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Abstract

We study an optimal control problem of crop irrigation and fertigation with treated wastewater that contains vital crop nutrients, with the objectives of maximizing crop production and minimizing environmental and farming costs. A double modelling method is proposed that allows to use both a modern detailed crop model – the simulation model – together with a low-order dynamical systems model – the control model. The method is based on the design of the control model which, after calibrating its parameters, is capable of reproducing simulations of the complex model for a range of controls. With an dedicated dynamic programming algorithm we can then solve the optimization problem on the control model. We show that irrigation and fertigation strategies obtained as optimal controls for the reduced crop model behave well on the simulation model. This methodology allows to obtain efficient and simple controls that could be applied in practice.

1 Introduction

The continued population increase and associated rise in food demand, lead to the necessity to safeguard surface waters of high quality for human consumption, especially in the context of climate change. The reuse of treated wastewater offers an alternative water resource for agriculture, which is, by far, the human activity that consumes the most water [18]. In addition, wastewater contains nutrients vital for crop growth and therefore reuse irrigation has the potential to become a renewable fertilizer resource. It is still a real challenge to manage water treatment systems to keep nutrients while guaranteeing a water free of pathogens and micro-pollutants, but technologies are being developed, such as membrane filtration systems, precisely allowing to deliver safe water.

Crop water and nutrient needs are fundamentally dynamic, changing throughout plant life, and therefore, to optimize crop growth, it is necessary to adapt the treatment of wastewater, in terms of nutrient quality and quantity. Furthermore, to achieve efficient reuse irrigation and avoid nitrate leaching, it is also important to control the irrigation volume dynamically according to crop needs and variations in weather.

Determining efficient irrigation and fertigation strategies can be investigated by using optimization techniques with crop models. Such studies have received great attention in the literature and have been mainly done according to one of the following approaches: (i) applying a generic numerical optimization procedure to a complex crop model ([6, 15, 7, 13]) or (ii) by using a dedicated dynamic programming approach on a simple crop model ([3, 17, 16, 10]).

A lot of knowledge has been embedded in state of the art crop models since their early development in the 1980's and they now take into account all aspects of a cropping system. These models simulate, on a daily basis, crop growth as influenced by interactions between plant, soil, weather and farming practices. They have been validated for a wide range of crops and climates, and therefore are the preferred tools to investigate the optimization of management strategies. However, these are generally computer models with a complex mathematical structure that makes it difficult to directly apply dynamic programming techniques, as noted by Schütze [16]. Moreover, generic optimization algorithms will also have difficulties in finding the global optimum of management strategies at a fine time step.

On the other hand, decision models do not necessarily need to be as detailed as models for deep understanding of internal processes. Limited decision variables and relatively poor online measurements also advocate for simple models. For models expressed as dynamical systems, it is then possible to leverage the structure for a better resolution of optimization and control problems, in terms of computational time and guarantee of optimality.

We propose here a hybrid approach, the double modelling method, that takes advantage of both types of models to derive efficient control laws for a complex system. Double modelling is a term already used to refer to multi-scale modelling, for the representation and understanding of the emergence of macroscopic laws [12]. However, double modelling has been very rarely considered with the primary objective of designing control strategies, apart from a few particular studies [8, 1]. The present work goes further towards the integration of both models and we show how the double modelling method can be an iterative process, going back and forth between models to compute controls.

2 Principles of the double modelling method for optimal control

It has been shown, for some time now, that relatively simple models can reproduce complex real world systems, albeit with a limited domain of validity. Similarly, we have found that it is also possible to replicate a simulation of a complex model with a low-order dynamical system. Indeed, we can calibrate the parameters of a reduced model to get a good agreement with specific outputs of a detailed model, for a range of controls and a given scenario (i.e. a fixed set of parameters of the complex model). This is the key observation underpinning the double modelling method and allows us to use both a simulation model, for a detailed representation of the system of study, together with a control model, that is better suited for the resolution of optimal control problems.

In the following, we present the main steps of the double modelling method, as shown in Figure 1. As input to the method, we assume that an optimal control problem has been defined in the context of a given simulation model.

