



PREVIVAZ – Improving Weekly Streamflow Time Series Forecasts With the Current Hydrologic State of the River Basin

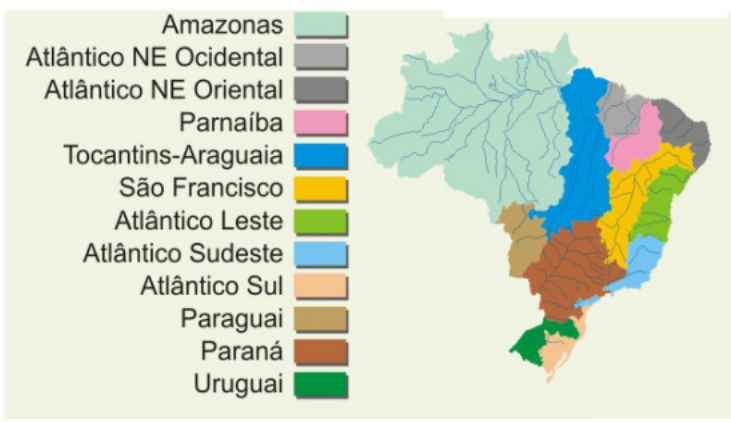
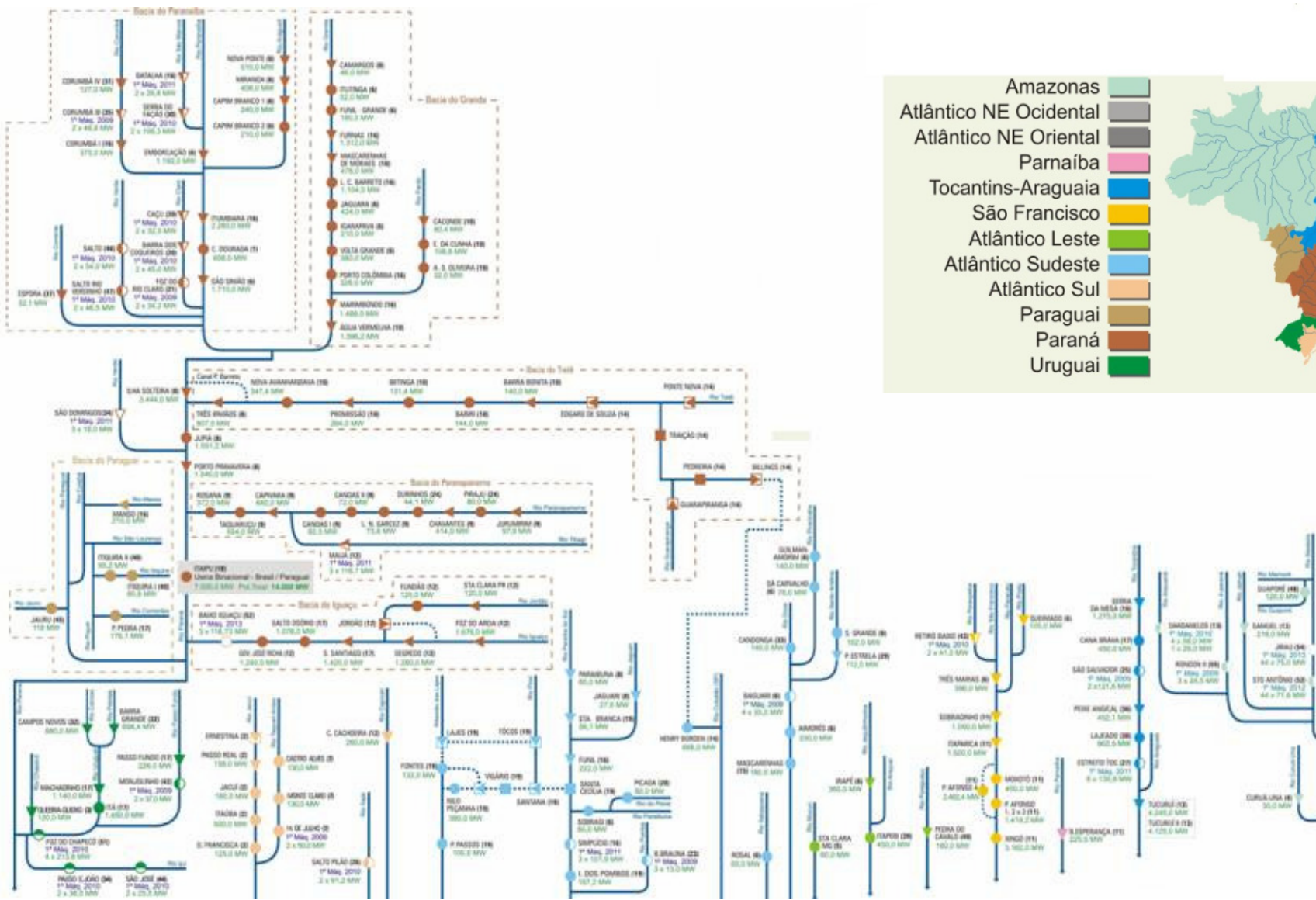
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OPERATION PLANNING OF BRAZILIAN HYDRO THERMAL SYSTEM



- Hydraulic based (> 80% Total Power Generation)
 - 12 large watersheds (cascades)
 - Many large reservoirs (> **1 km³**)
 - Inter-annual streamflow regulation
 - Other uses (e.g.: Flood control)
- Planning problem
 - Load supply with **minimum expected total cost** (Thermal Units operation + deficits)
 - Energetic Modeling System
 - Optimization models (planning, dispatch)
 - **Hydrological models (streamflow forecasting & scenarios generation)**

