Applied Energy 294 (2021) 116960

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Characterizing weather-related biophysical and financial risks in algal biofuel production

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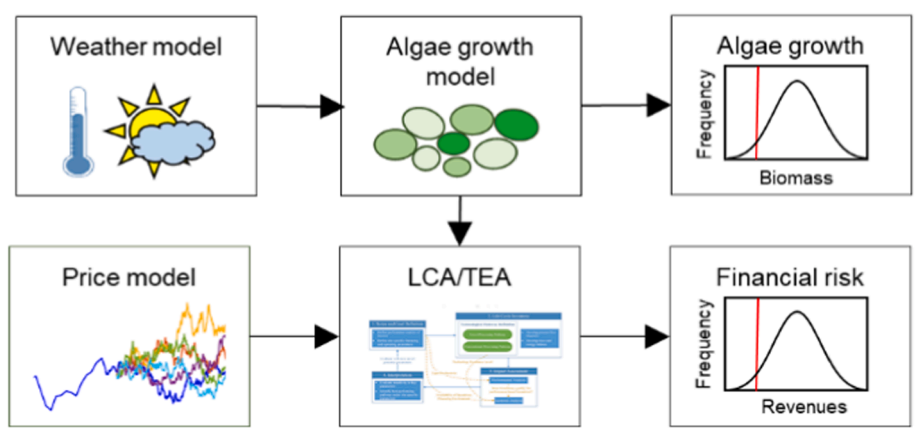
HIGHLIGHTS

- Algal biofuel production is vulnerable to weather and market fluctuations.
- Higher revenue volatility translates to increased financial risk and financing costs.
- A probabilistic analysis of weather impacts on biorefinery revenues is performed.
- Revenue variability due to different weather factors is significant.
- Solar irradiance and air temperature extremes are the largest weather-related risks.

GRAPHICAL ABSTRACT



ARTICLE INFO

Keywords:
Algal biofuels
Biophysical modelling
Weather uncertainty
Financial risk

ABSTRACT

Algal biofuels are a renewable liquid fuel with advantages over crop-based biofuels, including higher yield per acre, the ability to recycle production inputs, and the option to create valuable co-products. Previous analyses suggest that algal biofuels could become cost-competitive if technological improvements are achieved. Most previous research, however, does not consider the impact of seasonal and year-to-year uncertainty in weather factors, such as solar irradiance and temperature, on biomass productivity, and those that do are based on limited meteorological records. This study explores the influence of weather uncertainty on biomass growth and biorefinery revenues as well as impacts from market price uncertainty. The performance of a hypothetical algal biorefinery in Vero Beach, Florida is explored by combining stochastic weather generation, biophysical growth modelling, stochastic market price generation, and techno-economic analysis. Results show coefficient of

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https://doi.org/10.1016/j.apenergy.2021.116960
Received 17 December 2020; Received in revised form 2 April 2021; Accepted 15 April 2021

variation values of 8–15% in seasonal revenues for an algae producer, and that the variation in annual revenues was lower than that of corn, soybean, and cotton. In sensitivity analyses, both weather and price fluctuations are found to be significant sources of financial risk. This is the first probabilistic quantification of weather-related production impacts for algae producers, which is relevant given global growth in the algae industry as evidenced by the new eligibility of algae for crop insurance in the US 2018 Farm Bill.

1. Introduction

Microalgae ("algae") are a scalable biofuel feedstock with potential to reduce transport sector carbon emissions and improve energy security [1–3], which may provide multiple advantages over crop-based biofuels. For example, algae growth does not require arable land and thus does not compete with food production for land [4,5]. The engineered processes used for algal biofuel production also facilitate recycling of water, nutrients, and solvent inputs, lowering overall resource requirements [6]. The ability of algal biorefineries to use saline/brackish or wastewater in the algae growth process is another attractive feature [2,7]. In addition, algal biofuels can be produced alongside valuable co-products (e.g., bulk chemicals, food/feed products, nutraceuticals, bioplastics) [2] and can be combined with beneficial processes such as anaerobic digestion for electricity generation [8], combined heat and power production [9], carbon capture and storage [10,11], and wastewater treatment [2,12]. Furthermore, desirable algae characteristics such as high lipid productivity can be achieved through genetic [13,14], metabolic [15,16], and process engineering [17,18].

Despite these advantages, the commercial viability and environmental impacts of algal biofuels remain indefinitive [19]; previous techno-economic analysis (TEA) and life cycle analysis (LCA) studies indicate a range of cost and environmental impact estimates, both of which depend heavily on model assumptions [20]. Algal biofuels could become cost-competitive, contingent on technological improvements, production of high-value co-products, and/or policy support. Previous LCA and TEA studies on algal biorefineries generally assume stable performance [19,21], but there is likely to be significant annual, seasonal, and intra-seasonal variability in algal biomass growth [22] and thus revenues associated with algae production.

In particular, weather conditions that result in suboptimal or adverse growth conditions can give rise to significant reductions in algae production. Outdoor open raceway ponds (ORP) are the primary means by which algal biomass is grown due to their scalability and low costs relative to photobioreactor systems [23]. However, standard ORP systems are vulnerable to uncertainties in biomass growth due to variability in solar irradiance and water temperature, among other factors [9,24]. This uncertainty is important to consider as algal biomass productivity strongly influences project revenues [10,20,25], and the financial risk (i.e., the likelihood and consequences of an inability to meet cash flow obligations) associated with unpredictable revenues can create challenges for algae producers. An unstable revenue stream can cause failure to meet debt payments and/or issue returns to investors [26], resulting in difficulty in accessing capital (i.e., project financing). This would be particularly detrimental given the "capital intensive" nature of algal biorefineries compared to crop-based and cellulosic biofuel technologies [19]. The United States Department of Agriculture (USDA) has recently acknowledged the weather-related financial risks inherent in algae production by naming algae an "agricultural commodity" in the 2018 Farm Bill. Algae is therefore now eligible for US crop insurance programs, a trend that could extend to other countries such as Japan, Canada, and Spain that have similar crop insurance support programs [27]. For most agricultural commodities, elaborate efforts have been dedicated to quantifying weather-related financial variability [28]. Thus far, however, no published study has performed a robust analysis of annual, seasonal, and intra-seasonal weather-related financial risk in algae production and the potential for associated financial consequences for biorefineries, which will be key in the development of crop insurance programs. Although there are existing datasets that allow for exploratory analysis of the link between algae growth and weather [29], these data are generally the result of experiments conducted intermittently over a few months or years. As such, they reflect a relatively small subset of meteorological conditions that do not often include extremes. Thus, basing expectations of algae performance on limited meteorological records can lead to poor estimates of both production and financial risk.

