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Observability-based sensor selection in fish ponds: Application to pond aquaculture in Indonesia

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ABSTRACT

Water quality plays an important role in aquaculture since it affects the growth, survival, and production of aquaculture species. Consequently, measurement devices are needed to monitor water quality. However, this requires significant capital and extensive knowledge of the farmers, especially for smallholder farmers in developing tropical countries like Indonesia. As a cheaper alternative to using only hardware sensors, soft(ware) sensors may be used, as well. However, before designing feasible soft sensors, a so-called (theoretical) observability analysis needs to be done, where observability is a measure of how well internal states of a system can be inferred from measured system inputs and outputs. The aim of this study was to investigate the selection of sensors, such that a full reconstruction of the internal pond constituents, in tropical fish ponds, from the selected external sensor outputs can be realized at any time. A system theoretical observability analysis of a published antecedent dynamic model, describing the complex interactions between the pond constituents (states), was conducted to determine the minimum set of sensors that makes the pond system fully observable, thus in principle allowing a full reconstruction of all states at any time. Using only a DO sensor does not suffice. The minimum set of sensors that guarantees full observability of the pond system were two during the day and three during the night. The observability analysis showed that 11 possible combinations of two sensors provide a fully observable system during the day. In contrast, only one combination of sensors, that is CO_2, NO_3 and phosphorus, guarantees a fully observable system during day and night. Observability analysis is crucial for understanding the systems' behaviour and sensor selection, and supports the design of reliable soft sensors for better control and management of fish ponds.

1. Introduction

The aquaculture sector is one of the main food producers in the world. In 2018, the aquaculture production has reached 96.4 million tonnes (FAO, 2020). Indonesia is the second-largest producer of aquaculture in the world (FAO, 2020). The total production of the Indonesian inland aquaculture was around 5.5 million tonnes in 2018 (FAO, 2018). In 2030, the total projected output of Indonesian aquaculture will be around 10 – 15 million tonnes with tilapia as the main contributor (Phillips et al., 2015).

Also nowadays, tilapia is one of the most important fish species in Indonesia with a mixed demand from domestic and international markets. On the international market, Indonesian tilapia has a stable market share of 10% in the USA for over 10 years (Dai et al., 2020). Besides huge demands, tilapia producing companies are the largest employer in the Indonesian aquaculture sector (Phillips et al., 2015). Most Indonesian tilapia ponds use extensive or semi-intensive culture systems (FAO, 2018). These production systems are mostly operated by smallholder

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farmers which accounts for 80% of the total Indonesian aquaculture production (YIDH, 2018).

Investment in smallholder farms is advised to only those ponds that promote data management tools and water quality sensors to boost sustainable aquaculture practice in Indonesia (YIDH, 2018). According to government publications, smallholder farms use simple technology in aquaculture and own a maximum of 2 of hectares freshwater ponds (YIDH, 2018). Sophisticated technology can be expensive for the Indonesian smallholder ponds as they have limited access to capital (YIDH, 2018).

The success of aquaculture food production systems strongly depends on the water quality in the pond, since it affects the growth, survival, and production of aquaculture species (Junaidi and Kartiko, 2020). However, especially for smallholder farmers, the number of measurement devices should be limited. Hence, in addition to hardware sensors to monitor and control water quality, so-called soft(ware) sensors may be used, as well.

A soft sensor is a virtual on-line analyser that reduces the measurement requirements of a system. Although it has slightly less accuracy, a soft sensor is much cheaper and reliable (Torgashov and Zmeu, 2015). In agriculture, recently a soft sensor has already been used for the estimation of a leaf area index (García-Mañas et al., 2020) and in many more implementations in biotechnology (Keesman, 2002; Luttmann et al., 2012; Price et al., 2015).

However, before designing feasible soft sensors, a so-called (theoretical) observability analysis needs to be done, where observability is a measure of how well internal states of a system can be inferred from measured system inputs and outputs.

