A Stacked Machine Learning Algorithm for Multi-Step Ahead Prediction of Soil Moisture

Francesco Granata[1*], Fabio Di Nunno[2], Mohammad Najafzadeh[3], Ibrahim Demir[4]

[1] Associate Professor

University of Cassino and Southern Lazio, Department of Civil and Mechanical Engineering, via G. Di Biasio 43, 03043 Cassino, Italy - https://orcid.org/0000-0002-2268-6600, f.granata@unicas.it

[2] Research Fellow

University of Cassino and Southern Lazio, Department of Civil and Mechanical Engineering, via G. Di Biasio 43, 03043 Cassino, Italy - https://orcid.org/0000-0002-8411-574X, fabio.dinunno@unicas.it

[3] Associate Professor

Department of Water Engineering, Faculty of Civil and Surveying Engineering, Graduate University of Advanced Technology, P.O. Box 76315116, Kerman, Iran. https://orcid.org/0000-0002-4100-9699; moha.najafzadeh@gmail.com; m.najafzadeh@kgut.ac.ir

[4] Associate Professor

University of Iowa, Department of Civil and Environmental Engineering, Iowa City, Iowa, United States - https://orcid.org/0000-0002-0461-1242, ibrahim-demir@uiowa.edu

This manuscript is a non-peer reviewed preprint submitted to EarthArXiv. The manuscript has been submitted for publication in HYDROLOGY.

Abstract

A trustworthy assessment of soil moisture content plays a significant role in irrigation planning and in controlling various natural disasters such as floods, landslides, and droughts. Various Machine Learning Models (MLMs) have been used to increase the accuracy of soil moisture content prediction. The present investigation aims to apply MLMs with novel structures for the estimation of daily volumetric soil water content, based on the stacking of the Multilayer Perceptron (MLP), Random Forest (RF), and Support Vector Regression (SVR). Two groups of input variables were considered: the first (Model A) consisted of various meteorological variables (i.e., daily precipitation, air temperature, humidity, and wind speed), and the second (Model B) included only daily precipitation. The Stacked Model (SM) had the best performance (R^2 = 0.962) in the prediction of daily volumetric soil water content for both categories of input variables when compared with the MLP (R^2 = 0.957), RF (R^2 = 0.956), and SVR (R^2 = 0.951) models. Overall, the SM, which in general allows the weaknesses of the individual basic algorithms to be overcome while still maintaining a limited number of parameters and short calculation times, can enhance the precision level of water moisture content more than other well-known MLMs.

Keywords: Machine learning models; Soil moisture content; Stacked Model; Statistical measures.

1. Introduction

Soil moisture is a variable that substantially affects the interactions between the earth's surface and the atmosphere, both in meteorological and climatic aspects (Seneviratne et al. 2010). It plays a fundamental role in rainfall-runoff processes (Sit and Demir, 2019), influencing the division of precipitation into surface runoff, subsurface flow, and infiltration. It also affects the transformation of incoming radiation fluxes to the soil into latent and sensible heat fluxes from the soil to the atmosphere. Soil moisture also strongly impacts the interaction between climate and vegetation in its multiple aspects, primarily the phenomenon of evapotranspiration. Moreover, soil moisture is a major discriminating factor in the type and condition of vegetation in a region. Variations in soil moisture can therefore have a massive impact on agriculture, forestry, and ecosystems.

Soil moisture measurement can be conducted by using in-situ probes (Walker et al. 2004, Demir et al. 2015) or by remote sensing methods (Mohanty et al. 2017). The significant impact on infiltration and runoff phenomena gives soil moisture prediction a key role in flood risk management (Yildirim & Demir 2022) and landslide risk monitoring (Brocca et al. 2017). Furthermore, predicting soil moisture and its changes is essential for predicting the onset of drought and planning irrigation (Soulis et al. 2015), as soil moisture is a critical limiting factor for crop growth.

Traditional soil moisture prediction techniques include empirical formulas, models based on soil water balance, models based on soil water dynamics, and autoregressive moving average models (ARMA). Compared to these traditional methodologies, higher prediction accuracy can be achieved by models based on Artificial Intelligence algorithms, which have found increasingly widespread use in the prediction of hydrological quantities over the past two decades (Kisi 2007, Nourani et al. 2011, Di Nunno & Granata 2020, Xiang & Demir 2020, Granata & Di Nunno 2021, Granata et al. 2022a).

A large number of studies on soil moisture estimation were carried out using various machine learning algorithms: Support Vector Regression (SVR), Artificial Neural Networks (ANNs), Model

Tree (MT), Multivariate Adaptive Regression Spline (MARS), and Adaptive Neurofuzzy Inference System (ANFIS) (Elshorbagy & Parasuraman 2008, Si et al. 2015, Zanetti et al. 2015, Cui et al. 2016, Prasad et al. 2018a, Prasad et al. 2018b, Prasad et al. 2019, Maroufpoor et al. 2019, Achieng 2019, Yuan et al. 2020, Heddam 2021).

Elshorbagy & Parasuraman (2008) employed two types of ANNs, i.e., Multilayer Perceptron (MLP) and the Higher-Order (HO-NN) types, to estimate soil moisture by accumulating field data at three subwatersheds soil covers. They considered precipitation, air temperature, net solar radiation, and soil temperature at various depths for feeding MLP and HO-NN models. They found that HO-NN model had better performance than MLP. Liu et al. (2008) proposed a hybrid ANN – SVR architecture to estimate water content at a study site located in Chongqing, China. The authors noted that the hybrid model clearly outperformed the individual models. Additionally, Ahmad et al. (2010) used SVR to assess soil moisture at 10 sites in the Lower Colorado River Basin. SVR models were trained using 5 years of data. The best results obtained were characterized by correlation coefficients between 0.34 and 0.77, with a root mean square error (RMSE) of less than 2%. Furthermore, the authors made a comparison with the results obtained from models based on ANN and Multiple Linear Regressions (MLR), showing that they were outperformed by SVR.

Si et al. (2015) employed ANFIS, MLP, and the Bayesian Regularization Neural Network (BRNN) in order to estimate soil moisture content at two various depths: 40 and 60 cm. They applied 900 data sets from field measurement in order to develop the AI models. From their results, it was found that ANFIS provided more accurate prediction soil moisture than the BRNN and the MLP models. In addition, Zanetti et al. (2015) employed MLP model to assess soil moisture content while considering various properties of five types of soils such as the apparent dielectric constant, clay and organic matter contents, bulk density and sand, and the silt content. They found that the MLP model with various combinations of input variables, such as organic matter combined with apparent dielectric constant, was particularly effective. Karandish & Simunek (2016) evaluated superiority of ANFIS and SVR with HYDRUS-2D for predicting time dependent-soil moisture content obtained by a physical model under various water stress circumstances over the maize growing time-period of 2010 and 2011. Later, Cui et al. (2016) utilized successfully the MLP-NN using a good many MODIS optical products for soil moisture retrieval and found permissible level of precision. In another study, Prasad et al. (2018b) developed an ensemble Committee Machine (CoM) learning model based on ANN (ANN-CoM) and utilized it to predict monthly soil moisture at upper and lower layer of soil. From their study, statistical results indicated outperformance of the ANN-CoM model in comparison with those yielded by the ELM, RF, and M5Tree.

