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Research Article

Meteorological Data-Based Optimal Control Strategy for Microalgae Cultivation in Open Pond Systems

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Outdoor biofuel production from microalgae is a complex dynamical process submitted to climatic variations. Controlling and optimizing such a nonlinear process strongly influenced by weather conditions is therefore tricky, but it is crucial to make this process economically sustainable. The strategy investigated in this study uses weather forecast coupled to a detailed predictive model of algal productivity for online optimization of the rates of fresh medium injection and culture removal into and from the pond. This optimization strategy was applied at various climatic conditions and significantly increased productivity compared to a standard operation with constant pond depth and dilution rate, by up to a factor of 2.2 in a Mediterranean climate in summer. A thorough analysis of the optimizer strategy revealed that the increase of productivity in summer was achieved by finding a trade-off between algal concentration to optimally distribute light and pond temperature to get closer to optimal growth temperature. This study also revealed that maintaining the temperature as high as possible is the best strategy to maximize productivity in cold climatic conditions.

1. Introduction

Microalgae cultivation for biofuel and food production has been the focus of many studies for the past 20 years [1]. Several environmental [2, 3] and technoeconomic assessments [4–6] aimed to quantify the profitability of algal cultivation systems and compare algalfuel to other biofuels.

It turns out that culturing process optimization is required to reduce the energy need, reduce the environmental footprint, and make algal biofuel cleaner and profit earning. Among the strategies to reduce impacts and costs while increasing productivity, online control and optimization has proven to be very efficient [7]. However, it becomes very challenging for microalgae which receive their energy from the sun. In particular, the combination of light and temperature both influencing the system dynamics must be anticipated to maintain the process in adequate production domains. Regulating the temperature by heating and cooling, or lighting the process to maintain the algae closer to their optimum would increase the productivity, but it would immediately jeopardize the benefit of this clean energy source [8], and there is a need for a passive strategy to avoid any additional energetic inputs.

Several models have been published in the last decade, which can accurately predict algal yields at full-scale depending on the species, weather conditions, system design, and operation [9–11]. Some studies have even proposed full scale validation when weather fluctuations were recorded [12, 13].

When assuming rudimentary weather patterns, these models were used to support the optimization of the system design [14, 15] and operation [16, 17]. With the development and the miniaturization of computational power, it is now conceivable to locally compute an advanced control strategy based on weather forecasts to optimize system operation maximizing algal productivity.

Model Predictive Control (MPC) has already been applied to microalgae culture for controlling pH [18], optimization of CO_2 fixation [19, 20], or optimization of more specific criteria including microalgal products [21, 22]. The MPC approach revealed efficient to manage the complexity of the model, but these approaches implicitly admitted that light pattern was perfectly known well in advance. Recently, [23, 24] proposed an online control strategy based on the knowledge of future weather conditions to online optimization system operation, namely, the inflow and outflow rates of the photobioreactor. The MPC strategy consisted of determining iteratively the optimal inflow and outflow hourly rates for an entire week based on the weekly weather forecasts. Unlike in [16], the culture depth could vary and thus thermal inertia of the cultivation system could be modified to optimize system temperature fluctuations. The benefits of this approach were briefly assessed on the basis of a week of cultivation in Nice (France) in summer.

The objective of this new study is first to more extensively investigate how this MPC framework can, without additional energy input, manage different climates (given by different seasons and locations). Furthermore, with a reverse engineering approach, a second goal is to analyse the strategies of the MPC and derive a reduced number of operational rules. Such simplified framework may be applied even without the need of implementing advanced automatic control/optimisation techniques. Finally, we compute the water need associated with each control strategy, and we identify paths to reduce the water use and tailor it to the local water availability.

This work is organised as follows: in Section 2 a brief description of the model used for describing microalgae productivity in open ponds is given; moreover, the description of the cultivation system and the definition of the adopted optimisation function are reported at the end of this section. Section 3 deals with the productivity results obtained with different climatic conditions in Nice and Rennes (France); then, after a brief discussion about the theoretical control logic ensuring the highest possible productivity, a detailed analysis of the optimization strategy is reported. The analysis of the optimization scheme, split into four phases, aims to extract a reduced set of ‘rules to be used as a future practical guideline. Finally, Section 4 presents a brief discussion of the key aspect of the resulting control logic, whereas Section 5 presents the main conclusions and some hints for future research.

2. Materials and Methods

The optimization strategy investigated in this study requires a model predicting algal productivity in outdoor open ponds. The selected model combines three submodels predicting *(i)* the temperature fluctuations in an open pond [9], *(ii)* the light distribution in the culture medium, and *(iii)* the algal productivity as a function of temperature fluctuations and light distribution. The model equations are presented and described in the following two paragraphs.

2.1. Productivity Model. The high rate open pond is a standard process to grow microalgae with reduced energy inputs. It consists of a raceway shaped reactor mixed with a paddle wheel. In general, medium depth is fixed between 0.1 m and 0.5 m (typically 0.3 m). Here, we consider possible fluctuations of depth between these bounds. The reactor is modeled as an ideally mixed system, with a fresh medium inflow (flow rate q^{in}, in m^3 s^{-1}) and a culture outflow for extraction (q^{out}, in m^3 s^{-1}). The pond is inoculated at the beginning of the cultivation period. The evolution of the biomass concentration can be expressed from the following mass balance:

$$\frac{d(x(t)V(t))}{dt} = -x(t)q^{out}(t) + G(\cdot)V(t) - R(\cdot)V(t), \tag{1}$$

where t is the time variable (s), $x(t)$ is the algal biomass concentration (kg m^{-3}), $G(\cdot)$ is the algal specific growth rate (kg m^{-3} s^{-1}), $R(\cdot)$ is the respiration rate (kg m^{-3} s^{-1}),s and $V(t)$ is the pond volume (m^3). $V(t)$ varies over time according to the following equation:

$$\frac{dV(t)}{dt} = q^{in}(t) - q^{out}(t) + v_r(t)S - \frac{m_e(t)S}{\rho_w}, \tag{2}$$

