

NWP at METEOCAT

Firenze, 13-14 June 2018







- METEOROLOGICAL MODELS
- WRF CONFIGURATIONS
- DATA ASSIMILATION
- WRF NOWCASTING
- PROBABILISTIC NWP
- WAVE MODELS
- VERIFICATION





METEO MODELS

MODEL	DOMAIN	IC/BC	UPDATE	LEAD TIME	NOTES
WRF-ARW	27 – 9 – 3 km	IFS - <mark>0.5</mark> °	12 h	72 – 72 – 48 h	3DVAR
WRF-ARW	9 – 3 km	GFS - <mark>0.25</mark> °	12 h	72 – 48 h	-
BOLAM	8 km	GFS - <mark>0.5</mark> °	12 h	72 h	-
MOLOCH	2 km	BOLAM	12 h	48 h	-
UM	4 km	UM	12 h	54 h	UK Met Office
AROME	1 km	ARPEGE	12 h	42 h	Météo France
WRF-ARW	16 – 4 km	IFS - <mark>0.5</mark> °	12 h	72 – 72 h	-
WRF-ARW	3 km	WRF	3 h	12 h	3DVAR
WRF-ARW	3 km	WRF	3 h	12 h	LAPS/STMAS

ECMWF from AEMet

Limited set of variables & levels – top level 100 hPa – 0.5°





METEO MODELS





WRF - CONFIGURATIONS

Options	WRF v3.5	WRF v3.5 - WAVE
Microphysics	WSM5	WSM3
Long-wave rad	RRTM	RRTMG
Short-wave rad	Dudhia	RRTMG
PBL	YSU (from v2.2)	YSU (from v2.2)
Surface layer	MM5 Monin-Obukhov	MM5 Monin-Obukhov
Cumulus	Kain-Fritsch (even at 3 km)	Kain-Fritsch (16 km) + explicit (4 km)
Surface model	Noah LSM	Noah LSM
Other	topo_wind = 2 (UW method)	topo_wind = 2 (UW method)

Vertical levels: 31 user specified

eta_levels =
1.000,0.998,0.993,0.986,0.975,0.960,0.940,0.910,
0.880,0.840,0.800,0.760,0.720,0.680,0.640,0.600,
0.560,0.520,0.480,0.440,0.400,0.360,0.320,0.280,
0.240,0.200,0.160,0.120,0.080,0.040,0.000

Analysis nudging on the coarsest domain





WRF - CONFIGURATIONS

Options	WRF v3.5	WRF v3.9
Type of levels	Sigma	Hybrid
Microphysics	WSM5	WSM6
Long-wave rad	RRTM	RRTM
Short-wave rad	Dudhia	Dudhia
PBL	YSU (from v2.2)	QNSE-EDMF
Surface layer	MM5 Monin-Obukhov	QNSE (+ increased U*)
Cumulus	Kain-Fritsch (even at 3 km)	Multiscale KF (decoupled from YSU) even at 3 km
Surface model	Noah LSM	Noah MP (+ dveg = 5)
Other	topo_wind = 2 (UW method)	time-varying SST, seaice, vegetation fraction, albedo, leaf-area index and deep layer soil temperature
Dynamics	damp_opt = 0	damp_opt = 3 + zdamp = 2000



Vertical levels: 31 user specified Analysis nudging on the coarsest domain



DATA ASSIMILATION

Data Assimilation systems



ТҮРЕ	SOURCE	NUMBER	AVAIL.	PARAMETERS
	XEMA	~ 170	30′	T / RH / pmsl / PCP
SFC	METAR	~ 10	60'	T / Td / pmsl / visibility / clouds
	SYNOP	~ 10	180'	T / Td / pmsl / visibility / clouds
RADAR	XRAD	4	6'	Reflectivity / Radial velocity
SATELLITE	MSG	1	15′	<mark>0.6 um /</mark> 3.9 um / 10.8 um





WRF - NOWCASTING

Our current model setup





WRF - NOWCASTING







PROBABILISTIC NWP

PRESCAT

Consisting of two-step process :

1- Development of statistical relationships between local variables (surface air temp, RH and precipitation) and large-scale predictors (e.g., pressure fields)

2- Application of such relationships to the output of mesoscale model.







