Agricultural Water Management 289 (2023) 108536

Contents lists available at ScienceDirect

Agricultural Water Management

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

# The potential of a coordinated system of gates for flood irrigation management in paddy rice farm

Giovanni Zoffoli [a], Fabiola Gangi [b], Gianni Ferretti [a,*], Daniele Masseroni [b,*]

[a] Department of Electronics, Information and Bioengineering, Politecnico di Milano, Via Ponzio 34/5, 20133 Milano, Italy
[b] Department of Agricultural and Environmental Sciences, University of Milan, Via Celoria 2, 20133 Milano, Italy

ARTICLE INFO

Handling Editor - J.E. Fernández

*Keywords:*
Paddy rice
Irrigation management
Automatic system for irrigation
Predictive control model

ABSTRACT

Rice is one of the most important staple foods in the world. In Europe, Italy is the main producer of rice, with almost all production concentrated in the northeast of the country. Traditionally, rice is grown in fields that are flooded from before planting until just before harvest. This water management technique requires a great deal of labour for farmers who have to manually adjust the inlet and outlet gates to maintain a constant ponding water level in the fields, especially when there is fluctuation of water supply at the farm inlet, for example as a result of rainfall. In addition, the practice of flood irrigation is very water-intensive. New technologies based on remotely and automatically controlled gates are being studied to increase the efficiency of this irrigation method. The objective of this work is to explore the potential of a coordinated and intelligent system of gates for efficient farm irrigation management and ponding water level maintenance. Based on information and measurements from a real case study consisting of a 40-hectare paddy rice farm located in northern Italy, where automatic gates and water level sensors were placed at strategic points of the farm canals and fields, respectively, a proportional-integral (PI) and a non-linear model predictive control (NMPC) of water levels were implemented and compared through modelling and simulation experiments. The results show that the proportional-integral control reproduces the actions that the farmer uses when faced with situations of surplus of water in the fields or a shortage of water in the farm canal. In particular, the general coordination of the gates is lost, and the individual binomial field-gate prevails as an independent system in the farmer's operation. Conversely, non-linear predictive control coordinates the gate operation to obtain a uniform ponding water level in the fields when there is a shortage of water, or significant water conservation when there is an excess of water as a result of rainfall. In conclusion, a nonlinear predictive control model seems to be a suitable strategy to advance irrigation management in rice farms, allowing rice farmers to continue the tradition of flooding while increasing its performance.

## 1. Introduction

Rice is the third most produced crop in the world and a staple food for more than half of the world's population, mostly living in developing countries (Fukagawa and Ziska, 2019). In this context, Italy is the leading rice producer in Europe, accounting for more than half of the total production of this high-value crop (Facchi et al., 2018). Typically, rice is grown in fields that are flooded from planting to pre-harvest, and this traditional irrigation technique (i.e., continuous submergence) is considered an important sink of water resources. This technique is dominant in most areas and is characterized by low irrigation efficiency (Cesari de Maria et al., 2016). In addition, irrigation management requires a lot of human labour, as it is still based on maintaining a predetermined water level in the paddies by manually regulating the irrigation inflow rate (Masseroni et al., 2017). In this context, the application of flexible and automatic control devices for irrigation management in paddy rice farms appears to be a viable solution that can be exploited to (i) increase the water use efficiency of rice cultivation and (ii) reduce the effort dedicated to irrigation flow rate regulation at field and farm scale, without changing the traditional irrigation flooding practices. More specifically, hydraulic infrastructures based on a system of coordinated gates located at strategic points of the farm irrigation network can allow to maintain optimal water levels in the farm channels and rice plots, providing more consistent and reliable irrigation flows

* Corresponding authors.
*E-mail addresses:* gianni.ferretti@polimi.it (G. Ferretti), daniele.masseroni@unimi.it (D. Masseroni).

https://doi.org/10.1016/j.agwat.2023.108536
Received 18 June 2023; Received in revised form 22 September 2023; Accepted 25 September 2023
Available online 26 September 2023

through the farm service points. A recent review on the identification of smart automatic irrigation techniques for sustainable rice environments shows that there is a great potential for water conservation through the use of automatic and coordinated gate systems in permanently-flooded rice farms, with benefits in terms of both increasing the quality and quantity of crop production (Champness et al., 2023). Nevertheless, the review highlighted that these systems applied in paddy rice contexts are still in an embryonic stage and their application is limited to individual rice plots (Masseroni et al., 2018). Table 1 shows the degree of automation and sensor components developed in the main automated gravity surface irrigation system experiments for rice. In general, all have successfully developed a desktop-based system for remote control of irrigation, but only Masseroni et al. (2018) have developed a system using commercially available infrastructure in a commercial-scale.

The development of these automatic systems aimed to improve the sustainability of agricultural water use has indirectly stimulated irrigation modernisation projects. For example, the Lombardy region (the most important region in Italy from an industrial and agricultural point of view, with over 7000 km2 of irrigated land) is promoting bottom-up initiatives in the form of "information and pilot project actions". The main aim of these initiatives is to demonstrate the potential of innovative irrigation management systems at farm and district level, and to promote a shared understanding of modernisation objectives. In this study, we analyse and reflect on the results achieved in one of these pilot initiatives. Specifically, the project represents a pioneering example of the transition to a flexible and harmonised approach to irrigation management in paddy farms. In particular, a new modelling framework adopted for a coordinated and centralized flowrate regulation is described. The control algorithm implemented to maintain a predetermined ponding water level in the fields according to site-specific conditions is presented and tested under two different scenarios of shortage and surplus of water supply to the farm. The impact of this new centralised management of farm gates on water conservation was compared with the impact of a traditional decentralised management of gates, which roughly simulates the operations carried out manually by the farmer. The results may provide indications for improving flood management in rice cultivation, taking into account the effects of climate change on freshwater availability and rainfall patterns.

## 2. Control strategies for a sustainable agricultural water management

Advanced but still little explored strategies for achieving coordinated control of complex systems of physical devices for irrigation (e.g. gates, valves, pumps) are those represented by proportional-integral-derivative (PID) or predictive controls (van Overloop et al., 2005; Bertsekas, 2005). The first class of controls offers a mid-point between simple bang-bang controls (i.e. feedback controllers that switches abruptly between two states - on or off - when a desired target (setpoint) has been reached) and model-based controls such as predictive ones (Huang et al., 2022). In agricultural water management, PID control has been mainly used for real-time control of soil moisture (Harper, 2017), management of sprinkler irrigation equipment (Jacob et al., 2019), and control of irrigation canal operations (Litrico et al., 2007).

A good description of the application of predictive control in the field of water resource systems is provided by Castelletti et al. (2023). In particular, they consider three main areas of interest in the application of the model predictive control (MPC), namely the water reservoir, the open channels and the urban water network. In the first case, reservoirs are usually multi-purpose systems serving power plants, irrigation districts, urban and industrial water users, as well as contributing to other objectives such as flood control, environmental management, navigation, water quality, etc. Traditionally, reservoir control is implemented by a human operator who can act on the basis of static control curves or control actions proposed in real time by a decision support system (DSS). In this case, the predictive control strategy can help to decide the release from the reservoir at time $t + 1$ depending on the release decision, the storage and the net inflow (usually affected by potential disturbances) to the reservoir at time t. In the second case, open channels are stretches of water between two control structures. Actuators are hydraulic infrastructure, such as gates, weirs and dams, available for water control purposes. Finally, nodes represent channel junctions, i.e. locations where a stream flows into or branches off from the main stream (these are known as tributaries and distributaries, respectively). The dynamics of open channels are best described by the Saint-Venant equations, a set of coupled nonlinear partial differential equations. In this case, the predictive control strategy can help, for example, to maintain a pool between two actuators (to limit fluctuations in water diverted by tributaries). It can also support a bottom-up approach to gravity water distribution for irrigation, where the actual irrigation requirements of the fields are incorporated into the gate operations on the irrigation canals and ultimately the release function from the reservoir. In the third case, the urban water network is affected by the integrated urban water cycle, which consists of several infrastructural and operational components, including water source management, water treatment, water transport and distribution, sewerage/sewage collection and rainwater/stormwater drainage systems, with the main objective of providing water for human needs reliably, efficiently and safely, and then returning it to the environment with the least possible impact. Taking water transport and distribution networks as an example, an optimal control problem (possibly involving a predictive control strategy) is typically formulated as an optimal pump operation and valve setting control problem, aiming at resource and economic savings in energy consumption and associated costs, while ensuring that water is delivered to end users to meet their water needs.

The main application of predictive control strategy (Bwambale et al., 2023) in irrigation management is in water, energy and fertiliser conservation. In particular, this strategy has largely been applied in the

**Table 1**
Summary of the components and capabilities of the automated rice irrigation systems (rearranged from Champness et al., 2023). ✓ is used if the elements listed in the first column are present in the work, ✕ if they are not present, ? if they are not mentioned.

| | Inoue et al. (1999) | Pfitscher et al., (2011, 2012) | Setiawan et al. 2011 | Miskam et al. (2013) | Arif et al. (2018) | Masseroni et al. (2018) |
|---|---|---|---|---|---|---|
| **Country** | **Japan** | **Brazil** | **Indonesia** | **Malaysia** | **Indonesia** | **Italy** |
| **Research site size** | Field | 0.02 ha | 0.01 ha | Laboratory | Pot | 7.8 ha |
| **Water height sensing (in the field)** | ? | ✓ | ✓ | ✓ | ✓ | ✓ |
| **Forecast crop water requirements** | ✓ | ✕ | ✕ | ✕ | ✕ | ✕ |
| **Real time sensing** | ? | ✓ | ✓ | ✓ | ✓ | ✓ |
| **Wireless infrastructure sensing & control** | ? | ✓ | ✓ | ✕ | ✕ | ✓ |
| **Supply inlet control** | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| **Drainage outlet control** | ? | ✕ | ✓ | ✓ | ✓ | ✕ |
| **User friendly web interface** | ✕ | ✓ | ✕ | ✕ | ✕ | ✓ |
| **Smartphone based application** | ✕ | ✕ | ✕ | ✕ | ✕ | ✓ |
| **Alert system** | ✕ | ✓ | ✕ | ✕ | ✕ | ✓ |

areas of irrigation canal flow control and regulation (Álvarez et al., 2013), while limited experiences were found in irrigation scheduling (Abioye et al., 2021), soil water potential regulation (Chen et al., 2020), soil moisture regulation (Ayaz et al., 2020) and lastly prediction of precipitation and evapotranspiration (Guo and You, 2018). Nothing to the author's knowledge has been found on the application of predictive control model on irrigation management at field or farm scale and in particular on paddy rice.

## 3. Material and methods

### 3.1. The pilot case study

The flexible and coordinated irrigation management system was implemented at *Cascina Ca' Granda Milano*, a rice paddy farm (40 ha in size) located in the south of Milan, consisting of 10 fields with an average size of about 4 ha each (Fig. 1). The fields are characterized by a toposequence (from north to south), which facilitates the irrigation procedures. More specifically, the fields are divided into five different blocks (i.e., *bc*, *d*, *ehi*, *fg*, *lm*), which are characterized by a single point of entry of the water flow. For example, in block *bc*, the only entry point is located in *b*. From *b*, the water flows into *c*, since it is topographically lower than *b*. According to the toposequence, the fields are irrigated as follows: block *bc* is irrigated first, followed by block *d*, third block *ehi*, then block *fg*, and finally block *lm*.

All the fields have been sown with rice (Leonida variety) and the irrigation practice adopted is continuous flooding. In particular, rice is sown in dry soil at the end of April and the fields are flooded when the rice is around the three-leaf stage (i.e. about one month after sowing). Harvesting is typically scheduled for mid-September, while the fields are drained at the end of August. Eleven boreholes were drilled within the fields to determine soil hydraulic properties. On average, the soils are characterized by a silt loam texture with slight variability between blocks. The low conductivity layer thickness was approximately 30 cm, characterized by an average saturated hydraulic conductivity of approximately 1.8 mm/h.

The nominal flow rate delivered to the farm by the irrigation agency is about 200 l/s continuously during the irrigation season (i.e., April to September). The water is delivered to the farm from the north, i.e. upstream of points P1 and P2. There are no drainage points in the fields, while only one farm canal drainage point is activated in case of overflows.

#### 3.1.1. Equipment

At strategic points of the farm canal (P1–4 in Fig. 1) four automatic and remote controlled PikoMeter® gates (Rubicon Water, AU) were installed (Fig. 2a) to control the irrigation within the blocks. The PikoMeter® consists of three main components: an ultrasonic level sensor inside the gate frame, a flow meter and a steel gate. The flow meter measures the flow rate across the gate; hence the volume integrating the flow rates during irrigation. This meter consists of a cylindrical box with 20 ultrasonic transducers in 5 measurement planes. The flow meter can measure with an accuracy of + /- 2.5% for velocities greater than 25 mm/s. The water level obtained by the ultrasonic level sensor is measured with an accuracy of 0.5 mm and a resolution of 0.1 mm. The gates are equipped with adaptive control software that allows their operation to be managed through three different setpoint configuration levels, i.e. maintaining a fixed (i) gate opening, (ii) upstream water level (U/S) or (iii) downstream flow (D/S).

