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# A spatially explicit techno-economic model of bioenergy and biofuels production in California

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ABSTRACT

This study presents a spatially explicit techno-economic Bioenergy Siting Model (BSM) of the bioenergy production system in California. The model describes the bioenergy system in terms of facility siting and size, conversion technology, feedstock profile, and feedstock supply chain configuration for the year 2015. The BSM expands upon previous bioenergy siting work by optimizing the system using spatially explicit feedstock supply curves, multiple potential conversion technologies and geographically determined bioenergy demand. We present sensitivity analysis demonstrating the effect of market and policy change scenarios. The model couples transportation network analysis using a Geographic Information System (GIS) with a mixed integer-linear programming (MIP) optimization model. Scenario results show total biomass resource utilization between 18 and 25 million dry tons annually at biofuel prices from \$2.20 to \$4.00/gallon of gasoline equivalent.

## 1. Introduction

The geographic distribution and cost of feedstock supply and energy product demand are critical in predicting the geography of bioenergy production. At present much of the available biomass feedstock goes un-utilized. However, climate change mitigation policies such as Renewable Energy Standards (RES) (US Congress, 2009), Renewable Fuel Standards (EPA, 2009), and Low Carbon Fuel Standards (LCFS) (Farrell et al., 2007) will likely increase demand for renewable and low-carbon fuels and electricity derived from biomass resources. Policies aimed at reducing greenhouse gas (GHG) emissions from the transportation and electricity generation sectors via the use of biomass feedstocks must consider capacity of each sector to compete for limited biomass resources. This research presents a biorefinery siting model (BSM) of state-wide bioenergy production (fuel and electricity) derived from best available techno-economic data on all components of the production and distribution system that maximizes the aggregate system-wide profit for bioenergy producers.

California's farms, forests, and cities produce more than 80 million dry tons of biomass per year. Substantial additional feedstock may be developed in the future through production of dedicated energy crops. Between 30 and 40 million dry tons of biomass have been estimated to be recoverable as feedstock for energy conversion to heat, electricity, and biofuels (Williams, 2006). California's successful transition to second-generation biofuels will depend on these resources. Understanding the capacity of each biomass-consuming sector to compete for these resources is critical to crafting policy to maximize climate benefit and minimize the impact of unintended cross-sector competition for resources.

The federal Energy Independence and Security Act (EISA) of 2007 (US Congress, 2007) includes a renewable fuel standard (RFS) that anticipates annual renewable fuel supplies to achieve 36 billion gallons by 2022. EISA requires 20.5 billion gallons of renewable fuel by 2015, of which 5.5 billion gallons are from advanced biofuels and 3 billion are from cellulosic biofuels. The BSM base case uses a 2015 planning horizon to project the capacity to meet EISA goals in California. The BSM uses projected labor costs, machinery costs, and commodity prices for that planning horizon.

The BSM presented here predicts biofuel and electricity production presuming the continued technological development of biochemical and thermochemical biorefinery, electricity, and combined heat and power generation systems. Fuel production facilities, biomass power plants, and combined heat and power facilities are referred to here as biorefineries, except when specifically delineated otherwise.

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Facility siting is a classic problem in industrial organization. Weber (1929) provided a foundational theoretical framework for locating a factory minimizing the cost of raw material transport and final product. Melo et al. (2009) provided a comprehensive review of optimal facility siting in the context of supply chain management (SCM). The trade-offs between economies of scale and transportation costs are also a central theme of this research and have been outlined by many including Karnani (1983). The use of specific geographic information in location–allocation problems has many precedents as well, beginning perhaps with the ReVelle and Swain (1970) formulation of the *p-median* model which locates *p* facilities and allocates demand nodes to their nearest facilities to minimize total distance traveled. Other models have been developed that can be used for biorefinery siting using geographic resource assessments. Oak Ridge National Laboratory has developed nationally oriented resource assessments (Perlack et al., 2005; Walsh et al., 2000). Graham et al. (2000) developed a geographic model that optimally locates biorefineries of a given feedstock input based on the marginal cost of an energy crop feedstock delivered to the site. Biorefineries are located sequentially to avoid over-allocation or double-counting of the resources. The method was demonstrated using a case study of switchgrass in Tennessee. Kaylen et al. (2000) incorporated competition between economies of scale in production and transportation cost of feedstock using a nonlinear programming model for a single lignocellulosic ethanol facility. Freppaz et al. (2004) developed a decision support system (DSS) to aid regional authorities in making the most of available forest resources for heat and electricity generation. A regional application of the BSM outlined here was used in an analysis of transportation fuel production capacity from the western United States but did not include the competition between electricity and biofuels for biomass feedstock (Parker et al., 2008).

This analysis expands upon previously published research in several ways. The BSM uses mixed integer-linear programming to simultaneously site and size future biorefineries accounting for economies of scale, feedstock delivery costs, and fuel demand. All production, transportation, conversion and distribution costs and scaling factors are inputs to the model. Further, we place spatially explicit demand constraints on the production system, which forces the model to consider variability in demand between regions *as well as* spatial variability in feedstock supply. The BSM also expands upon previous work by integrating competition for resources between electricity and fuel production. The objective function for the BSM presented here is the maximization of system-wide profit.

## 2. Methods

The bioenergy system is modeled geographically. Potential locations for future biorefineries were established using a heuristic approach based upon proximity to existing infrastructure. Transportation and loading costs are calculated using a geographic network connecting nodes (feedstock source locations, inter-modal facilities, potential biorefineries, and petroleum distribution terminals) via road, rail, and marine routes. The BSM determines the optimal biorefinery location, size, and type. The conversion of biomass to energy products, transportation of finished fuel products, as well as geographic variability in biofuel demand are considered endogenously. Geographic demand constraint is accomplished by imposing a capacity constraint on the total volume of product that can be delivered to a distribution terminal. Estimates of demand are derived using population statistics. Thus biorefineries are sited and sized based on their optimal location with regard to the supply chain and the delivery of a product to a distribution terminal with unmet demand.

The BSM is solved using the Mixed Integer-linear Program (MIP) solving algorithm in CPLEX optimization software from ILOG™ using the General Algebraic Modeling System (GAMS) model language (McCarl, 2004). The computational intensity of the BSM depends on the number of variables, with the number of binary variables being most important. Spatial data were compiled and analyzed with ESRI ArcGIS software (McCoy, 2005) and the PostgreSQL database with PostGIS extension(The PostgreSQL Global Development Group, 2005).

### 2.1. BSM formulation

The BSM seeks to maximize the total industry profit from the production of bioenergy at a given market price for fuels, electricity, and their co-products. Multiple model runs are performed over a range of projected fuel prices. Fuel prices are inputs to the model. The BSM is run once for each fuel price point. Plotting the industry production against a range of fuel prices gives the supply for each bioenergy product type at a given fuel price. The bioenergy product produced at each fuel price is an output of the model.

Given feedstocks of type $f$ at supply location $i$, potential biorefinery locations $j$, bioenergy product types $q$ (electricity and combined heat and power products are distinguished from fuel products as $e \in q$), conversion technologies $t$, fuel terminals $k$, and feedstock prices $p$, the BSM makes the following decisions:

1. whether to build a biorefinery at a location $j$ using a specific technology $t$ ($X_{jt}$);
2. how large the biorefinery at $j$ of product type $q$ and conversion technology $t$ will be in terms of product output ($Yb_{jqt}$);
3. how much of each feedstock of type $f$ will each refinery $j$ of conversion technology $t$ consume ($Yf_{fjt}$);
4. how much of each feedstock type $f$ at specific feedstock price levels $p$ are transported from the supply location $i$ to the biorefinery $j$ ($F_{fijp}$);
5. and how much biofuel of each type $q \neq e$ is transported from the biorefinery $j$ to each fuel terminal $k$ ($T_{jkq}$).

The known parameters include:

1. the supply of ($S_{fip}$) and prices for ($P_{fip}$) feedstock $f$ at a supply location $i$ and price point $p$;
2. the parameters of the conversion cost function for technology $t$ (annual fixed cost $a_t$, feed dependent cost $b_t$, and fuel dependent cost $c_t$);
3. the maximum size of any facility employing conversion technology $t$ ($M_t$);
4. the efficiency of each technology $t$ in terms of the quantity of bioenergy product $q$ produced from the conversion of a ton of feedstock of type $f$ ($\eta_{fqt}$);
5. the cost of transporting feedstock $f$ from source $i$ to biorefinery $j$ ($TC_{fij}$) and fuel from biorefinery $j$ to terminal $k$ ($DC_{jk}$);
6. the maximum terminal throughput ($MaxDemand_{kq}$) defined by the fraction of total demand ($\phi_q$) assigned to fuel terminal $k$;
7. the bioenergy product $q$ price ($ProductPrice_q$).