In this study, weather-related variability in algae growth and the resulting financial risks experienced by a hypothetical algal biorefinery are characterized, as are the relative contributions of the underlying variability in temperature, solar irradiance, relative humidity, and wind speed. Weather-related risks are then combined with better-understood risks from market-based uncertainty in biofuel and co-product prices to provide a comprehensive assessment of the financial risks facing algae producers. To do so, a stochastic weather generator, a biophysical algae growth model, and a stochastic market price generator are integrated with a previously developed LCA/TEA [30,31] model of an algal biorefinery. An example site of Vero Beach, FL, is chosen due to its warm, sunny climate, relatively low seasonal variability, and freshwater availability, all of which make it attractive for algae production [25,32]. Empirical biomass growth data for Vero Beach from the Algae Testbed Public Private Partnership (ATP3) Unified Field Study [29] are used as the basis for model calibration and validation. Results from this study yield insights into the relative vulnerability of algae producers to growth variability (weather- and non-weather-related) and market-based financial risks.

2. Methods

The model framework developed in this study is shown in Fig. 1 and further described in the following sections.

2.1. Stochastic weather generator

In order to explore the joint uncertainties in four weather factors that affect algae growth (solar irradiance, air temperature, relative humidity, and wind speed [33–34] at the model site (Vero Beach, FL), historical weather data are used to train a synthetic weather generator. This allows for stochastic modelling of daily weather for 500 model runs of 20 years (10,000 synthetic years total) assuming climate stationarity (i.e., that the future climate resembles the past) to give enough data to represent extremes. A 20-year lifetime for the algal biorefinery is assumed in evaluating its financial performance.

Meteorological data for Vero Beach were collected at 30-minute intervals for 1998–2016 from the NREL's National Solar Radiation Database [35]. This includes full spectrum global horizontal irradiance (GHI) for cloud cover and clear sky irradiance from the Physical Solar Model v3, as well as air temperature, relative humidity, and wind speed data derived from the NASA Modern Era-Retrospective Analysis for Research and Applications [36]. These data are used to create a multivariate, synthetic weather dataset that reproduces the time series and statistical characteristics of the historical record and accesses values more extreme than the observed record.

First, "losses" in daily solar irradiance due to cloud cover (i.e., the difference between clear sky and cloud cover GHI) are detrended monthly by subtracting the monthly mean, dividing by the monthly standard deviation, and log-transforming the resulting data to obtain approximately normal residuals [37]. Similar detrending is performed

on the other weather data, followed by a Burr transformation for wind speeds [38] and Weibull transformations for air temperature and relative humidity [39]. Detrended, transformed residuals are used to fit a vector auto-regression model which generates 500 runs of 20 years (10,000 years total) of daily whitened residuals. Seasonality (monthly summary statistics) is reincorporated into the simulated residuals, yielding synthetic weather data that captures seasonal statistical moments (Fig. 2), autocorrelation (Fig. S1 in Supporting Information (SI)), and cross-correlations between the variables (Fig. S2). Note that some outliers in Fig. 2 are not captured for wind speed, but this difference involves only a few outliers that are not far outside the modeled range, and therefore make very little difference when evaluated over 10,000 simulated years. Daily weather values are disaggregated to an hourly time step for agreement with algae growth data and to capture the effect of diurnal fluctuations (e.g., damage to algal cells from low nighttime temperatures or extreme mid-day sunlight). The synthetic weather data are then used to simulate pond temperatures at 30-minute intervals in model that simulates temperature changes in a thoroughly mixed ORP by considering heat fluxes between the pond, sun, and air, evaporation/condensation, and convection [34]. Further details about the weather model and pond temperature model can be found in the SI (see Weather Model and Temperature Model).

2.2. Biophysical growth model

Many studies have modelled algae growth in order to estimate the feasibility of current algal biomass technologies and products [40], optimize productivity [41–43], and aid in the scale-up of microalgae production systems [44]. A common limitation in growth modelling is that most models are based on indoor, lab-scale studies, resulting in less accurate models for outdoor systems [41]. Algal productivity is especially sensitive to fluctuations in light intensity and temperature [45] and, given that these factors are difficult to control in outdoor settings [34,46–47], many outdoor growth models are strongly influenced by variation in sunlight and temperature [24]. One such model is a biophysical algal growth model developed by Wigmosta et al. [33], which estimates biomass productivity by considering energy flows, light and water requirements, and photosynthetic limits to predict algal biomass growth, $Prod_{mass}$:

$$Prod_{mass} = \frac{\tau_p C_{PAR} \varepsilon_a E_s}{E_a} \tag{1}$$

where τ_p is the transmission efficiency of incident solar radiation to algal cells, C_{PAR} is the fraction of photosynthetically active radiation (PAR), E_s is the cloud cover GHI, and E_a is the energy content per unit of biomass. The efficiency of photon conversion to biomass, ε_a, is found by:

$$\varepsilon_a = \frac{E_c \varepsilon_S \varepsilon_t \varepsilon_b}{Q_r E_p} \tag{2}$$

where E_c is the carbohydrate energy content, ε_t is the effect of suboptimal water temperature, and ε_b is the biomass accumulation efficiency, which accounts for cell functions aside from biomass growth. Additionally, Q_r is the quantum requirement to liberate one mole of oxygen, E_p is the photon energy, and ε_S is the effect of light saturation, given by:

$$\varepsilon_S = \frac{E_S}{S_o}\left(ln\left(\frac{S_o}{E_s}\right) + 1\right) \tag{3}$$

where S_o is the light saturation constant, a strain-specific coefficient that represents photolimitation and photoinhibition [48,49] that is fitted to the experimental data (see *2.3 Validation/fitting*).

