Development of Generalized Neural Network Based ETo Models from Limited Climatic Data for Different Agro-Ecological Regions in India

Sirisha Adamala
ICAR-CIARI

N. Raghuwanshi
Indian Institute of Technology Kharagpur

Ashok Mishra
Indian Institute of Technology Kharagpur

agriculture production processes, a large amount of water embedded in agriculture produce may be unlocked for fulfilling competing demands from other sectors of economy.

Keywords: *virtual water, agriculture, agroclimatic regions, green water, blue water*

INVESTIGATION IN OBSERVATIONAL RAINFALL CHARACTERSTICS IN GANGOTRI GLACIER BASIN

Manohar Arora[1], Rakesh Kumar, R D Singh, Jatin Malhotra and Naresh Kumar
National Institute of Hydrology, Roorkee, Uttarakhand, India 247 667
Email[1]: arora@nih.ernet.in

ABSTRACT

The majority of rainfall studies of Himalayan basins lack due to the region's extreme, complex topography and lack of adequate rain-gauge data. Gangotri Glacier is one of the biggest glaciers in the Indian Himalayas. The melt-water stream emerging from the snout of the Gangotri Glacier at an elevation of 4000 m a.s.l is known as Bhagirathi River. It receives significant contribution from snow and glacier melt, rainfall and sub surface flow. The analysis of rainfall characteristics presented here is based on 14 years of data collected near the snout of the Gangotri glacier (2000 – 2013). All the major storms have been identified and four rain-depth thresholds in continuous spell: (a) light rain rate (d"5 mm), and (b) light to moderate rain (5-10 mm) (c) moderate rain (10-15mm) and moderate to heavy rain(> 15mm) have been considered . The results suggest that on average nearly 75% of the rainfall is light rain and very less rain spells are of heavy rain in the Gangotri glacier valley. There were 7 major storms in this study period of which four have been in the last 5 years. The total rainfall in the high rainfall years varied between (199 to 425 mm) during the ablation period. The light to moderate conditional rain rate exhibits a relatively stronger diurnal cycle of precipitation in this region.

Keywords: *Gangotri Glacier, Rainfall, Himalayas, Snow & Glacier*

DEVELOPMENT OF GENERALIZED NEURAL NETWORK BASED ET_O MODELS FROM LIMITED CLIMATIC DATA FOR DIFFERENT AGRO-ECOLOGICAL REGIONS IN INDIA

Sirisha Adamala[1], N. S. Raghuwanshi[2], Ashok Mishra[3]
[1]Research Scholar, Agricultural and Food Engineering Department, Indian Institute of Technology (IIT), Kharagpur-721302, India, E-mail: sirisha@agfe.iitkgp.ernet.in
[2]Professor, Agricultural and Food Engineering Department, IIT, Kharagpur, E-mail: nsr@agfe.iitkgp.ernet.in
[3]Associate Professor, Agricultural and Food Engineering Department, IIT, Kharagpur, E-mail: amishra@agfe.iitkgp.ernet.in

ABSTRACT

This study aims at developing generalized quadratic synaptic neural (GQSN) reference evapotranspiration (ET_0) models corresponding to Hargreaves (HG) method. The GQSN models were developed using pooled climate data of different locations under four agro-ecological regions in India. The inputs for the development of GQSN models include daily climate data of minimum, maximum air temperatures and extra terrestrial radiation and the target consists of the FAO-56 PM estimated ET_0. The performance indices used for comparison include root mean squared error and coefficient of determination. Based on the comparisons, it is concluded that the GQSN along with generalized linear synaptic neural (GLSN) models performed better than conventional HG method. Comparison of GQSN and GLSN models among themselves, reveal that the GQSN models performed superior than the GLSN models for all regions. Further, GQSN models were applied to model development and model testing locations to test the generalizing capability. The testing results suggest that, the GQSN and GLSN models have a good generalizing capability for almost all regions.