The aim of this study was to investigate the selection of sensors, such that, in principle, a full reconstruction of the internal fish pond constituents from known feed inputs and selected external sensor outputs can be realized at any time.

In this study, an observability analysis was performed based on the pioneering aquaculture model of Svirezhev et al. (1984), which is a biomass-based model, and adjusted for an individual fish weight using the model of Nath (1996). Recently, Varga et al. (2020) has validated the usability of the models of Svirezhev et al. (1984) and Nath (1996), with some modifications to evaluate various climate and management scenarios. As yet, as in Varga et al. (2020), the bacterial population was not explicitly modelled to keep the model relatively simple.

Because of the relevance of pond aquaculture in Indonesia, as shown in the reports of FAO (2018, 2020) and YIDH (2018), the sensor selection procedure is demonstrated to a virtual tropical fish pond in Indonesia.

2. Material and method

2.1. Dynamic modelling of tropical pond system

Dynamic mathematical models from previous studies (Fritz et al., 1979; Jimenez-Montealegre, 2001; Svirezhev et al., 1984) were used to describe the biophysical behaviour of an aquaculture pond. However, the reference model of Svirezhev et al. (1984) was used as a starting point, since it provides a general description of the pond dynamics in the water column. Model parameters were subsequently adapted from (Fritz et al., 1979; Jimenez-Montealegre, 2001). Fig. 1 presents an overview of the complex pond dynamics described in this study. In total, 11 state variables were defined, namely tilapia (C), phytoplankton (F), zooplankton (Z), benthos (B), dissolved oxygen (O), total ammonia nitrogen (TAN), nitrate (NO_3), phosphorus (P), carbon dioxide (CO), detritus (D) and artificial feed (A). Uptake rate of Nile Tilapia on artificial feed, benthos, and zooplankton follows a switching function, as in Svirezhev et al. (1984), thus leading to a non-linear dynamic model.

The feeding rate (U) was calculated using the following non-linear expression from Ursin (1967):

$$U = h * C^m \tag{1}$$

The power law coefficients h and m represent tilapia's coefficient of food consumption (g^{1-m} h^{-1}) and the order of body weight for net anabolism, respectively. In this study, h= 0.033 g^{1-m} h^{-1} (Nath, 1996) and m= 0.67 (Ursin, 1967) Feeding was done every 12 h.

The non-linear dynamic model of Svirezhev et al. (1984) and Nath (1996) was used and adapted to a tropical tilapia pond setting in Indonesia. For a detailed model description, see Supplementary Materials SM1. Pond rearing parameters are listed in Table 1.

The system was limited to the water column in an ideally mixed tropical tilapia pond with measured concentrations. Thus, pond sediment dynamics and stratification in the water column were not taken into account.

Furthermore, we assumed constant solar radiation, constant wind speed over the pond, constant water temperature and no fish mortality due to low stocking density. Solar radiation, wind speed and water

Table 1
Pond rearing parameters.

Parameters	Unit	Value
Pond area	ha	1
Pond depth	m	1
Stocking density	#fish ha^{-1}	4.000
Individual fingerling size	gr	10

