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Managing weather- and market price-related financial risks in algal biofuel production

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ABSTRACT

Large-scale algae production has garnered interest due to its potential as a biofuel feedstock. Previous research assessing the profitability of algae products has been mostly based on values averaged over time, but algae production and resulting financial returns exhibit significant variability due to weather and fluctuations in selling prices for algae-based products. In other sectors, producers often reduce weather- and market price-related financial risk with financial instruments such as insurance, but little research has been performed on the design of insurance products to protect algae producers. This study develops a novel index-based insurance instrument that pays-out during unfavorable weather and market conditions, then explores the instrument's effectiveness, combined with a cash reserve, in reducing revenue stream variability for an algae producer. Results indicate that a biophysically based index-insurance product tailored to the specific financial risks in algae production can reduce variability in net revenues and can do so at a lower cost than relying solely on cash reserves, the most common financial risk management tool. Assessing the performance of index-insurance in algae production is particularly timely given the passage of the 2018 Farm Bill, which newly opens opportunities for the USDA to provide crop insurance to algae producers.

1. Introduction

Microalgae ("algae") production has received increasing interest as a potential low-carbon biorefinery feedstock for many reasons, including its ability to produce both biofuel and valuable co-products such as nutraceuticals, bioplastics, high-value chemicals, animal feed, and pigments [1,2]. Algae can utilize wastewater and waste carbon dioxide as production inputs [3] while providing wastewater treatment [4] and carbon sequestration [5,6]. The highly engineered growth and processing systems also allow for recycling of nutrient and water inputs [7] and anaerobic digestion/combined heat and electricity production [8,9]. In addition, as algae growth facilities do not require arable land, neither do they compete with food production for land resources, which is a downside of crop-based biofuels [10].

Despite these advantages, algal biofuels are not currently cost-competitive [11,12]. Previous studies predict that future profitability is contingent on several factors, including: cultivation improvements that increase algal productivity and lipid accumulation [13], reduced costs in harvesting and cultivation pathways [14,15], increased production of high-value co-products [16,17], and utilization of beneficial co-processes (e.g., wastewater treatment or carbon capture) with potential associated subsidies [18,19]. For cultivation systems, open (outdoor) raceway ponds have been shown to be a more cost-effective configuration than enclosed photobioreactor systems [20,21]. Open ponds, however, are subject to weather-related vulnerabilities [22] as algae growth is highly dependent on factors such as solar irradiance and temperature. These factors are sufficiently important that they are likely to play an important role in siting algae biorefineries, as demonstrated by studies that use biophysical growth modeling and geospatial feasibility analysis to estimate algal and lipid productivity at various

Abbreviations: ATP3, Algae Testbed Public-Private Partnership; LCA/TEA, life cycle analysis/techno-economic analysis; IQR, interquartile range; ROI, return on investment; VAR, value-at-risk.

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locations across the US [23,24]. These studies provide insight into the effects of weather variability that an algae producer would expect and plan for, such as lower algae productivity in winter months and higher productivity in summer months. However, unexpected variability in weather within these seasons, such as an unusually cool or cloudy summer, can lead to unexpected reductions in algae production and accompanying revenue losses. Similar weather variability has been a longstanding concern for crop-based biofuels, as well in the solar and wind energy industries, but relatively little work has been done to explore this relationship in biofuels. In order to analyze the effect of weather variability, existing techno-economic analysis (TEA) work has simulated stochastic weather inputs to assess financial outcomes for algae producers [25,26], and this study takes the next step to consider how this financial risk could be managed.

In addition to weather-based financial risk, market risk related to variability in the price of algae-based products represents another concern for algae producers. The subject of market-based financial risk has been studied in many industries and has given rise to a number of studies which inform how this risk can be managed [27,28]. Nonetheless, little research of this type has been conducted in the area of algae production. One exception is recent research [26], which jointly performed stochastic weather and price modelling on an algal biorefinery and found that deviations from expected weather patterns, in addition to market price fluctuations, can give rise to large and disruptive variability in an algae producer's net revenues. The resulting financial losses can impair an organization's ability to meet its cash flow obligations, such as debt service and investor payouts, leading to more expensive and/or difficult borrowing arrangements [29,30]. This would be especially detrimental to the development of a financially sustainable algal biorefinery industry, particularly given the "capital intensive" nature of algae production compared to crop-based and cellulosic biofuel technologies [18]. In the worst cases, financial losses can result in insolvency for the algae producer [31] but even less severe outcomes can ultimately increase the costs of biofuels, adding to the challenges of making them commercially viable.

To manage weather-related risk faced by algae producers, the research community has thus far focused on physical and technical actions such as improving algae's resilience to weather variability through strain rotation [13], genetic engineering [32,33], and system engineering and optimization [34,35]. These physical adaptations can effectively manage some weather-related risk, but as in agriculture, significant vulnerability to weather variability remains. In other industries that are vulnerable to weather and price risk, many firms also make use of financial tools to reduce financial risk. The most common of these is some form of self-insurance via a (cash) reserve fund that can be used to compensate for periodic losses. However, maintaining a large reserve fund in a highly accessible "liquid" form (e.g., money market) typically earns very little interest and can thus be expensive in terms of the "opportunity cost" (i.e., the difference between what could be earned via a less liquid investment with a higher interest rate), making this approach unattractive for managing infrequent, large losses arising from more extreme weather events [36].

Many firms transfer some portion of their financial risk to a third party by using some form of insurance. This approach can allow for a smaller reserve fund, designed to mitigate smaller and more frequent losses, to be combined with insurance that is relied on to manage losses from less common but more severe events. In some cases, insurance contracts designed to pay-out based on the value of an "index" (e.g., temperature) can be especially cost-effective for reducing the impact of weather-related events [37,38]. With such an instrument, the location, duration, and/or severity of the event are defined relative to the index, as is the amount of the payout to the insured party [39]. Index-insurance enjoys several advantages over conventional indemnity-based insurance including reduced moral hazard (as payouts are not linked to reported losses), less subjectivity in assessing losses, lower transaction costs, and quicker resolution of payouts [40]. The key is that the index must be highly correlated with the financial metric of interest (e.g., net revenues, costs, or damages) for the contract to be effective, otherwise there exists high "basis risk" in which contract payouts and losses are not well aligned [41]. Examples of effective index-based contracts exist in many sectors, including in electricity production to manage temperature-related deviations in heating and cooling demand [42], in agriculture to reduce financial risk from rainfall and temperature deviations [40,43,44], and in hydropower production to manage hydrologic and price variability [45,46]. Most indices have thus far been based on a single weather metric [38,47], or a probabilistic combination of multiple metrics [48,49], but highly tailored indices for specific financial risks have been shown to be more attractive to users [45,50,51].

Despite the similarities of algae production to many of the aforementioned economic sectors in terms of weather-related risk (e.g., agriculture), no study has yet explored the development of an index-based instrument for algae producers nor how it might be integrated into an effective financial risk management strategy. These issues are of particular interest given passage of the 2018 Farm Bill in the United States, a bill in which algae was named an "agricultural commodity", making it newly eligible for federal crop insurance programs [52]. There are currently no insurance products designed specifically for algae producers, nor is there research on the types of insurance products that could effectively reduce their financial risk. With these new opportunities in mind, this study seeks to assess strategies for managing financial risk experienced by an algal biorefinery using both cash reserves and a newly designed index-based financial instrument: a multi-weather, biophysical-based index that also incorporates market prices as a risk management product that can be tailored to an algae producer's specific vulnerabilities to variable weather and market conditions.

The paper is organized as follows: a stochastic model of both weather and market conditions is used to simulate dynamic algal biomass growth and relevant prices (sections *2.1-2.2)*, which are used as inputs to a previously developed life cycle analysis/techno-economic analysis (LCA/TEA) model of an algal biorefinery [26,53,54]. Output from this LCA/TEA model includes distributions of algal biomass, biodiesel, and algal meal (an animal feed) produced, as well as associated biorefinery net revenues. These distributions are used to design index-insurance contracts (sections *2.3-2.6*) which are then evaluated in terms of their effectiveness as a complement to, or substitute for, a cash reserve when managing financial risk (section *3*). This analysis is developed using data from a pilot-scale algae production facility in Vero Beach, Florida, a site chosen based on data availability as it was used to develop the Algae Testbed Public-Private Partnership (ATP3) datasets [55]. Results from this study should yield insights into the ability of financial risk management strategies to reduce net revenue variability and improve the commercial viability of investments in algae production facilities.

