VIRTUAL WEATHER STATIONS FOR METEOROLOGICAL DATA ESTIMATIONS

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ABSTRACT

Meteorological data is an important series of observations for agricultural, energy, scientific, financial applications. The data is generally obtained from automatic weather stations; however, the data can be acquired from Virtual Weather Stations (VWS). A VWS is an integration of algorithms to estimated meteorological data from nearby weather stations real data to other locations with no stations. To develop the VWS, the performances of different interpolation methods were evaluated to test the accuracy. Daily data from an automatic weather station network, such as precipitation, air temperature, air relative humidity, mean wind speed, total solar irradiation, and reference evapotranspiration were used to perform the interpolations. Artificial neural networks with the hardlim, sigmoid, hyperbolic tangent, softsign, and relu activations functions were employed, as well as inverse distance weighting, inverse squared distance weighting, multilinear regression, and random forest regression to interpolate the daily observations. To validate the models, a randomly selected weather station was removed from the daily dataset and the interpolated values were compared with the actual station records. Additionally, interpolations in the summer and winter months were performed to check the capability of the models during periods with more extreme phenomena. The results showed that the interpolation methods have an R^2 up to 0.98 for variables such as temperatures for the period of one year. Meanwhile, during the summer and winter, the models presented lower accuracy. From a practical perspective, the methods here described could be useful to produce meteorological time series data with the VWS.

LIST OF ABBREVIATIONS

ANN	Artificial neural networks
EDA	Exploratory data analysis
ETo	Reference evapotranspiration
FTP	File transfer protocol
IDW	Inverse distance weighted
ISDW	Inverse square distance weighted
MRL	Multiple linear regression
Precip	Precipitation
relu	Rectified linear unit
RF	Random forest regression
RH	Relative humidity
RMSE	Root mean squared error
tanh	Hyperbolic tangent
Temp	Temperature
TSI	Total solar irradiation
VWS	Virtual weather stations

1. INTRODUCTION

Agriculture is one of the most sensitive activities to weather conditions and the climate change have impacts to this sector, from food production to economic problems in agriculture and related industries, making food security a tangible problem in the next few decades (Mason d'Croz et al., 2013; Springmann et al., 2016). More information, research and strategies are needed to minimize the adverse effects of the uncertain scenario. The knowledge of weather conditions helps to make better decisions in crops management; elaborate sowing calendars, pest population models (Naylor et al., 2018) and precision irrigation dosage (Teshome et al., 2018). For instance, irrigated agriculture is the primary water user, accounting for nearly 70% of total water consumption in the world (Conforti, 2011) and that consumption can be reduced using evapotranspiration models that require prior knowledge of meteorological variables such as the proposed by the FAO (Allen et al., 1998)

Meteorological observations are obtained through automatic weather stations, which are increasing throughout the world in the form of station networks (Estévez et al., 2011). Nonetheless, the cost of an automatic weather station still expensive and are not an attractive investment for most farmers. Considering the complex nature of the atmosphere and the massive computational power required to solve all of the equations that describe the atmosphere, the forecasts is also an expensive technique and new manners to obtain metrological information more efficiently and less costly is becoming an interesting matter (Akram and El, 2016).

With new techniques for data processing and analysis, such as artificial neural networks (ANNs), novel methods have been developed for forecasting; precipitations (Hung et al., 2009; Partal et al., 2015) wind speed (Cao et al., 2012), forecasting sea level in coastal areas (de Oliviera et al., 2009; Filippo et al., 2012) and air quality forecasting (Feng et al., 2015; Hrust et al., 2009). ANNs were also used for daily estimation of solar radiation (Amrouche and Le Pivert, 2014; Hasni et al., 2012; Şenkal and Kuleli, 2009) and power generation in wind energy systems (Fan et al., 2009; Olaofe, 2014; Sideratos and Hatziargyriou, 2007) and the estimation of evapotranspiration (Abrishami et al., 2018; Ballesteros et al., 2016; Chowdhury et al., 2017; Cooper, 2010). However, all these studies worked based on measured data, i.e., were driven with previous known meteorological data to use them as the input to create models, there is a lack of studies focused in generate the first data and validate its quality using ANN.

Interpolation is a way to generate data in geographical locations where no data acquired. Although deterministic and parametric statistical models have been the traditional approaches for data interpolation, such as inverse distance weighting, inverse squared distance weighting (Li and Heap, 2011; Lu and Wong, 2008) and multilinear regression (Jin et al., 2016; Nalder and Wein, 1998), there studies with new approach such as random forest (RF) machine learning method (Li et al., 2011; Li and Heap, 2014). Regarding interpolation studies of meteorological variables, methods such as Thiessen polygons, kriging, regressions, nearest neighbor and inverse to distance weighted were employed to mainly interpolate precipitations and temperatures with different levels of accuracy (Berndt and Haberlandt, 2018; Jeffrey et al., 2001; Mendez and Calvo-Valverde, 2016; Wagner et al., 2012; Wu and Li, 2013).

Considering these facts, an ANN approach for data interpolation can be an exciting alternative given its capability in modeling and solving complex non-linear problems (Voyant

et al., 2017). Generating more data and time series in various locations can be the basis for other studies, for instance, pathogen infestation in farms (Tripathy et al., 2011), planning water management (Chowdhury et al., 2017; Valipour, 2016) or check the performance of solar energy based equipment and building in terms of energy consumption, especially for heating and cooling (Kumar et al., 2015; Shu Fan et al., 2009), using good quality interpolated data.

