Machine Learning Approaches for Model Identification
Applications in Agriculture Systems

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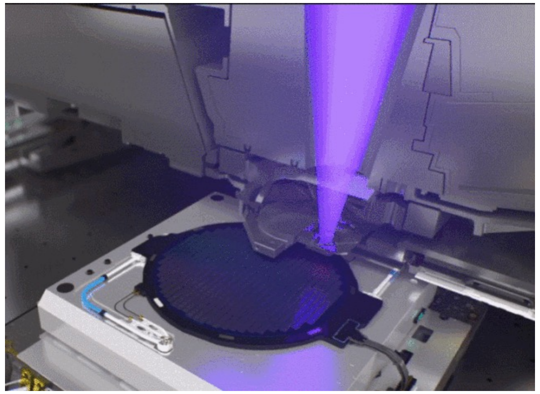
Outline

- **Domain Background**
  - Control Systems
  - Model Identification
- **Climate-Crop Modelling in Greenhouse**
  - Bayesian Neural ODE
  - Sparse Identification
- **Other applications**

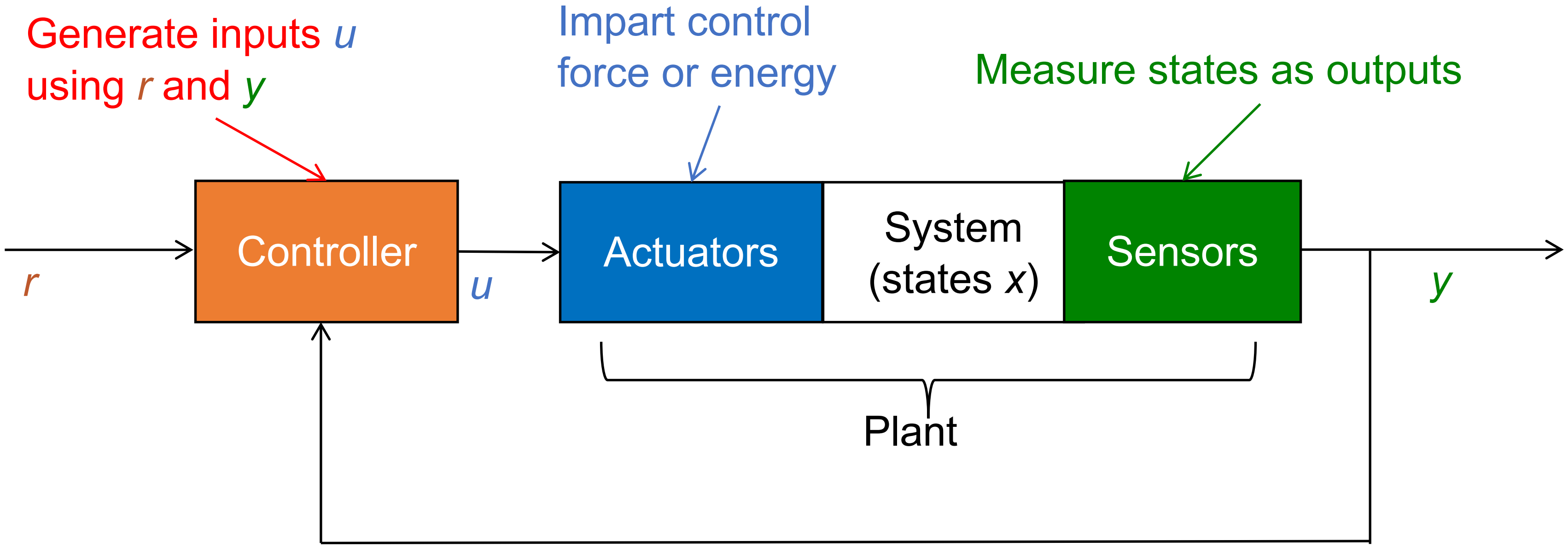
Control Systems

Landing of reusable rocket



Semiconductor manufacturing

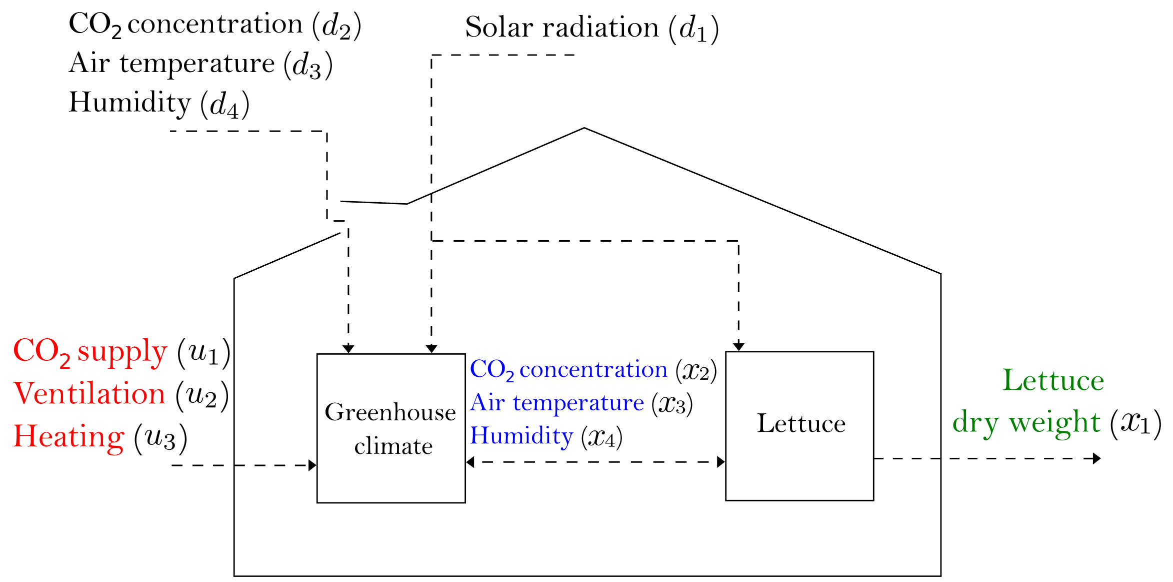
Vertical farming system

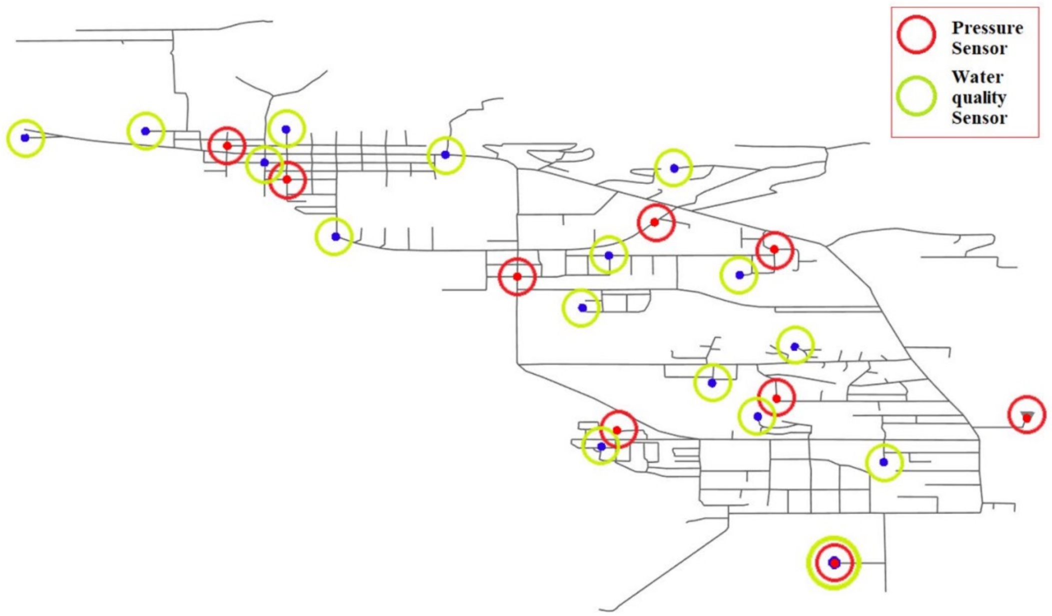


State space equation:

$$\dot{x}(t) = f(x(t), u(t))$$
$$y(t) = g(x(t), u(t))$$

Controller Design and Sensor Placement

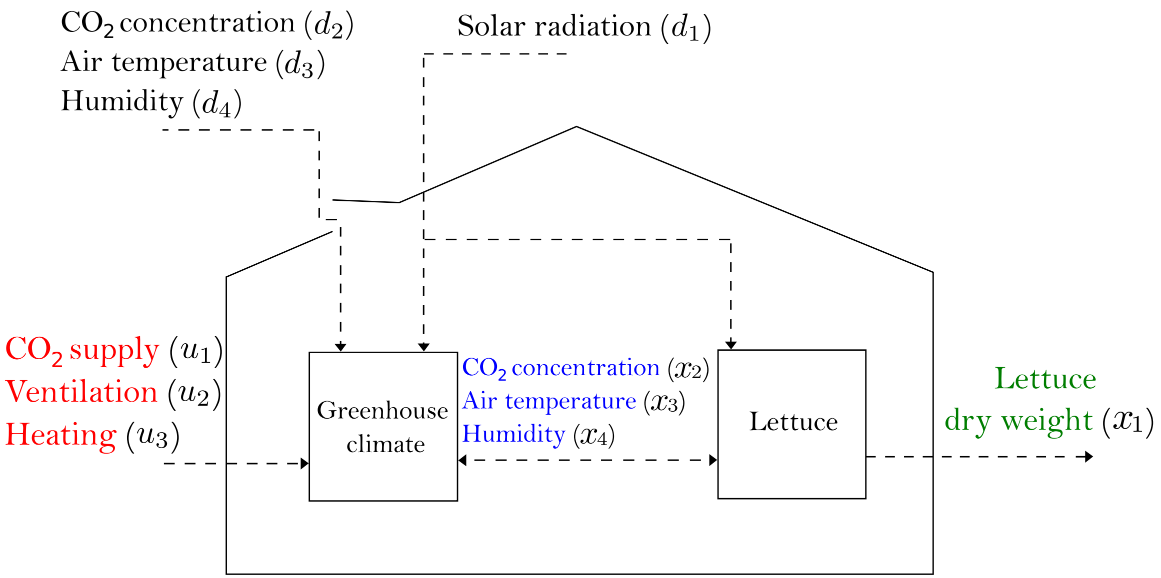




Design control signals to find a trade-off between the maximization of yield and the minimization of control energy

Place sensors in a water network to observe and predict water quality

Control Systems – A Greenhouse Example



$$\begin{pmatrix}\frac{\mathrm{d}x_1(t)}{\mathrm{d}t}\\ \frac{\mathrm{d}x_2(t)}{\mathrm{d}t}\\ \frac{\mathrm{d}x_3(t)}{\mathrm{d}t}\\ \frac{\mathrm{d}x_4(t)}{\mathrm{d}t}\end{pmatrix} = \underbrace{\begin{pmatrix} p_{1,1}\phi_{\mathrm{phot,c}}(t) - p_{1,2}x_1(t)2^{x_3(t)/10-5/2} \\ \frac{1}{p_{2,1}}\left(-\phi_{\mathrm{phot,c}}(t) + p_{2,2}x_1(t)2^{x_3(t)/10-5/2} + u_1(t)10^{-6} - \phi_{\mathrm{vent,c}}(t)\right) \\ \frac{1}{p_{3,1}}\left(u_3(t) - (p_{3,2}u_2(t)10^{-3}+p_{3,3})(x_3(t)-d_3(t)) + p_{3,4}d_1(t)\right) \\ \frac{1}{p_{4,1}}\left(\phi_{\mathrm{transp,h}}(t)-\phi_{\mathrm{vent,h}}(t)\right)\end{pmatrix}}_{f_c(x(t),u(t),d(t),p)}$$

with

$$\phi_{\mathrm{phot,c}}(t) = \Big(1-\exp\big(-p_{1,3}x_1(t)\big)\Big)\Big(p_{1,4}d_1(t)\big(-p_{1,5}x_3(t)^2 + \ldots$$

$$p_{1,6}x_3(t) - p_{1,7}\big)\big(x_2(t)-p_{1,8}\big)\Big)/\varphi(t),$$

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

$$\phi_{\mathrm{vent,c}}(t) = \big(u_2(t)10^{-3} + p_{2,3}\big)\big(x_2(t) - d_2(t)\big),$$

$$\phi_{\mathrm{vent,h}}(t) = \big(u_2(t)10^{-3} + p_{2,3}\big)\big(x_4(t) - d_4(t)\big),$$

$$\phi_{\mathrm{transp,h}}(t) = p_{4,2}\Big(1-\exp\big(-p_{1,3}x_1(t)\big)\Big)$$

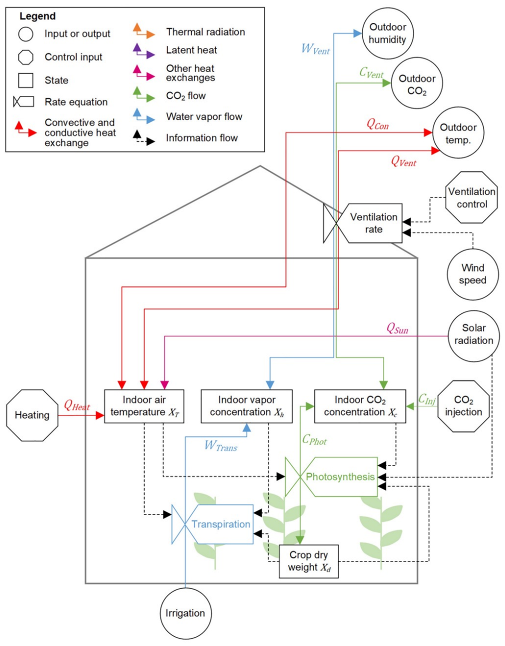
$$\left(\frac{p_{4,3}}{p_{4,4}(x_3(t)+p_{4,5})}\exp\left(\frac{p_{4,6}x_3(t)}{x_3(t)+p_{4,7}}\right) - x_4(t)\right).$$

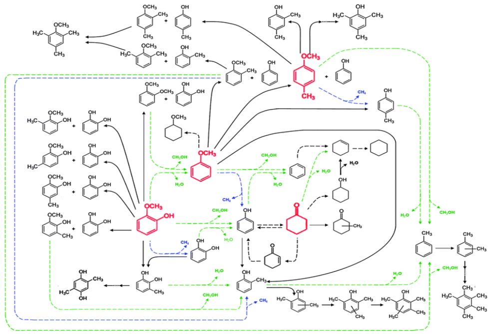
$$\begin{bmatrix}\dot{x}_1\\ \dot{x}_2\\ \dot{x}_3\\ \dot{x}_4\end{bmatrix} = f\left(\begin{bmatrix}x_1\\ x_2\\ x_3\\ x_4\end{bmatrix}, \begin{bmatrix}u_1\\ u_2\\ u_3\end{bmatrix}, \begin{bmatrix}d_1\\ d_2\\ d_3\\ d_4\end{bmatrix}\right)$$

$$f: (\mathbb{R}^4, \mathbb{R}^3, \mathbb{R}^4) \rightarrow \mathbb{R}^4$$

State-space model

Control Systems – Research Topics





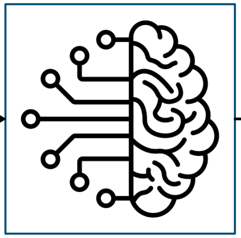
Real System

Domain Knowledge

Time-Series Data

$$\dot{x}(t) = f(x(t), u(t))$$
$$y(t) = g(x(t), u(t))$$

Dynamic Model (Differential Equations)

y →  → u

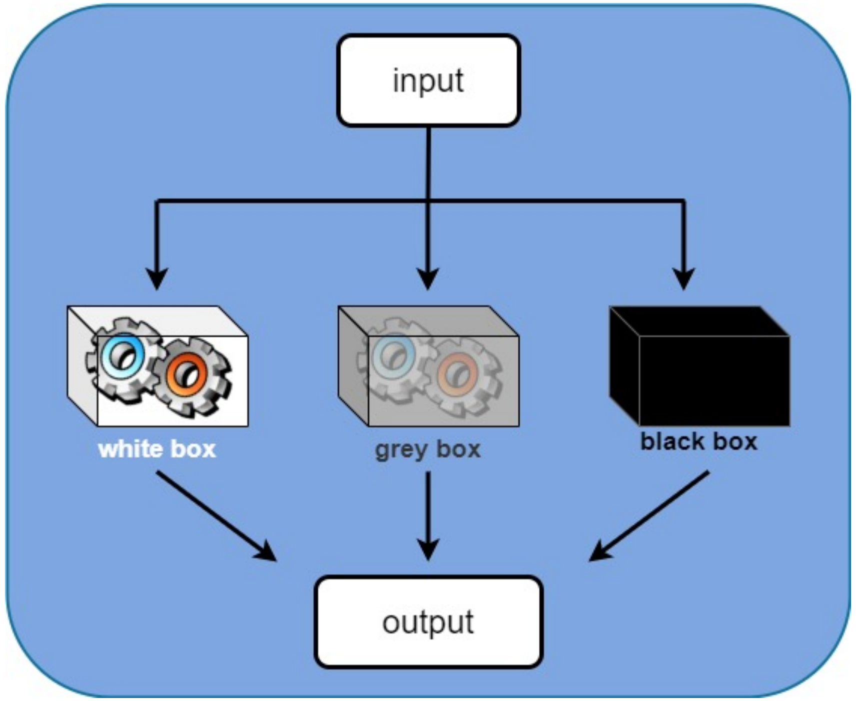
Control Design

Control Commands

Research Topics:

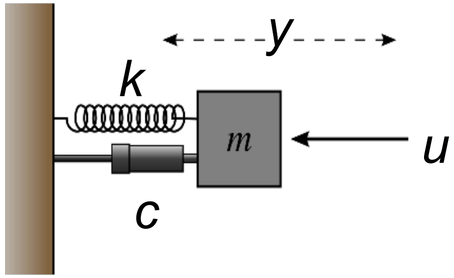
- Model identification: build mathematical input-output predictive models of dynamical systems
- Control optimization: sensor/actuator allocation, state estimation (soft sensing), design control signals

Model Identification



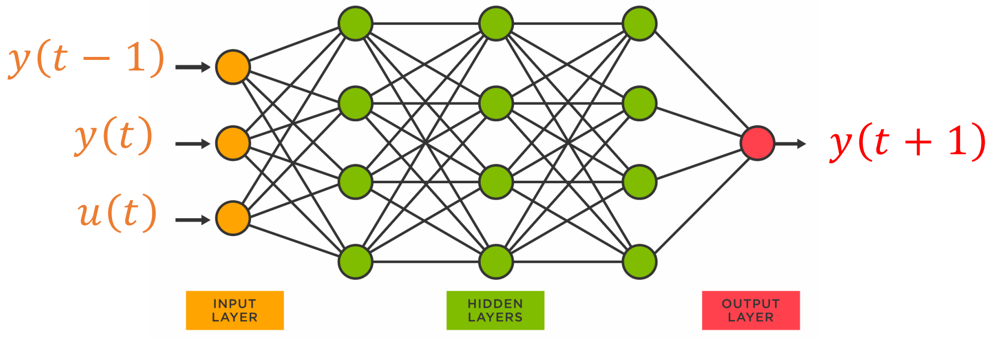
- Grey-box modeling combines data and physical/physiological knowledge
  - Physical guided machine learning
  - Modeling with uncertainty
  - Parameter identification

- White-box models are based mainly on knowledge about the system (differential/difference equations)



$$\ddot{y} + \frac{c}{m}\dot{y} + \frac{k}{m}y = \frac{1}{m}u$$

- Black-box models are built only on statistical information from the data (deep learning, transfer functions id)



$$y(t+1) = f(\, y(t), y(t-1), u(t))$$

Applications in Agriculture Systems

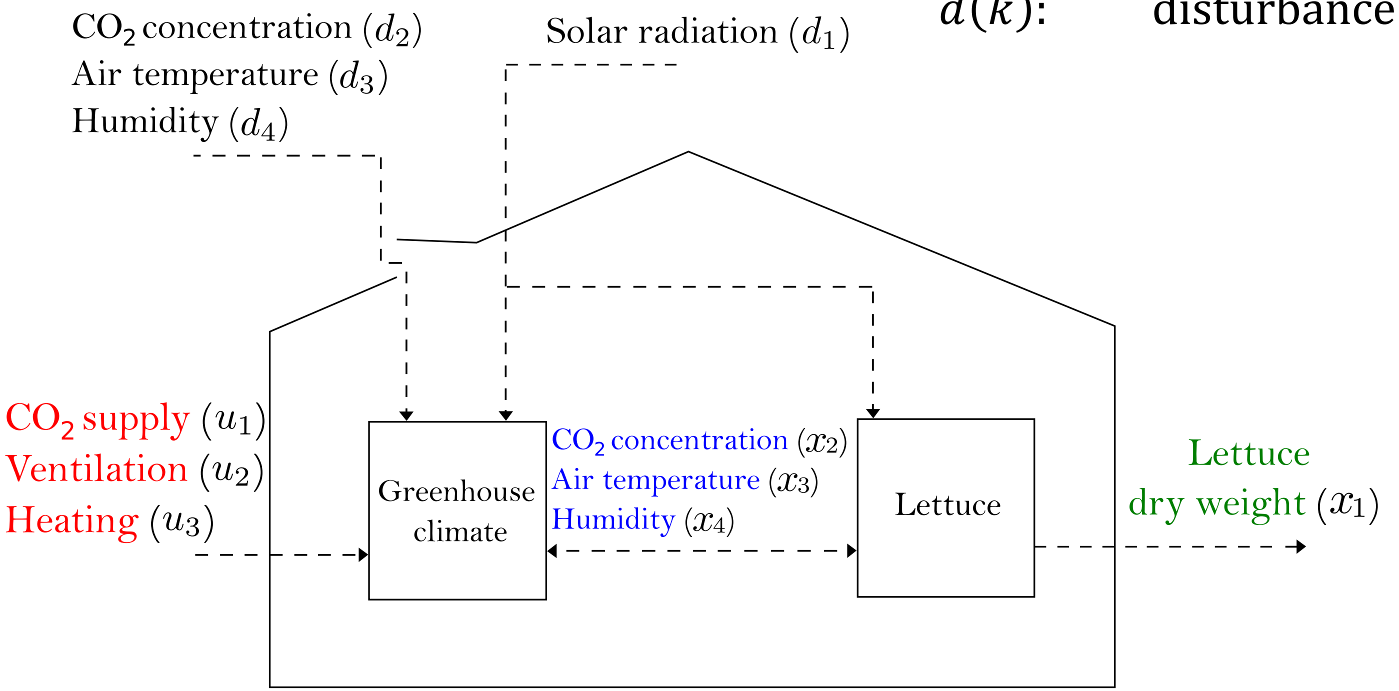
- Bayesian deep learning for greenhouse crop-climate modelling
  (uncertainty, Bayesian Neural ODE)

- Sparse identification in greenhouse crop-climate modelling
  (sparse regression, library of nonlinear functions, interactions)

Bayesian Neural ODE in Lettuce Greenhouse

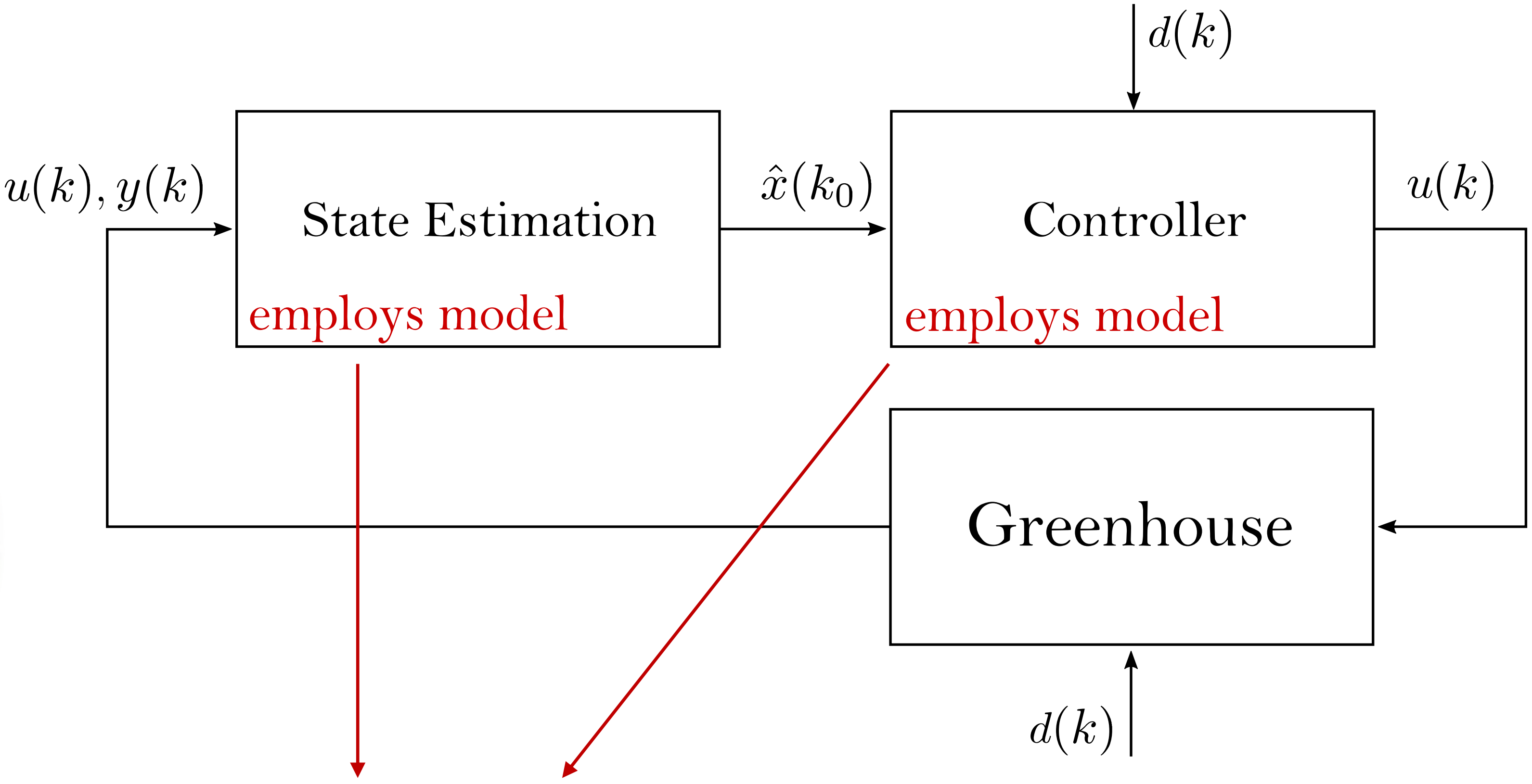
System Setup

$x(k)$: state
$u(k)$: control signal
$d(k)$: disturbance



Bayesian Neural ODE in a Lettuce Greenhouse

Problem Statement



- identify a surrogate model for estimation and control
- characterize uncertainties

$$
\begin{aligned}
x(k+1) &= f\big(x(k), \dots, x(k-N_p), u(k), d(k), \theta\big) \\
y(k) &= g\big(x(k), \dots, x(k-N_p), u(k), d(k), \theta\big)
\end{aligned}
$$