OPERATION PLANNING OF BRAZILIAN HYDRO THERMAL SYSTEM



OPERATION PLANNING OF BRAZILIAN HYDRO THERMAL SYSTEM



**Inflow
representation**

**Hydrological
models**

**Planning
Horizon**

Monthly inflow scenarios

GEVAZP

NEWAVE

5 years

Weekly inflow forecasts

Monthly inflow scenarios

**PREVIVAZ
GEVAZP**

DECOMP

2 months

Daily inflow
forecasts

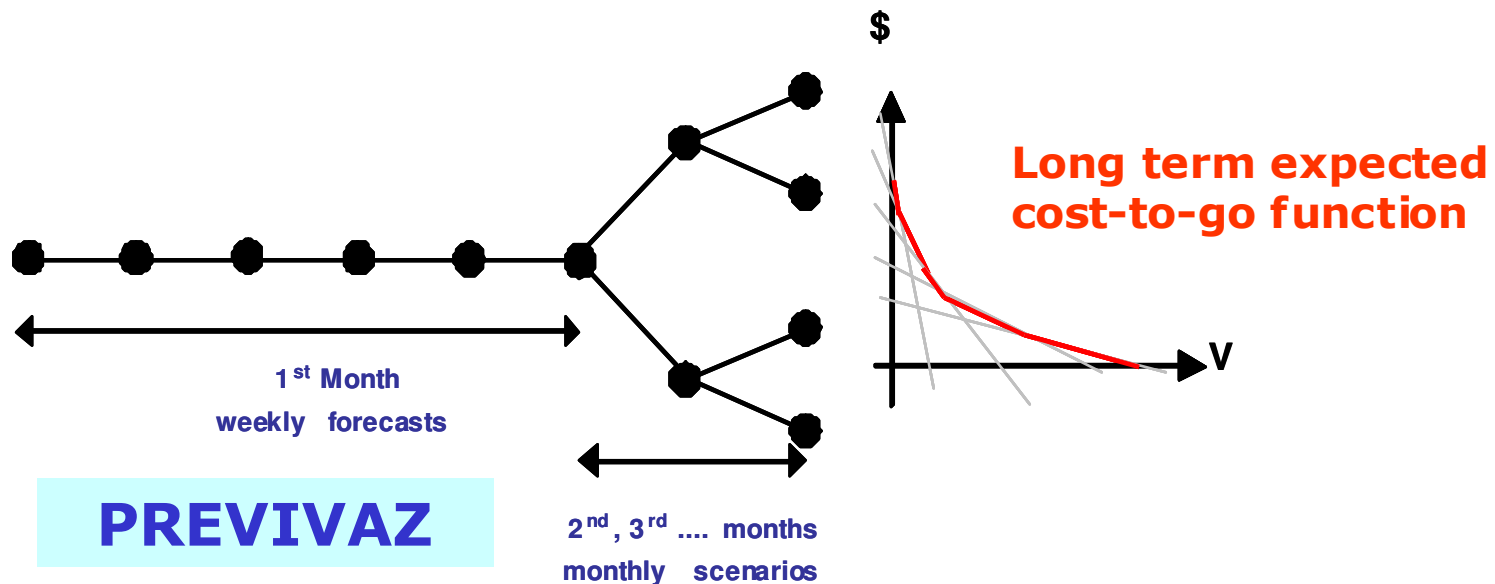
PREVIVAZH

DESSEM

2 weeks

OPERATION PLANNING OF BRAZILIAN HYDRO THERMAL SYSTEM

- (Short-term) Weekly Operation Scheduling
 - Operational constraints
 - Initial reservoirs' storage
 - Last weeks observed inflows
 - Future inflows: Weekly forecasts + monthly scenarios



- Stochastic univariate model
- Weekly streamflow forecasts (up to 6 weeks ahead)
- Used in short-term Planning Operation (DECOMP model)

PREVIVAZ model consider **different modeling strategies** based on:

- Linear ARMA(p,q) models, periodic/non-periodic
- Different **estimation methods** (moments, regression)
- Series transformation (Box & Cox)
- Best model: select by RMSE (cross-validation)