In addition to the PikoMeter®, five ultrasonic water level sensors (Ferit®) were installed in each field block (Fig. 2b). The position of the Ferit® in the field was decided according to the farmer's experience, i.e. where its measurement would be representative of the water level in the block (L1-L5 in Fig. 1). Each Ferit® continuously monitors the water level in the rice field (with a resolution of +/- 1 mm) and sends the information to a master control system (FarmConnect® Gateway - Rubicon Water AU). The FarmConnect® Gateway can potentially provide a cellular network interface between PikoMeter® and Ferit®, but it has not yet been developed to control the gate operations. This interface uses the Telstra NextG protocol to routinely upload the data [via a Global System for Mobile Connection (GSM)] to a host server for remote monitoring and control.

Biophysical parameters were continuously measured over the agricultural season by a standard agro-meteorological station of the Regional Environmental Protection Agency (ARPA), located a few kilometres from the rice farm.

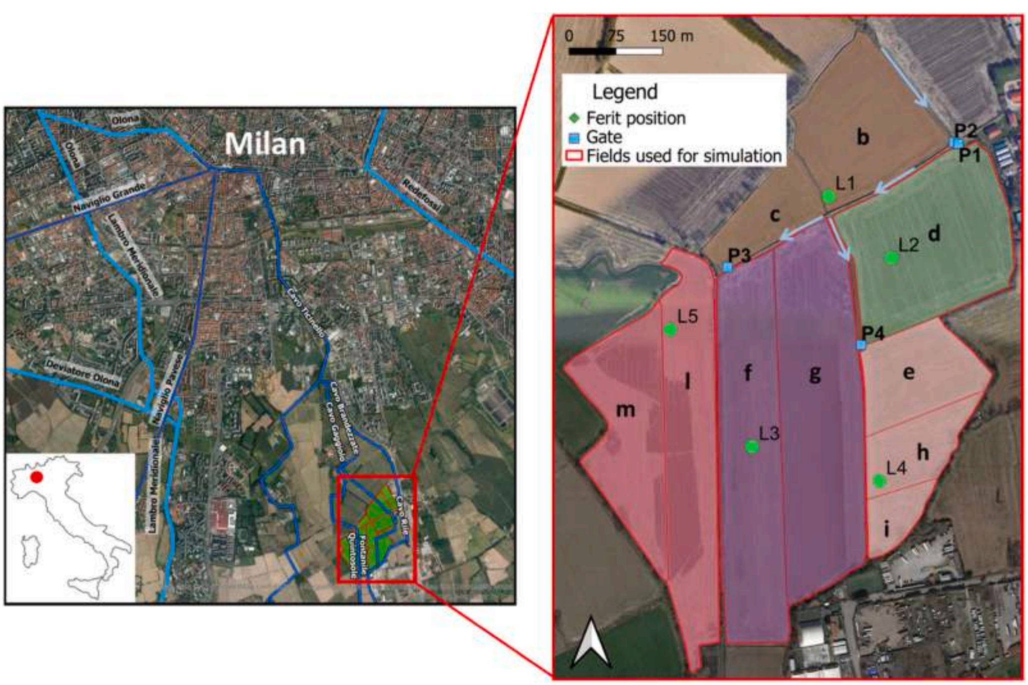



**Fig. 1.** Cascina Ca' Granda Milano pilot farm. The position of gates (square [P1–4]), and water level sensors – Ferit® (dot [L1–5]) are included in the picture. Flow rate direction into the farm canal network is indicated by blue arrows. Subdivision of fields [b,c,d,e,f,g,h,i,l,m] in block is shown in red.

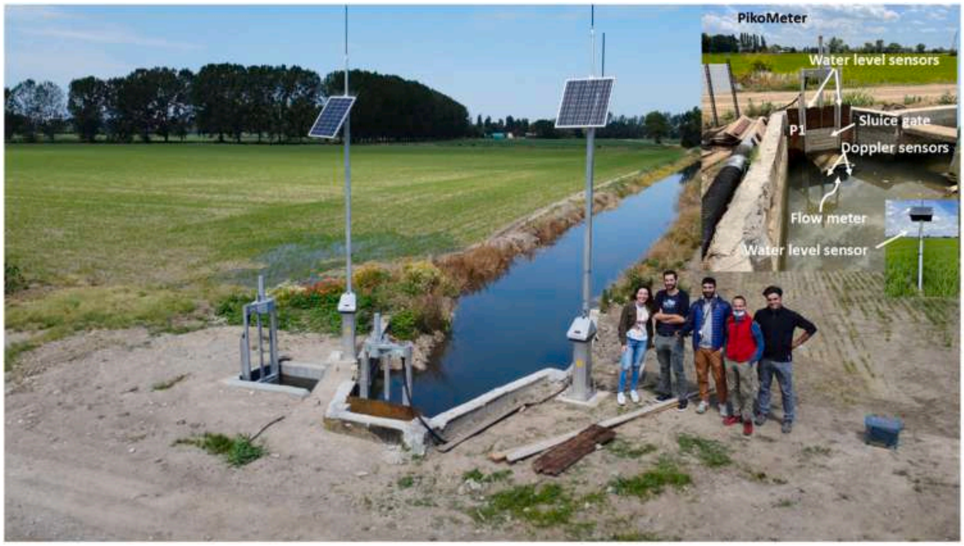



**Fig. 2.** Instruments installed in the pilot farm of Cascina Ca' Granda Milano. The PikoMeter® gate and the field's water level sensor, known as Ferit®, are depicted in the upper right corner of the image.

### 3.2. Rice farm modelling framework

The main elements of paddy rice farm (i.e. fields, canal, gates) were modelled using the Modelica simulation environment (Modelica Association, 2021). Modelica is an object-oriented, declarative, multi-domain modelling language for component-oriented modelling of complex systems.

There are two main differences between Modelica and common object-oriented programming languages such as C+ + or Java. First, Modelica is a modelling language, not a traditional programming language: Modelica classes are not compiled in the conventional sense, but are translated into objects which are then exercised by a simulation engine. Second, Modelica is essentially based on equations, not assignments, although algorithmic components are still allowed, such as algorithms in programming languages or blocks in causal simulation environments (e.g. Simulink). In other words, Modelica allows an acausal approach to physical modelling: equations have no predefined causality and can have expressions on both the right and left sides. The simulation engine symbolically manipulates the equations to determine the order in which they are solved, as well as to determine the overall inputs and outputs of the model. Because of these features, the Modelica language allows a truly modular approach to the modelling of complex systems. This improves the readability, modifiability, and reusability of plant component models (Mattsson and Elmqvist, 1997), as well as the

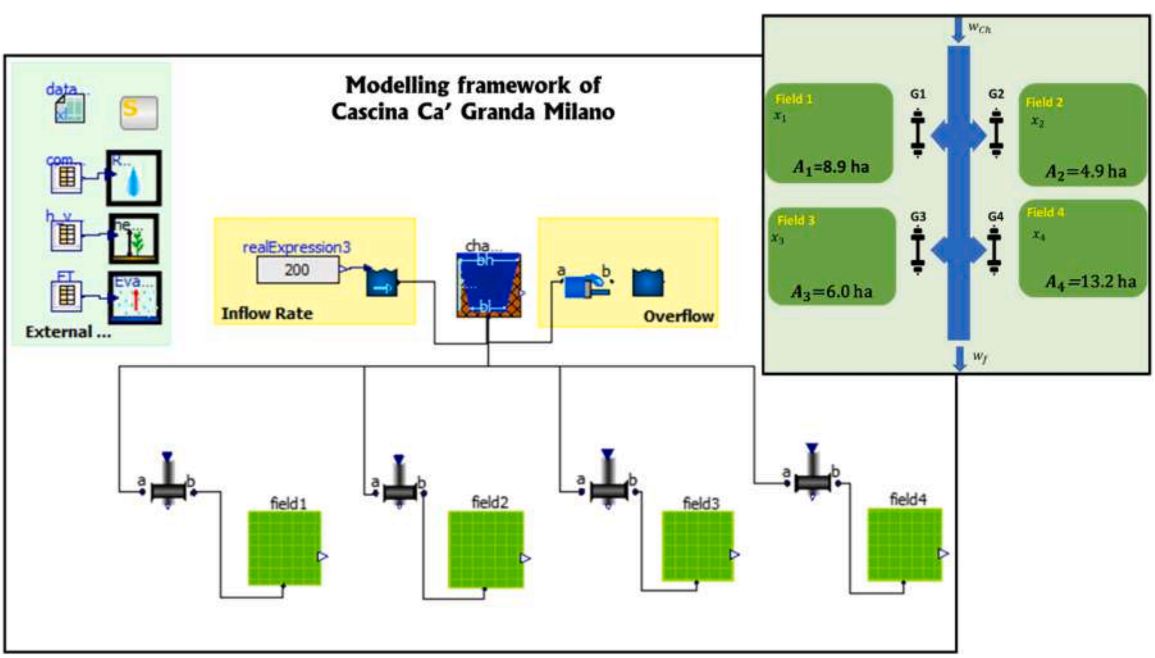



**Fig. 3.** Modelling framework of the Cascina Ca' Granda Milano rice farm implemented in Modelica environment. The scheme represents all physical objects of the rice system and connections between the modelling elements (e.g. canal, fields, gates). [Field 1–4] - irrigated block, [G1–4] - gates, wch - water inlet in the farm canal, wf - water outlet from the farm canal, [realExpression3] is the Modelica block that allows to enter the nominal flow rate (Inflow Rate) in the farm canal, [Overflow] represents the Modelica block that simulates the farm canal outlet, while the blocks on the top left represent the storage elements of the meteorological data. Additional information about the symbols can be found in the Supplementary Material.

extension of the packages of physical domains by adding models of new components. In addition, models can be assembled graphically by dragging, dropping and connecting component icons, taking advantage of the graphical capabilities of the adopted (open source) interpreter, OpenModelica.

The basic modelling components of the pilot rice farm were collected in a Modelica library (`Field_Package`). It contains definitions of constants (e.g. atmospheric pressure, gravity acceleration, water density etc.), classes (e.g. connectors), and subpackages (e.g. fields, canals, gates). Each element included in the `Field_Package` is described in detail in the Supplementary Material, whereas at the link https://github.com/looms-polimi/Field_Package the reader can freely download the rice farm Modelica library. In Fig. 3 the general modelling framework of Cascina Ca' Granda Milano rice farm is presented.

Since in the control theory the number of control and controlled variables must be equal (Glasser, 1985), only the blocks *d* (6 ha), *ehi* (4.9 ha), *lm* (8.9 ha) and *fg* (13.2 ha) were considered in the modelling experiment. These blocks are directly irrigated by the water flows through P1, P3, P4 and by the difference of the flow rate derived between the gate P2 and the combination of P3 and P4. For simplicity, the blocks *d, ehi, lm, and fg* will be referred to as Field 1, 2, 3, and 4, respectively, and the gates P1, 2, 3, and 4 will be referred to as gate G1, 2, 3, and 4, respectively.

The core of the rice farm modelling is the field water balance. Rainfall, irrigation, evapotranspiration, and percolation were considered as dominant water fluxes, while surface drainage was neglected because each field has no outflow. The details of the field water balance are entirely reported in the Supplementary Material. The water balance was calibrated based on ponding water level measurements in the fields under a condition of near steady flow into the fields. Specifically, the calibration involved adjusting the percolation flux (through a percolation coefficient) so that the simulated ponding water level matched the real one. Fig. 4 shows the comparison between the measured and modelled ponding water levels within Field 3, the latter obtained with different percolation coefficients. We found that the range of percolation coefficient between 0.01 and 0.04 allowed a good fit between the observed and simulated ponding water levels in all fields. However, in the modelling framework we decided to use a single percolation coefficient equal to 0.01 for all fields. The Supplementary Material also presents all rice farm model settings.

### 3.3. Control strategy

The goal of the control system is obviously to regulate the ponding water level within the fields. This is done by modulating the opening of the sluice gates (G1–4). The controlled variables are therefore the water levels within the fields, while the control variables are the opening height of the gates. The main disturbances are essentially the rainfall, percolation, evapotranspiration, and the flow rate in the canal. All states of the model are measured, including the farm canal levels. Therefore, there was no need to implement state estimators.

A first simple approach to the design of the control system was to consider the binomial field-gate as an independent system. This approach can be defined as a *decentralized control strategy*. The interactions that occur mainly through the connection between fields and farm canal can be neglected with this approach (i.e. canal water is not considered a limiting factor for field water supply). For this strategy, a Proportional-Integral (PI) controller was used to control the ponding water level within the fields (Ang et al., 2005). However, the decentralized control system based on PI regulators suffers from three main drawbacks. First, each control system tries to achieve its goal independently of the others, which would be plausible under conditions of dynamic decoupling and unlimited water availability, while in reality the water availability in input to the farm could be reduced as a results of upstream regulations controls or water scarcity. Secondly, the adoption of anti-wind-up algorithms makes it possible to manage the return from saturation conditions of the control variables, but it is obviously not able to predict or avoid them. Finally, the decentralized controllers act on the error, i.e. the consequence of any disturbances, only after these disturbances have produced their effect, which does not allow, for example, to exploit perturbation forecast systems and thus anticipate the control action.

