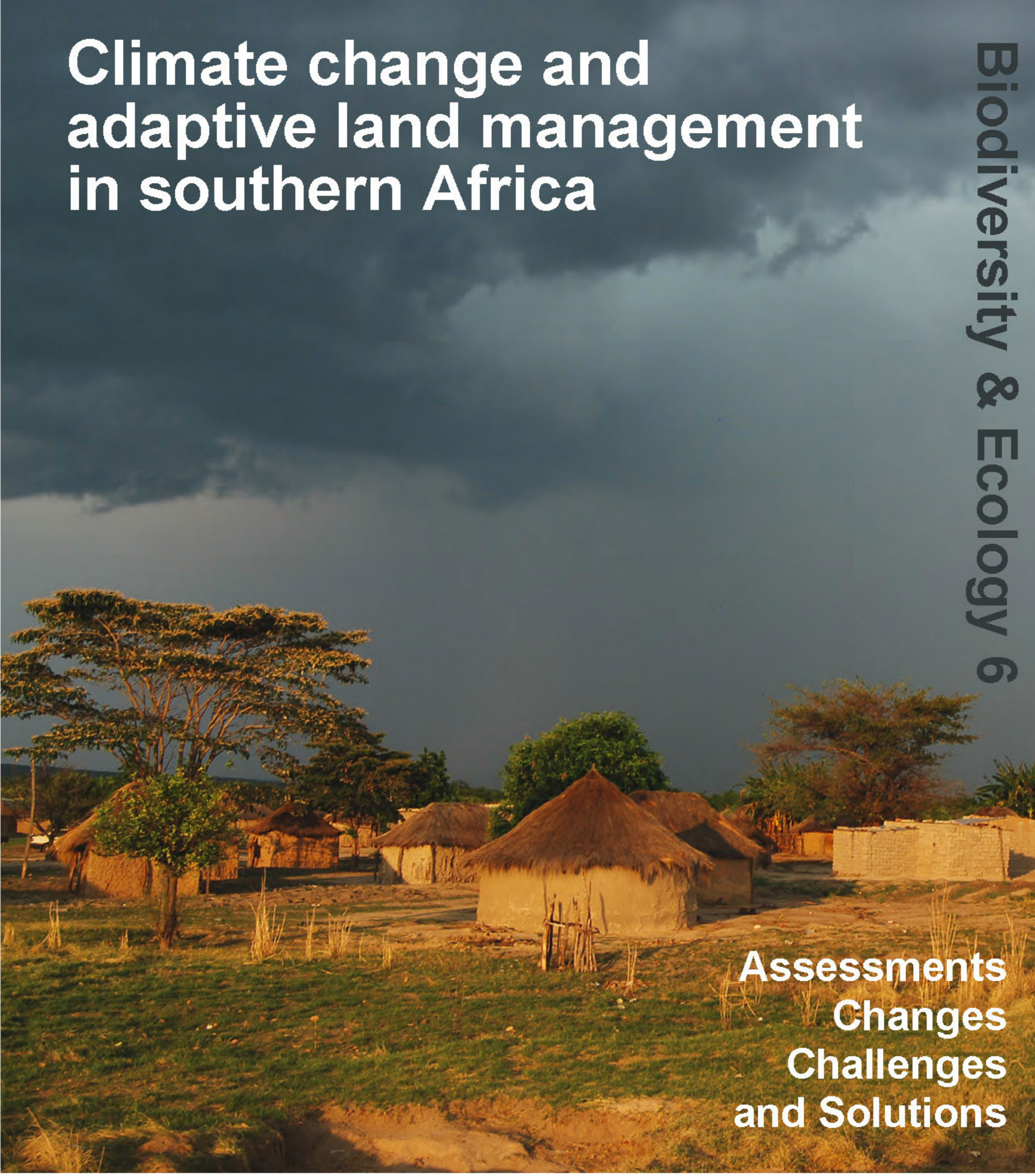
Climate change and adaptive land management in southern Africa

Biodiversity & Ecology 6



Assessments
Changes
Challenges
and Solutions

Product of the first research portfolio of

SASSCAL 2012–2018

Southern African
Science Service Centre for
Climate Change and
Adaptive Land Management

SPONSORED BY THE

Federal Ministry
of Education
and Research

Klaus Hess Publishers
Göttingen & Windhoek
www.k-hess-verlag.de

ISBN: 978-3-933117-95-3 (Germany), 978-99916-57-43-1 (Namibia)

Language editing: Will Simonson (Cambridge), and Proofreading Pal
Translation of abstracts to Portuguese: Ana Filipa Guerra Silva Gomes da Piedade
Page desing & layout: Marit Arnold, Klaus A. Hess, Ria Henning-Lohmann
Cover photographs:
front: Thunderstorm approaching a village on the Angolan Central Plateau (Rasmus Revermann)
back: Fire in the miombo woodlands, Zambia (David Parduhn)
Cover Design: Ria Henning-Lohmann

ISSN 1613-9801

Printed in Germany

Suggestion for citations:
Volume:
Revermann, R., Krewenka, K.M., Schmiedel, U., Olwoch, J.M., Helmschrot, J. & Jürgens, N. (eds.) (2018) Climate change and adaptive land management in southern Africa – assessments, changes, challenges, and solutions. *Biodiversity & Ecology*, **6**, Klaus Hess Publishers, Göttingen & Windhoek.

Articles (example):
Archer, E., Engelbrecht, F., Hänsler, A., Landman, W., Tadross, M. & Helmschrot, J. (2018) Seasonal prediction and regional climate projections for southern Africa. In: *Climate change and adaptive land management in southern Africa – assessments, changes, challenges, and solutions* (ed. by Revermann, R., Krewenka, K.M., Schmiedel, U., Olwoch, J.M., Helmschrot, J. & Jürgens, N.), pp. 14–21, *Biodiversity & Ecology*, **6**, Klaus Hess Publishers, Göttingen & Windhoek.

