LAAS-CNRS · CNRM-GAME · ENAC · ISAE · ONERA

Project supported by the STAE foundation, 2014 / 2016
Stemmed from the Micro Air Vehicle Research Center

https://www.laas.fr/projects/skyscanner

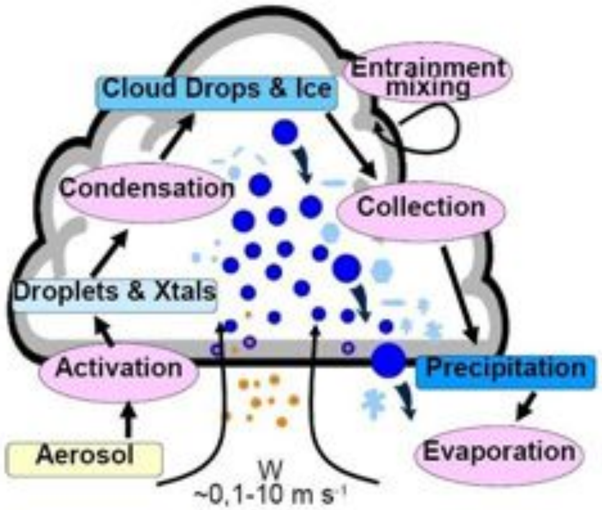
(Administrative start on June, 2014 – actual start on Oct. 2014)

Scope of the project

- Overall target: follow the evolution of a cumulus cloud with multiple drones to study entrainment and the onset of precipitation

✓ Characterize state of boundary layer below and surrounding a cloud

atmospheric stability
lifting condensation level
cloud updraft



✓ Follow 4D evolution of the cloud

entrainment at edges
inner winds
amount of liquid water
cloud microphysical properties

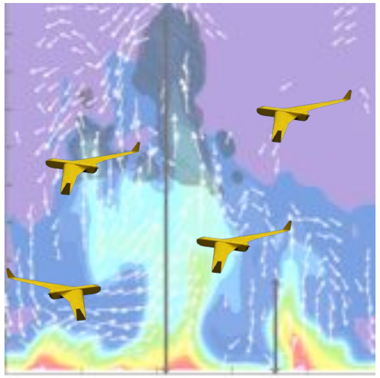
➡ Impacts the drone conception and the fleet control

Scope of the project

- 3 research axes:
  - Refine aerologic models of clouds

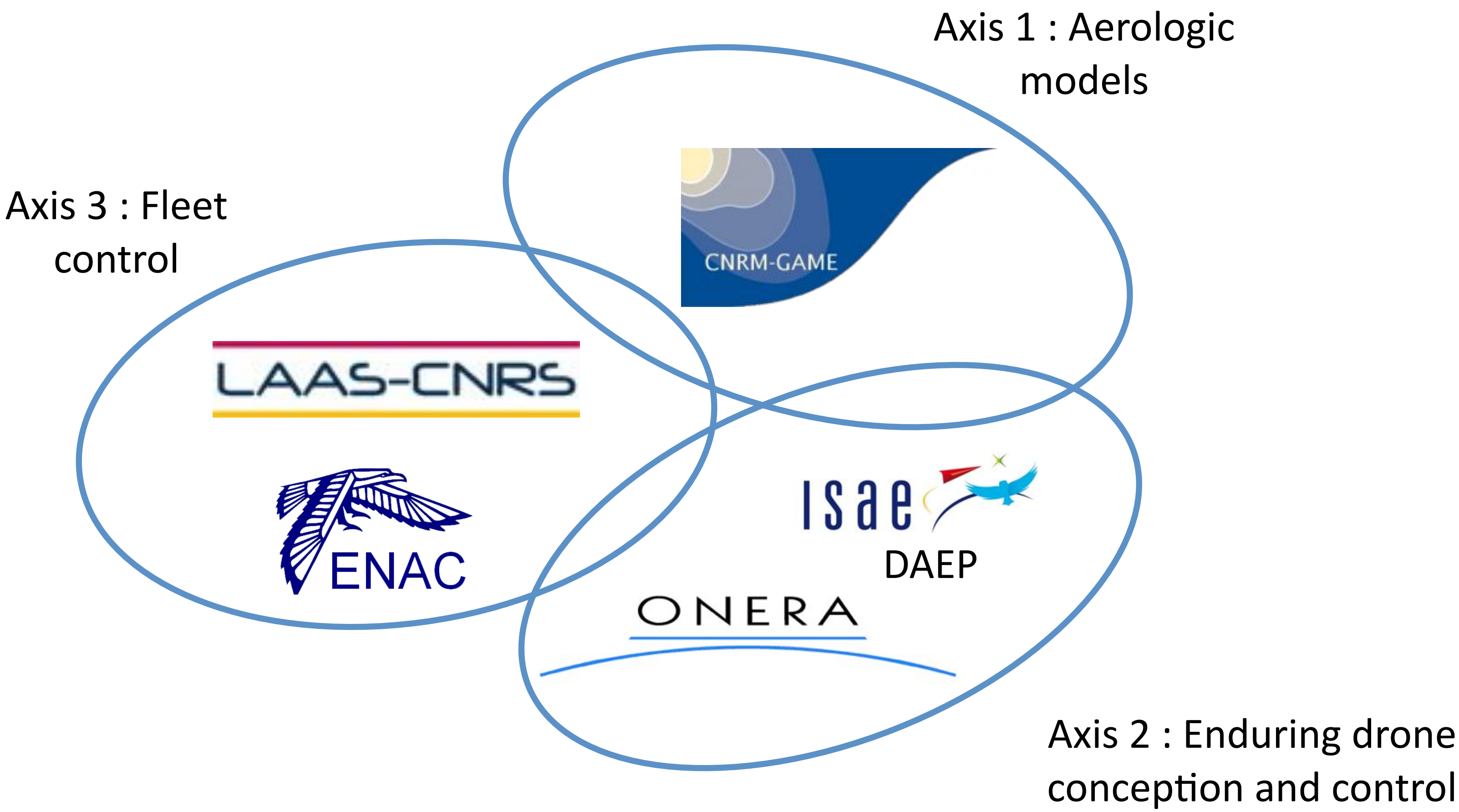
  - Conceive enduring micro-drones

  - Fleet control



Plus: experimental developments and validations

Research axes / partners



- Funding amounts to five 18 months postDocs / Research Engineers

Partners and people

CNRM

- Greg Roberts
- Frédéric Burnet
- Fayçal Lamroui (Research Engineer since Feb 15th 2015)

ISAE

- Emmanuel Bénard
- Elkhedim Bouhoubeiny (PostDoc since Feb 1st 2015)

ONERA

- Carsten Döll
- X (PostDoc to hire – fall 2015)

ENAC

- Gautier Hattenberger
- Murat Bronz
- Jean-Philippe Comdomines (Research Engineer since March 1st 2015)
- Jean-François Erdelyi (M1 internship since April the 1st 2015)

LAAS

- Simon Lacroix
- Alessandro Renzaglia (Postdoc since Oct 1st 2015)
- Christophe Reymann (Master internship since Feb 1st 2015)

What is the problem to solve?

"Deploy a fleet of drones so as to maximize the amount of gathered information on the cloud" (~ adaptive sampling)

- Where to gather information?
- How to represent / maintain the gathered information?
- Which drone(s) allocate to which area?
- How to optimize the trajectories to reach these areas?
- …

Fleet control

- How to optimize the conception of the drones?
- How to optimize the control of the drones?
- …

Drones conception and control

Fleet control

Overall approach:

- Models

+ Hierarchized approach

- Algorithms

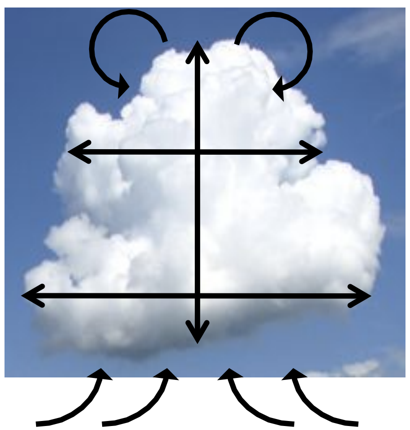
- Architecture

Fleet control

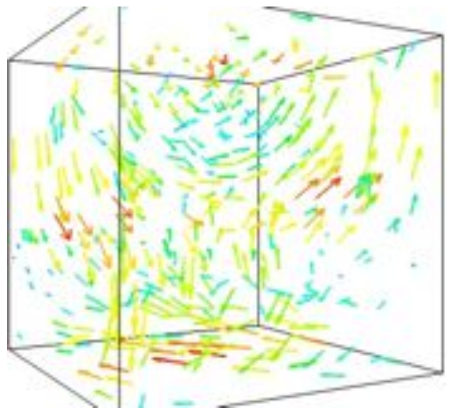
Overall approach:

- Models

1. Models of the environment: winds, atmospheric parameters, geometry



"Conceptual" model
(macroscopic, coarse scale)



Dense model
(~ *10m* scale)

➔ Need to estimate these models (that evolve over time) from data acquired online

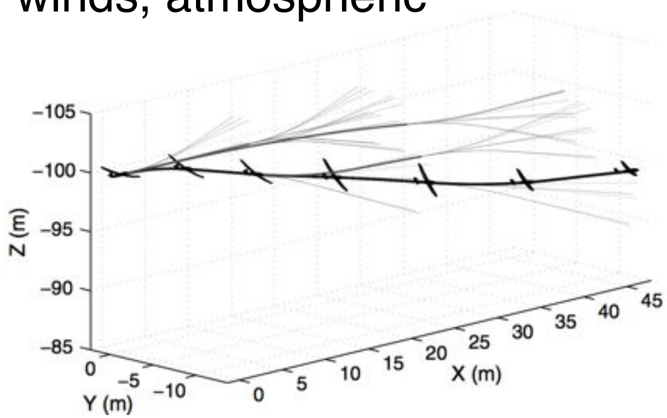
Fleet control

Overall approach:

- Models

1. Models of the environment: winds, atmospheric parameters, geometry

2. Model of the drones
   - Kinematic constraints



   - Express energy variations
     Kinetic (airspeed)
     Potential
     Stored (battery)

➔ Simulations
- Of the dense cloud models: Meso-NH, JSBSim
- Of the drones : New Paparazzi Simulator
- Finer drone model(s) will be defined and exploited

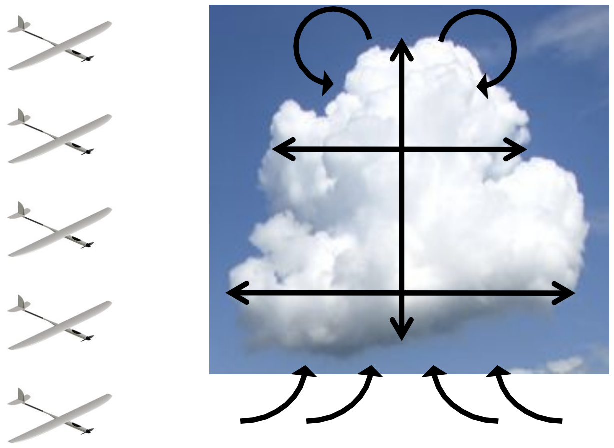
Fleet control

Overall approach:

- Models

  1. At a coarse (symbolic level, ΔT ~ 10sec)

- Algorithms



➔ Where should what information be gathered?
➔ Who goes where?

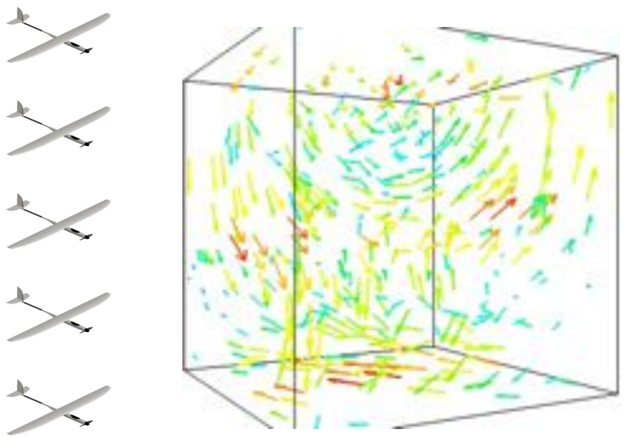
Fleet control

Overall approach:

- Models

1. At a coarse (symbolic level, ΔT ~ 10sec)
2. At a finer level (ΔT ~ 1sec)

- Algorithms



➔ Who goes where?

Fleet control

Overall approach:

- Models

- Algorithms

- Architecture
    1. Where are the information processed?
    2. Where are the decisions taken?
    3. Will there be men in the loop?

Drone conception and control

Overall approach:

- Models

- Algorithms

- Architecture

Outline of the presentations / discussions

Fleet control

- Models

1. Fayçal Lamraoui (CNRM):
   - First thoughts on the conceptual model
   - Setting up Meso-NH simulations
2. Christophe Reymann (LAAS)
   - Cloud modeling from sparse data

- Algorithms

3. Christophe Reymann (LAAS)
   - First thoughts on high-level planning
4. Alessandro Renzaglia (LAAS)
   - Optimal motions in wind fields

- Architecture

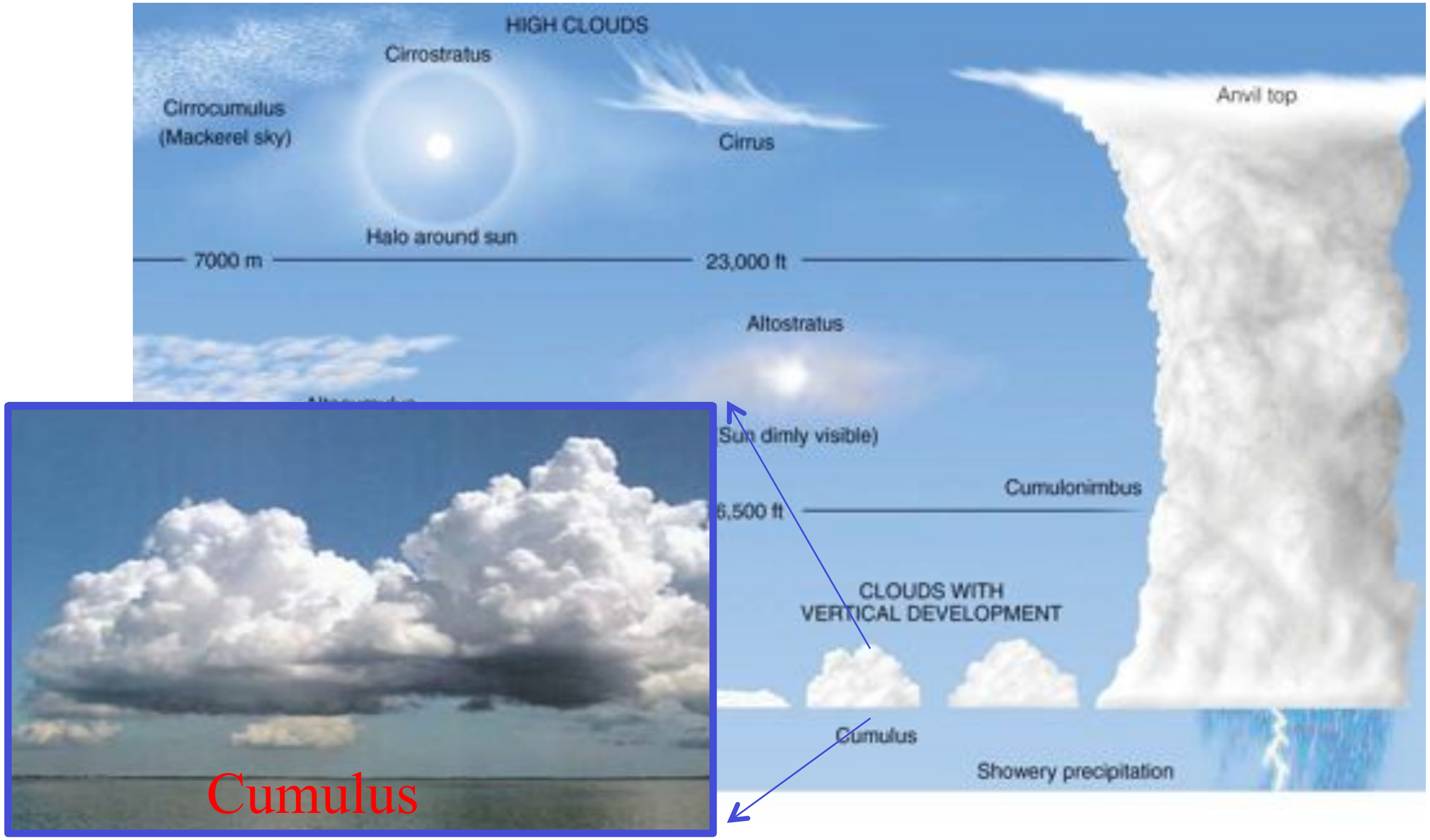
5. Jean-Philippe Condomines (ENAC)
   - The New Paparazzi Simulator
   - First thoughts on the overall architecture
   - First hardware developments

- Drones conception and control

6. Elkhedim Bouhoubeyni (ISAE)
   - Towards optimized drone conception
7. Carsten Döll (ONERA)
   - Travaux planifiés en commande

Shallow convective clouds

Introduction



Shallow convective clouds

Why we study ?