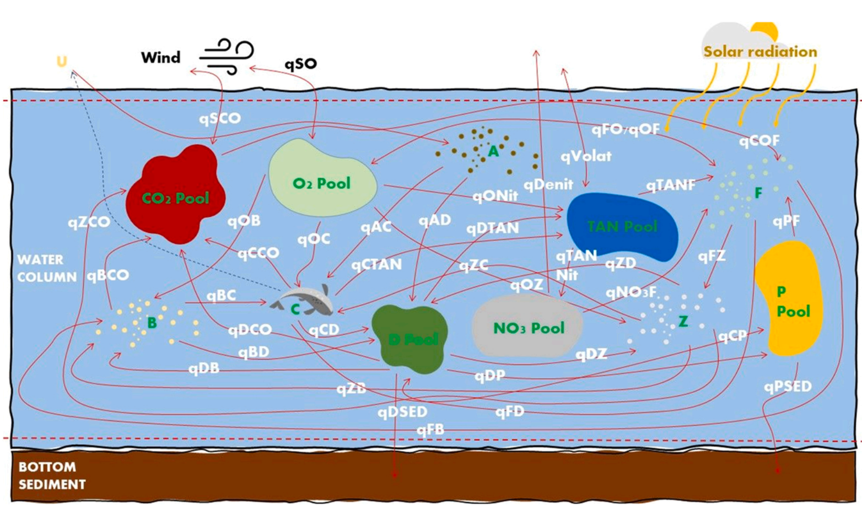

Fig. 1. Complex pond dynamics, in which green text represents state variables and qXY represents material flow rate from X to Y. C= tilapia, F = phytoplankton, Z = zooplankton, B= benthos, O= oxygen, TAN= total ammonia nitrogen, NO_3 = nitrate, P = phosphorus, CO= carbon dioxide, D= detritus, A= formulated feed; Nit = material flow rate due to nitrification, SED = sedimentation of material X, Volat = TAN volatilize to the air, S = mass transfer of X to the air due to surface aeration, Denit = Denitrification of NO_3; Red arrows show the fluxes between state variables. Blue dashed arrow represents the control signal from tilapia (C) to feeding rate (U), Eq. 1. For a detailed description of variables and parameters, see Tables in Supplementary Materials SM1.

temperature values were aligned with the reported Indonesian climate (BMKG, 2021; Morrison and Sudjito, 1992).

While wind speed and temperature were assumed constant for 24 h, solar radiation was different between day and night, but constant within day and within night. At night, solar radiation was set to zero. Table 2 shows the values of the microclimate for the studied pond system.

In what follows, for the analysis a linearized version of the non-linear dynamic model is required.

2.2. Linearization of a non-linear system

To linearize the non-linear models of Svirezhev et al. (1984) and Nath (1996) Taylor expansion was applied under the assumption of small deviations in the state variables (Δx) and inputs (Δu) around the linearization points ($\overline{x}$,$\overline{u}$). The initial conditions for each of the n (= 11) state variables is given in Table 3.

Further, a linearized state-space representation of the original non-linear model was derived by defining matrices $A(t)$ (Eq. 2) and $B(t)$ (Eq. 3), as follows:

$$A(t) = \left(\frac{\partial f_i}{\partial x_j}\right)\Big]_{\overline{x}(t),\quad \overline{u}(t)} \tag{2}$$

$$B(t) = \left(\frac{\partial f_i}{\partial u_k}\right)\Big]_{\overline{x}(t),\quad \overline{u}(t)} \tag{3}$$

for i,j = 1, 2,., n (number of state variables) and k = 1,., m (numbers of input variables). Furthermore, f_i represents the right-hand side of the differential equation related to the ith (with i = 1, 2,., 11) state variable (see Supplementary Materials SM2 for details of the matrix $A(t)$). Consequently, the time-varying, linear state space model, in terms of the deviation variables, is given by:

$$\frac{d}{dt}\Delta x(t) = A(t)\Delta x(t) + B(t)\Delta u(t) \tag{4}$$

$$\Delta y(t) = C\Delta x(t) + D\Delta u(t) \tag{5}$$

In which, $A(t)$ is an $n \times n$ and $B(t)$ an $n \times m$ matrix with $n = 11$ (see Table 3) and $m = 1$. As these matrices are evaluated along dynamic trajectories, indicated by $\overline{x}(t)$ and $\overline{u}(t)$, these are time-varying matrices. However, on a small time interval in the neighbourhood of the linearization points these matrices can be considered constant, thus A and B. The matrix C in the algebraic output Eq. (5) is a $p \times n$ matrix with p the number of sensors, and filled with zeros and ones. Hence, C represents the selection of states that are measured and thus sensor outputs. Furthermore, the matrix $D = 0$, i.e. none of the inputs affects the outputs directly.