■ Models evaluated by PREVIVAZ

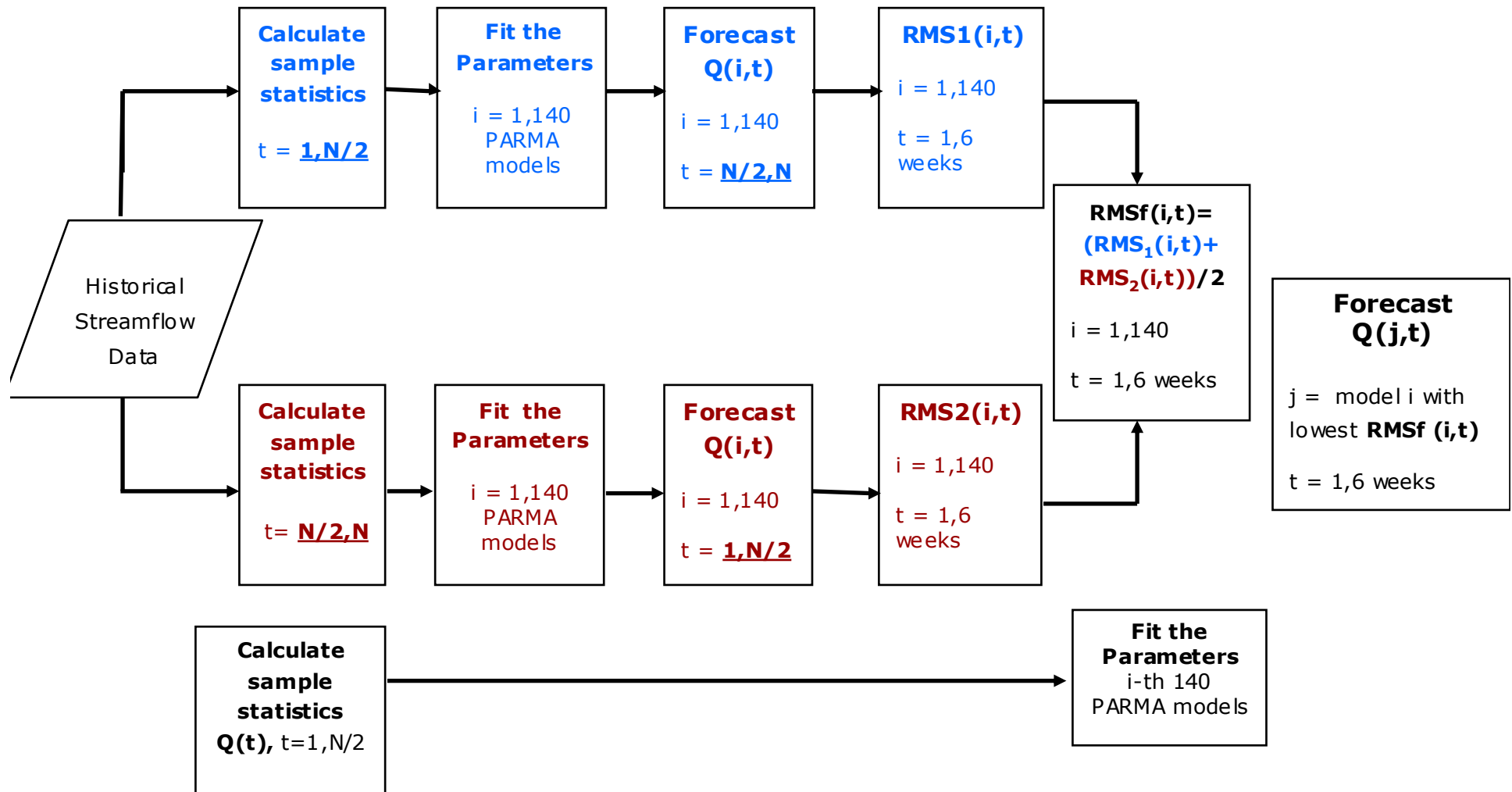
Forecasting Model	Characteristic	Estimation Method
<i>Constant</i>	<i>Annual average</i>	<i>Moments</i>
<i>Seasonal</i>	<i>Weekly average</i>	
<i>AR(p) (1 ≤ p ≤ 4)</i>	<i>Stationary correlation structure</i>	
<i>ARMA(p,1) (1 ≤ p ≤ 3)</i>		
<i>PAR(p) (1 ≤ p ≤ 4)</i>	<i>Seasonal correlation structure (weekly, monthly, quarterly, semi-annual)</i>	<i>Moments and regression</i>
<i>PARMA(p,1) (1 ≤ p ≤ 3)</i>		

=> Up to 140 models (including B&C transformation)

■ PREVIVAZ: estimation procedure

1. Evaluate the discharge series statistics for week t ;
2. Taking into account these series statistics, estimate M different linear PARMA models (up to 140);
3. For the i -th PARMA model, forecast $Q_i(t)$ on the period spanning the first half of historical record and calculate the mean RMS error over this period, RMS_{1i} ; repeat this for the M alternative PARMA models;
4. The same as 3, but for the period spanning the second half of historical record;
5. Evaluate each PARMA Model forecast, $i=1,\dots,M$, taking into account their mean RMS error, RMS_i (average of RMS_{1i} and RMS_{2i});
6. Rank the M alternative models with respect to their average RMS_i errors; chose the best one ($k = 1$);
7. With the model chosen in Step 6, forecast the discharge $Q^*(t)$ to week t and calculate the forecast confidence intervals;
8. Repeat the procedure describe in Steps 1 to 7 for the next weeks ($t+1$ to $t+5$). The last weeks ($t,\dots,t-4$) forecast will be considered as trend to the model's choice for the next weeks($t+1,\dots,t+5$)

PREVIVAZ: estimation procedure



- Problem: some **great errors** caused by
 - Unlikely large/small forecasts obtained on calibration period (inducing the rejection of an alternative model)
 - Weak time correlation structure
 - Last observed values statistics different from the historical record ones (short record?)
 - Unlikely large streamflow forecasts after inversion (from B&C transformed values)

=> Unlikely $Q(t)$ variations

How could these unlikely forecasts be eliminated on estimation procedure?

How could these unlikely forecasts be rejected on estimation procedure?

