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On sensor configurations in a lettuce greenhouse via observability analysis using the empirical gramian

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Abstract

Estimating crop states accurately through combining measurements and a dynamical model in a data assimilation algorithm is a promising alternative for high tech crop sensing investments. In order to successfully do this, the employed model and chosen sensor configuration need to be observable. This paper demonstrates, in a lettuce greenhouse model, the applicability of an observability analysis that shows a large potential for soft sensing in a greenhouse where only a small subset of states is monitored. The analysis is done using the empirical gramian, which only requires simulation data. It is shown that measuring the indoor CO_2 and humidity is in theory sufficient to estimate the lettuce's biomass and the indoor carbon dioxide, temperature, and humidity through data assimilation assuming knowledge on the outdoor weather and control signal. The demonstrated method can be applied to any simulator that models a different application and can be used to find an optimal sensor configuration.

Keywords: crop sensing, horticulture, crop states, data assimilation, simulator

INTRODUCTION

Climate control of high-tech greenhouses with high energy efficiency require accurate information about climate states like humidity and crop states like biomass (Bontsema et al., 2011). Climate states can be measured reasonably accurately with a sufficiently dense sensor grid (Balendonck et al., 2014). However, monitoring crop states such as leaf area, weight, and fruit content remain challenging due to reasons such as occluded leaves and vegetables. One way to deal with this challenge is by estimating crop states from measured climate variables using a data assimilation technique (combining measurements with model predictions) such as Kalman filtering (Piñón et al., 2000; Ruíz-García et al., 2014; Boersma et al., 2022a). For such an approach, an observable dynamical model with specified sensor configuration is required that simulates the climate and crop's state evolution over time. The sensor configuration determines which states are actually measured (measurements). Observability analysis can provide a measure of how well, through data assimilation, internal states of a system can be inferred from measurements. This effectively boils down to analyzing the sensitivity of the states on the measurement. Different methods exist to verify if a model with sensor configuration is observable, like the Hautus test (Hautus, 1969) or via the observability matrix (Kalman, 1963). These methods are suitable for linear dynamical models and require explicit model equations. Another method employs the empirical gramian (Hahn and Edgar, 2002), which is a matrix that is constructed from simulation data. This can be an advantage over other methods since it is suitable for any relatively complex simulator and thus, no explicit model equations are required. In addition, this method is suitable for nonlinear models although the conclusions are valid around a trajectory starting from specific initial conditions. In this work, the empirical gramian is used in order to assess observability of a dynamical lettuce greenhouse model for different sensor configurations. Stated differently, this work investigates for which sensor configuration (measurement) the state variable can be estimated through data assimilation.

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MATERIALS AND METHODS

Lettuce greenhouse model

The nonlinear model considered in this work is taken from (van Henten, 1994) and written in the general state-space form:

$$\frac{\mathrm{d}x(t)}{\mathrm{d}t} = f(x(t), u(t), d(t), p)\ , y(t) = \ g(x(t), p) \tag{1}$$

with continuous time $t\ \in \mathbb{R}$, state $x(t) \in \mathbb{R}^{n_x=4}$, measurement $y(t) \in \mathbb{R}^4$, controllable input $u(t) \in \mathbb{R}^3$, weather disturbance $d(t) \in \mathbb{R}^4$ and model parameter $p \in \mathbb{R}^{28}$ (Table 1).

