**Title**

# Amastacomod - Mathematical and Statistical Analysis of Data-Model Coupling

## Context

**Keywords:** Smart Agriculture; Stability Analysis; Data Assimilation; Database; Data-Model Coupling; Environment; Artificial Intelligence; Territorial Artificial Intelligence; Data flow; Data Driven Methods; Model Selection; Simulations; Tests.

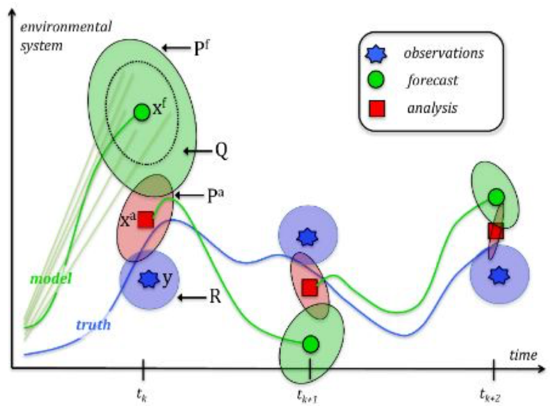


***Fig 1. Data Assimilation Principle***

Data Assimilation from a system that needs to be piloted (for example a territory, an environmental system or a breeding) is essential. It makes it possible to have a precise idea, at any moment, of the state in which the system is located; then to define how to act on it to direct it in the desired direction (see **M. Nodet & A. Rousseau** (2013)).

It is well known (since the use of the Kalman filter to locate the Apollo capsules on their journey to the moon) that to correctly perform the Data Assimilation, it is essential to have a mathematical or statistical model describing the dynamics of the system to be piloted. Indeed, the data coming back from the system being generally unreliable, they are used not in a raw way, but like a corrector of the evolution of the solution of the model. Data assimilation methods are used in this context to find an optimal mathematical compromise between the model and the available observations. The relative weight given to the model and observations is controlled by parameters that describe the model error and observations (see **P. Tandeo, P. Ailliot *et al.*** (2018)).

## Objectives

The Goal of the PhD thesis proposed here is to contribute to the formalization of the Data Assimilation approach and its applications in the targeted areas, namely the piloting of towns and counties, environmental systems or farms). Among the objectives, there will be

- identification of models used for targeted applications;
- their understanding;
- search for application-related data; their setting in database; the organization of data flow reporting;
- the discussion of the relevance of models for Data Dssimilation by building a test environment; their evolution, even their questioning;
- identification of the properties to be established for each of them
- the identification of what is settable by a mathematical analysis
- identify what can be brought by coupling this with a statistical approach using simulation;
- apply this approach to some models for some applications.

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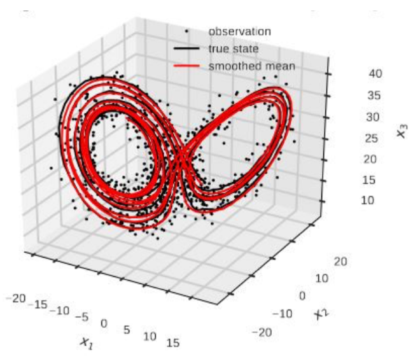
| **Novelty of the project** | <br>***Fig 2. Data assimilation in the Lorenz 63 model***<br>In the case of the systems considered for the applications of this project, given their complexity, the mathematical models used to describe the evolution of the system are of high level (see **H. Flourent, E. Frenod & V. Sincholle** (Submitted) or **E. Frenod** (2017) for example). Their properties (especially stability), whose knowledge is important for their proper use, are not immediately accessible. Their setting requires a long-term approach involving mathematical analysis and a statistical approach based on simulation. For example, such an approach is described in **P. Ailliot, E. Frénod & V. Monbet** (2006).<br>With the rapid increase in the amount of available data, it sometimes becomes possible to replace or supplement the information provided by the mathematical model using automatic learning methods (see **R. Lguensat, P. Tandeo, P. Ailliot *et al.*** (2017)). The combination of mathematical models and data-oriented statistical approaches can improve the predictive capacity of the model and thus the result of data assimilation (see **TT Chau, P. Ailliot & V. Monbet** (2018)) while reducing the numerical complexity. |
| **International collaboration** | Ernest Fokoué (RIT - NY - US) |
| **Expectations** | The repercussions will be the improvement of farm management systems, environmental piloting systems and towns and countries planning systems on which the project holders are currently working (in the framework of Hélène Flourent's Cifre thesis at Neovia and collaborations with Ifremer, for example). |

## Références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