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A Method for Predicting Long-term Municipal Water Demands Under Climate Change

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Abstract

The accurate forecast of water demand is challenging for water utilities, specifically when considering the implications of climate change. As such, this is the first study that focuses on finding associations between monthly climate factors and municipal water consumption, using baseline data collected between 1980 and 2010. The aim of the study was to investigate the reliability and capability of a combination of techniques, including Singular Spectrum Analysis (SSA) and Artificial Neural Networks (ANNs), to accurately predict long-term, monthly water demands. The principal findings of this research are as follows: a) SSA is a powerful method when applied to remove the impact of socio-economic variables and noise, and to determine a

21 stochastic signal for long-term water consumption time series; b) ANN performed better when
22 optimised using the Lightning Search Algorithm (LSA-ANN) compared with other approaches
23 used in previous studies, i.e. hybrid Particle Swarm Optimisation (PSO-ANN) and
24 Gravitational Search Algorithm (GSA-ANN); c) the proposed LSA-ANN methodology was
25 able to produce a highly accurate and robust model of water demand, achieving a correlation
26 coefficient of 0.96 between observed and predicted water demand when using a validation
27 dataset, and a very small root mean square error of 0.025.

28 **Keywords**

29 Artificial Neural Network, climate change, Lightning Search Algorithm, Singular Spectrum
30 Analysis and water prediction

31 **1 Introduction**

32 Nowadays, many countries face numerous concurrent challenges in the management of, and
33 access to, potable water. The authors in UNDP (2013), Ferguson et al. (2013) and Hossain et
34 al. (2018), among many others, have identified the impact of global warming and related
35 climate change, such as an increased frequency and severity of drought and flooding as one of
36 the most significant impacts on our aquatic environment. As a result, considerable pressure is
37 being placed on water infrastructures. It has also been reported that global warming generates
38 considerable uncertainties on the long-term planning projections of water demand in urban
39 areas (Urich and Rauch (2014). These uncertainties can lead to significant problems in other
40 related areas such as supply, operation and cost, which traditional planning methods cannot
41 solve.

42 The aforementioned increasing concerns about the impact of climate change have led to the
43 need to plan and manage water in advanced, to guarantee meeting municipal water demand to
44 the satisfaction of the consumer (Zhang et al., 2019). This type of strategic planning, as
45 conveyed by Cutore et al. (2008), means planning now for an uncertain future. However, since
46 conventional models are no longer adequate to predict urban water consumption under the
47 pressure of climate change in the future, several researchers have been investigating and
48 improving various mathematical models to develop techniques to better estimate essential
49 parameters and better model forecast uncertainties (Marlow et al., 2013).

50 The accurate water demand prediction can play an important role in optimising the design,
51 operation and management of municipal water supply infrastructures (Pacchin et al., 2019).
52 This can also minimise the uncertainty that results from a rapid increase in water demand due
53 to the impact of climatic factors (Bougadis et al., 2005). Previous studies such as Gato et al.
54 (2007), Tian et al. (2016) and Brentan et al. (2017), have established that water consumption
55 is affected by weather variables throughout the year. In this area of research, Artificial Neural
56 Networks (ANNs) have been developed and compared with various traditional statistical
57 models, the results indicating that ANN techniques offer better forecasting models such as
58 those in Sebri (2013), Behboudian et al. (2014), Mouatadid and Adamowski (2016) and Guo
59 et al. (2018).

60 The need for increased reliability, capability and accuracy regarding data-driven techniques
61 has motivated the development of hybrid models, which would integrate two or more
62 techniques with the aim of outperforming the capability of single models. In these hybrid
63 approaches, typically one of the techniques would be deemed as the primary one, and the others
64 would work as pre-processing or post-processing methods (Araghinejad, 2014). Recently,

65 several hybrid techniques have been applied to predict water demand, for example Anele et al.
66 (2017), Altunkaynak and Nigussie (2018) and Seo et al. (2018).

67 Although previous studies have recognised the impact of weather factors, research has yet to
68 thoroughly and systematically investigate the effect of these factors in terms of using adequate
69 data pre-processing to remove the impact of socio-economic factors, which are insensitive to
70 climate change, and to apply a powerful and effective forecasting technique on a systematic
71 basis, instead of a commonly used trial and error approach. As such, studies to date have not
72 been able to detect to what extent climate factors have driven municipal water demands, the
73 debate continuing about the best strategies for the management of municipal water demand,
74 under the impact of climate change.

75 Previous research on the influence of climate change on municipal water demand using a
76 recommended baseline period has not been properly conducted. These studies have suffered
77 from inadequate sample size, the mixing of evidence for climate change impact with
78 socioeconomic factors and several conceptual and methodological weaknesses.

