Drought forecasting: A review of modelling approaches 2007–2017

K. F. Fung, Y. F. Huang, C. H. Koo and Y. W. Soh

ABSTRACT

Droughts are prolonged precipitation-deficient periods, resulting in inadequate water availability and adverse repercussions to crops, animals and humans. Drought forecasting is vital to water resources planning and management in minimizing the negative consequences. Many models have been developed for this purpose and, indeed, it would be a long process for researchers to select the best suited model for their research. A timely, thorough and informative overview of the models' concepts and historical applications would be helpful in preventing researchers from overlooking the potential selection of models and saving them considerable amounts of time on the problem. Thus, this paper aims to review drought forecasting approaches including their input requirements and performance measures, for 2007–2017. The models are categorized according to their respective mechanism: regression analysis, stochastic, probabilistic, artificial intelligence based, hybrids and dynamic modelling. Details of the selected papers, including modelling approaches, authors, year of publication, methods, input variables, evaluation criteria, time scale and type of drought are tabulated for ease of reference. The basic concepts of each approach with key parameters are explained, along with the historical applications, benefits and limitations of the models. Finally, future outlooks and potential modelling techniques are furnished for continuing drought research.

Key words | artificial intelligence, dynamic modelling, hybrid, probability, regression analysis, time series analysis

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ABBREVIATIONS

AC	anomaly correlation
AIC	Akaike information criterion
AICC	Akaike information criterion corrected
ANFIS	adaptive neuro-fuzzy inference system
APE	absolute percentage error
AR(2)	second order auto-regressive multivariate model
ARID	agricultural reference index for drought
ARIMAX	multivariate autoregressive integrated moving average
AUC	area under the curve
AVHRR	advanced very high-resolution radiometer
AWRI	available water resource index
BCSD	bias correction and spatial downscaling
BI	bilinear interpolation
BIC	Bayesian information criterion
BP-ANN	back propagation artificial neural network
BRT	boosted regression trees
CFS	climate forecast system
CRPS	continuous ranked probability score
CSS	climatology skill score
d	Willmott's index
dMSE	means squared error in derivatives
DDR	developed discrepancy ratio

doi: 10.2166/wcc.2019.236

DEMETER	development of a European multimodel ensemble system for seasonal to interannual prediction
DLSTM	dynamic linear spatiotemporal model
DMSGRNN	direct multi-step generalized regression neural network
DMSMLP	direct multi-step multi-layer perceptron
DMSNN	direct multistep neural network
DMSRBF	direct multi-step radial basis function
EDI	effective drought index
ELM	extreme learning machine
ENSO	El Niño Southern Oscillation
ESP	ensemble streamflow prediction
FFNN	feed forward neural networks
FPE	final prediction error
GFS	global forecast system
GLM	generalized linear model
GMSS	Gandin-Murphy skill score
GPCP	global precipitation climatology project
HMM	hidden Markov chain model
HSNNDA	hybrid stochastic neural network of direct approach
HSNNRA	hybrid stochastic neural network of recursive approach
IIS-W-ANN	iterative input selection wavelet artificial neural network
IoAd	index of agreement
LEPS	linear error in probability score
MAD	mean absolute deviation
MAE	mean absolute error
MAPE	mean absolute percentage error
MARE	mean absolute relative error
MBE	mean bias error
MCFO	first order Markov chain
MCSO	second order Markov chain
MCTO	third order Markov chain
ME	mean error
MEI	multivariate ENSO index
MLM	multiple linear model
MLP-ANN	multilayer perceptron artificial neural network
MODIS	moderate resolution imaging spectroradiometer
MPE	mean percentage error
MSE	mean square error
NADI	nonlinear aggregated drought index
NAO	North Atlantic oscillation
NCEP	National Centers for Environmental Prediction
NDVI	normalized difference vegetation index
NDVI-DEV	deviation of normalized difference vegetation index
NLDAS	North American land data assimilation system
NMSE	normalized mean square error
NOAA	National Oceanic and Atmospheric Administration
NSE	Nash–Sutcliffe efficiency coefficient
NSSS	Nash–Sutcliffe sufficiency score
PC	proportion of correct predictions
Pdv	peak percentage deviation
PDSI	Palmer drought severity index
PERSIANN	precipitation estimation from remotely sensed information using ANN
PHDI	Palmer hydrological drought index
PMDI	Palmer's modified drought index
PI	persistency index
PPMC	Pearson product moment correlation
R	coefficient of correlation
R^2	coefficient of determination
R^2_{McF}	McFadden pseudo-coefficient of determination
RAE	relative absolute error
RCP	representative concentration pathway
RF	random forest
RFOR	random forest regression tree
RMSD	root mean square difference
RMSE	root mean square error
RMSGRNN	recursive multi-step generalized regression neural network
RMSMLP	recursive multi-step multi-layer perceptron
RMSNN	recursive multi-step neural network
RMSRBF	recursive multi-step radial basis function
ROC	receiver operating characteristic
RPS	ranked probability score
RRMSD	relative root mean square prediction
RS	remote sensing
RSM	regional spectral model
SARIMA	seasonal ARIMA
SBC	Schwarz Bayesian criterion

SD	standard deviation
SDI	streamflow drought index
SHDI	standardized hydrological drought index
SHI	standardized hydrological index
SLP	sea level pressure
SPI	Standardized Precipitation Index
SOI	Southern Oscillation index
SSE	sum of squares of errors
SST	sea surface temperature
SSTA	sea surface temperature anomalies
T2M	2 m temperature
T850	850 hPa temperature
TCI	temperature condition index
TLRN	time lagged recurrent network
TMPA	TRMM multisatellite precipitation analysis
TRMM	Tropical Rainfall Measuring Mission
U200	200 hPa meridional wind
U850	850 hPa meridional wind
V200	200 hPa zonal wind
V850	850 hPa zonal wind
VCI	vegetation condition index
VTCI	vegetation temperature condition index
WN	white noise variance
WRF	weather research and forecasting
Z500	500 hPa geopotential height.

INTRODUCTION

Droughts are overland events of prolonged periodic extreme climate described by below-normal precipitation over months or years (Dai 2011). Droughts can be categorized into four classes depending on the conditions: meteorological, agricultural, hydrological and socioeconomic droughts. Conceptually, a meteorological drought is expressed as a precipitation deficit over a region for a period of time (Mishra & Singh 2010). A drought is considered to be specific to a region for the fact that weather conditions of low precipitation, dry winds and high temperature are highly variable and do vary from region to region. When atmospheric moisture is reduced to a level where the soil moisture is affected, the onset of an agricultural drought is imminent (Zargar et al. 2011). During this period, crops and animals are affected as the decline in soil moisture content leads to reduction in crop production, which subsequently affects the balance of the food chain in the ecosystem. A hydrological drought is defined as dry periods that are very long, to the extent that affected river streamflows and water storages in aquifers, lakes or reservoirs fall below long-term mean levels (Dai 2011). Its development is slower than the previous two classes because it covers not only the process of depletion, but also the replenishing phase. When the water resources systems fail to achieve water demand for the economic good, accordingly, a socioeconomic drought happens (Mishra & Singh 2010). Practically, droughts can also be categorized based on the timescales of precipitation anomalies. For example, the Standardized Precipitation Index (SPI) is commonly used to define droughts based on timescales; SPI-1 and SPI-2 for meteorological droughts, anywhere from SPI-1 to SPI-6 for agricultural droughts and SPI-6 to SPI-24 for hydrological droughts, where the associated number is timescale in months (World Meteorological Organization 2012). The types of drought reviewed in this paper, unless otherwise clearly clarified in the study of drought type being investigated, are classified into the meteorological, agricultural and hydrological drought categories and are based on the respective purpose of the study, the inputs of the study, the drought indices and the timescale of the study.

Given that the occurrence of drought can lead to crop failures, interrupted food chains and reduced water supply, forecasting of drought events is indeed a vital component of water resources planning and management. While compounded by the fact that the starts and ends of droughts are very difficult to determine precisely, however, many drought forecasting models have been developed to improve the drought forecasting capability. These models are founded on sound methodologies such as: regression analysis, autoregressive integrated moving average (ARIMA), Markov chain, artificial neural network (ANN), fuzzy logic (FL), support vector regression (SVR) and different hybrid models (Han et al. 2010; Ozger et al. 2011; Belayneh et al. 2014; Masinde 2014; Stagge et al. 2015; Taormina et al. 2015; Belayneh et al. 2016; Sun et al. 2016; Ghorbani et al. 2018; Moazenzadeh et al. 2018). With the large variety of forecasting models available, it can be very difficult for researchers to decide which model is best suited to their research work, not to mention that there is a slight chance that researchers may overlook the best models for their problem if they are not aware of the potential types of model available. Hence, a study to compile the details of model studies undertaken over the last decade with analyses of the pros and cons of different models is undoubtedly beneficial to readers.

Despite the review paper on drought modelling that had been comprehensively done by Mishra & Singh (2011), review papers evaluating applications of forecasting models in these areas pertaining to the overview of the latest trends are still limited at the present state of model development. This is attributed to the rapid development in drought forecasting modelling with many different studies using new approaches being developed thereafter. For example, based on our findings, 18 new hybrid drought forecasting studies were carried out from 2011 to 2017. Apart from this, ANN and hybrid models were the focus of artificial intelligence (AI) based models in the paper. In order to allow readers to have a better overview of AI models available, reviews of FL and SVR were also included in this paper. Furthermore, the dynamic modelling approach, which has been emerging rapidly in recent years, has yet to be reviewed in any recent research.

The main objectives of this review paper are to categorize drought forecasting models and to specify their applications along with their limitations and benefits. This paper covers reviews of different drought forecasting approaches associated with drought indices and rainfall predictions, for the years 2007–2017. Details of the selected papers, including modelling approaches, authors, and year of publication, methods, input variables, evaluation criteria, time scale and type of drought are given in Table 1. This is followed by sections on the basic concepts of various approaches, discussion of the limitations and benefits of approaches and a conclusion of the whole review paper. This paper also discusses the future development direction of modelling approaches for drought applications.

REGRESSION ANALYSIS

Regression analysis is considered one of the early candidates and widely adopted forecasting approach used for time series predictions. Regression analysis is a statistical method to examine the relationships between variables (Sykes 1993). The performance of this method highly relies on the number of independent variables, type of dependent variables and shape of the regression line. In essence, the wide range of regression analysis used for time series forecasting includes logistic regression and loglinear regression.

In 2015, Stagge et al. (2015) applied the logistic regression to forecast the SPI and Standardized Precipitation Evapotranspiration Index (SPEI) in Europe. The assessment was included for the four impact types spanning the fields of agriculture, energy and industry, public water supply, and freshwater ecosystems across the five European countries. The Generalized Additive Models (GAMs) for the two-dimensional interactions of two closely correlated predictors (SPI and SPEI) was pursued. The performance of the logistic regression was assessed by a pseudo-R^2 and the area under the receiver operating characteristic curve (AUC) which showed a reasonably good prediction. Similarly, Tatli (2015) also adopted logistic regression for the modelling of statistical downscaling in the study of drought events in Turkey from 1940 to 2100. Unlike using the downscaled precipitation to predict the SPI, it is easier to downscale the drought categories instead of precipitation. The resulting probabilistic patterns were considered acceptable based on the proportion of correct predictions (PC) as the model captured the main features of the climatic data. A year later, Meng et al. (2016) also applied logistic regression for the analysis of drought persistence in East China. The study depicted the impact of previous SPI and the Southern Oscillation Index (SOI) on the seasonal drought that differs in different regions and seasons. It was observed that the drought persistence over the summers is longer than in the other seasons.

