A Bivariate SWAT-Copulas-based Approach for Detection of Agricultural Drought Year in a Tropical Canal Command

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Drought– A Natural Phenomenon That Can Cause Disasters

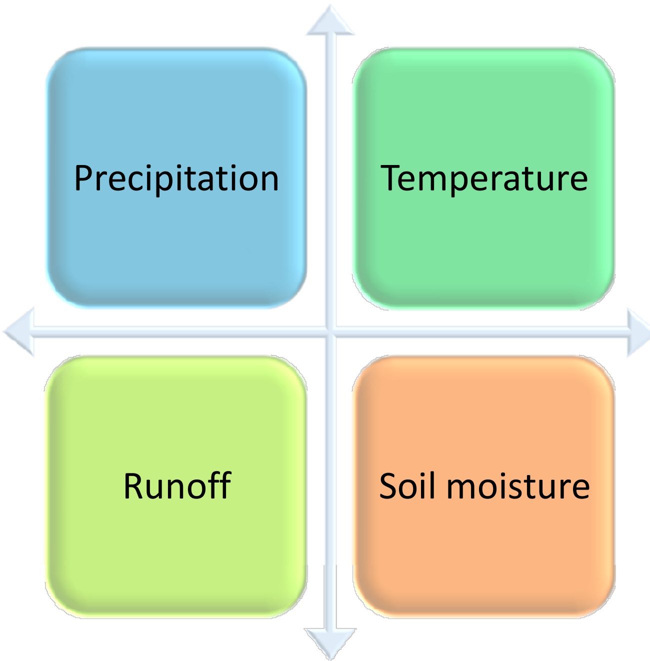
Drought is a consequence of planet earth's atmospheric-oceanic-lithospheric interactions.

Causes rapid ground water depletion.

Reduces irrigation efficiency and results in higher ground water extraction.

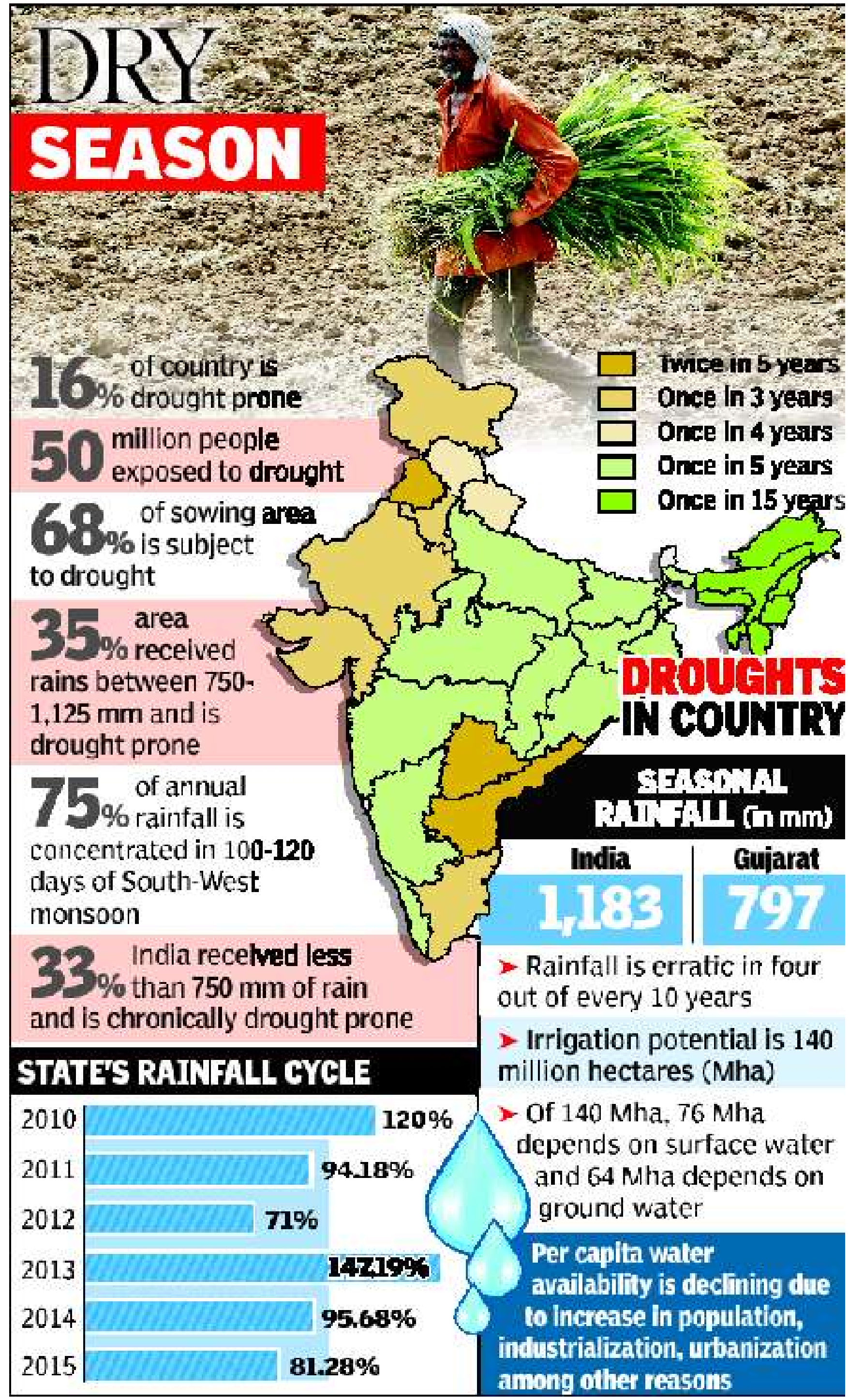
Low flow rate encourages the mortality of aquatic species.