Table 1. Meaning of state $x(t)$, measurement $y(t)$, control signal $u(t)$ and disturbance $d(t)$.

x_1 (t)	Dry weight (kg m^{-2})	y_1 (t)	Dry weight (g m^{-2})	d_1 (t)	Radiation (W m^{-2})
x_2 (t)	Indoor CO_2 (kg m^{-3})	y_2 (t)	Indoor CO_2 (ppm)	d_2 (t)	Outdoor CO_2 (kg m^{-3})
x_3 (t)	Indoor temperature (°C)	y_3 (t)	Indoor temperature (°C)	d_3 (t)	Outdoor temperature (°C)
x_4 (t)	Indoor humidity (kg m^{-3})	y_4 (t)	Indoor humidity (%)	d_4 (t)	Outdoor humidity (kg m^{-3})
u_1 (t)	CO_2 injection (mg m^{-2} s^{-1})	u_2 (t)	Ventilation (mm s^{-1})	u_3 (t)	Heating (W m^{-2})

Figure 1 graphically depicts the greenhouse model with lettuce and the interactions between states (measurements), disturbances and control signals.

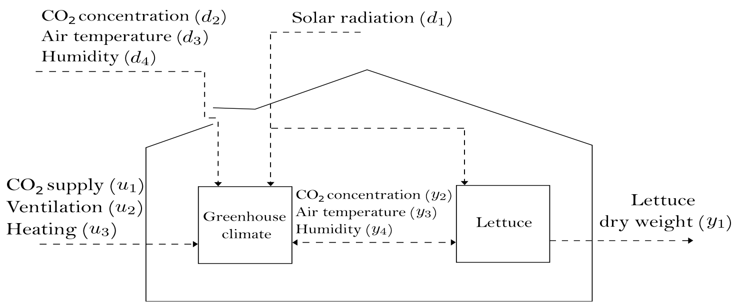

Figure 1. Schematic representation of the greenhouse with lettuce. The arrows indicate the interaction between the greenhouse and lettuce model with the control signal $u(t)$ and meteorological disturbance $d(t)$.

The nonlinear functions $f(\cdot), g(\cdot)$ in Equation 1 are defined as:

$$\frac{\mathrm{d}x(t)}{\mathrm{d}t} = \underbrace{\begin{pmatrix} p_{1,1}\phi_{\text{phot,c}}(t) - p_{1,2}x_1(t)2^{x_3(t)/10-5/2}, \\ \frac{1}{p_{2,1}} - \phi_{\text{phot,c}}(t) + p_{2,2}x_1(t)2^{x_3(t)/10-5/2} + u_1(t)10^{-6} - \phi_{\text{vent,c}}(t), \\ \frac{u_3(t)}{p_{3,1}} - \left(p_{3,2}u_2(t)10^{-3} + p_{3,3}\right)\left(x_3(t) - d_3(t)\right) + p_{3,4}d_1(t), \frac{\left(\phi_{\text{transp,h}}(t) - \phi_{\text{vent,h}}(t)\right)}{p_{4,1}} \end{pmatrix}}_{f(x(t),u(t),d(t),p)} \tag{2a}$$

$$\phi_{\text{phot,c}}(t) = \frac{\left(1-\exp\left(-p_{1,3}x_1(t)\right)\right)\left(p_{1,4}d_1(t)(-p_{1,5}x_3(t)^2 + p_{1,6}x_3(t) - p_{1,7})(x_2(t) - p_{1,8})\right)}{\varphi(t)} \tag{2b}$$

$$\varphi(t) = p_{1,4}d_1(t) + \left(-p_{1,5}x_3(t)^2 + p_{1,6}x_3(t) - p_{1,7}\right)\left(x_2(t) - p_{1,8}\right) \tag{2c}$$

$$\phi_{\text{vent,c}}(t)\ = \left(u_2(t)10^{-3} + p_{2,3}\right)\left(x_2(t) - d_2(t)\right) \tag{2d}$$

$$\phi_{\text{vent,h}}(t)\ = \left(u_2(t)10^{-3} + p_{2,3}\right)\left(x_4(t) - d_4(t)\right) \tag{2e}$$

$$\phi_{\text{transp,h}}(t) = p_{4,2}\left(1-\exp\left(-p_{1,3}x_1(t)\right)\right)\left(\frac{p_{4,3}}{p_{4,4}(x_3(t)+p_{4,5})}\exp\left(\frac{p_{4,6}x_3(t)}{x_3(t)+p_{4,7}}\right)-x_4(t)\right) \quad (2f)$$

