WEATHER FORECAST DOWNSCALING FOR APPLICATIONS IN SMART AGRICULTURE AND PRECISION FARMING USING ARTIFICIAL NEURAL NETWORKS

Di Paola F.[1], *Cimini D.*[1], *De Natale M.P.*[1], *Gallucci D.*[1], *Geraldi E.*[1], *Gentile S.*[1], *Genzano N.*[2], *Larosa S.*[1], *Nilo S. T.*[1], *Ricciardelli E.*[1], *Romano F.*[1], *Tramutoli V.*[2], *Viggiano M.*[1]

1) National Research Council, Institute of Methodologies for Environmental Analysis, Tito (PZ), Italy

2) University of Basilicata, School of Engineering, Potenza, Italy

ABSTRACT

This study proposes an *Artificial Neural Network* (ANN) algorithm for downscaling weather forecasts of some variables useful for agriculture in Southern Italy. Using the *Weather Research and Forecasting* (WRF) model at 1.2 km spatial resolution, the algorithm performs downscaling at 240 m resolution using an operation similar to bilinear interpolation, but with enhanced performance. To train the ANNs, a database was built using the WRF model in *Large Eddy Simulation* (LES) mode with 240 m grid spacing. Particular attention was paid to defining the architecture of the ANNs and selecting the inputs. The comparison of the algorithm's performance against spline interpolation shows a reduction of the mean squared error (MSE) ranging from a minimum of 6% for solar irradiance to a maximum of 87% for surface pressure.

Index Terms — Precision agriculture; Precision farm; Smart agriculture; WRF; downscaling.

1. INTRODUCTION

Precision agriculture can be defined as a management strategy that aims for increased profitability, sustainability, and product quality using modern technologies to support decision-making processes [1]. In this context, weather forecasts provide valuable support by allowing for the planning of various operations such as sowing, weed control, pruning, or harvesting. They facilitate the rationalization of resources such as water, energy, or fertilizers and enable the prevention and timely response to issues such as drought, disease development, or insect infestation [2]. Weather forecasts can also be used as inputs for agro-meteorological models, allowing for detailed predictions of weather-related impacts on crops. To support precision agriculture, weather forecasts should be accurate and precise with high spatial resolutions. However, numerical weather prediction (NWP) models are subject to limitations imposed by high computational costs that significantly increase with the grid spacing used for forecasting decreases. To overcome this limitation, many studies have been conducted in recent years aimed at downscaling meteorological fields to support agriculture [3, 4]. The aim of this study is to describe the development of an Artificial Neural Network (ANN)-based algorithm for downscaling the meteorological fields forecasted by the *Weather Research and Forecasting* (WRF) model over an area of approximately (480 x 380) km^2 in Southern Italy. The WRF model is a mesoscale NWP system widely used for both operational and research purposes. It was developed since the end of the last century through collaboration among various research institutes coordinated by the *National Center for Atmospheric Research* (NCAR). The ANN-based algorithm mainly uses as input the WRF output calculated on a 1.2 km regular grid and outputs the following fields on a 240 m regular grid: *(i)* 2-meter temperature (T2), *(ii)* 2-meter water vapor (Q2), *(iii)* accumulated 1-hourly precipitation (RAIN), *(iv)* surface pressure (PSFC), *(v)* global horizontal solar irradiance (SWD), *(vi)* 10-meter zonal wind component (U10) and *(vii)* 10-meter meridional wind component (V10).

2. MATERIALS AND METHODS

The core of the algorithm consists of 7 different ANNs, one for each of the 7 meteorological fields previously listed. These ANNs are trained with a database of high spatial resolution simulations developed using the WRF model in *Large Eddy Simulation* (LES) mode [5]. The model outputs the meteorological fields on three nested domains with grid spacing of 3.6 km, 1.2 km and 240 m. Once the networks have been trained, they can be applied to the output of the operational WRF model at 240 m to downscale its output from the coarser resolution to the finer one.