Keywords: *Neural networks, synaptic operation, higher-order, evapotranspiration*

ISSN:2319-6890)(online),2347-5013(print)
18-19, Dec. 2014

Table 1. Change in cropped area and virtual water content in year 2010
(as % values of year 2000)

Agroclimatic Zone	Rabi			Kharif			Overall		
	Area	VW	VW/Area	Area	VW	VW/Area	Area	VW	VW/Area
Chhattisgarh plains	80	184	57	0	63	63	6	68	59
N. Hill Reg. of Chh.	93	160	35	16	68	45	31	79	37
Kym. Plat., & Satpura Hills	-4	21	26	-10	85	105	-7	51	62
Central Narmada Valley	3	26	22	-4	51	58	0	37	37
Vindhya Plateau	19	31	10	48	131	56	30	80	38
Gird Region	-3	15	19	7	52	42	1	31	30
Bundelkhand	-7	-23	-16	-21	18	48	-11	-14	-4
Satpura Plateau	140	287	61	31	143	86	53	165	74
Malwa Plateau	281	337	15	6	56	47	47	93	31
Nimar Plains	146	305	65	-5	90	101	26	140	91
Jhabua Hills	2674	6287	130	13	133	105	48	203	106
OVERALL CHANGE	43	68	18	10	81	63	23	76	43

It is seen that there is an overall increase in virtual water content in the most of the agroclimatic zones except in Bundelkhand which may be due to reduction in cropped area. Apart from Bundelkhand, an overall increase has been observed in all other agroclimatic zones. Khymore and Satpura Hills and Gird region have shown reduction in rabi area though the virtual water content in these agroclimatic zones has increased.

Rabi area in the state has shown significant increase of 43% against kharif area which is about 10%. As rabi areas are dependent on blue water sources hence this is an important indication on emphasizing need for better irrigation methods as well as initiatives for conservation of water through storage and recharge. This trend also points towards increasing stress on groundwater resources, which may adversely affect the water balance in as well as among the regions. Virtual water content of a product depends upon the technology and conditions of production. Considerable saving of water is possible if water-efficient technology is employed to produce the product (Kumar & Jain, 2007).

Kharif crops take water mostly from green water resources. Thus the large increase in virtual water content in kharif crops is manageable. Aldaya et. al.(2008) have critically evaluated the strategic importance and implications of green virtual water in relation to international crop trade. As per their study, due to a lower opportunity cost, the use of green water in the production of crops is considered more sustainable than the use of blue water. The importance of international green virtual-water 'trade' and its contribution to water security in the future will depend on factors such as the productivity of blue and green water, water pricing, international trade agreements, the costs of engaging in trade, and the nature of domestic economic objectives and political considerations (Aldaya, Hoekstra, & Allan, 2008).

4. CONCLUSIONS

Agriculture sector is the largest consumer of water in the country and Madhya Pradesh. With the increase in population there has been an increasing load on water resources to match the water demands of population. An analysis by virtual water approach may provide a common platform for issues related to regional water management. For sustainable water management in the state and respective agroclimatic regions, the interventions for blue water management and green water management need to be indentified to ensure optimum consumption of water. The savings resulting from efforts for efficient use of water, both hardware and software, including technological, managerial and policy interventions in agriculture will help in reducing virtual water content of agriculture products. By vigilant examination and introducing suitable interventions for improvement in agriculture production processes, a large amount of water embedded in agriculture produce may be unlocked which may be used for fulfilling competing demands from other sectors of economy.

