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Romain Lardy, Anne-Isabelle Graux, Michael M. Gaurut, Gianni Bellocchi, David Hill

Model Driven Reverse Engineering For A Grassland Model With Design Of Experiments In The Context Of Climate Change

Romain Lardy(1,3,4), Anne-Isabelle Graux(1), Michaël Gaurut(1), Gianni Bellocchi(1), David R.C. Hill(2,3,4)

(1) Grassland Ecosystem Research Unit, French National Institute for Agricultural Research (INRA), 234 Avenue du Brézet, 63100 Clermont-Ferrand, France
(2) Clermont Université, BP 10448, F-63000 CLERMONT-FERRAND
(3) CNRS, UMR 6158, Université Blaise Pascal, LIMOS, F-63173
(4) ISIMA, Computer Science & Modelling Institute, BP 10125, F-63177

Abstract
Vulnerability is the degree to which human and environmental systems are likely to experience harm due to a perturbation or stress. In the study of climate change impacts on grassland, we have run various experimental plans and with a reverse engineering approach we build the models of our design of experiments. This modelling helps identifying a common pattern seen as a metamodel to which parts of our models can be conformed to. The Model Driven Engineering approach will help us to propose a software framework that will deal with the distribution of experimental plans under vulnerability constraints.

Keywords:
Model Driven Engineering, Reverse Engineering, Experimental Design, Grassland simulations, Climate change

1. INTRODUCTION

Vulnerability is the degree to which human and environmental systems are likely to experience harm due to a perturbation or stress. It has become in recent years a central focus of the global change (including climate change) and sustainability science research communities [Füssel 2007]. Such new emphasis on vulnerability marks a shift away from traditional scientific assessment, which limits analysis to the perturbing agents (e.g. climate change, extremes) and the corresponding impacts, towards an examination of the system being stressed and its ability to respond [Luers et al., 2003].

Grassland/livestock system vulnerability to climate should be evaluated both in terms of biophysical vulnerability (production losses and increased greenhouse gas emissions) and in terms of socio-economic vulnerability (e.g. for smallholders and pastoralists in developing regions). As shown by the IPCC AR4 report [Easterling et al., 2007], potential adaptation strategies for livestock farms have seldom been studied, and without adequate assessment of adaptation the vulnerability to climate change could be overstated.

Significant advances in the domain were made thanks to the development and use of advanced modelling approaches to simulate mechanistically grassland and livestock systems. This was partly done thanks to the PASIM model (Pasture Simulation Model, https://www1.clermont.inra.fr/urep/modeles/pasim.htm) [Riedo et al., 1998] and its improvements [Graux et al. 2009], [Graux et al., 2011b], [Graux 2011].

Vulnerability assessment requires a huge amount of runs of the studied model, and distributing the computation is therefore necessary. We plan to propose a generic framework to deal with distribution of experimental plans under a set of specific constraints. Some preliminary work we have done with PASIM can be used for vulnerability assessment in two ways: firstly, by using the knowledge of previous results to drive and speed up vulnerability assessment; secondly, by reusing and retro-engineering the Design of Experiments (DoE) previously achieved. Indeed, three kinds of design were used, one for each different purpose: climate-projection impacts assessment, sensitivity analysis, optimal management research.

The following section presents the PASIM model. Section 3 to 5 describe the methodology used, with special focus on DOE and MDE techniques, and present the design of experiments we have retained in the past 3 years. PASIM has been ported form ACSL to Fortran in order to be integrated in complex climate models for High Performance Computing. We aim at “encapsulating” this old school approach within Model Driven Engineering (MDE). A reverse engineering based on MDE is considered to present UML models of what has been done. The reverse engineering is completed by the proposal of abstractions to tackle the distribution of experimental plans on high performance computing platforms.

