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Summary

Atmospheric Surface Layer (SL) conditions over land have a strong impact on agricultural production and forest fire triggering and propagation. Hence, its accurate diagnosis and forecasting is crucial for a National Weather Service (NWS). Nowadays, Numerical Weather Prediction (NWP) systems, like ALADIN (Termonia *et al.*, 2018), provide assimilation and forecast tools essential to simulate the time evolution of SL conditions from sparse and different observation types. Since June 2017, IPMA keeps a surface Data Assimilation (DA) cycling to initialize a local version of the model Applications of Research to Operations at Mesoscale (AROME, see Termonia *et al.* 2018 and Seity *et al.* 2011) and, more recently, its forecasts are used as first estimates to produce standalone optimal interpolation hourly analysis of near-surface fields (see Section 2). The evaluation of this tailor-made analysis scheme from the ALADIN system is on-going and the first results are illustrated in Section 3. It is shown that the NWP model forecast is improved with the surface refreshing provided by the surface DA cycling. Moreover, it is shown that the hourly analysed mapped fields are generally closer to observations than any other NWP product locally available.

The sequential surface DA cycling + hourly analysis scheme

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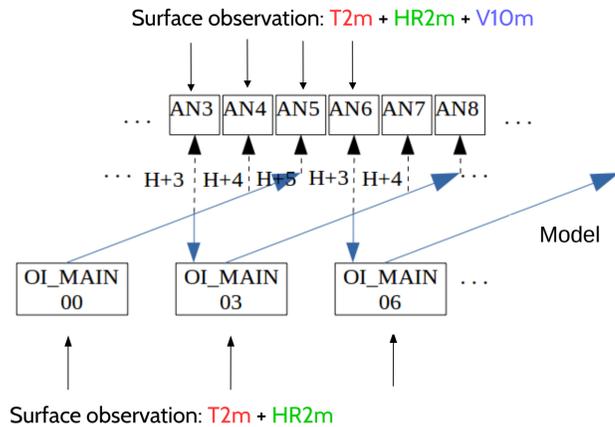


Figure 1: Scheme of the local OI_MAIN sequential surface DA (Giard & Bazile, 2000) + OI hourly analysis (Taillefer, 2002).

In the version CY38T1 of the ALADIN system locally available, the OI method is implemented in-line on the Code d'Analyse Necessaire ARPEGE pour ses Rejets at son Initialisation (CANARI, Taillefer (2002)). Therefore, it was possible to generate a surface DA cycling by the so-called OI_MAIN method as illustrated in Figure 1. At the analysis network time, surface observations over the Iberian Peninsula (see Figure 2) provide screen-level parameters information to correct the AROME model forecasts (2,5 km horizontal resolution) at the observations points. The observations increments are then used to extrapolate the model soil conditions corrections according to the linear equations system:

$$\Delta T_{2m} = T_{2m}^a - T_{2m}^b \quad \Delta RH_{2m} = RH_{2m}^a - RH_{2m}^b$$

$$T_p^a - T_p^b = \Delta T_{2m} / 2\pi \quad T_s^a - T_s^b = \Delta T_{2m}$$

$$W_s^a - W_s^b = \alpha_{WST} \Delta T_{2m} + \alpha_{WsrH} \Delta RH_{2m}$$

$$W_p^a - W_p^b = \alpha_{WpT} \Delta T_{2m} + \alpha_{WpRH} \Delta RH_{2m}$$

where the superscripts *a* and *b* stand for analysed and background (or first estimate), respectively; the subscripts *s* and *p* stand for surface soil and deep soil, respectively; *T* for temperature; *RH* for relative humidity; and *W* for Water content. The linearity factors, α , are not constant and depend on several physiographic and weather conditions.

The surface DA system has a 3-hour cycling: at each analysis network the model surface conditions are refreshed and a new 3-hour full atmospheric model integration is performed to become the new background for the OI_MAIN analysis. In order to account for surface coastal conditions, the Sea Surface Temperature (SST) is updated each two networks, by interpolating SST from the coupling model ARPEGE.

At each analysis network a 6-hour forecast is also prepared in order to provide 2-m fields that act as background to a standalone univariate OI analysis of 2-m temperature, 2-m relative humidity and 10-m wind that are used for downstream agricultural and forest fire applications. The choice of AROME forecasts on the time integration interval 3- to 5-hour relies on the fact that they are more realistic than those obtained by a the pure downscaling initialization (see next section).