2.1. Artificial neural network

An ANN is a computational model inspired by biological neural networks that can approximate any complex and non-linear function to any desired degree of accuracy [6]. The structure consists of an input layer, one or more hidden layers consisting of a certain number of neurons and an output layer. The ANNs used in this study are of the feedforward type, i.e. with the information proceeding forward from the input layer to the output one, and fully-connected, i.e. with all inputs or neurons connected to all the neurons in subsequent layers. The neuron is the elementary unit whose output is calculated by multiplying its inputs with suitable weights and added together, with the subsequent addition of a bias and the final application of a suitable transfer function. Two training algorithms were used for the weights and biases estimation, the *Resilient Backpropagation* [7] and the *Levenberg-Marquardt* [8, 9]. The former is a first-order method that requires low computational cost, and it was therefore used for determining the number of neurons in the hidden layers and input selection. The latter is a second-order method with higher computational costs, but which generally produces better results, and it was therefore used for the final training of the ANNs.

2.2. WRF-LES model

The training database was built on the basis of 12 WRF-LES 30-hour simulations: the first 6 were discarded for model spin-up, corresponding to 12 days of 2017, i.e. one for each month of the year. The simulations were conducted on three nested domains, with grid spacing of 3.6 km, 1.2 km, and 240 m. For the initial and boundary conditions, the *European Centre for Medium-Range Weather Forecasts* (ECMWF) model at 0.125° latitude and longitude spatial resolution and 6hour temporal resolution were used. The surface data of the two coarser domains are based on the *Land Use/Land Cover* (LULC) and *Global Multi-resolution Terrain Elevation Data 2010* (GMTED2010) with nominal spatial resolution of 30 arc-seconds (about 900 m) and provided by the *U.S. Geological Survey*. For the domain at 240 m, the surface data are obtained from the *Coordination of Information on the Environment* (CORINE) LULC *Programme* with 3 arc-seconds spatial resolution (about 90 m) and the *Digital Elevation Model* (DEM) of the *Shuttle Radar Topography Mission* (SRTM) with 1 arc-second (about 30m) spatial resolution. The main model settings are: *(i)* Thompson aerosol-aware microphysics; *(ii) Rapid Radiative Transfer Model for Global Circulation Models* (RRTMG) for shortwave and longwave radiation schemes; *(iii)* nonlocal Yonsei University for planetary boundary layer (PBL); *(iv) Noah Land Surface Model* [10]. The choice of grid spacing at 3.6 km, 1.2 km and 240 m takes into account both the constraint of the ratio 1:3 or 1:5 imposed by the WRF model between parent and child domains, and the need to avoid the range between 1 km and a few hundred meters, defined as "terra incognita". This range of lengths is indeed comparable to those of the most energetic turbulent eddies, which are not accurately resolved by either the microscale LES formulation or the mesoscale 1D PBL scheme.

2.3. ANN configuration and training

2.3.1 Definition of the ANN input/output

The basic idea for building the training database was to use the WRF fields at 1.2 km grid spacing as input and the WRF fields at 240 m as output. However, there are small differences in the meteorological fields in the overlapping areas of the two domains that go beyond the different grid spacing and do not allow using the fields on the two domains as input and output. To overcome this limit, the fields at 1.2 km were simulated starting from those at 240 m, degrading their resolution and sampling them on the grid points of the domain at 1.2 km. More in detail, the 240 m input fields were convolved via an iterative procedure with a two-dimensional Gaussian kernel with axial symmetry, testing many Full Width at Half Maximum (FWHM). For each iteration, the resulting blurred and sampled field was compared with the original field at 1.2 km, analyzing the spatial frequency by Fourier transform, and finally choosing the FWHM that minimizes the mean squared difference (MSD). Once the fields were built using this procedure, the following inputs were preliminarily considered: *(i)* the values of the field to be downscaled in a (5x5) pixel box at 1.2 km, *(ii)* the values of the remaining fields in a (3x3) pixel box at 1.2 km, and *(iii)* the values in a (7x7) pixel box at 240 m of the static surface data related to altitude, three angles necessary to define orientation of the unit vector normal to the surface, and surface roughness. *Principal Component Analysis* (PCA) was then applied to each input/output variable to eliminate the less significant ones. Using the 12 WRF simulations, two databases consisting of 10^5 and 10^6 input/output pairs, or training patterns, were created. The smallest database was used with the *Resilient Backpropagation* algorithm for the preliminary operations of architecture definition and input selection, while the largest database was used for the final ANN training using the *Levenberg-Marquardt* algorithm. Both databases were divided into three datasets in a 60:20:20 ratio: *(i)* the *Training* dataset for the training operations, *(ii)* the *Validation* dataset for the tuning and optimization procedures, *(iii)* the *Test* dataset for performance assessment.