Bayesian Neural ODE in a Lettuce Greenhouse

Problem formulation as optimalization

Prediction data
(generated by model)

Measurement data

$$\min_{f,g,\mu_\theta,\sigma_\theta} \mathbb{E} \sum \|y(k) - \hat{y}(k)\|_2 + \text{regularisation}$$

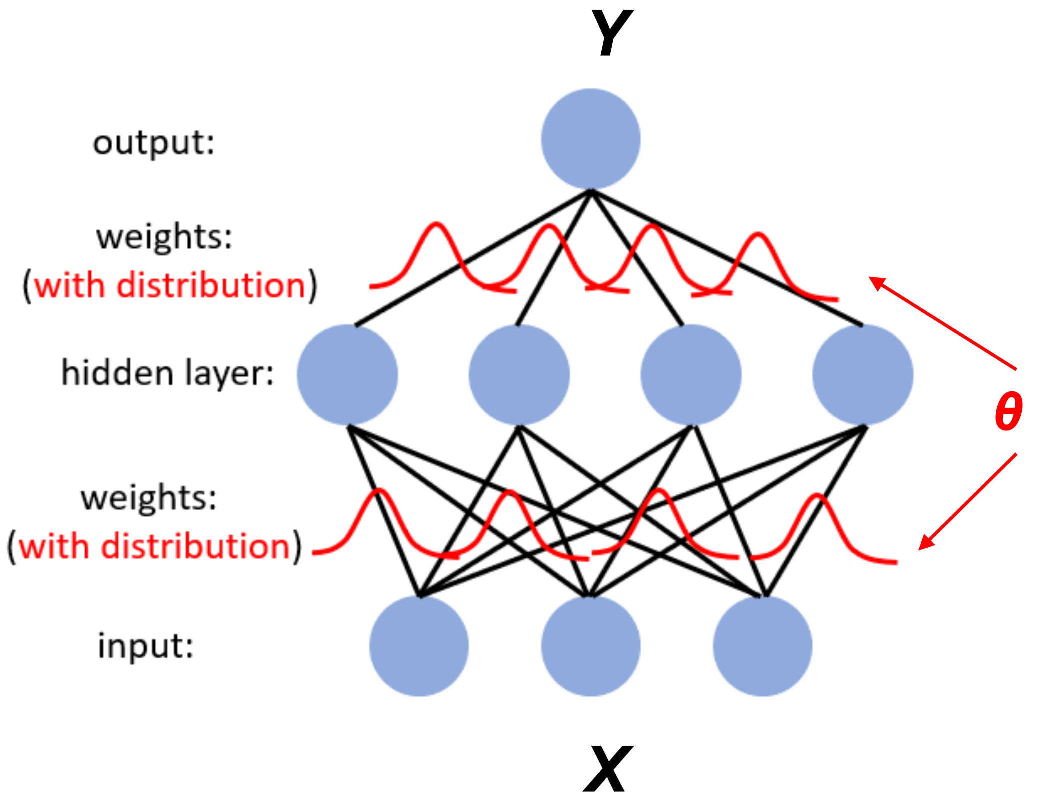
subject to

$$\begin{aligned} x(k+1) &= f\left(x(k), \dots, x\left(k - N_p\right), u(k), d(k), \theta\right) \\ y(k) &= g\left(x(k), \dots, x\left(k - N_p\right), u(k), d(k), \theta\right) \\ x(0) &= \hat{x}(0) \\ \theta &\sim \text{Gaussian}(\mu_\theta, \sigma_\theta) \end{aligned}$$

Bayesian Neural ODE in a Lettuce Greenhouse

Method: Bayesian deep learning

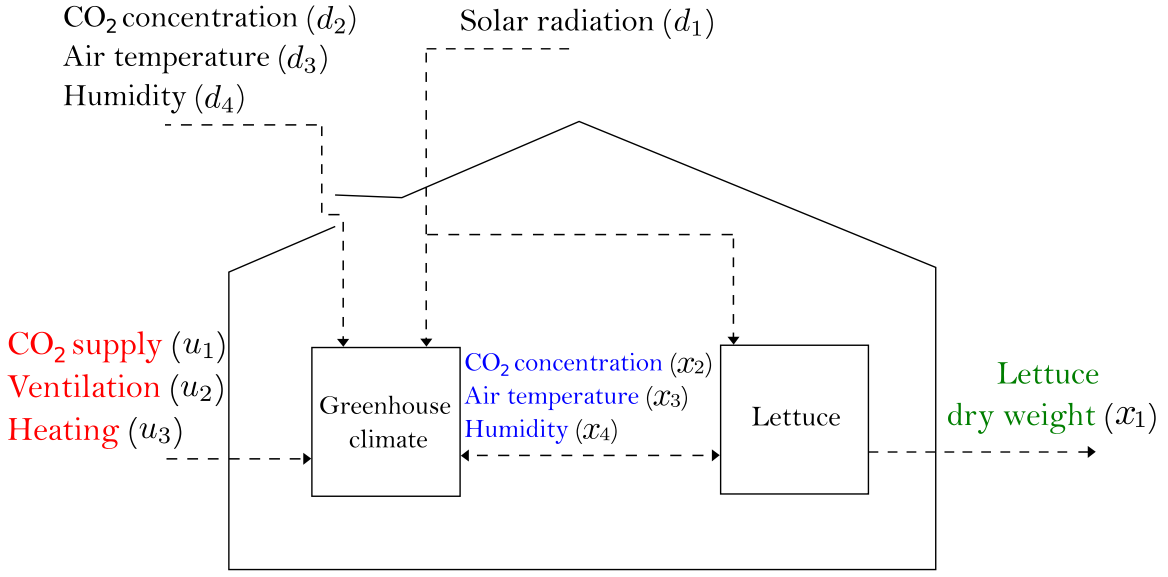
- Dataset ***D***: input ***X*** and output ***Y***
- Deterministic NN: find $\boldsymbol{\theta}$ leading to max likelihood
  - Likelihood ***P*(*D*|$\boldsymbol{\theta}$)** with $\boldsymbol{\theta}$ the NN weights: the probability of data ***D*** given $\boldsymbol{\theta}$
- In Bayesian NN, $\boldsymbol{\theta}$ have distribution ***P*($\boldsymbol{\theta}$)** (e.g., normal distribution)
  - parameters in ***P*($\boldsymbol{\theta}$)** : means and variances
- Bayesian inference is to estimate the distribution from data ***D***, i.e. ***P*($\boldsymbol{\theta}$|*D*)**