Besides using logistic regression to predict the drought event, Sohn & Tam (2016) performed a bivariate pattern-based downscaling for the assessment of droughts prediction in South Korea. The SPEI with 6-month lead time for 60 stations in South Korea was determined. The results obtained from the downscaled multi-model ensemble (DMME) were reported to be better than the raw multi-model ensemble (MME) in describing the extreme floods and droughts, which was proven by the better linear error in probability score (LEPS). Li et al. (2016) applied the loglinear

Table 1 | Details of the papers reviewed

Type of approach	Number of papers	Authors (year of publication)	Method	Input variables	Evaluation criteria	Time scale	Type of drought
Regression analysis	6	Stagge *et al.* (2015)	Logistic regression	Precipitation, temperature, wind speed	R^2_{McF}, AUC	Day	Meteorological
		Tatli (2015)	Logistic regression, statistical downscaling	Precipitation	PC	Month	Meteorological
		Meng *et al.* (2016)	Logistic regression	Precipitation	Confidence level	Day	Meteorological
		Sohn & Tam (2016)	Bivariate pattern–based downscaling	Surface air temperature, precipitation, SLP, T2M, Z500, T850, UV850, UV200, SST	LEPS	Season	Hydrological
		Li *et al.* (2016)	Loglinear regression	Precipitation	R^2	Month	Hydrological
		Park *et al.* (2016)	BRT, RF, Cubist	MODIS data (RS), TRMM rainfall data (RS)	R^2 and RMSE	Month	Meteorological, agricultural
Time series analysis	22	Mishra *et al.* (2007)	ARIMA, RMSNN, DMSNN, HSNNDA, HSNNRA	Precipitation	MAE, R^2, RMSE	Month	Meteorological, agricultural, hydrological
		Ochoa-Rivera (2008)	AR(2), ANN	Streamflow	RRMSD	Month	Hydrological
		Abebe & Foerch (2008)	SARIMA	Precipitation, temperature, normalized digital vegetation index, streamflow	log (likelihood), AIC, AICC, FPE, MAPE, WN Variance, SBC, SSE	Month	Hydrological
		Durdu (2010)	ARIMA, SARIMA	Precipitation	AIC, SBC, Z-test and F-test	Month	Meteorological, agricultural, hydrological
		Han *et al.* (2010)	AR(1)	VTCI (RS)	AIC, SBC	Day	Meteorological, agricultural
		Fernandez-Manso *et al.* (2011)	SARIMA	Precipitation, temperature, NOAA-AVHRR images (RS), vegetation information	MAE, MAPE, ME, MPE, RMSE	Day	Meteorological, agricultural
		Barua *et al.* (2012)	ARIMA, DMSNN, RMSNN	NADI, precipitation, potential evapotranspiration, storage reservoir volume, streamflow, soil moisture content	MAE, R, RMSE	Month	Meteorological, hydrological
		Chun *et al.* (2012)	ARIMA, GLM	Precipitation, streamflow	Graphical comparison	Month	Agricultural, hydrological
		Chen *et al.* (2012)	ARMA, RF	Precipitation	Bias, MAE, RMSE	Month	Agricultural, hydrological
		Han *et al.* (2013)	ARIMA, SARIMA	SPI	APE, R	Month, annual	Meteorological, agricultural, hydrological
		Shatanawi *et al.* (2013)	ARIMA, 1st-order Markov-ARIMA, 2nd-order Markov-ARIMA	Precipitation	Graphical comparison	Day, month, annual	Meteorological
		Woli *et al.* (2013)	ARMA, ANFIS, ANN, ENSO approach, linear regression	Day weather data, ARID	NSE, RMSE	Month	Agricultural
		Shabri (2014)	ARIMA, ANFIS, W-ANFIS	Precipitation	MAE, RMSE	Month	Meteorological
		Belayneh *et al.* (2014)	ARIMA, ANN, W-ANN, SVR, W-SVR	Precipitation, SPI	MAE, R^2, RMSE	Month	Hydrological
		Alam *et al.* (2014b)	ARIMA, SARIMA	Precipitation	AIC, SBC, R^2	Month, annual	Meteorological
		Mossad & Alazba (2015)	ARIMA, SARIMA	Precipitation, temperature	AIC, SBC, MAE, R^2, RMSE	Month, annual	Agricultural, hydrological
		Bazrafshan *et al.* (2015)	ARIMA, SARIMA	Discharge volume	R, RMSE, MAE	Month, annual	Hydrological
		Djerbouai & Souag-Gamane (2016)	ARIMA, ANN, W-ANN	Precipitation	MAE, NSE, RMSE	Month	Agricultural, hydrological
		Tian *et al.* (2016)	AR(1), SARIMA	VTCI (RS)	Absolute errors, average, RMSE	Day	Agricultural
		Mahmud *et al.* (2016)	SARIMA	Precipitation	Normalized BIC criteria, R^2, RMSE	Month	Meteorological, agricultural
		Chen *et al.* (2016)	ARMA, ANN, HMM, HMM-RCP	Precipitation	CSS, RMSE	Month	Meteorological, agricultural
		Karthika *et al.* (2017)	ARIMA	Precipitation	AIC, SBC	Annual	Meteorological

(*continued*)

Table 1 | continued

Type of approach	Number of papers	Authors (year of publication)	Method	Input variables	Evaluation criteria	Time scale	Type of drought
Probability models	15	Paulo & Pereira (2007)	Homogeneous Markov chain, non-homogeneous Markov chain	SPI	-	Month	Agricultural, hydrological
		Jiang & Chen (2009)	Weighted Markov SCGM(1,1)c	Drought crop area	Example study, prediction error	Annual	Agricultural
		Sharma & Panu (2012)	MCFO, MCSO, MCTO	Streamflow, SHI	Graphical comparison	Week, month, annual	Hydrological
		Chen & Yang (2012)	Weighted Markov chain	Precipitation	Prediction accuracy	Month	Agricultural, hydrological
		Alam *et al.* (2014a)	Markov chain	Precipitation	Hypothesis testing	Week	Agricultural
		Avilés *et al.* (2015)	MCFO, MCSO	Precipitation, streamflow	GMSS, RPS	Month	Meteorological, hydrological
		Yeh *et al.* (2015)	Markov chain	Precipitation, streamflow, SDI	-	Month	Hydrological
		Rezaeianzadeh *et al.* (2016)	Markov chain, ANN	Precipitation, evaporation, inflow volume	R^2, RMSE	Month	Hydrological
		Nnaji *et al.* (2016)	Semi-Markov model	Streamflow	R, RMSE	Month	Hydrological
		Khadr (2016)	HMM	Precipitation	MAD, R, R^2, RMSE	Month, annual	Meteorological
		Chen *et al.* (2016)	HMM, HMM-RCP, ANN, ARMA,	Precipitation	CSS, RMSE	Month	Meteorological, agricultural
		Avilés *et al.* (2016)	MCFO, MCSO, Bayesian network first order, Bayesian network second order	Precipitation, streamflow	RPS	Month	Meteorological, hydrological
		Rahmat *et al.* (2016)	Non-homogeneous Markov chain	Precipitation	-	Annual	Hydrological
		Sun *et al.* (2016)	MCFO, MCSO	Precipitation, temperature, streamflow	AIC	Month	Meteorological, hydrological
		Zhang *et al.* (2017)	Weighted Markov chain, Volterra adaptive filter, 3D loglinear	Precipitation, runoff	Rates of accuracy	Month	Meteorological, hydrological
Artificial neural network (ANN)	31	Mishra *et al.* (2007)	RMSNN, DMSNN, ARIMA, HSNNDA, HSNNRA	Precipitation	MAE, R^2, RMSE	Month	Meteorological, agricultural, hydrological
		Ochoa-Rivera (2008)	ANN, AR(2)	Streamflow	RRMSD	Month	Hydrological
		Bacanli *et al.* (2009)	FFNN, ANFIS	Precipitation	NSE, R, RMSE	Month	Meteorological, agricultural, hydrological
		Cutore *et al.* (2009)	ANN	PHDI, climatic indices data	R^2	Month	Hydrological
		Dastorani *et al.* (2010)	TLRN, ANFIS	Precipitation, temperature, wind speed, intensive wind direction, relative humidity	R^2, RMSE	Month	Meteorological
		Marj & Meijerink (2011)	ANN	SOI, NAO	R^2, RMSE, SD	Month	Agricultural
		Deng *et al.* (2011)	BP-ANN, ANFIS, LS-SVM	Soil water content, precipitation, temperature, evaporation	MARE, R, RMSE	Day	Agricultural
		Barua *et al.* (2012)	DMSNN, RMSNN, ARIMA	NADI, precipitation, potential evapotranspiration, storage reservoir volume, streamflow, soil moisture content	MAE, R, RMSE	Month	Meteorological, hydrological
		Chiang & Tsai (2012)	ANN, Bayesian classifier, maximum likelihood classifier, SVM	Reservoir storage capacity, inflows, critical limit of operation rule curves, no. of ten-days in a year	Prediction accuracy	Day	Hydrological
		Belayneh & Adamowski (2012)	ANN, W-ANN, SVR	Precipitation, SPI	MAE, R^2, RMSE	Month	Agricultural, hydrological
		Belayneh & Adamowski (2013)	ANN, W-ANN, SVR	Precipitation, SPI	R^2, RMSE	Month	Agricultural, hydrological
		Woli *et al.* (2013)	ANN, ANFIS, ARMA, ENSO approach, linear regression	Day weather data, ARID	NSE, RMSE	Month	Agricultural
		Shirmohammadi *et al.* (2013)	ANN, W-ANN, ANFIS, W-ANFIS	Precipitation	NSE, R^2, RMSE	Month	Meteorological

