A SPATIOTEMPORAL DEEP LEARNING FORECASTING MODEL FOR LONG-TERM DROUGHT PREDICTION

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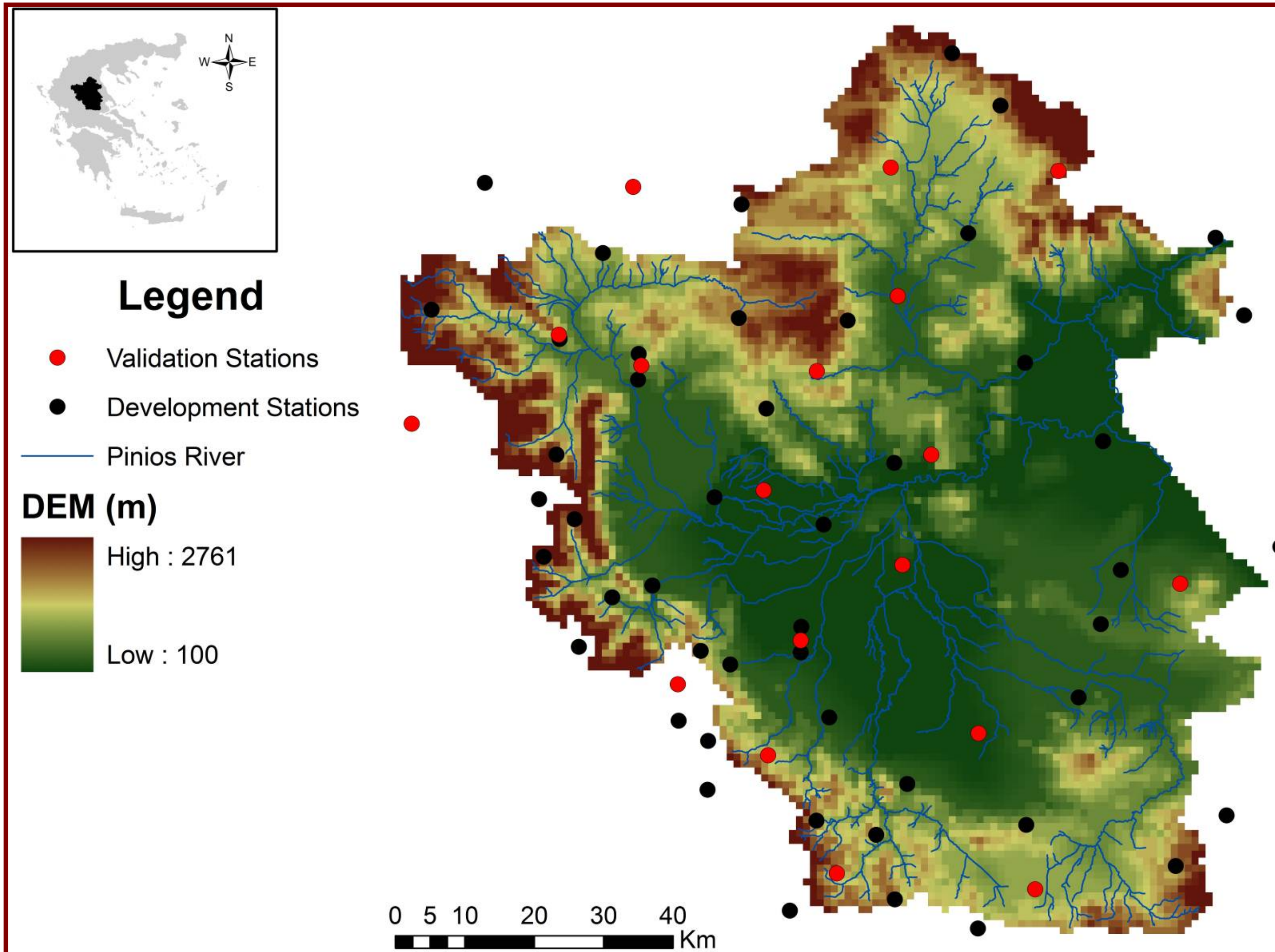
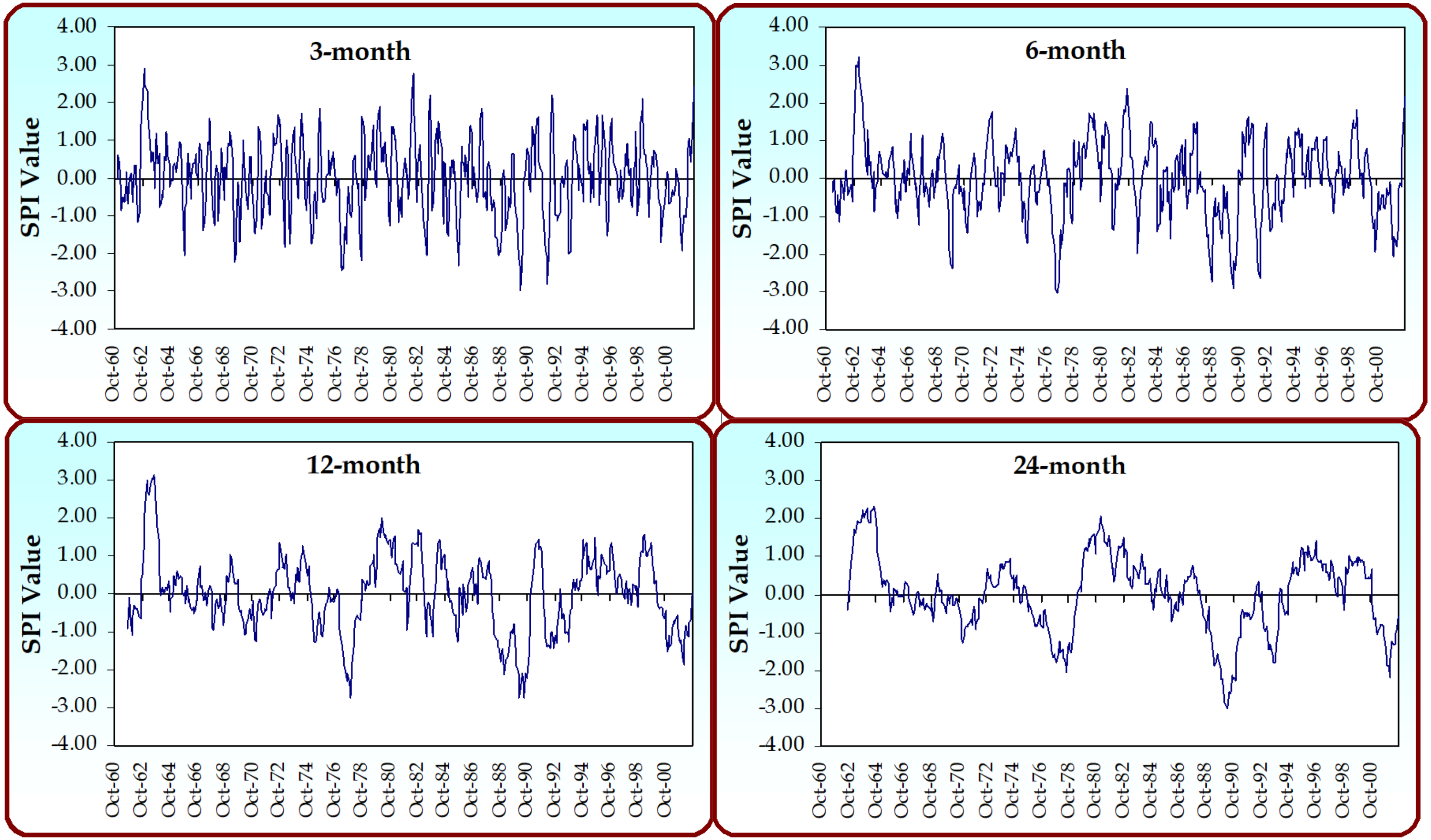
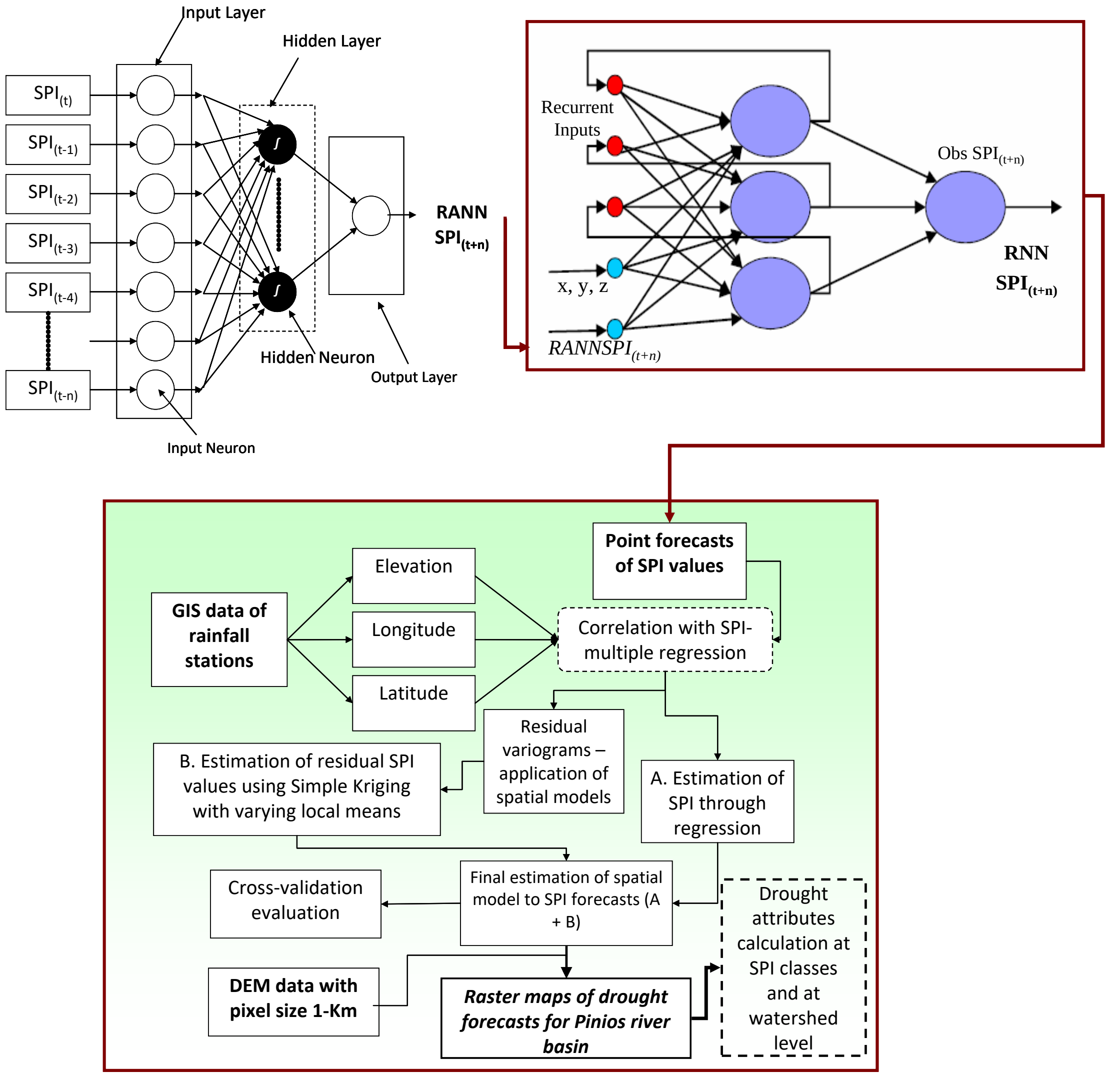
PINIOS RIVER BASIN AND DATABASE