2. MODEL DESCRIPTION

The PASIM [Riedo et al., 1998] is a process-based grassland biogeochemical model based on the Hurley Pasture Model [Thornley 1998]. Grassland processes are simulated on a time step of a 1/50th of a day. Simulations are limited to the plot scale and may run over one or several years. Likewise other advanced biogeochemical models, PASIM simulates water, carbon (C) and nitrogen (N) cycles, the latter being improved by [Schmid et al., 2001]. Photosynthetic-assimilated C is either respired or allocated dynamically to one root and to three shoot compartments (each of which consisting of four age classes). Accumulated aboveground biomass is used by either cutting or grazing, or enters a litter pool. The N cycle considers three types of N inputs to the soil via atmospheric N deposition, fertilizer N addition, and symbiotic N fixation by legumes. The inorganic soil N is available for root uptake and may be lost through leaching, ammonia volatilization and nitrification/denitrification, the latter processes leading to nitrous oxide (N_2O) gas emissions to the atmosphere. Management includes N fertilization, mowing and grazing and can either be set by the user or optimized by the model [Vuichard et al., 2007].

The animal module was recently improved by [Graux et al., 2011b] to simulate the performance of grazing ruminants (suckler cows with their calves, dairy cows and heifers) in response to climate and management and enteric methane emissions based on [Vermorel et al., 2008].

3. DESIGN OF EXPERIMENTS

Design of experiments (DOE) has a rich history, with many theoretical developments and practical applications in a variety of fields. In the modelling field, DOE is a needed tool for efficiently testing and analysing the behaviour of a model [Kleijnen 1987]. Most of model simulations aim at exploring and/or testing the behaviour of the model.

Whatsoever for verification and validation or for the uses of a model, a huge number of simulation runs are needed. In particular, for environmental dynamics modelling, models have become increasingly more complex at the pace of computer power. Due to the high number of parameters required by the model, the computation time of a single run, the needed time for complete uniform and factorial DOE is usually too expensive. That is why the use of other DOE, dispatching and parallelization are needed. The uses of a proper DOE will help to get, firstly, all the information we are looking for. For example in the case of sensitivity analysis, the DOE is important to get relevant sensitivity of all parameters and not to neglect their interactions. The second point is to have the smallest number of simulations for the best quality results and so a smaller computation time. The latter is also reached by dispatching processes to parallel architectures.

4. SIMULATIONS WITH PASIM

PASIM is a simulation software implemented in FORTRAN 95 (~60 000 code lines). The code is divided in modules, each one dealing with the modelling of a specific part of the system: microclimate module for light interception, energy balance; soil physics module for soil moisture and temperature profile; soil biology module with soil organic matter, nitrate, ammonium and nitrous oxide (N_2O) dynamics; animal module for intake, performance and methane emission at pasture. All these modules contain many parameters, some of them are input variables, others are usually considers as constant in the field validity of the model. In the UML diagram below (Figure 1) we present the organization retained to manage PASIM inputs. These parameters can be classified in three classes: **Site**, **Soil**, and **Vegetation**. In addition, the model uses some meteorological input variables at hourly time step: air temperature, wind speed, global radiation, precipitations, water vapour pressure, CO_2 and NH_3 atmospheric concentrations. Such inputs are in the **Climate** class. The Field management is handled by the **Management Policy** class, which has two subclasses: **Model proposed policy** and **Prescribed policy**. The model can run the subclass policies independently or simultaneously. The **Model proposed policy** gives a set of rules for automatic management which affect the behaviour the model. The policy specifies the fertilization dates, types and amounts (**Fertilization** class), the grass cutting date (**Mowing** class), and grazing information (**Grazing** class) including dates, instantaneous stocking rate, initial animal liveweight and body score condition, and complementation at pasture if required.