In addition to sensitivity to light inputs, algal cells have pond temperature ranges at which they can achieve optimal growth rates [50]. The optimal temperature range varies by strain and is affected by cell adaptation and acclimation [41]. Some models capture the synergistic or antagonistic effects of light and temperature on photosynthetic rate [51,52], yet uncoupled models have been shown to provide accurate estimates [53]. To represent this relationship, a piecewise function

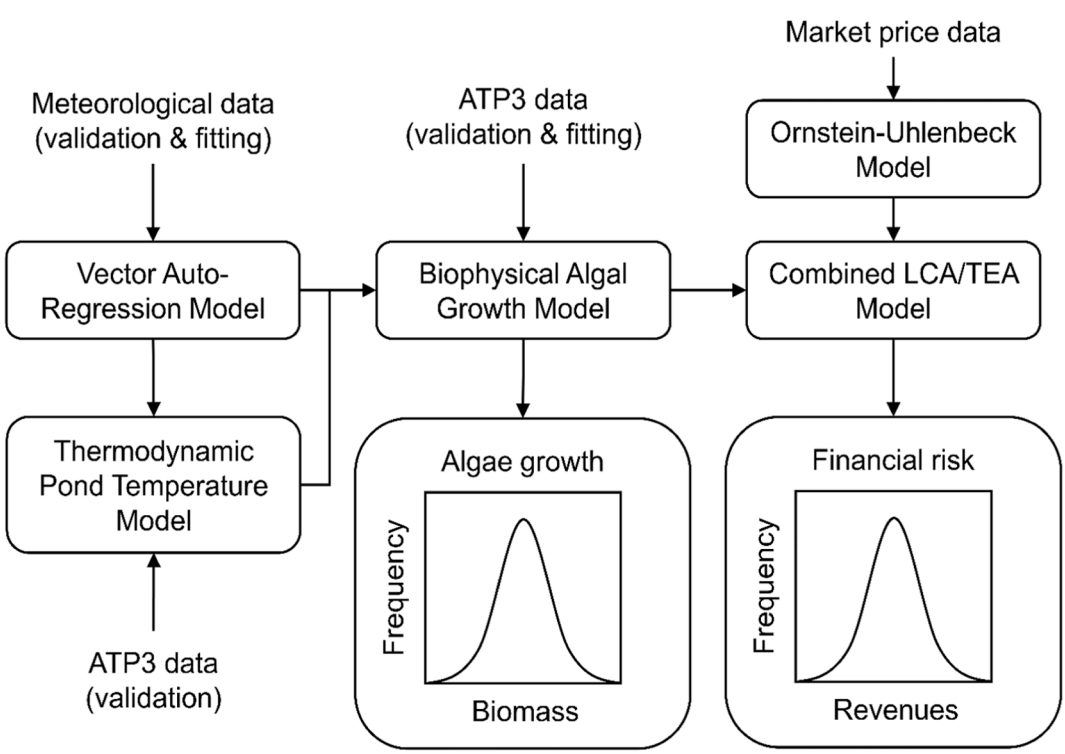

Fig. 1. Model schematic describing the flow of information: meteorological, algae growth (ATP3), and price data are fed into stochastic, thermodynamic, biophysical, and life cycle analysis/techno-economic analysis (LCA/TEA) models to give insight into algae growth and financial risk to an algae producer under stochastic uncertainty.

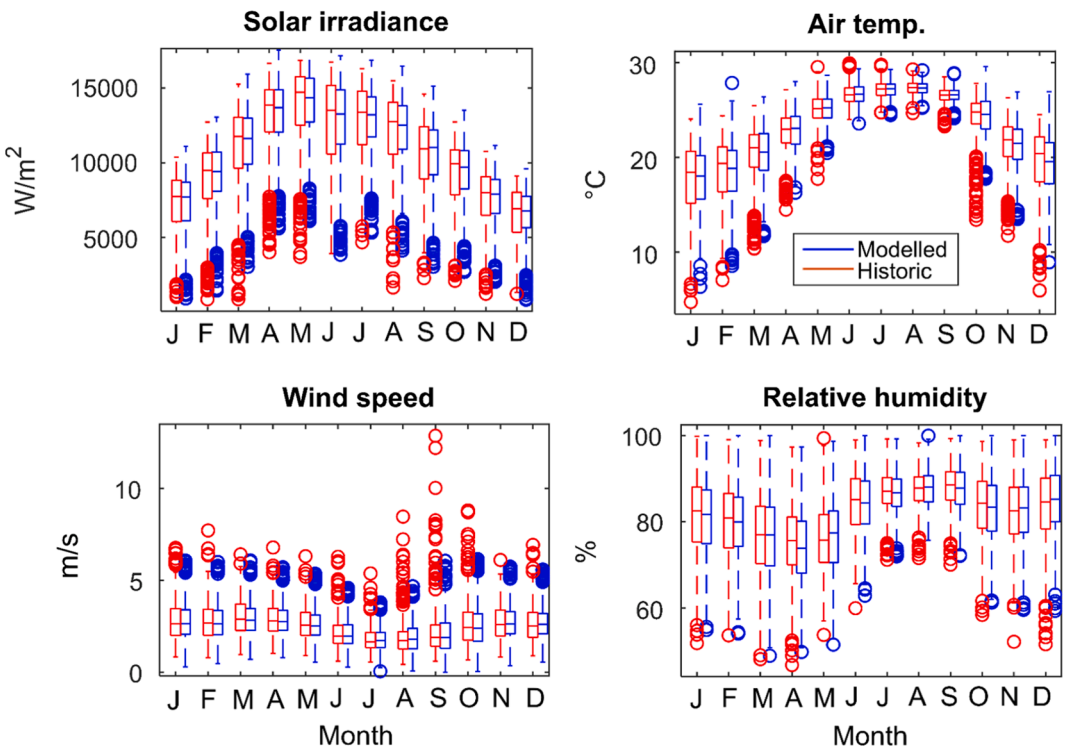

Fig. 2. Modelled and historic seasonality in weather data for Vero Beach, FL, where the box plots show the monthly median, IQR, and outliers for modelled and historic data.

describing the effect of dynamic temperature on growth rate (ε_t) with *optimal*, *suboptimal*, and *no growth* ranges [33] is used:

$$\varepsilon_t = \begin{cases} 0, T < T_{min}(no\ \ growth) \\ \dfrac{T - T_{min}}{T_{opt_{low}} - T_{min}}, T_{min} \le T < T_{opt_{low}}(suboptimal) \\ 1, T_{opt_{low}} \le T < T_{opt_{high}}(optimal) \\ \dfrac{T_{max} - T}{T_{max} - T_{opt_{high}}}, T_{opt_{high}} \le T < T_{max}(suboptimal) \\ 0, T_{max} \le T(no\ \ growth) \end{cases} \tag{4}$$

The temperature range values are fitted to the experimental data (see *2.3 Validation/fitting*). All model parameters are listed in Table S1.