		Chiang & Tsai (2013)	ANN, Bayesian classifier, maximum likelihood classifier, SVM	Reservoir storage capacity, inflows, critical limit of operation rule curves, no. of ten-days in a year	Prediction accuracy	Day	Hydrological
		Masinde (2014)	ANN	Precipitation, EDI, AWRI	MSE, R	Month	Meteorological, agricultural
		Belayneh *et al.* (2014)	ANN, W-ANN, ARIMA, SVR, W-SVR	Precipitation, SPI	MAE, R^2, RMSE	Month	Hydrological
		Jalili *et al.* (2014)	MLP-ANN, RBF-ANN, SVM	NDVI (RS), NDVI-DEV (RS), TCI (RS), VCI (RS)	Prediction accuracy	Month	Meteorological, agricultural
		Jalalkamali *et al.* (2015)	MLP-ANN, ANFIS, ARIMAX, SVM	Precipitation	R^2, RMSE	Month	Meteorological
		Deo & Sahin (2015)	ANN, ELM	Precipitation, temperature, evapotranspiration	d, NSE, MAE, R^2, RMSE	Month	Meteorological
		Hosseini-Moghari & Araghinejad (2015)	DMSMLP-ANN, RMSMLP-ANN, DMSRBF-ANN, RMSRBF-ANN, DMSGRNN-ANN, RMSGRNN-ANN	Precipitation	MAE, R^2, RMSE	Month	Meteorological, agricultural, hydrological
		Belayneh *et al.* (2016)	ANN, B-ANN, BS-ANN, W-B-ANN, W-BS-ANN, SVR, B-SVR, BS-SVR, W-B-SVR, W-BS-SVR	Precipitation, SPI	MAE, R^2, RMSE	Month, annual	Meteorological, agricultural, hydrological
		Rezaeianzadeh *et al.* (2016)	ANN, Markov chain	Precipitation, evaporation, inflow volume	R^2, RMSE	Month	Hydrological
		Djerbouai & Souag-Gamane (2016)	ANN, W-ANN, ARIMA	Precipitation	MAE, NSE, RMSE	Month	Agricultural, hydrological
		Deo *et al.* (2016)	ANN, W-ANN, ELM, W-ELM, LS-SVR, W-LS-SVR	Precipitation	d, MAE, NSE, Pdv, R, R^2, RMSE	Month	Meteorological, agricultural, hydrological
		Maca & Pech (2016)	Feedforward MLP-ANN, integrated-ANN	Precipitation, temperature	MAE, MSE, dMSE, NSE, PI	Month	Meteorological, hydrological
		Borji *et al.* (2016)	ANN, SVR	Streamflow	R^2, RMSE	Month	Hydrological
		Chen *et al.* (2016)	ANN, ARMA, HMM, HMM-RCP	Precipitation	CSS, RMSE	Month	Meteorological, agricultural
		Deo & Sahin (2016)	ANN, ELM	Streamflow	d, MAE, NSE, R^2	Month	Hydrological
		Ali *et al.* (2017)	MLP-ANN	Precipitation, temperature	MAE, R, RMSE	Month	Meteorological, agricultural, hydrological
		Kousari *et al.* (2017)	ANN	Precipitation, MEI, NAO, SOI, NINO1 + 2, anomaly NINO1 + 2, NINO3, anomaly NINO3, NINO4, anomaly NINO4, NINO3.4, anomaly NINO3.4	R, RMSE	Month	Agricultural, hydrological
		Seibert *et al.* (2017)	ANN, MLM, RFOR	Streamflow, climate indices and gridded sea surface temperature anomalies	NSE, ROC	Month	Hydrological
Fuzzy Logic (FL)	5	Keskin *et al.* (2009)	FL, ANFIS	Precipitation	R^2	Month	Meteorological
		Ozger *et al.* (2011)	FL, WFL	Precipitation, temperature, PDSI	R, R^2	Month	Meteorological, agricultural
		Ozger *et al.* (2012)	W-FL, ANN, W-ANN	NINO 3.4 index, PMDI	R, NSSS	Month	Meteorological
		Agboola *et al.* (2013)	FL	Temperature, pressure, humidity, dew point, wind speed	Prediction error, prediction accuracy, MAE, RMSE	Hour, day, week, month	Meteorological
		Mehr *et al.* (2014)	FL, W-FL, ANN, W-ANN, LGP, W-LGP	NINO 3.4 index, PMDI	R^2, RMSE	Month	Meteorological, agricultural, hydrological
Support vector machine (SVM)	12	Deng *et al.* (2011)	LS-SVM, ANFIS, BP-ANN	Soil water content, precipitation, temperature, evaporation	MARE, R, RMSE	Day	Agricultural
		Chiang & Tsai (2012)	SVM, ANN, Bayesian classifier, maximum likelihood classifier	Reservoir storage capacity, inflows, critical limit of operation rule curves, no. of ten-days in a year	Prediction accuracy	Day	Hydrological
		Belayneh & Adamowski (2012)	SVR, ANN, W-ANN	Precipitation, SPI	MAE, R^2, RMSE	Month	Agricultural, hydrological

(*continued*)

Table 1 | continued

Type of approach	Number of papers	Authors (year of publication)	Method	Input variables	Evaluation criteria	Time scale	Type of drought
		Belayneh & Adamowski (2013)	SVR, ANN, W-ANN	Precipitation, SPI	R^2, RMSE	Month	Agricultural, hydrological
		Chiang & Tsai (2013)	SVM, ANN, Bayesian classifier, maximum likelihood classifier	Reservoir storage capacity, inflows, critical limit of operation rule curves, no. of ten-days in a year	Prediction accuracy	Day	Hydrological
		Ganguli & Janga Reddy (2014)	SVM-without seasonal partition, SVM-combined seasonal	Precipitation	CRPS, NSE	Month	Meteorological
		Belayneh *et al.* (2014)	SVR, W-SVR, ANN, W-ANN, ARIMA	Precipitation, SPI	MAE, R^2, RMSE	Month	Hydrological
		Jalili *et al.* (2014)	MLP-ANN, RBF-ANN, SVM	NDVI (RS), NDVI-DEV (RS), TCI (RS), VCI (RS)	Prediction accuracy	Month	Meteorological, agricultural
		Jalalkamali *et al.* (2015)	SVM, ANFIS, ARIMAX, MLP-ANN	Precipitation	R^2, RMSE	Month	Meteorological
		Belayneh *et al.* (2016)	SVR, B-SVR, BS-SVR, W-B-SVR, W-BS-SVR, ANN, B-ANN, BS-ANN, W-B-ANN, W-BS-ANN,	Precipitation, SPI	MAE, R^2, RMSE	Month, annual	Meteorological, agricultural, hydrological
		Deo *et al.* (2016)	LS-SVR, W-LS-SVR, ANN, W-ANN, ELM, W-ELM,	Precipitation	d, MAE, NSE, Pdv, R, R^2, RMSE	Month	Meteorological, agricultural, hydrological
		Borji *et al.* (2016)	SVR, ANN	Streamflow	R^2, RMSE	Month	Hydrological
Hybrid models	23	Mishra *et al.* (2007)	HSNNDA, HSNNRA, ARIMA, RMSNN, DMSNN	Precipitation	MAE, R^2, RMSE	Month	Meteorological, agricultural, hydrological
		Bacanli *et al.* (2009)	ANFIS, FFNN	Precipitation	NSE, R, RMSE	Month	Meteorological, agricultural, hydrological
		Keskin *et al.* (2009)	ANFIS, FL	Precipitation	R^2	Month	Meteorological
		Dastorani *et al.* (2010)	ANFIS, TLRN	Precipitation, temperature, wind speed, intensive wind direction, relative humidity	R^2, RMSE	Month	Meteorological
		Farokhnia *et al.* (2011)	ANFIS	Precipitation, SST, SLP, EDI	MAE, R^2, RMSE	Day, month	Meteorological, agricultural, hydrological
		Ozger *et al.* (2011)	W-FL, FL	Precipitation, temperature, PDSI	R, R^2	Month	Meteorological, agricultural
		Deng *et al.* (2011)	ANFIS, BP-ANN, LS-SVM	Soil water content, precipitation, temperature, evaporation	MARE, R, RMSE	Day	Agricultural
		Ozger *et al.* (2012)	W-FL, W-ANN, ANN	NINO 3.4 index, PMDI	R, NSSS	Month	Meteorological
		Belayneh & Adamowski (2012)	W-ANN, ANN, SVR	Precipitation, SPI	MAE, R^2, RMSE	Month	Agricultural, hydrological
		Shatanawi *et al.* (2013)	1st-order Markov-ARIMA, 2nd-order Markov-ARIMA, ARIMA	Precipitation	Graphical comparison	Day, Month, Annual	Meteorological
		Belayneh & Adamowski (2013)	W-ANN, ANN, SVR	Precipitation	R^2, RMSE	Month	Agricultural, hydrological
		Woli *et al.* (2013)	ANFIS, ANN, ARMA, ENSO approach, linear regression	Day weather data, ARID	NSE, RMSE	Month	Agricultural
		Shirmohammadi *et al.* (2013)	W-ANFIS, ANFIS, W-ANN, ANN	Precipitation	NSE, R^2, RMSE	Month	Meteorological
		Mehr *et al.* (2014)	W-ANN, ANN, W-FL, FL, W-LGP, LFP	NINO 3.4 index, PMDI	R^2, RMSE	Month	Meteorological, agricultural, hydrological
		Shabri (2014)	W-ANFIS, ANFIS, ARIMA	Precipitation	MAE, RMSE	Month	Meteorological
		Belayneh *et al.* (2014)	W-ANN, ANN, W-SVR, SVR, ARIMA	Precipitation, SPI	MAE, R^2, RMSE	Month	Hydrological
		Nguyen *et al.* (2015)	ANFIS	Precipitation, temperature, SSTA	NSE, R, RMSE	-	Meteorological, agricultural, hydrological
		Jalalkamali *et al.* (2015)	ANFIS, MLP-ANN, ARIMAX, SVM	Precipitation	R^2, RMSE	Month	Meteorological
		Belayneh *et al.* (2016)	W-BS-ANN, W-B-ANN, BS-ANN, B-ANN, ANN, W-BS-SVR, W-B-SVR, BS-SVR, B-SVR, SVR	Precipitation, SPI	MAE, R^2, RMSE	Month, annual	Meteorological, agricultural, hydrological

		Djerbouai & Souag-Gamane (2016)	W-ANN, ANN, ARIMA	Precipitation	NSE, MAE, RMSE	Month	Agricultural, hydrological
		Memarian *et al.* (2016)	C-ANFIS	Precipitation, climatic indices	NMSE, MSE, R, R^2, Adjusted R^2	Month, annual	Meteorological, agricultural
		Deo *et al.* (2016)	W-ANN, W-ELM, W-LS-SVR, ANN, ELM, LS-SVR	Precipitation	d, MAE, NSE, Pdv, R, R^2, RMSE	Month	Meteorological, agricultural, hydrological
		Prasad *et al.* (2017)	IIS-W-ANN, M5 Tree	Streamflow	d, NSE, MAE, R, RMSE	Month	Hydrological
Dynamic modelling	8	Luo & Wood (2007)	CFS	Precipitation, temperature, NLDAS data (RS)	RMSD	Month	Hydrological
		Luo & Wood (2008)	CFS, CFS + DEMETER, ESP	Precipitation, temperature, streamflow, NLDAS data (RS), CFS data, DEMETER data	RPS	Day, month	Meteorological, agricultural, hydrological
		Yoon *et al.* (2012)	RSM dynamical downscaling, BI, BCSD, Bayesian, multimethod ensemble, the Schaake method	Precipitation	RMSE, AC	Month	Meteorological
		Shukla & Lettenmaier (2013)	CFS	Runoff, soil moisture, snow water equivalent	PPMC	Month	Hydrological
		Hao *et al.* (2014)	Baseline probability distributions	Precipitation (RS), soil moisture (RS)	-	Month	Meteorological, agricultural
		Sheffield *et al.* (2014)	CFS	Precipitation (RS), temperature (RS), wind speed (RS)	Brier skill score	Month	Meteorological, agricultural, hydrological
		Bowden *et al.* (2016)	WRF	Precipitation	Historical case comparison	Month	Meteorological, agricultural, hydrological
		Dehghani *et al.* (2017)	DLSTM, ANN	Discharge, streamflow, SHDI	DDR, IoAd, NSSS, RAE	Month	Hydrological

regression approach for the prediction of short-term future SPI and Standard Runoff Index (SRI) in the Luanhe river basin, northeast China. The results obtained using the three-dimensional loglinear approach provided a satisfactory coefficient of determination (R^2) with only a few forecasted values in some cases where it did not match the observed drought class, especially for the 2-month lead time. A conclusion is that the loglinear models are not recommended for prediction of increased lead time as the considerable number of parameters will increase the complexity of the modelling for a 2-month lead time and above. Park *et al.* (2016) proposed to use the machine learning approaches including the random forest (RF), boosted regression trees (BRT) and Cubist to assess and monitor the drought events over different regions of the USA. It was found that the random forest provided the best performance for SPI prediction compared with the other methods. The drought indicators were further used to generate the drought distribution maps and the maps were favourably compared with the U.S. Drought Monitor (USDM) maps.