Moreover, Prasad et al. (2019) found superiority of ELM with ensemble empirical mode decomposition and the Boruta wrapper algorithm (EEMD-Boruta-ELM) over standalone MARS, ELM, and the EEMD-Boruta-MARS models for estimating weekly values of soil moisture content. Cai et al. (2019) found that the Deep Learning NN (DLNN) provided a more accurate prediction of daily soil moisture based on various meteorological factors (e.g., daily precipitation, daily mean surface temperature, average wind speed, average relative humidity, average air pressure, and average temperature) than the MLP model at depths of 10 and 20 cm. Achieng (2019) used successfully SVR model by Gaussian kernel to simulate soil moisture content when compared with SVR models developed by polynomial and linear kernels, MLP, and the DLNN models. In recent years, Yuan et al. (2020) reported permissible level of accuracy when the Generalized Regression NN (GR-NN) was employed in order to estimate the regional surface soil moisture by means of satellite observations as input factors. Adab et al. (2020) used RF, SVR, ANN and Elastic Network (EN) regression to estimate soil moisture from data obtained from Landsat 8 optical and thermal sensors, and knowledge of land use in a semi-arid region of Iran. The best results, characterised by a Nash-Sutcliffe efficiency value of 0.73, were obtained with the RF algorithm. In Heddam's (2021) study, four MLMs (i.e., MT, RF, MARS, and MLP-NN) have been successfully employed to estimate soil moisture content while considering only hourly soil temperature as input variable (obtained from two USGS stations) and compared with Multivariate Linear Regression (MLR) technique.

Therefore, in the current literature, various MLMs indicated promising performance in the estimation of soil moisture content for various conditions of soil physical properties. However, there is a shortage of models for predicting future soil water content (SWC), even in the short term, that are both simple, based on a few easily measurable input variables, and highly accurate. The main objective of this study is to propose a novel ensemble daily SWC prediction model obtained by stacking (Granata et al. 2022b) three individual Machine Learning algorithms: MLP, RF, and SVR. These three standalone algorithms were chosen both because individually they showed good predictive capabilities, and because they have different structures and thus their combination can overcome the weaknesses of each algorithm. Furthermore, these three algorithms, compared with more complex algorithms such as Deep Learning, have the advantage that they depend on few parameters, facilitating training and optimisation operations, and are characterised by significantly shorter calculation times. To the best of the authors' knowledge, there are no applications of stacked algorithms for short-term prediction of SWC in the literature so far. The performance of the stacked model is compared with that of the individual algorithms considering two different scenarios of input variables. The proposed model is trained and tested with data obtained from a measurement site in East Anglia, UK. In addition, changes in model accuracy are statistically analysed as the prediction horizon increases, while remaining within the scope of short-term forecasts.

2. Materials and Methods

2.1. Standalone Machine Learning Algorithms

In this research, MLP, RF, and SVR algorithms were used both individually and combined through stacking. An MLP is a simple feedforward (Rosenblatt 1961, Murtagh 1991) ANN that can approximate any continuous function. An MLP consists of at least three layers of nodes: an input layer, at least one hidden layer, and an output layer. The input layer includes the nodes that acquire the input data. Each node of the hidden layer processes the values of the previous layer using a weighted linear sum, followed by a non-linear activation function. The output layer receives the processed data from the last hidden layer and transforms it into the resulting values. The training of the algorithm is performed using the back-propagation technique. The neural networks employed in this study had only one hidden layer.

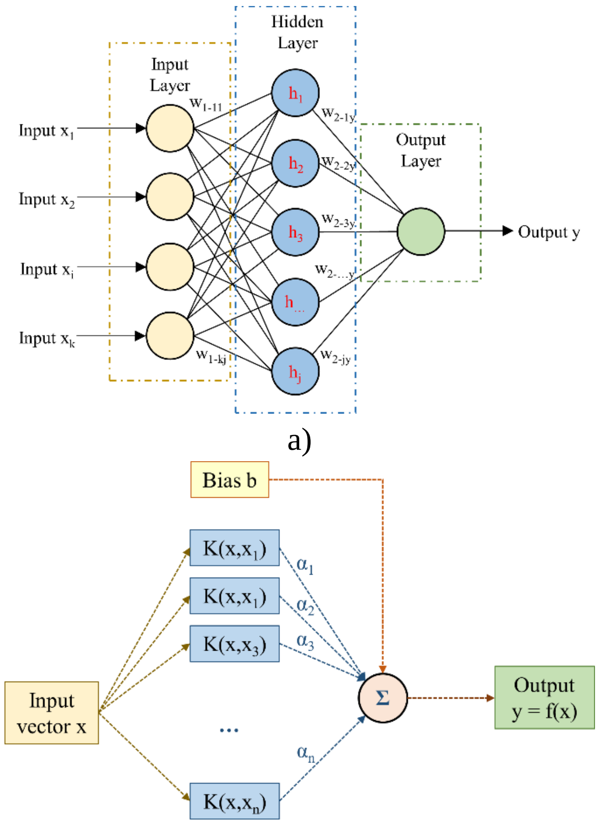
RF (Breiman 2001) is an ensemble prediction algorithm obtained by combining a set of individual regression trees in order to predict a single value of the target variable. In each individual regression tree (Breiman et al. 2017) it is possible to identify a root node, which comprises the training dataset, a number of internal nodes, which define the conditions on the input variables, and leaves, which represent the actual values assigned to the target variables. A tree regression model is developed by recursively dividing the input dataset into subsets, conducted in such a way as to minimise the internal node variance. A multivariable linear regression model provides predictions for each subset. Each tree grows from a different bootstrap of the training dataset. In addition, at each node, only a portion of the variables are randomly chosen with respect to which to split. The number of these variables is kept constant during the growth of the forest. A pruning process significantly reduces the risk of overfitting.

The idea behind the SVR algorithm (Cortes & Vapnik 1995) is to provide an approximation of the true value with a function that is as flat as possible, and that brings the error within a certain threshold, defined by an ε-value. A simple way to understand the SVR algorithm is to imagine a "tube" with an estimated function (hyperplane) as the centre line and boundaries on both sides defined by ε. The goal of the algorithm is to minimise the error by identifying a function that places as many points of the training dataset as possible within the tube, while reducing the "slack". The concept of slack variables is simple: for any value that falls outside ε, its deviation from the margin is denoted as ξ. When these deviations are to be tolerated, the algorithm tends to minimise them as well. Therefore, the deviations ξ are added to the objective function to be minimised in the constrained optimisation problem into which the regression problem turns. The need to ensure a balance between the flatness of the regression function and the tolerated slacks is met by tuning a regularisation parameter C. In SVR, regression is performed in a higher dimension. For this purpose, a function is required that maps the data points in a higher dimension. This function is defined as kernel. In this study, the radial basis function (RBF) was chosen as the kernel $K(x_i, x_j)$:

$$K(x_i, x_j) = \exp\left(-\gamma \left\| x_i - x_j \right\|^2\right), \ \gamma > 0 \tag{1}$$

where x_i, x_j are two input vectors.

Fig. 1 shows a schematic representation of the architectures of the algorithms introduced above.



c)

Figure 1. Architecture of individual algorithms considered in the study: a) Multilayer Perceptron, b) Random Forest, c) Support Vector Regression

2.2. Evaluation Criteria

Four different evaluation criteria were employed to assess the accuracy of the prediction models: coefficient of determination (R^2), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). The R^2 coefficient is an estimation of goodness of fit, taking values in the range [0, 1]. The more accurate a model's predictions are, the closer its R^2 will be to 1. It is defined as:

$$R^2 = \left(1 - \frac{\sum_t \left(f_t - y_t \right)^2}{\sum_t \left(y_a - y_t \right)^2} \right) \quad (2)$$

where f_t is the predicted value at time t, y_t is the measured value at time t, and y_a is the averaged value of the measured data.

