National microalgae biofuel production potential and resource demand

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[1] Microalgae are receiving increased global attention as a potential sustainable "energy crop" for biofuel production. An important step to realizing the potential of algae is quantifying the demands commercial-scale algal biofuel production will place on water and land resources. We present a high-resolution spatiotemporal assessment that brings to bear fundamental questions of where production can occur, how many land and water resources are required, and how much energy is produced. Our study suggests that under current technology, microalgae have the potential to generate 220×10^9 L yr^{-1} of oil, equivalent to 48% of current U.S. petroleum imports for transportation. However, this level of production requires 5.5% of the land area in the conterminous United States and nearly three times the water currently used for irrigated agriculture, averaging 1421 L water per liter of oil. Optimizing the locations for microalgae production on the basis of water use efficiency can greatly reduce total water demand. For example, focusing on locations along the Gulf Coast, southeastern seaboard, and Great Lakes shows a 75% reduction in consumptive freshwater use to 350 L per liter of oil produced with a 67% reduction in land use. These optimized locations have the potential to generate an oil volume equivalent to 17% of imports for transportation fuels, equal to the Energy Independence and Security Act year 2022 "advanced biofuels" production target and utilizing some 25% of the current irrigation demand. With proper planning, adequate land and water are available to meet a significant portion of the U.S. renewable fuel goals.

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1. Introduction

[2] There are a number of factors driving an increase in United States demand for alternative transportation fuels. Currently, the United States consumes approximately 1131×10^9 L (GL) of petroleum per year, of which 57% is imported (Energy Information Administration Independent Statistics and Analysis, Petroleum basic statistics, 2010, Energy Information Agency, U.S. Department of Energy, available at www.eia.gov/basics/quickoil.html). Of the petroleum consumed, 71% is used for transportation fuels. The U.S. Energy Information Administration (EIA) projects that by 2020 U.S. energy consumption will grow by 50% and our reliance on foreign oil production will increase by 30% by 2030 [*Biomass Research and Development Board* (*BRDB*), 2008]. There are national energy security concerns as worldwide oil demand outpaces growth in global oil supplies and downstream refining capacity, leading to increased market volatility [*U.S. Energy Information Administration Independent Statistics and Analysis* (*USEIA*), 2006]. Furthermore, there are serious concerns about greenhouse gas (GHG) emissions from petroleum-based fuels contributing to climate change and ocean acidification [*Munday et al.*, 2010; *Ormerod et al.*, 2002].

[3] The Energy Independence and Security Act (EISA) was enacted in 2007 to address energy security concerns. EISA established production targets for alternative fuels under the renewable fuels standard (RFS) in recognition that biomass is a domestic source of liquid biofuels that can readily reduce the nation's dependence on imported oil and decrease climate impacts [*U.S. Department of Energy* (*USDOE*), 2010]. Under the RFS there is a requirement to produce 136×10^9 L of renewable fuels by 2022. Of this total, at least 79.5×10^9 L must be "advanced biofuels" that are not sourced from corn ethanol, and life cycle GHG emissions must be reduced by at least 50% compared to petroleum-based transportation fuels [*USDOE*, 2010].

[4] There have been a number of studies estimating water requirements for biomass feedstock production [e.g., *Chiu et al.*, 2009; *Gerbens-Leenes et al.*, 2009; *National Research Council*, 2008; *Wu et al.*, 2009a]. For example, *Wu et al.* [2009a] estimates the irrigation water consumed in farming to produce 1 L of ethanol to range from 7 to 321 L, with an additional 3 L of water consumed in the ethanol production process. The U.S. Geological Survey stopped publishing national consumptive water use statistics after 1995, at which

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time the total U.S. freshwater consumption (i.e., water withdrawn that is evaporated, transpired, incorporated into products and crops, consumed by humans or livestock, or otherwise removed from the immediate water supply) was 379 GL d^{-1} [*Solley et al.*, 1998]. Of this 82%, or 310 GL d^{-1} was used for irrigation [*Roy et al.*, 2005]. Using the last available consumptive water use statistics from the U.S. Geological Survey, the EISA 2022 total renewable fuel target of 136.3 GL of biofuels would require a significant proportion of the water currently consumed for irrigation.

[5] To support achievement of a sustainable biofuels industry and meeting the ambitious RFS goals, a portfolio of "generational" feedstocks are being considered over the near and long term [*BRDB*, 2008].

[6] 1. First-generation feedstocks are currently in large-scale commercial production and include corn-based ethanol and soybean-based biodiesel; however, lessons learned require careful consideration of competition for food-producing lands and environmental impacts on air, water, and soil quality.

[7] 2. Second-generation feedstocks are emerging and focus on cellulosic conversion of residual biomass from crop and forest harvest practices. These feedstocks are thought to have fewer environmental impacts; however, fuel production availability, quantity, and economic viability still need to be evaluated.

[8] 3. Third-generation feedstocks, or "energy crops," are designed exclusively for fuel production and include perennial grasses, some oil seed crops, fast-growing trees, and algae. These crops require further research and development to understand large-scale production potential, logistics, environmental impacts, and economic viability.

1.1. Background

[9] Energy crops are viewed as key to the long-term sustainability of a biofuels industry. Of the energy crops being investigated, microalgae offers several advantages. Microalgae can produce a variety of fuel end products, including hydrogen, hydrocarbons, and methane from the biomass and bioethanol and biodiesel from the algal lipids. It has been shown through numerous studies that microalgae have a much higher biomass yield and lipid content per unit area per unit time than other biomass feedstocks [*Mata et al.*, 2010; *Chisti*, 2007]. For example, numerous algal strains have been shown to produce 20%–50% of their dry weight biomass as lipids, resulting in oil yields of 14,000 L ha^{-1} yr^{-1} [*Mascarelli*, 2009], compared to 172 L ha^{-1} yr^{-1} for corn, 636 L ha^{-1} yr^{-1} for soybean, 974 L ha^{-1} yr^{-1} for canola (rapeseed), and 1070 L ha^{-1} yr^{-1} for sunflower [*Mata et al.*, 2010; *Williams and Laurens*, 2010; *Schenk et al.*, 2008; *Chisti*, 2007; *Sheehan et al.*, 1998]. Depending on the strain, microalgae can be grown using fresh, saline, and/or brackish water that can come from a variety of sources, including traditional surface freshwater sources, pumped groundwater or seawater, treated industrial wastewater, municipal sewage effluent, irrigation return canals, wastewater from poultry or livestock facilities, and produced water generated from oil and gas drilling operations. Clearly, some of these water resources may not be appropriate because of chemical compositions that would be toxic to microalgae; however, microalgae require ammonia and/or nitrates and phosphates as nutrients and could therefore provide significant cobenefits to municipalities, industry, and the environment for what would normally be potentially harmful wastewater [*Mata et al.*, 2010].

[10] An additional nutrient requirement for microalgae is CO_2, which provides potential synergies with other CO_2 capture and GHG reduction technologies. The potential exists for microalgae to contribute to GHG mitigation, to provide a carbon-neutral fuel source, and to biofixate CO_2 produced by power plant and other industrial emissions [*Huesemann et al.*, 2009; *Wang et al.*, 2008; *Chisti*, 2007; *Huesemann et al.*, 2003; *Pedroni et al.*, 2001; *Feinberg and Karpuk*, 1990]. Microalgae have been shown to fixate carbon and convert solar energy to chemical energy at a rate an order of magnitude higher than those of higher-order terrestrial plants [*Wang et al.*, 2008; *Gordon and Polle*, 2007]. Potential sources of high-concentration CO_2 can be harvested from commercial or industrial flue and flare gases produced at electrical generating units; petroleum refineries; and cement, ammonia, hydrogen, and ethanol plants or retrieved through natural underground reservoirs; however, without CO_2 separation processes in place, NO_x, SO_x, and other contaminants found in emission gases have the potential to stress and inhibit biomass growth and lipid content [*Mata et al.*, 2010; *Wang et al.*, 2008; *Feinberg and Karpuk*, 1990]. The biofixation rate of CO_2 will depend on the strain of algae, method of CO_2 injection, and pond conditions such as temperature, light intensity, nutrient concentrations, and pH. Past research indicates that an approximate range of 1.5–3.0 t of CO_2, considering fixation inefficiencies and pond outgassing, is required to produce 1 t of dry algal biomass [*Park et al.*, 2011; *Verma et al.*, 2010; *Wang et al.*, 2008; *Chisti*, 2007; *van Harmelen and Oonk*, 2006; *Ono and Cuello*, 2003].