Although the studies above showed that regression analysis provided reasonably good results but with simple and direct algorithms, this method tends to show weak performance in longer-lead time forecasting for the assumption on linearity between predictor and predictand. Other than that, if there exists a nonlinear relationship, the assumption on linearity cannot produce a good model, although it can be compensated by log or square root transformation in some cases. Similar to other machine learning methods, overfitting may also arise if the regression begins to model the random error (noise) in the data, rather than just the relationship between the variables, especially when there are too many parameters compared with the number of samples. Hence, the application of regression analysis has been reduced in recent years, unless evidence of causality is required.

STOCHASTIC MODELLING: ARIMA AND SARIMA

Stochastic models have been widely used for scientific applications, including analysing and modelling of the hydrologic time series. The advantages of stochastic models include better consideration of the serial linear correlation characteristic of time series; capability to search systematically for identification; estimation and diagnostic check for model development; and SARIMA requires only a few parameters to describe non-stationary time series for both within and across seasons. Two important and popular classes of stochastic models are the ARIMA and the SARIMA (Mishra *et al.* 2007). For both variants of these stochastic models, they contain three important parameters; namely the autoregressive order of p, the d^{th} difference of the time series z_t and the moving average order of q, where iterative tuning has to be carried out to generate a robust model. With the parameters defined, the models are normally described as ARIMA (p,d,q) for ARIMA and ARIMA (p,d,q) $(P,D,Q)_s$ for SARIMA, where (p,d,q) is the non-seasonal part of the model and $(P,D,Q)_s$ is the seasonal part of the model.

Abebe & Foerch (2008) had carried out a study to identify a time series forecasting model for mathematical description, simulation and short-term forecasting of hydrological drought severity at the Wabi Shebele river basin, Ethiopia. Prominent homogeneous pools were developed using the parameters mean rainfall, temperature, normalized digital vegetation index and stream flow. Thereafter, forecasting using SARIMA models was carried out and the results showed that the $(0, 1, 1)\ (0, 1, 1)_{12}$ was the best among the candidate models. Two years later, Durdu (2010) used ARIMA and SARIMA to predict the SPI at the Büyük Menderes river basin. The results suggested that the linear stochastic models were suitable to predict multiple time scales of SPI time series for the Büyük Menderes river basin and other hydrometeorologically similar basins. In the same year, Han *et al.* (2010) used ARIMA to forecast the Vegetation Temperature Condition Index (VTCI) in the Guanzhong Plain. Thirty-six pixels of VTCI were first studied for their model fitting, and then a first order autoregressive multivariate model, AR(1) was chosen as the best model to be used in each pixel of the whole area. In the study, remote sensing images for years 1999 to 2006 was acquired; each image reflects the drought condition for a ten-day period. The data set before the last ten days of March in 2006 is used for model development while the data set after that period is used for model validation. The validations were done in 1 and 2 steps, which represent the first ten and middle ten days of April in 2006, respectively. The results showed that the forecasting ability of 1 step was better than 2 steps after comparing the simulating data with the historical data. Yet, most of the simulating errors were small and with that, it was concluded that AR (1) model created for VTCI series is suitable for the drought forecasting in the Guanzhong Plain.

Fernandez-Manso *et al.* (2011) also developed the SARIMA for drought prediction in the areas of Castile and Leon, Spain. A 10-day maximum value composite (MVC) band of the normalized difference vegetation index (NDVI) was analysed using stochastic processes and then, NDVI in the following 10-day periods was forecasted using the developed SARIMA model. The results showed that using climatic variables as regressors of MVC-NDVI can improve the accuracy of forecasting models if the species considered are subjected to summer water stress. Hence, the use of SARIMA is suitable to extend its use for short-term forecast of agricultural drought, with NDVI as the drought index. In the following year, Chun *et al.* (2012) investigated and modelled the drought severity indices of six catchments in UK using ARIMA models and the generalized linear model (GLM). The ARIMA was used to identify the autocorrelation structures for the drought indices and to establish empirical relationships between climate variables and drought. Then, GLM was used to simulate the incidents and quantities of rainfall with the conditioning on climate variables. The results showed that ARIMA underestimated the magnitude of drought severity but it provided good short-term forecast fit. The GLM was concluded as being suitable for the local drought assessment at seasonal scale but needs improvement for rainfall simulations of more than six months. Chen *et al.* (2012) also used ARIMA for drought forecasting at the Haihe river basin, China. The performance of ARIMA with RF in predicting SPI was the subject of interest. Accordingly, the RF-based models have the advantages of nonparametric forecasting, flexibility to capture the basic relationship of time series and able to generate ensemble of drought forecast rather than a mean prediction. The results also showed that RF-based model was more reliable than ARIMA for both short- and long-term drought forecasting.

Han *et al.* (2013) developed ARIMA models to forecast the SPI at the Guanzhong Plain, China. The forecast results showed that the ARIMA models are efficient in forecasting all SPI series with 1-month lead time and SPI-9, SPI-12, SPI-24 with 6-month lead time. In other words, the ARIMA models were reflected as more convincing for the short-term forecasting. Over the same year, Shatanawi *et al.* (2013) used the Markov chain to support ARIMA in forecasting the SPI for the Jordan River Basin in the Middle East. It was observed that the ARIMA models were not able to produce exact predictions for the SPI series, and that the Markov chain models can give only the likely condition based on the precursor condition of the one or two previous seasons. Hence, both models were used to support each other in order to get better drought predictions. The results showed that ARIMA models can be used to forecast long-term future drought trends and with the aid of Markov transitional probabilities, and early warning of developing droughts can also be deduced. Two years later, the ARIMA was used to assess the meteorological drought severity at the Bundelkhand, Central India (Alam *et al.* 2014b). The SPI series at 3-month, 6-month, 9-month, 12-month and 24-month time scales had been used, and the statistical analysis revealed that the non-seasonal ARIMA model was suitable for the 3-month SPI series, while seasonal ARIMA models had been found assuring for the other longer SPI time scales. Then, the forecasted data from the best ARIMA model was compared with the observed data in which the forecasted data showed a good bond with the observed data.

Mossad & Alazba (2015) developed a linear ARIMA model to forecast the hyper-arid climate based on the SPEI. The few statistical parameters including the R^2, mean absolute error (MAE), root mean square error (RMSE), Akaike information criterion (AIC) and Schwarz Bayesian criterion (SBC) were used to evaluate the performance of different ARIMA models. The results demonstrated that the ARIMA models can accurately predict the drought event for a longer time scale like SPEI-24. On the other hand, the performance was less reliable over a shorter time scale such as SPEI-3. In the same year, Bazrafshan *et al.* (2015) assessed the efficiency of ARIMA and SARIMA for monthly and seasonal hydrologic drought forecasting, and determined the amount of lead time for effective forecasting, in the Karkheh Basin, Iran. The SRI in the study was generated using monthly and seasonal discharges from ten hydrometric stations for the years 1974 to 2013. The results showed that the ARIMA model performed better for the two months and one season lead-time forecasts. For the SRI values forecasts, the SARIMA model performed better over the monthly time scale than the seasonal time scale. Tian *et al.* (2016) explored the effectiveness of AR(1) and SARIMA forecasting VTCI in the Guanzhong Plain of China. In the study, VTCI of the first 10 days of March 2000 to the last ten days of March 2009 was used as input to develop the models. The results showed that the SARIMA has better performance compared with AR (1) as it can predict both no-drought grades and drought grades, unlike AR(1) which can only predict no-drought grades although it has lower absolute errors compared with SARIMA. Mahmud *et al.* (2016) also adopted the SARIMA for drought forecasting in the same year. Rainfall data from 30 stations in Bangladesh was used as input to forecast monthly rainfall for 12 months lead-time in the region. Based on R^2, RMSE and normalized BIC criteria, it was found that the SARIMA can predict monthly rainfall with reasonable accuracy and was established as a suitable model to forecast year-long rainfall for Bangladesh. A year later, Karthika *et al.* (2017) used ARIMA models for short-term annual forecasting of meteorological drought at the Lower Thirumanimuthar Sub-basin, India. One-year to 3-years lead-time of forecasting was considered and the results showed that the developed model can be used to design a drought preparedness plan for the region, ensuring sustainable water resources planning in the sub-basin.

However, despite all the continuing improvements associated with this well-known and widely used linear stochastic model, it is, slowly but surely, being replaced by the newer AI models which have the advantages of inborn nonlinear property and flexibility for modelling (Mishra *et al.* 2007). In order to identify the correct model from the class of possible models, identification techniques with complicated computations are required. Furthermore, these traditional model identification techniques are difficult to understand and, thus, the process is also subjective as the reliability of the chosen model is heavily dependent on the skills and experience of the user.

PROBABILISTIC MODELLING: MARKOV CHAIN (MC)

Markov chain is a memoryless random process in which, if a present state has been known or given, the future and the past are independent of each other (Chen & Yang 2012). It is a mathematical technique to obtain the probabilities of the system using a set of transition probabilities from one state to another. Generally, when the transitional probability is dependent on the conditions in the previous m time periods, it is called an mth order Markov chain. Details of the algorithm can be found in Avilés *et al.* (2016).

Paulo & Pereira (2007) investigated the efficacy of non-homogeneous formulation for the Markov chain model. Sixty-seven years of monthly SPI from Alentejo, southern Portugal were utilized for model development. The authors predicted drought class transitions up to 3 months ahead and the results showed that the non-homogeneous Markov chain model has the advantage of distinguishing among months when drought is computed, compared with the homogeneous Markov chain model. Then, Jiang & Chen (2009) developed a new model named weighted Markov SCGM(1,1)c for the prediction of drought crop area. This model combined the advantages of cloud grey system and Markov chain to improve drought prediction accuracy. By using data from China as an example, it was proven that this model can predict drought crop area with high precision. Sharma & Panu (2012) used Markov chain to forecast hydrological drought durations for the case of the Canadian prairies. Modelling was done using the SHI series derived from annual, monthly and weekly streamflow series. The results showed that the first-order Markov chain was suitable for the forecasting of annual drought lengths, while the second-order was found to be satisfactory on monthly and weekly time scales. Subsequently, Chen & Yang (2012) carried out SPI-based regional drought prediction using a weighted Markov chain model. In the study, monthly precipitation data from Anhui Province of Huaihe River in China was used to compute the SPI series which was used for model development. Based on the outcomes, it was concluded that the model is a useful tool for drought prediction and can be helpful for regional drought disaster management. Two years later, Alam *et al.* (2014a) used a Markov chain model to analyse long-term rainfall data of 12 rainfall stations at the semiarid Barind region. The results were tested with hypothesis testing (χ^2 test) and the model was termed as statistically satisfactory.

