THEME [ICT-2009.8.0]
[FET-Open: Challenging current thinking]

Grant agreement for: Collaborative project*

Annex I - "Description of Work"

Project acronym: SUMO

Project full title: " Supermodeling by combining imperfect models "

Grant agreement no: 266722

Version date: 2011-07-26

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Part A

Workplan Tables

A1:
Project summary

Project Number [1]	266722	Project Acronym [2]	SUMO

One form per project

General information			
Project title [3]	Supermodeling by combining imperfect models		
Starting date [4]			
Duration in months [5]	36		
Call (part) identifier [6]	FP7-ICT-2009-C		
Activity code(s) most relevant to your topic [7]	ICT-2009.8.0: FET-Open: Challenging current thinking		

Abstract [9]

Scientists develop computer models of real, complex systems to increase understanding of their behaviour and make predictions. A prime example is the Earth's climate. Complex climate models are used to compute the climate change in response to expected changes in the composition of the atmosphere due to man-made emissions. Years of research have improved the ability to simulate the climate of the recent past but these models are still far from perfect. The model projections of the globally averaged temperature increase by the end of this century differ by as much as a factor of two, and differ completely in regard to projections for specific regions of the globe.
Current practice commonly averages the predictions of the separate models. Our proposed approach is instead to form a consensus by combining the models into one super model. The super model has learned from past observations how to optimally exchange information among individual models at every moment in time. Results in nonlinear dynamics suggest that the models can be made to synchronize with each other even if only a small amount of information is exchanged, forming a consensus that best represents reality. This innovative approach to reduce uncertainty might be compared to a group of scientists resolving their differences through dialogue, rather than simply voting or averaging their opinions.
Experts from non-linear dynamics, machine-learning and climate science are brought together within SUMO to produce a climate change simulation with a super model combining state-of-the-art climate models. The super-modelling concept has the potential to provide improved estimates of global and regional climate change, so as to motivate and inform policy decisions. The approach is applicable in other situations where a small number of alternative models exist of the same real-world complex system, as in economy, ecology or biology.

A2:
List of Beneficiaries

Project Number [1]	266722	Project Acronym [2]	SUMO

List of Beneficiaries

No	Name	Short name	Country	Project entry month[10]	Project exit month
1	MACEDONIAN ACADEMY OF SCIENCES AND ARTS	MASA	Former Yugoslav Republic of Macedonia	1	36
2	LEIBNIZ-INSTITUT FUER MEERESWISSENSCHAFTEN AN DER UNIVERSITAET KIEL	IFM-GEOMAR	Germany	1	9
3	KONINKLIJK NEDERLANDS METEOROLOGISCH INSTITUUT (KNMI)	KNMI	Netherlands	1	36
4	POTSDAM INSTITUT FUER KLIMAFOLGENFORSCHUNG	PIFK	Germany	1	36
5	STICHTING KATHOLIEKE UNIVERSITEIT	RU	Netherlands	1	36
6	INSTITUT JOZEF STEFAN	JSI	Slovenia	10	36
7	UNIVERSITETET I BERGEN	UIB	Norway	10	36

Workplan Tables

Project number

266722

Project title

SUMO—Supermodeling by combining imperfect models

Call (part) identifier

FP7-ICT-2009-C

Funding scheme

Collaborative project

WT1
List of work packages

Project Number [1]	266722	Project Acronym [2]	SUMO

LIST OF WORK PACKAGES (WP)

WP Number [53]	WP Title	Type of activity [54]	Lead beneficiary number [55]	Person-months [56]	Start month [57]	End month [58]
WP 1	General theory of supermodeling with ODE systems	RTD	4	57.00	1	36
WP 2	Learning of connection coefficients in ODEs	RTD	5	55.00	1	36
WP 3	Learning of connection coefficients in PDE systems	RTD	1	50.00	1	36
WP 4	Supermodeling with intermediate complexity climate models	RTD	3	49.00	1	36
WP 5	Supermodeling with large climate models	RTD	7	50.00	1	36
WP 6	Management	MGT	1	22.00	1	36
WP 7	Learning complete supermodels	RTD	6	54.00	10	36
			Total	337.00		

WT2:
List of Deliverables

Project Number [1]	266722	Project Acronym [2]	SUMO

List of Deliverables - to be submitted for review to EC

Deliverable Number [61]	Deliverable Title	WP number [53]	Lead beneficiary number	Estimated indicative person-months	Nature [62]	Dissemination level [63]	Delivery date [64]
D1.1	Report on models and metrics	1	4	16.00	R	PU	12
D1.2	Report on connectivity and optimization	1	4	16.00	R	PU	24
D1.3	Report on potentials and limits	1	4	16.00	R	PU	36
D1.4	Report on domain knowledge for the automated construction/ revision of climate models	1	6	9.00	R	PU	24
D2.1	Report low complexity and intermediate complexity models	2	5	20.00	R	PU	12
D2.2	Report on quality of local optima and global optimization methods	2	5	19.00	R	PU	24
D2.3	Report on learnability and on performance estimation	2	5	16.00	R	PU	36
D3.1	Report on connections learning approaches for PDEs	3	1	17.00	R	PU	12
D3.2	Report on different learning approaches for QG channel models	3	1	15.00	R	PU	24
D3.3	Report on methods developed for connecting	3	1	18.00	R	PU	36

Deliverable Number [61]	Deliverable Title	WP number [53]	Lead beneficiary number	Estimated indicative person-months	Nature [62]	Dissemination level [63]	Delivery date [64]
	intermediate complexity climate models						
D4.1	Report on the issues of the connections	4	3	14.00	R	PU	12
D4.2	Report with guidelines for a climate super model	4	3	19.00	R	PU	24
D4.3	Report on the behaviour of the supermodel in a perturbed climate regime	4	3	16.00	R	PU	36
D5.1	Report on super climate model with manually chosen connections	5	7	15.00	R	PU	12
D5.2	Report on super climate model behaviour after learning	5	7	18.00	R	PU	24
D5.3	Report on updated super climate model and summarizing results on super climate modeling	5	7	17.00	R	PU	36
D6.1	Project flyer	6	1	1.25	O	PU	3
D6.2	Project website	6	1	1.50	O	PU	3
D6.3	Project periodic report 1	6	1	2.25	O	PU	12
D6.4	Project periodic report 2	6	1	2.25	R	PU	24
D6.5	Project periodic report 3	6	1	2.25	R	PU	36
D6.6	International SUMO summerschool	6	1	5.50	O	PU	34
D6.7	Brochure with SUMO results	6	1	3.25	R	PU	36
D6.8	Final report	6	1	3.75	R	PU	36

Deliverable Number [61]	Deliverable Title	WP number [53]	Lead beneficiary number	Estimated indicative person-months	Nature [62]	Dissemination level [63]	Delivery date [64]
D7.1	Report on the generation of a diverse set of ODE models	7	6	18.00	R	PU	18
D7.2	Report on the selection of a complementary set of ODE models	7	6	18.00	R	PU	27
D7.3	Report on learning to interconnect ODE models	7	6	18.00	R	PU	36
			Total	337.00			

WT3:
Work package description

Project Number [1]	266722	Project Acronym [2]	SUMO

One form per Work Package

Work package number [53]	WP1	Type of activity [54]	RTD
Work package title	General theory of supermodeling with ODE systems		
Start month	1		
End month	36		
Lead beneficiary number [55]	4		

Objectives

To develop the general theory of a supermodel apart from the learning aspect. Specify how models with different structure should be connected. Specify conditions under which connecting variables among different models will lead to superior skill, and the form of those connections. Determine limitations of the supermodeling strategy. In addition to machine learning we develop a strategy how to define connections based on insight, mathematical arguments or whatever that lead to a useful supermodel. We do this because the automatic learning might be too complex, or lead to suboptimal solutions and we spread the risk this way. To develop domain knowledge for machine learning of the structure of models and interconnections. This WP will serve as input for WP 2-5, as well as WP7.

Description of work and role of partners

General Approach:
In this WP assume a given set of imperfect models described by deterministic ODEs with limited (1 - 1000) degrees of freedom. In addition, we will assume a ground truth model, which is given by a possibly stochastic ODE with about the same degrees of freedom. The ground truth model allows us generate data both for modeling and for model validation. This allows us to explore and develop strategies and by considering different model classes and parameter regimes, it allows us to explore and study the application range and limitations of these strategies. The work in this WP will be performed in close interaction with WP2 but also with the WPs 3-5.

Task 1.1 Setting of the scope (models, metrics, data). What scope of general model fusion is a useful playground for the task of fusing different climate models.

Task 1.1.1 Model classes: Determination of the model classes that we will study in WP1 and WP2. In the scope of this project, we will concentrate on models that mimic to some extend the behavior of realistic climate models. We will also include model classes that have dynamics at different time scales, to anticipate on the differences in time scales of atmosphere and ocean in realistic climate models. We intend to study to what extend different qualitative behaviour of the subsystems can be combined in a supermodel and how to treat cases when there are coexisting (multiple) attractors for some parameter configurations. In such a case special combination strategies have to be designed.

Task 1.1.2 Metrics: Determination of metrics and appropriate test criteria that define how well a model (or a supermodel) performs with regard to the truth. Which are the important statistics to consider? How to deal with variables that have different physical meaning. Metrics are needed both to optimize the supermodel and to evaluate the performance of the supermodel compared to the state of the art.

Task 1.1.3 Data and prior knowledge: Determination of the data and prior knowledge that one may assume to be available for the purpose of supermodeling. The following questions will be addressed:
What variables are assumed to be observed?
How many observations (length of data) may one assume?
What is the assumed noise in the observations?
How can we include non-stationarities which are typical in climatology?
What is the prior knowledge that one may assume, e.g. about the ``physics'' of the ground truth model?

Task 1.2 Connection mechanisms: we will study how to connect models under different assumptions. This ranges from models that have the same structure and differ only in parameter values to models that have different structure and/or different spatial resolution. We will also study different formulations for the interactions in the supermodel and ways to limit the dimensionality and/or the degrees of freedom of the connection matrix. Another issue to be studied is whether and how connections and connection mechanisms should be constrained so that the supermodel obeys certain given symmetries, physical logics and balances.

Task 1.3 Manual optimization strategies: We will research and develop strategies how to define connections that lead to a useful supermodel. In this task we consider manual strategies from domain experts that are based on physical insights and mathematical arguments in relation of the imperfect models and what can be assumed to be known about the ground truth as well as considerations that make use of the prediction performances of the imperfect models in relation to the data generated by the assumed ground truth.

Task 1.4 Potential and limits of supermodeling: We will research the potential benefit and limits of supermodeling assuming knowledge of the ground truth. This enables us to explore the solution spaces of the connections as well as to explore the application range in which the supermodeling approach might be beneficial (i.e. better than any single model and the result of averaging models) as function of the degree of model imperfections. We will also research its potential added value when considering models with slowly changing parameters, this to anticipate on its application in the research of climate change.

Task 1.5 Interpretation of connections determined by learning: Can we understand why the supermodel works with a certain set of connections.

Task 1.6: The domain knowledge resulting from Tasks 1.1 and 1.2 will be formulated in a way suitable for use in computational scientific discovery. It will describe the basic processes typically captured in the models and typical alternative ODE templates used to model them. It will be represented in a process-based modelling formalism.

Person-Months per Participant

Participant number [10]	Participant short name [11]	Person-months per participant
1	MASA	10.00
3	KNMI	1.00
4	PIFK	30.00
5	RU	6.00
6	JSI	9.00
7	UIB	1.00
	Total	57.00

List of deliverables

Deliverable Number [61]	Deliverable Title	Lead beneficiary number	Estimated indicative person-months	Nature [62]	Dissemination level [63]	Delivery date [64]
D1.1	Report on models and metrics	4	16.00	R	PU	12
D1.2	Report on connectivity and optimization	4	16.00	R	PU	24
D1.3	Report on potentials and limits	4	16.00	R	PU	36

List of deliverables

Delive-rable Number [61]	Deliverable Title	Lead benefi-ciary number	Estimated indicative person-months	Nature [62]	Dissemi-nation level [63]	Delivery date [64]
D1.4	Report on domain knowledge for the automated construction/revision of climate models	6	9.00	R	PU	24
		Total	57.00			

Description of deliverables

D1.1) Report on models and metrics: This report contains the outcomes of Task 1.1 [month 12]

D1.2) Report on connectivity and optimization: This report contains the outcomes of Tasks 1.2 and 1.3 [month 24]

D1.3) Report on potentials and limits: This report contains the outcomes of Tasks 1.4 and 1.5 [month 36]

D1.4) Report on domain knowledge for the automated construction/revision of climate models: This report contains the outcomes of Task 1.6 [month 24]

Schedule of relevant Milestones

Milestone number [59]	Milestone name	Lead benefi-ciary number	Delivery date from Annex I [60]	Comments
MS1	Decision on model classes	4	12	Deliverables D1.1 and D2.1
MS2	Decision on initial super modeling strategy for climate super models	1	12	Deliverables D3.1, D4.1 and D5.1
MS3	Evaluate the initial super model experience with climate super models	3	24	Deliverables D4.2 and D5.2
MS4	Decision on an updated strategy for climate super models	5	24	Deliverables D1.2, D2.2, D3.2 and D4.2
MS6	Domain knowledge and methods for generating diverse models developed	6	18	Deliverables D1.4 and D7.1

WT3:
Work package description

Project Number [1]	266722	Project Acronym [2]	SUMO

One form per Work Package

Work package number [53]	WP2	Type of activity [54]	RTD
Work package title	Learning of connection coefficients in ODEs		
Start month	1		
End month	36		
Lead beneficiary number [55]	5		

Objectives

To research and develop efficient, robust and scalable learning strategies to optimize connection coefficients for dynamical systems of low and intermediate size complexity (up to 1000 variables). The resulting learning strategies are to be used to guide the development of methods in WP3 and WP4.

Description of work and role of partners

General Approach: The work in this WP will be performed in close interaction with WP1. The scope of the research, e.g. the imperfect models and/or model classes, ground truths, as well as the metrics, connection mechanisms, parameterizations and constraints will be decided on and/or developed in WP1. Furthermore, WP1 provides manually optimized connections that may serve as initial condition for learning strategies or serving as idealized solutions. In this WP we will explore approaches, develop methodologies and do many simulations and analyses in a variety of ways. The scalability to the higher dimensional climate models of WP4 and WP5 is an important issue. The general approach will iterative. Feedback from WP4 and/or WP5 will serve as a guide to improve the developed methods.

Task 2.1: Study and comparison of different learning algorithms. We will design, and research different approaches to optimize the connection coefficients in the supermodel. The methods will be assessed using the metrics defined in WP1 as well as by their computational scalability to systems with many degrees of freedom. This task is divided into two subtasks:

- Study of learning in ODEs in the most simple case. We will first research and develop learning algorithms to handle the more straightforward ODEs (with O(10) degrees of freedom), in which all variables are observed, and have dynamics with similar time scales.

- Study of learning in ODEs in more complex cases. Next, we will research and develop learning algorithms to be applied systems with: incomplete data, incomplete knowledge, constraints on the connections, time varying parameters, slow and fast time scales, Intermediate size dimensionality (<O(1000) degrees of freedom)

Task 2.2 Globally optimal learning In the presence of local optima, learning algorithms might lead to a solution that is suboptimal. This is addressed in the following subtasks:

- Local and global optima. Under what conditions are local optima acceptable. Can global methods help to find better optima.

- Global optimization methods. We will research the use of global optimization methods, such as simulated annealing, genetic algorithms and other meta-heuristic approaches, to escape local optima in favor of global ones.

Task 2.3: Potential of learning of supermodeling: In this task we study the application range in which the supermodeling learning approach might be beneficial compared to more straightforward approaches. Questions that we address are divided in subtasks:

- Learnability: We will study the ability to successfully learn the coefficients of the supermodel in relation with underlying model complexity (as in task 2.1.2), the degree of imperfection of the individual models, the amount of data, and the number of independent connection coefficients.

- Performance estimation: We will research validation methods and measures that aim to estimate the supermodel's future performance using only data that is available at current time.

Person-Months per Participant

Participant number [10]	Participant short name [11]	Person-months per participant
1	MASA	18.00
3	KNMI	4.00
4	PIFK	3.00
5	RU	20.00
6	JSI	9.00
7	UIB	1.00
	Total	55.00

List of deliverables

Deliverable Number [61]	Deliverable Title	Lead beneficiary number	Estimated indicative person-months	Nature [62]	Dissemination level [63]	Delivery date [64]
D2.1	Report low complexity and intermediate complexity models	5	20.00	R	PU	12
D2.2	Report on quality of local optima and global optimization methods	5	19.00	R	PU	24
D2.3	Report on learnability and on performance estimation	5	16.00	R	PU	36
		Total	55.00			

Description of deliverables

D2.1) Report low complexity and intermediate complexity models: Report with the outcomes of Task 2.1 [month 12]

D2.2) Report on quality of local optima and global optimization methods: Report with the outcomes of Task 2.2 [month 24]

D2.3) Report on learnability and on performance estimation: Report with the outcomes of Task 2.3 [month 36]

Schedule of relevant Milestones

Milestone number [59]	Milestone name	Lead beneficiary number	Delivery date from Annex I [60]	Comments
MS1	Decision on model classes	4	12	Deliverables D1.1 and D2.1
MS2	Decision on initial super modeling strategy for climate super models	1	12	Deliverables D3.1, D4.1 and D5.1

Schedule of relevant Milestones

Milestone number [59]	Milestone name	Lead beneficiary number	Delivery date from Annex I [60]	Comments
MS3	Evaluate the initial super model experience with climate super models	3	24	Deliverables D4.2 and D5.2
MS4	Decision on an updated strategy for climate super models	5	24	Deliverables D1.2, D2.2, D3.2 and D4.2

Project Number [1]	266722	Project Acronym [2]	SUMO

One form per Work Package

Work package number [53]	WP3	Type of activity [54]	RTD
Work package title	Learning of connection coefficients in PDE systems		
Start month	1		
End month	36		
Lead beneficiary number [55]	1		

Objectives

1. Prescribe learning algorithms to determine optimal connection coefficients in a general PDE supermodel, that will be applicable to large climate models
2. Understand the importance of local vs. global optima in such coefficients, and to prescribe algorithms to avoid local optima if necessary

Description of work and role of partners

MASA will investigate learning algorithms in a hierarchy of models, starting from the results with simple ODEs emerging from WP2. We will further investigate the relative merits of the two broad types of algorithms considered in WP2 in PDEs. In PDE systems, we will determine general conditions under which local optima present a problem, and study methods to avoid them in those situations. Then the approaches developed for ODEs and simple PDEs will be refined for intermediate- and high-level climate models, in cooperation with KNMI and UiB, resp., referring any new issues back to the simpler models for additional study.

To achieve the desired goals, the work within WP3 will be directed towards completion of four consecutive tasks:

Task 3.1 Development of learning strategies for PDE supermodels: Both learning algorithms introduced in WP2 will be applied to various simple systems of PDEs, with accent set on Kuramoto-Sivashinsky system (KS). KS is a natural choice for preliminary investigation on the subject, due to the following reasons: in the past the system was already used as a natural bridge between ODEs and PDEs; it is used to represent turbulent fluid dynamics, therefore is relevant to geophysical situations. Galerkin projections of different orders will give rise to hierarchy of systems in which supermodeling approach can be explored. Both the number of connections as well as the number of interdependently trained connections can be varied as the order increases. Previous results obtained on simple parameter estimation models will be further analyzed here in regards to possible lessons about performance vs. density of required connections for analyzed algorithms.

Task 3.2 Comparison of learning algorithms for connections in PDE supermodels: The conclusions emerging from WP2 about the relative merits of different learning approaches will be re-examined in PDEs context. A comparison of the spatial density of connections required in each approach will be examined. Special attention will be paid to the issue of locally optimal supermodel in the PDE context, with accent on the system dimensionality. The software frame for supermodeling that will later be applied to climate models, will be constructed at this stage.

Task 3.3 Develop learning strategies for intermediate complexity climate supermodels: The work will be further continued on analysis of quasi-geostrophic (QS) channel model, which is a relatively simple geophysical model. MASA investigators have previously worked on this model showing that a single connection coefficient in a supermodel consisting of two QG channel models could be adapted using the incremental learning approach. It had been shown in previous work that two such models, one with a forcing jet in the Atlantic, and another with a jet in the Pacific, could be made to synchronize when connected, each model inducing the missing jet in the other (Duane and Tribbia, 2001, 2004). This model configuration in these studies was originally researched as to predict new types of Atlantic-Pacific teleconnections. But it is also a supermodel. It can be trained by connecting to a third “real” channel with two jets and provides an ideal test case to further develop an incremental learning approach. The QG channel investigation will form the basis for the subsequent study of the more realistic quasi-geostrophic model, the Ecbilt model, that will be studied in WP4.

Task 3.4 Develop learning strategies for state-of-the-art climate supermodels: While with T3.1, T3.2 and T3.3 most issues regarding training of connections coefficients in climate supermodels will be resolved, this task will focus on some remaining issues that are peculiar to full climate simulations. One of those issues is that of possible trends due to gradual changes in CO_2 forcing; another arises from the arbitrariness in radiative forcing in climate models. This will further increase in complexity of the learning algorithms.