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Development Of Generalized Neural Network Based Et_0 Models From Limited Climatic Data For Different Agro-Ecological Regions In India

Sirisha Adamala[1] N.S. Raghuwanshi[2] Ashok Mishra[3]

[1]Research Scholar, Agricultural and Food Engineering Department, Indian Institute of Technology (IIT), Kharagpur-721302, India, **E-mail: sirisha@agfe.iitkgp.ernet.in**
[2]Professor, Agricultural and Food Engineering Department, IIT, Kharagpur, **E-mail: nsr@agfe.iitkgp.ernet.in**
[3]Associate Professor, Agricultural and Food Engineering Department, IIT, Kharagpur, **E-mail: amishra@agfe.iitkgp.ernet.in**

ABSTRACT:* This study aims at developing generalized quadratic synaptic neural (GQSN) reference evapotranspiration (ET_o) models corresponding to Hargreaves (HG) method. The GQSN models were developed using pooled climate data of different locations under four agro-ecological regions in India. The inputs for the development of GQSN models include daily climate data of minimum, maximum air temperatures and extra terrestrial radiation and the target consists of the FAO-56 PM estimated ET_o. The performance indices used for comparison include root mean squared error and coefficient of determination. Based on the comparisons, it is concluded that the GQSN along with generalized linear synaptic neural (GLSN) models performed better than conventional HG method. Comparison of GQSN and GLSN models among themselves, reveal that the GQSN models performed superior than the GLSN models for all regions. Further, GQSN models were applied to model development and model testing locations to test the generalizing capability. The testing results suggest that, the GQSN and GLSN models have a good generalizing capability for almost all regions.

Keywords: *Neural networks, synaptic operation, higher-order, evapotranspiration*

1. INTRODUCTION

Reference evapotranspiration (ET_o) is one of the significant components of the hydrologic cycle. Accurate estimation of ET_o is important for carrying out many water resources and hydrological studies. There exist a number of direct and indirect ET_o estimation methods. But, most of the existing ET_o estimation methods have the number of limitations such as errors in measurement, lack of data availability, applicability to specific locations etc. (Adamala et al., 2014). To avoid the limitations of existing ET_o models, the artificial neural networks (ANNs) are used in ET_o modeling. These ANNs can model the complex non-linear ET_o without having a complete understanding of it. Generally ANNs are characterized as first order or higher order depending on the synaptic operation involved in a node or neuron (Gupta et al., 2003). The most widely used multilayer feed-forward neural network models are also called as "first-order neural networks or linear synaptic neural (LSN) models." These employ a linear correlation between the input vector and the synaptic weight vector and they can capture only first-order correlations between inputs and weights. Kumar et al. (2011) presented an exhaustive review on ET_o modeling using different LSN models. These LSN models can exhibit some of the limitations such as (i) long training times to a solution, (ii) no guarantee of convergence and nature to stuck in local optima, (iii) prone to over-fitting, and (iv) no reproducibility of results for the same set of data when they are run several times using different initial weights.

To overcome the above limitations associated with the LSN models, many researchers have focused on using quadratic synaptic neural (QSN) models which employ a second order synaptic operation between inputs and synaptic weights to extract non-linear correlations (Chakra et al., 2013). The QSN models are capable of capturing not only the first order correlations but also the second-order correlations that exist between the components of the input patterns. This property makes them superior models as compared to the LSN models. One limitation associated with these QSN models is their lack of generalizing capability because they are applicable to those locations data which are used in training or model development (so these locations are indicated as 'model development locations'). When new location data i.e. data not used during model development (so these locations are represented as 'model test locations') are given to developed network, is fails to provide good performance: indicating poor generalizing capacity. This limitation can be overcome by developing generalized quadratic synaptic neural (GQSN) and generalized linear synaptic neural (GLSN) models which not only perform well for model development locations but also for model test locations. This can be achieved by considering pooled data of various locations which have properties of both spatial and altitudinal variations during model development.

In a developing country like India with higher spatial variation in climate, the required climatic data for ET_o estimation may be difficult to obtain at all locations. The most readily available data for India may be the maximum and minimum air temperatures. This shows the need of developing GQSN models with minimum available climatic input data for ET_o estimation. Therefore, for the purpose of this study, the Hargreaves (HG) method is selected. Therefore, the objectives of this study are formulated as: (i) to develop GQSN models for the estimation of ET_o for different agro-ecological regions (AERs) (semi-arid, arid, sub-humid, and humid) of India corresponding to HG method; (ii) to compare the developed GQSN models with the GLSN models; and (iii) to test the generalizing capability of GQSN models to model development locations and model test locations.