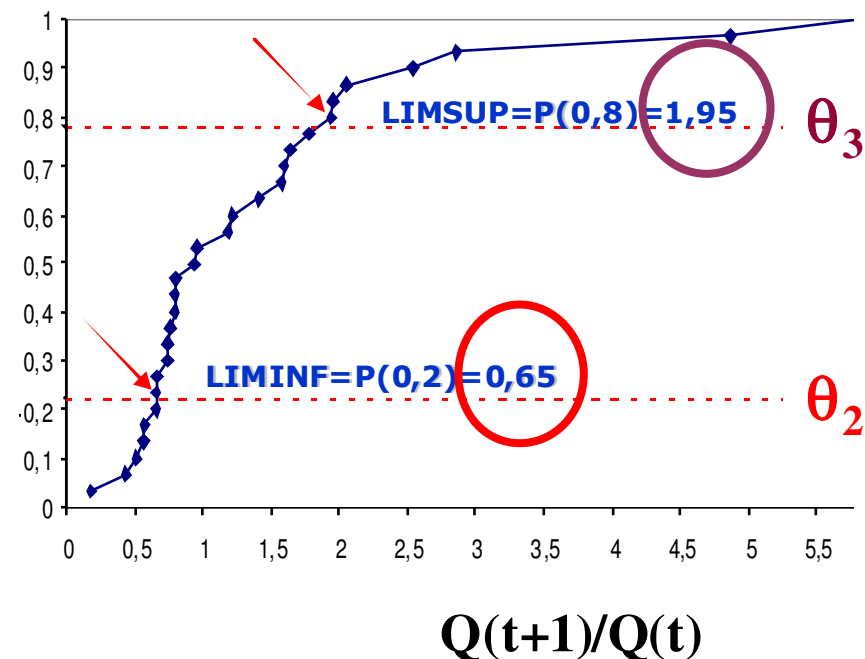
- Approach: **to limit the $Q(t)$ variations between two consecutive weeks:**
 - Analyzing the $Q(t)/Q(t-1)$ *cumulative distribution function* (historical record)
 - Defining probabilities of **minimum/maximum acceptable** $Q(t)$ variation
 - With the last observed $Q(t-1)$ values, defining a **range (bounds) of acceptable** $Q(t)$ forecasts
 - Once this range has been defined, taking it into account on model selection procedure

How the forecast bounds can be defined?

1) Build the $Q(t+1)/Q(t)$ *cdf* (from historical record), having defined:

- i) The **period** (week, month etc) where the *cdf* will be estimated;
- ii) The θ_1 ranges of **$Q(t)$ magnitude** to which the *cdf* will be estimated

2) Establish the minimum/maximum **probabilities of non-exceedance** $\{\theta_2, \theta_3\}$



Thus, with the **$Q(t-1)$ value** no week $t-1$:

Lower bound = $Q(t-1) * (\text{value corresponding to the } \theta_2 \text{ percentile})$

Upper bound = $Q(t-1) * (\text{value corresponding to the } \theta_3 \text{ percentile})$

How the forecast bounds can be defined?

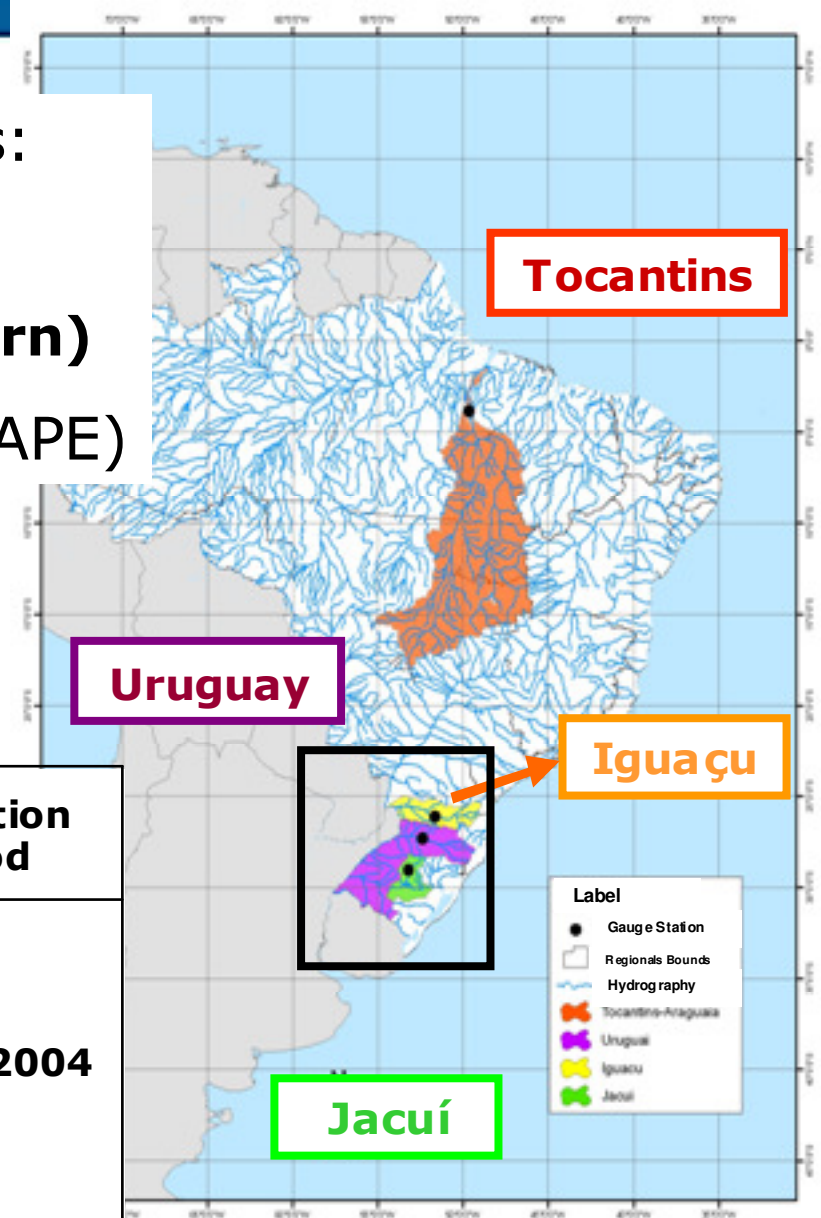
1. Define (i) the period on which the cdf will be estimated, (ii) the q_1 streamflow magnitude ranges, (iii) the minimum/maximum allowed variation probabilities $\{q_2, q_3\}$;
2. With the procedure described in Item 2.1 calculate the $i=1, \dots, M$ alternative PARMA models to the week t and rank ($k=1, \dots, M$) them following their average RMS_i errors;
3. Estimate the q_1 variation ratio ($Q(t)/Q(t-1)$) cdf's from the historical inflow time series;
4. From these q_1 cdf's and the $\{q_2, q_3\}$ values, calculate the q_1 discharge variation bounds $\{LB_k(t), UB_k(t)\}$;
5. For the $k=1, \dots, M$ alternative models, calculate $Q_k(t)$ and verify if it lies in the correspondent (according to the magnitude of $Q_k(t)$) bounds $[LB_k(t), UB_k(t)]$; if not, $Q_k(t)$ will be replaced by the lower or upper bound, and the their RMS_k error, re-evaluated; a new ranking ($k'=1, \dots, M$) is then performed;
6. Taking into account the whole time series, and the ranking done in Step 5, evaluate if the best model ($k'=1$) forecast $Q_1(t)$ lies in $[LB_1(t), UB_1(t)]$;
7. If the Step 6 verification does not hold, take the second best model ($k'=2$) and perform again the Step 5 verification; if this second verification does not hold neither, take the third best model ($k'=3$) forecast $Q_3(t)$ and so on, until finding the best model ($k^* = k'$) whose forecast respect the bounds defined in Step 4 and that will be retained thereafter;
8. Repeat the procedure described in Steps 1 to 6 to the next 5 weeks ($t+1, \dots, t+5$).