Another Markov chain study was done by Avilés *et al.* (2015). Unlike other studies, the performance of Markov chain-based drought forecasts was evaluated using skill scores, namely the ranked probability score (RPS) and the Gandin-Murphy skill score (GMSS). The results indicated that drought events with greater severity were more accurately forecasted. In the same year, Yeh *et al.* (2015) also adopted a Markov chain model for drought forecasting for Lanyang River and Yilan River basins in Taiwan. Precipitation and streamflow data were used to compute the streamflow drought index (SDI) as an input to the model. The results showed that the Markov chain model can produce reliable drought frequency and occurrence probabilities using short-term data. A year later, Nnaji *et al.* (2016) used a semi-Markov chain model, which is capable of preserving longer memory persistence than the simple Markov process, to predict monthly streamflow series for Apalachicola-Chattahoochee-Flint, USA. The results showed that the model can predict streamflow near drought and critical drought conditions with high accuracy. Khadr (2016) also investigated the use of the homogeneous hidden Markov chain model (HMM) to forecast SPI for the Blue Nile river basin, Egypt. A set of procedures for meteorological drought forecasting using homogeneous HMM to predict SPI with multiple timescales with lead-time of more than 1-month was produced.

Chen *et al.* (2016) proposed a new approach called the HMM aggregated with the RCP 8.5 precipitation projection (HMM-RCP). A probabilistic forecast of SPI-3 with the inference on the model parameters through reversible jump Markov chain Monte Carlo algorithm and weight-corrected post-processing on the RCP precipitation projection transformed SPI (RCP-SPI) was the subject of investigation. The proposed approach showed good results of accurately predicting 71.19% of drought events, and forecasted the mean duration with an error of less than 1.8 months and a mean severity error of <0.57. Next, Avilés *et al.* (2016) produced another paper comparing the performances of Markov chain and Bayesian network models. Monthly rainfall and streamflow data from the Chulco River basin, located in southern Ecuador were used to develop the models. According to the results of the RPSS, the authors concluded that MC-based models have higher prediction accuracy for wet and dry periods, and BN-based models forecast better for extreme droughts. A Markov chain model was also used to forecast short-term droughts in Victoria, Australia (Rahmat *et al.* 2016). The estimated drought probabilities and drought forecasts up to three months lead time using a non-homogeneous Markov chain model were analysed. The results showed that the model developed forecasted drought situations one month ahead reasonably well, but further development was required to forecast drought situations of two and three months ahead.

Sun *et al.* (2016) also evaluated the efficiency of Markov chain models in forecasting two drought indices, SPEI and SRI. The first order Markov chain (MCFO) and second order Markov chain (MCSO) were developed in the study and the results showed that the first-order Markov chain model was acceptable for the modelling practice of the SPEI–SRI integrated drought events. Recently, a weighted Markov chain model was also evaluated by Zhang *et al.* (2017). The performance of the model was compared with the Volterra adaptive filter model and the three-dimensional (3D) loglinear model, based on the accuracy in forecasting SPI and SRI series. The results showed that the 3D loglinear model can forecast drought class but limited to within one month, and the precision decreases with timescales. For the weighted Markov chain, it is suitable for drought early warning as the precision is the highest for non-drought, followed by moderate and severe/extreme, and lowest for near-normal. The Volterra adaptive filter model is capable of forecasting long-term drought.

Although the Markov chain has been giving good results, even when dealing with complex distributions of data, the use of the Markov chain may be limited by the performance of the researchers' computers. This is because Markov chain models require a large number of states to be constructed and solving models with so many states does not only challenge the computational resources of memory and execution time offered by computers, but more importantly, tests the users' patience, and in a world of more automation and robotics, this can be the ultimate reason for its demise. In addition, the problem of correctly specifying states and inter-state transitions is generally difficult and awkward. This is especially so if the formulated model is very large and complex. It may be very difficult for the researcher to construct a model of a large system and verify that it is correct. Hence, if the system behaviour to be modelled is too complex or too detailed to be expressed in a Markov type model, then an alternative method capable of representing the behaviour of interest should be more likely of use instead of Markov modelling.

ARTIFICIAL INTELLIGENCE-BASED MODELS

Artificial neural network (ANN)

Artificial neural networks are flexible, nonlinear models that resemble the structure of a nerve system. They can adapt the data inserted and analyse and discover patterns from it. Theoretically, by giving an adequate amount of nonlinear processing units, neural networks are able to gain experiences and learn to estimate any complex functional relationship accurately (Mishra & Singh 2011). The ANNs learn based on a black-box process, the main factors affecting the performance of the model are input adequacy, network architecture and model validation. The network of ANNs are constructed from three major components: input layer, hidden layer and output layer. To generate an ANN model, researchers are required to tune the parameters: namely, the number of neurons in hidden layers, the learning rate (training parameter that controls the size of weight and bias changes in learning of the training algorithm) and the momentum (weightage of precedent input to be updated to the subsequent input). Thus, ANNs have the clear advantage of not needing to define the procedures or processes between the inputs and outputs. Also, the flexibility in the network architecture also allows for the cases to be extended easily from the univariate to the multivariate cases. Due to the differences in network architecture, there are thus many variants in ANNs and the multilayer perceptron feed forward model is the most popular neural network architecture (Djerbouai & Souag-Gamane 2016). However, the discussion of the applications of ANNs in this paper is not limited to any particular variant of ANN.

Ochoa-Rivera (2008) investigated the performance between ANN and second order auto-regressive multivariate model (AR(2)) in generating stream-flows for the Alto Tajo River Basin in Spain. The ANN architecture used was the popular multi-layer perceptron ANN model. Average values of the mean, standard deviation, and skewness coefficient and correlation function of the synthetic series were estimated to compare with the historical series to analyse the goodness of fit of the developed models, while the relative root mean square prediction (RRMSD) was used for the model comparisons. The results showed that ANN performed better than AR(2) and according to the authors this was due to the nonlinear structure of the ANN models. Following closely, Cutore *et al.* (2009) also applied ANN models to carry out forecasts of Palmer index series in Sicily, Italy. The aim of the study was to investigate influence of the North Atlantic Oscillation (NAO) and European blocking (EB) indices on the Palmer index series. The results showed that there was a significant improvement during the winter and autumn forecasts when NAO and EB were included in the ANN models. Next, Dastorani *et al.* (2010) evaluated the applicability of ANN and ANFIS to predict dryland precipitation in Yazd, Central Iran. Different architectures of ANN were constructed to compare with ANFIS. The best architecture time lagged recurrent network (TLRN) ANN were then chosen as the best ANN model, and used to compare with ANFIS. The results showed that both models have similar efficiency in the dryland precipitation prediction and were efficient in predicting precipitation 12 months in advance.

Marj & Meijerink (2011) also conducted a study on drought forecasting for the Ahar-chay Basin, Iran. A feed-forward multiple neural network was used in the study to forecast the NDVI. The SOI and NAO was adopted as the input for ANN model and the results showed that the predicted NDVI has R^2 of 0.79, RMSE of 0.011 and the discrepancies are less than 1 SD compared with the observed NDVI. Barua *et al.* (2012) conducted a study to evaluate the effectiveness of an ANN-based model in forecasting the nonlinear aggregated drought index (NADI). Two ANN forecasting models, namely the recursive multistep neural network (RMSNN) and direct multistep neural network (DMSNN), were developed in the study. Forecasted data from these two models were compared with ARIMA, and the results showed that both RMSNN and DMSNN models had better performance than the ARIMA model. It was also found that the RMSNN model forecasted slightly more accurately than the DMSNN model for 2–3 months lead times, while the DMSNN model produced forecasts with higher accuracy than the RMSNN model for forecast 4–6 months lead times. ANN was also used by Masinde (2014) to overcome the drawbacks of old drought forecasting approaches in Kenya that were unable to provide short- and long-term forecasts and severity of the drought. The effective drought index (EDI) was combined with ANN in the study, and accuracies as high as 98% were achieved, concluding that ANN can be a great enhancement to the old approaches practised in Kenya.

Other than forecasting the NADI and EDI, the SPEI were also forecasted using ANN by Deo & Sahin (2015). In their study, the feasibility of the ANN was tested to predict the monthly SPEI for eight stations in eastern Australia. Different architectures of ANNs were tested in the study and the structure with 18 input neurons, 43 hidden neurons and 1 output neuron was established as the best architecture. In addition, the results from performance measures of R^2, MAE and RMSE revealed that the ANN model was a useful data-driven method to forecast the monthly SPEI in the region. Hosseini-Moghari & Araghinejad (2015) also used ANN to forecast short-, mid-, and long-term droughts in the Gorganroud basin (northern Iran). Different architectures of ANN including the recursive multi-step multi-layer perceptron (RMSMLP), the direct multi-step multi-layer perceptron (DMSMLP), the recursive multi-step radial basis function (RMSRBF), the direct multi-step radial basis function (DMSRBF), the recursive multi-step generalized regression neural network (RMSGRNN), and the direct multi-step generalized regression neural network (DMSGRNN) were used to forecast SPI on 3, 6, 9, 12 and 24-month time scales. The results showed that recursive models performed better at smaller time scales, whereas direct models performed better at longer time scales. Rezaeianzadeh *et al.* (2016) compared the performance of ANN and Markov chain models in drought forecasting for the Doroodzan reservoir dam, Iran. The 1-month lead time inflow volume using current reservoir inflow volumes and other hydroclimatic variables were forecasted. The results showed that the ANN model performed better than the Markov chain model and it was concluded that simultaneous application of both models can reduce both the uncertainty and error of the models. Maca & Pech (2016) also used ANN models for the forecasting and analysis of SPI and SPEI. The models they used are a feed forward multilayer perceptron based ANN and an integrated neural network model. Datasets from two different areas in USA were used, which were the Leaf River near Collins, Mississippi and Santa Ysabel Creek near Ramona, California. For data performance evaluation, the results of four from five performance measures showed that the integrated neural network model outperformed the feed forward multilayer perceptron-based ANN. Deo & Sahin (2016) used ANN as a benchmark to elucidate the predictive accuracy of the extreme learning machine (ELM) model for prediction of streamflow water levels. The streamflow water levels were predicted from a set of nine variables for three hydrological catchments in eastern Queensland, namely Gowrie Creek, Mary River and Albert River. The authors carried out correlation analysis for the selection of inputs in the training process of both models. The results showed that ANN was outperformed by ELM. However, both models performed better when the selection of variables was done.

Ali *et al.* (2017) applied the MLP-ANN model to forecast the SPEI for 17 climatology stations in the Northern Area and Khyber Pakhtunkhwa of Pakistan. Based on the outcomes, it was reported that the ANNs were able to capture the variation in selected drought indices with one-month time scale. The results from the MAE, R and RMSE also showed that the MLP-ANN has potential capability for the SPEI forecasting. Kousari *et al.* (2017) also explored the potential of ANN in forecasting drought. They forecasted SPI in 3, 6, 9, 12, 18 and 24 monthly series for the Fars Province of Iran. It was reported that increasing the lead-time of forecasting leads to decreasing accuracy of the models. In order to obtain successful performance of drought forecasting, a set of procedures to be followed was given. Seibert *et al.* (2017) also used ANN for seasonal forecasting of hydrological drought in the Limpopo Basin, Africa. Streamflow data, climatic indices and gridded sea surface temperature anomalies were used as predictands for the models and SPI with lead-time up to 12 months were the outcomes of the models. The performance of ANNs was compared with the multiple linear model (MLM) and the random forest regression tree (RFOR) models and the results showed that MLMs are the best while ANNs and RFORs were likely to suffer from overfitting.

