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## Kalman Filter and Box-Jenkins Techniques for Monthly and Annual Streamflows Prediction in Northern Algeria

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**Keywords:** Kalman Filter, Box-Jenkins, Stream Flows, Prediction, Algeria

Analyzing stream flow records can give significant ideas for both past and future characteristics of stream flows. Therefore, recording and analyzing stream flow measurements have highly important roles in water resource management, planning and design. Unfortunately, hydrological processes, such as stream flows, are very complex because they are dependent of many hydro-physiographic parameters, additionally they vary with time and space. To cope with these difficulties, two different techniques have been applied to the modeling and prediction of the monthly and annual stream flow data in Northern Algeria: 1) the conventional time series approach of Box-Jenkins (BJ), a class of stochastic processes that is known by its good modeling of hydrological time series, so as stream flows, and many other environmental relating variables. Such time series are generally characterized by a strong temporal dependence between successive observations. In addition, they can be represented by some linear models, which means that the concerned time series can be considered as the output of a linear system whose input is a discrete white noise. Unfortunately, this class of stochastic processes presents the limitation of working under the restrictive assumptions of stationary and normality, in addition it needs large amount of available data, 2) the adaptive prediction approach of Kalman filtering (KF) is considered to be one of the most well-known and often-used significant mathematical tools that can be used for stochastic estimation from noisy measurements. It is as an optimal recursive data processing algorithm, which is constituted essentially by a set of 5 mathematical equations that implement a predictor-corrector type estimator that is optimal, in the sense that it minimizes the estimated error covariance, when some presumed conditions are met. Those equations are recursive and present the great advantage to provide accurately with the prediction error. The obtained results show the superiority of Kalman filter. The best model is sought using the performance measures including mean square error and determination coefficient.

## Kalman Filter and Box-Jenkins Techniques For Monthly and Annual Streamflows Prediction in Northern Algeria

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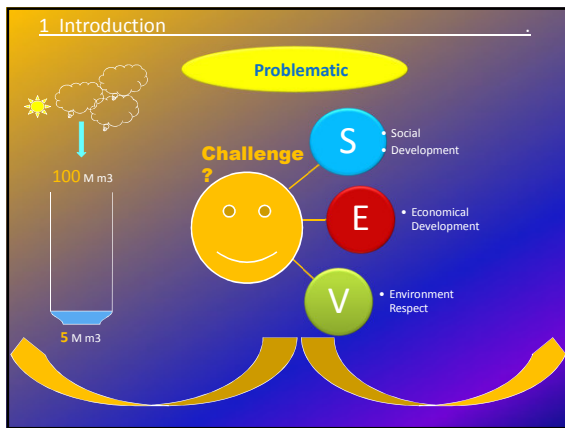
2) Research laboratory of Water Sciences (LRS-EA), Ecole Nationale Polytechnique (E.N.P)-Algiers, 10 Av. Hacène-badi BP182, El-Harrach 16200-Algeria.

### Outlines

1. Introduction
2. Material and methods
3. Results and discussion
4. Conclusion

2

### 1 Introduction



**Problematic**

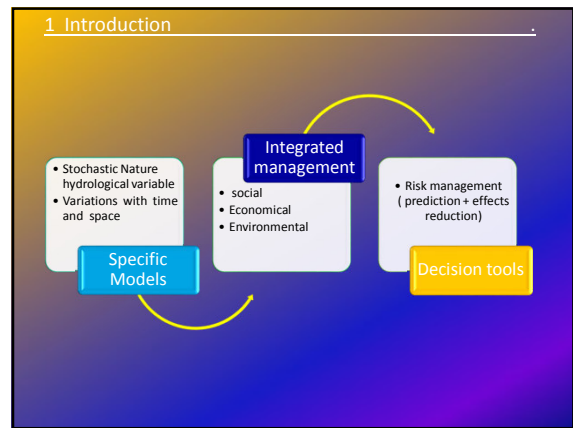
**Challenge**

- S** • Social Development
- E** • Economical Development
- V** • Environment Respect

100 M m<sup>3</sup>

5 M m<sup>3</sup>

### 1 Introduction



**Specific Models**

- Stochastic Nature hydrological variable
- Variations with time and space

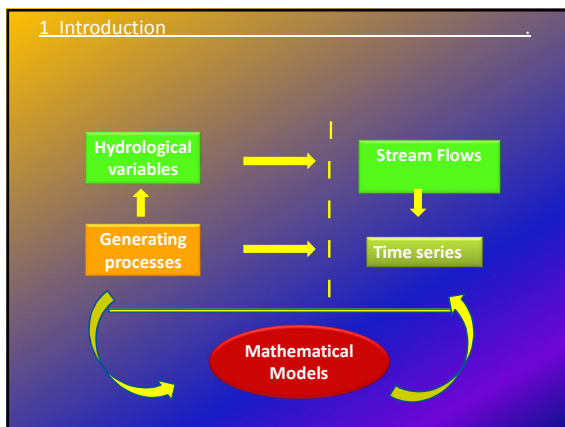
**Integrated management**

- social
- Economical
- Environmental

**Decision tools**

- Risk management (prediction + effects reduction)