The RMSE is the standard deviation of the prediction errors, the so-called residuals, which measure the distance of the experimental points from the regression line. In practice, the RMSE quantifies the dispersion of the data around the line of best fit. It is evaluated as:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_t \left(f_t - y_t \right)^2}{N}} \quad (3)$$

in which N is the total number of predicted values in the time series.

The MAE estimates the average size of errors in the forecasts as a whole, without taking their direction into account:

$$\mathrm{MAE} = \frac{\sum_t \left| f_t - y_t \right|}{N} \quad (4)$$

The mean absolute percentage error (MAPE) evaluates the average of the absolute percentage errors of the prediction model. For the purpose of calculating MAPE, percentage errors are considered without taking the sign into account:

$$\mathrm{MAPE} = \frac{100}{N} \sum_t \left| \frac{y_t - f_t}{y_t} \right| \quad (5)$$

2.3. Stacked Model Development

Stacking is an ensemble machine learning procedure that combines a number of classification or regression models through a metaclassifier. Stacking can exploit the capabilities of several well-performing models on a regression task in order to outperform standalone models in achieving predictions. The individual regression models are developed on the basis of the entire training data set, then a metaclassifier is applied on the basis of the outputs (meta-features) of the individual models. The Elastic Net (EN) algorithm was selected as the meta-classifier to develop the stacked prediction models. EN algorithm (Zou & Hastie 2005) is a combination of the two most commonly used regularised variants of linear regression: the Least Absolute Shrinkage and Selection Operator (LASSO) method and the Ridge method. The LASSO method selects the most explanatory variables by introducing an absolute penalty in the ordinary least squares (OLS) regression. Ridge regularisation also introduces a penalty in the OLS formulation by penalising square weights instead of absolute weights. Thus, large weights are penalised significantly, and many small weights are distributed over the feature spectrum.

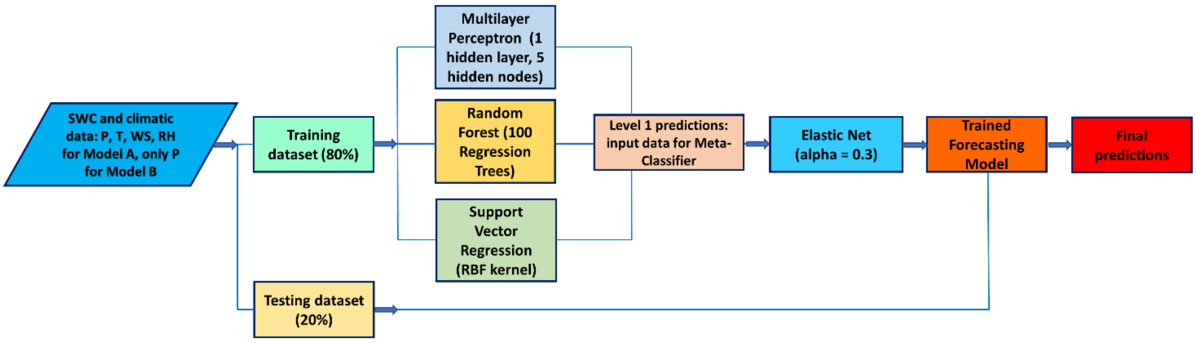


Figure 2. Flowchart of the Stacked model implementation

Two prediction models, differing in input variables, were developed in this study. Each model was developed in four variants, each based on one of the different ML algorithms introduced before, namely MLP, RF, SVR and the combination by stacking of the previous ones. Model A includes the following exogenous input variables: cumulative daily precipitation (P), average daily air temperature T, average daily wind speed (WS), and average daily relative humidity (RH). On the other hand, Model B only includes cumulative daily precipitation P as an exogenous input. In addition, both models include lagged values of SWC as input variables.

The optimal number of lagged values of SWC, as well as the optimal values of the hyperparameters of the individual ML algorithms, were chosen by means of a grid search optimisation procedure aimed at minimising the RMSE of individual forecasting algorithms. It was found that in the case study investigated, the optimal number of lagged values of SWC to be considered as input is 7. In addition, the main hyper-parameters of the forecast models are shown in Table 1. Therefore, based on the optimisation process, the following input and output values can be indicated for the two forecast models:

- Model A – input: SWC_{t-6}, SWC_{t-5}, …, SWC_t, P_t, T_t, WS_t, RH_t; output: SWC_{t+1}, SWC_{t+2}, SWC_{t+3}
- Model B – input: SWC_{t-6}, SWC_{t-5}, …, SWC_t, P_t; output: SWC_{t+1}, SWC_{t+2}, SWC_{t+3}

where subscripts indicate the number of the day. The generic variable was normalized according to the equation:

$$x_{Ni} = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \tag{6}$$

The training of each model was carried out using 80% of the time series data, while testing was conducted on the remaining 20%. This division allowed the most accurate results to be obtained.

Table 1. Main hyperparameters of the forecasting algorithms.

Algorithm	Hyperparameter	Value
MLP	Number of hidden layers	1
	Number of hidden neurons	5
	Activation function	Sigmoid
RF	Number of trees	100
SVR	Kernel function	RBF
	C	2
	ε	0.01
EN	α	0.3

2.4. Case Study

The data used in this study were provided by the COSMOS-UK network of the UK Centre for Ecology & Hydrology. Specifically, data were obtained from the COSMOS-UK site in Fincham (https://cosmos.ceh.ac.uk/data), East England (Fig. 3). The Fincham site is located in a large flat field planted with winter wheat, oilseed rape and sugar beet in a 6-year rotation. The soil type is a chalky loam, a calcareous mineral soil. Like the other sites in the network, the Fincham site is equipped with an instrument that uses cosmic rays to measure soil moisture. More details on the measurement technique can be found in Zreda et al. (2008), Desilets et al. (2010), and Andreasen et al. (2016). Experimental data are related to volumetric SWC (%) = (volume of water/volume of soil) × 100. The time series of daily hydrological variables of interest analysed (soil water content, cumulative rainfall, average air temperature, average wind speed, average relative air humidity) include data collected from 22/06/2017 to 31/12/2019. Figure 4 shows the time series of cumulative daily rainfall and SWC during the period under investigation, while Table 2 shows the essential statistical parameters of the SWC time series and climate variables of interest, excluding rainfall.