[11] Outside of the necessary nutrient requirements, microalgae growth is governed by climatic controls on precipitation, solar radiation, humidity, wind, and temperature. These controls exhibit characteristic seasonal and diurnal patterns that vary spatially, often over relatively short distances. Climate also exhibits a stochastic component due to large excursions from mean regional patterns. The timing, sequence, and persistence of these excursions (e.g., prolonged drought) are critical to the performance and sustainability of commercial open pond microalgae production. Studies of microalgae production potential heretofore have used single time-invariant, large-scale values of production per unit area, ignoring important spatial and temporal variations [*Chisti*, 2008]. More recent studies have used a regional-based approach to capture broad climatic differences or have targeted specific locations for analysis [*James and Boriah*, 2010; *Williams and Laurens*, 2010; *Weyer et al.*, 2010].

[12] Microalgae production technology is currently the focus of considerable private and government-funded research around the world. A distinct dividing line in microalgae biofuels cultivation research is the use of open ponds or closed-system photobioreactors. Closed systems are assumed to be less prone to contamination by invasive species, are thought to lose little or no water through evaporation, and can maintain higher temperatures than open ponds during cold periods. While closed systems are the focus of many ongoing research and development projects, in general, they present operational and technological challenges due to overheating, fouling, cost efficiency, and scaling of individual units for large-scale production. Open ponds, specifically mixed raceway-type ponds, are more

economical to construct and operate and can be scaled up to several hectares. Commercial production in open ponds, at least for the nutrient market, has been in place since the early 1950s [*Spolaore et al.*, 2006; *Lee and Shen*, 2004]. While it is recognized that the methods used for nutritional microalgae production and biofuels production are different, open ponds are currently the most economical and feasible approach for nearly all large-scale algal biomass produced commercially throughout the world and thus are the focus of this study. Because microalgae do not require soils for rooting, open pond culture production facilities can and should be developed on land that is otherwise unsuitable for conventional food production or other competing land use, thereby addressing a significant factor realized in first-generation feedstocks.

1.2. Approach

[13] We present a high-resolution national-scale resource and production assessment for algal biofuels produced from open pond facilities. Potential oil production, land resources, and water requirements are simulated using a series of coupled model components developed at a high spatiotemporal scale on the basis of the dominant physical processes affecting algal growth. Land suitable for open pond microalgae production is identified in section 2 using topography and existing land cover data. Physics-based biomass growth and pond temperature models are described in section 3 and then are used with location-specific meteorological and topographic data to estimate potential biofuel production and consumptive water demand in sections 4 and 5. In section 5.1, these production and water use data are compared to other transportation fuels on the basis of water use per kilometer traveled.

[14] Large-scale production of biomass, whether for food or energy, typically requires significant quantities of energy and water in "upstream" processes associated with the production and transportation of fertilizers. In the case of microalgae, the use of off-site CO_2 would add an additional burden. In many cases, upstream water and energy requirements may greatly exceed those associated with on-site feedstock production [*Clarens et al.*, 2010]. As indicated in section 1.1, microalgae have a significant advantage over other energy crops given the potential for synergistic colocation with sources of water and nutrients (including CO_2), greatly reducing upstream lifecycle resource demands and energy costs associated with their production and transport [*Clarens et al.*, 2010; *USDOE*, 2010]. For example, routing or incorporating nutrient-rich municipal wastewater to algae feedstock production provides multiple cobenefits, including the reduction of energy, water, and externally sourced fertilizer consumption, improved water quality through the removal of inorganic nutrients (i.e., nitrogen and phosphorous), production of biofuel feedstock, a reduced environmental footprint, and economic efficiency [*Park et al.*, 2011; *Clarens et al.*, 2010]. Colocation with point-source CO_2 emitters, such as coal-fired power plants, will reduce CO_2 supply costs and can provide a supplemental heat source for maintaining optimal pond temperature. Water and energy consumption associated with on-site feedstock production can also be reduced through recycling of nutrients and on-site energy production (e.g., through biodigester biogas combustion).

[15] Although the suite of models developed and presented here can evaluate the use of alternative water sources, including municipal and livestock-based wastewater streams, produced water, and saline water from seawater and groundwater sources, the analysis presented considers only freshwater. The analysis estimates land and consumptive water use for feedstock production under conditions where water supply, water quality, nutrients, and CO_2 are not limiting. Water demand considers only evaporative loss from the pond; it does not consider water demand to maintain water quality, potential infiltration, or the microalgae biofuels lifecycle beyond feedstock production. We do not consider energy demand associated with feedstock production. Our growth model does not consider supplemental heating of the pond during winter months, and water temperature is calculated through natural surface energy exchange.

[16] Our study provides a necessary step to evaluate the viability of microalgae by providing a detailed screening of required on-site land and water requirements at a high spatiotemporal resolution. Our theoretical maximum and best estimates of open pond microalgae production under conditions of unlimited nutrient and water supply provide a national baseline to indicate whether open pond production has the potential to make a significant contribution to renewable fuels targets and warrants additional research. The high spatiotemporal detail of this work allows optimization based on colocation with existing and future nutrient and CO_2 sources and alternative sources of water; this is a subject of ongoing research.

2. Characterization of Suitable Lands

[17] Potential land resources were assessed using spatial suitability modeling based on multiple facility siting criteria to determine potential land resources [*Sheehan et al.*, 1998; *Maxwell et al.*, 1985]. Explicit considerations are made to consider land use and land cover, environmental and ecological requirements, and topography. Further considerations not addressed in this paper involve evaluating locations and transport of potential water and nutrient sources, location of potential processing facilities, and general transportation infrastructure.

[18] A national geographic information system (GIS) resource database and modeling framework was developed using the highest-resolution, nationally consistent, and most current elevation, vector feature delineations, and remotely sensed Earth systems data allowing for multiscale (i.e., individual site to the nation) spatial analysis including multicriteria spatial suitability modeling and multiparameter spatial optimization (see Table 1). The GIS database and modeling framework enables the determination of suitable land resources throughout the conterminous United States on the basis of user-specified criteria at a high 30 m spatial resolution. In addition, this biomass assessment tool allows for the determination of proper meteorological inputs to drive the mass and energy balance hydrodynamic pond temperature and microalgae growth models at individual open pond facilities (i.e., suitable areas), multiscale visualization, analysis of spatiotemporal patterns of microalgae biofuels production potential and resource requirements, and finally, optimization of high biomass production locations using minimal land and water resources.