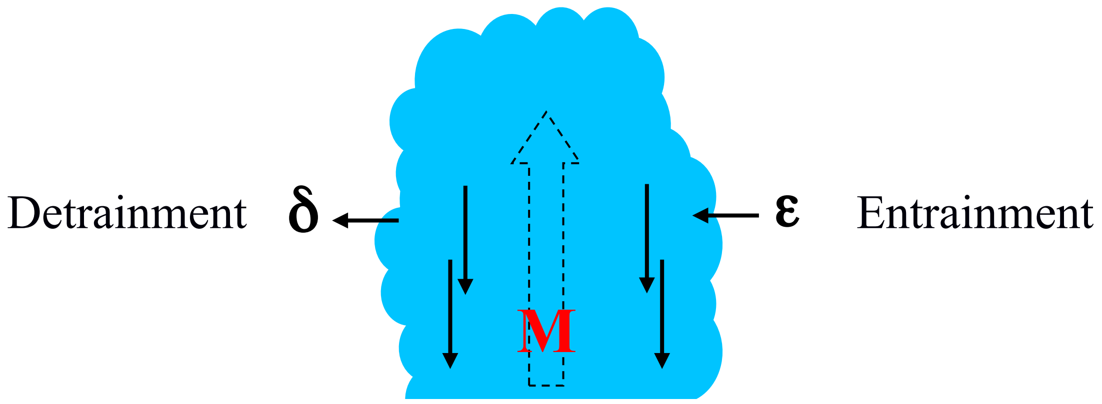
- Significant role in controling Earth's global energy budget

- A proper parametrization of shallow cumulus is necessary to accurately model the global radiation balance in General Circulation Models

- NWP (**N**umerical **W**eather **P**rediction) and climate models have coarse resolution to resolve cumulus process ===> LES (**L**arge **E**ddy **S**imulation)

Determination of cloud properties still a persistant challenge for cloud modelling

Entrainment/Detrainment are Key processes for cumulus convection



1- Dynamics of Entrainment : effect on mixing rate, buoyancy, vertical velocity

2- Microphysics of Entrainment : effect on nucleation, particle size distribution

Problem/Challenge

What is the dominant mixing mechanism ?
The Dilution of cloudy updraft is mainly cause by ?

1- Lateral Entrainment *or/and* 2- Cloud-top Entrainment

⇓

Long-lasting controversy

Entrainment/Detrainment → is still an active field of research
problem for > half a century

The existing **mixing models** are of very diverse

Lateral mixing models

Hu 1997
Heus et al. 2008
De Rooy et al. 2012
Stevens et al 2014
.

Cloud-top mixing models

Raymond and Blyth 1986
Emanuel 1991
Yamaguchi and Randall 2008
.
.

The lack of **observations** of cumulus clouds properties has caused a divergence in the formulation of cloud models

Problem/Challenge

Clouds are easily identifiable
(**Visualy** and amount of **liquid water content**)

- Do properties at cloud base determine the upper-level properties of the clouds ??

Are cloud properties determined by the environmental conditions they encounter ??

- **None** of the previous studies were able to examine how individual clouds might be affected by the presence of many other clouds in a cloud field ??

<u>To explore</u>

(1) Cloud cover Vs height ?
(2) The profiles of : temperature, humidity, and vertical velocity ?
(3) The lateral and cloud top mixing rate of the cloud (Single + ensemble) Vs (1), (2) ?
(4) The effect of aerosols upon cloud lifetimes ?

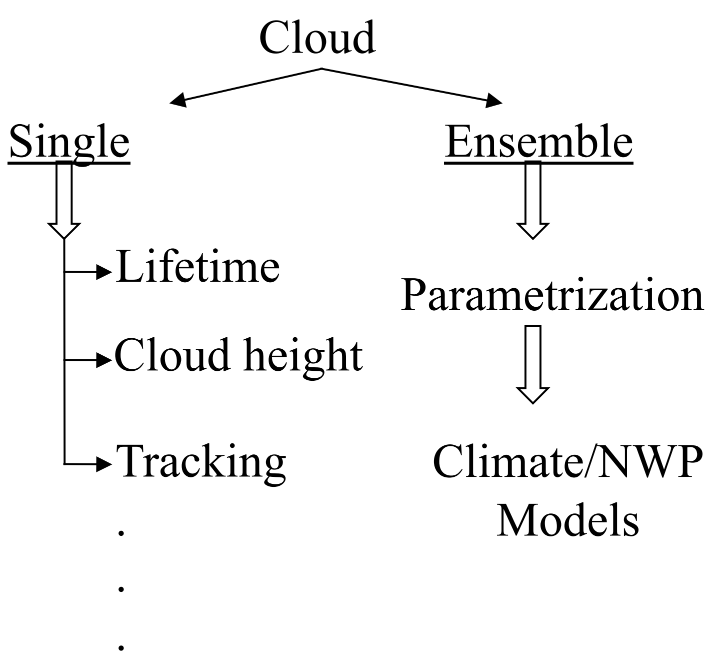
Studies of shallow cumulus

Field experiments

intercomparison

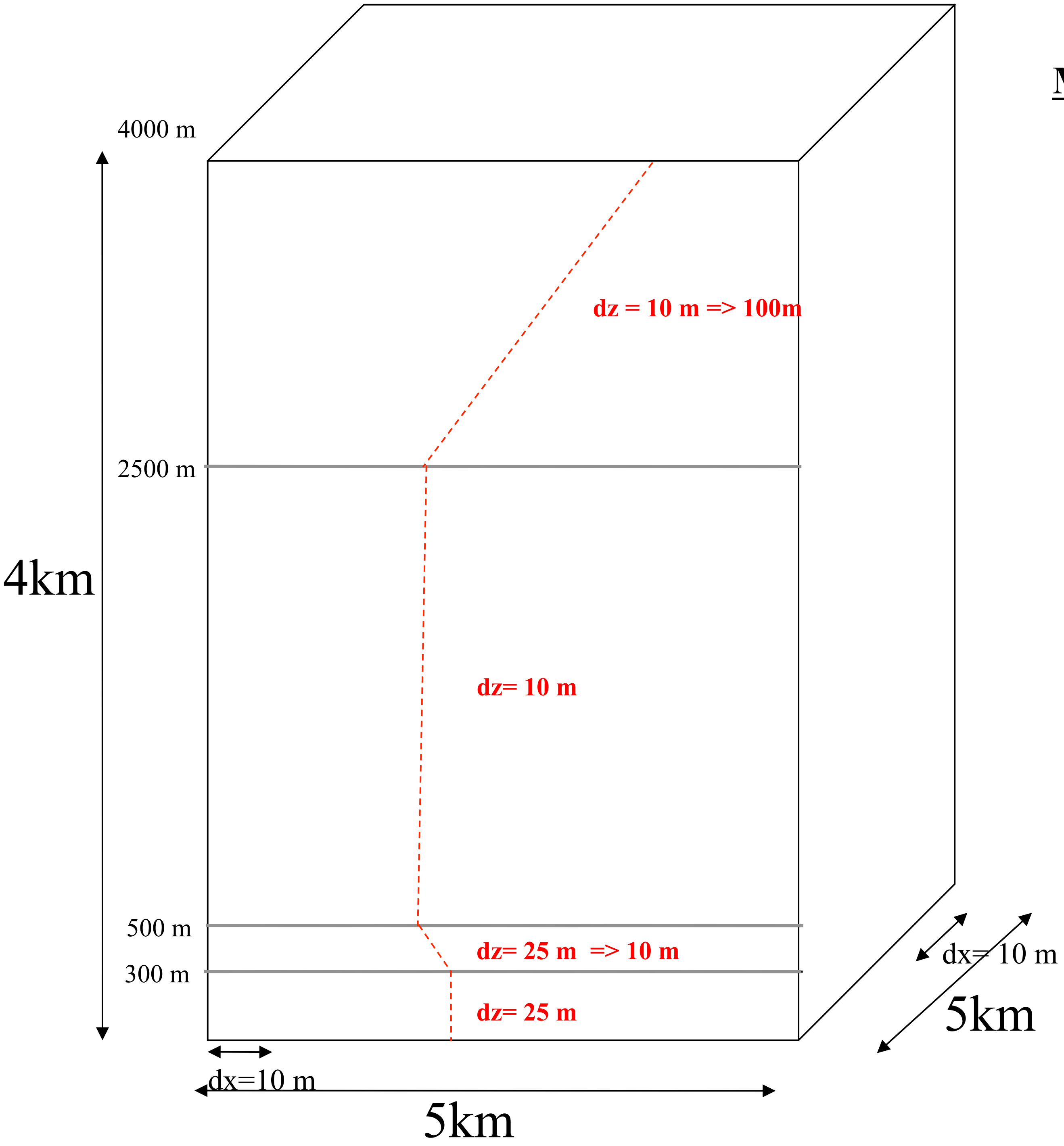
LES (Large Eddy Simulation)

ARM Atmospheric Radiation Measurement	Diurnal Cycle Cumulus
BOMEX Barbados Oceanographic and Meteorological Experiment	Steady state Trade wind cu
ATEX Atlantic Trade-wind Experiment	Trade wind cu topped with Scu
RICO Rain in cumulus over the Ocean experiment	Precipitating trade wind cu