2. Methods

The modeling framework used in this study is shown in Fig. 1 and further described in the following sections. This analysis is composed of three elements: weather and price modelling, risk characterization, and risk management. Development of the weather-based algal growth, price, and combined LCA/TEA models used in risk characterization are described in Kleiman et al. [26]. This research builds on the previous work in many ways (as detailed below) in order to analyze the effectiveness of the index-based financial instrument on its own, in combination with, and in comparison to a reserve fund, in managing both the market- and weather-related financial risk for an algal biorefinery.

2.1. Weather and price modelling

The weather-based algae growth model first involves stochastic weather modelling of four parameters that affect algae growth: solar irradiance, air temperature, relative humidity, and wind speed, each of which was demonstrated to contribute to weather-related fluctuations in

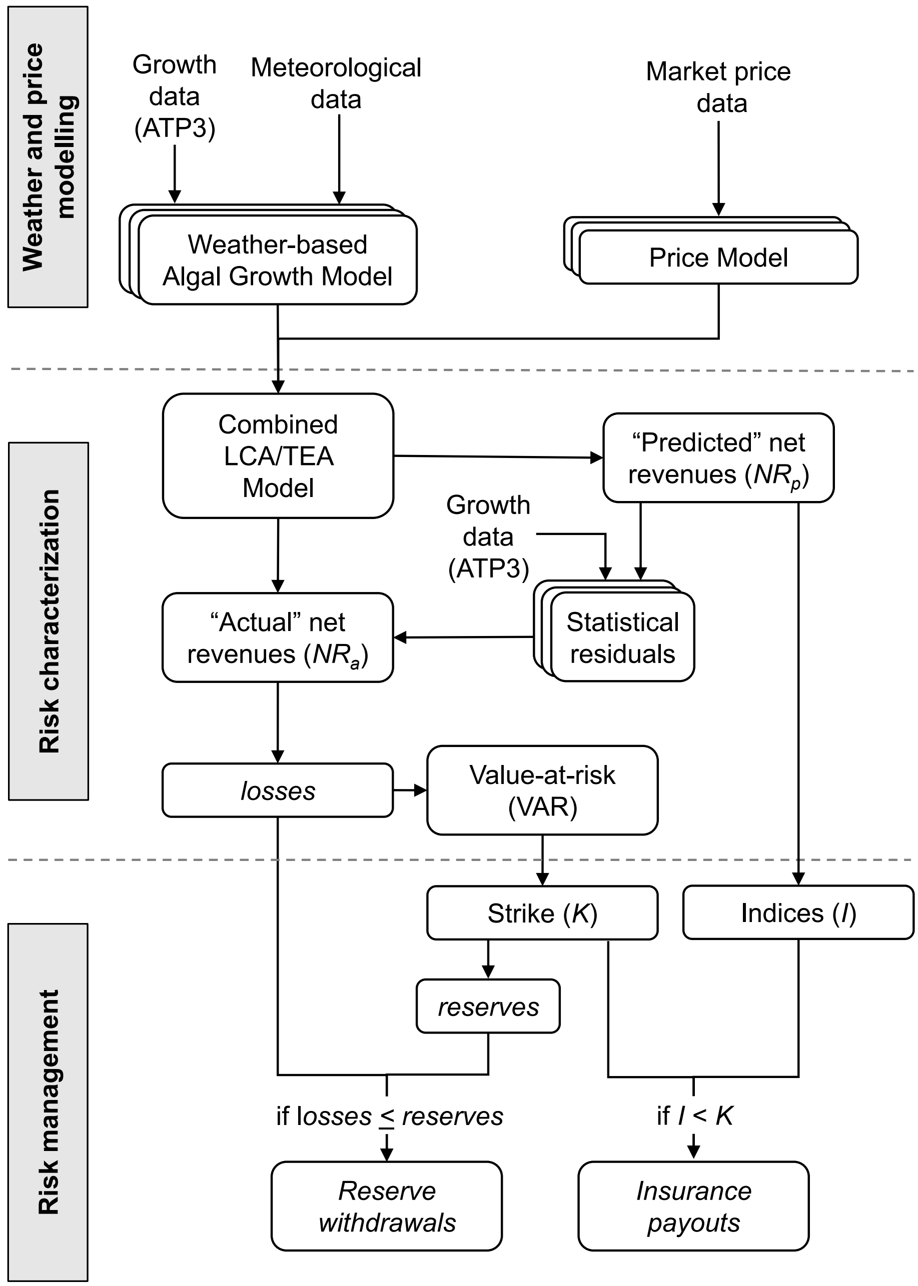

Fig. 1. Model schematic describing the flow of information, separated into weather and price modelling, risk characterization, and risk management sections, where stacked boxes represent stochastic processes; note that in-depth methods for Weather and price modeling can be found in Kleiman et al. [26], while this paper mainly discusses the Risk characterization and Risk management sections.

algae production [26]. This model is used to generate 500 realizations of 20-year investment horizons (10,000 years total) at a daily time step using a vector auto regression model for Vero Beach, FL. Kleiman et al. [26] demonstrated that this approach effectively captures seasonality and auto-correlation for each parameter, as well as cross-correlations between parameters, while also generating conditions outside of (more extreme than) the relatively short historic records for each parameter. These synthetic data are fed into a model of algae production in outdoor raceway ponds that includes both a pond temperature model [56] and biophysical growth model [57]. This model also includes a seasonal bias correction based on experimental algae growth data [55] to yield 10,000 years of synthetic daily estimates for algal biomass productivity, which is referred to in the remainder of this work as "predicted" productivity. These values represent the extent to which any group (e.g., algae producers or insurance underwriters) attempting to deterministically model algae growth for the purpose of evaluating weather-related algae growth risks would be able to do so.

A second 10,000-year synthetic dataset of biomass productivity referred to in the work as "actual" productivity is developed using an additional stochastic term: error residuals between the observed (i.e., experimental data from the ATP3 database at Vero Beach) and "predicted" productivity, which were fitted to a normal distribution, sampled via Monte Carlo simulation, and added to the "predicted" productivity values. These "actual" productivity values represent a synthetic dataset that characterizes the risk of deviations from "predicted" growth patterns arising from factors related to algae growth that are not included in the biophysical model, such as nutrient and carbon availability, light gradients within the culture, culture conditions such as salinity and pH, cell acclimation/adaptation, and biological contamination.

In addition to weather-based production risks, there is also interest in understanding how fluctuations in the price of fuel and other high-value products contribute to financial risk for an algae producer. As outlined in Kleiman et al. [26], market prices are modeled stochastically using an Ornstein-Uhlenbeck model which generates a 10,000-year stochastic ensemble for prices. The biorefinery modeled in this work produces biodiesel with an algal meal co-product, so biodiesel (B99/100) and soybean meal (a proxy for algal meal) prices are modeled. The synthetic price and productivity datasets are fed into a combined LCA/TEA model that simulates an algal biorefinery scaled to produce (on average) 10 million gallons of biodiesel annually in open raceway ponds [26,53,54]. The LCA/TEA model dynamically simulates biodiesel and algal meal production and associated net revenues (which includes revenues, capital and operational costs, and financing costs) at a daily time step, then aggregates these values to yearly intervals over 500 model runs of 20-year plant/investment lifetimes. Further details on cash flows can be found in Hise et al. [53], Kleiman et al. [26], and in Appendix A.

As algae-based biodiesel is not currently cost-competitive with other fuels, several assumptions were made in this study to bring the algal biorefinery to a status of expected profitability (a presumed prerequisite for investment) but still with some probability of experiencing losses under uncertain weather and market conditions. The most straightforward way to accomplish this, and one that seems in line with the current trajectory of technological improvement [18], is to reduce the costs of production significantly from current levels while continuing to base revenues on a distribution of current market prices. Therefore, the distribution of costs (including operational, capital, and financing) is scaled down while maintaining a constant coefficient of variation such that the expected annual return on investment (ROI) for the biorefinery is 8%. This allows for a risk of negative net revenues based on poor weather and/or market conditions, both in individual years and cumulatively over the entire 20-year investment horizon.