[19] For the land suitability analysis, we assume that each open pond microalgae biofuel facility consists of one hundred 30 cm deep, 4 ha ponds requiring about 400 ha of

Table 1. Spatial Data Sources and Descriptions Used in the Nationwide Suitability Analysis

Data Set	Description	Source
30 m digital elevation model	elevation data providing the basis for slope and land suitability analysis	*U.S. Geological Survey* [1999]
Hydrography	surface water delineations including streams, rivers, canals, lakes, and other open water.	*U.S. Geological Survey* [2009]
National Land Cover Database	standardized 25-category land cover classification	*Multi-Resolution Land Characteristics Consortium* [2001]
Impervious surfaces	subset of the National Land Cover Database detailing impervious surfaces	*Multi-Resolution Land Characteristics Consortium* [2001]
Urban area boundaries	delineation of concentrated populations ≥50,000	Geography Division (U.S. Census Bureau, Census 2000 urban and rural classification, http://www.census.gov/geo/www/ua/ua_2k.html)
Federal or state land ownership	federal and state protected areas such as national and state parks and monuments, designated wilderness areas, and wildlife refuges	Earth Science Information Center, U.S. Geological Survey (National Atlas, 2010, http://nationalatlas.gov/maplayers.html) and *Environmental Systems Research Institute* [2008]
National Wetlands Inventory	wetland delineation and classification	U.S. Fish and Wildlife Service (National wetlands inventory, 2010, http://www.fws.gov/wetlands)
Road network	interstate, major highways, secondary highways, and street level data	*Environmental Systems Research Institute* [2008]
Airport locations	point locations of all major or minor airports	*U.S. Bureau of Transportation Statistics* [2010]
Cropland data	cultivated croplands and orchards	*Johnson and Mueller* [2010]
Environmentally protected/sensitive areas	compilation of terrestrial and aquatic protected and environmentally sensitive areas	2009 World Database on Protected Areas [*IUCN*, 2010]
Gridded mean monthly climate	30 year long-term monthly normals for minimum temperature, maximum temperature, dewpoint, and precipitation	Parameter-elevation Regressions on Independent Slopes Model [*Daly et al.*, 2008] and PRISM Climate Group (800m Normals (1971–2000), Oregon State University, http://www.prism.oregonstate.edu/index.phtml)
Climate stations	Point locations of climate stations used in the Cligen model	National Soil Erosion Research Laboratory, Agricultural Research Service, U.S. Department of Agriculture (U.S. Department of Agriculture Cligen stations, 2000, http://www.ars.usda.gov/Research/docs.htm?docid = 18094)

land for ponds and another 90 ha for operational infrastructure. Additionally, the ponds and associated infrastructure are situated on potentially nonsensitive flat land to avoid conflicts with existing land use and to minimize soil excavation and water pumping costs [*Maxwell et al.*, 1985]. *Benemann et al.* [1982] researched the economic factors in using various sloped land and determined that 1% slope would be an upper limit for suitable slope. A 30 m digital elevation model consisting of 43.3×10^9 elevation postings was constructed for the conterminous United States and was used to identify contiguous areas that meet a ≤1% slope criterion. From the suitable slope areas, only nonagricultural, undeveloped or low-density developed, nonsensitive, generally noncompetitive land was considered for microalgal culture facilities. Specifically, this excludes open water, urban areas, airports, cultivated cropland and orchards, federal and state protected areas such as national and state parks, wilderness areas, wildlife refuges, wetlands, and other areas that are deemed environmentally sensitive according to the 2009 World Database on Protected Areas (International Union for the Conservation of Nature, The World Database on Protected Areas (WDPA): Annual release, 2010, available at www.wdpa.org). A spatial grow, shrink, and sieve model was implemented (1) to fill small data holes and to remove artificial striping effects remaining from the digital elevation model–based slope analysis, (2) to eliminate artificially segmented lands, (3) to eliminate "thread corridors" artificially linking discontiguous areas resulting primarily through various transportation corridors, and (4) to include only land areas sized at ≥490 ha to meet the established minimum open pond production facility requirements. This analysis identified 11,588 noncompetitive areas (i.e., potential pond facilities) totaling approximately 430,830 km^2, or 5.5% of the conterminous United States, that are potentially suitable for large-scale open pond microalgae production. In some cases there are small islands of unsuitable land within an otherwise suitable area that exceed the slope or land use and land cover criterion; these areas are specially coded and are eliminated from the analysis. To understand the distribution of land cover types in the resulting suitable lands, an area analysis was conducted using the 2001 National Land Cover Data (NLCD) set [*Multi-Resolution Land Characteristics Consortium*, 2001]. The resulting analysis concludes the following land cover types from largest to smallest area: 42% shrub or scrub, 19% herbaceous, 14% evergreen forest, 10% pastureland, 8% deciduous forest, and 7% other lands including mixed forest, barren, and low-intensity developed. Additional criteria and/or adjustments to parameters in the suitability model are easily made, for example, eliminating additional land cover types, factoring in slightly higher slope areas and/or integrating industrial, commercial, and/or low residential density that lie within urban area boundaries. As a general consideration, it is not conducive to site open ponds within highly populated areas because of space requirements and the high cost of land ownership. Given these stipulations,

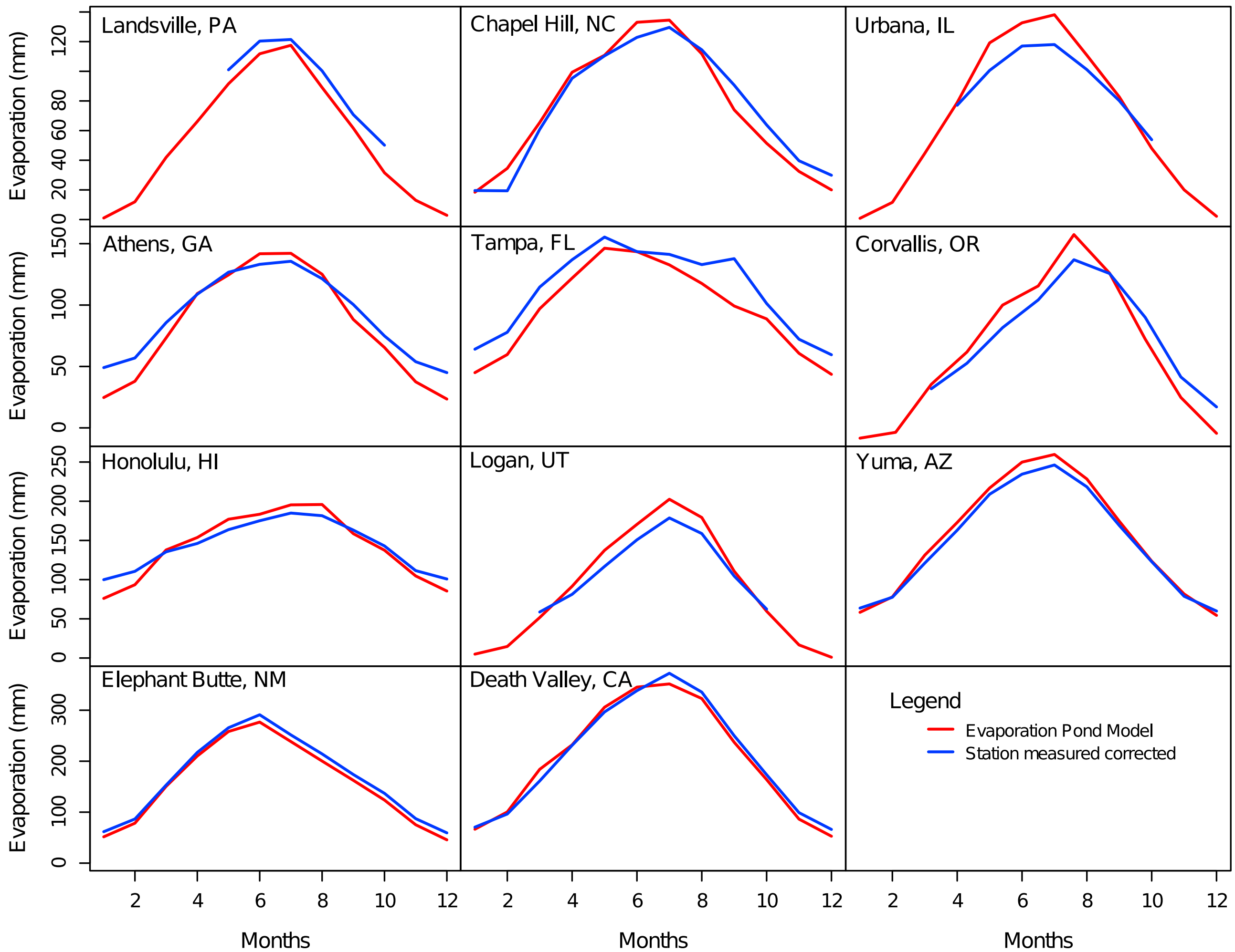

Figure 1. Model-simulated mean monthly evaporation (red) versus corrected pan evaporation data (blue) for 11 stations around the country.

this study did not consider areas within urban area boundaries; however, there may be cases that refute this notion and prove its economic and social viability otherwise. For instance, ponds located within or adjacent to urban areas have the potential to access abundant sources of waste stream nutrients and CO_2 from industrial or commercial processes and could provide a balance of need and use.