Units of measure are shown in Table 1.

The profit function (1) is defined as the sum of the revenue from fuel and co-product sales less the sum of the costs. These costs consist of feedstock procurement, which includes production, harvest, and nutrient replacement for agricultural residues, feedstock transportation and storage, conversion of feedstock to fuel, transport of fuel to distribution terminals, and the local distribution costs from these terminals to the refueling stations. The total industry-wide profit is calculated as such:

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$$Profit = \sum_j \sum_k \sum_{q \neq e} ProductPrice_q \cdot T_{jkq} + \sum_j \sum_t \sum_{q=e} ProductPrice_q \cdot Yb_{jqt} - Cost \qquad (1)$$

where

$$Cost = \sum_i \sum_j \sum_f \sum_p ((P_{fip} + TC_{fij}) \cdot F_{fijp}) + \sum_j \sum_t \left( a_t \cdot X_{jt} + \sum_f b_t \cdot Yf_{fjt} + \sum_q c_t \cdot Yb_{jqt} \right) + \sum_j \sum_k \sum_{q \neq e} DC_{jk} \cdot T_{jkq} \qquad (2)$$

The supply $S_{fip}$ and prices $P_{fip}$ together define supply curves for each feedstock resource type at each location. The aggregated biomass feedstock supply curve for California is shown in Fig. 1.

These curves indicate how much feedstock producers would be willing to produce at given price levels. How much of which resources will actually be used depends on the fulfillment of the objective function in the model. When applying the model, multiple model runs are performed over a range of product prices for biofuels or electricity ($ProductPrice_q$).

CONSTRAINTS

Constraints impose physical or regulatory limitations on the biomass industry in the mathematical model. The first set of constraints limits the biomass type *f* originating from a source *i* at price level *p* to be less than the maximum supply of biomass of that type *f* at that feedstock price level *p* at that source *i*.

$$\sum_j F_{fijp} \leqslant S_{fip} \quad \forall_{f,i,p} \qquad (3)$$

For each biorefinery location *j* and feedstock *f* the total biomass feedstock input to biorefineries of any type must equal the amount of biomass feedstock transported to that location.

$$\sum_t Yf_{fjt} = \sum_i \sum_p F_{fijp} \quad \forall_{f,j} \qquad (4)$$

The biofuel or electricity produced at biorefinery *j*, $Yb_{jqt}$, is equal to the quantity of biofuel or electricity from conversion technology type *t* that can be produced from the biomass input, $Yf_{fjt}$, given the conversion efficiency $\eta_{fqt}$ including handling loss.

$$Yb_{jqt} = \sum_f \eta_{fqt} \cdot Yf_{fjt} \quad \forall_{j,q,t} \qquad (5)$$

**Table 1**
Units of BSM variables and parameters.

| Variable | Unit |
|---|---|
| $X_{jt}$ | Binary |
| $Yb_{jqt}$ | Megawatt-hours (MW h) or gallons year$^{-1}$ |
| $Yf_{fjt}$ | Oven-dry ton (ODT) year$^{-1}$ |
| $F_{fijp}$ | ODT year$^{-1}$ |
| $T_{jkq}$ | Gallons year$^{-1}$ |
| **Parameter** | **Unit** |
| $a_t$ | \$ year$^{-1}$ |
| $b_t$ | \$ ODT$^{-1}$ |
| $c_t$ | \$ gallon$^{-1}$ |
| $MaxDemand_{kq}$ | Gallons year$^{-1}$ |
| $\eta_{fqt}$ | MW h or gallons ODT$^{-1}$ |
| $\Phi_q$ | Fractional |
| $M_t$ | MW h or gallons year$^{-1}$ |
| $S_{fip}$ | ODT year$^{-1}$ |
| $P_{fip}$ | \$ ODT$^{-1}$ |
| $TC_{fij}$ | \$ ODT$^{-1}$ |
| $DC_{jk}$ | \$ gallon$^{-1}$ |
| $ProductPrice_q$ | \$ gallon$^{-1}$ or \$ MW h$^{-1}$ |

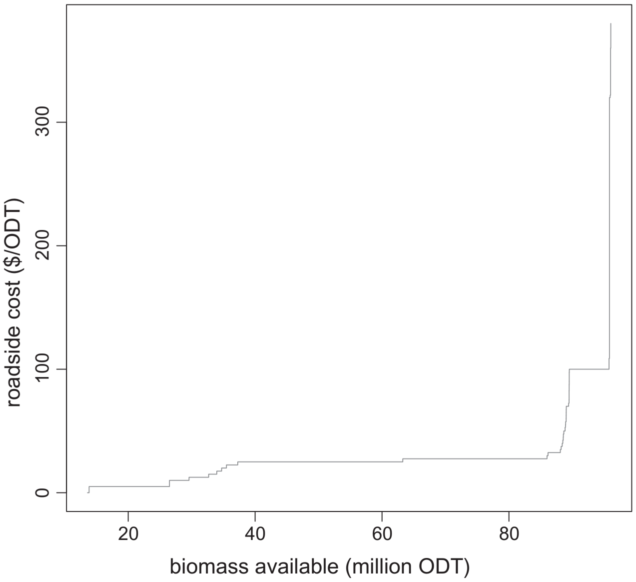

**Fig. 1.** Aggregate biomass feedstock supply curve for California.

The fuel products $q \neq e$ leaving biorefinery *j* must be less than or equal to the biofuel produced at the biorefinery.

$$\sum_k T_{jkq} \leqslant \sum_t Yb_{jqt} \quad \forall_{j,q \neq e} \qquad (6)$$

There can be no biorefinery input if the fixed cost has not been paid ($X_{jt} = 0$) at that site. If $X_{jt} = 1$ then the feedstock inputs to biorefinery *j* cannot be greater than its maximum capacity $M_t$ from the engineering cost model for type *t*.

$$\sum_f Yf_{fjt} \leqslant M_t \cdot X_{jt} \quad \forall_{j,t} \qquad (7)$$

The total biofuel $q \neq e$ delivered to each distribution terminal *k* must be less than a maximum fraction ($\Phi_q$) of the fuel demand assigned to that terminal. This would assume that the biofuels could be freely blended with conventional fuels up to a maximum blending limit, such as the current E10 limit. In the scenarios, the fraction could range between zero and 100% and vary depending on the state or region where the fuel is sold. We do not limit the quantity of electricity or heat that can be sold at a given location although in practice certain locations will be limited by transmission capacity and co-located heat demand.

$$\sum_j T_{jkq} = \phi_q \cdot MaxDemand_{kq} \quad \forall_{k,q \neq e} \qquad (8)$$

Biorefineries of type *t* at potential locations *j* are either built or not built.

$$X_{jt} = \begin{cases} 0 & \text{if biorefinery is not built,} \\ 1 & \text{if biorefinery is built.} \end{cases} \qquad (9)$$

All other variables must be equal to or greater than 0.

$$F_{fijp}, \quad Yf_{fjt}, \quad Yb_{jqt}, \quad T_{jkq} \geqslant 0 \qquad (10)$$

### 2.2. Geographic model

GIS is used to provide routing and transport cost data and to determine the maximum demand for fuel at distribution terminals. The transportation network includes road, rail, and marine transportation routes, as well as inter-modal facilities capable of loading and unloading bulk dry and liquid products. Routing and cost is calculated between all feedstock source locations and all existing

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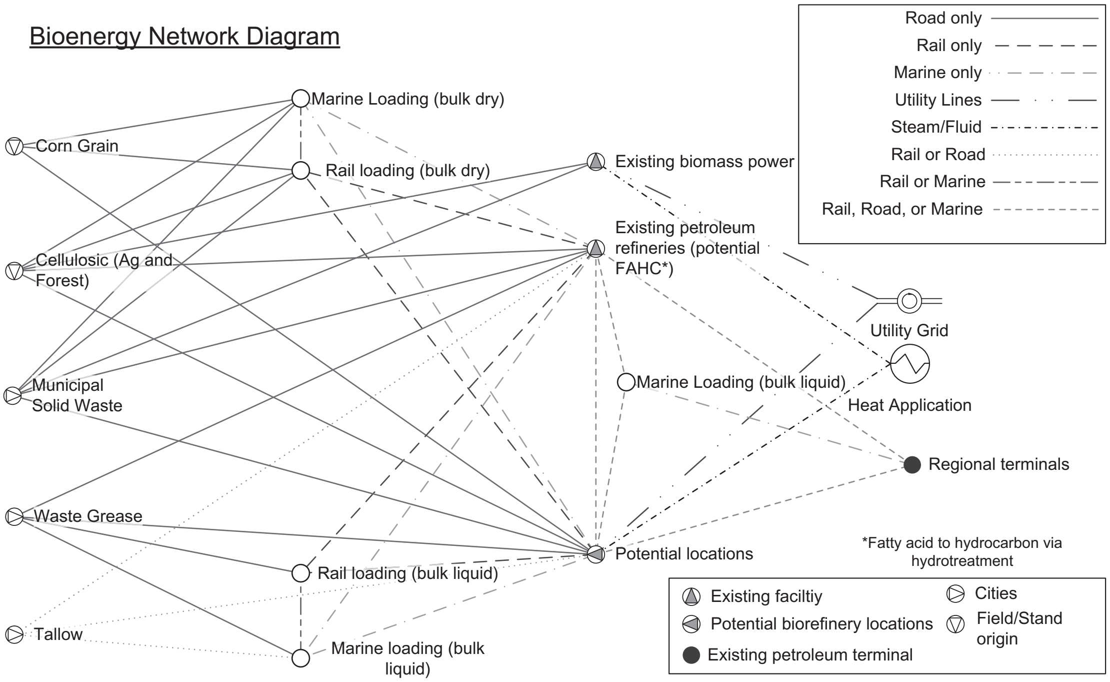

