Capturing Biocides Uptake: Model Development Under Uncontrolled Uncertainties

E. Sangoi * **F. Cattani** ** **F. Galvanin** *

* *Department of Chemical Engineering, University College London (UCL), Torrington Place, WC1E 7JE, London, United Kingdom (e-mail: enrico.sangoi.19@ucl.ac.uk, f.galvanin@ucl.ac.uk)*
** *Process Studies Group, Global Sourcing and Production, Syngenta, Jealott's Hill International Research Centre, Berkshire, Bracknell, RG42 6EY, United Kingdom (e-mail: federica.cattani@syngenta.com)*

1. INTRODUCTION

Crop protection science plays a role in responding to the challenge of food demand with growing population and climate change. Mathematical models able to predict the interactions between the biocides and the crops can be exploited to develop new products that are also safer for the environment, aligning with sustainable agricultural practices (Umetsu and Shirai (2020)), at a lower cost and time to the market.

This project focuses on modelling the foliar uptake of pesticides (Wang and Liu (2007)). The goal is to obtain a reliable model to describe the phenomena taking place when the formulated active ingredients (AI) are sprayed on the crops leaves and to predict the percentage of AI uptake by the crop. Since plants are biological systems, there is biological variability between different species, between plants of the same species, and also between leaves of the same plant. This variability is reflected in the large variance observed in the experimental data used to calibrate the model. Another source of uncertainty is the fact that the physico-chemical phenomena affecting it are strictly correlated and observing them independently is extremely challenging. Therefore, an objective is also to understand the trade-off between complexity and explainability of the model, to guarantee that eventually the uncertainty in the model predictions and the correlations between the model parameters are acceptable.

In the literature there has been several works towards the modelling of the foliar uptake of pesticides, ranging from simple empirical correlations (Forster et al. (2004)), to compartmental models (Bridges and Farrington (1974)), up until more detailed physics-based ones (Tredenick et al. (2019)). However, the effect of the parametric uncertainty in order to guarantee the applicability of the model in predictions has not been addressed in detail in the previous works.

The novelty in this research is that the predictive mathematical model is used also to optimize the experimental campaigns, allowing a better exploitation of time and resources, and to achieve this result is fundamental to systematically take in to account the uncertainty in predictions.

2. METHODOLOGY

The modelling procedure is adapted from Franceschini and Macchietto (2008) and the framework is shown in Fig. 1.

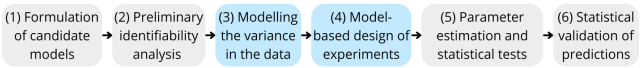

Fig. 1. Model building approach based on Franceschini and Macchietto (2008). The focus of this paper is on the steps 3 and 4, highlighted in blue.

The framework consists of 6 key steps:

(1) Formulation of different candidate models to describe the system under study.
(2) Preliminary analyses on the identifiability of the model parameters are conducted and any identifiability issue is addressed.
(3) A model is fit to characterise the variability in the experimental data.
(4) The application of Model-Based Design of Experiments (MBDoE) techniques for model discrimination and for parameter precision (Franceschini and Macchietto (2008)).
(5) The model parameters are precisely estimated and validated statistically.
(6) The model predictions are validated based on new experimental data and the statistics of model predictions.

Steps (1) and (2) of this procedure have been addressed by the authors in Sangoi et al. (2024a,b), where different formulations of dynamic models for foliar uptake mechanism are presented, while this paper focuses on the MBDoE (step 4 of the procedure).

2.1 Model-Based Design of Experiments

To describe the dynamics of AI leaf uptake we consider dynamic models generally formulated as in

$$\begin{aligned} \dot{\boldsymbol{x}}(t) &= \boldsymbol{f}(\boldsymbol{x}(t), \boldsymbol{u}(t), \boldsymbol{\theta}, t) \\ \hat{\boldsymbol{y}}(t) &= \boldsymbol{g}(\boldsymbol{x}(t), \boldsymbol{u}(t), \boldsymbol{\theta}) \end{aligned} \tag{1}$$

where $\boldsymbol{x} \in \mathbb{R}^{N_x}$ is a vector of state variables, $\dot{\boldsymbol{x}} \in \mathbb{R}^{N_x}$ indicates the time derivatives of the states, $\hat{\boldsymbol{y}} \in \mathbb{R}^{N_y}$ the

DOI: 10.34726/9002

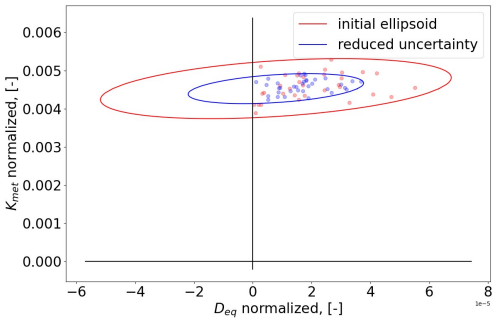

Fig. 2. Sampling of the parameter uncertainty region.

vector of predicted model outputs, $\boldsymbol{u} \in \mathbb{R}^{N_u}$ the vector of known system inputs, $\boldsymbol{\theta} \in \mathbb{R}^{N_\theta}$ the model parameters vector. The model considered in this paper is diffusion-based with no flux boundary conditions (Sangoi et al., 2024a), with three parameters: i) the partition between the droplet and the leaf K_{DL}, ii) the equivalent diffusion of AI through the leaf D_{eq}, iii) the metabolism rate constant (AI consumption) K_{met}. MBDoE techniques allow to exploit the mathematical formulation of the dynamic model to optimize the experimental campaigns, so that the data obtained are the most informative for the modelling task, e.g. to improve parameter precision (MBDoE-PP), and that model and experiments are coupled in a bi-directional way. To apply MBDoE-PP the information content of the experiments is generally quantified through a metric of the Fisher Information Matrix $\hat{\mathbf{H}}$ (2) or the covariance matrix of the parameter estimates $\hat{\mathbf{V}}_\theta$ (3).