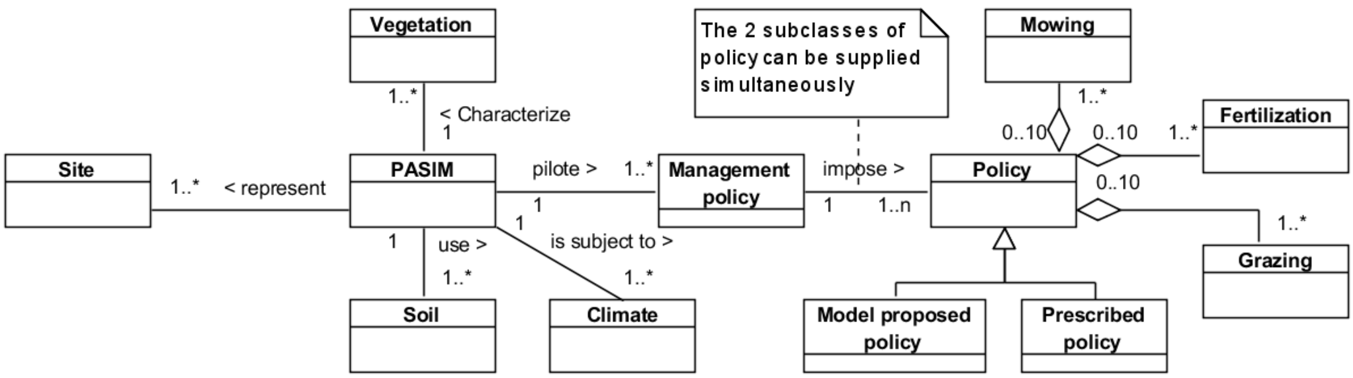

Figure 1. UML metamodel of the PASIM input model

Due to its ability to simulate a great number of processes (including biogeochemical cycles, grassland services and greenhouse gas emissions) and to its research objective, the potential outputs variables of PASIM are many (~500). But just a few one are usually looked and analyzed at one time according to the user objective.

A)

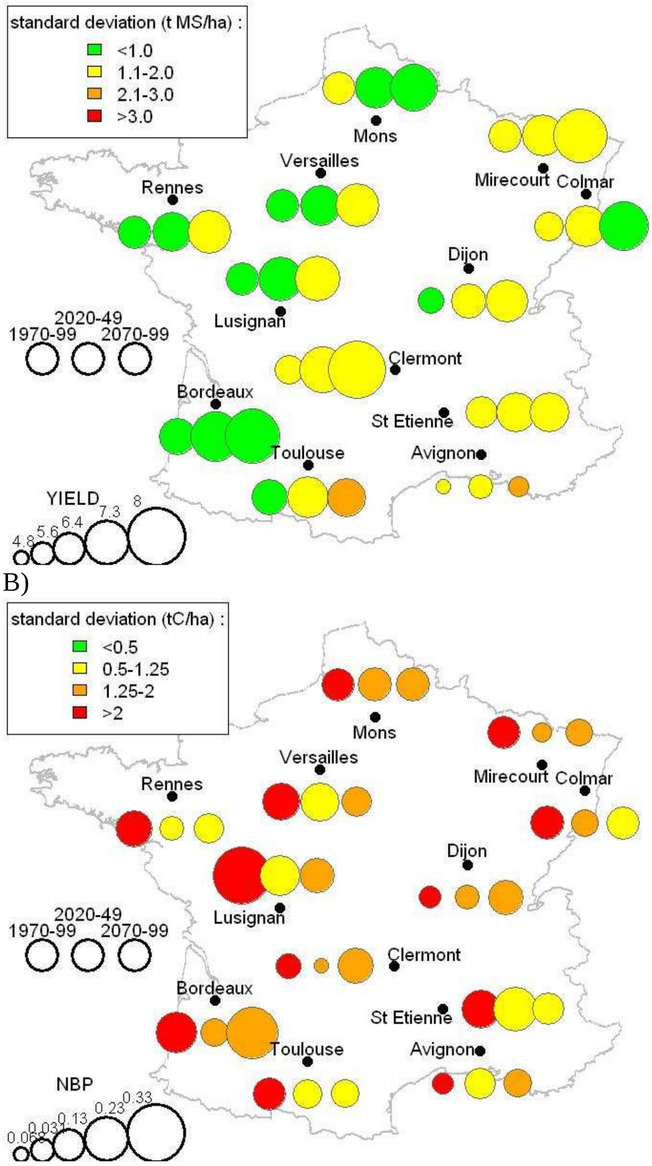

Figure 2. A) Dry matter yield and B) Net Biome productivity (NBP) evolutions for intensive permanent grasslands established on a shallow soil under the SRES A1B scenario simulated by the ARPEGE climate model and downscaled with variable correction method. A NBP positive value means that grasslands store carbon in their soil.