Corrections brought to our attention will be published at the following location:
http://www.biodiversity-plants.de/biodivers_ecol/biodivers_ecol.php

Biodiversity & Ecology

Journal of the Division Biodiversity, Evolution and Ecology of Plants,
Institute for Plant Science and Microbiology, University of Hamburg

Volume 6:

Climate change and adaptive land management in southern Africa

Assessments, changes, challenges, and solutions

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Hamburg 2018

Please cite the article as follows:

Moalafhi, D.B., Kenabatho, P.K., Parida, B.P. & Matlhodi, B. (2018) Predictability of daily precipitation using data from newly established automated weather stations over Notwane catchment in Botswana. In: *Climate change and adaptive land management in southern Africa – assessments, changes, challenges, and solutions* (ed. by Revermann, R., Krewenka, K.M., Schmiedel, U., Olwoch, J.M., Helmschrot, J. & Jürgens, N.), pp. 46-51, *Biodiversity & Ecology*, **6**, Klaus Hess Publishers, Göttingen & Windhoek. doi:10.7809/b-e.00304

Climate

Predictability of daily precipitation using data from newly established automated weather stations over Notwane catchment in Botswana

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Abstract: Already semi-arid, due to the effects of climate change, Botswana has been experiencing unreliable water supplies over the past several years. However, the limited climate information over different catchments makes engaging in an informed decision-making process difficult. The Notwane catchment at Gaborone dam, located in the headstreams of the Notwane River in eastern Botswana, is a major water supply for the country. However, due to the sparse network of hydro-meteorological measurement stations, no reliable predictions can be made and, thus, creating a reliable runoff estimation for the reservoir has been difficult. Through SASSCAL, an experimental set of automated weather stations has been set up in the Notwane catchment. Preliminary analysis using artificial neural networks (ANNs) to examine the predictive capacity of the monitored variables (from July 15, 2016, through June 25, 2017: 346 days) on precipitation at four individual stations reveals that the gathered hydro-meteorological data may be useful given an increase in record length coupled with consideration of different modeling approaches to validate inherent relationships with precipitation. Study also revealed that simulated precipitation for the area exhibits similar mean and variability to the observations despite poor simulations for extreme precipitation events. These results give insight into prospects for improved hydrologic and water resource modeling over the catchment.

Resumo: O Botswana semi-árido tem sofrido com um fornecimento incerto de água ao longo dos anos, devido aos impactos das alterações climáticas. Mesmo as informações climáticas escassas/limitadas das diferentes bacias hidrográficas dificultam o processo de tomada de uma decisão informada. A bacia hidrográfica de Notwane na barragem de Gaborone, localizada na nascente do Rio Notwane no Este do Botswana, é uma importante fonte de abastecimento de água no país. Porém, devido à esparsa rede de estações de medição hidrometeorológica, não foi possível fazer previsões fiáveis e, por isso, foi difícil estimar de forma segura a escorrência para o reservatório. Através do SASSCAL, foi criado um conjunto experimental de Estações Meteorológicas Automáticas na bacia de Notwane. Uma análise preliminar usando Redes Neuronais Artificiais (ANNs) na capacidade preditiva de variáveis monitorizadas (de 15/07/2016 a 25/06/2017: 346 dias) na precipitação em quatro estações individuais revela que os dados hidrometeorológicos poderão ser possivelmente úteis com o aumento do número de registos, juntamente com a consideração de diferentes abordagens de modelação para validações de relações inerentes com a precipitação. É também evidenciado que a precipitação simulada exibe uma média e variabilidade semelhantes às observadas, apesar das escassas simulações para eventos de precipitação extremos. Estes resultados dão-nos uma expectativa para uma melhor modelação dos recursos hídricos e hidrológicos na bacia hidrográfica.

Introduction

Gaborone, the capital city of Botswana, is the country's major population cluster, with accelerated rural-urban migrations to the city leading to increased water demand. As a result, the Notwane catchment, which is the main source of water for the city, has required inter-basin transfer of water from the relatively wet northeastern part of Botswana. However, transporting water over 500 km to supplement the Gaborone reservoir comes at great costs. Despite this, hydro-meteorological data availability regarding the catchment is almost nonexistent (Kenabatho et al., 2017). The very sparse stations over the catchment monitor only precipitation and temperature, and leave considerable data gaps. With the installation of automated weather stations (AWS)