### 1 Introduction

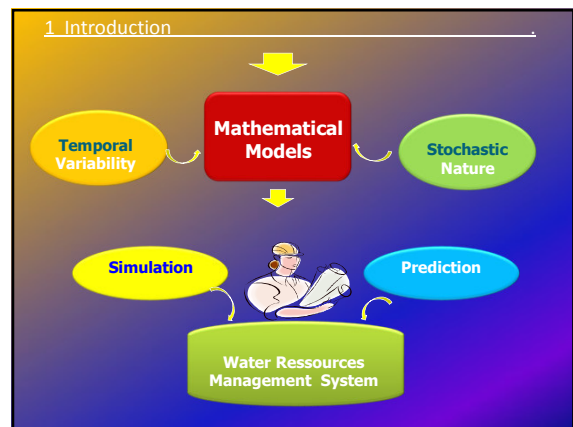


**Hydrological variables** → **Stream Flows**

**Generating processes** → **Time series**

**Mathematical Models**

### 1 Introduction



**Temporal Variability** → **Mathematical Models** → **Stochastic Nature**

**Simulation** → **Prediction**

**Water Resources Management System**

2 Material and method

**a) Material**

Stream flows  
(monthly and annual) observed at 10 hydro stations in northern Algeria (1968-1992)

Fig. 1 : Location of the hydrometric Stations in Northern Algeria.  
(Source: ANRH)

2 Material and method

**b) Methods**

Linear Stochastiques Models

BOX-JENKINS (ARMA)

KALMAN FILTER

2 Material and method

**BOX -JENKINS method**

- Time serie  $Z_t$  with  $\mu$  mean is considered as the output of a linear system whos input is a discrete white Gaussian noise  $\varepsilon_t$ .

$$\varepsilon_t \longrightarrow \text{Linear System} \longrightarrow Z_t$$

$$Z_t = \mu + \varepsilon_t + \psi_1 \varepsilon_{t-1} + \psi_2 \varepsilon_{t-2} + \dots$$

$$B^k \varepsilon_t = \varepsilon_{t-k}$$

$$Z_t = \mu + (1 + \psi_1 B + \psi_2 B^2 + \dots) \varepsilon_t$$

$$Z_t = \mu + \psi(B) \varepsilon_t$$

Look for the serie  $\varepsilon_t$  and the parameters  $\psi_i$  allowing to go from  $\varepsilon_t$  to  $Z_t$

2 Material and method

**Models**

1) **AUTOREGRESSIVE model of p order AR(p)**

The centred output  $Z_t$  of the system is the weighted finite sum of  $p$  precedant values plus a random term  $\varepsilon_t$ .

$$Z_t = (\phi_1 Z_{t-1} + \phi_2 Z_{t-2} + \dots + \phi_p Z_{t-p}) + \varepsilon_t$$

$$Z_t = (\phi_1 B^1 + \phi_2 B^2 + \dots + \phi_p B^p) Z_t + \varepsilon_t$$

$$(1 - \phi_1 B^1 - \phi_2 B^2 - \dots - \phi_p B^p) Z_t = \varepsilon_t$$

$$\phi(B) Z_t = \varepsilon_t$$

$\phi(B)$  is the operator AR(p) which is a polynôme in B with ordre  $p$  that converges for  $|\phi_i| < 1$ , to insure the stationarity condition of the process.

2 Material and method

2) **MOVING AVERAGE model of q order MA(q)**

The centred output  $Z_t$  is the weighted sum of  $q+1$  precedant values of a white noise  $\varepsilon_t$ .

$$Z_t = \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \dots - \theta_q \varepsilon_{t-q}$$

$$Z_t = (1 - \theta_1 B^1 - \theta_2 B^2 - \dots - \theta_q B^q) \varepsilon_t$$

$$Z_t = \theta(B) \varepsilon_t$$

$\theta(B)$  is the operator MA(q) which is a polynôm in B of ordre  $q$  that converges for  $|\theta_i| < 1$ , to insure the invertibility condition of the process.