SPI TIMESERIES



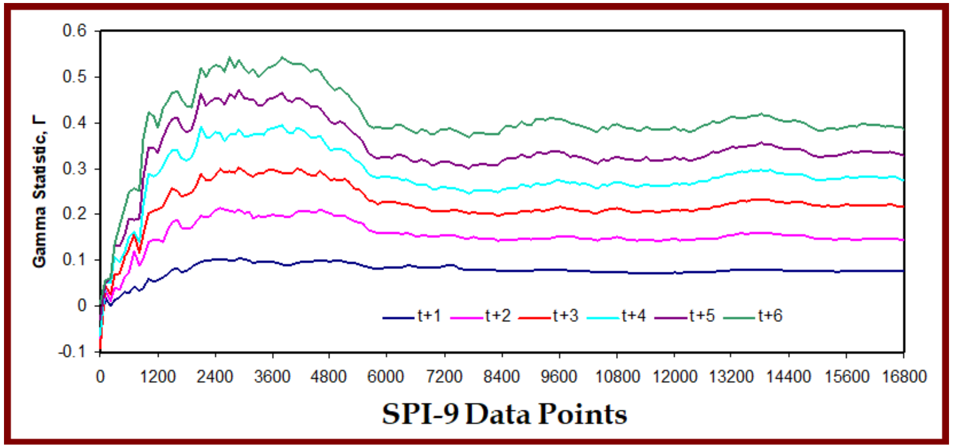
FLOW DIAGRAM OF THE FORECASTING DROUGHT SYSTEM



DETERMINATION OF INPUT DATASETS

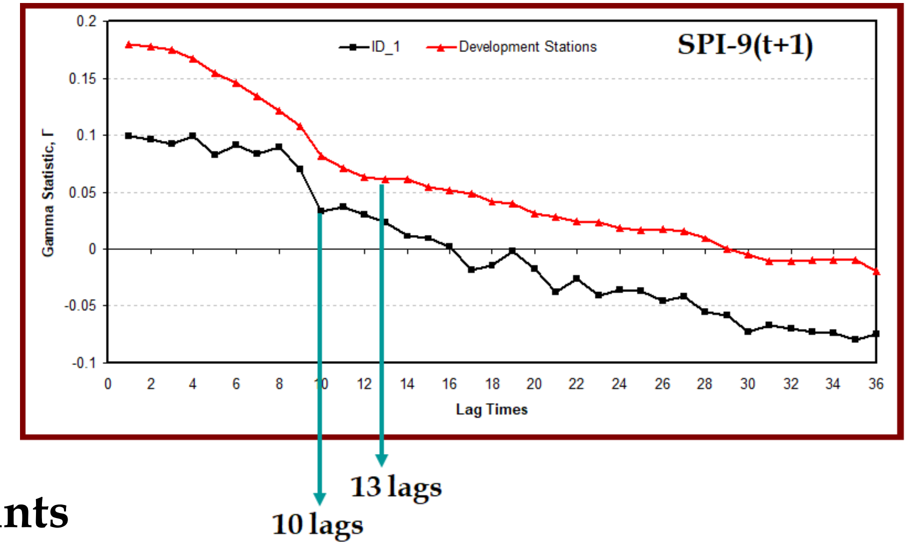
- Application of the **Gamma Test (GT)** to select the input variables (lagged SPI values) and the training data length prior to model construction
- Use of **Genetic Algorithms** for optimum input matrix determination for different lead times based on the GT

Identification of useful data points
Bootstrap resampling with replacement



10500 points = 30 ensembles * 350 data points were produced for each station

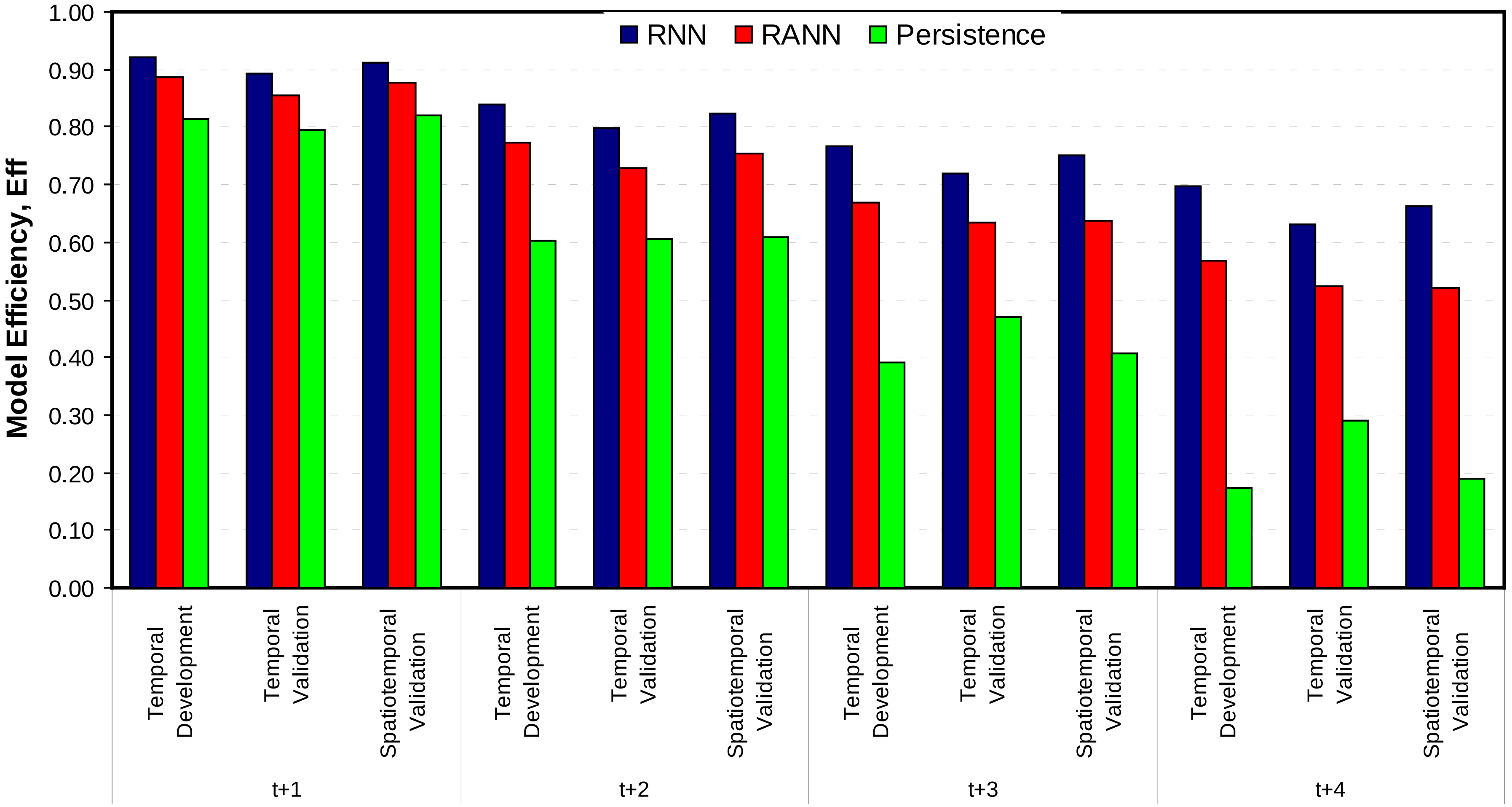
Identification of useful lag times
Lead time: 1-month



