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Spatial Modeling of Evapotranspiration for Efficient Water Management at Regional Scale

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ABSTRACT: The meteorological data on maximum and minimum temperature, maximum and minimum humidity, wind speed and sunshine hours were collected from IMD-AWS as open source data for 373 stations for 50th and 20th meteorological week of 2011 and 2012, respectively. The data of 353 stations were used to develop water balance model and 20 stations were used for validation and testing of the model. Data were used to compute potential evapotranspiration using Penman-Monteith method. These locations with their respective latitude, longitude and elevation were brought under GIS environment for spatial database management. Separate layer of water deficit/surplus database was generated using derived evapotranspiration and rainfall data. The derived water deficit/ surplus data was further interpolated into 2 km x 2 km grid using RBF (radial basis function) interpolation algorithm to produce spatial water balance model for the given week. The developed methodology was tested for 20 different locations. It was found that the model overestimated lower values and underestimated higher values. Overall, for all 20 locations, the model estimated 7.6% higher PET with average of 18.55 mm for the week under consideration (50th and 20th meteorological week of year 2011 and 2012, respectively). The range of the model prediction was found to be 26.86 mm as compared to observed value of 34.80 mm. The standard error was computed as 1.91 mm for estimates while it was 2.19 mm for observed.

Key words: Spatial interpolation, evapotranspiration, water management

Evapotranspiration (ET) that includes the evaporation from the surface and transpiration of water from plant stomatal activities form an important basis for water resource management in agricultural sector. The basic of agricultural water management involves replenishment of water into the root zone of soil due to evapotranspiration. Two broad methods in the estimation of ET are adopted, namely direct and indirect. Direct methods includes estimation of ET through lysimeter and require well planned field experiments that involve huge manpower and investment. The other methods, indirect method involve estimation of ET using climatic data and suitable parameters. The indirect methods calculate the ET using number of mathematical models that has been calibrated using actual ET from well watered grass surface often denoted as ET_o. The indirect method further divided into different classes depending on the data requirement, data quality and accuracy level. The mathematical models for ET estimation are classified as (i) evaporation based, where pan evaporation data are primary requirement such as FAO-24 PAN method (Doorenbose and Pruitt, 1977); (ii) temperature based, where temperature data are the primary requirement such as Thornthwaite (Thornthwaite, 1948), Hargreaves (Hargreaves, 1975;Hargreaves and Samani (1985) and FAO-24 Blaney Criddle (Doorenbose and Pruitt 1977; Allen 1986; Allen and Pruitt 1986 and Alen *et al.,* 1989); (iii) radiation based, where solar radiation and humidity data are prevalent such as Turc (Turc 1961, Jensen *et al.,* 1966) and Prestley-Taylor (Priestley and Taylor, 1972); and (iv) combination methods where all data like temperature, humidity, solar radiation and wind velocity are represented. Although several combination methods are available in literature and Penman-Monteith model is considered as the best model to estimate ET_o (Monteith 1965, Allen *et al.,* 1989 Jensen *et al.,* 1990).

The evapotranspiration modeling indeed is data intensive and require to handle huge datasets. There is some latest development in the field of evapotranspiration modeling after the advent of next generation computation techniques. These includes adaptation of artificial neural networks, ANN, (Kumar *et al.* 2002, 2009 and 2011), genetic algorithm (Kisi, 2010; Kim and Kim, 2008; Parsuraman, *et al*., 2007), fuzzy-logic (Kisi and Ozturk, 2007) and support vector machines (Kisi and Cimen, 2009). These methodologies are however, in the initial stages of development and can prove as the advanced techniques in evapotranspiration modeling. Kumar *et al.,* 2011, suggested that there is a need to develop a model or protocol as global predictor of the ETo. These advance models however, are, good to interpolate than to extrapolate.

The present study thus involves collection of climatic data from different meteorological stations, collate the respective ETo and interpolate spatially to a smaller grid size so that representative ETo values could be determined for small region for effective water management.