3. Biophysical Models

[20] Our approach relies on physics-based modeling to drive high-resolution spatial and temporal analysis that can account for critical threshold events (e.g., wind and temperature) to capture nonlinear dynamics (sensible and latent heat transfer) and can account for antecedent conditions. Physics-based, spatially distributed, coupled water-energy balance models are used with the meteorological and topographic data to generate high-resolution spatial and temporal data sets of land surface water and energy fluxes. These data drive the simplified open pond microalgae growth model discussed in section 3.1.

3.1. Open Pond Microalgae Biomass Growth Model

[21] Algae grow by converting solar energy during photosynthesis to chemical energy storage in the form of oils and other biomass. Following the work of *Zemke et al.* [2010] and *Weyer et al.* [2010], the rate of biomass production (P_{mass} in mass per unit area per unit time) can be expressed as

$$P_{\text{mass}} = \frac{\tau_p C_{\text{PAR}} \varepsilon_a E_s}{E_a}, \qquad (1)$$

where E_s is the full-spectrum solar energy at the land surface (MJ m^{-2}), C_{PAR} is the fraction of photosynthetically active radiation (PAR), τ_p is the transmission efficiency of incident solar radiation to the pond microalgae, ε_a is efficiency by which algae convert photons to biomass, and E_a is the energy content per unit biomass (MJ kg^{-1}). The assimilated biomass energy content is given by [*Zemke et al.*, 2010]

$$E_a = f_l E_l + f_{\text{pr}} E_{\text{pr}} + f_c E_c, \qquad (2)$$

where f_l, f_{pr}, f_c and E_l, E_{pr}, E_c represent the fraction and energy content of lipids, proteins, and carbohydrates, respectively. The fraction of photosynthetically active radiation is approximately 0.43–0.46 [*Weyer et al.*, 2010; *Zemke et al.*, 2010], and representative energy contents E_l, E_{pr},

Table 2. Open Pond Microalgae Biomass Growth Model Parameters for Theoretical Maximum and Current Technology Cases

Term	Theoretical Maximum Case	Current Technology Case	Units
τ_p	0.95[a]	0.90[a]	
C_{PAR}	0.46[b]	0.46[b]	
E_a	38[a]	21.7	MJ kg^{-1}
E_p	0.2253[b]	0.2253[b]	MJ mol^{-1}
Q_r	8[b]	8[b]	mol mol^{-1}
E_c	0.4825[b]	0.4825[b]	MJ mol^{-1}
ε_b	1.0[b]	0.80	
ε_p	1.0	equations (4), (5), (6)	
ρ_{oil}	0.92[a]	0.92[a]	kg L^{-1}
f_{oil}	1.0	0.20	

[a]*Zemke et al.* [2010].
[b]*Weyer et al.* [2010].

and E_c are 16.7, 15.7, and 37.6 MJ kg^{-1}, respectively [*Weyer et al.*, 2010].

[22] The photoconversion efficiency is composed of several terms [*Weyer et al.*, 2010]:

$$\varepsilon_a = \frac{E_c \varepsilon_p \varepsilon_b}{Q_r E_p}, \tag{3}$$

where the photon energy E_p (MJ mol^{-1}) converts PAR as energy to the number of photons and ε_p accounts for reductions in photon absorption due to suboptimal light and water temperature. The quantum requirement Q_r is the number of photons required to liberate one mol of O_2 and together with the carbohydrate energy content E_c represents the conversion of light energy to chemical energy through photosynthesis [*Weyer et al.*, 2010]. The quantum requirement is 8–10 (mol mol^{-1}) with E_c approximately equal to 0.48 MJ mol^{-1} [*Weyer et al.*, 2010]. The biomass accumulation efficiency ε_b is a poorly understood function of species, water temperature, and other growing conditions accounting for energy required for cell functions that do not produce biomass (e.g., respiration).

[23] Under suboptimal light and water temperature conditions some of the absorbed photons will cause cell damage or will be reemitted as heat [*Weyer et al.*, 2010]. We express this reduction in photon absorption by

$$\varepsilon_P = \varepsilon_S \varepsilon_t. \tag{4}$$

The light utilization efficiency ε_S, including light saturation and photoinhibition, was modeled using the Bush equation [*Huesemann et al.*, 2009]:

$$\varepsilon_S = \frac{E_S}{S_o}\left(\ln\left(\frac{S_o}{E_S}\right) + 1\right), \tag{5}$$

with E_s in μmol m^{-2} and a light saturation constant S_o of 150 μmol m^{-2} s^{-1} [*Chisti*, 2007; *Huesemann et al.*, 2009].

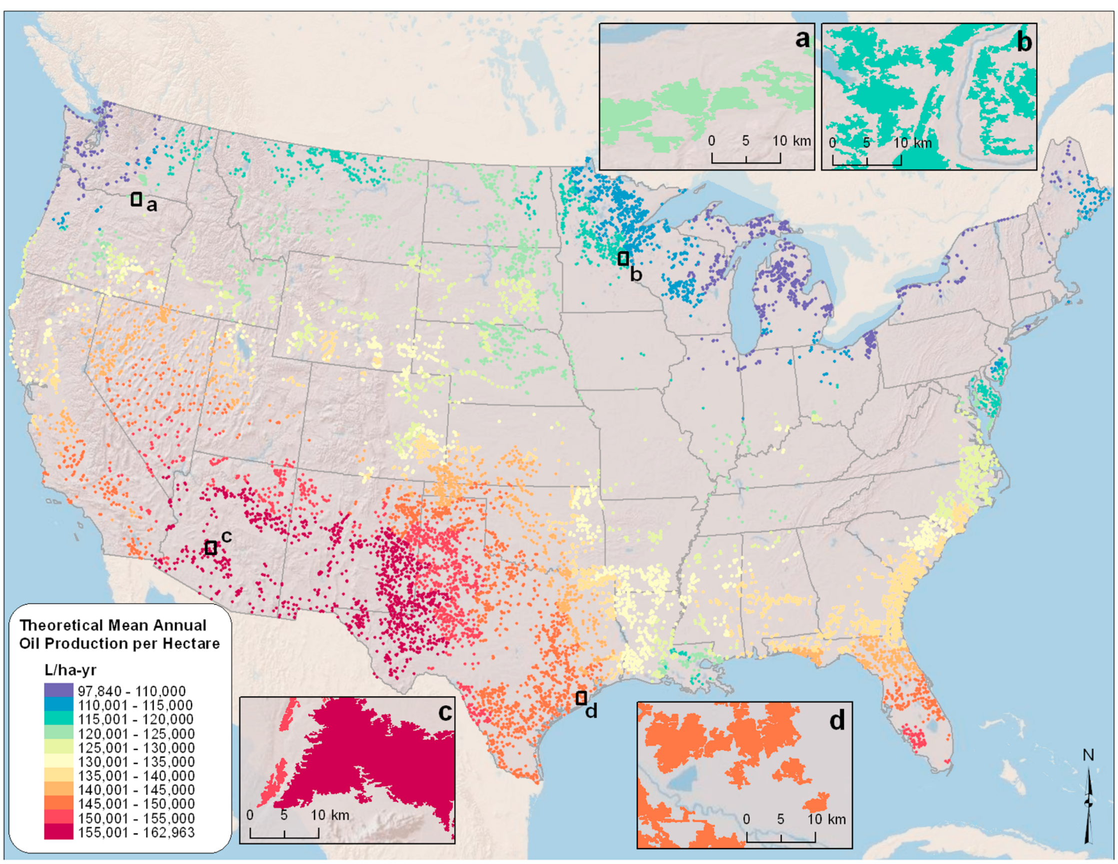

Figure 2. Mean annual theoretical maximum biofuel production (L ha^{-1} yr^{-1}) plotted at the centroid of each pond facility. Insets illustrate underlying detail at the pond facility (490 ha) scale.