2.3. Validation/fitting

The ATP3 datasets [29] are used to validate the pond temperature model and to fit and validate the biophysical growth model. The experimental data for six ponds at the Vero Beach site involving either *Nannochloropsis maritima* (KA32) or *Chlorella vulgaris* (LRB-AZ-1201) are used, as these strains were both grown year-round; note that all of the six ponds had the same strain for each experimental batch, rather than mixed cultures. Both strains have high biomass productivity and lipid contents, making them attractive for biodiesel production, and have the potential to produce co-products such as nutraceuticals (e.g., Omega-3 fatty acids) and animal feed [54,55]. Measurements characterizing the cultivation media (e.g., pH, salinity, temperature) were taken at least daily, and algal biomass production and composition data were collected upon harvesting. For each site, harvesting is recorded as simultaneous at each of the six ponds, and the period of time prior to and including each harvest (2–11 days) is referred to as the "cultivation period".

The ash free dry weight (*AFDW*) and pond temperature data from each cultivation period in the ATP3 datasets are used, with the initial and final harvests for each strain eliminated in order to approximate continuous conditions for scale-up [22]. The following equation is used to calculate *areal productivity* in g m^{-2} d^{-1} (also presented as g/(m^2*d) and g/m^2/d), where S is the surface area:

$$areal\ \ productivity = \frac{AFDW}{S{*}days\ \ since\ \ last\ \ harvest} \tag{5}$$

Average values across the six ponds for temperature and *areal productivity* measurements are used for validation. To do so, historical weather data for Vero Beach are fed into the previously described temperature and growth models. System configurations for the ATP3 experiment were used in the pond temperature and biophysical growth models for validation/fitting, such as the surface area (4.2 m^2) and volume (1000 L).

The model's ability to capture the diurnal pond temperature is shown in Fig. 3A. The modelled pond temperature has an average error ($T_{modelled}$-$T_{experimental}$) of 2.6 °C, which compares favorably to literature average errors in the range 1.3–3.4 °C [53]. Error may be due to site specific conditions that are not captured in the model, such as air emissivity and pond shading, the latter of which explains the occurrence of over-predictions.

Since both *So* (the light saturation parameter) and ε_t (the effect of dynamic temperature on growth rate) are strain-specific, these parameters are fitted for use in the biophysical model. The fitting captures observed dependence on temperature and light, allowing for this relationship to be represented in the stochastic model. Long-term photoacclimation at each location is also represented by fitting the model to

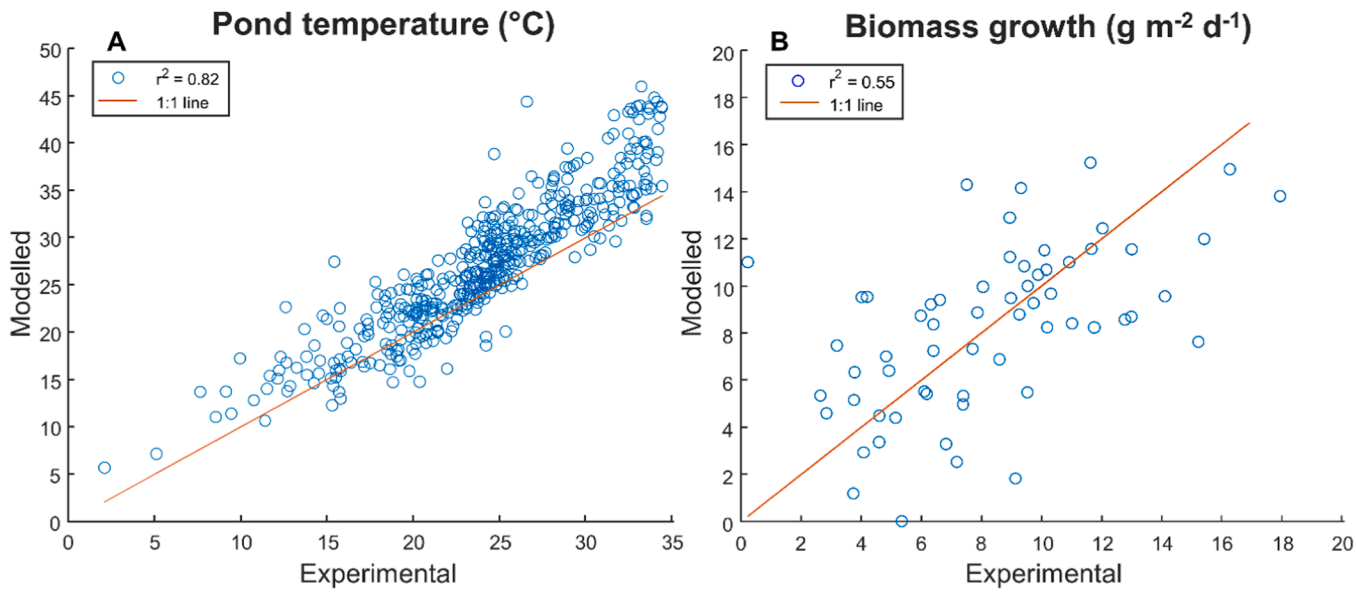

Fig. 3. Experimental and modelled data for (A) pond temperature and (B) algal biomass productivity at the Florida Algae testbed in Vero Beach, FL. Note: modelling of biomass growth error residuals (i.e., the difference between the blue dots and the 1:1 line) was performed and used in the stochastic simulations to probabilistically account for error shown in (B).

experimental data. The *fmincon* function in MATLAB is used to jointly solve for *So* and the appropriate temperature range (T_{min}, T_{opt_low}, T_{opt_high}, and T_{max}) by minimizing the least squares error between the modelled and experimental data. Experimental data for both strains are used jointly in order to have sufficient data, which is consistent with similar studies [25]. Following a seasonal bias correction (see *2.5 Stochastically modelling residuals*), the model captures 55% of the observed variability in biomass growth, without consistently over- or under-predicting biomass productivity (Fig. 3B). The remaining variability that is not captured in the biophysical growth model is represented probabilistically as described in the following section.