For example, in the case the French ANR Project CLIMATOR (http://w3.avignon.inra.fr/projet_climator/), climate projections were evaluated at 12 French sites. In particular, the evolution of yields on intensive permanent grasslands on shallow soils from past (1950) to far future (2100) were studied (Figure 2A). However studying impacts on productivity is not enough, investigating the feedbacks of grassland on the climate is also a key issue. This could be partly assessed by evaluating the carbon balance of the system (Net Biome Productivity), which is representative of CO_2 emission or absorption (Figure 2B).

5. MODEL DRIVEN ENGINEERING

Model Driven Engineering (MDE) is a part of software engineering that studies, since more than a decade, the software development, maintenance and evolution with a unifying modelling approach [Favre 2006]. The Model Driven Architecture (MDA) is a set of industry standard promoted by the Object Management Group (OMG). The separation between the descriptions of the platform independent system part (PIM Platform Independent Model) and of the platform specific one (PSM Platform Specific Model) characterizes the MDA, whereas the MDE is a global integrative approach [Favre 2006] for various technological spaces. MDE relies on three fundamental concepts: the “model”, the “metamodel” and the “transformation procedure”. A model is a simplified representation of a system. The system is an entity modelled in order to study it, to understand it, and to predict in a mastered context other than reality. The model could be defined by the relation “is a representation of” between itself and the studied system [Hill 1996] [Atkinson and Kuhne 2003], [Seidewitz and Technologies, 2003] and [Bézivin 2004]. Nevertheless, in the MDE context, this definition is not enough because it does not allow the model to become “productive” (i.e. interpretable and exploitable by a machine). That is why many authors use the following definition [Kleppe et al., 2003]: “A model is a description of (part of) a system written in a well-defined language”.

The notion of well-defined language indirectly points to the second MDE principle, i.e. the “metamodel”. Different definitions exist in the literature: “a metamodel is a model that defines the language for expressing a model” [OMG 2002]; “a metamodel is a specification model for a class of SUS (System Under Study) where each SUS in the class is itself a valid model expressed in a certain modelling language” [Kleppe 2003]. Unlike to the popular opinion, a metamodel is not a model of model, it is better defined as a model of modelling language. This definition is based on the following relation: a model “is conform to” a metamodel. For instance, in the context of Object-Oriented Programming, if we consider the object as a model of reality, then the class is a metamodel and the object “is conform to” its class. But metamodels can have specific forms depending on the technical domain such as:

- XML technologies: an XML file is conform to a DTD or XML scheme
- language theory and compilation: a source code is conform to its grammar

- in cartography, if our system is France, our model could be an IGN (French National Geographic Institute) map and its metamodel its legend: a map is conform to his legend
- Standard Template Library (STL): a vector<int> is conform to Vector<T> model

Contrary to MDA, MDE principles are relevant for all type of models, either object-oriented or not. MDE is not restrained to a technical domain.

Nevertheless, to get a productive model, it is necessary to describe how to transform it. This aspect corresponds to the third MDE concept: "transformation of model". Unlike the two other notions, there is no consensus for its definition [Rahim and Mansoor 2008], [Lano and Clark 2008], [Iacob et al., 2008]. According to [Favre 2004], the relation could be defined as "is transformed in". As for the metamodel, the transformation can take different forms under the technical domain [Favre 2006], for example:
- eXtensible Stylesheet Language (XSLT) into XML language
- compilation and code generation for language theory

6. USES OF DESIGN OF EXPERIMENTS

High performance computing was required to run all the simulations we needed in the recent studies conducted with PASIM. These studies aimed at assessing climate change impacts on grasslands, performing a sensitivity analysis of most of PASIM parameters (with respect to different outputs), and optimizing grassland management under climate change. The DOE associated with these three studies are described hereafter.

6.1 Climate change impact projections

An important work, based on a huge amount of simulations, has been done to assess climate impacts on grasslands as well as to characterize different levels of incertitude on these impacts. To do this, an incomplete factorial design of experiments was used. Projections were achieved for 12 French sites and, for each site, PASIM was forced with 12 plausible future climatic conditions that combined a range of SRES (Special Report on Emission Scenarios) [Nakićenović et al., 2000], climate models and downscaling methods. Since it was not possible to generate all combinations of scenarios (1), climate models (2) and downscaling methods (3), then a complete factorial design was not feasible. However, if we consider these three elements: SRES, climate models and downscaling methods as a unique entity, then the design is complete factorial.