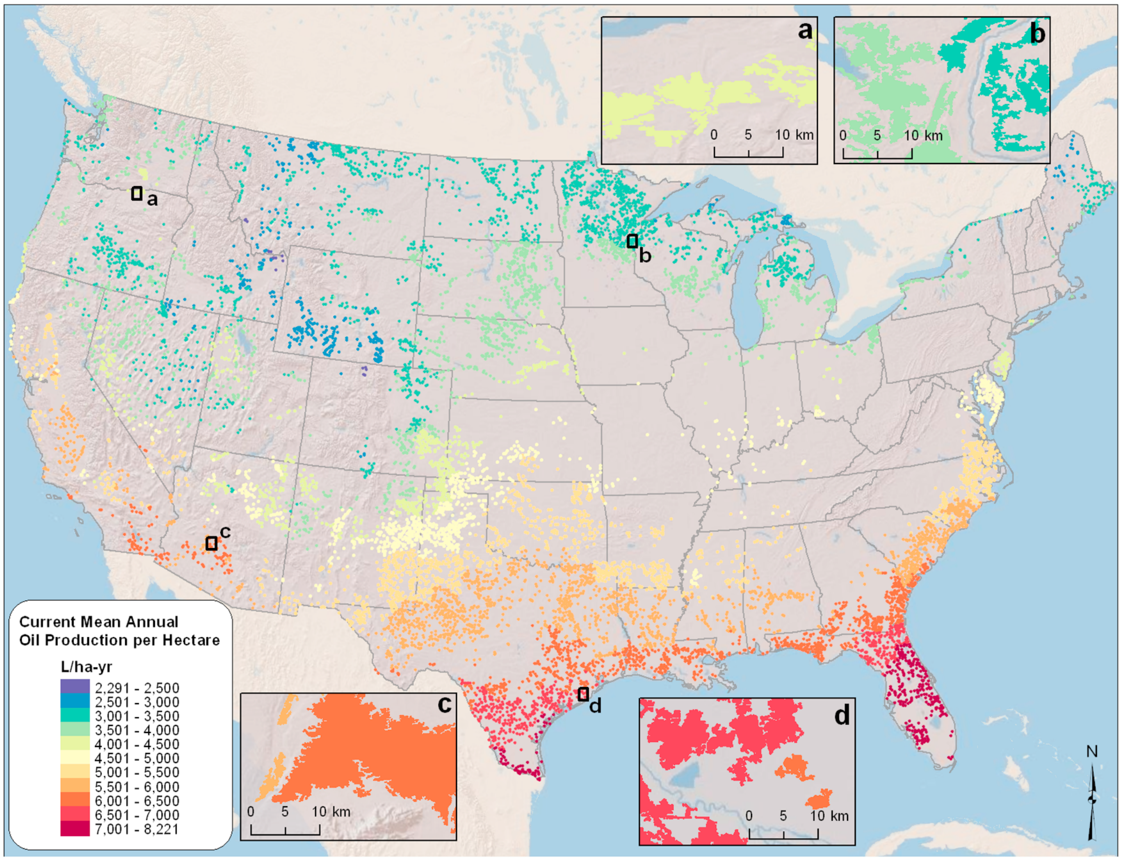

Figure 3. Mean annual biofuel production (L ha^{-1} yr^{-1}) under current technology plotted at the centroid of each pond facility.

[24] The correction for water temperature ε_t in equation (4) is given by

$$\begin{array}{lll} 0 & \text{for} & T < T_{\min} \\ (T - T_{\min})/(T_{\text{opt\_low}} - T_{\min}) & \text{for} & T_{\min} \le T \le T_{\text{opt\_low}} \\ \varepsilon_t = 1.0 & \text{for} & T_{\text{opt\_low}} \le T \le T_{\text{opt\_high}} \\ (T_{\max} - T)/(T_{\max} - T_{\text{opt\_high}}) & \text{for} & T_{\text{opt\_high}} \le T \le T_{\max} \\ 0 & \text{for} & T > T_{\max}, \end{array} \tag{6}$$

where $T_{\min}$ is the minimum water temperature for zero productivity (°C), $T_{\text{opt\_low}}$ is the lower water temperature for optimal productivity (°C), $T_{\text{opt\_high}}$ is the upper water temperature for optimal productivity (°C), and $T_{\max}$ is the maximum water temperature for zero productivity (°C).

[25] The optimal pond water temperature for growing microalgae varies by strain and is the subject of continuing research. The literature suggests that optimal temperatures are generally between 20°C and 35°C [*Chisti*, 2007; *Sheehan et al.*, 1998]. Many microalgae can easily tolerate temperatures as much as 15°C lower than their optimal, but exceeding the optimal temperature by 2°C–4°C can cause total culture loss [*Mata et al.*, 2010]. To provide a conservative estimate, we set $T_{\min}$ = 10°C, $T_{\text{opt\_low}}$ = 20°C, $T_{\text{opt\_high}}$ = 30°C, and $T_{\max}$ = 35°C.

[26] The oil volume per unit area is given by

$$P_{\text{oil}} = \frac{f_{\text{oil}} P_{\text{mass}}}{\rho_{oil}}, \tag{7}$$

where f_{oil} is the lipid fraction of biomass suitable for biofuel production and ρ_{oil} is its density (0.92 kg L^{-1}).

3.2. Open Pond Water Temperature Model

[27] An unsteady, two-dimensional hydrodynamic and water quality model, the Modular Aquatic Simulation System 2-D (MASS2) [*Perkins and Richmond*, 2004], was used to estimate water temperature and evaporative water loss at the pond facility scale. The model uses a structured multiblock, curvilinear computational mesh to represent the channel geometry. Finite volume methods [*Patankar*, 1980] are used to discretize and solve the conservation equations for mass, momentum, and water quality constituents.

[28] Water temperature in the ponds is computed by MASS2 using the following depth-averaged equation that is derived by applying the principle of conservation of energy to a fluid volume:

$$h_1 h_2 \frac{\partial(dT)}{\partial t} + \frac{\partial(h_2 dUT)}{\partial \xi} + \frac{\partial(h_1 dVT)}{\partial \eta} = \frac{\partial}{\partial \xi}\left(h_2 \frac{\varepsilon_1}{h_1} d \frac{\partial T}{\partial \xi}\right) + \frac{\partial}{\partial \eta}\left(h_1 \frac{\varepsilon_2}{h_2} d \frac{\partial T}{\partial \eta}\right) + \frac{h_1 h_2 H}{\rho c_v}, \tag{8}$$