2. METHODOLOGY

Generally, neural networks are categorized as GLSN and GQSN models based on type of synaptic operation. The processing of information in any biological or artificial neural models involves two distinct operations: (a) synaptic operation; and (b) somatic operation. In synaptic operation, different weights are assigned to each input matrix based on past experience or knowledge with an addition of bias or threshold. In somatic operation, the synaptic output is applied to a nonlinear activation function ($\phi[.]$). Mathematical representation of synaptic and somatic operations in a neural network is shown in Eqs. (1) and (2), respectively.

$$y = \sum_{i=0}^{n} w_i x_i = w_0 x_0 + w_1 x_1 + \ldots + w_n x_n \quad (1)$$

$$z = \phi[y] \quad (2)$$

where y = neural synaptic output; z = neural somatic output; w_0 = threshold weight; x_0 = constant bias (=1); x_i = neural inputs at i^{th} step; w_i = synaptic weights at i^{th} step; and ϕ = activation function (sigmoidal).

2.1 Generalized linear synaptic neural (GLSN) model

In GLSN model, the synaptic operation is of the first order which means that there exist only first order correlations in between its inputs and synaptic weights. Let N and n be the order and the number of inputs to the neuron, respectively. For N = 1, the mathematical expression of GLSN model is given as (Redlapalli, 2004):

$$(z)_{N=1} = \phi\left(\sum_{i_1=0}^{n} w_{i_1} x_{i_1}\right) \quad (3)$$

where x_{i_1} = neural inputs at i_1^{th} step; w_i = synaptic weights at i_1^{th} step.

2.2 Generalized quadratic synaptic neural (GQSN) model

In GQSN model, the synaptic operation in a neural unit or a node is of the second order which means that there exists not only first order but also second order correlations with second order terms between inputs and synaptic weights. For N = 2, the mathematical model of GQSN is represented as (Redlapalli, 2004):

$$(z)_{N=2} = \phi\left(\sum_{i_1=0}^{n}\sum_{i_2=i_1}^{n} w_{i_1 i_2} x_{i_1} x_{i_2}\right) \quad (4)$$

where x_{i_2} = neural inputs at i_2^{th} step; $w_{i_1 i_2}$ = synaptic weights at $i_1\, i_2^{th}$ step.

2.3 Study area and climate data

The climatic data required to carry out this study were collected from All India Coordinated Research Project on Agrometeorology (AICRPAM), Central Research Institute for Dryland Agriculture (CRIDA), Hyderabad, Andhra Pradesh, India. The data sample consisted of daily climate data of minimum air temperature (T_{min}), maximum air temperature (T_{max}), and extra terrestrial radiation (R_a). Due to the unavailability of measured lysimeter ET_o data for the selected study locations, it was estimated by the FAO-56 PM method which is proposed as the sole and standard method for the computation of ET_o in the absence of lysimeter data (Allen et al., 1998). The data pertaining to 25 meteorological stations distributed over four agro-ecological regions (AERs): semi-arid, arid, sub-humid, and humid with 8, 3, 9, and 5 locations lie in respective regions. Table 1 presents information related to altitude and observation periods of the chosen locations.