These experiments have been already used with MesoNH

MesoNH simulation



Grid Setup

Ni=500
Nj=500
Nk=205

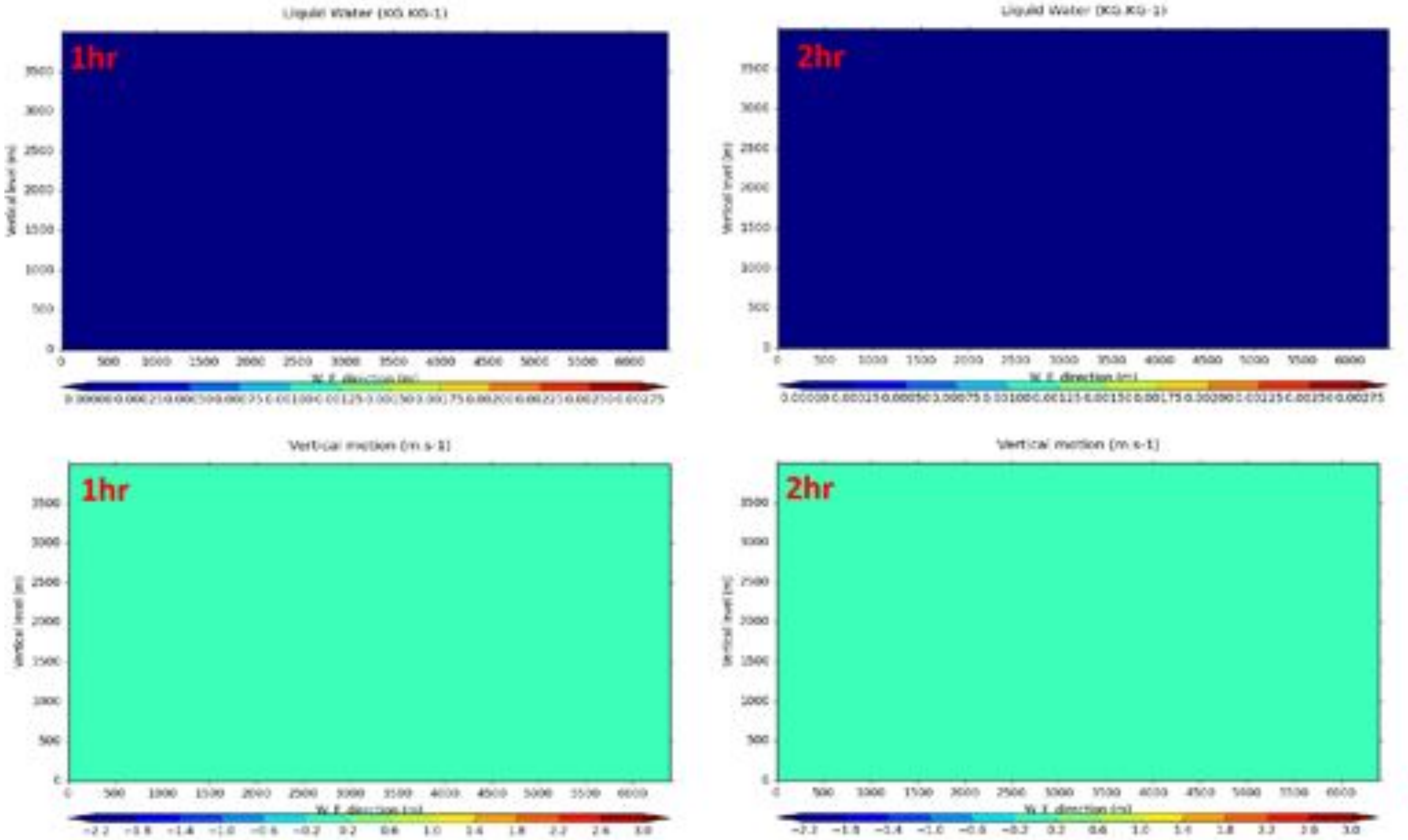
Timestep=0.5 sec

MesoNH simulation

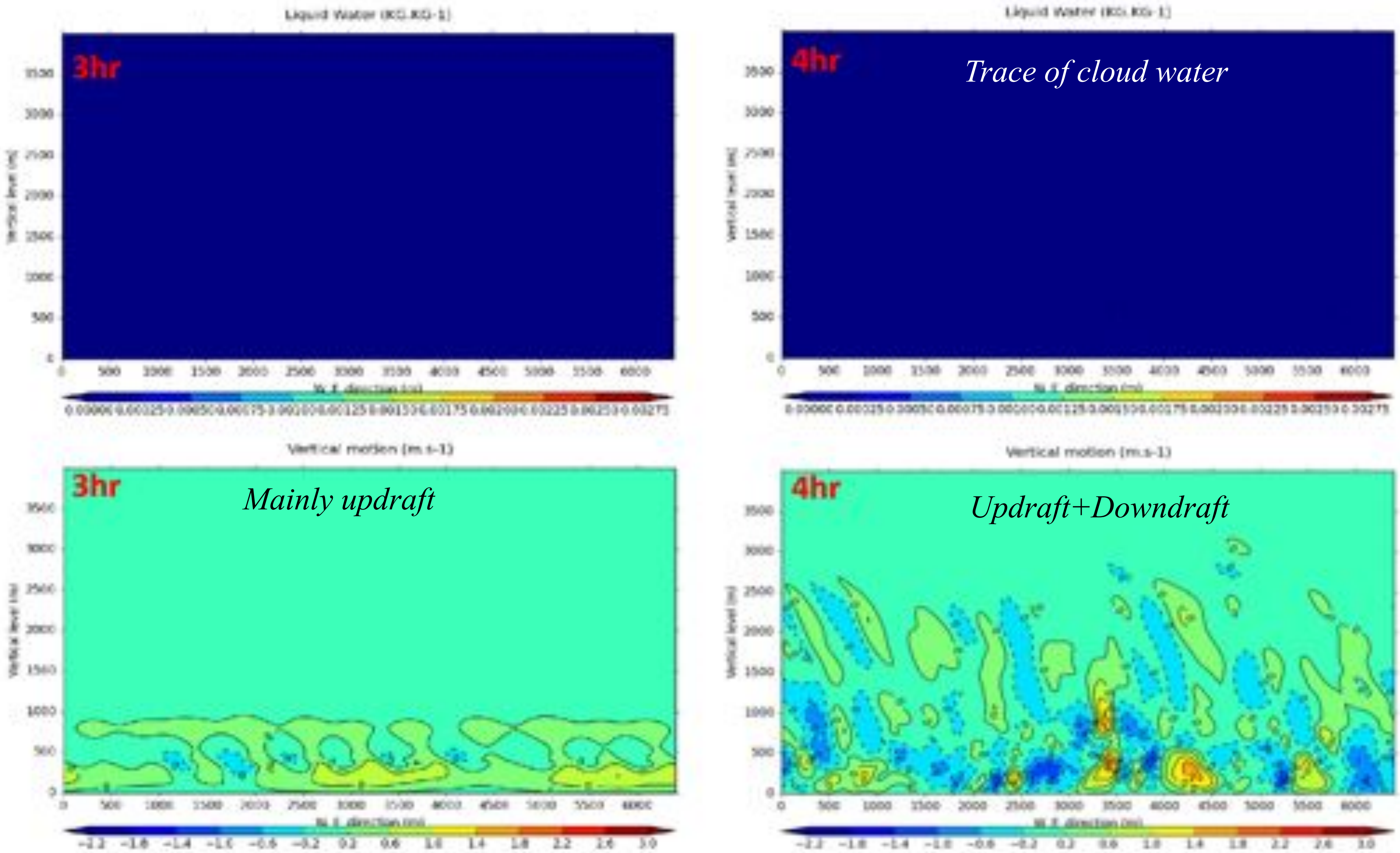
dx=dy=50 m
dz=40 m
Ni=Nj=128
Nk=90

Initial+Environment conditions

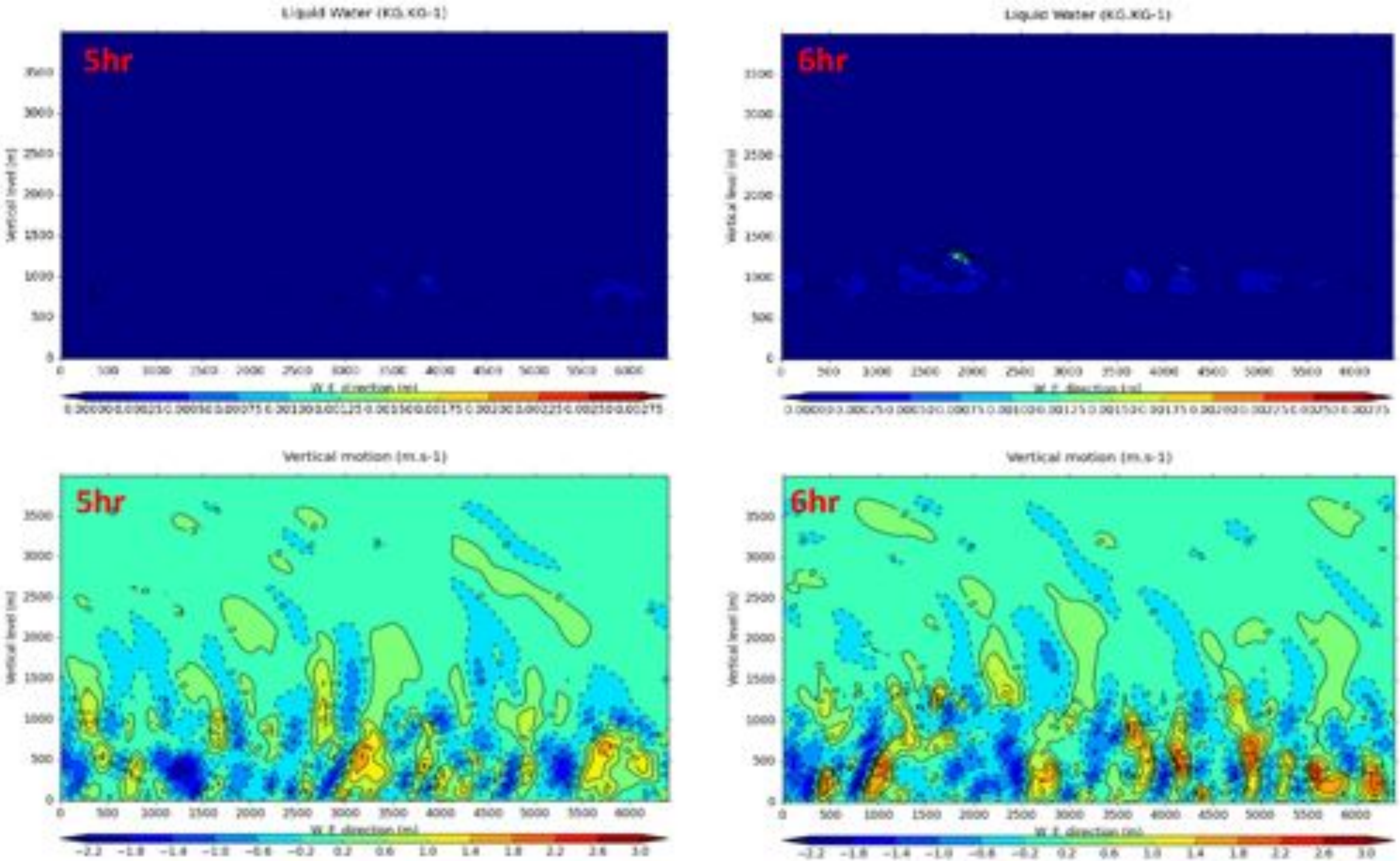
ARM (Atmospheric Radiation Measurement)



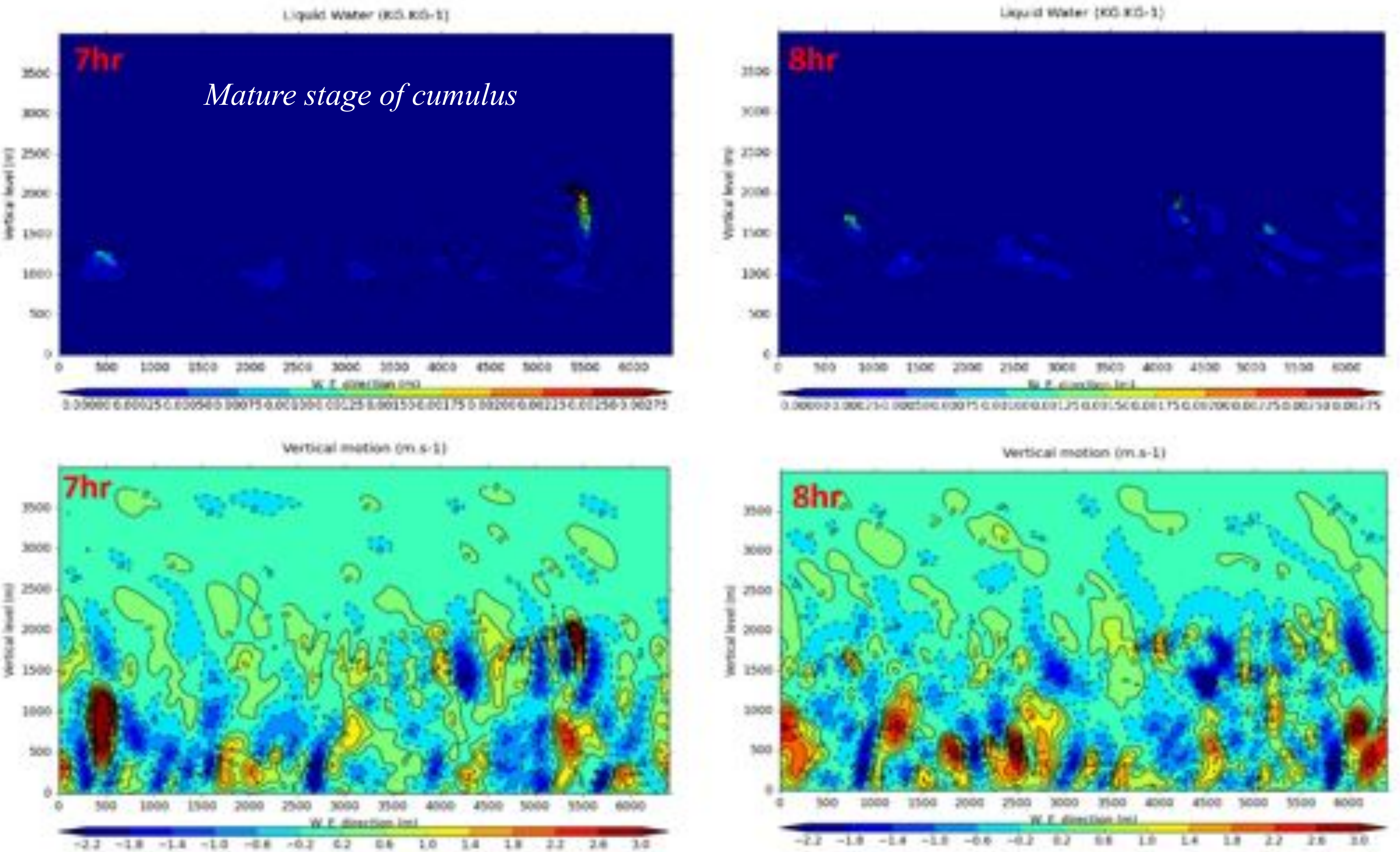
1st & 2nd hours : No appearance of cloud water + Vertical velocity=0



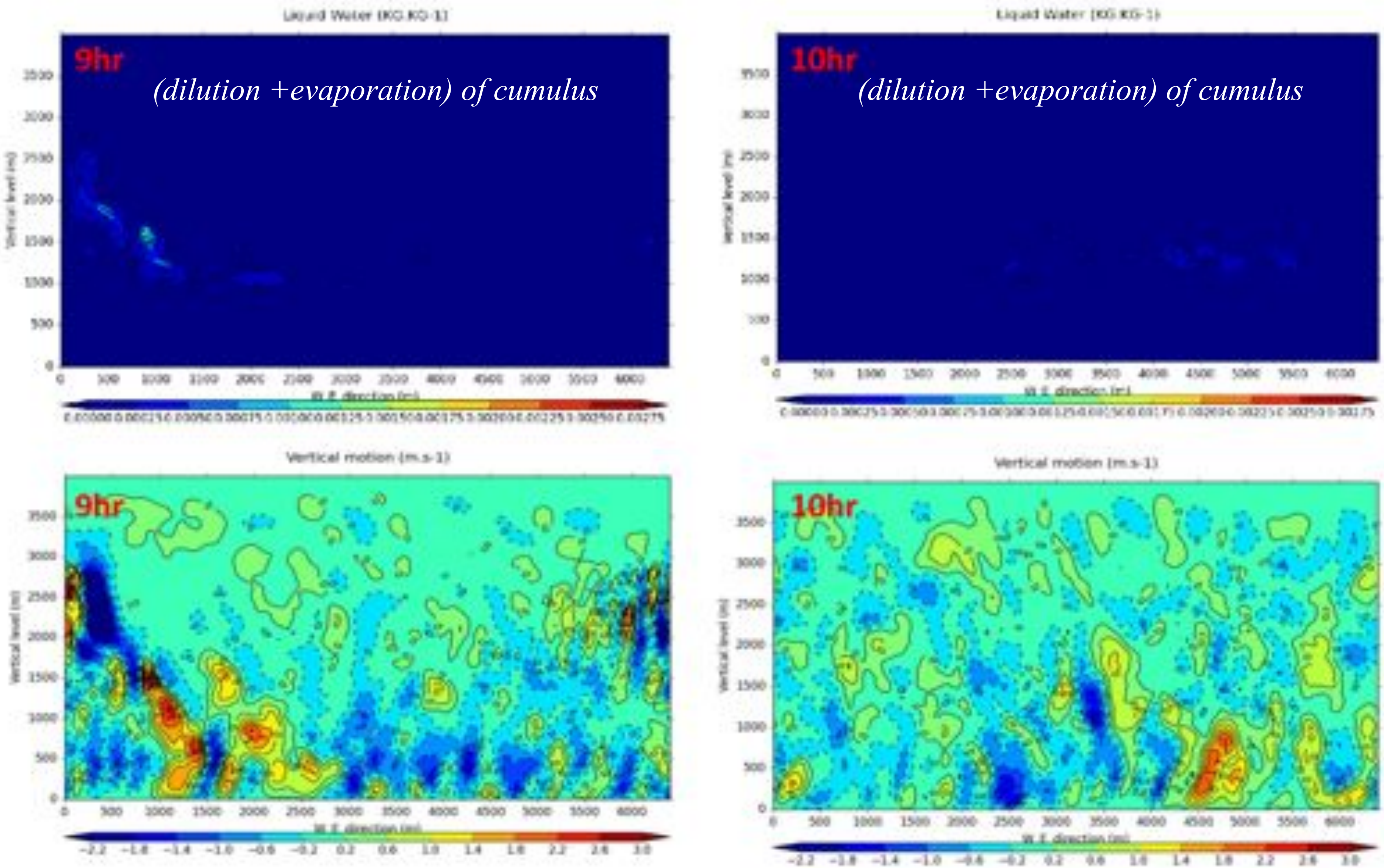
3rd & 4th hours : Early response to the forcing (Increase of vertical velocity)



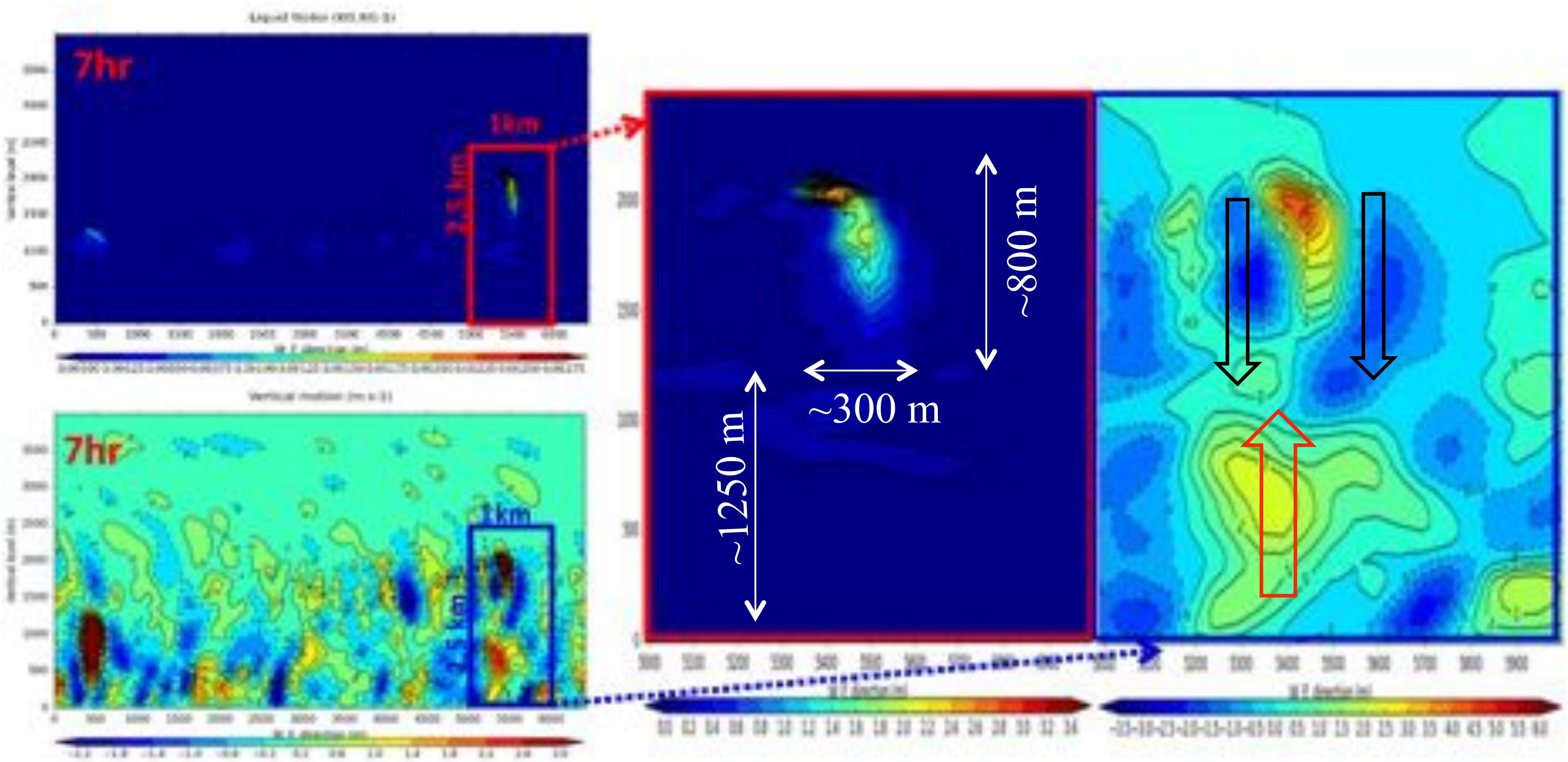
5th & 6th hours : Early stage of Cumulus formation + Intensification of the vertical velocity



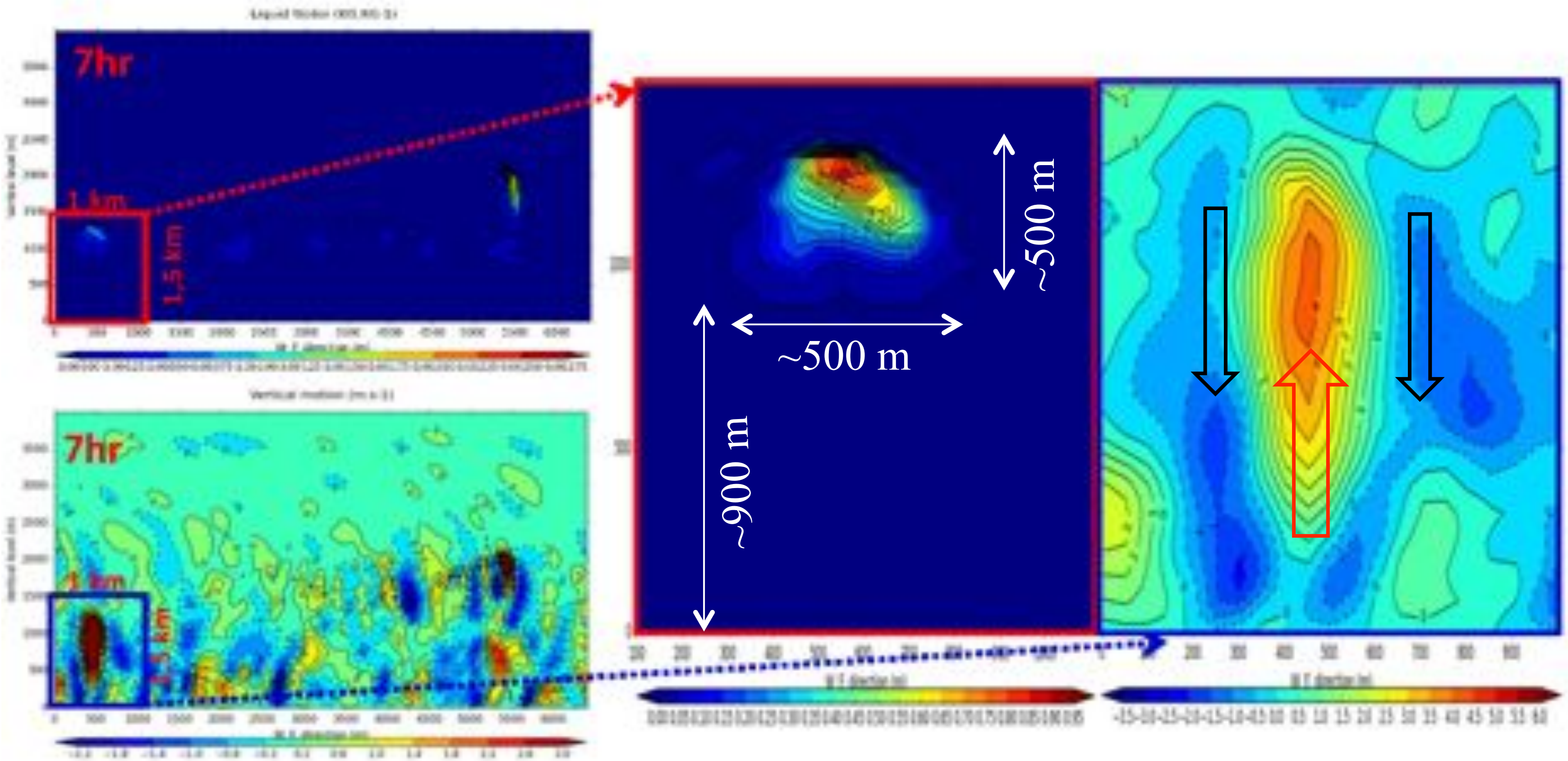
7th & 8th hours : Max of Cloud water + Max of vertical velocity [-7 m.s-1 10 m.s-1]



9th & 10th hours : decrease of (Cloud water + vertical velocity)



Zoom : 7^{th} hour



Zoom : 7^{th} hour

Skyscanner Update

Christophe Reymann

April 7, 2015

Macroscopic to local model

A *macroscopic* (parametric) model is needed to guide the fleet towards *zones of interest*.

