Improving Performance of Conceptual Flood Forecasting Model Using Complementary Error Model

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Content

- Conceptual Rainfall-Runoff Model: TUWmodel
- Error modeling
- Case study: Improving TUWmodel forecast for Karnali using error model
- Conclusions

TUWmodel

- TUWmodel: a conceptual rainfall-runoff model developed at the Vienna University of Technology (TU Wien)
- The model consists of a snow routine, a soil moisture routine and a flow routing routine.
- The model takes precipitation, air temperature, potential evapotranspiration and catchment area as input parameters.
- The model has 15 parameters.
- The model is available freely as R library (See https://cran.r-project.org/package=TUWmodel).

TUWmodel Parameters

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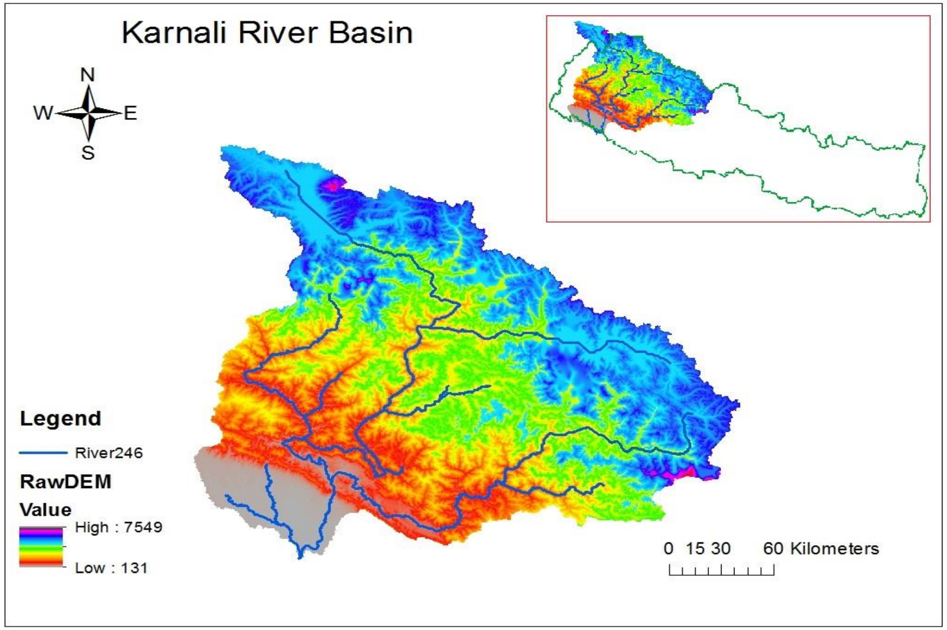
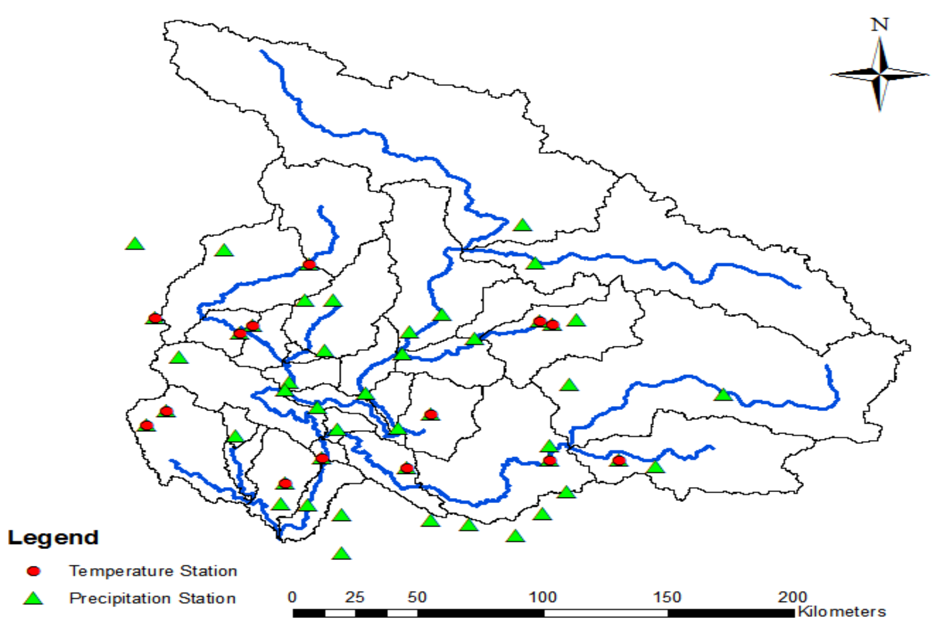
S No.	Parameter	Description	Range	Unit
1	SCF	snow correction factor	0.9-1.5	
2	DDF	degree day factor	0.0-10.0	mm/degC/timestep
3	Tr	threshold temperature above which precipitation is rain	1.0-3.0	degC
4	Ts	threshold temperature below which precipitation is snow	-3.0-1.0	degC
5	Tm	threshold temperature above which melt starts	-2.0-2.0	degC
6	LPrat	parameter related to the limit for potential evaporation	0.0-1.0	
7	FC	field capacity, i.e., max soil moisture storage	0-600	mm
8	BETA	the nonlinear parameter for runoff production	0.0-20.0	
9	k0	storage coefficient for very fast response	0.0-2.0	timestep
10	k1	storage coefficient for fast response	2.0-30.0	timestep
11	k2	storage coefficient for slow response	30.0-250.0	timestep
12	lsuz	threshold storage state, i.e., the very fast response start if exceeded	1.0-100.0	mm
13	cperc	constant percolation rate	0.0-8.0	mm/timestep
14	bmax	maximum base at low flows	0.0-30.0	timestep
15	croute	free scaling parameter	0.0-50.0	$timestep^2/mm$