2.1 Design of control model

The first step is to design a model suitable for the resolution of the dynamic optimization problem and that is adapted to the general control methodology. Therefore the selection of an adequate mathematical structure and attention to model complexity is essential.

An important aspect of this method is that the control model is not only intended as a computational device but is also meant to provide insights into the optimal control problem. Indeed, designing a physically meaningful model with relevant variables that actually represent key elements of the system, allows to qualitatively analyze the relation between the computed solutions and system components. Then, it is also essential to select the represented processes based on the optimization objective and decision variables in

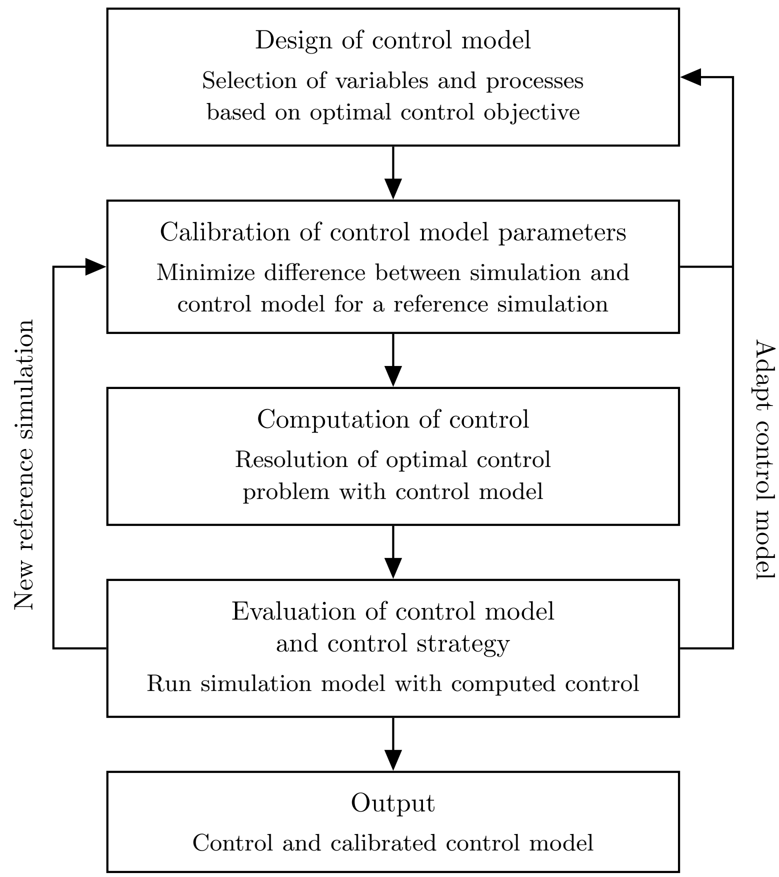

Figure 1: Double modelling Method

order to model the impact of controls and thus understand the input-output behavior of the system.

In addition, the link between the simulation and control model should be clearly established, in order to compare the variables, processes and outputs of both models and thus further help to understand the computed control. This also allows the interpretation of simulations of the two models together and will be particularly helpful to guide the calibration of the control model parameters.

2.2 Calibration of control model parameters

This step consists in identifying the control model parameters in order to approximate as best as possible the simulation model for the chosen scenario.

The first task is to select the reference simulation of the complex model that will be used to compare both models. It is important to consider a case that covers a range of phenomena in order to capture, in the control model, the essential behavior relevant to the optimal control problem.

A sensitivity analysis can help to select the parameters to calibrate and also determine which variables are impacted by which parameter. For the less sensitive parameters, values from literature can be used and eventually they can be fine tuned after the main calibration has been done. For parameters with a strong physical meaning and that are particularly relevant to the control objective, an interesting possibility is to use directly a corresponding parameter from the simulation model.

For the selected parameters, the calibration can be carried out by minimizing the difference between models with standard optimization algorithms. Several error functions are possible, either the difference for one variable or a (weighted) sum of errors over several variables. It is also important to consider the error on the model outputs relevant to the control problem, such as the optimization objective and the constraints.