79 Various optimisation approaches can be adopted to handle a range of issues for different
80 application domains. The goal of the optimisation algorithm is to determine the best parameter
81 values of the system under different conditions (Ahmed et al., 2016). Recently, the gravitational
82 search algorithm (GSA) proposed by Rashedi et al. (2009) has been applied to tackle various
83 optimisation issues such as unconstrained global optimisation problems (García-Ródenas et al.,
84 2019), hydrology (Karami et al., 2019) and in the geothermal power plant optimisation
85 (Özkaraca and Keçebaş, 2019). Particle Swarm Optimisation (PSO) algorithm has been used
86 in different fields such as sediment yield forecasting (Meshram et al., 2019), operation rule

87 derivation of hydropower reservoir (Feng et al., 2019) and semi-supervised data clustering (Lai
88 et al., 2019).

89 Following the above review, the principal objectives of this paper are:

- 90 1) To remove the effect of socioeconomic factors which are insensitive to weather and
91 have a deterministic relationship with water consumption, and also to remove noise
92 from water consumption for a long-term, monthly time series.
- 93 2) To provide a new reliable and efficient hybrid technique (LSA-ANN) to forecast long-
94 term monthly municipal water demands and evaluate how it compares with hybrid
95 (GSA-ANN and PSO-ANN) models.
- 96 3) To assess the long-term influence of climate change using monthly municipal water
97 demand relative to the period 1980-2010.

98 To the best of our knowledge, this is the first study that tackles the aforementioned
99 objectives to assess long-term influence of climate change using monthly municipal water
100 demand from the baseline period 1980-2010.

101 **2 The study area**

102 One catchment area in Australia, Greater Melbourne, Victoria, was employed to evolve the
103 water demand model. Yarra Valley Water (YVW), is one of three retail water utilities that
104 deliver essential municipal water supplies and sewerage services to more than 1.8 million
105 people and 50,000 businesses, in the catchment area of Yarra River, Melbourne City. YVW
106 buy water wholesale from Melbourne Water, which is usually harvested from protected
107 catchments in the mountains. They deliver water to different sectors including commercial,
108 industrial and residential (indoor and outdoor uses) users. The service area managed by the

109 company is approximately 4,000 square kilometres, covering the northern area of Melbourne
110 and the eastern suburbs, from Wallan in the north to Warburton in the east (YVW, 2017).

111 **3 Model data set**

112 This study will use monthly historical data containing information such as measured municipal
113 water consumption (Megalitre, ML), maximum temperature ($^{\circ}\text{C}$), minimum temperature ($^{\circ}\text{C}$),
114 mean temperature ($^{\circ}\text{C}$), rainfall (mm) and solar radiation (MJ/m^2) over the periods 1980-2010.
115 These data were collected from the Yarra Valley Water Company from areas they serve in
116 Melbourne city.

117 This range of climate factors have been used by several researchers (Kadiyala et al., 2015,
118 Osman et al., 2017, Fenta Mekonnen and Disse, 2018) in different areas of study, to assess the
119 impact of climate change as they are considered robust predictors, able to simulate municipal
120 water demands, as shown in Zubaidi et al. (2018a). Socioeconomic variables such as
121 population, water price and household income are deterministic signals (Zhoua et al., 2000,
122 Gato et al., 2005) and for this reason, were not included in the current analysis, as these signals
123 are out of the scope of this study.

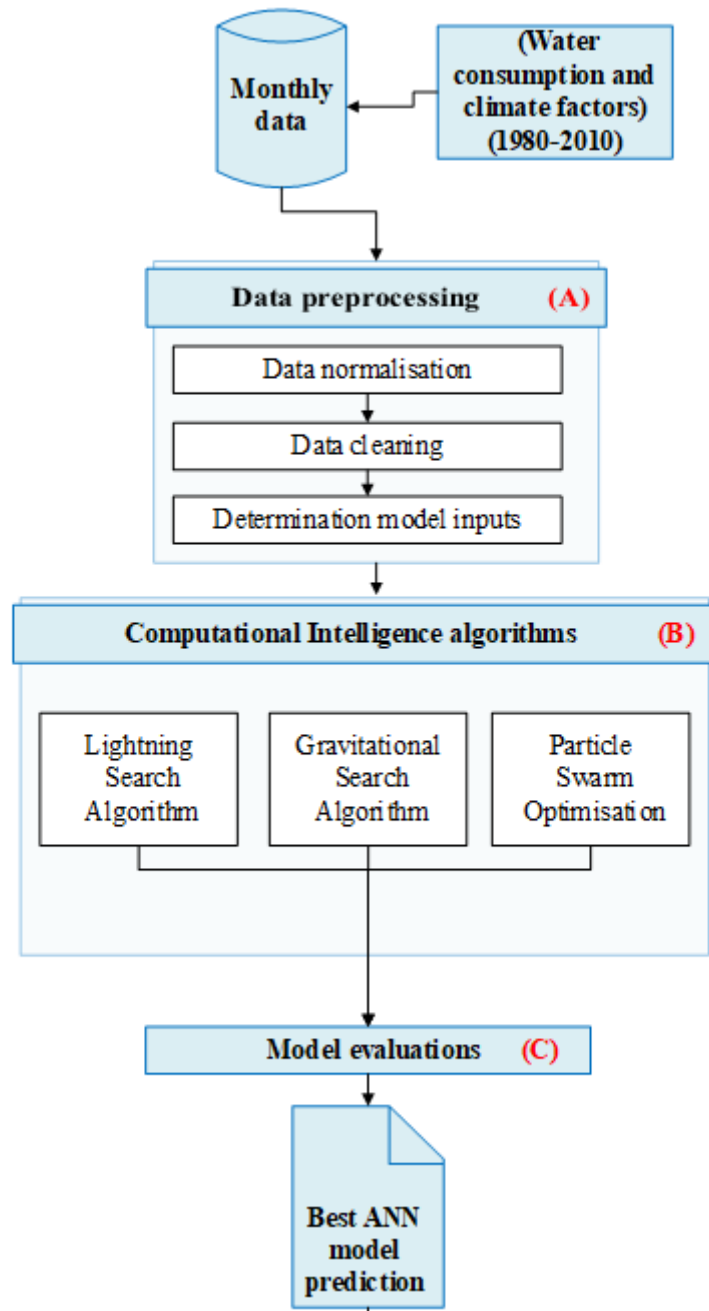
124 Melbourne City has various meteorological stations that are spread throughout the city. The
125 Yarra Valley Company provided us with the average daily values of all the climate factors
126 covered by its service area. The aforementioned company had obtained these data from the
127 Australia Bureau of Meteorology, which had applied the arithmetic mean method to calculate
128 average values of climate factors. With this technique, all climate variable values from different
129 metrological stations are added together and then divided by the total number of stations, to get
130 the mean value of that variable as shown in Eq. (1). This is a simple and standard technique to