Need for a denser, local model :

For *navigation* : predict short term winds around the drone

For *exploration* : quantify the *knowledge* of the (meteo.) state of a zone

Gaussian processes - Introduction

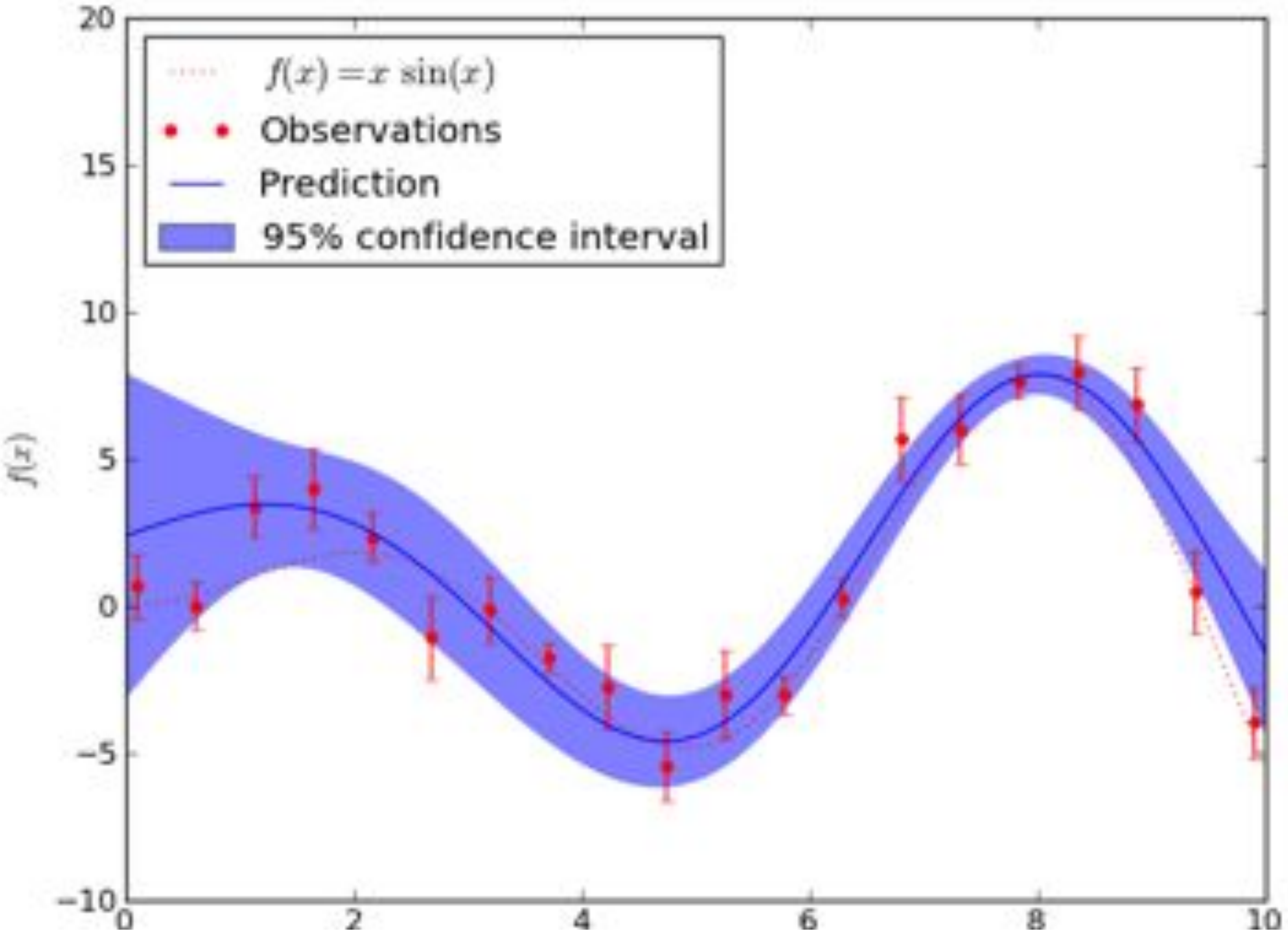
Problem : predict a *value* and a *confidence* from (very) sparse observations.

Gaussian process : collection of random variables with a joint Gaussian distribution

Mean : $m(x) = E[f(x)]$
Covariance : $k(x, x) = E[(f(x) - m(x))(f(x') - m(x'))]$

$f(x) \sim GP(m(x), k(x, x'))$

Gaussian processes - Introduction



Gaussian processes - Introduction

After some math... predicting for a single point $x_\star$:

$$\bar{f}_\star = k_\star^T (K + \sigma_n^2 I)^{-1} y$$

$$V[f_\star] = k(x_\star, x_\star) - k_\star^T (K + \sigma_n^2 I)^{-1} k_\star$$

Where K is the $n \times n$ covariance matrix between examples.

Complexity using Cholesky decomposition : $\mathcal{O}(n^3/3)$

Gaussian Processes - Algorithmics

Seems to work well on 2D mesoNH examples

Algorithmic cost: how to scale on 3D with potentially more points?

Existing solutions seem good, ideas :

- *local* GP models : several local models for prediction
- *sparse* Models : Retaining only key points
- *update* : Avoid recalculating whole model (Cholesky decomposition update)

Gaussian Processes - Quality of solution

Open questions:

- *Sparsity* : will we gather enough points for Gaussian Process to work well in 4D (x,y,z,t)?
- *Kernel* : Mostly kernels make *locality* and *stationarity* assumptions. Is there room for improvement (overcome sparsity) by injecting situation specific knowledge?

Gaussian Processes - Quality of solution - Sparsity

Space sparsity : nothing we can do about it. Shannon theorem : if we want to measure small scale fluctuations we need observations at twice the frequency.

Time sparsity : time is a problematic dimension

- No observation after $t = present$
- All our predictions will be at $t > present$

GP are known to handle poorly this in the general case (no prior, standard kernels)

Gaussian Processes - Quality of solution - Kernels

Handling time in kernels (state of the art) :

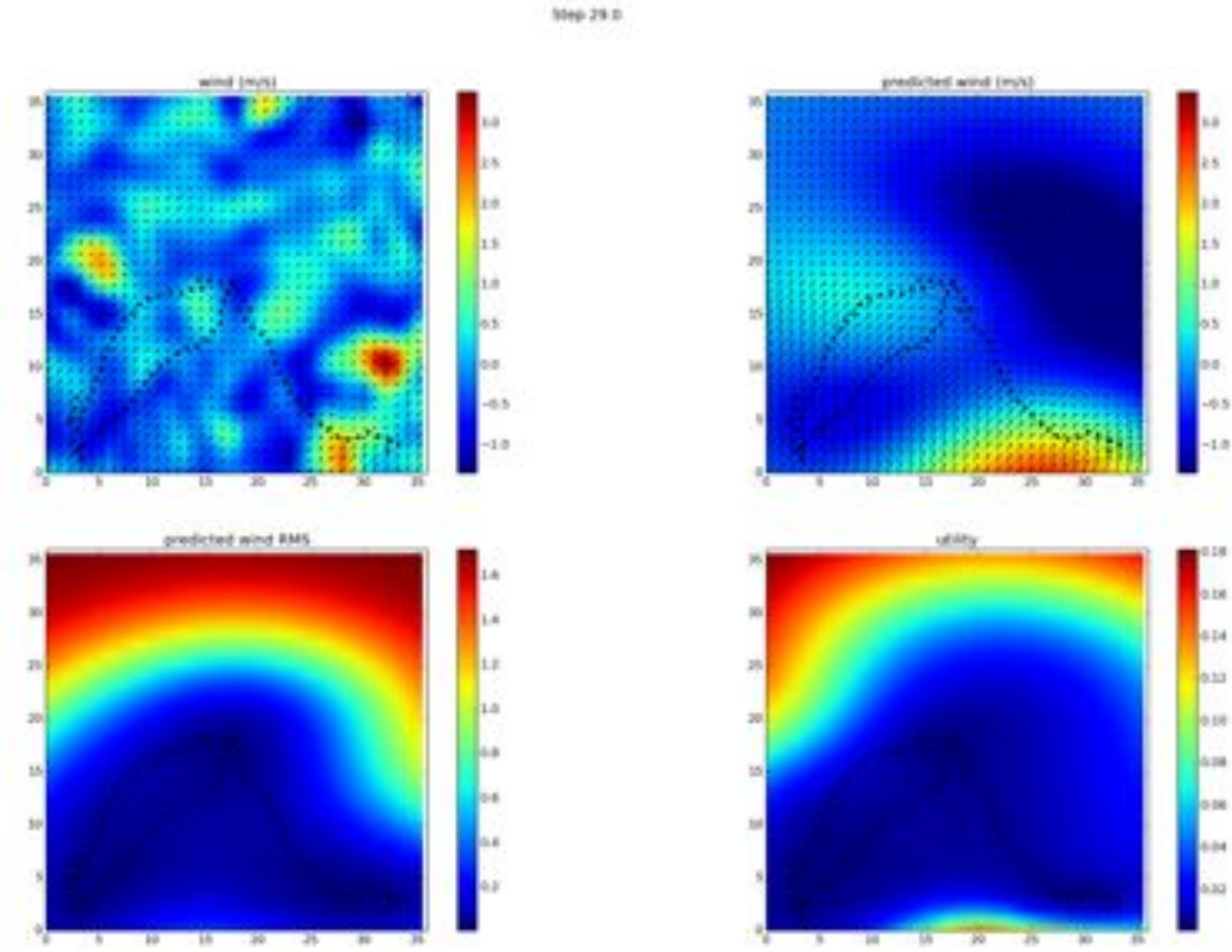
- If *slow dynamics* : treating time as a normal dimension.
- Time series : *Recursive kernels* (STORKGP) / ESN (OESGP)
- S. Sukkarieh : add mean wind drift (2D) estimation into kernel.

New solution ?

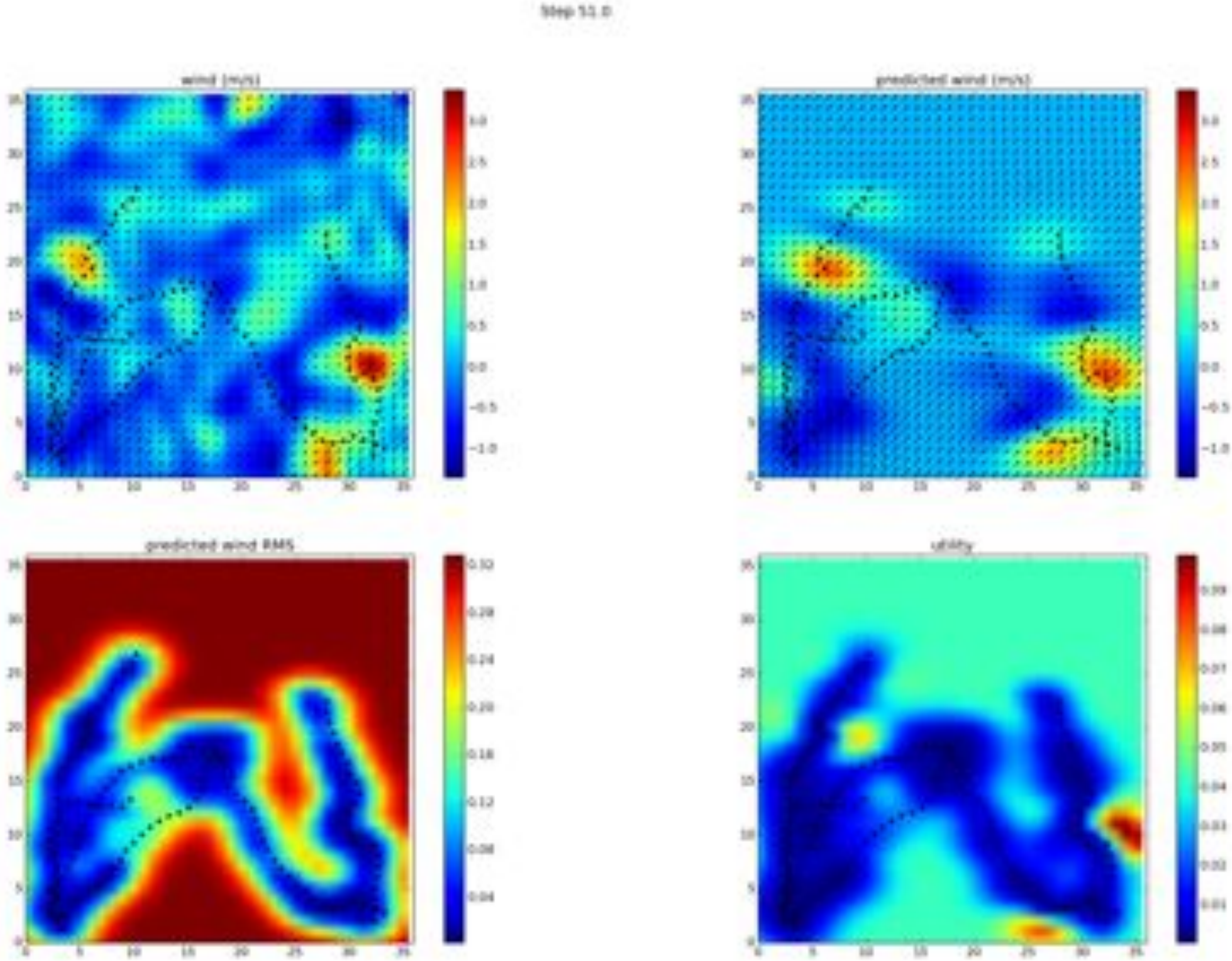
- Add local 3D wind drift into kernel (2D drift maybe exhibits local variance, model up- & down-drafts)
- ???