CASE STUDY

Gauge Stations in 4 Brazilian Basins:

- Tocantins (Northern)
- Jacuí, Uruguay and **Iguaçu (Southern)**

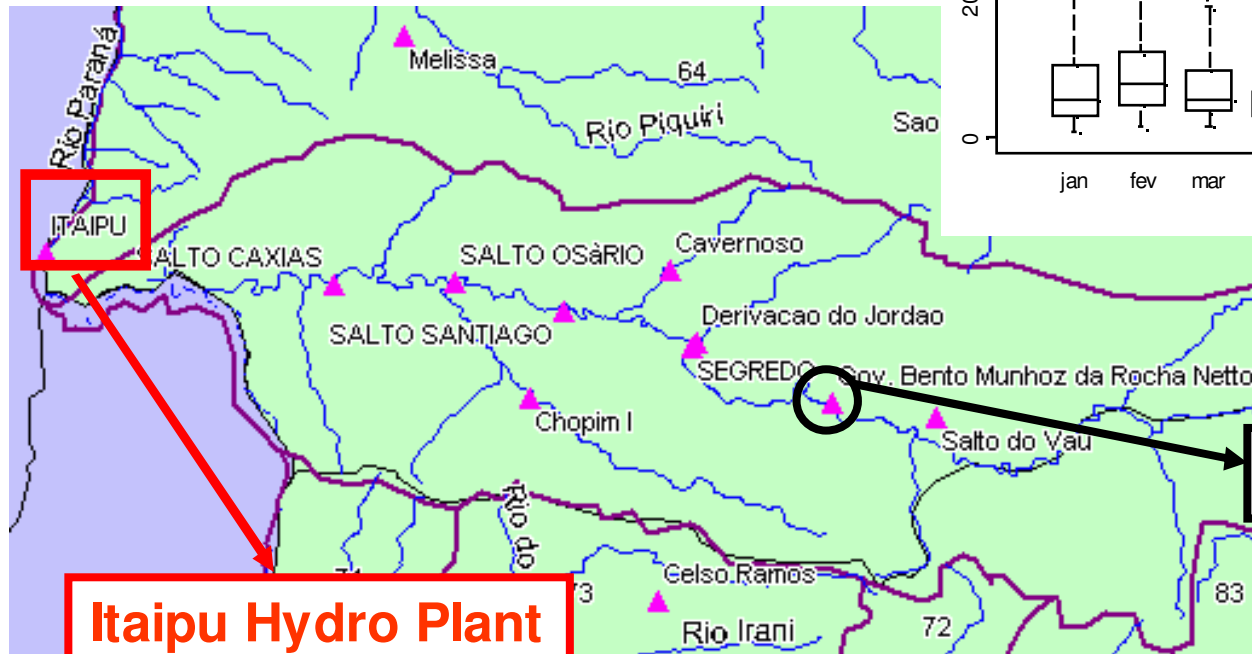
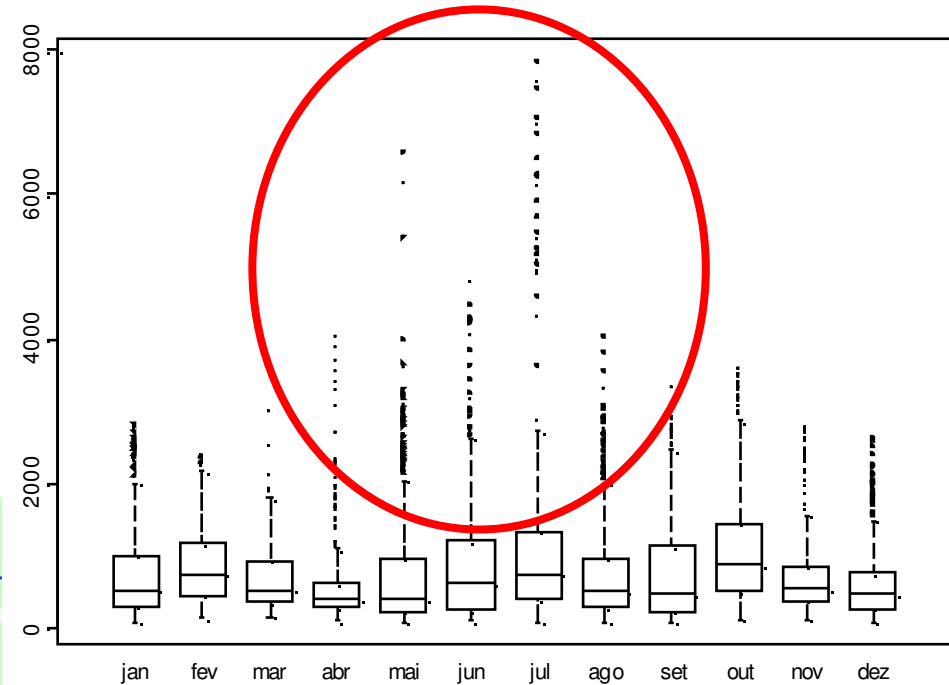
Different goodness-of-fit criteria (MAPE)