131 calculate average daily values. Each metrological station has equal weight, regardless of its
132 location (Bhavani, 2013).

$$p_m = \{(p_1 + p_2 + p_3 + \dots + p_n)/n\} \quad (1)$$

133 **4 Methodology**

134 The municipal water demand model proposed here allows a long-term time series demand
135 prediction to be calculated regarding climate change. Figure 1 presents a diagrammatic
136 representation that contains the steps required to build the water prediction model.



137

138 **Fig. 1** Flowchart showing the steps required to forecast future municipal water demand

139 4.1 Pre-processing of data

140 The data pre-processing approach followed in this study comprises three techniques:

141 normalisation, cleaning and determination model input. They are detailed below.

142 4.1.1 Normalisation

143 In this study, the natural logarithm method was used to normalise the data to be more static and
144 to remove any collinearity from the independent variables (Behboudian et al., 2014).

145 4.1.2 Cleaning

146 Data cleaning includes the identification and removal of trends and non-stationary components
147 from a data set, as explained in Abrahart et al. (2004). A time series y_t can be decomposed into
148 trend (T), oscillatory (O), stochastic (S) and noise (ϵ) components (trend and oscillatory
149 considered deterministic signals) as shown in Eq. (2) (Araghinejad, 2014).

$$y_t = T_t + O_t + S_t + \epsilon_t \quad (2)$$

150 To identify outliers, the box and whisker method was used, and the outliers then treated. The
151 SSA technique was also used to detect the stochastic signals for long-term monthly municipal
152 water consumption and the climate variables time series (i.e. to remove the impact of
153 socioeconomic variables and noise from the municipal water consumption data).

154 SSA is a robust method used to decompose the raw time series, which may exhibit nonlinear
155 properties, and to uncover the stochastic component after the removal of noise, trend and
156 oscillatory components, as illustrated by Khan and Poskitt (2017). The stochastic component
157 helps to identify the impact of climate volatility on water consumption, to enhance the accuracy
158 of the forecasting and to decrease the scale of error between measured and predicted water
159 demand (Zubaidi et al., 2018a). The SSA method consists of two steps: analysis of the original
160 time series into various principal components (PCs) containing trend, oscillatory and irregular
161 components, followed by noise removal to allow the reconstruction of a new time series that
162 has less noise (Zubaidi et al., 2018a). This approach does not require the imposition of any

163 statistical assumptions such as normality or linearity. It has been successfully applied in
164 different sectors including industry (Al-Bugharbee and Trendafilova, 2016), mid-term water
165 demand prediction (Zubaidi et al., 2018c) and hydrology (Ouyang and Lu, 2017). Further
166 details about SSA can be found in Golyandina and Zhigljavsky (2013).

167 4.1.3 Determination model input

168 The choice of the explanatory variables that influence water consumption as model input data,
169 is an important step in the development of not only an ANN forecasting model, but any good
170 model (Maier and Dandy, 2000). In this study, cross-correlation and variance inflation factor
171 (VIF) techniques were applied to select the model input and examine for multicollinearity
172 among them, as previously carried out by Zubaidi et al. (2018a).

173 To decide on the appropriate sample size needed to develop a good model, Tabachnick and
174 Fidell (2013) propose using a sample size that is dependent on the number of predictors, as
175 shown in Eq. (3). In this study, the sample size is 372.

$$N \geq 104 + m \quad (3)$$

176 where N = sample size and m = number of independent variables.