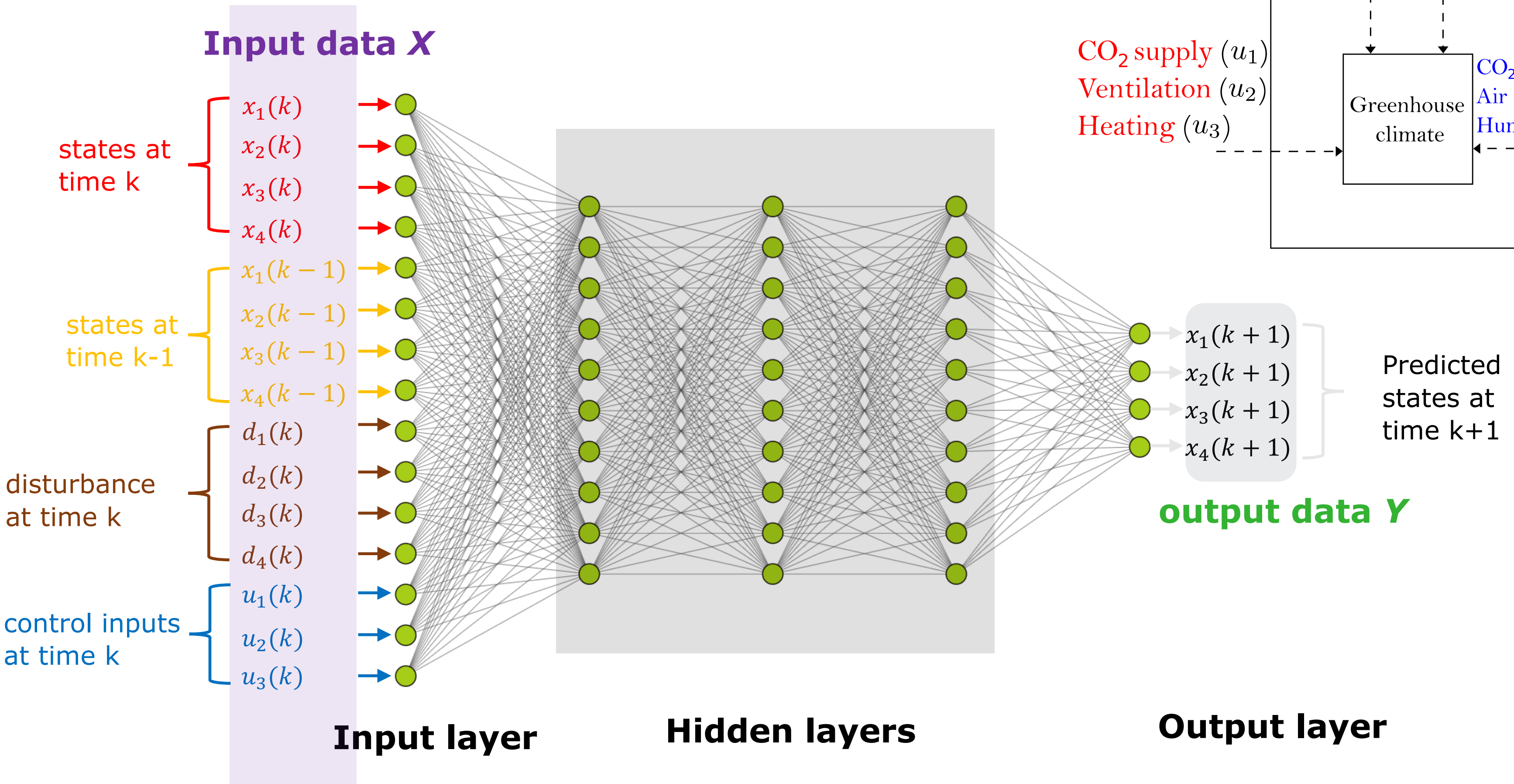


- model parameters and prediction uncertainties can be quantified with probabilities
- Bayesian method enables to train a neural network with a relatively small dataset

Bayesian Neural ODE in a Lettuce Greenhouse

states	disturb.	control
x_1: dry-weight	d_1: radiation	u_1: CO2 injection
x_2: indoor CO2	d_2: outdoor CO2	u_2: ventilation
x_3: indoor temp.	d_3: outdoor temp.	u_3: heating
x_4: indoor humidity	d_4: outdoor humidity	

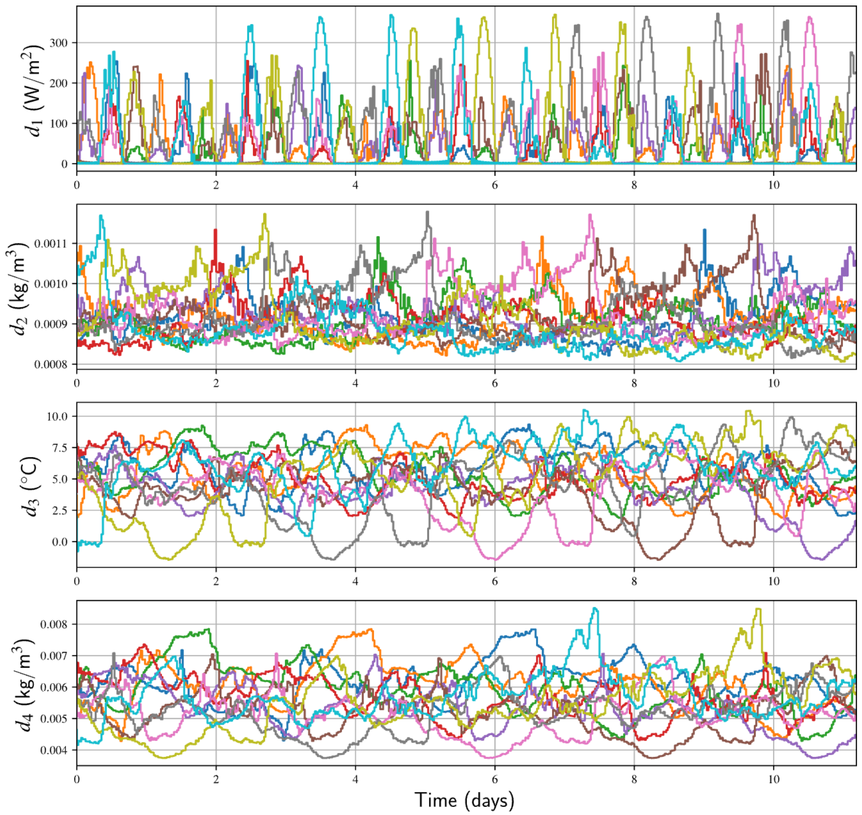


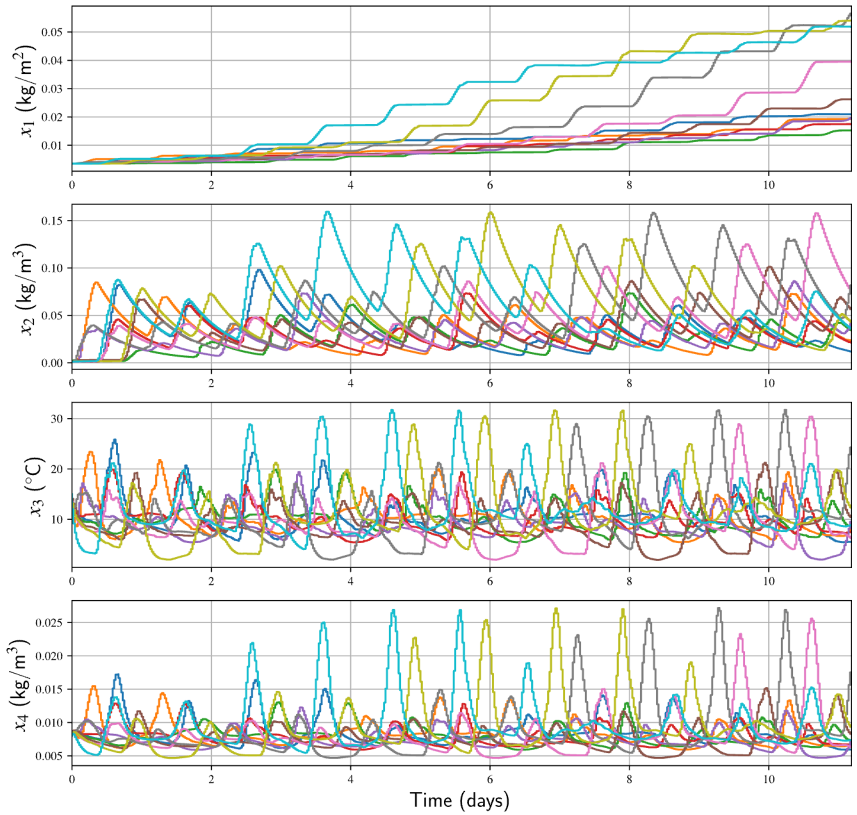


Use a neural network to approximate the system's differential equation

Bayesian Neural ODE in a Lettuce Greenhouse

Training data – multiple scenarios (different weather conditions and plant growth)





d_1: radiation

d_2: outdoor CO2

d_3: outdoor temp.