In what follows, and for ease of notation, Δx, Δu, and Δy in Eqs. 4–5 were denoted by x, u, and y. The linearization process was conducted in MATLAB and linearization points were hourly updated along each state's trajectory. These new linearization points were obtained from the non-linear model simulation. Every 12 h the solar radiation interchanged between zero and a non-zero value. This corresponds to day and night conditions in a tropical environment.

In this study, the evaluated time was limited to 24 h to demonstrate the cycle of day and night. Time instant $t = 0$ corresponds with 6 am while $t = 11$ is at 6 pm.

Table 2
Pond microclimate setting.

Variable	Unit	Value
Temperature	°C	31
Wind speed	m/s	4
Solar radiation	kWh m^{-2} h^{-1}	0.243

Table 3
Initial values of the state variables, at t = 0.

State Variables	Description	Initial conditions (g m^{-3})
F	Phytoplankton	4
Z	Zooplankton	0.2
B	Benthos	0.1
C	Fish	4
D	Detritus	0.001
TAN	Total ammonia nitrogen	0.25
NO_3	Nitrate	0.5
P	Phosphorus	0.0003
O_2	Dissolved oxygen	6.5
CO_2	Carbon dioxide	1
A	Formulated feed	0

2.3. Pond system observability analysis

System observability was checked by the rank of the following np x n matrix:

$$\mathscr{O} = \begin{bmatrix} C \\ CA \\ CA^2 \\ \vdots \\ C\quad A^{n-1} \end{bmatrix} \tag{6}$$

The observability matrix $\mathscr{O}$ (Eq. 6), as well as the rank test of $\mathscr{O}$, were evaluated in MATLAB, using hourly values of states and inputs along the trajectories. When the rank (r) of $\mathscr{O}$ equals n, the system is said to be fully observable and thus allowing a full reconstruction of all predefined pond constituents at any time. Consequently, through appropriate choices of non-zero elements in matrix C a feasible combination of sensors can be obtained.

The analysis started with one sensor and with matrix A evaluated at $t = 0$. The maximum rank of one sensor was recorded for 24 h and plotted to investigate the dynamics of the system observability. Thus, initially $\binom{11}{1} = 11$ potential sensors, directly related to each of the 11 states, were evaluated. In case of rank deficiency, thus when $r < n$, the analysis can be further explored to find the unobservable states during the day from the null space of the matrix $\mathscr{O}$. This analysis will not be shown here. Instead, a second or third sensor was added when the system turned out to be not fully observable.

In order to end up with a fully observable system, in this study, $\binom{11}{2} = 55$ combinations of two sensors and $\binom{11}{3} = 165$ combinations of three sensors were investigated, as well.

3. Result

Given the initial states in Table 3, Fig. 2 shows the state trajectories for a period of one day.

Due to the relationship between states as shown in Fig. 1, some state trajectories show a similar trend to the other states (Fig. 2). For instance, fish and detritus trajectories show a similar increasing trend since the biggest detritus source is the fish faecal waste. In addition to this, the artificial feed given to the pond is also a major source of detritus. Notice that artificial feed concentration in the water column is in line with the feeding rate (U) and feeding time instances every 12 h. This effect of the feeding strategy is also visible in the trajectories of fish biomass and detritus.