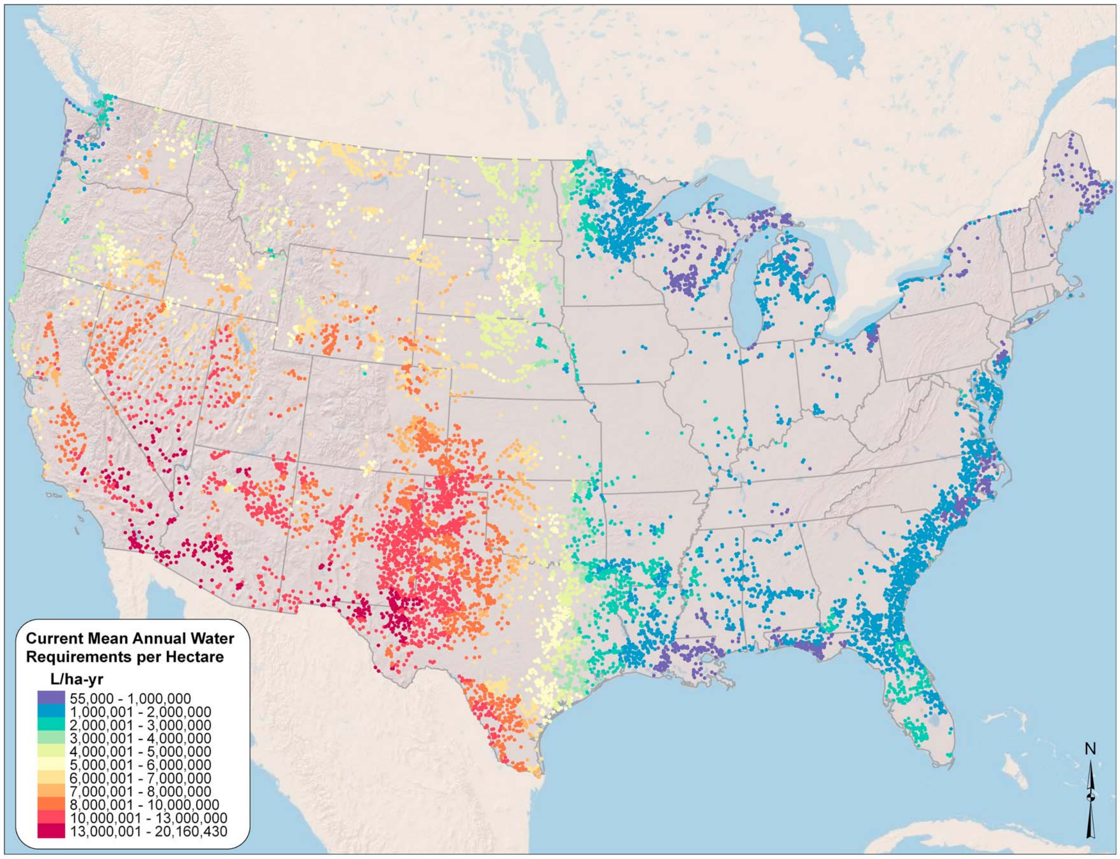

Figure 4. Mean annual water requirements (L ha^{-1} yr^{-1}) for microalgae biofuels production using current technology plotted at the centroid of each pond facility.

where T is the depth-averaged water temperature (C^o) used in equation (6), d is the water depth (m), U is the depth-averaged velocity in the ξ direction, V is the depth-averaged velocity in the η direction, H is the net surface heat flux at the water surface (W m^{-2}), ρ is the water density, c_v is the specific heat of water (J kg^{-1} per degree Celsius), h_1 and h_2 are curvilinear grid metric coefficients in the ξ and η directions, and ε_1 and ε_2 are the turbulent eddy diffusion coefficients in the ξ and η directions.

[29] Heat exchange at the water surface is computed as the net heat flux, given by [*Perkins and Richmond*, 2004]

$$H = H_{sn} + H_a - (H_b + H_e + H_c), \tag{9}$$

where H is the net surface heat flux (W m^{-2}), H_{sn} is the net solar shortwave radiation ($\tau_p E_s$ in equation (1)), H_a is the net atmospheric longwave radiation, H_b is the longwave back radiation, H_e is the heat flux due to evaporation, and H_c is the heat flux due to conduction.

[30] Evaporative water loss (E) is given by

$$E = H_e/(\rho\lambda_v), \tag{10}$$

where λ_v is the latent heat of vaporization. Evaporative loss (through latent heat transfer) is a highly nonlinear process driven by local meteorological conditions and pond characteristics. These water-energy interactions are simulated in detail by the open pond temperature model, which provides hourly evaporative loss through equation (10). Evaporative losses determined by the open pond temperature model were compared to 11 pan evaporation stations throughout the country representing a range of climatic conditions. The results of the 11 stations are presented in Figure 1. The open pond temperature model simulated evaporation is generally in good agreement with corrected pan evaporation measurements. These results show the impact of local climate on evaporative water loss, ranging from a high 350 mm month^{-1} in Death Valley, California, down to a high of 120 mm month^{-1} in Landisville, Pennsylvania. Seasonal patterns are also evident, with Honolulu, Hawaii, and Tampa, Florida, showing more uniform seasonal loss than northern sites such as Urbana, Illinois, and Landisville, Pennsylvania.

3.3. Meteorological Inputs

[31] A major obstacle in the use of high spatiotemporal resolution, physics-based models is the lack of sufficient and readily available meteorological data at the appropriate scale. To address this issue, the current study used the following approach to develop a database of spatially based, 30 year, hourly meteorology at potentially suitable land areas or pond facilities across the United States: (1) the U.S. Department of Agriculture Cligen stochastic weather generator [*Meyer et al.*, 2008; *Nicks et al.*, 1993; *Nicks and Lane*, 1989] was used to produce a 30 year record of daily estimates of precipitation, temperature, dewpoint, wind, and incident solar radiation (E_s) at approximately 2600 locations around the United States using the model's parameter database;

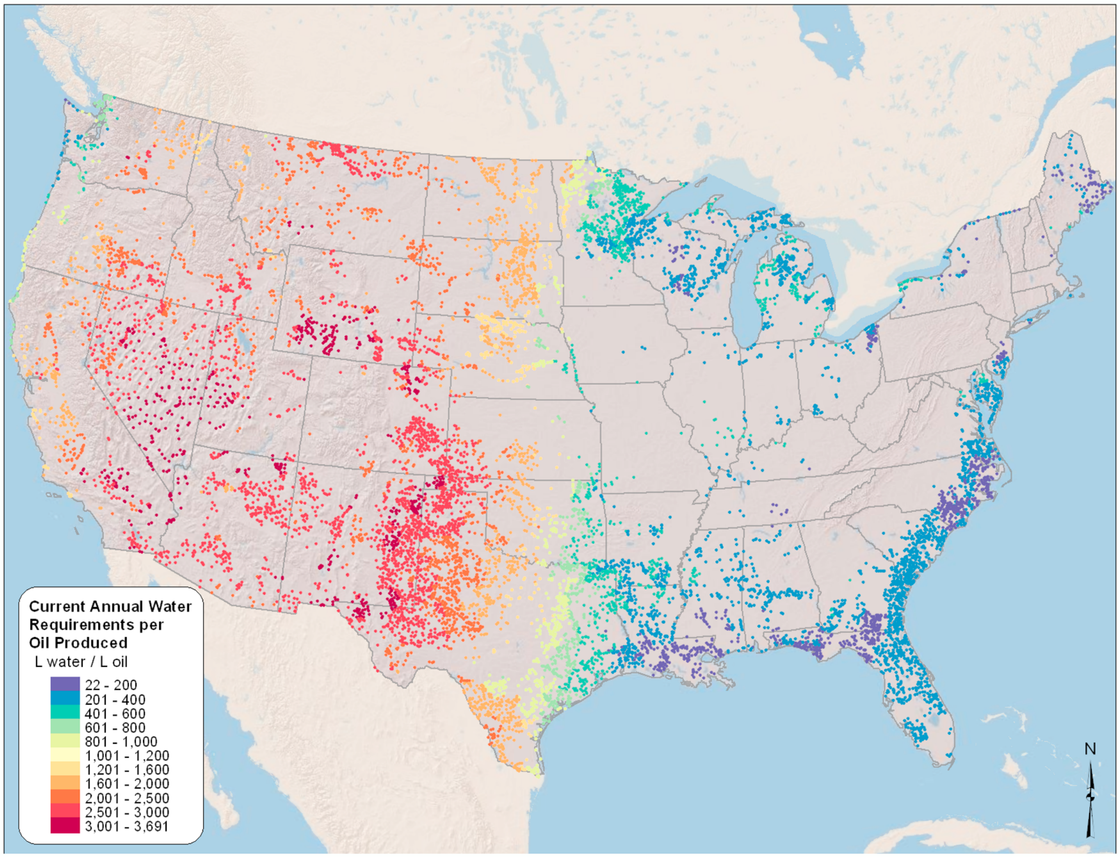

Figure 5. Mean annual microalgae biofuel water requirements per liter of biofuel produced plotted at the centroid of each pond facility.