Person-Months per Participant

Participant number [10]	Participant short name [11]	Person-months per participant
1	MASA	32.00
3	KNMI	4.00
4	PIFK	3.00
5	RU	4.00
6	JSI	6.00
7	UIB	1.00
	Total	50.00

List of deliverables

Deliverable Number [61]	Deliverable Title	Lead beneficiary number	Estimated indicative person-months	Nature [62]	Dissemination level [63]	Delivery date [64]
D3.1	Report on connections learning approaches for PDEs	1	17.00	R	PU	12
D3.2	Report on different learning approaches for QG channel models	1	15.00	R	PU	24
D3.3	Report on methods developed for connecting intermediate complexity climate models	1	18.00	R	PU	36
		Total	50.00			

Description of deliverables

D3.1) Report on connections learning approaches for PDEs: Report with the outcomes of Task 3.1 and Task 3.2 [month 12]

D3.2) Report on different learning approaches for QG channel models: Report with the outcomes of Task 3.3 [month 24]

D3.3) Report on methods developed for connecting intermediate complexity climate models: Report with the outcomes of Task 3.4 [month 36]

Schedule of relevant Milestones

Milestone number [59]	Milestone name	Lead beneficiary number	Delivery date from Annex I [60]	Comments
MS1	Decision on model classes	4	12	Deliverables D1.1 and D2.1
MS2	Decision on initial super modeling strategy for climate super models	1	12	Deliverables D3.1, D4.1 and D5.1
MS3	Evaluate the initial super model experience with climate super models	3	24	Deliverables D4.2 and D5.2
MS4	Decision on an updated strategy for climate super models	5	24	Deliverables D1.2, D2.2, D3.2 and D4.2

Project Number [1]	266722	Project Acronym [2]	SUMO

One form per Work Package

Work package number [53]	WP4	Type of activity [54]	RTD
Work package title	Supermodeling with intermediate complexity climate models		
Start month	1		
End month	36		
Lead beneficiary number [55]	3		

Objectives

In this work package we develop and test the super modeling approach using climate models of intermediate complexity. We follow the suggestions from WP1, WP2 and WP3 that developed and tested the approach in simpler systems guided by theoretical considerations and report back whether the approach needs rethinking and redesigning. The main objective is to develop a super modeling approach, that is applicable to the state-of-the-art climate models of WP5. In this work package we will create imperfect models by perturbing model parameters and formulations and regard the original model as a virtual truth.

Description of work and role of partners

Task 4.1 Formulation of the connections
Experiment with the formulation of the connections following suggestions from WP1, WP2 and WP3. Questions to be addressed are:
should the imperfect models be connected through the state variables or through the physical tendencies ?
how many state variables or linear combinations of the state variables (Empirical Orthogonal Functions for instance) need to be connected ?
how should we define the connections to prevent the introduction of imbalances ?
how should the domain knowledge for machine learning of interconnection structure be formulated?

Task 4.2 Learn how to deal with different timescales in the learning task
In this task we deal with the differences in timescale between the atmosphere and the ocean. This has implications for the learning task. Questions to be addressed are:
should we connect only through the fast, atmospheric variables or should we also connect the slower oceanic variables ?
should we keep the ocean fixed while learning the connections between the fast atmospheric variables ?
should we design a separate supermodel for the atmosphere and for the ocean and connect these instead of connecting coupled atmosphere-ocean models ?

Task 4.3 Provide guidelines for a supermodel using state-of-the-art climate models
Based on the results obtained with the intermediate complexity models guidelines will be developed for the construction of a supermodel using state-of-the-art climate models.

Task 4.4 Investigate the ability of the supermodel to simulate a realistic response
After learning the supermodel to reproduce the present-day climate, we will test its ability to simulate a realistic response to increasing concentrations of greenhouse gasses.

Person-Months per Participant

Participant number [10]	Participant short name [11]	Person-months per participant
1	MASA	6.00
3	KNMI	27.00
4	PIFK	3.00

Person-Months per Participant

Participant number [10]	Participant short name [11]	Person-months per participant
5	RU	4.00
6	JSI	3.00
7	UIB	6.00
	Total	49.00

List of deliverables

Delive-rable Number [61]	Deliverable Title	Lead benefi-ciary number	Estimated indicative person-months	Nature [62]	Dissemi-nation level [63]	Delivery date [64]
D4.1	Report on the issues of the connections	3	14.00	R	PU	12
D4.2	Report with guidelines for a climate super model	3	19.00	R	PU	24
D4.3	Report on the behaviour of the supermodel in a perturbed climate regime	3	16.00	R	PU	36
		Total	49.00			

Description of deliverables

D4.1) Report on the issues of the connections: In Task 4.1 various issues on the definition of the connections are researched in intermediate complexity climate models. These issues need to be shared with the other work packages to decide on an initial super modeling strategy. [month 12]

D4.2) Report with guidelines for a climate super model: Guidelines for the construction of a climate super model in WP5 that are developed in Task 4.3 based on the results of Tasks 4.1 and 4.2 are formulated in this report to share with the other work packages. [month 24]

D4.3) Report on the behaviour of the supermodel in a perturbed climate regime: The ability of the super model to faithfully simulate the true model in a perturbed climate regime is assessed in Task 4.4 and shared with the other work packages in this report. [month 36]

Schedule of relevant Milestones

Milestone number [59]	Milestone name	Lead benefi-ciary number	Delivery date from Annex I [60]	Comments
MS1	Decision on model classes	4	12	Deliverables D1.1 and D2.1
MS2	Decision on initial super modeling strategy for climate super models	1	12	Deliverables D3.1, D4.1 and D5.1
MS3	Evaluate the initial super model experience with climate super models	3	24	Deliverables D4.2 and D5.2

Schedule of relevant Milestones

Milestone number [59]	Milestone name	Lead beneficiary number	Delivery date from Annex I [60]	Comments
MS4	Decision on an updated strategy for climate super models	5	24	Deliverables D1.2, D2.2, D3.2 and D4.2
MS5	Showcase for intermediate and complex climate super models	7	36	Deliverables D4.3 and D5.3

WT3:
Work package description

Project Number [1]	266722	Project Acronym [2]	SUMO

One form per Work Package

Work package number [53]	WP5	Type of activity [54]	RTD
Work package title	Supermodeling with large climate models		
Start month	1		
End month	36		
Lead beneficiary number [55]	7		

Objectives

1. Develop a super climate model by coupling three different climate models together, using observations for the period 1870-1980 to train the model

2. Assess the benefits and drawbacks of the super climate modelling strategy against conventional approaches (i.e., multi-model mean) and the best model through simulating climate from 1980-2010 and retrospective-prediction of seasonal-to-decadal fluctuations during the same period.

3. Demonstrate that the super modelling strategy can be applied to make climate projections, by performing a scenario simulation for the 21st century with the super climate model and contrasting it with conventional multi-model scenario simulations

Description of work and role of partners

The overarching aim of this WP is to construct, assess, and apply a super climate model to simulate and predict climate over the 20th and 21st century. Theory on constructing and training super-model (WPs 1-3) will be applied to complex climate models (with order 106 degrees of freedom) based on results from tests on intermediate climate models (WP4).

Three different climate models will be applied: ECHAM5/NEMO, ECHAM5/MPIOM, and IFS/NEMO coupled models; the first two will be provided by UiB and the last by KNMI. Two classes of simulations will be performed to assess the super climate model: externally forced (i.e., boundary value problem) and initialised (i.e., initial condition and boundary value problem).

The WP objectives will be achieved as follows:

Task 5.1 (month 1-6), develop technical capability to construct and run a super climate model: The three models will be installed on a single super computer in Germany (HLRN, https://www.hlrn.de/home/view). A coupling interface based on OASIS4 (http://www.prism.enes.org/PAEs/coupling_IO/software_OASIS4.php) will be implemented in each of the individual model component to facilitate efficient exhange of information among model components on a time step basis. [UiB, KNMI]

Task 5.2 (month 7-16), construct a super climate model with manually chosen connection (i.e., with out a learning algorithm): The three climate models will be coupled via their atmospheric convective parameterisation. The constructed model will be tested and refined in coupled ocean-atmosphere and atmosphere prescribed boundary conditions (sea surface temperature (SST) and sea ice cover) simulations. Uncoupled simulations will cover the period 1980-2010, while coupled simulations for both fixed (present-day) and time varying (20th century) radiative forcing will be performed. [UiB, KNMI]

Task 5.3 (month 13-20), construct a super climate model using a learning strategy: A first version of the super-climate model will be developed based on initial results of WP 1-4. The development will involve continued input from other WPs. Recommendations will be taken on the following:
• Whether to couple state variables or physical tendencies
• How to reduce of data dimensionality
• How to deal with fast atmospheric and slow ocean processes
• How to train the model on observational data

The supermodel will be trained over the period 1870-1980. [UiB, MASA, KNMI, RU, PIK]

Task 5.4 (month 19-24), test the super-climate model using independent data: Simulations will be made with the super climate model for the period 1980-2010 as well as a set of retrospective seasonal-to-decadal forecasts for the period 1980 till 2010. [UiB]

Task 5.5 (month 7-24), assess the super climate models constructed with connections chosen manually and using a learning strategy: The ability of the models to simulate the mean, variability, and global warming of climate over the independent period from1980-2010 will be assessed. The skill of the trained super-model in predicting seasonal-todecadal fluctuations (i.e., an initial condition and boundary value problem) will be quantified. Agreement and skill will be quantified using metrics developed in WP4 and compared to that of the individual models and their weighted average. [UiB, KNMI]

Task 5.6 (month 24-28), define a second version of the super-climate model: A refined version of the model will be made based on results of task 1-4 and recommendations from WP1-4. It will be trained over the period 1870-1980, and tested on the period 1980-2010. [UiB, MASA, KNMI, RU, PIK]

Task 5.7 (month 29-36), perform a scenario simulation for the 21st century with the super climate model and contrast it with conventional multi-model scenario simulations. [UiB]

Task 5.8 (month 33-36), final recommendation on the super climate modelling strategy: Results of the application of the super-modelling strategy to the hierarchy of models in the whole project will be summarised. The utility of the approach to climate modelling and the potential to reduce uncertainties in future climate projections will be assessed. Recommendations on future work on this topic will be made. These will be described in a
report. [UiB, MASA, KNMI, RU, PIK]

Person-Months per Participant

Participant number [10]	Participant short name [11]	Person-months per participant
1	MASA	6.00
2	IFM-GEOMAR	3.00
3	KNMI	6.00
4	PIFK	1.00
5	RU	1.00
6	JSI	3.00
7	UIB	30.00
	Total	50.00

List of deliverables

Delive-rable Number [61]	Deliverable Title	Lead benefi-ciary number	Estimated indicative person-months	Nature [62]	Dissemi-nation level [63]	Delivery date [64]
D5.1	Report on super climate model with manually chosen connections	7	15.00	R	PU	12
D5.2	Report on super climate model behaviour after learning	7	18.00	R	PU	24

List of deliverables

Deliverable Number [61]	Deliverable Title	Lead beneficiary number	Estimated indicative person-months	Nature [62]	Dissemination level [63]	Delivery date [64]
D5.3	Report on updated super climate model and summarizing results on super climate modeling	7	17.00	R	PU	36
		Total	50.00			

Description of deliverables

D5.1) Report on super climate model with manually chosen connections: Report describing the super climate model with manually chosen connections (i.e., with out a learning algorithm) and its ability to simulate the mean and variability of present-day climate (Tasks 5.1, 5.2 and 5.5) [month 12]

D5.2) Report on super climate model behaviour after learning: Report describing the first version of the super climate model constructed using a learning strategy, quantifying its ability to simulate the mean, variability, and global warming of climate over the independent period from1980-2010, and evaluating its skill in retrospective prediction of seasonal-to-decadal climate fluctuations over the same period. Comparison will be made with the transient forcing simulations made with the super climate model with manually chosen connections. (Tasks 5.1, 5.2, 5.3, 5.4 and 5.5) [month 24]

D5.3) Report on updated super climate model and summarizing results on super climate modeling: Report describing the second version of the super climate model constructed using a learning strategy, and presenting the results of the scenario simulation for the 21st century performed with the model and contrasting them with those of conventional scenario simulations. This report summarizes the overall results of the project and provides an assessment of the potential of the super climate model approach to reduce uncertainties in future climate projections and recommendations on this approach (Tasks 5.6, 5.7, and 5.8) [month 36]

Schedule of relevant Milestones

Milestone number [59]	Milestone name	Lead beneficiary number	Delivery date from Annex I [60]	Comments
MS1	Decision on model classes	4	12	Deliverables D1.1 and D2.1
MS2	Decision on initial super modeling strategy for climate super models	1	12	Deliverables D3.1, D4.1 and D5.1
MS3	Evaluate the initial super model experience with climate super models	3	24	Deliverables D4.2 and D5.2
MS4	Decision on an updated strategy for climate super models	5	24	Deliverables D1.2, D2.2, D3.2 and D4.2
MS5	Showcase for intermediate and complex climate super models	7	36	Deliverables D4.3 and D5.3

WT3:
Work package description

Project Number [1]	266722	Project Acronym [2]	SUMO

One form per Work Package

Work package number [53]	WP6	Type of activity [54]	MGT
Work package title	Management		
Start month	1		
End month	36		
Lead beneficiary number [55]	1		

Objectives

1. Manage efficiently the project.
2. Communication between the European Commission and SUMO, including all forms of reporting specified in the consortium contract agreement.
3. Provide the communication tools for the project: public and internal web sites.
4. Organise annual general assemblies and project meetings.
5. Organise a SUMO international dissemination Workshop.
6. Ensure promotion of clustering and cooperation with related projects (both in FP7 and other international and national projects).

Description of work and role of partners

Task 6.1: Project Management
The coordinator supported by the project office and the administrative staff are in regular contact with the Management Board of SUMO and the European Commission. The project office will prepare the necessary scientific and financial reports for the EC. The project office will communicate all necessary information from the EC to the participants for the preparation of the due reports and for the financial aspects. The project will set up and maintain a public and an internal project website.

Task 6.2: Annual general assemblies and project meetings
The project office prepares the general assemblies and project meetings. Together with the SSC, the project office produces the programme of the meeting, invites the key scientists (guest speakers), and representatives from other related projects (FP7 projects and international projects).

Task 6.3: Contribution to portfolio and concertation activities at FET-Open level
The project office will actively promote dissemination activities. It will make sure that all scientific knowledge acquired in SUMO is freely available for external users. This will be done through promotion of the SUMO achievements, tools and data in meetings of national and international organisations and through a SUMO organised summer school in the 3th year for a wide scientific audience. The project office will produce a flyer and a brochure.

Person-Months per Participant

Participant number [10]	Participant short name [11]	Person-months per participant
1	MASA	17.00
3	KNMI	1.00
4	PIFK	1.00
5	RU	1.00
6	JSI	1.00
7	UIB	1.00

Person-Months per Participant

Participant number [10]	Participant short name [11]	Person-months per participant
	Total	22.00

List of deliverables

Delive-rable Number [61]	Deliverable Title	Lead benefi-ciary number	Estimated indicative person-months	Nature [62]	Dissemi-nation level [63]	Delivery date [64]
D6.1	Project flyer	1	1.25	O	PU	3
D6.2	Project website	1	1.50	O	PU	3
D6.3	Project periodic report 1	1	2.25	O	PU	12
D6.4	Project periodic report 2	1	2.25	R	PU	24
D6.5	Project periodic report 3	1	2.25	R	PU	36
D6.6	International SUMO summerschool	1	5.50	O	PU	34
D6.7	Brochure with SUMO results	1	3.25	R	PU	36
D6.8	Final report	1	3.75	R	PU	36
		Total	22.00			

Description of deliverables

D6.1) Project flyer: Flyer with information about the SUMO project (Task 6.3) [month 3]

D6.2) Project website: An internal SUMO website to exchange information with webconferencing capability (Task 6.1) [month 3]

D6.3) Project periodic report 1: The project office prepares the general assemblies and project meetings. Together with the SSC, the project office produces the programme of the meeting, invites the key scientists (guest speakers), and representatives from other related projects (FP7 projects and international projects). (Task 6.1) [month 12]

D6.4) Project periodic report 2: Progress report on the activities in the second year. (Task 6.1) [month 24]

D6.5) Project periodic report 3: Progress report on the activities in the third year. (Task 6.1) [month 36]

D6.6) International SUMO summerschool: Promotion of the SUMO achievements, tools and data is realised through a SUMO organised summer school in the 3th year for a wide scientific audience. (Task 6.3) [month 34]

D6.7) Brochure with SUMO results: The project office will produce a brochure highlighting the achievements in the SUMO project. (Task 6.3) [month 36]

D6.8) Final report: A final report describing the achievements of the SUMO project and recommendations for further developments. (Task 6.1) [month 36]

Schedule of relevant Milestones

Milestone number [59]	Milestone name	Lead benefi-ciary number	Delivery date from Annex I [60]	Comments

WT3:
Work package description

Project Number [1]	266722	Project Acronym [2]	SUMO

One form per Work Package

Work package number [53]	WP7	Type of activity [54]	RTD
Work package title	Learning complete supermodels		
Start month	10		
End month	36		
Lead beneficiary number [55]	6		

Objectives

The objective of this WP is to develop methods for computational scientific discovery that can learn complete supermodels (ensembles of ODE models) of dynamic systems. Its sub-objectives include the development of techniques for the (semi)automated generation of constituent models, for the selection of an appropriate subset of models, and for learning the form and coefficients of the interconnections among the models.

Description of work and role of partners

This workpackage will develop methods for learning complete supermodels. We expect that supermodels will be built in three phases: first generate diverse models, then select a set of complementary models, and finally learn the interconnections between the constituent models of an ensemble. These three phases naturally lead to the three tasks that constitute this WP.
JSI will lead this WP and the constituent tasks. MASA will also contribute significantly, in close collaboration with JSI, providing insights from non-linear dynamics.

Task 7.1 Generate a diverse set of ODE models
To generate a diverse set of models, we will adapt existing approaches from the area of ensemble learning. These include taking different subsamples of the data, taking different projections of the data, and taking different learning algorithms (or randomized algorithms). Different subsets of domain knowledge may also be considered.

Task 7.2 Select a complementary set of ODE models
Given a set of models, we will use a measure of similarity between models to select models that are complementary. Different measures of similarity (or model performance/quality) will be considered. Besides the sum of squared errors and correlation, other measures might be considered such as weighted sum of squared errors or robust statistical estimators.

Task 7.3 Learn to interconnect ODE models
In learning the interconnections between the constituent models of the ensemble, we will consider searching through the space of possible structural forms of the interconnections, coupled with parameter fitting for a selected functional form of the possible connections. For parameter fitting, we will use global optimization methods based on meta-heuristic approaches. The use of such parameter estimation methods is of crucial importance in supporting the use of different quality criteria, as well as avoiding local optima in search.