Meteorological data is an essential class of temporal record that can be useful for agricultural, energy, scientific, financial and other applications. Since it is not possible to emplace a weather station in every location where data is needed, a virtual weather station (VWS) can be used as an alternative to acquiring meteorological data. The VWS is an integration of algorithms to estimate meteorological data from nearby weather stations real data to other given location with no stations; the estimations can be done through interpolation methods and meteorological records. Hence, this study was planned with the primary objective of evaluate and compare the accuracy of several interpolation algorithms, ANN approaches and the most used interpolation methods to create the VWS as an option to acquiring accurate data economically and straightforwardly.

The remaining section of this paper is organized as follows: Section 2 explains the methodology of the work, the meteorological data source, processing, the development of the VWS, the interpolations algorithms ANNs, deterministic methods, statistical methods, and random forest regression; and statistical tests. Section 3 illustrates the results of interpolation methods for the VWS along with the relevant discussion. Section 4 concludes the paper and gives suggestions for future work.

2. MATERIALS AND METHODS

2.1 Meteorological dataset

The data was obtained from the InfoRiego metrological station network records of the Agrarian Technological Institute of Castilla y León (Spain), the locations are represented in **Figure 1**. The meteorological records were downloaded from the file transfer protocol (FTP) server available; a Python script automates the download of the data by dates. The registers consisted of daily data summaries registered by 53 meteorological stations distributed throughout the territory of the autonomous community of Castilla y León. The records date from July 1st, 2017 to June 30th, 2018 to compile information for a whole year.
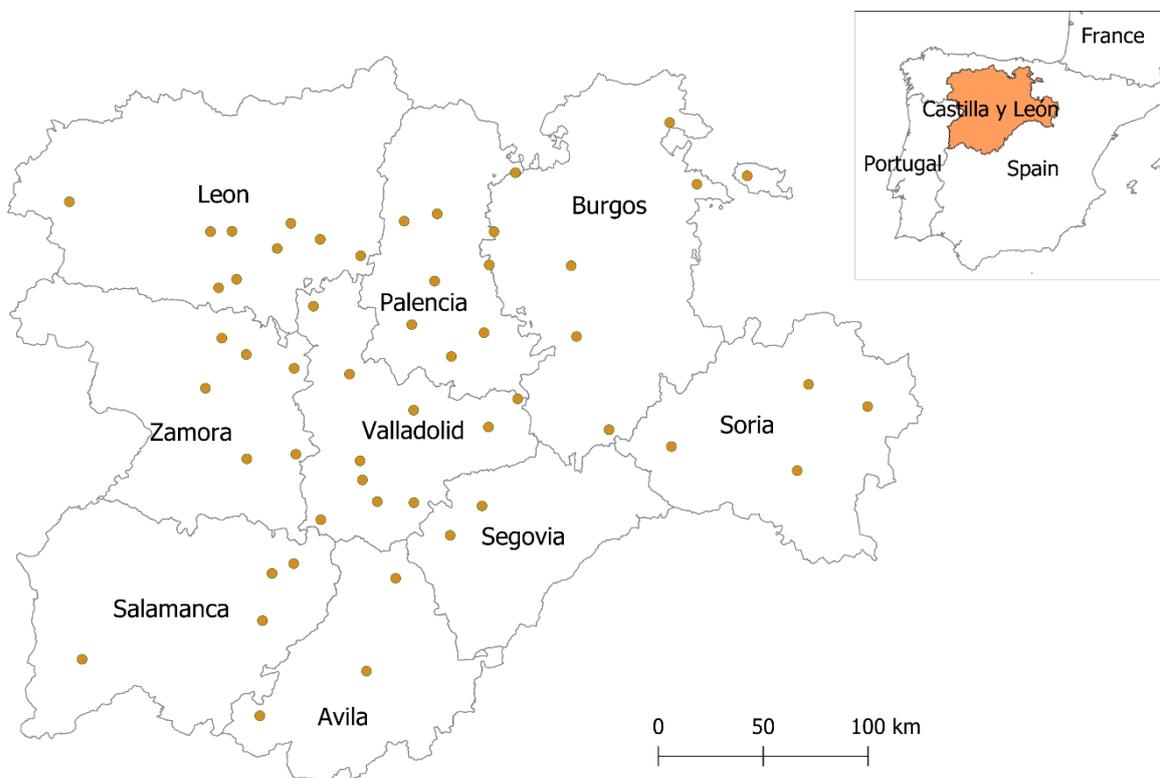

Figure 1. Meteorological station network of the InfoRiego program of the Agrarian Technology Institute of Castilla y León.

The meteorological observation records were grouped into a set of daily precipitation (Precip) in mm of rainfall, reference evapotranspiration (ETo) in mm of water, daily mean air temperature (Mean Temp), maximum registered temperature (Max. Temp) and minimum registered temperature (Min. Temp) in ºC, daily mean air relative humidity (Mean RH), maximum registered air relative humidity (Max. RH) and minimum registered air relative

humidity (Min. RH) in percentage (%), mean wind speed (Mean WS) in m/s and total solar irradiation (TSI) in MJ/m^2 from all the 53 weather stations. Additionally, the UTM X and Y geographical coordinates, in ETRS89 geodetic system, and the Z coordinate of the meteorological stations were added to the dataset to perform the interpolations.

2.2 Dataset statistical analysis

An exploratory data analysis (EDA) was performed to the whole dataset, the weather stations with reading errors and the days with less than 90% of the wheater station in the records were removed to ensure a minimum of observations per day. The dataset resulted in 18,234 sets of observations from 355 days. A statistical summary was generated with the purpose of describing the behavior of the studied meteorological variables in the period from July 2017 to June 2018. In the same manner, data from the summer season months (July, August and September) and from the winter months (December, January and February) were filtrated to analyze the registers in periods with higher peaks phenomena such as high or low temperatures, rainy periods and other meteorological events.