with $\phi_{\text{phot,c}}(t)$, $\phi_{\text{vent,c}}(t)$, $\phi_{\text{transp,h}}(t)$ and $\phi_{\text{vent,h}}(t)$, the gross canopy photosynthesis rate, mass exchange of CO_2 through the vents, canopy transpiration and mass exchange of H_2O through the vents, respectively. The measurement equation is a function of parameters $p_{i,j}$ (Table 2):

$$y(t) = \underbrace{\begin{pmatrix} 10^3 x_1(t) \\ \frac{10^6 p_{2,4}(x_3(t)+p_{2,5})}{p_{2,6}p_{2,7}}\cdot x_2(t) \\ x_3(t) \\ \frac{10^2 p_{2,4}(x_3(t)+p_{2,5})}{11\cdot\exp\left(\frac{p_{4,8}x_3(t)}{x_3(t)+p_{4,9}}\right)}\cdot x_4(t) \end{pmatrix}}_{g(x(t),p)} \quad (3)$$

Table 2. Values of the model parameters that are taken from (van Henten, 1994).

$p_{1,1}$	0.544	$p_{2,1}$	4.1	$p_{3,1}$	$3\cdot10^4$	$p_{4,1}$	4.1
$p_{1,2}$	$2.65\cdot10^{-7}$	$p_{2,2}$	$4.87\cdot10^{-7}$	$p_{3,2}$	1290	$p_{4,2}$	0.0036
$p_{1,3}$	53	$p_{2,3}$	$7.5\cdot10^{-6}$	$p_{3,3}$	6.1	$p_{4,3}$	9348
$p_{1,4}$	$3.55\cdot10^{-9}$	$p_{2,4}$	8.31	$p_{3,4}$	0.2	$p_{4,4}$	8314
$p_{1,5}$	$5.11\cdot10^{-6}$	$p_{2,5}$	273.15			$p_{4,5}$	273.15
$p_{1,6}$	$2.3\cdot10^{-4}$	$p_{2,6}$	101325			$p_{4,6}$	17.4
$p_{1,7}$	$6.29\cdot10^{-4}$	$p_{2,7}$	0.044			$p_{4,7}$	239
$p_{1,8}$	$5.2\cdot10^{-5}$	$p_{4,8}$	17.269			$p_{4,9}$	238.3

The model of Equation 1 is used throughout this work for observability analysis. To can simulate this model, meteorological disturbances $d(t)$ and control signal $u(t)$, initial condition of the state $x(0)$ and integration method are detailed in the following subsections.

Meteorological disturbance $d(t)$

The weather data $d(t)$ used throughout the simulations is real-life data (Kempkes et al., 2014), collected during experiments performed in the greenhouse called "the Venlow Energy greenhouse" located in Bleiswijk (Holland). The collected data points are sampled at 5 min and for the simulations re-sampled to sample period h.

Control signal $u(t)$

The control signal $u(t)$ is evaluated using a nonlinear model predictive controller (Boersma et al., 2022b) with the objective of maximize efficiency of the lettuce greenhouse, using a set of control signals found by solving an optimization problem in the controller.

Initial condition $x(0)$

The (nominal) initial condition is defined as:

$$\mathrm{x}(0) = (0.0035 \quad 0.001 \quad 15 \quad 0.008)^{\mathrm{T}} \stackrel{\text{def}}{=} \bar{x}(0) \quad (4)$$