To overcome the above drawbacks an advanced *centralized control strategy* was implemented. For this strategy, the Non-linear Model Predictive Control (NMPC) was used (Blanco et al., 2010), since it is suitable to deal with nonlinear systems with slow dynamics such as represented by the management of rice irrigation during flooding period (Ding et al., 2018). NMPC is a control strategy based on the sequential, online resolution of multiple open-loop optimal control problems defined over a finite, receding time horizon (Bertsekas, 2005). At each time step, the resolution of an NMPC problem yields a sequence of optimal control

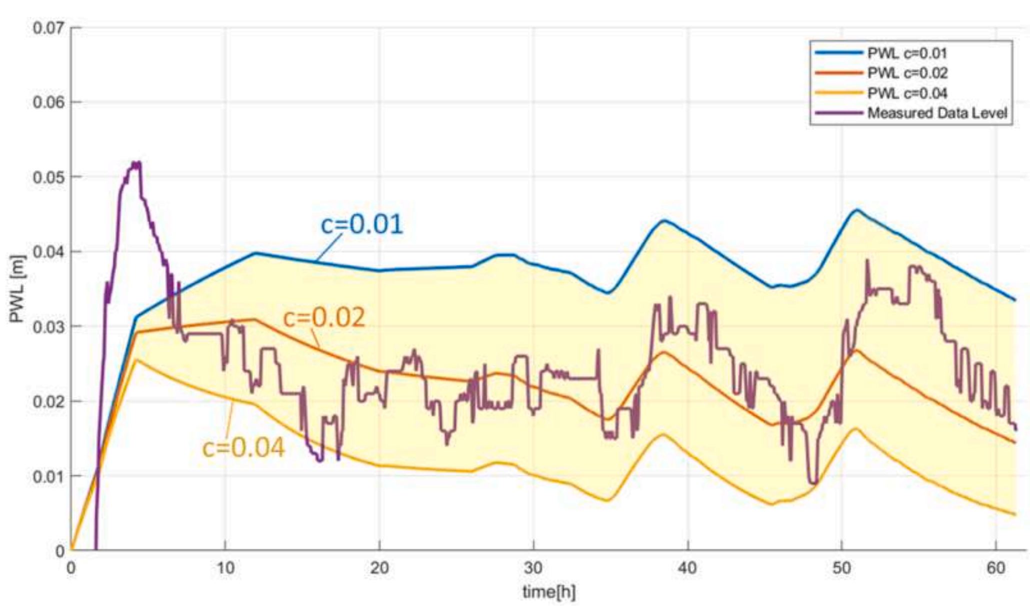



**Fig. 4.** Measured and modelled ponding water level in one of the monitored fields (Field 3) in a period of time included between the 29 and 30 August 2021. The yellow band represents the best fit of the observed ponding water level derived from a range of percolation coefficients between 0.01 and 0.04. PWL – ponding water level, c – percolation coefficient.

actions (i.e., gate openings) over the future horizon, given a predicted trajectory of the disturbances over the same horizon. The optimization is generally formulated considering a single objective; when the problem involves multiple objectives (e.g., water supply, hydropower production, flood control, environmental protection, irrigation, transport, etc.), these are generally aggregated using a scalarization function (e.g., weighted combination) or via the lexicographic goal programming technique in cases where there is a clear hierarchy of priorities across the objectives (e.g., Horváth et al., 2022). The online optimization scheme is reiterated forward in time over a receding horizon during the operational life of the system. After each optimization, only the control action in the current time step of the optimized control sequence is actuated, before reiterating the optimization at the next time step. Through this reiteration of the model-based optimization, NMPC determines the control law implicitly in a closed-loop form, as it computes the optimal control action at each time step *t* based on the observed state of the system. The flexibility to directly use any models available for the systems to be controlled is one of the main advantages of this approach, especially for the control of highly nonlinear systems, while the flexibility to work with (nonlinear) constraints, either explicit physical constraints (e.g. limits of actuators) or legal constraints, is another advantage of MPC compared to other control methods.

The Supplementary Material provides the mathematical details of each control strategy applied to the Cascina Ca' Granda pilot case study.

### 3.4. Simulation experiments

The performances of the decentralized and centralized controls, based on Proportional Integral (PI) and Model Predictive Control (NMPC) strategies, respectively, were evaluated in terms of the system's adaptive capacity to respond to external requirements or disturbances, using three different modelling experiments.

The objective of the first experiment was to verify the correct operation of the two control systems under standard flood management conditions. Specifically, the modelling exercise simulates a theoretical situation in which the control system works to change the ponding water level in the fields from an initial condition to a new reference one (in this example from 4 cm to 5 cm). This is a typical operation that could occur when the ponding water level needs to be adjusted during an irrigation season. The simulation assumes no external disturbances, such as the presence of rainfall events, and a constant nominal flow rate at farm inlet of 200 l/s.

The second experiment examined the response of the control systems to a reduction in the flow rate at the input to the farm. In particular, starting from a standard water level within the farm canal and rice plots, the effect of reducing the nominal flow rate at farm inlet (200 l/s) to 100 l/s on the ability of both control systems to maintain a uniform ponding water level within the blocks is investigated. This scenario can happen if water becomes scarce during the agricultural season (dry season), or if the water supply changes as a result of gates being maneuvered on irrigation district channels upstream of the farm.

The response of both control systems to an external disturbance derived from a rainfall event was evaluated in the third experiment. Specifically, the possibility of taking advantage of rainfall forecasts and using them to predict the advance status of water levels in farm canals and rice blocks was used to evaluate the adaptive capacity of the control systems. Specifically, the selected event occurred in the 2021 agricultural season on the case study and consisted of a rainfall volume of about 33 mm and duration of 10 h, with a peak of 18 mm. In this case the nominal flow rate was maintained at 200 l/s in input to the farm.

The potential water conservation of the PI and NMPC strategies was also investigated. Specifically, using the decentralized strategy (i.e., PI control) as a benchmark, the benefits of adopting centralized control (i.e., NMPC) in terms of water conservation were estimated as additional information on the performance of a coordinated system of gates.

## 4. Results

### 4.1. Performance of PI and NMPC under standard conditions of flood management

The performance in time of both control strategies (i.e. PI and NMPC) under standard conditions of flood management are presented in Fig. 5. In particular, the comparison between the PI and NMPC approaches was evaluated for (i) the ponding water level in the fields, (ii) the opening height of the gates and finally (iii) the water level in the farm canal. In general, both control strategies respond effectively to bring the system to the new ponding water level configuration (i.e., from 4 cm to 5 cm). The new ponding level is reached gradually for both control strategies in a similar time horizon (about 10 h), depending on real inertias observed in the field system. The objective of increasing the water level in the fields led to the initial opening of the gates and their subsequent gradual adjustment. In both strategies, because the area of each field is different and therefore the flow rate needed to raise the ponding water level in each field is different, the initial gate opening height was different for each field. The adjustment of the gate opening after the initial moment is managed in a different way by the control action for each gate, both for PI and for NMPC. This is due to the need to have different flow rates in the input to the fields in order to reach the new ponding water level. However, since the opening height of the gates is similar at the end of the control action, both strategies can be considered coherent. Finally, the increase in the flow rate required to reach the new pond level in the fields influenced the water level in the farm canal, which at first quickly dropped below its initial height (about 1 m) and then returned to a level suitable to meet the water needs of the fields, since the inflow to the farm is not limited. In this case, the differences between the two control strategies are particularly evident. PI causes the water level in the canal to fall by approximately half compared to the initial condition, while the fall in the water level is less pronounced with NMPC. The return to the initial state of the water level in the canal takes twice as long for PI than for NMPC.

The effects of both control actions on the ponding water level of the other fields and on the other gate opening are presented in Appendix 1.

### 4.2. Performance of PI and NMPC under limited water supply conditions

Often the water supply at the head of a farm is not constant over time. This can happen when a dry agricultural season is expected. Fig. 6 shows for the Field 1 the performance of PI and NMPC control actions on ponding water level and gate opening when the nominal inflow rate to the farm canal was rapidly reduced from 200 l/s to 100 l/s. The ponding water level in the field decreases as a result of the inflow rate reduction. At the end of the simulation time, the levels reached are very similar (2 mm of difference). The PI control action responds to the falling of ponding water level in the field by opening the gate to draw as much water as possible from the farm canal. The gate changes its opening height up to the maximum allowed (i.e. 1), since the gate operates independently of the others and responds only to the needs of its own field. The gate takes about 20 h to saturate. In the other fields and gates, similar behaviour was observed. The general effect of this action is to remove almost all the water from the canal, which is reduced to a water level of a few centimetres. It follows that, the new inflow rate (i.e. 100 l/sec) is not sufficient to maintain the reference water level inside the fields (i.e. 5 cm). As a result, at the end of the control action, the ponding water level was lower than the reference threshold.

The ponding water level inside Field 1 (and thus for the other fields as well) was also lower than the reference threshold at the end of the NMPC control action. However, the NMPC uses a completely different strategy to reach this new configuration. The gate does not only look at the state of its own field, but also at the state of the other gates and at the farm canal. This integrated approach ensures that the gate does not saturate when it opens (i.e. it never reaches the maximum opening

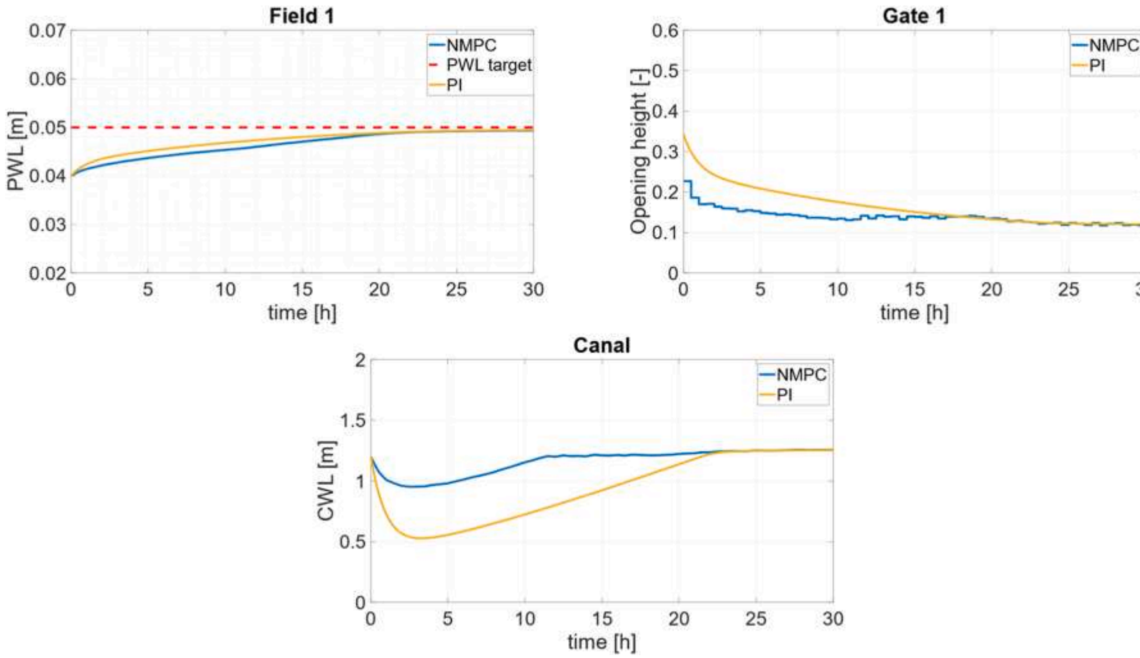



**Fig. 5.** Comparison between decentralized (PI) and centralized (NMPC) control strategies on (i) Ponding Water Level (PWL) adjustment, (ii) gate opening height (i.e. the degree of gate open) and (iii) water level in the farm canal (CWL). Scenario 1: standard condition of flood management.