Study area: Karnali Basin





- Catchment Area: 42890 km^2
- Calibration Set: 01/01/2008 to 31/12/2011
- Validation Set: 01/01/2012 to 31/12/2014
- Codes written in R to customize the TUWmodel for Karnali River
- R function *optim()* used to optimize model parameters automatically using quasi-Newton BFGS (Broyden, Fletcher, Goldfarb and Shanno) method

Optimal Parameters

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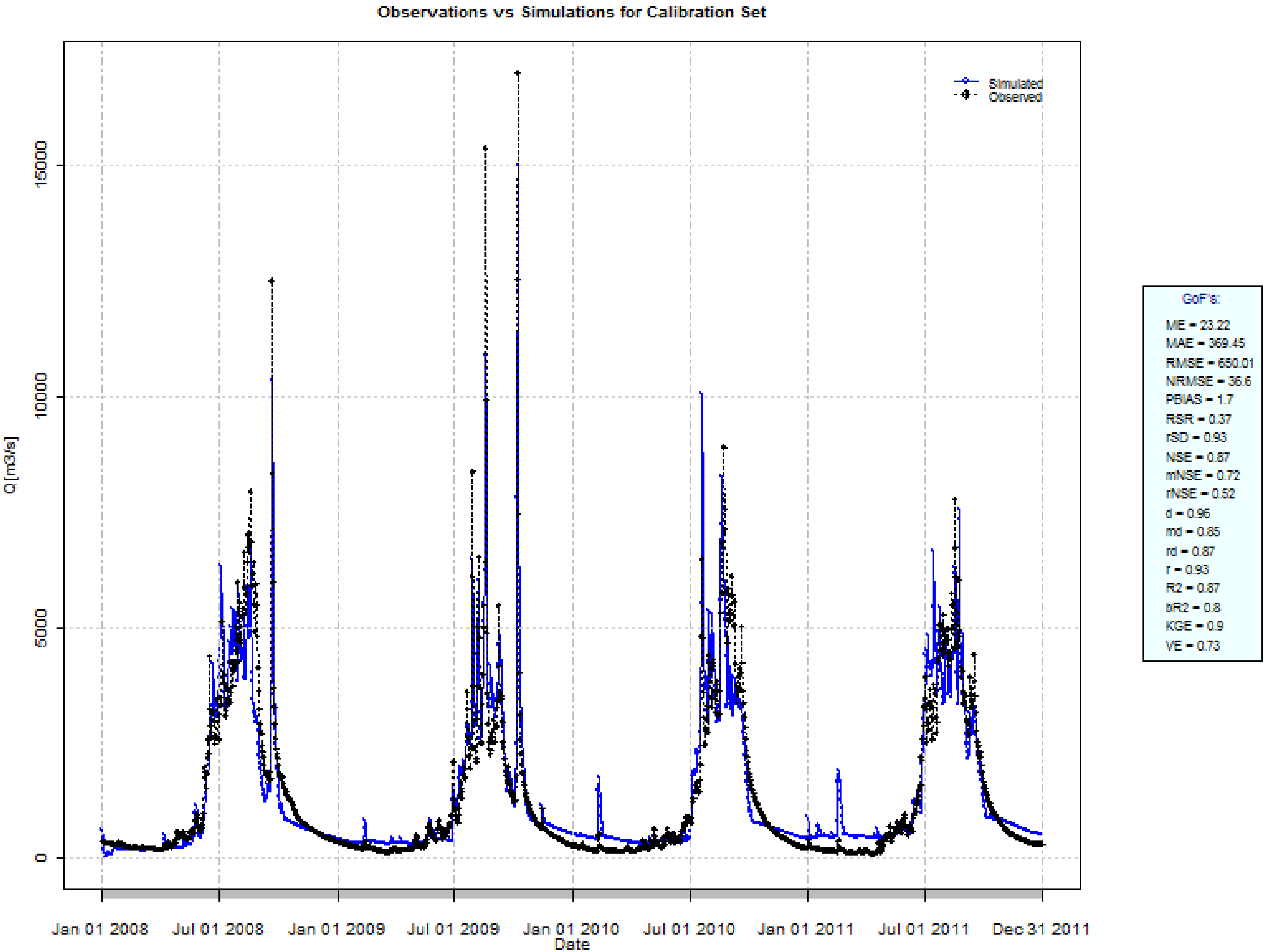
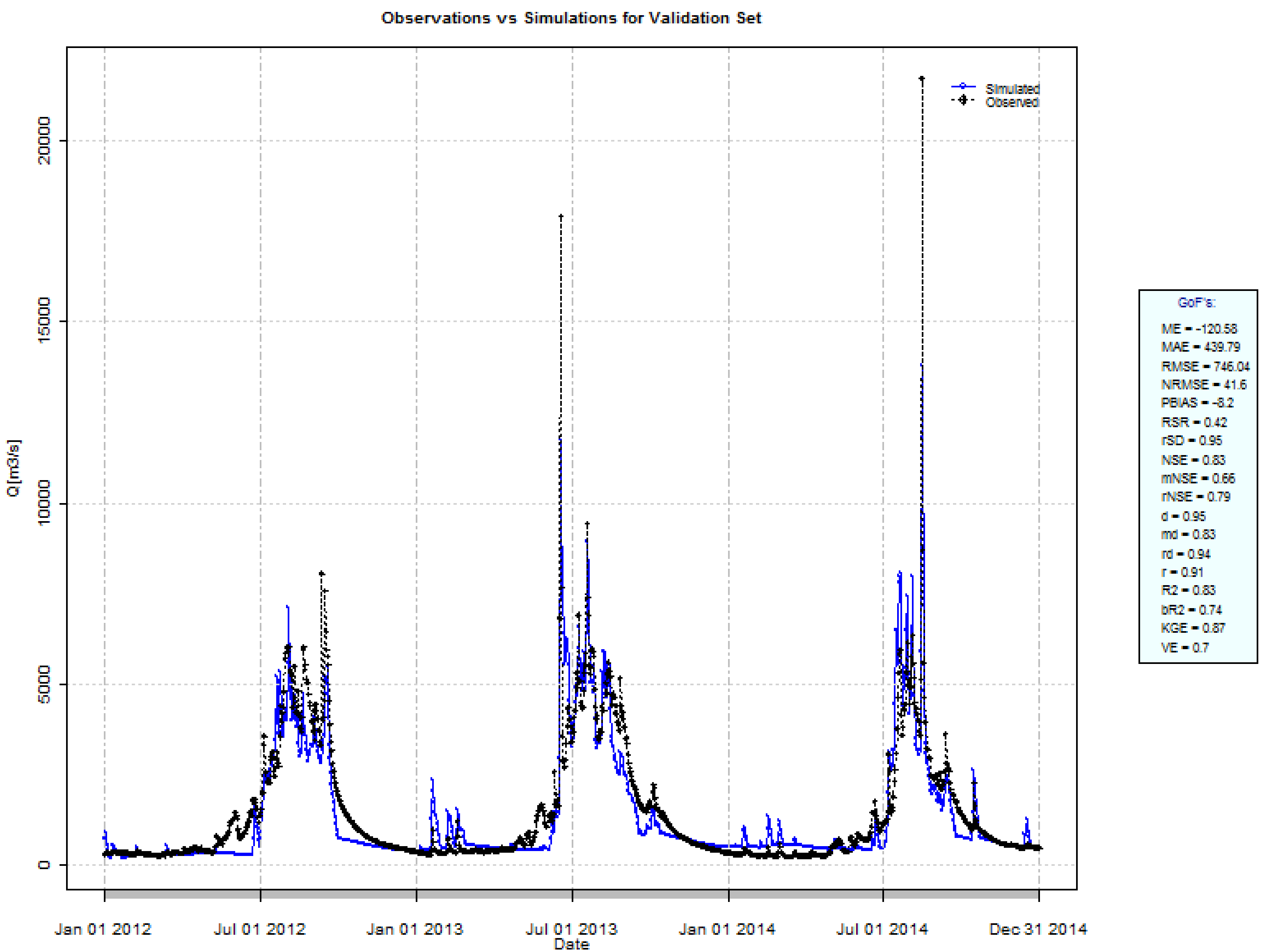
S No.	Parameter	Description	Optimal value	Unit
1	SCF	snow correction factor	1.2	
2	DDF	degree day factor	4	mm/degC/timestep
3	Tr	threshold temperature above which precipitation is rain	1	degC
4	Ts	threshold temperature below which precipitation is snow	0	degC
5	Tm	threshold temperature above which melt starts	1	degC
6	LPrat	parameter related to the limit for potential evaporation	0.12	
7	FC	field capacity, i.e., max soil moisture storage	40	mm
8	BETA	the nonlinear parameter for runoff production	0.06	
9	k0	storage coefficient for very fast response	0.67	timestep
10	k1	storage coefficient for fast response	7.45	timestep
11	k2	storage coefficient for slow response	104.93	timestep
12	lsuz	threshold storage state, i.e., the very fast response start if exceeded	50.35	mm
13	cperc	constant percolation rate	2.11	mm/timestep
14	bmax	maximum base at low flows	9.98	timestep
15	croute	free scaling parameter	26.51	$timestep^2/mm$