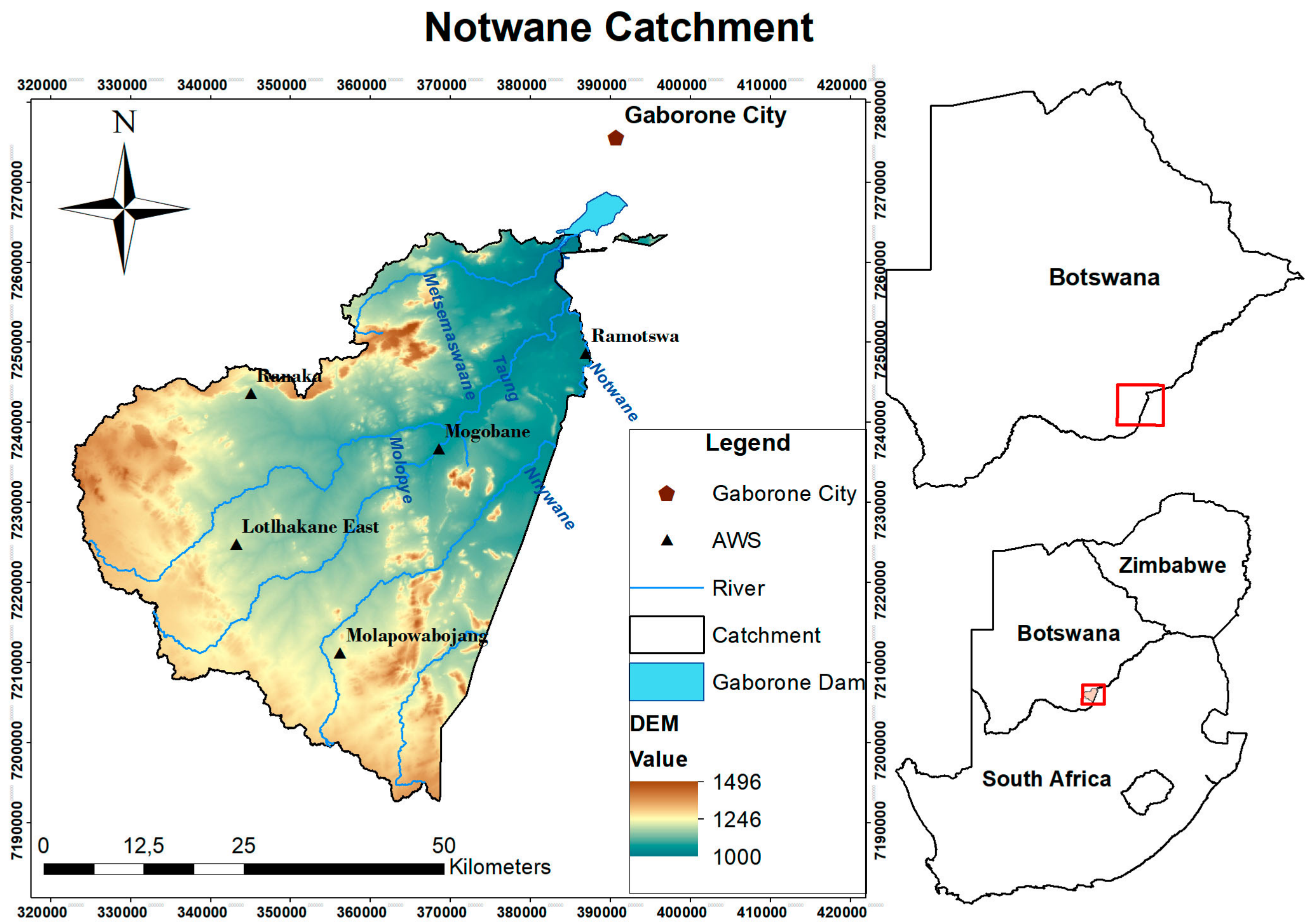

Figure 1: Locations of the automated weather stations (AWS) over Notwane catchment in Botswana.

made possible through the Southern African Science Service Centre for Climate Change and Adaptive Land Management (SASSCAL) project, efforts towards improving hydro-meteorological monitoring to aid hydrologic modeling and river basin and water resource management could be realised. The weather stations are already operational and have alleviated the challenge of working with only limited, poor-quality data.

Artificial neural networks (ANNs), a computational tool based on the neural structure of brain systems, have been adopted for the study. ANNs have gained prominence in data science, being particularly useful in modelling the complex interactions between rainfall and runoff in flow regime studies. These are uniquely powerful tools in applications where formal analysis would be difficult or impossible, such as pattern recognition and nonlinear system identification and control (Furundzic, 1997; Anmala et al., 2000; Uvo et al., 2000; Sivakumar et al., 2002). ANNs were also found to be better than using the multiplicative autoregressive integrated moving average (MARIMA) when forecasting rainfall and temperature over Botswana (Kenabatho et al., 2015). Non-linearity is a prime characteristic of issues related to the atmospheric and hydrologic sciences and thus, ANNs are ideally suited for such problems because, like their biological counterparts, a neural network can learn, and therefore can be trained to find solutions, recognise patterns, classify data, and even forecast future events (Hsu et al., 2002; Parida & Moalafhi, 2008; Kenabatho et al., 2015). The feedforward multi-layer architectures of ANNs have been shown to have computational superiority in comparison to other paradigms (Adeloye & Munari, 2006; Parida et al., 2006; Kenabatho et al., 2015).

The main aim of this paper is to test the utility of the hydro-meteorological variables from the newly developed SASSCAL AWS in modelling rainfall by way of establishing and using the relationships between the measured independent/predictor variables (i.e,. temperature and humidity) and the predictand/target variable (rainfall). This will assist in improved simulation of rainfall events at these sites, especially during instances when rainfall data become unavailable as a result of malfunctions by rainfall recorders, among other situations. The model results will also give an indication of the data's potential utility for simulating rainfall events, urgently needed for future water resources planning. It is anticipated that future operation and maintenance of the AWS, supplemented with streamflow gauging, will help to improve hydrologic and water resources modelling and, therefore, improve water resources management over the highly urbanised Notwane catchment of Botswana. The catchment, with improved monitoring, will also play an important role as an experimental basin for teaching regarding hydrology and water resources management, especially at the University of Botswana.

Climate

Methods

Study site

The catchment is located upstream of the Gaborone dam within the south-east district, and within close proximity to Gaborone, the capital of Botswana (Fig. 1). Its spatial extent is longitude 25.5°E to 26.0°E, and latitude 24.5°S to 25.5°S. Due to its proximity to the capital and the associated 'pull factors of modernity', there have been rapid land use changes and increased demand for water with implications for runoff generation and water supply, respectively. In 1991, census data showed that about 50% of Botswana's population lived within a 100 km radius of the capital, Gaborone (CSO, 2001). Inhabitants of Gaborone and its immediate surroundings within the Notwane catchment have become more affluent, which, coupled with the boom in population over the catchment, has led to an ever-increasing per-capita water demand (Moalafhi et al., 2012).