Five soil profiles were also chosen from a database designed to include the major soil types (by texture, water characteristics and soil depth) and land uses in France (DONESOL Base). We could consider that each soil can be split into two sub-soils, depending on whether the ground water table is nearby or not, reflecting that there is capillary rise from soil boundary layer or not. Six different grassland field management policies and associated vegetations were defined. The DOE is therefore the complete product of:
- one site
- one soil
- one management and his associated vegetation
- one climate (note that the available climates do not cover the complete product of scenario, climate model and downscaling method)

All theses simulations would take about one year of computing time on a single modern CPU (2010). Since these runs were independent, they were distributed on clusters. This was done by dividing the amount of simulations by the number of available processors. We proposed an additional script to list all incomplete simulations and then to generate the needed scripts to launch the remaining simulations until every simulation has been launched. Interpretation of the results obtained in the computing campaign can be found in [Graux 2011] and [Graux et al., 2011a].

6.2 Sensitivity Analysis

In order to reduce the number of PASIM parameters, a sensitivity analysis was performed. An implementation of the Morris screening method [Morris 1991] based on [Campolongo et al., 2007] was used to assess the sensitivity of the model to 133 input parameters at three French sites. For each site, three years of climate data were used, representing a gradient of aridity conditions (minimum, median, maximum aridity year on the period 1950-1999) as defined by the De Martonne-Gottmann index [De Martonne 1942]. Two management policies were defined, with one generic soil. The parameters used in the sensitivity analysis are in the **vegetation**, **site**, and **soil** and **prescribed policy** inputs classes (Figure 1). The main idea of the Morris method [Morris 1991] is to determine for each parameter whether their effect could be considered as negligible, linear and additive, or non-linear or involved in interaction with other factors.

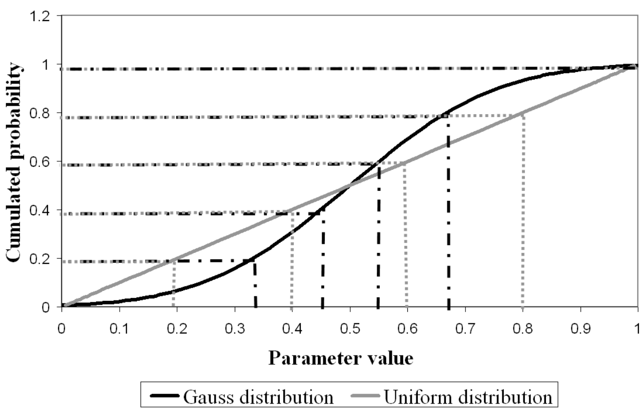

Figure 3. Cumulated probability distributions and levels for a Uniform (dark) and Gaussian (grey) variates.

The Morris method for designing experiments is composed of individually randomized “one-factor-at-the-time” experiment. Thanks to that, a trajectory is described in the space of all factors. Few trajectories are necessary; in our case six trajectories of 134 points (133 parameters + 1 initial point) were used. For each parameter, six levels were defined. Each level corresponds to (0, 0.2, 0.4, 0.6, 0.8, 1) values in the distribution function (Figure 3). This design was repeated for a supposed Uniform or Gaussian parameter distribution. Note that for computability reason Gaussian distribution was limited at its extremity.

The same pattern was used to make sensitivity analysis for all kind of outputs (greenhouse gases, plant growth, carbon and nitrogen plant content…), so that the same “pack” of simulations was enough to perform sensitivity analysis for the different outputs. As for climate projection impacts, theses simulations can be easily distributed. To sum up, the DOE was the product of:

- one site
- one climate
- one management
- one set of parameters for soil, site, vegetation and managements parameters, for Uniform or Gaussian distribution

Although the computing time is smaller than required for climate impact simulations, it was however necessary to distribute simulations on local clusters.