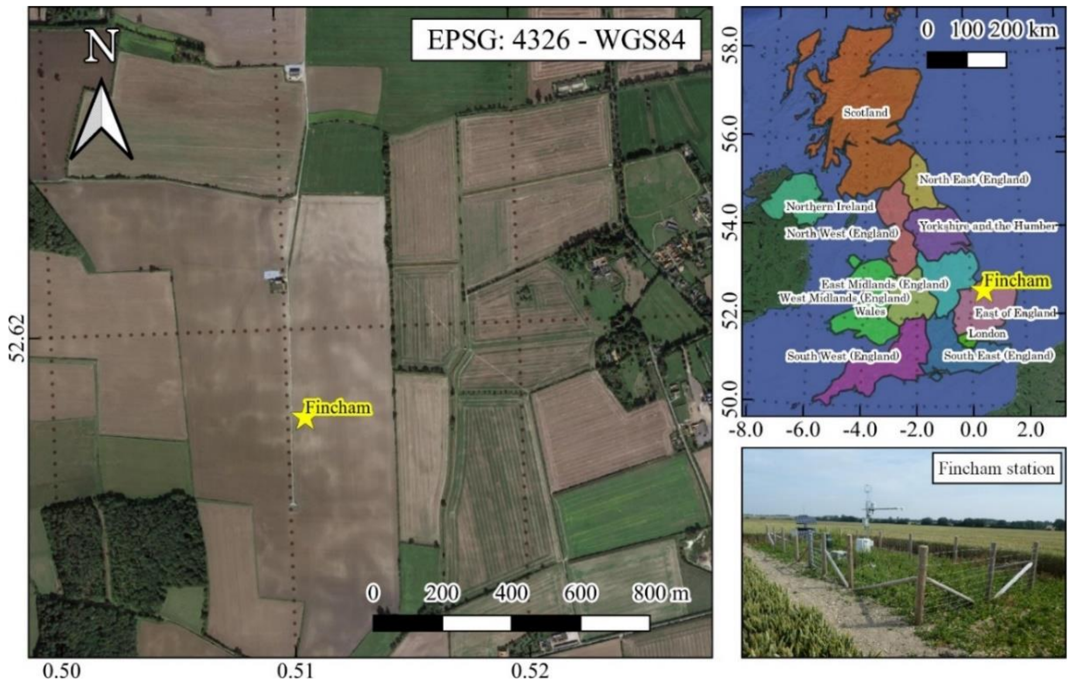


Figure 3. Case study location at the Fincham measurement site

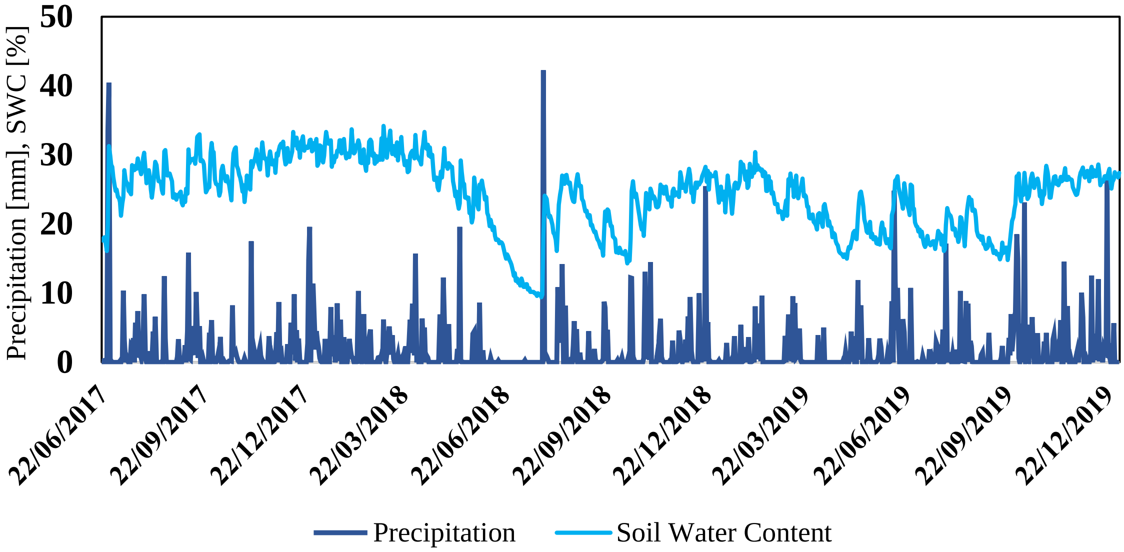


Figure 4. Time series of cumulative daily rainfall and SWC during the period under investigation

Table 2. Essential time series characteristics of measured SWC and other climatic variables

	SWC [%]	Air Temp. [°C]	Wind Speed [m/s]	Rel. Hum. [%]
Mean	24.18	11.06	3.28	80.12
Median	25.00	11.12	3.03	81.43
Max	34.20	27.36	8.52	99.62
Min	9.40	-4.82	0.67	53.36
St. Deviation	5.16	5.54	1.42	9.50
CV	0.21	0.50	0.43	0.12
1st Quartile	20.55	6.79	2.20	73.00
3rd Quartile	27.90	15.50	4.14	87.82
Skewness	-0.57	0.00	0.88	-0.31

3. Results

Table 3 shows the values of the evaluation metrics for the prediction model A with reference to the 1 day-ahead, 2 days-ahead and 3 days-ahead SWC. The table shows the metrics for both the training and testing phase, for each of the individual algorithms and for the SM.

With reference to the 1-day ahead forecast, in the testing phase the three standalone algorithms showed roughly equivalent accuracies, with R^2 varying between 0.957 (MLP) and 0.951 (SVR), while MAPE varies between 3.35% (SVR) and 3.62% (RF). The SM outperformed all other forecasting algorithms, being characterised by a higher R^2 of 0.961 and smaller errors, with MAPE of 3.05%. It should be noted that the metrics values for the testing phase were absolutely comparable to those for the training phase. The only algorithm for which there was a perceptible difference between the two phases was RF.

Table 3. Model A evaluation metrics

			MLP	RF	SVR	Stacked Model
Model A (Training)	1 day-ahead	R^2	0.957	0.992	0.942	0.968
		RMSE	1.092	0.49	1.267	0.937
		MAE	0.816	0.356	0.911	0.694
		MAPE	3.36%	1.49%	3.73%	2.85%
	2 days-ahead	R^2	0.940	0.985	0.912	0.953
		RMSE	1.285	0.663	1.569	1.137
		MAE	1.009	0.469	1.139	0.861
		MAPE	4.22%	1.94%	4.68%	3.56%
	3 days-ahead	R^2	0.928	0.977	0.891	0.941
		RMSE	1.406	0.829	1.752	1.276
		MAE	1.101	0.571	1.266	0.959
		MAPE	4.66%	2.36%	5.24%	3.99%
Model A (Testing)	1 day-ahead	R^2	0.957	0.956	0.951	0.962
		RMSE	0.924	0.985	0.996	0.877
		MAE	0.741	0.787	0.744	0.673
		MAPE	3.41%	3.62%	3.35%	3.05%
	2 days-ahead	R^2	0.940	0.938	0.927	0.946
		RMSE	1.146	1.217	1.264	1.053
		MAE	0.942	0.990	0.945	0.821
		MAPE	4.40%	4.59%	4.27%	3.74%
	3 days-ahead	R^2	0.921	0.929	0.911	0.935
		RMSE	1.355	1.360	1.442	1.169
		MAE	1.105	1.113	1.069	0.921
		MAPE	5.25%	5.22%	4.83%	4.22%

Figure 5 shows the scatter plots of the predicted SWC values versus the measured values. The plots show the excellent performance of all forecast models, with the points lying along the line of perfect agreement. With reference to the Stacked model for the 1-day-ahead forecast, Fig. 6a shows the time series of the predicted and measured SWC, while Fig. 6b shows the relative error in the same time series. The relative error is defined as the absolute error in the forecast divided by the actual value of the SWC. The SM could accurately reproduce both SWC peak values and value fluctuations. Moreover, the relative error was almost always in the range -5%, +5%, and in a few cases approached ±10%.

