

Effect of Different Areal Precipitation Estimation Methods on the Accuracy of a Reservoir Runoff Inflow Forecast Model

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Abstract. Areal precipitation estimation directly affects the accuracy of reservoir runoff inflow forecasts and flood dispatching decision-making. Because of the heterogeneous spatial and temporal precipitation distributions in large basins, inadequate precipitation stations normally have a negative impact on forecast accuracy. Using the Panjia-kou reservoir runoff inflow forecast as the research subject, this paper adopts the Thiessen polygon block, square grid computing, and DEM (digital elevation model) methods to estimate average regional areal precipitation. Based on the estimation, a model for the Panjia-kou reservoir runoff forecast is developed. The results indicate that different areal precipitation estimation methods have significantly different effects on the accuracy of the reservoir runoff inflow forecast. When the average regional precipitation estimation from the DEM method is used as an input to the model, the simulation results are accurate and are much better than those from the other two average regional precipitation estimation methods.

1. Introduction

Variables and parameters in existing hydrology models are normally set to average values, and the entire basin is simplified as a single research object. However, the basin runoff rule actually permits spatial variability in variables and parameters. Not only do rainstorms have time-variant spatial distributions, but the spatial distributions of basin attributes, such as topography and landform, are also heterogeneous. Therefore, it is improper to treat basins with a heterogeneous underlying surface as a spatially uniform entity.

Currently, DEM is the primary data source for basin topography analysis and water system construction (Turcotte et al.2001). GIS software ARCVIEW together with DEM data can automatically generate a Thiessen polygon for a precipitation station and calculate each precipitation station's weight. The Thiessen polygon can also automatically generate the topography structure of a basin hydrology model and provide information such as basin watercourse length, average watercourse gradient, average slope length, average gradient for a long slope, and average ground elevation.

In this paper, using the Panjia-kou reservoir runoff forecast as the research object, a TOPMODEL-based reservoir runoff forecast model is established. Average regional precipitation estimations from three methods (block method, grid computing method, and DEM hydrology model method) are used as inputs into the model, and a parallel genetic algorithm is designed to calibrate the model parameters to



forecast reservoir runoff volume. The forecast accuracies and efficiencies of the models built from the three different average regional precipitation estimation methods are then compared.

2. Modelling and Analysis

2.1. Panjia-kou reservoir inflow flood forecast modeling

The basin runoff forecast model will be built in this section, and the precipitation estimation results will be imported into the model. A conventional conceptual model (TOPMODEL in this paper) is applied to each grid unit (or sub-basin) to calculate the runoff yield and confluence, and to obtain runoff at the exit section.

2.2. Unit confluence model.

TOPMODEL defines the total basin runoff as the sum of interflow and saturated surface flow, which excludes the effect of spatial distribution factors, such as precipitation and evaporation, on the basin runoff yield and confluence. This type of runoff simulation is only a simple aggregate of the runoff yield, and ignores the time-lag effect of the confluence process (Guo & Chen, 2005). To improve the forecast accuracy of the model, the numeric algorithm proposed by Todini (1996) was used as theoretical basis for enhancement. A confluence coefficient ξ is introduced to perform the layered calculation of confluence in a better way to establish the distributed unit confluence model. The Todini confluence calculation formula is as follows:

$$Q_{t+\Delta t}^i = \frac{2k - \Delta t}{2k + \Delta t} Q_t^i + \frac{\Delta t}{2k + \Delta t} (Q_{t+\Delta t}^{i-1} + Q_t^{i-1}) \quad (1)$$

Now, the confluence coefficient ξ is introduced to convert formula (2) to formula (3):

$$Q_{t+\Delta t}^i = \Delta t \times [\xi Q_t^i + (Q_{t+\Delta t}^{i-1} + Q_t^{i-1})] \quad (2)$$

Where $Q_{t+\Delta t}^i$ is the calculated exit flow in the (i)th sub-basin area at $t + \Delta t$ ($i=1 \dots n$); when $i=n$, the flow is the basin exit flow. Q_0^0 is the basin runoff yield, i.e., $Q_0^0=R$, which is the initial condition for the calculation using the above formula. After n rounds of calculations, the basin exit flow process can be obtained from the basin runoff yield. In this paper, formula (3) is used to calculate all the confluences for the ground surface runoff, interflow, and underground runoff. ξ is a model parameter, where ξ_u , ξ_m , and ξ_s represent the confluence coefficients of the saturated slope flow, interflow, and underground runoff, respectively. Therefore, the calculation method for different sub-basin units is identical despite the parameters being different.