Only requirement : keep the covariance matrix symmetric positive-definite

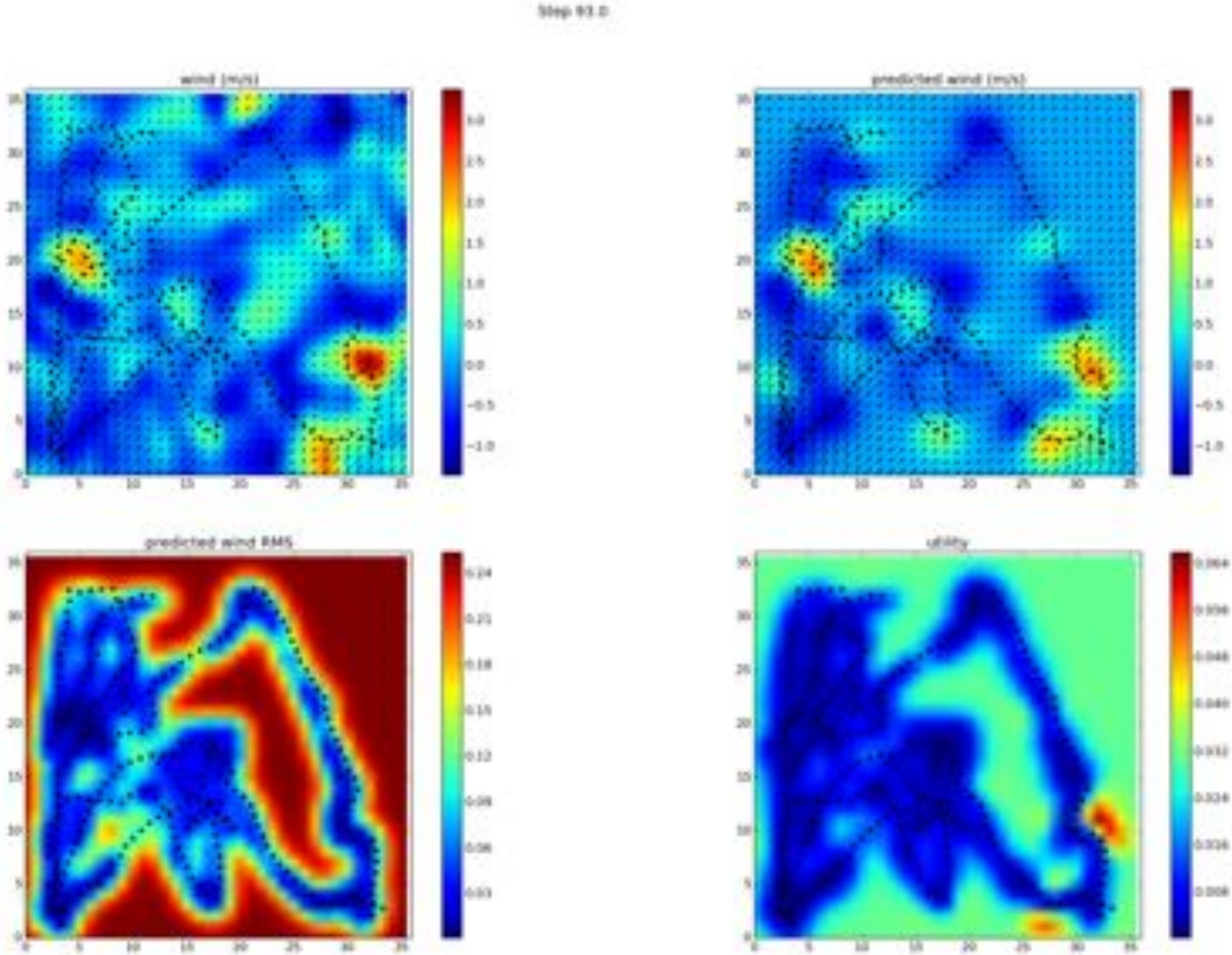
Gaussian Processes - MesoNH Tests



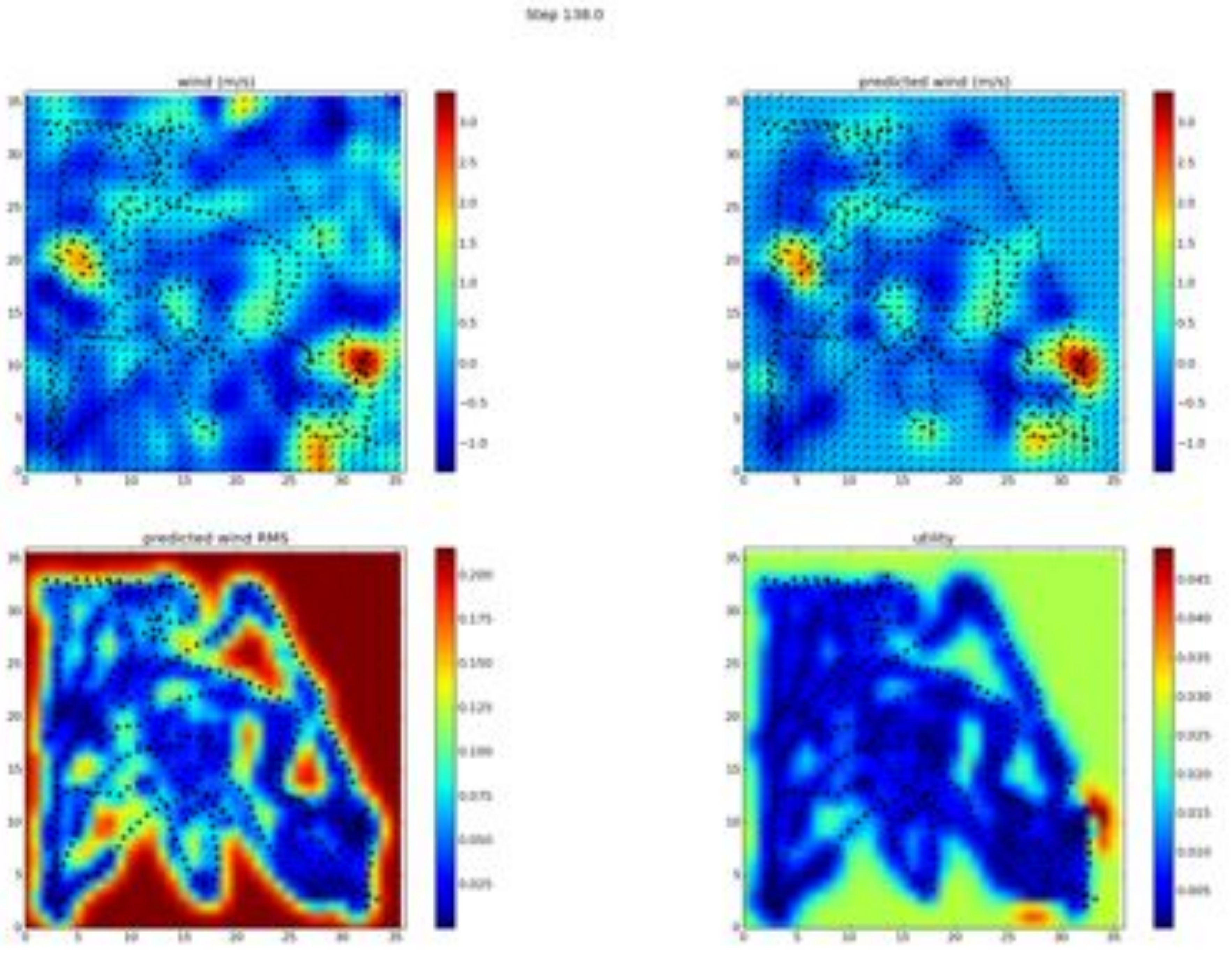
Gaussian Processes - MesoNH Tests



Gaussian Processes - MesoNH Tests



Gaussian Processes - MesoNH Tests



High Level Planning - Model 1

We have a set of n homogeneous robots. Total energy of robot i is E_i.

We are trying to estimate m variables :
$V(t) =< V_1(t), ...V_m(t) >$ with associated uncertainties :
$U(t) =< U_1(t), ...U_m(t) >$.

That is minimize $U(t)$.

And maximize mission time, that is maximize the energy E.

So we have at least $m + 1$ criteria : how-to evaluate a cost function ?

High Level Planning - Model 1 - Recipes

We dispose of a set of given S recipes.
Each recipe :

- Uses k robots
- Has a duration t
- Has a reward $< R = R_1, ...R_n >$
- Is (roughly) localized in space location : L_{start}, L_{end} (for each drone ?)

Precondition : the k robots are in L_{start}
Postcondition : the k robots are in L_{end}

Modelling *uncertainty* ?

High Level Planning - Model 1 - Expressing Recipes ?

Task example : measure cloud's approximate radius at altitude z

Strategy 1 : One/Many drones sample boundary points then ransac approximation

Strategy 2 : 3 drones perform curve level tracking

High Level Planning - Model 1 - Expressing Recipes ?

Task example : measure cloud height

Strategy 1 : One drone goes from bottom to top

Strategy 2 : Two drones synchronize each other, measuring resp. bottom and top.

High Level Planning - Model 1 - Expressing Recipes ?

Task example : map some variables in a zone

Variant 1 : Continuous mapping

Variant 2 : Take Snapshots regularly

What's next ?

Dense environment model (Gaussian Processes) :

- implement one appropriately fast method
- test some kernels asa we get new MesoNH data
- integrate with local path planner
- interface local planner with paparazzi for simulation

High level Planning : discuss and refine model

Cooperative Data Gathering in Presence of Air Flows

Alessandro Renzaglia, Christophe Reymann, Simon Lacroix

LAAS-CNRS

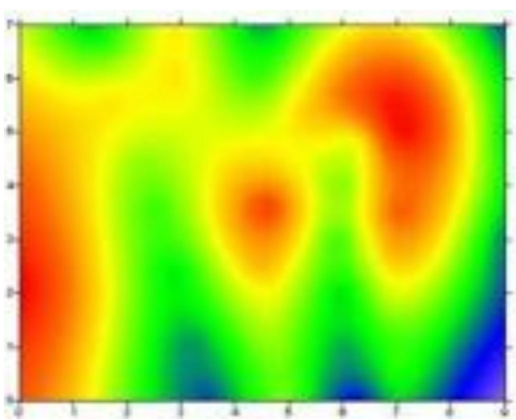
SkyScanner meeting, 07/04/2015

Local Trajectory Generation

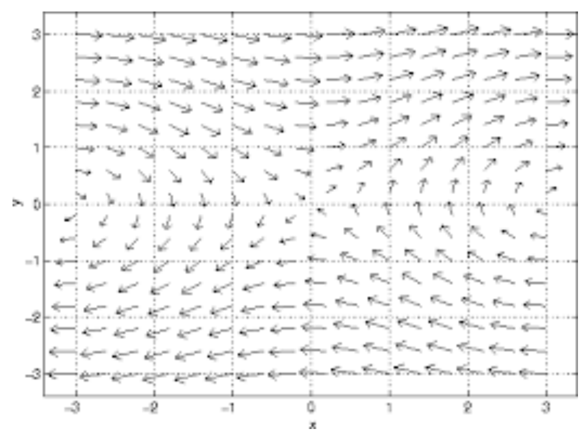
Maximizing collected data taking into account air flows for navigation (energy constraint)

Two different fields as input of our optimization problem:

- Scalar utility field

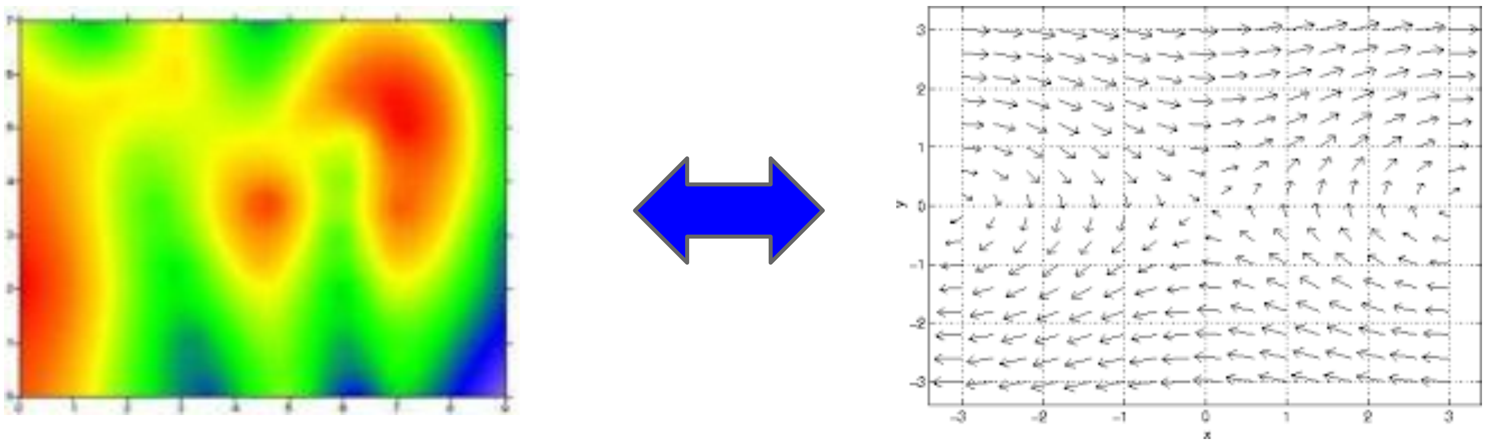


- Currents vector field

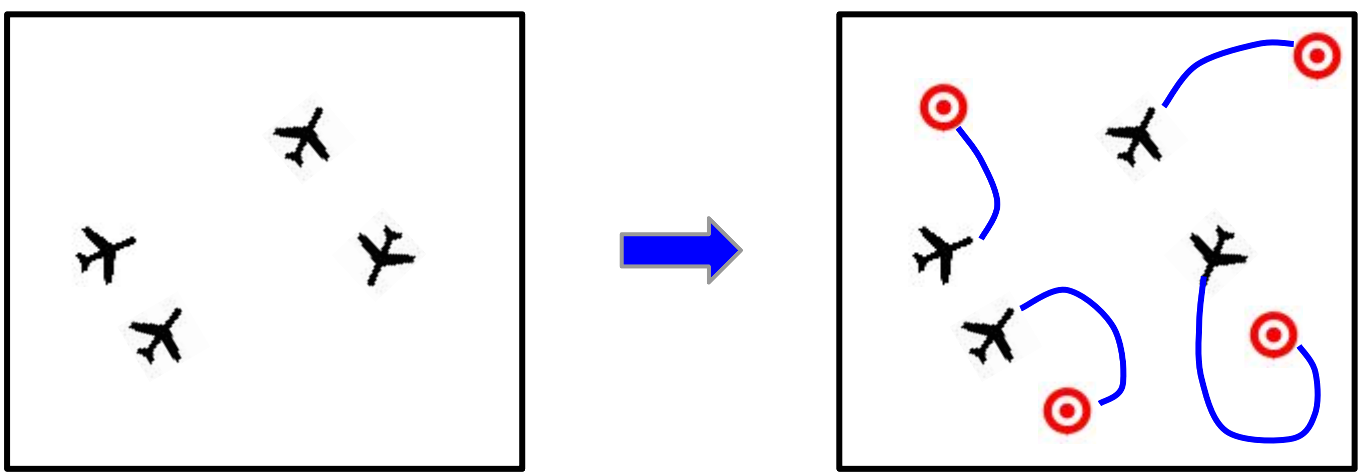


- Both fields are: 3-dimensional and time dependent

Local Trajectory Generation



By merging the available information, decide who goes where and how!



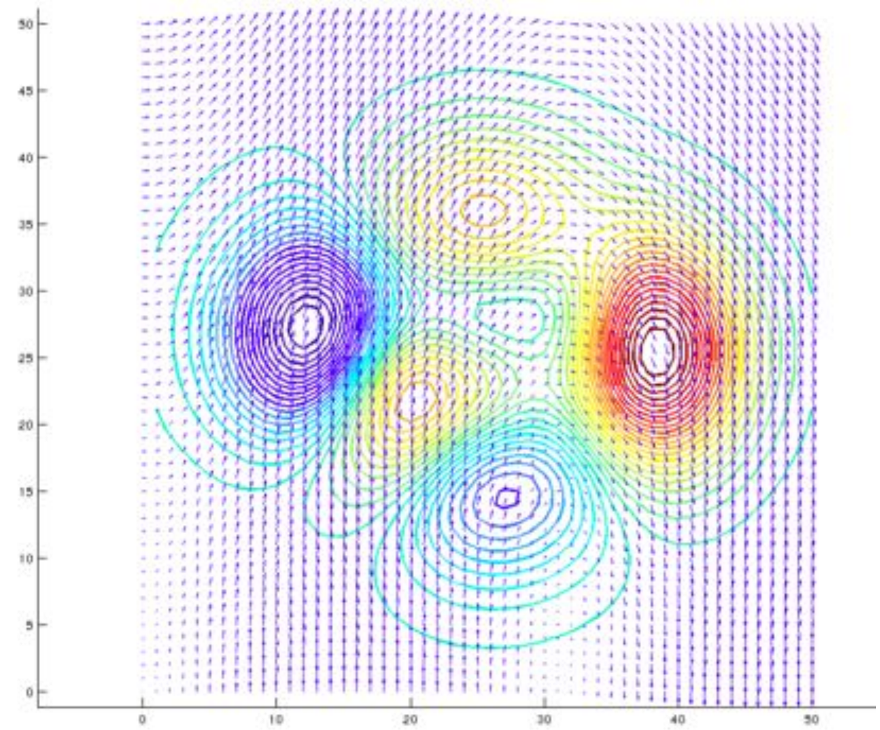
Problem Formulation

First assumptions:

- Definition of a time-window ΔT (in which the maps are static), continuous re-planning
- Single robot solution
- Centralized multi-robot solution (no communication problems)

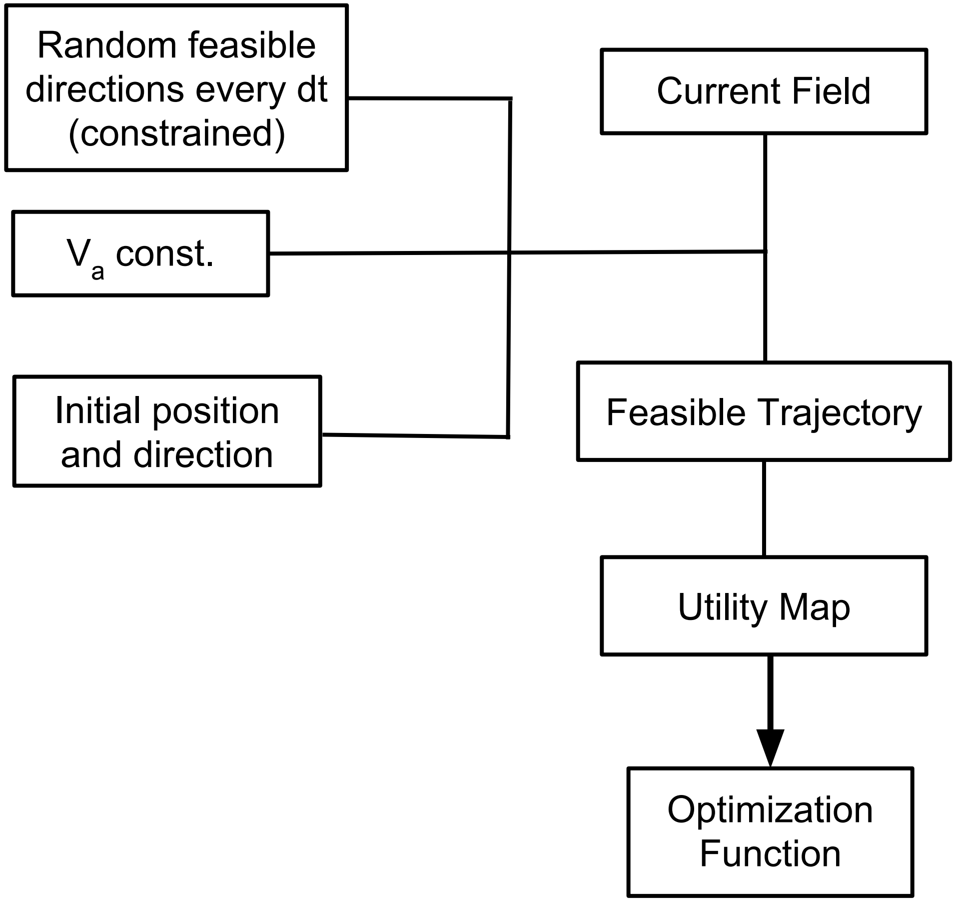
Preliminary Results

- 2D environments
- Fictitious utility map and currents fields



Preliminary Results

- 2D environments
- Fictitious utility map and currents fields
- Trajectories generation: Random sampling of feasible trajectories for each ΔT time interval
  - Trajectory divided in sub-intervals
  - Sampling in control space