2.4 Data preparation

For the development of GQSN models for different AERs, locations having daily data for the period of 2001-05 were chosen. The data were divided into training, validation, and testing sets. The locations with 'Tr, V, Ts' role (Table 1) were used to develop GQSN models (model development locations). These locations for the model development were selected due to the availability of a larger set of data as compared to other locations during the study period. For these locations, 70% and 30% of data for the period of 2001-04 were used for training and validation, respectively. The data for the year 2005 were used for model testing. The data were pooled from (PR, SL, BN, KV, and UD), (AT and HS), (RP, FZ, LD, and RN), and (PL, JR, MH, and DP) locations to develop GQSN models for semi-arid, arid, sub-humid, and humid regions, respectively. To test the generalizing capability of developed models (applicability or testing only), the data from remaining locations that were not used during model development which consists different observation periods were used. The locations with only 'Ts' role (Table 1) were used to test the generalizing capability of the developed models (model testing locations). For example, the pooled data of 2001-04 and 2005 for the locations lie in semi-arid region (PR, SL, BN, KV, and UD) were used to train (validation also) and test GQSN models, respectively. The generalizing capability of GQSN models was tested using data from locations (KN, AN, and AK) that were not included during development in semi-arid region. In a similar way, different GQSN models were developed and tested for their generalization capabilities under arid, sub-humid, and humid regions.

Table-1: Characteristics and summary statistics of daily FAO-56 PM ET_o for the study locations

Location	Index	Alt. (m)	Role[a]	Period
Semi-arid				
Parbhani	PR	423	Tr, V, Ts	2001-05
Solapur	SL	25	Tr, V, Ts	2001-05
Bangalore	BN	930	Tr, V, Ts	2001-05
Kovilpatti	KV	90	Tr, V, Ts	2001-05
Udaipur	UD	433	Tr, V, Ts	2001-05
Kanpur	KN	126	Ts	2004-05
Anand	AN	45	Ts	2002-05
Akola	AK	482	Ts	2001-03
Arid				
Anantapur	AT	350	Tr, V, Ts	2001-05
Hissar	HS	215	Tr, V, Ts	2001-05
Bijapur	BJ	594	Ts	2001-04
Sub-humid				

Raipur	RP	298	Tr, V, Ts	2001-05
Faizabad	FZ	133	Tr, V, Ts	2001-05
Ludhiana	LD	247	Tr, V, Ts	2001-05
Ranichauri	RN	1600	Tr, V, Ts	2001-05
Jabalpur	JB	393	Ts	2002-05
Samastipur	SM	52	Ts	2004-05
Bhubaneshwar	BB	25	Ts	2002-05
Ranchi	RC	625	Ts	2005
Rakh Dhiansar	RD	332	Ts	2005
Humid				
Palampur	PL	1291	Tr, V, Ts	2001-05
Jorhat	JR	86	Tr, V, Ts	2001-05
Mohanpur	MH	10	Tr, V, Ts	2001-05
Dapoli	DP	250	Tr, V, Ts	2001-05
Thrissur	TR	26	Ts	2001-04
Note: [a] Tr: Train; V: Validation; and Ts: Test				

2.5 Estimation of ET_o

The HG method uses only temperature and latitude data for estimating ET_o. The Hargreaves equation is one of the simplest equations used to estimate ET_o. It is expressed as:

$$ET_o = 0.0023 R_a \sqrt{TD}\left(T_{avg} + 17.8\right)$$

(5)

where ET_o = reference evapotranspiration (mm day^{-1}); R_a = extraterrestrial solar radiation (function of latitude and day of the year) (MJ m^{-2} day^{-1}); T_{max}= maximum daily air temperature at 2 m height (^oC); T_{min}= minimum daily air temperature at 2 m height (^oC); TD = difference between T_{max} and T_{min} (^oC); T_{avg} = average daily air temperature at 2 m height (^oC).

The FAO of the United Nations reported that the definition ET_o from Smith et al. (1997) and it accepted the FAO-56 PM method as a standard equation for estimating ET_o and for evaluating other methods (Allen et al., 1998).

$$ET_o = \frac{0.408\Delta\left(R_n - G\right) + \gamma \dfrac{900}{T_{avg} + 273} W_s\left(e_s - e_a\right)}{\Delta + \gamma\left(1 + 0.34 W_s\right)}$$

(6)

where ET_o = reference evapotranspiration (mm day^{-1}); R_n = daily net solar radiation (MJ m^{-2} day^{-1}); G = soil heat flux (MJ m^{-2} day^{-1}); e_s = saturation vapor pressure (kPa); e_a = actual vapor pressure (kPa); Δ = slope of saturation vapor pressure versus air temperature curve (kPa $^oC^{-1}$); W_s = wind speed at 2 m height (m s^{-1}); γ = psychrometric constant (kPa $^oC^{-1}$).