where S is the pond surface area (m^2), ρ_w is water density (kg m^{-3}), $v_r(t)$ is the rainwater flow (m s^{-1}), and $m_e(t)$ is the mass flux caused by evaporation at the pond surface (kg m^{-2} s^{-1}). Changes in pond volume are associated with changes in pond depth $l_p(t) = V(t)/S$. The specific growth rate $G(\cdot)$ in (1) depends on the biomass concentration $x(t)$, the solar irradiance at the pond top surface $H_s(t)$ (W m^{-2}), and the pond temperature $T_p(t)$. By using a modified Beer-Lambert law to model light distribution within the algal culture, $G(t, x(t), H_s(t), T_p(t))$ was expressed as [25]

$$G(t, x(t), H_s(t), T_p(t)) = \frac{1}{l_p(t)} \int_0^{l_p(t)} \mu_m x(t) \frac{\sigma \eta_H H_s(t) e^{-\sigma x(t) z}}{K_I + \sigma \eta_H H_s(t) e^{-\sigma x(t) z}} dz \tag{3}$$

where μ_m is the maximum specific growth rate (s^{-1}), σ is the extinction coefficient (set at 120 m^2 kg^{-1}; see [9]), η_H is the photosynthetically active radiation (PAR) fraction of solar light (set at 0.47), z is the local depth (m), and K_I is a half-saturation parameter (W kg^{-1}). The specific respiration rate $R(\cdot)$ in (1) depends on pond temperature $T_p(t)$ and biomass concentration $x(t)$ through the following equation [25]:

$$R(t, x(t), T_p(t)) = \lambda_r x(t), \tag{4}$$

where λ_r is the respiration coefficient (s^{-1}). As μ_m, K_I, and λ_r values change with temperature (see [25]), these three parameters were henceforth renamed $\mu_m(T_p(t))$, $K_I(T_p(t))$, and $\lambda_r(T_p(t))$, respectively. Reference [26] showed that the evolution of parameter $\mu_m(T_p(t))$ with temperature could be fitted to the following function:

$$\mu_m(T_p(t)) = \mu_{m,max} \phi_T(T_p(t)), \tag{5}$$

where $\mu_{m,max}$ is the maximum value of $\mu_m(T_p(t))$ (s^{-1}) and $\phi_T(T_p(t))$ is the temperature-dependent function reported in the following equation [26]:

$$\phi_T\left(T_p(t)\right) = 0 \quad \text{if } T_p \le T_{min} \text{ or if } T_p(t) \ge T_{max}$$

otherwise

$$\phi_T\left(T_p(t)\right) = \frac{\left(T_p(t) - T_{max}\right)\left(T_p(t) - T_{min}\right)^2}{\left(T_{opt} - T_{min}\right)\left[\left(T_{opt} - T_{min}\right)\left(T_p(t) - T_{min}\right) - \left(T_{opt} - T_{max}\right)\left(T_{opt} + T_{min} - 2T_p(t)\right)\right]}, \tag{6}$$

where T_{min} is the temperature below which the growth is assumed to be zero, T_{max} is the temperature above which there is no growth nor respiration, and T_{opt} is the temperature at which $\mu_m(T_p(t)) = \mu_{m,max}$. This model does not explicitly represent mortality for temperatures above T_{max} [27]. As it will be discussed later on, the optimisation strategy will always maintain temperature below T_{max}, so that mortality will eventually not occur.

Experimental values of $\mu_m(T_p(t))$, $K_I(T_p(t))$, and $\lambda_r(T_p(t))$ were extracted from the study of [25] conducted on *Chlorella vulgaris* as the model of [25] was shown to accurately predict algal productivity in outdoor photobioreactors under various weather conditions [28]. As $\lambda_r(T_p(t))$ and $K_I(T_p(t))$ exhibited similar evolution with temperature, the same function $\phi_T(T_p(t))$ was used for fitting the behavior of these two parameters at different temperatures:

$$\begin{aligned} K_I\left(T_p(t)\right) &= K_{I,max}\phi_T\left(T_p(t)\right), \\ \lambda_r\left(T_p(t)\right) &= \lambda_{r,max}\phi_T\left(T_p(t)\right). \end{aligned} \tag{7}$$

Fitting these parameters was performed by using the Maximum Likelihood method included in the entity *Parameter estimation* of the gPROMS™ software (4.1 version). The complete set of the parameter values used to describe the temperature function ϕ_T is reported in Table 1.

2.2. Temperature Model. The universal model for temperature prediction in shallow algal ponds developed by [29] has been used in this work. This model was validated against data collected from a high rate algal pond [13, 25]. The temperature model, valid for any opaque water body having a uniform temperature profile, is based on eight heat fluxes that can be expressed from available meteorological data/system design parameters. Pond temperature obeys the following equation [29]:

$$\begin{aligned} \rho_w V(t) c_{p_w} \frac{dT_p(t)}{dt} &= Q_{ra,p}(t) + Q_{ra,s}(t) + Q_{ra,a}(t) \\ &\quad + Q_{ev}(t) + Q_{conv}(t) + Q_{cond}(t) \\ &\quad + Q_i(t) + Q_r(t), \end{aligned} \tag{8}$$

where c_{p_w} is the specific heat capacity of water (J kg^{-1}K^{-1}), $Q_{ra,p}(t)$ is the radiation flow from the pond surface (W), $Q_{ra,s}(t)$ is the global (direct and diffuse) solar irradiance (W), $Q_{ra,a}(t)$ is the radiation flow from the air to the pond (W), $Q_{ev}(t)$ is the evaporation heat flow (W), $Q_{conv}(t)$ is the convective heat flow at the pond surface (W), $Q_{cond}(t)$ is the conductive heat flow with the ground at the pond bottom (W), $Q_i(t)$ is the heat flow associated with the water inflow (W), and $Q_r(t)$ is the heat flow associated with rainfall (W). A detailed description of the equations used to describe each heat flux can be found in the supplementary material (S1.1).

2.3. Weather Data. Weather data originates from the European Centre for Medium-Range Weather Forecast (ECMWF) website (year 2012). This data, available every 6 hours, includes the air temperature T_a, the relative humidity RH, the wind velocity v_w, the rain volumetric flux v_r, and the sky cloudiness CC (see supplementary material (S2) for complete description). The solar irradiance at the ground level, H_s, was determined combining the solar irradiance at the top of the atmosphere (determined by the latitude and the solar declination angle) with the sky cloudiness CC (see supplementary material (S1.2) for further details).

