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Zubaidi, S, Dooley, J, Alkhaddar, R, Abdellatif, M, Al-Bugharbee, H and Ortega-Martorell, S

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### Article

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# A Novel Approach for Predicting Monthly Water Demand by Combining Singular Spectrum Analysis with Neural Networks

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## Abstract

Valid and dependable water demand prediction is a major element of the effective and sustainable expansion of municipal water infrastructures. This study provides a novel approach to quantifying water demand through the assessment of climatic factors, using a combination of a pretreatment signal technique, a hybrid particle swarm optimisation algorithm and an artificial neural network (PSO-ANN). The Singular Spectrum Analysis (SSA) technique was adopted to decompose and reconstruct water consumption in relation to six weather variables, to create a seasonal and stochastic time series. The results revealed that SSA is a powerful technique, capable of decomposing the original time series into many independent components including trend, oscillatory behaviours and noise. In addition, the PSO-ANN algorithm was shown to be a reliable prediction model, outperforming the hybrid Backtracking Search Algorithm BSA-ANN in terms of fitness function (RMSE). The findings of this study also support the view that water demand is driven by climatological variables.

23 **Keywords**

24 Melbourne, Neural network model, Particle Swarm Optimization, Singular Spectrum Analysis,  
25 Urban water demand, Water sustainability

26 **1 Introduction**

27 Climate change causes considerable problems for the ecosystem, for example, fluctuation of  
28 precipitation where scarce precipitation can lead to drought, which can, in turn, cause  
29 desertification. Freshwater resources are widely depleted, particularly in city centres, the  
30 problems this causes likely to be exacerbated because of increasing demands on freshwater  
31 (Davies and Simonovic, 2011). Hot weather conditions, extended dry periods and a general  
32 reduction in rainfall, also increase the consumption of and demand for water. As it is anticipated  
33 that climate change will cause substantial increases in temperature, a decrease in rainfall and a  
34 more droughts, it is necessary to analyse these issues and explore the relationships between  
35 climate and water consumption used to predict water demand (Zhou et al., 2000).

36 Forecasting municipal water consumption, a task of considerable significance for water  
37 utilities, aims to minimise the risks involved in decision-making (Walker et al., 2015). Marlow  
38 et al. (2013) point out that accurate prediction can improve the performance of water  
39 distribution systems and encourage better water management in addition to urban water  
40 sustainability. However, the problems faced by the water sector as a result of global warming,  
41 has increased pressure on its infrastructure.

42 Previous studies have highlighted the importance of precise water demand predictions, several  
43 documenting that municipal water sectors depend on the development of both infrastructure  
44 and investment, making accurate advanced planning a central issue (Adamowski et al., 2012;  
45 Donkor et al., 2014).

46 Existing urbanised water infrastructures are coming under considerable stress because of  
47 extreme weather phenomena linked to global warming. This situation increases blue water

48 demand and leads to high levels of uncertainty regarding mid-term projections for key drivers  
49 of climate change, during the planning process. The conventional methods used to predict these  
50 projections can lead to considerable problems for water system decision makers and cause  
51 increased operational costs (Urich and Rauch, 2014).

52 Previous studies have established that artificial neural network (ANN) approaches have  
53 outperformed traditional methods (e.g. regression and time series) in different fields e.g. Jain  
54 et al. (2001), Mohammadi et al. (2005) and Azadeh et al. (2007). As such, a number of studies  
55 have used ANN techniques to predict the monthly time series for urban water demand  
56 including:

57 a) Liu et al. (2003), proposed a combined model that included water demand forecasts and  
58 artificial neural networks (WDF-ANN). This study used historical monthly water consumption  
59 and socio-economic data for Weinan city, China, from 1991 to 2000, to establish a water  
60 prediction model. The results indicated that a WDF-ANN model has the ability to simulate  
61 monthly water consumption patterns.

62 b) Firat et al. (2009) evaluated three types of ANN; Generalized Regression Neural Networks  
63 (GRNN), Feed Forward Neural Networks (FFNN) and Radial Basis Neural Networks (RBNN).  
64 This study used monthly socio-economic and weather variables as the model input, from 1997-  
65 2005, for Izmir city, Turkey. The outcome, when using twenty-five different input variables,  
66 revealed that a model consisting of multiple input variables is better than a single variable input.  
67 The GRNN outperformed all other ANN techniques and Multiple Linear Regression (MLR)  
68 when predicting monthly water demand.

69 c) A year later, Firat et al. (2010) assessed three ANN models, including two of the techniques  
70 evaluated previously (FFNN, GRNN) and the Cascade Correlation Neural Networks (CCNN).  
71 This study also used historical monthly data from Izmir city, Turkey, over the same period  
72 (1997-2005). The model input for the ANN techniques included several combinations of

73 previous water consumption values. The results showed that using five of these values resulted  
74 in the best model input, CCNN consistently outperforming both FFNN and GRNN.

75 To date, previous studies have used different types of factors as forecast model input including  
76 socio-economic data, a mixture of socio-economic and weather variables and a combination of  
77 previously recorded values of water consumption. However, no previous study has considered  
78 the impact of climate on water demand or employed a pretreatment signal technique, which  
79 has the ability to decompose the time series into different components such as trend, oscillatory  
80 behaviour (periodic or quasi-periodic components) and noise filtering. These components help  
81 to determine the effect of weather volatility on water consumption, to improve the accuracy of  
82 prediction and reduce the scale of error between observed and forecast water demand.

83 Different optimisation methods can be used to tackle problems in applications. The aim of  
84 optimisation algorithms is to locate the optimum values for a system's parameters, under  
85 different conditions (Ahmed et al., 2017). Recently, the backtracking search optimisation  
86 algorithm (BSA), a new evolutionary algorithm (EA), has been applied to solve a range of  
87 optimisation problems (Chen et al., 2017). It has been used to solve optimisation problems such  
88 as real-value numerical problems (Civicioglu, 2013), economic dispatch (Modiri-Delshad et  
89 al., 2016) and home energy management systems (Ahmed et al., 2017).

90 Ferguson et al. (2013) stated that currently, water managers and stakeholders are struggling to  
91 adapt municipal water systems to the increasingly complicated challenges of climate change.

92 With this in mind, this paper has three aims:

- 93 1- To reduce the uncertainty of the relationship between water demand and climate  
94 variables at mid-term.
- 95 2- To identify seasonal and stochastic patterns and noise filters, for water consumption  
96 and different weather factors by applying an SSA technique.

