Regionalized life-cycle water impacts of microalgal-based biofuels in the US

David Quiroz[a], *Jonah M. Greene*[a], *Jason C. Quinn*[a]*

[a]Mechanical Engineering Department, Colorado State University, 1374 Campus Delivery, Fort Collins, Colorado 80522, United States

*Email: jason.quinn@colostate.edu

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ABSTRACT. While algal biofuels have the potential to reduce the national reliance on fossil fuels, the high water consumption associated with algal biomass cultivation represents a major concern compromising the sustainable commercialization of this technology. This study focuses on quantifying the water footprint (WF) and water scarcity footprint (WSF) of renewable diesel derived from algal biomass and provides insights into where algal cultivation is less water-intensive than traditional ethanol and biodiesel feedstocks. Results are generated with an engineering process model developed to predict the life cycle water consumption, considering green, blue, and gray water, of algae facilities across the United States at a high spatiotemporal resolution. The model predicts average blue WFs of 1.6 and 14.9 m^3 GJ^{-1} in Florida and Arizona, respectively. When total WFs are compared, the total WF in Arizona is 26% larger than that of Florida, with dramatic differences between blue and green WFs locations. The analysis reveals

that the total life cycle WFs of algal renewable diesel are smaller than the optimal WFs of corn ethanol and soybean biodiesel. Algal systems benefit from higher growth rates and offer the opportunity to manage wastewater streams, therefore generating smaller green and gray WFs than those of conventional biofuels. The WSF analysis identifies the Gulf Coast as the most suitable region for algal cultivation, with cultivation in the western US shown to exacerbate local water stress levels.

1. Introduction

Microalgae-derived fuels are perceived as promising alternatives to decarbonizing the transportation sector. As a third-generation biofuel, cultivation of algal biomass does not compromise food security and multiple algae species possess higher photosynthetic efficiencies and generate greater oil yields than terrestrial energy crops [1,2]. In addition, algae-to-fuel pathways have the potential to generate a variety of high-value co-products, which could potentially improve the economics of algae systems, while concurrently reducing greenhouse gas emissions [3]. However, additional research and development are required not only to reach economic parity with conventional fuels but also to understand the local and regional environmental impacts of commercial-scale algal biofuel production.[3]

Although there are multiple life-cycle assessments (LCA) focused on algal biofuels in the literature, the lack of freshwater consumption impacts represents a major research gap in the field.[3] Understanding the added water demand that algal cultivation will have on local water sources is paramount to avoid future water-related risks, particularly when the cultivation of algal biomass is envisioned to be deployed in locations that are experiencing considerable water shortages such as the southwest United States (US).[4] Water consumption is often measured using

a water footprint (WF) methodology, where the WF of a product is the sum of direct and indirect water consumption.[5] More recently, a new method to assess the water scarcity footprint (WSF) of a product has been proposed by the Water Use in LCA (WULCA) research group.[6] The Available Water Remaining (AWARE) is a consensus-based model used to determine a WSF based on a characterization factor that quantifies water availability and demand in a specific region over a set timeframe.[7]

In previous assessments, the water consumption of algal systems has been estimated using the discussed methods. However, studies often employed one method exclusively resulting in either a WF[8–13] or WSF accounting[14,1] and fail to provide a complete assessment of the water impacts. Previous studies do not account for geographic considerations or are restricted to a few locations.[8,10,13,16] In addition, multiple studies do not use a life-cycle assessment framework and neglect water consumption of upstream processes or the direct consumption of the conversion to fuel process[8,11,14,17], which underestimates the total water consumption of the algae to fuels process.[10,18] More importantly, quantifying the contribution of rainwater to the water footprint of algal systems is important to make an objective comparison to terrestrial crops. An accurate water balance requires models able to calculate evaporation rates at a high spatiotemporal scale[11] and careful tracking of algal pond depth to avoid culture dilution caused by high precipitation rates.[8] Wigmosta et al.[17] is the only study that includes rainwater in water balance calculations, however, the evaporation model used in the analysis was validated with small-scale pond data and was not designed to estimate the evaporation rates of commercial-scale systems accurately.[11] This is critical as evaporation rates not only impact water balances but also propagate to temperature and growth rate calculations.[11] The WF of algal systems has not been clearly defined

64 in the literature due to a lack of appropriate models and incorrect modeling assumptions or
65 methodological inconsistencies.
66 This study focuses on estimating the WF and WSF of renewable diesel derived from algal
67 biomass by integrating water life cycle assessment methodologies with a robust dynamic
68 cultivation model. This work builds upon previous modeling work[11] with novel aspects including
69 a thorough investigation of the impacts of water recycling, rainwater, and indirect water
70 consumption on the WF of the system. By using the high-fidelity model validated by Quiroz et
71 al.[11], the impacts of system scale on evaporation rates and consequently on water consumption,
72 pond temperatures, and growth rates are accurately modeled. In addition, ~~Results from the model~~
73 ~~provide freshwater and rainwater consumption of the biomass production process with a high~~
74 ~~spatial and temporal resolution that is. Furthermore,~~ the cultivation model was coupled with a
75 state-of-the-art conversion model[19] to analyze the direct and indirect water consumption of the
76 biomass-to-fuel process. The local water scarcity impacts associated with the deployment of
77 commercial-scale algal biofuel systems across the US are also investigated. When integrated, the
78 models provide a geospatial analysis of the life cycle WF, including blue, green, and indirect
79 WFs, and WSF of the algae to renewable diesel process. Results identify the most water-
80 intensive processes in the algae-to-fuel pathway, compare the magnitudes of direct and indirect
81 water consumption, and illustrate the most suitable locations for algae fuel production based on
82 water consumption impacts. The discussion focuses on comparing these results to the water
83 intensity of saline algal cultivation and traditional biofuel systems. ~~feedstocks and biofuels~~. This
84 is the first work to complete a holistic life cycle water assessment and water scarcity evaluation
85 for the entire US of an algal-based biorefinery.