2.4. System Description. The optimization strategy was investigated at two different locations in France, representing two very different climates: a Mediterranean climate in Nice (43°42′11″N, 7°15′57″E) and a temperate climate in Rennes (48°06′ 53″N, 1°40′46″W). Simulations were performed over one week at three different seasons at each location (winter: January; spring: March; summer: July). The pond surface area S was 100 m^2. The initial conditions were as follows:

(i) The initial pond temperature $T_p(t = 0)$ was set at the average value of air temperature $T_{a,avg}$ over the period τ of simulation as a reasonable estimation of T_p in the absence of actual measurements.

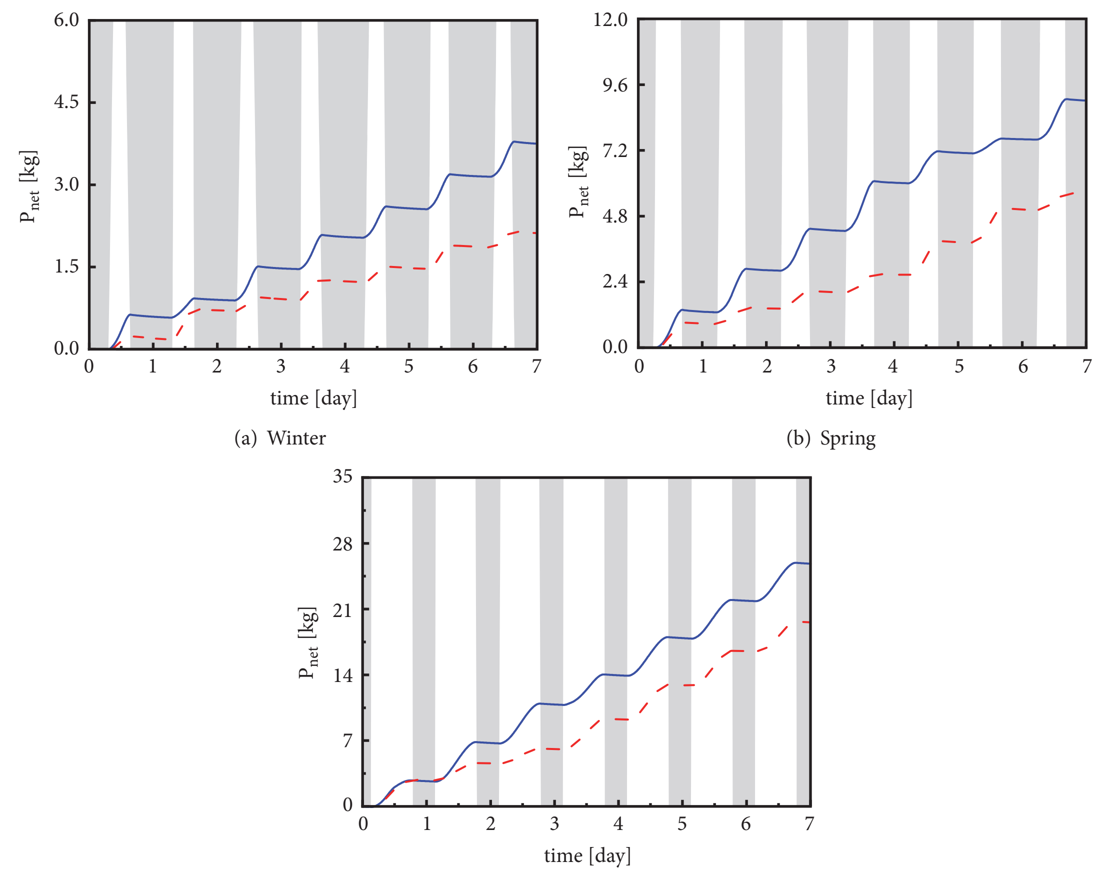
(ii) the initial biomass concentration x was set to 0.4 kg/m^3.

(iii) the initial pond depth l_p was set to the typical value of 0.3 m [30].

(iv) the inflow temperature T^{in} was set at a value equal to $T_{a,avg}$.

Standard pond operation consisted of maintaining the pond depth and dilution rates at typical values during the entire cultivation period (depth of 0.25 m and dilution rate of 0.1 day^{-1}, as discussed in [31–33]).

2.5. Numerical Optimization. The optimization strategy consisted of permanently adjusting inflow and outflow rates (q^{in}



(a) Winter

(b) Spring

(c) Summer

Figure 1: P_{net} obtained with the optimal control strategy (blue continuous line: Nice; dashed red line: Rennes. The background is colored in white at daytime and in grey at nighttime).

and q^{out}, respectively) to maximize the productivity over the period of time considered (1 week), defined by the following equation (see [34]):

$$P_{net}(t) = \int_0^{\tau} \left(G\left(t, x(t), H_s(t), T_p(t)\right) - R\left(t, x(t), T_p(t)\right)\right) V(t)\, dt. \quad (9)$$

The pond depth changed with time since q^{in} and q^{out} were not identical. These two control inputs were taken as piecewise constant variables within the range $[0 \div 1]$ m^3/s. The pond depth was constrained between 0.05 m and 0.5 m. The optimization was implemented through the gPROMS™ software (4.1 version) by using the default optimization solver NLPSQP, which uses a sequential quadratic programming method for the solution of nonlinear programming problems.

2.6. Water Demand. The net water demand ($WD(t)$) associated with algal cultivation was calculated as follows:

$$WD(t) = \int_0^{\tau} q^{in}(t)\, dt + \max\left(0, V_0 - V_{\tau}\right), \quad (10)$$

where V_0 and V_{τ} are, respectively, the pond volume at the beginning and at the end of the cultivation period. This expression accounts for both water use for fresh water injection and change in pond volume between initial and final times.

Table 1: Values of the parameters used in the temperature function ϕ_T.

Parameter	Description	Value
T_{min}	Minimum growth temperature	-10.0 (°C)
T_{max}	Maximum growth temperature	42.1 (°C)
T_{opt}	Optimum growth temperature	35.8 (°C)
$\lambda_{r,max}$	Max. respiration coefficient	$2.01 \cdot 10^{-6}$ (s^{-1})
$\mu_{m,max}$	Max. specific growth rate	$6.48 \cdot 10^{-5}$ (s^{-1})
$K_{I,max}$	Max. half-saturation constant	7192.92 (W kg^{-1})

3. Results

3.1. Strategy Impact on Productivity. Figure 1 shows the algal productivity obtained during optimized and standard cultivation, at Nice and Rennes for three seasons (winter, spring, and summer). The reported results (see Table 2) show that the optimization strategy significantly increased productivity compared to standard operation, by up to a

Table 2: Standard cultivation versus optimal control strategy: productivity and water demand.