2.6 Preprocessing and parameters estimation criteria

As a priori step in developing GQSN models, normalization process before presenting data as input to network and denormalization procedure after developing optimum network were performed using a Matlab built-in function called 'mapstd' which processes data such that its mean and standard deviation equal to 0 and 1, respectively. The inputs for developing GQSN models include T_{max}, T_{min} and R_a and the target consists of the FAO-56 PM ET_o. During model development, the training of the network starts with random initialization of weights and proceeds by applying 'Levenberg-Marquardt' algorithm which simply tries to find those weights which optimize an error function (RMSE). Sigmoidal activation function was employed in the output layer neurons. The optimum number of hidden nodes were found as i+1 and 2 (where i = number of nodes in the input layer) for GLSN and GQSN models, respectively after number of trial and error experiments with 1 to 15 hidden nodes based on minimum RMSE criteria. For developing GQSN based daily ET_o models, the code was written using Matlab 7.0 programming language.

2.7 Performance evaluation

In order to evaluate the performance of the GQSN models, two statistical indices, namely, the root mean squared error (RMSE, mm day^{-1}) and coefficient of determination (R^2, dimensionless) were considered. The expressions for the aforementioned statistical indices are given below.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(T_i - O_i)^2}$$

(7)

$$R^2 = \frac{\left[\sum_{i=1}^{n}\left(O_i - \bar{O}\right)\left(T_i - \bar{T}\right)\right]^2}{\sum_{i=1}^{n}\left(O_i - \bar{O}\right)^2 \sum_{i=1}^{n}\left(T_i - \bar{T}\right)^2}$$

(8)

where T_i and O_i = target (FAO-56 PM ET_o) and output (ET_o resulted from GQSN models) values at the i^{th} step, respectively; n = number of data points; $\bar{T}$ and $\bar{O}$ = average of target and output values, respectively.

3. RESULST AND DISCUSSION

All the GQSN models were trained with the above mentioned criteria during model development and after each training run, the performance indices such as RMSE and R^2 were calculated using training and validation data set, to find the optimum neural network. This section presents the best achieved results of GQSN models corresponding to HG conventional ET_o method under four AERs during testing.

3.1 Simulation results of developed GQSN models

Table 2 shows the performance of GQSN, GLSN and HG models in terms of RMSE and R^2 under four different AERs. The GQSN models were compared with the GLSN models to test the relative performance of second order over first order neural models. Further, both the GLSN and GQSN models were compared with the conventional HG method to test the accuracy of neural models. Fig. 1 shows the scatter plots and part of Table

ISSN:2319-6890)(online),2347-5013(print)
18-19, Dec. 2014

3 confirms the performance statistics in terms of RMSE and R^2 of HG estimated ET_o with respect to the FAO-56 PM under four AERs. The GQSN models with RMSE (mm day^{-1}) of 0.668, 0.911, 0.663 and 0.646 performed superior as compared to their conventional method (HG) with RMSE (mm day^{-1}) of 0.962, 1.247, 1.058 and 0.959 for semi-arid, arid, sub-humid, and humid regions, respectively (Table 2). Similarly, the GQSN models performed better than GLSN models for all regions. These results suggest that the GQSN and GLSN models have better accuracy compared to conventional methods for the estimation of ET_o.