The parameter identification can be done in several steps, starting with the error on a single variable and calibrating only the parameters that impact that variable the most. By iterating in this fashion through all the variables it is possible to get a first estimation of the parameters. However, to get coherent results, it is necessary to conduct a final calibration that considers the error on all control model variables. It is also important to pay attention to the proper fit of processes, to make sure that the control model remains relevant and not just a computational model.

Finally, it is essential to assess the robustness of the parameter calibration, in particular with respect to the control objective. This can be done by evaluating the difference between models for other controls than the one used for the calibration.

This calibration process can be unsuccessful as it might not be possible to find parameters such that the difference between models is sufficiently small or such that the domain of validity is satisfying. In this case, the control model should be modified, by changing the variables or adapting the processes for which the errors are the most important.

2.3 Computation of control

Once a control model has been designed and calibrated, it can then be used to compute a control by solving a dynamic optimization problem. Here, the advantage of using a dedicated control model is that we can use adapted methods and algorithms for an efficient resolution. If the system of study can be reduced to a sufficiently simple model, it could also be possible to establish qualitative results concerning the optimal control or even solve analytically the problem to obtain an explicit solution.

2.4 Evaluation of control model and control strategy

To evaluate the quality of the control model, simulations of the complex model are run with the computed control. If there is an important difference between models, this indicates that there is a problem with the parameter calibration or with the control model. In this case, it is possible to restart the parameter estimation with a new reference simulation based on the computed control. However, if it is necessary to calibrate the model for each computed control, this is a sign that the control model is not well suited for the problem and should be adapted. On the other hand, if there is still a good agreement between models with the computed control and for the same set of parameters calibrated with the reference simulation, then this demonstrates the quality of the control model and of its calibration.

Finally, the computed control should be evaluated with the simulation model. Indeed, the more detailed model can be used to study the computed control in a more realistic setting and, for instance, allows to ensure that the computed control satisfies constraints adequately. It is also possible to estimate the optimality of the computed control for the simulation model by comparing with other controls to see if a better value of the objective function is attained.

2.5 Output

First, this method offers a means to propose a candidate optimal control for a problem associated with a complex model, for which standard optimization methods can be inefficient. An argument can be made that the resulting control is at least locally optimal for the simulation model if there is a good agreement between models for a range of controls. In this case, the control model can be considered as a local approximation of the simulation model in the region of the computed control. Then, since this control is optimal for the control model, it should also be a local optimum for the simulation model.

However, the output of the method is also the control model and the set of calibrated parameters that characterize the computed control. The design process of the control model can be seen as a method of determining, in the context of the optimal control problem, the most important variables and processes and how the inputs impact the control objective. Then, the control model is a valuable tool in understanding a complex problem and provides a means to interpret the optimal control.

3 Application to Wastewater Reuse: Case Study

The double modelling method is illustrated here with a case study in wastewater irrigation. We consider a crop grown in mono-culture and irrigated with treated wastewater and suppose that the only fertilizing nutrient present in the irrigation water is nitrogen. Indeed, this is one of the most important nutrients for crops and currently, its impact and dynamics in the soil plant system are the most well modeled. The controls considered here are thus the irrigation flow rate I [mm d^{-1}] and nitrogen concentration of irrigation water C_N [g m^{-3}].

The aim is to solve the optimal control problem of maximizing crop production, represented by the plant biomass at the end of the growth cycle, whilst minimizing the various costs and impacts due to reuse irrigation. Farming costs are considered proportional to the total water volume and total mass of nitrogen added by irrigation and environmental impacts are considered with nitrogen leaching. However, other environmental and health hazards are neglected as we suppose that they are managed by the wastewater treatment or a multi-barrier approach [19].

The scenario that we work with consists of a modern corn cultivar grown on a loam type soil, with data from a field in the south of France, near the city of Toulouse. We will not consider issues due to weather uncertainties in our study of the control problem and instead we assume that it is known in advance and use for all simulations weather data from 2013.