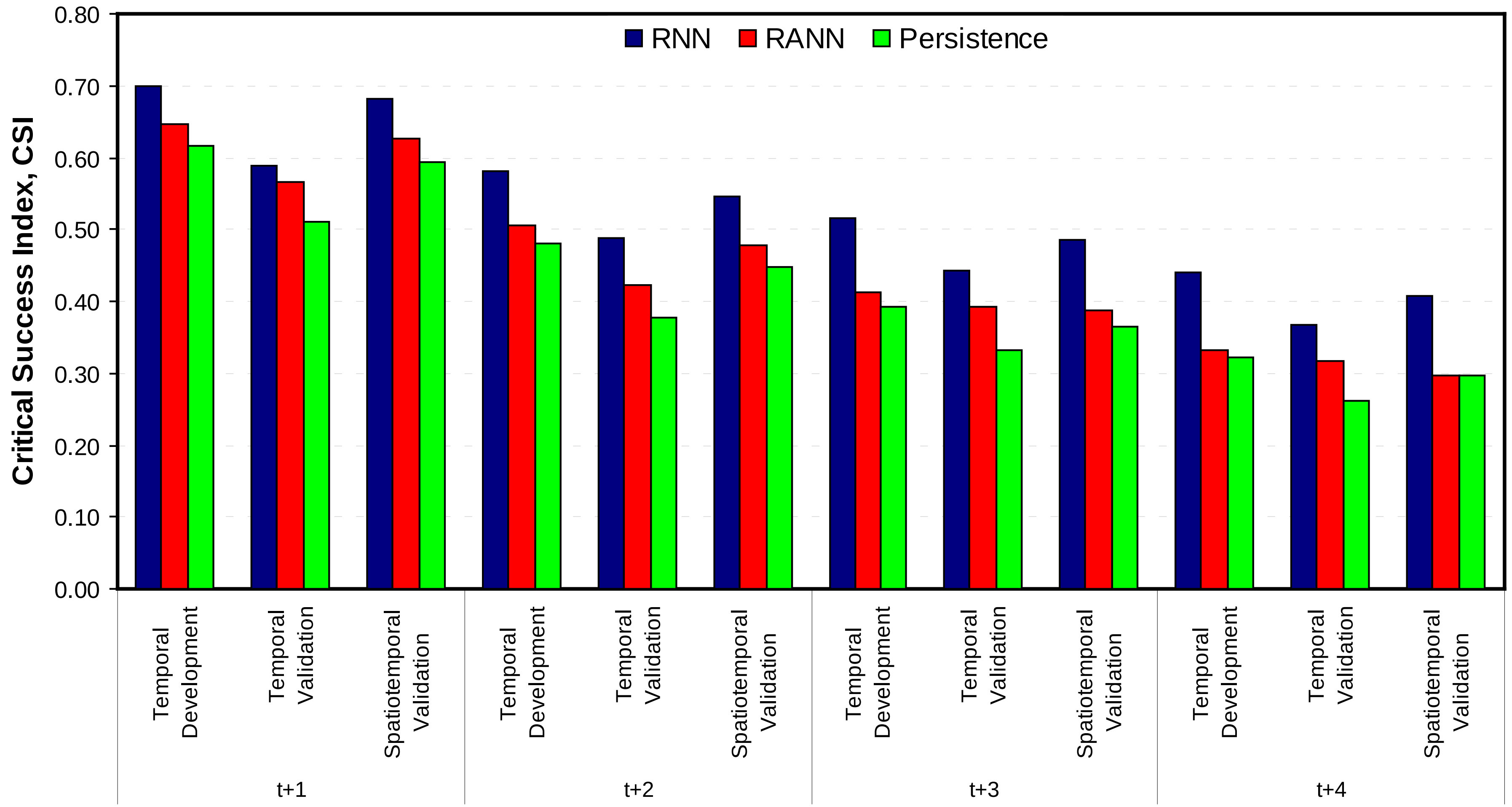
HYBRID SPATIOTEMPORAL FORECASTING SCHEME

- **Temporal forecasting**
- **Deep Recursive** (or iterative) multi-step artificial neural networks models for hydrologic period Oct 1960-Sep 1992 and temporal point validation (Oct 1992-Sep 2002) for 48 development stations
- **Spatial and Temporal Forecasting**
  - **Long Short-Term Memory** (LSTM) neural networks (Recurrent Neural Networks, RNNs) forecasting models using temporal forecasts and spatial information (spatial coordinates and elevation) of the rainfall stations
  - Spatiotemporal point validation of the developed ANN models for period Oct 1960-Sep 2002 for 18 validation stations
- **Testing forecasting accuracy** over different lead times (1 month up to 6 months ahead)
  - **Use of performance criteria** to evaluate the forecasting efficiency of the hybrid spatiotemporal forecasting model