2. Methods

This study assesses the geographically resolved water consumption of algal biofuels through two different water LCA methodologies. Both are informed by mass and energy balances calculated from an engineering process model encompassing the geographically resolved biomass cultivation, dewatering, and fuel conversion stages, as shown in Figure 1. The following subsections provide detailed descriptions of the cultivation (including the growth model), conversion, and water LCA methods adopted in this study.

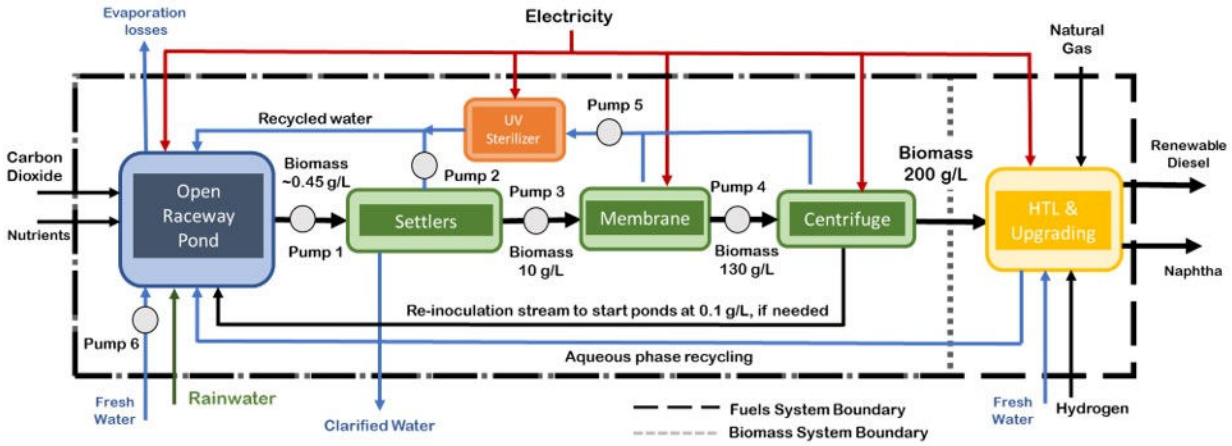


Figure 1. System diagram illustrating the microalgae cultivation process in open-raceway ponds, three-step dewatering process, and conversion and upgrading to renewable diesel through hydrothermal liquefaction (HTL) and hydrocracking.

2.1 Cultivation Model

The cultivation model used in this analysis includes the biomass growth process in commercial-scale open-raceway pond (ORP) systems followed by a three-step dewatering process consisting of settlers, membranes, and centrifuges. Detailed descriptions of these modules are provided in the following subsections.

2.1.1 Open-Raceway Pond Model

ORPs have been the most studied algae growth architecture in the literature due to their low cost and simplicity. Given the open nature of these systems, ORPs are subjected to the changing

conditions of the environment, therefore, models with hourly timescales are required to accurately simulate pond conditions. Thermal conditions in the ORP system were calculated using the model validated by Quiroz et al.[11], while growth rates were simulated using the dynamic growth model validated by Greene et al.[20] Temporally and spatially resolved outputs for a 400-hectare facility cultivating the strain UTEX 393 were generated following the framework in previous modeling work with results presented in the Supporting Information (SI).[11]

The foundational model from Quiroz et al.[11] was modified to include precipitation data to model realistic pond operations. Daily precipitation data for 21 years, retrieved from the Center for Hydrometeorology and Remote Sensing database, was disaggregated into hourly time steps and included in the water balance.[21] The depth of the ponds was kept between 15 and 25 cm by tracking hourly net evaporation rates, defined as the difference between evaporation and precipitation rates. If the pond depth exceeded the allowable maximum, the pond was harvested and reset to 15 cm and a concentration of 0.1 g L^{-1}. Similarly, potential culture dilution caused by incoming precipitation was prevented by ensuring the concentration in the ponds was maintained above 0.1 g L^{-1}. Further details on model calculations, implementation, and data curation are presented in the SI.

2.1.2 Dewatering Model

The dewatering module is composed of a three-step dewatering process to remove excess water from the biomass, 0.45 g L^{-1} to 200 g L^{-1}, based on the modeling work of Davis et al.[22] The biomass was first routed through settlers where it exits with a concentration of 10 g L^{-1}. The water retrieved from the biomass stream is recycled back to the ponds except for when the ponds are drained due to excess precipitation. During pond drainage, the clarified water was routed back to the local water source. The clarified water stream exiting the settlers was assumed to contain a negligible concentration of nutrients and algae.[22]

Subsequently, the biomass stream is routed to the remaining dewatering processes depicted in **Error! Reference source not found.**, and recycled water is sterilized in an ultra-violet sterilizer before being returned to the ORPs. For the case when ponds do not have enough biomass to be restarted to 0.1 g L^{-1}, mainly caused by constant harvesting during intense precipitation periods, a fraction of biomass is routed from the exit stream of the centrifuge back to the ponds. This pond operating strategy reduces freshwater consumption by storing all available rainfall and preventing culture failure induced by diluted cultures.

Energetics and recycling efficiencies of the dewatering and cultivation equipment are presented in Table 1. The recycling efficiencies used in this study are informed by previous modeling work in the literature[22] and represent a current technical hurdle that must be addressed for the optimal performance of commercial-scale systems. The impacts of these assumptions and other key model inputs were tested through a sensitivity analysis, and further methods are presented in the SI.

Table 1. Primary model inputs used for the calculation of mass and energy flows in the biomass production process.