The Notwane, Taung, Metsemaswaane, and Nywane rivers drain the area. These rivers are intermittent due to the semi-arid conditions of the region. The catchment experiences annual rainfall averaging 500 mm, with high mean annual temperatures averaging 25˚C that lead to high evaporation rates. Rainfall, as is the case for the rest of the country, is seasonal. Rains mostly start around November and end in April.

Data

Six variables are considered at daily time steps from 15 July 2016 to 25 June 2017 (346 days) from four out of a total of five AWS over Notwane catchment in Botswana. Only four stations were chosen based on data availability. The variables are precipitation (mm); temperature (maximum, average, and minimum in ˚C); relative humidity (%); and global radiation (mJ/km^2). Currently, there is no river discharge monitoring over the catchment; thus, precipitation is being used as a key hydro-meteorological variable with implications for runoff generation at the atmosphere-biosphere interface. Precipitation is therefore being used as a proxy for river discharge; it is also used for demonstration purposes regarding the predictive capacity of the AWS variables among themselves. For this reason, the measured rainfall values (dependent variable) together with temperature (minimum, average, and maximum), relative humidity, and global radiation (independent/predictor variables) are used to develop an ANN model structure to simulate rainfall for the catchment. The model is run for each of the four AWS stations—Ranaka, Mogobane, Molapowabojang, and Lotlkhakane East—to assess the predictability of rainfall at locations of the newly established AWS.

Back-propagation artificial neural network (BPANN) modelling

The dependent variables are used as the inputs to the ANN model architecture, while precipitation is used as the output (target variable) being simulated. A multi-layer feedforward back-propagation ANN is adopted.

The back-propagation training algorithm begins by setting a set of random weights; during training, weights are iteratively modified on the basis of the differences between the training output and the desired output. To facilitate this, a rule or function $g(x)$ together with an initial value P_0 is set for computing successive terms. A sequence of values $\{P_k\}$ is then obtained using the iterative rule $P_{k+1} = g(P_k)$. In this case, an ANN is presented with inputs (here, five independent hydro-meteorological variables) and the target variable to be reproduced (precipitation in this case). The network is then trained to learn the relationships between the input variables and the target variable, with the ultimate aim of reproducing the target variable (precipitation) based on the learned relationships. The structure of the ANN topology adopted in this study is shown in Figure 2; it consists of five input variables (predictors), 25 neurons for processing the information, and one output neuron for the target precipitation (predictant).

The Levenberg–Marquardt (L-M) algorithm, which is commonly used for back-propagation algorithm training (Hagan & Menhaj, 1994; Samani et al., 2007), is adopted in this study. Early stopping is implemented by dividing data randomly into three subsets: training, validation and testing (Adeloye & Munari, 2006). Selecting the three subsets randomly helps accommodate a reasonable range of extreme events, which helps to make good predictions (Minns & Hall, 2004; Thirumalaiah & Deo, 1998). The training set is used for computing the gradient and updating the network weights and biases, in which the error on the validation set is monitored during the training process. When the validation error increases for some specified and/or default number of iterations, training is stopped and the weights and biases at the minimum of the validation error are returned. The model is then ready to be tested using the remaining dataset. The log-sigmoidal is used for the hidden layer neurons and the linear transfer function is used for the output layer neuron.

For model performance evaluation, the closeness of fit of the simulated precipitation to the observed precipitation is assessed through Pearson correlation coefficient (r) and mean squared error (MSE). The Pearson correlation coefficient (r-value) evaluates the goodness of fit by performing linear regression between the predicted and target precipitation, while mean squared error is the average sum of squares of the difference between predictions and targets.

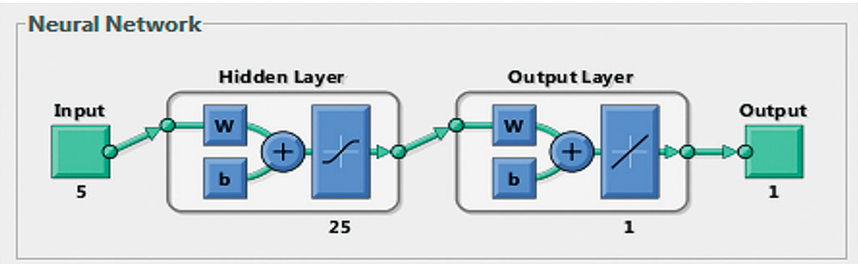

Figure 2: The ANN structure showing the average optimum network architecture that was adopted with five (5) input layers and twenty-five (25) hidden layer neurons (where a hidden layer neuron is a neuron whose output is connected to the inputs of other neurons and is therefore not visible as a network output; W and b represent weights and activity patterns, respectively, assigned to the independent variables).