Person-Months per Participant

Participant number [10]	Participant short name [11]	Person-months per participant
1	MASA	27.00
6	JSI	27.00
	Total	54.00

List of deliverables

Delive-rable Number [61]	Deliverable Title	Lead benefi-ciary number	Estimated indicative person-months	Nature [62]	Dissemi-nation level [63]	Delivery date [64]
D7.1	Report on the generation of a diverse set of ODE models	6	18.00	R	PU	18
D7.2	Report on the selection of a complementary set of ODE models	6	18.00	R	PU	27
D7.3	Report on learning to interconnect ODE models	6	18.00	R	PU	36
		Total	54.00			

Description of deliverables

D7.1) Report on the generation of a diverse set of ODE models: This report contains the outcomes of Task 7.1 [month 18]

D7.2) Report on the selection of a complementary set of ODE models: This report contains the outcomes of Task 7.2 [month 27]

D7.3) Report on learning to interconnect ODE models: This report contains the outcomes of Task 7.3 [month 36]

Schedule of relevant Milestones

Milestone number [59]	Milestone name	Lead benefi-ciary number	Delivery date from Annex I [60]	Comments
MS6	Domain knowledge and methods for generating diverse models developed	6	18	Deliverables D1.4 and D7.1
MS7	Methods for selecting a set of complementary models developed	6	27	Deliverable D7.2
MS8	Methods for learning functional form and coefficients of interconnections developed	6	36	Deliverable D7.3

WT4:
List of Milestones

Project Number [1]	266722	Project Acronym [2]	SUMO

List and Schedule of Milestones

Milestone number [59]	Milestone name	WP number [53]	Lead beneficiary number	Delivery date from Annex I [60]	Comments
MS1	Decision on model classes	WP1, WP2, WP3, WP4, WP5	4	12	Deliverables D1.1 and D2.1
MS2	Decision on initial super modeling strategy for climate super models	WP1, WP2, WP3, WP4, WP5	1	12	Deliverables D3.1, D4.1 and D5.1
MS3	Evaluate the initial super model experience with climate super models	WP1, WP2, WP3, WP4, WP5	3	24	Deliverables D4.2 and D5.2
MS4	Decision on an updated strategy for climate super models	WP1, WP2, WP3, WP4, WP5	5	24	Deliverables D1.2, D2.2, D3.2 and D4.2
MS5	Showcase for intermediate and complex climate super models	WP4, WP5	7	36	Deliverables D4.3 and D5.3
MS6	Domain knowledge and methods for generating diverse models developed	WP1, WP7	6	18	Deliverables D1.4 and D7.1
MS7	Methods for selecting a set of complementary models developed	WP7	6	27	Deliverable D7.2
MS8	Methods for learning functional form and coefficients of interconnections developed	WP7	6	36	Deliverable D7.3

WT5:
Tentative schedule of Project Reviews

Project Number [1]	266722	Project Acronym [2]	SUMO

Tentative schedule of Project Reviews			
Review number [65]	Tentative timing	Planned venue of review	Comments, if any
RV 1	14	Skopje	
RV 2	26	Potsdam	
RV 3	38	De Bilt	

WT6:
Project Effort by Beneficiary and Work Package

Project Number [1]	266722	Project Acronym [2]	SUMO

Indicative efforts (man-months) per Beneficiary per Work Package

Beneficiary number and short-name	WP 1	WP 2	WP 3	WP 4	WP 5	WP 6	WP 7	Total per Beneficiary
1 - MASA	10.00	18.00	32.00	6.00	6.00	17.00	27.00	116.00
2 - IFM-GEOMAR	0.00	0.00	0.00	0.00	3.00	0.00	0.00	3.00
3 - KNMI	1.00	4.00	4.00	27.00	6.00	1.00	0.00	43.00
4 - PIFK	30.00	3.00	3.00	3.00	1.00	1.00	0.00	41.00
5 - RU	6.00	20.00	4.00	4.00	1.00	1.00	0.00	36.00
6 - JSI	9.00	9.00	6.00	3.00	3.00	1.00	27.00	58.00
7 - UIB	1.00	1.00	1.00	6.00	30.00	1.00	0.00	40.00
Total	57.00	55.00	50.00	49.00	50.00	22.00	54.00	337.00

WT7:
Project Effort by Activity type per Beneficiary

Project Number [1]	266722	Project Acronym [2]	SUMO

Indicative efforts per Activity Type per Beneficiary

Activity type	Part. 1 MASA	Part. 2 IFM-GEO	Part. 3 KNMI	Part. 4 PIFK	Part. 5 RU	Part. 6 JSI	Part. 7 UIB	Total
1. RTD/Innovation activities								
WP 1	10.00	0.00	1.00	30.00	6.00	9.00	1.00	57.00
WP 2	18.00	0.00	4.00	3.00	20.00	9.00	1.00	55.00
WP 3	32.00	0.00	4.00	3.00	4.00	6.00	1.00	50.00
WP 4	6.00	0.00	27.00	3.00	4.00	3.00	6.00	49.00
WP 5	6.00	3.00	6.00	1.00	1.00	3.00	30.00	50.00
WP 7	27.00	0.00	0.00	0.00	0.00	27.00	0.00	54.00
Total Research	99.00	3.00	42.00	40.00	35.00	57.00	39.00	315.00
2. Demonstration activities								
Total Demo	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
3. Consortium Management activities								
WP 6	17.00	0.00	1.00	1.00	1.00	1.00	1.00	22.00
Total Management	17.00	0.00	1.00	1.00	1.00	1.00	1.00	22.00
4. Other activities								
Total other	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Total	116.00	3.00	43.00	41.00	36.00	58.00	40.00	337.00

WT8:
Project Effort and costs

Project Number [1]	266722	Project Acronym [2]	SUMO

Project efforts and costs

Benefi-ciary number	Beneficiary short name	Estimated eligible costs (whole duration of the project)						Requested EU contribution (€)
		Effort (PM)	Personnel costs (€)	Subcontracting (€)	Other Direct costs (€)	Indirect costs OR lump sum, flat-rate or scale-of-unit (€)	Total costs	
1	MASA	116.00	217,000.00	0.00	75,750.00	175,650.00	468,400.00	356,200.00
2	IFM-GEOMAR	3.00	16,911.00	0.00	1,940.00	11,310.00	30,161.00	22,620.00
3	KNMI	43.00	239,580.00	0.00	21,500.00	220,414.00	481,494.00	361,120.00
4	PIFK	41.00	159,800.00	0.00	18,000.00	113,388.00	291,188.00	219,891.00
5	RU	36.00	216,426.00	0.00	9,600.00	196,445.00	422,471.00	316,853.00
6	JSI	58.00	229,666.00	15,000.00	26,000.00	116,928.00	387,594.00	292,189.00
7	UIB	40.00	187,437.00	0.00	8,560.00	117,598.00	313,595.00	233,994.00
	Total	337.00	1,266,820.00	15,000.00	161,350.00	951,733.00	2,394,903.00	1,802,867.00

Part B

Project number
266722

Project title
SUMO — “Supermodeling by combining imperfect models” (Extended)

Call (part) identifier
FP7-ICT-2009-C FET-Open, FP7-ICT-2011-7

Funding scheme
Collaborative project

Version Number – Date of Preparation
Version 3 – 30 May 2011

Date of Approval
Not approved

B.1 Concept and objectives, progress beyond state-of-the-art, S/T methodology and work plan

B.1.1 Concept and project objective(s)

This section should be based on Part B Section 1.1 of the original proposal. Explain the concepts of your project. What are the main ideas that lead you to propose this work? Describe the objectives of the project in detail, in particular in a measurable and verifiable form. Objectives should be achievable within the project (not through subsequent developments); they should be specific and timed (e.g. by which date/milestone the objectives will be achieved), well in line with the milestones that will be indicated under Section 1.3 below.

The ***novelty*** of this proposal is summarized in the concept of supermodeling: a supermodel is an interconnected ensemble of existing imperfect models of a real, observable system. The connections between the models can be learned from observational data using methods from machine learning: This includes both the coefficients and form of the interconnections. The supermodel outperforms the individual models in simulating the behavior of the real system since it has learned to combine the strengths of the individual models. The concept of supermodeling is based on a ***new combination*** of insights from ***climate science, nonlinear dynamical systems***, and ***machine learning***. Before we get to these, we briefly discuss the approach in a concrete example of an interconnected ensemble of imperfect Lorenz models (Lorenz, 1963) in order to make the concept of a supermodel more explicit.

B.1.1.1 Illustration of the supermodeling concept

The Lorenz equations are given by:

$$\begin{aligned} \frac{dx}{dt} &= \sigma\left(y-x\right) \\ \frac{dy}{dt} &= x\left(\rho-z\right)-y \qquad \text{with} \qquad (1) \\ \frac{dz}{dt} &= xy-\beta z \end{aligned}$$

	σ	ρ	β
Truth	10	28	8/3
Model 1	9	31	13/6
Model 2	8	30	19/6
Model 3	12	25	71/30

Three imperfect models are obtained by perturbing the parameters as indicated in the table. A supermodel is formed by connecting the three imperfect models:

$$\begin{aligned} \frac{dx^k}{dt} &= \sigma^k\left(y^k-x^k\right) + \sum_{l\neq k} C_x^{kl}\left(x^l-x^k\right) \\ \frac{dy^k}{dt} &= x^k\left(\rho^k-z^k\right)-y^k + \sum_{l\neq k} C_y^{kl}\left(y^l-y^k\right) \qquad \text{with } k = 1..3 \qquad (2) \\ \frac{dz^k}{dt} &= x^k y^k-\beta^k z^k + \sum_{l\neq k} C_z^{kl}\left(z^l-z^k\right) \end{aligned}$$

The choice of the connections *C* are learned from data from the truth or set manually on the basis of mathematical and/or physical insight.

Figure 1.1 shows the solution of the true Eq. (1) in green in the three dimensional state space of the model and in red for the supermodel before learning with all connections set to 1 (left panel) and after learning (right panel).

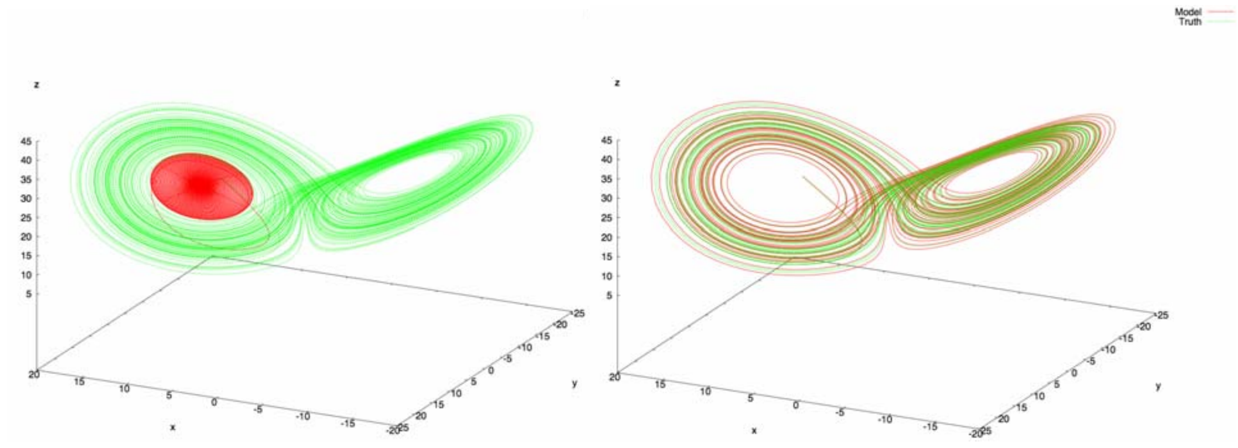


Figure 1.1: The solution for the true Lorenz equations is plotted in green in both panels. In the left panel the red trajectory denotes the solution of the supermodel with connections set to unity and in the right panel with connections learned from data.

The supermodel accurately reproduces the true solution after learning and illustrates the potential of the supermodeling approach. The imperfect models are connected in such a way that the true evolution is simulated quite accurately.

B.1.1.2 Insights from climate science

The existing approach to simulate and predict the behavior of real, complex systems like the Earth's climate system is to solve the governing equations in a suitable approximate form numerically using discretization techniques. In addition, empirical formulations are implemented for unresolved physical processes. These numerical models contain numerous uncertain parameters that are given values by trial and error (`tuned') in order to produce model simulations that are as close as possible to observations of the real system. A dozen or so very advanced climate models have been developed that differ in discretization techniques, spatial resolution, the range of processes that are explicitly modelled and the empirical formulations of the unresolved processes. Each model provides reasonable simulations of the observed climate, each with its own strengths and weaknesses.

The current approach to the climate prediction problem is to combine a posteriori the outcomes of the existing, individual models in various ways. Progress over time is achieved by improving the resolution and empirical formulations of the individual models.

It has been observed by climate researchers that the imperfections of these models are often complementary; for instance one atmospheric model might produce more realistic heat fluxes for the ocean, while another produces more realistic momentum fluxes. An improved simulation was obtained in a recent study (Kirtman, 2002) in which two atmospheric models were coupled to one oceanographic model, one provided the more realistic heat fluxes at every time step, the other the more realistic momentum fluxes. Importantly, it was not known *a priori* that one model produced a more realistic heat flux at the ocean surface and that the other model produced a more realistic momentum flux. Rather, those relative advantages became apparent only in the context of the behavior of the entire model with exchanged variables. Running models in parallel and allowing a dynamic exchange of information appears a feasible avenue to improve the simulation performance by combining the strengths of the individual models. This particular modelling approach is called an interactive ensemble.

B.1.1.3 Insights from non-linear dynamics

Our atmosphere and ocean are examples of (very complex) nonlinear dynamical systems with forcing and dissipation. The temporal evolution of such systems can be viewed in the state space of the system (Eckmann and Ruelle, 1985). Starting from an arbitrary, initial state, a point in state space, the system will evolve along a trajectory that after a certain transient period will settle on an attractor which consists of the set of states that the trajectory will visit repeatedly and arbitrarily close in due time. A system might have multiple attractors, each with its own basin of attraction, consisting of the set of initial conditions that end up on that attractor. If the system comes to a state of rest, the attractor is a point. If the system undergoes periodic behavior, the attractor is a closed loop or limit cycle. If the system displays a-periodic behavior and its evolution depends sensitively on the initial condition (a small perturbation to the initial conditions grows in time or, put differently, nearby trajectories diverge), the attractor is a fractal set and is referred to as a strange attractor or chaotic attractor. An example of this is the Lorenz attractor depicted in Fig. 1.1. A change in parameter values brings about a change in the attractor. If a large, qualitative change occurs, the system undergoes a bifurcation, for instance from a state of rest (point attractor) to a periodic motion (periodic attractor or limit cycle). Bifurcation studies on atmosphere and ocean models suggest that both evolve on complicated, high-dimensional strange attractors (Itoh and Kimoto, 1996, Simonnet et al, 2008). The properties of the attractor characterize the climate. Changes in the attractor due to a change in parameter values (for instance the amount of CO_2 in the atmosphere) characterize the climate change.
If two dynamical systems with the same or very similar attractors are loosely connected, it often happens that the evolution on both attractors synchronize, not just for periodic attractors but also in the case of strange attractors (Yang et al, 2006), despite the sensitive dependence on initial conditions that is characteristic of chaotic systems. Feeding weather models with observations can be viewed from the perspective of synchronization; if the attractor of the weather model is sufficiently close to the attractor of the atmosphere, it is able to recover the full state of the atmosphere on the basis of a limited set of observations. Whether or not synchronization occurs also depends on the characteristics of the connections, for instance the strength, density and particular formulation of the connections. In supermodeling, the synchronization paradigm enters in a new way: The goal is to choose or learn the connections between the models in such a way that the models fall into synchronization with each other, as well as with reality, with limited exchange of information between the models, effectively forming a consensus on the best representation of the real system. It is a fundamental assertion of this proposal that such an effect is possible for the same reasons - rooted in the dynamical structure of the separate models – that make numerical weather prediction possible despite chaos.
To illustrate synchronization we turn again to the Lorenz system (1). The equations of the supermodel are extended with connections K to the true system (x,y,z):

$$
\begin{aligned}
\frac{dx^k}{dt} &= \sigma^k \left(y^k - x^k\right) + \sum_{l \neq k} C_x^{kl} \left(x^l - x^k\right) + K_x\left(x - x^k\right) \\
\frac{dy^k}{dt} &= x^k \left(\rho^k - z^k\right) - y^k + \sum_{l \neq k} C_y^{kl} \left(y^l - y^k\right) + K_y\left(y - y^k\right) \quad \text{with } k = 1..3 \qquad (3) \\
\frac{dz^k}{dt} &= x^k y^k - \beta^k z^k + \sum_{l \neq k} C_z^{kl} \left(z^l - z^k\right) + K_z\left(z - z^k\right)
\end{aligned}
$$

The left panel of Fig. 1.2 depicts short time-series of the averaged *y*-component of the supermodel with learned connections integrated with the *y*-components connected to a time-series of *y* of the true model (K_x , K_z = 0 and K_y = 3) in green and the time-series of *y* of the true model in black. The model starts from a different initial condition and after a transient period both time-series merge and remain close together: the supermodel synchronizes with the truth. Repeating the same integration but with all connections *C* set to zero, the average of the imperfect models does not synchronize with the truth (middle panel). When we replace the imperfect models by the perfect model (1) itself, we find that the ability of the supermodel to synchronize with the truth is similar to that of the perfect model (see right panel).

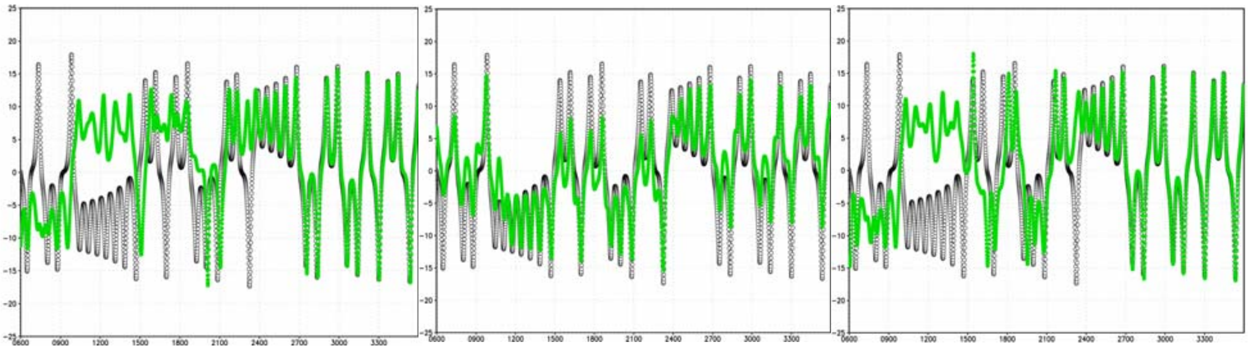


Figure 1.2: Time-series of the y-component of synchronization experiments between the perfect Lorenz model in black and (left panel) the supermodel, (middle panel) the average of the imperfect models and (right panel) the perfect Lorenz model in green.

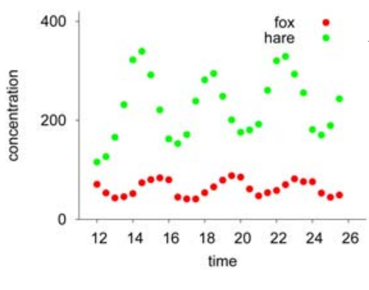
B.1.1.4 Insights from machine learning

Machine learning (Bishop, 2006) has developed methods and algorithms for automatic modelling by training general approximators, such as neural networks, on the basis of data. This is an efficient alternative for the conventional approach in which models are to be explicitly designed and parameterized in detail by humans.

The standard learning paradigm in machine learning is to fit the parameters of a model by minimizing a cost function. The choice of the cost function depends on the model task. In conventional time series modelling, the task of the model is to make a prediction of the value at the next time step (the output) given the value at the current time (the input). The training set consists of measurements at subsequent times, which can be viewed as set of (input, target output) examples. For a model with a given parameter setting, we can compute the model output for each of the inputs in the training set. The standard choice for the cost function to be minimized is the sum of squared differences between model and target outputs.

To optimize a model for predictions over longer time, multi-step ahead learning has been proposed (Kuo and Principe, 1994, Deco and Schürmann, 1994). The cost functions for these tasks are constructed by selecting a number of initial states from the measured time series and then taking

the sum of prediction errors over the small prediction sequence starting at the selected initial states.
In this proposal, we are interested in climate models. Assuming that the weather system is deterministic chaotic, the climate can be defined as the attractor of the weather system. The goal of the climate model is to find statistical properties of the attractor, rather than day-to-day predictions. Unfortunately, no dedicated algorithm exists to perform attractor learning. Instead, models are trained to make good predictions, and then the model attractor is obtained as a by-product by simulating the model autonomously over a long time (Bakker, 2007).
It has been observed (Kuo and Principe, 1994) that multi-step ahead learning provides better solutions in attractor terms than the more conventional one-step ahead approach. A one-step ahead trained model may yield good short term predictions, starting exactly on a given data point. However, if the model runs autonomously for longer time, the model drifts away from the observed data due to sensitive dependence on initial conditions and the transition to its own attractor. This is in contrast to a multi-step ahead trained model that has been tuned to stay close to the data trajectory for a certain amount of time. Another way to improve robustness of learning is to reduce the drift due to sensitive dependence on initial conditions by loosely connecting the model to the data during learning as illustrated above in Eq. (3). This will tend to keep the model state close to the data, allowing the models to synchronize with the data and allowing extension of the learning horizon (Bakker et al, 2000, Bakker, 2007, Duane et al, 2007).
Multi-step ahead learning has only recently been considered in the context of machine learning of systems dynamics (Bridewell et al. 2008) within the paradigm of ***computational scientific discovery*** (Langley et al. 1987; Džeroski and Todorovski, 2007). In this paradigm, complete models in the form of ordinary differential equations (ODEs) can be learned, including both the structure of and the parameters in the equations. Furthermore, the paradigm facilitates the combination of both observational data and existing background/domain knowledge.
Different types of ***domain knowledge*** can be used in ODE discovery (Todorovski and Džeroski, 2007). We can start from existing ODE models for the system at hand (that are partial, incomplete, and/or inaccurate) and revise/improve them in light of observed data. We can also provide a set of basic components as building blocks from which ODE models can be built. The domain knowledge can be provided in different forms, including grammars, constraints, and process-based modeling formalisms.