177 4.2 Artificial neural network techniques for forecasting municipal water demand

178 This section will briefly present the techniques used in this study, including ANN, LSA as an
179 optimisation algorithm, and the hybrid LSA-ANN technique.

180 4.2.1 Artificial Neural Networks (ANN)

181 Previous studies have demonstrated the power of ANN to produce good non-linear models for
182 urban water demand (Toth et al., 2018). However, unlike other applications of hydrology, ANN
183 has not been extensively used in municipal water demand modelling (Zubaidi et al., 2018b),
184 even when it has proven to be able to deal with a large number of input and output patterns,
185 and is capable of handling different complex nonlinear environmental problems, making it
186 appropriate for long-term prediction modelling (Mutlu et al., 2008).

187 For this study, a multilayer perceptron (MLP) network was used (a feed-forward,
188 backpropagation network), along with the Levenberg-Marquardt learning algorithm (LM). The
189 *tansigmoidal* activation function was adopted in both hidden layers to cover all negative input
190 values, while the output layer operated under a *linear* activation function to cover the positive
191 values of water demand. The model was implemented using the MATLAB Neural Network
192 Toolbox (Mathworks, 2017). The data was randomly separated into three sets include training,
193 testing and validation sets, using 70%, 15% and 15% instances for each set, respectively, as
194 previously done in Zubaidi et al. (2018b) and Zubaidi et al. (2018a).

195 4.2.2 Overview of the Lightning Search Algorithm for ANN optimisation

196 Optimisation in this context refers to the process of determining the best solution for issues
197 relying on input variables after locating the fitness function as a constraint. Often, the
198 formulation of this function is dependent on a certain application and can be expressed as
199 minimal error / cost, or optimal design / management. LSA is a new, nature-inspired
200 metaheuristic optimisation algorithm, based on the natural phenomenon of lightning to tackle
201 constraint optimisation issues. The hypothesis of this algorithm is inspired by the probabilistic
202 nature and tortuous characteristics of lightning discharged during a thunderstorm. The

203 generalisation of the LSA algorithm is via the mechanism of step leader propagation. This
204 algorithm allows for the involvement of fast particles, identified as projectiles, in the
205 configuration of the binary tree structure of a step leader. Three kinds of projectiles are
206 developed to represent transition projectiles: the 1st step leader population N; the space
207 projectiles that attempt to be the leader, and the lead projectile representing the optimum
208 positioned projectile found amid N number of step leaders (Mutlag et al., 2016, Shareef et al.,
209 2015).

210 LSA is similar to other metaheuristic algorithms in that it needs a population to start the search
211 (Ahmed et al., 2016). Further details about LSA algorithm, including a review of its basic
212 concepts, can be found in Shareef et al. (2015).

213 4.2.3 Hybrid Lightning Search Algorithm-Based Artificial Neural Network

214 ANN can be employed to predict municipal water demands using climate variables as the
215 model input (Zubaidi et al., 2018a). To do so, it is important to consider the number of neurons
216 in the hidden layers and the learning rate coefficient as these are essential factors of an ANN
217 architecture. These factors are responsible for mapping the relationship between the input and
218 output variables used to develop the ANN model and to minimise error (Gharghan et al., 2016).
219 However, the choice of neurons and learning rate are dependent on trial and error processes
220 that may not offer an optimal solution. LSA addresses this issue, thus enhancing the
221 performance of ANN, by estimating the best values for learning rate coefficients and the
222 number of neurons in each hidden layer of the ANN model. It uses a root mean squared error
223 (RMSE) based fitness function to improve the performance of the LSA-ANN by minimising
224 the error function.

225 4.3 Performance measurement criteria

226 After calibrating all the model structures using the calibration/training data set, performance
227 was assessed using several standard statistical criteria which identify the errors related to the
228 model simulations (Adamowski, 2008). These criteria offer a means of measuring estimate
229 accuracy, this implying that estimate errors play an important role in the selection of an
230 appropriate model and in providing insight for alterations to current models to reduce
231 deviations in future simulations (Donkor et al., 2014). The following statistical criteria will be
232 used in the current model's calibration: mean absolute error (MAE), mean squared error (MSE),
233 root mean squared error (RMSE) and correlation coefficient (R). These criteria are defined in
234 Eq.s (4) through to (7).

$$MAE = \frac{\sum_{m=1}^N |y_o - y_p|}{N} \quad (4)$$

$$MSE = \frac{\sum_{m=1}^N (y_o - y_p)^2}{N} \quad (5)$$

$$RMSE = \sqrt{\frac{\sum_{m=1}^N (y_o - y_p)^2}{N}} \quad (6)$$

$$R = \left[\frac{\sum_{m=1}^N (y_o - \bar{y}_o)(y_p - \bar{y}_p)}{\sqrt{\sum (y_o - \bar{y}_o)^2 \sum (y_p - \bar{y}_p)^2}} \right] \quad (7)$$

235 where y_o represents observed water consumption; y_p , simulated water demand; N, sample size;
236 \bar{y}_p , mean of simulated demand, and \bar{y}_o , the mean of observed consumption.