Based on the papers reviewed, studies are showing that the ANN is outperforming other traditional non-AI based models with the advantages of less statistical training and its nonlinear property. The availability of different variants is another advantage of using ANN to cope with different needs and situations compared with the other methods. This, despite the fact that the 'black-box' nature of ANN causes it to be lacking in interpretation of the model's functional behaviour. As the computing process dependent on the size of input space, model performance is affected by availability of data. The model performance can be unsatisfying when the data size is small, while the model can become complex and computationally expensive when input space is large, not to mention the fact that the increase in model complexity may also result in overfitting. Hence, researchers are required to carry out an in-depth model evaluation in order to produce a robust model.

Fuzzy logic (FL)

Fuzzy logic was conceptualised by Zadeh (1965) and is defined as a handy way to map an input space to an output space (Prasad & Sudha 2011; Sandya *et al.* 2013). Among the several advantages of using fuzzy logic, the most relevant for our subject matter is the fact that it can model imprecise data and nonlinear functions of arbitrary complexity and that it is based on a natural language. In classical (Boolean or crisp) set theory, membership of an element x in a set A, is defined by a characteristic function, which assigns a value of either 1 (true) or 0 (false) to each individual in the universal set X. That it is to say 'every proposition is either true or false'. But, fuzzy logic violates both 'excluded middle' and 'contradiction' laws (Klir & Yuan 2008). Fuzzy logic is based on fuzzy sets in that, unlike classical sets, their membership is not a 'true-false' but 'not-quite-true-or-false' answer. Hence, the general concept behind fuzzy logic is that a set of pre-defined rules (if-else statements) are applied in parallel to interpret some values in the input vector and then assign values to the output vector. And to achieve that, a fuzzy membership function (FMF) curve is used to define the way to map points in the input space (universe of discourse) to a membership value (or degree/grade of membership) between 0 and 1.

Compared with ANN which incorporates the human-like thinking process to solve problems, fuzzy logic allows definite decision making based on imprecise or ambiguous data. Both try to exploit the scope of using 'Tolerance towards uncertainty and imprecision', but the approaches used by each are starkly different. While the fuzzy logic is based on mathematical modelling to incorporate imprecision and tolerance towards uncertainty, the ANN follows the human brain's biological model to solve the same problem. Thus, there is a possibility of evolution and learning for ANN whereas fuzzy logic is pure calculative logic taking into its fraction (wherever possible), the scope of tolerance for imprecision and uncertainty and does not evolve by itself.

Keskin *et al.* (2009) applied FL models to analyse meteorological droughts at nine stations located around the Lakes District, Turkey. Using monthly historical precipitation data and expert knowledge, rule bases were created for the fuzzy logic models. Analyses were performed on SPI of 3, 6, 9 and 12 months long. The simulated data from FL models were compared with data sets from ANFIS and the results showed that R^2 values of ANFIS models were higher than those of the FL models, especially for SPI-12. It was concluded that ANFIS models were effective for extreme point predictions. However, the advantage of FL models of not requiring the model structure to be known a priori can be used for hybrid models in the future. Agboola *et al.* (2013) investigated the ability of fuzzy rules/logic in modelling the precipitation of south-western Nigeria for better drought management. In the study, membership functions were assigned for each fuzzy variable, namely temperature, pressure, humidity, dew point, wind speed and rainfall. The model-predicted outputs were compared with the observed rainfall data and it was concluded that fuzzy rule-based models were flexible, suitable for modelling of ill-defined, scattered data. FL has also been proven to be useful in forming hybrid models for drought forecasting. Ozger *et al.* (2011) combined wavelet transformation and fuzzy logic to forecast PDSI for the ten climate divisions in Texas and continued studies of the hybrid models by adopting the wavelet fuzzy logic (W-FL) and wavelet artificial neural network (W-ANN) to predict future long-term drought events in Texas (Ozger *et al.* 2012). The results showed that W-FL was more accurate for drought forecasting compared with W-ANN.

Although the FL can model imprecise data and is able to read 'natural language' rules applied by the users, the limitation of increase in computational time when the set of fuzzy rules increases makes it less versatile and popular.

The lack of an evolution and learning element of the FL is also holding it back from being utilized now as self-learning is important in the era of real time forecasting. However, its advantage of modelling imprecision in data is being used to developed hybrid models. This shall be discussed along with some examples in the section headed 'Hybrid models', below.

Support vector regression (SVR)

In 1997, Vapnik (1997) introduced support vector machines (SVM) to describe properties of learning machines so that they were able to simplify unseen data (Kisi & Cimen 2011). The learning process is unresponsive to the relative number of training examples in positive and negative classes. Unlike other empirical risk minimization based learning algorithms (e.g. ANNs) that classify only the positive class correctly to minimize the error over the data set, SVM aims at minimizing a bound on the generalization error of a model in high dimensional space, so-called structural risk minimization. In short, SVMs seek to minimize the generalization error, while ANNs and other empirical risk minimization based learning algorithms seek to minimize training error. SVMs can be categorized into two types: support vector classification (SVC) and support vector regression (SVR), where SVR is the preferable type for forecasting tasks. The important parameters for the tuning of SVMs include kernel type and parameter (classes of algorithms for pattern analysis), regularization parameter (the trade-off between achieving a low training error and a low testing error), Gamma parameter (complexity of model) and margin of error acceptance. Through an iteration process, researchers are able to develop a robust SVM model using the availability of different types of kernel and through the tuning of the aforementioned parameters.

Deng *et al.* (2011) used least squares support vector machine (LS-SVM) to simulate the daily soil water content of Hunan Province, southern China. Compared with conventional SVM, LS-SVM is an improved algorithm using equality type constraints instead of inequalities. The model's performance was compared with BP-ANN and ANFIS in terms of MARE, R and MRSE. The results showed that LS-SVM was more stable and superior at soil water simulation compared with BP-ANN and ANFIS. Chiang & Tsai (2012) compared the performance of SVM model with three other models (ANN, maximum likelihood classifier, Bayesian classifier). The models were used to predict reservoir drought status in the next 10–90 days in Tsengwen Reservoir, Taiwan. The results showed that SVM had better performance than the other three approaches in drought forecasting. Even with the evidence that the longer the prediction time period the lower the prediction accuracy, the accuracy of forecasting the next 50 days was still high with percentages of about 85% both in training and testing data set by SVM. Hence, SVM was concluded to have high accuracy in drought forecasting.

Later, Chiang & Tsai (2013) improved the SVM model into a two-stage SVM model. The two-stage SVM outperformed the original SVM and the three other approaches (ANN, maximum likelihood classifier, Bayes classifier) that were used for evaluation through comparisons. Ganguli & Janga Reddy (2014) also applied SVM for drought forecasting over western Rajasthan, India. Two variants of SPI-based drought forecast models were developed to simulate SPI up to 3 months lead time, which were the SVM-copula approach without seasonal partition and the SVM-copula approach with seasonal partition. It was found that the developed SVM-copula approach improved the drought prediction capability for the combined seasonal model compared with the model without seasonal partition. Jalili *et al.* (2014) also explored the use of SVM in drought forecasting, comparing the SVM with other models, namely the MLP-ANN and RBF-ANN in the study. The SPI drought index was used in the study but the results showed that MLP-ANN was the best performing model. The advantages of SVM were utilized by Belayneh *et al.* (2016) to combine with wavelet, bootstrap and boosting techniques, forming different hybrid models. The performance measures results showed that all SVM-based hybrid models outperformed the ANN-based hybrid models in drought forecasting. Borji *et al.* (2016) also explored the usage of SVR in drought forecasting and compared its performance with ANNs. Runoff data from Jajrood River, Iran was used to predict SDI for hydrological drought analysis. The conclusion was that the SVR has better efficiency in forecasting long-term droughts compared with ANNs because the SVR does not fall into the trap of local errors.

Through the papers reviewed, SVR models seemed to be outperforming other machine learning models, especially for the long-term forecasting. This may be due to its advantage of avoiding overfitting and local minima through proper tuning of regularization parameters and convex optimization, respectively (Jalalkamali *et al.* 2015). Due to its difference in risk minimization algorithms, the independence of the SVR model complexity from the dimensionality of the input space has also brought advantage to the SVR over other empirical modelling models. Apart from that, Kernel tricks that allow development of the SVR models to suit different conditions is also one of the factors for its outstanding performances. However, it has the same weakness shared among models with nonlinear property; that is, it is just as computationally inefficient.

Hybrid models

Hybrid models is a new category of hydrology modelling which has emerged in the last decade. To the best knowledge of the authors, the first drought forecasting hybrid model used in the hydrology field since 2007 was introduced by Mishra *et al.* (2007). According to the papers reviewed, the authors observed that the hybrid models can be grouped into two variants, first, the hybrid between machine learning models and, second, the hybrid between data pre-processing techniques and machine learning models.

Coupled machine learning models

For the first variant, machine learning models were coupled to rectify respective incompetency. For example, Mishra *et al.* (2007) coupled the advantages of both a linear stochastic model (ARIMA) and a nonlinear ANN model to forecast droughts in the Kansabati River basin in India using the SPI. Two kinds of hybrid ARIMA-ANN models were created in the study, namely the hybrid stochastic neural network of recursive approach (HSNNRA) and the hybrid stochastic neural network of direct approach (HSNNDA). The performance of the hybrid models were compared with individual ARIMA and ANN models, and the results showed that the hybrid models were able to forecast droughts with greater accuracy. Two years later, another hybrid model ANFIS was tested for its applicability for SPI forecasting in Central Anatolia, Turkey by Bacanli *et al.* (2009). The basic problems of fuzzy systems are the difficulties in defining the membership function parameters and the design of fuzzy if–then rules. To overcome this, the authors utilized the learning capability of ANN for automatic fuzzy rule generation and parameter optimization. Therefore, a hybrid model combining the advantages of fuzzy system and ANN, the so-called ANFIS was developed in the study. Monthly mean precipitation was used to compute the values of SPI for different time scales of 1 month to 12 months. The feed forward neural networks (FFNN) were used to compare with ANFIS for their performance. The results demonstrated that ANFIS was more accurate and reliable for drought forecasting. Besides, the finding described the ANFIS model as a suitable approach for drought forecasting as it combined the advantages of neural network and fuzzy logic methods.