d_4: outdoor humidity

x_1: dry-weight

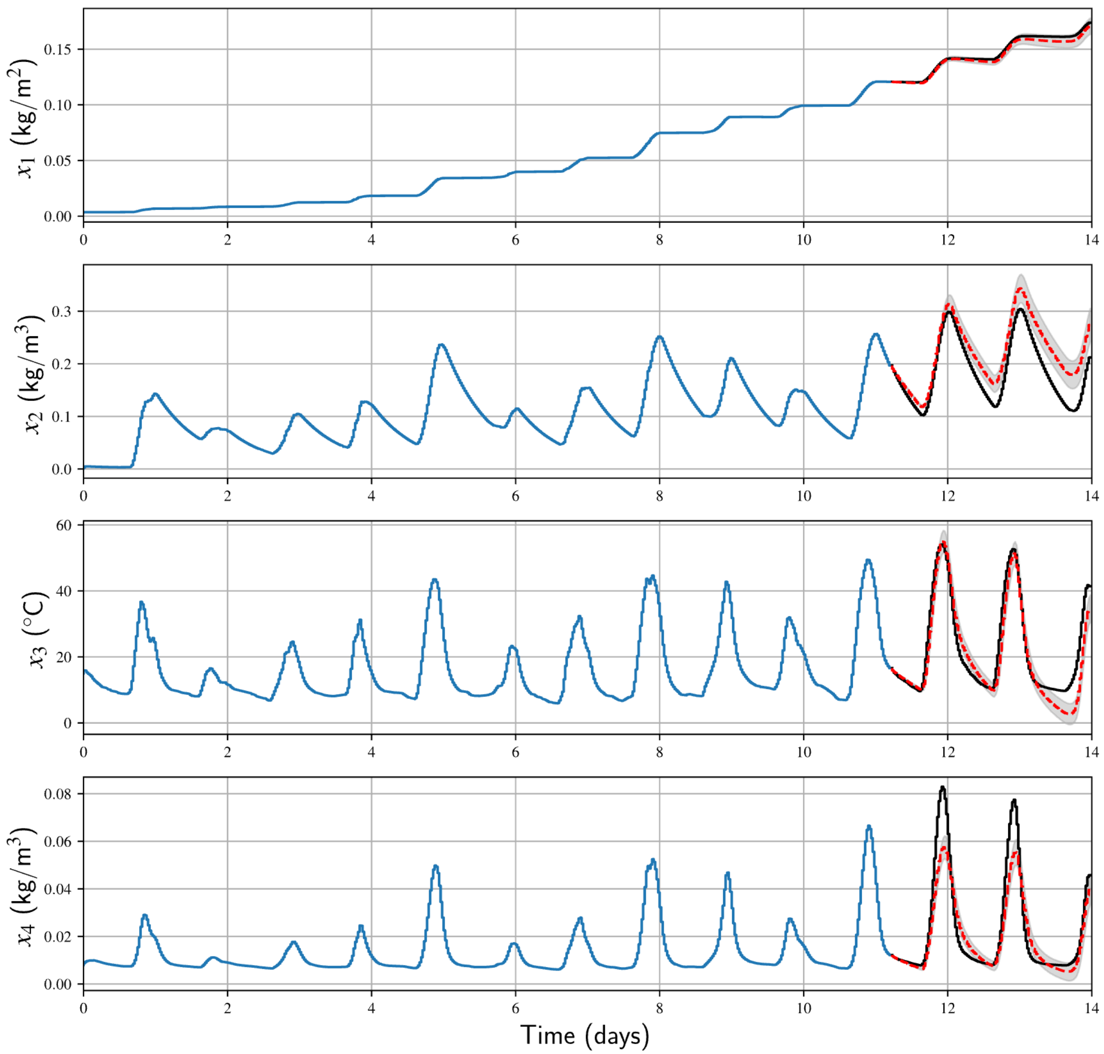
x_2: indoor CO2

x_3: indoor temp.

x_4: indoor humidity

Bayesian Neural ODE in Lettuce Greenhouse

Validation



x_1: dry-weight

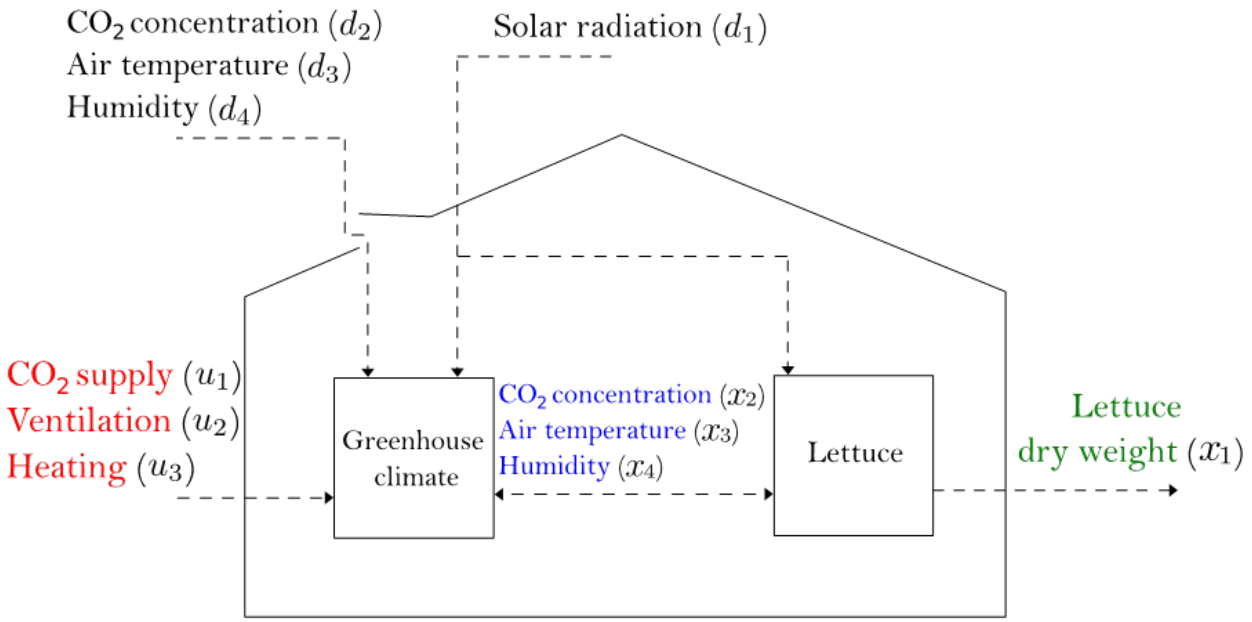
x_2: indoor CO2

x_3: indoor temp.

x_4: indoor humidity

posterior predictive distribution

Greenhouse Crop-Climate Modelling



Can we learn ordinary differential equations from input-output data?

$$\frac{dx}{dt} = f(x(t), u(t), d(t), \theta)$$
$$\frac{dy}{dt} = g(x(t), u(t), d(t), \theta)$$