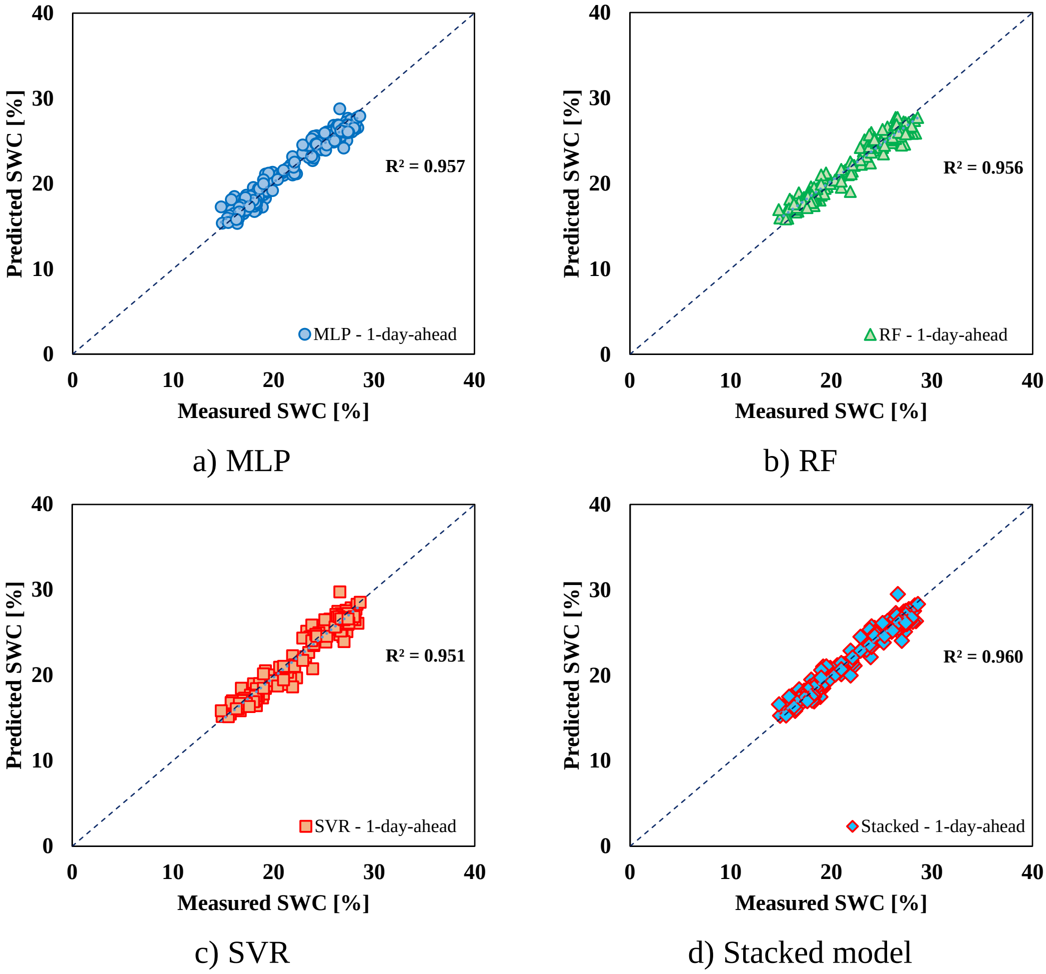
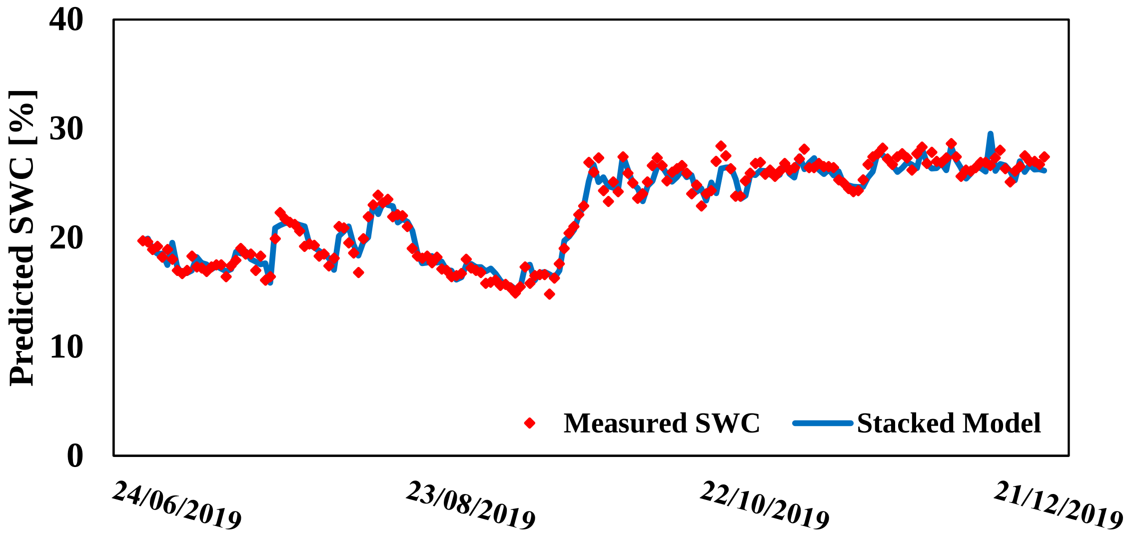


Figure 5. Predicted versus measured SWC, 1-day-ahead predictions, model A.



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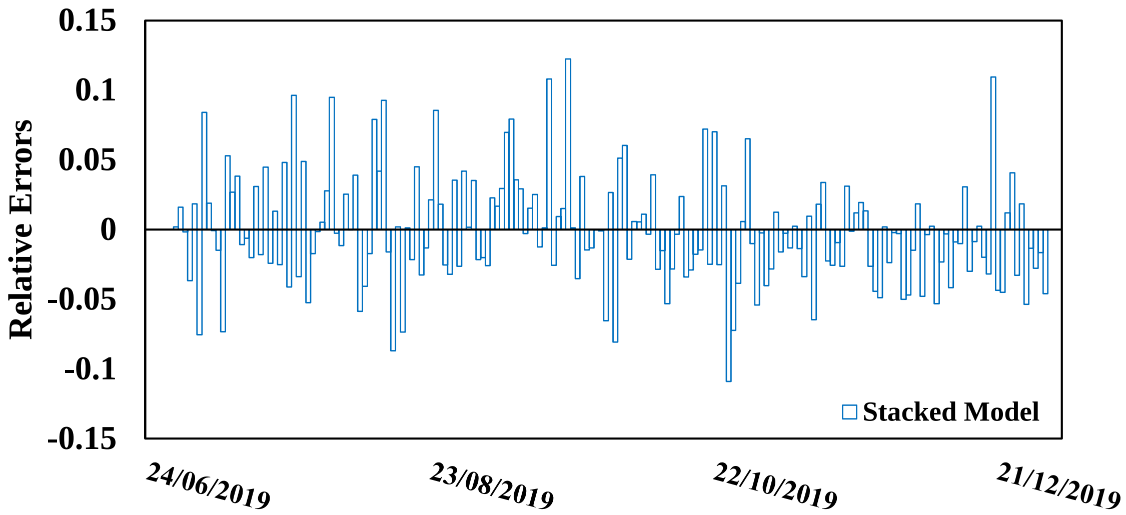


b)

Figure 6. a) stacked model time series (Model A), b) relative errors for each point in the time series