Factors affecting drought phenomena:



Drought Quantification:

- ✓ Standarised precipitation index (SPI)
- ✓Standardised soil moisture index (SSI)
- ✓Standardised Precipitation - Evapotranspiration index (SPEI)



Constraints associated with Drought monitoring

- Un-availability of long term observed data like soil moisture
- Difficulty in obtaining data by indirect means in remote areas
- Lack in accuracy associated with data collection
- Understanding the dependence structure between the input variables

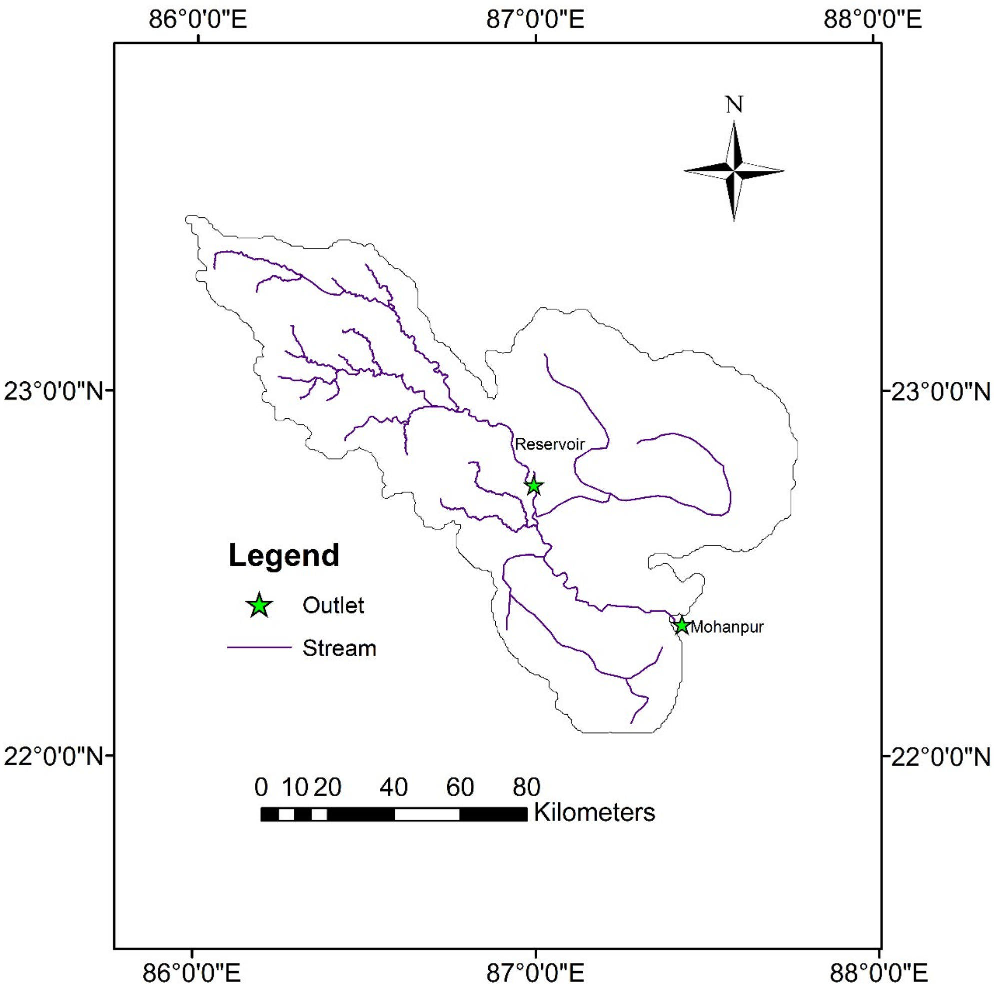
❖ To represent this large heterogenity and un-certainty associated with drought phenomena , a multivariate index having combination of two drought causing factors have been introduced in this study.

Objective

❖To develop a multivariate standardized drought index (MSDI) using SWAT-copulas based approach

❖To inter-compare the performances of the MSDI and SPI based drought indices

Description of Study Area



- Contributing river to Ganges river
- Area is 12014 km^2
- Length of mainstream is 327 km.
- Average annual precipitation is around 1400 mm
- Nearly 80% was concentrated during June to September.
- Mostly tropical dry climate
- Elevation ranges from 19m to 656m.
- Paddy is the major crop covering around 48% of total area.

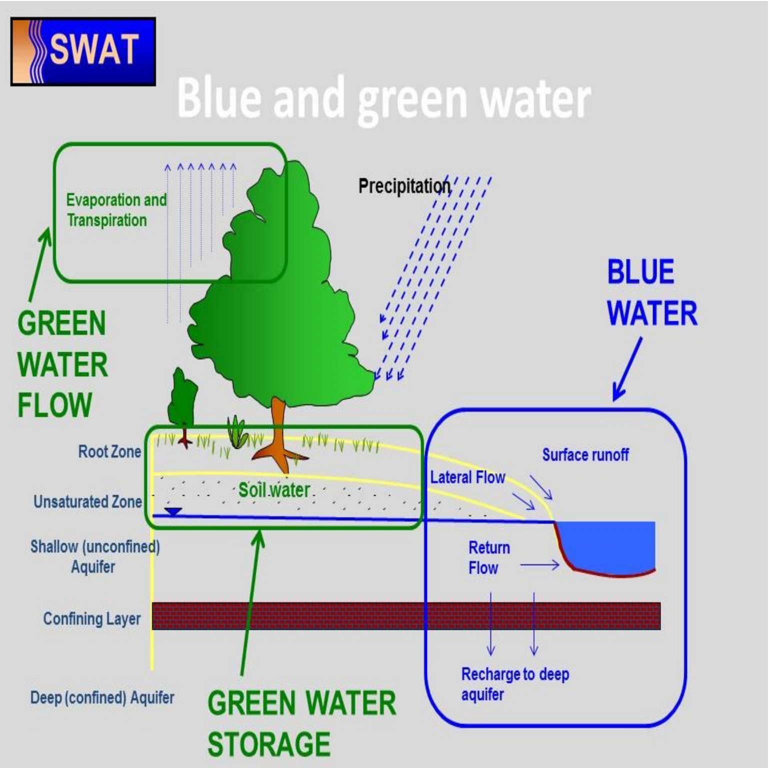
SWAT-Copula

- **Soil and Water Assessment Tool (SWAT)**

✓ Uses concept of water balance model.