Table-2: Performance statistics of HG, GLSN and GQSN models during model development

AER	Model	RMSE (mm day^{-1})	R^2
Semi-arid	HG	0.962	0.776
	GLSN	0.682	0.825
	GQSN	0.668	0.830
Arid	HG	1.247	0.685
	GLSN	1.023	0.771
	GQSN	0.911	0.820
Sub-humid	HG	1.058	0.812
	GLSN	0.671	0.869
	GQSN	0.663	0.872
Humid	HG	0.959	0.724
	GLSN	0.663	0.739
	GQSN	0.646	0.754

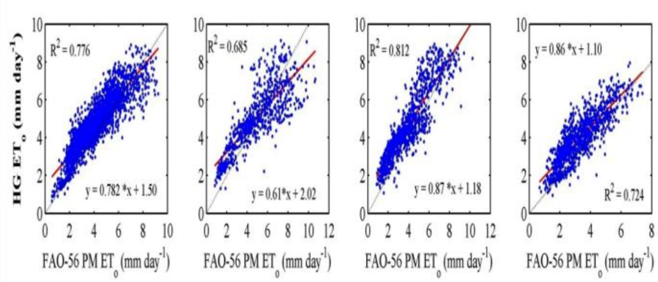

Figure-1: Scatter plots of HG method with respect to the FAO-56 PM under (a) Semi-arid, (b) Arid, (c) Sub-humid, and (d) Humid regions

Due to the superior performance of GQSN models over other, the scatter plots were drawn only for these models corresponding to four AERs and are shown in Fig. 2 which confirms the statistics given in Table 2. Fig. 2 results illustrate that the agreement between GQSN models simulated ET_o with respect to the FAO-56 PM was good for all regions except humid. The GQSN model, gave R^2 values>0.820 in all regions except for humid region (R^2=0.754). The reason for this underperformance might be due to the absence of relative humidity as an input during model development because this is an important variable under humid region than other regions.

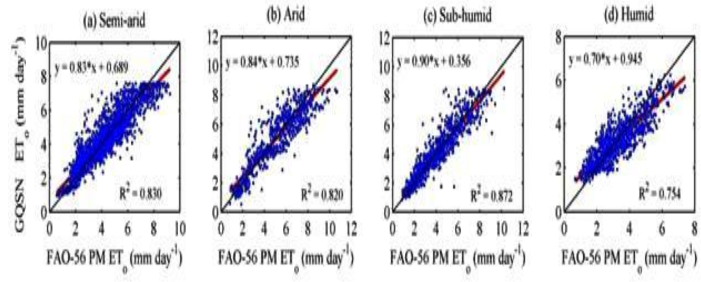

Figure-2: Scatter plots of GQSN models with respect to FAO-56 PM ET_o under (a) Semi-arid; (b) Arid; (c) Sub-humid; and (d) Humid regions

3.2 Application of GQSN models

To test the generalizing capability of developed GQSN models under different regions, these were applied or tested with two different scenarios: (i) with individual locations data which are used during model development (model development locations); and (ii) with new individual locations data which are not used during model development (model testing locations). Table 3 shows the performance statistics of GQSN models with individual locations data under scenario (i) for different regions. Under semi-arid region, the GQSN models were tested for 5 locations, namely PR, SL, BN, KV, and UD (2005 year data for each individual location). Similarly, GQSN models were tested with AT and HS (arid), RP, FZ, LD, and RN (sub-humid), and PL, JR, MH, and DP (humid) locations data. For all the above cases, performance of GQSN models was in the order of GQSN>GLSN. Here the greater order indicates model with a lower RMSE compared to others. The results conclude that the under scenario (i) the performance of the GQSN models were good compared to GLSN for all locations under four AERs.