3.1 Models

The simulation model considered here is STICS [4, 5], a generic and robust crop model that is developed and used by an international community of researchers. It is based on a mechanistic approach and centered around the water, nitrogen and carbon balances of the cropping system, with a detailed representation of the soil and plant. This complex computer model has over 600 parameters to simulate a variety of farming systems and has been validated for a diversity of crops in different climatic conditions. STICS has been used in a wide range of studies, such as the effects on cropping systems of climate change [11] or biotic stresses, and has also been used for recommendations of farming practices such as the application of nitrogen fertilizers [9].

For the control model, we start from a continuous time dynamical system developed by Pelak et al. [14] that is based on a simple representation of the crop-soil system, focusing on the water and nitrogen dynamics. The crop is represented by the above-ground dry biomass per unit area B [kg m^{-2}] and the canopy cover C [m^2 m^{-2}], which is the fraction of ground covered by the crop. The soil variables are the vertically averaged relative soil water content S [m^3 m^{-3}] and soil nitrogen mass per unit area N [g m^{-2}].

We have decided to change the soil water variable which is expressed as content relative to porosity in [14] and instead we consider water content relative to total soil volume. Indeed, we have found that the dynamics are very sensitive to the porosity parameter, which is difficult to measure in practice. This modification of the soil water variable allows to eliminate this parameter from the model and also makes it easier to compare with STICS.

In the control model, the soil variable are computed from balance equations and for the soil water, the model considers rain R and irrigation I as inputs and accounts for losses due to crop transpiration T, evaporation E and leakage Q.

$$z\dot{S}(t) = R(t) + I(t) - T(t, C, S) - E(t, C, S) - Q(S) \tag{1}$$

where z is the active depth. The detail of the functions involved are described in the Appendix. Transpiration and evaporation are both computed from the reference evapotranspiration $ET_0(t)$, which is an essential weather input that combines solar radiation, temperature, wind and vapor pressure, and limited by crop and stress coefficients.

The soil nitrogen balance equation considers losses due to plant uptake U and leaching L, as well as input from fertigation, which in the context of reuse irrigation, is taken as the product of the irrigation flow rate I and the nitrogen concentration of the irrigation water C_N.

$$\dot{N} = I(t)C_N(t) - U(t, C, S, N) - L(S, N) \tag{2}$$

Plant nitrogen uptake U is the product of transpiration and a nitrogen uptake limitation function $f(S, N)$, which models crop growth reduction in case of nitrogen stress.

A logistic growth of the canopy cover is considered in [14], with limitations due to water and N stresses,

$$\dot{C} = r_G f(S, N)T(t, C, S) - M(t, C) \tag{3}$$

with r_G the canopy cover growth rate and $M(t, C)$ accounts for the metabolic limitation and also, at the end of the growth cycle, leaf senescence.

The model supposes that the accumulation of biomass is proportional to crop transpiration, with again a limitation of growth in the case of water and nitrogen shortage, and can be computed from C, S and N with

$$\dot{B} = \frac{W_*}{\eta_c ET_0(t)} f(S, N)T(t, C, S) \tag{4}$$

where η_c is the maximum nitrogen concentration taken up and W^* is the normalized daily water productivity.

Since STICS represents the soil in detail, dividing the soil profile in 1 cm layers, we compare the soil variables of the control model with the average of the STICS values over the active soil depth, which we take to be the maximum rooting depth calculated by STICS. The concept of Leaf Area Index (LAI) is used in STICS but it has been shown that an optical analogy (Beer's law) can be used to convert LAI to canopy cover [5]. For plant biomass, the two models can be compared directly as they both output the above-ground dry biomass per unit area.

For the control model, the crop development process is idealized and thus does not represent the germination process adequately. Moreover, the initial stages of crop life are critical and they should be optimized with other objectives than those under consideration here. The time interval of optimization is therefore taken from the stages of emergence to maturity, as computed by STICS. The initial conditions for the control model are then taken by converting the values of the corresponding variables of the simulation model.

3.2 Calibration of control model parameters

The water and nitrogen dynamics play an essential role in the problem that we study and therefore we select a reference simulation where the crop experiences water and nitrogen stresses, in order to capture these effects in the control model.