2.2. Risk characterization

Under the assumptions outlined in the previous section, the LCA/TEA first simulates “predicted” net revenues (NR_p) as a function of weather-based productivity, and the NR_p values are then used as the indices for the index-insurance contracts (see section 2.4). Prices and “actual” productivity values (the latter including model residuals) are fed into the LCA/TEA to yield “actual” net revenues (NR_a), which are used to evaluate effectiveness of the risk management scenarios and for risk characterization. Histograms of the two 10,000 distributions are shown in Fig. 2A. From the NR_a distribution, *losses* are found, such that:

$$losses = \max\left(-NR_a, 0\right) \tag{1}$$

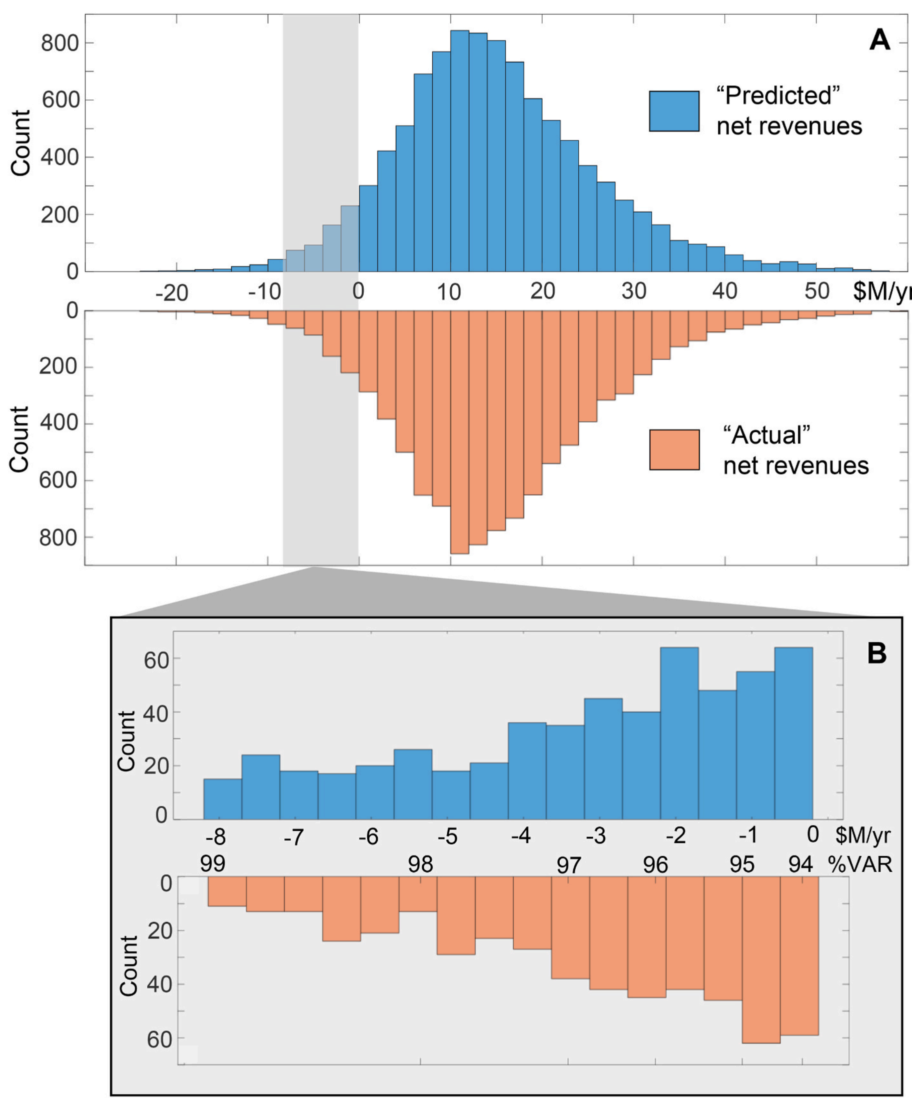

Fig. 2. The “predicted” and “actual” distributions of net revenues for an algal biorefinery, including (A) the complete distributions for the 10,000 modeled years, and (B) a zoom-in of the distributions of negative net revenues (up to the 99% VAR) that are expected to occur with no risk management.

A common risk characterization metric is the value-at-risk (VAR) which is frequently used in commercial settings as a basis for risk management [58]. In general, the VAR can be found using financial data that is historic or simulated and represents a specific probability of losses. For example, the 95% VAR refers to the worst (highest) *losses* that can be expected to occur 5% of the time. The VAR can be identified at different loss probabilities, and these values are used in this work to determine both the size of the reserve fund (see section *2.3*) and the thresholds triggering payouts for the insurance contracts (see section *2.4.1*). The distributions of negative NR_a (*losses*) and NR_p values up to the 99% VAR are shown in Fig. 2B.

When creating the index-insurance contract, the strike value (identifying the point at which insurance coverage begins) is determined relative to NR_a (based on "actual" biomass), while the payouts are determined when the index (based on "predicted" biomass) declines below the strike. For example, the 95% VAR with respect to the NR_a distribution is $-1.2 M. The NR_a distribution also informs the limits for all risk management strategies: a range of risk management strategies are developed to prevent against outcomes worse than the 93.5% VAR (where $NR_a = \$0$), representing a more risk averse goal, and the 99% VAR (where $NR_a = \$\text{-}8.51$ M*)*, representing less risk aversion.

2.3. Reserves

Most organizations cover some portion of their losses with a reserve (contingency) fund, a form of self-insurance, where withdrawals from the reserve are used to mitigate losses in years when net revenues are negative. Withdrawals from the reserve fund ($withdrawals_{res}$) are triggered by *losses* and bounded at the size of *reserves*:

$$withdrawals_{res} = \min\ (losses, reserves) \tag{2}$$

The size of the *reserves* is set using the VAR, as determined by the distribution of expected losses, where, for example, a reserve fund that protects against losses at the 95% VAR holds in reserve an amount that would compensate for the 95th percentile of the *losses* expected to occur (i.e., net revenues are below the 5th percentile) [58]. Varying reserve sizes are evaluated, for which tradeoffs between cost and effectiveness are considered (see section *3.1*).

The reserve fund is assumed to be initially established by borrowing at an interest rate (IR_{bond}) of 4%, which assumes the algae producer qualifies for a U.S. Department of Energy loan guarantee rate [59]. The debt incurred is repaid over 20 years in fixed increments, which are referred to as the *debt service costs*:

$$debt\ service\ costs = P\ * \frac{IR_{bond}(1 + IR_{bond})^{20}}{(1 + IR_{bond})^{20} - 1} \tag{3}$$

where *P* represents the principal and is equal to the size of the reserve at the beginning of the 20-year investment horizon. As the reserves are depleted in years with net revenue losses, more debt is issued to replenish the reserves; thus, debt service costs may continue after the 20-year investment horizon.

The reserve funds must be readily available to compensate for losses, so they must be kept in a highly liquid form (e.g., money market). This liquidity comes with *opportunity costs*, as these funds could easily be invested in a less liquid but similarly secure form and earn a higher return. Opportunity costs are represented by the difference in interest earnings between illiquid and liquid, but similarly secure, investments, such that:

$$opportunity\ costs = reserves * (IR_T - IR_{MM}) \tag{4}$$

where IR_T and IR_{MM} correspond, respectively, to the 10-year averaged interest rates of a 10-year treasury bond (2.27%) [60] and an average of money market rate offerings (0.61%) [61].

Both *debt service costs* and *opportunity costs* increase for a larger reserve, one that would be sized to compensate for very large losses that occur very infrequently (e.g., the 99% VAR) or for consecutive multi-year losses. The *debt service costs* increase as new debt is issued to replenish the reserves (see Appendix D for more details).

2.4. Index-insurance

2.4.1. Index contract creation

Beyond a reserve fund, instruments that transfer financial risk to a third party, such as insurance, can also be used to cover revenue shortfalls. In the case of protecting against extreme events, a reserve fund would need to be very large, with opportunity costs to match, and in such cases insurers are often able to provide coverage at a lower expense through some combination of risk pooling, diversification, and better risk quantification [62].

While weather-related impacts on algae growth are significant, variability in prices for biodiesel and algal meal also have a substantial influence on net revenues of the modeled facility. Therefore, the index used in this analysis is a function of weather factors that affect biomass productivity and prices for diesel and algal meal.

Insurance payouts ($payout_{ins}$) are equal to the difference between the strike (*K*) and the index value (*I*):

$$payout_{ins} = max(0, I - K) \tag{5}$$

In this work, the index is "predicted" net revenues, NR_p; thus, *I* values correspond directly (inversely) to *losses*. As insurers often times limit payouts to protect themselves against extraordinarily high payouts, $payout_{ins}$ are capped when *I* is equal to the 99% VAR (i.e., net revenues below the 1st percentile).