Material and Methods

Data collection

Six climatic parameters namely maximum and minimum temperature (°C), maximum and minimum relative humidity (%), sunshine hours (h) and wind speed (m/s) were collected on weekly basis for 373 stations. Rainfall data were also collected for computing climatic water balance. The weekly data of 50th and 20th meteorological week of 2011 and 2012 respectively, representing mid *Rabi* and *kharif* season respectively, were obtained from IMD-AWS site (http://www.imdaws.com/

ViewAwsData.aspx). The data of 353 stations were used to develop water balance model and 20 stations were used for testing and validation of the model. These data were used to compute potential evapotranspiration using Penman-Monteith method. The information on latitude, longitude and elevation of the respective stations were also collected. The location map of these stations are presented in Figure 1.

Computaion of ETo

The Penman-Monteith ETo model is a combination method which uses six basic climatic variables mentioned above and also perform energy balance.

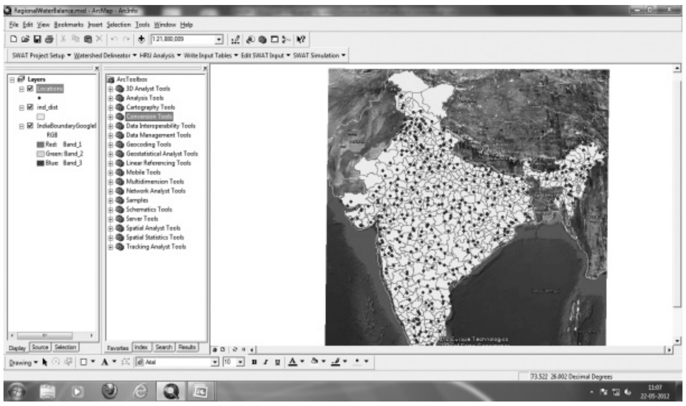

Fig. 1: Location map of meteorological stations in India

The typical Penman-Monteith equation is given as

$$ETo = \frac{0.408\Delta(R_n - G) + \gamma \frac{900}{(T_{mean}+273)} u_2 (e_a - e_d)}{\Delta + \gamma^*} \quad \ldots (1)$$

Where,

ETo = Reference Evapotranspiration, [mm/d]

Δ = Slope of the saturation vapor pressure-temperature curve, [kPa $^oC^{-1}$]

R_n = Net Radiation, [MJ m^{-2} d^{-1}]

G = Solar Heat flux density to the ground, [MJ m^{-2} d^{-1}]

γ = Psychrometric constant, [kPa$^oC^{-1}$]

T_{mean} = Mean of maximum and minimum temperature, [$^oC^{-1}$]

u_2 = Horizontal wind speed at 2 meter height, [m/s]

e_a = Mean saturation vapor pressure at air temperature, [kPa]

e_d = Actual saturation vapor pressure at air temperature, [kPa]

The standard computation procedure as described in FAO-56 (Allen *et al.,* 1998) was adopted in computing ETo values for the selected 373 stations. Since available models allow computation of ETo for single location at any given time, a spreadsheet was developed to simultaneously compute ETo for all locations.

Climatic water balance model

The water surplus/deficit using the values of ETo and rainfall were computed for the individual stations. The generalized form of water balance model is given below:

$$SI_i = PET_i + SP_i + SR_i - P + \Delta S \quad \ldots(2)$$

Where,

ΔS is soil moisture storage in the root zone (mm), P is rainfall (mm), SI is irrigation or irrigation water requirement, PET is potential evapotranspiration (ETo), SP is seepage and percolation from the root zone, SR is surface runoff from the cropped field and i is time index. Ideally, the irrigation water needed to maintain the soil moisture storage such that no water is lost in surface runoff as well as seepage and percolation in order to attain 100% irrigation efficiency. In the present study, SI is zero since the crop is completely rainfed. Hence, for this condition the eq. 2 takes the form of eq. 3

$$SI_i = PET_i - P \quad \ldots(3)$$

Application of GIS

The computed ETo with respective stations and its latitude and longitude were brought under GIS environment for better representation of data and spatial database management. The rainfall data were also included for climatic water balance. For this purpose, GIS (Arc Info version 9.3) were used. The latitude and longitude with PET values, rainfall and water surplus/deficit calculated using eq. 3 were defined as attributes of locations. District wise shapefile also created in the GIS environment for better representation of locations.