**Fig. 2.** Bioenergy network schematic flow diagram.

and potential bioenergy production locations as well as between production locations and distribution terminals. The schematic network is represented in Fig. 2. Each feedstock originates at either a municipality or a county centroid. The material type (liquid or dry bulk) determines the transport type and cost. We assume that material originating at a field, forest stand, or municipal recycling facility will be transported via truck to either an inter-modal facility for loading onto rail or barge or trucked directly to the biorefinery. Material originating at an animal processing plant is assumed to be loaded directly onto rail cars for transport. For biofuels, transport from biorefinery to distribution terminal can be accomplished using rail, marine, or road transport and is determined based upon the least cost route to access each terminal. Electricity and combined heat and power facilities are modeled as the termini of the bioenergy network. As such we assume heat applications are close to the biorefinery.

### 2.2.1. Feedstock

Biomass resources are, by nature, distributed across the landscape. Biomass feedstocks originating in agricultural or forest landscapes are aggregated to the county. These resources are assigned to the centroid of the county with an intra-county transportation cost applied based on the size of the county. Waste grease from commercial food preparation, animal fats, and municipal solid wastes (MSW) are mapped to the municipality in which they originate. Feedstock data are represented as a supply curve indicating the incremental increase in biomass available of a given type over a \$2.50/ton price increment. Prices range from \$0 to \$100/ton.

Biomass feedstock data were compiled from a variety of sources. Data on the agricultural crops and residues including orchard and vineyard wastes were collected from a recent statewide resource assessment (Williams, 2006). Other biomass resources including waste grease and beef tallow were provided by Nelson et al. (2008). We use forest supply estimates from the US Forest Service Forest Products Laboratory (Skog et al., 2008). MSW estimates were developed from a database of 2006 solid waste from the California Integrated Waste Management Boards Disposal Reporting System (California Integrated Waste Management Board, 2009). The quantity of MSW available was calculated on a *per-capita* basis and modified based on 2015 population projections from the California Department of Finance (CDF, 2007). Fig. 3 shows the distribution of biomass feedstocks throughout the state.

### 2.2.2. Facility siting

The method for siting potential biorefineries was to choose suitable representative locations throughout California based on a set of defining conditions or criteria. Potential biorefinery locations are limited to existing cities and towns. From the set of potential locations, the MIP determines which sites are constructed. These are not intended to be exact locations, but rather generalized areas that have the required infrastructure for a biorefinery. This narrows the search space of potential locations, and also allows information about California cities to be used in the selection criteria. City data were acquired from the National Atlas of the United States (2004). To reduce computational demands stemming from multiple similar sites, potential locations within 20 km of each other were merged. Determining potential locations was therefore a two-step process: first determine all cities that match the required criteria for hosting a biorefinery; then limit the matching cities to a representative sample of potential locations.

In this analysis, renewable diesel (FAHC) production facilities must be coincident with an existing petroleum refinery. Potential locations $P$ for all other types of facilities are a subset of cities $C$ in California ($P \subset C$). The attributes of cities $C$ used to create the subset $P$ include the existence of petroleum refineries ($C_r$), existent or proposed biomass conversion facilities ($C_b$), or existence of an industrial facility with similar requirements ($C_i$). Cities without existing facilities but with connectivity to infrastructure ($C_{inf}$) are considered if their population is greater than 10,000 and the maximum distance to a railroad is less than 5 km *or* the maximum distance to a marine terminal is less than 15 km. $P$ is defined in Eq. (11).

$$P = C_r \cup C_b \cup C_i \cup C_{inf} \tag{11}$$

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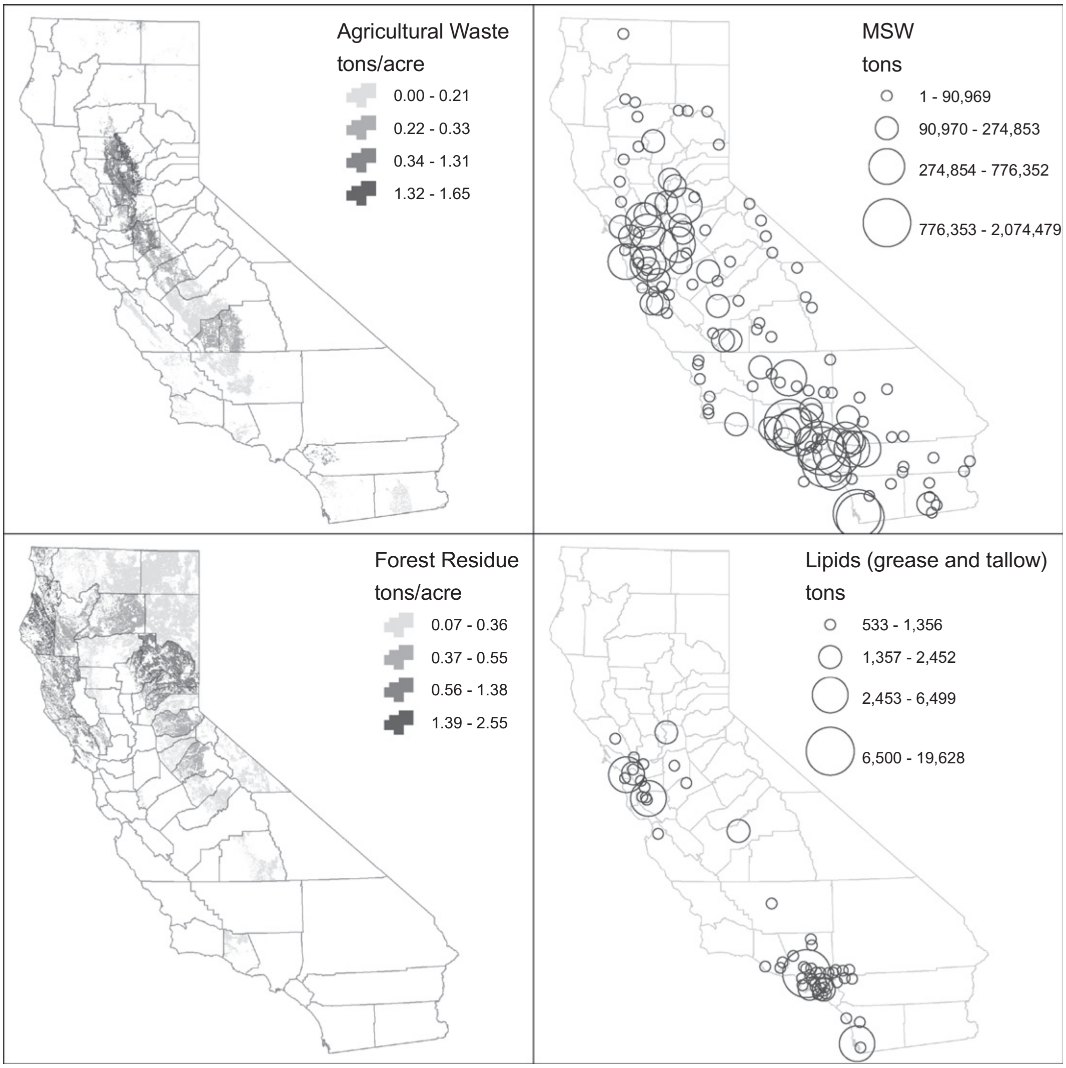

**Fig. 3.** California's biomass feedstocks.

Our siting approach uses population as a surrogate for availability of essential services, including trucking companies, skilled labor, and materials. Fig. 4 shows a map exemplifying the geographic network including potential biorefinery locations, transportation network, and fuel terminal locations.

Terminal locations are compiled from a database published by the Oil Price Information Service (OPISnet.com, 2007). All existing petroleum distribution terminals are included.