PPModel → *PreyChange, PredatorChange*

PreyChange → *PreyGrowth - Interaction*
PredatorChange → *const * Interaction + PredatorLoss*

PreyGrowth → $const * V_{Prey}$
PreyGrowth → $const * V_{Prey} * (1 - V_{Prey} / const)$

Interaction → $const * V_{Predator} * V_{Prey}$
Interaction → $const * V_{Predator} * V_{Prey} / (V_{Prey} + const)$

PredatorLoss → $- const * V_{Predator}$

V_{Prey} → *hare*
$V_{Predator}$ → *fox*

$$\frac{d}{dt} hare = 2.5 \cdot hare - 0.3 \cdot hare \cdot fox$$
$$\frac{d}{dt} fox = 0.1 \cdot 0.3 \cdot hare \cdot fox - 1.2 \cdot fox$$

An example input and output for an ODE discovery task of modeling population dynamics is given above. At the far left, the observed data are given, consisting of the densities of two populations. In the middle, the domain knowledge is given in the form of a context-free grammar specifying the functional form of the ODEs to be considered. At the far right, the output is given, consisting of two ODEs describing three population dynamics processes (prey growth in green, predator-prey interaction in blue, predator loss in red).
The use of domain knowledge allows for the convergence of the two major modeling paradigms, ***theoretical (knowledge-driven) modeling*** and ***empirical (data-driven) modeling.*** In the first ap-

proach, a domain expert derives a proper model structure based on domain-specific modeling knowledge: Extensive knowledge and little data are needed. In the second approach, different model structures are explored to fit observed data in a trial and error process: Extensive data and little domain knowledge are necessary. The integrated approach to automated modeling allows us to trade between the quantity and quality of domain knowledge and observed data in the effort to achieve good simulations of the modeled system.

Another paradigm from machine learning that we will draw upon is the paradigm of **ensemble learning** (Dietterich 2000; Džeroski et al. 2009). Typically employed in the context of predictive modeling in general and classification/regression in particular, ensemble methods create a set (ensemble) of predictive models instead of a single one. The predictions of the individual models from the ensemble are then combined by averaging or in a more complicated fashion: The form and parameters of the **combination function can be learnt by** the method of **stacking** (Wolpert ; 1992; Džeroski and Ženko 2004).

Our atmosphere and ocean can be viewed as nonlinear dynamical systems. Indeed machine learning methods can be applied to model nonlinear dynamical systems from data only, e.g. by using neural networks. However, this approach is limited to low (order 1 to 10) dimensional systems, since the amount of data needed to tune the model parameters typically scales exponentially with the dimension of the system (Bishop, 2006). This is known as the curse of dimensionality. Models to describe climate systems have at least several thousand dimensions or millions in case of the state-of-the-art climate models, which makes a neural network (or similar) approach infeasible. But the story does not end here: The approaches we propose do not only use data, but build upon existing models and other types of domain knowledge.

B.1.1.5 Combination of insights

Combining the insights outlined above, we believe that with supermodeling, machine learning methods can indeed be applied to high dimensional nonlinear dynamical systems with thousands of variables. This belief is based on the fact that supermodeling starts from existing models that were developed by domain experts, while conventional machine learning using general approximators starts from scratch. The power of supermodeling is further increased by the ability to use other forms of domain knowledge, as in computational scientific discovery. This gives supermodels a lead in the learning task.

Another way to put this is that in supermodeling the internal degrees of freedom are constrained by the underlying components models or the additional domain knowledge, making the curse of dimensionality much less severe. The insight that chaotic systems are able to synchronize when connected will be exploited in the development of a suitable learning strategy. The insight that well-chosen dynamic information exchange between state-of-the-art climate models can improve the simulation performance, as was accidently found in the interactive ensemble experiment described above, strengthens our belief that there is a huge potential for improving the quality of current climate simulations and predictions by combining the state-of-the-art climate models in a cleverly designed supermodel.

B.1.1.6 Objectives and Milestones

By bringing together experts from the fields of ***climate science***, ***non-linear dynamical systems*** and ***machine learning***, we believe we are in an excellent position to develop a strategy that by the end of the project leads to a supermodel consisting of an ensemble of interconnected state-of-the-art climate models with improved simulation accuracy as compared to the current standard, multi-model ensemble mean approach. We propose a balanced approach with theoretical and experimental work to develop the supermodeling strategy using low-dimensional model systems of up to a hundred dimensions and study the behaviour of such connected non-linear dynamical systems in great detail. We also propose an extension towards developing new computational scientific discovery approaches for learning supermodels of non-linear dynamic systems, i.e., ensembles of constituent ODE models and their interconnections, and using them to explore the fundamental issues in supermodeling (e.g., what are suitable forms for the connections).

We focus on fundamental questions such as:

- How can one ensure that the supermodel outperforms the individual models?
- What are suitable measures of performance?
- How far from the truth can the individual models be and still make a useful contribution to the supermodel?
- What are suitable forms for the connections?
- What is the minimum density of connections between the models?
- Is learning enhanced by coupling the supermodel to data during learning?

and so on. Systems described by partial differential equations will be used in order to extend this work to higher dimensions.

The ***first milestone*** (see WT4 of the workplan table) identifies the model classes that are studied in this phase that are thought to be relevant for the application of the supermodeling approach to climate models. Results from this fundamental work are used to guide the construction of a supermodel consisting of interconnected intermediate complexity climate models of order several thousands degrees of freedom. The ***second milestone*** identifies this stage. Lessons learned with these systems provide input to the final construction of a supermodel of interconnected, state-of-the-art climate models. Solutions for problems encountered with the climate models are sought for on the basis of additional work on lower dimensional systems or theoretical considerations. The resulting final approach developed on the basis of this mutual feedback is identified in the ***third and fourth milestones***. The connections between the imperfect models are both learned from data as well as chosen manually in order to gain insight how to choose connections properly if it turns out that the learning strategies fail in higher dimensional systems.
In case that we are not able to implement the supermodeling approach successfully by the end of this project in the real setting of climate simulation and prediction as identified by the ***fifth milestone***, we will at least have contributed a body of knowledge on the behaviour of connected systems of varying degree of complexity and have opened up new avenues for further research and development in the modelling of real, complex systems.

The remaining three milestones are related to the development of computational scientific discovery approaches to learning supermodels and their use in the context of climate modeling. The ***sixth milestone*** marks the time point by which domain knowledge for the automated construction/revision of climate models should be formulated. At this point, we should also have developed methods for generating a diverse set of ODE models. By the ***seventh milestone,*** we will have methods for selecting a complementary set of ODE models. Finally, by the ***eighth milestone***, we will have methods able to learn interconnections in supermodels, including both their form and coefficients.

B.1.2 Progress beyond the state of the art

This section should be based on Part B Section 1.2 of the original proposal, but the description of the state-of the-art should be shorter while the "baseline" descriptions and a description of the performance / research indicators have to be added.

Describe briefly the state-of-the art in the area concerned, and the advance that the project will bring about. Include also a part which clearly describes the "baseline" of the project in terms of "where does the project work start", and "the baseline data" against which the project will measure its progress and the results the project aims to achieve (e.g. advances over the state of the art, increase of innovation / exploitation potential, etc.). The Consortium should in particular include the definition of criteria and "performance / research indicators" for the project along which results, progress and impact of the project will be measured in later reviews and assessments.

B.1.2.1 Current practice of climate simulations

Climate scientists are faced with the challenge to provide society with ***credible scenarios of future climate change***. At a dozen or so institutes around the world, comprehensive climate models are being developed and improved. Over time, the capability of these models to simulate the observed climate of the last 100 years has improved due to increased spatial resolution and improved descriptions of unresolved processes, but large systematic errors remain and ***the models are still far from perfect*** (Reichler and Kim, 2008). Nevertheless, these models are time-integrated into the future to simulate the response of the climate system to so-called scenarios of future anthropogenic emissions of greenhouse gasses. The outcomes of these models are archived at a central repository and form the basis of extensive studies on future climate change by climate scientists (http://www-pcmdi.llnl.gov/). Studies based on these outcomes are used by policy-makers to assess the impact of climate change on society.

A crucial question that arises is how the outcomes of these different models should be combined to get the most realistic estimate of the unknown true response of the climate system to the expected future emissions of greenhouse gases, etc. Large differences do indeed exist in model-based predictions of future climate, in regard to the overall extent and regional characteristics of warming and concurrent changes in the geographical distribution of winds, clouds and precipitation. Common practice is that some form of a weighted average is applied to all model outcomes with greater weight given to those models that in some sense better reproduce the historically observed climate evolution (Tebaldi and Knutti, 2007). We question that such a posteriori combination of the individual imperfect model outcomes uses the full potential of the model ensemble.

B.1.2.2 A radically new multi-model approach

Instead, we propose a ***radically*** different ***computational*** strategy that ***combines ideas*** from the machine learning, dynamical systems and climate science community to improve our ability to simulate the observed, historical evolution of climate and obtain more realistic estimates of future climate change using the existing ensemble of state-of-the-art climate models. This approach is ***new*** and ***timely*** since the models are there, the need for better-constrained predictions is urgent and most importantly the computational resources will hopefully soon be there through for instance advanced grid technologies to allow the simultaneous integration of an ensemble of state-of-the-art climate models that exchange information on a time-step basis.

Our targeted ***breakthrough*** is to provide a more realistic simulation of the observed historical evolution of climate and make actual predictions of our changing climate system with a climate "***supermodel***", consisting of an ensemble of interconnected state-of-the-art climate models that has "***learned***" to reproduce the observed, historical evolution of the climate system. The supermodel will be superior to any of the individual models in the ensemble since it has learned to combine the strengths of the individual models. Information is exchanged between the models on a time-step basis in such a way that the observed evolution of the climate system is best reproduced in a suitably chosen measure.

In this proposal we ***bring together*** a small group of experts from the fields of ***non-linear dynamics***, ***machine-learning*** and ***climate science*** to develop and implement the supermodeling strategy. With this approach we move into ***uncharted*** territory and many ***educated*** choices need to be made on the basis of ***fundamental*** research on the behavior of connected complex systems as well as more ***experimental*** research to evaluate the effect of different choices on the behavior of the supermodel.
To achieve this ***breakthrough***, we need to:

- develop the approach in which a supermodel emerges in an interconnected ensemble of imperfect models by applying machine learning techniques
- ***prove*** that this approach works using an intermediate complexity climate model in an idealized setting in which one model version is regarded as "truth" and imperfect models are created by introducing various changes to the model formulation and show that the supermodel outperforms the constituent models
- ***demonstrate*** that this approach leads to better predictions of the climate change of the "true" system than integrating the imperfect models separately and do a weighted ensemble averaging a posteriori.
- demonstrate the ***technical feasibility*** of running an ensemble of interconnected state-of-the-art climate models simultaneously

Through the extension of the SUMO project, we will further increase the power of supermodeling by applying computational scientific discovery to learn supermodels. We will use existing and new approaches to explore the fundamental issues in supermodeling (e.g., suitable forms for the connections). Finally, we will explore the use of the mentioned methods in the practical context of climate modelling, e.g., to learn improved climate models and supermodels (ensembles thereof).
Concrete deliverables are described in the next section to follow the progress that we will make in SUMO in developing the scientific basis of the supermodeling approach and implement the approach in a hierarchy of models, from low-order ODE's, PDE systems and intermediate complexity climate models to finally state-of-the-art climate models.
Our ***long-term vision*** is that the methods to be developed in our project will be applied to combine expert models of objective processes generally. Complex systems of partial differential equations (PDEs) or lattice maps can represent social, economic, biological, ecological, or physical processes. Typically, as with various commercial enterprises, the world's expertise is commonly distilled into a handful of competing brands. Coalescence of alternative approaches does not proceed all the way to a single product that is universally recognized as optimal. While the residual competition that results is arguably helpful in commercial spheres, there are other situations, as in climate modeling, in which a single optimal model, even a tentative one, would be in the public interest. An automated scheme to complete the unification process would be a ***transformative*** development in artificially intelligent computing.

The application domain in this proposal is restricted to climate research, which will provide a challenging and convincing test. Any limits of applicability of the proposed approach will become clear. There is as yet ***no guarantee*** that the supermodeling approach will work in the high-dimensional, complex application domain of climate prediction, but, if successful, supermodeling will also open possibilities to ***boost quantitative modeling*** in other scientific disciplines that study complex systems, e.g. biology and economics that are beyond the scope of this proposal.

B.1.3 S/T methodology and associated work plan

This section is based on Part B Section 1.3 of the proposal. It describes the scientific and technical (S&T) approach and provides in detail the work planned, over the full duration of the project, to achieve the objectives.

A detailed work plan should be presented broken down into work packages (WP) which should follow the logical phases of the project implementation. It must include consortium management and assessment of progress and results (Please note that your overall approach to management will be described later, in Section 2 of Annex I).

If appropriate, the work plan should also include a separate work package for dissemination and use / exploitation planning. Overall, the work plan should be sufficiently detailed to justify the proposed effort and allow progress monitoring by the Commission.

B.1.3.1 Overall strategy and general description

This section should outline the strategy for the work plan, provide a general description of the structure of the work plan and explain how it will lead the participants to achieve the objectives of the project. It should also identify any significant risks and describe contingency plans.

B.1.3.1.a An hierarchical project structure

In the original SUMO project, we adopted a hierarchical approach in the form of 5 work packages, with WP1, WP2 and WP3 focusing on fundamental questions raised in the previous section. Most of the work in these work packages concerns relatively low-dimensional systems of up to a hundred dimensions and is extended to infinite dimensions in the work on partial differential equations in WP3. WP1 focuses on the possibility of synchronizing different models, given that the connections can be chosen manually, WP2 on strategies to learn the connections from observational data. WP4 is a step up in the hierarchy in that it uses the results from these work packages in the construction of a supermodel consisting of interconnected intermediate complexity climate models of order several thousand degrees of freedom. Results from this work package feed into the construction of a supermodel consisting of state-of-the-art climate models in WP5. Problems encountered in WP4 and WP5 are fed back to the other work packages that suggest solutions on the basis of additional work on lower dimensional systems or theoretical considerations.
In the extended SUMO project, a new work package has been added (WP7), concerned with learning complete supermodels.
Due to the strongly interactive nature of the chosen project strategy, the five work packages WP1-WP5, as well as WP7, are active throughout the three year duration of SUMO.
Figure 1.3 provides a graphical representation of the nature of and interconnections between the work packages. The horizontal dimension of the ovals indicating each work package reflects the

dimensionality of the model systems that are subject of research, the vertical dimension the amount of experimentation that is possible in that work package. The vertical ordering of the work package reflects the nature of the research from more fundamental at the bottom to more applied research to the top. The colors indicate the prevailing expertise needed in each work package. The arrows reflect the flow of information between the work packages. The overlap indicates the amount of joint work on the same model systems.

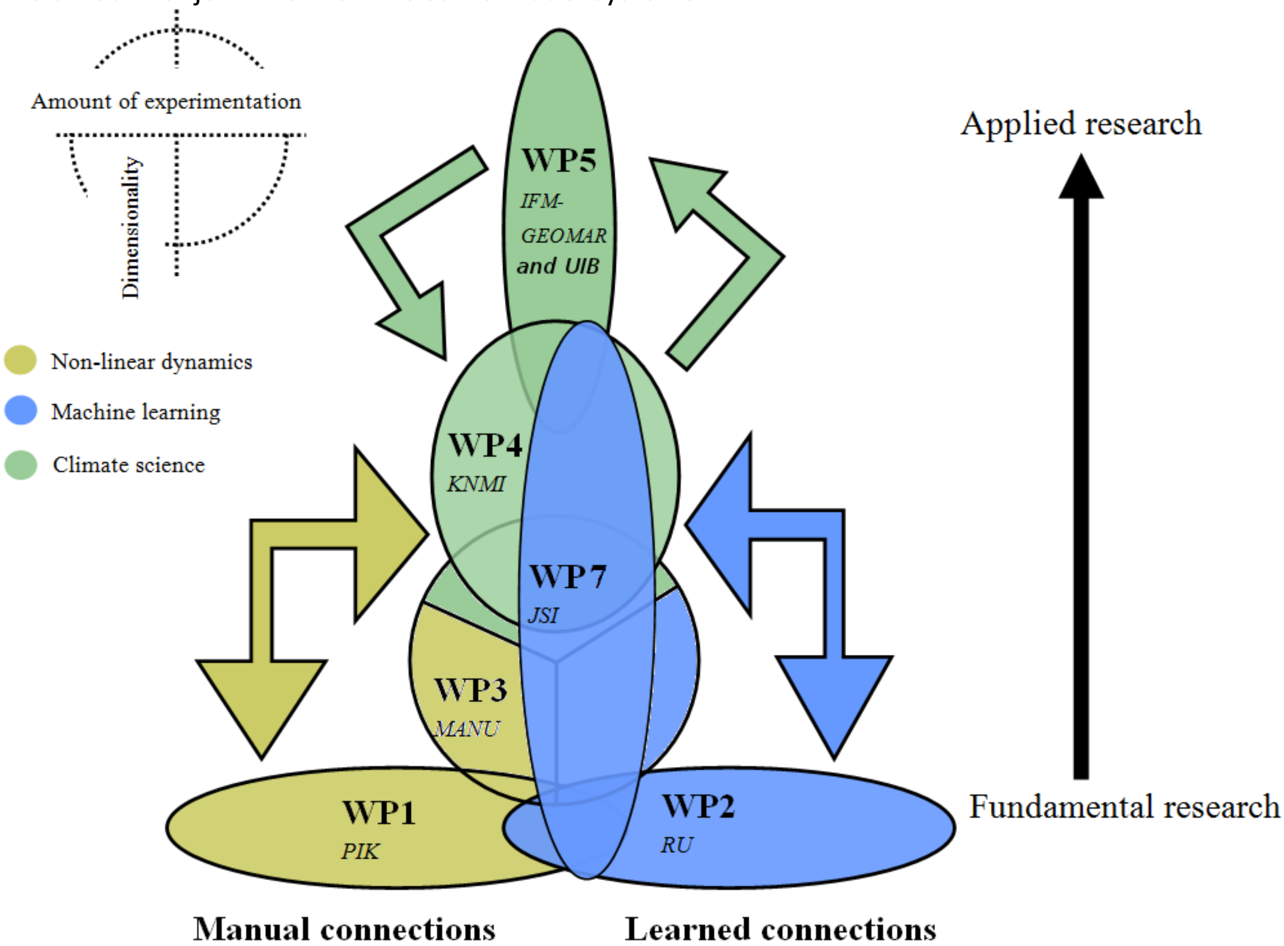


Figure 1.3: Graphical representation of the nature of and interconnections between the work packages. The vertical dimension of the ovals representing each work package reflects the dimensionality of the model systems that are subject of research, the horizontal dimension the amount of experimentation that is possible in that work package. The vertical ordering of the work package reflects the nature of the research from more fundamental at the bottom to more applied to the top. The colours indicate the prevailing expertise needed in each work package. The arrows reflect the flow of information between the work packages. Note, WP5 is now lead by UiB following the relocation of PI Keenlyside

In addition to sharing methodologies between the work packages as reflected in the table with the milestones in WT4 of the workplan tables, we will also share a common technical software framework to exchange information between imperfect models. Such software exists in the climate modelling community and is commonly referred to as a coupler. We will adopt the OASIS coupler in this project, since this is already in use by UiB and KNMI to provide the information exchange between the different model components (atmosphere, ocean and sea-ice) on a time step basis.

B.1.3.1.b Risks and how to deal with these

The aim of SUMO is develop a climate super model, by applying ideas from non-linear dynamics and machine learning to climate science and develop the necessary scientific foundation for that. Scientific work is generally risky, as no absolute certainty exists that all tasks of the project are completed successfully and in time. It is expected however that these risks can be handled within SUMO because:

- A careful planning of the project has started in fact already 2 years ago. Several preliminary results with simple models have confirmed that the proposed strategy can be further developed and applied to climate models.
- Most participants have a long history in running EU projects and delivering top scientific results
- The project group has the necessary expertise and ability to come to creative solutions. During the writing phase of this proposal, we worked intensely together using web conferencing software that turned out to be a very efficient tool to focus on particular issues and resolve these interactively and efficiently. During the project we will continue to work this way.

Below is a list of possible technical and scientific problems that we expect to encounter in the project. We first consider risks for the SUMO project as originally planned, and then risks for the SUMO extension.

Changes in dynamics, bifurcations, due to increased CO_2 may invalidate the results of the training.
Strategy: Preliminary experiments with Lorenz systems show that if a supermodel is constructed from models with parameters that are systematically shifted from the values used in training, that supermodel can track a `real' model with similarly shifted parameter values to some degree. The error increases, but still seems reasonable, even after a large number of bifurcations in the Lorenz system dynamics. It is possible that the behaviour will be worse in the climate system. In that case the plan is to understand qualitatively how much of a shift is tolerable, and to specify the fraction of the 21st century, using standard projections of greenhouse gas levels over time, over which reasonable performance can still be expected. Experimentation with the intermediate complexity climate models are foreseen in WP4 to deal with this issue.

Similarities between models may preclude meaningful improvement in important state space dimensions
We should be able to identify the specific state space dimensions in which the supermodeling procedure is not helpful for the specific set of constituent models in our experiments. We could address this issue with experimenting with negative connection coefficients, which have the effect of extrapolating from the least erroneous model. The effectiveness of this approach can be assessed in experiments with simple models constructed to have the problem of over-similarity.