237 The stationarity of the stochastic time series for all variables has been examined by the
238 Augmented Dickey-Fuller (ADF) test and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS)
239 test. A residual analysis will also be used to check the goodness of fit of the ANN model.

240 **5 Results and discussion**

241 5.1 Model inputs

242 This section corresponds to step A in Fig. 1. Five monthly climate factors have been used to
243 assess the impact of climate change on monthly water consumption. These factors are
244 maximum temperature (Tmax), minimum temperature (Tmin), mean temperature (Tmean),
245 solar radiation (Radi) and rainfall (Rain). Following data pre-processing, which included
246 normalisation by natural logarithm and cleaning data outliers, a pre-treatment signal analysis
247 (SSA) was used to uncover the stochastic component. Components of the original time series
248 were examined to detect the stochastic signal. It represents the third signal in water
249 consumption and all the climate factors time series, except the solar radiation time series, which
250 was the second signal. The stationarity of the stochastic signals has been examined using ADF
251 and KPSS tests. Figure 2 presents the original time series and the first four components of water
252 consumption and all the climate factors.

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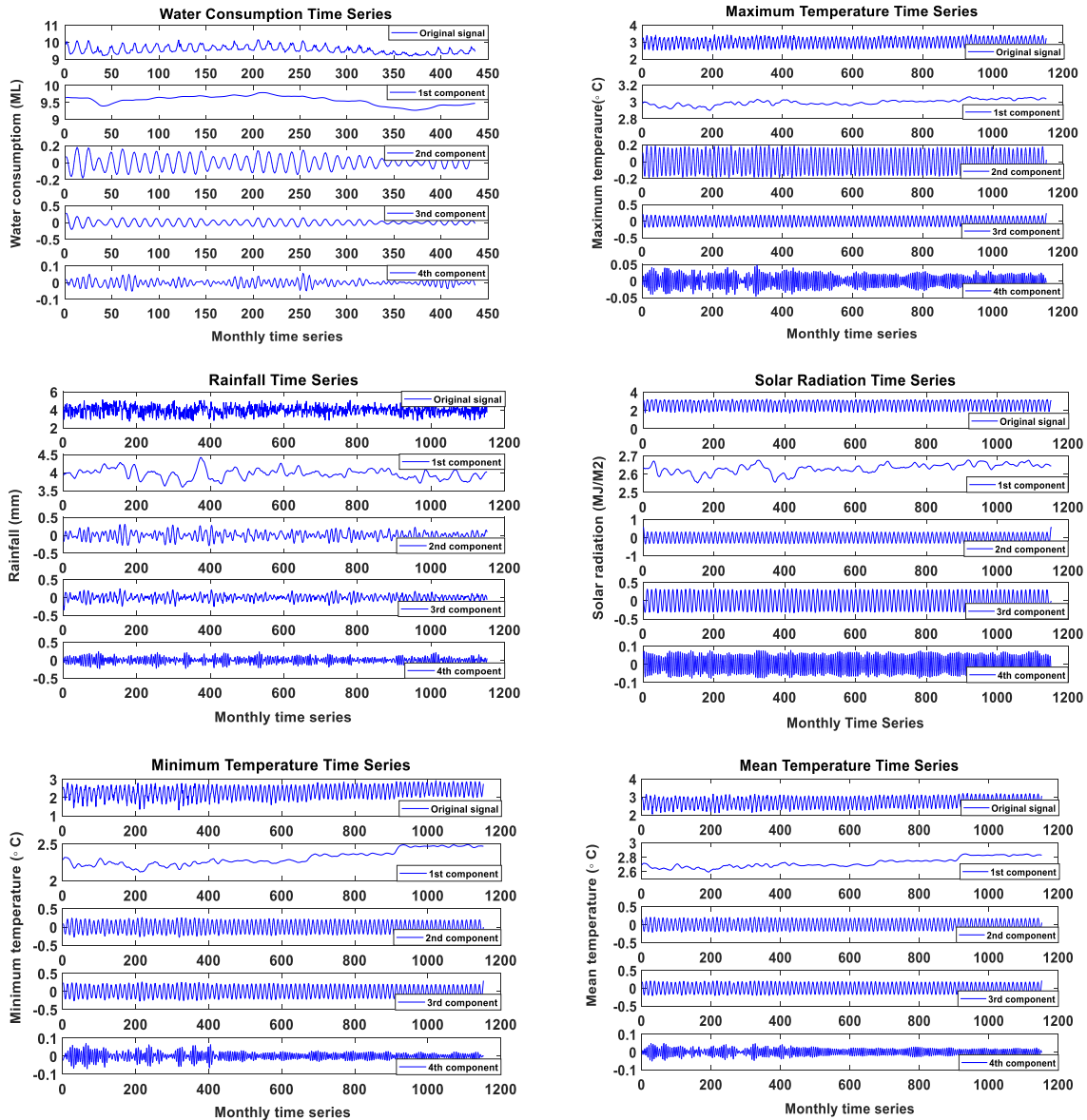


Fig. 2 Original signal and the 1st four components obtained by SSA

257 To detect noise components, Ghodsi et al. (2009) pointed out that a significant drop in
 258 eigenvalue spectra values could be assumed as the beginning of pure noise. Figure 4-a shows
 259 the graph of the eigenvalue spectra for the water consumption time series, where it can be seen
 260 that the first signal, which represents a trend, was prevailing and covered all the details.
 261 Therefore, the first signal was removed, and the graph redrawn in section b. In this section, a
 262 significant drop occurred in the third signal, this representing the beginning of the noise floor.