Spatial Interpolation

Twenty stations out of 373 stations, were used for testing and evaluation. Thus the data from 353 stations were used for spatial interpolation. The interpolation was carried out in a grid of 2 km x 2 km, thus one representative ETo values related to the area of 4 km^2 or 400 ha. The radial basis function (RBF) algorithm was used for spatial interpolation. The details of radial basis functions are given below (Kumar 2011).

The radial basis function networks (RBF networks) have been extensively employed in modeling of evapotranspiration process. Radial basis functions (RBF) are built onto distance criteria with respect to centre. The interpretation of its output layer value is the same as a regression model in statistics. The RBF consists of basis function (most commonly used is Gaussian Bell function). At the input of each neuron, the distance between two values are calculated and the output is determined by summation of dot products of basis function and distance with respect to each input. Thus, the RBF have an advantage of not suffering from the problem of local minima. The linearity ensures that the error surface is quadratic and therefore a global minimum is found easily. The principle of radial basis function is derived from the theory of functional approximation.

Given N pairs $(\vec{x}_i, y_i)$ and $(\vec{x} \in \Re^n, y \in \Re)$, the output function of the network is

$$\int(\vec{x}) = \sum_{i=1}^{K} c_i h(|\vec{x} - \vec{t}_i|) \quad \ldots(4)$$

Where, K is the number of neurons in the hidden layer, $\vec{t}_i$ is the centre vector for neuron i, and c_i is the weight of the linear output. h is the radial basis function applied to the Euclidian distance between each centre $\vec{t}_i$ and the given argument $\vec{x}$. The function h is basically a Gaussian function which has its maximum value at a distance of zero. When values of $\vec{x}$ equals to centre, $\vec{t}_i$, the function h yields output value of 1 and becomes zero for larger distances. Hence, the function $\int$ is an approximation of the N given pairs $(\vec{x}_i, y_i)$ and therefore minimizes the following error function, H:

$$H[f] = \sum (y_i - f(\vec{x}_i))^2 + \lambda \| Pf \|^2 \quad \ldots(5)$$

The first part of the function, H, is the condition which minimizes the local error of the approximation and the second part of H, i.e. $\| P \|^2$ is a stabilizer which forces f to become continuous. The factor λ determines the influence of the stabilizer.

Evaluation

Several performance criteria were selected to evaluate the performance. These are listed in Table 1.

Table 1 : Summary of performance criteria and definition

Performance Criteria	Definition
Sum of square error	$SSE = \sum_{i=1}^{n} (y_o - y_c)^2$
Relative error	$RE = \frac{y_o - y_c}{y_o} \times 100$
Mean absolute error	$MAE = \frac{1}{n}\sum_{i=1}^{n} \lvert (y_c - y_o) \rvert$
Coefficient of correlation	$r = \frac{\frac{1}{n}\sum_{i=1}^{n}(y_c - \bar{y}_c)(y_o - \bar{y}_o)}{\sigma_y \sigma_y}$
Nash and Sutcliffe efficiency	$\eta = 1 - \frac{\frac{1}{n}\sum_{i=1}^{n}(y_c - \bar{y}_c)^2}{\frac{1}{n}\sum_{i=1}^{n}(y_o - \bar{y}_o)^2} \times 100$
Root mean square error	$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\bar{y}_c - y_c)}$
Model efficiency	$\eta = 1.0 - \frac{\sum_{i=1}^{n}(y_c - y_o)^2}{\sum (y_o - \bar{y}_o)^2} \times 100$

Where,

y_o = observed values, y_c = computed values, $\sigma_c and \sigma_o$ = standard deviation of observed and computed values respectively,

Development of graphic user interface

A graphic user interface (GUI) was developed to retrieve the interpolated data for specific location. The GUI queries the ETo for specific latitude and longitude and thus display the ETo for the current location. The ETo values obtained from the query was further computed for irrigation water requirement based on local information on crops and soil etc. The whole process of database management and retrieval system is presented in Figure 2.