Watershed	Gauge station	Estimation period	Validation period
Iguaçu	Foz do Areia	1969 – 1994	1995 – 2004
Uruguay	Itá	1973 – 1994	
Jacuí	Passo Real	1940 – 1994	
Tocantins	Tucuruí	1970 – 1994	

CASE STUDY – Foz do Areia

Mean	780 m³/s
S.Deviation	710 m³/s
Maximum	7830 m³/s
Minimum	68 m³/s



Foz do Areia Hydro Plant

Itaipu Hydro Plant

CASE STUDY – Foz do Areia



- Foz do Areia gauge station
 - 1969 – 1994 : parameter estimation
 - 1995 – 2004 : validation

Bounds

- *Cdf* estimation: weekly, monthly, quarterly and semi-annual;
- 4 $Q(t)$ magnitude ranges: $\{0;25\%;50\%;75\%;100\%\}$;
- Minima/maxima probabilities: $\{10\%;90\%\}$, $\{20\%;80\%\}$ and $\{30\%;60\%\}$

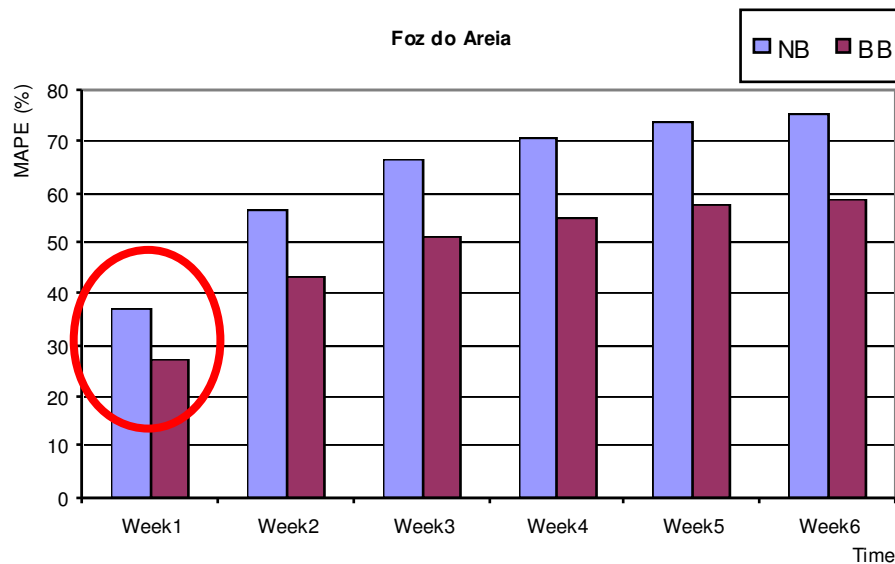
=> 48 bounds parameterizations to be evaluated

CASE STUDY – Foz do Areia

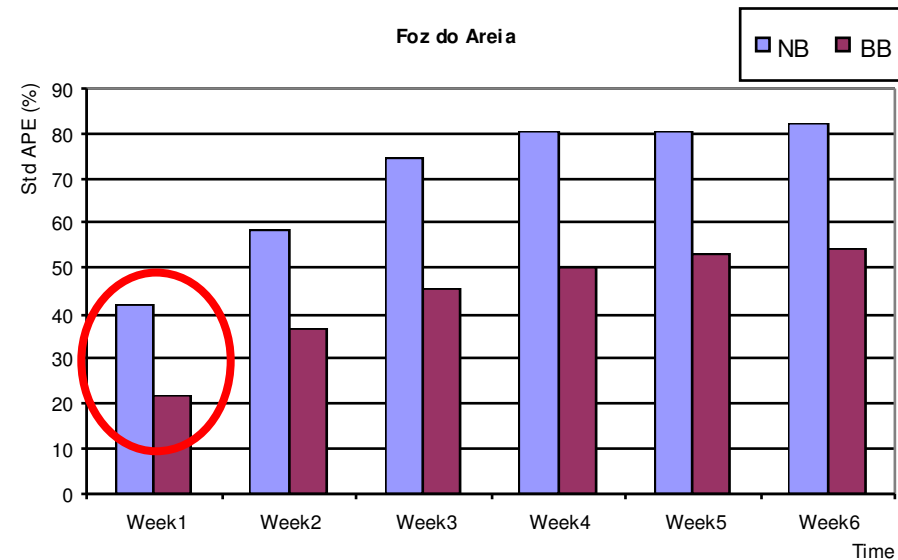
Goodness of fit criterion: Mean Absolute Percentage Error