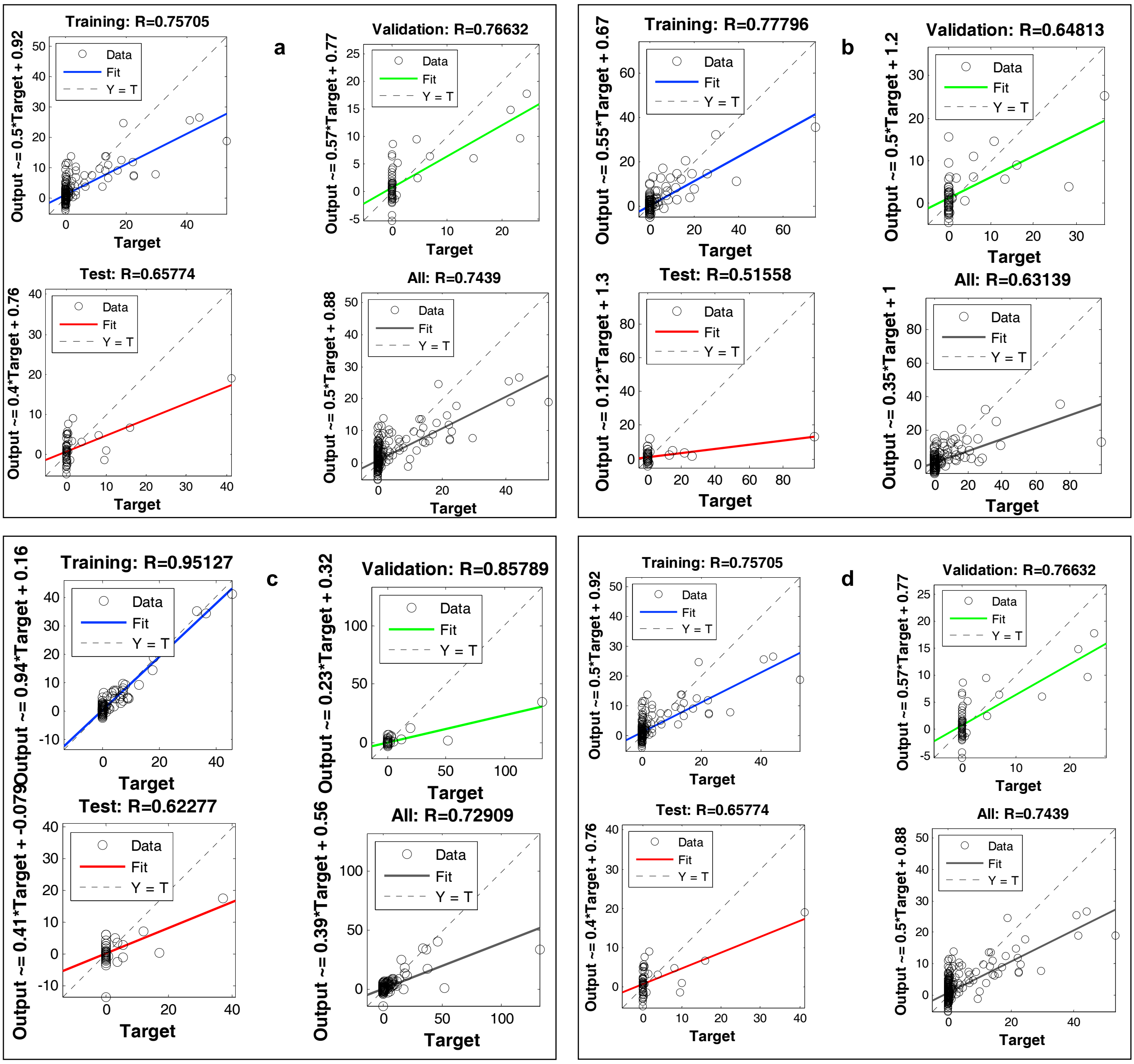

Figure 3: Correlation coefficients of precipitation simulations with observations for (a) Ranaka; (b) Mogobane; (c) Molapowabojang; and (d) Lotlhakane East.

Results

For each station (Fig. 3), four plots are given for model performance through correlation coefficient of the predicted precipitation and the observed precipitation during training, validation, and testing and when all the three subsets are combined together. The individual plots are labeled 'Training', 'Validation', 'Test', and 'All', showing blue, green, red, and grey best linear fit lines, respectively. The dotted lines show how the best-fit lines would appear for correlation coefficients of 1.

Each plot shows the observed precipitation as the target ('Target' or 'T') on the x-axis and the predicted precipitation ('Output' or 'Y') on the y-axis. The label of the y-axis shows the equation of the best linear fit relating the predicted precipitation (Output) and the observed precipitation (Target). The predictions show correlation coefficients well over 0.5 at all the stations. The highest correlation (0.85) was achieved at Lotlhakane East and the lowest (0.63) at Mogobane, considering the three subsets combined (Tab. 1).

Table 1: Summary performance of precipitation simulations at the individual stations over the catchment. r= correlation coefficient, rcomb. = r for combined data set; MSE = root mean square error (mm).

Statistic	Ranaka			Mogobane			Molapowabojang			Lotlhakane East		
	Training	Validation	Testing	Training	Validation	Testing	Training	Validation	Testing	Training	Validation	Testing
r	0.76	0.77	0.66	0.78	0.52	0.82	0.95	0.86	0.62	0.88	0.90	0.82
$r_{comb.}$		0.74			0.63			0.73			0.85	
MSE		13.53			28.26			24.04			17.42	

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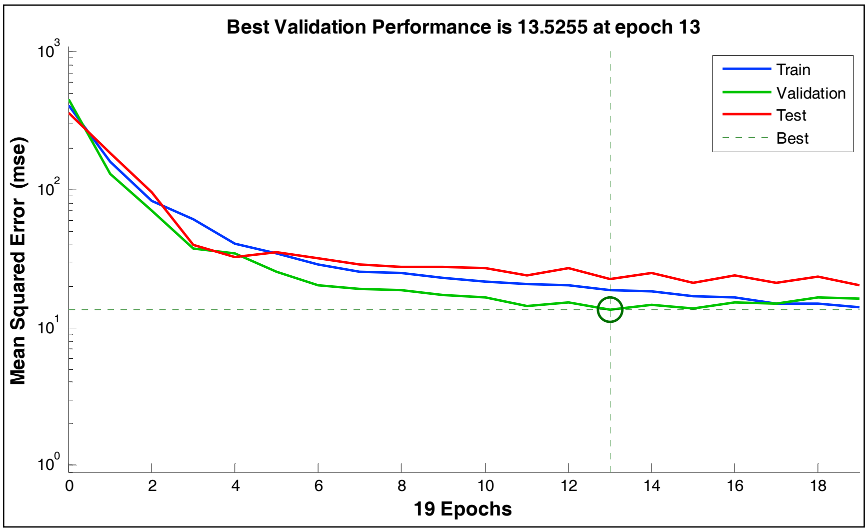

Figure 4: Performance of simulations during training, validation, and testing using mean squared error (MSE) for Ranaka station.