### 2.2.3. Demand modeling

The siting of a biorefinery must take into account the market demand within a geographic area as well as the availability of feedstock. To address the geographic variation in demand, we embed explicit limits to biofuels demand that reflect projected fuel demands and fuel blending limits. Ethanol is limited to 20% of the gasoline market on an energy equivalent basis for a given terminal. Diesel replacement fuels are allowed to replace the full diesel demand for a given terminal. We have estimated the transportation fuel demand in California to be 18 billion gge of gasoline-like fuels and 5 billion gge of diesel-like fuels in 2015 (Kavalec et al., 2005).

The demand for transportation fuel was allocated to existing fuel distribution terminals by defining geographic service areas for each terminal and aggregating the demand contained within the service areas. The service areas for each terminal were produced using the Network Analyst extension in ArcGIS and the transportation network described in Section 2.2. The service areas are the regions that each fuel terminal can serve with lower local distribution costs than any other fuel terminal, and are calculated based upon trucking costs from existing distribution terminals. The population in each service area is summed and used to define the fraction of the 2015 projected fuel demand that is assigned to that terminal. Demand service areas can be seen in Fig. 5. The terminals serving more rural areas have large areas over which they must distribute fuel while the service areas in urban areas are generally smaller.

The market for electricity produced from biomass is considered as an unlimited demand at the market price referent (MPR) set by the California Public Utilities Commission. For 2008, the MPR for a base-load bio-power facility is $0.093/kW h. For the CHP market, the demand is not spatially resolved in the current version of the BSM. The state-wide potential for CHP is taken from the Electric Power Research Institute (EPRI) 2005 assessment of the market (Electric Power Research Institute, 2005). That assessment placed the likely additional market at 1,966 MW and a high deployment case at 7340 MW by 2020. Heat is assumed to have a value equal to half the projected natural gas price or $11.92/MW h .

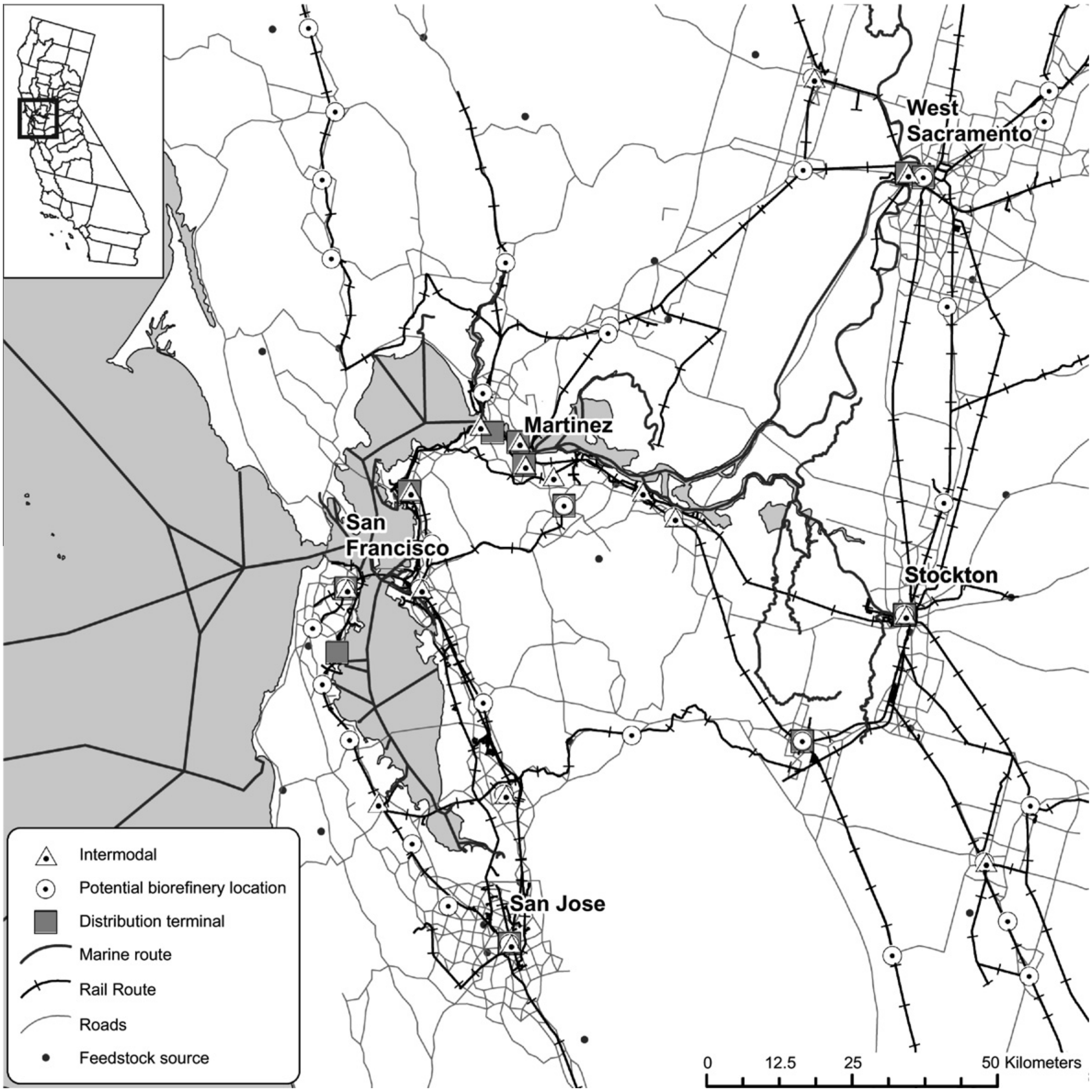

**Fig. 4.** Example detail of transportation network.

### 2.2.4. Transportation

Biomass and liquid fuel transportation costs were modeled using three modes: truck, rail, and barge. Fig. 4 shows an example of this network. Trucking costs have three components: a loading/unloading cost, a time-dependent travel cost, and a distance-dependent travel cost. The time and distance dependence allow for differential cost between traveling on slow local roads versus fast interstate highways.

The costs of biomass and fuel transport by road, rail and marine are described in Table 2. Trucking costs (Jenkins et al., 2000; Perlack and Turhollow, 2003; Reynolds, 2002) do not vary by feedstock type and depend only on truck payload. Network trucking costs are calculated from the cost/ton-mile and distance traveled. Biomass transportation costs are assumed to be on a wet basis. Diesel fuel cost is assumed to be $2.50 per gallon. The cost of transporting all liquids (oils, grease, and fuel products) is considered to be the same on a volumetric basis. Rail costs are calculated from a mileage-based rate schedule for agricultural products (Union Pacific Railroad, 2007).

Marine transportation costs are based on a published rate schedule for inland barge transport (Tidewater, 2007). The rates were fitted to a linear function of distance similar to the rail rates above.

As mentioned above, all field or stand-sourced feedstocks are located to the county centroid, which is located on the network, enabling transportation costs calculation. To address the costs associated with transport within a county, an additional transportation cost is added. This cost is calculated using the average city-block distance from any point in the county to the centroid. This geometric measure uses the perimeter of the county to estimate average travel distance (average distance is approximately $P_s/8$ where $P_s$ is the perimeter of the service area or county). Additionally, it is assumed that the average travel speed along this route is 35 mph. These intra-county costs are then combined with the county centroid-based network transportation model.

Transportation infrastructure data were assembled from Bureau of Transportation Statistics sources (NHPN, 2005; FRA, 2007; RITA, 2003). The inclusion of inter-modal facilities allows for the calculation of loading and unloading costs associated with the transfer of feedstock or fuel from one mode of transport to another. The network was built to enable the calculation of both time and cost of travel between two locations. Cost is used as the impedance factor in calculating routes. We performed origin-destination routing on all feedstock source-potential biore-