The frequency of connections (in time and/or space) required for synchronization of the models may be impractically high.
Partial synchronization will be defined in a way that is both general and useful in the climate modelling context. It is already known that coupling of fluxes at the ocean surface, while resulting in nearly complete synchronization over the Pacific, results in correlated, but incompletely synchronized behaviour over the Indian Ocean. The supermodel can be expected to do at least as well.

There may be too many local optima in the space of connection coefficient values to effectively find a global one.
It is known that manual adjustment strategies can be used without a prescribed learning algorithm. Such strategies can be generalized to mutation rules in genetic algorithms for some improvement. Local optima remain a source of at least partial improvement as compared to individual models or output averaging.

Technical difficulties in coupling models and running them on a single computer
These will be largely addressed in the first year of the project. Feasibility of this type of work has already been demonstrated through the interactive ensemble (Kirtman and Shukla, 2002). Furthermore, Noel Keenlyside and Frank Selten have extensive experience in working with complex climate models on various high-performance computers (IBM, NEC, SGI, Fujitsu) at a number of different computing centres in Germany (DKRZ, HLRN, University of Kiel), Netherlands (SARA), and England (ECMWF). This includes code porting and optimisation. Both Keenlyside and Selten have significant experience with the climate models to be used in SUMO, being involved in their development. In particular, Noel Keenlyside contributed to the OASIS coupling interfaces in KCM and MPI climate models. The OASIS software will be used in SUMO to couple models together. In addition, technical support for KCM and ECEARTH is available at KNMI.

Theoretical constraints: addressed through interaction with WP1-4.

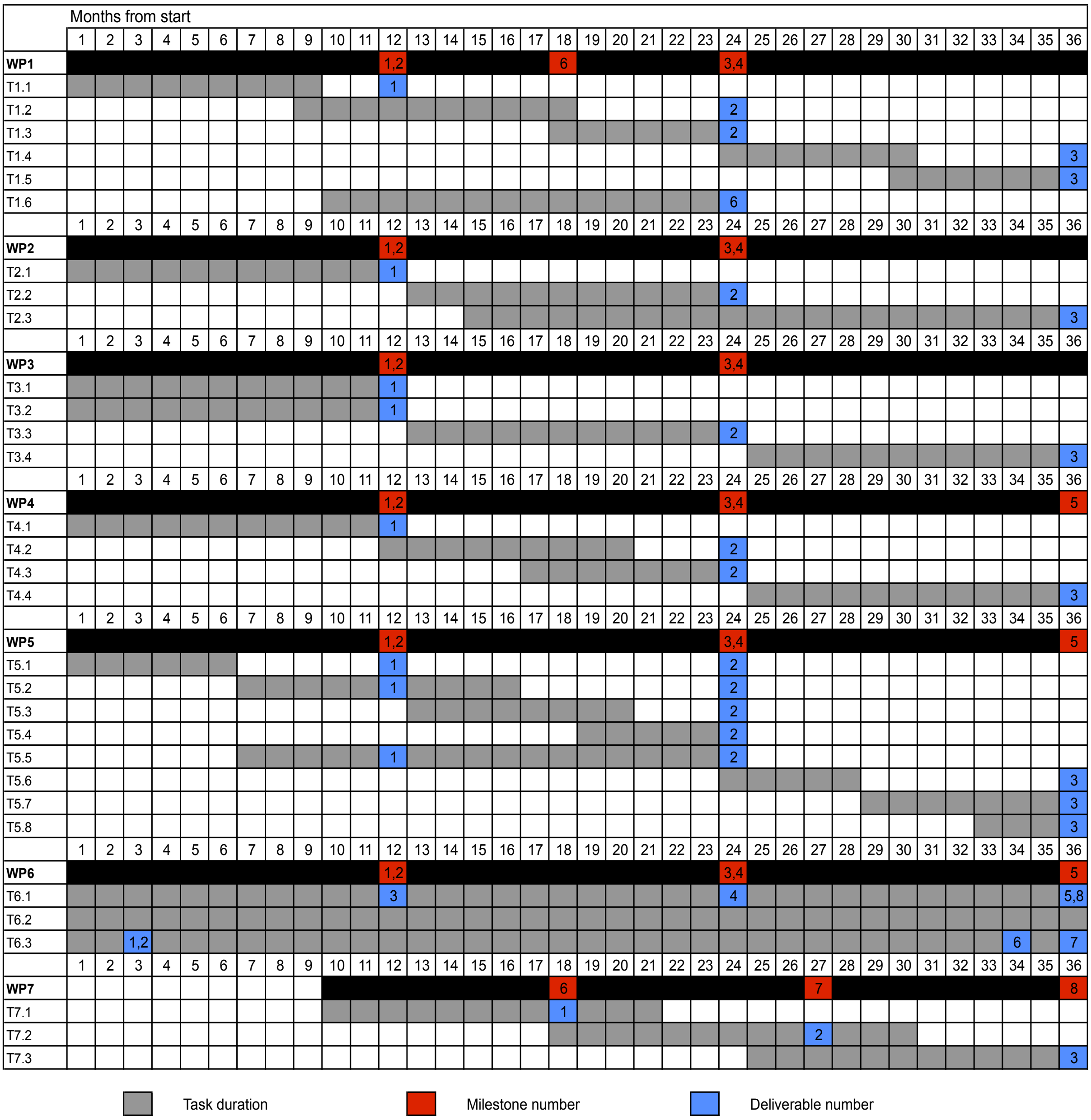
Computational cost: resolution and connection (number of fields) strategies will be adapted to fit CPU time available.

In the SUMO extension, the computational complexity of the learning tasks may be prohibitive. In particular, the space of possible models to be considered by the methods for learning complete supermodels can be too large to be effectively searched.
While the space of possible structures to be considered may indeed be large, the ability of our methods to use domain knowledge allows for trading off between the expressiveness and diversity of the model space and its size. The user/domain expert has explicit control of this trade-off.

For the SUMO extension, potential impact is strongly dependent on whether the proposed work can go beyond so-called models of intermediate complexity and really create a supermodel using coupled atmosphere/ocean/land-models of high horizontal resolutionas promised in the original proposal.
The complexity of the learning tasks considered does not directly depend on the complexity of the models in the supermodel: Rather, it depends on the complexity of the interconnections or parts of the constituent models that are not fixed and have to be learned and the corresponding number of alternative structures that have to be considered. Again, the ability of our methods to use domain knowledge allows us to fix smaller or larger parts of the constituent models and interconnections and thus control the number of structures considred – This increases the likelihood of arriving at a climate supermodel with component models of high resolution.

B.1.3.2 Timing of work packages and their components

Include a graphic representation, e.g. GANTT chart or similar, of the planned timing of the different work packages and their components. Timing should be relative, expressed in months (e.g. project month 3, project month 18 etc.). Month 1 is the month that starts at the start date of your grant agreement.



B.1.3.3 [Work package list /overview]

See section WT1.

B.1.3.4 [Deliverables list]

See section WT2.

B.1.3.5 Detailed work package descriptions

The key description of each work-package is done via NEF, section WT3.

This section allows detailed descriptions to supplement the tables introduced via NEF if necessary.

B.1.3.5.a General theory of supermodeling with ODE systems (WP1)

The main objective of WP1 is to develop the general theory of supermodeling. In particular we will consider the model classes of imperfect models and ground truth, as well as the metrics, connection mechanisms, connection parameterizations and constraint schemes. We will specify how models with different structure should be connected and we will develop conditions under which connecting variables among different models will lead to superior properties, and the form of those connections. These will set the scope of research in WP2 and partially in WP3. Furthermore, in this WP we will develop, in lieu of the machine learning techniques discussed in WP2, strategies to define connections based on physical insights, mathematical arguments or other analyses that lead to a useful supermodel.

In this work package, five objectives were originally set, to be reached in five tasks, each related to specific issues that need to be solved if we are to realise a supermodel based on climate models. First, in the **Task 1.1** we will consider several model classes described by low-dimensional deterministic ODEs. We will concentrate on models that mimic to some extent the behaviour of realistic climate models as well as the models relevant for other scientific disciplines. Then, we will specify metrics and test criteria that define how well a model, (or a supermodel), performs with regard to the truth. In this task, we will also determine the data and prior knowledge that may be necessary for the purpose of supermodeling. Second, **Task 1.2** aims to study connections and connection mechanisms of supermodeling. In **Task 1.3**, we will consider manual strategies for supermodeling, which are based on physical insights and mathematical arguments. Manual optimization strategies may serve as initialization for learning in later WPs, as a benchmark to assess learning strategies from later WPs and as an independent method for supermodeling. By considering different model classes and parameter regimes, we will explore and study the application range and limitations of super modeling (**Task 1.4**). Finally, in the **Task 1.5**, we will try to understand why the supermodel works with a certain set of connections, since we have seen in our preliminary experiments that the learning algorithms commonly choose values for the connection coefficients that are effective but differ from the values one would choose manually. In depth understanding of the mechanisms of supermodeling, using the connection coefficients determined with learning techniques in WP2, will enable us to develop techniques for supermodeling of large models, including climate models (to be discussed in WP4 and WP5). The work in this WP will be performed in close interaction with WP2 but also with the WPs 3-5.

The **Task 1.6** (added with the extension of the project) aims to develop domain knowledge for the automated construction and improvement of climate models and supermodels. This will be based on input from other tasks in this WP, and in particular **Tasks 1.1** and **1.2**, concerned with the scope of supermodeling and the connection mechanisms used therein. The resulting domain knowledge will be used in the machine learning approaches newly developed in WP7.

B.1.3.5.b Learning of connection coefficients in ODE systems (WP2)

The primary goal of this WP is to research and develop learning algorithms for supermodels formed from systems of ODEs, less complex than climate models, that will be applied to PDE's and to climate models in WP3 and WP4, respectively. A second objective is to assess performance of the obtained supermodeling learning strategies and research and develop methods to estimate model performance based on available data.

This WP restricts itself to ODE models of relatively low dimension. Furthermore, we assume access to a ground truth model. This allows us to take an explorative approach, in which we study and develop a wide variety of methods and do many simulations and analyses in a variety of ways. The strategies and methods, that we will research and develop in this WP, find their origin in machine learning and non-linear dynamical systems theory (see sections 1.1 and 1.2 and references there-in).

In order to focus the research on models and assumptions that are relevant for supermodeling in climate science, we restrict ourselves to the scope that is set in WP1. In particular we will consider the model classes of imperfect models, ground truth, as well as the metrics, connection mechanisms and connection parameterization and constraint schemes, which have been decided on and/or developed in WP1. Furthermore, we will use any manually optimized connections that emerge from WP1 as a starting point.

The main research effort will be focused on exploring and improving existing learning strategies. Methods will be experimentally assessed by their performance on systems agreed upon in WP1 while keeping their scalability to the higher dimensional climate models of WP4 and WP5 in mind. Later in the project, feedback from WP3-5 will further guide the research directions in this WP. Issues that arise in those work packages will be referred back to WP1 and this WP for further analysis and improvement.

B.1.3.5.b.1 Study and comparison of different learning algorithms

This primary **Task 2.1** focuses on more traditional methods from machine learning, i.e., the more local gradient-based optimization methods. Algorithms for attractor learning rely to a certain extent on design of an appropriate cost function. Here we will explore several approaches, with short time integrations and hard or soft coupling to the data, e.g. using ideas from nonlinear synchronization. We will first research and develop learning algorithms to handle the more straightforward ODEs (with O(10) degrees of freedom), in which all variables are observed, and have dynamics with similar time scales. Next we will research and develop learning algorithms to be applied to systems under more complex model assumptions – for example, learning in which not all variables are observed, or in which data is incomplete otherwise. Another issue is learning when connections are constrained, either to limit the degrees of freedom of the parameters to be learned, or because of physical constraints, defined in WP1. For the main goal of this purpose, being able to do climate predictions in a scenario with increasing greenhouse gasses, we need to anticipate on systems with parameters that slowly vary in time. Somewhat related, we need to anticipate on systems with different time scales in the variables, due to the atmosphere and ocean. Finally, we will investigate the robustness and scalability of the methods by scaling up the models to intermediate size (up to 1000 variables in this WP).

B.1.3.5.b.2 Globally optimal learning

The learning algorithms considered in the previous section may get stuck in local optima. In **Task 2.2** we research how to deal with these. One way is to try to remedy these by gradually changing parameters in the cost function, e.g. increasing the data set that is considered. A completely different approach is to consider algorithms that are specifically designed for global optimization algorithms such as genetic algorithms. We will address the question: under what conditions are local optima acceptable? To answer this question we will assess and compare the different local optima obtained by different initialized runs. Then the second question is whether global methods help to find better optima. To answer this question, we will specifically research the use of global optimization methods such as simulated annealing and genetic algorithms to escape local optima in favour of global ones. A detailed sub-question could be if we can make the algorithm to recognize a local optimum, so that it can e.g. trigger a mutation in a genetic scheme. We will also consider the use of meta-heuristic global optimization methods, which have been recently applied to the task of estimating parameters in dynamic systems and shown to perform very well, and further develop such methods in the direction of hybrid optimization methods and dynamic optimization methods.

B.1.3.5.b.3 Potential of learning of supermodels

Task 2.3 is concerned with the second objective of this WP and addresses the question: ``how good are the supermodels that we obtain by learning?'', and the related but very different question: ``how can we predict the quality of the supermodels in advance?''. In the scope of this WP, the supermodels are straightforward to validate, since in the simulated world of this WP, we have access to the ground truth model.

The first question, concerns the application range of supermodeling learning, in particular where the approach might be beneficial (i.e. better than any single model and/or average of all models, and better than a manually set initialization of the connection coefficients). More specific questions are: Is there a minimum amount of data that is needed to learn the supermodel (beyond its manually set initialization)? How many observed variables and how many data points for each variable are needed? Are there limitations on the assumed measurement errors in the observations? To what extent will imperfect models that are very far from the truth obstruct the feasibility of supermodel learning? To what extent does the existence of slow and fast time scales hinder learning? In particular, the learnability of the supermodel will be studied in relation to the number of independent connection coefficients as it is expected that in the range in which the number of coefficients is large compared to the number of data, the supermodel might have the risk to over-fit the data. The performances will be compared to the standard competing methods (average model, etc.). The answers to these questions will be primarily obtained by gathering statistics over many simulations and instances.

The second more practical question, is whether we can predict for a supermodel that is trained on a given set of data how good it will perform. Therefore we will research methods and measures that aim to predict the supermodels future performance based on current data. A starting point for these methods and measures will be related to cross-validation techniques in machine learning (Bishop 2006). These and related methods might be applied directly with the defined cost function, or using other metrics defined in WP1.

B.1.3.5.c Learning of connection coefficients in PDE systems (WP3)

The goals of WP3 are to validate and refine the learning algorithms for a supermodel formed from several systems of partial differential equations that are imperfect counterparts of a single "true" system of PDE's. General lessons from this investigation will be applied to climate models in WP4 and WP5. Issues that arise in those work packages will be referred back to WP2 for further exploration.

B1.3.3.c.1 Develop learning strategies for PDE supermodels

In the simple configuration of Lorenz systems discussed in WP2 connections were introduced between all pairs of corresponding variables. Since that is very far from what is generally feasible for climate models, we shall explore reduced connection schemes in systems of partial differential equations (PDEs), **Task 3.1**. The Kuramoto-Sivashinsky (KS) (Kuramoto 1978) system has been used to represent turbulent fluid dynamics and can provide a natural bridge between ODEs and PDEs (Hyman and Nicolaenko 1986). Supermodels will be formed from Galerkin projections of the full KS system to different orders. We will study the efficacy of learning in the resulting hierarchy of supermodels, as we vary the connection structure.

In **Task 3.1,** different learning algorithms will be applied to KS and other simple systems of PDEs to be identified. The question of the required density of connections arises in simple data assimilation or parameter estimation tasks, outside of the supermodeling framework, as we attempt to synchronize one PDE system with a parameter-shifted counterpart. Previous work by Duane and Hacker (2008) on simple parameter estimation, using the incremental approach, in a one-space-, one-time-dimensional PDE of geophysical significance will be analyzed in regard to possible lessons about performance vs. density of required connections. That work examined a single-column version of the Weather Research and Forecasting (WRF) model. It was found that connection just at one point in the column was adequate to bring about convergence of a model parameter quantifying the availability of soil moisture to its value in a "true" system, but the convergence was highly unstable. We will study the dependence of the behaviour found as observations at more than one level are assimilated and/or used in parameter estimation.

Next, we will consider the use of meta-heuristic optimization methods, such as the Differential Ant Stigmergy Algorithm. DASA has been shown to perform very well in estimating parameters for ODE models, but has as yet not been applied to PDE models. We will investigate its use for determining connection coefficients in PDE models, motivated also by the fact that this an efficient global optimization method that can take into account different quality criteria.

In **Task 3.2**, we will return to the issue of the relative merits of the different learning approaches, but now in a PDE context. The connection structures required for the different approaches will be compared. Special attention will be paid to the issue of locally optimal supermodel configurations in the PDE context. The higher dimensionality of these systems may give rise to extra directions of possible escape from the local optima, if enough independent connections are introduced, but there may also be more optima. The issue will be addressed both theoretically and experimentally. The use of spatial patterns to define “trigger” conditions for random mutations in a genetic algorithm framework will be explored.

B1.3.5.c.2 Develop learning strategies for intermediate-complexity climate supermodels

In **Task 3.3** we will first consider a relatively simple geophysical model in two space dimensions (with two layers to represent the vertical dimension), the quasi-geostrophic (QG) channel model on which the MASA investigators have previously worked. That work showed that two such models, each missing a key physical feature, could be made to synchronize. The synchronized model behaviour incorporated all the relevant physics (Duane and Tribbia, 2001, 2004). More recently, it was shown that the single independent connection coefficient linking the two models would attain the correct value by training with input from a third model, representing reality.

The QG channel investigation will form the basis for the subsequent study of the more realistic quasi-geostrophic model, the Ecbilt model that will be studied in WP4. After an appropriate configuration of models, with an effective connection scheme, is determined in that work package, we will investigate alternative schemes for training the connection coefficients. Some connection coefficients will vary in space (e.g. depending on land surface characteristics) while others are expected to be translationally invariant. For the latter type, following Duane, Yu, and Kocarev (2007), a given coefficient will be adapted according to a rule that averages over all points in space, as in the previous work with the QG channel described above. Simulations with the optimally tuned combination of models will be compared with the best weighted average of outputs. Results will be evaluated in terms of the reproduction of specific qualitative features of the “real” model, as well as in terms of more general metrics developed in WP1 and WP2.
Most issues regarding training of connection coefficients will be resolved before the supermodel constructed from full climate models is constructed in WP5. But there will be some remaining issues that are peculiar to full climate simulations. This will be the main goal of the **Task 3.4**. One issue is that of possible trends in connection coefficients due to gradual changes in CO2 forcing. Such trends might be represented by introducing a second parameter for each connection coefficient, quantifying a linear (or other pre-specified form of) time dependence in the connections. Such parameters could be trained in the same manner as the connection coefficients themselves. Experimentation in WP3 will guide this approach. Is there enough training data for this? The results of WP2 will be used in answering this question.

Another peculiar issue arises from the arbitrariness in radiative forcing in climate models. It is well known that different climate models differ considerably in their representation of radiative forcing processes, even in quantities that should correspond to the same physical value. Such quantities seem to play a role of parameterizing or offsetting other physical processes that are not well represented in the model. In the multi-model scheme, such differences would be handled in two ways.
At an initial stage of development, *weak fusion* of the models would allow the differences to remain, but the coupling of some prognostic variables would reduce the effects, so that important variables could still partially or completely synchronize. That regime corresponds to the actual re-

sults of the Lorenz system experiment in the incremental learning scheme, in which the models synchronize almost completely, without full replacement of the erroneous variables. The configuration is given by a set of connection coefficients that is only locally optimal.
In a different regime of *strong fusion*, corresponding to globally optimal connections, the forcing parameters themselves might be effectively replaced or shifted based on their values in other models. It is thought that such a regime might be reached by simulated annealing, genetic algorithms (Fogel 1998, Haupt and Haupt 1998), or related stochastic learning method without too much difficulty (i.e. not too many local optima) - a conjecture that will be tested.

It is important that in the training process, more free parameters (connection coefficients) will be available than with a single model, allowing a more detailed match to 20th century climate states than in training schemes that match only globally averaged temperature, for instance. In particular, *phenomenological metrics*, based for instance on the reproduction of major teleconnection patterns or the unimodality of the Inter-Tropical Convergence Zone (ITCZ) - a common problem for climate models - will be tried in the training process.

B.1.3.5.d Supermodeling with intermediate complexity climate models (WP4)

In this work package we develop and test the supermodeling approach using climate models of intermediate complexity. This is a necessary phase between the construction of supermodels using the simpler and more general model systems of WP1, WP2 and WP3 and the application of the supermodeling approach to state-of-the-art climate models in WP5. The intermediate complexity models resemble these models in their structure, but differ in that the parameterization schemes for the physical processes are much less elaborate, fewer processes are explicitly modelled and the spatial resolution is much coarser. The main objective is to develop a supermodeling approach that is applicable to the state-of-the-art climate models of WP5. We will employ different climate model systems, starting from a relatively simple climate model and add to the complexity in small steps and address a specific issue at each step. We will assume a ground truth model at each step and create an ensemble of imperfect models by perturbing parameters and/or using different formulations for unresolved processes.
This work packages receives guidance and advice in the construction of the supermodels from WP1, WP2 and WP3 and reports back outstanding issues for further research to these work packages. We will use the OASIS coupler software as the standard for the technical implementation of the exchange of information between the models as is also done in WP5 to be able to closely work together on this practical issue of implementing the super modelling strategy as well.