$$\hat{\mathbf{H}}(\boldsymbol{\varphi}) = \nabla\hat{\mathbf{y}}(\boldsymbol{\varphi}, \hat{\boldsymbol{\theta}})\boldsymbol{\Sigma}_y^{-1}\nabla\hat{\mathbf{y}}(\boldsymbol{\varphi}, \hat{\boldsymbol{\theta}}) \tag{2}$$

$$\hat{\mathbf{V}}_\theta(\boldsymbol{\varphi}) \simeq \left[\hat{\mathbf{H}}(\boldsymbol{\varphi})\right]^{-1} \tag{3}$$

In equation (2), the symbol $\boldsymbol{\varphi}$ stands for the experimental design vector, in this application defined by the sampling times in biokinetic experiments of uptake, and $\boldsymbol{\Sigma}_y$ represents the covariance matrix of the measurement error. Therefore in order to apply successfully MBDoE techniques it is crucial to characterise the uncertainty associated to the experiments (step 3 of the procedure in Fig. 1). MBDoE allows to optimise the experimental design vector $\boldsymbol{\varphi}$. This can be approached also by minimising the uncertainty in model predictions $\hat{\mathbf{V}}_y$ (Cenci et al. (2023)) instead of $\hat{\mathbf{V}}_\theta$, an option that can be useful in the foliar uptake case study to guarantee that the final model is reliable in its predictions.

3. RESULTS

As a preliminary study before the application of MBDoE, the results of the error propagation from the parameters to predictions are presented. Samplings are collected from the parameters uncertainty region, obtained from parameter estimation, with a Monte Carlo simulation (Fig. 2). An uncertainty reduction scenario is considered, assuming a 50% reduction in the standard deviation of parameters, and their effect is propagated to model predictions, i.e. the AI mass on the leaf surface and in the tissue (spatial

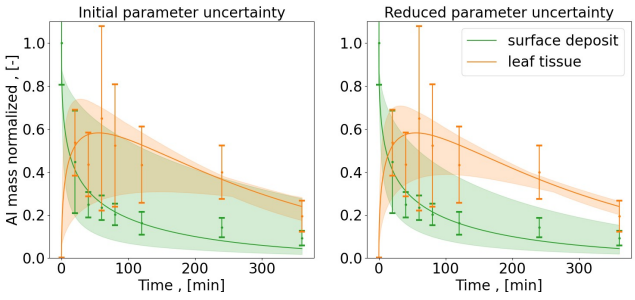

Fig. 3. Monte Carlo based uncertainty propagation from model parameters to the predictions.

integral of the discretized variable). Results on prediction uncertainty are shown in Fig. 3: the lower parameter uncertainty allows to sensibility reduce the prediction uncertainty for the AI on the leaf surface (green area), aligning with the observed experimental variability shown via the error bars. This analysis paves the way to the application of MBDoE techniques in the context of biological systems, in particular for the foliar application of biocides.

ACKNOWLEDGEMENTS

The authors gratefully acknowledge the support of the Department of Chemical Engineering - UCL and Syngenta.

REFERENCES

Bridges, R. and Farrington, J. (1974). A compartmental computer model of foliar uptake of pesticides. *Pest. Sci.*, 5, 365—-381.

Cenci, F., Pankajakshan, A., Facco, P., and Galvanin, F. (2023). An exploratory model-based design of experiments approach to aid parameters identification and reduce model prediction uncertainty. *Comput. Chem. Eng.*, 177, 108353.

Forster, W., Zabkiewicz, J., and Riederer, M. (2004). Mechanisms of cuticular uptake of xenobiotics into living plants: 1. influence of xenobiotic dose on the uptake of three model compounds applied in the absence and presence of surfactants into chenopodium album, hedera helix and stephanotis floribunda leaves. *Pest Manag. Sci.*, 60, 1105—-1113.

Franceschini, G. and Macchietto, S. (2008). Model-based design of experiments for parameter precision: State of the art. *Chem. Eng. Sci.*, 63, 4846—-4872.

Sangoi, E., Cattani, F., Padia, F., and Galvanin, F. (2024a). Foliar uptake models for biocides: Testing practical identifiability of diffusion-based models. *IFAC-PapersOnLine*, 58(23), 73–78.

Sangoi, E., Cattani, F., Padia, F., and Galvanin, F. (2024b). Foliar uptake models for biocides: Testing structural and practical identifiability. *Comput. Aided Chem. Eng.*, 53, 37–42.

Tredenick, E., Farrell, T., and Forster, W. (2019). Mathematical modelling of hydrophilic ionic fertiliser diffusion in plant cuticles: Lipophilic surfactant effects. *Plants*, 8, 202.

Umetsu, N. and Shirai, Y. (2020). Development of novel pesticides in the 21st century. *J. Pest. Sci.*, 45, 54–74.

Wang, C. and Liu, Z. (2007). Foliar uptake of pesticides—present status and future challenge. *Pestic. Biochem. Physiol.*, 87, 1–8.