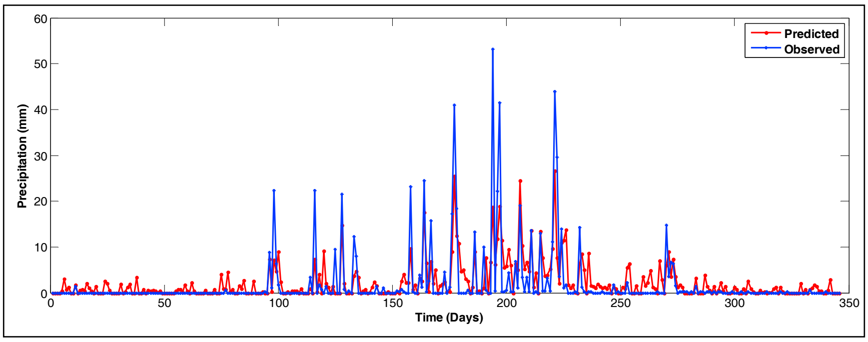

Figure 5: Observed and simulated precipitation at Ranaka station showing deteriorating performance especially for low precipitation events. Blue = observed precipitation; red = predicted precipitation.

Mean squared error (MSE), based on the validation component, showed that the best predictions were obtained at Ranaka station, while Mogobane displayed the worst performance (Tab. 1). An example of performance using MSE is shown in Figure 4, taken from Ranaka station, which shows performance during training, validation, and testing before the model convergence. The minimisation of error during the model run is shown for the three subsets of 'Training', 'Validation', and 'Testing'. These are shown in blue, green, and red, respectively. The minimum validation error during the model run was achieved after 13 epochs (iterations) with MSE of 13.5, as shown by Figure 4. Using Ranaka station as an example, low and high precipitation events are simulated relatively poorly (Fig. 5). Here, the predicted precipitation is shown in red while the observed precipitation is shown in blue.

Discussion

The hydro-meteorological variables did not predict precipitation very well at the individual stations (Tab. 1). In particular, extreme precipitation events (e.g., very low and very high amounts of rainfall) were predicted poorly. This poor performance might be a result of limitations of the model itself, and possibly due to the short length of data records (less than one year). As can be seen from the correlation plots (Fig. 3), there is a possibility that the network architecture is not learning the relationships sufficiently, as is especially visible with its failure to simulate extreme precipitation events well (Fig. 5). The model also demonstrates some challenges in differentiating between rain and no rain as shown in Figure 5. For most zero-rainfall events, the model predicted at least some rainfall. Despite these complications, training, validation, and testing runs converged closely as shown in Figure 5, where there are no noticeable improvements across the three data divisions in minimisation of mean squared error beyond 13 iterations.

There is another variation of the commonly used BPANN, the nonlinear autoregressive network with exogenous inputs (NARX), which appears to be gaining popularity in modelling processes related to climate sciences, including in semi-arid environments. Predictions made over longer time frequencies like months and the addition of more exogenous variables of precipitation with consideration of lag times have been found to significantly improve precipitation predictions using the NARX (Abarhouei and Hosseini, 2016). NARX is an important class of discrete-time nonlinear systems which predicts a current value of a time series based on current and past values of the exogenous series (Safavieh et al., 2007). Byakatonda et al. (2016) used the NARX to forecast dryness severity over the iconic Okavango Delta in Botswana with impressive model performance. Thus, this ANN variant configuration could be considered in the future.

Some correlations between the predicted and observed precipitation are below 0.60 in certain instances. These correlations were, however, found to be statistically significant, as they are greater than the p-critical values at 0.05 significance level. Simulations at Molapowabojang station are almost joint second best with those at Ranaka station in terms of reproducing temporal correlations between predicted and observed precipitation. Reproduction of precipitation mean via the simulations at Mogobane station is slightly worse than at the rest of the stations, with mean squared error of 28.26. All the stations are within the influence of the easterlies, and this could partly explain the similarities in performance of the model across the stations. Notably, rankings of performance of the model at the individual stations differ between MSE and temporal correlation. It is thus important to always use both mean and variability performance measures in evaluating simulations. In this regard, recommendations can be made on suitability of simulations for both mean and variability individually and collectively (Moalafhi et al., 2016).

Inclusion of other independent predictors like El Niño Southern Oscillations (ENSO), and reanalysis precipitation and temperature data may possibly improve simulation of extreme events (Kenabatho et al., 2012). It would also be interesting to determine how much of total variation in precipitation each individual hydro-meteorological predictor variable contributes. Through principal component analysis, it would be important to remove redundant input variables for improved efficiency if more exogenous variables with some delayed times are to be considered.

Conclusion

The modelling exercise revealed that the chosen modeling framework using ANNs was suitable for this catchment. However, precipitation is not simulated very well at each individual station. Predicted precipitation was found to exhibit similar mean and variability with the observations. However, stations for which precipitation variability was simulated best do not necessarily show the best precipitation mean simulations, emphasising the need to use both mean and variability performance measures in assessing simulations. Simulations tend to deteriorate towards low and high precipitation events. During the refinement of this work, other model algorithms will be tested.

These results give some insight into the challenges of short time series and limited numbers of predictor variables, as well as illustrating the need for further reflection on which model algorithm is best suited to the situation being evaluated. Furthermore, exogenous variables like ENSO, reanalysis temperature, and precipitation should be incorporated to improve the simulations. With improvements, AWS data could be used to simulate future rainfall, assisting in cases where measurements may not be available, as is common in monitoring networks. Ultimately, this will support hydrological modeling applications and water resource management over the catchment.