Case studies		Productivity (kg·week^{-1})		Water demand (m^3·week^{-1})	
		Nice	Rennes	Nice	Rennes
Winter	Standard cultivation strategy	2.59	1.25	17.53	17.53
	Optimal control strategy	3.73	2.12	26.83	25.02
Spring	Standard cultivation strategy	5.60	3.96	17.53	17.33
	Optimal control strategy	9.02	5.61	32.60	27.48
Summer	Standard cultivation strategy	11.62	12.71	17.53	17.53
	Optimal control strategy	25.83	19.59	122.98	45.97

factor of 2.2 for the summer case in Nice. Interestingly, Table 2 shows that productivity was slightly higher in Rennes than in Nice in summer under standard operation. This result is explained by the high temperature peaks in Nice, which cause productivity to significantly drop. Figure 2 shows the optimal q^{in} and q^{out} profiles maximizing algal productivity over the entire cultivation period.

Figure 2 reveals that medium injection or culture extraction only occurred at day time. Although the resulting control strategy was different for the two locations, a qualitatively recurrent behavior can be identified despite the weather variability along cultivation and for the different periods of the year. The behavior of the optimizer was therefore analyzed on a time window of three cultivation days only.

3.2. Optimal Operation Strategy: Key Features. The ideal control logic to enhance productivity should result from several considerations.

Firstly, algal concentration must be optimized at daytime by accounting for two processes: (1) biomass losses through respiration linearly increase with the algal concentration, and (2) the amount of light intensity captured by algal cells, hence photosynthetic rate, increases with algal concentration. As a result, there is an optimal algal concentration that should ensure that most of the light entering the pond is captured by algae while still maintaining respiration rates at a low value. Previous studies show that this optimal concentration is reached when the specific rate of photosynthesis at the pond bottom equals the specific rate of respiration [35]. Mathematically, these conditions are reached when the 'compensation function' defined below is equal to 1 [35]:

$$f_{comp}(t) = \mu_{m,max} \cdot \frac{\sigma\eta_H H_s(t)\, e^{-\sigma x(t) l_p(t)} / \left(K_{I,max}\phi_T(t) + \sigma\eta_H H_s(t)\, e^{-\sigma x(t) l_p(t)}\right)}{\lambda_{r,max}}. \quad (11)$$

If this function is higher than 1, the pond productivity could be improved by increasing biomass in the system. Conversely, values lower than 1 indicate that the net rate of growth at the pond bottom is negative: diluting the system would increase productivity. In summary, the ideal optimal biomass concentration at daytime $x_{opt}(t)$ is the algal concentration that guarantees that the compensation function defined in (11) equals 1.

Secondly, maximal productivity is achieved when the pond temperature $T_p(t)$ is maintained at T_{opt} at daytime. At nighttime, the pond temperature $T_p(t)$ and the biomass concentration $x(t)$ should be maintained as low as possible in order to minimize respiration rates, hence biomass losses. The ideal optimal pond operation would therefore require a drastic change of the algal concentration and pond temperature at sunrise and sunset to stay optimal at daytime and nighttime. Such drastic changes are in practice difficult to achieve and the next paragraph discusses how they are handled by the optimization scheme.

3.3. Detailed Analysis of the Optimization Scheme. The analysis of the optimization scheme is split into four phases, from morning to night.

Morning. Focusing first on the summer case study, Figures 3(a) and 3(b) show that no water was injected to or extracted from the pond in the morning ($q^{in}(t), q^{out}(t) = 0$), to maintain the pond depth in Rennes at a constant and low value ($l_p(t) = 0.05$ m; see Figure 3(c)). Very small depths indeed minimize the thermal inertia of the pond and thus allow a fast increase of the pond temperature $T_p(t)$ (see Figure 3(d)), hence a greater productivity increase. The same control strategy was used in Nice although the pond depth in Nice was slightly above its minimal constraint (see Figure 3(c)). Removing culture from the pond would lead to lower the biomass content and therefore increase the compensation function which is already significantly higher than 1 (Figure 3(f)). Removing more biomass would thus cause productivity losses.

The morning control strategies in spring and winter were similar (Figures 4(a), 4(b), 5(a), and 5(b)), except for Nice in winter. In this particular case, a fraction of the culture was replaced by fresh medium at sunrise of days 4 and 5. It slightly increased temperature (see Figure 4(d)) as injected medium was hotter than the algal culture.

Based on these observations, the optimizer behavior in the *Morning* phase can be schematized by the following simple rules:

(i) During the morning the pond depth is maintained as low as possible in order to rapidly reach both optimal pond temperature and biomass concentration.

(ii) In winter, if pond temperature is lower than inflow temperature and if the biomass content in the pond