2.4. Growth model limitation

Modelling algae growth is challenging given data limitations and the complex processes involved, and while some models have accurately predicted growth in controlled, small-scale environments, modelling at a commercial scale will inherently be more uncertain and require more assumptions [41]. One such assumption in this study, for example, is the usage of areal productivity values from the 1000L pond experimental results to model 8100L ponds. The 1000L experiments were non-optimized trials, so they likely exhibit relatively low productivity values for this scale. Additionally, the temperature and irradiance relationships were jointly fitted for the two strains due to data limitations, but these strains are likely to have differing dependencies on these factors. Finally, the effect of variable water levels (i.e., due to evaporation and precipitation) in the ponds on algae growth was not considered, but it was assumed that water was replenished to compensate for this. As described in the following section, concerns over some of these modelling assumptions are addressed by stochastically reincorporating growth model residuals into growth model estimates of biomass production, and these provide a quantification of sources of growth variability that were not modeled deterministically.

2.5. Stochastically modelling residuals

Residuals from the biophysical growth model (i.e., the difference between each point and the 1:1 line in Fig. S7a) are represented stochastically. First, the difference between the modelled productivity ($modelled_t$) and the productivity values for the experimental harvests ($ATP3_t$) at each of the 61 cultivation periods (2–11 days), *t*, is found:

$$residual_t = modelled_t - ATP3_t \tag{6}$$

Seasonal differences in bias are corrected by separating the residuals into quarterly (3-month) bins and then adding the mean of the residuals for each quarter to the estimated daily productivity. These bias corrected model values represent the current ability of a universal model to predict site-specific, weather-dependent biomass growth in ORP systems, given some observed growth data used for model fitting.

After bias correction, errors in the modelled productivity values are still apparent (Fig. 3B). These post-bias correction residuals represent factors affecting algae growth that are not captured in the biophysical model. These include weather-related factors that are not captured in the model as well as non-weather related variables that may impact growth, including nutrient and carbon availability, light gradients within the culture, culture conditions such as salinity and pH, cell acclimation and/or adaptation, and biological contamination. In order to capture these factors, post-bias correction residuals are fitted to representative probability density functions and synthetically generated via Monte Carlo simulation. Generated errors are incorporated into bias-corrected biomass productivity values. For the remainder of this paper, these values are referred to as "non-weather growth factors" (see Growth Model in the SI for more details).

2.6. Combined LCA/TEA

A previously developed LCA/TEA model [30,31] is used to evaluate the effect of weather variability on biodiesel and algal meal (a co-product) production. The resulting uncertainty in biorefinery revenues is quantified over a 20-year lifetime, a period of time commonly used to evaluate investment in physical assets. The functional unit of the biorefinery is 10,600 ha [56], the amount of land to produce, on average, 10 million gallons of biodiesel annually. After cultivation, biomass is harvested via flocculation and dissolved air flotation, dried via centrifugation and thermal drying, and converted via lipid extraction and transesterification. These extraction and conversion techniques were chosen instead of wet extraction techniques in order to simulate production of algal meal, which increases expected revenues (Fig. S17). More information on the development of the LCA/TEA and various process assumptions can be found in the SI (see Lipid Extraction and

Combined LCA/TEA Process) and in Hise et al. [30] and Kern et al. [31].

Pond surface area (S), process retention efficiency (ε_r), and biodiesel density (ρ_{bd}), which are pre-defined model parameters, are used to estimate volumetric biodiesel produced, $prod_{bd}$ along with modelled biomass productivity ($Prod_{mass}$) and lipid percent (pct_{fame}):

$$prod_{bd} = Prod_{mass} * pct_{fame} * S * \frac{\varepsilon_r}{\rho_{bd}} \tag{7}$$

Dynamic pct_{fame} values are Monte Carlo simulated seasonally based on literature mean and coefficient of variation values [22]; additional details on these methods, including seasonal values, can be found in the SI (see Lipid Extraction and Combined LCA/TEA process).

Nutrient, water, and solvent recycling occurs throughout the process, and lipid-extracted biomass is sold as feed. The algal meal produced, $prod_f$, is found by:

$$prod_f = Prod_{mass} * S - prod_{bd} * \rho_{bd} \tag{8}$$

There is also interest in understanding how the weather-based production risks compare alongside other risks that an algae producer would experience, particularly fluctuations in the price of fuel and other high-value products. In order to facilitate this comparison, biodiesel and algal meal prices are stochastically modelled by fitting historical diesel prices to a stochastic difference model (Orenstein-Uhlenbeck) and using regression to predict biodiesel and algal meal prices as a function of diesel prices. Additional details about the stochastic price modelling can be found in the SI (see Price Model). Revenues are then calculated by multiplying production and prices for biodiesel and adding the product of algal meal production and prices. Financial performance is evaluated based on quarterly (3-month, or seasonal) revenues, a time period that is consistent with both differences in weather patterns/variability and with the quarterly financial reporting requirements that are standard for most firms; fortunately, these quarterly periods mostly coincide with seasonal periods. Costs were not included in this study as they are likely to decrease with technology improvements, but revenue variability will persist. Financing assumptions are outlined in the SI (see "Combined LCA/TEA Process") and described thoroughly in earlier publications [30,31] related to model development.