Integration method

The explicit fourth order Runge-Kutta method is used for discretizing the model described by Equation 1. This results in the following discrete time state-space model:

$$x(k+1) = f_{\mathrm{d}}(x(k), u(k), d(k), p), y(k) = g(x(k), p) \quad (5)$$

with discrete time k and $f_{\mathrm{d}}(\cdot)$ evaluated as:

$$f_d(x(k), u(k), d(k), p) = x(k) + h/6 \cdot (k_1 + 2k_2 + 2k_3 + k_4) \quad (6)$$

with sample period h and:

$$k_1 = f(x(k), u(k), d(k), p);\; k_2 = f(x(k) + h/2 \cdot k_1, u(k), d(k), p) \quad (7)$$

$$k_3 = f(x(k) + h/2 \cdot k_2, u(k), d(k), p);\; k_4 = f(x(k) + h \cdot k_3, u, d(k)$$

Sensor configuration

This paper investigates the observability property of the model given in Equation 1. If the model is observable, then the state $x(k)$ can be estimated from the chosen measurement. The latter is defined by the sensor configuration for which the observability analysis has to be performed. For example, is it possible to estimate the state $x(k)$ from the indoor CO_2 and temperature measurements via data assimilation? Or is it possible to estimate the state $x(t)$ from only the indoor temperature? Thus, for each m^{th} defined sensor configuration $y_r^m(k)$, this paper investigates if the state $x(k)$ can be estimated by doing an observability analysis using the empirical gramian. The following sensor configurations are defined (Table 1):

$$y_r^1(k) = (y_2(k),\quad y_3(k),\quad y_4(k))^T;\; y_r^2(k) = (y_2(k),\quad y_4(k))^T;\; y_r^3(k) = (y_3(k),\quad y_4(k))^T \quad (8)$$

$$y_r^4(k) = (y_2(k),\quad y_3(k))^T;\; y_r^5(k) = y_2(k);\; y_r^6(k) = y_4(k)$$

Empirical gramian

As mentioned, in order to estimate $x(k)$ from the measurement $y_r^m(k)$, the model presented in Equation 1 needs to be observable. Since the model in Equation 1 is nonlinear, the observability gramian (from which observability can be concluded) cannot directly be evaluated. One option is to linearize Equation 1 and subsequently determine observability for this linear model. Conclusions will then hold locally for the nonlinear model. Another approach is to directly use Equation 1 and determine its observability around a trajectory via the use of the so-called empirical observability gramian. The main advantage of this approach is that it only requires to do multiple simulations with the model defined in Equation 1 and no symbolic and differentiable expressions of the differential equations are required. We used the exact empirical observability gramian method (Krener and Ide, 2009) summarized as:

i) Simulate Equation 1 for N time steps, a given $d(k), u(k)$ and initial condition $\bar{x}(0)$, and store the subsequent trajectory as $\bar{y}_r(k)$. Around this trajectory, observability is verified.

ii) Simulate Equation 1 again n_x times (dimension of $x(k)$) for N time steps by using the same $d(k), u(k)$ as before through changing the initial condition as follows:

$$x^i(0) = \left(\alpha \cdot e_i e_i^T + I_{n_x}\right)\bar{x}(0) \quad (9)$$

for $i = 1, \ldots, n_x$ with e_i the unit vector, identity matrix $I_{n_x} \in R^{n_x \times n_x}$ and $\alpha \in R$. Define each of these subsequent trajectories as $y_r^{m,i}(k)$ as responses to different initial conditions.

iii) Evaluate the empirical observability gramian:

$$W_o^m = \frac{h}{\alpha^2} \sum_{k=1}^{N} \psi(k) \;\in R^{n_x \times n_x} \quad (10)$$

with sample period h and $\psi(k) \in R^{n_x \times n_x}$ where each element is evaluated as:

$$\psi_{ij}(k) = \left(y_r^{m,i}(k) - \bar{y}_r(k)\right)^T \left(y_r^{m,j}(k) - \bar{y}_r(k)\right) \quad (11)$$

and $y_r^{m,i}(k)$ the measurement from Equation 1 given sensor configuration m and having the initial condition $x^i(0)$. One can observe that the covariance of the measurement is calculated to construct the empirical observability gramian. In fact, the diagonal elements W_o^m represent the variance of the measurements caused by perturbations in the state and these diagonal elements give relative degree of observability of each state (Singh and Hahn, 2006). This can also be interpreted as the sensitivity of the state's perturbation on the measurement.