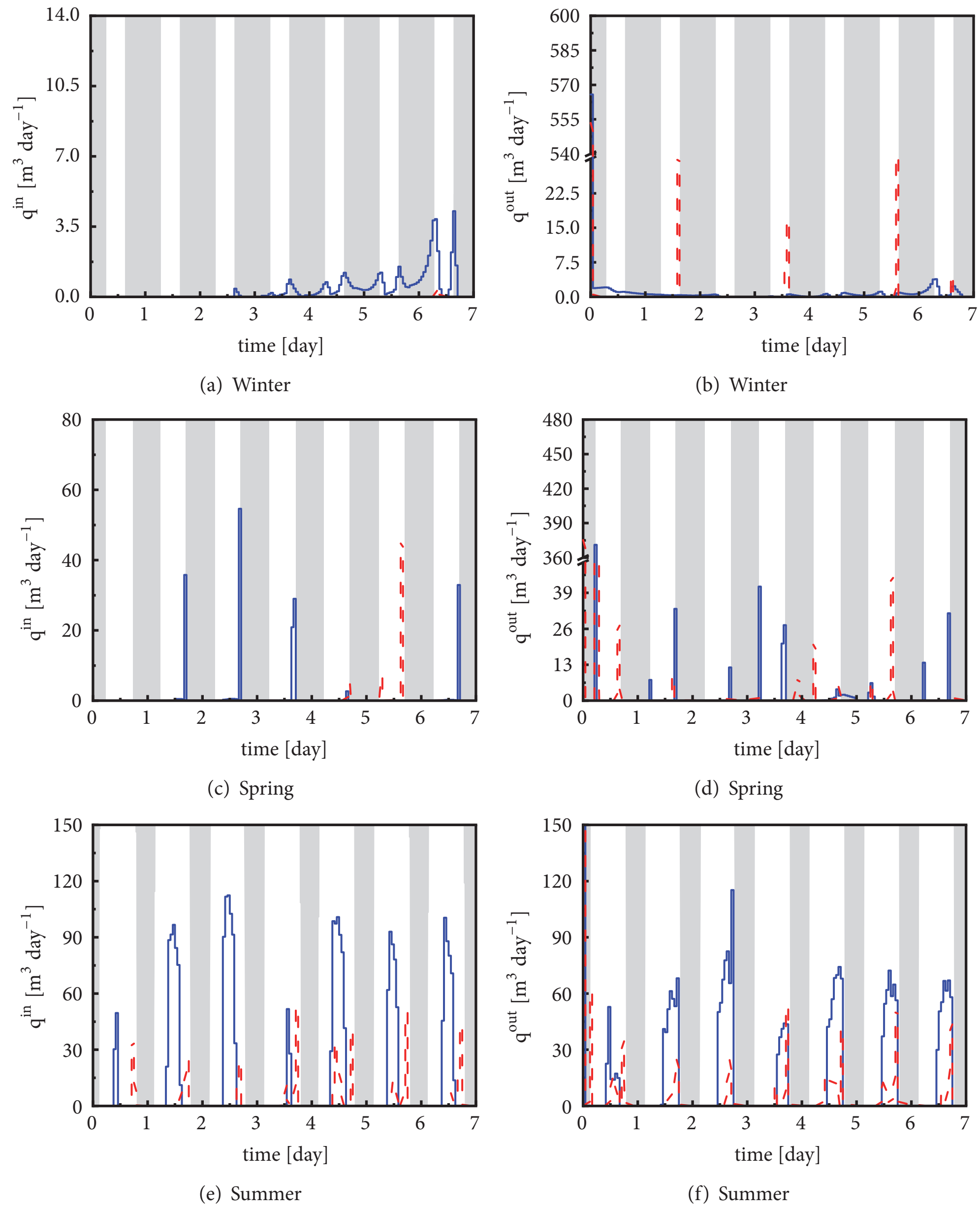


Figure 2: q^{in} and q^{out} optimized profile (blue continuous line: Nice; dashed red line: Rennes. The background is colored in white at daytime and in grey at nighttime).

is high enough to avoid 'washout' conditions, the culture can be partially replaced with fresh medium to increase temperature.

Afternoon. Figures 3(a) and 3(b) show that the inflow rate $q^{in}(t)$ in Nice exhibits a 'bell curve' profile from midday until late afternoon in summer. $q^{out}(t)$ followed the same dynamics but started slightly later in the day. In other words, the control strategy was mainly based on replacing the pond culture by fresh medium ('flushing' strategy). This culture replacement had two main consequences. Firstly, as shown in Figure 3(f), the compensation function $f_{comp}(t)$ was maintained at a value close to 1 during the afternoon, indicating that the algal concentration was kept at its optimal value $x_{opt}(t)$. Secondly ('flushing strategy'), replacing algal culture by relatively cold fresh medium helped maintaining pond temperature close to optimal level T_{opt} (35.8°C, Figure 3(d)). Figure 3(c) shows that the pond depth l_p in Nice increased until mid-afternoon and then decreased, which indicates that culture replacement was not sufficient to maintain pond temperature at the optimal level. Increasing the pond depth increased its thermal inertia and eventually limited temperature increase ('depth strategy'). Figures 3(a), 3(b), and 3(c) show that the same 'flushing' and 'depth' strategies were used in Rennes in summer during day 5, but not during days 3 and 4. As Figure 3(f) shows that the compensation function was significantly lower than