(2) the daily time series was disaggregated to hourly values using the physics-based approach of *Waichler and Wigmosta* [2003]; and (3) using the adaptive landscape classification procedure [*Coleman*, 2009] on the long-term mean monthly Parameter-Elevation Regression on Independent Slopes Model (PRISM) [*Daly et al.*, 2008; *Di Luzio et al.*, 2008] data set, it was possible to classify the spatiotemporal data signatures and assign meteorological inputs to the pond temperature model from the most representative, not necessarily the closest, Cligen station for each pond facility.

4. Biofuel Production Potential

[32] The open pond water temperature and microalgae biomass growth models were applied to 11,588 pond facilities located throughout the conterminous United States assuming a 30 cm deep open pond. There is significant uncertainty in the biophysics of microalgae growth, particularly processes associated with the conversion of incoming solar radiation to biomass and determining these conversions for many different algal strains. Thus, we present results for both perfectly efficient algae, to define a theoretical maximum production potential, and results for production under current technology using our best estimates of biomass growth parameters (see Table 2). Biomass growth model parameters for these two scenarios are presented in Table 2.

4.1. Theoretical Maximum Algae Production

[33] The product $\tau_p C_{\mathrm{PAR}} \varepsilon_a$ in equation (1) represents the fraction of incoming solar radiation utilized in biomass production. The transmission coefficient τ_p is at most 0.95, and C_{PAR} is approximately 0.43–0.46 [*Zemke et al.*, 2010; *Weyer et al.*, 2010]. Regarding ε_a, reasonable values for E_p, Q_r, and E_c in equation (3) are 0.2253 MJ mol^{-1}, 8 mol mol^{-1}, and 0.4825 MJ mol^{-1}, respectively [*Weyer et al.*, 2010]. For the theoretical case of perfectly efficient algae, both ε_p and ε_b are set equal to 1.0. Using these values in equations (1) and (2) indicates that perfectly efficient algae can convert at most 11% of the available solar energy into biomass. This is in general agreement with *William and Laurens*' [2010] conclusion that the maximum conversion efficiency is approximately 10%.

[34] For the hypothetical calculation of perfectly efficient algae, only lipids for biodiesel are being converted, $f_{\mathrm{oil}} = 1.0$ and $E_a = E_l = 38$ MJ kg^{-1} with a density of 0.92 kg L^{-1} [*Zemke et al.*, 2010]. We assume a vegetable oil to biofuel conversion efficiency of 80% [*Chisti*, 2007]. The pond temperature and algal growth models were driven by 30 years of site-specific stochastic weather data. As expected, algae biomass and oil production varied in time and space as a function of incident solar radiation at the ground surface (Figure 2), with a 30 year national mean of 50.3 g m^{-2} d^{-1} biomass production and 133,054 L ha^{-1} yr^{-1} of biofuel. Theoretical maximum biofuel production ranges from 97,000–125,000 L ha^{-1} yr^{-1} in the northern latitudes to 140,000–165,000 L ha^{-1} yr^{-1} in the southwest and Florida. The correlation with latitude is not exact because of the effects of local meteorology, particularly the influence of clouds on solar radiation received at the ground surface.

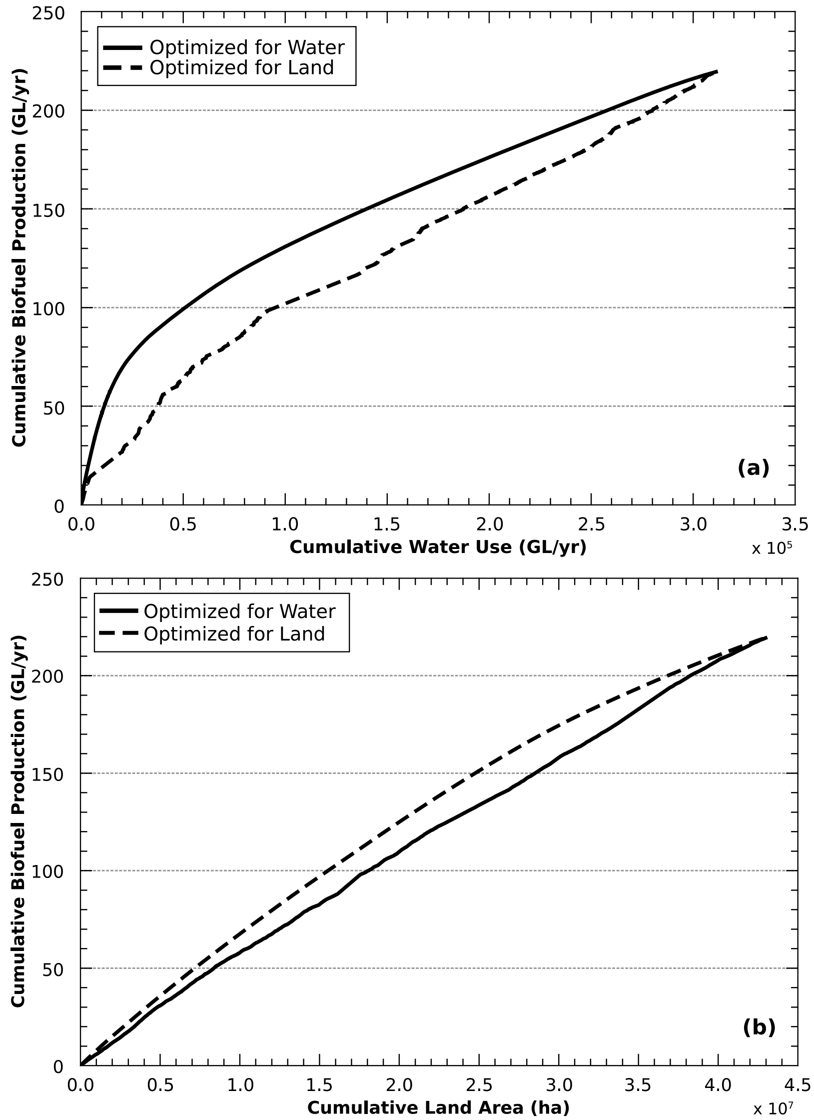

Figure 6. Annual cumulative biofuel production as a function of (a) cumulative water use and (b) cumulative land use. The solid line is based on pond facilities sorted from lowest to highest in water use (L water per liter biofuel). The dashed line is based on pond facilities sorted from lowest to highest in land use (ha land per liter biofuel).

4.2. Algae Production Using Current Technology

[35] The biomass growth model was run using our best estimate of microalgae efficiencies and lipid contents as published in current literature, and parameter values are presented in the third column of Table 2. The biomass accumulation efficiency ε_b was reduced to 80%, ε_p was calculated through equations (4)–(6) to account for the influence of light and water temperature on photon utilization, and the lipid content usable for biofuel production was reduced to 20%, which resulted in a corresponding reduction of E_a to 21.7 MJ kg^{-1}.