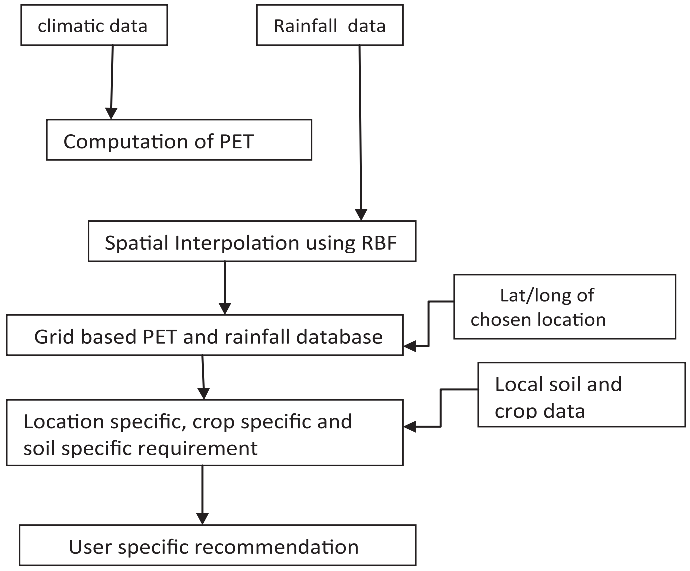

Fig. 2 : Database creation and retrieval system

Results and Discussion

Grid based water balance model

Separate layer of water deficit/surplus database was generated using derived evapotranspiration and rainfall data. The derived water deficit/surplus data were further interpolated into 2 km x 2 km grid using RBF (radial basis function) interpolation algorithm to produce spatial water balance model for the given week and the same has been presented in Figures 3 and 4 (for 20th and 50th week, respectively). This model is dynamic in nature since the values are changed according to current meteorological parameters and thus can be used for real time estimation of climatic water balance in order to design dynamic allocation of irrigation water.

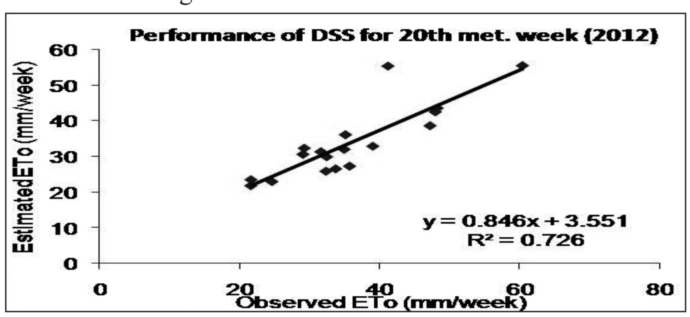

Fig. 3 : Performance for 50th met week

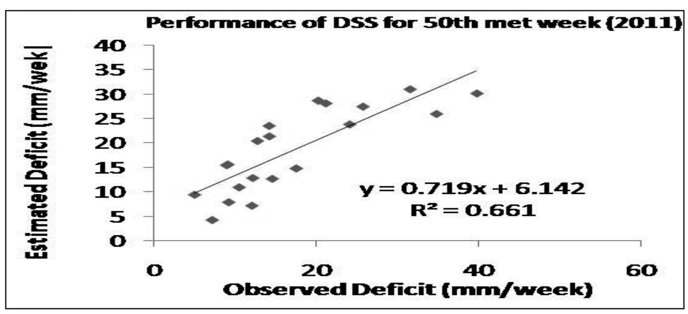

Fig. 4 : Performance for 20th met week

Performance evaluation and testing

The developed methodology was tested for 20 different locations. It was found that the model overestimate the lower values and underestimates the higher values. Overall, 20 locations, the model estimated 7.6% higher PET with average of 18.55 mm for week under consideration (50th and 20th meteorological week of year 2011 and 2012, respectively). The range of the model prediction was restricted to 26.86 mm as compared to observed value of 34.80 mm. The standard error was computed as 1.91 mm for estimates whereas same was computed as 2.19 mm for observed. The observed and computed ETo values for these test locations are presented in Table 2.