The means of the meteorological events during summer months, winter months and the rest of the year were compared. The Kolmogorov-Smirnov and Levene tests were performed, data normality and equality of variances were discarded according to the tests. The means were compared with non-parametric tests; the Kruskal–Wallis H test to verify differences between groups and the Mann–Whitney U test was used to compare the groups based on the season of occurrence, all statistical analyses were performed in R programing language version 3.4.4.

2.3 Virtual weather station development

The VWS is composed of algorithms capable of getting and processing data from weather station networks and predict the possible meteorological state in a given location. For that, records from the InfoRiego station network were massively downloaded from the FTP server of the ITACYL through a Python script and used to interpolate values of daily Precip (mm), ETo (mm), Mean Temp (ºC), Max. Temp (ºC), Min. Temp (ºC), Mean RH (%), Max. RH (%), Min. RH (%), Mean WS (m/s) and TSI (MJ/m^2).

To evaluate the quality of interpolated data, a randomly selected weather station was daily removed from the dataset and the results of the interpolations were compared with the actual records from the stations. The interpolations method approaches were through ANNs, deterministic and statistical interpolations methods, and random forest regression. All the interpolation algorithms were evaluated with the same validation dataset, the accuracy was measured with the regression coefficient (R^2) between meteorological observations and interpolated values, and the root mean squared error (RMSE). All statistical tests were performed in R programing language version 3.4.4.

2.4 Interpolation methods

For the ANN approach in data interpolation, the performance of 5 ANNs with different activation functions such as hardlim, sigmoid, hyperbolic tangent (tanh), softsign and rectified linear unit (relu) were programmed. The ANNs were multilayer perceptron, fully connected feed-forward neural networks, programmed in Python 3.6.5 language using the TensorFlow 1.8.0 machine learning library. After various attempts, the ANNs structures were set with 2 neurons in the input layer, one neuron for each geographical position coordinate (X and Y); 1 hidden layer with 15 neurons; and 10 neurons in the output layer, one neuron for each meteorological variable to interpolate; using this protocol for modeling, with the XY coordinates is possible to estimate the meteorological observations. The Z geographical coordinate was not used after verifying that its inclusion leads to less accurate results; selecting the appropriate input variables is a crucial step in ANN modeling (López et al., 2005).

The dataset was filtered by day to create a daily re-trained model to each of the 355 days of the study. The daily subset of meteorological observations was divided into a train, test and validation sets; a randomly selected weather station, with its respective set of measurements, was separated for validation and the remaining stations were used in the training and testing phases, with 10% of stations reserved for testing. The ANNs were re-trained and validated for interpolations every day with their respective datasets. The dataset with the XY geographical position and the meteorological observations were normalized to obtain better ANN performance (Gnana Sheela and Deepa, 2013), the Z-score normalization was applied to the dataset (*Eq. 1*), where x is the datum of the variable, $\bar{x}$ is the mean of the variable, σ is the standard deviation and z is the normalized datum.

$$z = \left| \frac{x - \bar{x}}{\sigma} \right|$$

Eq. 1

For the alternative approaches, the following methods were applied; the deterministic methods inverse distance weighted (IDW) **Error! Reference source not found.**and the inverse square distance weighted (ISDW) were performed using the Eq. 2; the statistic method multiple linear regression (MRL); and another machine learning method, the random forest regression (RF) to contrast the ANNs performance. For the RF, the Scikit-Learn machine learning for Python in the version 0.20, the number of trees or estimators were 15, the same train, test and validation datasets used for the ANNs were used for the RF. For the deterministic and statistic methods the train and test sets were used to generate the models, and the validation set remains the same.

$$\hat{v} = \frac{\sum_{i=1}^{n} \left(\frac{v_i}{d^p} \right)}{\sum_{i=1}^{n} \left(\frac{1}{d^p} \right)}$$

Eq. 2

Eq. 2, were v_i is the known value; d^p is the distance to the point to be estimated to the power of $p = 1$ for IDW and $p = 2$ for the ISDW; and $\hat{v}$ is the value to be estimated.

Additionally, all interpolations methods were tested in summer and winter months by separate to check the capability of the models during periods with more extreme phenomena, and the results of the interpolation of the entire year were compared to the results in these two seasons.

3. RESULTS AND DISCUSSION

3.1 Statistical summary of the dataset

The statistical summary of the whole dataset is presented in **Table 1**. During the studied period (from July 2017 to June 2018), 18,234 observations were recorded for the 53 meteorological stations. The maximum registered precipitation was 42.85 mm in a day, with a mean 1.24 mm in all 53 stations. The mean ETo was 2.82 mm, which mean that the overall water balance is negative. Temperatures were 11.01ºC on average, 42.97ºC and -19.75ºC for

maximum and minimum. RH was 71.06 % on average, mean WS was 1.92 m/s^2 and mean TSI was 15.99 MJ/m^2.