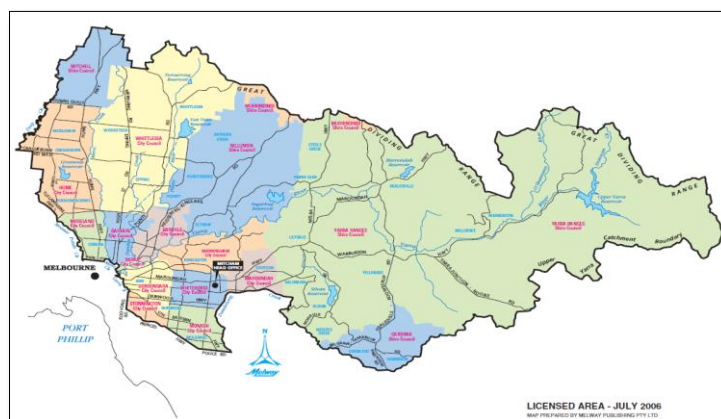
97 3- To assess the capability and reliability of a hybrid PSO-ANN model to predict mid-  
98 term water demands taking climatological variables into consideration, and to assess  
99 how it compares with a hybrid BSA-ANN technique.

100 To the best of our knowledge, no previous study has been conducted that integrates the above  
101 three aims.

## 102 2 Study Area and Data Set

103 A catchment area in Australia located in Melbourne city, has been used to evaluate the water  
104 demand model. Yarra Valley Water is one of three retail water companies delivering municipal  
105 water supplies and sewerage services to more than 1.5 million people in the Yarra River  
106 catchment area. Figure 1 shows the Licence Service Area of the Yarra Valley company (YVW,  
107 2006).

108 Historical monthly water consumption data and information on six weather variables were  
109 gathered from the Yarra Valley Water Company covering 2006-2015. This data comprised  
110 water consumption (Mega litre), Maximum Temperature ( $^{\circ}\text{C}$ ), Mean Temperature ( $^{\circ}\text{C}$ ),  
111 Minimum Temperature ( $^{\circ}\text{C}$ ), Rainfall (mm), Solar Radiation ( $\text{mj}/\text{m}^2$ ) and Vapour Pressure  
112 (hpa).



113

114

Figure 1: Yarra Valley's water licence service area (YVW, 2006)

### 115 3 Pre-processing data

116 Pre-processing data techniques are deemed a significant step in the data mining process. These  
117 techniques play an important role in ANNs by fostering high precision and minimal  
118 computational costs at the training stage as noisy and unreliable information that could be  
119 present in data records will adversely affect the learning phase and result in a poor model  
120 (Kotsiantis et al., 2006). Zhang and Qi (2005) used ANN to evaluate the effect of two pre-  
121 processing techniques; the detrending and deseasoning of nonlinear monthly data. Their results  
122 showed that both techniques can minimise prediction errors, the combination of both found to  
123 be the most efficient pre-processing method. In the current research, Singular Spectrum  
124 Analysis (SSA) was used for detrending, deseasoning and noise removal.

#### 125 3.1 Singular Spectrum Analysis (SSA)

126 SSA is a powerful method used to analyse time series to uncover significant prediction  
127 characteristics. It can be used for both linear and nonlinear time series and small sample sizes.  
128 It does not rely on any statistical assumptions based on the stationarity and linearity of the  
129 series, or on the normality of the residuals (Hassani et al., 2009).

130 SSA has been used in different fields including medical engineering (Ghodsi et al., 2009),  
131 economics (Hassani et al., 2015) and hydrology (Marques et al., 2006) amongst others. The  
132 SSA approach consists of two stages: decomposition of the original time series into different  
133 principle components (PC<sub>s</sub>) including trend, oscillatory components and irregular components,  
134 and noise removal and reconstruction of a new time series that has less noise (Al-Bugharbee  
135 and Trendafilova, 2016).

136 In the decomposition step, a signal  $y$  of length  $T$ ,  $y_1, y_2, \dots, y_T$ , is mapped onto a length window  
137 ( $L$ ) to create the so-called trajectory matrix, the Hankel matrix,  $X (L \times K)$  where  $K=T-L+1$  (Eq.  
138 (1)).

$$X = \begin{bmatrix} y_1 & y_2 & y_3 & \Lambda & y_K \\ y_2 & y_3 & y_4 & \Lambda & y_{K+1} \\ M & M & M & O & M \\ y_L & y_{L+1} & y_{L+2} & \Lambda & y_T \end{bmatrix} \quad (1)$$

140 The Hankel matrix ( $X$ ) will be subject to singular value decomposition to get ( $L$ ) eigenvectors  
 141 ( $U_i$ ,  $i= 1, 2, \dots, L$ ) corresponding to ( $L$ ) eigenvalues ( $\lambda_i$ ,  $i=1, 2, \dots, L$ ). Any  $\lambda_i$  refers to the partial  
 142 alteration of the original time series in a  $U_i$  direction. The corresponding principal components  
 143 ( $PC_i$ ) can be obtained by projecting the Hankel matrix onto every eigenvector:

$$PC_i(m) = \sum_{j=1}^L X'(m + j - 1) * U_i(m) \quad (2)$$

144 where  $i=1,2,\dots,L$ ,  $m= 1,2,\dots,n$ ,  $j=1,2,\dots,L$ , and the prime means transpose.

146 Projecting the  $PC_s$  on the eigenvectors ( $U$ ) will get the primary matrices  $L$  ( $EI_i=U_i PC'_i$ )  
 147 where  $i= 1, 2, \dots, L$  and the prime denotes transposition.

148 In this study,  $L$  will be equal to 12 so as to extract all the seasonal components together (12, 6,  
 149 4, 3, 2.4, and 2-months harmonics), the trend and noise (Golyandina et al., 2001) .

150 The contribution of these primary matrix norms to the original Hankel matrix norm follows a  
 151 singular values trend, meaning that the highest contribution will go to the first matrix, the  
 152 lowest contribution to the last.

153 As mentioned above, the signals can be reconstructed via a linear combination of several, or  
 154 all, the  $PCs$ . When choosing the number of  $PCs$ , there are various criteria to observe (Kilundu  
 155 et al., 2011). In this study, valuable insight is offered via inspection breaks testing in the  
 156 eigenvalue spectra to select the number ( $w$ ) of  $PCs$ . A slight decrease in singular sequence  
 157 values, indicates pure noise according to the latter test. The seasonal signal of the original sub-  
 158 signal is contained in the new reconstructed signal ( $yr$ ). The process of reconstruction is  
 159 achieved via the diagonal averaging mechanism that is depicted below (Ghil et al., 2002).