In contrast, the concentrations of phytoplankton, zooplankton, benthos, and TAN decline during the first day. Notice that the phosphorus concentration declines exponentially to a low level. This decay affects the phytoplankton photosynthesis which subsequently influences

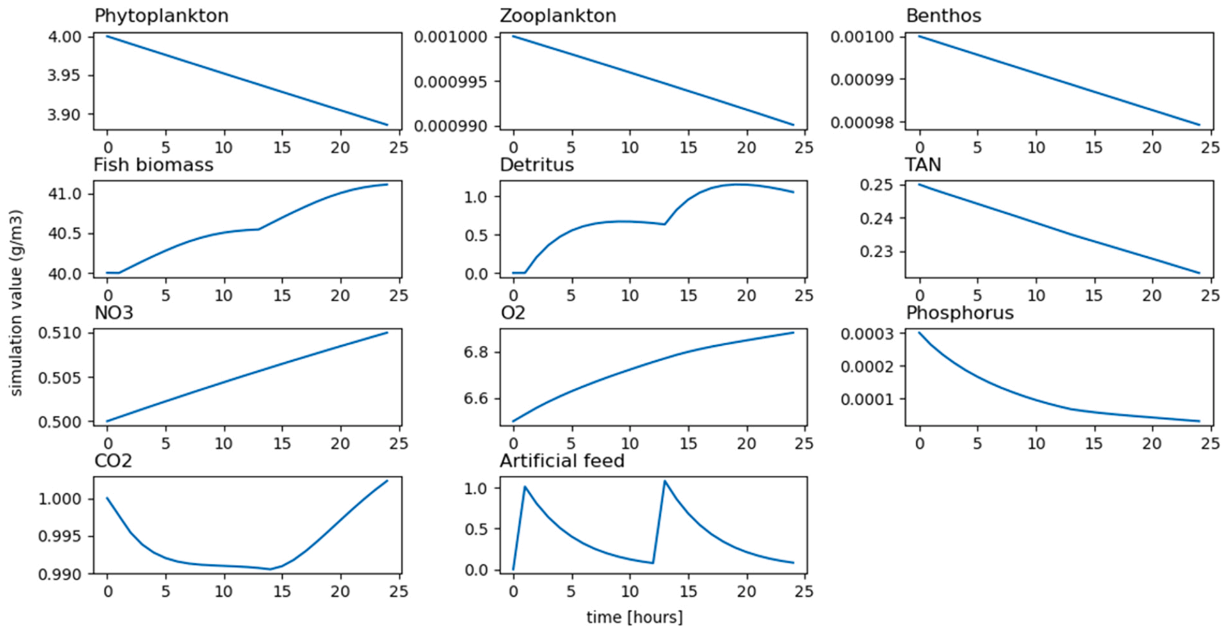

Fig. 2. State trajectories for one day.

other states. In the food web (Fig. 1) phosphorus is determined by tilapia and detritus, thus, phosphorus concentration was expected to increase. However, the phosphorus trajectory, during the first 24 h, shows a contrasting trend. During this stage, the rate of phosphorus production (qCP) by the fish was still low due to small biomass. More importantly, dissolved oxygen concentration was still abundant during the first 24 h, thus, the detritus mineralization rate (qDP) was insignificant. As the fish grows and the dissolved oxygen starts to deplete, phosphorus concentration is expected to increase, as shown in Supplementary Materials SM3.

Ranks of the observability matrix were constant for every six hours, thus, it is only shown for every 6 h (Fig. 3). No single sensor showed full system observability since for every hour of the day all individual sensors showed a maximum rank smaller than $n = 11$ (Fig. 3). The maximum rank for a single sensor case is equal to 8, meaning the minimum number of combinations of unobservable states equals 3.

The observability measure (rank of observability matrix $\mathscr{O}$) of the system was constant during day-time and night-time for nitrate, phosphorus, benthos, and artificial feed (Fig. 3). The ranks related to fish and detritus measurements were constant only for 17 h (until 11 pm) before rising to 8 at 24 h (6 am the next day). The ranks related to measurements of phytoplankton, TAN, O_2, and CO_2 rank show more variations.