Table 4. Model B evaluation metrics for MLP, RF, SVR and Stacked Model

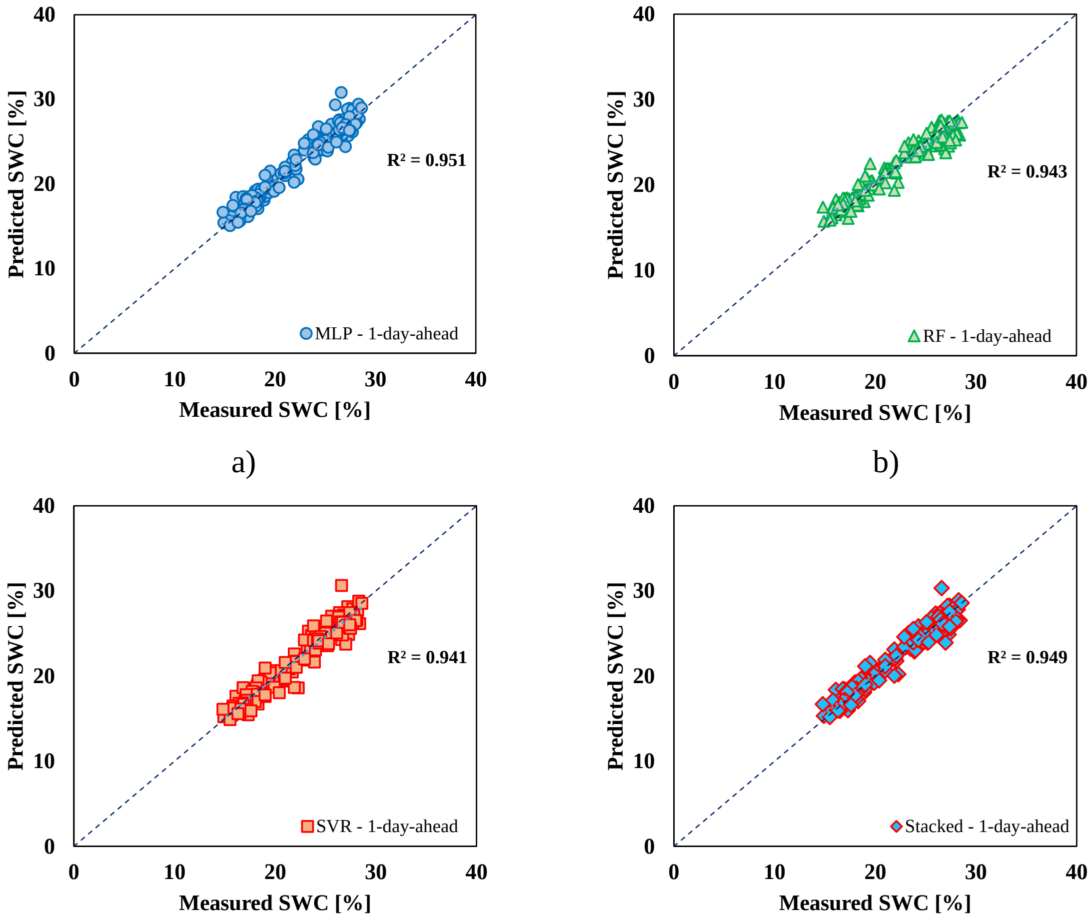
			MLP	RF	SVR	Stacked Model
Model B (Training)	1 day-ahead	R^2	0.946	0.990	0.934	0.965
		RMSE	1.222	0.533	1.365	0.989
		MAE	0.914	0.394	0.979	0.737
		MAPE	3.72%	1.62%	3.94%	3.02%
	2 days-ahead	R^2	0.919	0.976	0.892	0.943
		RMSE	1.495	0.835	1.749	1.258
		MAE	1.161	0.586	1.274	0.964
		MAPE	4.77%	2.38%	5.13%	3.98%
	3 days-ahead	R^2	0.900	0.960	0.863	0.925
		RMSE	1.658	1.073	1.989	1.441
		MAE	1.286	0.745	1.479	1.109
		MAPE	5.32%	3.01%	5.98%	4.62%
Model B (Testing)	1 day-ahead	R^2	0.951	0.943	0.941	0.949
		RMSE	0.982	1.145	1.069	0.976
		MAE	0.745	0.937	0.810	0.751
		MAPE	3.42%	4.28%	3.64%	3.39%
	2 days-ahead	R^2	0.928	0.916	0.907	0.924
		RMSE	1.249	1.456	1.381	1.224
		MAE	0.964	1.198	1.028	0.973
		MAPE	4.48%	5.53%	4.59%	4.45%
	3 days-ahead	R^2	0.903	0.896	0.880	0.902
		RMSE	1.513	1.667	1.606	1.411
		MAE	1.185	1.381	1.193	1.144
		MAPE	5.56%	6.43%	5.32%	5.29%

Considering the 2-day-ahead forecasts, it can be seen that all variants of Model A underwent a very slight reduction in accuracy, but the forecasts were still very good. With regard to the SM metrics, for example, it can be observed that R^2 decreased from 0.962 to 0.946, RMSE increased from 0.877 to 1.053, MAE increased from 0.673 to 0.821, and MAPE increased from 3.05% to 3.74%. Again, the Stacked model outperformed the standalone models.

Even with regard to 3-day-ahead forecasts, all variants of Model A showed a further slight decrease in accuracy. Again, the three individual algorithms led to comparable results, while the SM outperformed them all, as proved by the higher R^2 value and lower RMSE, MAE, and MAPE values. Table 4 shows the values of the metrics for the forecast model B with reference to the 1 day-ahead, 2 days-ahead and 3 days-ahead SWC. Again, the table shows the metrics for the training and testing phase, for each of the individual algorithms and for the Stacked model.

With regard to 1-day-ahead forecasts, MLP (R^2 = 0.951, RMSE = 0.982, MAE = 0.745, and MAPE = 3.42%) led to better results in the testing phase than RF and SVR. The SM (R^2 = 0.949, RMSE = 0.976, MAE = 0.751, MAPE = 3.39%) led to results practically equivalent to those obtained with MLP. The ensemble model in this case did not lead to better results than the most accurate standalone algorithm. Furthermore, the predictions provided by model B were slightly less accurate than the corresponding ones provided by model A, with the exception of the MLP algorithm, for which negligible differences were observed.

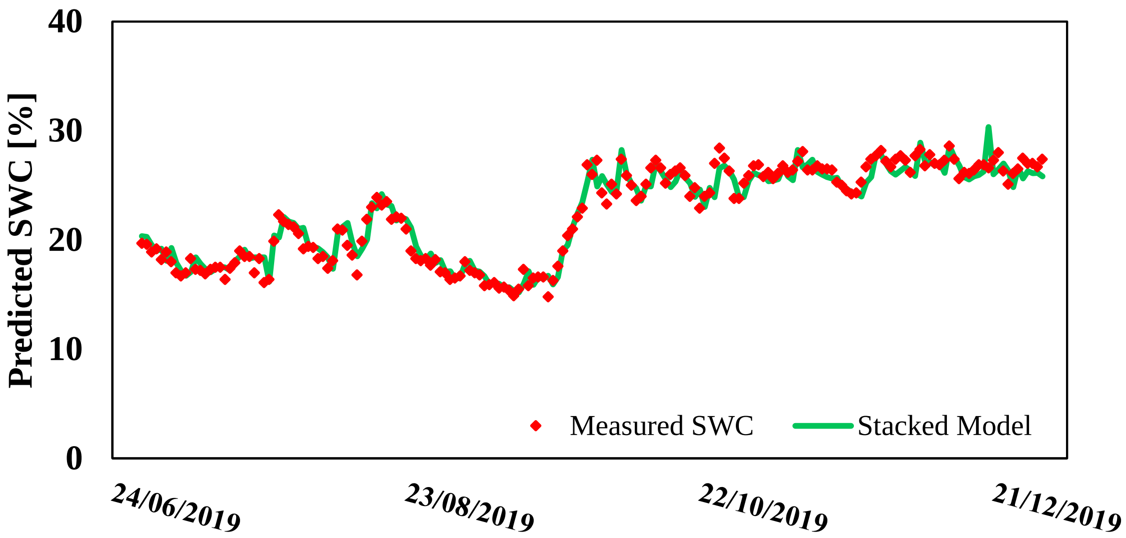
Figure 7 shows the scatter plots of the predicted SWC values compared to the measured values for model B. Again, the regular arrangement of the points along the line of perfect agreement can be seen, with small deviations.