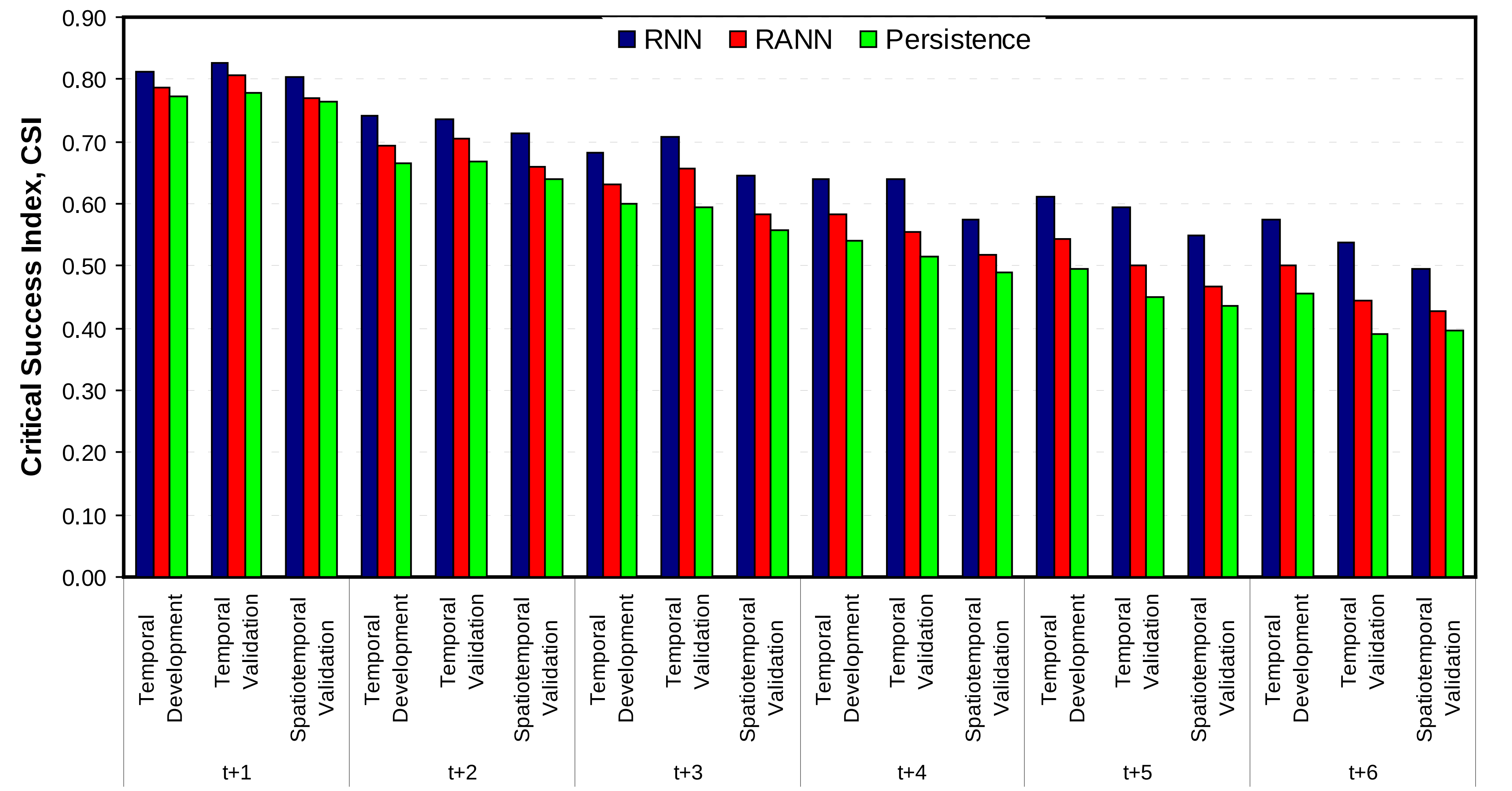
FORECASTING RESULTS (N.S. Eff)
SPI-9



FORECASTING RESULTS (CSI)
SPI-9

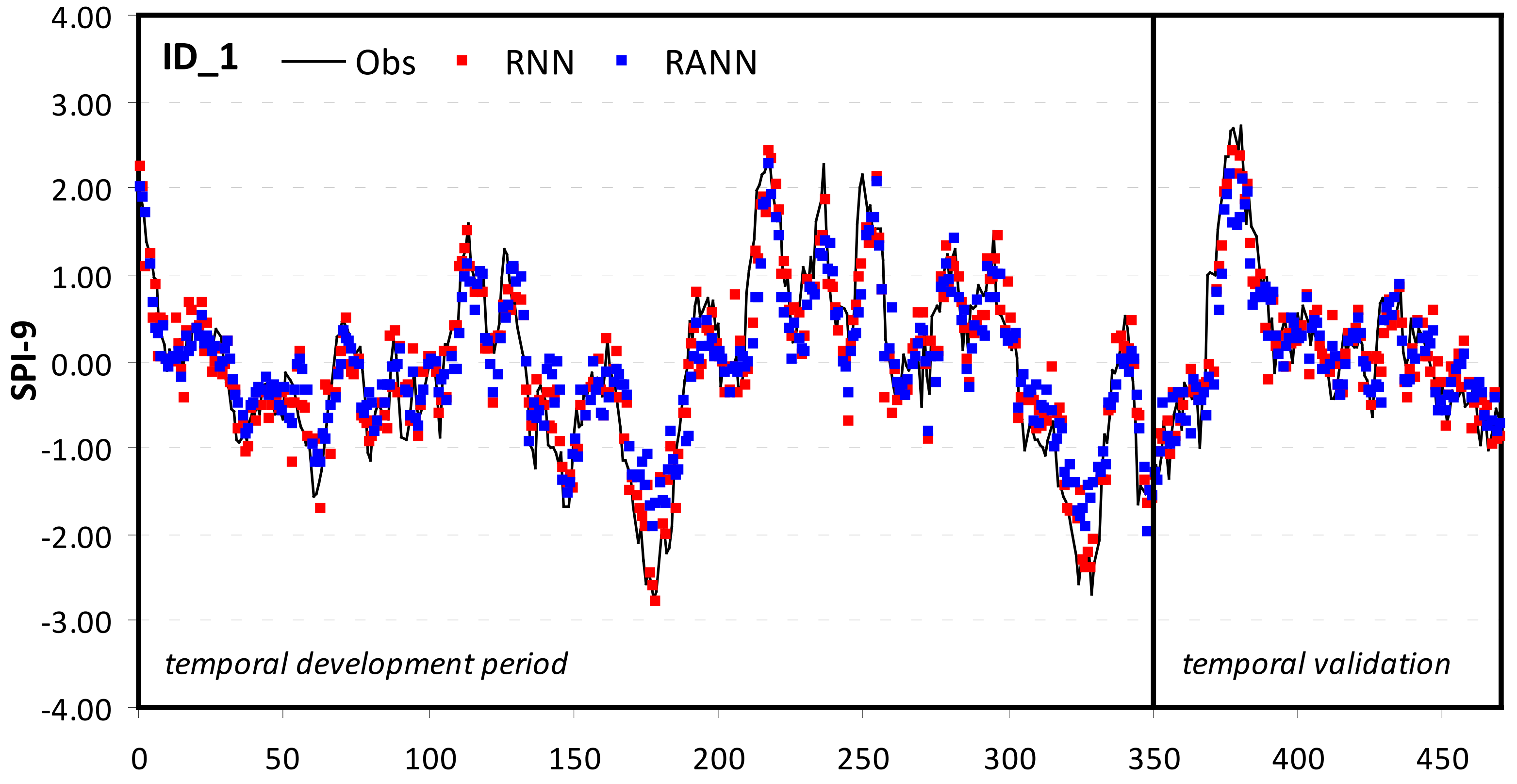


FORECASTING RESULTS (CSI)