	Value	Unit
Open-Raceway Ponds		
Inoculation density [11]	100	g L^{-1}
Harvest density [11]	450	g L^{-1}
Harvest volume [23]	75	%, fraction of pond
CO_2 utilization [22]	90	%
Biomass Elemental Composition		
Carbon (C) [22]	48.3	%, AFDW basis
Nitrogen (N) [22]	9.5	%, AFDW basis
Phosphorous (N) [22]	1.2	%, AFDW basis
Others (H, O, S) [22]	41.0	%, AFDW basis
Biomass Component Composition		
Lipids [22]	22.1	%, AFDW basis
Protein [22]	25.4	%, AFDW basis
Carbohydrates [22]	52.5	%, AFDW basis
Ash [22]	8.00	%, DW basis
Diammonium Phosphate Composition		
Phosphorous [20]	20	%, weight
Nitrogen [20]	18	%, weight
Ammonia Composition		
Nitrogen [20]	82	%, weight
Dewatering		
Settlers target concentration [22]	10	g L^{-1}
Biomass blowdown loss [22]	0.1	%
Settlers separation efficiency [22]	90	%
Membrane target concentration [22]	130	g L^{-1}
Membrane separation efficiency [22]	99.5	%
Centrifuge target concentration [22]	200	g L^{-1}
Centrifuge separation efficiency [22]	97	%
Energy Consumption		
CO_2 delivery power [22]	0.0439	kWh kg^{-1} CO_2
Paddlewheel power [22]	55.1	kWh $hectare^{-1}$ day^{-1}
Membrane power [22]	0.04	kWh m^{-3}
Centrifuge power [22]	1.35	kWh m^{-3}
UV sterilizer power [22]	2.71e-03	kWh m^{-3}
Freshwater pump power [22]	0.257	kWh m^{-3}
Ponds to settlers pump power [22]	0.0189	kWh m^{-3}
Settlers recycling pump power [22]	0.0177	kWh m^{-3}
Settlers to membrane pump power [22]	0.129	kWh m^{-3}
Membrane to centrifuge pump power [22]	0.0194	kWh m^{-3}
Recycling stream pump power [22]	0.184	kWh m^{-3}

2.2 Conversion Model

After dewatering the biomass to 20% solids, the biomass was converted to biocrude via hydrothermal liquefaction (HTL) based on the work of Chen et al.[19] Inputs to the HTL model include biomass composition and biomass productivity yields. The ash-free lipid, protein, and carbohydrate content of the biomass were set to 22%, 25%, and 53%, respectively.[23] The ash content of the biomass was assumed to be 8%.[23] After the biomass is processed to a biocrude, upgrading to renewable diesel and naphtha is done via hydrocracking.[19] The nutrient-rich aqueous stream exiting the HTL module is recycled back to the ponds, while the gaseous stream is utilized for on-site heat and power.[19]

2.3 Water LCA Methods

The primary goal of this study is to determine the WF and WSF of microalgae biomass and biofuels. The direct and indirect water consumption of the supply chain was included to provide a final value of life cycle water consumed per functional unit. Two different system boundaries were established to facilitate comparison to other energy crops and biofuels from previous assessments. The first system boundary includes the biomass cultivation and dewatering to 20% solids processes while the second system boundary is expanded to incorporate the fuel conversion process (Fig. 1). Similarly, the functional units for each system configuration were set to one metric ton of ash-free dry weight biomass and one GJ of renewable diesel, respectively.

2.3.1 Water Footprint Methodology

The most common method used to quantify the water consumption of bioenergy systems is the water footprint method developed by Hoekstra et al.[5] The total WF of a product is defined as the addition of three different WF components: blue, green, and gray WFs. Each component is further divided into a direct and indirect WF. The indirect WF measures upstream water consumption in the supply chain, while the direct WF refers to on-site water consumption. It is

181 worth noting that this method considers water consumption only and neglects the impacts to
182 water quality.[5]
183 The blue WF of a product measures the amount of water consumed from surface or
184 groundwater sources.[5] In the case of algal cultivation, freshwater consumption is equal to the
185 difference between the volume of water withdrawn from the water source (to make up for
186 evaporation losses and water incorporated in the biomass stream) and the volume of clarified
187 water returned to the catchment area, due to system drainage. Accordingly, an increase in the
188 water discharged due to inefficiencies in the dewatering equipment has no impact on the net
189 freshwater consumption of the system. However, an increment in the volume of discharged water
190 could have implications for the gray WF of the system, as discussed below. The water used for
191 cooling equipment and other processes in the conversion stage was assumed to all be consumed,
192 making the total blue water demand equal to the sum of the water consumed in the cultivation
193 and conversion processes.
194 In addition to estimating blue WFs, computing the green WF is essential in the water analysis
195 of energy crops. The green WF measures the volume of rainfall that is not returned to
196 groundwater sources and is either stored or consumed.[5] Green water demand was calculated by
197 tracking the volume of rain entering the ponds. This study assumed that all rainwater is stored in
198 the ponds and therefore all precipitation contributes to the green WF.
199 In contrast to the blue and green components, the gray WF measures freshwater pollution and
200 is defined as the volume of freshwater required to dilute pollutants to meet water quality
201 standards.[5] Different from terrestrial crops, the gray WF of algal cultivation can be minimized
202 by proper nutrient recycling and treating waste streams before disposal.[16] For example, all
203 disposed water from cultivation is previously clarified in the settlers to reduce the concentration

of suspended solids in the clarified water stream. Based on experimental data reported in the literature[24–27], the algae culture was assumed to consume all available nutrients and therefore the nutrient load in the harvested and water discharged streams was assumed to be negligible. For the same means, the effluent from the conversion stage was recycled back to the ponds instead of being directly disposed. Considering the above assumptions, algal cultivation does not generate a gray WF and the analysis focused on blue and green WFs with a sensitivity to this assumption explored.

The indirect WFs attributed to process consumables were retrieved from different LCA databases and literature. Water consumption associated with the production of diammonium-phosphate, ammonia, hydrogen, and natural gas was retrieved from the GREET 2021 model.[28] The water consumed in electricity generation was determined by expanding the methods presented in Lee et al.[29] to an eGRID subregion level.[30] More detailed indirect WF calculations are provided in the SI.

2.3.2 Available Water Remaining Methodology

The Available Water Remaining in the US (AWARE-US) model[31] was used to calculate the WSF of algal biomass and biofuels based on a monthly analysis that is averaged into seasonal results. This model defines the WSF as the product of direct freshwater consumption and a characterization factor (CF). The CF is a water-stress indicator characterizing the water availability and demand of a given location relative to the water availability of a specific location.[6,7] The AWARE-US model provides monthly characterization factors for US counties relative to the US average freshwater availability.[31] The output of the analysis is a monthly WSF at a county level. The methods used to interpolate model outputs to a county level are described in the SI.