WAVE MODELS

MODEL	DOMAIN	IC/BC	UPDATE	LEAD TIME
SWAN	11 – 3 km	WRF 16 – 4 km	12 h	72 – 72 h
WW3	12 – 3 km	WRF 16 – 04 km	12 h	72 – 72 h
ROMS	1 km	IBI-MFC / WRF 04 km	24 h	72 h









WAVE MODELS

EXEMPLES

SWAN model DX=3km



ROMS model DX=1km - testing







VERIFICATION

- Operational verification:
 - Daily & monthly (intranet)
 - Seasonal & yearly (<u>reports</u>)
- MET (*Model Evalution Tools*) software
- STATIONS (grid to point)
 - SYNOP/METAR: pmsl, t2, td2m, v10m
 - AWS: t2m, rh2m, v10m, PCP
 - RAOB: t, td, v, gh
- ANALYSIS (grid to grid):
 - EHIMI (radar + pluviometers): PCP









CURRENT & FUTURE WORK

- NWP migration to a new cluster
- Introduce changes in the NWP operational suite:
 - Increase lead-time (WRF 3 km: 48 h -> 72 h)
 - Increase spatial resolution (WRF 1 km?)
 - Adjust WRF 3.9.1
 - Improve initial SFC fields (HRLDAS)
- Probabilistic NWP:
 - Poor man's ensemble operational
 - PRESCAT v2: 1 km / 6 h
- Very Short-Range NWP
 - Hot cycle
 - Flow-dependent B-Matrix (Hybrid 3DVAR Time Lagged Ensemble)





SUPLEMENTARY SLIDES



c) October 12th, 2016: Record-breaking intensity and stream overflowing





1. Our data assimilation (DA) systems

WRFDA Radar

• Minimisation of the cost function J(x)

$$J(\mathbf{x}) = \frac{1}{2} (\mathbf{x} - \mathbf{x}_b)^T \mathbf{B}^{-1} (\mathbf{x} - \mathbf{x}_b) + \frac{1}{2} (\mathbf{y} - \mathbf{H}[\mathbf{x}])^T \mathbf{R}^{-1} (\mathbf{y} - \mathbf{H}[\mathbf{x}])$$

 $v_T = 5.40a \cdot q_r^{0.125}, \quad a = (p_0/\overline{p})^{0.4}$

- The observation operator H(x) for reflectivity (Z) and radial wind (v_r) is

$$Z = 43.1 + 17.5 \log_{10}(\rho q_r)$$
$$v_r = u \frac{x - x_i}{r_i} + v \frac{y - y_i}{r_i} + (w - v_T) \frac{z - z_i}{r_i}$$

Sun & Crook (1997)

 \mathbf{w} and \mathbf{q}_{r} are estimated trough diagnostic relations:

w using the Richardson's Equation
 q_r using a warm-rain scheme to partition q_t

• Xiao & Sun (2007) approach (the only available on WRFDA v3.5).

1. Our data assimilation (DA) systems



Obs error specification:

- Reflectivity: set to 5 dBZ

• Radial velocity (m/s): $\varepsilon(v_r) = \frac{4d}{150} + 1$ d = distance from the radar (km)

Schwitalla & Wulfmeyer (2014), Xiao et al. (2008), Montmerle & Faccani (2009)

2. Our data assimilation (DA) systems

Space-Time Multiscale Analysis System (STMAS)

- Evolution of the LAPS system.
- Sequential variational analysis based on a <u>multigrid descomposition</u> technique.