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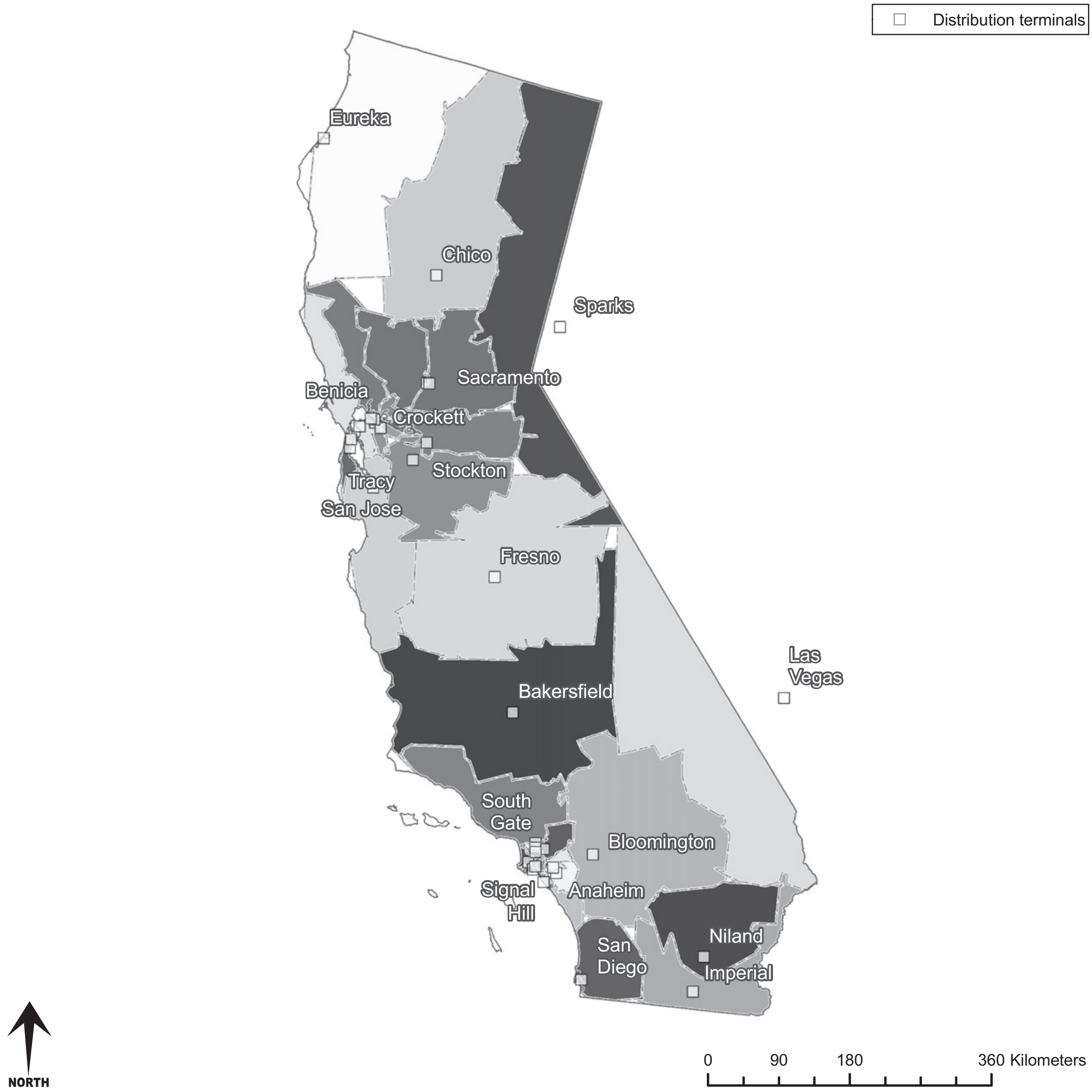

**Fig. 5.** Fuel demand service areas in California.

**Table 2**
Transportation cost factors. Time dependent road costs include labor and capital. Distance dependent road costs include fuel, insurance and maintenance.

| Mode | Cost component | Liquids | Bulk solids |
|---|---|---|---|
| Road | Loading/unloading | \$0.02 gallon$^{-1}$ | \$5 wet ton$^{-1}$ |
| Road | Time dependent | \$32 h$^{-1}$/truckload | \$29 h$^{-1}$/truckload |
| Road | Distance dependent | \$1.30 mile$^{-1}$/truckload | \$1.20 mile$^{-1}$/truckload |
| Road | Truck capacity | 8000 gallons | 25 wet tons |
| Rail | Loading/unloading | \$0.015 gallon$^{-1}$ | \$5 wet ton$^{-1}$ |
| Rail | Fixed cost | \$8.80 100 gallons$^{-1}$ | \$27 wet ton$^{-1}$ |
| Rail | Distance dependent | \$0.0075 mile$^{-1}$/100 gallons | \$0.023 mile$^{-1}$/wet ton |
| Rail | Rail car capacity | 33,000 gallons | 106.5 wet tons |
| Marine | Loading/unloading | \$0.015 gallon$^{-1}$ | \$5 wet ton$^{-1}$ |
| Marine | Fixed cost | \$1.40 100 gallons$^{-1}$ | \$3.85 wet ton$^{-1}$ |
| Marine | Distance dependent | \$0.015 mile$^{-1}$/100 gallons | \$0.043 mile$^{-1}$/wet ton |
| Marine | Barge capacity | 1.26 million gallons | 4000 wet tons |

finery destination pairs and potential biorefinery locations-petroleum distribution terminal pairs. Least cost origin-destination cost matrix data were calculated using the Network Analyst extension in ArcGIS™.

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### 2.3. Conversion technologies

We consider seven bioenergy conversion technologies. We have selected technologies from a 2008 technical report (Antares Group, Inc., 2008) which presents cost models for a wide range of experimental and demonstration scale conversion technologies derived from existing literature and subjected to an expert review panel. The technologies are limited in the resources they can exploit. Four technologies are capable of exploiting the lignocellulosic resources Fischer–Tropsch diesel referred to as lignocellulosic middle distillates (LCMD), biomass power via direct solid-fuel combustion for electricity (BP), direct combustion for combined heat and power (CHP), and lignocellulosic ethanol through hydrolysis and fermentation (LCE), which is limited to the clean fraction of the resource. Two technologies are considered for the conversion of oils to diesel-replacement fuels: conventional biodiesel as fatty acid methyl esters (FAME) and hydrotreatment of lipids to make hydrocarbons (FAHC). The dry-mill ethanol process is considered for utilizing corn resources. Table 3 identifies BSM conversion technologies and the feedstocks amenable to each.

**Table 3**
Feedstock conversion pathways.

| Feedstock category | Feedstock type | Conversion technologies |
|---|---|---|
| Clean lignocellulosics | Forest biomass | LCE |
| | Straw, stover, and vegetable agricultural residues | LCMD |
| | Dry food processing wastes | BP |
| | Orchard/vineyard wastes | CHP |
| | Municipal solid wastes (MSW) | |
| | Clean mixed paper | |
| | Clean wood wastes | |
| | Clean yard wastes | |
| Lignocellulosics | Remainder of biomass | LCMD |
| | MSW, remainder from sorting | BP |
| | | CHP |
| Lipids | Yellow grease | FAME |
| | Animal fats | FAHC |
| Grains | Corn | Dry mill ethanol |

Conversion costs for biofuels have been taken predominantly from the work of the Antares Group, Inc. (2008). Electricity generation and CHP costs and scaling factors are derived from the California Biomass Collaborative Energy Cost Calculator (California Biomass Collaborative, 2009). To convert the investment costs of the biorefineries to annual costs, the biorefineries are assumed to operate at design capacity for 20 years. The investment cost is amortized over the lifetime and added to the annual operating costs to give the annual cost of producing bioenergy from a given biorefinery.

The conversion technologies demonstrate economies of scale in the relationship between biorefinery size and production capacity, which are captured in the form of integer-linear equations.

Feedstock input capacity and product output capacity determine the capital requirements. The yield of product per ton of feedstock input is not constant across feedstock types, which can lead to significantly different conversion costs between feedstocks.

**Table 4**
Conversion cost components (Antares Group, Inc., 2008).

| Model parameter | | Fixed cost (million \$) *a* | Feed dependent (\$ ODT$^{-1}$) *b* | Fuel dependent (\$ gallon$^{-1}$) *c* | Maximum capacity *M* |
|---|---|---|---|---|---|
| Grains to ethanol (GE) | | | | | |
| | Dry mill | 2.17 | – | 0.30 | 1 million tons |
| Lignocellulosic ethanol (LCE) | | 6.16 | – | 0.58 | 1.3 million tons |
| Lignocellulosics to middle distillates (LCMD) | | 19.72 | 95.80 | – | 5 million tons |
| Fatty acids to methyl esters (FAME): | | | | | |
| | Yellow grease | 0.93 | 170 | – | 320,000 tons |
| | Virgin oil/tallow | 1.81 | 60.30 | | 320,000 tons |
| Fatty acids to hydrocarbons (FAHC) | | 1.55 | 36.60 | – | 800,000 tons |
| Biomass to electricity | | 0.60 | – | 0.06 kW h$^{-1}$ | 410,000 tons |
| Combined heat and power (CHP) | | 0.60 | 32.10 | | 410,000 tons |

**Table 5**
Conversion efficiencies (gallons fuel or kW h electricity ton$^{-1}$ biomass) (Antares Group, Inc., 2008).

| Biomass type | | GE | LCE | LCMD | FAME | FAHC | Electricity |
|---|---|---|---|---|---|---|---|
| Corn (dry mill) | | 100 | – | – | – | – | – |
| Corn stover | | – | 80.6 | 36.8 | – | – | 889 |
| Rice straw | | – | 76.8 | 33.1 | – | – | 857 |
| Other straws | | – | 76.8 | 38.7 | – | – | 880 |
| Vegetable residues | | – | 76.8 | 36.5 | – | – | 907 |
| Orchard vineyard waste | | – | 76.9 | 40.6 | – | – | 1008 |
| Forest | | – | 90.2 | 42 | – | – | 1007 |
| *MSW* | | | | | | | |
| | – Mixed paper | – | 86 | 37.1 | – | – | 896 |
| | – Wood waste | – | 78.9 | 41.5 | – | – | 974 |
| | – Yard waste | – | 70 | 38.4 | – | – | 756 |
| | – Mixed waste | – | – | 31.6 | – | – | 446 |
| *Food processing* | | | | | | | |
| | – Dry | – | 80 | 40 | – | – | 976 |
| | – Wet | – | 80 | – | – | – | – |
| Yellow grease | | – | – | – | 249 | 250 | – |
| Tallow and lard | | – | – | – | 260 | 250 | – |

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The biorefineries are modeled to consume a constant mix of feedstock for the entire production period. The feedstock type designates the conversion costs. This approach allows the biorefineries to take advantage of the resource mix in proximity and to not be constrained to a single feedstock type. Variation in the feedstock profile resulting from seasonal availability is not yet explicitly accounted for in the BSM. Further work will also address the sensitivity of some conversion technologies such as LCE to diverse feedstocks.