3. Results

3.1. Biophysical and financial risk characterization

Strong seasonality in biomass production across quarters is apparent (Fig. 4), and Fig. S3-6 suggest that season-to-season weather conditions have a significant effect on productivity. The lowest expected productivity values are in Q1 (Jan.-Mar.) and Q4 (Oct.-Dec.) due primarily to lower temperatures and irradiance, both of which are higher in Q2 (Apr.-Jun.) and Q3 (Jul.-Sep.), leading to higher expected productivity. These seasonal differences are expected results and would likely be considered in the planning of the biorefinery. However, the extent of variability in expected productivity within each quarter (represented by the spread of each histogram in Fig. 4), and consequently annually as well, has not been explored in previous work. Each quarter has significant variability in productivity, with standard deviations of 49, 48, 53, and 52 g m^{-2} qtr^{-1}, respectively. The coefficients of variation (CoV, found by σ/μ) are higher for Q1 (11.3%) and Q4 (13.0%) than for Q2 (4.4%) and Q3 (7.3%) due to the variation in expected productivity. Additionally, the CoV of the aggregated annual productivity is 3.9%, suggesting low autocorrelation between quarterly productivity within a year (i.e. low growth in one quarter does not necessarily lead to low growth in another). In comparison, the CoV of annual yields for corn, soybeans, and cotton in the US are typically 13–39% [28,57]; the highly engineered nature of this technology, as well as inherent biological resilience of algae compared to other crops, may lead to these differences.

The extent to which extreme inter-annual seasonal variation in

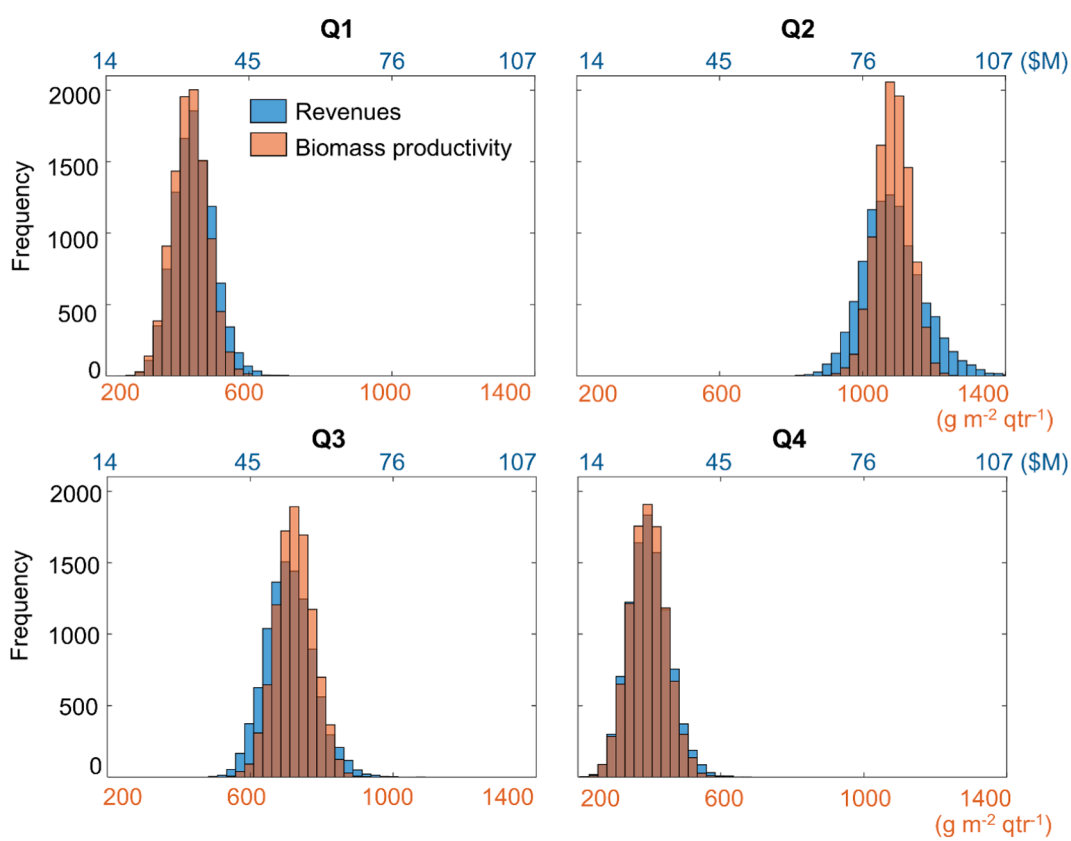

Fig. 4. Quarterly histograms for biomass productivity (orange, with axes below each figure) and revenues (blue, with axes above).

biomass productivity is driven by weather is illustrated for Q2, the quarter with the highest expected productivity, in Fig. 5, where the highest and lowest 1% productivity pathways are highlighted. This is the quarter with the highest expected solar irradiance and therefore ample energy for photosynthesis. However, algal cells can be damaged by the very high levels of sunlight frequently exhibited in Q2, so the moderate (low, for Q2) levels of irradiance in the same quarter are more favorable. High air temperatures, high relative humidity, and lower wind speeds also correlate with high productivity in Q2. This can be explained in part by the impact of these conditions on pond temperature, where warmer temperatures are generally favorable (the pond temperature rarely exceeds 38 °C, the fitted value of T_{max} in Eq. (4), above which growth does not occur). Air temperature affects heat fluxes from air, convection, and evaporation, with hotter air causing higher pond temperatures. Wind speed and relative humidity both impact evaporation rate, so lower wind speed and higher relative humidity result in less heat loss due to evaporation and thus to warmer ponds. These patterns are generally constant but vary slightly across quarters. For example, Q3 has the highest and least variable air temperatures of all the quarters. Since these high temperatures tend to be favorable for algae growth, the productivity is less dependent on fluctuations in air temperature within that already favorable range, and more sensitive to the other factors. Analysis for Q1, Q3, and Q4 can be seen in Figs. S20–22.

Patterns in biomass productivity are closely linked to fluctuations in biorefinery revenues, shown in blue in in Fig. 4, where variability in product (biodiesel and algal meal) prices is also considered. The distributions of historic product prices were found to not show seasonal patterns in variability (Fig. S10), but prices do amplify the seasonal variability in biomass productivity. For example, there is higher revenue variability for Q2 ($\sigma = 2.6$ \$M/qtr) and Q3 ($\sigma = 2.1$ \$M/qtr) compared to Q1 and Q4 ($\sigma = 1.7$\$M/qtr for both). The CoV of revenues from year-to-year, a measure of volatility, are 12.9%, 7.9%, 9.7% and 14.5% in the respective quarters; when aggregated yearly, the revenue CoV is 7.3%. Thus, an algae producer may expect higher returns in Q2 and Q3 yet still be concerned about financial risk from the revenue variability due to weather-related and market forces in all quarters. These values are lower than the CoV range of 28–43% for farm-level revenues for corn, soybean, and cotton revenues; in comparison, algal biofuels are less susceptible to financial variability from weather and market fluctuations, which is an attractive finding for the algae industry. Note, however, that since costs are not included in this evaluation, these results are not indicators of profitability, and further advancements are necessary for algae production for biofuel is to reach profitability. Extended financial results can be found in the SI (see Yearly Revenues).