Best bounds parameterization leads to:

- Average error reduction: **17.4 %** (6 weeks)
- Great reduction of Error standard deviation : **43.1%** (6 weeks)



Reduction : 26.4 % (1st Week)



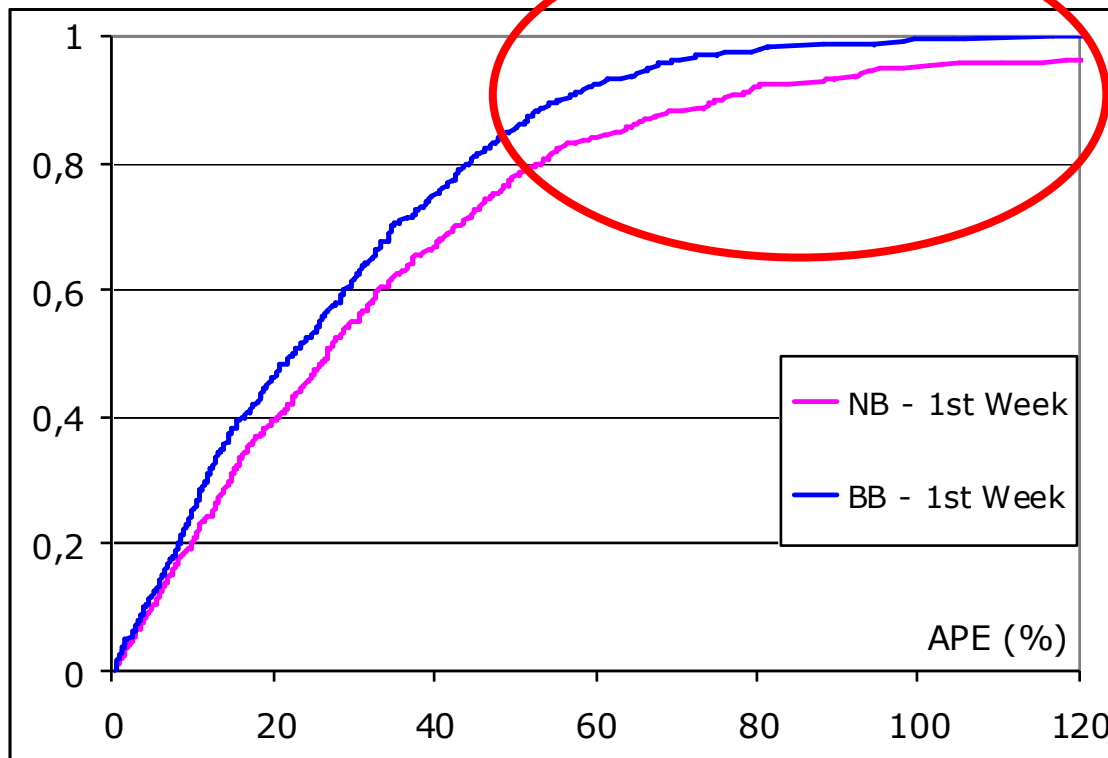
Reduction : 50.2 % (1st Week)

CASE STUDY – Foz do Areia

Goodness of fit criterion: Mean Absolut Percentage Error

Best bounds parameterization leads to:

- Remarkable reduction of large errors (over the whole period)