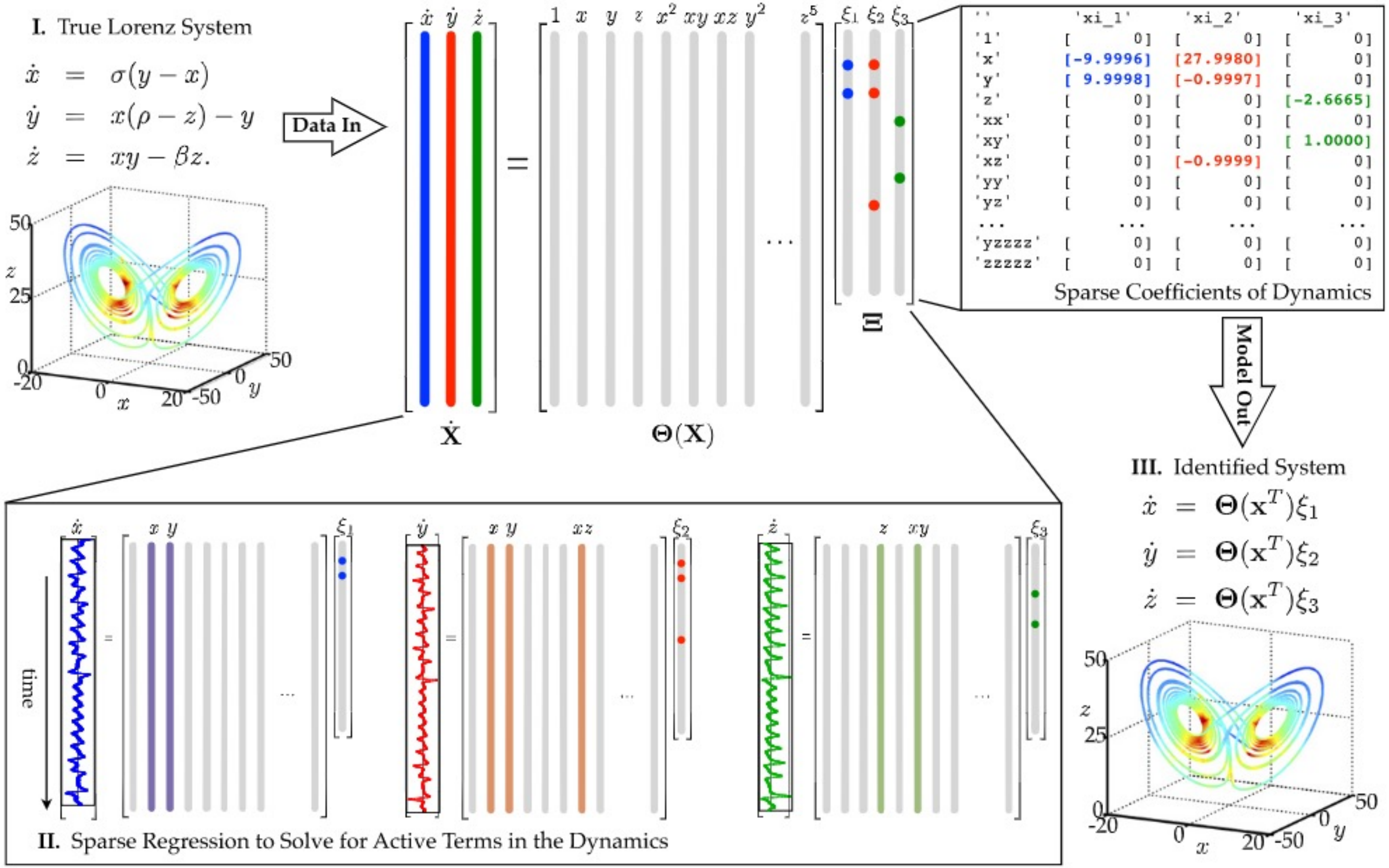
f and g are differential equations

Sparse Identification of Crop-Climate Models

SINDy:
sparse identification of nonlinear dynamical systems

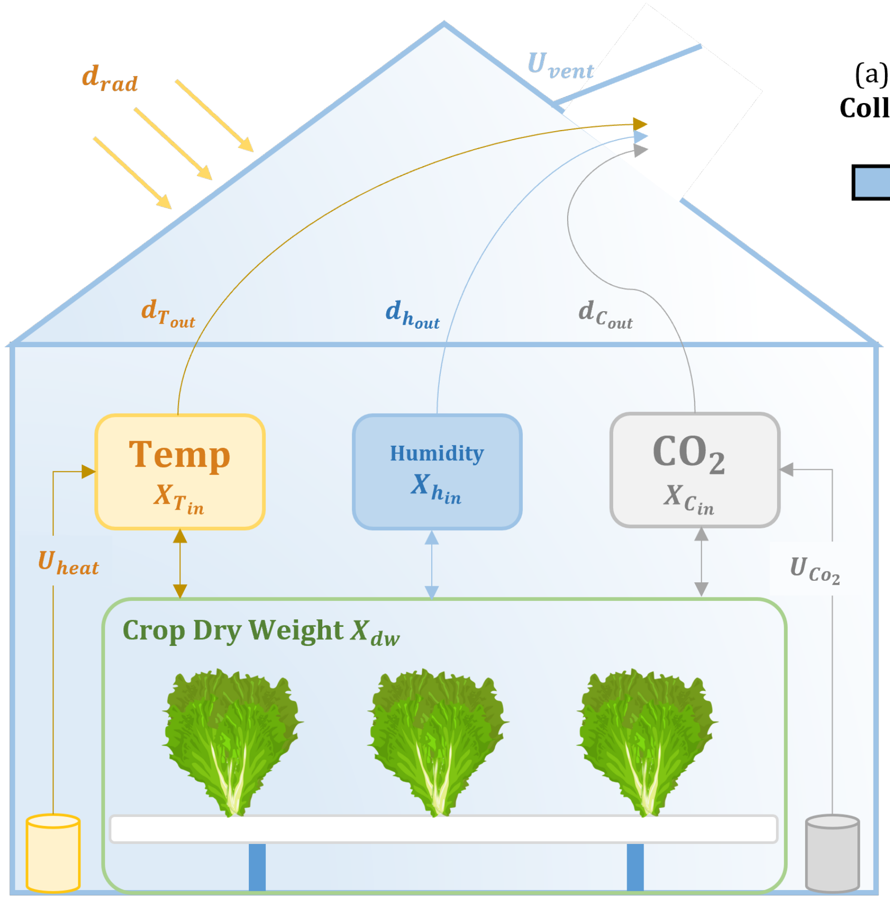
- a library of nonlinear candidate functions
- a sparsity-promoting regression

$$\boxed{\xi_k = \arg\min_{\xi'_k} ||\dot{\mathbf{X}}_k - \boldsymbol{\Theta}(\mathbf{X})\xi'_k||_2 + \lambda||\xi'_k||_1}$$

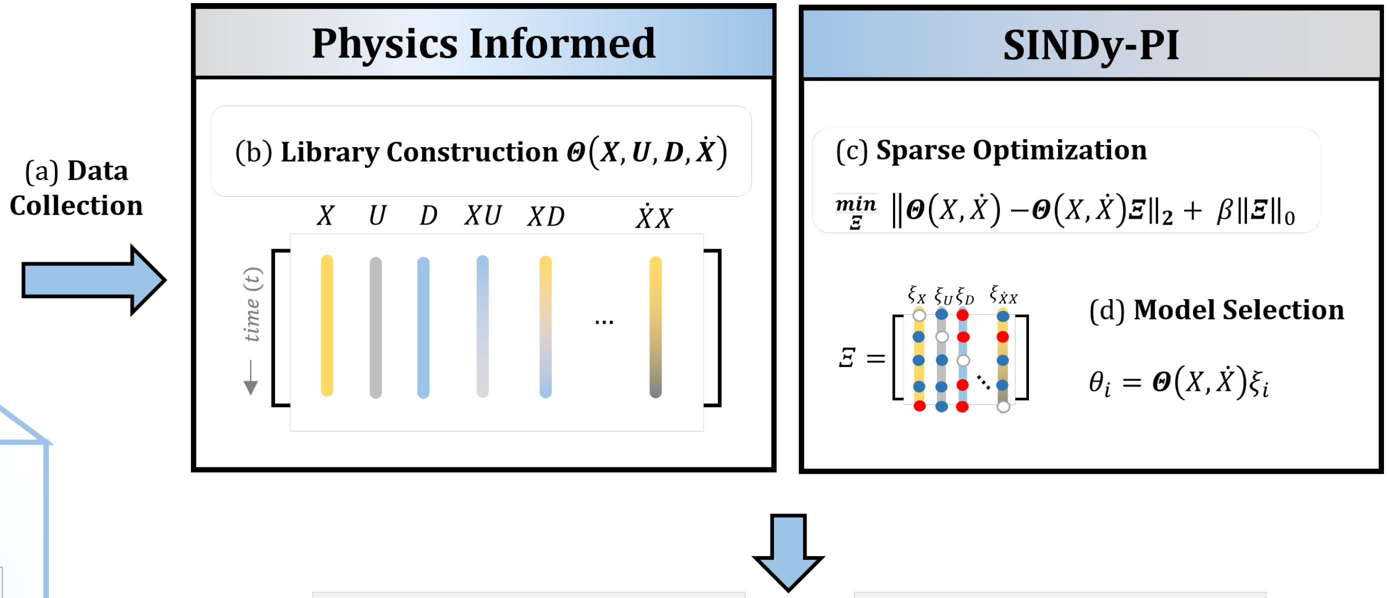


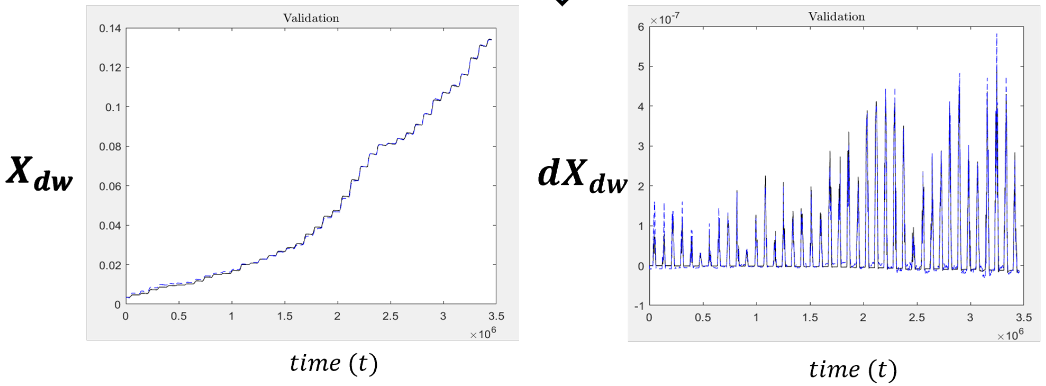
Brunton S., Proctor J., and Kutz J. (2015). Discovering governing equations from data by sparse identification of nonlinear dynamical systems. *Proceedings of the National Academy of Sciences of the United States of America, (2016), 3932-3937, 113(15)*

Greenhouse Crop-Climate Modelling



Lettuce Greenhouse System





Extracted Equation

$$\boldsymbol{dX_{dw}} = (5.0e^{-13}(5.34e^{-5} + d_{rad} - 2.67e^{9}X_{dw} + 1.1e^{11}X_{C_{in}} - 1.03e^{-7}X_{T_{in}} + 1.36e^{7}d_{rad}X_{dw} + 7.46e^{8}d_{rad}X_{C_{in}} + 49370\, d_{rad}X_{T_{in}} + 2.8e^{12}X_{dw}X_{C_{in}} + 5.13e^{7}X_{dw}X_{T_{in}} + 7.214e^{9}X_{C_{in}}X_{T_{in}} + 4.33e^{9}{X_{dw}}^{2} - 1.11e^{14}{X_{C_{in}}}^{2} + 2.01e^{5}{X_{T_{in}}}^{2}))/(34690{X_{dw}}^{2} + 5e^{5}X_{C_{in}})$$

