Plans for surface processes and surface data assimilation in HARMONIE-AROME

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with acknowledgements to colleagues within HIRLAM, at Météo-France, MetCoOp



The **ALADIN-HIRLAM** cooperation

... uses the ALADIN-HIRLAM NWP system which includes three different configurations:

- HARMONIE-AROME
- AROME-France
- ALARO

All of them relate to the model SURFEX for surface processes.



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Operational cooperation among HIRLAM countries:

- MetCoOp (Sweden, Norway, Finland) runs HARMONIE-AROME in ensemble system (10 members). Negotiations are ongoing with Estonia and Lithuania to join.
- Iceland, Denmark, Ireland and the Netherlands have the intention to form an operational collaboration.



The three main components of surface modelling for NWP

Physiography



orographic friction Snow processes : Bulk to detailled snow processes models oproach rocesses Land surface : energy, water, carbon fluxes Aerosols: drological and chemical emission getations processes aerosols, dust, lk lake mode vashe Sea: Surface fluxes 1D mixing layer arv laver

Processes

Assimilation





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Processes by SURFEX





SURFEX/SODA and their options



SURFEX is designed to work from ESM scale to very high resolution and offline. The exact combination of options depends on application!





Surface processes in HARMONIE-AROME (current and future) and HIRLAM



An example to motivate why we need better physics again...

Diurnal cycle of Rh2m over Finland for observations, operational HARMONIE-AROME and operational HIRLAMv7.4:



It is believed that the positive daytime bias in HARMONIE-AROME is partly due to too warm soil (due to shallow soil and short memory) which makes soil water available for transpiration. While HIRLAM still has cooler soil (longer memory) which prevents vegetation to become active.

Details in physical processes

1st generation

Manabe (1969)

sensible latent heat heat reference Τr er height aerodynamic pathway in ≥ ra ₹ $r_a \beta$ lower atmosphere e*(T_s) T_{s} fixed surface properties W_{max}= 150 mm w/ bucket hydrology runoff



3rd **generation** with carbon

Collatz *et al*. (1991); Sellers *et al*. (1992)



Details in physical processes



The ALADIN-HIRLAM system: HARMONIE-AROME

The ALADIN-HIRLAM NWP system (based on IFS) includes a few configurations: ALARO, AROME-France, HARMONIE-AROME, Climate

The latest release of the HARMONIE-AROME configuration is based on cy40h.

The surface perspective of the cycles:

	cy40h	cyxxh (long term ambition)				
Land	-					
Patches Soil Snow Glacier Assimilation	1 or 2 Force-restore D95 (composite) "Pile of snow" CANARI-OI	2-4 patches with explicit canopy Diffusion (14 layers) Explicit snow (12 layers) Explicit snow as glacier MESCAN/gridpp-EKF/EnKF				
Sea Lake Town	SICE FLake (optional) TEB	Sea ice (SICE) FLake (later with EKF) TEB (more options)				
Physiog.	ECOCLIMAP-II 1 km resolution	ECOCLIMAP 2 nd generation 300 m resolution				

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SURFEXv8.0 with its patches (sub-tiles) for the land tile

ECOCLIMAP 19 vegetation types

	Bare soil
	Rocks
ор	Permanent snow/ice
ed	C3 crops
ociato AI, al)	C4 crops
	Grassland
ISS J. L J,	Boreal grass
e a e.c nin	Tropical grass
ar e (ßsn	Irrigated crops
Providence L'H	Wetlands, parks, irrigated grass
number of paramete ith each vegetation t oot depth, tree height	Temperate broadl. cold-dec. summergr
	Tropical broadleaf deciduous
	Temperate broadleaf evergreen
	Boreal broadl. cold-dec. summergr.
	Shrubs
	Tropical broadleaf evergreen
	Boreal needleleaf evergreen
	Temperate needleleaf evergreen
A 3 5	Boreal needlel. cold-dec. summergr.