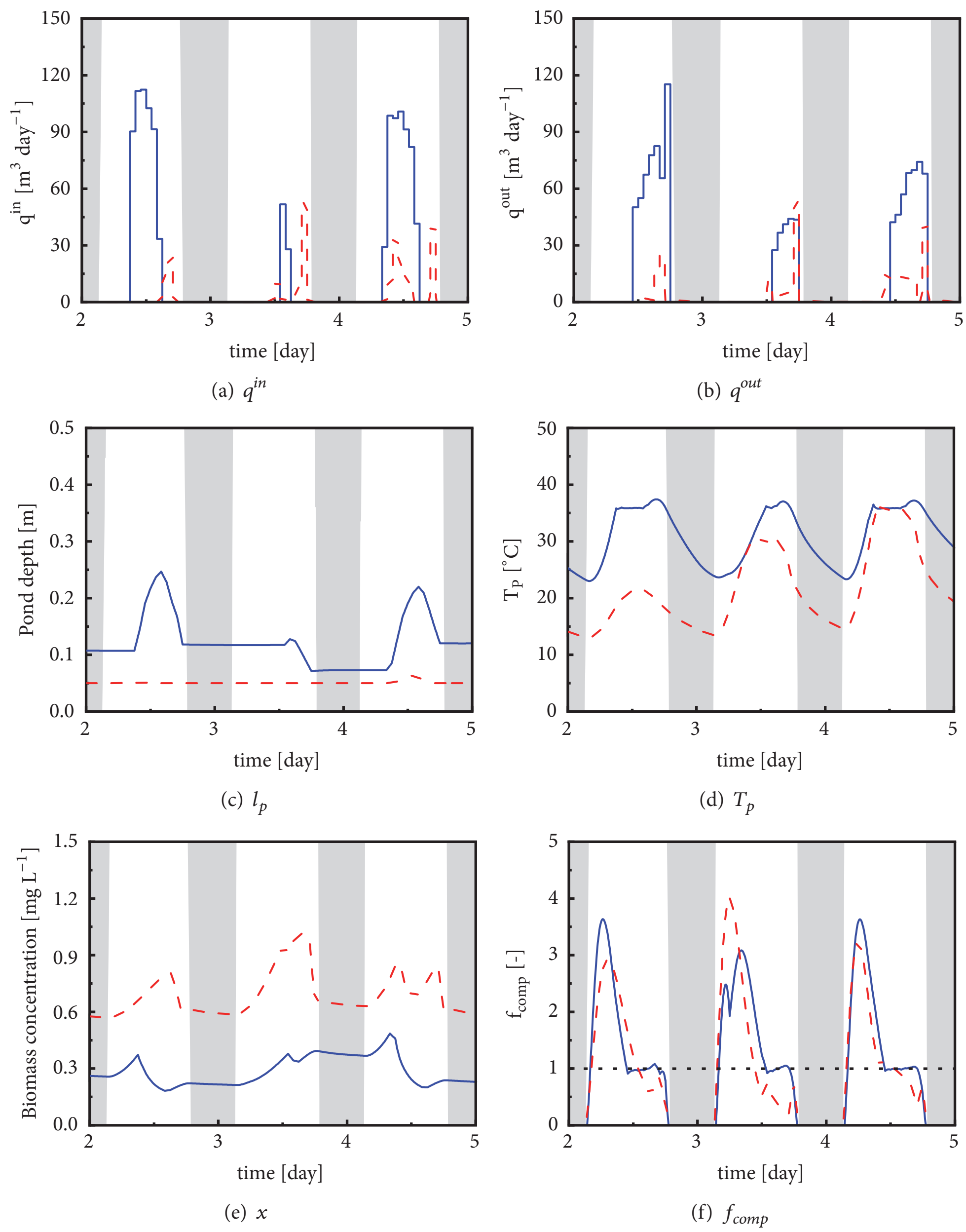


FIGURE 3: July. Three-day zoom of the optimized profiles (blue continuous line: Nice; dashed red line: Rennes. The background is colored in white at daytime and in grey at nighttime).

1 during the afternoons of days 3 and 4, further culture replacement could have theoretically been used to maintain the biomass concentration at its optimal value. Yet, replacing the culture by colder fresh medium would have significantly decreased the pond temperature and therefore lower biomass productivity. Figure 3(d) shows indeed that days 3 and 4 were relatively cold, differently from day 5 in which the pond temperature reached its optimal value. In other words, the optimizer found the best trade-off between optimal biomass concentration and optimal temperature conditions in the case of warm but not hot weather conditions. In addition, Figure 3(c) shows that in Rennes the depth was maintained at its lowest value in the afternoon of days 3 and 4 (warm days) in order to maximize the temperature increase. Figures 4(a), 4(b), 5(a), and 5(b) show that both $q^{in}(t)$ and $q^{out}(t)$ were maintained at 0 in winter and spring in Rennes and Nice. As a result, the biomass concentration slightly increased at daytime (Figures 4(e) and 5(e)). In addition, the depth was left at its lowest value (0.05 m) all day long. These observations indicate that the optimal strategy during cold days consists of maintaining the pond temperature as high as possible even if biomass concentration is significantly higher than