2.4.2. Basis risk

The effectiveness of index-insurance is a function of the correlation between the index and the financial outcome of interest, which in this case is "actual" net revenues. Basis risk is evaluated by comparing $payouts_{ins}$ to the amount that insurance payouts would fully compensate the algae producer's losses if the index and the losses were perfectly correlated. However, this is rarely the case, and many successful financial instruments still exhibit significant basis risk [40,63].

Basis risk is evaluated for the previously described index, which incorporates both weather-based and price variability. In Fig. 3, using a strike (*K*) value equal to the 93.97% VAR (the lowest cost K value; see section *3.1*), insurance payouts ($payout_{ins}$) are compared to *losses – K,* as *losses* less than *K* are covered by the reserve fund. Ideally, all data points would fall on the 1:1 line, indicating that *losses* and $payouts_{ins}$ are perfectly correlated, a situation indicating no basis risk. Here, basis risk is low, with points falling close to the 1:1 line, and an r^2 value of 0.92, suggesting that this index is likely to be effective. For comparison, contracts with r^2 values as low as 0.32 have been shown to be successful in managing net revenue shortfalls for farmers [63,64]. These results suggest that an index that includes consideration of both market price dynamics and weather-based biomass growth has the potential to serve as the foundation of an index-insurance contract that could be useful in managing an algae producer's financial risk.

A sensitivity analysis on a fixed-price index, which solely incorporated weather variability and not price variability, is also performed. The fixed-price index is poorly correlated to losses ($r^2 = 0.16$) and thus was not used in further analysis. Details can be found in Appendix B.

2.4.3. Premium pricing

The insurance premium is priced based on the distribution of expected payouts (*E[*$payouts_{ins}$*])* to the insured (i.e. algae producer), plus an additional "loading", which represents administrative costs, product development, return on investment, and opportunity cost of reserves, such that:

$$premium = E[payouts_{ins}] + loading \tag{61}$$

As is standard in premium pricing, a Wang transformation was used

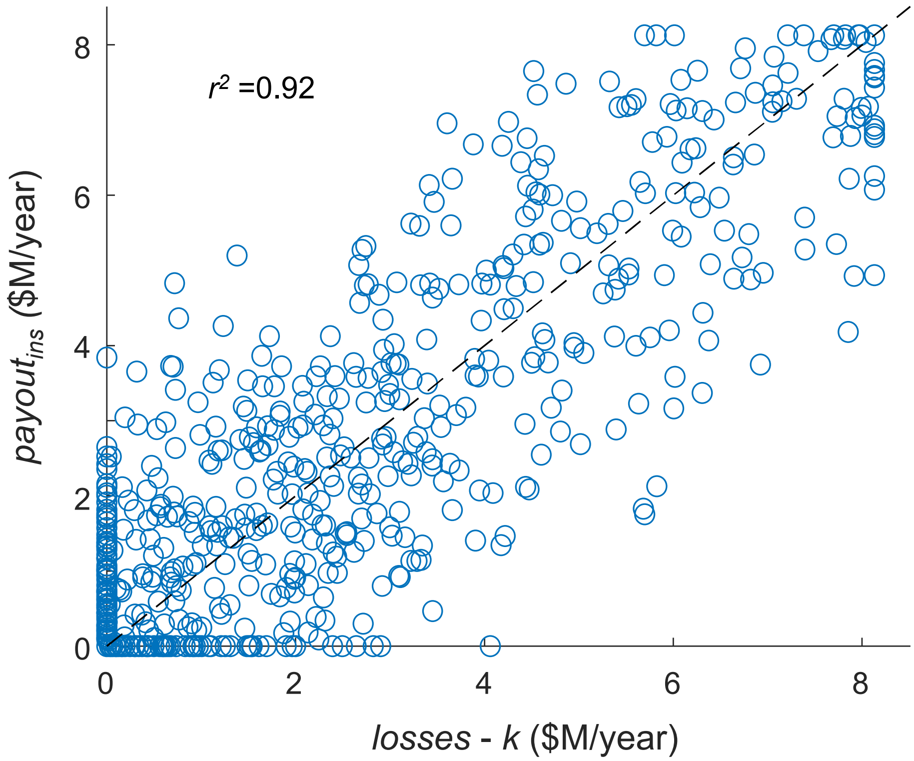

Fig. 3. *Basis risk for the index contract with a strike (k) value corresponding to the 93.97% value-at-risk (VAR), the lowest-cost risk management strategy; the dotted line corresponds to the 1:1 line, around which $payouts_{ins}$ would ideally occur (coefficient of determination = 0.92).*

on the *E[$payouts_{ins}$]* distribution [65]; further details on pricing can be found in Appendix C.

2.5. Combining reserves and index-insurance

Risk management strategies using both reserves and an index-based insurance are often combined in various proportions to minimize the costs of achieving risk management goals [66,67]. The costs of an index-based insurance instrument and the opportunity cost of maintaining a reserve vary with the level of risk mitigation they provide, with the opportunity costs of a reserve climbing steeply if it is sufficiently large to protect against very large (and rare) events, while conversely insurance is quite expensive when it covers frequent, small losses.

For scenarios involving combinations of both a reserve and index-insurance, the *losses* threshold where coverage transitions from reserve payouts (i.e., less severe losses) to insurance payouts (i.e., more severe losses) is an important consideration and is represented by *K*, the strike value identifying the point at which insurance coverage begins. Fig. 4 shows an example contract payout structure, which has a *K* value of $-3.0 M and a payout cap of $5.5 M. For different values of *K*, tradeoffs exist between the cost of maintaining a reserve of a specific size (debt service and opportunity costs) and the cost of insurance (loading). More coverage with the reserve (higher *K*) requires a larger reserve, resulting in higher debt service and opportunity costs, and higher coverage with the insurance (lower *K*) results in higher loading costs. For cases where *losses* are rare, but substantial, reserve costs can exceed loading costs, making a lower *K* more cost effective. Aside from costs, tradeoffs may also exist in the effectiveness of these tools. The basis risk associated with the index-insurance tools means that some portion of *losses* are typically not covered by $payouts_{ins}$. With the reserve, all *losses* up to the reserve size are covered, but with costs that rise as the size of the reserve coverage increases. To evaluate these tradeoffs, a range of combinations of reserves and insurance contracts are evaluated across multiple *K* values, and the *K* value with the lowest cost is found and used to identify a combined reserve and insurance strategy.

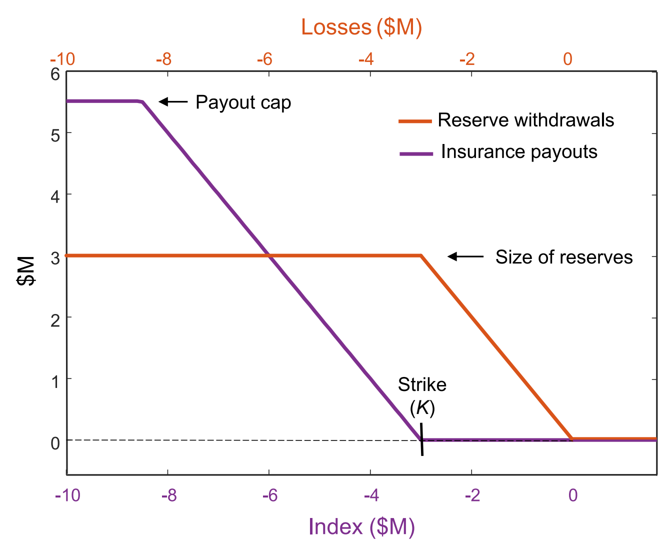

Fig. 4. *Overview of the relationship between reserve withdrawals and losses (red), and insurance payouts and the indices (purple) using a K value of $-3.0M as an example.*

2.6. Risk management strategies

Three risk management strategies are considered in this analysis: 1) Reserve-Only, 2) the minimum cost combined reserve and insurance ("Reserve & Insurance"), and 3) Insurance-Only; these are all compared to a scenario involving no risk management. For each of these strategies, weather-related revenue shortfalls are covered up to the 99% VAR (as defined by *losses*) by reserves, index-insurance, or a combination of these tools. For the Reserve-Only strategy, debt is issued to initiate the reserve fund at a level equivalent to the 99% VAR, and *losses* trigger a reserve transfer to compensate fully for these losses up to the 99% VAR. For the Insurance-Only strategy, the strike (K) is set to a net revenue level of \$0, with payouts scaling up as losses become larger and eventually being capped at the 99% VAR. Details on the methods used to evaluate these strategies over the 20-year investment horizon can be found in Appendix D.