Table 4 gives the values used for the cost functions in the BSM for each technology type. Fixed costs in this table represent the minimum fixed capital cost from the linearized conversion technology models. Scaling factors are used to estimate capital requirements beyond the minimum. The maximum size constraint is given as the parameter $M_t$. No minimum facility size is specified in the BSM.

For existing biomass power plants the capital expense is arbitrarily reduced to 50% of an identical new facility. This reflects the repayment of remaining initial capital expense or the cost of purchasing the power plant by a new investor.

**Table 6**
Biofuel gasoline equivalents.

| Fuel type | LHV gallon$^{-1}$ (Btu) | gge gallon$^{-1}$ |
|---|---|---|
| Conventional gasoline | 116,093 | 1 |
| Conventional diesel/H-diesel | 128,445 | 1.11 |
| Ethanol | 76,330 | 0.66 |
| FT diesel | 123,669 | 1.07 |
| FAME/biodiesel | 119,553 | 1.03 |

The conversion efficiency impacts the cost of production in two ways. First, lower conversion efficiencies require greater capital investment in the facility such that unit process efficiencies resulting in economies of scale can be exploited. Second, lower conversion efficiencies require more feedstock per unit of product resulting in increased procurement cost per unit of product. The conversion efficiencies for each biomass type/technology pair are given in Table 5.

In the model, biofuels compete for fuel market share based on the energy (MJ) that they can provide at a given price in order to provide a uniform means of comparison (see Table 6). The competition is significantly more complex than this, but a more general market model has not yet been incorporated. Biofuel supply is presented in units of gallons of gasoline equivalent (gge).

## 3. Results

The BSM was run as a base case with several sensitivity cases. The base case assumes the basic model formulation as described in Section 2.1. The sensitivity cases conducted analyze the impact of two scenarios on biomass utilization pathways. In the first sensitivity case we require 20% of California's Renewable Portfolio Standard to be met using biomass resources, as currently called for by the state's Bioenergy Action Plan. The second scenario describes the impact of an additional co-product value to heat produced from electricity generation. The BSM base case results indicate that if the market price for biofuel is below \$1.55/gallon of gasoline equivalent (gge), no biofuels will be produced in competition with electricity at \$0.093/kW h. Above \$1.55/gge, biofuel

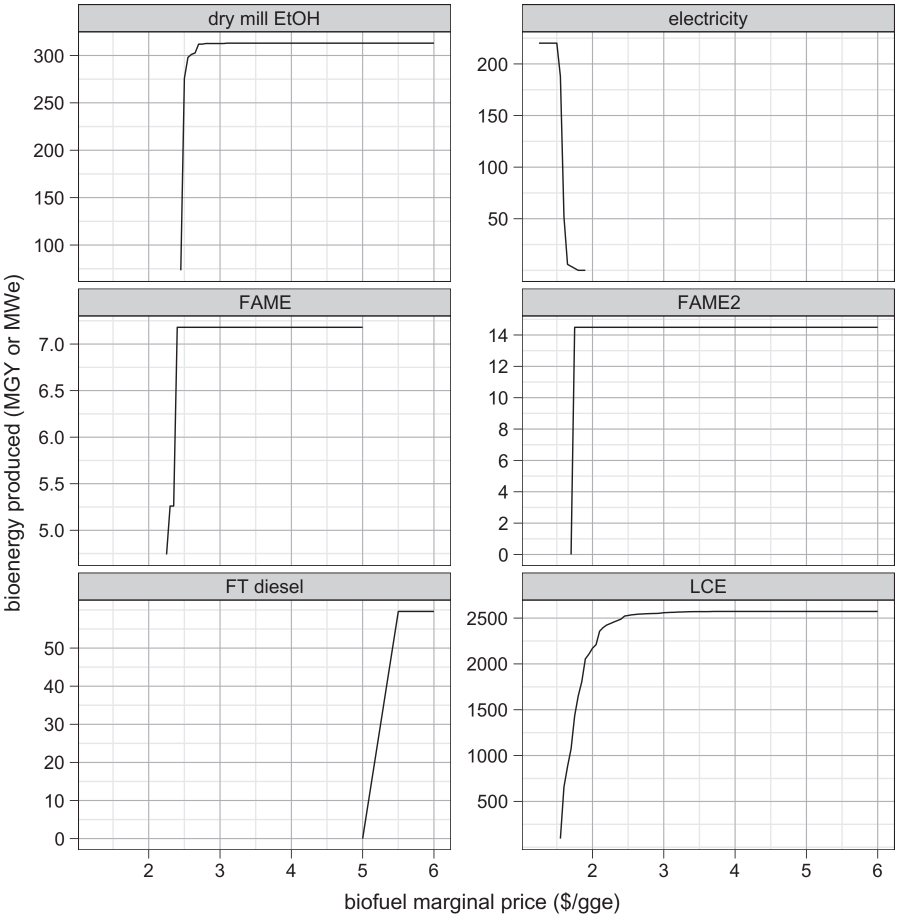

**Fig. 6.** Electricity and biofuel production as a function of fuel price for the base case.

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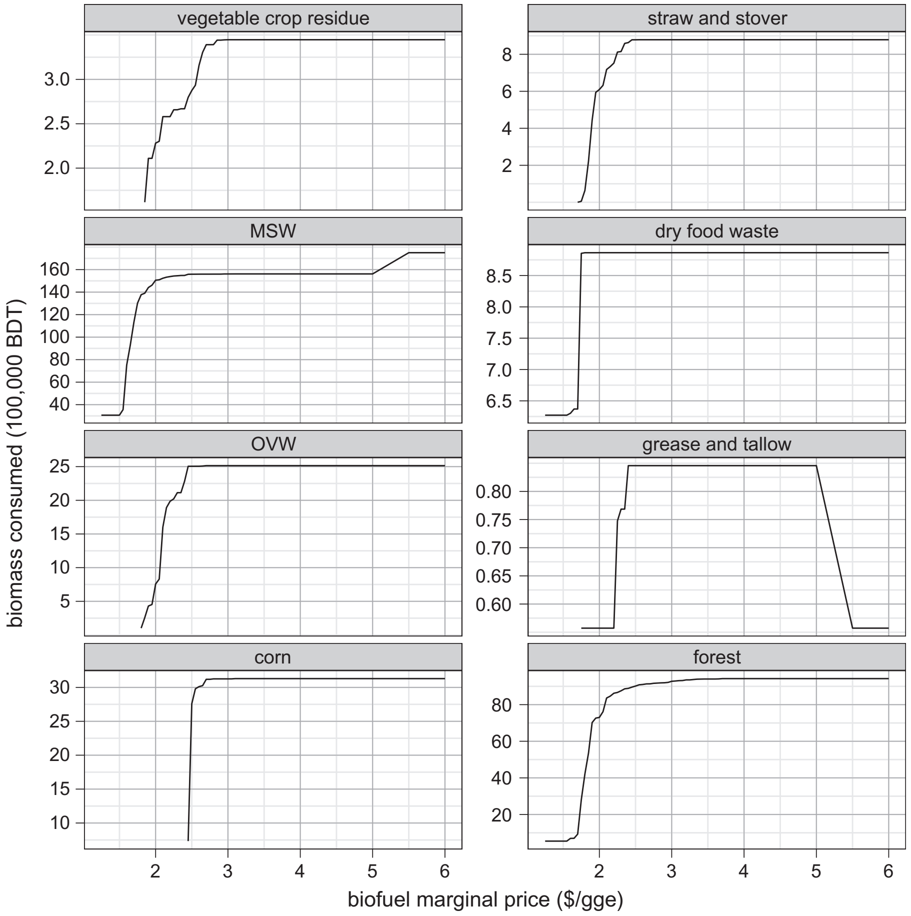

**Fig. 7.** Feedstock consumption by type as a function of fuel price.

production out-competes electricity generation for biomass resources. At this price, electricity generation consumes 3.6 million tons of biomass producing 220 MW of electricity. This result is consistent with the current use of biomass for electricity generation – around 5 million dry tons. Fig. 6 demonstrates the bioenergy production by type as a function of fuel price. At $1.55/gge, 94 million gallons of ethanol are produced via the hydrolysis and fermentation pathway. Between $1.55/gge and $1.65/gge, however, resource consumption for ethanol production via enzymatic hydrolysis and fermentation pathway increases to 89% of the resource resulting in the production of 873 million gallons of ethanol and just 11 MW of electricity. Both ethanol production from fermentation and biodiesel production from esterification pathways are utilized at fuel prices above $1.75/gallon (Fig. 6).