2 Material and method

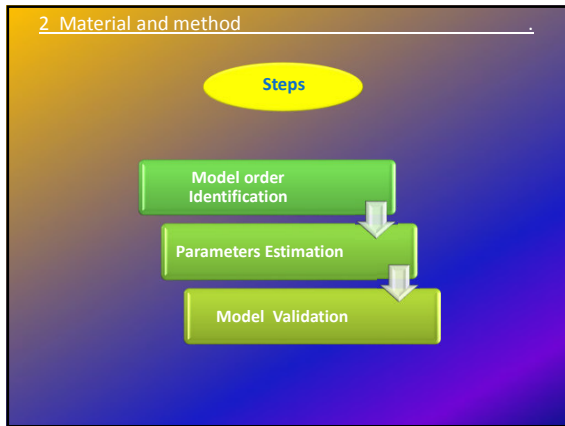
3) **AUTOREGRESSIVE and MOVING AVERAGE ARMA(p,q)**

a mixture of AR(p) and MA(q) models

$$\phi(B) Z_t = \theta(B) \varepsilon_t$$

$$Z_t = [\theta(B) / \phi(B)] \varepsilon_t$$

$\theta(B) / \phi(B)$  is the operator ARMA(p,q) which converges for  $|\theta_i| < 1$ , and  $|\phi_i| < 1$ , to insure the conditions of stationarity and invertibility.



2 Material and method

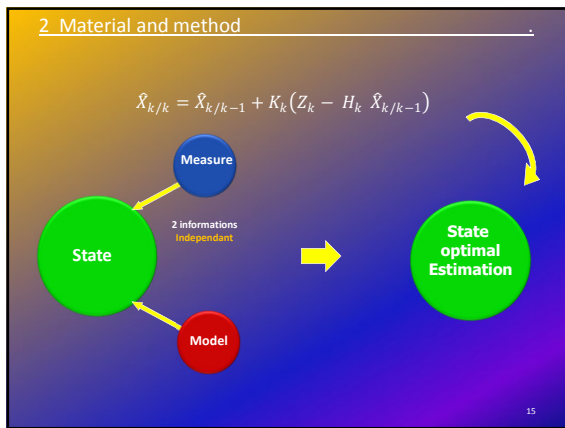
**KALMAN filter method**

- Fondamental equations of Kalman Filter (KF)
  - > **State equation**

$$\dot{X}_k = \phi_{k/k-1} X_{k-1} + W_{k-1} \quad (\text{State dynamical Model})$$
  - > **Measure equation**

$$Z_k = H_k X_k + V_k \quad (\text{State variable Measure})$$

to combine these 2 pieces to get an **OPTIMAL** estimation of the state



2 Material and method

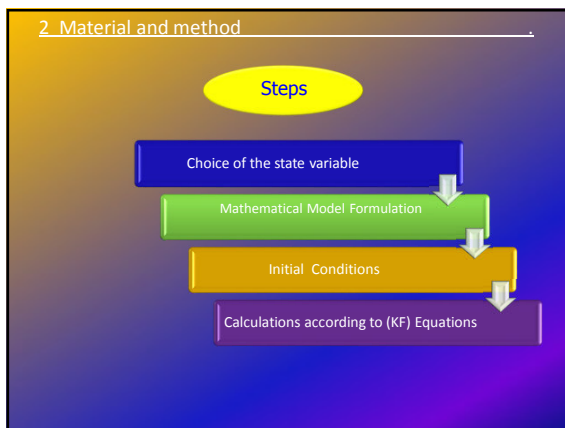
**KF Equations**

$$\hat{X}_{k/k} = \hat{X}_{k/k-1} + K_k (Z_k - H_k \hat{X}_{k/k-1}) \quad (\text{Updated state vector})$$

$$K_k = P_{k/k-1} H_k^T (H_k P_{k/k-1} H_k^T + R_k)^{-1} \quad (\text{gain estimation})$$

$$P_{k/k} = (I - K_k H_k) P_{k/k-1} \quad (\text{correction of the estimation error covariance})$$

$$\hat{X}_{k+1/k} = \phi_{k+1/k} \hat{X}_{k/k} \quad (\text{prediction of the state vector})$$

$$P_{k+1/k} = \phi_{k+1/k} P_{k/k} \phi_{k+1/k}^T + Q_k \quad (\text{Prediction of the prediction error covariance})$$


3 Results and Discussion

**Results and Discussion**

- BJ estimation
- KF multisite estimation
  - Optimality of estimation
  - Trend to over estimation
- Comparison of results

### 3 Results and Discussion KF Estimation

**Table 1:** BJ Annual modeling results

N°	Station	N	Transf	VT	Model	VR (est)	VR (cal)	VE (%)	TEM	TEV
01	Ain berda	31	d=0	119,08	--	--	--	--	--	--
02	Béni bahdel	69	d=1	1304,74	ARIMA(0,1,2)	1220,21	1030,72	21,00	OK	OK
03	Boucheouf	94	d=0	5016,59	--	--	--	--	--	--
04	Bouhniafa	59	d=0	4049,08	ARIMA(1,0,3)	3031,81	3015,51	25,00	OK	OK
05	Cheffia	27	d=0	8735,7	--	--	--	--	--	--
06	Ksob	27	d=0	509,51	ARIMA(2,0,0)	487,31	307,92	39,50	OK	OK
07	Mefrouche	50	d=0	84,47	ARIMA(2,0,3)	71,67	73,28	13,24	NO	OK
08	Mirebeck	27	d=0	72451	--	--	--	--	--	--
09	Pierre du chat	42	d=1	15644,7	--	--	--	--	--	--
10	Remchi	43	v	15,42	ARIMA(1,0,3)	10,83	9,83	35,25	OK	OK
<b>Average</b>				<b>1192,64</b>			<b>887,45</b>	<b>26,99</b>		

Notation : N: number of observations; Transf: transformation; VT: total variance; VR(est): estimated residual variance; VR(cal): calculated residual variance; VE(%): explained variance in %; TEM: Average equality test ; TEV: variance equality test.