Table 2 : Comparison between observed (Ob) and computed (Com) ETo for test locations

Stations	20th week		50th week	
	Ob.	Com.	Ob.	Com.
Dharwad	-	-	14.21	21.35
Dantewara	33.66	25.56	12.06	7.12
Dantiwada	32.37	29.96	9.11	15.57
Faizabad	60.3	55.61	8.94	15.43
Hissar	31.56	31.38	14.58	12.63
Indore	38.96	32.93	34.81	25.96
Jabalpur	48.15	43.64	14.19	23.51
Kota	47.88	42.61	24.11	23.81
Kovilpatti	47.13	38.7	21.18	28.13
Meerut	21.59	23.5	9.21	7.82
Nagpur	29.18	32.37	5.00	9.36
Navasari	35.64	27.32	39.8	30.17
Parbhani	-	-	12.17	12.79
Pusa	34.87	32.06	7.17	4.16
Rewa	35.06	36.15	10.49	10.88
Roorkee	24.57	22.98	31.56	31.02
Raipur	32.29	25.89	25.76	27.46
Solapur	29.0	30.65	20.24	28.69
Shillong	21.57	21.82	12.75	20.4
Udaipur	41.12	55.49	17.53	14.77
Mean	35.83	33.87	17.24	18.55
SD	9.63	8.52	9.63	8.52

The scatter plot between the observed and computed values for 20th and 50th meteorological week is presented in Figures 3 and 4 respectively. For 50th met week (winter season), the model overestimate by 7.6% whereas for 20th met week, model underestimate by 5.47%.

The water balance computed using spatial interpolation was further statistically tested for the 20 locations. Different testing parameters were evaluated and are presented in Table 3.

Table 3 : Results of statistical estimates of computed water balance using spatial interpolation

Performance Criteria	20th week (2012)	50th week (2011)
Sum of square error	586.95	640.61
Relative error	5.47	7.59
Mean absolute error	4.21	4.65
Coefficient of correlation	0.89	0.77
Nash and Sutcliffe efficiency	88.42	78.35
Root mean square error	9.26	8.32
Model efficiency	66.31	63.64

The developed model performance for *kharif* and *rabi* season are almost at par. The model performance was found fairly good in all the parameters tested. It is observed that model performed slightly better during the summer season (20th week) than winter season (50th week). This implies that the model estimated higher values more accurately than lower values. However, this does not affect the efficacy since water requirement is more crucial during summer season.

Graphic user interface

The graphic user interface has been developed to retrieve the value of water surplus/deficit for any location based on the latitude and longitude query that is to be supplied by the user. The GUI retrieve the ETo value as per the latitude and longitude of the location and considers the crop type to get a value of crop coefficient to convert the potential evapotranspiration (ETo) in to crop evapotranspiration (ETc). A typical GUI for data retrieval is presented in Figure 5.

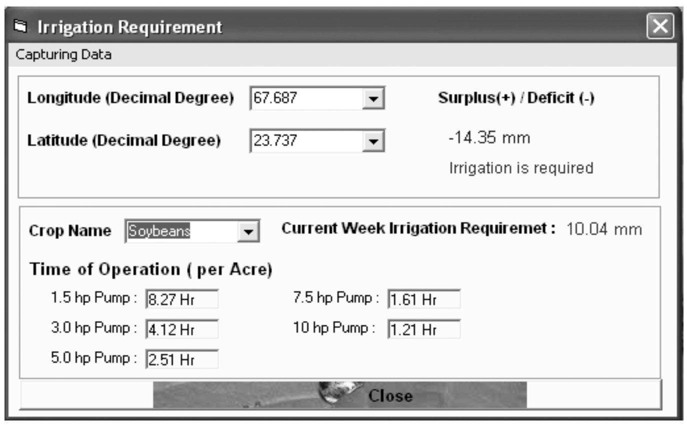

Fig. 5 : GUI for data retrieving and decision support

Conclusions

The present study envisaged to use the spatial interpolation techniques for regional scale simple water balance modeling using climatic data on real time basis. The model performance and testing was found to be satisfactory. The data can be retrieved for any location in 2 km x 2 km grid, that enable the water resource management at micro-watershed level. The model uses the data available in open source and hence it is cost effective. However, further study can be made using open source GIS that would significantly reduce the cost. The model is dynamic in nature and so the estimate changes according to progressing week. The model can be linked with real time water management system and has the potential to automate the reservoir meant for irrigation.