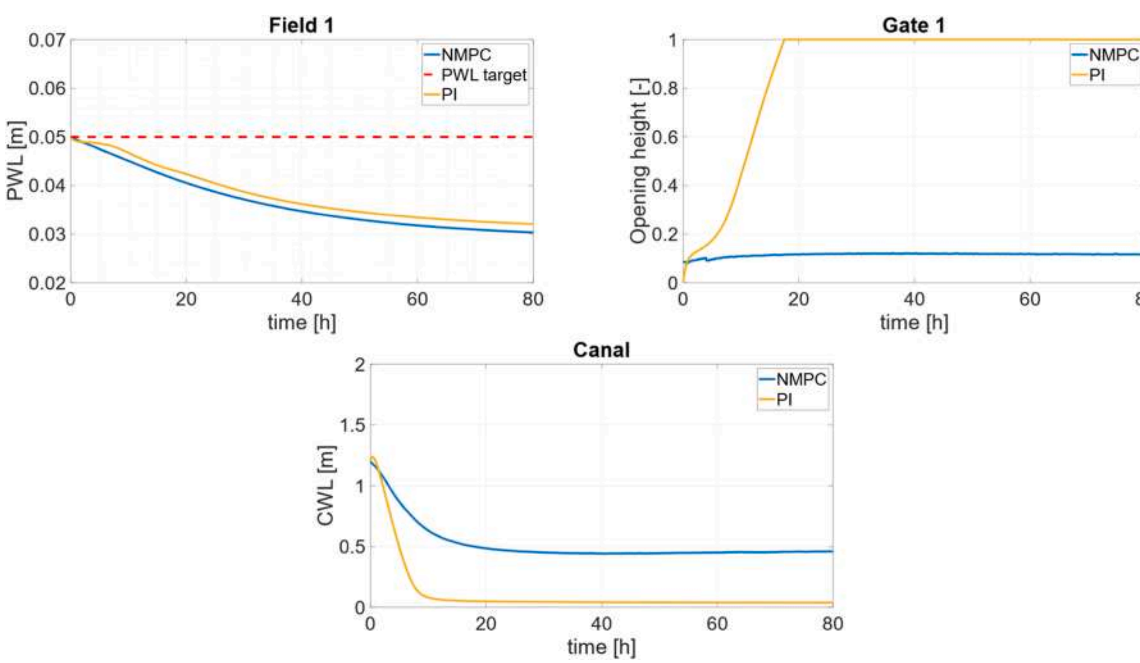



**Fig. 6.** Comparison between decentralized (PI) and centralized (NMPC) control strategies on (i) Ponding Water Level (PWL) adjustment, (ii) gate opening height and (iii) water level in the farm canal (CWL). Scenario 2: limited water supply.

height) and the water level in the farm canal is not drastically depleted (as properly shown in Fig. 6). Furthermore, the gate opening equilibrium was achieved in about half time with respect to the PI control.

The effects of both control actions on the ponding water level of the other fields and on the other gate opening are presented in Appendix 2.

A positive feature of the NMPC strategy is that it allows for compensation of flood conditions among fields even when ponding water levels cannot be maintained at the target level for the reduced inflow rate in input to the farm. This is clearly shown in Fig. 7, which compares the effects of PI and NMPC approach on the ponding water level within the fields. A decentralized control action approach results in different ponding water levels within the fields, while a centralized control action approach makes the ponding water level between the fields uniform (although lower than the target water level).

It is interesting that a uniform PI controller response corresponds to a varying ponding water level between the fields. In fact, every gate responding to a field's request for water opens and gets saturated (Fig. 7). Conversely, a tailored control action by the NMPC system for each gate results in a uniform ponding water level between the fields. In this case, the opening height of each gate is related to the water demand of the field, which in this case study strictly depends by the field area. In fact, the opening height of gate 4 (which serves Field 4 - of about 13 ha

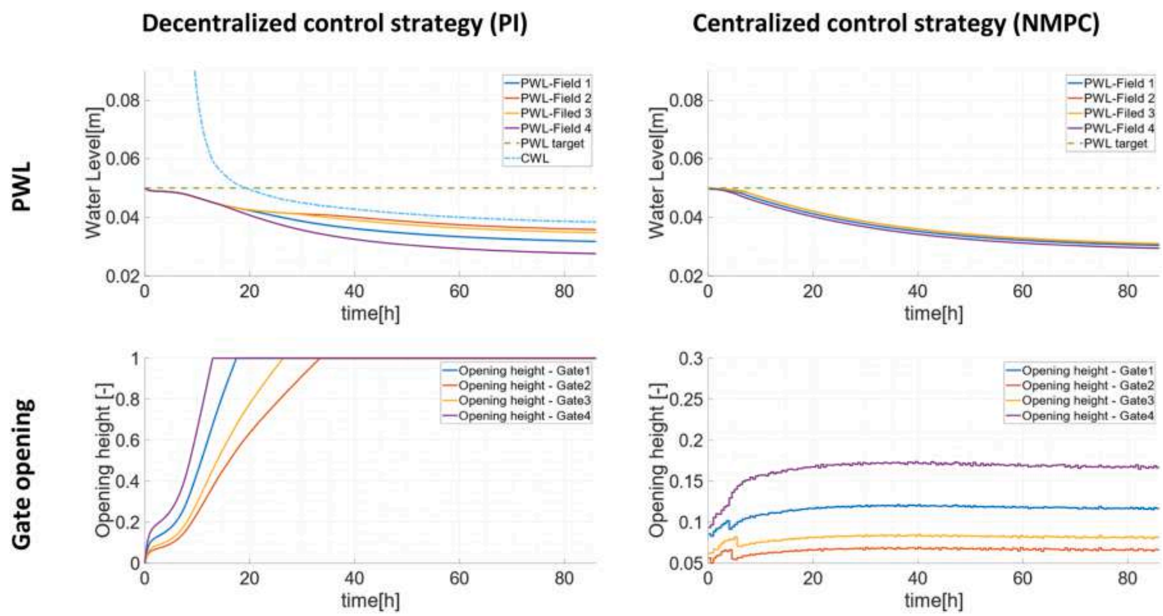



**Fig. 7.** Comparison between decentralized (PI) and centralized (NMPC) control strategies on (i) Ponding Water Level (PWL) adjustment with respect to the target (PWL target), and (ii) gate opening height of all fields (Field 1–4)and gates (Gate 1–4). Scenario 2: limited water supply.

in size) at the end of the control action is about three times greater than the opening height of gate 2 (which serves Field 2 - of about 4 ha in size) and two times greater than the opening height of gate 3 (which serves Field 3 - of about 6 ha in size). In the NMPC strategy, the gates are not saturated (i.e., the gates do not reach their maximum opening height), but are opened only to the extent necessary to meet the predictive water request.

### 4.3. Performance of the PI and NMPC in the presence of an instantaneous water supply

The effect on ponding water level and gate operations of the decentralized (i.e. PI) and centralized (i.e. NMPC) strategies stressed by an instantaneous water supply disturbance to the farm generated by a rainfall event is presented in Fig. 8 for the Field 1 and Gate 1. The PI approach works only when the precipitation starts. In particular, when rainfall begins, the gate begins to close until the opening height is equal to zero (i.e. gate completely closed) when rainfall has reached the peak. The ponding water level in the field increased up to 7 cm (i.e. 2 cm above the reference target), with a peak around the moment of maximum rainfall intensity. At the end of rainfall event the ponding water level within the field return to the target value. The same behaviour was observed in the other fields and gates as reported Appendix 3. The PI strategy reproduces the behaviour of a farmer and the effect it has on the water level in the fields when it rains. In fact, the farmer operates on the gates only when he sees that the water level in the fields is changing. This difficulty in adapting the system before the rain starts leads to a significant perturbation in the ponding water level inside the fields, as a consequence of the inertia that a real system composed of large fields has in recovering the initial configuration after a disturbance. On the contrary, the NMPC approach tries to prevent the additional volume of water supplied to the fields before the rainfall event, modifying the state of the system so that it can absorb the disturbance without excessive change in the ponding water level. Specifically, the forecasting model that constitutes the NMPC works by closing the gates in anticipation of the onset of rain (about 5 h on average before the rain, but the beginning of the gate closing action can vary between fields). The ponding water level drops a few centimetres below the target and then rises when it rains. However, the increase of ponding water level is less than about 20% of that obtained with the PI, highlighting the great capacity of the NMPC to maintain the target ponding water level even under instantaneous disturbances.

Fig. 9 shows the general effect of both control actions (i.e., PI and NMPC) on the ponding water level within the fields and on the gate opening height under the rainfall disturbance, whereas Fig. 10 shows the input flow rate within each rice field under the PI and NMPC strategies.

By integrating the water flows entering each field over time of rainfall event, the potential water conservation operated by NMPC with respect to the PI action has been calculated. Specifically, the NMPC results in 11% on average of water conservation with respect to PI strategy. This conservation is due to the anticipation of closing the gates in preparation for the rain event.

The NMPC control action was further stressed by assuming an hour advance or delay in the rainfall event. This simulation was used to investigate the response of the NMPC strategy when potential errors in the weather forecasts occur. The results of these two additional simulations are presented in Fig. 11, where the effects of NMPC strategy on ponding water levels and gate opening heights are shown for all fields and gates. The advance of the rainfall event has no significant effect on the control action, except for the anticipation of the closure of the gates. Conversely, the delay of the rainfall event leads to a temporary opening of the gates due to the fact that in the window of the prediction horizon (i.e. 15 h - see Supplementary Material) the forecast of the rainfall evolution pattern was not fully included. In fact, the model is not able to predict what will happen after the prediction horizon, so since the ponding water level decreased excessively, the control action ordered the opening of gates. However, when the rainfall increase was detected, the controller sent a signal to close the gates again.

In Appendix 4 the details of the effects of the NMPC strategy on ponding water level, sluice gate opening height, and farm canal level are presented for an hour advance or delay in the rainfall event.

## 5. Discussion

One of the main challenges for the future of sustainable rice irrigation is to cope with climate change and adapt to fluctuations in freshwater availability. Without improvements in irrigation management (data-driven modelling and management of irrigation interventions, flexible and predictive gate operation, real-time flow control, etc.), traditional rice irrigation practices of flood irrigation may be abandoned

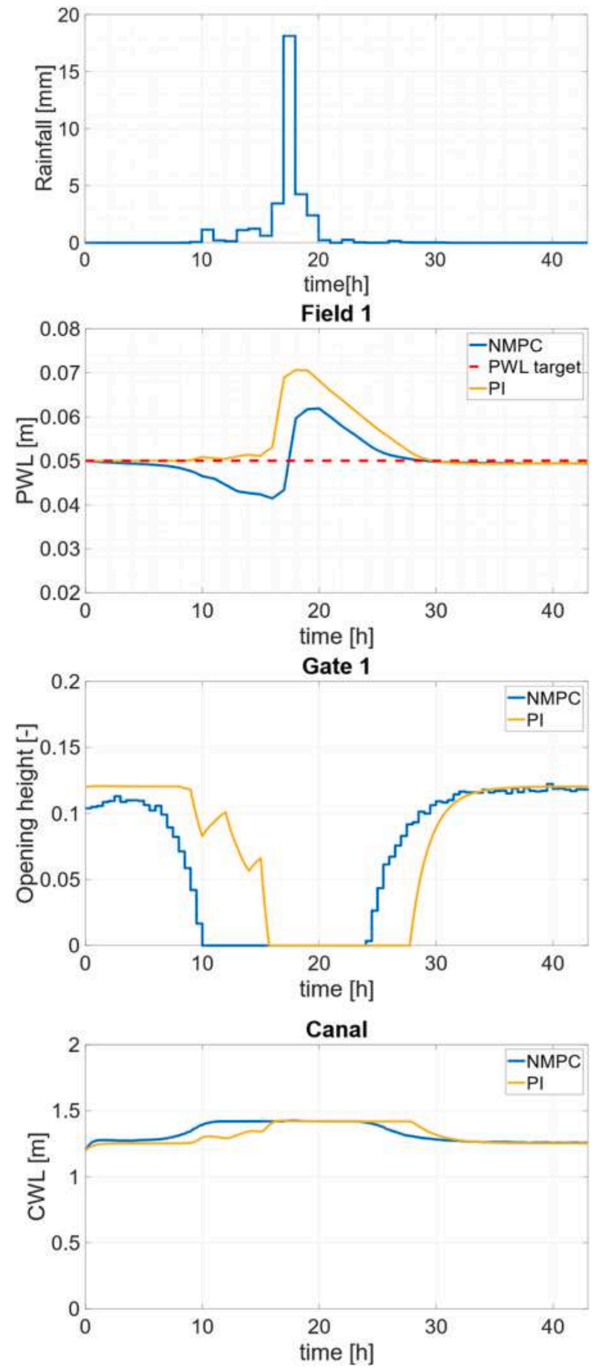



**Fig. 8.** Comparison between decentralized (PI) and centralized (NMPC) control strategies on (i) Ponding Water Level (PWL) adjustment with respect to the target (PWL target), (ii) gate opening height and (iii) water level in the farm canal (CWL). Scenario 3: presence of an instantaneous water supply as a result of rainfall event.

in favour of other less water-intensive irrigation techniques (Lampayan et al., 2015). Although the modelling framework presented in this paper offers the possibility to safeguard the traditional method of rice irrigation (i.e. flood irrigation), in practice, the transition to a new irrigation technique does not affect the ability to use the automatic technologies and control approaches presented in this paper.

The ability to well regulate the ponding water level within rice fields during the season has potential water saving and environmental benefits. In the case of the rice water balance (see Supplementary Material), it shows a proportional relationship between ponding water level and percolation flux (Toung et al., 1994). This relationship illustrates how a good control of the ponding water level within the fields can provide direct control of hydrological losses at field/farm scale by minimising the latter. This could be seen as an important achievement of the coordinated control approach, as hydrological losses are beyond the control of the farmer. Finally, previous studies have shown that continuous submergence and good control of ponding water levels during the rice growing season are more effective in controlling weeds, reducing herbicide use and improving the environmental sustainability of flooding practices. (Aravinth et al., 2023). Therefore, the NMPC could enable this weed control at farm level more efficiently than the PI approach, as shown in scenario 2, where the centralised control of the gates attempts to equalise the ponding water level within the fields. Given these examples, the introduction of automatic control into current flooding management practice could increase the sustainability of traditional rice irrigation. This would require the installation of a new hydraulic infrastructure (automatic gates) to replace the manual one, capable of accepting control software. The costs of this modernisation are relevant but sustainable, as already shown by Masseroni et al. (2018), and will become even more so as the cost of water increases.