The parameters that have strong physical meaning and that we use directly from STICS concern the soil water levels (field capacity and wilting point) and guarantee that the hydraulic properties of the soil are preserved in the control model. From a sensitivity analysis,

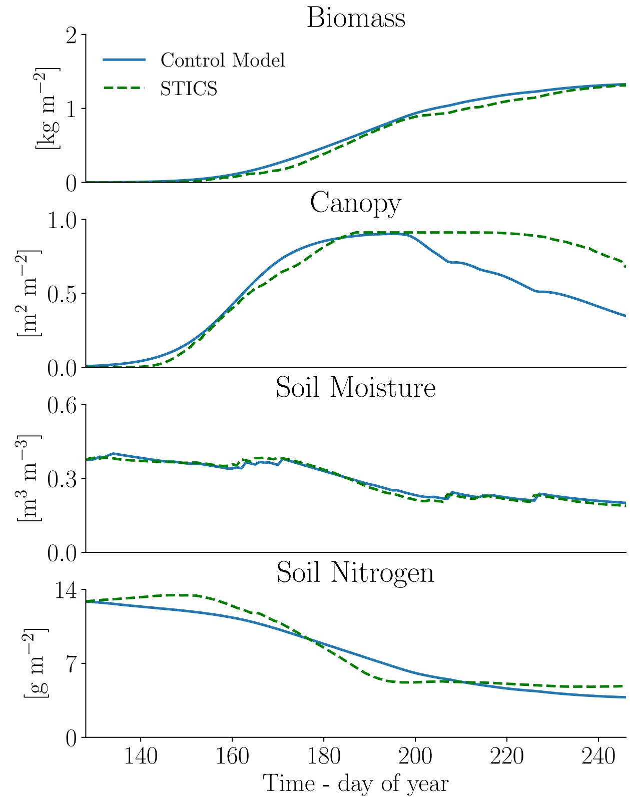

Figure 2: First calibration of control model (solid blue lines) with STICS model (green dash lines) for reference scenario

we have determined 7 important parameters that we will calibrate. For all other parameters, we initially use values from [14].

We start the parameter identification with the calibration of the water dynamics, as they play a central role in the soil crop system, and minimize the difference between models only in soil water content, to estimate S^*, K_{cb} and d. Likewise, we then calibrate only the soil nitrogen content (for η_C), followed by canopy cover (r_G and r_M) and finally crop biomass (W^*). This allows to get a decent first estimation of parameters but to get coherent results, we need to run a final calibration by minimizing the error on all variables.

At first, we used a time dependent reference evapotranspiration ET_0, using values that are computed from daily weather data, as in STICS. We obtained a very good agreement between both models for the soil water and nitrogen content and for plant biomass but not for the canopy cover. It appears that the dynamics, from Pelak et al. [14], of this variable are very sensitive to time variations of ET_0 and far more than in STICS. We therefore used a constant ET_0, taking the average over the growth cycle of the time dependent data and this produced better results. The canopy cover seems also very sensitive to water and nitrogen stress, as seen at end of growth cycle for the reference simulation (Figure 2), and to get a better fit between models, it would be necessary to adapt the dynamics of the canopy cover.

Nonetheless, the calibrated control model is very successful at reproducing the STICS reference simulation (Figure 2). In particular, for the optimal control problem, we have a good prediction of the biomass and the dynamics of soil water and nitrogen are captured well with the control model. Furthermore, the water and nitrogen stress indicators of both models show similar behavior and when testing with different controls, the same set of parameters still produces a good agreement between models.

3.3 Computation of control

We formulate a constrained optimal control problem to account for the different, possibly conflicting objectives of maximizing crop production and minimizing the various costs. Indeed, we can implement the various costs as constraints with limits that must not be exceeded and thus we consider the problem of maximizing the final crop biomass, with a constraint on the total mass of nitrogen added through irrigation. We also impose restrictions on the controls with limits $I_{\max}$ to the daily irrigation volume and $C_{N\max}$ to the maximum nitrogen concentration of the irrigation water. Denoting t_0 and t_f the fixed initial and final time and $\overline{F}$ the maximum total mass of nitrogen allowed, the problem is

$$\begin{cases} \text{Maximize} & B(t_f), \\ \text{over all} & (I, C_N) : [t_0, t_f] \to [0, I_{\max}] \times [0, C_{N\max}], \\ \text{such that} & S(\cdot), N(\cdot), C(\cdot) \text{ and } B(\cdot) \text{ satisfy } (1) - (4), \\ & \displaystyle\int_{t_0}^{t_f} I(t) C_N(t)\, dt \leqslant \overline{F}. \end{cases}$$

We do not consider other constraints as we have found that the solution is also efficient in terms of the total irrigation volume and also avoids nitrogen leaching. This can be explained by the fact that excess irrigation would lead to nitrogen loss through leaching.