B.1.3.5.d.1 Hierarchy of intermediate complexity climate models

The following table lists the range of intermediate complexity climate models that we will employ and the issues that are addressed specifically at each model level. At the final model level all issues that play a role in the case of the state-of-the-art climate models can be addressed, except that there is difference in dimensionality of over two orders of magnitude. All models are available and are used in the Global Climate Division of KNMI, the leader of this work package. Most of the development of these models was done in this group as well.

Name of the model	Main Characteristics	Issues addressed
T21QGL3 Marshall and Molteni, 1993	One variable: quasi-geostrophic vorticity	Density and form of the connections
ECBilt Opsteegh et al, 1998	More variables: still quasi-geostrophic formulation but simple parameterisations for hydrological cycle and radiation	Connections between different state variables and/or physical tendencies
ECBilt-CLIO Goosse et al, 2003	Coupled atmosphere/ocean /sea-ice model	Implication of the introduction of the slow oceanic time-scale for the learning phase
SPEEDO Severijns et al, 2010	Primitive Equation atmosphere model coupled to ocean/sea-ice model	Possibility of disrupting the geostrophic balance by the connections

B.1.3.5.d.2 Steps toward a state-of-the-art climate supermodel

The work in this work package is split into four well defined tasks, each addressing specific issues that need to be solved if we are to realise a supermodel based on state-of-the-art climate models. The work in **Task 4.1** and **4.2** focuses on a number of questions with regard to the definition of the connections between the imperfect models. We will apply methods developed in WP7 to empirically explore different possible types of interconnections. These will consider both different connection forms and coefficients in an automated way. The outcome of this research with feedback from the work in WP1-WP3 will lead to specific guidelines developed in **Task 4.3** for the implementation of the super modelling strategy with the complex climate models in WP5. To check whether the super model is able to follow the truth outside of the climate regime in which the super model was trained, we will perform climate change simulations with the super model and the perfect model in **Task 4.4.** There is room for quite some experimentation in adjusting the super modelling strategy to improve the super model in the perturbed climate regime and provide input to WP5 for the final demonstration run. We will detail the different tasks below and point out how we will use the available model hierarchy in addressing the specific issues.

In **Task 4.1** we start with the issue of the density and particular formulation of the connections:

- How many state variables or linear combinations of the state variables (Empirical Orthogonal Functions for instance) need to be connected? We will employ the dry global quasi-geostrophic model **T21QGL3** to address this issue and be guided by the work in WP1, WP2 and WP3 on this issue.
- How should we define the connections? Most uncertainties in climate models are related to the representation of the so-called physical processes. These are the processes that determine the total diabatic heating and friction, like surface fluxes of heat, moisture and momentum, radiational fluxes, convection, latent heat release, cloud formation. Instead of connecting state variables, we can connect the models through the tendencies in the state variables that are produced by these processes. We will employ the moist quasi-geostrophic model **ECBILT** with relatively simple parameterisations of these physical processes to address this issue. Since this model is structurally similar to the complex models of WP5, this approach is also feasible in that case.

- How do we need to formulate the connections to avoid disruption of the geostrophic balance and not to violate conservation laws? This issue will be addressed with the moist primitive equation model **SPEEDY** which is the atmospheric component of the coupled climate model **SPEEDO**.

The learning task needs to take into account the slow time scales of the ocean component. In **Task 4.2** we will address this issue using the **ECBilt-CLIO** coupled atmosphere/ocean/sea-ice model that has a three-dimensional ocean component that simulates the basic ocean current fairly realistic and is computationally cheap enough to allow for quite some experimentation. We will specifically look at the impact of the slow oceanic time scales on the learning phase. We will again heavily rely on the experience with simpler model systems gained in WP1, WP2 and WP3.
We will finally construct in **Task 4.3** a supermodel based on **SPEEDO** after having addressed the issues and hopefully solved the issues in the previous tasks. Specific guidelines and recommendations will be provided to WP5 for the construction of a supermodel based on state-of-the-art climate models. If the learning turns out to be difficult in this case, then we will resort to manually chosen connections focussed on the cloud related processes since this are the source of the largest uncertainties in the response of the climate to increasing levels of greenhouse gasses.
After learning the supermodel to reproduce the present-day climate, we will test in **Task 4.4** its ability to simulate a realistic response to increasing concentrations of greenhouse gasses. We will employ **ECBilt-CLIO** in this task since it allows for more experimentation and has an explicit formulation for the radiative effects of a number of greenhouse gasses.

B.1.3.5.e Supermodeling with large climate models (WP5)

Large uncertainties exist in our essentially model-based predictions of future climate (IPCC, 2007). A significant fraction of this uncertainty arises from model systematic error (Hawkins and Sutton, BAMS, 2009). Significant socio-economic gains may be made if these uncertainties are reduced. The overarching goal of this WP is to assess the applicability of the super modelling strategy, as developed in WP 1-4, to the climate problem, and evaluate its potential to reduce these uncertainties. This pragmatic approach may lead to significant benefit long before it could be provided through the slow, but essential process of model improvement. This WP has three main objectives:

B.1.3.5.e.1 Develop a super climate model

The development of a super climate model poses many practical and theoretical problems. Additionally, the complexity of climate models is a major constraint on the amount of experimentation possible. Thus, a focused approach is required; ours is as follows:
Models: three state-of-the-art-climate models will be used: ECHAM5/NEMO (Park et al., 2009), ECHAM5/MPIOM (Jungclaus et al., 2006), and IFS/NEMO (http://ecearth.knmi.nl/). All were either developed or are extensively used by SUMO partners (UiB and KNMI).
Tasks 5.1 and 5.2 aim at identifying and addressing practical issues through the construction of a supermodel by coupling the three models via their atmospheric convective parameterisations with manually selected connection coefficients.

We choose to couple atmospheric convective parameterisations, as improvements here may reap the largest rewards. Physical parameterisations are at the heart of many systematic model errors.

Those related to *atmospheric convection and cloud processes are most troublesome,* and probably cause the *largest uncertainty in future global warming* (Dufresne and Bony, 2008). These errors are reflected in simulated tropical sea surface temperature (SST) biases (Yu and Mechoso, 1999; Davey et al., 2002; Richter and Xie, 2008; Wahl et al., 2009), and a double inter-tropical convergence zone (Lin, 2007). They give rise to errors in simulated tropical climate variability (Lin et al., 2006; Guilyardi et al., 2009) and uncertainty in its response to global warming (Latif and Keenlyside, 2009). Although the convective parameterisation in the three models is based on (Tiedtke, 1989), the implementation and tuning are different. The schemes will be coupled via the model tendency equations; this method foresees the coupling of intrinsically different parameterisations of the same process. Tendencies will be exchanged among the three models using the OASIS4 coupler (http://www.prism.enes.org/), software for efficient exchange of data among independent parallel code. OASIS is used in the three models to couple the ocean and atmosphere components. To ensure exchange of tendencies on a near-time step basis, data dimensionality may need to be reduced, by for example Empirical Orthogonal Function (EOF) decomposition.
At this stage, tendencies will be combined using manually chosen weights, as a test of the general approach. Weights will be tuned in both coupled and atmosphere only (SST forced) simulations for the period 1980-2010 with time varying radiative forcing. The manually trained super model extends the interactive ensemble (Kirtman and Shukla, 2002) to convective parameterisation, and in this sense although a significant challenge has a high chance of success.
Task 5.3: the theoretical problem of coupling models through different parameters and learning connection coefficients will be tackled by introducing results/software from WPs 1-4. Methods developed in WP7 will be applied to empirically explore different possible types of interconnections among large climate models; these will consider both different connection forms and coefficients in an automated way. The supermodel will be trained over the period 1870-1980. In close cooperation with the other WPs, choices will be made on the following:

- Whether to couple state variables or physical tendencies
- How to reduce the data dimensionality
- How to deal with fast atmospheric and slow ocean processes
- How to train the model on observational data

B.1.3.5.e.2 Assess the super climate modeling strategy

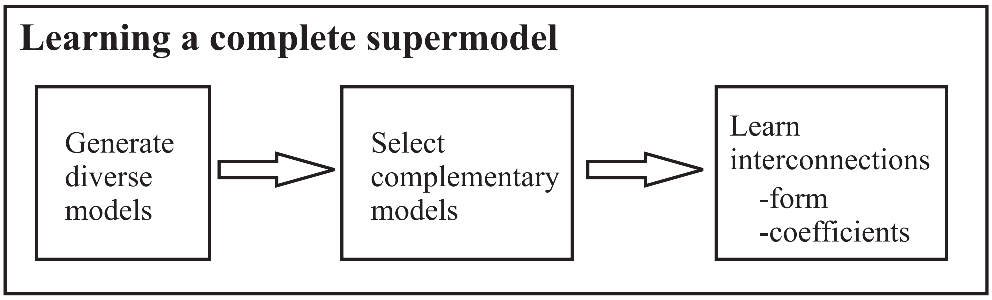
To utility of the super climate model will be demonstrated by assessing its performance in simulating and predicting observed climate (**Task 5.4**), for the independent period 1980-2010. The climate simulation will simply be an extension of the trained model with training switched off. These are a good test case for the planned climate projections, as greenhouse gas concentration increased strongly over this period. The retrospective seasonal-to-decadal forecasts are a further test the super model's ability to synchronise with observations and eliminate model systematic error, which is often reflected in large forecast drift (Keenlyside et al., 2005). Initial conditions will be provided by synchronisation (the forecast beginning when the synchronisation is switched off) or by SST restoring (Keenlyside et al., 2008). Seasonal (decadal) forecasts will be six-months (10 yrs) long and performed once per season (every five yrs) and in ensemble mode.
Task 5.5: model performance will be assessed using metrics developed in collaboration with WP4 and other WPs. These metrics will quantify the models ability to simulate the climate mean and variability, and global warming. We will focus on ubiquitous model error such the double ITCZ and others described above. Deterministic and probabilistic skill scores will be used to assess retrospective predictions, and forecast drift will be quantified. The performance and skill of the super model will be compared against the multi-model mean (Palmer et al. 2004) and best model.

B.1.3.5.e.3: Perform climate projections with the super model

The ultimate goal of the project is to demonstrate that the super modelling strategy can be applied to make climate projections. We may expect these projections to be more reliable (i.e., reflect true uncertainty) than current models, as we anticipate the super model will exhibit a significant reduction in model systematic error.
The climate change projections will be performed with a refined version of the super model, based on experiments already performed and updated recommendations from WP1-4 (**Task 5.6)**. The model will be trained over the period 1870-1980, and tested on the period 1980-2010. The scenario simulation for the 21st century will be started in 2010, initialised by synchronising with observations; results will be contrasted with conventional multi-model scenario simulations to identify key differences (**Task 5.7**). To understand these differences they will be compared to improvements in model systematic error.
Task 5.8, finally, results of the application of the super-modelling strategy to the hierarchy of models in the whole project will be summarised. The utility of the approach to climate modelling and the potential to reduce uncertainties in future climate projections will be assessed. Recommendations on future work on this topic will be made. These will be described in a report.

B.1.3.5.f Learning complete supermodels (WP7, added with the extension of the project)

WP7 will be concerned with the development of methods for computational scientific discovery that can learn ensembles of ODE models of dynamic systems. Existing methods that can take into account observed data and domain knowledge, such as LAGRAMGE2.0 (Todorovski and Džeroski, 2007) will be taken as a starting point. They will be extended or upgraded to first generate diverse models, then select a set of complementary models, and finally learn the interconnections between the constituent models of an ensemble.



The three phases of learning complete supermodels generally follow sequentially, as depicted in the figure above. If we have the necessary prerequisites, we can enter the process at any of the stages: For example, if the constituent models have been already selected (as will be the case in constructing a supermodel of climate), we can directly proceed to learning (the form and coefficients) of the interconnections among the models. The three phases of learning a complete supermodel will be explored in tasks 7.1, 7.2, and 7.3, resp.

B.1.3.5.f.1 **Generate a diverse set of ODE models**

To generate a diverse set of models, **in Task 7.1,** we will adapt existing approaches from the area of ensemble learning. These include taking different subsamples of the data, taking different projections of the data, and taking different learning algorithms (a randomized algorithm with different seeds for the random number generator is a special case of the latter). However, the above basic ideas from ensemble learning do not carry over to learning ensembles of ODE models in a straightforward fashion. For example, random subsamples of arbitrary time points from an observed trajectory would not be appropriate. An alternative to be considered might be taking a set of contiguous subintervals with starting points and durations selected randomly. Randomized versions of the algorithms for automated modeling of dynamic systems (ODE discovery), such as LAGRAMGE2.0 also need to be developed.

To adapt the random subspaces approach of taking random projections of the data, we can take at least two alternative roads. First, we can randomly project on the observed data, selecting some of the variables as observed and declaring the others as unobserved. Alternatively, we can consider only a (randomly selected) subset of the domain knowledge available for the modeling task at hand.

B.1.3.5.f.2. Select a complementary set of ODE models

In Task 7.2, to select a set of models for an ensemble we first need a measure of similarity between models. This would allow us to assess whether two models are complementary. Typically, the similarity measure takes into account the outputs of the model simulation and not the structure of the model or its parameters. We might also generate new models that are as different as possible from an existing model by taking into account their similarity to the latter during the learning process: A similar approach has been taken in the learning of multi-target regression trees (Kocev et al. 2007).

This type of model similarity (based on the model simulation outputs) is related to the issue of model performance or quality of the model simulations. Besides the sum of squared errors, which is typically used to estimate model performance, other measures might be considered such as weighted least squares or robust statistical estimators (including M-estimators or R-estimators). An example of a R-estimator is the Spearman rank-order correlation coefficient.

The developed approaches to learning ODE models and supermodels from data and domain knowledge will also have the ability to consider different quality criteria. The quality criteria might address multi-scale issues, for example consider the accuracy of the simulation at different time scales. They might also consider simulations for different periods of time in advance, i.e., for a different number of time steps into the future.

B.1.3.5.f.3. Learn to interconnect ODE models

The final step (**Task 7.3**) in constructing an ensemble of ODE models of a dynamic system (a supermodel) is the learning of the interconnections between the constituent models of the ensemble. To learn the interconnections, we might consider searching through the space of possible structural forms of the interconnections, coupled with parameter fitting for a selected functional form of the possible connections. For parameter fitting, we will use global optimization methods based on meta-heuristic approaches such as the Differential Ant Stigmergy Algorithm (DASA, Korošec e tal. 2010). The use of such parameter estimation methods is of crucial importance in supporting the use of different quality criteria, as well as avoiding local optima in search.

B2. Implementation

B.2.1 Management structure and procedures

This section describes the project's organisational structure and high-level decision-making mechanisms. It should describe how the project management will enable the project to achieve its goals. If the addition of beneficiaries during the lifetime of the project is foreseen, describe how the management structure will adapt for this.

Because of its small size, a simple management structure is proposed for SUMO. It will facilitate the production of deliverables and an efficient flow of funds and information between the partners, administration, the European Commission and the outside world. The management structure builds on proven concepts of other ongoing and successful EU projects. SUMO will be organised from the Project Coordinator's institute, the Macedonian Academy of Sciences and Arts (MASA). The organisation of the consortium will consist of the Project Coordinator (PC), the Project Assistant Manager (PAM), a Financial Officer, all located at MASA, the Work Package (WP) leaders, and a Management Board (MB) and is presented schematically in Figure 2.1 and will be further detailed below.

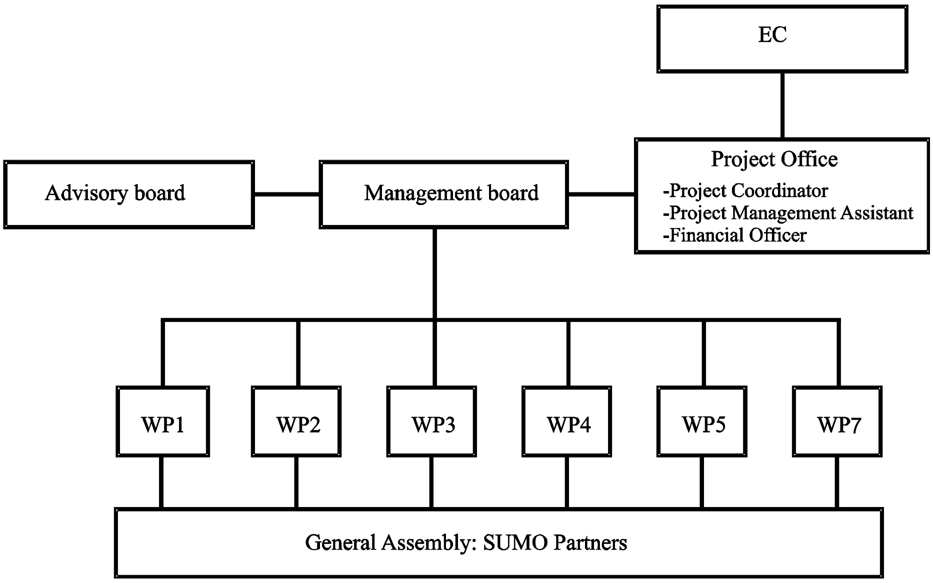


Figure 2.1 Management structure of SUMO

The Project Coordinator (L. Kocarev, MASA) of SUMO leads WP6 (Project Management) and has the overall responsibility for the project. The Project Coordinator oversees and evaluates the progress of the WPs, and reports, stimulates and monitors collaboration between the partners and between the consortium and international organisations, and encourages publications in peer reviewed journals. The Project Coordinator is also responsible for the activities defined in WP6. These include the overall responsibility for the SUMO web site, the organisation of all the SUMO meetings, an international workshop on the results of SUMO, for communication with national and international climate programmes. Furthermore the Project Coordinator is responsible for all the communication between SUMO and the European Commission, including all forms of reporting to the EC. Finally the Project Coordinator will chair the Management Board (see below) which will carry out the top level management of the project.
The Project Assistant Manager (located at MASA) will assist the Project Coordinator with the internal and external communication of the project. This includes the maintenance of the SUMO

web site, the production of flyers and brochures, the organisation of the annual meetings and the international workshop, the administration and archiving of all reports and communication to the European Commission.

The Financial Officer (located at MASA) is responsible for the financial administration of the project and the flow of the financial information between the partners and the project office and the provision of necessary documentation to the European Commission. MASA has an experienced staff in the project administration unit for this task and has extensive experience with coordination of previous and present European Projects.

The Work Package Leaders are responsible for the efficient running and the progress of the respective WPs. They are responsible for the organisation for WP meetings during the annual assembly or extra focused meetings whenever considered necessary. They also contribute to the top level management of the project through participation in the Management Board (MB).

The Management Board consists of the WP leaders and representatives of all partners and is chaired by the Project Coordinator. The MB will meet during the kick-off meeting and afterwards in principal twice a year, alternating physical and virtual meetings, but more frequent meetings are possible if necessary. Furthermore they will be in frequent contact through email and web conferences. SUMO has been put together on the basis of a dozen web conferences of the WP leaders and this has turned out to be a very efficient way of collaboration. The MB will have the responsibility to review the progress in each WP, and decide on success criteria to continue or stop an activity. It is also responsible for the coordination of flow of information and data between the WPs and responsible for cross-cutting themes that involve more than one WP. The MB is also the place to resolve conflicts.

The General Assembly will consist of representatives of all institutions presented in section 2.2 “Individual Participants” and any additional contractors entering the project during its life time. They will meet on an annual basis together with invited key scientists to present and discuss the progress of the tasks such as defined in the work plan. The General Assembly is the overall platform for direct interaction between all the participants of SUMO.

B.2.2 Beneficiaries

This section should be based on Section 2.2 of Part B of the proposal but possibly in a reduced format, if requested by the Project Officer. Upon request of the Commission you may be asked to include a full description in an Appendix to your Annex I.

For each beneficiary provide a brief description of the organisation (including names of key persons to be involved), the main tasks attributed to them in the project, and the previous experience relevant to those tasks. Provide also a short profile of the personnel who will be undertaking the work. If the named key persons do not in fact take part in the work, or are substituted by other persons without the knowledge of the Commission, this could be seen as beneficiaries not fulfilling their obligations towards the technical quality of the work. This could lead to a more in-depth review of the project.’

The sections below will describe the participating institutes, and how the involved key personnel, is well equipped to obtain successfully the goals of the project.