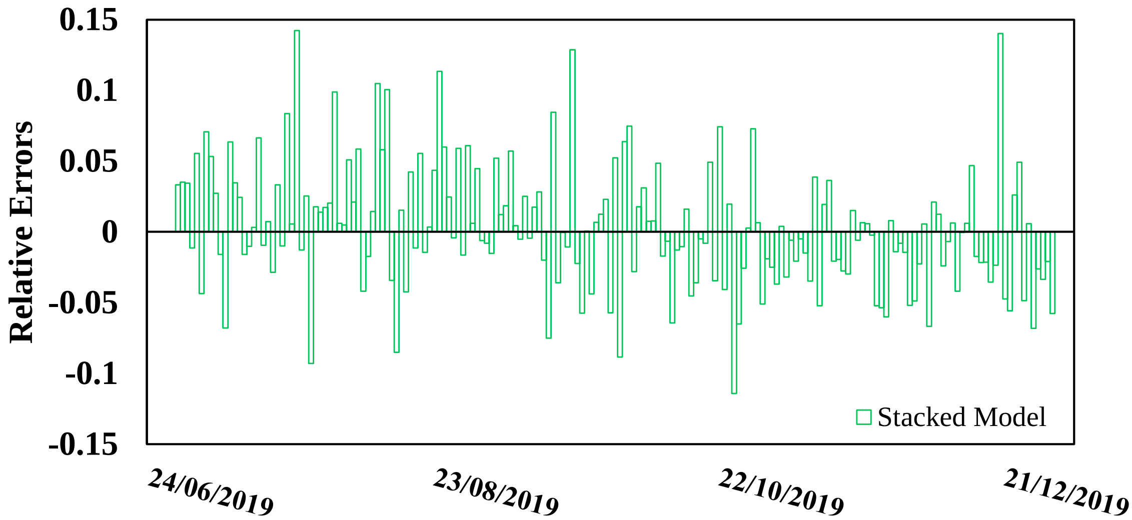
c) d)

Figure 7. Predicted versus measured SWC, 1-day-ahead predictions, model B.

Referring to the SM for the 1-day-ahead prediction, Fig. 8a shows the time series of the predicted and measured SWC, while Figure 8b shows the relative error in the same time series, in the case of model B. Again, the SM was able to accurately reproduce both the peak values of the SWC and the value fluctuations. Moreover, the relative error, although again almost always in the range of -5%, +5%, in some cases exceeded ±10%, even approaching 15%.



a)



b)

Figure 8. a) Stacked model time series (Model B), b) relative errors for each point in the time series

Focusing on the 2-day-ahead forecasts, it can be seen that, even for model B, all variants suffered a reduction in accuracy. Furthermore, all variants underperformed the corresponding variants of model A. However, the forecasts were still satisfactory. MLP (R^2 = 0.928, RMSE = 1.249, MAE = 0.964, MAPE = 4.48%) and the SM (R^2 = 0.924, RMSE = 1.224, MAE = 0.973, MAPE = 4.45%) again led to the best results. Finally, 3-day-ahead forecasts showed a further reduction in accuracy. The SM provided the best results, and its metrics took the following values: R^2 = 0.902, RMSE =

1.411, MAE = 1.144, MAPE = 5.29%. The forecasts were still very good, even though all model B variants underperformed the corresponding model A variants.

4. Discussion

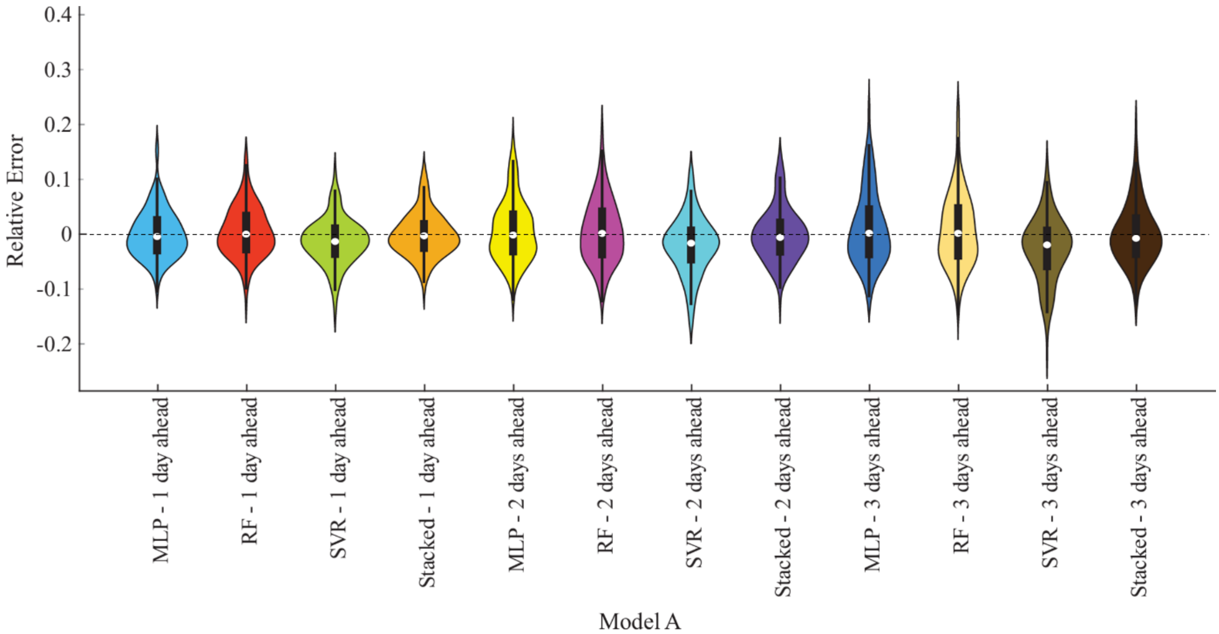
The results shown above demonstrated that both model A and model B are able to provide satisfactory predictions of short-term SWC. Model A proved to be more accurate. The presence of air temperature, relative humidity and wind speed among the input data allows for the consideration of evapotranspiration, which depends on the aforementioned climatic variables and in most cases is the main outflow of moisture from the soil. However, even the availability of daily cumulative rainfall data as the only exogenous variable allowed for accurate short-term SWC forecasts.

The SM generally outperformed the standalone models. In some cases, for model B, it provided comparable performance to the most accurate individual algorithm. It seems that the SM performs significantly better than the individual models from which it is combined if the number of input variables is increased. This statement, however, needs further investigation.