3. Results and Discussion

The WF of algae biofuels is presented and disaggregated into the direct blue, green, and indirect blue, and then summed for a total WF. The grey water footprint is regarded as negligible assuming optimal operation of the system. Process model outputs are then analyzed to understand the parameters that have a major impact on WF results. Results are combined with AWARE-CF to determine the WSF of algal-based biofuels with seasonal resolution. The results presented in this section are the averages of the 21-year simulation.

3.1 National Water Footprint Mapping

The life cycle WF for all simulated sites were surface interpolated and results for the algal fuels system are summarized in Fig. 2. The range of total life cycle WF was calculated to be 30 m^3 GJ^{-1} with the maximum located in the northwest US (39 m^3 GJ^{-1}), while Hawaii and southern California yield the smallest WFs, ranging between 9 and 10.6 m^3 GJ^{-1}. The large WFs in the Pacific Coast are explained by the high precipitation rates and low biomass yields in the region. Similarly, the large WF of hydroelectricity has a modest impact on the indirect water consumption of algae farms located across the northwestern US (Fig. 2C). While the larger indirect WF of sites in Florida is correlated to the energy penalty associated with elevated rainwater usage. These results show that even in scenarios with high energy consumption, the indirect WF is an order of magnitude lower than the direct blue and green components of freshwater cultivation. In conclusion, direct freshwater and rainwater consumption are the largest contributors to the total WF and the indirect WF of upstream processes was found to be strongly dependent on the WF of electricity generation.

The results from the work illustrate that the indirect WF of freshwater cultivation is low and dominated by electricity usage in the system. Contrastingly, the indirect WF is dramatically impacted in a saline cultivation scenario, where ~~the indirect WF component is particularly~~

~~relevant to saline cultivation, where freshwater is mostly consumed upstream and~~ there is an increase in electricity consumption due to higher pumping and blowdown energy needed to maintain adequate salinity levels. The differences in WFs between freshwater and saline cultivation scenarios for Tampa, FL, and Corpus Christi, TX were quantified following the saline modeling assumptions provided in the SI. Results show that saline cultivation in Corpus Christi, TX provides a 30% reduction in the total WF by eliminating freshwater consumption to make up for evaporation which exceeds the increased indirect water consumption from pumping (Fig S13). In Tampa, FL saline cultivation increased the indirect WF component by an order of magnitude, which resulted in similar total WFs as the freshwater cultivation scenario. These two case studies highlight the potential of coastal areas for reducing the WFs of algal systems through saline cultivation, but also show it is location-dependent.

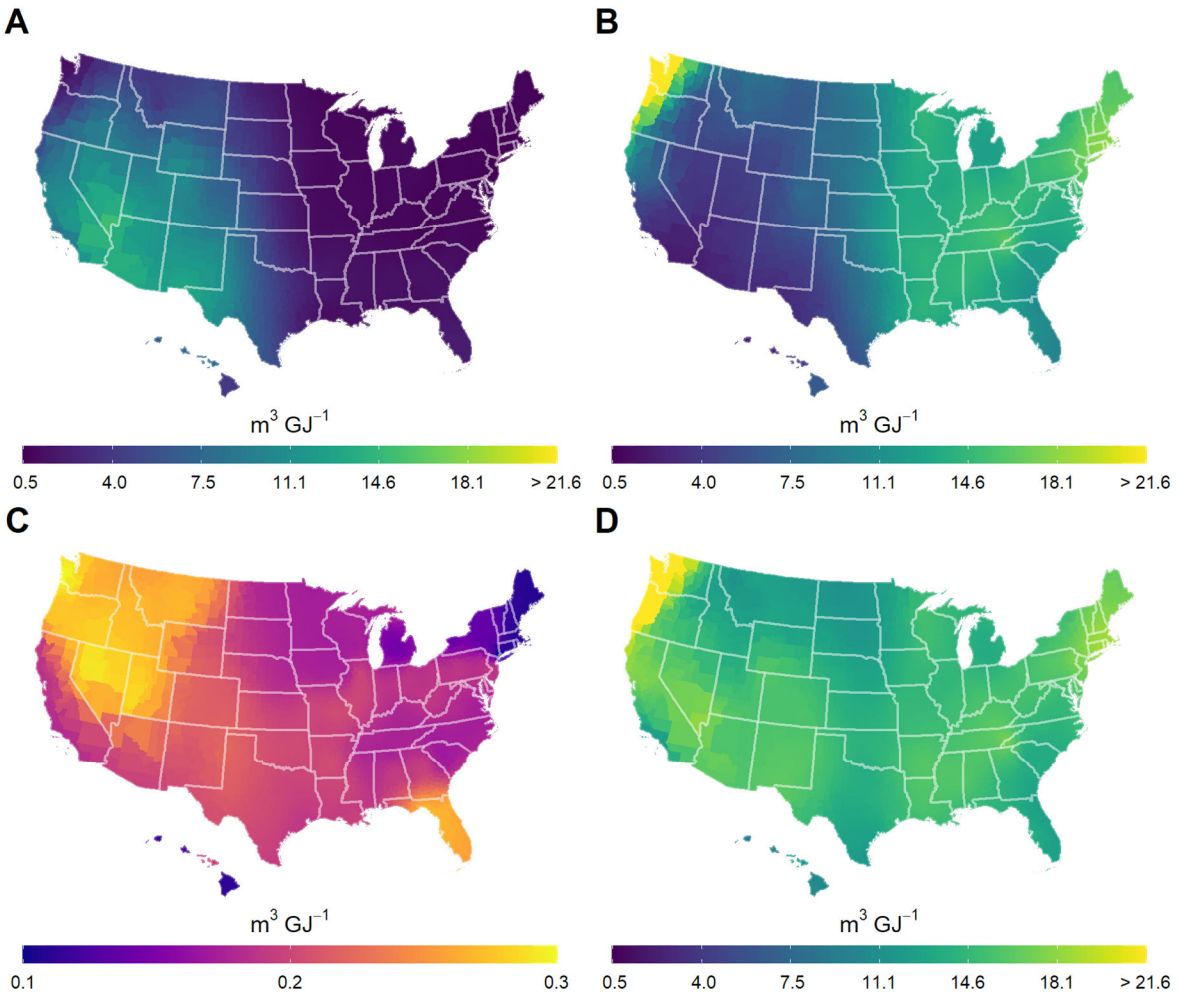


Figure 2. Life cycle water footprint breakdown of algal diesel: (A) direct blue water footprint, (B) direct green water footprint, (C) indirect blue water footprint, and (D) total water footprint.