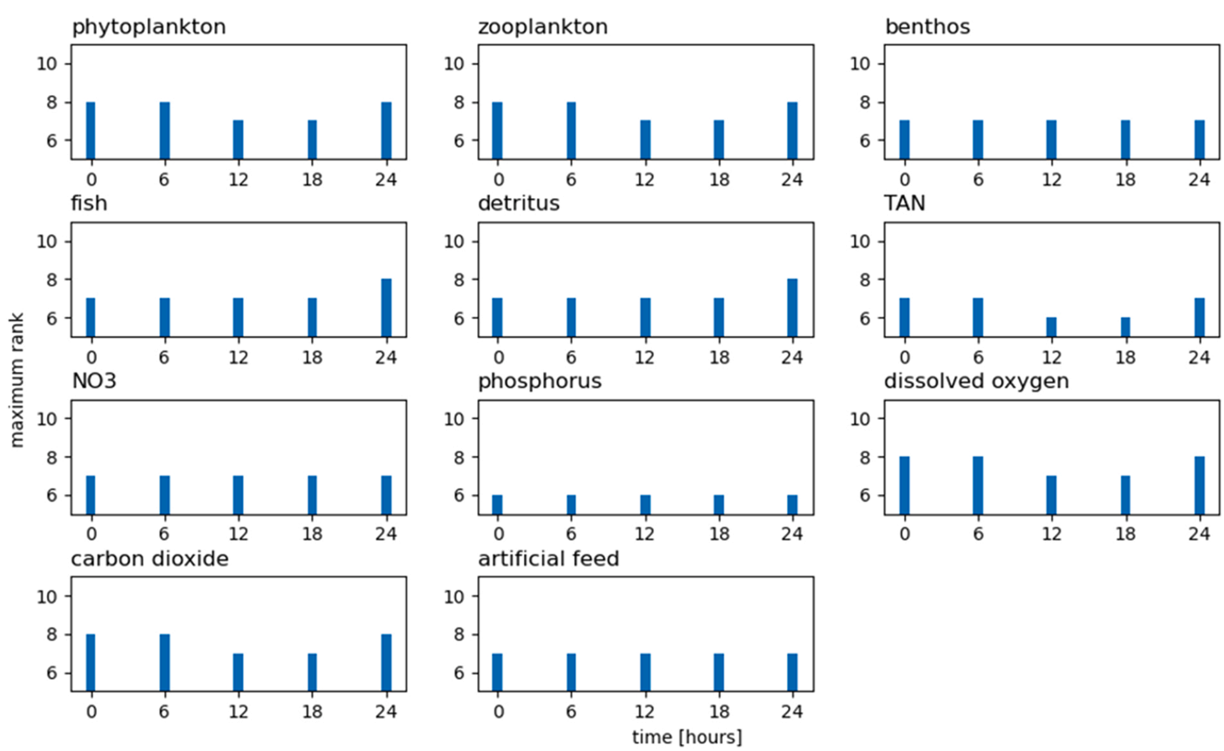

Fig. 3. Maximum rank of $\mathscr{O}$ with a single sensor in 24 h simulation, starting at 6 am.

For instance, when the solar radiation is not equal to zero (6 am – 5 pm), the ranks related to these state variables were constant. During night time (6 pm – 5 am) the rank decreased before increasing again to its initial value (at 6 am). Phytoplankton use solar radiation for photosynthesis to produce O_2 while consuming TAN and CO_2. It is thus reasonable to expect that the rank related to phytoplankton measurements will change as a function of solar radiation. As shown in Fig. 1, the state variables are complexly related, thus, a change in the rank related to phytoplankton will also affect the ranks related to O_2, CO_2, and TAN sensors.

The combination of two sensors that guarantee system observability during day-time is shown in Fig. 4.

During day-time, 11 combinations of two sensors give rise to full system observability. Sensor combinations of two sensors that contain an F, Z, O_2, CO_2, NO_3, or TAN sensor all show three options for full observability throughout day-time. In contrast, there are no pairs containing a D, B, or P sensor that guarantee full observability during day-time.

During the night at least a combination of three sensors is needed to guarantee full system observability. Only one sensor combination guarantees full observability at night, which is the combination of NO_3, CO_2, and P sensors. During day-time (Fig. 4), the sensor combination of NO_3 and CO_2 always shows full system observability. At night, a P sensor need to be added to keep the system fully observable throughout the 24 h.