160 
$$yr(m) = \frac{1}{N_m} \sum_{i \in w} \sum_{j=L_m}^{U_m} PC_i(m-j+1) \times U_i(m) \quad , m=1,2,\dots,n-1 \quad (3)$$

161 The normalisation factor ( $N_m$ ), the upper ( $U_m$ ) and the lower ( $L_m$ ) of sums vary for the centre  
 162 and edges of the signal. They are defined as shown below:

163 
$$\left(\frac{1}{N_m}, L_m, U_m\right) = \begin{cases} \left(\frac{1}{m}, 1, m\right), & \text{for } 1 \leq m \leq L-1 \\ \left(\frac{1}{L}, 1, K\right), & \text{for } L \leq m \leq K \\ \left(\frac{1}{n-m+1}, m-n+L, L\right), & \text{for } K+1 \leq m \leq n \end{cases} \quad (4)$$

164 The new reconstructed signals ( $yr$ ) will be utilised for seasonal forecasting.

165 In this study, the SSA technique has been used for the following purposes:

- 166 1- To decompose the original time series into different PCs and detect the stationary time  
 167 series, and  
 168 2- To reconstruct a new seasonal time series that is less noisy.

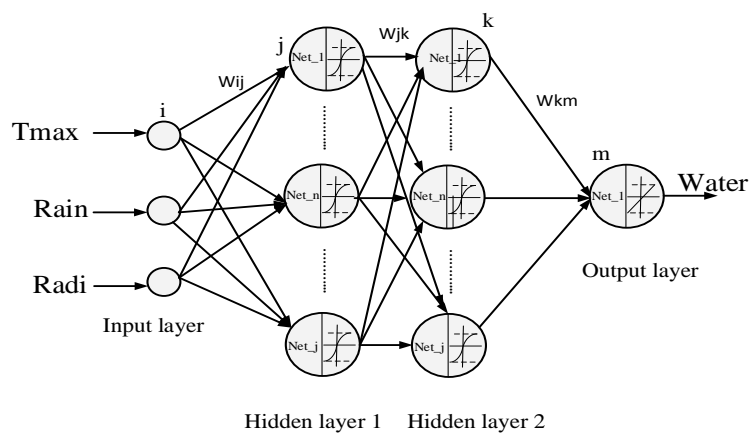
#### 169 **4 Hybrid Particle Swarm Optimisation-Artificial Neural Network (PSO-ANN)**

##### 170 4.1 Artificial Neural Network (ANN)

171 ANN is an information processing technique, which aims to emulate human brain functionality  
 172 by adopting the same connectivity and operations as biological neurones. It can capture  
 173 nonlinear relationships by system input and output training (Ahmed et al., 2016; Cutore et al.,  
 174 2008). In this research, a feed-forward neural network (FFNN), that uses the Levenberg–  
 175 Marquardt (LM) learning algorithm, was employed, implemented on a MATLAB Neural  
 176 Network Toolbox (Mathworks, 2017). The decision to adopt an LM learning algorithm was  
 177 because of the speed, efficiency and low level of error, as shown previously by Payal et al.  
 178 (2015). The ANN structure comprises three inputs representing weather factors (maximum  
 179 temperature, radiation and rainfall), two hidden layers with the *tansigmoidal* function as an  
 180 activation function and one output (water demand) with a *linear* activation function. Figure 2

181 shows the ANN architecture. The learning rate value and the number of neurones in both hidden  
 182 layers can be established by applying the PSO-ANN algorithm to avoid over- or under-fitting  
 183 the model.

184 The complete data set has been randomly divided into three sets: training (70%), testing (15%)  
 185 and validation (15%) (Babel and Shinde, 2011; Bennett et al., 2013). The ANN learning  
 186 process will repeat many times over an epoch (i.e., 1000 iterations), until the error between the  
 187 measured and forecast municipal water reaches its minimum.



188

Figure 2: The architecture of ANN

189

#### 190 4.2 Particle Swarm Optimisation (PSO)

191 A PSO algorithm is a computational iterative search and optimisation technique. It is  
 192 biologically inspired by the social behaviour of animal societies such as birds flocking or  
 193 schools of fish. This method comprises a swarm of particles where a particle denotes a possible  
 194 solution (Rini et al., 2011). The PSO algorithm is commonly utilised to settle optimisation  
 195 issues (Eberhart and Shi, 2001).

196 In each process of iteration, the velocity and position of each particle in the swarm is updated  
 197 according to the two "best" values. The first one is the local best (Pbest), indicative of the  
 198 particle's memory about its own best position (best fitness). The second is the global best

199 (gbest), this denoting global knowledge of the best position, or the best position in their  
200 neighbourhood. Particle positions are altered by adding velocity and updating, this dependent  
201 on equations 5 and 6 (Wang et al. (2010); Gharghan et al. (2016). The updating process  
202 continues until either an appropriate *gbest* is attained or the pre-set number of iterations (*kmax*)  
203 is reached.

$$204 \quad V_{id}(k + 1) = \omega V_{id}(k) + c_1 r_1(k)(Pbest_{id} - X_{id}) + c_2 r_2(k)(gbest_{id} - X_{id}) \quad (5)$$

$$205 \quad X_{id}(k + 1) = X_{id}(k) + V_{id}(k + 1) \quad (6)$$

206 Where  $V_{id}$  is the velocity of the particle,  $X_{id}$  indicating the position of the particle;  $k$  the  
207 iterations number;  $\omega$  the inertia weight;  $r_1(k)$  and  $r_2(k)$  random values ranging between 0 and  
208 1;  $c_1$  and  $c_2$  acceleration constants which are often equals;  $c_1 r_1(k)(Pbest_{id} - X_{id})$  and  $c_2 r_2(k)$   
209  $(gbest_{id} - X_{id})$  representing the updating of particles.