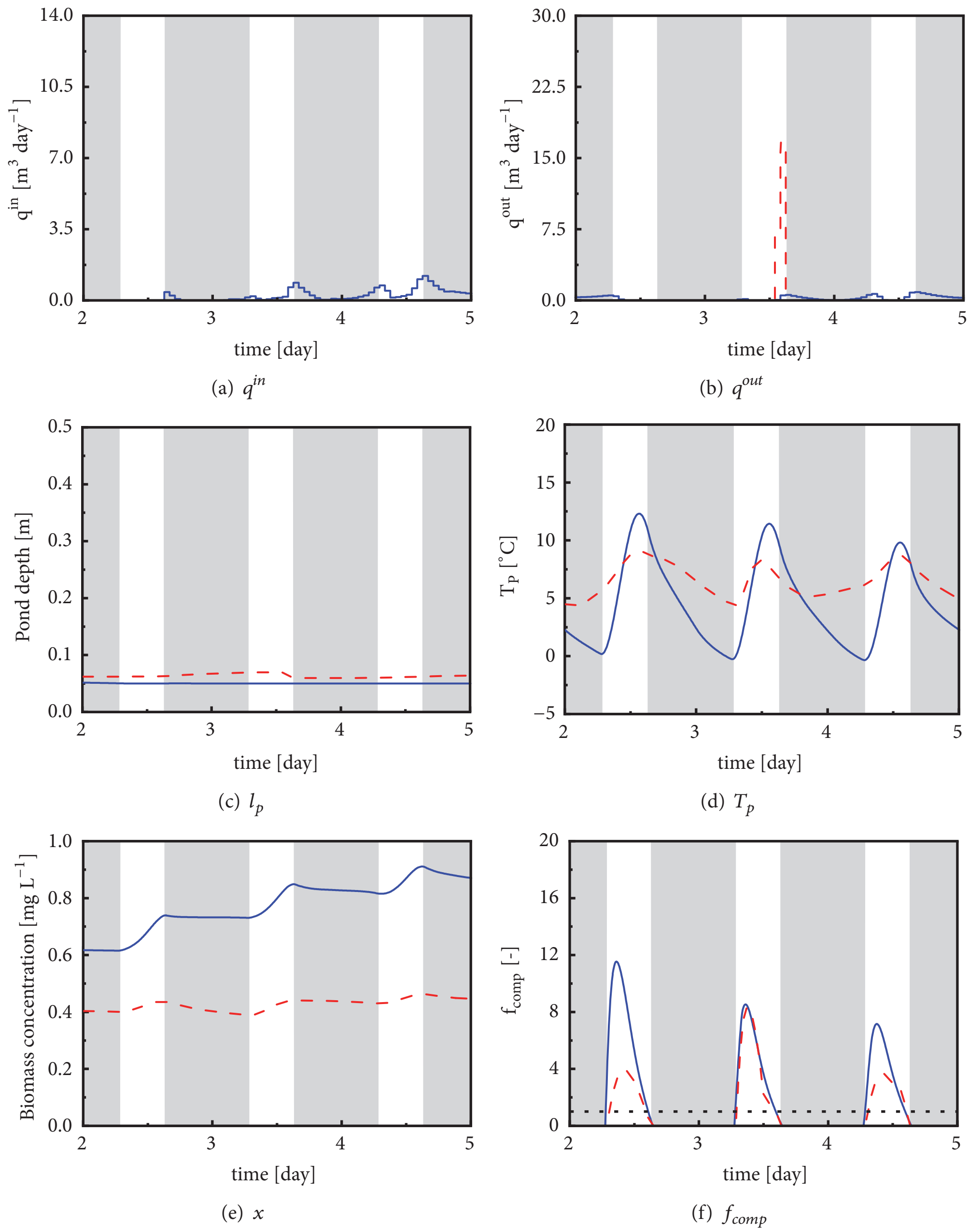
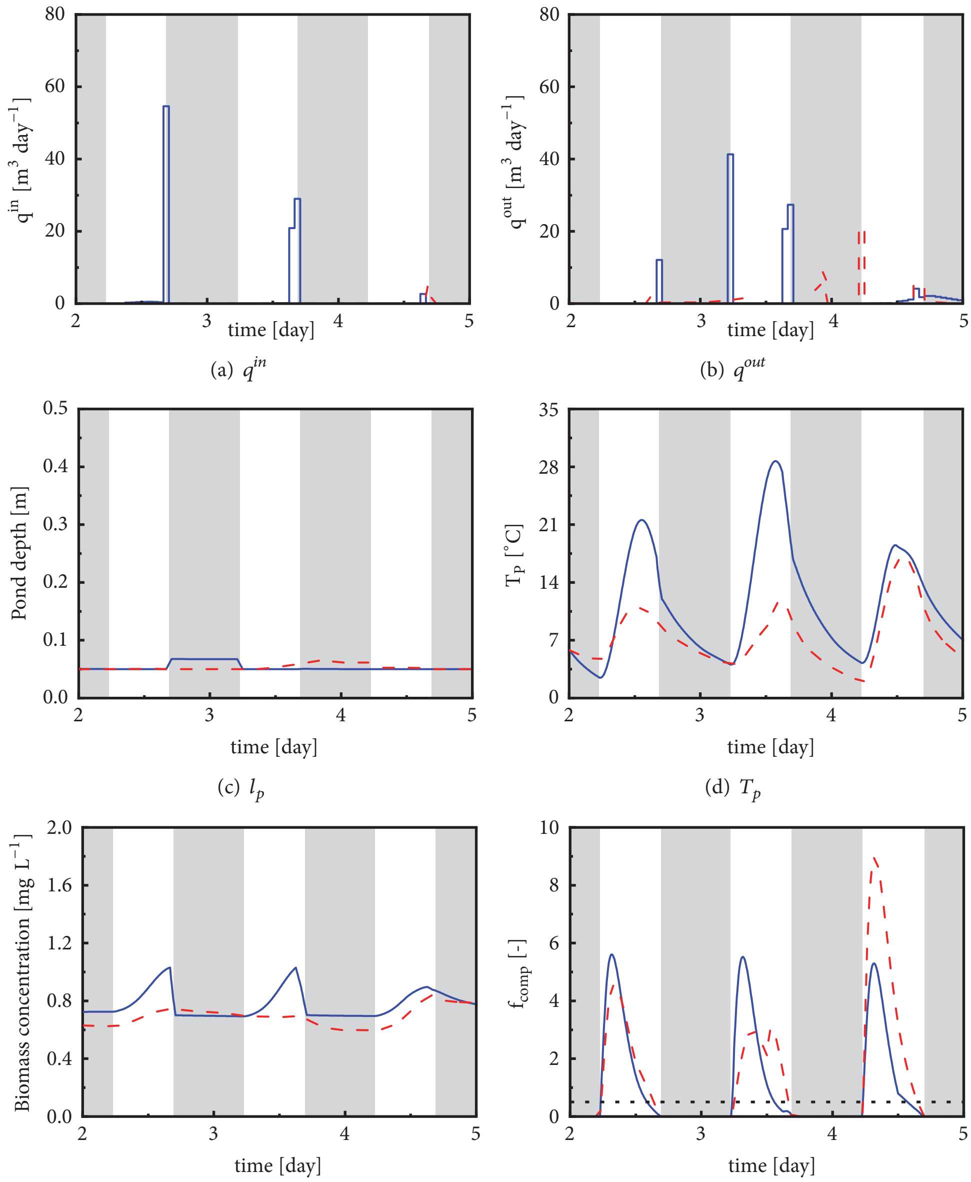


FIGURE 4: January. Three-day zoom of the optimized profiles (blue continuous line: Nice; dashed red line: Rennes. The background is colored in white at daytime and in grey at nighttime).

the optimal concentration. The optimizer behavior in the *Afternoon* phase can be schematized by the following simple rule:

(i) In the afternoon the culture can be flushed to maintain the algal concentration at its optimal level. In summer, this 'flushing strategy' can be combined with depth increase strategy to control temperature at its optimal level. In spring and winter, the optimal strategy consists in staying in batch at daytime while maintaining the pond depth at a minimal value, to ensure that pond temperature reaches the highest possible value.

Sunset. In summer, Figures 3(a) and 3(b) show that a high fraction of the culture was replaced by fresh medium at sunset in Rennes. 'Flushing' the system at sunset both lowered pond temperature (see Figure 3(d)) and biomass concentration (see Figure 3(e)), which in turn limited respiration rates at nighttime. The alternative strategy used in Nice was based on decreasing the pond depth when approaching sunset (Figure 3(c)), to remove a significant fraction of the biomass.



(a) q^{in} (b) q^{out} (c) l_p (d) T_p (e) x (f) f_{comp}

Figure 5: March. Three-day zoom of the optimized profiles (blue continuous line: Nice; dashed red line: Rennes. The background is colored in white at daytime and in grey at nighttime).

In addition, decreasing pond depth accelerates the pond temperature decrease at night. Similarly to the 'flushing' strategy used in Rennes, this 'depth-decrease' control strategy reduced respiration at nighttime. Removing too much biomass from the system would reduce respiration at nighttime but this would also cause the productivity to be low the day after. As a result, the optimizer finds the optimal algal concentration ensuring both low respiration rates at nighttime and sustained productivities the following morning. In winter only a small fraction of the culture was replaced by fresh medium in Nice (Figures 4(a) and 4(b)) as night-time respiration rates were limited by cold temperatures (Figure 3(d)). In Rennes the 'flushing strategy' at sunset was not applied, mostly because inflow temperature was higher (9.2°C) than pond temperature $T_p(t)$ at sunset. Injecting relatively warm water at sunset would therefore enhance respiration at nighttime. The optimal strategy at Nice in spring consisted on partly 'flushing' the system at sunset similarly to the summer case. In Rennes, culture was not replaced at sunset in spring, mostly because maintaining temperatures as high as possible was the best strategy to optimize productivity (Figures 5(a) and 5(b)). The optimizer behavior at *Sunset* can be schematized by the following simple rule:

(i) During hot days, a fraction of the culture is replaced with fresh medium at sunset to minimize nighttime respiration rates. Pond depth is also maintained at a low level to faster decrease temperatures at nighttime. In winter or in colder climates, culture is not replaced by fresh medium at sunset to maximize temperature during the following day.