3.2. Weather vs. prices as risk factors

A sensitivity analysis is performed to better understand the relative contributions of weather and non-weather growth factors as well as market prices to an algae producer's financial risk. This analysis proceeds by fixing all dynamic inputs aside from (1) weather variables, then (2) product prices, and for both cases evaluating the corresponding CoV in yearly revenues. Results show that while both are significant, market prices account for almost twice the amount of variation (6.2%) in yearly revenues than weather-related factors (3.9%). This method, however, ignores the effect of each dynamic variable on the entire distribution. For example, weather-based variability might be responsible for infrequent episodes of extreme losses but might have a lesser impact on the expected value of revenues. To explore this, another sensitivity analysis is performed to evaluate the contributions of different input parameters to the variation in quarterly revenues with the delta moment-independent method [58]. This method considers the variation in the

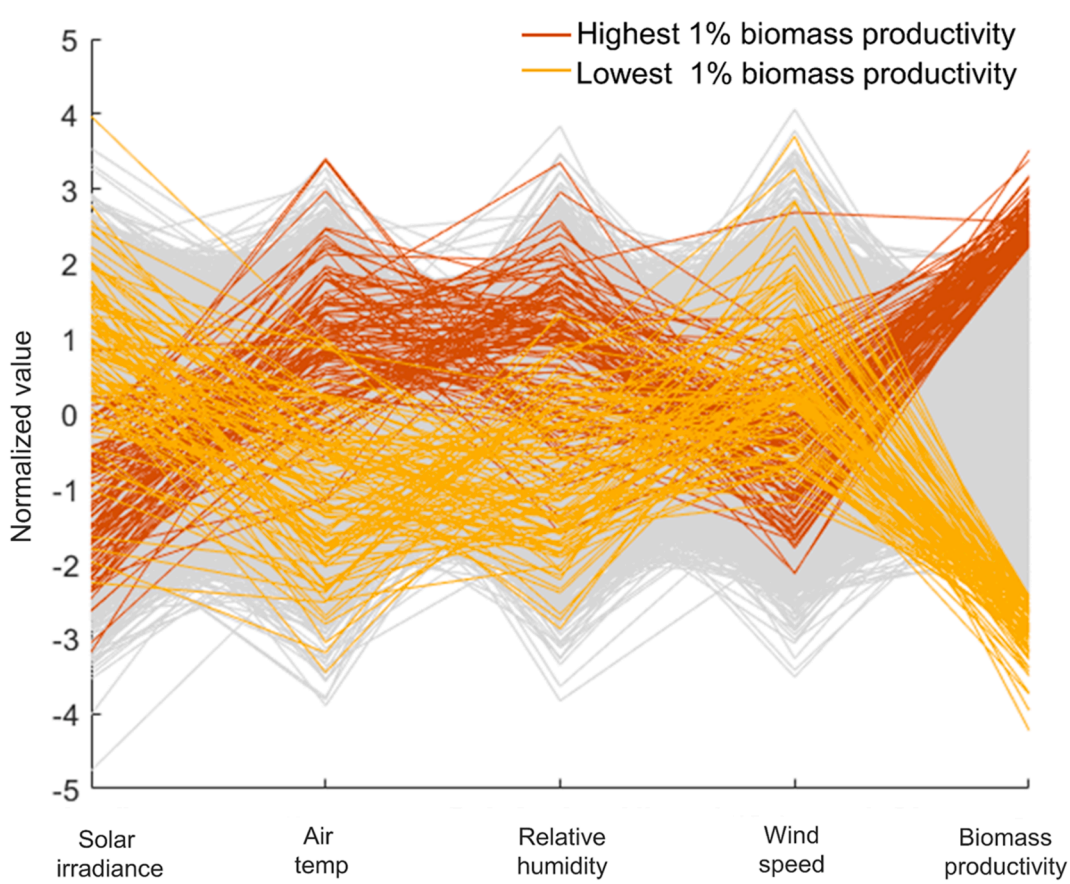

Fig. 5. Parallel axis plot connecting the weather variables and biomass productivity for Q2, where values are standardized to distributions with a mean of 0 and a standard deviation of 1; the pathways for the highest and lowest biomass productivity outcomes are highlighted.

individual inputs to determine the relative effect of each on the entire distribution of the output [59,60]. Results show that the price distribution affects the biorefinery revenue distribution more so than the other variables, though the weather distribution also significantly impacts revenues (Fig. 6A). The effect of the non-weather growth factors and lipid percent is comparatively small. The non-weather growth factors contribute most to revenue distribution in Q4, which has the highest variance in these values (Fig. S8).

Weather-related risk has the highest overall impact on the revenue distribution in Q1 and Q4, the quarters with lowest expected productivity. Fig. 6B further breaks down weather-related impacts for each of the weather variables considered. Generally, there is higher sensitivity to weather variables that tend to be less favorable in a given quarter, with the exception of relative humidity. For example, higher air temperatures are generally favorable (since they lead to warmer ponds), and the model is most sensitive to air temperatures in Q1 and Q4, the quarters with the lowest air temperatures. The sensitivity to air temperature also drives the overall higher sensitivity to weather seen in Fig. 6A.

Solar irradiance drives the performance largely in Q3 and Q2, the periods with the highest solar irradiance. Though more solar irradiance means more energy for photosynthesis, very high irradiance causes photoinhibition (represented by the effect of light saturation, ε_s, in Eq. (3)), which occurs frequently in these quarters. This explains the high sensitivity to solar irradiance in Q2 and Q3, as photoinhibition occurs less frequently in Q1 and Q4. This suggests that algae growth is more sensitive to suboptimal conditions such as photoinhibition than to energy limitations from the availability of sunlight. In addition, higher relative humidity and lower wind speeds almost always lead to higher biomass productivity due to their effects on pond temperature. Variability in wind speed has its largest effect in Q1 and Q4, the quarters with highest expected wind speeds. Finally, relative humidity has its largest effect in Q2 and Q3.