Table 1. Statistical summary of meteorological observations dataset (n = 18,234)

Parameter	Range	Min.	Max.	Mean	St. dev.
Precip (mm)	42.85	0.00	42.85	1.24	3.52
ETo (mm)	11.02	0.11	11.13	2.82	1.93
Mean Temp (ºC)	36.96	-8.95	28.01	11.01	7.19
Max. Temp (ºC)	42.97	-2.50	40.47	18.25	8.81
Min. Temp (ºC)	40.50	-19.75	20.75	4.31	6.04
Mean RH (%)	78.74	21.26	100.00	71.06	15.50
Max. RH (%)	63.05	36.95	100.00	92.68	8.55
Min. RH (%)	99.01	0.99	100.00	43.87	20.73
Mean WS (m/s)	17.72	0.01	17.73	1.92	1.22
TSI (MJ/m^2)	33.56	0.46	34.02	15.99	8.44

The mean temperature is similar to the previously described in the same region (del Río et al., 2005), 11.17 ºC for a 37 years dataset (from 1961 to 1997) in comparisons with the 11.01ºC obtained here in the season 2017-2018. Regarding the precipitations, the same authors postulated an average of 664 mm for the same period, the sum of the daily average rainfall was 441.12 mm, less than the minimum of 480 mm registered by the authors in 1996, the driest year. In a study from 1981 to 2010 in Castilla y León, the mean temperature likewise 11ºC (Nafría et al., 2013).

The statistical summary of the meteorological variables during the summer and winter months are presented in **Table 2**. The average precipitation during the winter is more than twice that in summer, 1.29 mm and 0.50 mm respectively, in this location, the summer is the driest season and the rainiest season is autumn or winter, depending on the specific site. (Nafría et al., 2013)

Table 2. Statistical summary of meteorological observations during the summer months (June, July, August) and the winter months (December, January, February)

Parameter	Range	Min.	Max.	Mean	St. dev.
Summer (n = 4,744)					
Precip (mm)	42.85	0.00	42.85	0.50	2.69
ETo (mm)	10.19	0.94	11.13	4.89	1.47
Mean Temp (ºC)	20.76	7.25	28.01	18.98	3.75

Max. Temp (ºC)	26.25	14.22	40.47	27.94	4.56
Min. Temp (ºC)	23.36	-2.61	20.75	10.12	3.63
Mean RH (%)	73.13	22.27	95.40	56.63	12.50
Max. RH (%)	60.96	39.04	100.00	87.58	10.59
Min. RH (%)	86.03	1.17	87.20	26.45	11.61
Mean WS (m/s)	17.34	0.39	17.73	1.79	0.95
TSI (MJ/m^2)	32.01	1.98	33.99	23.16	5.51
Winter (n = 4,538)					
Precip (mm)	39.76	0.00	39.76	1.29	3.63
ETo (mm)	3.11	0.11	3.22	0.86	0.43
Mean Temp (ºC)	23.36	-8.95	14.41	3.24	3.32
Max. Temp (ºC)	22.67	-2.50	20.17	8.62	3.66
Min. Temp (ºC)	32.63	-19.75	12.88	-1.46	4.17
Mean RH (%)	67.79	32.21	100.00	83.61	10.37
Max. RH (%)	37.44	62.56	100.00	95.99	4.36
Min. RH (%)	98.93	1.07	100.00	62.31	19.48
Mean WS (m/s)	11.18	0.01	11.19	2.09	1.37
TSI (MJ/m^2)	18.62	0.46	19.08	7.24	3.97

Other variables such as temperatures, ETo, TSI are higher in summer; meanwhile, the RH is generally higher in winter. The extreme temperatures, the minimum and maximum registered in the entire year, occurred during these two seasons. The standard deviation in these two seasons are lower in comparison with those seen in the whole year summary (**Table 1**), the range measurements of the phenomena were also narrow because of the uniformity of conditions during specific seasons in contrast to ranges of an entire year. The general behavior of the variables during the summer, winter and the rest of the year is presented in **Figure 2**.
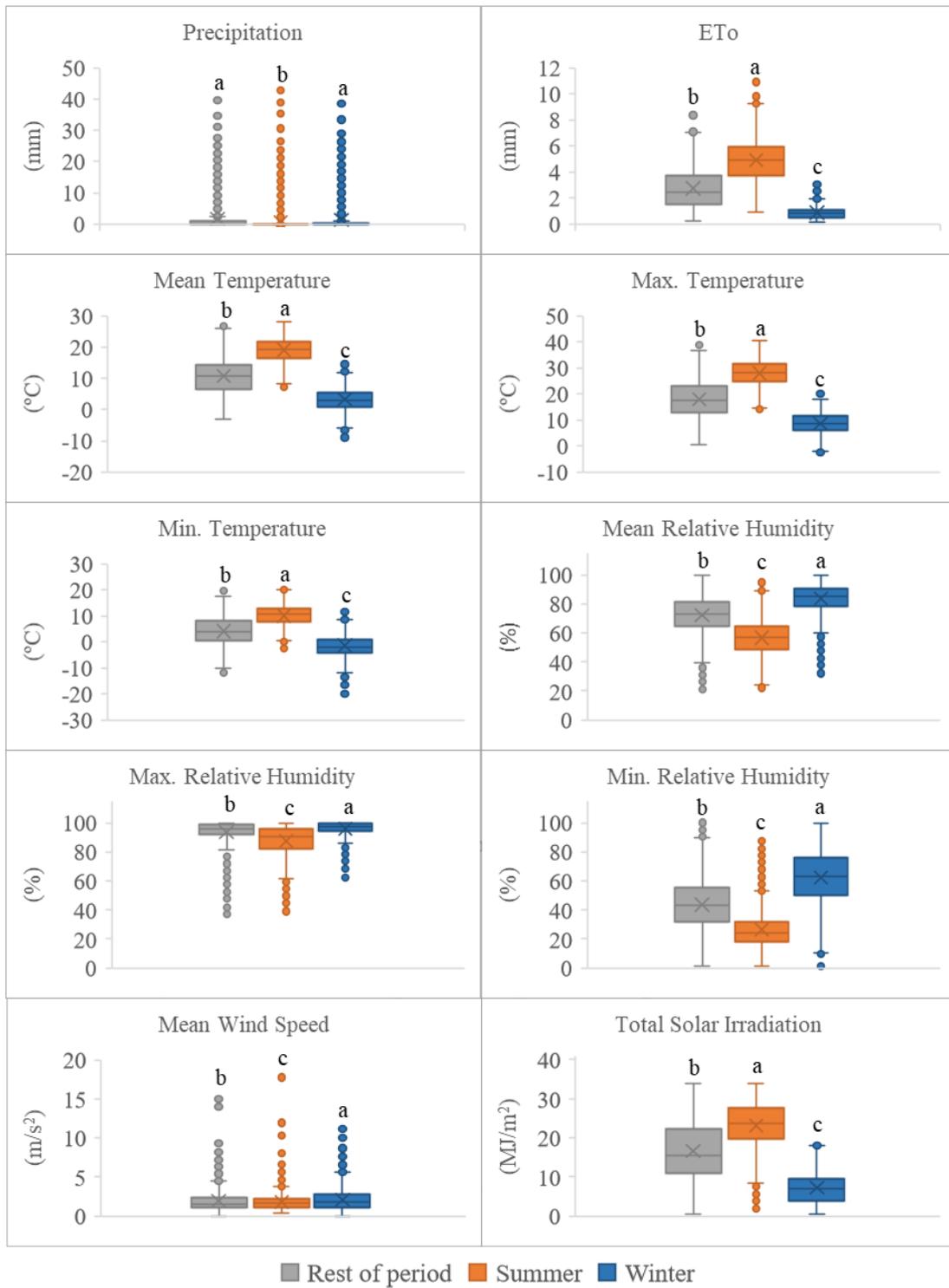
Figure 2. Boxplots and mean comparison of meteorological observations grouped by season of the year.

