Interactive Knowledge Integration in Modelling for Food Sustainability: Challenges and Prospects

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Abstract
The availability of reliable and trustworthy models for aggri-food processes is curial to evaluate and predict the environmental impact of the process and the final quality of the product. Experiments can be performed on models to optimise their features, and, if successful, the results can be integrated into the real-world. In this context, robust and user friendly interfaces that facilitate expert knowledge integration into existing models, can help steer and optimise both the model and the model-building process itself. This in turn may help improve the eco-design of sustainable agri-food processes. In this paper, we reflect upon our previous work and highlight existing challenges in building interactive modelling tools for sustainable food systems.

Author Keywords
modelling; visualization, knowledge integration; food; sustainability.

Introduction
The agriculture and food industry are now facing a new challenge: to produce more in order to meet the current environmental challenges while maintaining the level of production and quality expected by the consumer. To address this challenge, new methodologies are constantly being developed to analyse and optimise food growing and processing. Modelling in this context is key to help understand,

predict and ultimately control biological and food-related complex systems [4].

Building models is an iterative process, consisting of *defining* a model by finding a suitable representation for objects and their relationships, *exploring* the model parameter and data space, and *tuning* and *validating* the constructed models. As a result, modelling combines computational methods, formal reasoning and expert knowledge.

The derived models are often manipulated by model builders who need to examine the different parameter settings and their interactions; biologists/agronomists who understand the intricate mechanisms of the modelled system; and decision makers who translate findings and model predictions into policies. Providing suitable interfaces to support and enrich this *human-model interaction* is important, not only to get a clear understanding of the model and the phenomena we are studying, but also to help build user trust in the constructed models.

The specifics of the food domain raise the importance of considering domain experts as model co-builders. Even for the heavily computational approaches, human skills are essential to organise, generalise and validate the model [3]. However, modelling frameworks that take into account human-model interaction at all model development stages are only subject to ongoing research [6]. Some authors investigated how to dynamically update a mathematical model (e.g. for a Camembert-type cheese ripening process) each time a new piece of information is available [5], but typically it is the model builders themselves who carry out this update. Much work is still needed to enable domain experts to become truly co-builders of these models. This requires thinking about new human-model interfaces and visualization techniques to bridge the gap between modellers and domain experts.

Integration of User Expertise in Modelling

Our previous work looked at implicit ways to capture user expertise via optimisation and interactive learning. The proposed evolutionary framework (EVE) [2, 1] combines visual analytics with stochastic optimisation to aid the exploration of multidimensional datasets. Starting from a set of data dimensions, an interactive evolutionary algorithm progressively evolves non-trivial viewpoints in the form of linear and non-linear dimension combinations that are pertinent to the user, where pertinence of a view is partly learnt from user interactions with data visualizations. This method leverages automatic tools to detect interesting visual features and human interpretation to derive meaning, validate the findings and guide the exploration without having to grasp advanced statistical concepts.

Challenges and Prospects

A different approach to implicit knowledge integration in modelling, is to explicitly ask domain experts to modify agri-food models. This approach makes models less opaque and may help build user trust. However, having experts directly manipulate models, brings forth new challenges and research questions pertinent to the HCI community, such as: (1) What types of interfaces are needed to collect experts knowledge, e.g. are ontology-based or graphical (Bayesian) models more suitable? ; (2) How much of the model and its parameters need to be accessible and modifiable by domain experts; (3) What needs to be learnt automatically, semi-automatically and what can be directly specified by experts via suitable interfaces or visualizations; (4) How to reconcile conflicts between implicit (interactive) learning and explicit user feedback; (5) How to confront data and models in a coupled and coordinated manner ; (6) How to inform the user of imperfect knowledge in the data/model, and how to capture the uncertainty in experts knowledge and feedback; (7) How to avoid user fatigue.

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