The regional differences observed in Fig. 2 emphasize the need for water LCAs with geospatial resolution. For instance, the blue WF (Fig 2A) is driven purely by evaporation rates with the highest rates located in dry climates such as the Desert Southwest. Contrastingly, the southeastern US shows the largest green WFs (Fig 2B) and the smallest blue WFs, explained by the high precipitation rates in the region. However, when comparing the total WF of these regions, similar trends are observed in total WFs. For example, the total WF of Phoenix, AZ was

found to be only 3% larger than that of Macon, GA, although freshwater consumption in Phoenix represents 85% of the total water consumption compared to 14% in Macon, GA. The freshwater consumption in a water-scarce region such as the southwestern US will potentially bring about more severe environmental impacts than the consumption of rainwater in Georgia. This comparison stresses a limitation of the water footprint method, as it only accounts for water consumption, but does not consider water stress impacts. This is further explored in this study through water scarcity calculations.

The results from this study were also compared to published water LCAs using identical system boundaries and metrics. Compared to the algal WFs (m^3 GJ^{-1}) reported by Ou et al.[32], an average difference of 14% across the eight sites used for comparison was estimated. These discrepancies were larger in sites located in the Midwest US and are attributed to differences in evaporation modeling, meteorological data, and biomass yields. At the same time, the model used in this study predicts lower freshwater consumption per area (m^3 m^{-2} yr^{-1}) across the eight sites used for comparison, corresponding to an average difference of 38%. Moreover, the magnitudes of other water consumption sources (i.e. conversion and indirect) agree with the results from this analysis, implying that differences between water LCAs of algae systems are mainly attributed to variations in net evaporation rates and growth rates.

Furthermore, a WF comparison to first and second-generation biofuels shows blue WFs of algal fuel systems can approximate those of conventional corn ethanol and soybean biodiesel systems, and the difference depends on the location where algal biomass is cultivated. In particular, the blue WF of algal fuels in the southwestern US is generally larger than the average blue WFs of corn ethanol and soybean biodiesel cultivated in Iowa, but comparable if algal biomass is cultivated in the Gulf Coast region (Fig, 3A). A comparison to wheat straw ethanol

294 shows that algal production in California and Texas incurs smaller blue WFs; however, when
295 algal biomass is cultivated in Arizona, production of first and second-generation biofuels
296 generates a smaller blue WF. Although a larger volume of freshwater is required for algal
297 cultivation in these locations, the higher biomass yields make the blue WF of algal biofuels
298 comparable to those of its first and second-generation counterparts. In summary, the regional
299 variations of freshwater consumption and biomass yields must be considered to determine the
300 scenarios under which algal fuels present a smaller blue WF than conventional biofuel systems.
301 In the context of the green WF component, algal systems present some advantages over
302 terrestrial energy crops. Notably, the impact of higher growth rates achieved by algae systems is
303 best reflected when comparing the green WF between biofuels. The results illustrated in Fig. 3A
304 show that algal renewable diesel uses less rainwater per unit of energy than all other biofuel
305 systems.
306 In terms of gray water, algal cultivation presents the advantage of generating no gray WF if
307 pollutants loadings in waste streams are carefully tracked, ponds are properly managed, and
308 recycling across process stages is practiced.[16,33] It is important to note that complete nutrient
309 assimilation in the ponds is critical for maintaining negligible gray WFs in algae systems.
310 Negligible gray WFs in algal systems are dependent on proper pond management, and operating
311 the ponds without carefully tracking nutrient loadings and water discharged volumes could result
312 in considerable gray WFs (Fig. S2). Contrastingly, the gray WF of terrestrial crops is a function
313 of fertilizer loss and has been found to represent a large portion of the total WF[34,35], particularly
314 for corn ethanol (Fig. 3A). Based on the modeled gray WFs, findings of this comparison suggest
315 that a shift to algal biofuels has the potential to lower the gray and green water consumption of
316 bioenergy.

317 As shown in Fig. 3A, if all components are considered, the total WF of algal biofuel systems is
318 approximately four to six times smaller than the average WF of corn ethanol while an order of
319 magnitude smaller than that of soybean biodiesel. If only blue and gray WFs are compared, algal
320 systems have a larger total WF than soybean and switchgrass biofuels but a smaller total WF
321 than corn grain and wheat straw ethanol. This comparison indicates that from an overall WF
322 perspective, algal systems benefit from their higher growth rates and opportunity for recycling
323 nutrients.