It is observable that for ETo, temperatures, RH and TSI, more extreme lectures were obtained during summer and winter. Meanwhile, the rest of the year present more intermedium values, and the letters above the boxplots show the differences between groups by the Mann–

Whitney U test. The variations of the means for precipitation, mean WS and max. RH in the periods were not as notorious as the previous variables; nonetheless, the statistical test found significant differences in these variables.

3.2 Interpolation methods comparison

Different ANN models as well other interpolation methods were compared in terms results accuracy for meteorological variables. Generally, good agreement between the estimated values and the actual records from the weather stations were observed for the interpolation methods. Results from ANNs approach are shown in **Table 3,** and alternative approaches are shown in **Table 4**.

Between the 5 activation functions in the ANNs, the ANN with the softsign had the higher R^2, 0.84, following by the sigmoid and tanh with an R^2 of 0.83, the relu with an R^2 of 0.82 and the hardlim with the lowest R^2 result, 0.79. The mean and maximum Temp were the most accurate variable to predict, with R^2 in the range from 0.96 to 0.98; following by the ETo, TSI and minimum Temp with R^2 higher than 0.91. Lower R^2 were obtained for mean WS, maximum RH and Prep., range from 0.43 to 0.75. The temperature is a more precise variable to interpolate in comparison to the precipitations (Jeffrey et al., 2001).

The alternatives methods presented similar performance, the best performing was the ISDW with an R^2 of 0.84, following by the RF with an R^2 of 0.83 and IDW and MLR with an R^2 of 0.81. The mean and maximum Temp were the most accurate variable to predict, as in the ANN approach, with R^2 in the range from 0.97 to 0.98; following by the ETo, TSI and minimum Temp with R^2 higher than 0.93. Lower R^2 were obtained for mean WS, maximum RH and Prep., range from 0.48 to 0.72.

Although the performances of the methods were similar, the ANN with softsign activation function and the ISDW were slightly better considering the R^2. However, the deterministic method had the lowest RMSE, 2.72 in contrast to 2.82 of the machine learning method.

Table 3. Analysis of meteorological data interpolations results for the ANNs approach.

Parameter	Hardlim			Sigmoid			Tanh			Softsign			Relu		
	R^2	p	RMSE	R^2	p	RMSE	R^2	p	RMSE	R^2	p	RMSE	R^2	p	RMSE
Prep.	0.62	0.00*	2.22	0.73	0.00*	1.88	0.71	0.00*	2.04	0.75	0.00*	1.82	0.73	0.00*	1.87
ETo	0.92	0.00*	0.55	0.94	0.00*	0.48	0.94	0.00*	0.46	0.94	0.00*	0.48	0.93	0.00*	0.51
Mean Temp	0.96	0.00*	1.45	0.98	0.00*	1.03	0.98	0.00*	1.10	0.98	0.00*	1.04	0.97	0.00*	1.15
Max. Temp	0.96	0.00*	1.86	0.98	0.00*	1.23	0.98	0.00*	1.28	0.98	0.00*	1.28	0.97	0.00*	1.49
Min. Temp	0.91	0.00*	1.83	0.93	0.00*	1.55	0.94	0.00*	1.52	0.93	0.00*	1.57	0.92	0.00*	1.71
Mean RH	0.83	0.00*	6.64	0.87	0.00*	5.87	0.88	0.00*	5.63	0.87	0.00*	5.68	0.86	0.00*	6.05
Max. RH	0.51	0.00*	6.24	0.57	0.00*	5.71	0.60	0.00*	5.50	0.58	0.00*	5.62	0.58	0.00*	5.66
Min. RH	0.81	0.00*	9.18	0.84	0.00*	8.40	0.85	0.00*	8.08	0.85	0.00*	8.06	0.82	0.00*	8.86
Mean WS	0.43	0.00*	1.06	0.47	0.00*	1.01	0.51	0.00*	0.96	0.51	0.00*	0.97	0.50	0.00*	0.98
TSI	0.93	0.00*	2.25	0.96	0.00*	1.81	0.96	0.00*	1.75	0.96	0.00*	1.70	0.96	0.00*	1.79
Mean	0.79		3.33	0.83		2.90	0.83		2.83	0.84		2.82	0.82		3.01

* significative for p < 0.05

Table 4. Analysis of meteorological data interpolation results for alternative methods.