Model prediction for calibration set



Model prediction for validation set



Error Modeling

- Assimilates the latest observation and its corresponding prediction to inform the predictive distribution of the errors in future model predictions with respect to the observed data
- Uses difference between the observations and model predictions to generate error time series
- ARIMA model is fitted to error series and errors are forecasted
- Error forecasts are added to model predictions to obtain corrected forecasts
- Improves the skill of forecasts by reducing model error

Basis of Error Modeling

- Error model relies on temporal correlation within the residuals.
- Auto-Regressive Integrated Moving Average (ARIMA) models could be fitted if the residuals are highly correlated.
- These type of models are fitted for stationary time series.
- Two step approach
  - Process modeling using conceptual model (e.g. TUWmodel, HEC-HMS)
  - Error modeling using ARIMA times series models

ARIMA Model

- ARIMA modeling includes differencing, lagged values of the dependent variable, moving averages of residuals

$$\hat{y}_t = \mu + \emptyset_1 y_{t-1} + \cdots + \emptyset_p y_{t-p} - \theta_1 e_{t-1} - \cdots - \theta_q e_{t-q}$$

Constant AR terms MA terms

By convention, the AR terms are +ve and the MA terms are -ve

If the stationarized series has positive autocorrelation at lag 1, AR terms often work best.
If it has negative autocorrelation at lag 1, MA terms often work best.

ACF and PACF plots

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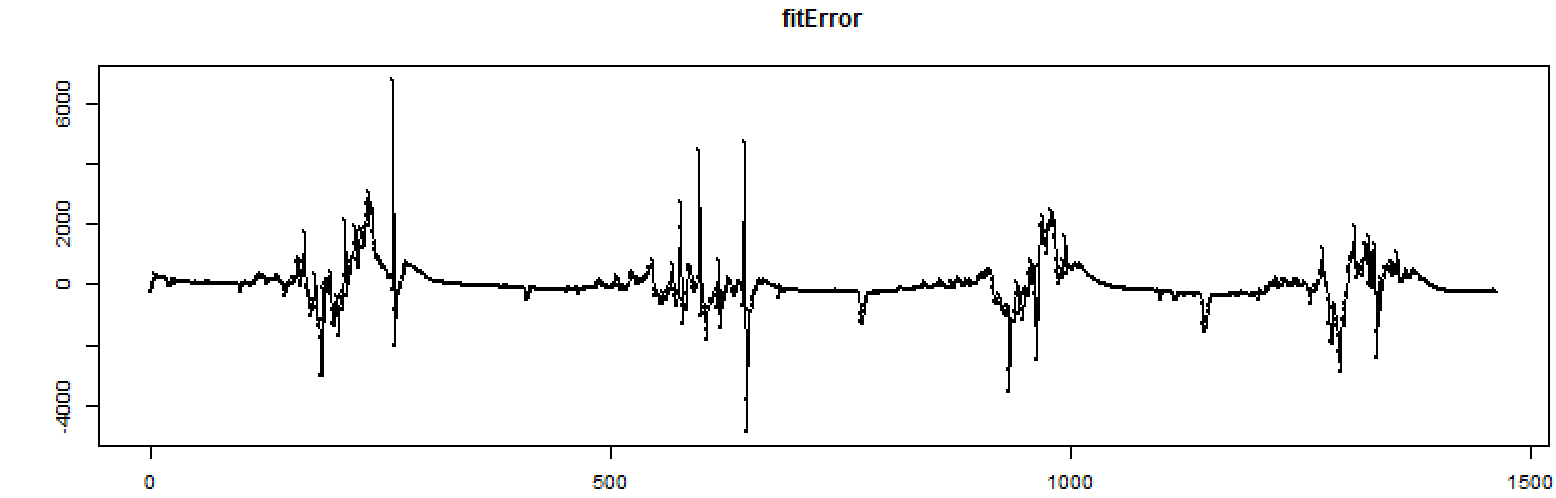
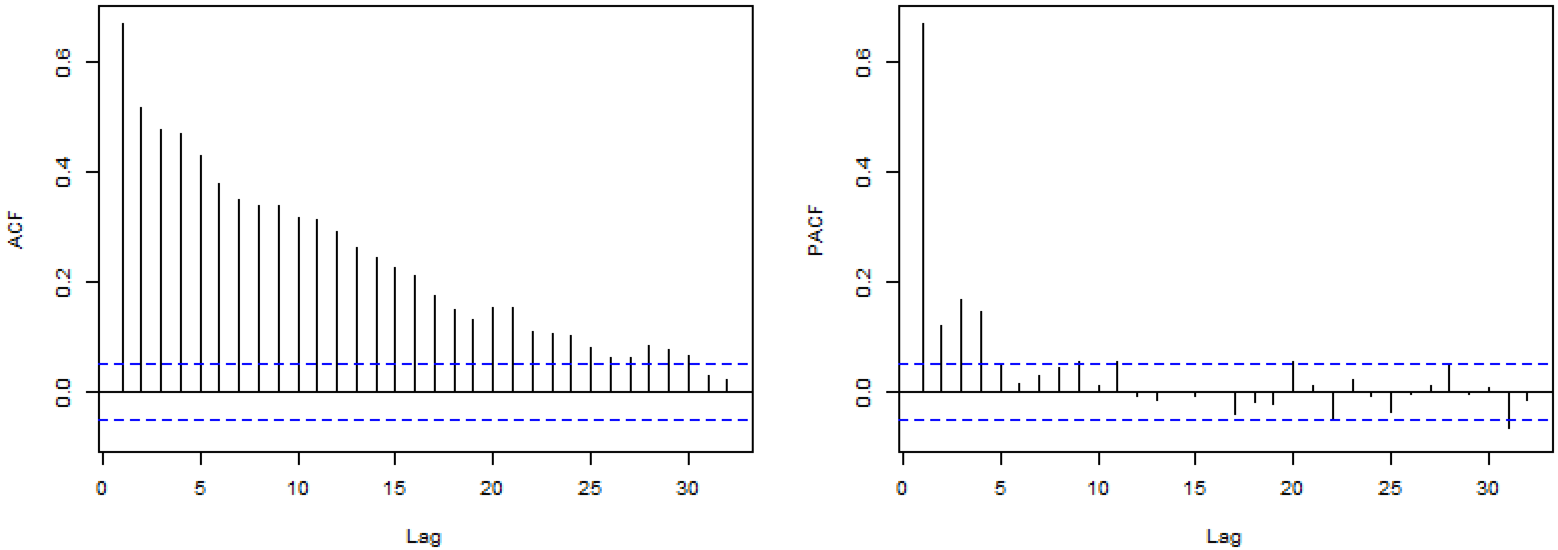
- The autocorrelation function (ACF) plot shows the *correlation* of the series with *itself* at different lags
- The *partial* autocorrelation function (PACF) plot shows the amount of autocorrelation at lag *k* that is *not explained by lower-order autocorrelations*
- ACF that dies out gradually and PACF that cuts off sharply after a few lags indicate AR series
- **An AR series is usually *positively autocorrelated at lag 1***
- **ACF declines in geometric progression from its highest value at lag 1**
- **PACF cuts off abruptly after lag 1**
- ACF that cuts off sharply after a few lags and PACF that dies out more gradually indicate MA series
- **An MA series is usually *negatively autocorrelated at lag 1***
- **ACF cuts off abruptly after lag 1**
- **PACF declines in geometric progression from its highest value at lag 1**