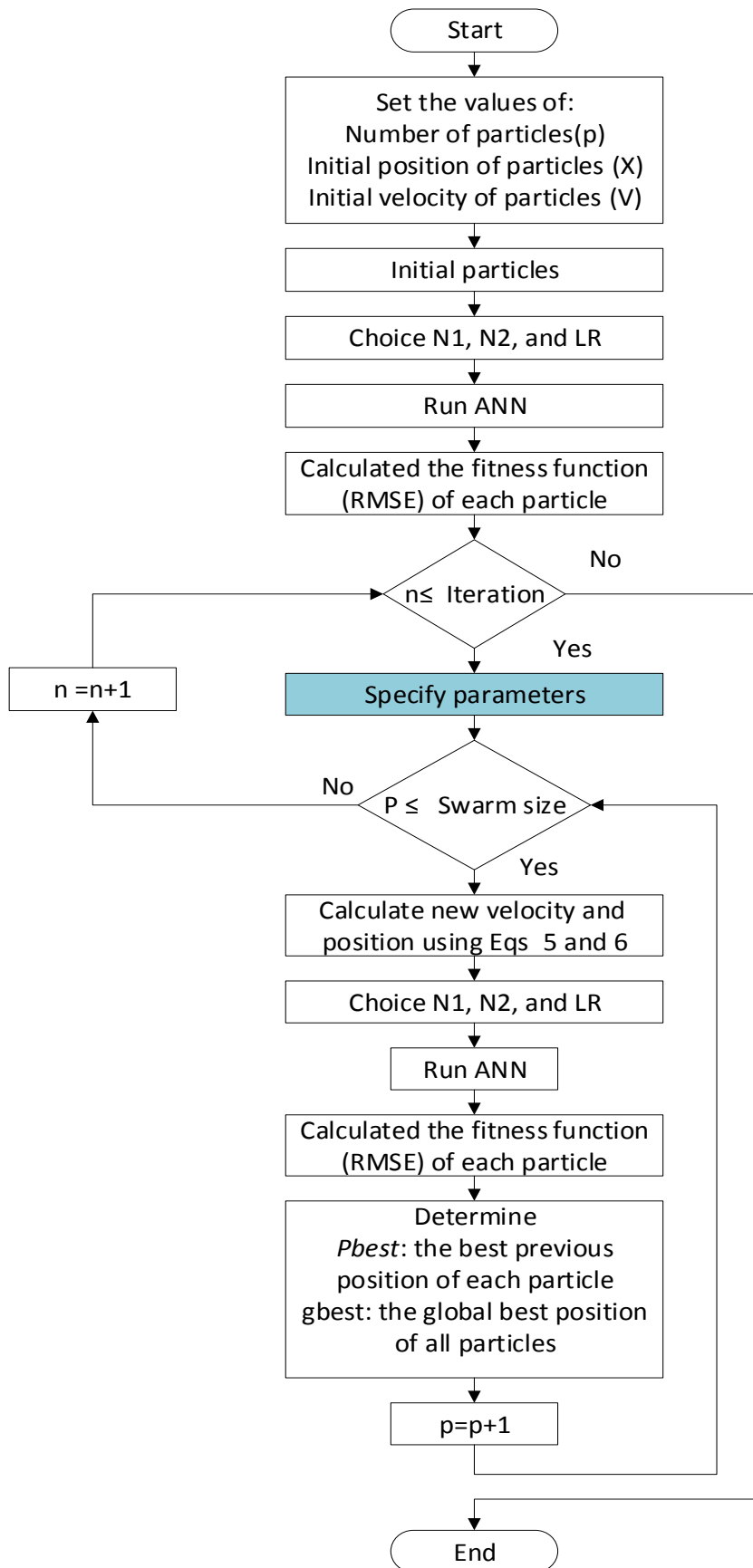
210 Recent research has emphasised the positive use of hybrid PSO–ANN models tackling  
211 engineering issues such as improving the precision of wireless sensor localisation mechanisms  
212 (Gharghan et al., 2016). Eberhart and Shi (2001) and Lavanya and Udgata (2011) both  
213 recommend  $\omega = 0.5$ , and  $c_1 = c_2 = 1.494$  to achieve faster convergence. Zhang et al. (2007)  
214 suggested that the swarm size could range from 20 - 50. In this research, the amount of  
215 iterations was 100 because the minimum value for the fitness function was 60, with 35  
216 iterations for seasonal and stochastic data, respectively.

217

218 MATLAB was used to run the PSO algorithm, the fitness function for optimising the model  
219 minimising the root-mean-squared error (Wang et al., 2010). Figure 3 shows the proposed  
220 hybrid PSO–ANN algorithm flow chart used to enhance water demand prediction accuracy.

221

222



223

224 Figure 3: Flow chart of hybrid PSO-ANN algorithm, adapted from Gharghan et al. (2016)

## 225 5 Model performance and accuracy measurements

226 Model performance can be assessed by using several conventional statistical measures. In this  
227 study, four criteria were used to examine prediction accuracy; mean absolute error (MAE),  
228 mean square error (MSE), root mean square error (RMSE) and Pearson's product moment  
229 correlation (R). The Augmented Dickey-Fuller (ADF) test and Kwiatkowski– Phillips–  
230 Schmidt–Shin (KPSS) test were also used to analyse the stationary case for the stochastic time  
231 series and residuals.

$$232 \quad MAE = \frac{\sum_{m=1}^N |y_o - y_p|}{N} \quad (7)$$

$$233 \quad MSE = \frac{\sum_{m=1}^N (y_o - y_p)^2}{N} \quad (8)$$

$$234 \quad RMSE = \sqrt{\frac{\sum_{m=1}^N (y_o - y_p)^2}{N}} \quad (9)$$

$$235 \quad R = \left[ \frac{\sum_{m=1}^N (y_o - \bar{y}_o)(y_p - \bar{y}_p)}{\sqrt{\sum (y_o - \bar{y}_o)^2 \sum (y_p - \bar{y}_p)^2}} \right] \quad (10)$$

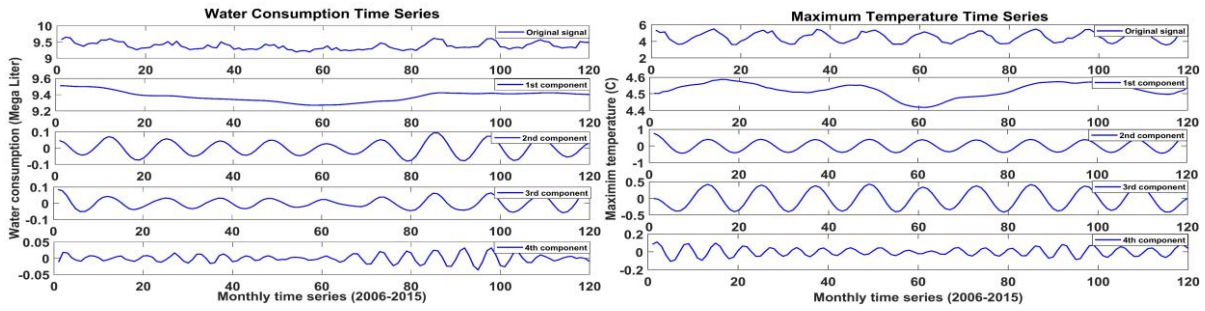
236 where  $y_o$  represents measured water consumption;  $y_p$ , forecasted water demand;  $N$ , sample size;  
237  $\bar{y}_p$ , mean of forecasted demand, and  $\bar{y}_o$ , mean of measured consumption.