Partner 1: (coordinator): Macedonian Academy for Sciences and Arts (MASA)

Expertise and experience of the organization

The Macedonian Academy of Sciences and Arts (MASA) is the highest scientific, scholarly and artistic institution in the Republic of Macedonia. The Research Centre for Energy, Informatics and Materials (ICEIM) exists as an integral part of MASA since 1986. The role of the Center is to initiate and coordinate the national research programs and to perform high-level research in particular fields. ICEIM has participated in five FP6 projects and is currently involved in one FP7 project. Some of the projects in which ICEIM has participated are RISE, LPAMS, MANMADE, and MORE MICROGRIDS. The permanent staff members of ICEIM includes: six academicians, one senior research scientist, five young research scientists, two research scientists-volunteers and one technician. In addition, thirty-five collaborators from other scientific institutions in Macedonia are permanent collaborators and are engaged within the ICEIM research projects.

Role and contribution

MASA will manage the SUMO project and lead WP6 and WP3. MASA will be responsible for designing learning algorithms to determine optimal connection coefficients in a general PDE supermodel that will be applicable to large climate models.

Principal personnel involved

Prof. Dr. Ljupco Kocarev is a member of MASA, professor at Ss. Cyril and Methodius University, Skopje, Macedonia, and research professor at University of California San Diego, USA. He has co-authored more than 100 journal papers in 18 different international journals, ranging from mathematics to physics, from electrical engineering to computer sciences. According to Science Citation Index his work has been cited more than 4200 times. He is a fellow of IEEE. His scientific interests include complex systems and networks, nonlinear systems and circuits; coding theory, information theory, and cryptography.

Dr. Greg Duane is a research scientist working in nonlinear physics, synchronization, and geophysics. He has co-authored more than 30 journal papers, including several papers on applications of synchronization in data assimilation and parameter estimation in geophysics.

Selected relevant publications

L. Kocarev, Z. Tasev, and U. Parlitz, 1997: Synchronizing spatiotemporal chaos of partial differential equations, Phys. Rev. Lett. 79, 51.

G. S. Duane and J.J. Tribbia, 2001: Synchronized Chaos in Geophysical Fluid Dynamics, Phys.Rev. Lett. 86, 4298.

G. S. Duane and J.J. Tribbia, 2004:Weak Atlantic-Pacific teleconnections as synchronized chaos, J. Atmos. Sci. 61, 2149.

G.S. Duane, D.C. Yu, and L. Kocarev, 2007: Identical synchronization, with translation invariance, implies parameter estimation, Phys. Letters A 371, 416.

G.S. Duane and J.J. Tribbia, 2007: Dynamical synchronization of truth and model as an approach to data assimilation, parameter estimation, and model learning, Ch. 17 in Nonlinear Dynamics in the Geosciences, ed. A. Tsonis, Springer.

Partner 2: Geophysical Institute, University of Bergen (UiB)

Expertise and experience of the organization

The GFI is an internationally acknowledged contributor to the development of marine research and weather forecasting methods, including the Bergen School of Meteorology. The department is an integral part of the Bjerknes Centre for Climate Research (www.bjerknes.uib.no), a Norwegian Centre of Excellence (CoE) and of the newly established Center for Climate Dynamics at UiB. GFI is also the coordinator of the Norwegian Research School in Climate Dynamics (ResClim). The institute´s research strategy rests upon use of own cutting-edge measurement techniques developed in collaboration with technology partners in combination with theoretical studies and modelling in geophysics.

Role and contribution

UiB will lead WP5 and be responsible for the construction and application of the climate supermodel. UiB has access to high performance computing facilities in Norway through the Norwegian Metacenter for Computational Science (NOTUR, http://www.notur.no/) and also at ECMWF (http://www.ecmwf.int). The climate model simulations will be primarily performed on two computers: a Cray XT4 (51 Tflop) and IBM p575+ (22.7Tflops).

Principal personnel involved

Noel Keenlyside holds a professorship in Tropical Meteorology at the GFI/UiB. He also heads a junior research group investigating the mechanisms of Atlantic decadal climate variability, funded through the prestigious Emmy-Noether Programme of German Science Council (DFG). Since completing his PhD in 2001, he worked in the area of climate variability, predictability, prediction and change, and has 32 referred publications, the most significant in the area of decadal climate prediction. Keenlyside has worked with climate models since his first postdoctoral position at the Max-Planck Institute for Meteorology. He was one of the developers of the Kiel Climate Model, and has also developed intermediate complexity models. Dr. Keenlyside is active in the international community, and has played significant leadership roles in several relevant EU projects (DEMETER, ENSEMBLES, and DYNAMITE). He actively inspires young researchers, and supervises PhD (4 graduated, and 4 current) and masters (3 graduated) students.

Months 1-10

During the first 10 months of the project PI Keenlyside was based mainly at IFM-GEOMAR, and thus the IFM-GEOMAR was the responsible for the actives of this partner during this period.

Selected relevant publications

Park, W., N. S. Keenlyside, M. Latif, A. Stroeh, R. Redler, E. Roeckner, G. Madec, 2009: Tropical Pacific Climate and its Response to Global Warming in the Kiel Climate Model, J. Climate, 22, 71-92.

Latif, M. and N. S. Keenlyside, 2008: El Niño/Southern Oscillation Response to Global Warming, PNAS, doi:10.1073/pnas.0710860105.

Keenlyside, N.S., M. Latif, J. Jungclaus, L. Kornblueh, and E. Roeckner, 2008: Advancing Decadal-Scale Climate Prediction in the North Atlantic Sector. Nature, 453, 84-88

Keenlyside, N.S., M. Latif, M. Botzet, J. Jungclaus, and U. Schulzweida, 2005: A coupled method for initializing El Niño Southern Oscillation forecasts using sea surface temperature. Tellus, 57A(3), 340-356.

Partner 3: Koninklijk Nederlands Meteorologisch Instituut (KNMI)

Expertise and experience of the organization

The KNMI (Royal Netherlands Meteorological Institute) is the Dutch national weather service and centre for climate research. Climate research at KNMI is aimed at observing, understanding and predicting changes in the climate system. KNMI produces climate scenarios for use by stakeholders for developing adaptation and mitigation strategies. Climate research is carried out in various divisions: Global Climate (global climate change, coupled atmosphere-ocean modeling), Regional Climate (boundary layer physics, regional climate modeling), Chemistry and Climate, Earth Observation and Climate and Climate Advice and Analysis.

Role and contribution

KNMI leads WP4 in developing the supermodeling approach using intermediate complexity climate models and works in WP5 to help connecting the EC-Earth climate model to the Kiel climate model in the development of the climate supermodel.

Principal personnel involved

Dr. Frank M. Selten is senior scientist in the Global Climate Division of KNMI. Educated as a physicist, he obtained his PhD degree in 1995 on the modeling of large-scale atmospheric dynamics. He has a profound experience in coupled atmosphere-ocean modeling. He has worked on the development of coupled climate models (ECBILT and SPEEDO) and is presently involved in climate studies with the new state-of-the-art climate model EC-EARTH. His main interest is in the understanding and predictability of large-scale climate variations and change using advanced statistical techniques and concepts from dynamical systems theory. He has been involved in conducting and analysing large ensemble experiments of global climate scenario simulations (CHALLENGE and ESSENCE). Currently he takes part in the FP7 project EUCLIPSE on the subject of cloud-climate feedbacks and supervises two PhD students and one PostDoc. He has (co)-authored over 30 peer-reviewed papers.

Selected relevant publications

Branstator, G. and F.M. Selten, 2009: Modes of variability and climate change. J. Climate, 22, 2639-2658.

Selten, F.M., G. Branstator, M. Kliphuis and H.A. Dijkstra, 2004: Tropical origins for recent and future Northern Hemisphere climate change. Geophys. Res. Lett., 31, L21205.

Selten, F.M. and G. Branstator, 2004: Preferred regime transition routes and evidence for an unstable periodic orbit in a baroclinic model. J. Atmos. Sci., 61, 2267-2282.

Goosse, H., F.M. Selten, R.J. Haarsma and J.D. Opsteegh, 2003: Large sea-ice volume anomalies simulated in a coupled climate model. Clim. Dyn., 20, 5, 523-536

J.D. Opsteegh, R.J. Haarsma, F.M. Selten and A. Kattenberg, 1998: ECBILT: a dynamic alternative to mixed boundary conditions in ocean models. Tellus, 50A, 348-367

Partner 4: Potsdam-Institute für Klimafolgenforschung (PIK)

Expertise and experience of the organization

PIK has a strong and influential nonlinear dynamics group with expertise in synchronization and stochastic influences on complex systems. This group has also strong experience in networks with complex dynamics on the nodes. For example, it successfully worked on the design of weighted coupling network structures to enhance synchronisation, on hierarchical network structures and on information transmission in active networks, mostly also in time-delayed systems. The group has much experience in the transfer of modern concepts and methods to interdisciplinary applications, i.e., how to develop complexity measures for the analysis of complex systems by means of recurrence plot, how to capture the information exchanges between the coupled nodes of spatially distributed complex networks, and how to deal with large scale data sets.

Role and contribution

PIK leads WP1 and its main task is foundational research on all aspects of the supermodeling approach without learning in relatively low-dimensional, chaotic systems.

Principal personnel involved

Prof. Juergen Kurths got his PhD in 1983 at the GDR Academy of Sciences and his Dr. habil. in 1990. He was full Professor at the University of Potsdam from 1994–2008 and has been Professor of Nonlinear Dynamics at the Humboldt Universität zu Berlin and chair of the research domain Transdisciplinary Concepts of the Potsdam Institute for Climate Impact Research since 2008. He is a fellow of the American Physical Society and of the Fraunhofer Society (Germany). He got a Humboldt-CSIR research price in 2005 and a Dr. h.c. in 2008. His main research interests are complex synchronization phenomena, complex networks, time series analysis and their applications in cognitive and neuroscience and climatology. He has published more than 400 papers in peer-reviewed journals and two monographs, which have been cited more than 13,000 times. His H-factor is 46. He has coordinated the RTN “COSYC of SENS” within FP5, has been an area head in the NoE BIOSIM (FP6), the vice speaker of SFB 555 “Complex Nonlinear Processes” (DFG), and Co-coordinator of SPP 1114 “Time Series Analysis and Image Processing” (DFG).

Selected relevant publications

J. Nawrath, M. Romano, M. Thiel, I. Kiss, J. Timmer, J. Kurths, B. Schelter, 2010: Distinguishing direct from indirect interactions in oscillatory networks, Phys. Rev. Lett. 104, 038701.

J. Donges, Y. Zou, N. Marwan, J. Kurths, 2009: The backbone of the climate network, Europhys. Lett. 87, 48007.

A. Arenas, A. Diaz-Guilero, J. Kurths, Y. Moreno, C. Zhou, 2008: Synchronization in complex networks, Phys. Reports 469, 93.

C. Zhou, A. Motter, J. Kurths, 2006: Universality in the synchronization of weighted random networks, Phys. Rev. Lett. 96, 034101.

A. Motter, C. Zhou, J. Kurths, 2005: Network synchronization, diffusion and the paradox of heterogeneity, Phys. Rev. E 71, 016116

Partner 5: Radboud University (RU)

Expertise and experience of the organization

The machine learning group at the Biophysics Department of the Faculty of Science of the RU is dedicated to research in machine learning and computational neuroscience. Topics include Bayesian networks, stochastic neural networks, approximate inference methods, time-series modeling, bio-informatics, brain-computer interfaces, stochastic control, and collaborative decision making. It is headed by Prof. Dr. H.J. Kappen and consists of 10 researchers, PhD students, and programmers. The group coordinates the national platform SNN (Foundation for Neural Networks) and has two spin-off companies: Smart Research BV (commercial applications of machine learning) and Promedas BV (medical expert systems). The group is node in the European networks of Excellence Pascal and Pascal2.

Role and contribution

RU will lead WP2 and its main task is research and development of machine learning techniques for supermodeling.

Principal personnel involved

Wim Wiegerinck studied theoretical physics at the University of Amsterdam. From 1988 to 1990 he worked as research assistant at the KNMI on nonlinear dynamical systems. He joined the Biophysics machine learning group at the RU as a PhD student. His thesis (1996) concerned stochastic learning in neural networks. He remained in the group as SNN researcher. He is assistant professor at the science faculty of the RU and vice-director/senior researcher at Smart-Research BV. His main expertise is in machine learning and Bayesian inference. He co-authored about 60 publications in this field.
Willem Burgers received his MSc degree experimental physics from the RU in 2007. Currently he works in the machine learning group as a researcher/scientific programmer for SNN and Smart-Research BV. His main expertise is development of algorithms and software for computational efficient implementations of machine learning methods for large scale problems.

Selected relevant publications

Heskes T. and Wiegerinck, W., 1996: A theoretical comparison of batch-mode, on-line, cyclic, and almost-cyclic learning. IEEE Transactions on neural networks, vol. 7, 919—925.
Wiegerinck W., 2000: Variational approximations between mean field theory and the junction tree algorithm, Proc. Uncertainty in Artificial Intelligence (UAI). vol.16, 626—633.
Heskes T., Spanjers J-J, Bakker B., and Wiegerinck W., 2003: Optimising newspaper sales using neural-Bayesian technology. Neural Computing and Applications, vol 12, no 3, 212-219.
van den Broek B. , Wiegerinck W., and Kappen H.J., 2008: Graphical model inference in optimal control of stochastic multi-agent systems. JAIR, vol 32, 95-122.
Bruijning-van Dongen C., Slooten K. , Burgers W., Wiegerinck W., 2009: Bayesian networks for victim identification on the basis of DNA profiles, Forensic Sci. Int. Gene. Suppl. Series 2, 466-468.

Partner 6: Jožef Stefan Institute (JSI)

Expertise and experience of the organization

The Jožef Stefan Institute (http://www.ijs.si) (founded 1949) is a research organization for basic and applied research in natural sciences and technology. At present the Institute has a total of 850 staff, of which 630 are research staff. It plays the role of a national institute, complementing the role of the universities and bridging the gap between science and industry. The Department of Knowledge Technologies performs research in advanced information technologies, aimed at acquiring and managing knowledge to be used in the development of knowledge-based applications. Research is performed in the areas of intelligent data analysis (machine learning, data mining, knowledge discovery in databases), language technologies, decision support and knowledge management. These technologies are applied to practical problems in the areas of environmental and life sciences, medicine, economy and marketing. The department's research program has been evaluated as the best research program in ICT (2004-2008) by the Slovenian Research Agency.

Role and contribution

JSI will lead WP7, where in collaboration with MASA, it will develop methods for learning complete supermodels. It will also contribute to the other WPs, especially WP1-3, where it will formulate domain knowledge for learning climate (super)models and use it with the methods developed in WP7 to learn a range of models, from simple to moderately complex ones.

Principal personnel involved

Sašo Džeroski is a scientific councilor at the Department of Knowledge Technologies at the Jožef Stefan Institute (JSI) in Ljubljana, Slovenia. He is also a full professor and teaches graduate level courses at the Jožef Stefan International Postgraduate School and the University of Nova Gorica regularly, and at several other universities as a visiting professor. His research focus is the development of machine learning techniques and their applications to practical problems in the areas of environmental and life sciences.
He has made significant contributions to several areas of machine learning, including computational scientific discovery and ensemble learning, two areas of direct relevance to the SUMO project. In computational scientific discovery, he has (co)developed a number of methods for automated modeling of dynamic systems from data and domain knowledge: These have been applied to learn and improve models of a number of environmental systems and processes, such as the net primary production of carbon. In ensemble learning, he has (co)developed methods for learning how to combine classifiers with stacking, thus improving the performance of ensembles beyond that of the best model in the ensemble. He has also made contributions to other areas of machine learning and data mining, such as relational learning, computational learning theory, reinforcement learning, constraint-based data mining and inductive databases. According to Science Citation Index his work has been cited more than 2000 times; according to Google Scholar he has a h-index of 35 and more than 6000 citations.
He has coordinated the EU FP6 IST FET project IQ: Inductive Queries for Mining Patterns and Models. He has also been actively involved in many other EU-funded research projects (ESPRIT III project ILP, ESPRIT IV projects ILP2 and METAL, FP5 projects ECOGEN and cInQ, FP6 projects SIGMEA, IQ and EETPipeline, FP7 project PHAGOSYS), as well as the the EU-funded Networks of Excellence in ILP (Inductive Logic Programming) ILPnet and ILPnet2, the latter of which he coordinated. He is co-author/co-editor of eleven books/volumes, of which the one titled »Computational Discovery of Scientific Knowledge« (Springer, Berlin 2007) is most relevant to the SUMO project.

Selected relevant publications

W. Bridewell, P. Langley, L. Todorovski, and S. Džeroski. Inductive process modeling. Machine Learning, Volume 71 (1), pages 1-32, 2008.

S. Džeroski and L. Todorovski, editors: Computational Discovery of Scientific Knowledge: Introduction, Techniques, and Applications in Environmental and Life Sciences. Springer, Berlin, 2007.

L. Todorovski, and S. Džeroski. Integrating knowledge-driven and data-driven approaches to modeling, Ecological Modelling, Volume 194 (1-3), pages 3-13, 2006.

S. Džeroski and B. Ženko. Is combining classifiers with stacking better than selecting the best one? Machine Learning, Volume 54, pages 255-273, 2004.

L. Todorovski, S. Džeroski, P. Langley, and C. S. Potter. Using equation discovery to revise an Earth ecosystem model of the carbon net production. Ecological Modelling, Volume 170, pages 141–154, 2003.

B.2.3 Consortium as a whole

This section is based on Part B Section 2.3 of the proposal.

Describe how the beneficiaries collectively constitute a consortium capable of achieving the project objectives, and how they are suited and committed to the tasks assigned to them. Show complementarities between beneficiaries. Explain how the composition of the consortium is well balanced in relation to the objectives of the project.

If appropriate, describe the industrial / commercial involvement foreseen to ensure exploitation of the results. Show how the opportunity of involving SMEs has been addressed.

The SUMO consortium comprises leading European Institutions: involved are research institutes and universities. The consortium has a broad base of expertise with world leading scientists on the different disciplines involved in this multidisciplinary project. Within all the different disciplines the partners have a strong expertise:

- Synchronization in dynamical systems (ODEs, PDEs): MASA and PIK
- Machine learning techniques: RU, MASA and JSI
- Climate modeling: UiB and KNMI

All these above described communities have worked until recently in relative isolation and SUMO offers a unique opportunity to combine all these expertise leading to new techniques in climate modeling.

SUMO will achieve its goals by assembling a team with diverse expertise and skills. The breadth of the expertise is already outlined in the previous section, reaching from nonlinear physics and synchronization in physics, biology, and geophysics, to machine learning, from observations, evaluation techniques to modeling techniques on various spatial and temporal scales. Furthermore, significant experience exists in developing and running complex climate models on high-performance computing platforms.

Virtually all partners have a long experience in either coordinating or contributing to EC projects so that smooth running of EC-related reporting (scientific, technical and financial) is expected.
The SUMO consortium originally comprised a total of 5 partners from 2 European countries (Germany and Netherlands) and 1 associated country (Macedonia). The management structure allowed including new partners at a later stage, depending on decisions of the Management Board. In this context, the consortium has been extended with an additional partner JSI (from Slovenia).

B.2.3.1 Sub-contracting

If any part of the work is foreseen to be sub-contracted by a participant, describe the work involved and an estimation of the costs, explain why a sub-contract is needed and how the selection will be performed. Please note that there are special conditions for subcontracting for the funding scheme "Research" for the benefit of specific groups (in particular SMEs).

Sub contracting was not planned in the original SUMO consortium. The new partner JSI will subcontract software maintenance and documentation services to the developer of LAGRAMGE2.0, Ljupco Todorovski. The LAGRAMGE2.0 software will be used as the basis for further development of methods for computational scientific discovery. The estimated cost of subcontracting is 15000 EUR..

B.2.3.2 [Third parties]

If any part of the work is foreseen to be carried out using financial resources or resources in kind provided by third parties, identify and describe these third parties and the amount involved and their relation to the respective beneficiaries.

There are no third parties involved in SUMO.

B.2.3.3 [Funding for beneficiaries from third countries]

If one or more of the beneficiaries requesting EU funding are based outside of the EU Member and Associated states and is not in the list of "International Cooperation Partner Countries", explain in terms of the project's objectives why such funding would be essential.

There are no third countries involved in SUMO.

B.2.3.4 Additional beneficiaries / Competitive calls

If there are as-yet-unidentified beneficiaries in the project, the expected competences, the role of the potential beneficiaries and their integration into the running project should be described. If any "competitive calls" for new beneficiaries are planned, describe the timing, expected budget, purpose, scope and procedure for publication and evaluation of the call.

While no additional beneficiaries were foreseen in SUMO, an additional beneficiary (partner) was added to the consortium through the Objective ICT 2011.11.3 Supplements to strengthen cooperation in ICT R and D in an Enlarged European Union of the call FP7-ICT-2011-7.

B.2.4 Resources to be committed

This section is based on Section 2.4 of the original proposal Part B, but may require more details than provided in the proposal.

In addition to the budget breakdown form (Part A) and the overviews of staff effort broken down to work package level in Section 1.3, please provide a management level description of resources and budget identifying personnel and any other major costs. Describe here the resources which are needed to carry out the project (personnel, indirect costs, equipment, etc. for each of the beneficiaries). The description should show that the project will mobilise the resources necessary to carry out the work for the overall duration, including those resources that will complement the EC contribution. It should also show how the resources will be integrated and used to form a coherent project within the overall financial plan.