3.3. Discussion

This study provides a better understanding of weather-related production and related financial risks for the algae industry, and can aid in biorefinery decision-making on physical adaptations, such as implementing systems or operations that control weather factors (e.g., photobioreactors or strain rotation), or financial strategies such as insurance. With regard to the latter, this analysis may be useful for crop insurance providers such as private companies and the USDA, who have the unique opportunity to develop new insurance products for algae producers as a result of the 2018 Farm Bill.

This modelling approach can be applied to other sites, growth configurations, and algal strains, for which the observed relationships would differ. For example, Vero Beach has a relatively favorable and invariant climate, which could result in weather-related risks having lesser impacts on production than in other locations. There are other attractive sites for algae production, such as the arid southwest US, that may experience larger seasonal weather fluctuations and therefore higher variability in algae growth and biorefinery revenues. In addition to exploring these sites, future modelling work could consider environmental impacts (e.g., greenhouse gas emissions, resource usage) under conditions with weather-based variability in a life cycle analysis. For algal biofuels to meet the US Renewable Fuel Standards, the biofuel life cycle must involve a 50% reduction in life cycle greenhouse gas emissions compared to petroleum fuels [61,62], which is likely to be affected by weather uncertainty.

The risks from variable productivity and revenues evaluated in this work are relevant in the context of the attention that "climate risk" (i.e., financial risk from increased frequency and severity of extreme weather events) is receiving from media, government, investors, and lenders [63]. Climate risk is projected to increasingly disrupt individual firms and financial markets by causing, for example, higher price volatility, higher costs for insurers, and general financial instability [64]. Therefore, analyses of systems with vulnerabilities to weather and market prices are growing in importance as industries seek to adapt to and mitigate the impacts of global changes. This systems-based approach

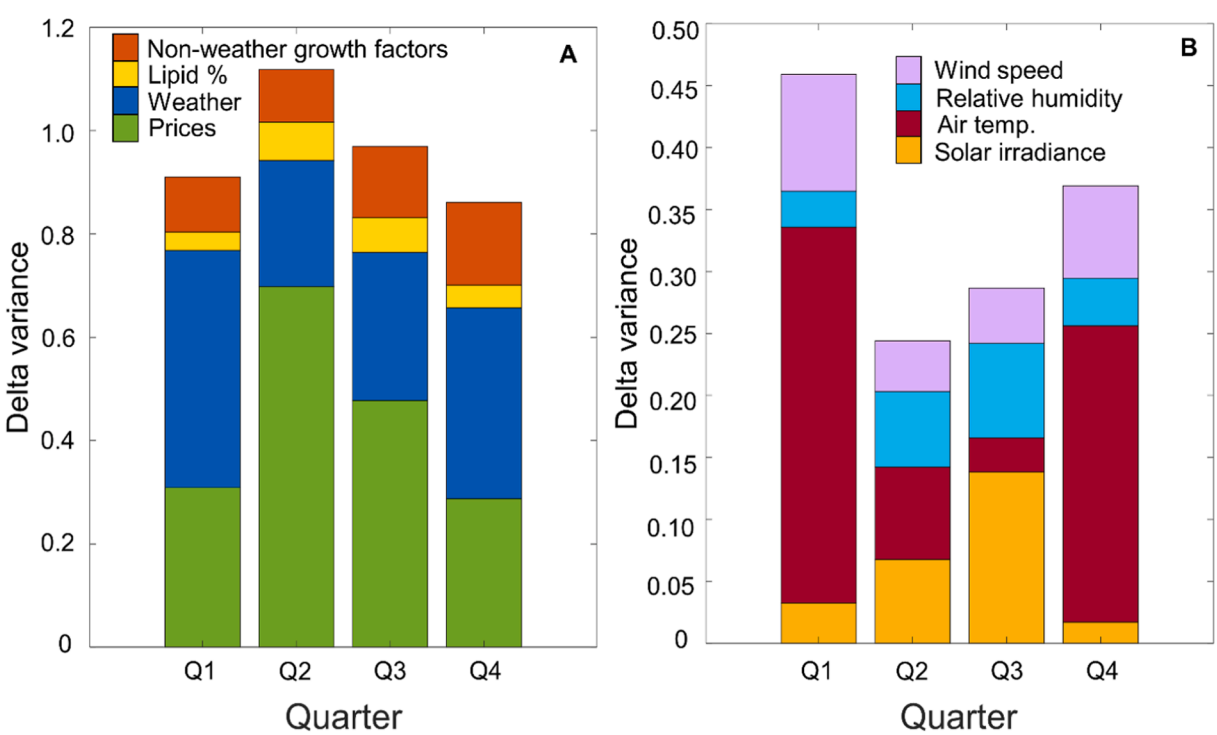

Fig. 6. Results of the delta moment-independent sensitivity analysis for (A) all parameters and (B) the weather parameters only; this shows the effect of input distributions (those listed in the legends) on the output distribution (revenues).

may thus prove valuable when considering the commercial scale-up of algal biofuels, both now and under conditions involving long term climatic shifts.

CRediT authorship contribution statement

Rachel M. Kleiman: Conceptualization, Methodology, Formal analysis, Data curation, Writing - original draft, Writing - review & editing, Visualization. **Gregory W. Characklis:** Conceptualization, Methodology, Validation, Resources, Writing - review & editing, Supervision, Project administration, Funding acquisition. **Jordan D. Kern:** Conceptualization, Methodology, Software, Validation, Resources, Writing - review & editing, Supervision, Funding acquisition. **Robin Gerlach:** Conceptualization, Validation, Resources, Writing - review & editing, Supervision, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

We are grateful to Dr. Sridhar Viamajala and colleagues at the University of Toledo and Montana State University for their expertise and support.

Funding

This work was supported by the Bioenergy Technologies Office (BETO) of the U.S. Department of Energy (DOE) for the Productivity Enhanced Algae and ToolKits (PEAK) program [grant number #DE-EE0008247/000].

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apenergy.2021.116960.

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