✓ Catchment scale hydrologic model

✓ HRU level variability in land, vegetation and weather can be incorporated.



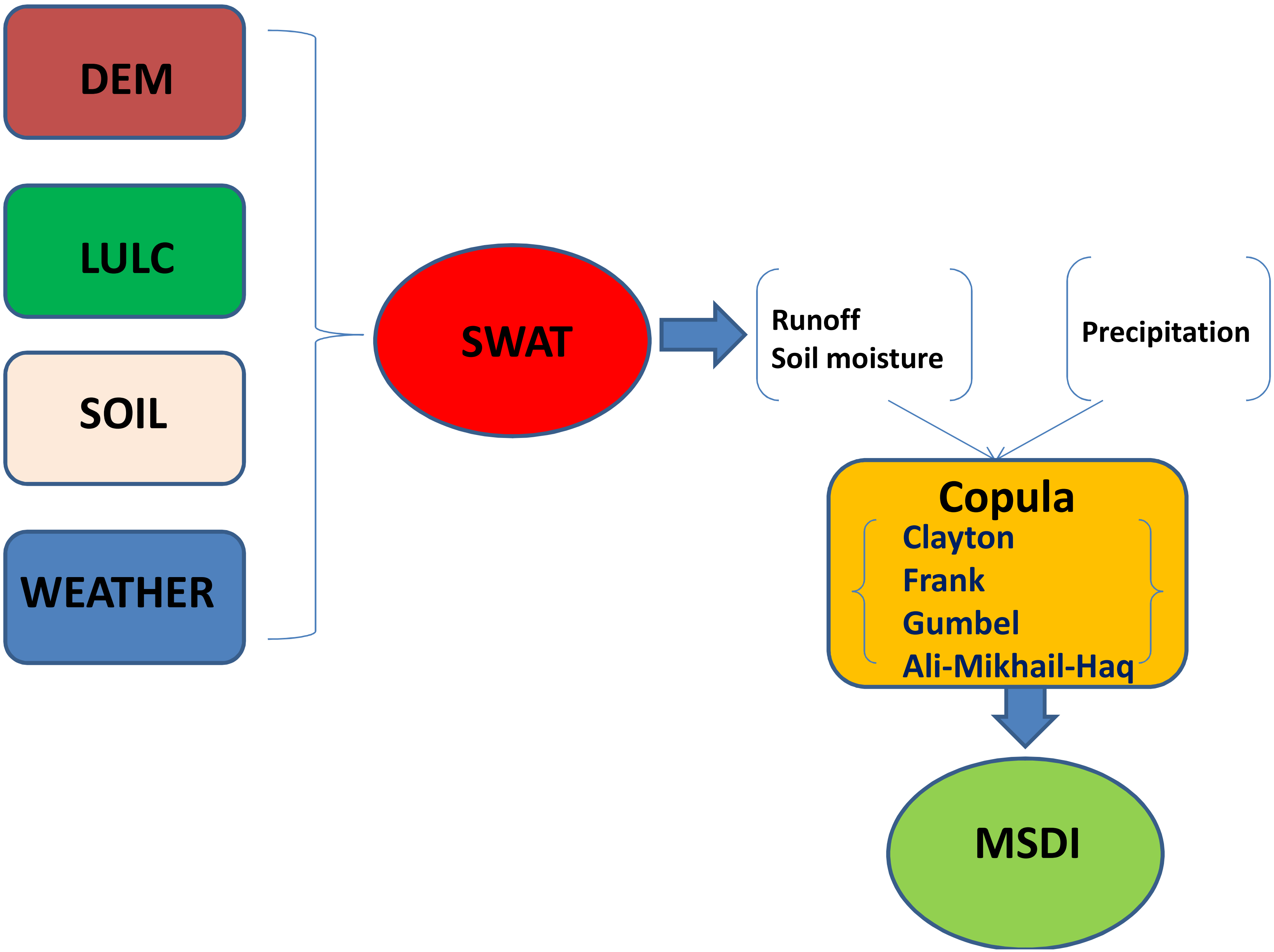
- **Copula**

✓ Links uni-variate marginal distributions to the full multivariate distribution.

✓ Serves as a basis for flexible techniques for simulating dependent random vectors.

✓ Random vectors having different distribution can be coupled with a suitable copula function.