2.3.2. Definition of the ANN architectures

Although only one hidden layer would have been sufficient for the algorithm development, with linear transfer function for the output layer and tangent hyperbolic for the other ones, two hidden layers were preferred [11-13]. To define the number of neurons in each hidden layer, an iterative procedure was adopted. Starting with a single node in both hidden layers, for each iteration two different ANNs were configured adding a new neuron separately to the 1st and 2nd hidden layer, and subsequently trained and compared to each other in terms of *Mean Square Error* (MSE) calculated on the *Validation* dataset. The most performing ANN was chosen and the iterations repeated until the addition of further neurons no longer leads to a significant reduction in MSE.

2.3.3 ANN input reduction

Input selection is generally an important task in machine learning because it mitigates the risk of overfitting and reduces the computational cost of training [14]. To this aim, an iterative procedure was adopted to evaluate the importance of all inputs. In the first iteration each input was removed one-by-one, the resulting ANN was consequently updated and its performances evaluated in terms of MSE on the Validation dataset. The input whose removal produced the lowest error was definitely removed and the procedure moved on to the next iteration. The process ended once the MSE exceeded its minimum value with a tolerance of 5%. Over half of the 250

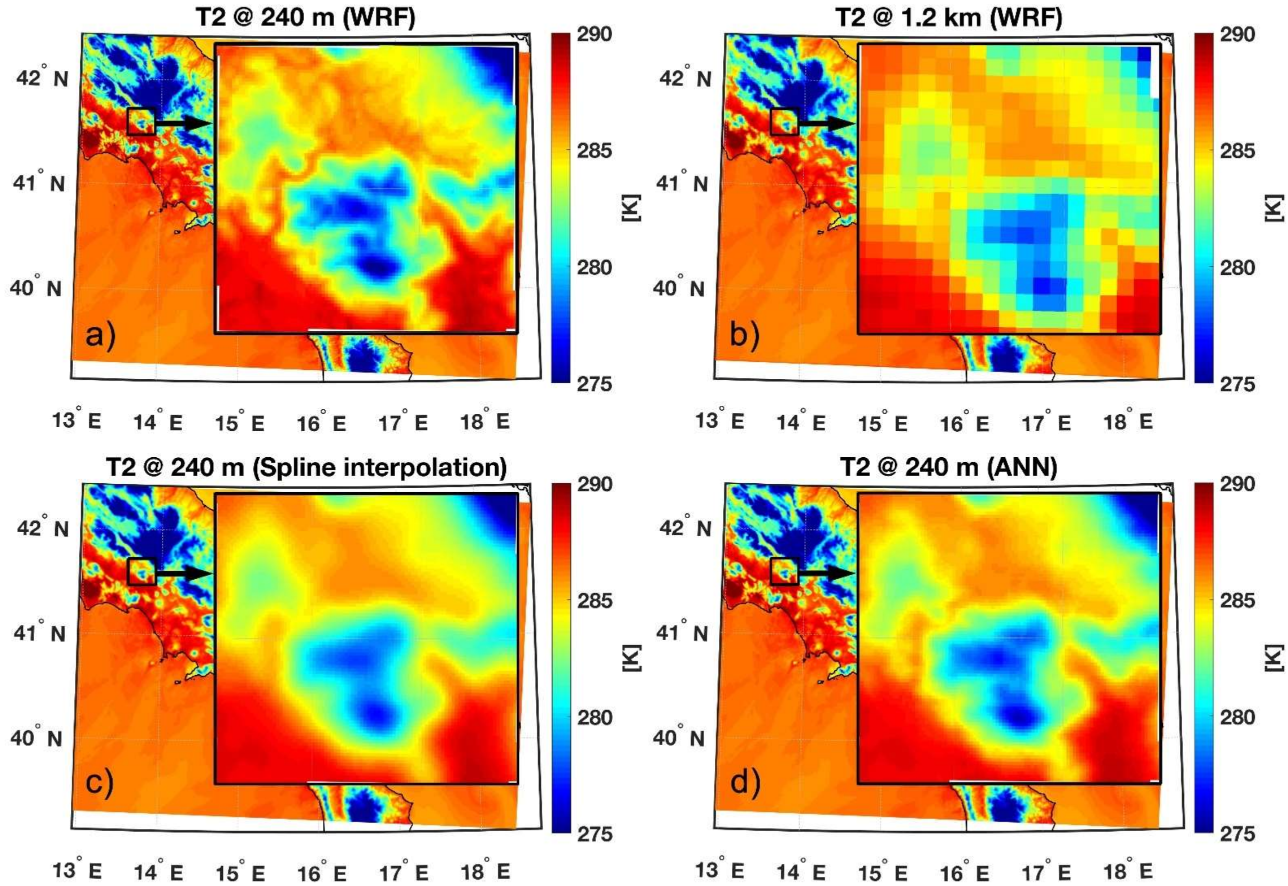

Figure 1 - Temperature at 2 m above the ground for 15/03/2017, 12:00 UTC - (a) WRF-LES at 240 m; (b) WRF-LES at 1.2 km; (c) Spline cubic interpolation at 240 m; (d) ANN-based algorithm at 240 m-

inputs initially considered were removed using this procedure. For each input removal, the weights of the resulting ANN were updated using the approach suggested in Castellano and Fanelli [15], based on the *Conjugate Gradient* method [16], thereby reducing the computational costs that would have otherwise been excessive.

2.3.3 Final training of the ANNs

Using the architectures and inputs selected as described in the previous sections, the ANNs were trained in their final version using the Levenberg-Marquardt algorithm with the largest database of 10^6 training patterns.

3. RESULTS AND DISCUSSION

Generally, the accuracy of the NWP models is closely related to a wide variety of configurations, parameters, and physical options, such as the number, extent, and resolution of the different domains and their nesting options, the surface model, initial and boundary conditions, and the parameterizations and schemes adopted for microphysics, convection, planetary boundary layer and radiation. For this reason, the performance of the proposed algorithm