3. Results

3.1. Minimizing risk management costs for the Reserve & Insurance strategy

An ideal risk management strategy is one that, in addition to effectively managing revenue variability, also comes at a low cost. To minimize risk management costs for the (combined) Reserve & Insurance strategy, the present values of risk management costs (*PV(costs)*) are described in Fig. 5 across various strike values (i.e., the point above which losses are covered by the insurance). The reserve costs are represented by the sum of *debt service costs* (both during and after the 20-year investment horizon), the *opportunity costs* of maintaining the reserves, and the amount in the reserve at the end of the 20-year period. The insurance costs represent the *loading*, which corresponds to the portion of the *premium* that is not expected to be returned in payouts.

The minimum cost strategy occurs when the insurance contract strike is set to the 93.97% VAR (*losses* = \$0.38 M) where *PV(costs)* is \$1.96 M, so 93.97% VAR is used as the strike value for the Reserve & Insurance strategy. However, the cost of the Reserve & Insurance strategy changes relatively little over the range between the 93.5% and 96% VAR. Especially high costs occur when reserves are increasingly used to manage very extreme risks (i.e., high VAR levels), as the combination of higher opportunity costs and the repeated issuance of debt to replenish reserves in years of extremes losses becomes very costly. Since *losses* are rare (i.e., in 6.5% of years) but substantial, the reserve costs increase steeply as the strike increases; thus, the minimum cost strategy heavily favors insurance.

3.2. Comparison of strategies

Risk management strategies are compared across 20-year planning

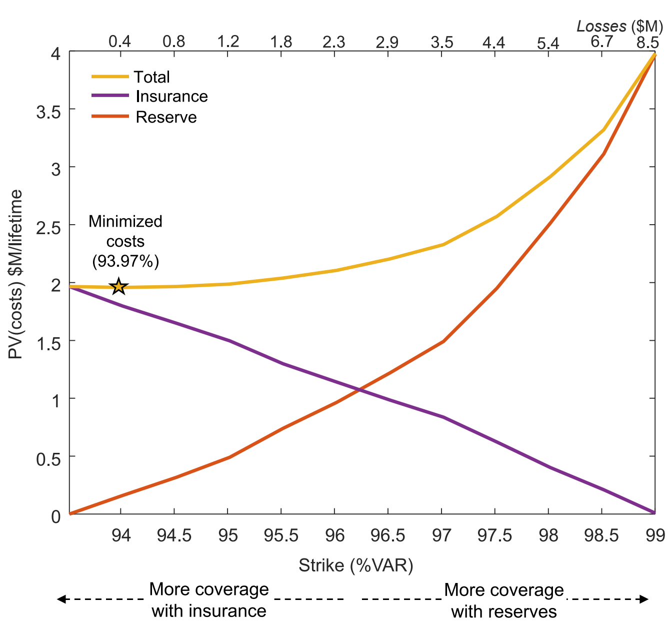

Fig. 5. Optimization of the present value of risk management costs across various strike values, where the lowest total cost (insurance + reserve costs) corresponds to the 93.97% VAR, which is starred.

horizons. A single, illustrative 20-year time series of yearly hedged net revenues (NR_h) is shown for the strategies, with all of these are compared alongside a “No Risk Management” (i.e., “actual” net revenues, NR_a) strategy in Fig. 6A. This particular 20-year period involves unfavorable weather and market price conditions in several years, such that *losses* occur in consecutive years during the middle of the period (years 12–15), an occurrence made more likely by auto- and cross-correlation in biodiesel and animal feed prices. This is not representative of all 20-year runs in which *losses* occur, but represents an especially unfavorable 20-year period in which an algae producer would want some financial protections. Overall, 31% of the 500 realizations of 20-year periods have *losses* in any year.

The decline in NR_a in years 12–15 lessened by the different risk management strategies to varying degrees, and Fig. 6B and C give further insight into the tradeoffs over this example period. Variability in cash flows in and out of the reserve fund are tracked in Fig. 6B, with reserve transfers matching *losses* for the Reserve-Only strategy (up to the cap at \$8.51 M, or the 99% VAR). However, the yearly debt service payments increase after years where reserve withdrawals occur as debt must be reissued to replenish reserves back to specified levels. For the Reserve & Insurance strategy, yearly debt service payments are lower as reserves are only drawn on to meet *losses* up to \$0.38 M, the cost-minimizing strike value of 93.97% VAR. *Losses* that exceed \$0.38 M are covered by insurance, with insurance payouts that are somewhat lower than when the Insurance-Only strategy is in use (Fig. 6C). Unlike the reserve transfers, the insurance payouts do not exactly match the portion of *losses* that they are intended to cover, and this is due to basis risk. For example, NR_a in year 15 is equal to -\$8.38 M (so *losses* = \$8.38 M), and the insurance payout for the Insurance-Only strategy is \$7.44 M; payouts are also lower than *losses* in year 12. However, in year 14, the insurance payout (\$3.43 M) exceeds *losses* (\$0.58 M). Across all of the simulated runs, payouts occur that are both higher and lower than *losses* (Fig. 3) with payouts lower than *losses* occurring somewhat more frequently when losses are more extreme (i.e., greater than \$1.2 M, the 95% VAR).

Results from 10,000 simulated years of annual net revenues (NR), derived from 500 realizations of 20-year periods are presented for multiple strategies in Fig. 7. The median of the No Risk Management strategy is \$14.42 M, which suggests that positive net revenues are expected yearly, but large year-to-year variability (as represented by the interquartile range (IQR) of \$13.69 M) leads to a risk of significant *losses*, as represented by the 1st percentile of -\$8.51 M.

For the Reserve-Only strategy, the reserve experiences withdrawals in 641 of the 10,000 synthetic years. These events are costly since new debt is then issued to raise the reserve back to the level of the 99% VAR. Especially costly events occur when the reserve falls to zero, which happens in 1% of the simulated years, consistent with a strategy designed to cover *losses* up to the 99% VAR. The annual median of hedged net revenues (NR_h) for this strategy is \$13.66 M, which is lower than that of no risk management (\$14.42 M), and the difference (\$0.76 M) represents the expected yearly costs of this risk management strategy. The strategy reduces the risk of extremely high losses (1st percentile = \$-4.80 M) relative to a no risk management (1st percentile = \$-8.51 M) scenario by mostly reducing the incidence of extreme events, as evidenced by the small increase in IQR (\$13.75 M). The Reserve-Only strategy, which is the status-quo for many businesses, can be effective, but comes at a high cost, particularly if the goal is to protect against extreme losses (i.e., the 99% VAR).

Both the Reserve & Insurance and the Insurance-Only strategies significantly reduce the risk of *losses* at a lower cost compared to the Reserve-Only strategy. The Insurance-Only strategy is slightly more effective at increasing the 1st percentile (\$-2.55 M) compared to that of the Reserve & Insurance strategy (first percentile = \$-2.57 M), and the two have about-equal yearly risk management costs (\$0.43 M and \$0.44 M). In addition, the changes in IQR for these strategies are small, and neither decreased the IQR as compared to a case with no risk