### 3 Results and Discussion KF Estimation

**Table 2:** BJ Annual modeling errors

N	Station	Model	MSE		MAE		ME	
			estimation	validation	estimation	validation	estimation	validation
01	Béni bahdel	ARIMA(0,1,2)	1170,67	809,39	27,48	23,77	3,58	-21,52
02	Bouhniafa	ARIMA(1,0,3)	3118,66	4164,25	42,05	56,52	31,56	113,57
03	Ksob	ARIMA(2,0,0)	477,72	191,00	13,878	12,40	-0,97	-3,46
04	Mefrouche	ARIMA(2,0,3)	73,41	88,74	5,97	8,38	0,15	0,15
05	Remchi	ARIMA(1,0,3)	5211,81	2379,47	53,66	42,35	6,02	37,92
<b>Average</b>			<b>2010,45</b>	<b>1526,57</b>	<b>28,61</b>	<b>28,68</b>	<b>8,07</b>	<b>25,33</b>

Notation : MSE : Mean square error ; MAE : mean absolute error ; ME : mean error.

### 3 Results and Discussion KF Estimation

**Table 3:** BJ monthly modeling results

N°	Station	N	Diff (d,D,S)	VT	Model	VR	VE(%)	TEM	TEV
01	Ain berda	372	(0,1,12)	10,00	SARIMA(1,0,0) x (0,1,1)12	4,17	58,3	OK	NO
02	Béni bahdel	828	(1,1,12)	103,73	SARIMA(1,1,1) x (2,1,1)12	39,37	62	OK	NO
03	Boucheouf	408	(0,1,12)	339,98	SARIMA(1,0,0) x (0,1,1)12	158,28	53,4	NO	OK
04	Bouhniafa	708	(1,1,12)	443,50	SARIMA(1,1,1) x (0,1,1)12	128,29	71	OK	NO
05	Cheffia	324	(1,1,12)	849,90	SARIMA(1,1,1) x (0,1,1)12	291,35	65,7	OK	OK
06	Ksob	324	(0,1,12)	29,34	SARIMA(0,0,3) x (0,1,1)12	12,83	56,2	OK	OK
07	Mefrouche	600	(0,1,12)	5,06	SARIMA(1,0,0) x (0,1,1)12	2,80	44,6	OK	OK
08	Mirebeck	324	(0,1,12)	4802,36	SARIMA(2,0,0) x (0,1,1)12	2020,58	58	OK	NO
09	Pierre du chat	504	(0,1,12)	709,00	SARIMA(1,0,0) x (1,1,1)12	443,3	37,4	OK	NO
10	Remchi	516	(0,1,12)	351,96	SARIMA(0,0,1) x (0,1,1)12	203,67	42	OK	NO
<b>Moyenne</b>				<b>764,48</b>		<b>330,48</b>	<b>54,86</b>		

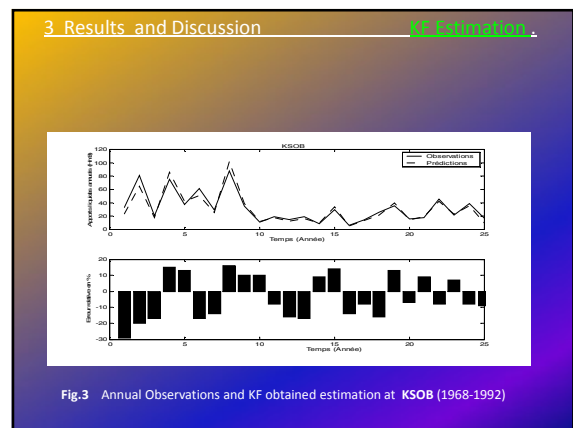
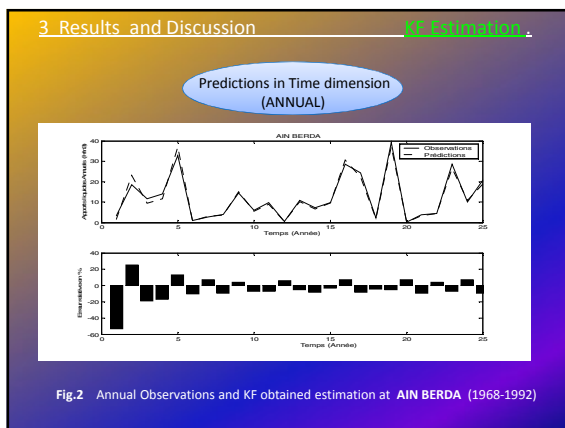
Notation : N: number of observations; Diff (d,D,S): differentiation of ordre (p,D,S); VT: total variance; VR:residual variance ; VE(%): explained variance in %; TEM: Average equality test ; TEV: variance equality test.