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Diagnostics & validation

Besides relying on a easily manageable set of observations, OI_MAIN has also a cheap computational coast suitable for operational implementation. Figure 3 shows the analysis of relative humidity at 06UTC of 15 November 2017: the hourly analysis is shown on the top right panel; the background, a 3-hour forecast, is shown at the top left panel and the analysis increments at its bottom. It is easy to recognise that the final analysis is more realistic since it adds moisture in the south part of Portugal and northern part of the Pyrenees and removes it around Barcelona region, at the southeastern part of the Iberian Peninsula, which is in accordance to the observations ("0" means missing). For the system validation, increments analysis has been done as well as single observation experiment diagnosis (not shown). Basic scores (Figure 4) show an added value on the short-term forecasts of screen-level parameters when the DA cycling was increased from 4 to 8 times a day. Thought the model spin-up seems to have been reduced (see the right hand panel for wind variable), the initialization of the other two parameters seems to still have place for improvements when compared to dynamical adaptation (blue curve). Finally, the hourly analysis (CAN-ARO, 2,5km resolution) has been compared to a CANARI version using ALADIN model forecasts has background (CAN-ALA, 9 km resolution) and also with to the AROME model initialization fields (ARO-OP, 2,5 km), over a Summer and a Winter seasons. Basic scores have shown added value on the new analysis.

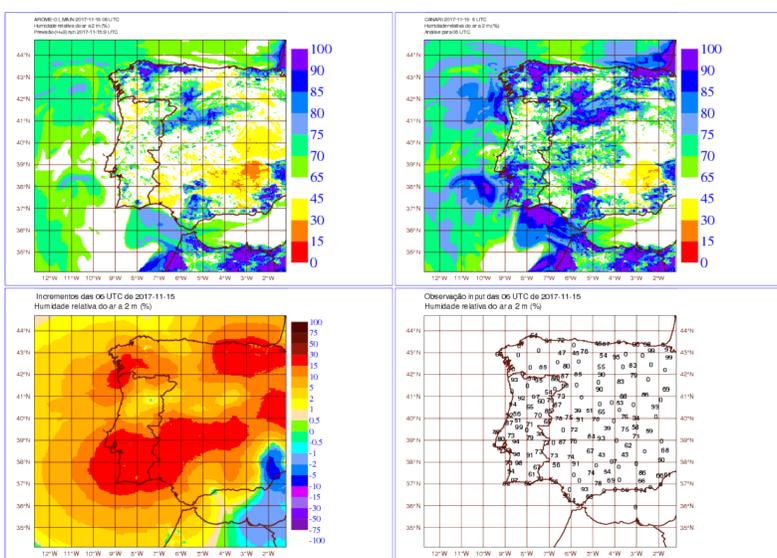


Figure 3: Hourly analysis (2,5 km resolution) of 2-m relative humidity at 06UTC of 15 November 2017

Conclusions & foreseen progress

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The new hourly analysis is closer to observations than any other locally available product at 00UTC and 12UTC (not shown); daily analysis monitoring shows the results are consistent at any hour of the day (not shown). Further validation should consider the comparison of the soil local model fields with an independent set of data, eventually derived from satellite radiances, like LST (see poster by Martins, J.P.) as well as its diagnosis under particular weather conditions. The physiography of the Alqueva Lake was locally validated in the frame of the local version of AROME (Assunção *et al.*, 2017) and should be included in the model physiography. The scheme should enter into operations this Summer.

Acknowledgments This work would not have been done without the support of Françoise Taillefer (GMAP/CNRM, Météo-France); I would like to express my warm thanks to her posthumously. Acknowledgements are also due to Alena Trojakova from CHMI on the pre-processing achievements and to AEMET for providing the data sets on a regular basis.

Assunção, S., Monteiro, M., Salgado, R. (2017). Impact of the Introduction of Alqueva Dam in the AROME Forecasting Model. Proceedings 10th Simpósio de Meteorologia e Geofísica Proceedings 10º Simpósio de Meteorologia e Geofísica; Douville, H., Viterbo, P., Mahfouf J.-F., Beljaars, A. (2000). Evaluation of the Optimum Interpolation and Nudging Technique for Soil Moisture Analysis Using FIFE Data. Monthly Weather Review, 128, 1733-1756; Giard, D., & Bazile, E. (2000). Implementation of a new assimilation scheme for soil and surface variables in a global NWP model. Monthly Weather Review, 128, 997-1015; Mahfouf, J.-F. (1991). Analysis of Soil Moisture from Near-Surface Parameters: A Feasibility Study. Journal of Applied Meteorology, 30, 1534-1544; Masson et al. (2013). The SURFEXv7.2 land and ocean surface platform for coupled or offline simulation of earth surface variables and fluxes. Geosci. Model Dev., 6, 929-960; Noilhan, J. and Planton, S. (1989). A simple parametrization of land surface processes for meteorological models. Mon. Weather Rev., 117, 536-549; Taillefer, F. (2002). CANARI (based on ARPEGE cycle CY25T1 for ALADIN). GMAP/CNRM Technical Documentation, Météo-France, Toulouse, France; Termonia et al. (2018). The ALADIN System and its canonical model configurations AROME CY41T1 and ALARO CY40T1. Geosci. Model Dev., 11, 257-281.