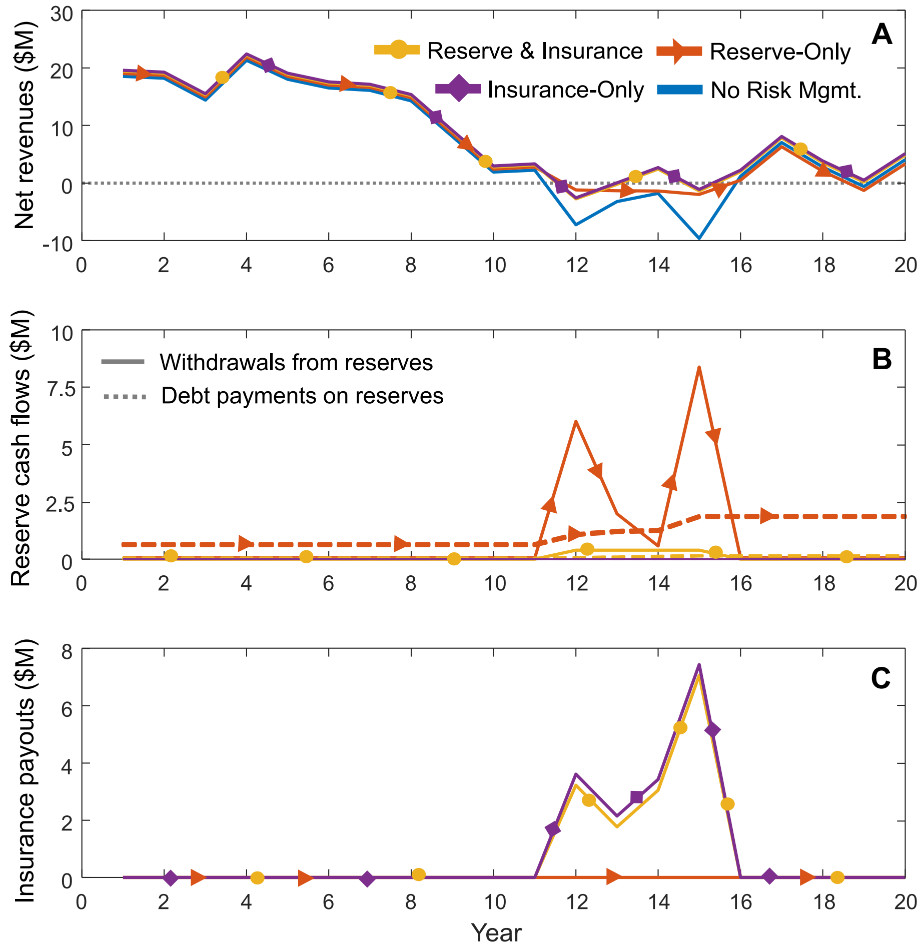

Fig. 6. Simulated yearly (A) net revenues, (B) reserves cash flows, and (C) insurance payouts for a realization with especially low net revenues for each of the risk management strategies.

management, suggesting that these strategies reduced the incidence of large losses but had a lesser effect on smaller losses. Tradeoffs between effectiveness and cost across these two strategies exist, but both strategies that include insurance are attractive compared to the No Risk Management and the Reserve-Only strategies because of their lower costs and effectiveness in reducing large *losses*.

Nonetheless, there are additional factors to consider as comparing yearly net revenues ignores the valuation of both the ending reserve balance and the debt service payments made after the end of the 20-year planning period, two important considerations for algae producers. Both can be incorporated into a measure of present value of net revenues (*PV (NR)*), and this value gives broader insight into the costs and effectiveness of these four strategies (Fig. 8). In this case, *PV(NR)* values exceeding 0 suggest profitability over the 20-year planning period. For the No Risk Management strategy, the median *PV(NR)* is $102.25 M, the first percentile is -$4.11, and the IQR is $62.16 M, which together indicate profitability overall, but with significant variability and downside risk. For the Reserve-Only strategy, over the 500 realizations of 20-year planning periods, 154 of these realizations see reserve withdrawals occurring in at least one year during the 20-year lifetime, and 5 realizations have negative *PV(NR)* values over the 20 years. The Reserve-Only strategy is effective at reducing downside risk such that the first percentile *PV(NR)* is only -$0.13 M; the variability is also reduced, though only slightly (IQR = $61.96 M). However, the costs of this risk management strategy ($4.55 M) are relatively high.

The Reserve & Insurance and Insurance-Only strategies significantly improve the first percentile of losses ($14.20 M and $14.91 M, respectively) and slightly reduce variability (IQR = $61.09 M and $60.96 M), with the Insurance-Only strategy performing slightly better in terms of both metrics. The cost of the Reserve & Insurance strategy, however, is less than that of the Insurance-Only strategy ($2.77 M and $2.85 M), even as both are much less costly than the Reserve-Only strategy. The differences in these two strategies are not large, though both significantly outperform the Reserve-Only strategy in terms of both risk management costs and effectiveness of reducing extremely high losses.

4. Discussion

Though past research has explored aspects of algal biorefinery modelling, this study provides a novel synthesis of multiple modelling components—stochastic weather-based biophysical growth modelling and LCA/TEA—with an area that has received less attention in the algae industry: financial risk management modelling. From a policy/management perspective, this study demonstrates that an index-insurance product can be an effective financial risk management tool for an algae producer. This is a useful finding given the current lack of algae insurance products. While the USDA does offer weather-index policies for other crops [68], none are tailored for algae as this work has done.

The results of this work are also potentially relevant across other industries that face weather- and price-related risk in that it describes effective use of a highly tailored index as a basis for an insurance contract. Such an index may be useful for other agricultural crops, including other biofuel feedstocks, where current indices have exhibited prohibitively high basis risk due to the complexities of biological growth [63]. Finally, the inclusion of variable market prices in the index newly combines price risk with weather-related risk into a single contract.

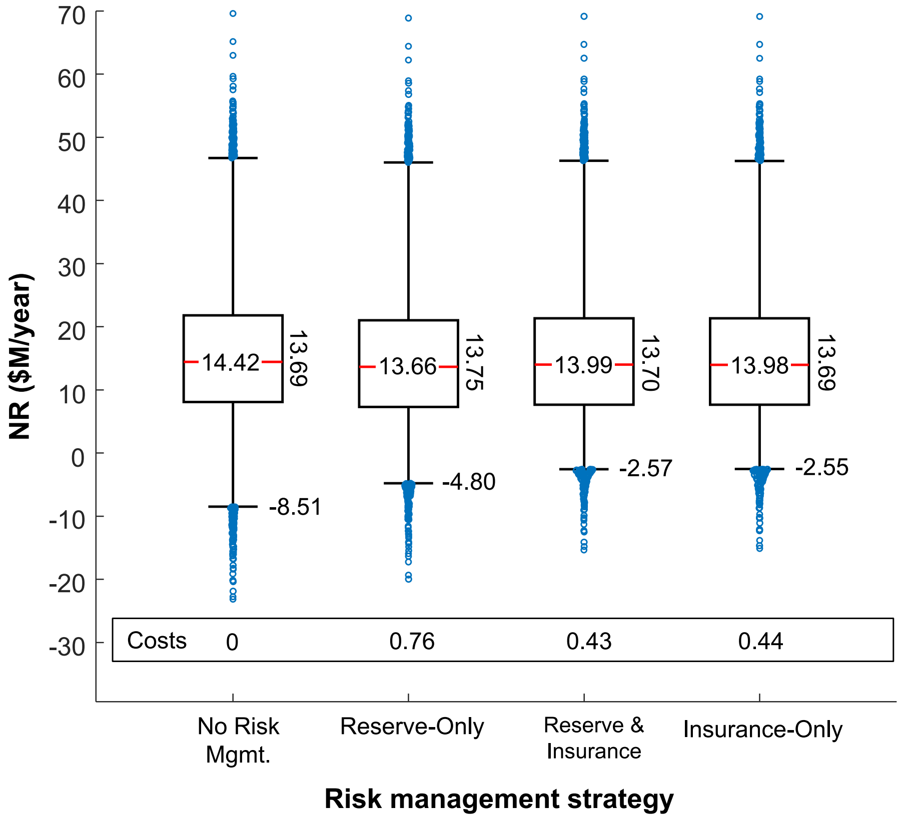

Fig. 7. Comparison of no risk management and risk management by yearly net revenues, NR, where labelled points correspond to median (on the red line), IQR (on the side of the boxes), first percentile value (below the boxes), and risk management costs (in the Costs box) across 10,000 synthetic years.

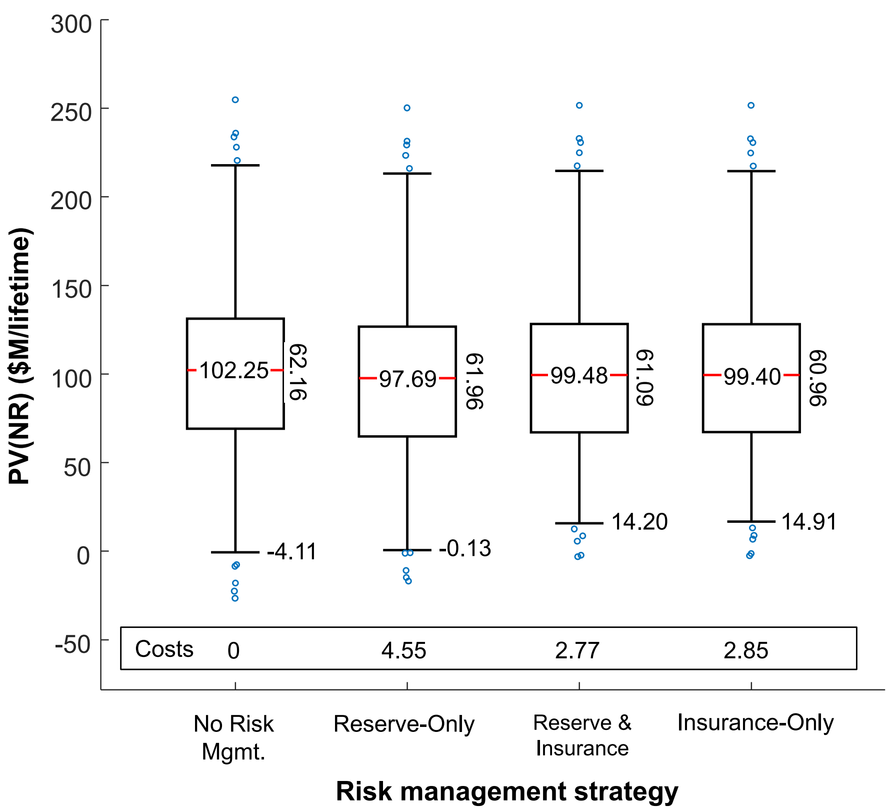

Fig. 8. Comparison of no risk management and risk management by present value of net revenues, PV(NR), where labelled points correspond to median (on the red line), IQR (on the side of the boxes), first percentile value (below the boxes), and risk management costs (in the Costs box) across 500 synthetic lifetimes.