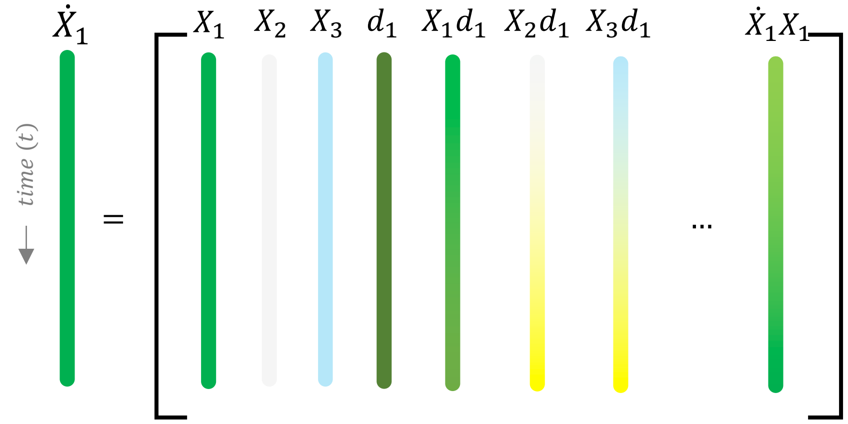
Greenhouse Crop-Climate Modelling

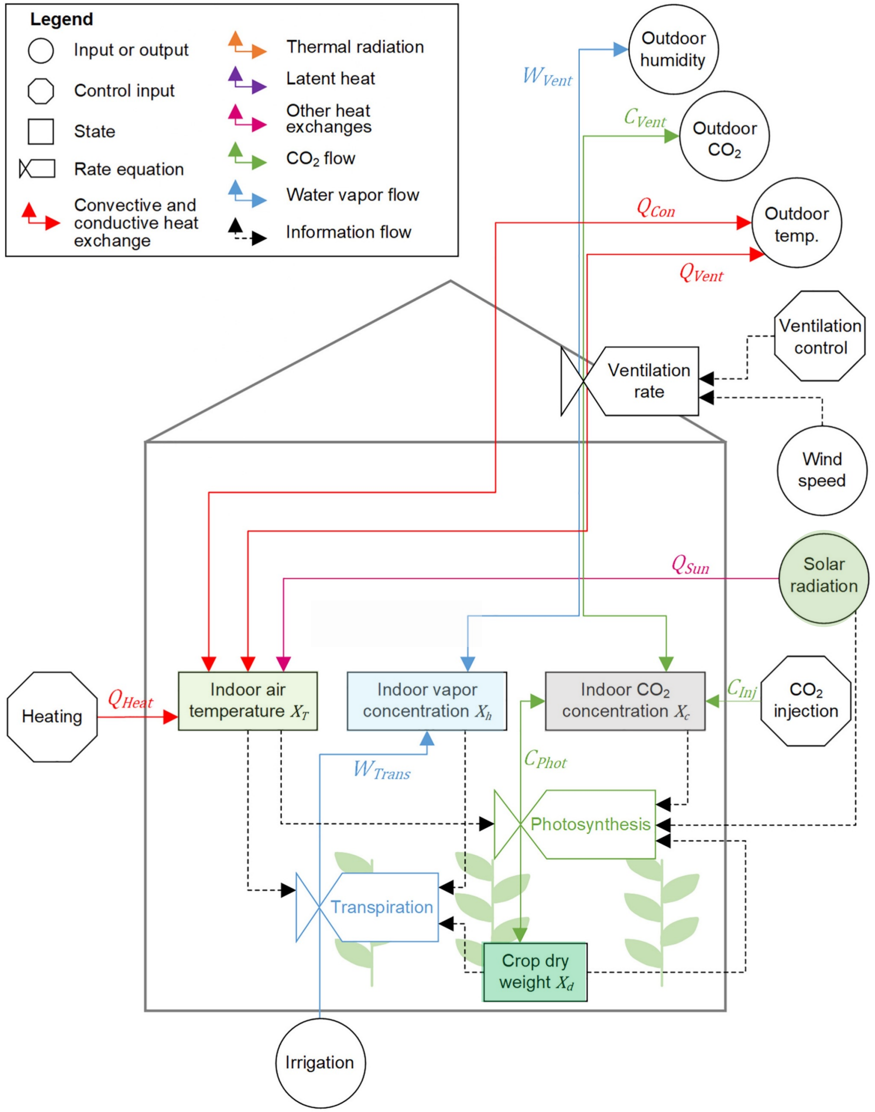
Physics-Guided ML:

- Incorporating interconnection structure of variables into library construction
- Reduce the size of function library

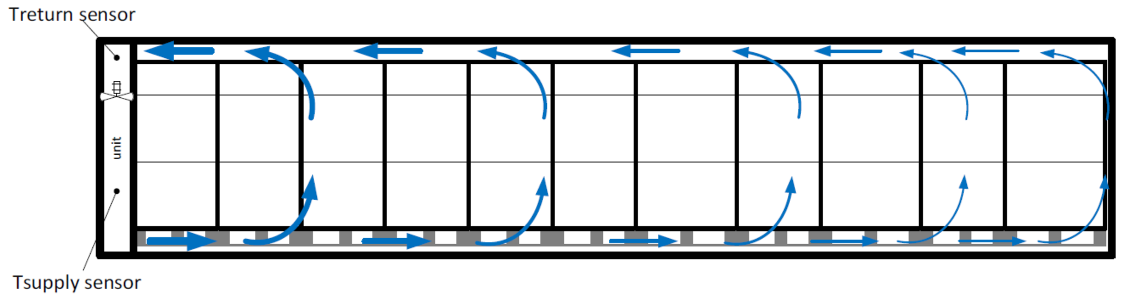
Library Construction $\boldsymbol{\Theta}(\boldsymbol{X}, \boldsymbol{U}, \boldsymbol{D}, \dot{\boldsymbol{X}})$

$X_1 = X_{DW}$(Lettuce Dry weight)

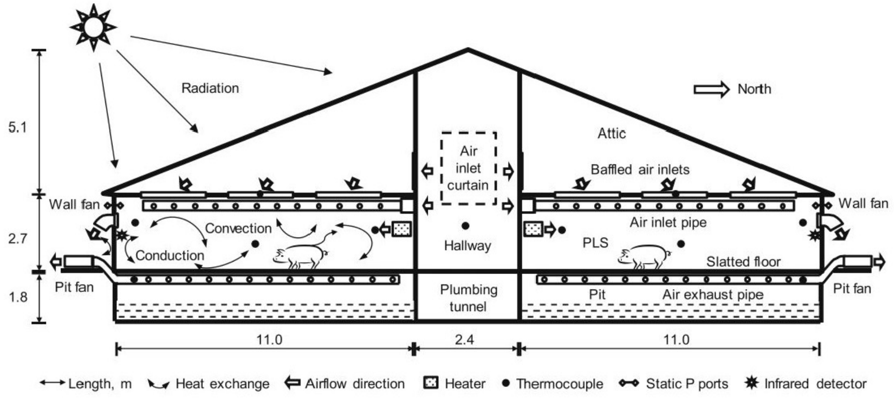




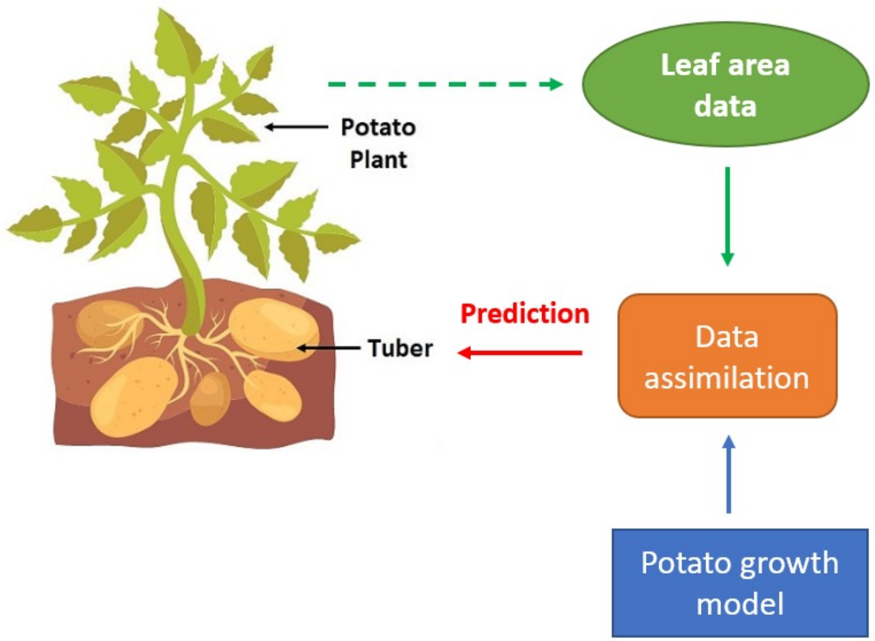
More Applications



Sensor placement in a reefer container
to gain a sufficiently accurate estimate of the temperatures of the complete cargo



Heat stress mitigation in livestock barns
Heat stress prediction using sensor data and animal behavior analysis



Tuber weight estimation
- Is it possible to estimate the tuber weight from a leaf area measurement?
- Can the measurement be combined with model prediction to give reliable tuber weight estimation and prediction?

Take-Home Messages

- "*All models are wrong, but some are useful*" (George E. P. Box)
  Usefulness depends on how you use your models
- Uncertainty and interpretability are also important factors, aside from accuracy
- Many applications of scientific machine learning in agriculture