Acknowledgements

The research was carried out in the framework of SASSCAL and was sponsored by the German Federal Ministry of Education and Research (BMBF) under promotion number 01LG1201M. The authors would like to thank SASSCAL and the Office of Research and Development (University of Botswana) for providing financial support to this research. Appreciation also goes to the Ministry of Basic Education and the Ministry of Land Management, Water, and Sanitation Services for hosting the automated weather stations in the Notwane catchment.

References

Abarghouei, H.B. & Hosseini, S.Z. (2016) Using exogenous variables to improve precipitation predictions of ANNs in arid and hyper-arid climates. *Arabian Journal of Geosciences,* **9**, 663.

Adeloye, A.J., & de Munari, A. (2006) Artificial neural network-based generalised storage-yield-reliability models using the Levenberg-Marquardt algorithm. *Journal of Hydrology,* 362, 215-230.

Anmala, J., Zhang, B. & Govindaraju, R.S. (2000) Comparison of ANNs and empirical approaches for predicting watershed runoff. *Journal of Water Resources Planning and Managment,* **126**, 156-166.

Byakatonda, J., Parida, B.P., Kenabatho, P.K.,& Moalafhi, D.B. (2016) Modeling dryness severity using artificial neural networks at the Okavango Delta, Botswana. *Global NEST Journal,* **18**, 463-481

Central Statistics Office. (2001) *Population and Housing Census Preliminary Brief.* Statistics Botswana, Gabarone, Botswana.

Coulibaly, P., Anctil, F., Aravena, R. & Bobée, B. (2001) Artificial neural network modelling of water table depth fluctuations. *Water Resources Research,* **37**, 885-896.

Furundzic, D. (1997) Application example of neural networks for time series analysis: Rainfall runoff modelling. *Signal Processing,* **64**, 383-396.

Hagan, M.T., & Menhaj, M.B. (1994) Training feedforward networks with the Marquardt algorithm. *IEEE Transactions on Neural Networks,* 5, 989-993.

Hsu, K., Gupta, H.V., Gao, X., Sorooshian, S. & Imam, B. (2002) Self-organising linear output map (SOLO): An artificial neural network suitable for hydrologic modelling and analysis. *Journal of Hydrology,* **38**, 1-17.

Johnson, V.M. & Rogers, L.L. (2000) Accuracy of neural network approximators in simulation optimisation. *Journal of Water Resources Planning and Management,* **126**, 48-56.

Kenabatho P.K., Parida B.P. & Moalafhi D.B. (2012) The value of large-scale climate variables in climate change assessment: The case of Botswana's rainfall. *Physics and Chemistry of the Earth* **50-52**, 64-71.

Kenabatho P.K., Parida B.P., Moalafhi D.B., & Segosebe T. (2015) Analysis of rainfall and large-scale predictors using a stochastic model and artificial neural network for hydrological applications in southern Africa. *Hydrological Sciences Journal*, **60**, 1943-1955.

Kenabatho P.K., Parida, B.P. Moalafhi D.B., & Matlhodi B. (2017) Linking scientific research to development agenda: The case of a hydro-meteorological project in the Notwane catchment. *Handbook of Research on Geospatial Science and Technologies* (ed. by J.G. Maphanyane & R. Mapeo), pp. 374–391. IGI Global, Hershey, Pennsylvania.

Lischeid, G. (2001) Investigating short-term dynamics and long-term trends of SO4 in the runoff of a forested catchment using artificial neural networks. *Journal of Hydrology,* **243**, 31-42.

Minns, A.W. & Hall, M.J. (2004) Rainfall-runoff modeling. *Neural Networks for Hydrological Modeling* (ed. by R.J. Hart, P.E. Kneale, & L.M. See), pp. 157–176. A.A. Balkema Publishers, Leiden, the Netherlands.

Moalafhi D.B., Evans J.P. & Sharma A. (2016) Evaluating global reanalysis datasets for provision of boundary conditions in regional climate modelling. *Climate Dynamics: Observational, theoretical and computational research on the climate system,* pp. 1-19, http://dx.doi.org/10.1007/s00382-016-2994-x.

Moalafhi D.B., Parida B.P., & Kenabatho P.K. (2012) New population forecasting techniques for realistic water demand management in urban centres of Botswana. Proceedings of the IASTED International Conference on Science and Technology: A Platform for Sustainable Development, Gaborone, pp191-197 (in CD).

Parida, B.P. & Moalafhi, D.B. (2008) Regional rainfall frequency analysis for Botswana using L-moments and radial basis function network. *Physics and Chemistry of the Earth,* **33**, 614-620.

Parida B.P., Moalafhi D.B. & Kenabatho P.K. (2006) Forecasting runoff coefficients using ANN for water resources management: The case of Notwane catchment in eastern Botswana. *Physics and Chemistry of the Earth,* **31**, 928-934.

Safavieh, E., & Andalib, S.A. (2007) Forecasting the unknown dynamics in NN3 database using a nonlinear autoregressive recurrent neural network. *International Joint Conference on Neural Networks*, pp. 2105-2109.

Sahoo, G.B., & Ray, C. (2006) Flow forecasting for Hawaii stream using rating curves and neural networks. *Journal of Hydrology,* 317, 63-80.

Samani, N., Gohari-Moghadam, M., & Safavi, A.A. (2007) A simple neural network model for the determination of aquifer parameters. *Journal of Hydrology,* 340, 1-11.

Shamseldin, A.Y. (1997) Application of a neural network technique to rainfall-runoff modelling. *Journal of Hydrology,* **199**, 272-294.

Sivakumar, B., Jayawardena, A.W. & Fernando, T.M.K.G. (2002) River flow forecasting: Use of phase-space reconstruction and artificial neural networks approaches. *Journal of Hydrology,* **265**, 225-245.

Thirumalaiah, K., & Deo, M.C. (1998) River stage forecasting using artificial neural networks. *Journal of Hydrologic Engineering,* 3, 26-32.