Error Time Series plot: Karnali



ARIMA(1,0,1)



R Package "forecast"

- https://cran.r-project.org/web/packages/forecast/index.html

- Automatically estimates the ARIMA model parameters (p,d,q)

Model prediction for calibration set after error correction

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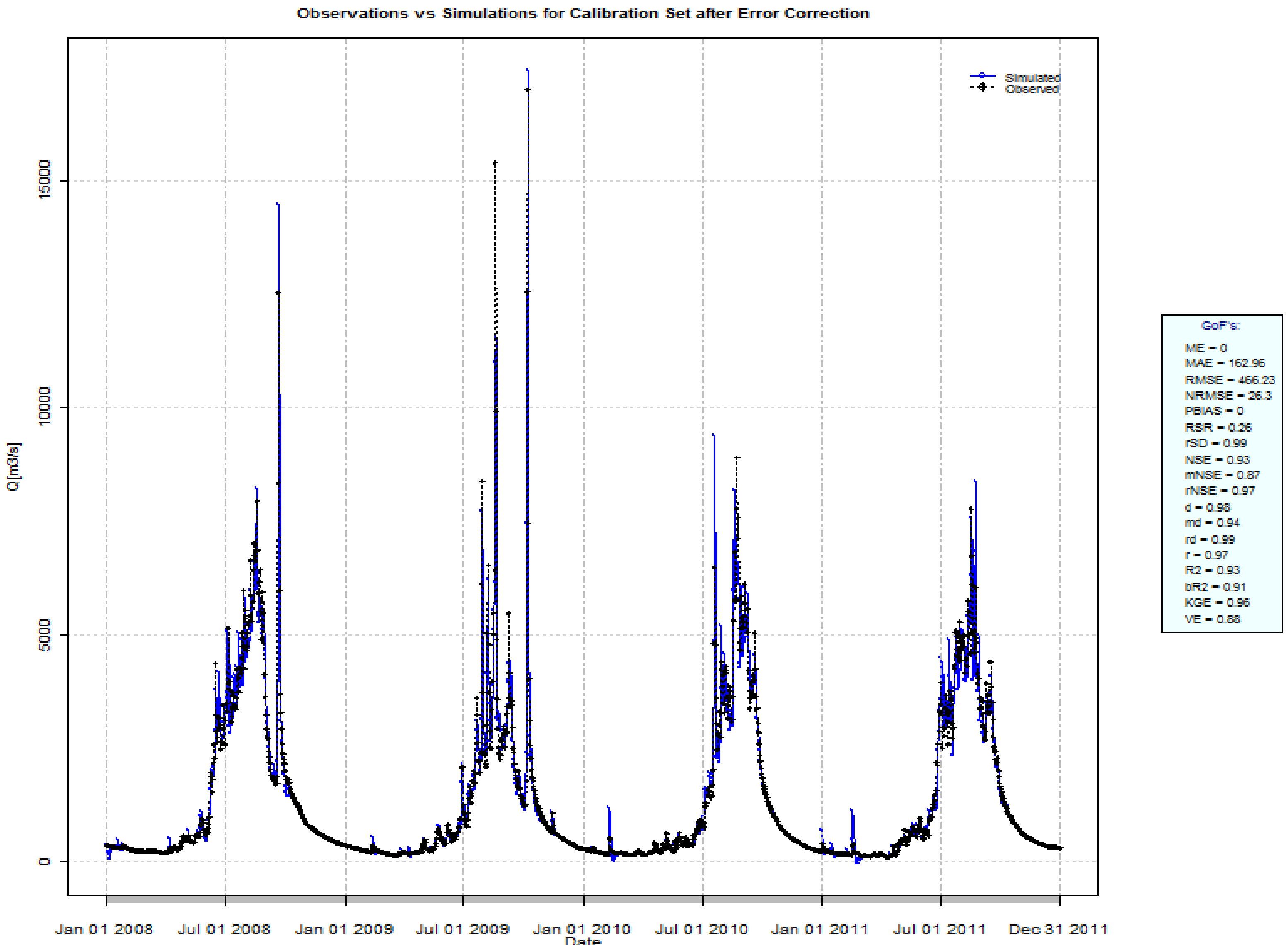
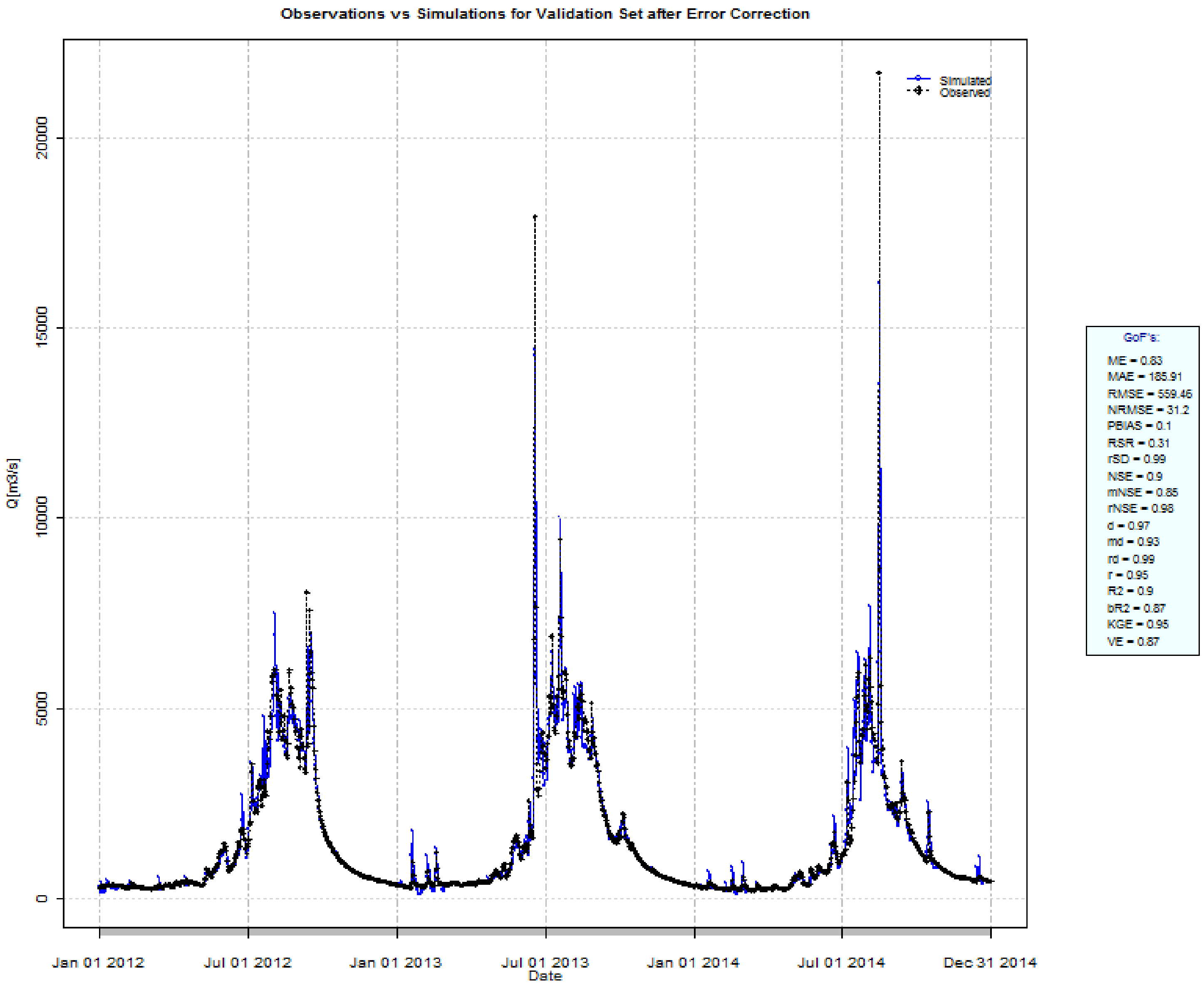


Model prediction for validation set after error correction



Performance

	calGOF	calArimaGOF	valGOF	valArimaGOF
ME	23.22	0	-120.58	0.83
RMSE	650.01	466.23	746.04	559.46
PBIAS %	1.7	0	-8.2	0.1
NSE	0.87	0.93	0.83	0.90
VE	0.73	0.88	0.70	0.87

Conclusions

- Every models are prone to errors.
- The errors may be systematic.
- Analysis of the errors could reveal important information (stationarity, persistence etc).
- An error model can be developed and errors could be forecasted.
- Flood forecasts can be significantly improved by integrating error forecasts into conceptual hydrological model forecasts.

Thank you

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