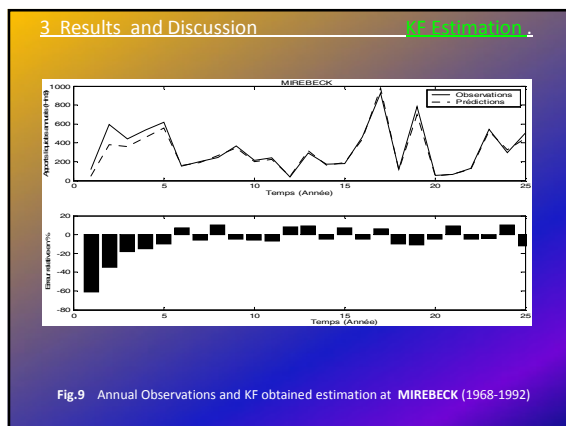
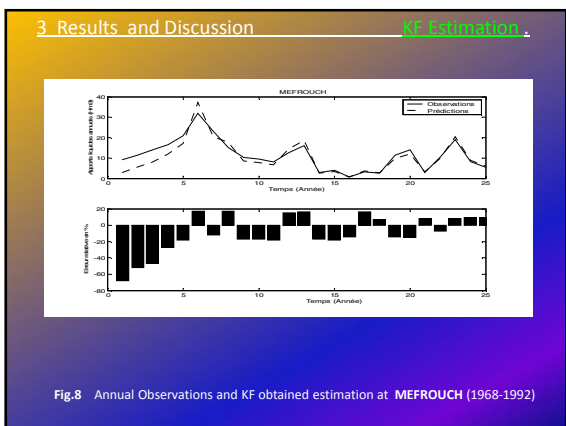
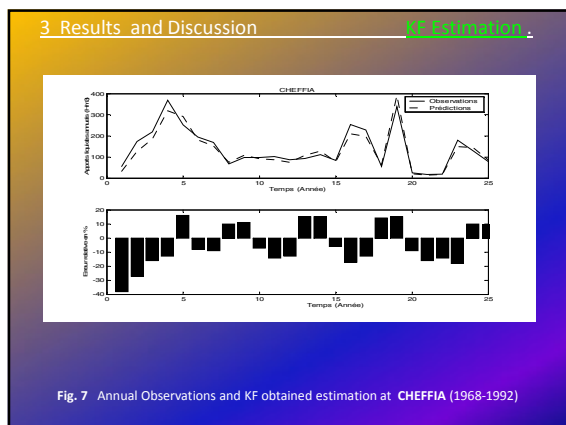
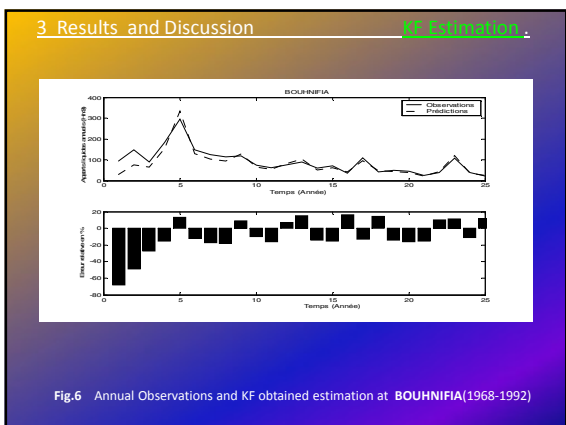
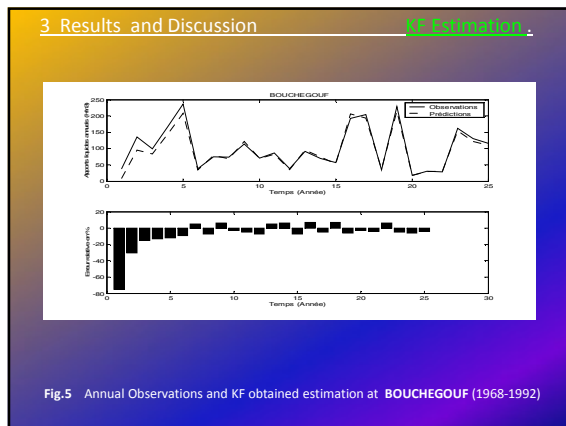
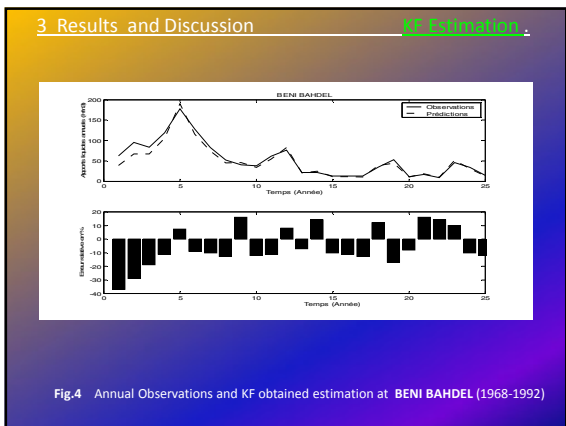
### 3 Results and Discussion KF Estimation