Concerning the modelling framework presented in this work, it has some simplifications, which can be more detailed if the Modelica library would really be included in the gate control software of the pilot farm. One of them is the choice of a single percolation coefficient for the fields. In our results, the differences in the control effect between the fields are exclusively due to the different field size, while specific characteristic of each field could be included in the water balance model equations. In this respect, it must be pointed out that the OpenModelica generated Functional Mock-up Unit (FMU) can already be used to calibrate uncertain model parameters (i.e. percolation coefficients), through Python optimization routines, thus paving the way to adaptive NMPC, while the use of the aforementioned FMU for the solution of the optimal control problem, also based on (open source) Python functions, is currently being studied.

Additionally, predictions are the key feature for an intelligent control action achieved by NMPC strategy. In our modelling experiments, only rainfall forecasts are included in the NMPC, while better control performance could be obtained if temperature forecasts (which affect crop development) were included in the centralized control strategy. For this purpose, the correct choice of the prediction horizon can help to avoid unexpected opening and closing of the gates during their operation, increasing water conservation. Long-term forecasts of biophysical variables could also be included in the model. However, this could increase both the uncertainty in the reliability and robustness of the control action and the computational time. Therefore, it would be optimal to combine the control action with the farmer's experience. The latter could, for example, help decide which fields should maintain the target ponding water level in case of water shortage, instead of having a uniform ponding water level between fields but below the threshold. Lastly, the ponding water level target could be variable during the agricultural season, following the flooding best practices for the specific rice cultivar or crop phenological stages, or to practice alternate wetting drying flood management (Rejesus et al., 2011; Mayer et al., 2019; Gilardi et al., 2023).

## 6. Conclusion

This paper presents an advanced control technique for precision flood irrigation in paddy rice farms. The proposed technique has been tested on a real case study through a series of simulation experiments in the Modelica environment and is based on a nonlinear model predictive control strategy. This strategy has been compared with that obtained by a proportional-integral control action, which roughly reproduces the traditional farmer gate operations. Simulation reveals that the nonlinear model predictive control strategy can accurately control ponding water level within the fields both under standard conditions of flood

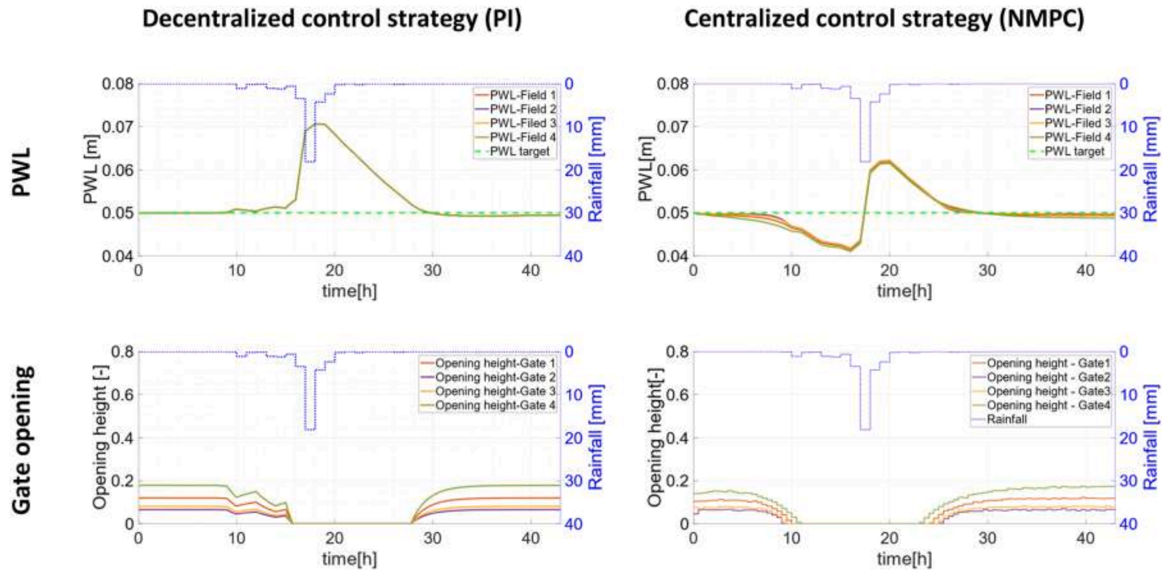



**Fig. 9.** Comparison between decentralized (PI) and centralized (NMPC) control strategies on (i) Ponding Water Level (PWL) adjustment with respect to the target (PWL target), (ii) gate opening height of all fields (Field 1–4) and gates (Gate 1–4). Scenario 3: presence of an instantaneous water supply as a result of rainfall event.

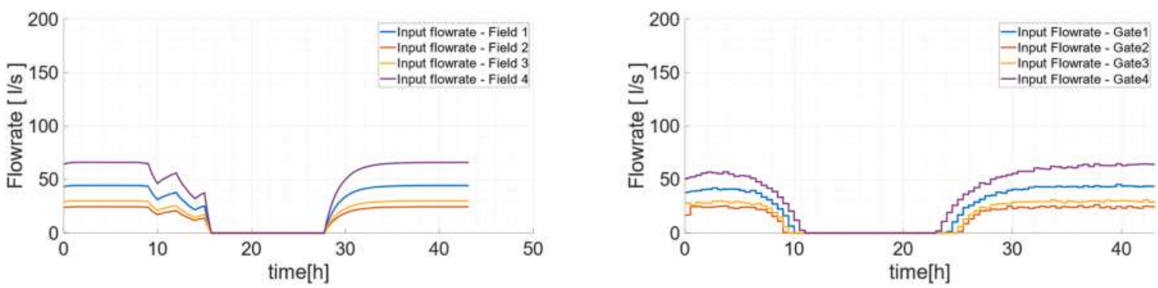



**Fig. 10.** Comparison between decentralized (PI) and centralized (NMPC) control strategies on flow rate in input to the fields (Field 1–4). Scenario 3: presence of an instantaneous water supply as a result of rainfall event.

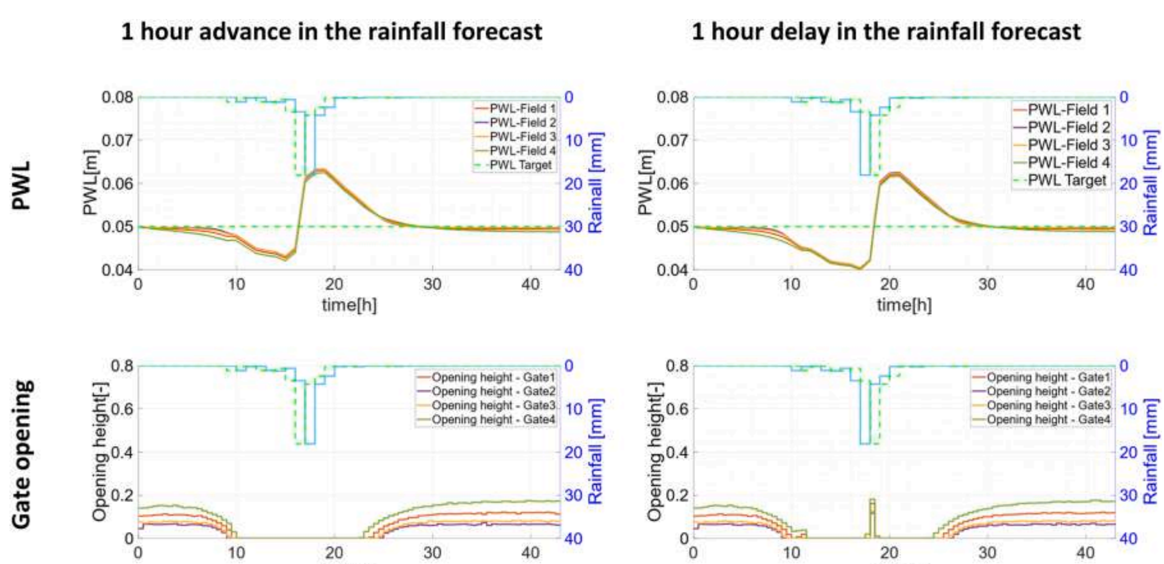



**Fig. 11.** Effects of a 1-hour advance and a 1-hour delay in the precipitation forecast on the NMPC control. Ponding Water Level (PWL) adjustment and gate opening height are shown.

management and under limited or instantaneous water supplies to the farm. Furthermore, its application to a real rainfall event showed that nonlinear model predictive control has the potential to significantly reduce water consumption compared to proportional-integral control. Therefore, the nonlinear model predictive control strategy appears to be a viable solution for improving the performance of flood irrigation in paddy rice farms, although some slight improvements in the modelling algorithm should still be made before implementing this technique in a real system of sluice gates. Implementing the nonlinear model predictive control strategy in the gate management software and testing its operation under different agricultural seasons will be the next step.

## Declaration of Competing Interest

All authors listed in the manuscript entitled "The Potential of a Coordinated System of Gates for Flood Irrigation Management in Paddy Rice Farm" contributed sufficiently to the project to be included as authors. To the best of our knowledge, no conflict of interest, financial or other, exists.

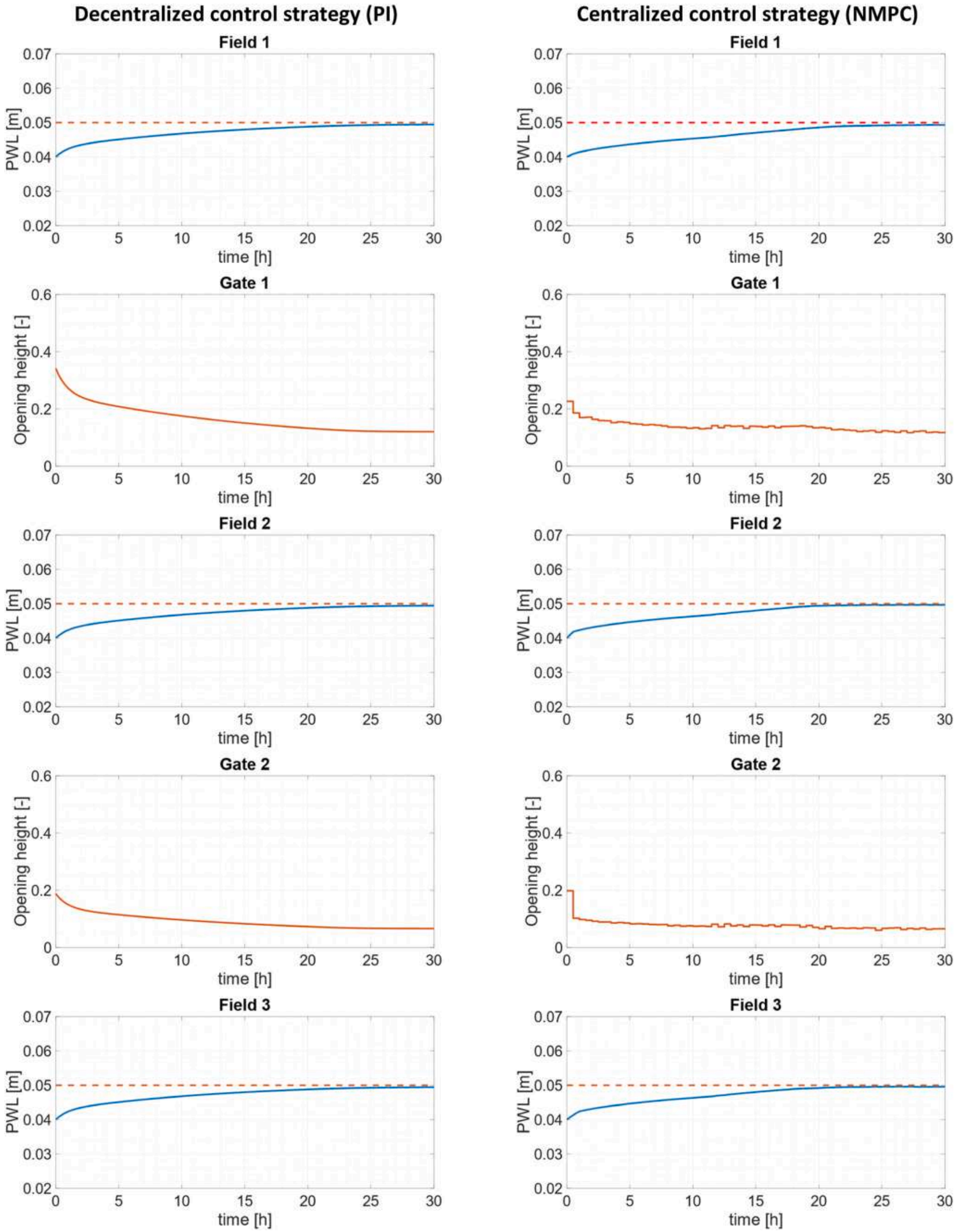
## Data Availability

Data will be made available on request.