[36] The average conversion efficiency of total solar energy to organic mass drops from the theoretical value of 11% to 1.15%, which is consistent with *Williams and Laurens*' [2010] estimate of 1%–3% for observed yields. As expected, biomass production varied in time and space with a 30 year national mean of 8.7 g m^{-2} d^{-1}. The maximum biomass production of 15.8 g m^{-2} d^{-1} is consistent with large-scale commercial productivities of 10–20 g m^{-2} d^{-1} [*USDOE*, 2010]. We calculated a national mean annual vegetable oil production rate of 5775 L ha^{-1} yr^{-1} (4620 L ha^{-1} yr^{-1}of biofuel considering the 80% conversion efficiency). This conservative estimate is well below published values for current production of 14,000 L ha^{-1} yr^{-1} [*Mascarelli*, 2009] and "best case" estimates of 37,000–53,000 L ha^{-1} yr^{-1} [*Weyer et al.*, 2010]; laboratory and theoretical maximum values range up to 136,900 L ha^{-1} yr^{-1} [*Mata et al.*, 2010; *Weyer et al.*, 2010]. The assessment framework can readily incorporate more accurate information on specific algae strains, environmental conditions, and downstream lifecycle processes as they become available. For example, the efficiency of oil extraction is an area of active research, assuming that an efficiency of 80% would reduce our production estimates by 20%.

Table 3. Water Intensity of Transportation Showing Mean and Range for Selected Transportation Fuels[a]

Fuel	Water Use[a]
Conventional petroleum gasoline[b,c]	(0.17–0.70)
Oil sand gasoline[c]	(0.24–0.70)
Electric plugin[b]	0.56
Corn ethanol[c]	(1.41–49.4)
Ethanol (E85) corn grain[b]	65.86 (3.06–145.84)
Ethanol (E85) corn stover[b]	44.70 (6.11–108.21)
Switch grass or forest-wood residue[c]	(0.24–1.41)
Soy biodiesel[b]	18.82 (1.41–56.46)
Microalgae, 50 GL yr^{-1}[d]	20.78
Microalgae, 79.5 GL yr^{-1} EISA target	32.08
Microalgae, 100 GL yr^{-1}[d]	46.70
Microalgae, 150 GL yr^{-1}[d]	87.74
Microalgae, 200 GL yr^{-1}[d]	118.13

[a]Units are L per kilometer driven. Range is given in parentheses.
[b]*King and Webber* [2008] for feedstock production and processing into fuel.
[c]*Wu et al.* [2009b] for feedstock production and processing into fuel.
[d]This study for feedstock production only.

[37] National patterns of microalgae biofuel production from algae show an expected strong linkage to climate, which in turn is tied to patterns of time, elevation, topography, and latitude (Figure 3). Evaluating annual patterns at the national scale, the low-elevation southern portions of the United States exhibit the highest production rates, ranging from 6000 to 8000 L ha^{-1} yr^{-1} of potential biofuel production. These areas are characterized by relatively warm year-round temperatures and additional hours of solar insolation over more northerly locales. Higher elevation and northern tier locations exhibit the lowest production rates, ranging from 2000 to 4000 L^{-1} ha^{-1} yr^{-1}. These areas exhibit a long winter season and thus a shorter growing season. The total production potential of all 430,830 km^2 of suitable (i.e., nonagricultural, noncompetitive, nonsensitive) land in the conterminous United States is 220 GL yr^{-1}, which is equivalent to nearly 48% of the U.S. petroleum imports required to meet transportation demand during 2008 (USEIA, Petroleum basic statistics, 2010, available at www.eia.gov/basics/quickoil.html).

5. Consumptive Water Use

[38] Microalgae must compete with multiple uses for both land and water. Previous estimates of microalgae water demand are typically based on the difference in large-scale estimates of mean annual or mean monthly precipitation and pan evaporation. These estimates ignore smaller-scale variations in the meteorology and frequency and persistence of extreme events such as drought, monsoons, and hurricanes. Our hourly open pond algae growth model is operated so that the water depth in the open pond can fluctuate over a limited range and the pond can thus store additional water when precipitation exceeds pond evaporation for later use when hourly evaporation exceeds precipitation. Water demand is defined as the amount of water required to keep the pond water depth from falling below 25 cm. Water demand is greatest in the western United States (Figure 4), exhibited by higher rates of evaporation, generally ranging from 4 to 21 ML ha^{-1} yr^{-1}, compared to the eastern United States, which ranges from <1 to 4 ML ha^{-1} yr^{-1}.

[39] Irrigated agriculture represents by far the largest consumptive use of freshwater in the United States with 113,135 GL yr^{-1} in 1995 [*Roy et al.*, 2005; *Solley et al.*, 1998]. If all 430,830 km^2 of land potentially available for microalgae production were used, the total freshwater consumptive demand to satisfy evaporative loss would be 312,079 GL yr^{-1}, which is 2.75 times the amount of water consumed nationally through irrigated agriculture, averaging 1421 L of water per liter of oil produced. One approach to minimize both the land and freshwater footprints of biofuel production is to preferentially select available land with the lowest water use per liter of biofuel produced. This favors locations around the Gulf Coast, most of the eastern seaboard, and areas adjacent to the Great Lakes (Figure 5). While these locations are favorable in their freshwater consumption requirement, considerations must be made for local and regional water availability and demand now and into the future.

[40] Cumulative biofuel production as a function of cumulative land and water use is presented in Figure 6. The solid line is based on pond facilities sorted from lowest to highest in water use per liter of biofuel to minimize water use. The dashed line is based on pond facilities sorted from lowest to highest in land use per liter of biofuel to minimize land use. By selecting land to minimize water use (Figure 6a), the EISA "advanced biofuels" renewable fuel target of 79.5 GL yr^{-1} would require about 28,000 GL of consumptive water use per year, a volume equivalent to 25% of the water consumed in irrigated agriculture [*Roy et al.*, 2005]. Compared to the average water use for all suitable land (1421 L water per liter oil), this represents a 75% reduction in water demand to 350 L of water per liter of oil produced and a 67% reduction in land use. Optimizing to reduce the land footprint (Figure 6b), regardless of water use, decreases the land area by less than 20% compared to optimization based on water use efficiency. However, optimizing to reduce the land footprint increases consumptive water use 3.3, 2.5, and 1.3 times for cumulative biofuel production rates of 50, 79.5 (EISA "advanced biofuels" renewable target), and 250 GL yr^{-1}, respectively.

5.1. Water Intensity of Transportation Fuels

[41] Recent studies by *King and Webber* [2008] and *Wu et al.* [2009b] compare alternative fuel types on the basis of water use intensity, the amount of water consumed in fuel production per unit distance traveled. Their results are presented in Table 3 along with our estimates for microalgae based on optimization to minimize water use. *King and Webber* [2008] and *Wu et al.* [2009b] include water consumption in feedstock production and processing into biofuel, whereas our results are for feedstock production only. Despite this difference, it is apparent that biologically based transportation fuels, including algae, generally consume significantly more water than conventional petroleum-based gasoline or electric plug-in vehicles. The water intensity of biologically based transportation fuels becomes even more apparent when compared to the daily per capita domestic indoor water use of 262 L.

6. Summary and Conclusions

[42] Our results demonstrate the value and insights gained from considering multiple resource constraints at a high spatial and temporal resolution when assessing the national potential for algal biofuel production using open pond

systems. Assuming that the numerous technical challenges to achieving commercial-scale algal biofuel production can be met, the results presented here suggest that adequate land and water are available to meet a significant portion of the U.S. renewable fuel goals. Locations in the Gulf Coast region are the most favorable in terms of both land and freshwater demand. Although additional land with relatively high production potential is available, availability of water is likely to be a limiting constraint in these locations. Moreover, the next step in assessing sustainable water resources availability is to explicitly consider current and future competing water demands, both freshwater and saline, for other biofuels, agriculture, withdrawals for thermoelectric cooling, etc. This study represents a necessary step in quantifying the U.S. potential for microalgae-based energy production that captures where to site facilities, how much land and water resources are used, and the amount of oil produced. However, additional resource and economic constraints must also be considered, including availability of nutrients, land cost and local regulations, feedstock processing logistics, and transportation infrastructure.

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