6.3 Automatic management simulations

To test potential adaptations of French grassland-based livestock systems to increasing climatic hazards, a two step procedure was developed [Vuichard et al 2007] then improved [Graux 2011] that first simulates grassland mown surfaces then grazed surfaces, by assuming that PASIM simulation can be extrapolated at forage system scale. Firstly, the model determines the optimal management policy for fertilization and cutting events on a mown grassland. Then, according to potential forage resources, the model optimizes iteratively the stocking rate at forage system scale, in order to reach equilibrium between potential forage resources and animal feed requirements at barn, when accounting for grazing coverage. This procedure assumes that all forage resources (no forage bought) are fully eaten by animals at barn. Each of the two steps of this procedure runs on the same meteorological year. To perform each year optimization, the information about the end of the previous year, is needed.

The automatic management was determined for two sites associated to six specific conditions (combination of calving period and forage/concentrate quality, and type of animal), two climate scenarios, and two soils. For the whole 150 year series, two algorithms were used, depending on whether the soil organic matter is at equilibrium with management and meteorological data, or not. To resume, in this case the DOE is the combination of:

- one soil
- one site
- one climate scenario
- one management (depending on the site) associated to one optimization method

Contrary to climate projections and sensitivity analysis, all runs cannot be parallelized. Indeed, each run of a given meteorological year must wait for the results of the previous year, so we could only parallelize blocks of 150 years. Interpretation of results can be found in [Graux 2011].

7 MODEL AND METAMODEL OF DOE

The purpose of this section is to propose abstractions, which will tackle the distribution of experimental plans with specified constraints. We think that a good way to do this is to start building a model of the experimental plans based on the past designs we proposed. Let’s firstly focus on the climate change experimental plan. As we previously saw, this plan is a nearly complete factorial one. It is not complete in the fact that climate, which is a composition of SRES forcing condition, climate model and downscaling method, is not complete. As said previously, when we consider our proposed climate as a whole scenario entity, then the experimental plan is complete. The resulting model of the experimental plan is given in Figure 4.

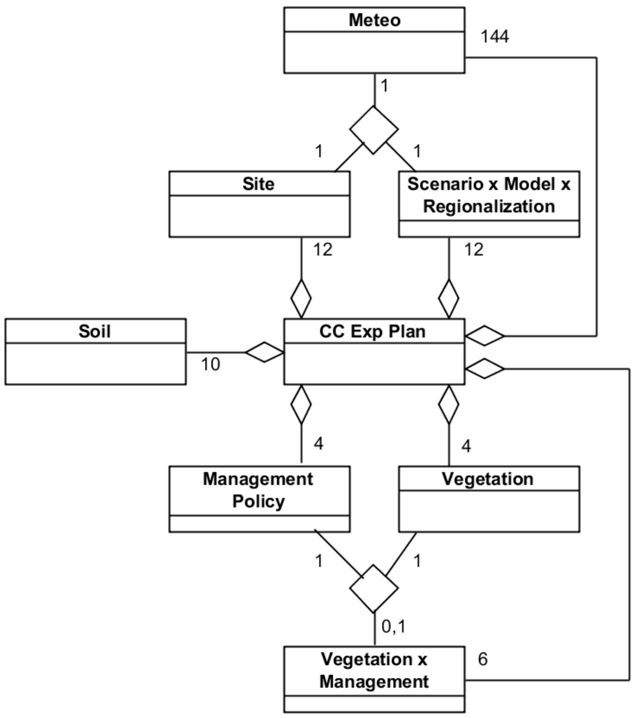

Figure 4. Model of the experimental plan in climate change impact simulations

It is interesting to note that for one **Site** and for one **Climate**, a unique **Meteo**rological dataset exists. This uniqueness is important in the way that the resulting cardinality is the product of site and climate cardinality. In the same way, **Management policy** and **Vegetation** can be composed in a consistent "**Vegetation and Management**" association class. In this case of association, we meet constraints to avoid inconsistent combinations of vegetation with field management policy. In our experiment, we had four management policies and four vegetations and only six valid combinations. The last element of the experimental plan is given by the **Soil** class, which does not have direct relationships with other model classes.

If we now consider the experimental plan for sensitivity analysis, we can also propose a model (Figure 5). As for the climate change experimental plan, there is a specific association of **Climate** and **Site** resulting into **Meteo**rological data. In this specific case, there is an association between **Parameter combination** and **Probability Distribution class**, resulting into the **Parameters values** class. Note that the parameter combination cardinality is 804 for six trajectories with 134 points (with a Morris DOE). In this case, the management class is simpler and does not present particular associations with other classes.