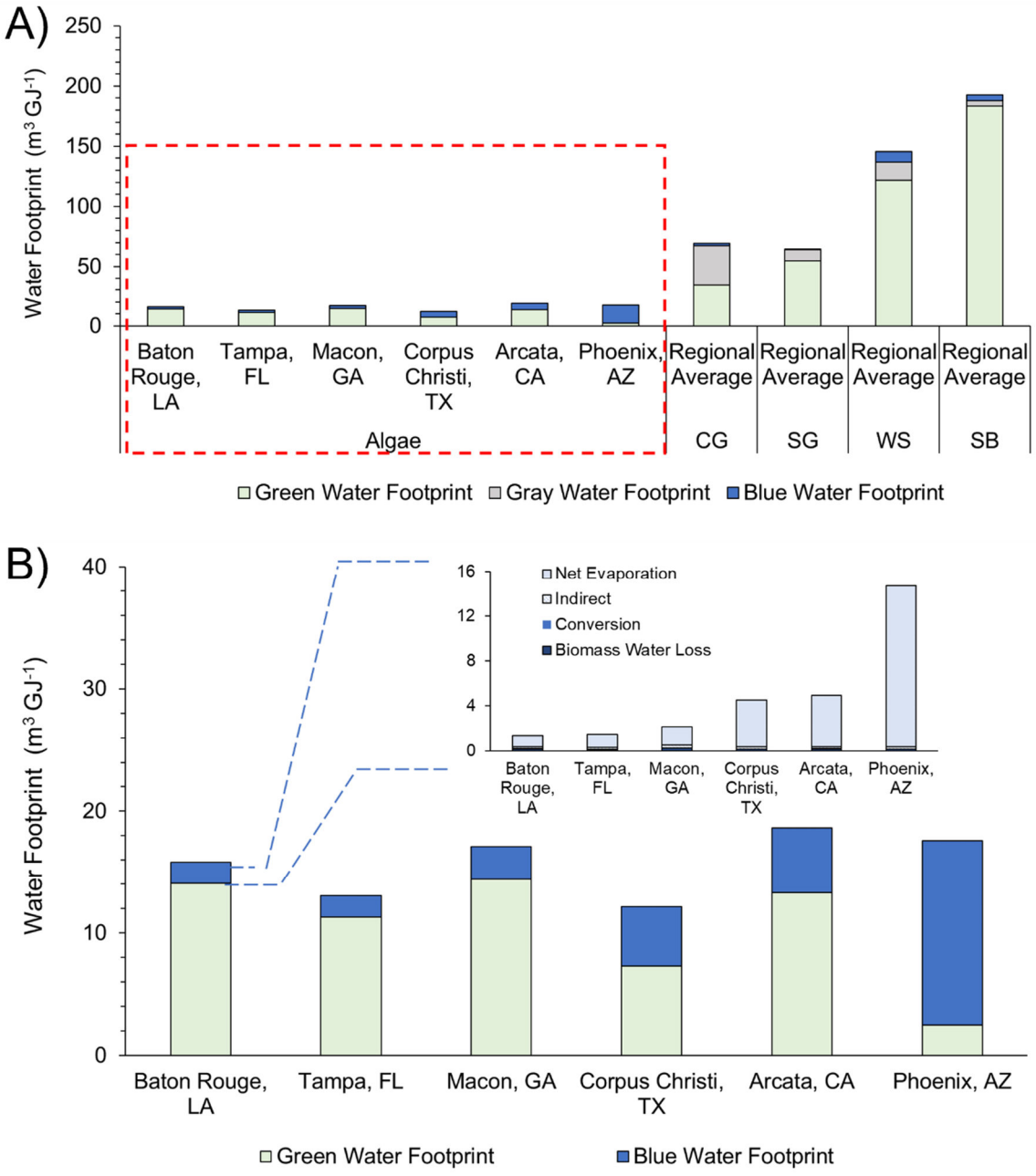


Figure 3. A) Life cycle water footprint comparison between renewable diesel from microalgal biomass for six locations in the United States and average regional life cycle water footprints for first and second-generation biofuels derived from corn grain (CG), switchgrass (SG), wheat straw (WS), and soybean (SB). The water footprints of corn grain and wheat straw ethanol, as well as those of soybean biodiesel and switchgrass biodiesel blend, were retrieved from the literature[36–39]

and represent average values of high crop production areas: corn and soybean are assumed to be grown in the Corn Belt and the southeastern US, while switchgrass and wheat straw are mainly cultivated in the central and eastern US. B) Life cycle water footprint of algal fuel systems across six locations in the US. Inset, the blue water footprint breakdown. The water footprint values of algae sites represent the average of the 21 simulated years.

3.2 Water Footprint Breakdown

The results shown are all driven by the different parameters calculated by the engineering process model, thus, evaluating the mass and energy balance is critical to identifying opportunities for reducing freshwater consumption. The analysis indicates that freshwater and rainwater consumption in the biomass production process dominates the overall water consumption of algae systems. As seen in the blue WF breakdown of the six case study locations shown in Fig. 3B, water consumed in the conversion process is minimal compared to the evaporation losses during the cultivation stage. Consequently, algae fuel systems benefit from the recycling of cultivation water embedded in the biomass making them less water-intensive than traditional terrestrial-based biomass systems, where the water leaving with the biomass is assumed to be consumed. The outcomes from both modeled system boundaries demonstrate that water consumed in the biomass production stage dominates the total WF and the co-location of biorefineries with farms decreases the WF of algae fuels by promoting water recycling across processes.

Beyond the effects of water recycling, the usage of rainwater also contributes to minimizing freshwater withdrawal and consumption. This is observed when comparing the net evaporation rates in this study, ranging from 0.05 to 1.47 $m^3\ m^{-2}\ yr^{-1}$, with the range previously calculated by Quiroz et al.[11] (0.30-1.68 $m^3\ m^{-2}\ yr^{-1}$). The wider range presented in Quiroz et al.[11] is expected,

as rainwater was not accounted for, and instead, a "gross" evaporation rate was estimated. The southeastern US is one of the regions that benefit the most from rainfall utilization. For example, in Tampa, FL most of the water consumption can be supplied with rainwater. The model outputs demonstrate that the net water consumption of algal systems is primarily influenced by evaporation losses and rainwater contributes to increasing the water efficiency of these systems.

The evaporation losses in the cultivation stage drive the water intensity of algal systems therefore it is critical to select sound evaporation models to reduce the uncertainty in evaporation estimates. To understand the importance of evaporation modeling in water usage metrics, net evaporation rates were compared to those of Wigmosta et al.[17] In general, the results from this study were found to be 31% lower, based on the 204 sites used for comparison. This difference is anticipated as Wigmosta et al.[17] used corrected pan evaporation data for model validation[17], which has been shown to differ by 45% from commercial-scale algae systems.[11] The differences in scales of the modeled facilities are critical as the surface area has a direct influence on evaporation rates.[11] Facility sizes modeled in Wigmosta et al.[17] were selected based on land availability, while this work fixed a standard 400-ha wetted area. Although direct comparison would require harmonizing model inputs, the comparison highlights the importance of selecting appropriate evaporation models when modeling water consumption in open algae systems

Biomass yields have a direct impact on the WF of the system, as it impacts the functional unit. The modeled productivity yields agree with experimental values for UTEX 393[23] with annual averages ~~areal productivity reached~~ reaching ~~a~~ maximum of 23.6 g m^{-2} day^{-1} in Hawaii and Florida (Fig S4A). It should be noted that these values represent optimistic yields for commercial microalgae cultivation since the impacts of culture failure are not accounted for in the analysis. The potential impacts of pond contamination on modeled areal productivity values are illustrated

by reducing biomass yields by a safety factor (Fig S5). The results presented here represent projections based on the current biomass production potential in pilot-scale systems and should be improved by considering the impacts of culture mixing in commercial-scale systems as well as pond contamination and reliability.