iv) Evaluate the singular value decomposition of the matrix W_o^m:

$$W_o^m = U\Sigma V^T \tag{12}$$

with diagonal matrix $\Sigma \in R^{n_x \times n_x}$ having the singular values σ_i on its diagonal and $U, V \in R^{n_x \times n_x}$ real orthogonal matrices. The columns of U represent a direction in the observable subspace, where the length of the vectors is given by the corresponding singular values.

v) Evaluate (van Doren, 2010):

$$u_z^m = \sum_{i=1}^{n_x} \frac{\sigma_i}{\sigma_1} |u_i| \quad \in R^{n_x} \tag{13}$$

with singular value σ_i representing the part of the measurement's energy along the direction of the singular vector u_i, the i^{th} column of U. The vector u_z^m characterizes the dominant directions of the observable subspace for the m^{th} sensor configuration.

Observability is concluded by verifying that:

$$\text{rank}(W_o^m) = n_x \tag{14}$$

Indeed, the rank of the empirical observability gramian is equal to the size of the state $x(k)$ when Equation 1 is observable, i.e., the state can be estimated from the measurement. Instead of a yes/no answer, it is also possible to obtain a more sophisticated answer about the observability of Equation 1. For this, the singular value decomposition of W_o^m is used to compute the vector u_z^m, which characterizes the dominant directions of the observable subspace. In other words, if, for example, the first element of the vector u_z^m is higher than the second element, then the first state variable is better observable than the second. If the third element of the vector u_z^m is zeros, then the third state $x_3(k)$ is not observable, i.e., it is not possible to estimate $x_3(k)$ from the defined sensor configuration. In the following section, the different sensor configurations that are studied in this work are defined.

The hyper parameters used throughout this work were the variable N=40 days is chosen such that one lettuce crop cycle is simulated, h=15 min and α=0.1.

SIMULATION RESULTS

As discussed in the previous section, the first step in the observability analysis is to perform a (nominal) simulation having initial condition $\bar{x}(0)$. The subsequent nominal trajectory is depicted in Figure 2. It is assumed that the outdoor climate variables (second row Figure 2) are measured. Around these trajectories, the observability analysis is performed. For this, all subsequent steps described in the previous section are followed and the results are, for each sensor configuration, presented in the following subsections.

Sensor configuration $\boldsymbol{y_r^1(k) = (y_2(k) \quad y_3(k) \quad y_4(k))^T}$

For this sensor configuration, the observability analyses give:

$$u_z^1 = (0.63 \quad 1.0 \quad 0.061 \quad 0.016)^T$$

and the rank of $W_o^1 = 4$ which is equal to the state dimension. Hence the state $x(k)$ can be estimated from the measurement $y_r^1(k)$ that comes from the given sensor configuration. Note that this implies that the lettuce's biomass can be estimated from the three indoor climate variables by using a data assimilation technique like Kalman filtering. This is in fact shown in (Boersma et al., 2022a).