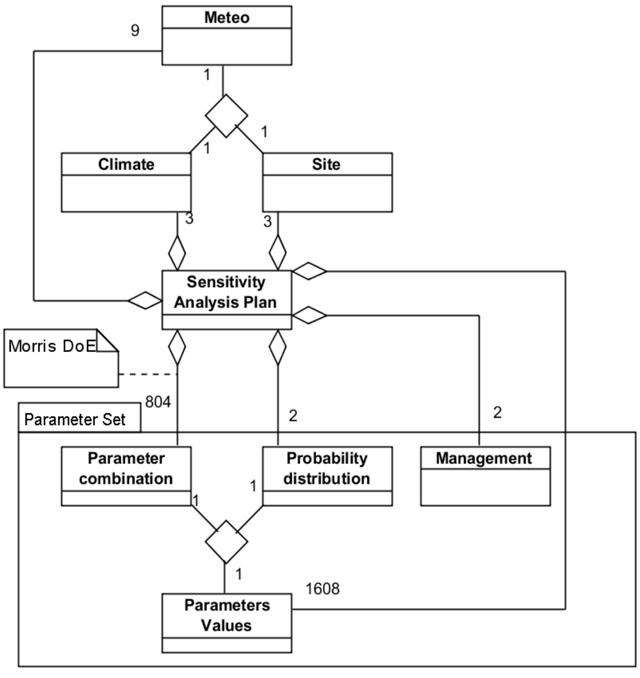

Figure 5. Model of the experimental plan in sensitivity analysis

For the automatic management experimental plan (Figure 6), two association classes can be found. The first one, as for the two previous models, deals with the meteorological data set. The second is the crossed information of the **Site** with his management **Policy**. In this case, we can note that factorial plan is not complete (e.g. we do not simulate each vegetation for each site). The last element of the experimental plan is the **Soil** class with no particular associations with the other classes.

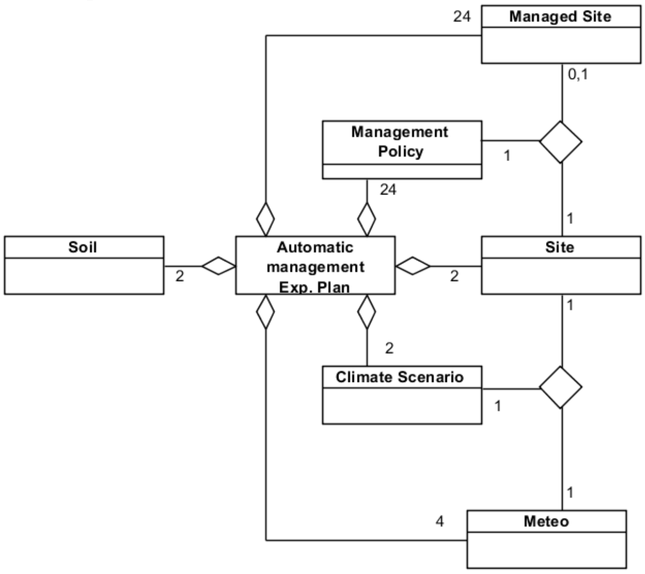

Figure 6. Model of the experimental plan in automatic management simulation

In these three models of experimental plan, we can identify a common pattern [Gamma et al., 1995] (Figure 7). This pattern can be seen as a metamodel to which some parts of our DOE models can be conformed to. The genericity is explained hereafter, we note that two elementary inputs of PASIM (class **B** and **C**) are part of the experimental design (class **A**). At the same time classes **B** and **C** are combined to make the **D** class, which can also be considered as part of the experimental plan.