The fraction of the technically available resource that is economically available depends on the market price of biofuels. Fig. 7 represents the consumption of feedstocks in generalized categories as a function of fuel price. Fig. 8 shows the total feedstock consumption at each fuel price point. In the range of $1.50–$2.50/gge there is a rapid increase in biomass consumption. This is due in part to the fact that 65% of the lignocellulosic biomass resource has procurement cost between $25 and $35 per dry ton. Thus, many of these resources become economical at approximately the same fuel price. A sharp increase in the production of corn ethanol occurs at about $2.50/gge because of the threshold in corn price that provides profit at any price above this. Additional economic modeling is required to assess market influences of corn price on biofuel production. BSM results shows near full utilization of all available biomass resources at biofuel prices above $2.50/gge. At the high end of the fuel price range low-quality mixed MSW is utilized in the more costly FT diesel process.

Electricity generation consumes significant amounts of lignocellulosic biomass when fuel prices are low. Low cost feedstock such as MSW, forest residues, and dried food wastes are consumed at fuel prices below $1.65/gge. As fuel prices increase, feedstock is

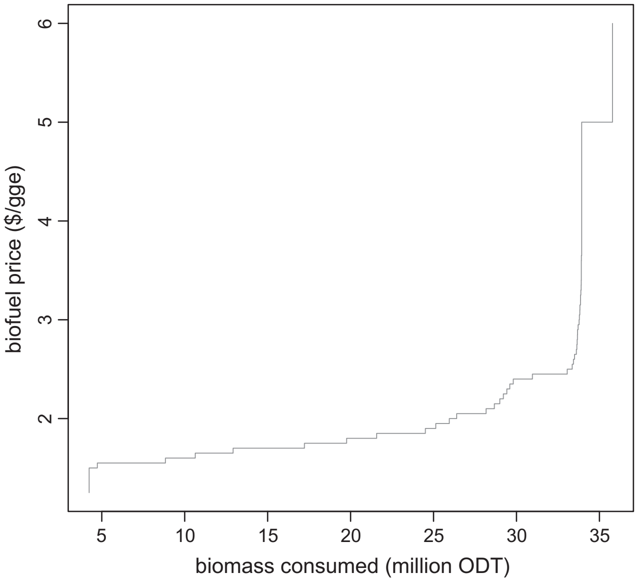

**Fig. 8.** Aggregate biomass consumption as a function of fuel price.

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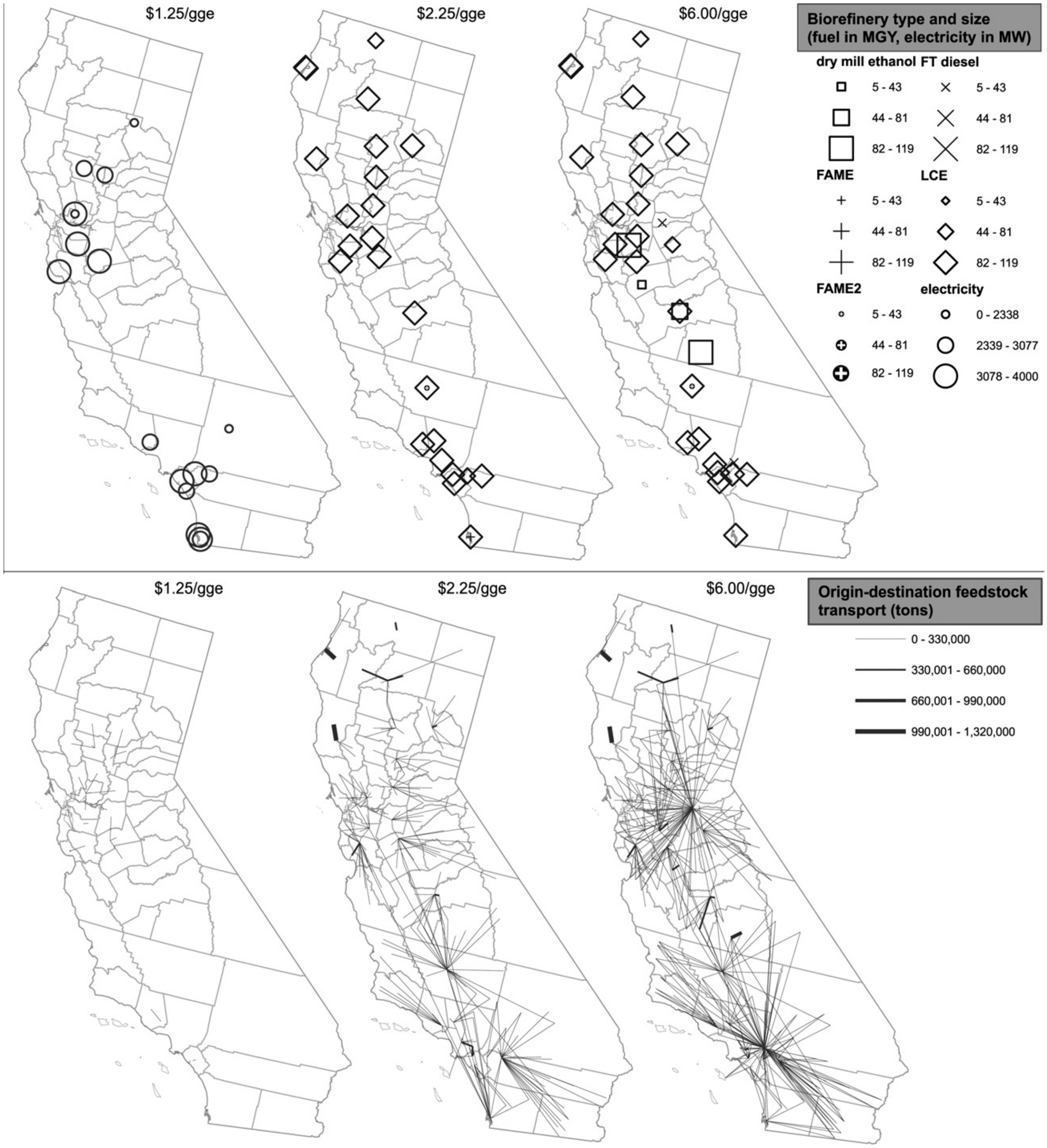

**Fig. 9.** Siting and feedstock transport at selected price points.

shifted to the production of higher value liquid fuels. Existing power facilities would continue to compete for feedstock at higher prices, but the model does not yet include this analysis.

Many of the resources demonstrate flat supply curves. The reason for this is that the procurement costs of most feedstocks are modeled as single price points that switch the supply from unavailable to fully available over a single increment shift in price. The variability in the feedstock cost in these cases is solely due to transportation cost.

### 3.1. Siting results

At each price point, the BSM selects locations and sizes for biorefineries. The model also allocates all feedstock available at a cost acceptable to the conversion technology to a sited plant. Fig. 9 presents the results of the BSM at three price points: $1.25/gge, $2.25/gge, and $6.00/gge. The maps in the upper panel show the location, size, and type of biorefineries at each price. The lower panel illustrates the feedstock quantity being transported from a source node to a sited biorefinery. The BSM uses the actual road distance to generate transport costs but the routes are simplified to straight lines here for purposes of clarity.

Siting results show the predominance of electricity generation at low marginal biofuel prices. These facilities are located near large population centers to access low-cost MSW feedstock. At $2.25/gge, electricity generation is replaced by biofuels production. Biofuels production at the intermediate fuel price level is mostly via the LCE pathway and still concentrated around urban centers.