SURFEXv8.0 with its patches (sub-tiles) for the land tile

Rules of parameter aggregation

Number of patches specified (NPATCH)		19	12	11	10	9	8	7	6	5	4	3	2	1]
	Bare soil	1	1	1	1	1	1	1	1	1	1	1	2	1	1
.	Rocks	2	2	2	1	1	1	1	1	1	1	1	2	1	
D D D	Permanent snow/ice	3	3	3	2	2	2	2	1	1	1	1	2	1	
	C3 crops	7	7	7	6	5	4	4	3	3	3	3	2	1	
5	C4 crops	8	8	8	7	6	5	4	3	3	3	3	2	1	
	Grassland	10	10	10	9	8	7	6	5	5	3	3	2	1	1
	Boreal grass	18	10	10	9	8	7	6	5	5	3	3	2	1	
J.	Tropical grass	11	11	10	9	8	7	6	5	5	3	3	2	1	
Ssi	Irrigated crops	9	9	9	8	7	6	5	4	4	4	3	2	1	-
Ľ,	Wetlands, parks, irrigated grass	12	12	11	10	9	8	7	6	4	4	3	2	1	-
gh	Temperate broadl. cold-dec. summergr	4	4	4	3	3	3	3	2	2	2	2	1	1	-
hei	Tropical broadleaf deciduous	13	4	4	3	3	3	3	2	2	2	2	1	1	-
e B	Temperate broadleaf evergreen	14	4	4	3	3	3	3	2	2	2	2	1	1	
Ę	Boreal broadl. cold-dec. summergr.	16	4	4	3	3	3	3	2	2	2	2	1	1	-
ţÌ,	Shrubs	19	4	4	3	3	3	3	2	2	2	2	1	1	Ĩ
ep	Tropical broadleaf evergreen	6	6	6	5	3	3	3	2	2	2	2	1	1	
t d	Boreal needleleaf evergreen	5	5	5	4	4	3	3	2	2	2	2	1	1	
00	Iemperate needleleaf evergreen	15	5	5	4	4	3	3	2	2	2	2	1	1	-
-	Boreal needlel. cold-dec. summergr.	17	5	5	4	4	3	3	2	2	2	2			

ECOCLIMAP 19 vegetation types

SURFEXv8.0 with its patches (sub-tiles) for the land tile

Rules of parameter aggregation



HARMONIE-AROME MetCoOp default **ECOCLIMAP 19 vegetation types** Number of patches specified (NPATCH) Bare soil Rocks AI, albedo, Permanent snow/ice C3 crops sociated C4 crops Δ Grassland Ĺ **Boreal grass** as (e.g. Rsmin **Tropical grass** are Irrigated crops vegetation type parameters Wetlands, parks, irrigated grass height, Temperate broadl. cold-dec. summergr **Tropical broadleaf deciduous** Temperate broadleaf evergreen tree Boreal broadl. cold-dec. summergr. of depth, 1 Shrubs each number **Tropical broadleaf evergreen** Boreal needleleaf evergreen with root Hir Temperate needleleaf evergreen ∢ Boreal needlel. cold-dec. summergr. Δ CIIIS

However, parameter values can be dubious...

During a development period we concluded that the ECOCLIMAP tree height (roughness) seemed to be overestimated in the northern half of the MetCoOp domain. Therefore, ECOCLIMAP tree height was replaced by laser estimated tree height. See article in No 10 of ALADIN/HIRLAM Newsletter: www.umr-cnrm.fr/aladin/IMG/pdf/nl10.pdf.



Difference (new – old) roughness :

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Processes

Assimilation



After a few hours of integration (here 3 hours) the prognostic variables in the soil have deviated from the truth (which we don't know) due to non-linearities of the system but also due to biases in the system.

 $\mathbf{X}_{\mathbf{A}} = \mathbf{X}_{\mathbf{B}} + \mathbf{K}(\mathbf{Y} - H(\mathbf{X}_{\mathbf{B}}))$

The job of the surface data assimilation is to utilize observations (currently T2m and Rh2m) to push a subset of the prognostic variables (the control variables) towards a new analysed state.



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Here, H, in $H(\mathbf{X}_{\mathbf{B}})$ represents the forward model or observation operator. I.e., the translation from model variables to observations if the variables representing the observations do not exist in the model already.



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If the observation errors are big compared to the model errors the new analysed state will be close to the first guess (or background, the value of the control variables after 3 hours in the previous forecast). On the other hand, if the model errors are big compared to the observation errors the new analysed state will be close to the observations. Here, H, in $H(\mathbf{X}_{\mathbf{B}})$ represents the forward model or observation operator. I.e., the translation from model variables to observations if the variables representing the observations do not exist in the model already.