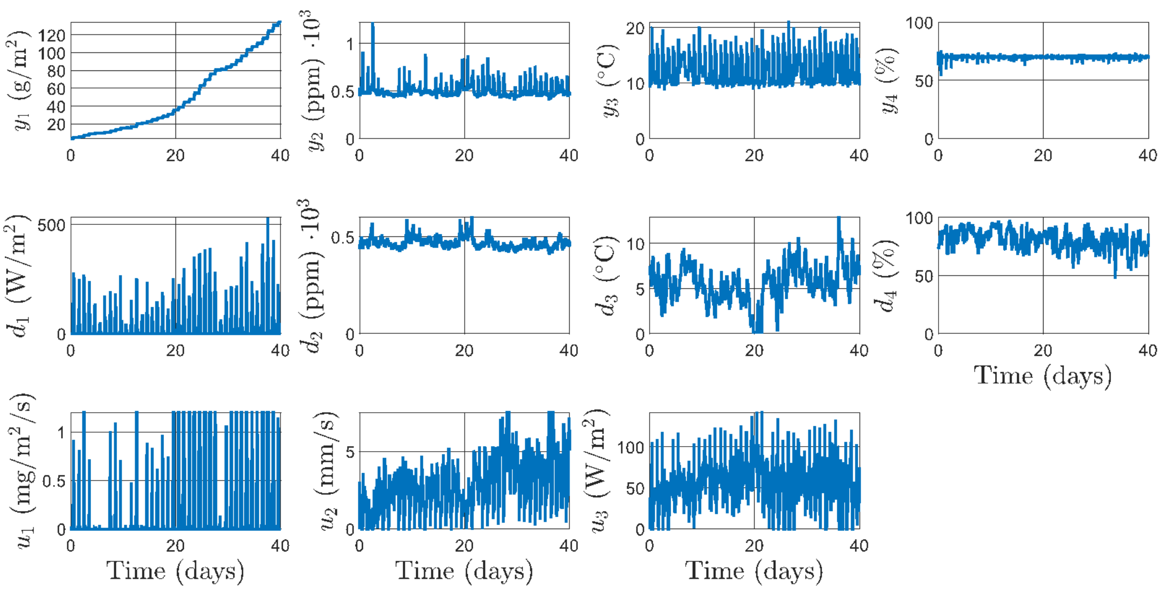

Figure 2. The 40 days nominal time series around which the observability analysis is performed. The meaning of the signals is described in Table 1.

Sensor configuration $\boldsymbol{y_r^2(k) = (y_2(k) \quad y_4(k))^T}$

For this sensor configuration, the observability analyses give:

$$u_z^2 = (0.63 \quad 1.0 \quad 0.060 \quad 0.016)^T$$

and the rank of $W_o^2 = 4$ which is equal to the state dimension. Since the results are almost equivalent to the previous sensor configuration, it can be concluded that measuring the temperature is not adding much value. Rather, no investments need to be done in indoor temperature measurement devices because it can be estimated from $y_r^2(k)$ (that contains the indoor CO_2 and humidity) using a data assimilation technique.

Sensor configuration $\boldsymbol{y_r^3(k) = (y_3(k) \quad y_4(k))^T}$

For this sensor configuration, the observability analyses give:

$$u_z^3 = (1.0 \quad 4.3 \cdot 10^{-7} \quad 0.48 \quad 0.60)^T$$

and the rank of $W_o^3 = 4$ which is equal to the state dimension. Looking at u_z^3, it must be noted that the second element is relatively small. This indicates that, even though it is possible to estimate the indoor CO_2 from the indoor temperature and humidity, it will be relatively more difficult with respect to estimating the other state variables from $y_r^3(k)$.

Sensor configuration $\boldsymbol{y_r^4(k) = (y_2(k) \quad y_3(k))^T}$

For this sensor configuration, the observability analyses give:

$$u_z^4 = (0.60 \quad 1.0 \quad 0.049 \quad 0)^T$$

and the rank of $W_o^4 = 3$ which is not equal to the state dimension hence the model is not observable. In other words, the indoor humidity cannot be estimated from the indoor CO_2 and the indoor temperature via data assimilation. This can be explained by looking at the model's state Equation 1. Indeed, the fourth state variable (indoor humidity) does not appear in one of the other equations. This implies that the indoor humidity is not influencing one of the other state variables and the observability analysis consequently indicates that the indoor humidity needs to be measured and cannot be estimated from other measurements when using the model of Equation 1. This conclusion is verified considering the following sensor configuration.