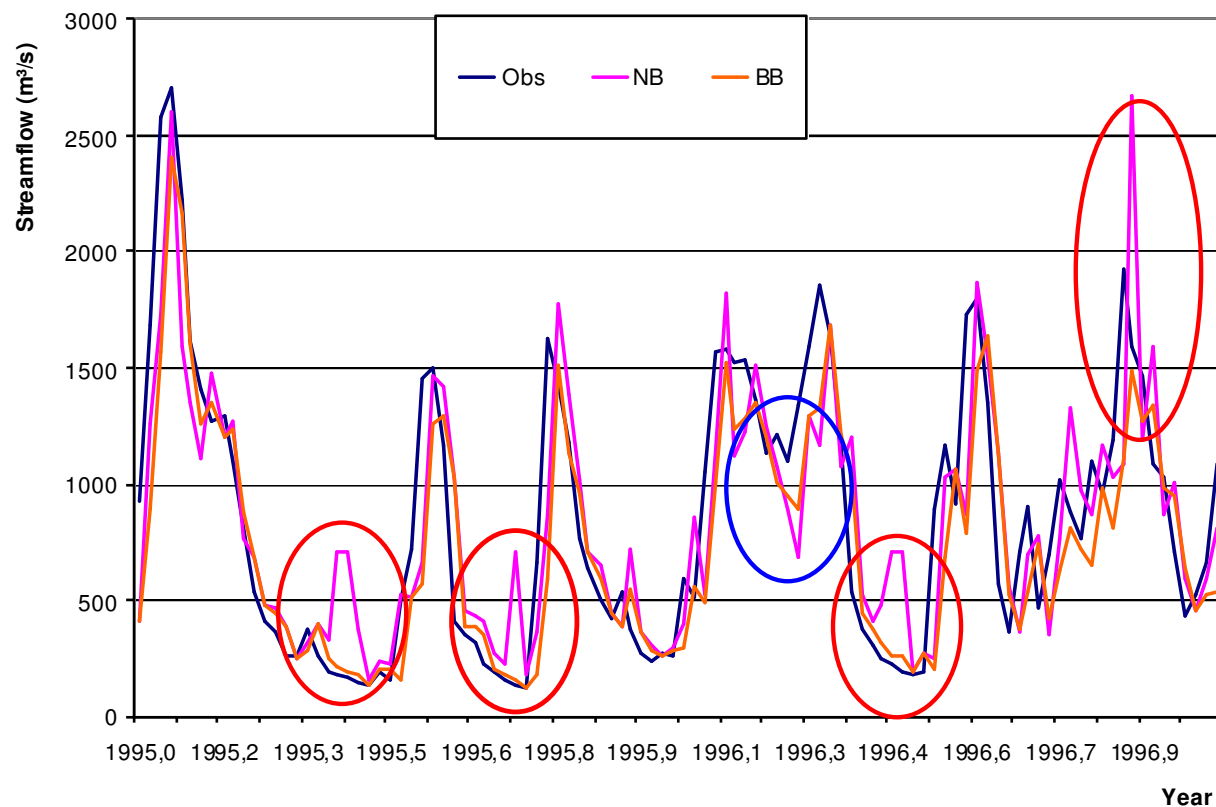
Week	Q25%	Q50%	Q75%	Q95 %
1	13,85	9,98	16,12	33,91
2	6,65	10,08	12,26	31,42
3	4,17	4,79	10,57	31,26
4	-4,05	1,98	14,56	32,78
5	0,76	-2,32	14,55	28,75
6	11,03	5,80	11,40	28,27

CASE STUDY – Foz do Areia

Goodness of fit criterion: Mean Absolut Percentage Error

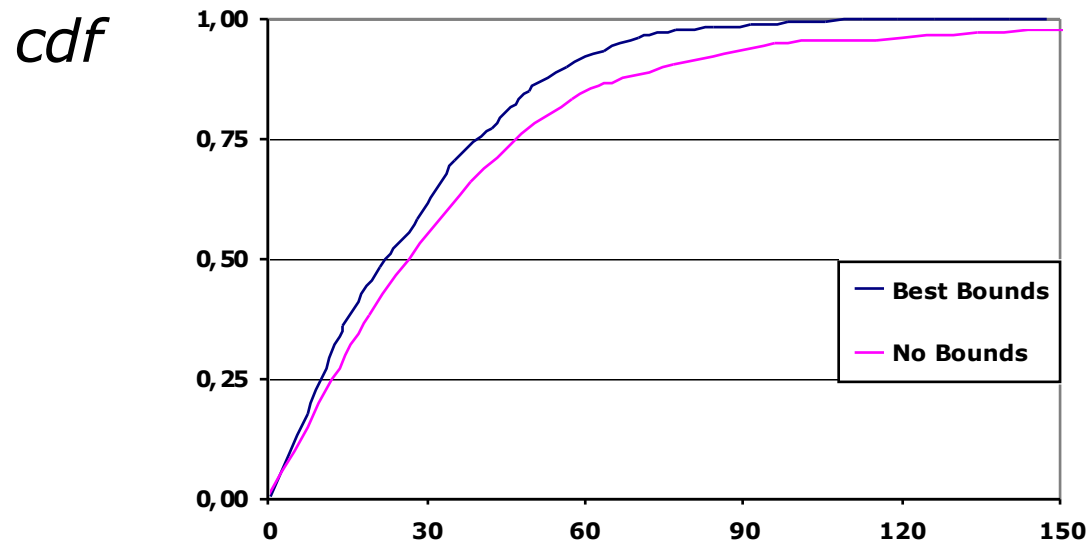
Best bounds parameterization leads to:

- Reduction of errors on recession periods



CASE STUDY – Foz do Areia

1st Week Statistics



1st Week	Mean	St. Dev.	Q25%	Q50%	Q75%	Q95%
No Bounds	37,16	42,07	12,43	26,79	47,32	98,26
Best Bounds	27,35	20,94	10,71	24,12	39,69	64,95
Reduction %	26,39	50,23	13,85	9,98	16,12	33,91

CONCLUDING REMARKS

- Considering the bounds on model selection led to smaller mean forecast errors over the validation period;
- A remarkable reduction of large errors has been obtained;
- The error reduction were observed to the 6 weeks;
- Similar results were obtained with the other metrics (RMSE, Nash-Sutcliffe index) considered in our study;
- Similar results were obtained to the other basins, especially to the other 2 basins in Southern Brazil (Uruguay and Jacuí);
- Other results (not presented) showed that the application of this approach to other watersheds whose hydrological features are similar to the ones considered herein leads to a similar error reduction pattern.

ONGOING WORK AND FUTURE DEVELOPMENTS



- Development of an automatic procedure aiming to define the “best bounds parameterization” to each series, taking into account:
 - Antecedent (wet/dry) conditions
 - Precipitation ; Moisture (estimated)
 - Seasonal hydrological response patterns
- Integrate daily forecasting (conceptual & stochastic) model results in 1st week PREVIVAZ modeling;
 - with forecasted “some-days ahead” precipitation
- Investigate the constraining of last weeks (5th/6th) PREVIVAZ modeling by a monthly forecasting model results.
 - Scenarios generation in 5th/6th weeks ahead?

Thank you !!!

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