Parameter	IDW			ISDW			MLR			RF		
	R^2	p	RMSE	R^2	p	RMSE	R^2	p	RMSE	R^2	p	RMSE
Prep.	0.63	0.00*	2.16	0.71	0.00*	1.89	0.65	0.00*	2.11	0.72	0.00*	1.95
ETo	0.94	0.00*	0.48	0.95	0.00*	0.44	0.93	0.00*	0.50	0.94	0.00*	0.47
Mean Temp	0.97	0.00*	1.14	0.98	0.00*	0.92	0.98	0.00*	1.02	0.98	0.00*	0.92
Max. Temp	0.97	0.00*	1.47	0.98	0.00*	1.16	0.98	0.00*	1.27	0.98	0.00*	1.12
Min. Temp	0.93	0.00*	1.61	0.94	0.00*	1.43	0.93	0.00*	1.62	0.94	0.00*	1.50
Mean RH	0.83	0.00*	6.52	0.88	0.00*	5.57	0.84	0.00*	6.41	0.86	0.00*	5.97
Max. RH	0.58	0.00*	5.63	0.64	0.00*	5.24	0.52	0.00*	6.02	0.53	0.00*	5.98
Min. RH	0.81	0.00*	9.09	0.85	0.00*	8.07	0.80	0.00*	9.42	0.84	0.00*	8.40
Mean WS	0.50	0.00*	0.98	0.53	0.00*	0.94	0.48	0.00*	1.00	0.52	0.00*	0.96
TSI	0.95	0.00*	1.90	0.97	0.00*	1.54	0.95	0.00*	1.89	0.97	0.00*	1.60
Mean	0.81		3.10	0.84		2.72	0.81		3.13	0.83		2.89

* significative for $p < 0.05$

In a study of daily rainfall interpolation with different spatial methods, the RMSE was between 9.7 to 12.3; the IDW error was 10.1 (Wagner et al., 2012), higher than the registered in this paper. Hourly interpolations of rainfall seem to perform better, with R^2 up to 0.75 using IDW, nearest neighbor and kriging (Mendez and Calvo-Valverde, 2016). Another study with daily interpolations of precipitations and temperatures registered RMSE from 0.546 to 0.742 and from 0.063 to 0.130 for rainfalls and temperatures respectively using IDW and kriging (Berndt and Haberlandt, 2018).

In general, climate and rainfall are highly non-linear and complicated phenomena, which require advanced computer modeling for an accurate prediction (Nayak et al., 2013). Others studies used meteorological variables as inputs in ANNs to estimate other meteorological variables, for instance, the ETo estimation with R of 0.89 and RMSE of 2.77 using temperatures (minimum and maximum) and WS as inputs in a period of 3 years (Falamarzi et al., 2014), the RMSE obtained for the ETo in the current assay are lower for any interpolation method. Using the only the temperatures (minimum and maximum) to estimate the ETo, the obtained RMSE were in the range from 0.54 to 0.66 (Diamantopoulou et al., 2011), compared to 0.44 to 0.55 obtained here. Local estimation of crop water requirements with ANN is as accurate as evapotranspiration models (Abrishami et al., 2018).

Global solar irradiation forecasting with ANN using temperature, RH, month, day and hour achieved an R^2 of 0.99 and an RMSE of 0.17 (Hasni et al., 2012), this prediction has more accuracy than the obtained here, using more input data and historical data of site for the forecast. More precision in models, including interpolations, could be achieved with increasing amounts of observation data (Valipour, 2016), in this case, increasing the number of weather stations to have more input data for to generate the models.

The ANN approach, except for the hardlim ANN, outperforms the MLR interpolation with higher R^2 and lower RMSE. ANN outperforming MLR is a tendency and have been reported previously in meteorological studies with wind speed forecasting (Bilgili and Sahin, 2010), seasonal rain (Mekanik et al., 2013) and ETo estimations (Laaboudi et al., 2012).

3.3 Season effect in data interpolation quality

Results from summer season for the ANNs approach are shown in **Table 5,** and for the alternative approaches are shown in **Table 6**. Regarding the results from the winter season,

for the ANNs approach are shown in **Table 7,** and for the alternative approaches are shown in **Table 8**. In comparison with the interpolations of an entire year, during summer and winter seasons the accuracy was lower, R^2 presented values in an average of 0.76 and 0.71 respectively in contrast to 0.82 of the overall year. The RMSE on the contrary, exhibited a slightly higher average value throughout the year, 2.97, in comparison to 2.91 and 2.84 for summer and winter respectively. The higher RMSE could be due that this error measurement penalizes the peaks which presented larger absolute values more weight than errors with smaller absolute values (Shao et al., 2014).