We solve this problem with the dynamic programming algorithm implemented in the toolbox BocopHJB [2].

3.4 Evaluation of control model and control strategy

The simulation of STICS with the computed control (Figure 3) shows that there is still a good agreement between models, with the same set of control model parameters found during the initial calibration. Actually, the canopy cover simulated here is much closer to the STICS model with the proposed control, which has a tendency to avoid nitrogen and water stress in order to maximize crop biomass. This would further indicate that the problems with the fit of the canopy cover for the reference simulation (Figure 2) is indeed due to plant stresses not being well accounted for in the canopy cover dynamics.

To check the performance of the computed control for the simulation model, we compare it to a reference control (Figures 3 and 4 and Table 1). For the water volume control, we use the automatic calculation of irrigation provided by STICS. Then we set a constant nitrogen concentration of the irrigation water such that total nitrogen added is same as the constraint $\overline{F}$ imposed in the optimal control problem. The result is that the control proposed here leads to 6.9% more crop biomass at harvest, corresponding to an extra 1.36 tons per hectare, for slightly less irrigation and similar nitrogen leaching.

The proposed control shows interesting properties and for example, adapts to weather by avoiding irrigation during rain events. Indeed, when the soil water content is already high, irrigation leads to losses due to leaking and would also cause nitrogen leaching. Around day 160, in Figures 3 and 4, there is important rainfall at the same time that the crop starts

Table 1: Comparison of controls performance,values from STICS.

	Proposed	Reference
Final Biomass [T/ha]	21.00	19.64
Total Irrigation [mm]	234	240
Total Nitrogen added ($\overline{F}$) [kg/ha]	70	70
Total Nitrogen leached [kg/ha]	4	4

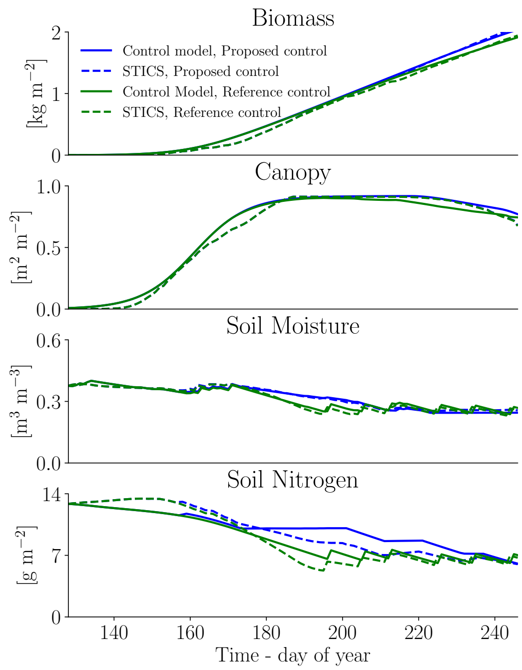

Figure 3: Comparison of the control model and STICS model with the proposed control computed with the double modelling method and a reference control computed from the automatic calculation of irrigation provided by STICS.