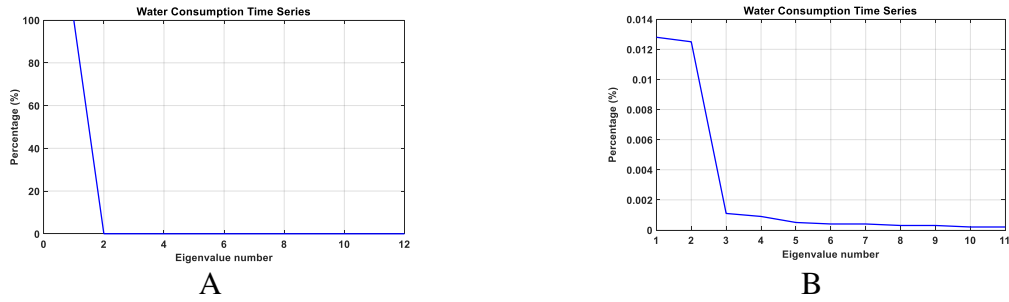
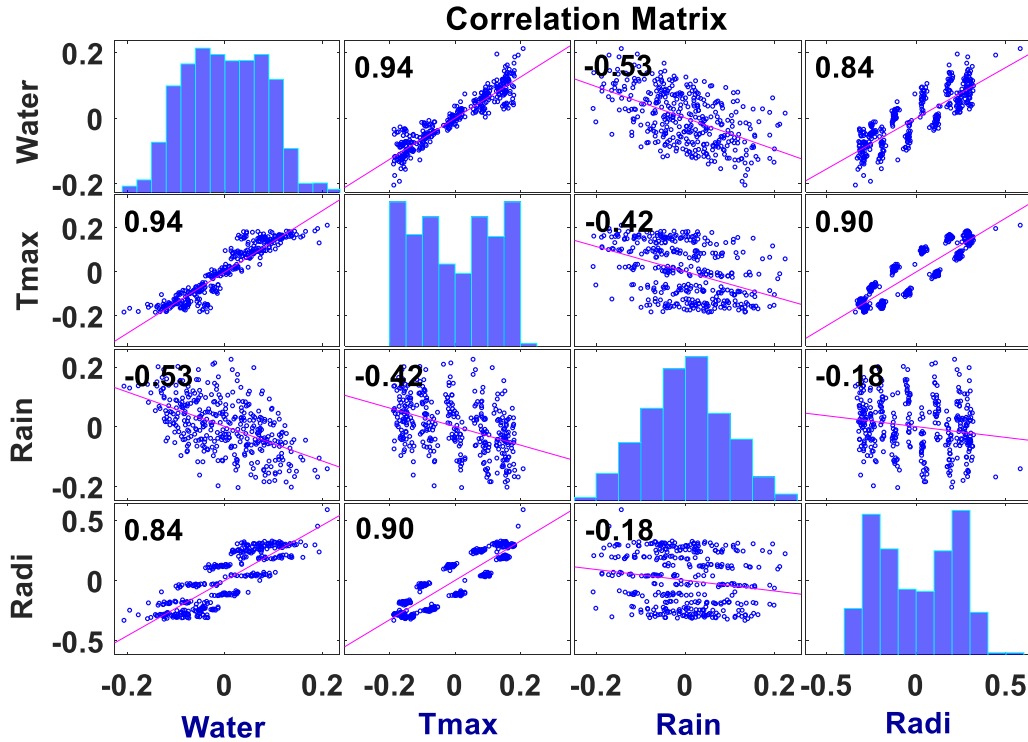


Fig. 3 Eigenvalues of water consumption time series

263 A variance inflation factor (VIF) was used to examine the multicollinearity between the model
 264 input variables. Three independent factors, Tmax, Radi and Rain, were selected as the model
 265 input. The sample size required for the model was estimated by using Eq. (3), which revealed
 266 that 107 (104+3) were needed. In this study, the number of cases is N=372, which is more than
 267 three times the minimum required.

268 A Pearson product-moment correlation coefficient was used to determine the relationship
 269 between the stochastic components of water consumption and the chosen climate variables.
 270 Figure 4 shows the correlation between the independent and dependent variables. A strong
 271 correlation was found between the stochastic signals of long-term water consumption and
 272 maximum temperature R=0.94. This result reveals that the data pre-processing techniques are
 273 powerful.



274

275

Fig. 4 Correlations between water consumption and climate factors

276

From these results, we can see that water demand (dependent variable) can be expressed as a function of Tmax, Radi and Rain (independent variables).