- STMAS sequentially iterates a variational analysis from larger to shorter scales similar to a successive correction technique within a variational framework:
 - > Minimisation of the cost function $J^{(n)}$ at every grid level:

$$J^{(n)}[\mathbf{X}^{(n)}] = \frac{1}{2} \mathbf{X}^{(n)^T} \mathbf{X}^{(n)} + \frac{1}{2} [H^{(n)} \mathbf{X}^{(n)} - \mathbf{Y}^{(n)}]^T \mathbf{O}^{(n)^{-1}} [H^{(n)} \mathbf{X}^{(n)} - \mathbf{Y}^{(n)}]$$

> Final analysis is obtained by summing the analyses from all the grid levels:

$$\mathbf{X} = \mathbf{X}^b + \sum_{n=1}^N \mathbf{X}^{(n)}$$

where $X^{(n)}$ is the analysis increment vector at grid level n

Xie, Y., S. E. Koch, J. A. McGinley, S. Albers, P. Bieringer, M. Wolfson, and M. Chan, 2011: A space and time multiscale analysis system: A sequential variational analysis approach. *Mon. Wea. Rev.*, 139, 1224–1240.

3. Improvements on DA systems

WRFDA Radar (1/2): Indirect assimilation (Wang et al., 2013)

• WRF 3D-Var minimises the cost function using a linearised observation operator

 $Z = 43.1 + 17.5 \log_{10}(\rho q_r) \xrightarrow{\text{Linearisation}} dZ = \frac{17.5 dq_r}{q_r \ln(10)} \qquad \qquad \text{LE} = dZ - dZ_n$ $dZ_n (dq_r) \xrightarrow{\text{Nonlinear perturbation}} dZ_n = 17.5 \log_{10}[(q_r + dq_r)/q_r]$



• Several drawbacks identified:

- \circ dZ > dZ_n \Rightarrow dry bias using dZ
- Large linear approximation errors (LE) easily reached (especially for a dry background).
- \circ dZ invalid when q_r = 0 on the background
- $(q_r \ge 0.05 \text{ g/kg imposed})$
- Indirect assimilation of reflectivity (WRFDA v3.7):

 Microphysics and water vapour are retrieved and assimilated.

 \odot Cloud control variables are added.

Additional microphysics (rain, snow and graupel)
 partition described in Gao & Stensrud (2012).

3. Improvements on DA systems

WRFDA Radar (2/2): Control variables CV7 (Sun et al., 2016)

• So far we used the **CV5** option: ψ , χ_u , T_u , RH_s , $P_{s,u}$

• Beginning in WRFDA v3.7 (corrected on v3.8) a new set of CV is available:

u, v, T, RH_s , $P_s \rightarrow CV7$

- Sun et al. (2016) show that:
 - CV5 decreases the variance & increases the length scale for u and $v \rightarrow$ analysis increments tend to miss small-scale features.

 Artificial tunning (decrease) of CV5 length scales can result in unrealistic correlations at long distances.

- CV7 allows closer fits to radar wind observations
- CV7 improves the 0-12 hour precipitation prediction



0.05

0.1 0.15 0.2

0.25

0.12 0.2 0.28 0.36

0.44

4. Conclusions

- STMAS outperforms LAPS for the cases under study → STMAS operational
- The original WRFDA Radar technique leads to unrealistic RH analyses → some forecasts perform worse than the control run.
- Indirect reflectivity DA + CV7 in WRFDA outperform the original approach → into operations at SMC this spring.
- Future work: <u>Many</u> components of the system need to be reconsidered
 - Cycling (hot vs cold start, refreshing) for both STMAS & WRFDA
 - Background error characterisation (hybrid approach) for WRFDA
 - Cumulus: scale-aware scheme / explicit
 - Improve cloud analysis (STMAS) / Microphysics partition (WRFDA)
 - ...
- Challenges
 - Major bug fix in WRFDA v3.9 (17/04/2017) \rightarrow repeat experiments
 - LAPS / STMAS no longer supported at NOAA/ESRL





References

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COARSER DOMAINS

- SFC: METAR/SYNOP
- OBS in common domain
- Grid Point: *nearest neighbour over land*
- Aggregation (all stations & selected period) MAE / ME computation







SFC - CONCLUSIONS



• T2m:

- Highest error in winter/summer
- Cold bias specially afternoon/evening
- Td2m:
 - Better than WRF!
 - Highest error in summer
 - Dry bias during daytime
- pmsl:
 - Slight underestimation specially in summer
- V10m
 - Slight overestimation specially during night





NESTED DOMAINS

- SFC: AWS
- OBS in common domain
- Grid Point: *nearest neighbour over land*
- Aggregation (all stations & selected period) MAE / ME computation





SFC - CONCLUSIONS

MOLOCH

• T2m:

- Positive/negative bias during night/day
- Highest error during night (also day in summer)
- RH2m:
 - Wet bias specially in winter (better in spring/autumn)
 - Highest error during sunrise/sunset periods
 - Dry bias at initial time (always)
- V10m:
 - Overestimation (specially during daytime)
 - A bit worse than WRF on average

WRF-ARW v2.2 YSU PBL scheme used!