## 238 6 Results and discussion

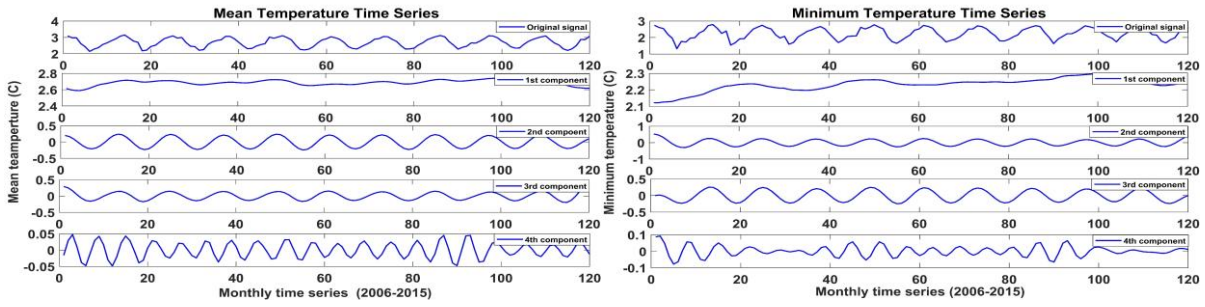
### 239 6.1 Signal pretreatment

240 After treating the outliers and transforming all the time series for water consumption and the  
241 weather factors, a singular spectrum analysis was used to decompose the time series into twelve  
242 different components. Figure 4 shows the original signal and the first four components  
243 produced by the SSA for water consumption, maximum temperature, minimum temperature,  
244 mean temperature, radiation, vapour pressure and rainfall, respectively.

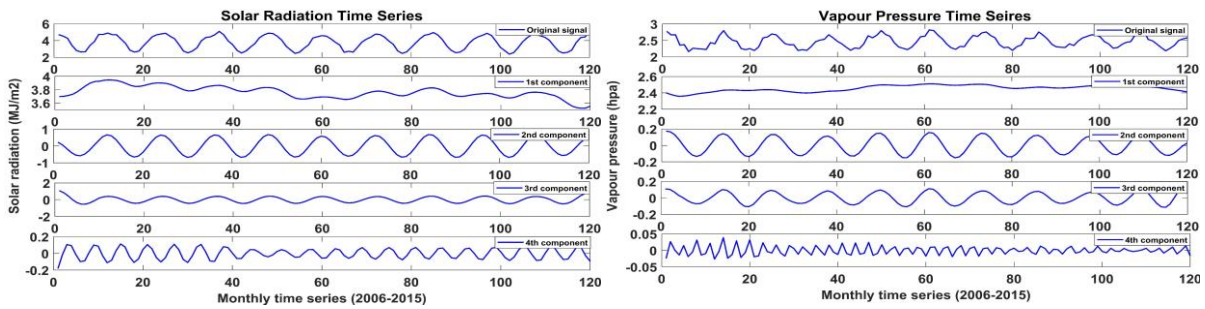
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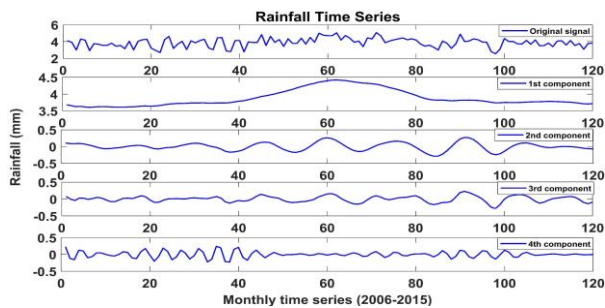
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247



248



249 Figure 4: Original signal and the 1<sup>st</sup> four components obtained from the SSA by water

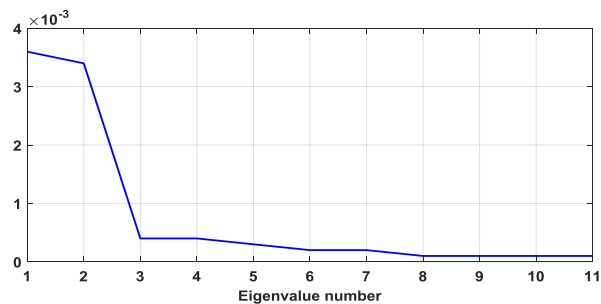
250 consumption and all the weather variables