Uvo, C.B., Tolle, U. & Berndtsson, R. (2000) Forecasting discharge in Amazon using artificial neural networks. *International Journal of Climatology,* **20**, 1495-1507.

References [CrossRef]

Abarghouei, H.B. & Hosseini, S.Z. (2016) Using exogenous variables to improve precipitation predictions of ANNs in arid and hyper-arid climates. *Arabian Journal of Geosciences*, **9**, 663. CrossRef

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Anmala, J., Zhang, B. & Govindaraju, R.S. (2000) Comparison of ANNs and empirical approaches for predicting watershed runoff. *Journal of Water Resources Planning and Managment*, **126**, 156-166. CrossRef

Byakatonda, J., Parida, B.P., Kenabatho, P.K.,& Moalafhi, D.B. (2016) Modeling dryness severity using artificial neural networks at the Okavango Delta, Botswana. *Global NEST Journal*, **18**, 463-481

Central Statistics Office. (2001) *Population and Housing Census Preliminary Brief*. Statistics Botswana, Gabarone, Botswana.

Coulibaly, P., Anctil, F., Aravena, R. & Bobée, B. (2001) Artificial neural network modelling of water table depth fluctuations. *Water Resources Research*, **37**, 885-896. CrossRef

Furundzic, D. (1997) Application example of neural networks for time series analysis: Rainfall runoff modelling. *Signal Processing*, **64**, 383-396. CrossRef

Hagan, M.T., & Menhaj, M.B. (1994) Training feedforward networks with the Marquardt algorithm. *IEEE Transactions on Neural Networks*, **5**, 989-993. CrossRef

Hsu, K., Gupta, H.V., Gao, X., Sorooshian, S. & Imam, B. (2002) Self-organising linear output map (SOLO): An artificial neural network suitable for hydrologic modelling and analysis. *Journal of Hydrology*, **38**, 1-17.

Johnson, V.M. & Rogers, L.L. (2000) Accuracy of neural network approximators in simulation optimisation. *Journal of Water Resources Planning and Management*, **126**, 48-56. CrossRef

Kenabatho P.K., Parida B.P. & Moalafhi D.B. (2012) The value of large-scale climate variables in climate change assessment: The case of Botswana's rainfall. *Physics and Chemistry of the Earth* **50-52**, 64-71. CrossRef

Kenabatho P.K., Parida B.P., Moalafhi D.B., & Segosebe T. (2015) Analysis of rainfall and large-scale predictors using a stochastic model and artificial neural network for hydrological applications in southern Africa. *Hydrological Sciences Journal*, **60**, 1943-1955. CrossRef

Kenabatho P.K., Parida, B.P. Moalafhi D.B., & Matlhodi B. (2017) Linking scientific research to development agenda: The case of a hydro-meteorological project in the Notwane catchment. *Handbook of Research on Geospatial Science and Technologies* (ed. by J.G. Maphanyane & R. Mapeo), pp. 374–391. IGI Global, Hershey, Pennsylvania.

Lischeid, G. (2001) Investigating short-term dynamics and long-term trends of SO4 in the runoff of a forested catchment using artificial neural networks. *Journal of Hydrology*, **243**, 31-42. CrossRef

Minns, A.W. & Hall, M.J. (2004) Rainfall-runoff modeling. *Neural Networks for Hydrological Modeling* (ed. by R.J. Hart, P.E. Kneale, & L.M. See), pp. 157–176. A.A. Balkema Publishers, Leiden, the Netherlands. CrossRef

Moalafhi D.B., Evans J.P. & Sharma A. (2016) Evaluating global reanalysis datasets for provision of boundary conditions in regional climate modelling. *Climate Dynamics: Observational, theoretical and computational research on the climate system*, pp. 1-19. CrossRef

Moalafhi D.B., Parida B.P., & Kenabatho P.K. (2012) New population forecasting techniques for realistic water demand management in urban centres of Botswana. Proceedings of the IASTED International Conference on Science and Technology: A Platform for Sustainable Development, Gaborone, pp191-197 (in CD). CrossRef

Parida, B.P. & Moalafhi, D.B. (2008) Regional rainfall frequency analysis for Botswana using L-moments and radial basis function network. *Physics and Chemistry of the Earth*, **33**, 614-620. CrossRef

Parida B.P., Moalafhi D.B. & Kenabatho P.K. (2006) Forecasting runoff coefficients using ANN for water resources management: The case of Notwane catchment in eastern Botswana. *Physics and Chemistry of the Earth*, **31**, 928-934. CrossRef

Safavieh, E., & Andalib, S.A. (2007) Forecasting the unknown dynamics in NN3 database using a nonlinear autoregressive recurrent neural network. *International Joint Conference on Neural Networks*, pp. 2105-2109. CrossRef

Sahoo, G.B., & Ray, C. (2006) Flow forecasting for Hawaii stream using rating curves and neural networks. *Journal of Hydrology*, **317**, 63-80. CrossRef

Samani, N., Gohari-Moghadam, M., & Safavi, A.A. (2007) A simple neural network model for the determination of aquifer parameters. *Journal of Hydrology*, **340**, 1-11. CrossRef

Shamseldin, A.Y. (1997) Application of a neural network technique to rainfall-runoff modelling. *Journal of Hydrology*, **199**, 272-294. CrossRef

Sivakumar, B., Jayawardena, A.W. & Fernando, T.M.K.G. (2002) River flow forecasting: Use of phase-space reconstruction and artificial neural networks approaches. *Journal of Hydrology*, **265**, 225-245. CrossRef

Thirumalaiah, K., & Deo, M.C. (1998) River stage forecasting using artificial neural networks. *Journal of Hydrologic Engineering*, **3**, 26-32. CrossRef

Uvo, C.B., Tolle, U. & Berndtsson, R. (2000) Forecasting discharge in Amazon using artificial neural networks. *International Journal of Climatology*, **20**, 1495-1507. CrossRef