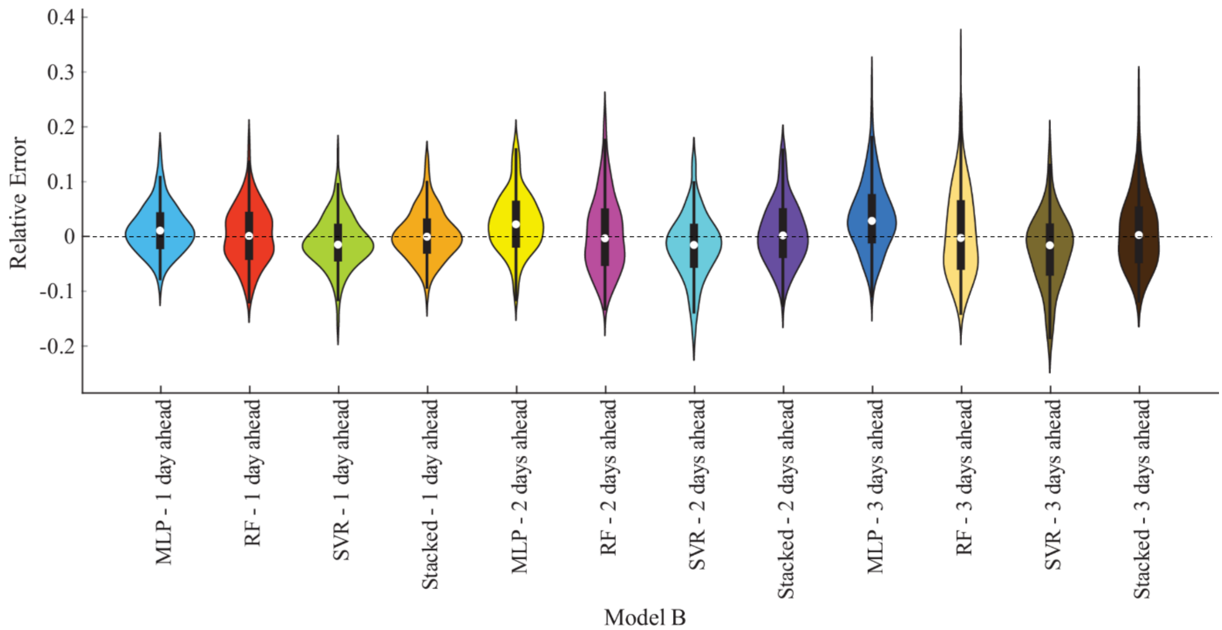
Further insight into the accuracy of the different prediction models can be pursued by analyzing the violin plots in Figure 9, which show the relative error distributions of all variants of model A and model B, for the three forecast horizons considered. The same violin plots also include the corresponding box plots. The following insights can be deduced from these plots:

a) In the case of model A, only the SVR-based variant was characterised by an appreciable bias, whereas in the case of model B, an appreciable bias could be found in both the MLP- and SVR-based variants.
b) The distribution of the relative error in both models was asymmetrical in many cases.
c) The error distribution tended to become flatter as the forecast horizon increased, and the IQR of the relative error expanded as the forecast horizon increased.
d) The number of outliers resulting from forecasting models was very low.

This additional information provided by the violin plots enhanced the understanding of the results described above in terms of metrics.



a)



b)

Figure 9. Violin plots of relative errors in a) Model A, b) Model B

The lack of benchmark datasets (Demir et al. 2022) and closely comparable studies prevents direct comparisons of the results. There are also very few studies focused on soil moisture that use stacking algorithms for purposes other than forecasting. A recent study by Das et al. (2022) aimed to map soil surface moisture with a spatial resolution of 30 m in a semi-arid region using optical, thermal, and microwave remote sensing data, and applying machine learning techniques such as bagging, boosting, and stacking. The authors found that the stacking of the cubist, gradient boosting machine (GBM), and RF algorithms led to better results than the individual algorithms, in agreement with the findings of this study.

Other recent studies on SWC forecasting are based on the use of hybrid models. In terms of quantitative comparisons, the statistical measures provided by Models A and B showed that an improved MLM (i.e., the Stacked Model) outperformed MLP. This finding was evident in the comparison with Ahmad et al. (2010) (R^2=0.2601 and 0.1764 for SVM and ANN, respectively). In the investigation by Ahmad et al. (2010), the main limitations were that the input variables were obtained through satellite images, producing a high degree of uncertainty in the angle of incidence from the Tropical Rainfall Measuring Mission (TRMM), and in the Normalized Difference Vegetation Index (NDVI) from the Advanced Very High-Resolution Radiometer (AVHRR).

The performance of the ML models considered in this study is slightly better than that seen in Si et al. (2015), who used ANN-Bayesian Regularization (R^2=0.929) and ANN-Levenberg-Marquardt [ANN-LM] (R^2=0.932). It can be noted that the general structures of some ML models used here (i.e., RF, SVM, and Stacked Model) are more complex than those applied in the research of Si et al. (2015). Prasad et al. (2018a) developed Extreme Learning Machine (ELM)-based models for the prediction of monthly soil moisture, hybridized with the complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) and the empirical ensemble mode decomposition (EEMD) algorithm, to address the problems associated with non-stationarity in the data. Also, in the study by Prasad et al. (2018a), hybrid models showed very high accuracy and outperformed standalone algorithms, in this case ELM and RF, as in the present study. Additionally, Prasad et al. (2019) developed the ELM (R^2=0.702), EEMD-Boruta (R^2=0.785) and MARS (R^2=0.712) models that have had rather lower accuracy than the present research due to a large number of field measurements with high uncertainty in the input variables (e.g., weekly values of temperature, runoff volume, evaporation, and heat flux).

Moreover, Cie et al. (2019) provided soil moisture content predictions by Deep Neural Network Regression (DNNR) with satisfying a degree of accuracy (R^2=0.98) as well as in the present research. Their success in the evaluation of soil moisture was due to considering a variety of input variables, such as average temperature, average pressure, relative humidity, wind speed, land temperature, daily precipitation, and initial soil moisture. Maroufpoor et al. (2019) proposed a hybrid model based on the adaptive neurofuzzy inference system (ANFIS) and grey wolf optimization (GWO) algorithms, which was then compared with ANN, SVR, and standalone ANFIS. The input parameters of the model were the dielectric constant, bulk soil density, clay content, and organic matter of 1155 soil samples. The ANFIS-GWO model proved to be the most accurate, followed by the standalone ANFIS and SVR models, while the worst accuracy was found in the ANN model, in contrast to what was observed in the present research, where MLP outperformed SVR. The different choice of input variables justifies this result, as this aspect is fundamental to the performance of forecasting models.

Furthermore, the performance of the present ML models was slightly better than that obtained by Heddam's (2021) investigation (R^2=0.925, 0.929, and 0.931 for M5MTree, MARS, and RF, respectively). In addition, the MLP-based model by Heddam (2021) had rather lower accuracy results (R^2=0.885) than those reported in the present research for both Model A and Model B. Heddam (2021) did not refer to the climatic variables that were considered in the present research. In fact, he used the soil temperature, the year number, the month number, and the day number in order to estimate the soil moisture content. His study indicated that climatic variables play a key role in improving the accuracy levels of ML models.

The main limitation of this study is that it considers only one case study. Therefore, the possible influence of different climatic conditions on the forecast models is not taken into account here. It will be interesting, in future developments of this study, to address the prediction problem under climatic conditions characterized by intense evapotranspiration and periods of widely varying rainfall (e.g., tropical climates). It will also be interesting to compare the results provided by the stacked model with those provided by models based on deep learning algorithms, which are known to perform very well in predicting time series (Sit et al. 2020). Finally, the most ambitious goals will be pursued, such as developing models with a more distant forecasting horizon and models dependent only on exogenous climate variables.

5. Conclusions

This study introduced a novel forecast algorithm of daily volumetric soil water content, based on the stacking of the Multilayer Perceptron, Random Forest, and Support Vector algorithms. Two different input variable scenarios were considered, in order to develop two forecast models: model A, which included daily precipitation, air temperature and humidity, and wind speed as exogenous variables, and model B, which instead included only daily precipitation as an exogenous variable.

Both models provided very accurate predictions, with the coefficient of determination R^2 greater than 0.9 and MAPE not exceeding 5% in almost all cases, and with model A generally outperforming model B. In addition, for both models, the Stacked algorithm-based variant generally outperformed the standalone algorithms. Both models experienced a modest reduction in accuracy as the forecast horizon increased, remaining within the range of short-term forecasts. In any case, even a model that only requires precipitation as an exogenous input variable is capable of providing adequate predictions for practical applications.

The proposed stacked model is simple, based on a few parameters, very accurate, and has a very limited computational time. In the context of current research, which shows a marked tendency towards increasingly complex models, the proposed model can be considered an effective tool for facilitating the planning of irrigation activities and supporting flood risk management (Yildirim & Demir 2021).

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