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It is the Kalman Gain, K, which represents the relationship between observation errors and model errors. E.g., a small K (small/big model/observation error) gives higher weight to the first gues

 $\mathbf{X}_{\mathbf{A}} = \mathbf{X}_{\mathbf{B}} + \mathbf{K} \big(\mathbf{Y} - H \big(\mathbf{X}_{\mathbf{B}} \big) \big)$

Surface data assimilation – Optimal Interpolation (OI)

In the current operational HARMONIE-AROME we use Optimal Interpolation (OI) as our surface data assimilation method. Here the Kalman Gain, K, is simply calibrated to find a relationship between observations and control variables.

Observations used are:

- T2m
- Rh2m

The control variables are, i.e. the prognostic variables which are assimilated:

- TG1 (surface temperature)
- TG2 (deep soil temperature)
- WG1 (surface soil moisture)
- WG2 (deep soil moisture)



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Such a calibration is difficult to make general and good for all possible situations (dry/moist soil, snow or no snow conditions, bare soil / inactive vegetation / active vegetation, ...)

Also, OI is difficult to expand to many control variables and to a combination of different types of observations (e.g. SYNOP and satellite).



Surface data assimilation – Simplified Extended Kalman Filter (SEKF)

Next step for HARMONIE-AROME is to apply Simplified Extended Kalman Filter (SEKF). Here the Kalman Gain, K, is calculated for each assimilation cycle to find the current relationship between observations and control variables:

$$\mathbf{K} = \mathbf{B} \cdot \mathbf{H}^{\mathsf{T}} \left(\mathbf{H} \cdot \mathbf{B} \cdot \mathbf{H}^{\mathsf{T}} + \mathbf{R} \right)^{-1}$$

Here, B represents the model (background) errors and R the observation errors. H is the Jacobian, which is estimated by running SURFEX offline for as many control variables that exist, where for each run, one control variable at a time is perturbed. Gives e.g. dT2m/dTG2.



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Pros:

- the current situation is used to estimate K. No calibration needed.
- New processes can easily be connected to the assimilation.
- Allows for several types of observations at the same time.

Cons:

- If the system behaves strongly non-linear, e.g. during precipitation events, the calculation of the Jacobians can break down. Safety actions are needed.
- Can become expensive if too many control variables are used.



Surface data assimilation – Satellite observations



We can utilize satellite data in two ways:

 Use a product where someone else has processed the satellite data to estimate e.g. soil moisture or snow extent. Not too complicated but another model is usually in between which increase uncertainties. Ongoing examples are:

Instrument	Satellite	Product	Comment
ASCAT	METOP-A/B	Surface soil moisture	
SEVIRI	MSG	Snow extent (H-SAF)	
SMMR, SSM/I, AVHRR GAC	several	Snow extent	Not for operational use



Surface data assimilation – Satellite observations



MIRAS/ SMOS

We can utilize satellite data in two ways:

• Use radiances directly. Good, less dependent on other models but requires a forward model which translate the model state to satellite radiances. Test and development are ongoing for:

Instrument	Satellite	Intention	Forward model H(X _b)
AMSR-2	GCOM-W1	surface soil moisture (7 GHz) shallow snow (89 GHz) moderate snow (37 GHz) deep snow (10, 19 GHz)	FASTEM + RTTOV?
MIRAS	SMOS	surface soil moisture (1.4 GHz)	CMEM + FASTEM (water)?
SAR-C (Sentinel-1)	Sentinel-1A	wet snow snow extent	MEMLS3-A (Proksch et al. 2015)



Nordic hydrometeorological system



Coupled to NWP/climate model or Offline with interpolation/downscaling to higher resolution and/or spatial/time correction or boundary layer processes...



OASIS coupler for deep and surface runoff, ground water, flooding, irrigation, MESAN analysis system + STRÅNG radiation analysis, MetCoOp operational + EPS, HARMONIE-Climate,

...

SURFEX

Nature-Town-Lake-Sea Nature potential: 19 patches, multi-layer snow and soil, explicit veg/snow, veg dynamics

...



Hydrological ground water and routing model, e.g. HYPE "light", CaMaFlood, something new,...



Takk! Kiitos! Tak! Tack!

Puffin at Cape Ingólfshöfði, southern Iceland June 12th 2018

With modified tree height/roughness U10m improves

m/s

U10m: 7 days statistics from last week over the MetCoOp domain



Previous version: SBL, 1 patch, TG2 for lake water ECMWF

People involved: Patrick Samuelsson, Mariken Homleid, Trygve Aspelien, Ulf Andrae, Matti Horttanainen (FMI).