In 2010, ANFIS were compared with ANN for their applicability in forecasting droughts for the Yazd meteorological station in Central Iran (Dastorani *et al.* 2010). Different architectures of ANN and ANFIS models together with various combinations of meteorological conditions were applied in the study. The results showed that both the ANN (with structure of TLRN) and ANFIS were efficient tools to forecast droughts in that area. In another study (Farokhnia *et al.* 2011), ANFIS was once again adopted as a drought forecasting tool. The study intended to examine the utility of SST and SLP global data for forecasting the likelihood of drought events compared with EDI by using them as inputs to the ANFIS model. It was found that in all the cases, those that had applied SST/SLP datasets had a higher accuracy. Woli *et al.* (2013) also used ANFIS to predict the agricultural reference index for drought (ARID) for five locations in the south-eastern United States. The performance of ANFIS were compared with other approaches, namely ANN, the autoregressive moving averages (ARMA), linear regression and the El Niño Southern Oscillation (ENSO) based approach (the ARID values were separated into three ENSO phases and averaged by phase). However, the results showed that ANFIS performed poorly, in general, due to the limited availability of the input data. To further study the application of hybrid models in drought forecasting, Nguyen *et al.* (2015) applied the ANFIS model for forecasting the drought event at the

Cai River basin in Vietnam. The precipitation, temperature and the sea surface temperature anomalies (SSTA) were used as the input for ANFIS to predict the SPI and SPEI. The results showed that the ANFIS model provided a satisfactory forecasted result, and it was further concluded that the SPI was more suitable in predicting the short-term drought event (1- and 3-month models) than the SPEI, while the SPEI was found to be more suitable in predicting the long-term drought event (6- and 12-month models). Jalalkamali *et al.* (2015) applied several AI models including ANN, SVM and ANFIS to compare with the performance of the ARIMAX model for drought forecasting at Yazd Province, Iran. The past monthly precipitation for a 51-year period was used to calculate the SPI values. All the performances of the models were evaluated by R^2 and RMSE. All the models had good capability and sensitivity to drought forecast in a 9-month period. The performance of the ARIMAX was slightly better for the 9-month SPI prediction, followed by ANFIS, ANN and SVM.

From the reviews, it was observed that the hybrid models can be customized to suit the problem of the researchers by coupling two different machine learning models together. For examples Mishra *et al.* (2007) coupled ARIMA and ANN models to overcome the respective incompetency in modelling linear and nonlinear data, while Bacanli *et al.* (2009) adopted the ANFIS to utilize the learning capability of ANN for automatic fuzzy rule generation and parameter optimization in FL. These two studies showed the capability and flexibility of first variant hybrid model in solving problems. However, similar to any other variants of single ANN models, the performance of these ANN-based hybrid models can also be unsatisfactory when there is limited availability of data, as found out by Woli *et al.* (2013). Other nonlinear modelling methods such as the SVR, which is less constrained by the dimensionality of input space, can be experimented as a substitution for ANN.

Data pre-processing techniques cum machine learning models

Further on, the second variant of hybrid model was first observed in the field of hydrology from a study that combined wavelet transformation and fuzzy logic (W-FL) that was applied to ten climate divisions in Texas to forecast the PDSI (Ozger *et al.* 2011). The performance of the model was compared with the traditional FL model. Better results from the W-FL model were obtained, where the annual cycle of precipitation was dominant. They concluded that using wavelet transformation to combine with FL model can improve the performance significantly in forecasting PDSI. W-FL can obtain a significant improvement over the FL model in the forecast of the PDSI, where W-FL was capable of modelling more complex problems. Ozger *et al.* (2012) further studied hybrid models by adopting the wavelet fuzzy logic (W-FL) and wavelet artificial neural network (W-ANN) approaches to forecast the long lead drought event in Texas. The results showed that W-FL was more accurate for drought forecasting. Belayneh & Adamowski (2012, 2013) also compared among W-ANN, ANN and SVR using data from the Awash River Basin of Ethiopia. The drought index chosen to represent drought in the basin was the SPI, and the results indicated that the forecasted SPI values over multiple lead times had the highest accuracy when W-ANN models were used. Belayneh *et al.* (2014) increased the number of model comparisons by developing a new W-SVR model for the same river basin as the previous studies. Accordingly, it was the first time that W-SVR models had been explored and tested for long-term SPI forecasting. However, the results of the RMSE, MAE and R^2 showed that W-ANN had better performance than W-SVR. Mehr *et al.* (2014) also developed a new hybrid model called wavelet-linear genetic programing (W-LGP), for long lead-time drought forecasting. The results were promising, showing that W-LGP can be effectively used for the forecasts of 3-, 6-, and 12-month lead time drought conditions. Additionally, they found that the W-LGP was slightly less precise than the W-FL and W-ANN models as the original time series in both W-FL and W-ANN models were decomposed prior to training.

The benefit of using the wavelet decomposition was further studied by Djerbouai & Souag-Gamane (2016), where the meteorological drought was forecasted in the western part of the Algerois Catchment. Similar to the previous studies, SPI-12 for all the models was considered the best parameter to model the drought event for all the lead times (1-month to 6-month). Additionally, the hybrid model W-ANN was better than the other two models

(ARIMA and ANN) for all the time scales and lead times. It was found that the wavelet transform had the ability to reduce the complexity of a given time series, thus managed to reduce the number of hidden neurones and saved the computation time. The extent of adopting the wavelet transform with the extreme machine learning was studied by Deo *et al.* (2016). A wavelet-based extreme learning machine (W-ELM) was proposed to forecast the monthly EDI for three hydrological stations in Australia. The performance of the W-ELM was compared with the ANN, LS-SVR and their wavelet-equivalent models (W-ANN and W-LS-SVR). The results showed that W-ELM was the best among the models. Moreover, W-ELM model was found to be computationally efficient as running time was faster, and most of the predicted errors were considered low.

In spite of the fact that previous hybrid models, with the combination of data pre-processing technique with standalone machine learning models, showed satisfactory prediction accuracy, many researchers attempted to improve the hybrid models further. For example, Shirmohammadi *et al.* (2013) came up with a three-layer hybrid model, wavelet-ANFIS (W-ANFIS) by combining wavelet transformation with the existing hybrid model, ANFIS. The capability of this model was evaluated by comparing with W-ANN, ANN and ANFIS. The results showed that ANFIS models forecasted more accurately than ANN models, and also demonstrated that wavelet transform can improve meteorological drought modelling. This showed that the performance of wavelet-hybrid models is quite promising. This was further proven by Shabri (2014) through his study on the W-ANFIS model in Malaysia. W-ANFIS was once again proven to be outperforming the traditional ANFIS and ARIMA models. Other than combining ANFIS model with the wavelet transform, Memarian *et al.* (2016) further improved the performance of ANFIS by integrating fuzzy inputs with modular neural network to increase the accuracy in estimating complex functions, namely the co-active neuro-fuzzy inference system (C-ANFIS). The results from performance metrics showed that the global indices with a time lag had better correlation with ENSO.

Belayneh *et al.* (2016) explored the ability of wavelet transforms, bootstrap and boosting ensemble techniques in developing reliable ANN and SVR models for drought forecasting. The bootstrap artificial neural network (BS-ANN), bootstrap support vector regression (BS-SVR) and their wavelet coupled bootstrap ensemble (W-BS-ANN and W-BS-SVR) models were used to forecast the SPI-3, SPI-12 and SPI-24. Compared with bootstrap that improves the model performance by increasing stability, the boosting technique that enhances weak learning effects showed better improvement in forecasting accuracy of SPIs. Besides, wavelet analysis also enhanced the performance of all models through its capability in de-noising. Thus, the wavelet boosting SVR (W-BS-SVR) model provided better forecast accuracies compared with other assessed models. A year later, Prasad *et al.* (2017) evaluated the capability of the iterative input selection (IIS) method in aiding W-ANN, benchmarking with the M5 tree model. The area selected in the study was the Murray-Darling Basin, Australia and monthly streamflow water levels of the basin were used as input to develop the models. The results showed that the IIS-W-ANN model outperformed W-ANN models and the IIS-W-ANN model accuracy outweighed the IIS-W-M5 model. Hence, IIS was concluded as a useful model-enhancing method for streamflow forecasting models.

It was observed that the second variant of the hybrid models, which possess the advantages of data pre-processing techniques to improve the performance of models, also gave satisfying results. The reviews have shown that data pre-processing techniques can be tied in with the machine learning models to generate higher performance hybrid models. The main function of the data pre-processing technique is to improve the quality of input data before the modelling process. Based on the different types of problem encountered, different techniques with desired functions have been adopted to accommodate with the machine learning models. For example, Djerbouai & Souag-Gamane (2016) adopted the wavelet transform to reduce the complexity of a given time series, which subsequently reduced the number of hidden neurones and thus saved on computation time. The bootstrap and boosting ensemble techniques were also adopted as data pre-processing techniques by Belayneh *et al.* (2016) to improve the quality of input data, where the bootstrap improved the performance stability and the boosting enhanced the performance of weak learners.

Given the flexibility and adaptability of both variants of hybrid models in modelling, researchers attempted to explore further the possible combinations of hybrid models in order to produce better and more robust forecasts. However, researchers are advised to identify the research's problem before selecting the hybrid models to be developed as they can be customized to suit different situations. Hence, the reviews are to provide an overview for researchers to differentiate the characteristics of both variants.

DYNAMIC MODELLING

Dynamic modelling is an approach which utilizes real time data to describe a phenomenon over time. Due to the rapid development of remote sensing in drought monitoring and impact assessment, the availability of drought-related real time variables has also increased. Thus, dynamic drought forecasts studies are increasing over the years. Unlike the statistical drought forecasting models that use long-term conventional gauge observations, dynamic drought modelling is highly dependent on the real time remote sensing data. Remote sensing is a technique of obtaining reliable information about objects, areas or phenomenon from afar and/or without making physical contact, typically from an aircraft or a satellite (NOAA 2017). Satellite remote sensing has been used for monitoring the Earth's weather or climate since the success of the Television and Infrared Observation Satellite (TIROS-1) mission in 1960 (NASA 1987). For the study on droughts, remote sensing observations can be used to monitor drought-related climatological variables and quantify drought impacts from an ecosystem perspective (AghaKouchak *et al.* 2015). For example, precipitation rate can be converted from satellite infrared and visible images of cloud top temperature using empirical statistical relationships (Arkin *et al.* 1994; Joyce & Arkin 1997); volumetric water content of the soil of 2–5 cm depths from the ground surface can be converted from passive microwave brightness temperature and active microwave backscattering through empirical relationships (Njoku *et al.* 2003); and quantification of temporal terrestrial water storage anomalies can be done by measuring the distance between two spacecraft (Rodell 2012).

Apart from drought monitoring and drought impact assessments, the use of remote sensing data for drought forecasting has also become relevant over recent years. In 2010, Han *et al.* used VTCI series (1999–2006, Guanzhong Plain of China) generated based on the remote sensing information of the land surface temperature versus the NDVI scatter plot falling into a triangular shape as the input for the forecasting model of AR(1). Compared with the conventional time series forecasting, the study tried to capture not only the variations of one pixel value over time, but also the spatial changes about all the 36 evenly distributed pixel values in the region. Fernandez-Manso *et al.* (2011) also used remotely sensed NOAA-AVHRR images (from 1993 to 1997), to forecast the short-term response of forest vegetation in Castile and Leon, Spain. The results showed that the different ARIMA models can be developed to suit the evolution of the NDVI series for various conifer species and the forecasting models can be improved by using climatic variables as regressors of the MVC-NDVI time series for the species considered being subjected to summer water stress. Jalili *et al.* (2014) explored the use of different remote sensing data to forecast the SPI in Iran. NDVI, TCI and VCI were extracted from NOAA-AVHRR images and used as input to forecast SPI. From the results, TCI was found to be the most suitable satellite feature to describe drought conditions. The results also showed that the drought conditions could be forecasted with accuracy up to 90% when the ANN model was applied with remote sensing data. AVHRR images were also adopted by Tian *et al.* (2016) for the agricultural drought forecasting of Guanzhong Plain, China. About 90 VTCI images of the years from 2000 to 2009 were derived from AVHRR data to develop ARIMA models. Similar to the study done by Han *et al.* (2010), 17 pixels were chosen based on the existence of weather stations. The results showed that the forecasted drought severity from ARIMA models were in good agreement with the categorized VTCI drought monitoring results.