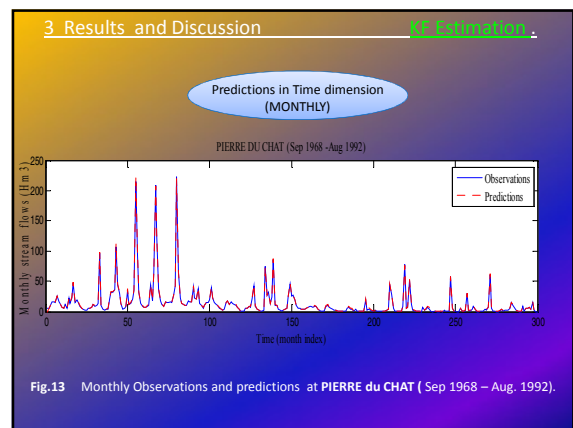
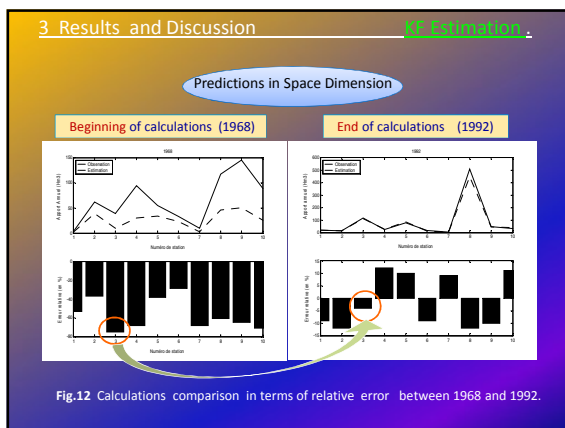
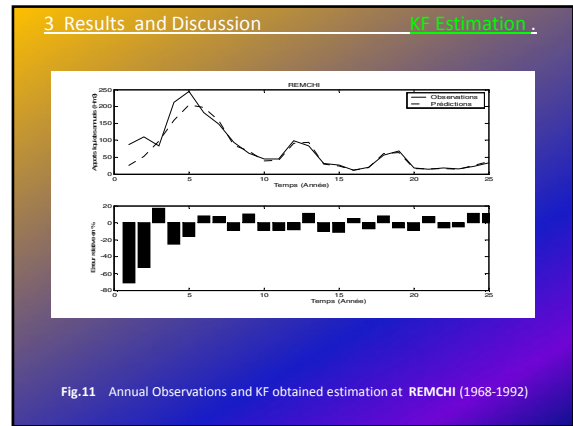
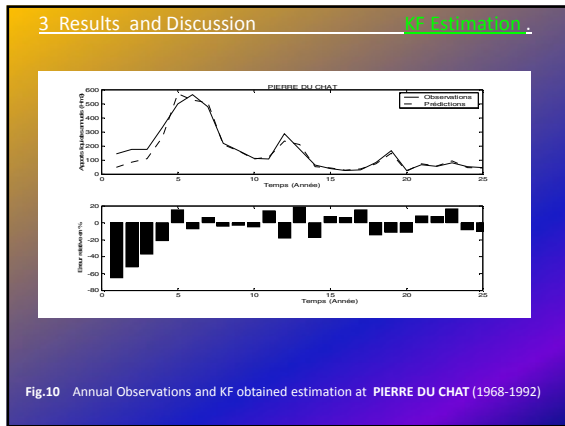
**Table 4:** BJ monthly modeling errors