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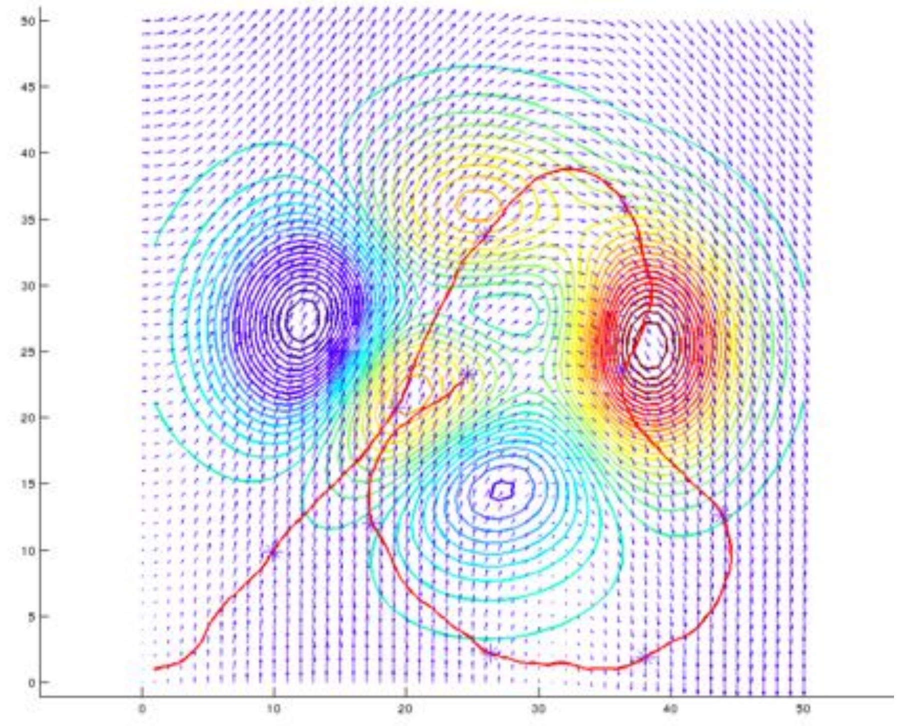

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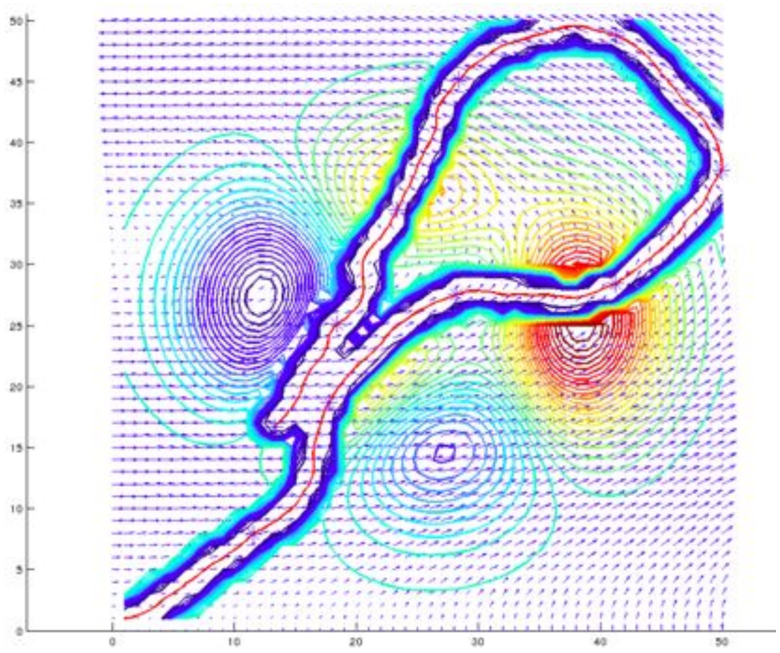
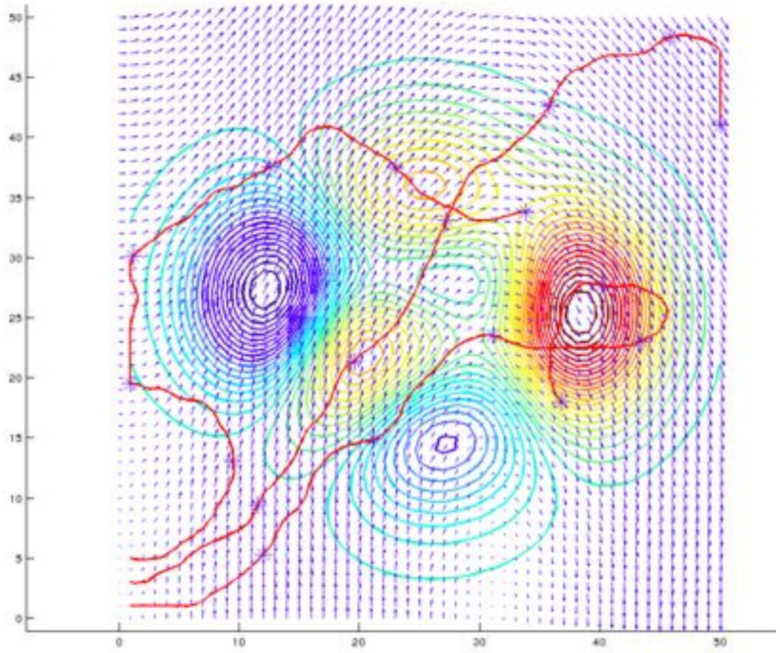
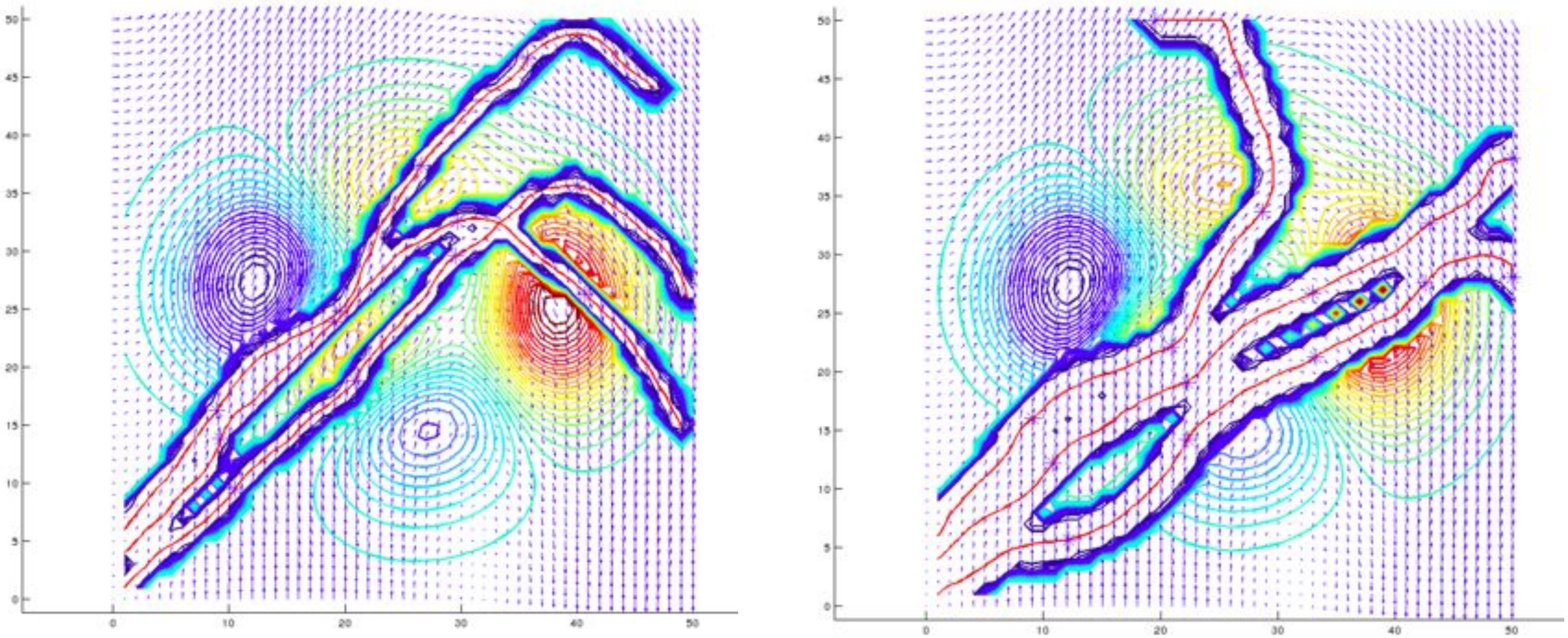




- Same initial utility
- Different current field
- Map of final utility

- Simultaneous evaluation of a set of 3 trajectories (centralized)

Preliminary Results



Same scenario but with different utility update, e.g. different spatial correlation

Optimization problem

Next steps:

- Variation in the optimization to reduce the explored space and converge to a local minimum (e.g. random sampling + gradient descent, SPSA algorithm, etc.)
- Beyond ΔT: including a heuristic to add information on what follows (e.g. high-utility region just beyond the fixed horizon)
- Realistic energy consumption
- Simulations with real data (GPR)

Energy Consumption

In 3D, considering the real energy consumption is crucial

- How to model energy consumption?
- Not clear how to include it in the optimization problem
- Two different planning problems:
  - discrete set of regions to explore
  - a minimum energy before to exit each region (different for every region)

Questions? Comments?

UAV fleet control :
« explore and exploit »

Implementation for estimating global atmospheric phenomena

Jean-Philippe Condomines

ENAC

SkyScanner meeting - 7 april 2015

STAE TOULOUSE

Paparazzi in a few words...

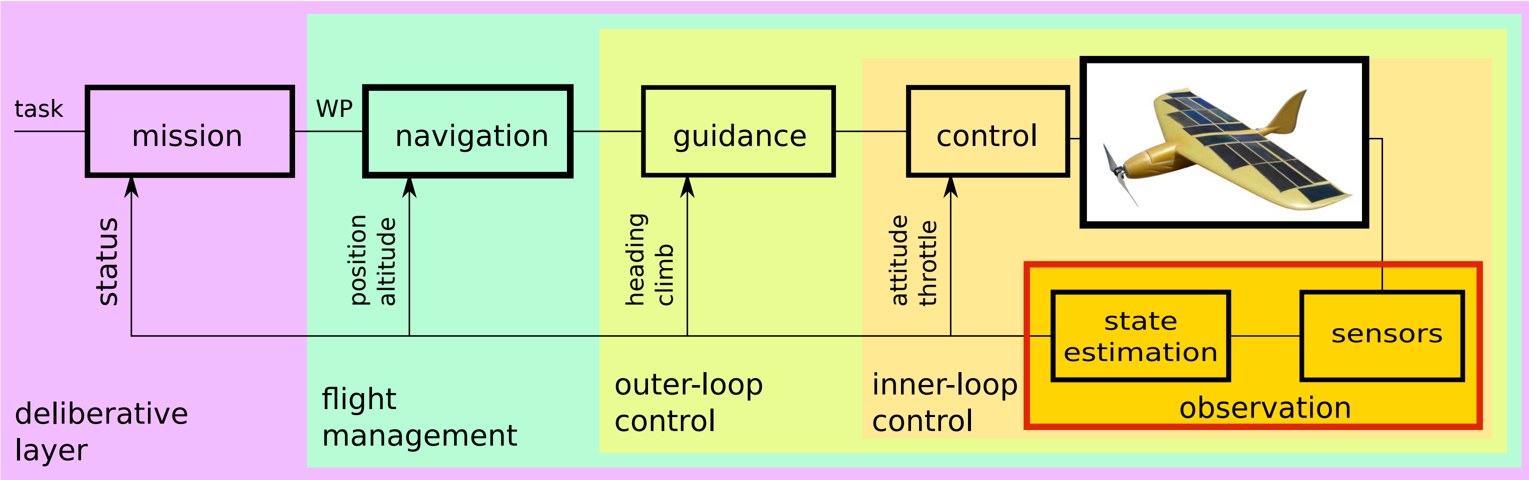
Objective of Paparazzi

Propose a complete autopilot system for micro- and mini-UAVs (rotary wings and fixed wings)

An open source development project

- created by Pascal Brisset and Antoine Drouin in 2003 ;
- each developer makes available, advanced methodological contribution, technology or software ;
- ENAC is the creator and one of the main contributor of the project.

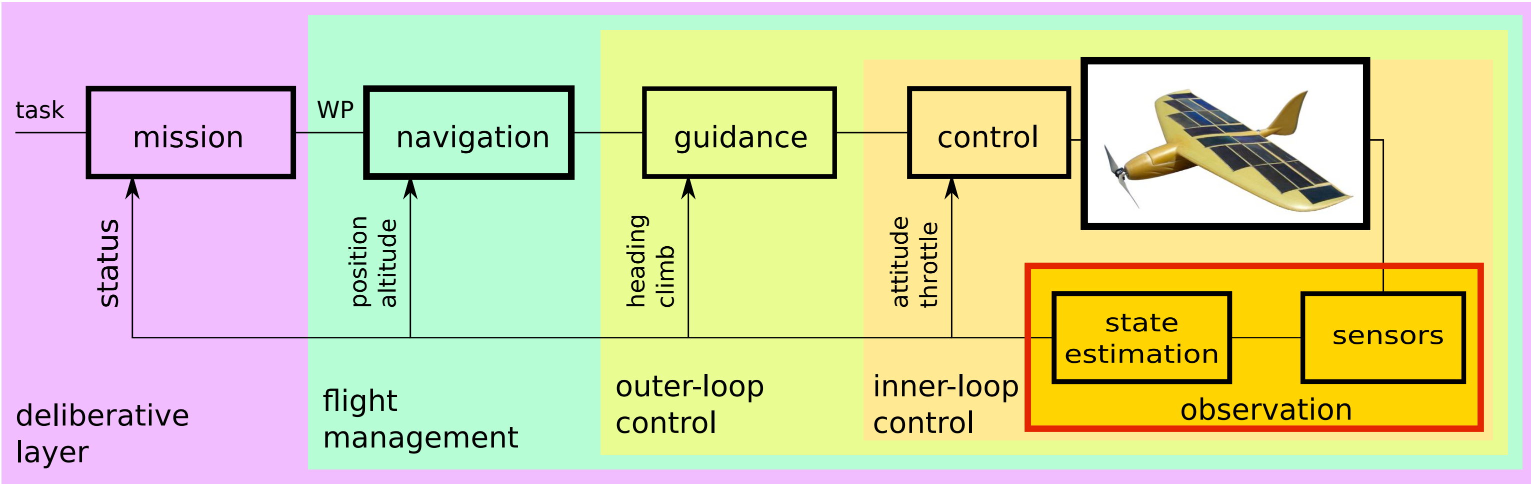
Control architecture



Software architecture

- task planning (mission $\sim 1Hz$) ;
- calculation of the trajectory (navigation $\sim 4Hz$) ;
- tracking of the trajectory (guidance $\sim 10Hz$) ;
- attitude control of the UAV (control $\sim 60Hz$) ;
- data acquisition and state estimation (observation $\sim 60Hz$).

Control architecture



Software architecture

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- tracking of the trajectory (guidance $\sim 10Hz$) ;
- attitude control of the UAV (control $\sim 60Hz$) ;
- state estimation (orientation, speed, etc.) of the UAV from imperfect measurements provided by several sensors (observation).

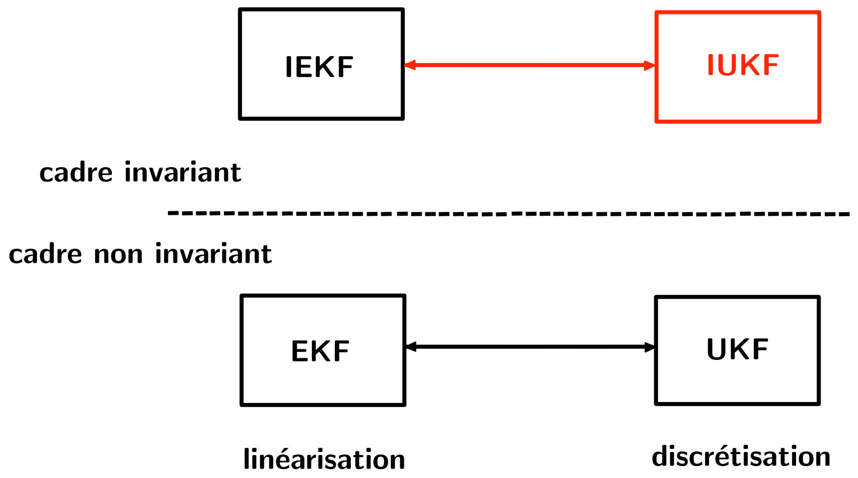
Main results of PhD work

Developed two algorithms for nonlinear estimation...