SPI-24



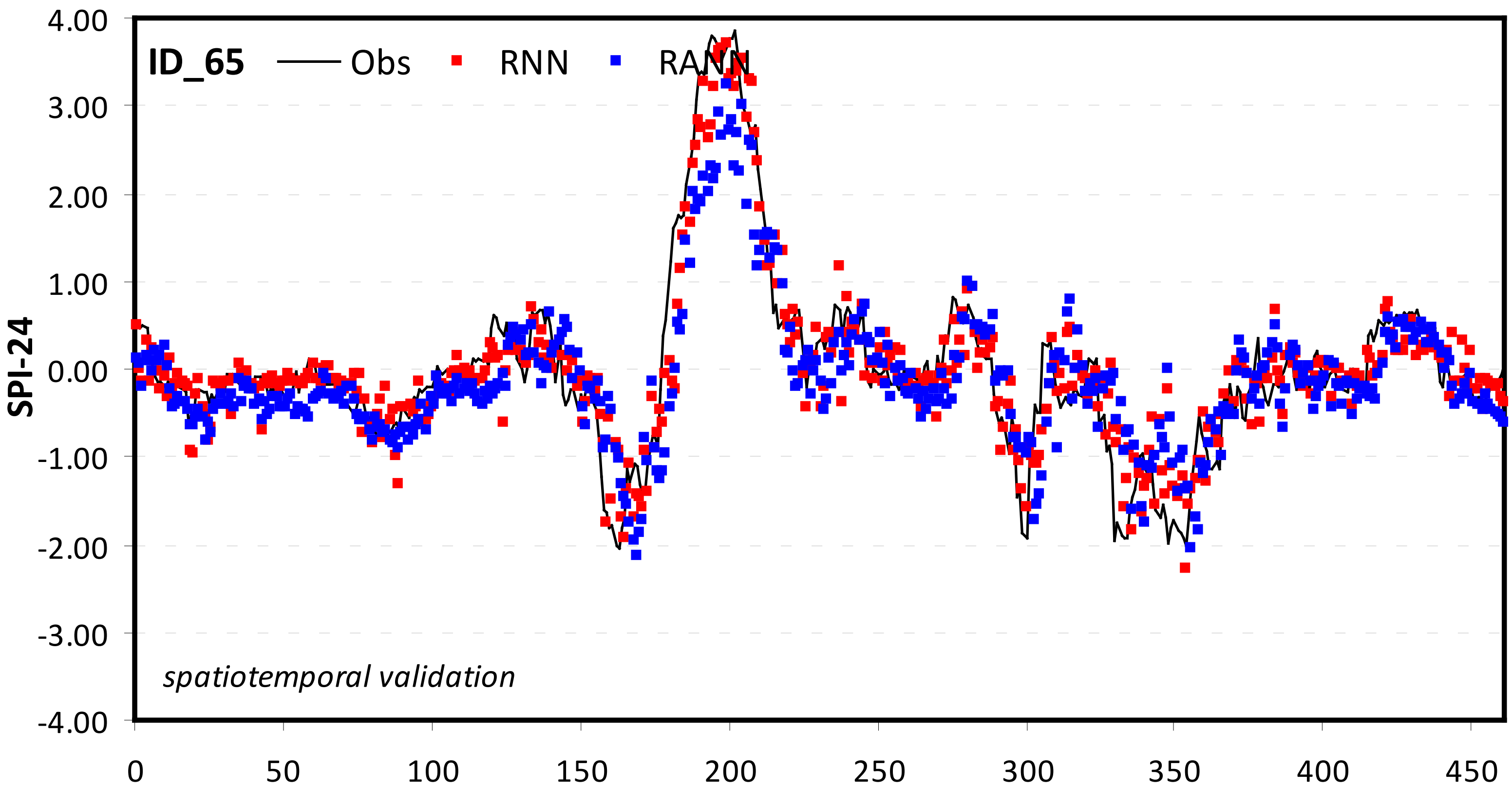
FORECASTING RESULTS
HYBRID SPATIOTEMPORAL FORECASTING MODEL

SPI-9: Operational use for 3-month ahead forecasting (3 months lead time)