N	Station	EQM		EAM		EM	
		estimation	validation	estimation	validation	estimation	validation
01	Ain berda	4,74	2,79	1,05	0,96	0,009	0,17
02	Béni bahdel	47,34	15,85	3,30	2,46	0,13	-0,39
03	Boucheouf	177,65	103,25	7,16	6,00	-0,05	-0,97
04	Bouhniafa	155,90	64,03	5,57	4,13	1,20	-0,10
05	Cheffia	301,22	246,25	9,91	9,70	0,23	-1,33
06	Ksob	13,01	12,98	2,41	2,13	-0,31	0,83
07	Mefrouche	3,59	1,18	0,99	0,66	0,05	-0,23
08	Mirebeck	2428,46	1240,27	24,39	19,36	-0,55	6,00
09	Pierre du chat	615,17	200,86	12,18	9,54	2,46	-5,49
10	Remchi	314,07	39,60	7,71	4,28	1,39	-2,48
<b>Average</b>		<b>406,11</b>	<b>192,70</b>	<b>7,46</b>	<b>5,92</b>	<b>0,45</b>	<b>-0,39</b>

Notation : MSE : Mean square error ; MAE : mean absolute error ; ME : mean error.







3 Results and Discussion KF Estimation

Predictions in Time dimension (MONTHLY)

**Table 5:** Mean and Standart Deviation of KF prediction error for monthly stream flows.

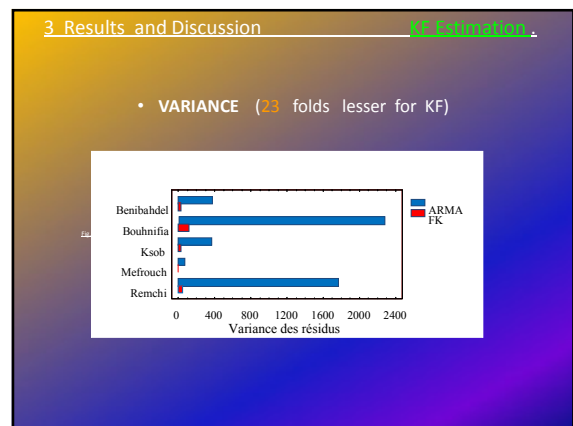
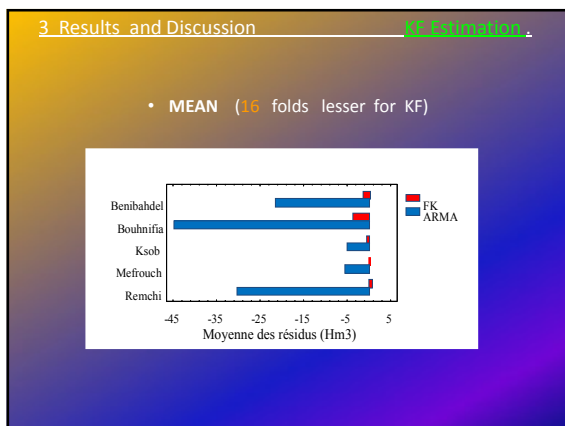
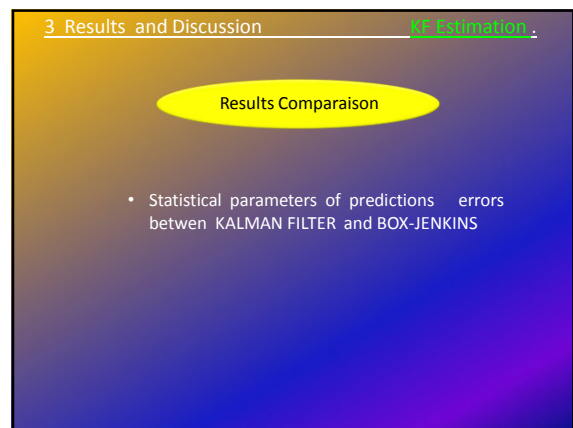
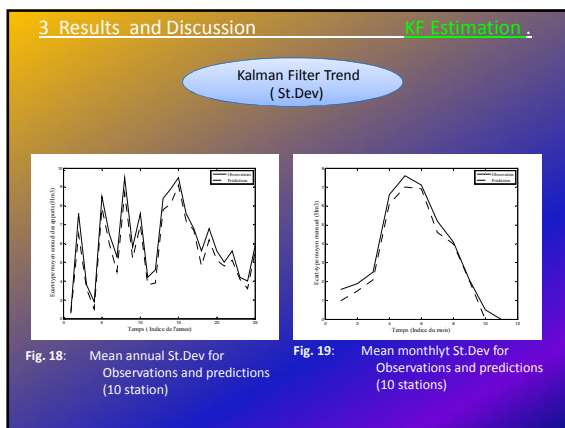
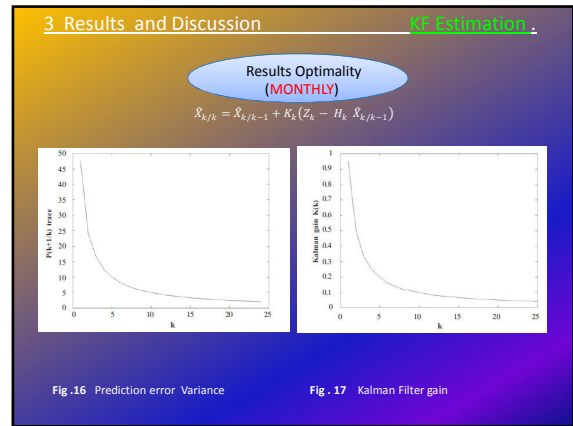
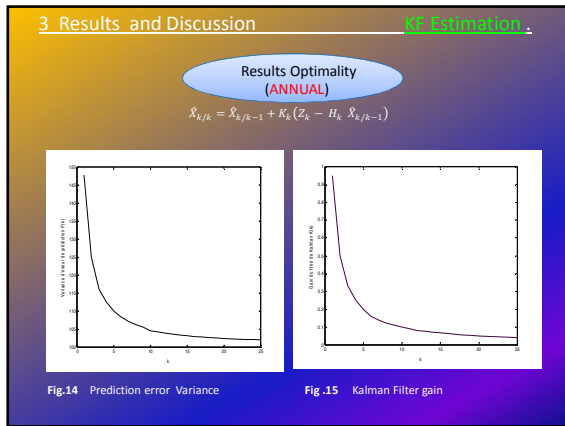
Predictions	Period	Mean	St.Dev
Temporal	Observation	101,34	75,95
	Estimation	100,11	70,03
	Err Rel (%)	1,21	7,79
Spatial	Observation	101,34	111,26
	Estimation	93,53	68,63
	Err Rel (%)	7,70	38,31