All state variables were (in)directly related as shown by the red arrows in Fig. 1. Notice that all species (F,B,Z,C,D) produce or consume CO_2 metabolically, which provides information about the other states. The metabolism occurs during day-time and night-time. Hence, measuring CO_2 the whole 24 h provides much information, and thus contributes to full system observability.

The intake of nutrients (NO_3, TAN, P) and CO_2 by the phytoplankton is missing during night-time because phytoplankton does not take up nutrients during the night. Phosphorus shows only a direct relationship with phytoplankton and detritus. During day-time, phytoplankton intake of phosphorus can provide information of phosphorus for full system observability. During night-time, this relationship is absent, thus measuring P is needed during the night.

The way to get information about NO_3 was from nitrification of TAN and phytoplankton intake of NO_3 during day-time. During the night, the intake of NO_3 by phytoplankton was absent. Thus, measuring NO_3 was the only way to get its information for full system observability over 24 h.

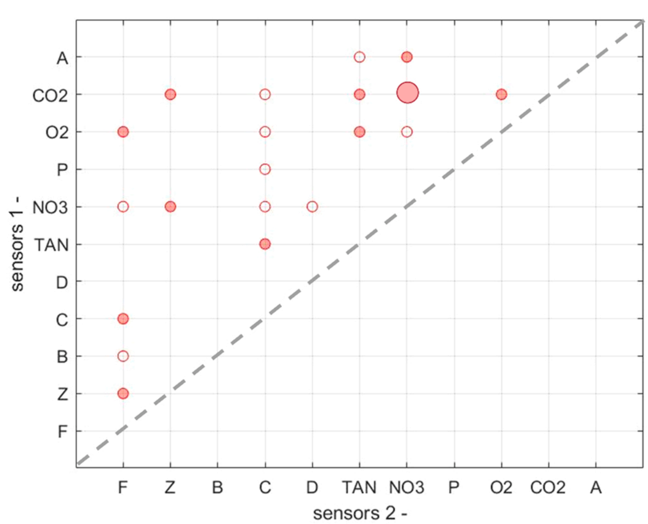

Fig. 4. Upper left sensor combinations that guarantee full observability of the pond system at the end of the day (11 h); Solid red circles represent sensor combinations that always show full system observability throughout day-time; Sensor combination of NO_3 and CO_2 guarantees full system observability during the day-time and night-time with additional P sensor.

4. Discussion

The manuscript focuses on sensor selection, given a non-linear model of fish pond dynamics, and was developed considering average environmental conditions in low intensity aquaculture ponds (0.4 fish m^{-2} at the start, Table 1) in Indonesia. The state variables used in the model include phytoplankton, zooplankton, benthos, fish (Nile tilapia), detritus, total ammonia nitrogen, nitrate, phosphorus, dissolved oxygen, carbon dioxide and formulated feed. The initial values and the range within which these state variables fluctuate during model runs were checked against values observed during tilapia pond experiments that were executed in Bangladesh (Kabir et al., 2019a, 2019b, 2020a, 2020b). The simulated and experimental values from these studies were in the same range. To the best of our knowledge no studies report all of the above-mentioned state variables in one experiment.

In mathematical systems theory it is well-known that linear, time-invariant systems need to be fully observable or at least detectable (Hautus, 1983; Tanwani and Trenn, 2019) before proceeding to the design of observers or so-called soft sensors. Detectability is a slightly weaker notion than observability. A system is called detectable if all the unobservable states are stable.