COARSER DOMAINS

- SFC: RAOB
- OBS in <u>common domain</u> 10 stations
- Grid Point: *nearest neighbour 850, 700, 500, 300 hPa*
- Aggregation (all stations & selected period) MAE / ME computation





UPA - CONCLUSIONS



- T:
 - Error increases at lowest levels in winter/summer
- Td:
 - Error increases at higher levels specially in winter
 - Wet bias in winter specially at highest levels
 - Dry bias in summer at lowest levels
- V:
 - Error increases at higher levels and in winter
- GH:
 - Error increases at higher levels and in winter
 - Slight underestimation





PRECIPITATION

- Precipitation analysis: radar + pluviometers EHIMI (1 km)
- Reprojection: <u>common domain</u>
- Grid Grid: dichotomous contingency tables computation (by thresholds)
- Aggregation (all domain & selected period) POD / FAR / CSI / BIAS







- BOLAM
 - Small differences with WRF-ARW
 - <u>Forecasters feedback</u>:
 - Similar than other models (with similar resolution)
- MOLOCH
 - A bit worse than WRF on average

MOLOCH explicit / WRF scheme KF – convection over sea areas?

- Forecasters feedback:
 - QPF overestimation
 - Problems in localization of maxima



SWAN

The wave forecasting system is composed of two numerical domains and is based on a downscaling technique.

The largest domain (SWAN11) covers the western Mediterranean Sea with a spatial resolution of 11 km and provides boundary conditions to a second-level domain (SWAN03), which covers the Balearic Sea with a spatial resolution of 3 km.

The SWAN11 run is forced with 10-m surface winds from WRF_ONA16 and the SWAN03 run is forced with 10-m surface winds from WRF_ONA04.

In both domains, the bathymetry used in the model is a 0.0083^o grid resolution bathimetric data from GEBCO.

The spectrum is discretized with a constant relative frequency resolution of $\Delta f = 1.1$ (logarithmic distribution) and a constant directional resolution of $\Delta \theta = 10^{\circ}$. The discrete frequencies are defined between 0.01 Hz and 1 Hz. Above the high-frequency cutoff, a diagnostic tail f⁻⁴ is added.

The model implementation considers wind growth, quadruplet wave interactions and whitecapping.

The model is run twice every day (00 h and 12 h).

The model output of the previous run is used as initial conditions.

ROMS

One domain with a horizontal resolution of 1 km and a vertical resolution of 20 sigma-levels.

The bathymetry of the domain was built using 0.0083° grid resolution bathymetric data from GEBCO. This data was interpolated to the domain mesh and smoothed by means of a Shapiro filter.

The model is forced with data from the WRF_ONA04 run: 10-m surface winds, atmospheric pressure, relative humidity, atmospheric surface temperature, precipitation and shortwave and longwave net heat fluxes.

The initial and boundary conditions are taken from the IBI-MFC (Iberian Biscay Irish – Monitoring and Forecasting Centre; (http://marine.copernicus.eu/) product, which has a horizontal resolution of 1/36^o. The parameters used are: 3D daily means of temperature, salinity and baroclinic water currents and 2D (surface) hourly means of sea surface height and barotropic water currents.

The model implementation includes a Generic Length-Scale turbulent vertical mixing scheme with the k – ω parametrization, a logarithmic profile for the bottom boundary layer and horizontal mixing terms in geopotential surfaces.

The Ebro River discharge is characterized with a climatology of river runoff and temperature. The river salinity is imposed as a constant value of 18 psu.

The model is in a pre-operative phase, running once a day.