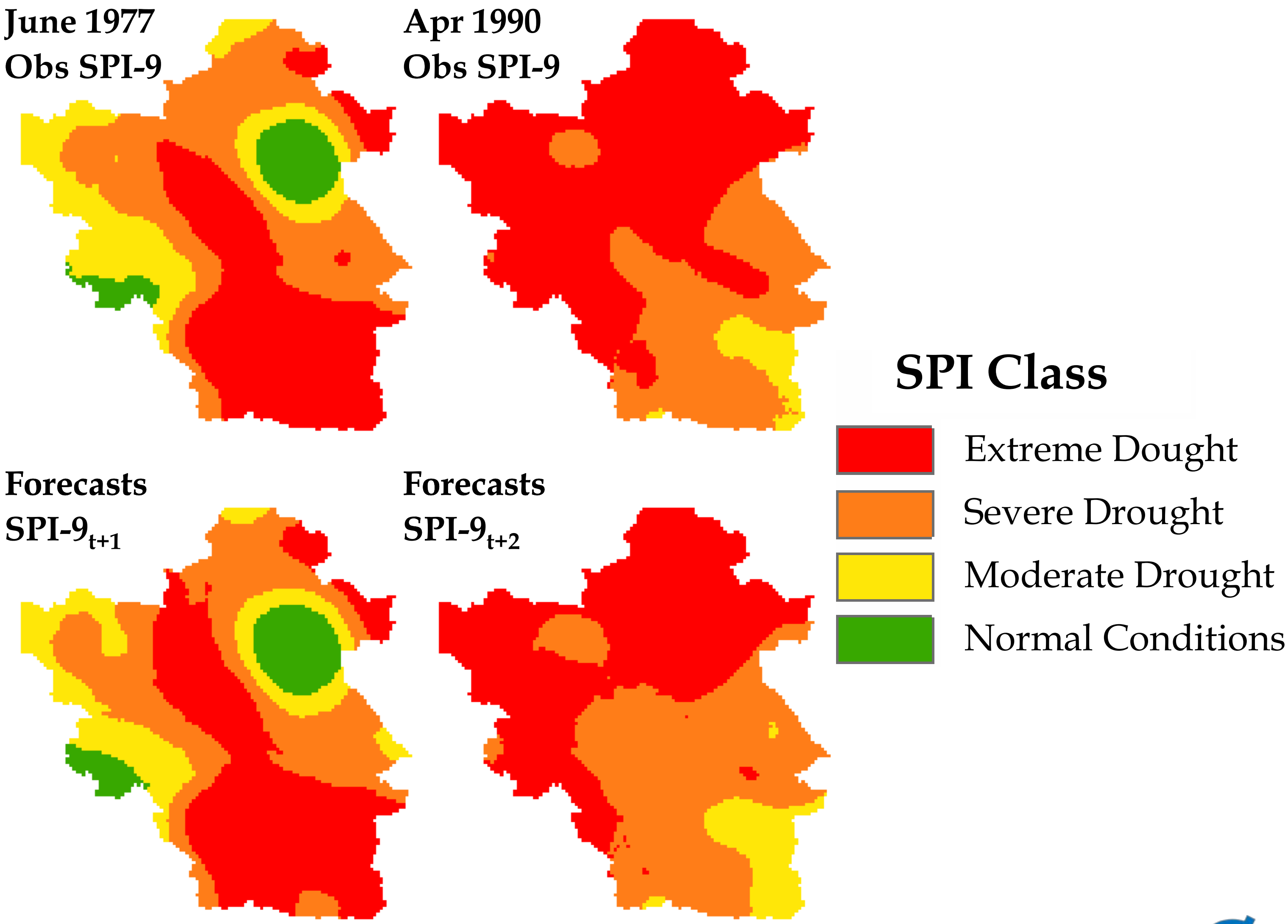


FORECASTING RESULTS
HYBRID SPATIOTEMPORAL FORECASTING MODEL

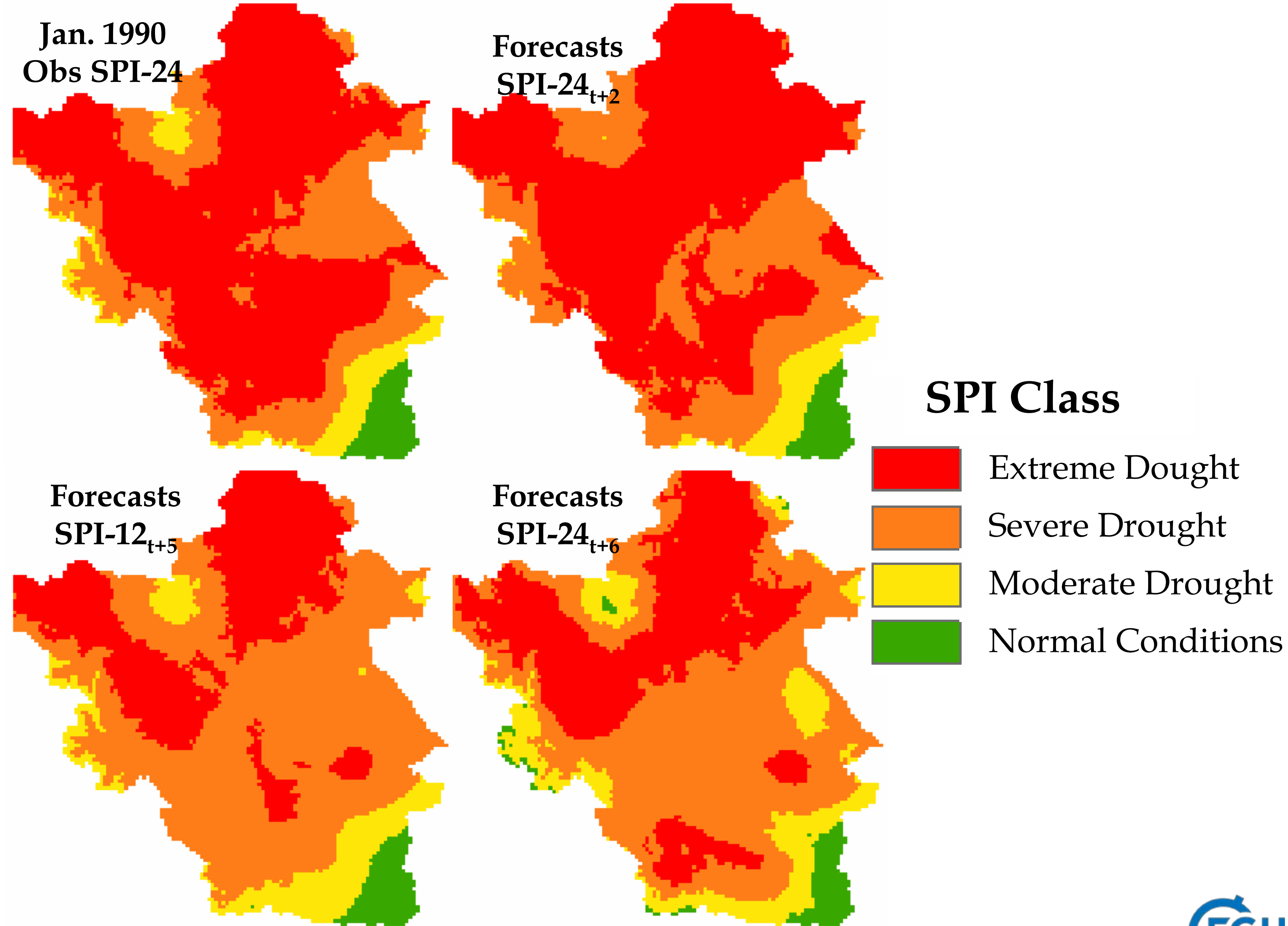
SPI-24: Operational use for 6-month ahead forecasting (6 months lead time)