277

278

5.2 Application of the hybrid LSA-ANN algorithm

279

This section corresponds to step B in Fig. 1. A MATLAB toolbox was used to run the LSA-

280

ANN, GSA-ANN and PSO-ANN algorithms. In order to estimate the best number of hidden

281

neurons and the optimum learning rate coefficient of all three techniques, five population sizes,

282

10, 20, 30, 40 and 50, were used. Note that these population sizes relate to the size of the swarm

283

which is different to the sample size mentioned before. As can be seen in Fig. 5, a population

284

size of 50 provides the best solution for all three algorithms. Closer inspection of the fitness

285

function values for all algorithms shows that the RMSE for the LSA-ANN algorithm (after 40

286

iterations) is 0.0236, whereas GSA-ANN does not improve beyond an RMSE of 0.0241. The

287

PSO-ANN algorithm only reaches its best RMSE of 0.0245 after 62 iterations. As such, the

288 LSA-ANN algorithm outperforms GSA-ANN and PSO-ANN, as it achieves a smaller error
 289 (better performance) in a smaller number of iterations, making it a less complex model. Table
 290 1 lists the design parameters of the ANN model based on the LSA-ANN algorithm.

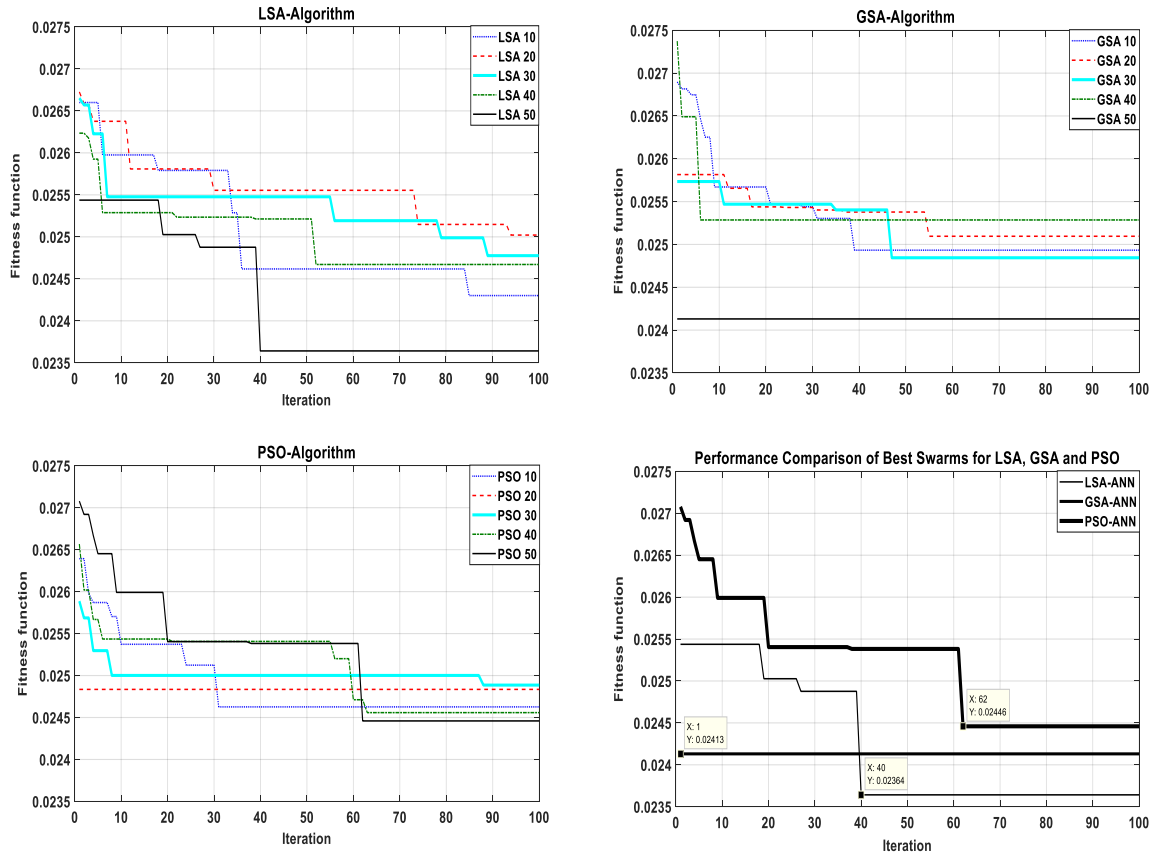


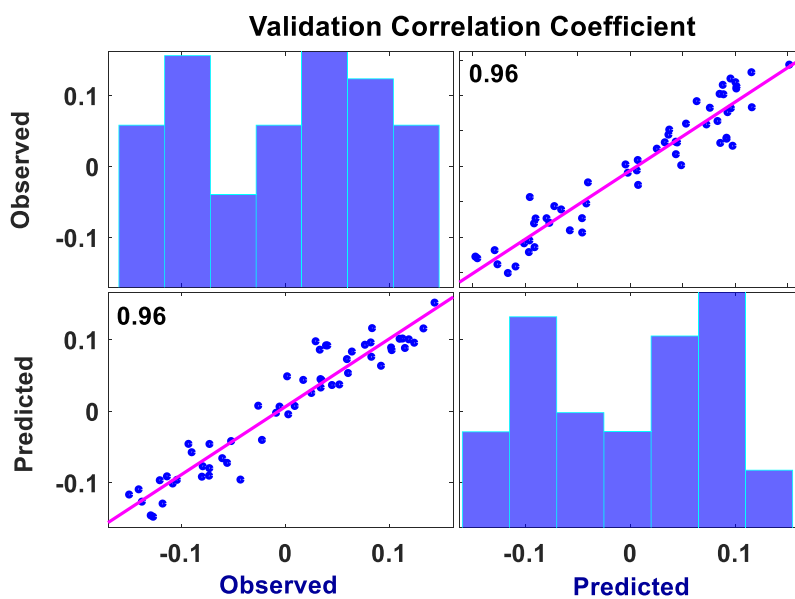
Fig. 5 Fitness function for various populations using the computational intelligence algorithms

291 **Table 1** ANN-designed parameters

Parameter	Value	Type
Number of inputs	3	As discussed in section 5.1
Number of outputs	1	Our target, which is water demand
Number of hidden layers	2	As used in (Zubaidi et al., 2018a)a
Number of neurons in hidden layer N1	3	Estimated by LSA
Number of neurons in hidden layer N2	4	Estimated by LSA
Learning rate coefficient	0.1988	Estimated by LSA

292 5.3 Application of Artificial Neural Networks

293 This section corresponds to step C in Fig. 1. After identifying the parameters for the ANN, the
 294 model was run several times to find the best neural network architecture to forecast municipal
 295 water demand. A range of statistical tests was applied to evaluate the performance of the model.
 296 Firstly, the results of the correlation analysis and residual distribution between observed and
 297 simulated municipal water, are presented in Fig. 6, the correlation coefficient for the validation
 298 stage, 0.96.



299

300 **Fig. 6** LSA-ANN algorithm performance for the validation data

301 Additionally, table 2 provides three measures of the differences between the predicted and
302 observed time series, to evaluate the model performance. It can be seen that the differences
303 between the observed and predicted water demands are negligible (MSE= 6.3911×10^{-4}).

304 **Table 2** Three statistical criteria for the validation data

Data	MAE	MSE	RMSE
Validation	0.0201	6.3911×10^{-4}	0.0253

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

306 All these results reveal and confirm that:

307 (1) Tmax, Rain and Radi are reliable predictors to use to simulate long-term municipal water
308 demand, which were successfully used previously to simulate mid-term water demand.