Thus, the runoff yield model is coupled with the confluence model to obtain the unit forecast model. The model structure is shown in Fig. 1. Here, TOPMODEL is used as the unit runoff yield model, and is coupled with the conceptual confluence model to improve model efficiency.

2.3. Major data and parameters for the model.

In a real scenario, the forecast model requires data that includes the following: digital elevation model, vegetation types, precipitation, and evapotranspiration data (Lin et al., 2010). Because there is no reference data from a temperature station, the basin evapotranspiration is estimated by converting the long-term average river surface evaporation observed by a hydrologic station at the reservoir dam site.

The sub-basin runoff yield and confluence calculation use the same calculation method; however, different underlying surface conditions mean the model parameters have different values, such as the ground surface gradient, flow distribution coefficient, unit water catchment area, humidity index, and landform index, which can be directly calculated from DEM data. In addition, several other parameters, such as T_0 - lateral water conductivity in saturated soil (m²/h); f - exponential drainage rate parameter SR_{max} - soil's effective water holding capacity (m); SR_{init} - root zone initial water deficit (m); and ξ_u , ξ_m , and ξ_s - confluence coefficients of saturated overland flow, interflow, and underground runoff,

respectively, have clear physical meanings and could theoretically be measured directly (Dong et al., 2006) However, measurements are obtained at a measurement point, which is insufficient to represent the entire area. In addition, several parameters have volatile temporal and spatial variations, which makes it difficult to determine via field measurements. Therefore, parameters should be calibrated in a practical application. The initial values of the parameters in the runoff yield model were calibrated by trial and error.