Other model outputs were found to be consistent with previous modeling work.[11] Nutrient demands were found to scale directly with biomass yields, while electricity consumption is a function of operational days, growth rates, and precipitation rates (Fig. S6). The high electricity demand in the Gulf Coast states is credited to the higher pumping and dewatering power needed to control the depth of the ponds during periods of intense rainfall. Energy balance results show that minimizing freshwater use through the effective use of rainwater in the cultivation process comes with an increase in electricity consumption caused by more frequent pond harvesting and larger processing volumes.

Moreover, the impacts of model inputs on the blue and indirect WFs for two case study locations were tested through a sensitivity analysis (details included in the SI). The results of the sensitivity analysis (Fig. S16) indicate that in sites with low precipitation such as Phoenix, AZ the parameters that directly impact evaporation losses and biomass yields are the most sensitive to both the direct blue water footprint and indirect water footprint. Contrastingly, in sites with high precipitation such as Tampa, FL, the depth limits of the ponds were found to be sensitive. These inputs have an impact on the amount of rainwater that can be stored in the ponds and consequently impact the amount of freshwater needed to refill the ponds at the minimum depth. Although a reduction in the separation efficiency reduces the amount of biomass converted into fuels, there is also a decrease in the amount of water needed to make up for losses, as more water is recycled back to the ponds. An increase in the separation efficiency increases the amount of

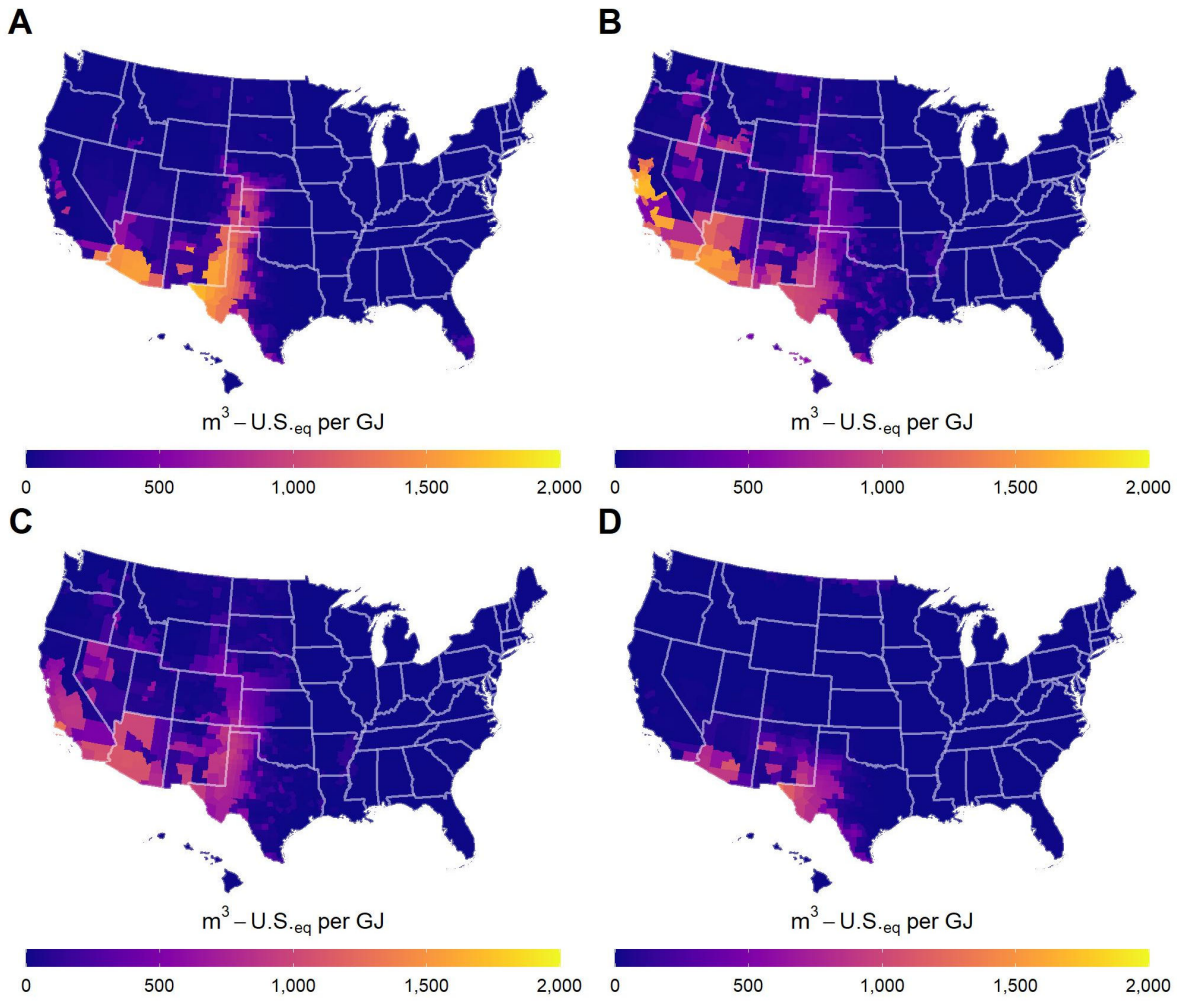
biomass that is sent to conversion but increases the volume of water needed to make up for water losses (less water is recycled) and therefore balances the impacts of increased yields on the blue water footprint of the system.