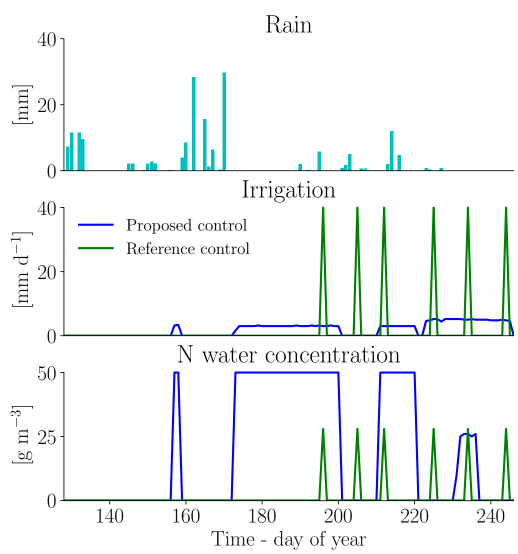

Figure 4: Rain and controls : proposed control computed with the double modelling method and a reference control computed from the automatic calculation of irrigation provided by STICS.

to deplete the nitrogen soil reserves. Fertigation during the rain events would be inefficient, only causing leaching, but the control is able to anticipate this, fertilizing in advance to build up nitrogen reserves before the rain events.

Another important observation is that, the irrigation control aims at maintaining the soil water content above a certain level, as seen in Figure 3. The threshold actually corresponds the S^* parameter of the control model, which can be interpreted as the soil water content under which the crop is stressed. This underlines the key role that the control model and its parameters can play in the definition of a control strategy to avoid water stress whilst using a minimal amount of water.

4 Conclusions

Although we have no formal proof of the optimality of the computed control for the complex model, double modelling appears as a promising method to obtain efficient and simple controls. The good agreement between simulations of both models across a range of inputs, demonstrates the quality of the control model, which can therefore serve as part of a future decision making tool.

The work presented here opens up possibilities for further investigations and clearly there is a potential for developing new strategies for irrigation and fertigation by adapting existing control methods to the framework of double modelling. To obtain robust and simple controls, state feedbacks could be designed and parametrized using the control model calibrated on the simulation model. To deal with weather uncertainties, techniques of adaptive control could be developed or the use of a receding horizon criterion could be considered, looking to optimize over a sliding time period for which a reliable weather forecast is available.

In the context of reuse irrigation, this work and in particular the control model, could be extended to account for other nutrients present in wastewater, such as the different types of nitrogen (nitrate and ammonium) and phosphorus, in order to further optimize the treatment quality to crop needs.

Appendix

We give here the details of the function of the control model. Parameters are defined in Table 4.

The transpiration rate is

$$T(t,S,C) = K_{cb}\ ET_0(t)\ K_s(S)\ C,$$

where $ET_0(t)$ is the reference evapotranspiration. The water stress coefficient is

$$K_s(S) = \begin{cases} 0 & S \leqslant S_w, \\ \frac{S-S_w}{S_*-S_w} & S_w \leqslant S \leqslant S_*, \\ 1 & S_* \leqslant S. \end{cases}$$

The evaporation rate is

$$E(t,C,S) = K_{ec}\ ET_0(t)\ K_r(S)\ (1-C),$$

and the evaporation reduction coefficient is

$$K_r(S) = \begin{cases} 0 & S \leqslant S_h, \\ \frac{S-S_h}{1-S_h} & S_h \leqslant S. \end{cases}$$

The crop nitrogen uptake is

$$U(t,C,S,N) = f(S,N)T(t,S,C)$$

and the nitrogen limitation function is

$$f(S,N) = \min\left(\frac{N}{zS}, \eta_c\right).$$

The leakage is $Q(S) = k_{sat}S^d$ and nitrogen leaching is $L(S,N) = \frac{N}{zS}Q(S)$.

The canopy metabolic limitation function is

$$M(t,C) = \begin{cases} r_m C^2 & t \leqslant t_{sen} \\ (r_m + \gamma(t - t_{sen}))\, C^2 & t \geqslant t_{sen} \end{cases}$$

Table 2: Control model parameters

	Description
r_G	Canopy growth per unit N uptake
r_M	Canopy decline due to metabolic limitation
K_{cb}	Transpiration crop coefficient
K_{ec}	Evaporation crop coefficient
S_h	Hygroscopic point
S_w	Wilting point
S_*	Point of incipient stomatal closure
η_c	Maximum nitrogen concentration taken up
W_*	Normalized daily water productivity
z	Soil depth
d	Leakage parameter
k_{sat}	Saturated hydraulic conductivity
t_{sen}	Date of onset of leaf senescence
γ	Slope of increase of senescence after t_{sen}

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