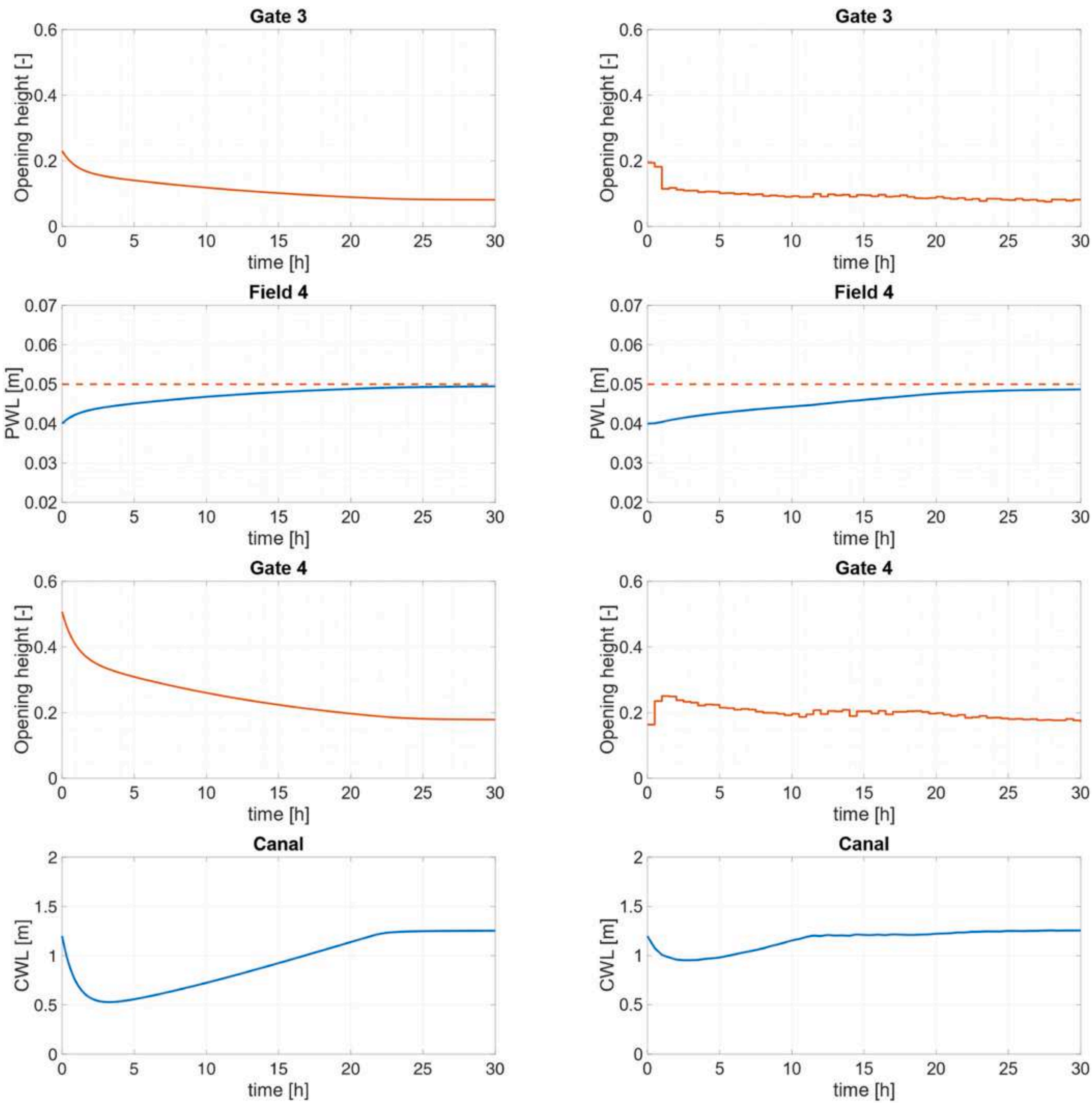
## Acknowledgements

This work was developed in the context of IrriGate, IrriSuS and MEDWATERICE projects funded respectively by Regione Lombardia (grant 201901319885 and 202202220204) and (PRIMA-Section 2-2018; https://www.medwaterice.org/). Additionally, this work is carried out within the Agritech National Research Center and received funding from the European Union Next-GenerationEU (missione 4 componente 2, investimento 1.4 – d.d. 1032 17/06/2022, cn00000022). The authors would like to thank the Rubicon Water technicians for their help in installing and testing the gates. They would also like to express their gratitude to the Fondazione Patrimonio Ca' Granda and to Mr Cesare and Mr Angelo Fedeli for kindly hosting the experiment. Lastly, the authors express their gratitude to prof. Lorenzo Fagiano for his invaluable support in the implementation of the predictive model control.

**Appendix 1. Comparison between proportional-integral and nonlinear model predictive control actions under standard conditions of flood management**

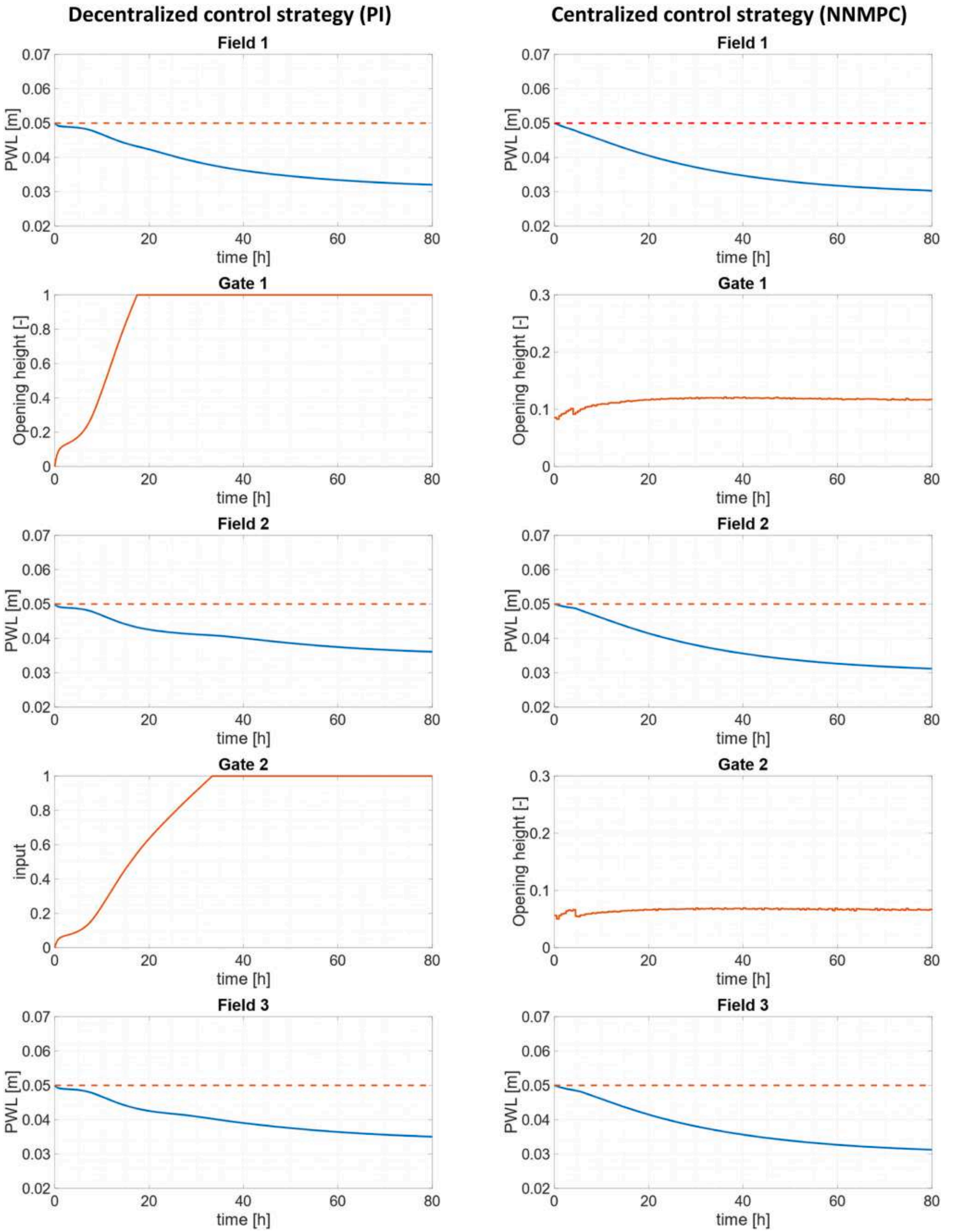


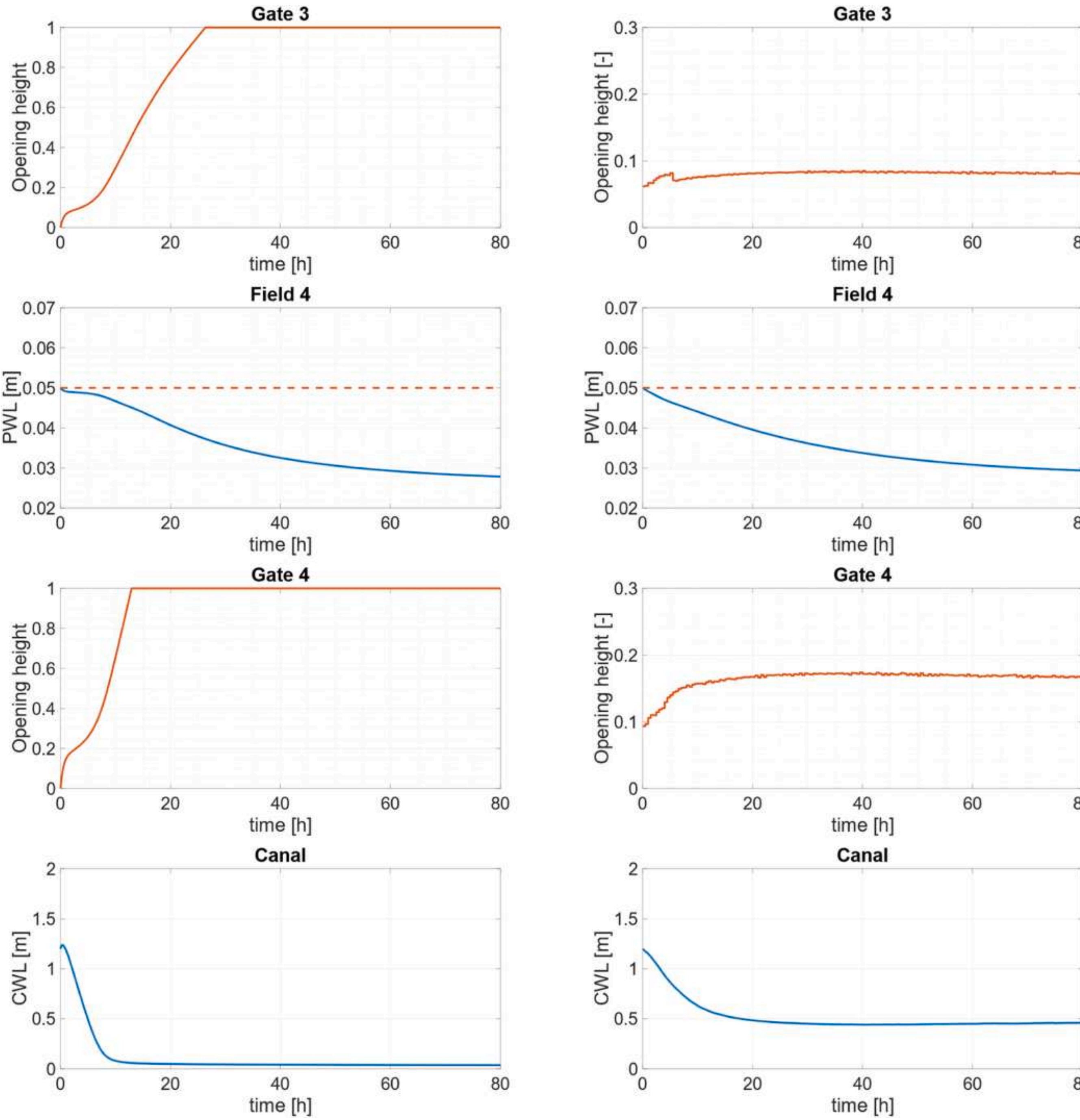
.