Night. The pond depth was maintained at its sunset value all night long independently on the season (Figures 3(c), 4(c), and 5(c)). In addition, Figures 3(a), 3(b), 4(a), 4(b), 5(a), and 5(b) show that, in general, no 'flushing' was used at nighttime ($q^{in} = 0$ and $q^{out} = 0$). The only exceptions were in spring at day 4 for Rennes and at day 5 for Nice, which correspond to culture extraction just after rainfall to maintain the pond depth at its lowest possible value. In summer, temperatures are minimized at nighttime. In winter, low thermal inertia and therefore low depth must be maintained at daytime to increase temperature and this constrains pond depths to be low at nighttime. The optimizer behavior at *Night* can be schematized by the following simple rule:

(i) The pond stays in batch and thus depth is maintained at the sunset value.

4. Discussion

The optimization technique significantly increased the productivity at the two locations and three seasons considered. The productivity boost in summer mainly results from the optimizer ability to maintain, during large periods of daytime, ideal growth conditions, i.e., providing efficient trade-off between optimal concentration and temperature (via the 'flushing' and 'depth' strategies). In spring and winter, the optimal temperature for the species *C. vulgaris* (35.8°C) cannot be reached, so the optimal strategy consists of limiting culture replacement to ensure higher temperatures, even if it leads to relatively high biomass concentrations. Because of relatively low temperatures, respiration rates are indeed relatively low, so these higher biomass concentrations is not too penalized by respiration.

The knowledge of future weather is crucial to optimize the process inflows and outflows, and this can be illustrated in several cases. Firstly, in hot days, slowly increasing the pond depth can help to maintain the pond temperature at its optimal value during daytime. As temperature dynamics is relatively slow due to the high thermal inertia of water, only an accurate knowledge of future weather conditions and their impact on pond temperature can help to maintain pond temperature as close as possible to its optimal value. Secondly, a fraction of the algal culture is replaced by fresh medium at sunset to minimize respiration losses at nighttime. However, removing too much biomass from the pond would lead to low productivity values the morning after, and especially if the day after is particularly sunny. Determining the optimal fraction of culture to remove from the pond at sunset therefore requires knowing the weather conditions of the following day. Sensitivity of the management strategy to accuracy in the future weather was assessed in [23]. It was shown that, especially for hot periods, biases in weather predictions can deeply affect the productivity. Higher frequency weather data acquisition will mitigate this risk. Weather predictions at short term should also be combined with actual measurements of water temperature and solar fluxes. Also, the main rules guiding the optimisation can be used to check that the logic of the control action stay coherent and possibly limit the controller action in case of conflict. These rules must also be used to initialize the MPC strategy with reasonable profile inflow and outflow profiles. It will reduce the risk of local minima in the determination of the optimal strategy.

This study covers most of the possible combinations of light and temperature ranges. Having in depth examined the control strategy has provided the keys for understanding the control under most of the possible climates. The study in [23] was focused on a hot climate. It proposed a first picture, but it is crucial to better understand how to manage the trade-off between light access and optimal temperature for a larger variety of seasons and latitudes. This MPC strategy must still be tested for a larger range of locations at all seasons. But the study with the climates of Rennes and Nice through all the seasons provide hints that it might stay efficient in many other locations. In the most extreme cases, complementary strategies could be jointly used to more efficiently heat water in winter or decrease temperature in summer. Heat exchangers have a potential here, provided that the unavoidable energy consumption (at least for pumps) is compensated by the productivity gain.

Temperature control by playing on thermal inertia and culture replacement by fresh medium is central in the optimization strategy. This point was so far never considered in the previous optimization studies which focused on optimizing algal access to light by playing on the compensation function. *Chlorella vulgaris* is relatively resistant to high temperatures (T_{max} = 42°C). However, for a cold-adapted algae species, the possibility of culture crashes due to temperatures above T_{max} triggering cell mortality [27, 36] would increase further the impact of temperature on productivity. In this case, the optimizer would likely place temperature control above concentration control in summer to avoid culture crashes.

In this study, we did not include the water cost in the optimization criterion. However, the optimal management induces high dilution rates, especially in summer, both to reduce temperature and to dilute culture at high density. Water demands were consequently higher than the standard management procedure (Table 2) which required a significantly lower amount of water (only 17.53 m^3 $week^{-1}$ for all the seasons). This shows that the management of process temperature must be designed to have a limited impact on water consumption.

In particular, the optimized control strategy increased the *WD* at Nice in summer up to a factor of 7.7, which means an increase by a factor of 3.2 per kg of produced algae: from 1.25 m^3 kg^{-1} up to 4 m^3 kg^{-1}. This computation also highlights the necessity to recycle water after biomass extraction to reduce the water need.

As a perspective, the same optimisation strategy should be studied when constraining the maximum amount of water that can be used in the process (based for example on the availability on rainwater at the location considered) and assuming that an important fraction of the water can be recycled, as suggested by [37].

5. Conclusions

The MPC scheme based on a complex dynamical model able to describe the algal growth in open ponds through meteorological data allows significant increase of the productivity efficiency compared to standard operation. Productivity gain was achieved via two main mechanisms: culture replacement (compensation condition) and pond depth control (thermal optimization). A short list of simple rules was extracted for simplified operation. Temperature control turns out to be a key factor to achieve maximal productivity. The drawback of this strategy is a relatively high water demand, especially in sunny and hot climates. Further research needs to address water recycling implementation and include it in the cost criterion to reach a compromise between maximizing productivity while reducing the water demand. The analysis of the optimal strategy for a diversity of heat fluxes and temperature conditions offer a general strategy which is likely to be efficient in many other locations. More extensive simulations must now consider other production sites to consolidate the management strategy and further generalise it.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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Supplementary Materials

The supplementary material contains details about the physical model for computing medium temperature and local illumination. It also presents the meteorological data used for the simulations. *(Supplementary Materials)*

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