Other sources of financial variability in algae production exist that were not included, such as market price fluctuations for inputs such as electricity, natural gas, and nutrients. However, these prices were shown to have a lower effect on financial outcomes for an algae producer than output prices [17]. Other financial risk management tools may be relevant to algae producers; for example, a biofuel producer with many facilities could use geographic diversification across regions with low correlation in weather conditions to manage weather-related risk [69]. This is an effect which should be evaluated in future work, particularly as algal growth data from multiple locations become available.

5. Conclusion

This work synthesizes many aspects of weather modelling, market price modelling, and algal biorefinery modelling under stochastic conditions to inform management of an algal biorefinery's weather- and market price-related financial risk. Through developing an analysis for an example site at Vero Beach, FL, financial risk management strategies to reduce variability in net revenues using both new and existing financial tools are explored for an algal biorefinery. A combination of self-insurance through a reserve fund and a novel form of index-insurance that protects against unfavorable weather and price conditions is shown to effectively reduce financial risk at the lowest cost. As insurance for algae production has become useful given the relative youth of the algae industry, recent availability of large-scale algae growth data, and new eligibility of algae for federal crop insurance, these findings are particularly timely to algae producers and the USDA, which now has an opportunity to provide federally supported insurance products to algae producers as of the 2018 Farm Bill. These financial risk management strategies may be expected to play an increasing role in sectors that are financially vulnerable to increasingly volatile weather and market conditions from "climate risk".

SI

Extended methods and results are available free of charge.

CRediT authorship contribution statement

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

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Appendix. A. Net revenue equations

The TEA yields simulated net revenues (*NR*) (essentially, after-tax profits), which are found at the quarterly time scale:

$$NR = revenues - expenses - taxes \tag{A.1}$$

where *revenues* are the product of production and prices for biodiesel (*bd*) as well as the production and prices of animal feed (*f*):

$$revenues = (prod_{bd} * price_{bd}) + (prod_f * price_f) \tag{A.2}$$

where *Expenses* are a function of operational costs (*opex*) and debt service payments (*interest* and *principal*). *Opex* include fixed operations/maintenance and input costs for electricity, thermal heat, nutrients/carbon dioxide, and other chemical inputs. *Opex* costs vary with algal productivity, as inputs scale linearly with biomass productivity ($prod_{mass}$):

$$expenses = opex(prod_{mass}) + interest + principal \tag{A3}$$

Taxes are a fraction of *revenues* less the *expenses*, asset depreciation ($assets_{dep}$) and *interest* assessed at the 2022 federal corporate tax rate, 21%:

$$taxes = 0.21 * (revenues - expenses - assets_{dep} - interest) \tag{A.41}$$

Appendix B. Fixed vs. floating price sensitivity analysis

In order to assess the relative importance of market prices for biofuels in the development of the index, two separate indices are tested, one with fixed and the other with floating prices. The fixed price index, I_{fix}, incorporates consideration of variable weather only by predicting net revenues with prices for biodiesel and algal meal fixed over the 20-year period. The floating price index (i.e., the index used in the main body of this work), I_{float}, incorporates consideration of stochastically simulated fluctuating prices (averaged yearly) in addition to variable weather. Total annual "predicted" net revenues found using fixed prices for I_{fix} and fluctuating prices for I_{float}. For clarity, a summary of I_{fix}, I_{float}, and NR_a can be found in Table B.1.

Table B.1
Summary of the differences in the fixed and floating price indices (I_{fix}, I_{float}) and the "actual" net revenues (NR_a).

	Unit	*prod*$_{mass}$		*price*$_{bd}$ and *price*$_f$	
		"Actual"	"Predicted"	Fixed prices	Floating prices
Fixed Price index (I_{fix})	$/yr		✓	✓	
Floating Price index (I_{float})	$/yr		✓		✓
"Actual" net revenues (NR_a)	$/yr	✓			✓

The "predicted" distribution of biomass is used, with either fixed or floating prices, to develop the two indices that form the basis for the insurance contracts, which determine the frequency and amount of insurance payouts (Figure B.1A). As expected, I_{float} has higher variability (blue) than I_{fix} (yellow) due to the incorporation of floating prices. The distribution of "actual" biomass, developed with the additional consideration of non-weather related growth factors, will be somewhat more variable than the "predicted" distribution, and is then combined with stochastic price distributions to arrive at a distribution of net revenues, NR_a (Figure B.1B).

When creating the index insurance contract, the strike (K) is determined relative to NR_a (based on "actual" biomass, while the payouts are determined when the index (based on "predicted" biomass) declines below the strike. For example, the 99% VAR with respect to the NR_a distribution is $-8.51 M. Thus, an algae producer can expect the worst case (defined here as the 99th percentile) *losses* to be $-8.51 M. The NR_a distribution also informs the limits for all risk management strategies: a range of risk management strategies are developed to prevent against outcomes worse than the 93.5% VAR (where NR_a = $0), representing a more risk averse goal, and the 99% VAR (where NR_a = $-8.51 M*)*, representing less risk aversion.

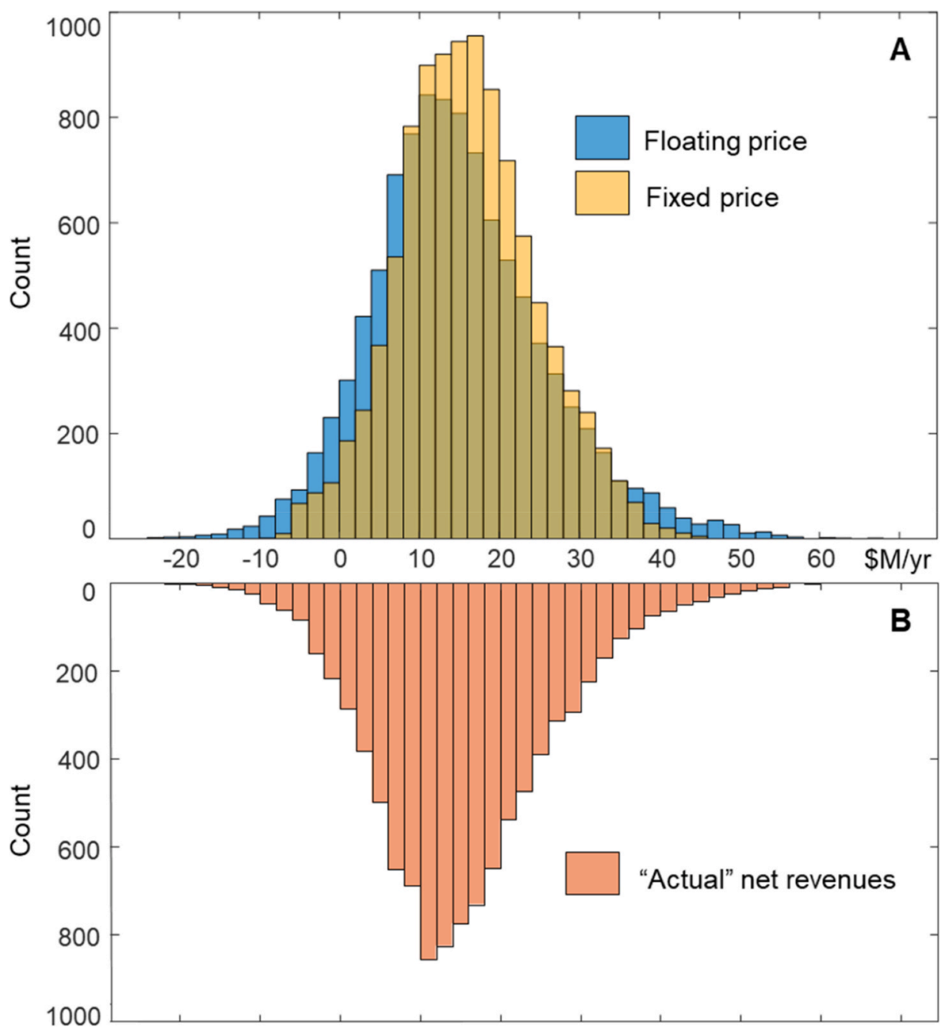

Fig. B.1. Histograms of (A) indices used in this analysis for the Floating Price and Fixed Price contracts, and (B) the "actual" net revenues distribution