309 (2) Data pre-processing techniques have a significant role to play, specifically the SSA method,
310 to uncover the stochastic signal and remove the impact of socio-economic factors and noise for
311 long term time series. That means these data pre-processing techniques are effective to apply
312 for the long term as well as for mid-term as shown in previous work.

313 (3) The LSA-ANN algorithm is a reliable model which can be successfully used to forecast
314 long-term municipal water demand, performing more accurately than the GSA-ANN and PSO-
315 ANN algorithms (used in previous studies for short and mid-term), evaluated in this study.

316 (4) The most important result to emerge from the results is the confirmation of the association
317 between climate change and water demand over the long term.

318 This study has been one of the first attempts to thoroughly examine the influence of climate
319 change on municipal water demand. The key strengths of this study are the use of data over an
320 extended baseline period, 1980-2010, and the use of climate factors, extending knowledge of

321 how climate change drives municipal water demand. Further research is however needed to
322 determine the long-term effects of global warming on water demands.

323 **6 Conclusion**

324 Estimating water demand is an essential component in the planning and management of water
325 resources as this can help to identify suitable alternatives to guarantee a balance between water
326 demand and supply in the future. This study explored the influence of climate change on
327 monthly, long-term, municipal water demand, using baseline period data from 1980-2010,
328 applying a coupled SSA and LSA-ANN technique. One of the more significant findings to
329 emerge from this study is the confirmation that maximum temperature, radiation and rain, are
330 reliable predictors when forecasting long-term municipal water demand, as previously seen for
331 mid-term. The SSA has revealed itself to be a powerful technique to uncover the stochastic
332 components of long-term water consumption, after removing the effect of noise and socio-
333 economic factor components that confirm the technique to work successfully in different
334 lengths as shown before. The LSA-ANN algorithm has proven successful, and indeed more
335 accurate than the GSA-ANN and PSO-ANN algorithms previously applied to different terms
336 time series. The paired SSA and LSA-ANN model had the ability to predict water demand with
337 an R of 0.96. The current findings clearly support the relevance of climate change on water
338 consumption, which are significant to both practitioners and policy-makers. More research,
339 however, is required to develop a deeper understanding of the relationship between climate
340 change and municipal water demand over the long-term and at different locations.

341 **Compliance with Ethical Standards**

342 Conflict of Interest Authors declare that they have no conflict of interests.

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