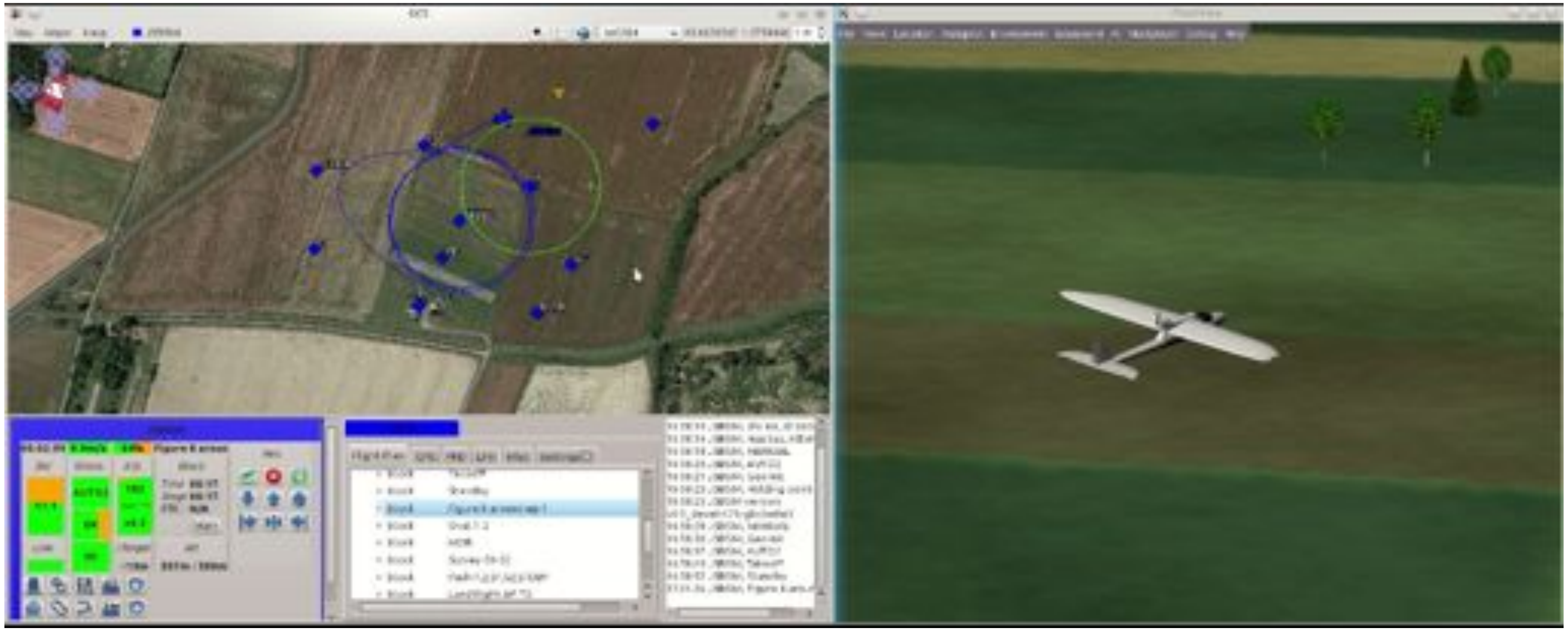
By redefining the estimation errors used in the standard version of the UKF.

...with interesting properties

- a systematic approach that provides a formal proof of convergence(useful for certification)) ;
- numerical values of the gains and the error covariance of the state converge to constant values (may be applied to improve the fault diagnosis and control loops) ;



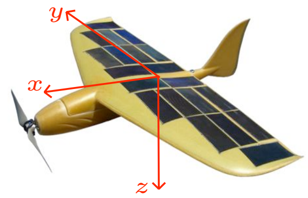
JSBSIM, Paparazzi and Flightgear visualisation



Obtain a UAV model as realistic as possible

- Extract aerodynamics coefficients and stability derivatives from wind-tunnel measurements and numerical analysis ;
- give a precise imperfections model of each sensor (accelerometer, pitot tube,etc.) ;
- Use an existing atmospheric model in Flightgear.

Wind estimation problem



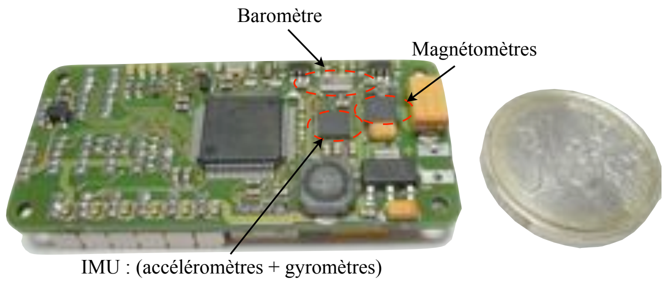
- Motion modeling UAV :
  - 3 gyro give $[p, q, r]$;
  - 3 accelerometers give $[ax, ay, az]$;
  - 1 GPS receiver gives the velocity vector $[uk_0, vk_0, wk_0]$;
  - 1 pitot tube gives the velocity airspeed Va.

Process equations

$$\begin{cases} \dot{u}_k = ax - g\sin\theta + r.v_k - q.w_k + \mu_1 \\ \dot{v}_k = ay - g\cos\theta\sin\phi + p.w_k - r.u_k + \mu_2 \\ \dot{w}_k = az - g\cos\theta\cos\phi + q.u_k - q.v_k + \mu_3 \\ u\dot{w}_0 = \mu_4 \\ v\dot{w}_0 = \mu_5 \\ w\dot{w}_0 = \mu_6 \end{cases}$$

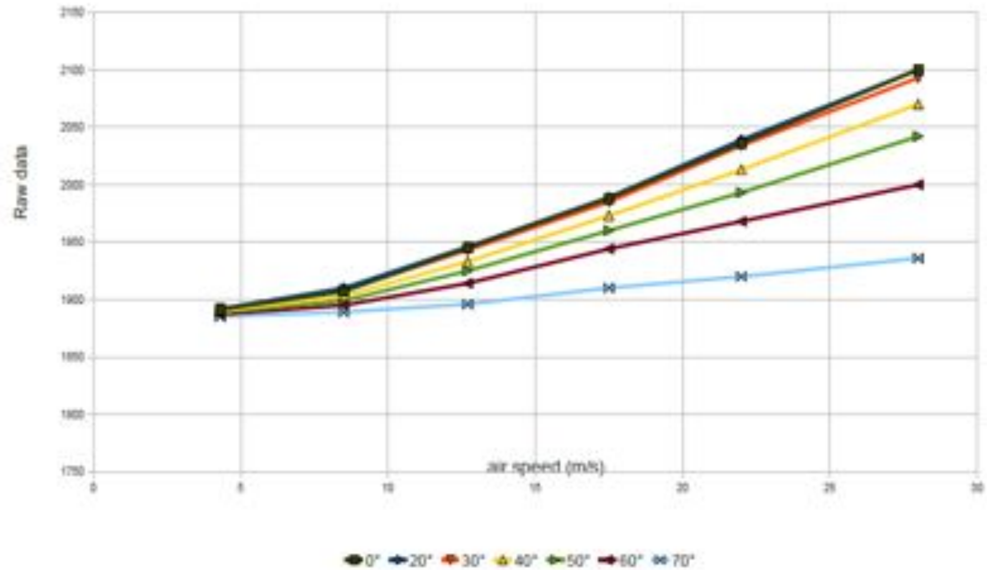
Measurement equations

$$\begin{cases} \begin{pmatrix} uk_0 \\ vk_0 \\ wk_0 \end{pmatrix} = B_b^n \begin{pmatrix} u_k \\ v_k \\ w_k \end{pmatrix} + \begin{pmatrix} \nu_1 \\ \nu_2 \\ \nu_3 \end{pmatrix} \\ Va = \| \begin{pmatrix} u_k \\ v_k \\ w_k \end{pmatrix} - B_n^b \begin{pmatrix} uw_0 \\ vw_0 \\ ww_0 \end{pmatrix} \| + \nu_4 \end{cases}$$

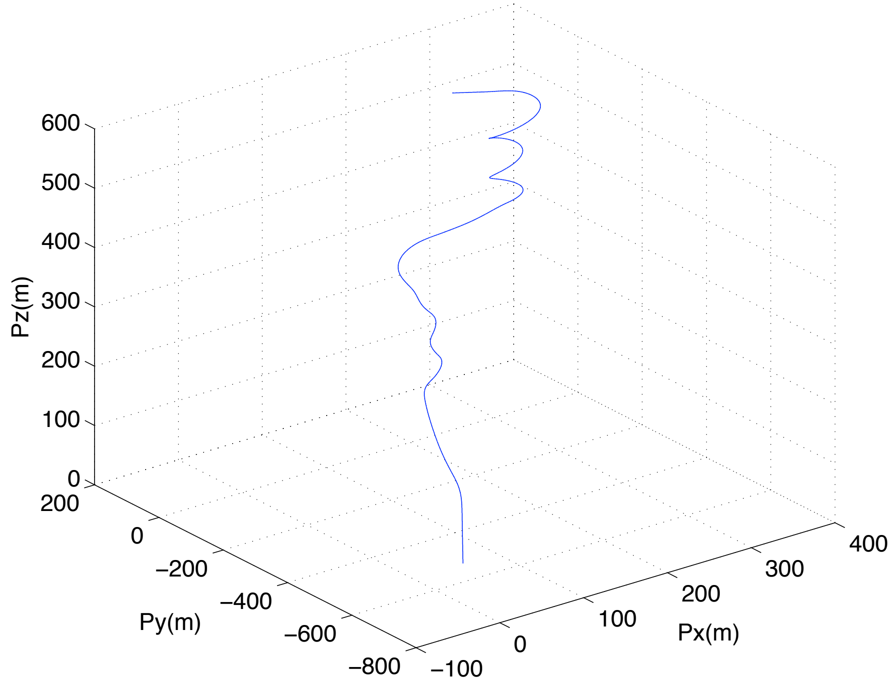


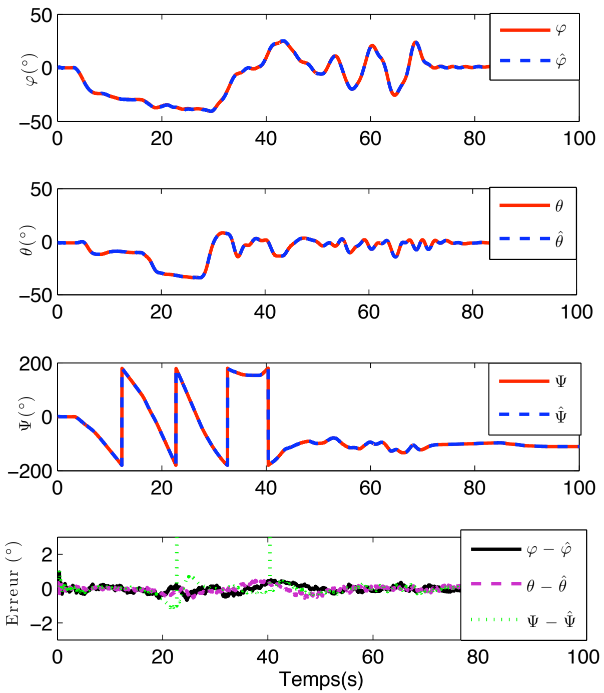
Airspeed

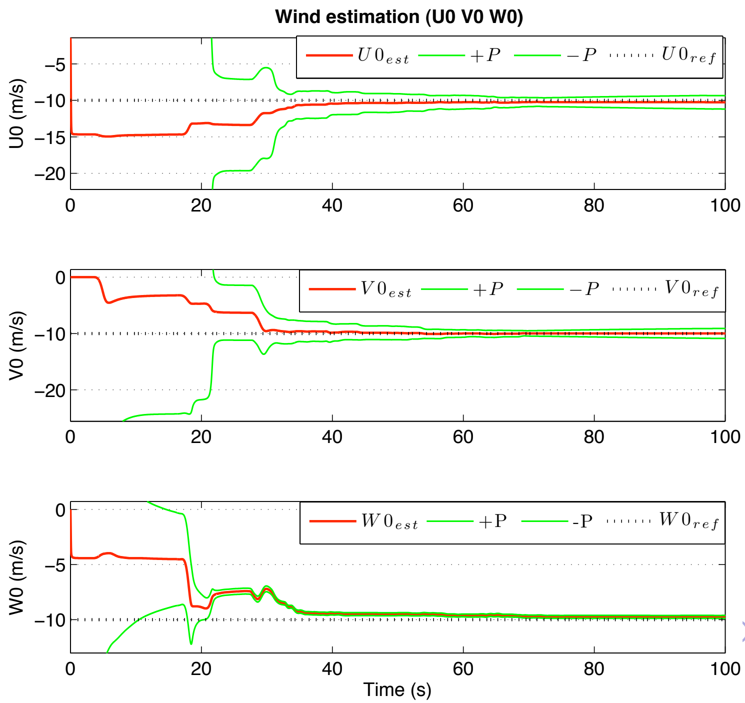
- Measurement of the aircraft true airspeed
- Sensors sensitivity and noise make it difficult to measure very low airspeeds (< 5 m/s) : issue on some MAV



First results : wind estimation in simulation

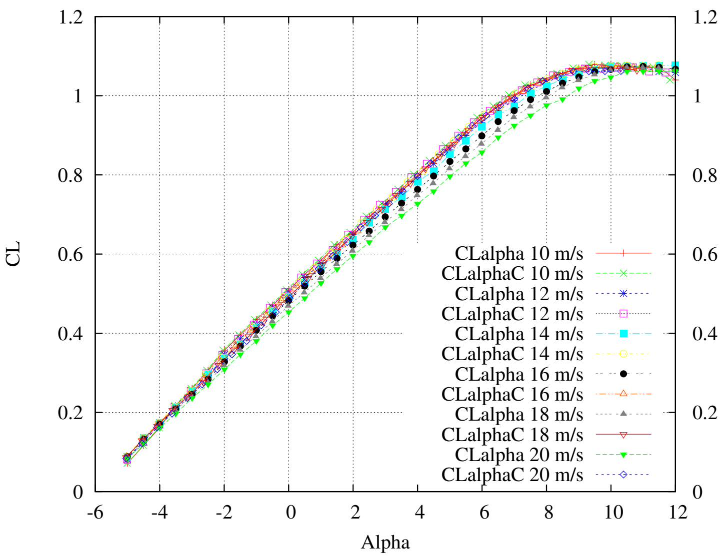


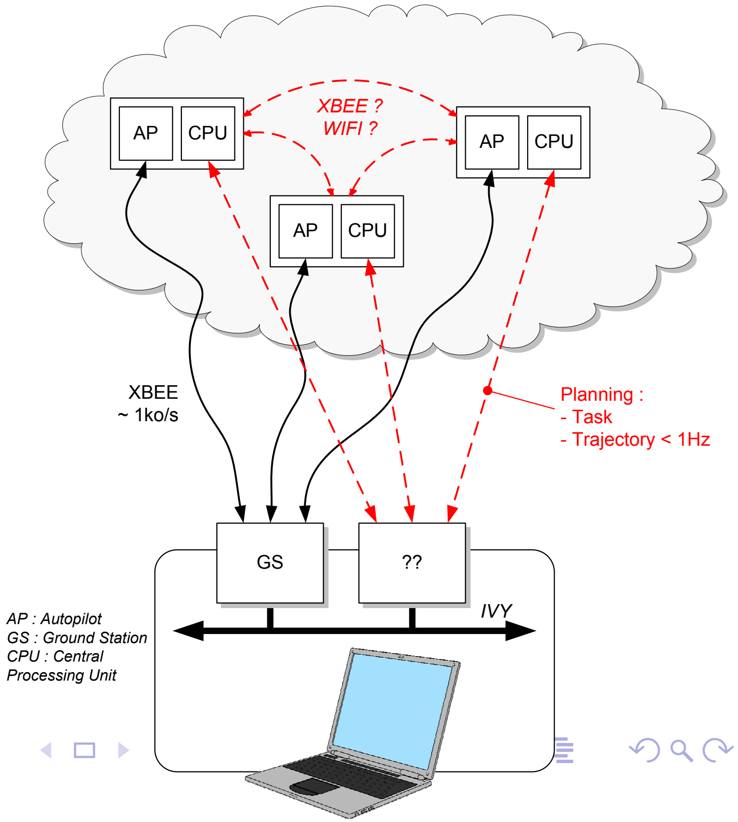




On going work...