cannot be assessed by comparing the downscaling results with a different source of validation data, as usually done, because both the algorithm and the WRF model would be evaluated together without distinguishing their individual contribution. To overcome this limitation, downscaling results were compared with those obtained using common spatial interpolation methods such as nearest, linear, cubic, piecewise cubic [17], modified Akima piecewise cubic Hermite [18], and cubic spline [19]. Among the different interpolation methods, the cubic ones yield better results, very similar to each other, with a slightly better performance for the spline cubic interpolation, which was then used as a benchmark for a quick comparison with the developed algorithm. Figure 1 shows, as an example, the temperature at 2 m above the ground for a WRF-LES simulation of 15/03/2017, 12:00 UTC, not used for the ANN training, at both 240 m and 1.2 km (panels a and b), and the downscaled fields obtained by using the spline cubic interpolation and the ANN-based algorithm (panels c and d). Each panel also contains a zoom of the same detail, to better evaluate the different spatial resolutions. Table 1 shows the comparison results between the ANN-based algorithm and Spline interpolation, obtained using the independent Test dataset not used for training process. 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 and precipitation, even if the results still showed a 6% improvement compared to the interpolation. The quality of the results probably depends on how close the relationship between the downscaled field and the orography is, and consequently how the corresponding ANN was able to exploit the inputs at 240 m relating to static surface data.

Fields	***RMSE ANN algorithm***	***RMSE Spline interpolation***	***Improvement***
$T2$	$5.79 \cdot 10^{-1}$ K	$6.72 \cdot 10^{-1}$ K	13.8%
$Q2$	$4.47 \cdot 10^{-4}$ kg/kg	$5.15 \cdot 10^{-4}$ kg/kg	13.2%
$PSFC$	12.0 hPa	1.61 hPa	86.6%
SWD	$1.05 \cdot 10^{2}$ W/m^2	$1.12 \cdot 10^{2}$ W/m^2	6.2%
$RAIN$	$2.03 \cdot 10^{-1}$ mm	$2.17 \cdot 10^{-1}$ mm	6.5%
$U10$	$7.32 \cdot 10^{-1}$ m/s	1.15 m/s	36.3%
$V10$	$6.97 \cdot 10^{-1}$ m/s	1.08 m/s	35.5%

Table 1 – Performance comparison between the ANN-based algorithm and Spline interpolation

4. CONCLUSIONS

In this study an ANN-based downscaling algorithm of weather forecasts useful for precision agriculture was proposed. The result is an operation similar to the usual 2-dimensional interpolations but with better performance.

5. ACKNOWLEDGEMENTS

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6. REFERENCES

[1] Sharma, A., Jain, A., Gupta, P., & Chowdary, V. (2020). Machine learning applications for precision agriculture: A comprehensive review. *IEEE Access, 9*, 4843-4873.