251 6.2 Reconstruction components

252 As a mechanism to filter particular signals, the time series has been reconstructed using only

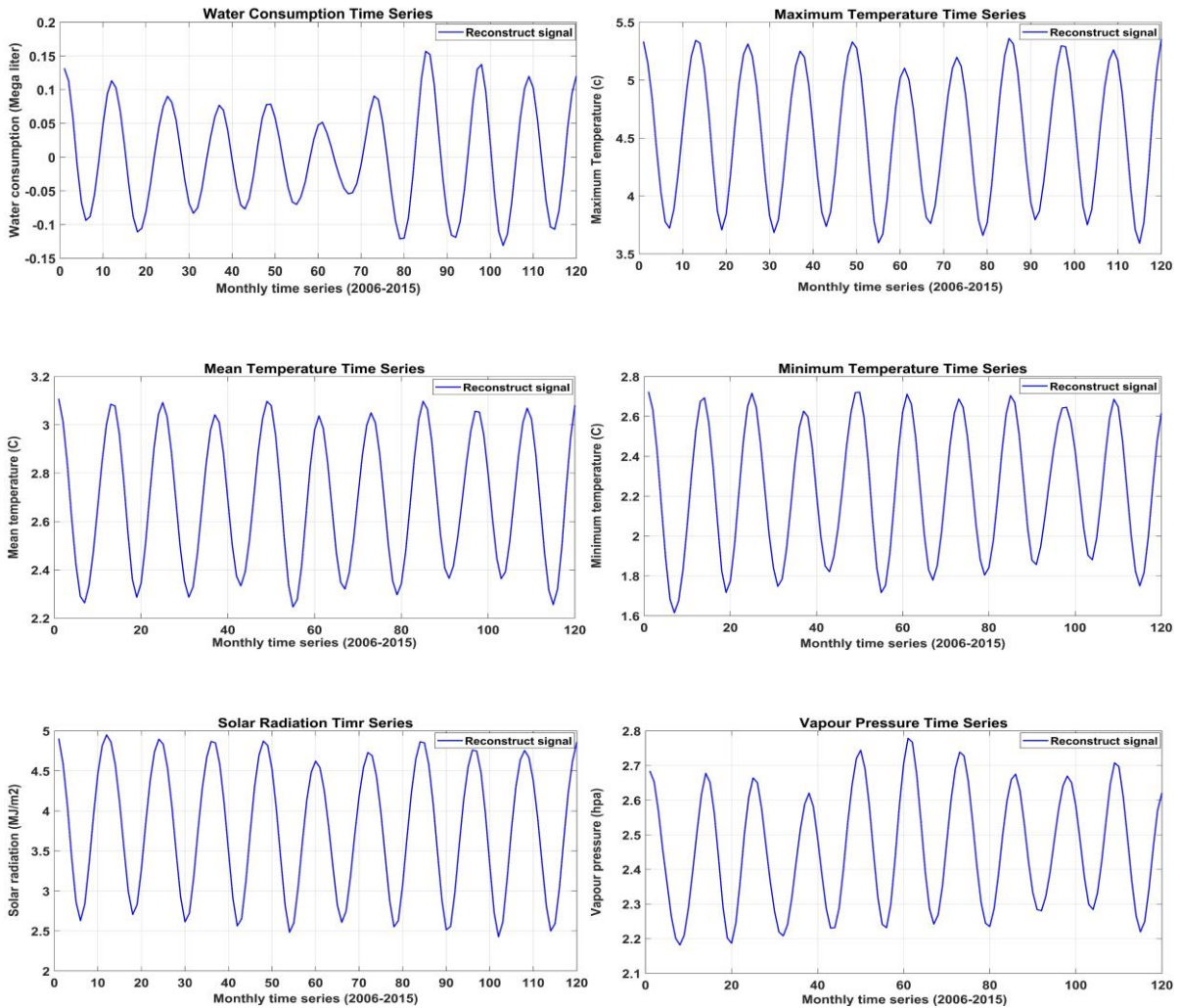
253 some of the principal components. The water consumption time series was reconstructed after

254 removing the components representing trend and noise. For the weather time series, the  
255 component representing noise was removed to generate a seasonal time series.  
256 Valuable insight is offered via an inspection breaks test in the eigenvalue spectra. A slight  
257 decrease in the singular sequence value, indicates pure noise according to the latter test.  
258 Eigenvalue spectrum breaks can therefore help to differentiate between signal eigentriples and  
259 noise. Figure 5 shows the plot of 11 eigenvalues for the water consumption time series, after  
260 removal of the trend component. For the water consumption series, the first component was  
261 omitted because it represents the trend, the new time series containing the 2<sup>nd</sup> and 3<sup>rd</sup>  
262 components. All the weather time series that have seasonal behaviour, were reconstructed using  
263 the first three components. In the case of the rainfall time series, which has irregular behaviour,  
264 the new time series comprised the 3<sup>rd</sup> component only. Figure 6 shows the new reconstructed  
265 series for all the different time series.



266  
267  
268 Figure 5: Eleven eigenvalues for the water consumption time series

269  
270  
271  
272  
273



274

275

276

277

Figure 6: Seasonal time series for water consumption and all the weather factors

278

The original time series were decomposed into twelve components. The trend, seasonal and

279

noise components were removed to detect the stochastic component for all time series. A

280

stochastic component represents the 3<sup>rd</sup> component in the water time series, the 4<sup>th</sup> component

281

in the rainfall time series and the 2<sup>nd</sup> for the remaining weather time series.

282

### 6.3 Selection of Explanatory Variables

283

284

A correlation matrix was used for water consumption and the weather variables across the raw,

285

seasonal and stochastic phases to show the impact of the SSA on the data (Table 1). What

286

stands out in this table is this significant increase in the correlation coefficient between water

287

consumption and climate factors (e.g. maximum temperature correlation increase from



288 approximately 0.72 to 0.96 after removing trend, seasonal and noise signals by using SSA).  
 289 These results confirm that adopting the SSA method as a pretreatment signal, helps to improve  
 290 the correlation between the dependent and independent variables, when forecasting water  
 291 demand models.

292 Table 1: Pearson’s correlation matrix analysis results for all data types

data kind	water	maximum temperature	minimum temperature	mean temperature	rainfall	radiation	vapour pressure
raw		.717**	.619**	.687**	-0.433**	.650**	.504**
seasonal	1	.945**	.901**	.933**	-0.497**	.875**	.838**
stochastic		.957**	.924**	.948**	-.616**	.900**	.877**

293 \*\*\*. Correlation is significant at the 0.01 level (2-tailed).

294 Further to this, the variance inflation factor (VIF) was applied to avoid multicollinearity. Three  
 295 weather variables; maximum temperature, radiation and rainfall, were selected to be input  
 296 factors in both seasonal and stochastic models.

297 According to Tabachnick and Fidell (2013), the required sample size is based on the number  
 298 of predictors as presented in equation 11.

$$299 \quad N \geq 104 + m \quad (11)$$

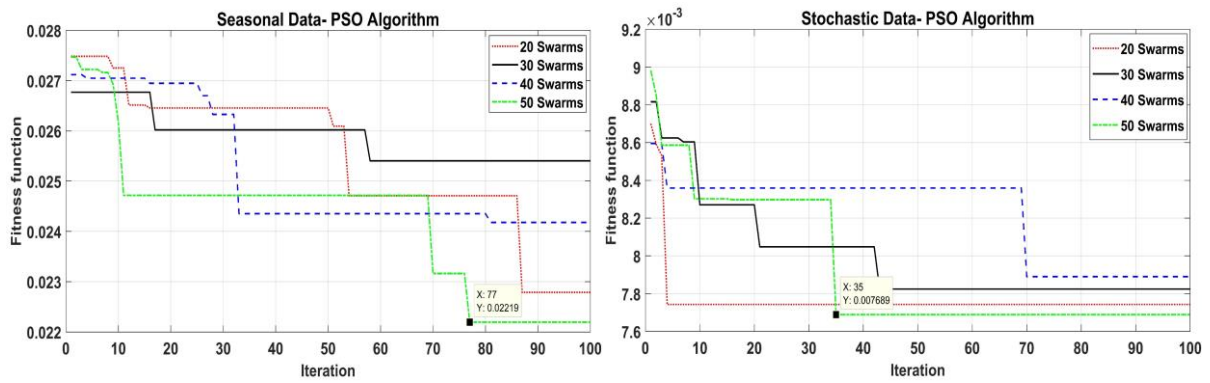
300 m= number of independent variables.