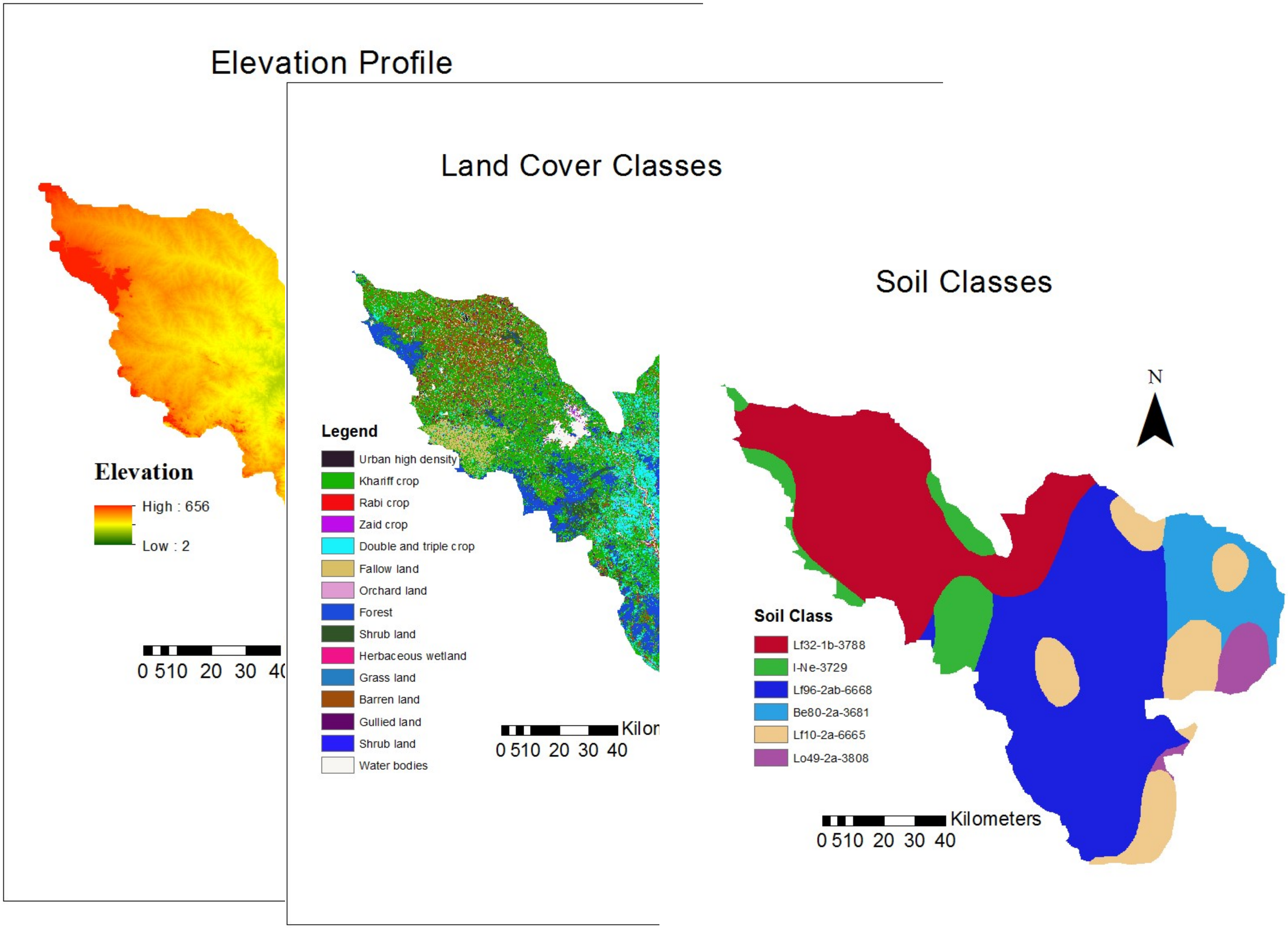
SWAT-COPULA approach



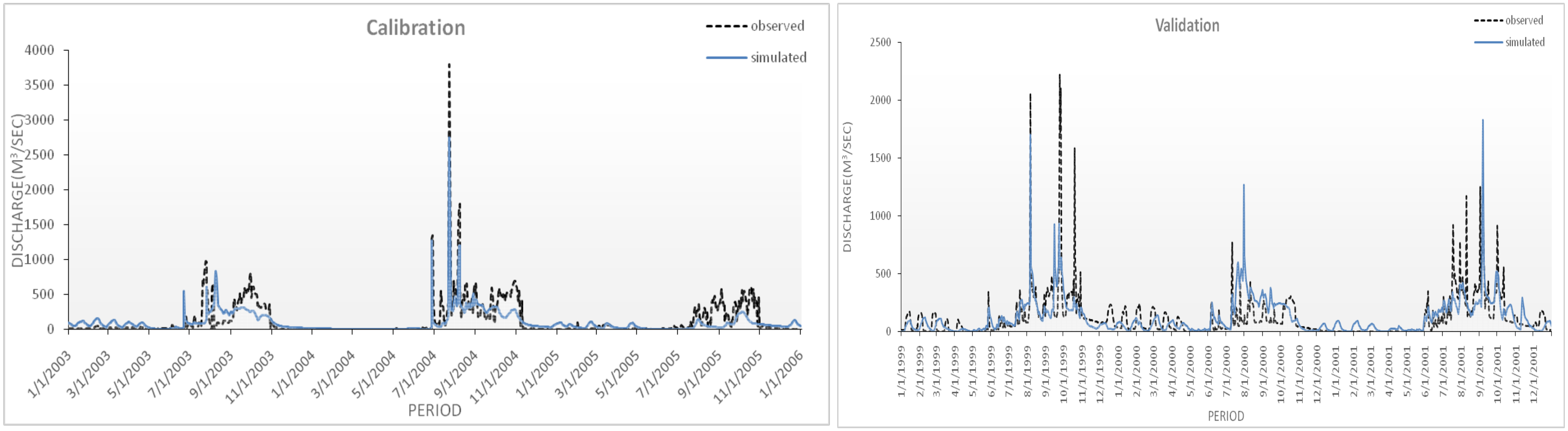
Description of Data

Input Data	Resolution	Data source
DEM	30m	SRTM
Land Use	23.5m	LISS-III
Soil Map	1km	FAO
Meteorological Data	Daily	IMD, Kolkata
Hydrological Data	Daily	Central water Commission