Gate 3
Opening height [-]
time [h]
Gate 3
Opening height [-]
time [h]
Field 4
PWL [m]
time [h]
Field 4
PWL [m]
time [h]
Gate 4
Opening height [-]
time [h]
Gate 4
Opening height [-]
time [h]
Canal
CWL [m]
time [h]
Canal
CWL [m]
time [h]

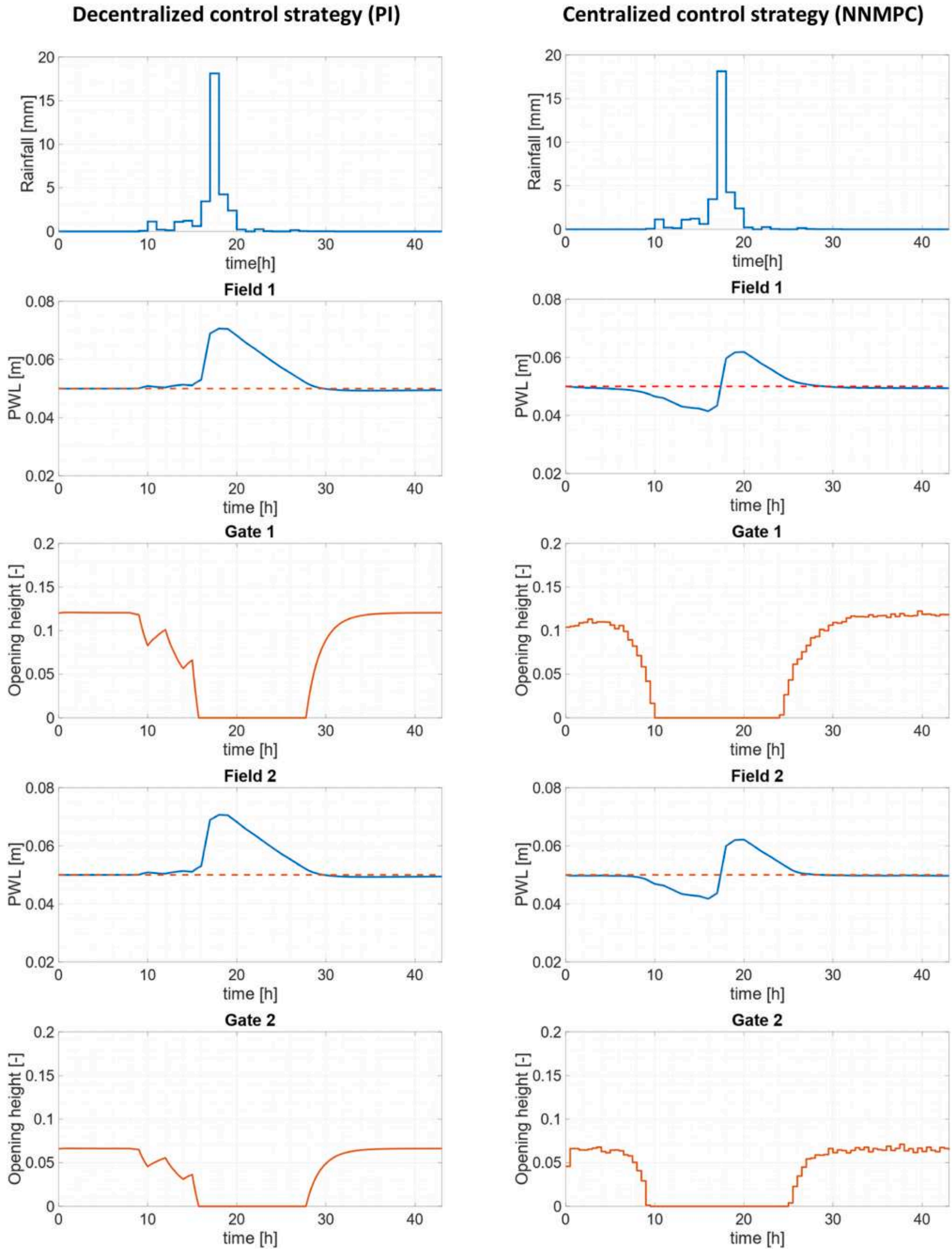
.

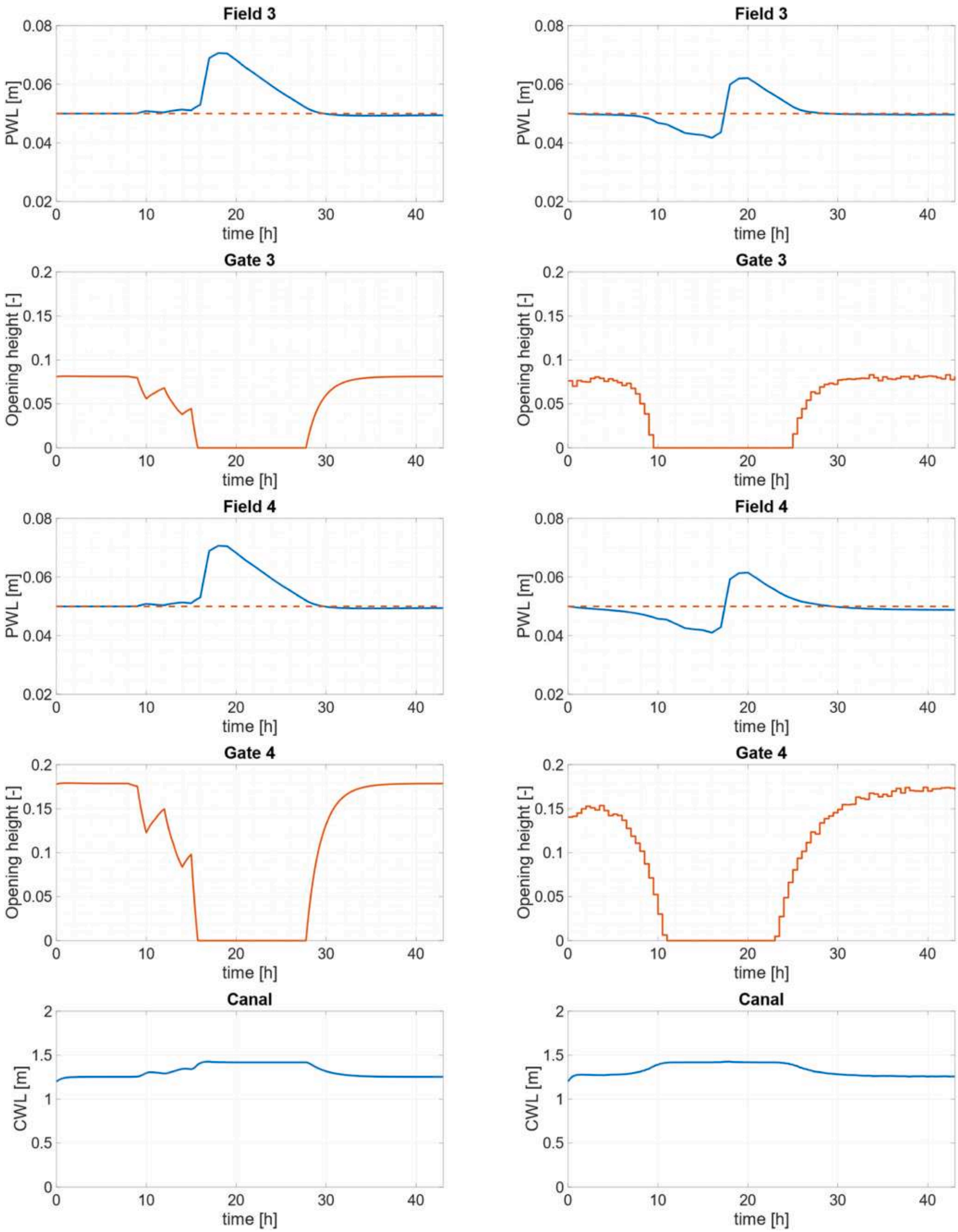
**Appendix 2. Comparison between proportional-integral and nonlinear model predictive control actions under limited supply conditions**



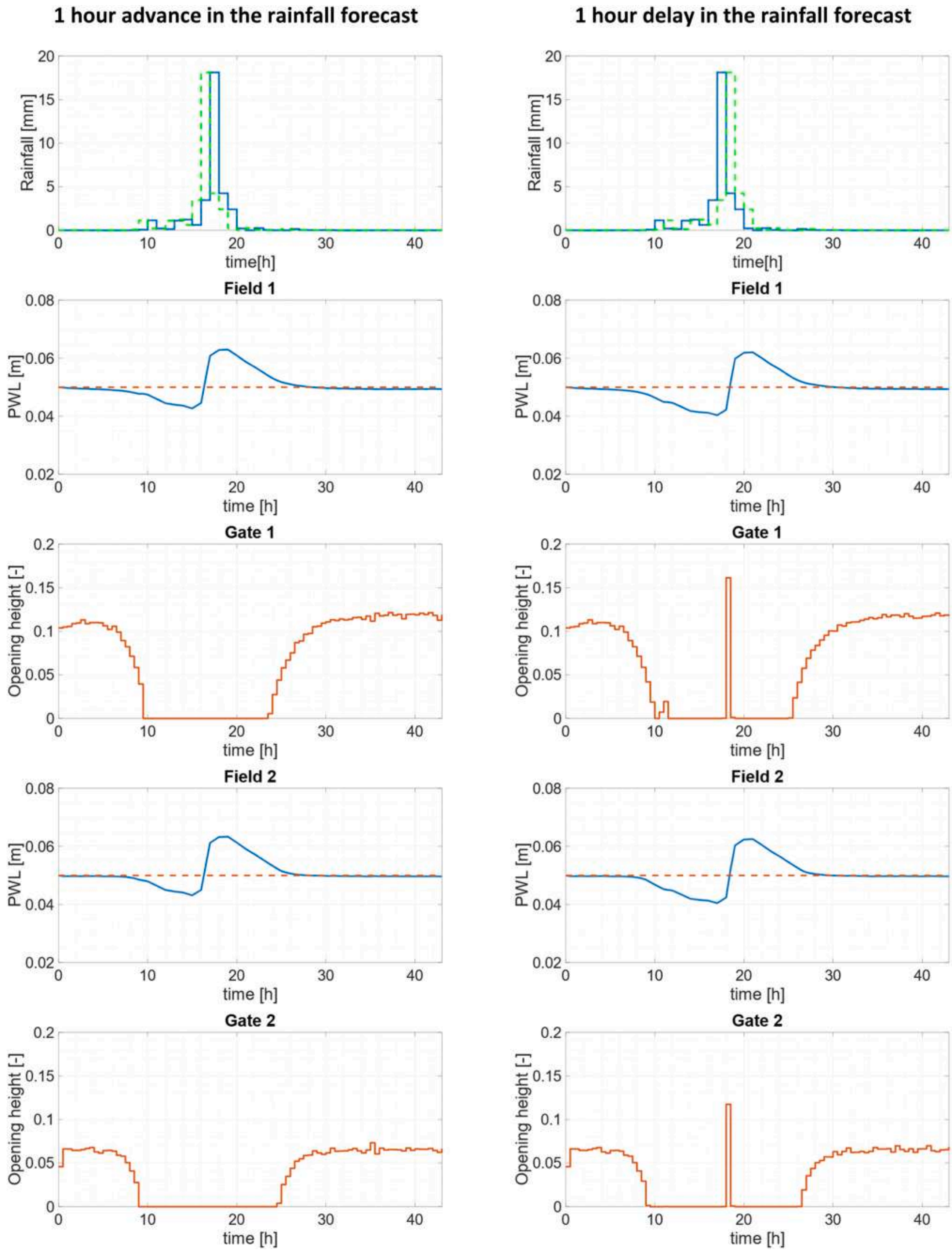

Gate 3
Opening height
time [h]
Gate 3
Opening height [-]
time [h]
Field 4
PWL [m]
time [h]
Field 4
PWL [m]
time [h]
Gate 4
Opening height
time [h]
Gate 4
Opening height [-]
time [h]
Canal
CWL [m]
time [h]
Canal
CWL [m]
time [h]