Thus, the sensor requirements for full observability in preceding sections can be relaxed. However, this needs a deeper mathematical analysis of the pond system (Fig. 1), as it is not clear beforehand that for a specific sensor combination all unobservable states will be stable. Consequently, for this we need to find the set of unobservable states and show that this subsystem is stable. On the basis of prior knowledge of the fish production system we can already identify two unstable states, which are tilapia and detritus (see Fig. 2). Nevertheless, our analysis showed (data not shown) that the linearized system along the state trajectories, thus for a sequence of relatively small time intervals of one hour, is detectable and thus in principle less than three sensors are needed for a full reconstruction of all 11 states.

So far, for all sensors or sensor combinations it was implicitly assumed that the sensors produce noise-free outputs. Thus, in addition to a theoretical observability or detectability analysis, as in this study, a soft sensor design procedure needs to be explored on the basis of noisy data in order to fully show which sensors and with what accuracy are needed for an accurate reconstruction of the state variables.

While multiple sensor combinations can guarantee full system observability during the day, only one combination of three sensors provided full system information during the night. So far, our results are shown only for the first day. However, the combination of sensors of CO_2, NO_3, and P was also validated over a period of 20 days, showing full system observability over a longer period (see rank of observability matrix in Supplementary Materials SM4).

The application of a sensor combination of CO_2, NO_3, and P measurement is not practical. However, more present and available sensors, such as a dissolved oxygen (O_2) sensor, did not provide full system information (see Supplementary Materials SM5). Not all pond constituents have a direct relationship to the O_2 pool (Fig. 1). Thus, O_2 measurement alone will not provide full system information.

Given the validity of the non-linear model (Supplementary Materials SM1) and linearized model (Section 2.2), a soft sensor using only O_2 measurements can still be designed as long as the linearized system along the state trajectories is detectable. However, in that case the state trajectories of the (stable) unobservable subsystem will only follow from model simulations, while only the observable subsystem (subset of states) will be corrected by the data. For a practical application of the research, system stability and detectability are thus essential.

Our methodological results show a fundamental first step in the design of soft sensors in aquaculture. Starting from an incomplete set of sensors with corresponding unobservable subsystem will in the end lead to inaccurate and uncertain estimates of some or all states. For a final test of the sensor selection procedure, however, real input and selected sensor output data should be collected from a pond, a soft sensor designed and its estimation uncertainties evaluated.

5. Conclusions

Given the non-linear models of Svirezhev et al. (1984) and Nath (1996) with corresponding linearized model, 11 model states (fish, phytoplankton, zooplankton, benthos, dissolved oxygen, total ammonia nitrogen, nitrate, phosphorus, carbon dioxide, detritus, and artificial feed) were defined. Eleven two-sensor combinations from the set of potential sensors, and directly related to the model states, that allow full observability during day-time were found. Only one three-sensor combination (CO_2, NO_3, and P) allows full system observability during day and night, and thus allowing a full reconstruction of all states at any hour of the day given data from this sensor combination.

Especially for small-scale resource-poor farmers in developing countries a well-functioning soft sensor system to monitor water quality will allow the farmer to observe shifts in food web dynamics and to maintain good water quality and a high feeding efficiency during the culture period. However, before designing a feasible soft sensor system with reliable state estimates, the dynamic mathematical model with selection of potential sensors must be observable, asking for a theoretical observability analysis as a necessary first step.

Further research into system stability, detectability and sensor accuracy can potentially help to reduce the number of affordable sensors needed to continuously monitor the states (water quality parameters) in aquaculture ponds.

CRediT authorship contribution statement

Bagoes M. Inderaja: Conceptualization, Methodology, Validation, Investigation, Data curation and analysis, Writing – original draft, Writing – review & editing, Funding acquisition, Project administration. **Nurhayati Br Tarigan**: Conceptualization, Methodology, Validation, Investigation, Data curation and analysis, Writing – review & editing, Supervision. **Marc Verdegem:** Conceptualization, Methodology, Validation, Investigation, Supervision. **Karel J. Keesman**: Conceptualization, Methodology, Validation, Investigation, Writing – review & editing, Supervision.

Declaration of Competing Interest

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

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.aquaeng.2022.102258.

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