301 In this study the number of cases is N=120, more than the 107 required.

#### 302 6.4 Application of the hybrid Algorithm technique

303 Different swarm sizes (20, 30, 40 and 50) were used to run a PSO-ANN algorithm in MATLAB  
 304 toolbox, to establish the optimum swarm size and identify the most appropriate learning rate  
 305 and number of neurons in both hidden layers. Figure 7 shows that a swarm size of 50 offers the  
 306 best solution for both seasonal and stochastic time series. The best fitness function was 0.02219

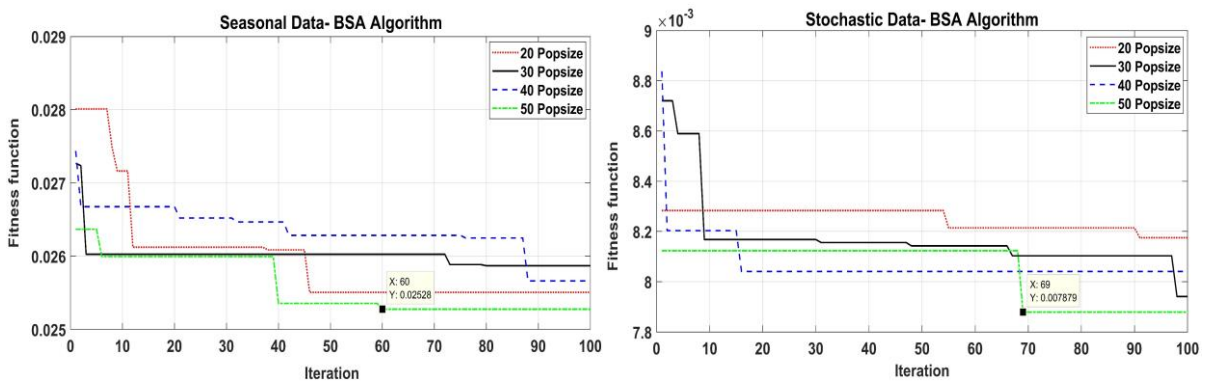
307 after 77 iterations and 0.007689 after 35 iterations, for the seasonal and stochastic phases,  
 308 respectively.



309

310 Figure 7: Fitness function of various swarm sizes for seasonal and stochastic data (PSO)

311 A BSA-ANN algorithm is also used to achieve the same objective for populations of 20, 30,  
 312 40 and 50 to compare to the results from the hybrid PSO-ANN, as shown in Figure 8. On close  
 313 inspection of Figure 8, it can be seen that the RMSE = 0.02528 and 0.007879 for seasonal and  
 314 stochastic data, respectively.



315

316 Figure 8: Fitness function of various swarm sizes for seasonal and stochastic data (BSA)

317 The outcomes obtained from the hybrid PSO-ANN were compared with those from the BSA-  
 318 ANN in order to validate the new technique. The resulting models obtained when using PSO-  
 319 ANN, have a lower RMSE in comparison to the BAS-ANN for both seasonal and stochastic

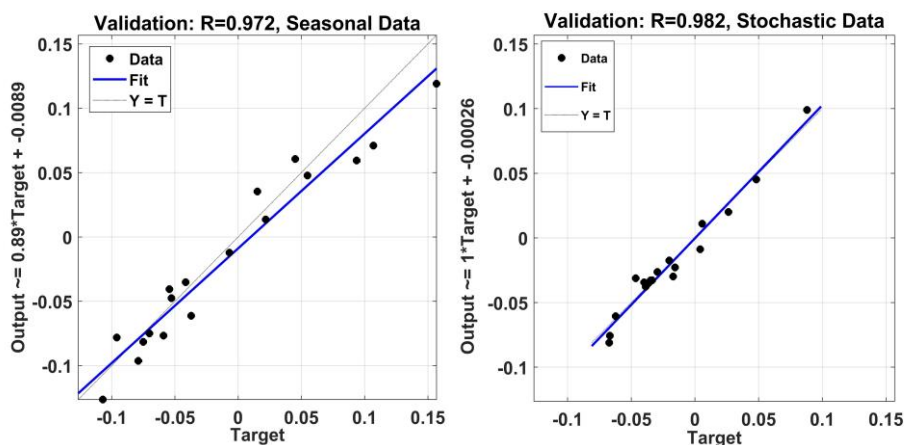
320 data. The optimum ANN parameters obtained from the PSO-ANN technique, are given in  
 321 Table 2.

322 Table 2: ANN parameters based on PSO-ANN algorithms for seasonal and stochastic data

Data Type	Parameters	PSO-ANN
Seasonal	N1	5
	N2	12
	LR	0.5696
Stochastic	N1	3
	N2	11
	LR	0.1594

323 N1, N2 = number of neurons in hidden layers one and two, respectively. LR = ANN's learning rate

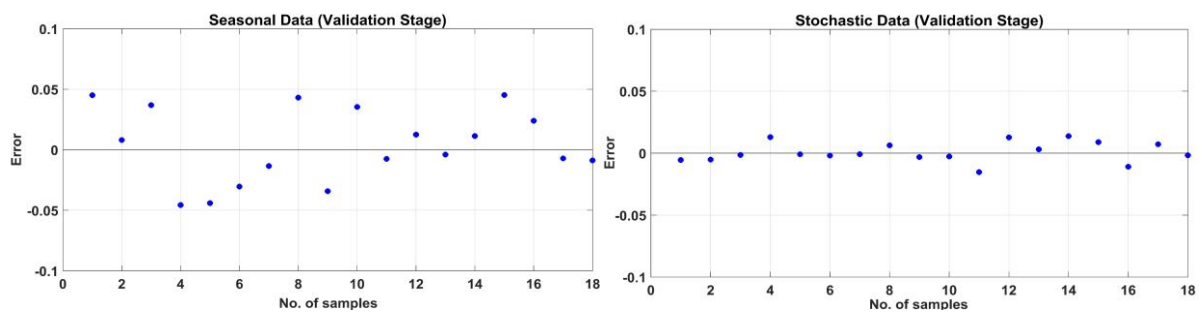
324 To explore the predictive performance of the hybrid model, the coefficient of regression (R)  
 325 was determined between the measured and predicted water demands, as shown in Figure 9.  
 326 The observed water consumption (i.e., the target on the x-axis) is plotted against the predicted  
 327 water demand (i.e., output on the y-axis). The combination model was significant R=0.972 and  
 328 R=0.982 for seasonal and stochastic data respectively, at the validation stage. These figures  
 329 emphasise the ability of the hybrid-PSO-ANN technique to accurately predict water demand  
 330 for both cases, the stochastic model performing slightly better than the seasonal.



