





WEATHER FORECAST DOWNSCALING FOR APPLICATIONS IN SMART AGRICULTURE AND PRECISION FARMING USING ARTIFICIAL NEURAL NETWORKS (PAPER NUMBER: 4731)

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The goal is to develop a **weather forecast service** for applications in smart agriculture for the following variables:

- temperature at 2m (T2)
- water vapor mixing ratio (Q2)
- surface pressure (PSFC)
- downward surface shortwave radiation (SWD)
- > 1-hour accumulated precipitation (RAIN)
- horizontal wind components at 10 m (U10 and V10)

Constrains of the service:

- 96-hour forecast calculated every 24 hours
- Southern Italy, about (400 x 400) km²

Using on *Weather Research and Forecasting* (WRF) model **the high computational costs** do not allow to go below a grid spacing of about 1.2 km, which is a bit too coarse for precision agriculture.





To overcome this limitation an **ANN-based algorithm** was developed to downscale the WRF output.

The database used for the ANNs training is based on WRF model in *Large Eddy Simulation* (WRF-LES) mode. 12 days x 24 hours in 2017 WRF simulations were run in reanalysis mode with 3 nested domains at 3.6 km, 1.2 km and 240 m.

The basic idea was to train the ANN by using the WRF output at 1.2 km (D02) as input and WRF-LES output at 240 m (D03) as output.

In this way it is possible to apply the ANNs to the outputs of the WRF D02 to get the variable at higher ³ spatial resolution





7 different ANNs were developed, for the separate downscaling of T2, Q2, PSFC, SWD, RAIN, U10 and V10.

The outputs are the PCA (σ^2 >99.9%) of the downscaled variable at 240 m output calculated on the (7x7) grid points rearranged from left to right and from bottom to top;

The larger (7x7) @ 240 m box was preferred to allow 2 or 4 point output overlapping between adjacent boxes, thus avoiding the boxy artifact.





The input consists of:

the PCs (σ2>99.9%) of the variable that need to be downscaled at 1.2 m in the (5x5) box at 1.2 km (yellow and red cross markers)



- The PCs (σ2>99.9%) of some meteorological fields reported above in the (3x3) box at 1.2 km, useful to characterize the atmosphere (red cross markers)
- the PCs (σ2>99.9%) of some static fields in the same (7x7) box at 240 m considered for the output (green circle markers)
- > Latitude, longitude, solar zenith angle



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The ANNs' architectures were defined with 2 hidden layers, hyperbolic tangent and with pure line activation function.

The number of the nodes was defined using an iterative trialand-error search approach.

The procedure ended when the MSE of the ANN does not significant reduce (MSE).







To reduce the risk of overfitting the preliminary considered inputs were evaluated and removed if it doesn't reduce the MSE



T2 - ANN with nodes [6,9] - Inputs analysis





Using the ANNs trained as explained, it is possible to downscale the operative output of WRF forecast.

Since the ANN algorithm operates similarly to bidimensional spatial interpolations — i.e., bringing from a coarser regular grid (1.2 km) to a finer one (240 m) — the algorithm's performance was evaluated against the most common interpolation method such as Linear interpolation, Spline interpolation, Akima interpolation, Hermite interpolation.

We show the results of comparison only with the Spline interpolation that among all the considered interpolations shows the best results.





Temperature 2 m



WRF [K]





May 25, 2017, 12:00 p.m. UTC







0.12

0.1

0.08

0.04

0.02

0

25

Downscaled fields [g/kg]

5

0

0

density 90.0

Water Vapor mixing ration 2 m







Surface pressure







May 25, 2017, 12:00 p.m. UTC









Global horizontal solar irradiance



13[°]E 14[°]E 15[°]E 16[°]E 17[°]E 18[°]E

13[°]E 14[°]E 15[°]E 16[°]E 17[°]E 18[°]E











1-h accumulated rainfall



WRF [mm/h]

RAIN density plot



May 25, 2017, 12:00 p.m. UTC

[mm]







Zonal wind component 10 m



[ms'

[m s⁻¹]





Meridional wind component 10 m









Synthesis of performance

Fields	ANN Architecture*	RMSE ANN algorithm	RMSE Spline interpolation	Improvement
<i>T</i> 2	(289)33-6-9-36	0.58 K	0.67 K	13.4%
<i>Q</i> 2	(289)28-12-9-42	0.45 g/kg	0.51 g/kg	11.7%
PSFC	(280)144-17-18-12	1.7 hPa	12.0 hPa	85.8%
SWD	(306)28-16-14-46	105 W/m ²	112 W/m ²	6.2%
RAIN	(289)28-11-17-15	0.31 mm	0.37 mm	16.2%
<i>U</i> 10	(302)59-23-14-37	0.73 m/s	1.15 m/s	36.5%
<i>V</i> 10	(302)67-25-10-37	0.70 m/s	1.08 m/s	35.2%

*(#initial inputs)#inputs - #nodes 1st hidden layer - #nodes 2nd hidden layer - #outputs

- Overall, the proposed algorithm outperforms the interpolation method.
- The best results were obtained for surface pressure, followed by the horizontal wind components.
- The worst results were obtained for solar irradiance even if the results still showed a 6% improvement compared to the spline interpolation