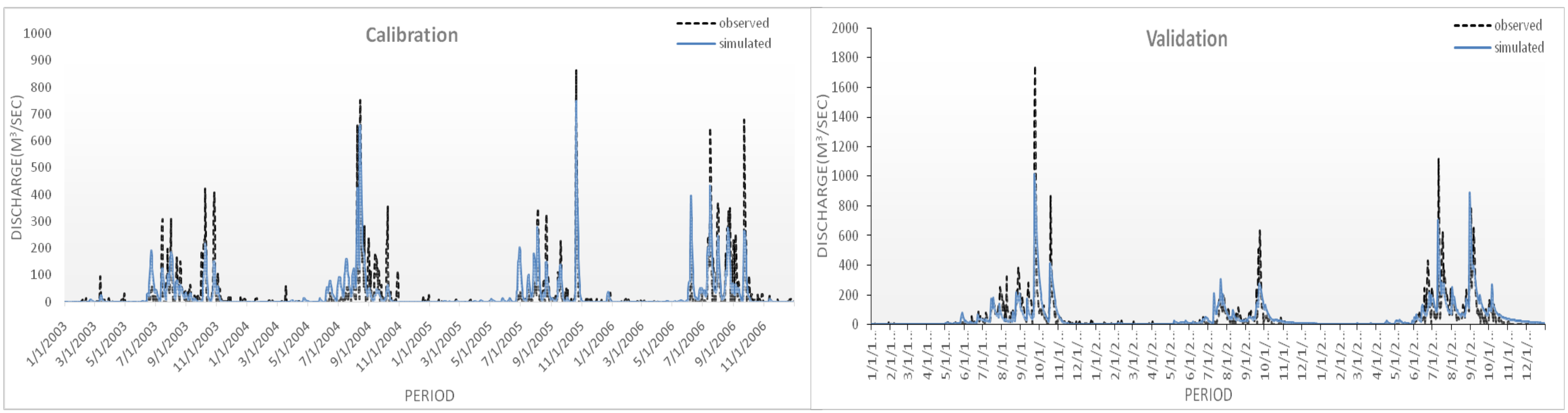
Inputs for SWAT Model



Calibration and Validation



Mohanpur Station



Reservoir inflow

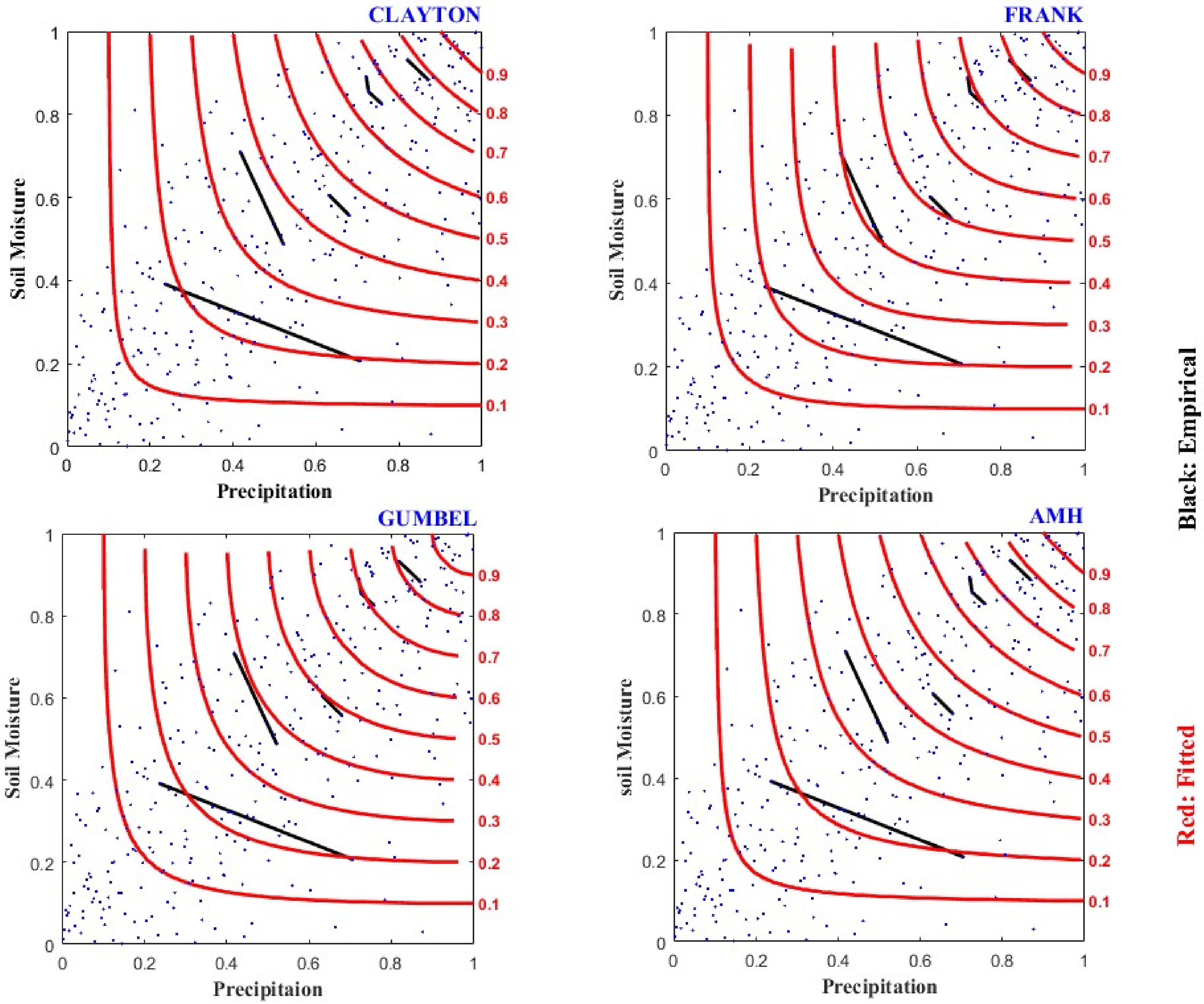
Calibration parameters and Sensitivity Analysis

No	Parameter	Sensitivity Ranking
1	R__CN2.mgt	1
2	V__ALPHA_BF.gw	2
3	V__GW_DELAY.gw	3
4	V__REVAPMN.gw	10
5	V__GW_REVAP.gw	5
6	R__SOL_AWC.sol	9
7	V__ESCO.hru	6
8	R__SOL_K.sol	8
9	V__GWQMN.gw	4
10	V__CH_K2.rte	7