331

332 Figure 9: PSO-ANN algorithm performance for seasonal and stochastic data

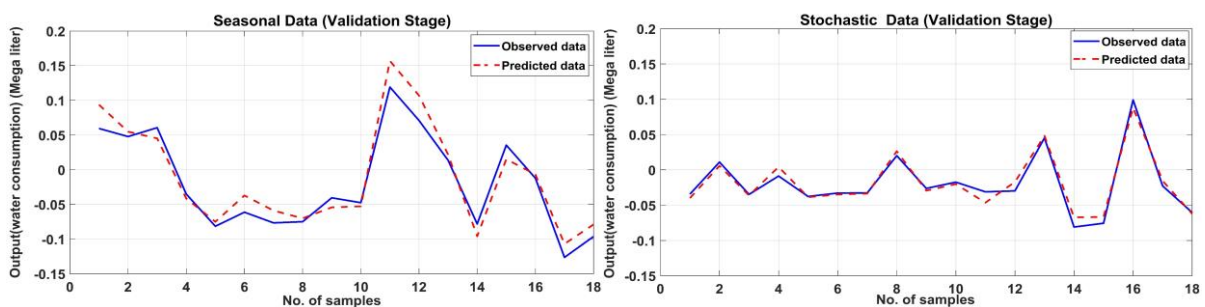
333 In order to examine the goodness of fit of the model, an error analysis was performed. The  
 334 scatter plots of error, versus a number of samples for seasonal and stochastic phases, are  
 335 presented in Figure 10. In all figures, three important patterns have emerged from the data; the  
 336 mean error was very close to zero, no special trend exists for the pattern of distribution and the  
 337 distribution of error density for all data is regular. In addition, the stochastic data had a smaller  
 338 error scale between -0.02 and 0.02 in comparison to the seasonal data scale, which was between  
 339 -0.05 and 0.05 at the validation stage.



340

341 Figure 10: Residual scatterplots for seasonal and stochastic data

342 Both the stochastic and seasonal graphs depicted in Figure 11, show an excellent fit between  
 343 actual and predicted municipal water supplies demonstrating the capacity of this model to  
 344 simulate both time series accurately. This model has the ability to accurately capture the pattern  
 345 of water consumption, for seasonal and stochastic data, at the validation stage. The prediction  
 346 is more accurate for the stochastic time series than the seasonal, a result which is in line with  
 347 the scale of error for each of these series, as detailed previously.



348

349 Figure 11: Measured and predicted water demand for stochastic and seasonal data

350 Table 3 shows the results for RMSE, MSE and MAE, used to evaluate the performance of the  
 351 models. An important point that emerged from the data was the ability of both models to predict  
 352 water demand. The stochastic time series was more accurate when simulating observed water  
 353 data in comparison to the seasonal phase (MAE= 0.0064 for stochastic data compare with  
 354 MAE= 0.0165 for seasonal data).

355 Table 3: Three statistical criteria for seasonal and stochastic data

Data	RMSE	MSE	MAE
Seasonal	0.0196	$3,8288 e^{-04}$	0.0165
Stochastic	0.0080	$6.3277 e^{-05}$	0.0064

356 RMSE: root mean square error, MSE: mean square error, MAE: mean absolute error

357 The use of data pre-processing, specifically the pretreatment signal technique, has played an  
 358 important role in obtaining these results. The use of a hybrid PSO-ANN model has also proven  
 359 to be a successful choice for this particular application. This technique has resulted in stronger  
 360 correlation coefficients and less error, for the prediction of municipal water demand based only  
 361 on climatic factors. The results obtained with this combination of techniques support the  
 362 conceptual premise that water demand is driven by climatic factors in the mid-time period, thus  
 363 decreasing the uncertainties around the impact of climate change.

## 364 7 Conclusion

365 The starting point of this study was the need for the precise prediction of municipal water  
 366 demand for water utilities, stakeholders and policy makers. A high degree of seasonality and  
 367 trend variability in municipal water demand not only intensifies this need but also creates a  
 368 demand for predictive methods that are able to accurately deal with these variations. The  
 369 motivation for this study was to develop a novel methodology to investigate the impact of  
 370 climate change on water consumption, for a mid-term time series. This methodology comprised  
 371 two sections: (1) to investigate the ability of SSA to extract tendencies, harmonic components  
 372 and irregular components, as well as filtering the noise from different time series and, (2) to

373 examine the reliability of a hybrid PSO-ANN model to forecast monthly water demand time  
374 series.

375 The first major finding was that maximum temperature, rainfall and solar radiation were robust  
376 predictors, able to simulate municipal water demand. The power of the SSA technique proved  
377 it able to detect both stochastic and seasonal components of the model. The PSO-ANN  
378 algorithm yielded a RMSE of 0.02219 and 0.007689 for seasonal and stochastic data. It  
379 performed better than the BSA-ANN algorithm, which yielded a RMSE of 0.02528 and  
380 0.007879 for seasonal and stochastic data, respectively. The combination SSA and PSO-ANN  
381 technique was reliable and efficient when simulating municipal water demand based on  
382 climatic factors only, for a mid-term time series. This paired technique has correlation  
383 coefficients at the validation stage of  $R=0.972$  and  $0.982$  for seasonal and stochastic data,  
384 respectively. This study may be considered evidence to encourage water companies to adopt  
385 the combined technique of a pretreatment signal with a hybrid PSO-ANN model, to predict  
386 water demand across various situations and locations.

### 387 **Acknowledgements**

388 The first author thanks the Ministry of Higher Education and Scientific Research, Iraq, and the University of Wasit  
389 for the financial support for this study. Data on water consumption and weather variables was provided by Peter  
390 Roberts, Demand Forecasting Manager, Yarra Valley Water.

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