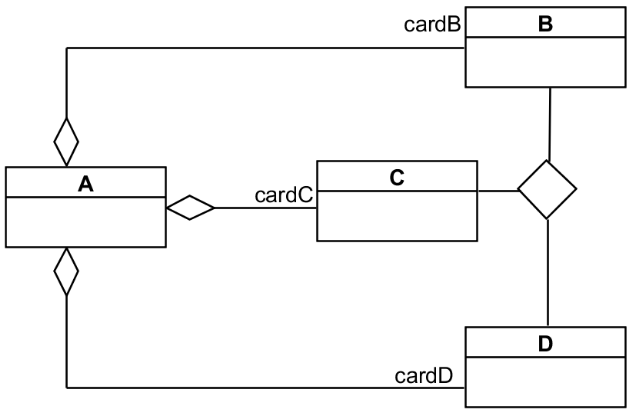

Figure 7. Pattern / Metamodel of an experimental plan (the **A** class) with two elementary inputs (**B** and **C** classes) and one resulting combination (**D** class, which is a kind of "BC" class).

If in our experimental plan models we consider the subparts made of the **Site** class, the **Climate Scenario** class, the **Meteo** and the **Experimental Plan** class, we can see the instantiation of our pattern / metamodel in all these three examples. These model subparts are conform to the metamodel [Bézivin 2005]. In our model (proposed in figure 5) we can consider that **Site** and **Climate Scenario**, as classes **B** and **C**, **Meteo** as class **D** and class **A** as the **Experimental Plan**. Another example is the sub-model, from the model of experimental plan for climate change impacts (figure 4), where **Vegetation** class and class **Management Policy** are class **B** and **C**, the class "**Vegetation x Management**" is the **D** class and class **A** is represented by the "**CC Exp Plan**". Two other examples can be found. One is in the sensitivity analysis model (A: **Sensitivity Analysis Plan**; B and C: **Parameter combination**, **Probability distribution**; D: **Parameters value**) and the other in the automatic management model (A: **Automatic management Exp. Plan**; B and C: **Site**, **Management Policy**; D: **Managed Site**).

The nature of the DOE will determine the value of the cardinality (**cardD**) between **A** and **D**. If the plan is complete factorial (as "**Site** - **Climate Scenario**" sub-model of experimental plan), then **cardD** is the product of **cardB** and **cardC**. But if the design is different, then **cardD** will be a different function of **cardB** and **CardC**. This is the case for the sub-model "**Vegetation** - **Management Policy**".

This metamodel, which is written for a three-element example, could be generalized. Indeed, this meta-model can be applied to any of the three examples of DOE models previously described.. If we consider any association class and its two elementary inputs as a new elementary input class, then we will get iteratively a model which is completely conform to this metamodel.

8. DISCUSSION AND POSSIBLE SOLUTIONS

Vulnerability assessment often uses sensitivity analysis, and adaptation options (optimization is included). Thus, based on the three examples of simulations studies given in this paper, we can conclude that a software tool that aims at assessing vulnerability will require a huge amount of simulations. This number of runs is an important issue for climate change projections due to multiple scenarios and the uncertainty cascade. It seems clear, on the one hand, that the choice of a suitable experimental design will be necessary to reduce the number of simulations as much as possible. On the other hand, distributed computation appeared to be absolutely necessary. In this way, different platforms are to be considered: clusters, grids or cloud computing. We have already tackled the design of such software tools, which provide distributed computation and platform independent DOE [Amblard et al , 2003], [Reuillon et al , 2008], [Reuillon et al , 2010]. However, theses tools do not take into account vulnerability assessment, in their actual state. To adapt them, we will need the model of PASIM inputs, models of experimental plans (old ones are rather similar to those required for vulnerability assessment) and the metamodel of the experimental plans.

9. CONCLUSION

Many simulations have been performed with PASIM by a set of carefully designed experimental plans to assess climate change impacts on grasslands. In this paper, we have presented our experience of a model reverse engineering approach. Retro-engineering, as defined in [Chikofsky 1990], is a preliminary task when designing a software framework from past experiences. This preliminary work has been oriented towards the proposition of models in order to build a dedicated software framework that supports vulnerability assessment in the context of climate change. This framework will tackle distribution of constrained experimental plans. Our proposal will rely on the study of previous simulations, with a model of our grassland simulation program and a metamodel for the experimental design. Model driven engineering will help us in the design and production of our future framework. The models and the metamodel presented within this paper enables establishing the first step towards the design of a generic tool for vulnerability assessment.

Acknowledgments

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