Calibration Statistics

Location	Calibration					Validation				
	P - factor	R - factor	E_{NS}	R^2	PBIAS	P - factor	R – factor	E_{NS}	R^2	PBIAS
Reservoir inflow	0.62	0.48	0.60	0.60	14.7	0.58	0.70	0.63	0.64	4.4
Mohanpur	0.66	0.34	0.53	0.54	13.4	0.63	0.59	0.60	0.69	22.1

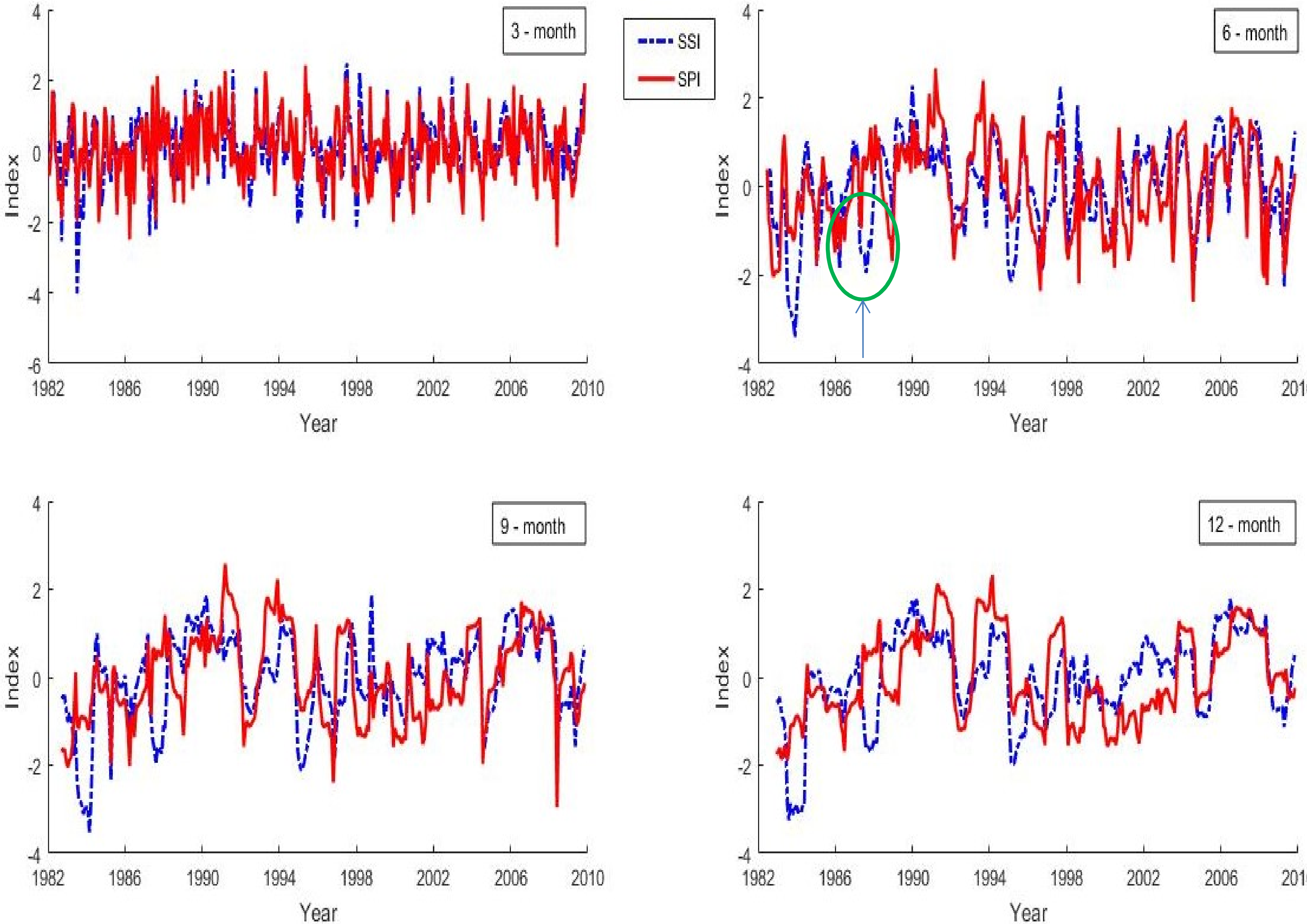
Probability iso-lines of copula

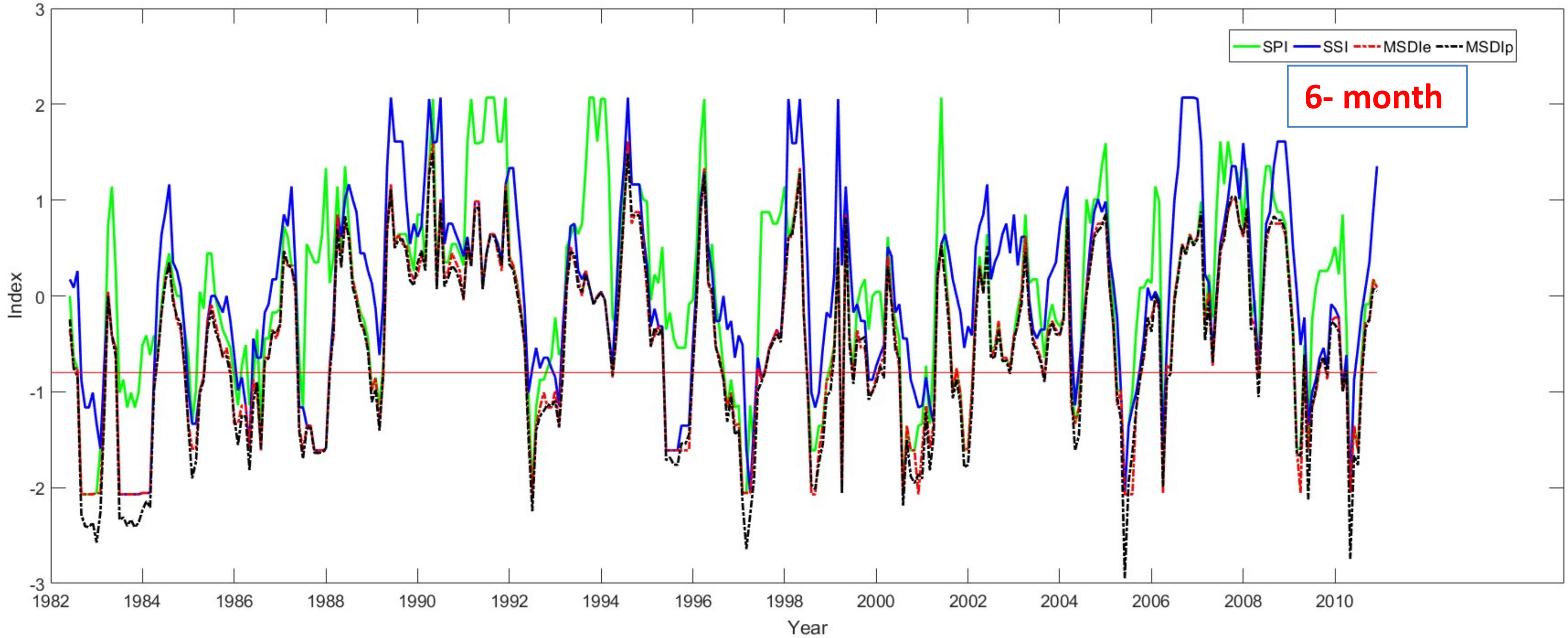


Selection of Best Copula

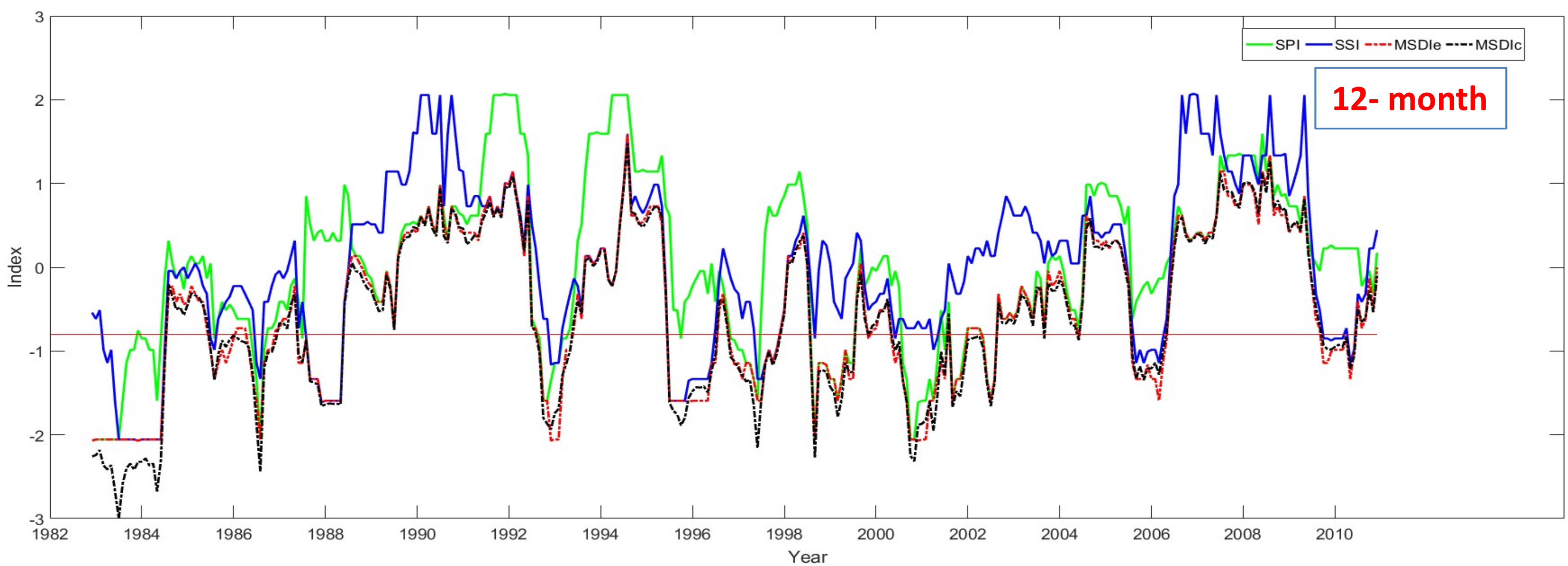
SPI Scale	Copula family	Parameter value	E_{NS}	RMSE	AIC (Rank)	Best Fit
3-month	Clayton	1.2007	0.9966	0.2955	3	
	Frank	6.1416	0.9995	0.1116	1	✓
	Gumbel	1.8345	0.9982	0.2151	2	
	AHM	1.0000	0.9834	0.6483	4	
6- month	Clayton	0.8763	0.9965	0.2869	3	
	Frank	4.7138	0.9992	0.1377	1	✓
	Gumbel	1.5712	0.9972	0.2587	2	
	AHM	1.0000	0.9909	0.4651	4	
9- month	Clayton	0.7172	0.9952	0.3369	3	
	Frank	4.1544	0.9982	0.2034	1	✓
	Gumbel	1.4918	0.9964	0.2914	2	
	AHM	1.0000	0.9926	0.4178	4	
12- month	Clayton	0.6483	0.9928	0.4243	3	
	Frank	3.8813	0.9970	0.2756	1	✓
	Gumbel	1.4727	0.9967	0.2891	2	
	AHM	0.9930	0.9922	0.4410	4	

SPI and SSI over all time scales





SPI
SSI
MSDIe
MSDIp
6- month
Index
Year
3
2
1
0
-1
-2
-3
1982
1984
1986
1988
1990
1992
1994
1996
1998
2000
2002
2004
2006
2008
2010



SPI
SSI
MSDIe
MSDIc
12- month
Index
Year
3
2
1
0
-1
-2
-3
1982
1984
1986
1988
1990
1992
1994
1996
1998
2000
2002
2004
2006
2008
2010

Characteristics of MSDI

❖ MSDI is capable of predicting the drought on set similar to SPI where as the consistency pattern is equivalent to SSI.