Accurate initialization of soil variables significantly influences atmospheric Numerical Weather Prediction (NWP) simulations over the short and medium ranges (see Douville *et al.* (2000), for instance). This is particularly true for soil moisture and Mahfouf (1991) demonstrated that it is possible to estimate soil moisture from the evolution of the atmospheric parameters near the surface, if realistic surface models (radiative, momentum and sensible and latent heat) are available. Moreover, he showed that the soil moisture retrievals produced by a sequential assimilation using an Optimal Interpolation (OI) technique - where observation and forecast errors statistics were taken into account - was performing reasonably well.

Nowadays, the OI method is still widely used operationally in NWP models. For instance, Giard and Bazile (2000) implemented the OI method in the Action de Recherche Petite Echelle Grande Echelle (ARPEGE) model by computing 2-m temperature and 2-m relative humidity increments to correct soil prognostic variables (temperature and volumetric water content), relying on the density of the surface observational network. The method is however sub-optimal, since under rain, at nighttime and with low solar insolation, forecast errors are not necessarily related to soil moisture errors and a conditional use of the OI technique has to be done to prevent undesirable soil corrections.

As mentioned in Termonia *et al.* (2018), AROME uses the surface modeling platform SURFACE Externalise (Masson *et al.* 2013), where the Interactions between Soil, Biosphere and Atmosphere (ISBA) parametrization (Noilhan and Planton, 1989) with three vertical layers inside the ground is activated over land.

336 (3-hour) Iberian SYNOP observations 2016.07.19 12UTC



Figure 2: Typical spatial distribution of daily available conventional surface observations (SYNOP) over the Iberian Peninsula at 12UTC network.

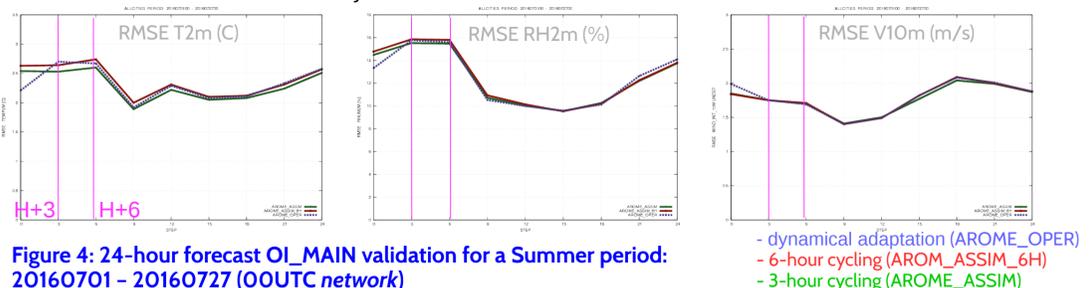


Figure 4: 24-hour forecast OI_MAIN validation for a Summer period: 20160701 - 20160727 (OOUTC network)

Figure 5: Hourly CANARI-AROME validation (OOUTC network): Summer (20170801 - 20170815) Winter (20170110 - 20170207)

Table - RMSE and BIAS of screen level parameters analysis over Mainland for Portugal CAN-ARO and CAN-ALA vs. ARO-OP initial fields

EXP	T2M		H2M		V10M	
	RMSE (C)	BIAS (C)	RMSE (%)	BIAS (%)	RMSE (m/s)	BIAS (m/s)
CAN-ARO(Summer)	1.52	0.18	8.86	-0.70	1.37	0.18
CAN-ARO(Winter)	1.63	-0.01	8.58	-1.36	1.35	0.03
CAN-ALA(Summer)	1.78	0.43	10.95	-0.76	2.18	0.92
CAN-ALA(Winter)	1.85	-0.09	10.66	-0.72	2.25	0.82
ARO-OP (Summer)	2.07	0.90	11.79	-4.69	2.50	1.63
ARO-OP (Winter)	2.06	0.27	12.69	-5.26	2.16	1.24