The total request of the SUMO consortium to the EC amounts to 1.8 million € (cf. form A3.2): The EC contribution originally amounted to 1.4 million € and was increased by 400 k€ with the extension. SUMO represents good value for money thanks to its far reaching expected impact for all stakeholders actively engaged in climate change issues such as described in section 3 on Impact. By giving scientists, policy makers and infrastructure developers access to improved climate information, new bounds on uncertainties on this information and new evaluation tools, savings across Europe could measure in billions of Euros. Most of the total budget (around 90%) is used to hire personnel for RTD (including overheads) and will be spent on science, to make available the acquired knowledge, the newly developed evaluation tools and the climate model and observational data sets. The other 10% will be spent on management (4%), and on travel (6%).

B.2.4.1 Justification of resources by the work packages

The total grant requested from the EU (1.8 million €) broken down per Work Package is as follows. For the management (WP6) we require 69.2 k€ (which is only 4% of the total budget). Work packages 1, 2, 3, 4 and 5 all have duration of 36 months and have comparable person man months (50-57). Workpackage 7 has a duration of 27 months (JSI is joining the consortium at month 10) and also a comparable number of man months (54). The budget spent on WPs is almost equally distributed. The differences in the requested amount for these work packages are simply due to the different personnel costs of the involved institutes. The management costs for WP6 are for overall financial management and coordination, while a small part is reserved for costs for audit certificates for the participants.

B.2.4.2 Travel and Other Direct Costs

Support of travelling and subsistence is needed for attending project meetings and workshops and for presenting SUMO results at conferences. The partners that are active in most WPs during the full 36 months period require travelling support in the range of 7.5 to 15 k€ for the whole duration of the project. This is reasonable as within SUMO there are 4 meetings plus an international workshop planned, to be visited by 2 to 3 representatives from each of the participating institutes.

The travel costs for MASA will be higher than for the other partners, due to the additional travel costs for coordination, especially given the addition of a new partner to the consortium. Additionally 10 k€ are reserved for inviting key scientists. Each year a workshop will be organized together with the General Assembly meeting to discuss the progress and open questions of SUMO. At these workshops, invited key scientists will deliver key lectures related to the work of SUMO.

The travel costs for JSI will also be higher than for the other participants (18 k€), as part of this budget will be used to invite researchers from the other SUMO partners to visit JSI in order to foster collaboration. Some funds will also be used to cover other costs, such as the costs of organizing a project meeting in Ljubljana (lunches, coffee breaks) and costs of occasional student programming services: These will amount to 8 k€ total.

B.2.4.3 International Summer-School

The MASA summer-school on supermodeling will provide an important way of disseminating the science findings and tools to a new generation of scientists. The material of the summerschool, including presentations, tutorials, model and observational data will be made available on the web. An edited book from this school will further advance the dissemination goals of the project. The costs for these activities were originally estimated to be 20 k€: In addition, we propose that the lectures of the school be recorded and made available via VideoLectures.Net or a similar service. This will incur additional costs of approximately 10 k€, but will significantly increase the outreach of the project and thus presents a good return on investment.

B.2.4.4 Computer time for climate model simulations

The computer time required to perform the climate model simulations in WP5 represent a significant in-kind contribution to the project. It will be provided through UiB, who through the Norwegian Metacenter for Computational Science (NOTUR, http://www.notur.no/) has access to high-performance computing at four different centres in Norway and also at the European Centre for Medium Range Weather Forecasts (ECMWF, http://www.ecmwf.int/). WP5 leader (Noel Keenlyside) has almost ten years of successful experience in applying for computer resources at ECMWF and various centres in Germany.

B3. Potential impact

B.3.1 Strategic impact

This section is based on Part B Section 3.1 of the proposal.

Describe how your project will contribute to the expected impacts listed in the work programme in relation to the topic(s) in question. Mention the steps that will be needed to bring about these impacts, for example in reinforcing competitiveness or in solving societal problems or addressing specific problems. If possible, identify specific areas in which the project results can have a genuine influence. Explain why this contribution requires a European (rather than a national) approach. Indicate how account is taken of other national or international research activities. Mention any assumptions and external factors that may determine whether the impacts will be achieved.

B.3.1.1 Transformational impact on science, technology and/or society

B.3.1.1.a Impact on climate-change predictions and their socio-political consequences

How will climate change during the next century in response to anthropogenic influences? This question is focus of much research, the results of which are published in regular reports by the Intergovernmental panel on climate change (IPCC)(IPCC, 2007).

While our understanding of climate change has increased significantly over the last decades, large uncertainties exist in our essentially model-based predictions of future climate (IPCC, 2007). Uncertainty is largest at regional scales, as illustrated by projection of precipitation for the end of the century, where model disagree strongly over large areas of the globe (Fig 1.3). Similar results are found for high-impact climate events, as well as for surface temperature.

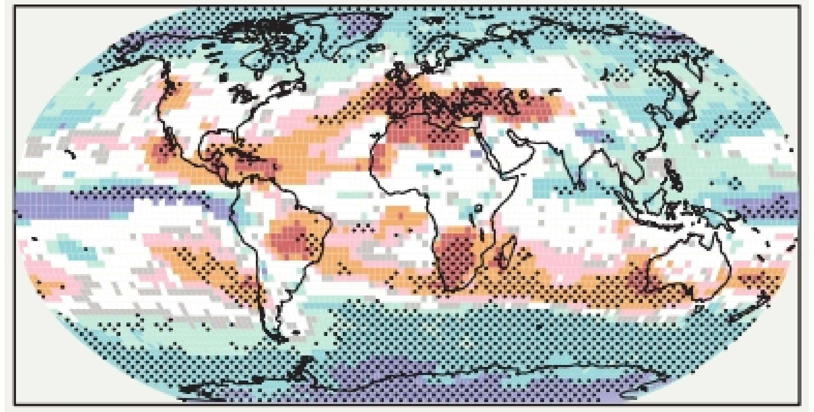


Figure 3.1 Projections of precipitation change for 2090–99. Blue indicates increases in precipitation and brown denotes drying. White represents areas of uncertainty, where less than two-thirds of models agreed on whether precipitation would increase or decrease. Stippled areas indicate where 90% of the models agreed on the sign of the change. (IPCC, 2007; Schiermeier, 2010)

Uncertainty in future climate projections arises from three sources:

1. Scenario, uncertainty in the evolution of external radiative forcing, such as resulting from changes in greenhouse gas concentrations
2. Model, uncertainty arising from the model formulation
3. Initial condition, uncertainty due to poor knowledge of the initial climate state

Quantification of these uncertainties over the coming century indicates that model systematic error contributes significantly out to 2100, and is particularly important on regional scales (Fig 3.2) (Hawkins and Sutton, BAMS, 2009). Significant socio-economic gains may be made if these uncertainties are reduced. As described in the proposal, the super-modeling strategy has the potential to significantly reduce model systematic error, long before it could be provided through the slow, but essential process of model improvement. Thus our pragmatic approach could have a very large impact on climate research, and bring significant socio-economic benefit.

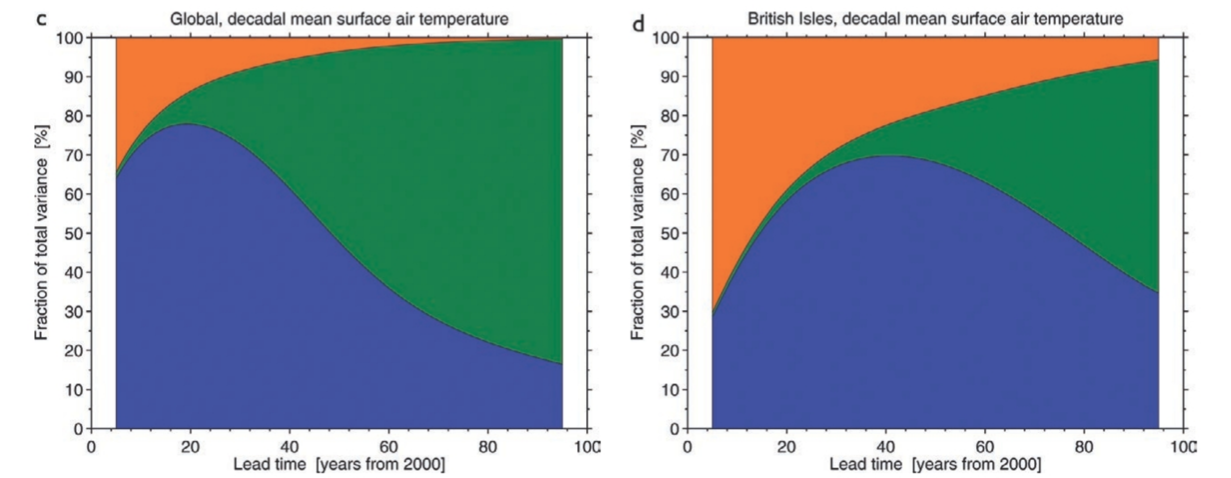


Figure. 3.2: The fraction of total variance in decadal mean surface air temperature predictions explained by the three sources of uncertainty for (c) a global mean and (d) a British Isles mean. Green regions represent scenario uncertainty, blue regions represent model uncertainty, and orange regions represent the internal variability component. As the size of the region is reduced, the relative importance of internal variability increases. (Hawkins and Sutton, 2009)

B.3.1.1.b Impact on computational science

Supermodeling will provide a generic approach for modeling in complex application domains where different expert models are available, as well as sufficient data to tune the connections. The use of advanced (but imperfect) models created by domain experts gives supermodeling a great advantage compared to machine learning modeling starting from scratch. Conversely, if supermodeling is successful, it can be expected to initiate new directions of machine learning research applied to domains of much higher inherent complexity than currently feasible.
The application domain in this proposal is restricted to climate research to keep research focused, while still having a challenging and convincing test. The supermodeling approach naturally extends to short-term weather prediction, where the same principles can be directly applied to combine different numerical weather prediction.
There are other situations in which there are a handful of expert dynamical models of the same real-world process that could be efficaciously combined. One can envision applications to complex biological, social, economic, and environmental processes, in situations where there are a small number of competing models, e.g. created in academic institutions. The only requirement is that the constituent models be equipped with a methodology to incorporate new data from the objective process, as the model runs. In that situation, the models can also assimilate data from each other, as here, and an adaptation procedure for connection coefficients can be defined.
The SUMO extension already initiates a new direction in machine learning research by addressing the task of learning complete supermodels. Besides complete models as constituents of the supermodels, the proposed approaches will be able to take into account partial models and other forms of domain knowledge. As such, they will be applicable to a broad range of practical problems, and not just climate modeling.

B.3.1.2 Contribution at the European level towards the expected impacts listed in the work program

The proposed effort will strengthen the future potential for research towards its long-term vision primarily by building interdisciplinary collaborations that will survive the funded effort and that will inspire similar collaborations. Specifically, the project will strengthen relationships among the three fields of *climate science*, *machine learning*, and *nonlinear dynamics*.

In regard to the relationship between climate science and machine learning, we note that parameter estimation in climate models is an unsolved problem of great significance, given the large amount of data on which models could be trained and the difficulty of estimating parameters in a purely theoretical treatment. Current methods usually treat unknown parameters simply as extra state variables, failing to exploit their relative constancy. Both the results of the super-modelling project and the relationships between scientists in the two areas that will emerge will encourage the use of other machine learning paradigms for parameter estimation in separate models that improve on the current methods. The use of meta-heurist ic approaches for parameter estimation, proposed within the SUMO extension, effect ively illustrates this. And as discussed above, super-modeling itself is a new approach to machine learning that can be applied in any situation where there are a small number of competing expert dynamical models, together with a data assimilation methodology.

While the simple Lorenz model, a prototypical example of chaos, arose from meteorology (Lorenz, 1963), subsequent work in nonlinear dynamics largely diverged from climate science, and research on synchronization has not found widespread geophysical application. That is largely because the essential issues of nonlinear dynamics can be explored in much simpler systems, while the availability of large computers has made simple models less relevant to climate science than they were in 1963. The proposed project will bring about a reunion, based on the realization that the same nonlinear properties that allow weather prediction from sparse observations will allow disparate models to achieve consensus with sparse connections. The fundamental nonlinear structure of climate dynamics that gives rise to both phenomena, in the form of the theory of inertial manifolds, for instance, will receive greater attention, spurring new theoretical developments in climate science. Conversely, researchers in nonlinear dynamics will “lose their fear” of large models defined by PDE’s, so that other paradigms from dynamical systems will be applied to such models that have heretofore been explored only in simpler contexts.

The simple parameter adaptation scheme used here is an example of such an extension of an ODE paradigm to PDE systems, as described in Duane et al (2007). That scheme also illustrates the potential for research in nonlinear dynamics to contribute to the theory of machine learning generally. Relationships between statistical learning algorithms and dynamical systems approaches remain to be explored, to the potential benefit of both fields.

With the SUMO extension, the link between nonlinear dynamics and machine learning will be strengthened further. The approaches of computational scientific discovery will allow the learning of nonlinear models from data and domain knowledge. On the other hand, knowledge of nonlinear dynamics will allow the development of more effective machine learning algorithms for automated modeling of dynamic systems. A possible way of achieving this is the development of more suitable model quality criteria (rather then the mean squared error of simulated behavior).

The potential effect of the proposed effort on the relationships between the specific individuals and institutions involved should also not be underestimated. PIK will benefit from a relationship with "hardcore" climate modellers at KNMI and UiB and the latter will benefit from the more theoretical approach of PI Kurths and his collaborators. Even within the climate science community, the two-way interactions between the KNMI/Nijmegen collaborators and PI Keenlyside at UiB, will strengthen the practical relevance of relatively idealized Ecbilt-like models on the one hand, and theoretical understanding of the large climate models at UiB on the other. PI Kocarev and his students/post-docs in Macedonia will be drawn into climate modelling, to the benefit of the rest of the climate modelling community that will gain an appreciation of essential and surprisingly simple nonlinear properties of their models. JSI will provide machine learning expertise directly relevant to MASA and RU/Nijmegen, while PI Dzeroski and his team will greatly benefit from the MASA expertise on nonlinear dynamics.

B.3.2 Plan for the use and dissemination of foreground

This section is based on Section 3.2 of the original proposal. If appropriate, a separate work package should be designed with the relevant activities to accomplish this task.

Appropriate measures should be planned and implemented to ensure the optimal dissemination and use / exploitation of project results. The description should cover the Consortium's strategy and measures regarding:

- *The management of knowledge and intellectual property.*
- *The plan for the use of results (e.g. further research or commercial exploitation) and for the dissemination of the foreground (knowledge generated during the project) beyond the Consortium; both during the lifetime of the project and afterwards.*

A plan for the use and dissemination of foreground is mandatory for all projects for the final report and form part of the compulsory deliverables. A basic version of the dissemination and use plan can be prepared in the first phase of the project (or at mid-term), and foreseen in Annex 1. A project website is required.

The WP6 Management consists of three tasks: T6.1 Project Management, T6.2 Annual general assemblies and project meetings, and T6.3 Contribution to portfolio and concertation activities at FET-Open level.
While the first two tasks are explained in detail in the previous chapters, here we describe the task T.6.3. In order to support scientific cooperation at the FET-Open level and broad public awareness of project achievements, in this task the following activities are planned:

1. Project results will be published throughout the duration of the project in widely accessible science and technology journals, as well as through conferences and through other channels, including the Web, reaching audiences beyond the academic community. In particular, scientific papers will be published in climate science, nonlinear dynamics (physics), and computer science/electrical engineering journals. The substance of the publications in journals in different fields will typically overlap, but the different papers will be written in a style appropriate for their respective audiences.

2. An electronic copy of the published version (or the final manuscript accepted for publication) of the scientific publication will be deposited in an institutional or subject-based repository at the moment of publication.
3. Electronic copies of the publications will become freely and electronically available to anyone through this repository: immediately if the scientific publication is published “open access”, i.e. if an electronic version is also available free of charge via the publisher, or within 6 months of publication.
4. To achieve the impacts discussed in Section 3.1, it is also important that results and methods be disseminated in a form that is appropriate for non-specialists. The question of what climate scientists do and don’t agree on is indeed a popular topic. We will seek speaking engagements before popular audiences to present our ideas about scientific differences regarding climate projections, synchronization, and consensus-formation. Periodic press releases will also be issued, and other means of disseminating project progress to a wider audience.
5. A summer school on super modelling will be organised at the end of the project. An edited book from this school will further advance the dissemination goals of the project. A brochure will also be prepared at the end of the project to convey the main results of the project to political and lay audiences.
6. Consortium members will participate in FET-organised events, for example conferences, dedicated work-shops and working groups, consultation meetings, summer schools, etc. In addition, the members will also participate in international cooperation whenever it is possible (especially with different US agencies).
7. The developed software for learning of complete supermodels, i.e., its components developed within the SUMO extension, will be made freely available to researchers.

The above activities will be reported in the project’s Dissemination Plan and in periodic progress reports. In addition, the consortium agrees to include the following reference in all project-related publications, activities and events:

“The project SUMO acknowledges the financial support of the Future and Emerging Technologies (FET) programme within the Seventh Framework Programme for Research of the European Commission, under FET-Open grant number: 266722”

If applicable this section should also include:

B.3.2.1 [Contributions to standards]

Contributions to national or international standards, which may be made by the project, if any should be described.

B.3.2.2 [Contribution to policy developments]

Any significant impacts the project may have on research or research-based policy development at regional, national or European level should be described together with a description, if relevant, of the policy process in which the project is embedded.

The wide divergence among the predictions of different climate models is simply unacceptable. See Fig. 3.1. The lack of reliable regional predictions is especially troublesome. Given a political climate in which there is much resistance to prioritizing concerns of long-term, global interest, it would be very helpful if the decision-makers in every locality were afforded a more detailed picture of the implications of climate change for their own constituents and if more could be said about expectations within their own lifetimes.
The systematic resolution of inter-model differences promised by the supermodelling approach will go far toward establishing a universally accepted view regarding detailed predictions. The approach promises to yield more reliable results at least for the first portion of the current century. As those results are adopted in the economic sphere, by insurance and re-insurance companies, their credibility in the rest of society will be enhanced. The impact on long-term policy decisions will grow with the length of time over which the supermodel's projections are skilful, as assessed internally, under conditions of changing radiative forcing.

B.3.2.3 [Risk assessment and related communication strategy]

Any potential risks (real or perceived) for society/citizens associated with the project and the communication strategy adopted in this regard should be fully described.

B4. Ethical issues

Please fill in the ethical issues table in all cases.

	YES	PAGE
Informed Consent		
• Does the proposal involve children?		
• Does the proposal involve patients or persons not able to give consent?		
• Does the proposal involve adult healthy volunteers?		
• Does the proposal involve Human Genetic Material?		
• Does the proposal involve Human biological samples?		
• Does the proposal involve Human data collection?		
Research on Human embryo/foetus		
• Does the proposal involve Human Embryos?		
• Does the proposal involve Human Foetal Tissue / Cells?		
• Does the proposal involve Human Embryonic Stem Cells?		
Privacy		
• Does the proposal involve processing of genetic information or personal data (eg. health, sexual lifestyle, ethnicity, political opinion, religious or philosophical conviction)		
• Does the proposal involve tracking the location or observation of people?		
Research on Animals		
• Does the proposal involve research on animals?		
• Are those animals transgenic small laboratory animals?		
• Are those animals transgenic farm animals?		
• Are those animals cloned farm animals?		
• Are those animals non-human primates?		
Research Involving Developing Countries		
• Use of local resources (genetic, animal, plant etc)		
• Benefit to local community (capacity building i.e. access to healthcare, education etc)		
Dual Use		
• Research having direct military application		
• Research having the potential for terrorist abuse		
ICT Implants		
• Does the proposal involve clinical trials of ICT implants?		
I CONFIRM THAT NONE OF THE ABOVE ISSUES APPLY TO MY PROPOSAL	**None**	None

If in the proposal you have answered some of the questions in the ethical issues table with "YES" or if your evaluation summary report mentions that ethical issues need to be addressed, then repeat your Section 4 of the proposal here and address any issues which may be requested in the Evaluation Summary Report or the separate ethical issues review report (ftp://ftp.cordis.europa.eu/pub/fp7/docs/fp7-ethics-eir.doc), if any. Please see Appendix 2 of the negotiation guidance notes for the negotiation of ethical issues.

B5. [Consideration of gender aspects, optional]

The Consortium or individual beneficiaries have the option to give an indication of the type of actions that will be undertaken during the course of the project to promote gender equality in the project, or in the specific research field.

Relevant activities might include actions related to the project consortium (e.g. improving the gender balance in the project consortium, measures to help reconcile work and private life, awareness raising within the Consortium) or, where appropriate, actions aimed at a wider public (e.g. events organised in schools or universities)

The gender dimension of the research content should also be considered.

Gender Aspects should be addressed in a work package or tasks within a work package.

Appendix A. List of references

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