For I_{fix} the extent of basis risk is contingent on the accuracy of the weather-based growth model, which correlates to experimental data with an r^2 value of 0.55, as well as errors in price representation. This suggests that 55% of algal biomass growth variability can be explained by the growth model based on weather conditions at the time step of the experimental cultivation periods (2–11 days). The remaining growth variability (45%), as well as price variability represent significant sources of basis risk and a challenge to developing this type of financial tool for biological systems, which are generally difficult to model. Previous studies, however, have found contracts with significantly lower correlations to be useful to hedge against weather events [70].

The low basis risk (r^2 = 0.92) for I_{float} suggests that these contracts are likely to be more attractive to the algae producer than the fixed price contracts, in which the index does not capture the risk as well. The high basis risk for the contracts based on I_{fix} confirms that product price variability is an important consideration for designing contracts that manage financial risk for algae producers. Furthermore, these results suggest that an index that includes consideration of both weather-based biomass growth and market price dynamics has the potential to serve as the foundation of an index-insurance contract that could be useful in managing an algae producer's financial risk. Based on this analysis, and the substantially lower basis risk exhibited by contracts based on I_{float}, only this contract type is explored in the main body of this work.

Appendix C. Pricing index-insurance contracts

Weather-based index-insurance, a type of contract that uses a weather-based metric ("index") to trigger insurance payouts, can be highly effective in protecting against revenue shortfalls due to unfavorable weather conditions. The index can be a function of a single or weather variables and can be used as the basis for effective contracts when it is strongly correlated with financial losses [71], whether these arise from increased costs, reduced revenues, or both. Of course, financial risk can be a function of more than just weather, and index-based contracts can sometimes be developed to account for more than one form of risk simultaneously. With an understanding of the relevant market price behavior, a composite index including both weather variables and market prices can be developed and lead to a contract that can effectively manages both risks [46]. Index-insurance payouts are triggered when observed or modeled index values cross a threshold, or "strike", specified in the contract, however, unlike conventional (indemnity-based) insurance and the reserve fund, these payouts are not directly linked to *losses* [72]. An effective index is transparent, publicly available, reliable, and difficult to manipulate so as to reduce any asymmetrical information advantages that might exist between the insurer and insured [70]. Presuming a relatively high correlation between the index and losses, this is advantageous as it results in reduced moral hazard (i.e., the incentive to take on risks when protected from consequences), less subjectivity in assessing damages, lower transaction costs (e.g., no adjustor is needed), and quick resolution of payouts [73].

The contract structure, including the strike and the slope of the payout function, are primary factors in the pricing of insurance. The *premium* a customer pays for an insurance contract includes the sum of *E[payouts$_{ins}$]* and the loading, an additional amount that covers the insurer's return on investment and costs (e.g., administrative, research, marketing). The *premium* in this work increases as the contract coverage increases: for example, the premium for a contract with a strike defined at 95% VAR exceeds that of one at 99% VAR, as payouts are expected to occur more frequently for the former. Less frequent, but large payouts require larger reserves for the insurer which raises the opportunity costs and consequently the *loading* also rises, as a fraction of *E[payouts$_{ins}$]*. One pricing method that incorporates these considerations and is commonly used for index-insurance contracts is the Wang transform, which accounts for the increased costs of managing low-probability events with large payouts [65]. To do so, a cumulative density function (cdf) of payouts (*F(x)*) is converted to risk-adjusted cdf, (*F*(x)*), where extreme payouts are more highly weighted, leading to loadings that make up a higher fraction of the premium, even as the premium may decline with reductions in expected payouts:

$$F^{*}(x)=\varphi\left[\varphi^{-1}(F(x))+\gamma\right] \tag{C.12}$$

where φ is the standard normal cumulative distribution and γ is the market price of risk. The γ value of -0.25 is commonly assumed for non-tradable assets such as weather-related contracts [45,65,69] and is used here. The *premium* corresponds to the expected payouts with this modified distribution:

$$premium_{wang}=\sum\left[x*F^{*}(x)\right] \tag{C.23}$$

Finally, the *loading* can be derived, such that:

$$loading=premium_{wang}-E[payouts_{ins}] \tag{C.3}$$

Appendix D. Long-term financial risk management

A financial risk management strategy, especially one that considers a reserve whose value will fluctuate based on multi-year events, is better evaluated over a multi-year time horizon. Evaluation of the range of strategies described in this work is conducted over multiple years using an approach developed by Baum et al. [66]. The effectiveness of the risk management strategies is evaluated across 20-year investment horizons and the resulting net revenues for each strategy are compared to net revenues in a scenario in which no risk management strategy is employed. Each strategy covers net revenues *losses* up to the 99% VAR and is evaluated via 500 realizations of 20-year periods (10,000 years).

At the beginning of the 20-year period, the reserve is established by issuing 20-year debt (at a 4% annual interest rate) in an amount determined by the chosen strike (*K*) (which corresponds to a VAR), and an index-insurance contract is written at a strike *(K)* equal to the size of the reserve. When triggered in each year (as described in previous sections), cash inflows from *payout$_{ins}$* and *withdrawals$_{res}$* occur and are added to the "actual" net revenues (NR_a), which include variability in productivity from weather and non-weather factors, as well as variable prices. To simulate yearly risk management costs, *premium*, *debt service costs*, and *opportunity costs* are deducted. If *withdrawals$_{res}$* occur in any year, and thus the reserve is partially or completely depleted, more debt is issued to re-establish the reserves to their intended size so the *debt service cost* increases. The annual *debt service costs* on the funds borrowed to maintain the reserve continue as necessary after the end of the 20-year lifetime, and this debt is tracked to facilitate cost comparisons across strategies in present value terms. The reserves also accrue yearly interest at a rate equivalent to the 10-year treasury note rate (IR_T = 2.27%) [60], a fund chosen due to its relatively high returns for a liquid fund. Under these assumptions, *hedged net revenues* (NR_h) are found in each year by:

$$NR_h=NR_a+payout_{ins}+withdrawals_{res}+reserves*IR_T-premium-debt\ service\ costs-opportunity\ costs \tag{D.1}$$

The distributions of the 10,000 realizations of yearly NR_h for each risk management strategy are compared using median, minimum, and inter-quartile range (IQR) values. In addition to comparing yearly net revenues, comparing the present value of net revenues (*PV(NR)*) allows for inclusion of the valuation of the ending reserve (*reserve$_{20}$)*, the debt service payments made throughout and after the 20-year lifetime, and the time value of money, all of which would be important considerations for algae producers and give broader insight into the effectiveness of these strategies. To facilitate comparison between the risk management strategies, the present value of the hedged net revenues, $PV(NR_h)$, for each of the 500 realizations per strategy is found:

$$PV(NR_h) = \frac{reserve_{20}}{(1+d)^{20-1}} + \sum_{t=1}^{40} \frac{NR_h}{(1+d)^{t-1}} \tag{D.2}$$

where d is the discount rate (10% in this case). For comparison to no risk management, the present value of “actual” net revenues, $PV(NR_a)$, is also found across 500 realizations:

$$PV(NR_a) = \sum_{t=1}^{lifetime} \frac{NR_a}{(1+d)^{t-1}} \tag{D.3}$$

The median, minimum, and interquartile range (IQR) of the distributions of $PV(NR_h)$ and $PV(NR_a)$ are also found.

Finally, the difference between the medians of $PV(NR_h)$ and $PV(NR_a)$ are used to represent the net costs of different risk management strategy, *PV (costs)*, across various strike values to determine the lowest-cost strike value.

$$PV(costs) = PV(NR_h) - PV(NR_a) \tag{D.4}$$

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