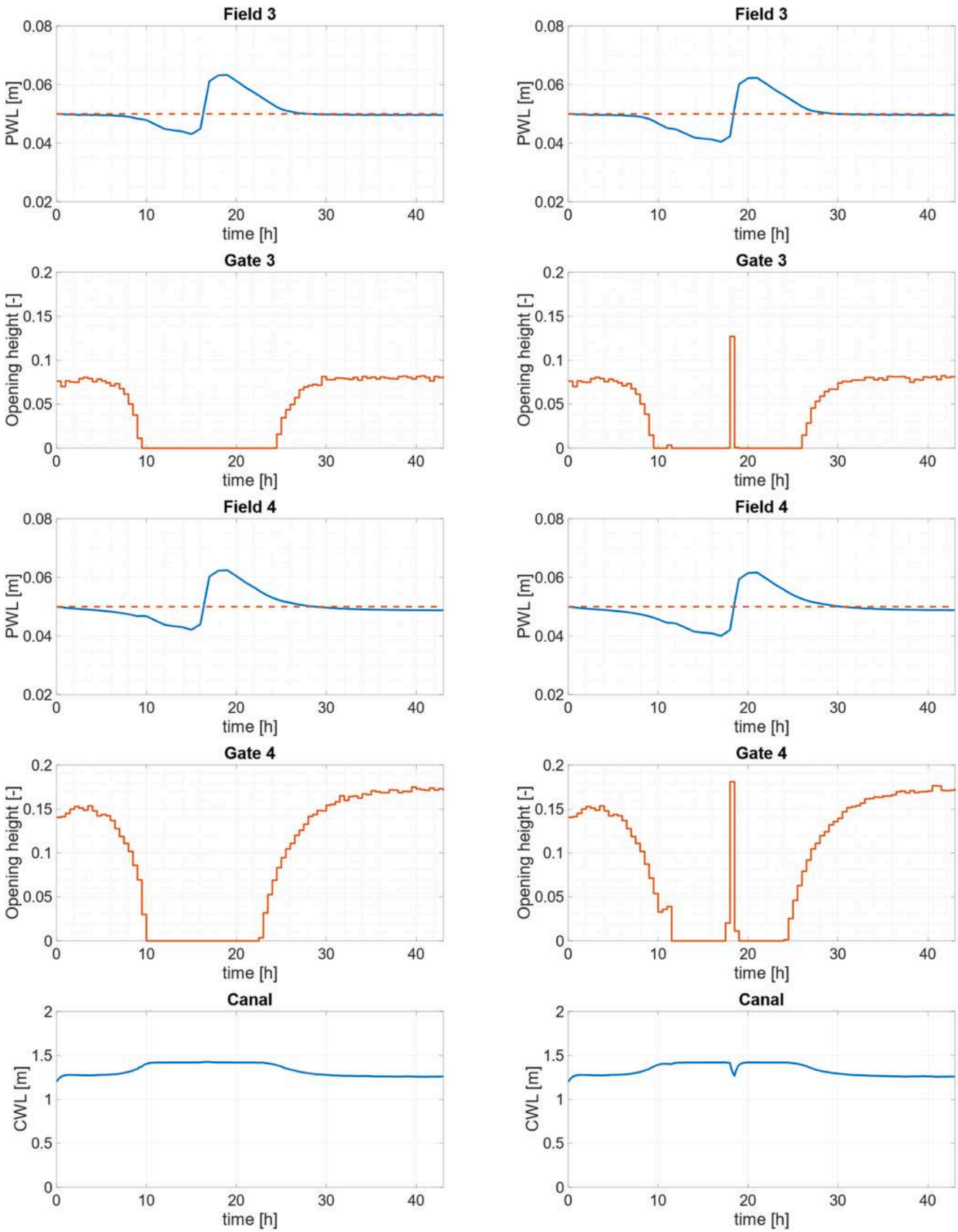
**Appendix 3. Comparison between proportional-integral and nonlinear model predictive control actions under an instantaneous water supply generated by a rainfall event**




Field 3
PWL [m]
time [h]
Gate 3
Opening height [-]
time [h]
Field 4
PWL [m]
time [h]
Gate 4
Opening height [-]
time [h]
Canal
CWL [m]
time [h]

**Appendix 4. Effects of the nonlinear model predictive control strategy on ponding water level, sluice gate opening height, and farm canal level under 1-hour advance and delay of rainfall**




Field 3
PWL [m]
time [h]
Field 3
PWL [m]
time [h]
Gate 3
Opening height [-]
time [h]
Gate 3
Opening height [-]
time [h]
Field 4
PWL [m]
time [h]
Field 4
PWL [m]
time [h]
Gate 4
Opening height [-]
time [h]
Gate 4
Opening height [-]
time [h]
Canal
CWL [m]
time [h]
Canal
CWL [m]
time [h]

## Appendix B. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.agwat.2023.108536.

## References


Abioye, E.A., Abidin, M.S.Z., Aman, M.N., Mahmud, M.S.A., Buyamin, S., 2021. A model predictive controller for precision irrigation using discrete lagurre networks. Comput. Electron. Agric. 181, 105953 https://doi.org/10.1016/j.compag.2020.105953.

Álvarez, A., Ridao, M.A., Ramirez, D.R., Sánchez, L., 2013. Constrained predictive control of an irrigation canal. J. Irrig. Drain. Eng. 139 (10), 841–854. https://doi.org/10.1061/(ASCE)IR.1943-4774.0000619.

Ang, K.H., Chong, G., Li, Y., 2005. PID control system analysis, design, and technology. IEEE Trans. Control Syst. Technol. 13 (4), 559–576 https://doi.org/ 10.1109/TCST.2005.847331.

Aravinth, K.V., Avudaithai, S., Ramesh, T., Balasubramaniam, P., Sundar, M., 2023. Impact of alternate wetting and drying irrigation and brown manuring on water use, weed control and yield of drum seeded rice. J. Appl. Nat. Sci. 15 (1), 75–84. https://doi.org/10.31018/jans.v15i1.4208.

Arif, C., Fauzan, M.I., Satyanto, K.S., Budi, I.S., Masaru, M., 2018. Developing Automatic Water Table Control System for Reducing Greenhouse Gas Emissions from Paddy Fields. In: In IOP Conf. Ser.: Earth Environ. Sci, 147. IOP Publishing, 012040. https://doi.org/10.1088/1755-1315/147/1/012040.

Ayaz, M.A., Manzoor, T., Muhammad, A., 2020. Mpc based soil moisture regulation of a canal-connected crop field. IFAC-Pap. 53 (5), 170–175. https://doi.org/10.1016/j.ifacol.2021.04.095.

Bertsekas, D.P., 2005. Dynamic programming and suboptimal control: a survey from ADP to MPC. Eur. J. Control 11 (4–5), 310–334. https://doi.org/10.3166/ejc.11.310-334.

Blanco, T.B., Willems, P., Chiang, P.-K., Haverbeke, N., Berlamont, J., De Moor, B., 2010. Flood regulation using nonlinear model predictive control. Control Eng. Pract. 18 (10), 1147–1157. https://doi.org/10.1016/j.conengprac.2010.06.005.

Bwambale, E., Abagale, F.K., Anornu, G.K., 2023. Data-driven model predictive control for precision irrigation management. Smart Agric. Technol. 3, 100074 https://doi.org/10.1016/j.atech.2022.100074.

Castelletti, A., Ficchì, A., Cominola, A., Segovia, P., Giuliani, M., Wu, W., Lucia, S., Ocampo-Martinez, C., De Schutter, B., Maestre, J.M., 2023. Model Predictive Control of water resources systems: a review and research agenda. Annu. Rev. Control. https://doi.org/10.1016/j.arcontrol.2023.03.013.

Cesari de Maria, S., Rienzner, M., Facchi, A., Chiaradia, E.A., Romani, M., Gandolfi, C., 2016. Water balance implications of switching from continuous submergence to flush irrigation in a rice-growing district. Agric. Water Manag. 171, 108–119. https://doi.org/10.1016/j.agwat.2016.03.018.

Champness, M., Ballester-Lurbe, C., Filev-Maia, R., Hornbuckle, J., 2023. Smart sensing and automated irrigation for sustainable rice systems: a state of the art review. Adv. Agron. 177, 259–285. https://doi.org/10.1016/bs.agron.2022.08.003.

Chen, W.H., Shang, C., Zhu, S., Haldeman, K., Santiago, M., Stroock, A.D., You, F., 2020. Theoretical Exploration of Irrigation Control for Stem Water Potential through Model Predictive Control. In 2020 American Control Conference (ACC). IEEE, pp. 1992–1997. https://doi.org/10.23919/ACC45564.2020.9147296.

Ding, Y., Wang, L., Li, Y., Li, D., 2018. Model predictive control and its application in agriculture: a review. Comput. Electron. Agric. 151, 104–117. https://doi.org/10.1016/j.compag.2018.06.004.

Facchi, A., Rienzner, M., Cesari de Maria, S., Mayer, A., Chiaradia, E.A., Masseroni, D., Silvestri, S., Romani, M., 2018. Exploring scale-effects on water balance components and water use efficiency of toposequence rice fields in Northern Italy. Hydrol. Res. 49 (6), 1711–1723. https://doi.org/10.2166/nh.2018.125.

Fukagawa, N.K., Ziska, L.H., 2019. Rice: importance for global nutrition. J. Nutr. Sci. Vitam. (Tokyo) 65 (Supplement), S2–S3. https://doi.org/10.3177/jnsv.65.S2. PMID: 31619630.

Gilardi, G.L.C., Mayer, A., Rienzner, M., Romani, M., Facchi, A., 2023. Effect of Alternate Wetting and Drying (AWD) and Other Irrigation Management Strategies on Water Resources in Rice-Producing Areas of Northern Italy. Water 15 (12), 2150. https://doi.org/10.3390/w15122150.

Glasser, W., 1985. Control theory. Harper and Row, New York. https://www.minessence.net/AVI_Accred/pdfs/control_theory.PDF.

Guo, C., You, F., 2018. A data-driven real-time irrigation control method based on model predictive control. In 2018 IEEE Conference on Decision and Control (CDC). IEEE,, pp. 2599–2604. https://doi.org/10.1109/CDC.2018.8619549.

Harper, S., 2017. Real. -Time Control Soil moisture Effic. Irrig. (Dr. Diss., Mass. Inst. Technol. ). http://hdl.handle.net/1721.1/111509.

Horváth, K., van Esch, B., Vreeken, T., Piovesan, T., Talsma, J., Pothof, I., 2022. Potential of model predictive control of a polder water system including pumps, weirs and gates. J. Process Control 119, 128–140. https://doi.org/10.1016/j.jprocont.2022.10.003.

Huang, M., Tian, M., Liu, Y., Zhang, Y., Zhou, J., 2022. Parameter optimization of PID controller for water and fertilizer control system based on partial attraction adaptive firefly algorithm. Sci. Rep. 12 (1), 12182 https://doi.org/10.1038/s41598-022-16425-7.

Inoue, K., Nakazono, K., Kanno, H., 1999. An automatic irrigation system for direct seeding Rice cultivation. J. Agric. Meteorol. 55 (2), 127–135 https://doi.org/10.2480/agrmet.55.127.

Jacob, A.I., Edokpolor, H.O., Johnson, E.H., 2019. Modeling of automatic sprinkler irrigation process using finite state machine (FSM) and proportional integral derivative (PID) controller. Univers. J. Eng. Sci. 7 (4), 75–81. https://doi.org/10.13189/ujes.2019.070401.

Lampayan, R.M., Rejesus, R.M., Singleton, G.R., Bouman, B.A., 2015. Adoption and economics of alternate wetting and drying water management for irrigated lowland rice. Field Crops Res 170, 95–108. https://doi.org/10.1016/j.fcr.2014.10.013.

Litrico, X., Malaterre, P.O., Baume, J.P., Vion, P.Y., Ribot-Bruno, J., 2007. Automatic tuning of PI controllers for an irrigation canal pool. J. Irrig. Drain. Eng. 133 (1), 27–37. https://doi.org/10.1061/(ASCE)0733-9437(2007)133:1(27).

Masseroni, D., Uddin, J., Tyrrell, R., Mareels, I., Gandolfi, C., Facchi, A., 2017. Towards a smart automated surface irrigation management in rice-growing areas in Italy. J. Agric. Eng. 48 (1), 42–48. https://doi.org/10.4081/jae.2017.585.

Masseroni, D., Moller, P., Tyrell, R., Romani, M., Lasagna, A., Sali, G., Facchi, A., Gandolfi, C., 2018. Evaluating performances of the first automatic system for paddy irrigation in Europe. Agric. Water Manag. 201, 58–69. https://doi.org/10.1016/j.agwat.2017.12.019.

Mattsson, S.E., Elmqvist, H., 1997. Modelica-an international effort to design the next generation modeling language. IFAC Proc. Vol. 30 (4), 151–155. https://doi.org/10.1016/S1474-6670(17)43628-7.

Mayer, A., Rienzner, M., Cesari de Maria, S., Romani, M., Lasagna, A., Facchi, A., 2019. A comprehensive modelling approach to assess water use efficiencies of different irrigation management options in rice irrigation districts of northern Italy. Water 11 (9), 1833. https://doi.org/10.3390/w11091833.

Miskam, M.A., Sidek, O., Abd Rahim, Omar, I., Ishak, M. Z, M.Q., 2013. Fully automatic water irrigation and drainage system for paddy rice cropping in Malaysia. In 2013 IEEE 3rd International Conference on System Engineering and Technology. IEEE, pp. 53–56 https://doi.org/10.1109/ ICSEngT.2013.6650142.

Pfitscher, L.L., Bernardon, D.P., Kopp, L.M., Ferreira, A.A.B., Heckler, M.V.T., Thome, B. A., Montani, P.D.B., Fagundes, D.R., 2011. An automated irrigation system for rice cropping with remote supervision. In Int. Conf. Power Eng. Energy Electr., (pp. IEEE, pp. 1–6. https://doi.org/10.1109/PowerEng.2011.6036452.

Pfitscher, L.L., Bernardon, D.P., Kopp, L.M., Heckler, M.V.T., Behrens, J., Montani, P.B., Thome, B., 2012. Automatic control of irrigation systems aiming at high energy efficiency in rice crops. In 2012 8th Int. Caribb. Conf. Devices Circuits Syst. (ICCDCS). IEEE, pp. 1–4. https://doi.org/10.1109/ICCDCS.2012.6188944.

Rejesus, R.M., Palis, F.G., Rodriguez, D.G.P., Lampayan, R.M., Bouman, B.A., 2011. Impact of the alternate wetting and drying (AWD) water-saving irrigation technique: evidence from rice producers in the Philippines. Food Policy 36 (2), 280–288. https://doi.org/10.1016/j.foodpol.2010.11.026.

van Overloop, P.J., Schuurmans, J., Brouwer, R., Burt, C.M., 2005. Multiple-model optimization of proportional integral controllers on canals. J. Irrig. Drain. Eng. 131 (2), 190–196. https://doi.org/10.1061/(ASCE)0733-9437(2005)131:2(190).