❖ The probability of MSDI was found to be higher than individual indices, hence it always predicts more drought severity.

❖When either of drought indices shows drought, MSDI also corresponds to drought.

Interpretation of MSDI

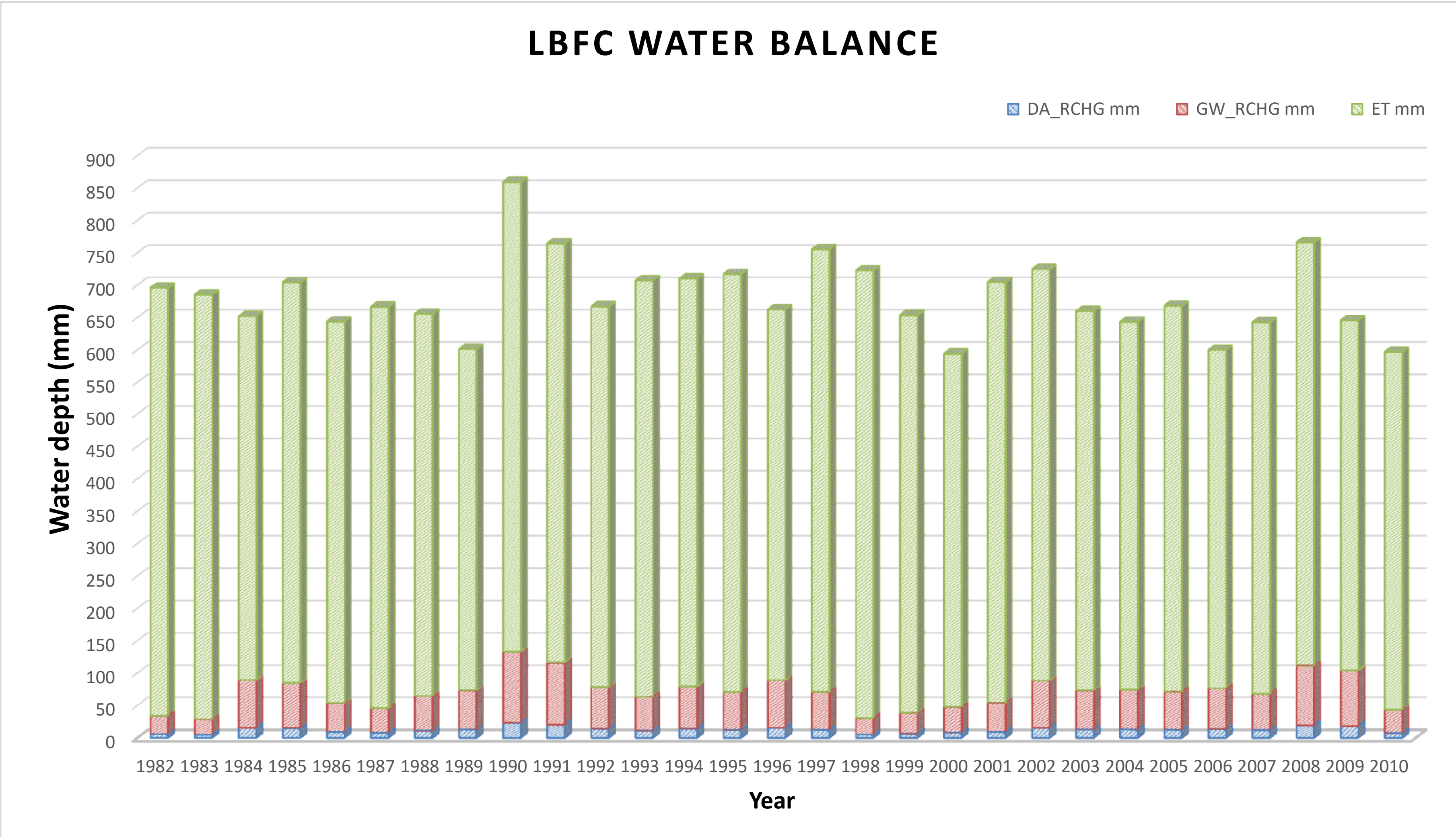
❖ Out of 29 years study period, historical dataset suggests in past there are 11 number of years those faced severe drought situation over the study basin.

❖ The developed MSDI (12-month time scale) is capable of predicting 9 drought years with very good accuracy whereas SPI is able to predict only 5 drought years.

❖ The drought assessment result was found to be in accordance with SWAT simulated water balance status of the study basin.

❖ The efficiency of MSDI is well observed from the quantitative assessment of various hydrological components like deep aquifer recharge, groundwater recharge and evapotranspiration.

Simulated Water balance status



CONCLUSION

- In case of MSDI it is observed that, with very good efficiency it replicates both severity and duration of drought events in result.

- $MSDI_c$ almost resembles the output characteristics of $MSDI_e$, but some under-prediction was found in case of $MSDI_e$.

- As a multivariate index, MSDI is capable enough to depict the effect of individual drought causing factors over the drought monitoring phenomena and has an edge over individual drought indices.

- This approach leads to its effective implementation over data scarce regions for more accurate drought monitoring.

- These results will be very much useful for policy makers to implement water conservation and distribution strategies in an optimal manner.

THANK YOU