3.3 Water Scarcity Implications

Aside from quantifying life cycle water usage, the local water stress associated with the deployment of algal systems was calculated and reported as a WSF. The seasonal results shown in Fig. 4 illustrate the temporal dynamics of water consumption, availability, and biomass yields. The largest WSFs are found in the southwestern US, where water stress levels vary between 1700 and 1760 m^3-$U.S._{eq}$ per GJ during spring (Fig 4A). Similar water stress levels propagate to southern and western California during the summer (Fig 4B). While there is an increase in water consumption during summer, this is balanced by an increase in biomass yields, consequently, the magnitude of WSFs during summer is comparable to those seen in spring. Similarly, the same regions present the highest water stress levels during the fall season (Fig 4C), but there is a reduction in the WSF compared to summer levels. The winter season experiences a reduction in water stress levels in California while southwestern Texas displays a minor change compared to fall. The seasonal analysis indicates that biomass yields drive the WSF during spring and summer, while water consumption is the driving factor during the fall and winter seasons.

As discussed above, the temporal variations of the WSF are a product of the seasonal variabilities of freshwater consumption and biomass yields. Potential algae sites must support high growth and low evaporation rates, in addition, sites must be located in areas with sufficient water availability to support a low WSF (low AWARE-US CF). Based on these criteria, the southeastern and Gulf Coast U.S are characterized as the most suitable regions for microalgal fuels (Fig. 4) and biomass production considering WSF (Fig. S14). The southeastern US region achieves the maximum biomass yields with average areal productivities above 20 g m^{-2} day^{-1} and

the abundant rainwater has a propitious effect on the WSF, by not only reducing the water consumption of algal systems but also increasing freshwater availability and therefore returning a low AWARE-US CF. There was found to be minimal variability among the distribution of WSF for counties in Gulf Coast states and Georgia. Even in the scenario of having below-average precipitation rates, the maximum seasonal WSF in the region remains between 5.2 and 5.8 m^3-$U.S._{eq}$ m^{-2} $month^{-1}$, suggesting that the WSF is more strongly correlated to biomass yields. The analysis reveals that the southeastern US is the best candidate for siting algal systems based on WSF due to the low water consumption, high growth rates, and low water stress levels.



433

434 **Figure 4**. Seasonal water scarcity footprints of renewable diesel from algal biomass: (A) spring,
435 (B) summer, (C) fall, and (D) winter.

436 Although sites in the southwestern US also present high biomass yields, low water
437 availability in the western US risks unsustainable cultivation of algal biomass in the region. For
438 instance, if algal farms are projected to be deployed in Arizona or southern California, these
439 facilities will need to be supported by saline water sources to avoid any negative water stress
440 impacts and minimize freshwater withdrawals. Furthermore, if freshwater were available in the
441 region, algal biomass proves to be a more efficient user of water than conventional energy crops

and could potentially substitute terrestrial protein crops (e.g., soybean) in water-scarce regions such as CA and AZ.

Moreover, the results presented here suggest that the deployment of algal systems would not stress water resources in the southeastern US and thus could be developed alongside traditional agriculture. Although this study is not meant to establish the freshwater, wastewater, or saline resource availability and the implications on the scalability of these systems, the water scarcity analysis shows that freshwater consumption should not be a deterrent against the scale-up of algal facilities in certain geographical locations. However, land and CO_2 availability in the southeastern US are resources that could risk the sustainable scaling of these systems.[17,40] Ultimately, freshwater is not a resource limiting the scale-up of algal biomass production and algal biomass can be characterized as a low water alternative to conventional terrestrial energy crops.

It is also important to note that the WSFs presented here consider only freshwater consumption impacts. As discussed, the cultivation of algal biomass in the southeastern US will require an appropriation of the available precipitation that could lead to changes in green water availability or impact the water supply of other crops in the area. Additionally, freshwater availability can also be reduced as groundwater will not be naturally recharged by rainwater.[41] Therefore, expansion of this analysis could investigate the green WSF of algal cultivation in areas where green water consumption dominates and analyze the tradeoffs between areas with large blue WSF and those with large green WSF.

4 Conclusions

The WF and WSF of microalgal biomass cultivation and conversion to fuel across the continental US and Hawaii are evaluated through a regionalized water LCA. The biomass cultivation stage was found to be the most water-intensive process with evaporation losses in open ponds representing the major source of freshwater consumption in the system. When all WF components are considered, the WF of algal renewable diesel was found to be smaller than that of traditional biofuels, however, algal biofuels generate larger blue WFs. The smaller WFs of algal renewable diesel are a result of both higher growth rates and the lack of a gray WF component stemming from nutrient recycling and proper waste stream management. In terms of WSF, sites in the Gulf Coast and the southeastern US were found to have the lowest water stress levels. Finally, cultivation in the southwestern US will cause substantial water stress in the region and saline algal cultivation is advised to reduce the water consumption of sites in these water-scarce regions. The potential of reducing the WF of algal systems in coastal areas by implementing saline cultivation was also explored. Although saline cultivation reduces freshwater consumption, there is an increase in indirect water consumption and future work should focus on better quantifying this component as it was shown to be equivalent to the water savings associated with evaporative makeup water. Finally, for a true understanding of the potential indirect water consumption impacts associated with cultivation in saline or brackish water, a detailed quantification of the energetics of groundwater pumping and brine disposal methods is required.

ASSOCIATED CONTENT

Supporting Information.

The following files are available free of charge.

Detailed model structure and assumptions, equations used in the water balance calculations, primary model inputs, life cycle inventory, county-level interpolation methods, additional model outputs, and additional water footprint and water scarcity footprint results. (. PDF)

County-level water footprints and water scarcity footprints for reproduction of Figure 2 and Figure 4 (.xlsx)

AUTHOR INFORMATION

Corresponding Author

David Quiroz – Mechanical Engineering Department, Colorado State University, 1374 Campus Delivery, Fort Collins, Colorado 80522, United States

* E-mail: david.quiroz_nuila@colostate.edu

Author Contributions

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Notes

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ABBREVIATIONS

AWARE, Available Water Remaining; CF, characterization factor; eGRID, Emissions and Generation Resource Integrated Database; GREET, Greenhouse Gases, Regulated Emissions, and Energy Use in Technologies Model; HTL, hydrothermal liquefaction; LCA, life-cycle assessment; ORP, open-raceway pond; US, United States; WF, water footprint; WSF, water scarcity footprint; WULCA, Water Use in LCA.

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