with high efficiency and low emissions. There remains the possibility to study the effects of increasing one of the costs individually to ascertain the possible effects of an optimistic viewpoint for costs of a certain SCP.

d - In no scenarios do we turn off the price elasticity of petroleum demand.

eum demand are low, such that very high price spikes are needed to induce demand reductions.

Exploratory scenarios

A number of exploratory scenarios will be implemented in future versions of ROMEO. These include policy-relevant scenarios such as a carbon tax scenario, or import limitation scenarios. These also might include geopolitical scenarios that involve oil production disruption due to conflict.

5.5 Post-optimization calculation of emissions

After production is modeled, the resulting emissions are calculated. The total volume of crude fuels produced is multiplied by production emissions. Only a portion of hydrocarbon output is refined, and the rest is used in chemical feedstocks or in an unrefined state (such as in power production or industrial boiler applications). The fraction refined is multiplied by production, and this quantity for each fuel is multiplied by refining emissions.[11] We use the fraction of crude production refined as given by IMAGE: FractionRefined[y] [23]. For simplicity, refining emissions are assumed to be equal for all fuels that require refining. Combustion of the finished, refined fuel is assumed to result in equal emissions for all fuel types. Three primary equations calculate emissions in each year:[12]

$$\text{(27)}\quad \mathsf{ModeledProductionEmissions[y]} = \sum_r \sum_f (\mathsf{FuelProduction[r,f,y]} \times \mathsf{ProductionEmissions[f]}),$$

$$\text{(28)}\quad \mathsf{ModeledRefiningEmissions[y]} = \sum_r \sum_f \mathsf{FuelProduction[r,f,y]} \times \mathsf{FractionRefined[y]} \times \mathsf{RefiningEmissions[f]},$$

and

$$\text{(29)}\quad \mathsf{ModeledCombustionEmissions[y]} = \sum_r \sum_f \mathsf{FuelProduction[r,f,y]} \times \mathsf{CombustionEmissions[f]}.$$

And, summing these emissions components we arrive at total emissions.

$$\text{(30)}\quad \mathsf{ModeledTotalEmissions[y]} = \mathsf{ModeledProductionEmissions[y]} + \mathsf{ModeledRefiningEmissions[y]} + \mathsf{ModeledCombustionEmissions[y]}.$$

These emissions can be compared to "baseline" emissions that would occur if fuel production were the same as our modeled cases, but demand until 2050 was filled with conventional oil with constant emissions per unit of energy:

$$\text{(31)}\quad \mathsf{BaselineProductionEmissions[y]} = \sum_r \sum_f (\mathsf{FuelProduction[r,f,y]} \times \mathsf{ProductionEmissions[oil]}),$$

[11] CTL and GTL synfuels produce synthetic finished fuels as modeled in this analysis, not synthetic crude oil.

[12] In the actual model code AnnualFuelProduction[r,f,y] is used, as this stores the values of FuelProduction[r,f,y] from each year.

$$(32)\quad \mathsf{BaselineRefiningEmissions[y]} = \sum_r \sum_f \mathsf{FuelProduction[r,f,y]} \times \mathsf{FractionRefined[y]} \times \mathsf{RefiningEmissions[oil]},$$

and

$$(33)\quad \mathsf{BaselineCombustionEmissions[y]} = \sum_r \sum_f (\mathsf{FuelProduction[r,f,y]} \times \mathsf{CombustionEmissons[oil]}).$$

Again, we can sum these emissions to arrive at total baseline emissions:

$$(34)\quad \mathsf{BaselineTotalEmissons[y]} = \mathsf{BaselineProductionEmissions[y]} + \mathsf{BaselineRefiningEmissions[y]} + \mathsf{BaselineCombustionEmissions[y]}.$$

The parameter $\mathsf{IncrementalSynfuelEmissions[y]}$ is the key diagnostic parameter used to understand the emissions consequences over the model run. It is plotted over time in Figure 11 and is defined as follows:

$$(35)\quad \mathsf{IncrementalSynfuelEmissions[y]} = \mathsf{ModeledTotalEmissions[y]} - \mathsf{BaselineTotalEmissions[y]}.$$

Even more concisely, $\mathsf{CumulativeIncrementalSynfuelEmissions}$ presents the total emissions impacts over the 50-year modeling period in a single value:

$$(36)\quad \mathsf{CumulativeIncrementalSynfuelEmissions} = \sum_{y=2000}^{2050} \mathsf{IncrementalSynfuelEmissions[y]}.$$

This value is used in tabular comparison of the results from different scenarios.

6 Acknowledgements

Preparation of this report was supported by a competitive grant from the University of California Energy Institute. Support was provided for an earlier incarnation of this research by the Climate Decision Making Center. This Center is supported by a cooperative agreement between the National Science Foundation (SES-034578) and Carnegie Mellon University. Richard Plevin provided the original translation of ROMEO from Excel to AMPL code, and offered much assistance along the way. Helpful comments were provided by members of the University of California Energy Institute, especially Jim Bushnell. Helpful comments were also provided by attendees of the DOE/EPA *Modeling the oil transition* workshop in April of 2006.

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