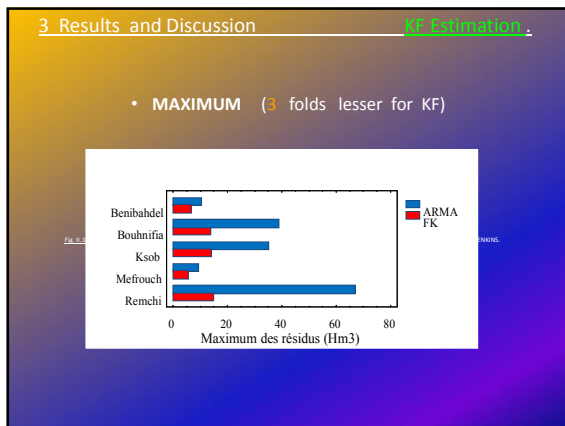
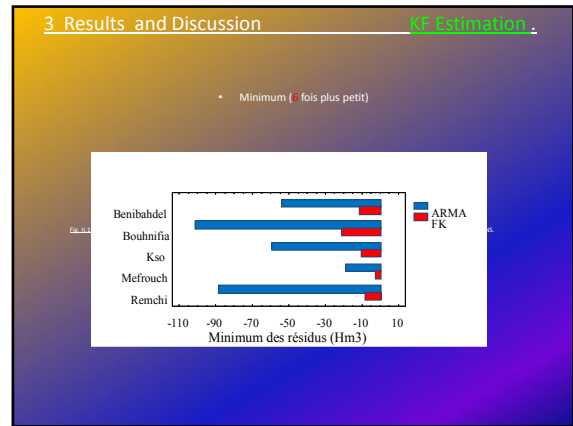
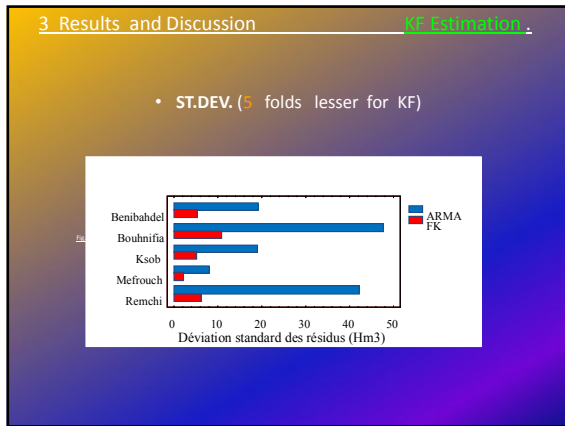
3 Results and Discussion KF Estimation

Results Optimality

$$P_{k/k} = (1 - K_k H_k) P_{k/k-1}$$

$$K_k = P_{k/k-1} H_k^T (H_k P_{k/k-1} H_k^T + R_k)^{-1}$$





4 Conclusion

4) CONCLUSION

46

- 4 Conclusion
- The Developed online operator
- ✓ KF more accurate than BJ
  - ✓ KF effective tool for adaptative prediction
  - ✓ Provide with spatio-temporal variations
  - ✓ Optimality of predictions
  - ✓ Prediction Absolute relative error < 10%
  - ✓ Trend to underestimation
  - + Starts with Little objective information
  - + Equations are recursive
  - + Respect of stochastique and non linear nature of stream flows
  - + Prediction error covariance is provided exactly
- 47

Thank you