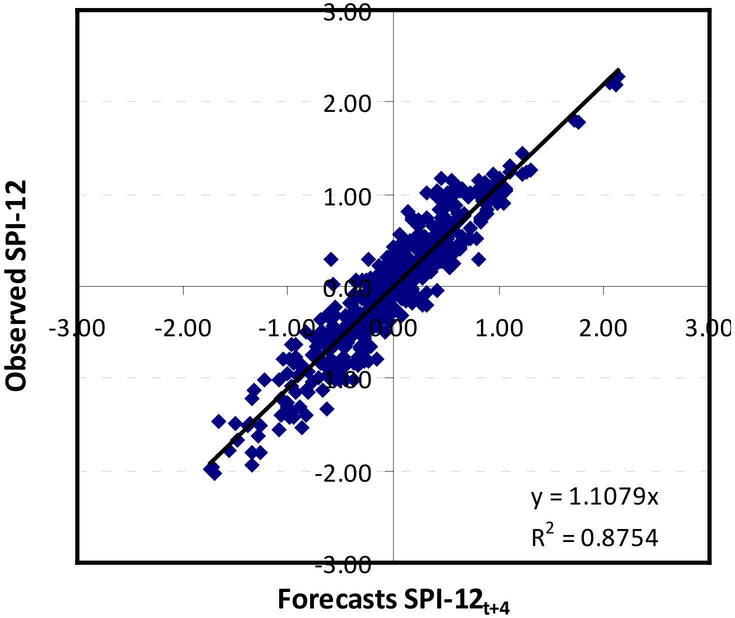
DROUGHT EARLY WARNING SYSTEM

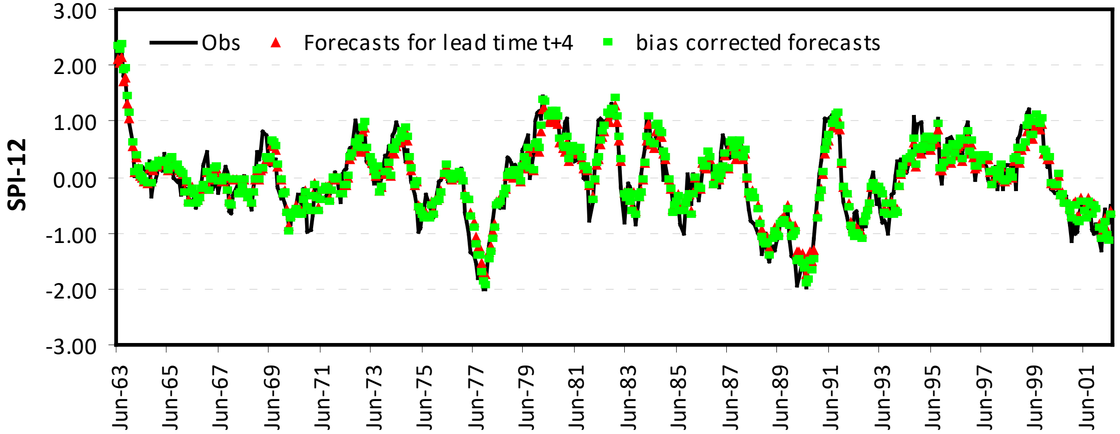


DROUGHT EARLY WARNING SYSTEM



AGGREGATED RESULTS AT WATERSHED SCALE (from 9500 pixels)





Statistics for forecasting SPI-12 4-months ahead at Pinios river basin (from 9500 pixels)

	Hybrid t+4	Hybrid $_{bias}$ t+4	Pers.
Eff	0.87	0.88	0.37
R	0.94	0.94	0.69
RMSE	0.26	0.25	0.57
MAE	0.21	0.20	0.45
CSI	0.55	0.60	0.40

CONCLUDING REMARKS

- The forecasting accuracy depends on the timescale of SPI. As time scale increases the forecasting horizon is also increased. Slightly underestimation of drought characteristics is observed as lead times are increased.
- Operational forecasting lead times: SPI-3_{t+1}, SPI-6_{t+2}, SPI-9_{t+3}, SPI-12_{t+4}, SPI-24_{t+6}
- Comparison of the forecasted drought maps with selected observed drought maps show that reliable and accurate predictions of drought characteristics (severity, duration and area) are estimated, hence the developed drought forecasting system could be used for operational drought management in the study river basin