Sensor configuration $y_r^5(k) = y_2(k)$

For this sensor configuration, the observability analyses give:

$$u_z^5 = (0.60 \quad 1.0 \quad 0.048 \quad 0)^T$$

and the rank of $W_O^5 = 3$ which is not equal to the state dimension hence the model is again not observable, and the same conclusion as made for the previous sensor configuration holds.

Sensor configuration $y_r^6(k) = y_4(k)$

For this sensor configuration, the observability analyses give:

$$u_z^6 = (1.0 \quad 4.3 \cdot 10^{-7} \quad 0.45 \quad 0.59)^T$$

and the rank of $W_O^6 = 4$ which is equal to the state dimension hence the model is observable. So, the analysis indicates that by only measuring the indoor humidity, the lettuce's biomass and other three indoor climate variables can be estimated via data assimilation. However, estimating the CO_2 appears again to be relatively difficult.

DISCUSSION

For precision horticulture, crop states are required. A controller can take these states into account to optimize the greenhouse's efficiency and crop quality. However, the desired crop states (like biomass) are in general not available in standard greenhouses. A grower can invest in relatively expensive measurement devices such as cameras and the development of algorithms that infer the required crop information from the captured images. Another approach is to estimate crop information from readily available measurements such as indoor CO_2 and temperature. One way to do this is via data assimilation (like Kalman filtering). Here, a model and measurement are used in an algorithm to estimate the desired state variable (such as crop biomass). In order to be able to do this, the employed model in the data assimilation algorithm needs to be observable.

Different methods exit in the literature to analyze observability. The method used in this work is based on the empirical gramian. This is a matrix that is constructed from simulation data given a specific sensor configuration. This implies that, for any simulator, the empirical gramian can be used to ensure observability. Even when the simulator contains nonlinearities like, e.g., if/else statements. However, due to these nonlinearities, the observability analysis is only valid for specific initial conditions $\bar{x}(0)$ (different stages in the growth cycle) and around a specific trajectory. It is indeed important to only consider realistic initial conditions and trajectories. Nevertheless, the analysis can reveal if crop states (or in general the complete state) can be estimated from standard measurements through data assimilation given these constraints.

CONCLUSIONS

This paper demonstrated the application of an observability analysis in a lettuce greenhouse for different sensor configurations assuming knowledge about the weather $d(k)$. The results show that the crop's biomass can be estimated from indoor climate measurements (sensor configuration $y_r^1(k)$). Moreover, measuring the indoor temperature does not yield an improvement of the observability measure (sensor configuration $y_r^2(k)$), which indicates that investing in indoor temperature measurement devices is not necessary. Rather, an estimation of the indoor temperature can be obtained via measuring the indoor CO_2 and humidity and use these in a data assimilation technique. Finally, the observability analysis indicated that measuring only the indoor humidity (sensor configuration $y_r^6(k)$) renders the model observable, i.e., the complete lettuce greenhouse state can be estimated through data assimilation. However, the results show that estimating the indoor CO_2 is in that case relatively difficult. Sensor configuration $y_r^2(k)$ is shown to be the superior sensor configuration for estimating the state through data assimilation considering the employed dynamical model with initial condition $\bar{x}(0)$, weather $d(k)$ and control signal $u(k)$. However, the observability analysis should be performed for other $\bar{x}(0)$, weather $d(k)$ and control signal $u(k)$ as well in order to validate the results.

It is important to note that the results in this paper are valid for the relatively simple lettuce greenhouse model that is here employed. It is advised to also do research on a more detailed lettuce greenhouse model, which captures more dynamics. Consequently, more meaningful results will be obtained that might correspond better to practice. Nevertheless, this paper describes the observability analysis method and presents initial results and discussions for a lettuce greenhouse model. Moreover, it highlights the large potential for soft sensing methods that employ the interactions between the states in a greenhouse where only a small subset of states is monitored. The method itself can be applied to any simulator. For example, spatial models can be investigated using the observability analysis method and optimal sensor locations can be found by formulating an optimization problem that employs the empirical gramian.

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