- Use real data to evaluate the wind estimator ;
- Improve UAV instrumentation (angle of attack sensor, internship Jean-François Erdelyi) ;
- Create an aerodynamic model of an existing UAV in order to run with Paparazzi - JSBSIM couple and visualize with FlightGear ;
- Finding appropriate hardware and software architecture for planning ;



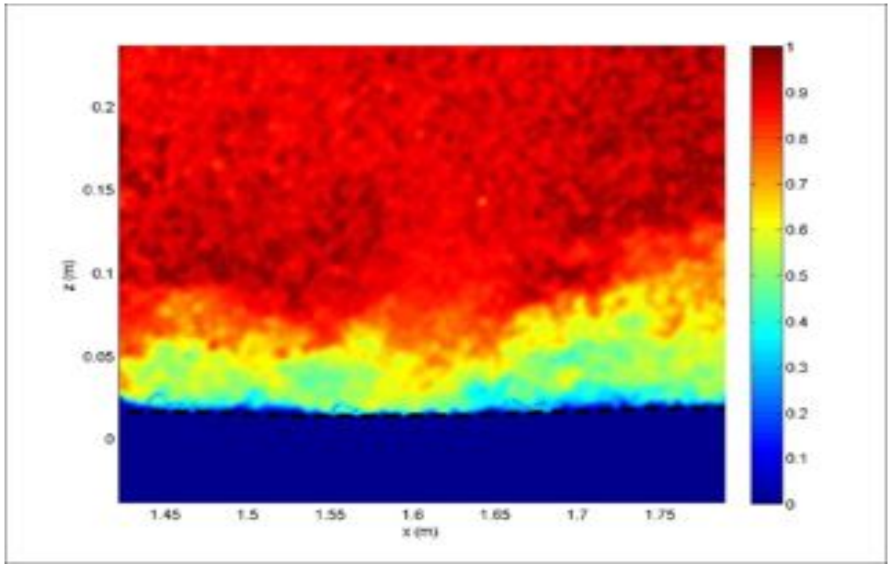


Phd thesis in fluid mechanics 2009-2012 (Paris 6/Ifremer)

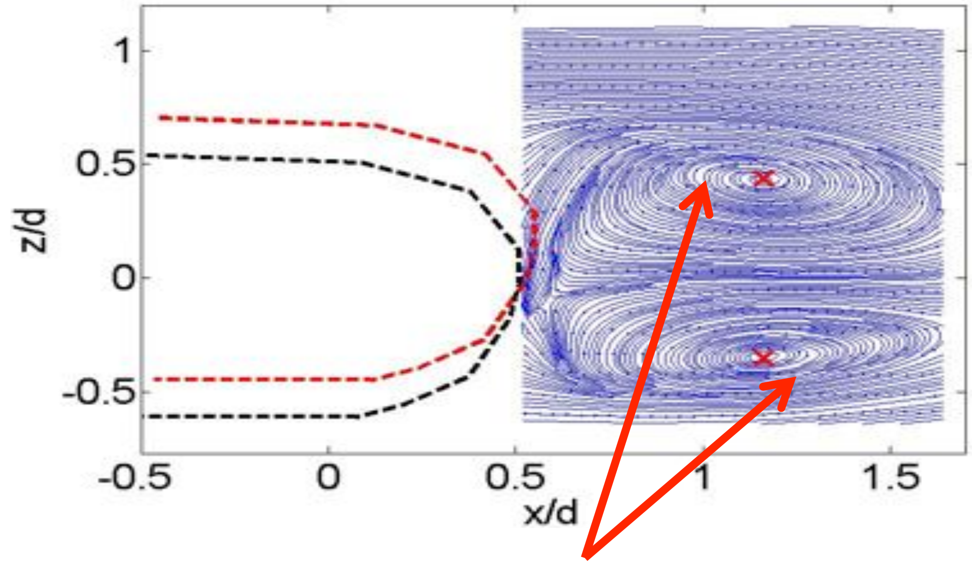
Fishing operation improvement : To minimize the drag of the fishing gear in order to reduce the fuel consumption (HydroPêche project, Germain et al. 2011)

Objective of thesis : To determine the flow characteristics governgin the hydrodynamic behaviour of porous structure

Keywords : porous structure, PIV, POD, vortex shedding, boundary layer, wake.



Developing boundary layer over flat plane
Drulaut et al 2012



Vortex shedding in the wake
Bouhoubeiny et al 2011

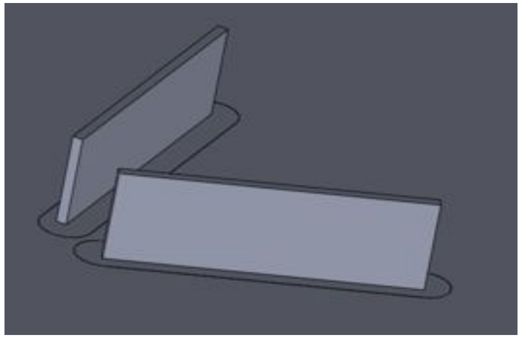
ISAE — Institut Supérieur de l'Aéronautique et de l'Espace

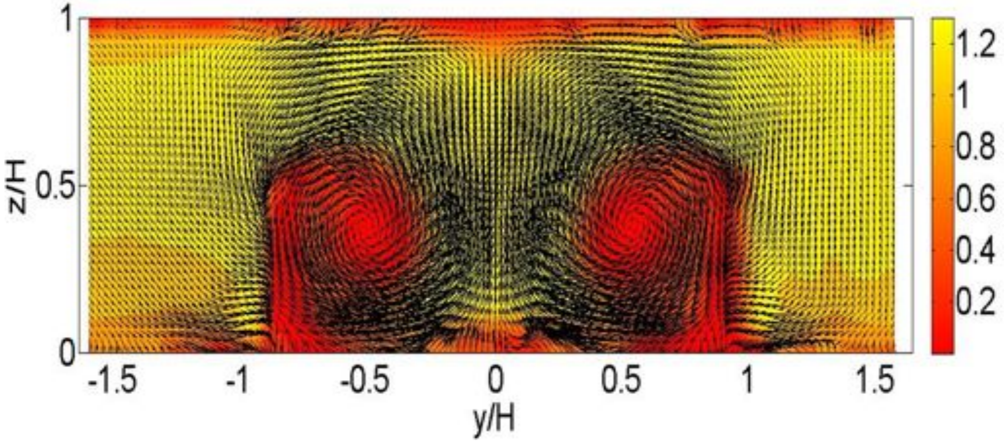
Post-doc in Mines Douai (2013-2014)

Enhancing the heat exchanger performance

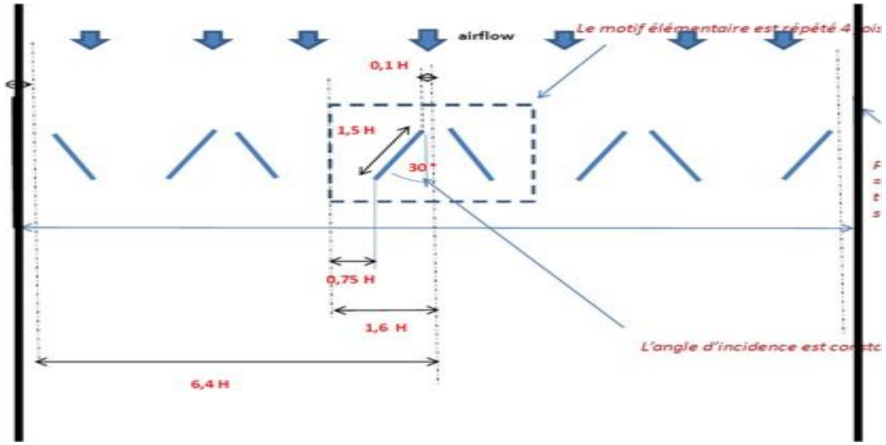
Objective : Experimental investigation of longitudinal Vortices Generated in channel flow by a pair of rectangular winglets

Pair of rectangular winglets





Example of mean velocity field at X=0 for Re=13200



Geometrical characteristics of the row of pairs of rectangular winglets

SkyScanner Project

Objective: the study and experimentation of a fleet of mini-drones that coordinate to adaptively sample cumulus-type clouds, over periods of the order of one hour.

The main tackled challenges are:

- A better understanding of clouds micro-physics
- A better understanding of aerodynamic phenomena at the scale of mini-drone
- Design optimization of enduring mini-drones
- Optimized flight control, energy harvesting
- Adaptive fleet control, dynamical driven by the gathered data

Present study : design optimization of enduring mini micro-drones

Aims :

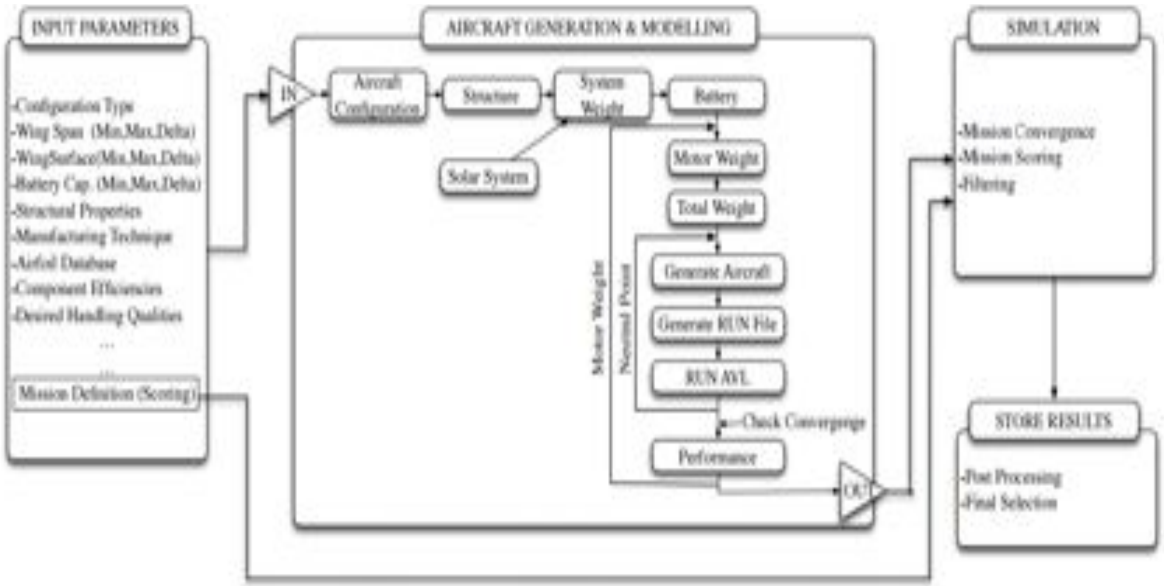
- To develop a conceptual design methodology of mini micro-UAV
- To improve the autonomous flight of the mini micro UAV by optimizing the trajectory (wind gradients, exploiting thermal?)

- Designing mini micro UAV : using and developing suitable models describing the characteristics of all components
- Integration of constraints related of environment : wind gradients, thermal?

State of the art

Conceptual design and performance for long-endurance mini-micro UAVs

CDSGN : The conceptual design tool M. Bronze et al (2009)



Solar Storm M. Bronze et al (2009)

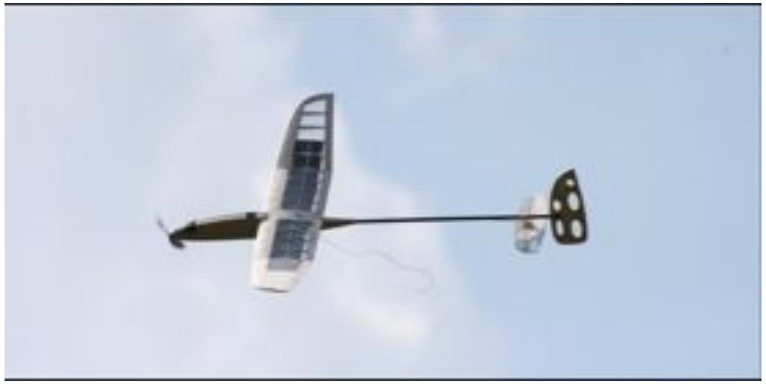
Several mini UAV were designed using Cdsgn program :
- Solar Storm : hybrid solar powered micro UAV in half a meter scale,
- SPOC : long range mini UAV
- Eternity : long endurance mini UAV

State of the art

Sloar airplanes were designed for continuous flight

Skysailor A. Noth (2008)

Sun Surfer MAV N. Diepeveen (2007)



Challenging:
- mass and energy models
- aerodynamics properties deteriorate due to the low Re
- efficiencies of motors and small-sized propeller

Current work

Procedure to establish a design methodology for micro UAV

- Configuration of the mini micro UAV
- Airfoil selection and performance
- Aerodynamics of wing

AVL, Xflr5 using panel Methods or vortex lattice
Creating an interface with Matlab, using OpenMdao?

Table 1 Summary of two-dimensional aerofoil performance data at $Re = 5 \times 10^4$

Aerofoil	General form	Maximum $C_l^{1.5}/C_d$	C_l achieved	$C_l^{1.5}/C_d$ at $C_l = 1.0$	$C_{l_{max}}$
Gö 801 (turbulated)		25	0.8 to 1.3	20	1.3
GM15		55	1.2	45	1.2
S7075		40	1.0	40	1.0
E-61		45	1.3	15	1.3
Göttingen flat plate		6	0.4	—	0.8
Gö 417a curved plate		54	1.2	31	1.2

- Powerplant and propulsion system

We need to define the mission profile

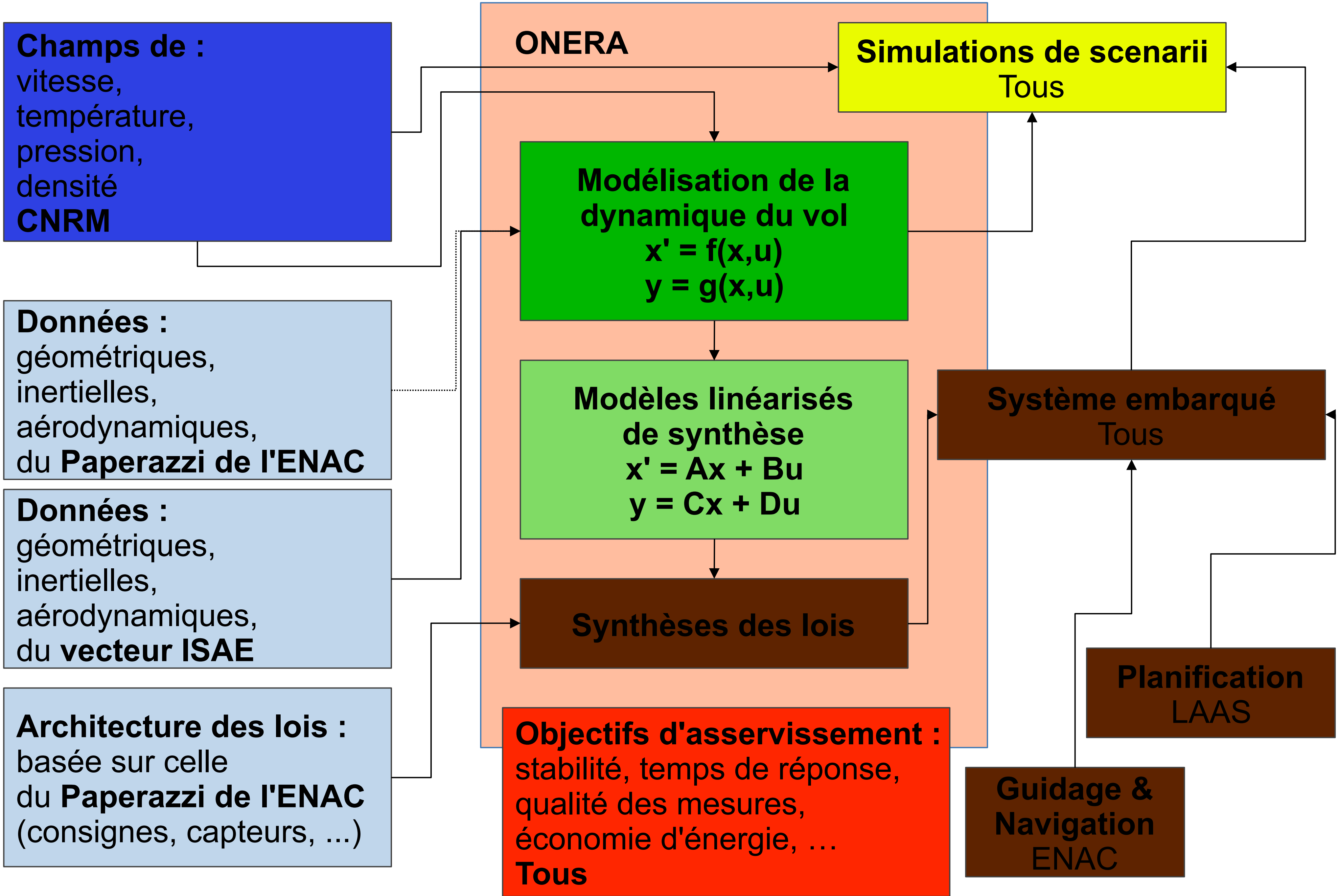
Skyscanner

Activités prévues pour le post-doctorant accueilli à l'ONERA à partir du mois 16

Présentés par Carsten DÖLL

Réunion d'avancement, 07/04/2015, LAAS

Synthèse de lois de pilotage



Objectifs antagonistes

	Rejet de perturbation	Profit de perturbation
Qualité de mesure	++	--
Maintien de vitesse	+	-
Maintien d'altitude	+	-
Activité de gouvernes	--	++
Consommation d'énergie	--	++
Exploration verticale fine du nuage	+	-
Exploration verticale rapide du nuage	-	+
Exploration horizontale fine du nuage	+	-
Exploration horizontale rapide du nuage	-	+

Au moins 2 lois différentes