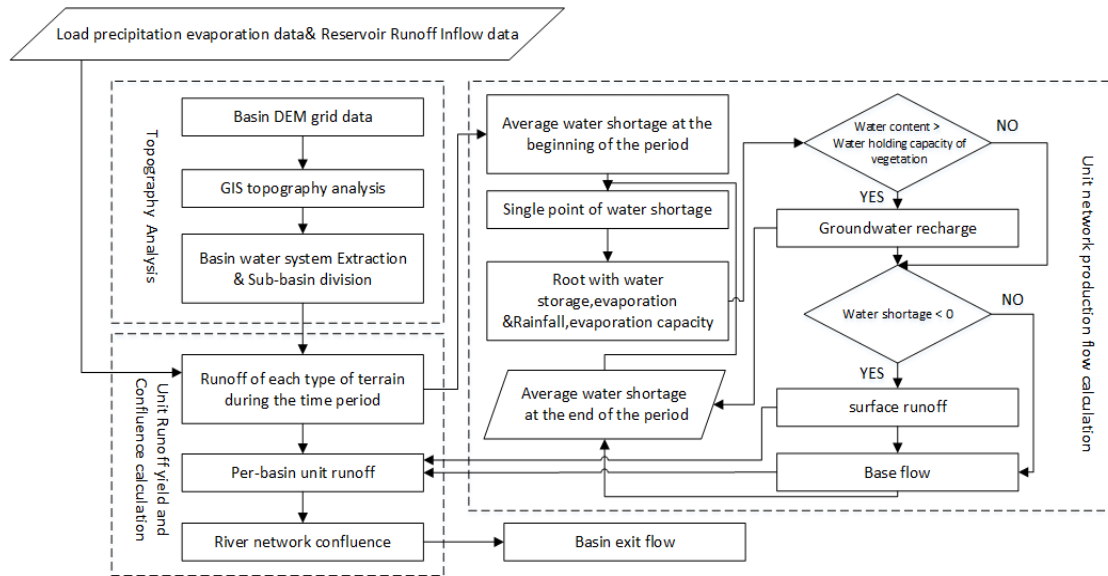


Figure 1. Unit forecast model calculation block diagram

2.4. Model parameter calibration and verification.

The runoff forecast model proposed in this paper has seven parameters that require calibration. Model parameters were calibrated using basin station distribution, precipitation and runoff discharge data from the hydrologic station on the reservoir dam site, and 2008-2014 flood seasons from the upstream basin. After the model parameters were determined, 2015 and 2016 flood season data from the above stations was used for model verification.

An adaptive accelerated genetic algorithm (Lu et al., 2001) was used for parameter optimization. The real number coding rule was used to generate the initial parameter population. To prevent premature variable convergence, variable Δ is introduced as an index to represent the degree of population premature convergence.

Assume the (t)th generation of the population comprises individuals x^1, x^2, \dots, x^N with corresponding fitness values of f^1, f^2, \dots, f^N ; then, the overall average individual fitness is

$$\bar{f}_t = (\sum_{i=1}^N f_t^i) / N \quad (3)$$

The optimum individual fitness is f_{\max} ; the average of the individual fitness above \bar{f}_t is \bar{f} ; and $\Delta = f_{\max} - \bar{f}$. The genetic algorithms crossover probability P_c and mutation probability are P_m defined as follows:

$$P_c = 1.5 - \frac{1}{1 + \exp(-\Delta)} \quad (4)$$

$$P_m = 1.0 - \frac{1}{1 + \exp(-\Delta)} \quad (5)$$

Thus, after every round of calculation, P_c and P_m are updated to ensure fast convergence of the genetic algorithm toward the target.

The model parameter estimation is expressed by formula (6) (principle of minimal absolute relative residual):

$$\text{Min}F = \sum_{i=1}^n | [T(Q'(i), X) - Q(i)] / Q(i) | \quad (6)$$

Where x the model parameter is vector; $Q'(i)$ represents the calculated value; and $Q(i)$ represents the field measurement. The calculation process of the parameter calibration model is shown in Fig. 2. (Pan et al.2004) The calibrated major runoff yield and confluence parameters are listed in Table 1. At this point, the basin runoff forecast model is determined.