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However, lower cost forest and agricultural residues available in the forested northern part of the state and the agricultural region of the Sacramento-San Joaquin Valley draw new facilities to those regions. Fatty acid conversion technologies also are sited at this price point, accessing waste grease from the Los Angeles metropolitan area and animal fats from slaughterhouses in the southern San Joaquin valley. The decline in utilization of lipids at $5/gge is a result of the construction of FT diesel plants (see Fig. 6). Once the high cost of construction of FT diesel plants can be justified lower cost lignocellulosic feedstocks are consumed and production shifts away from the more expensive lipid feedstocks. This shift can be seen in the increase in consumption of MSW at the $5/gge price point.

### 3.2. Sensitivity

#### 3.2.1. Policy: Renewable Portfolio Standard (RPS)

California's Renewable Portfolio Standard sets a goal of producing 20% of the state's electricity from renewable sources by 2010 and increasing to 33% in 2020. The BSM provides insight into the competition for feedstock between conversion platforms. Demand for biomass for electricity generation production will most certainly affect the availability of biomass for fuel production. To estimate the effect of the RPS and bioenergy targets in state policy on the mix of biofuel and electricity from biomass, we projected that 20% of the total renewable portfolio – 1.45 GW – would come from biomass. The results of the sensitivity analysis show that an increase in biomass utilization for electricity generation to 20% of the RPS for 2010 would dramatically affect biomass utilization pathways.

In the absence of competition from biofuels, the price of electricity would be required to increase to $0.103/kW h from $0.093/kW h in order to meet the RPS standard. As fuel prices increase, the required price for electricity to meet the RPS also increases. At $2.50/gge, electricity prices must increase to $0.153/kW h. Along with the competition leading to higher prices, the RPS would reduce the biomass available to produce biofuels by one third.

#### 3.2.2. Combined heat and power

The inclusion of an added value for heat production at electric power plants greatly increases the capacity of electricity producers to compete for feedstock at prices between $2.25 and $2.75/gge.

Fig. 10 demonstrates the effect of an additional $11.94/MW h of heat from the production of electricity on system-wide production across the price spectrum. Electricity generation in this scenario is much greater than in the base case at fuel prices between $1.20/gge and $2.40/gge. In the CHP scenario, maximum electricity generation is 2081 MWe at $1.25/gge in contrast with base case generation of 450 MWe at the same price point. With the ability to generate value from process heat, electricity producers are able to afford higher feedstock prices and can therefore consume more of the unused supply of biomass at lower fuel prices. The transition from the use of feedstocks for electricity to fuel production occurs over a narrow price window between $2.00 and 2.40/gge. The production of biofuels across the price spectrum is only affected at this point. Between $1.55 and $2.25/gge, the difference in fuel produc-

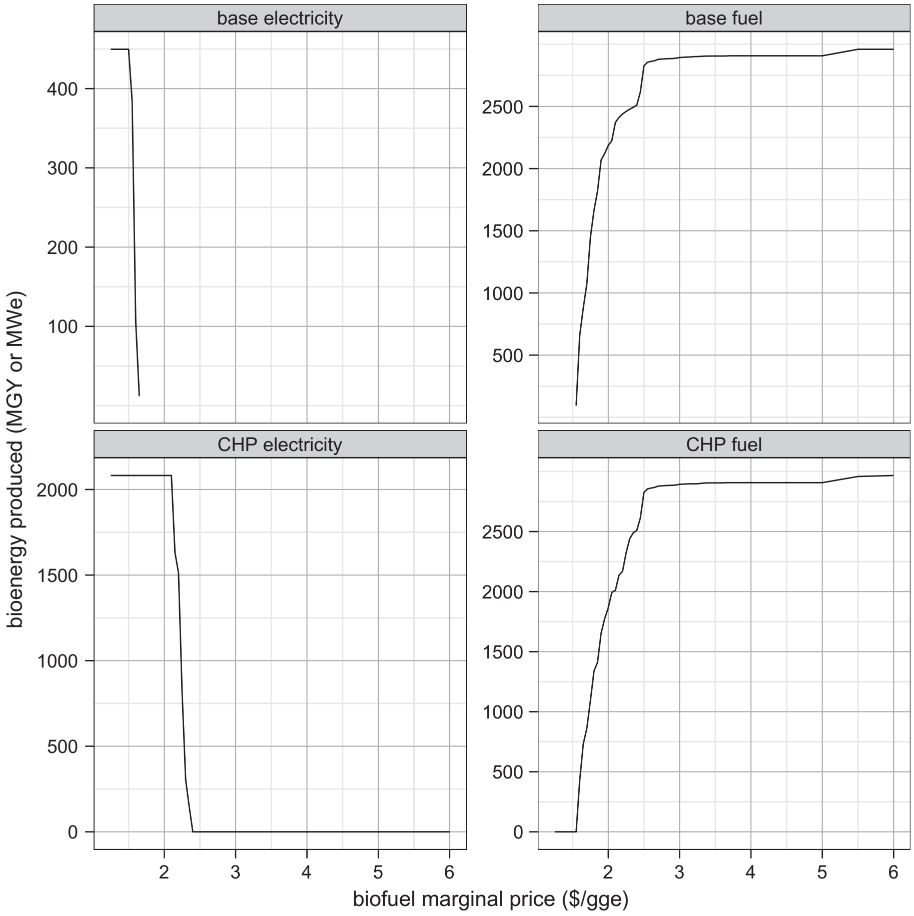

**Fig. 10.** Effects of process heat monetizing on the bioenergy system.

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tion between the base case and CHP cases is at least 93 MGY with its greatest divergence at the $1.90 price point with 414 MGY more biofuel produced in the base case than in the CHP scenario.

## 4. Discussion and conclusions

This study presents a novel approach to modeling the spatial and economic aspects of bioenergy production systems. We draw on a rich and growing body of research integrating geographic specificity into linear and mixed integer-linear programming approaches to production systems optimization. This study expands upon existing research by integrating multiple components of the supply system and optimizing across the entire production chain. The components include: spatially explicit feedstock production functions for a wide range of feedstocks, production functions for a range of technologies for conversion of biomass into multiple bioenergy products including electricity and heat, spatially explicit demand constraints reflecting population, and transportation costs reflecting existing multi-modal infrastructure.

The divergent market value for equivalent energy content in electricity versus transportation fuel, as well as the capital requirements for conversion technology, are the primary drivers in the bioenergy system configuration. Existing price structures for electricity and transportation fuel in California favor the production of liquid fuel over electricity and heat assuming substantial improvements in biofuel conversion technologies are realized. As a result, once sufficient return on investment for biofuels production can be realized from the market price of biofuels, the demand for transportation fuels will quickly draw the vast majority of the available biomass resources away from electricity generation. Policy mechanisms such as an RPS can have a significant effect in diverting biomass feedstock from fuel production to electricity generation. Also, realizing the added value of heat as a co-product with electricity can result in a much greater capacity for CHP producers to compete for feedstock as biofuel prices increase. CHP producers like electricity-only producers still bear significant risk as the threshold biofuel price needed to divert feedstock from electricity to fuel is still relatively low ($2.40/gge). Siting new biomass electricity plants in locations where process heat can be utilized may also result in the displacement of other non-renewable energy sources used for heating.

The BSM addresses important information gaps in the development of renewable energy policy. The model also sets forth a framework within which feasibility analysis for siting biorefineries can be conducted. Bioenergy is expected to be a critical tool to achieve state and federal renewable and low carbon energy goals (Yeh et al., 2009). The BSM results provide insight into the economic potential of biomass resources to meet policy goals. The model facilitates greater understanding of competition between energy generation and fuels production. Also the range of feedstock conversion technologies modeled is useful in predicting the economic conditions under which facilities of different types might be constructed and in what locations.

The present model is limited in several ways. Though demand for finished fuel is included in this analysis, trends in population growth, water supply, and the housing market could significantly change the geographic distribution and volume of demand centers. The BSM at present ignores imports of both biomass feedstock and finished biofuels from outside California. The model as presented assumes that conversion technology will improve or reach commercialization by 2015. We have used estimates of the resources available under assumed conditions. Yield variability could lead to different supply configurations with biorefineries looking to reduce their risk in low yield years, thus reducing the total supply of fuel. In addition, we have used point estimates for the commodity prices of corn. The corn ethanol production profile is erratic in the BSM because we assume no price response in the corn market for large changes in corn consumption. Also the geographic location of feedstock from natural forest stands and agricultural fields at the centroid of a county may overlook significant variation and subsequent cost within the county area. A continuation of this research looking at the effect of refined spatial supply data is currently underway.

Additional future work in this area needs to address more directly the dynamic effects of the often disconnected climate policies addressing renewable electricity, low-carbon fuels, and GHG offsets. Further, to adapt the BSM to the context of investment-driven feasibility analysis, higher resolution transport and feedstock data must be integrated. Agricultural production systems are generally susceptible to a range of economic, climatic, and policy changes. The introduction of stochasticity in feedstock supply will assist in understanding the effects of supply uncertainty on the production system.

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