However, remote sensing is a relatively new technique in which the data can only provide short-term information from recent decades. It is necessary to combine the remotely sensed information with the long-term climatology to reduce the bias of the model forecasts. For example, Luo & Wood (2007) used the Drought Monitoring and Prediction System (DMAPS) for US drought and in the prediction part (NCEP CFS), the system implemented the Bayesian merging procedure (Luo *et al.* 2007) to combine seasonal forecasts (outputted from NLDAS forcing datasets) with observed monthly climate data. By doing so, biases in the seasonal forecasts have been removed and the results showed that the system gave promising skills in the prediction. Luo & Wood (2008) carried out another study in eastern United States to compare the performances among multimodel dynamic modelling (CFS + DEMETER), conventional dynamic modelling (CFS) and non-dynamic modelling (ESP). Evaluation of the models was done using a case study of forecast in 1988 and 19-year period hindcasts. The results showed that CFS + DEMETER forecasts gave very promising skills over two other models in producing precipitation, soil moisture and streamflow over the Ohio River Basin. For the 19-year period hindcasts, CFS + DEMETER gave significant advantage over ESP for the first two months of the forecasts. Hao *et al.* (2014) presented data sets available from the Global Integrated Drought Monitoring and Prediction System (GIDMaPS) that showed relatively reasonable forecasts for 2 to 4 months of lead time using baseline probability distributions. In the system, one of the inputs called GDCDR also utilizes the benefits of combining PERSIANN satellite data with long-term GPCP observations for drought predictions. Sheffield *et al.* (2014) also carried out drought forecasting in sub-Saharan Africa using satellite-based TMPA (precipitation) and GFS (temperature and wind speed) data for the years 2002 to 2008. These data were bias corrected before being used as the input for the NCEP CFS. The results showed that the forecasts indicated good skills in early predictions but performance decreased when the lead time increased.

Dehghani *et al.* (2017) utilized real time information from real time gauges in Black River Basin, USA for dynamical drought forecasting. In the study, DLSTM and ANN were compared for their capability in the forecasting of SHDI. The results showed that DLSTM performed better than ANN especially for long lead time forecasting. Another approach to carry out dynamic modelling for drought prediction was carried out by Yoon *et al.* in 2012. They performed dynamical downscaling on the RSM forecasts over the contiguous United States and compared with five other statistical and error correction methods, which are BI, BCSD, Bayesian, the Schaake method and multimethod ensemble. The results showed that RSM dynamical downscaling is regionally and seasonally dependent. Four years later, Bowden *et al.* (2016) also performed dynamical downscaling over the contiguous United States using WRF to evaluate hindcast simulations of SPI. The results showed that dynamically downscaled fields were more suitable for water resource applications compared with the larger-scale fields, as WRF was able to improve the timing and intensity of moderate to extreme wet and dry periods. Shukla & Lettenmaier (2013) also compared dynamical downscaling of CFS forecasts to statistical downscaling. The results showed that dynamical multi-RCM ensemble downscaling performed better than statistical downscaling. However, significant differences were only limited to the northwest and north central regions. Hence, it was suggested that careful selection of regional climate models is crucial for dynamical downscaling. Dynamic modelling is a relatively new method in drought forecasting which exists due to the advances in real time data observation technology. However, due to the short period of information available, various data fusion methods to reduce the bias of model forecasts should be further explored in order to achieve better merging effects with long-term conventional observations. Studies can also be pursued to solve the problem of data continuity (due to satellite or gauges failure) as dynamic modelling requires good connection between the input and forecast systems.

FUTURE TRENDS IN DROUGHT MODELLING

With the presence of modern data collection methods and retrievals (such as smart sensors, remote sensing, the Internet of Things), the availability of water resources data is not only limited to recorded data from traditional sources, but also from a different variety of real time data. This allows analyses to be done by utilizing the integration of multiple datasets from different sources simultaneously, to discover the big trends. Hence, the future trend of drought modelling would be the utilization of the Big Data integrated system in producing real time and robust forecasts. For example, a big-data approach that integrates meteorological and remotely sensed data streams, together with other datasets such as vegetation type, wildfire occurrence and pest activity, can clarify direct drought effects while filtering indirect drought effects and consequences.

For hydroinformatics, although the research on Big Data is still at a very early stage, there is no doubt that drought modelling can achieve better results with the presence of Big Data. For instance, IBM has started its research on big data applications for watershed management by capturing meteorological, surface, sub-surface and groundwater data, monitoring rain, snow, soil moisture, water turbidity, flow rates, temperature, and groundwater quality using different sensors (IBM 2014a). In the same year, the Kerala Water Authority in India also used IBM Big Data and analytics technology for seamless water distribution for the city of Thiruvananthapuram with more than 3.3 million inhabitants (IBM 2014b). Ai & Yue (2014) also proposed a framework for processing water resources big data by describing the application based on the features of modern water resources data. The framework of the study mainly consists of four layers, the data acquisition layer, resource organization layer, data analysis layer and application service layer. For the data acquisition layer, real time water resources data with sufficient quantity, density and variety were collected. Then, based on water resources information organization theory, the data were extracted, integrated and transformed using SQL and NoSQL tools to form the master database. Data analysis layers were designed to mine the value of information using the Hadoop and MapReduce, and thereafter provide comprehensive information services in the last layer.

Other than data integration, fusing of data of the same nature but from different sources has also been performed by Verdin *et al.* (2015). The author used a Bayesian data fusion model to blend infrared precipitation data with gauge data on the Central and South American region. The results showed that data fusion significantly improved upon the satellite-driven estimates. Given the outstanding performances of the Big Data system, data integration and data fusion techniques in water resources management, it is without doubt that they are applicable to drought modelling for more robust and reliable forecasting.

CONCLUSIONS

The study of modelling approaches in drought forecasting is important in the field of meteorology, hydrology, and for managing agricultural systems and managing water resource systems. Indeed, precise prediction is required to enhance the multi-step-ahead prediction mandatory for the much-needed best management practices. Regression analysis is considered the earliest and one of the simplest and most direct methods to predict future drought conditions based on the relationship between the variables. The logistic and loglinear regressions are found useful to predict the drought index. However, the assumption on linearity between predictor and predictand reduced its capability in long-lead forecasting. Stochastic modelling can predict the drought index by determining the elemental parameters: autoregressive (AR), differencing (I) and moving average (MA). The ARIMA/SARIMA models are found to be more suitable to predict the higher time scale of drought index (12- or 24-month) with shorter lead time. Still, this linear approach cannot ideally capture the non-linearity component in the time series and thus it is gradually being replaced by the AI models.

The probabilistic modelling, Markov chain was another approach adopted to forecast future drought events based on probability theory. Similar to the ARIMA model, the MC model was identified to reasonably forecast the time series with short lead times. Undeniably, the AI models including the ANN, FL and SVR have been widely used in recent drought forecasting studies, as they can predict the drought events that do not have a good, straightforward mathematical solution. The AI models were proven to have the ability to capture the white noise, non-stationary and non-linearity in the time series. This review article has ascertained that modelling with AI models is reliable in predicting different types of drought indices including the NADI, SPI, SPEI, EDI and PDSI.

It is without doubt that the hybrid models have been extensively applied in drought forecasting throughout the past decade because their performances are dramatically better than the stand-alone models. In this paper, a thorough review of the hybrid models has shown that the hybrid model can be classified as either the hybrid between machine learning models or the hybrid between data preprocessing techniques and machine learning models. Since a hybrid model is combining the merits of each individual model, it thus has a better prediction accuracy to predict the time series with a shorter time scale and longer lead time. The hybrid models are extremely useful for the short-term and medium-term drought forecasting as well as multistep-ahead prediction and should pave the way for more advances in drought prediction in an era of climate change.

For real time forecasting, dynamic modelling is a well-known method in drought forecasting. Remote sensing data is usually used as the input for dynamic modelling due to its ability to provide real time information. However, remotely sensed data may carry biased information and thus, Bayesian merging with observed climatology is usually done as a bias correction to improve the forecasts. Other than remote sensing, real time gauges and dynamical downscaling were also adopted for dynamic modelling. The advantages and disadvantages of the models reviewed are summarized in Table 2.

In conclusion, there are multiple criteria influencing the performances and accuracies of forecasting models. Appropriate inputs with suitable time-scales as well as the length of lead-time are the key factors for accurate predictions. Literature also indicated that the use of pre-processing techniques can enhance the accuracy of models. Hybrid models that combine the advantages of various models or adopt the use of pre-processing techniques are trending in drought forecasting. Dynamic modelling is also very likely to be adopted for drought forecasting as the ease and availability of real time information is ever promising with the development in digital technology. The study from

Table 2 | Advantages and disadvantages of the models

Approach	Advantages	Disadvantages	Remarks
Regression analysis	• Simple and direct • Low computational cost	• Poor in long-lead forecasting due to the assumption of linearity	• Large number of variables are required to produce accurate predictions
Stochastic models	• Able to fit well to linear data • Systematic search for identification, estimation and diagnostic check for model development	• Poor capability to model data with nonlinear characteristics • Complicated computations	• Difficult to understand and require skilful users for reliable results
Probabilistic models	• Able to deal with complex distributions	• Computationally expensive	• Memoryless process
Artificial neural network	• Less formal statistical training • Nonlinear property • Able to detect all possible interactions between predictors • Able to do multiple training algorithm	• 'Black-box' nature • Computationally expensive • Prone to overfitting • Empirical nature of model development	• Theoretically fit to any types of data but required iterative tuning of parameters
Fuzzy logic	• Can model imprecise data and nonlinear functions of arbitrary complexity • Fuzzy rules can be interpreted using natural language	• Can be computationally expensive when the number of fuzzy rules increases	• Require expert knowledge to define rules
Support vector machine	• Able to avoid overfitting • No local minima • Different kernels are available for different datasets	• Limited choices of kernels • Can be computationally expensive in validation stage	• Theoretically fit to any types of data but required iterative tuning of parameters
Hybrid models	• Able to combine the pros of different models	• Required a thorough understanding of multiple models • Weaknesses from models may be carried forward	• Different combinations can be developed based on the problems encountered
Dynamic modelling	• Able to provide real time results	• Required good connection between the input and forecast systems (for drought forecasting)	• Good for both monitoring and forecasting purposes

Schepen *et al.* (2012) which showed promising results by combining the strengths of statistical and dynamical modelling should not be overlooked. Researchers should endeavour to combine the advantages from hybrid models, dynamic modelling and to produce better drought forecasts in the future. Finally, Big Data systems is expected to be a future trend in drought modelling given its capability to clarify direct drought effects while filtering indirect drought effects and consequences.

ACKNOWLEDGEMENTS

The authors wish to express their sincere gratitude to Universiti Tunku Abdul Rahman (UTAR) for the financial support through the UTARRF grant.

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First received 20 September 2018; accepted in revised form 12 December 2018. Available online 5 February 2019