In a study of temperature interpolations during the months of January and July, selected as representatives of winter and summer months respectively; the precision in terms of RMSE resulted in values between 1.35 to 2.62 in January and 1.20 to 3.47 in July for MLR and kriging algorithms, been the lower RMSE to the MLR algorithm (Wu and Li, 2013). During the summer and the winter months, the intensities of meteorological phenomena had more peaks and when modeling these non-common events, are more difficult to abstract and create a model able to predict its values in contrast to periods with less extreme values. Forecast the peaks of intensity still a tough task for models, including ANN, since those peaks appear with low frequency (Nastos et al., 2013).

Other intrinsic factors can alter the quality of the interpolated data such as episodes of high-intensity rains, densely cloudy days and frost in winters (Thorsen and Höglind, 2010), temperature inversions (Bailey et al., 2011) or heat waves in summers (Gerald A. Meehl and Claudia Tebaldi, 2004; Luber and McGeehin, 2008). In a study using ANN to forecast the TSI, the mean error was different according to the month and season in which the predictions were made, been higher in April and December (spring and winter) and lower in August and October (summer and autumn) (Kemmoku et al., 1999). The estimation of TSI by ANN using Meteosat-9 images as input was better in clear-periods than rainy or overcast ones, the RMSE was 21.20% against 5.13% for rainy and clear-sky days months respectively (Linares-Rodriguez et al., 2013).

Table 5. Analysis of meteorological data interpolations results for the ANNs approach for summer months.

Parameter	Hardlim			Sigmoid			Tanh			Softsign			Relu		
	R^2	p	RMSE	R^2	p	RMSE	R^2	p	RMSE	R^2	p	RMSE	R^2	p	RMSE
Prep.	0.91	0.00*	1.19	0.96	0.00*	0.82	0.95	0.00*	1.53	0.92	0.00*	1.47	0.90	0.00*	1.55
ETo	0.72	0.00*	0.83	0.81	0.00*	0.68	0.81	0.00*	0.67	0.80	0.00*	0.70	0.79	0.00*	0.71
Mean Temp	0.85	0.00*	1.56	0.93	0.00*	1.04	0.94	0.00*	0.99	0.92	0.00*	1.10	0.92	0.00*	1.12
Max. Temp	0.81	0.00*	2.16	0.93	0.00*	1.28	0.91	0.00*	1.44	0.92	0.00*	1.31	0.90	0.00*	1.47
Min. Temp	0.77	0.00*	1.86	0.78	0.00*	1.81	0.84	0.00*	1.55	0.79	0.00*	1.75	0.81	0.00*	1.66
Mean RH	0.68	0.00*	7.82	0.78	0.00*	6.40	0.80	0.00*	6.01	0.81	0.00*	5.93	0.79	0.00*	6.17
Max. RH	0.48	0.00*	7.93	0.50	0.00*	7.76	0.60	0.00*	6.95	0.55	0.00*	7.33	0.55	0.00*	7.38
Min. RH	0.63	0.00*	8.01	0.76	0.00*	6.14	0.78	0.00*	5.77	0.82	0.00*	5.32	0.77	0.00*	6.05
Mean WS	0.29	0.00*	0.77	0.27	0.00*	0.72	0.31	0.00*	0.70	0.34	0.00*	0.68	0.28	0.00*	0.72
TSI	0.87	0.00*	2.06	0.91	0.00*	1.69	0.90	0.00*	1.78	0.91	0.00*	1.70	0.92	0.00*	1.63
Mean	0.70		3.42	0.76		2.83	0.78		2.74	0.78		2.73	0.76		2.84

* significative for p < 0.05

Table 6. Analysis of meteorological data interpolation results for the alternative methods for summer months.

Parameter	IDW			ISDW			MLR			RF		
	R^2	p	RMSE	R^2	p	RMSE	R^2	p	RMSE	R^2	p	RMSE
Prep.	0.83	0.00*	2.10	0.96	0.00*	1.00	0.88	0.00*	2.09	0.95	0.00*	0.96
ETo	0.80	0.00*	0.71	0.84	0.00*	0.63	0.80	0.00*	0.70	0.80	0.00*	0.69
Mean Temp	0.91	0.00*	1.21	0.94	0.00*	0.98	0.93	0.00*	1.06	0.95	0.00*	0.92
Max. Temp	0.90	0.00*	1.53	0.93	0.00*	1.23	0.91	0.00*	1.41	0.94	0.00*	1.11
Min. Temp	0.83	0.00*	1.61	0.85	0.00*	1.51	0.83	0.00*	1.61	0.82	0.00*	1.61
Mean RH	0.72	0.00*	7.36	0.81	0.00*	6.00	0.73	0.00*	7.03	0.78	0.00*	6.30
Max. RH	0.57	0.00*	7.47	0.65	0.00*	6.64	0.47	0.00*	8.03	0.46	0.00*	8.20
Min. RH	0.69	0.00*	6.82	0.75	0.00*	6.10	0.68	0.00*	6.99	0.79	0.00*	5.69
Mean WS	0.38	0.00*	0.64	0.49	0.00*	0.59	0.28	0.00*	0.72	0.34	0.00*	0.68
TSI	0.89	0.00*	1.89	0.94	0.00*	1.39	0.91	0.00*	1.74	0.94	0.00*	1.41
Mean	0.75		3.13	0.82		2.61	0.74		3.14	0.78		2.76

* significative for p < 0.05

Table 7. Analysis of meteorological data interpolations results for the ANNs approach for winter months.