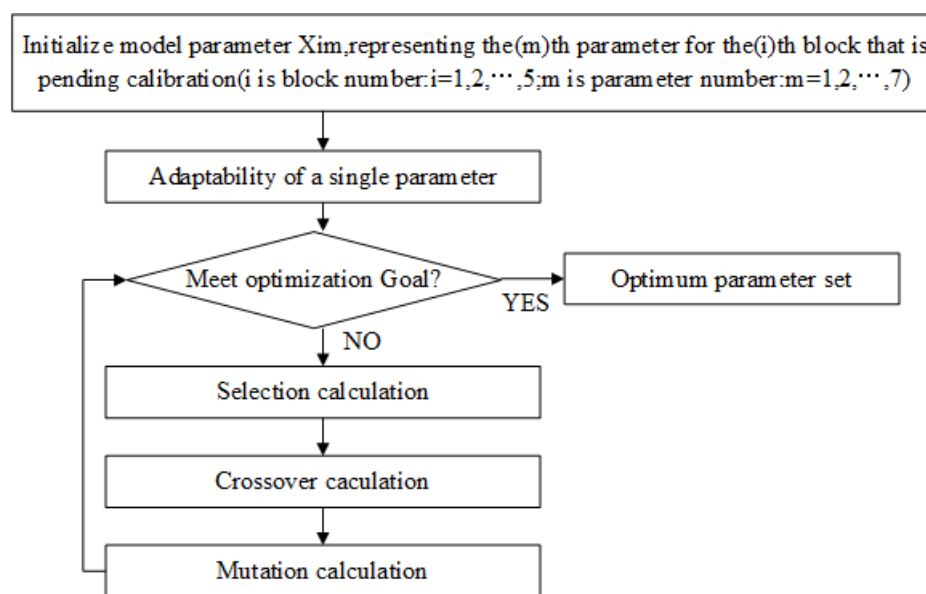


Figure 2. Adaptive genetic algorithm calculation process

Table 1. Optimized parameters in improved TOPMODEL model

Block#	Ln (T ₀)	f	SRmax	SRinit	ζ _u	ζ _m	ζ _s
1	6.1	66.2	0.25	0.7	1.1	0.1	0.09
2	6.8	62.1	0.23	0.5	1.1	0.1	0.1
3	6.4	61.1	0.26	0.7	1.3	0.11	0.08
4	6.25	61.7	0.22	0.6	1.2	0.09	0.09
5	6.1	60.9	0.24	0.7	1.3	0.1	0.07

The above model is used to forecast the reservoir inflow during the 2015 and 2016 flood seasons. The verification results show that application of the forecast model to the basin reservoir upstream area can obtain desirable results. Both forecasts resulted in good peak simulation results, where the flood peak flow estimation errors are 5.8% and 6.6%, respectively.

Comparison of the model simulation accuracy in Table 2 shows that there are significant variances in the model simulation results from the different average regional areal precipitation estimation methods, which include the block method, grid computing method, and DEM-based hydrology model method.

Table 2. Comparison of the simulation accuracy of different runoff forecast models for the Panjia-kou reservoir

Forecast year	2015			2016		
Model evaluation index	RE (%)	RP (%)	R (%)	RE (%)	RP (%)	R (%)
1. Regional block method	13.6	30.4	36.6	12.2	30.6	35.4
2. Grid computing method	9.8	33.4	34.4	9.3	32.2	32.7
3. DEM-based hydrology model method	5.8	18.2	14.5	6.6	16.8	14.3

Among these three methods, when the DEM is used to build the TOPMODEL and subsequent runoff forecast model (model evaluation indexes are the flood peak flow estimation error R, flood peak flow relative error coefficient RP, and overall runoff relative error coefficient RE), the forecast results are significantly better than those from the block method and grid computing method. The DEM simulations of both floods have R values of less than 6.6%, with an average of 6.2%, which is superior to the block method's value of 12.9% and the grid computing method's value of 9.55%. This result indicates that the forecast results are reliable. Moreover, when the average regional precipitation estimation based on the DEM hydrology model is used to build the forecast model, the model evaluation indexes are also better than those of the other two methods. The RP average errors are less than 14.3% and 14.5%, and the RE average errors are less than 16.8% and 18.2%. Thus, with the same number of basin precipitation stations, the precipitation station estimation results from different estimation methods have a significant effect on the simulation accuracy of the Panjia-kou reservoir inflow runoff forecast. The result from the DEM method is closer to the actual average regional precipitation. This method is used to estimate the basin average regional precipitation and establish a forecast model, which provide a valuable reference for the real-time flood forecasting of the Panjia-kou reservoir.

3. Conclusion

All in this paper, based on the Luanhe River upstream basin's geographic and climatic characteristics and historical flood data, the block method, grid computing method, and DEM-based hydrology model are used to estimate the average regional precipitation. In addition, a sub-basin or grid is used as a unit to build the runoff inflow forecast model of the Panjia-kou reservoir based on the Xinanjiang model. Differences between the simulation accuracies of the forecast models built from the different estimation methods are compared. A comparison of the model simulation results show that when the DEM average regional precipitation estimation is used as the input for the forecast model, the simulation results are much better than those of the other two average regional precipitation estimation methods. Therefore, this method is valid and can improve model simulation efficiency. However, because of the limitations and errors in the resolution of DEM, the boundaries of artificial reservoirs often have abrupt changes in elevation and direction of flow, and the formation of water network in a river basin is often the result of a combination of factors, which are not entirely dependent on the elevation distribution of space. The extracted river network often differs from real data. Therefore, the next research will supplement the existing DEM by increasing the amount of effective information in order to further improve the accuracy of the model.

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