[2] Ukhurebor, K. E., Adetunji, C. O., Olugbemi, O. T., Nwankwo, W., Olayinka, A. S., Umezuruike, C., & Hefft, D. I. (2022). Precision agriculture: Weather forecasting for future farming. In *AI, Edge and IoT-Based Smart Agriculture* (pp. 101-121). Academic Press.

[3] Viggiano, M., Busetto, L., Cimini, D., Di Paola, F., Geraldi, E., Ranghetti, L., Ricciardelli, E., & Romano, F. (2019). A new spatial modeling and interpolation approach for high-resolution temperature maps combining reanalysis data and ground measurements. *Agricultural and Forest Meteorology, 276*, 107590.

[4] Rodrigues, E. R., Oliveira, I., Cunha, R., & Netto, M. (2018, October). DeepDownscale: A deep learning strategy for high-resolution weather forecast. In *2018 IEEE 14th International Conference on e-Science (e-Science)* (pp. 415-422). IEEE.

[5] Moeng, C. H., Dudhia, J., Klemp, J., & Sullivan, P. (2007). Examining two-way grid nesting for large eddy simulation of the PBL using the WRF model. *Monthly weather review, 135*(6), 2295-2311.

[6] Hornik, K., M. Tinchcombe & H. White (1989). Multilayer Feedforward Networks are Universal Approximators. Neural Networks, 2, 359-366.

[7] Riedmiller, M., & Braun, H. (1993, March). A direct adaptive method for faster backpropagation learning: The RPROP algorithm. In *IEEE international conference on neural networks* (pp. 586-591).

[8] Levenberg, K. (1944). A method for the solution of certain non-linear problems in least squares. *Quarterly of applied mathematics*, *2*(2), 164-168.

[9] Marquardt, D. W. (1963). An algorithm for least-squares estimation of nonlinear parameters. *Journal of the society for Industrial and Applied Mathematics*, 11(2), 431-441.

[10] Skamarock, W. C., Klemp, J. B., Dudhia, J., Gill, D. O., Liu, Z., Berner, J., Wang, W., Powers, J.G., Duda, M. G., Barker, D. M., Huang, X.Y., (2019). A description of the advanced research WRF model version 4. National Center for Atmospheric Research: Boulder, CO, USA, 145.

[11] Thomas, A. J., Petridis, M., Walters, S. D., Gheytassi, S. M., & Morgan, R. E. (2017). Two hidden layers are usually better than one. In *International Conference on Engineering Applications of Neural Networks*, pp. 279-290

[12] Sanò, P., Panegrossi, G., Casella, D., Marra, A. C., Di Paola, F., & Dietrich, S. (2016). The new Passive microwave Neural network Precipitation Retrieval (PNPR) algorithm for the cross-track scanning ATMS radiometer: Description and verification study over Europe and Africa using GPM and TRMM spaceborne radars. *Atmospheric Measurement Techniques*, *9*(11), 5441-5460.

[13] Hornik, K. (1991). Approximation capabilities of multilayer feedforward networks. *Neural networks*, *4*(2), 251-257.

[14] Di Paola, F., Ricciardelli, E., Cimini, D., Cersosimo, A., Di Paola, A., Gallucci, D., Gentile, S., Geraldi, E., Larosa, S., Nilo, S. T., Ripepi, E., Romano, F., Sanò, P., Viggiano, M. (2018). MiRTaW: an algorithm for atmospheric temperature and water vapor profile estimation from ATMS measurements using a random forests technique. *Remote Sensing, 10*(9), 1398.

[15] G. Castellano, and A. M. Fanelli, "Variable selection using neural-network models", *Neurocomputing*, 31(1-4), pp. 1-13, 2000

[16] Hestenes, M. R., & Stiefel, E. (1952). Methods of conjugate gradients for solving. *Journal of research of the National Bureau of Standards, 49*(6), 409.

[17] F. N. Fritsch, and R. E. Carlson, "Monotone Piecewise Cubic Interpolation", SIAM Journal on Numerical Analysis. 17, pp.238–246, 1980

[18] H. Akima, "A new method of interpolation and smooth curve fitting based on local procedures", Journal of the ACM, 17(4), pp. 589–602, 1970

[19] C. De Boor, A Practical Guide to Splines, Springer-Verlag, New York, 1978.