References

Allen RG and Pruitt, WO. 1986. Rational Use of FAO Blaney-Criddle formula. Journal of Irrigation and Drainage Division, 112 (IR2): 139-155.

Allen RG. 1986. A Penman for all seasons. Journal of Irrigation and Drainage Engineering, 112(4): 348- 368

Allen RG, Jensen ME, Wright JL and Burman RD. 1989. Operational estimates of reference evapotranspiration. Agronomy Journal, 81: 650-662.

Allen RG, Pereira LS, Raes D, Smith M. 1998. Crop evapotranspiration – Guidelines for computing crop water requirements. Irrig. Drain., Paper 56, FAO, Rome, Italy.

Doorenbos J and Pruitt WO. 1977. Guidelines for predicting crop water requirements. Irrigation and Drainage Paper No. 24, (2nd Eds.) FAO, Rome, Italy.

Hargreaves GH and Samani ZA. 1985. Reference crop evapotranspiration from temperature. Applied Engineering in Agriculture, 1 (2): 96-99.

Hargreaves GH. 1975. Moisture availability and crop production. Transaction of American Society of Agricultural Engineers, 18(5): 980-984.

Jensen ME. 1966. Empirical methods of estimating or predicting evapotranspiration using radiation. In. Proc. Conf., Evapotranspiration and its role in water Resource Management, Americal Society of Agricultural Engineers, St. Joseph, Michigan, USA, pp 55-61.

Jensen ME, Burman RD and Allen RG. 1990. Evapotranspiration and irrigation water requirements. ASCE Manual and Reports on Engineering Practice, No. 70, ASCE, New York.

Kim S and Kim HS. 2008. Neural networks and genetic algorithm approach for nonlinear evaporation and evapotranspiration modeling. Journal of Hydrology, 351: 299-317.

Kisi O. 2010. Fuzzy genetic approach for modeling reference evapotranspiration. Journal of Irrigation and Drainage Engineering, Vol. 136 (3): 175-183

Kisi O and Ozturk O. 2007. Adaptive neuro-fuzzy computing technique for evapotranspiration modeling, Journal of Irrigation and Drainage Engineering,133(4): 368-379

Kisi O and Cimen M. 2009. Evapotranspiration modeling using support vector machine. Hydrology Science Journal, 54(5): 918-928

Kumar M, Raghuwanshi NS and Singh R. 2009. Development and validation of GANN model for evapotranspiration estimation. Journal of Hydrologic Engineering, Vol.44 (2): 131-140.

Kumar M, Raghuwanshi NS and Singh R. 2011. Artificial neural networks approach in evapotranspiration modeling: A review. Irrigation Science, Vol.29 (1): 11-25.

Kumar M, Raghuwanshi NS, Singh R, Wallender WW and Pruitt WO. 2002. Estimating evapotranspiration using artificial neural network. Journal of Irrigation and Drainage Engineering, 128(4): 224-233.

Monteith JL. 1965. Evaporation and environment. Proc., The State and Movement of Water in Living Organisms. XIXth Symposium, Soc. For Exp. Biol., Swansea, Cambridge University Press, New York, pp 205-234.

Parsuraman K, Elshorbgy A and Carey SK. 2007. Modelling the dynamics of the evapotranspiration process using genetic programming. Hydrologic Science, 52(3): 563-578.

Priestly CHB and Taylor RJ. 1972. On assessment of surface heat flux and evaporation using large-scale parameters. Monthly Weather Review, 100: 81-92

Thornthwaite CW. 1948. An approach towards a rational classification of climate. The Geographical Review, 30: 55-94.

Turc L. 1961. Estimation of irrigation water requirements, potential evapotranspiration: A simple climatic formula evolved up to date. Annals of Agronomy, 12: 13-14.

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