Parameter	Hardlim			Sigmoid			Tanh			Softsign			Relu		
	R^2	p	RMSE	R^2	p	RMSE	R^2	p	RMSE	R^2	p	RMSE	R^2	p	RMSE
Prep.	0.72	0.00*	1.76	0.83	0.00*	1.43	0.78	0.00*	1.56	0.82	0.00*	1.41	0.71	0.00*	1.80
ETo	0.46	0.00*	0.33	0.72	0.00*	0.20	0.51	0.00*	0.30	0.64	0.00*	0.23	0.71	0.00*	0.21
Mean Temp	0.89	0.00*	1.22	0.92	0.00*	0.93	0.90	0.00*	1.03	0.92	0.00*	0.98	0.94	0.00*	0.85
Max. Temp	0.82	0.00*	1.60	0.87	0.00*	1.30	0.89	0.00*	1.19	0.84	0.00*	1.48	0.88	0.00*	1.29
Min. Temp	0.84	0.00*	1.78	0.87	0.00*	1.49	0.87	0.00*	1.53	0.89	0.00*	1.38	0.90	0.00*	1.35
Mean RH	0.56	0.00*	6.49	0.65	0.00*	5.73	0.64	0.00*	5.85	0.67	0.00*	5.56	0.66	0.00*	5.62
Max. RH	0.05	0.03*	4.21	0.08	0.01*	3.84	0.12	0.00*	3.73	0.14	0.00*	3.64	0.15	0.00*	3.63
Min. RH	0.63	0.00*	11.82	0.73	0.00*	10.19	0.73	0.00*	9.99	0.69	0.00*	10.74	0.70	0.00*	10.62
Mean WS	0.76	0.00*	0.68	0.70	0.00*	0.72	0.79	0.00*	0.60	0.76	0.00*	0.65	0.72	0.00*	0.71
TSI	0.79	0.00*	1.85	0.83	0.00*	1.64	0.87	0.00*	1.43	0.87	0.00*	1.47	0.80	0.00*	1.81
Mean	0.65		3.17	0.72		2.75	0.71		2.72	0.72		2.75	0.72		2.79

* significative for p < 0.05

Table 8. Analysis of meteorological data interpolation results for the alternative methods for winter months.

Parameter	IDW			ISDW			MLR			RF		
	R^2	p	RMSE	R^2	p	RMSE	R^2	p	RMSE	R^2	p	RMSE
Prep.	0.49	0.00*	2.38	0.71	0.00*	1.80	0.76	0.00*	1.61	0.80	0.00*	1.50
ETo	0.71	0.00*	0.21	0.80	0.00*	0.17	0.69	0.00*	0.22	0.80	0.00*	0.17
Mean Temp	0.90	0.00*	1.06	0.94	0.00*	0.83	0.94	0.00*	0.84	0.94	0.00*	0.86
Max. Temp	0.82	0.00*	1.55	0.89	0.00*	1.19	0.89	0.00*	1.23	0.89	0.00*	1.21
Min. Temp	0.83	0.00*	1.75	0.88	0.00*	1.46	0.86	0.00*	1.60	0.88	0.00*	1.50
Mean RH	0.59	0.00*	6.27	0.68	0.00*	5.48	0.62	0.00*	6.07	0.66	0.00*	5.66
Max. RH	0.13	0.00*	3.60	0.16	0.00*	3.52	0.08	0.01*	4.01	0.08	0.01*	3.94
Min. RH	0.65	0.00*	11.46	0.74	0.00*	9.93	0.66	0.00*	11.36	0.74	0.00*	9.92
Mean WS	0.69	0.00*	0.72	0.75	0.00*	0.64	0.74	0.00*	0.66	0.80	0.00*	0.60
TSI	0.76	0.00*	1.98	0.86	0.00*	1.55	0.84	0.00*	1.63	0.89	0.00*	1.32
Mean	0.66		3.10	0.74		2.66	0.71		2.92	0.75		2.67

* significative for p < 0.05

3.4 Virtual weather station

The algorithms composing the VWS are capable of access the InfoRiego FTP server, other servers address can be configurable into the script in order to access a different FTP server. Once the access is done, the user performs a filtered selection of the files to download information of a specified period. Once the data are available in the user's computer, the interpolations algorithms can be carried out executing the preferred one by the user, introducing as input the XY UTM coordinates in the ETRS89 geodetic system.

According to the results, the most appropriate methods to perform the data estimation in a user digited geographical location are the IDSW and the ANN with the softsign function. The interpolations can be made to any given coordinate inside Castilla y León or other areas with a weather station network and FTP servers to access the data. The innovative aspect of the VWS lies in the possibility of the user to choose a specific location, and estimated temperatures, RH, ETo, precipitations, TSI, WS with just one method, other studies of interpolations are focused in a couple of variables using non-automated data access.

4. CONCLUSIONS

In the current study, the concept of VWS is introduced. The current state of the weather station networks and the online availability of the records makes possible to get the data and process them to perform estimations of the meteorological observations from the measurements of weather stations to other locations with no stations. In the present study, different interpolation methods of meteorological data were carried out by 5 ANNs with different activations function, IDW, ISDW, MLR and RF to compare the quality of the interpolated data.

The results show that the overall performances of the interpolation methods were accurate to estimate the meteorological variables; the IDSW and the ANN with the softsign activation functions were the most precise approach to perform the interpolations and to use in the VWS as preferred methods. The success of the models suggests that they could be used in situations where no weather stations are present, but meteorological data series is needed for diverse purposes, for instance, the register of the ETo and calculus of crop water requirements.

In the future, more interpolation techniques should be tested for improvements in the accuracy of the VWS. Other tasks can be oriented to increase the data source protocols to adopt new data sources to the VWS and add a user interface to the algorithms to make the proposed alternative available for more users.

5. ACKNOWLEDGEMENTS

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