Table-3: Performance statistics of models with model development locations

AER	Location	GLSN		GQSN	
		RMSE	R^2	RMSE	R^2
Semi-arid	PR	0.649	0.866	0.619	0.868
	SL	0.708	0.820	0.696	0.830
	BN	0.664	0.702	0.646	0.719
	KV	1.026	0.624	0.976	0.637
	UD	0.785	0.831	0.745	0.856
Arid	AT	1.094	0.680	0.973	0.721
	HS	0.839	0.822	0.753	0.860
Sub-humid	RP	0.713	0.865	0.689	0.867
	FZ	0.623	0.870	0.615	0.874
	LD	0.659	0.897	0.653	0.897
	RN	0.602	0.877	0.585	0.884
Humid	PL	0.691	0.765	0.647	0.797

ISSN:2319-6890)(online),2347-5013(print)
18-19, Dec. 2014

	JR	0.706	0.547	0.686	0.558
	MH	0.647	0.765	0.590	0.796
	DP	0.621	0.743	0.592	0.764
RMSE Unit = mm day^{-1}					

Table 4 illustrates the performance statistics of GQSN models with model testing locations under different regions (scenario (ii)). Under semi-arid region, the GQSN models were tested for three new locations, namely KN, AN, and AK. The performance of these models for KN and AK were in the order of GQSN>GLSN and for AN, the performance was GLSN>GQSN. Similarly, GQSN models were tested with different new locations data, namely BJ (arid), JB, SM, BB, RC, and RD (sub-humid), TR (humid). The performance of the developed GQSN models was in the order of GQSN>GLSN for all locations under arid and humid; whereas in sub-humid the performance was GLSN>GQSN. Therefore, under the scenario (ii) the superior performance of GQSN models were achieved for almost all locations under four regions except sub-humid where GLSN models found better. Here most interesting point observed was that, at TR location (humid), both the developed models i.e. GLSN and GQSN failed to show generalization (RMSE>1.456 mm day^{-1}). This may be due to the lack of relative humidity data as input during model development because; this is the most influential variable in humid regions. The GQSN models performed better than their conventional counterpart (HG) for all locations under four AERs except under humid region location (TR). The GQSN model underperforms than its conventional HG method for TR location. However, this model needs to be tested on more humid locations. These results suggest that the GQSN models have better accuracy compared to conventional method during their generalization testing also.

Table-4: Performance statistics of models with model testing locations

AER	Location	HG		GLSN		GQSN	
		RMSE	R^2	RMSE	R^2	RMSE	R^2
Semi-arid	KN	1.058	0.799	0.855	0.815	0.843	0.826
	AN	1.146	0.702	0.619	0.831	0.641	0.817
	AK	1.519	0.693	1.097	0.783	0.838	0.819
Arid	BJ	1.023	0.702	0.746	0.687	0.715	0.713
Sub-humid	JB	1.208	0.745	0.681	0.862	0.682	0.856
	SM	0.942	0.695	0.692	0.809	0.702	0.804
	BB	1.007	0.686	0.871	0.740	0.882	0.739
	RC	1.277	0.800	0.571	0.819	0.574	0.815
	RD	1.550	0.786	0.653	0.837	0.662	0.833
Humid	TR	0.932	0.485	1.493	0.031	1.456	0.026
RMSE Unit = mm day^{-1}							

4. CONCLUSIONS

The ability of GQSN models corresponding to HG method to estimate ET_o using pooled daily climate data from different locations under four AERs in India has been studies in this paper. The GQSN models were compared with the GLSN models find the relative performance of one model over the other. To test the accuracy of GQSN and GLSN models, their performance was also compared with the conventional HG method. The developed GQSN models were tested with two scenarios: (i) model development locations; and (ii) model testing locations to test the generalizing capability. The comparative results of GQSN models with the GLSN models confirmed that the GQSN models yield superior performance for all regions during model development. The developed GQSN and GLSN models performed much better than the corresponding conventional HG counterpart. During testing the generalizing capability of GQSN models for the above two scenarios, the GQSN models performed better than the GLSN models for all cases. Overall, better performance of GQSN models corresponding to HG conventional ET_o estimation method under different AERs in India showed that these models not only have the better potential but also have the good generalizing capability.

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