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## RESEARCH ARTICLE

# CEPHALOPOD FISHERIES MANAGEMENT AND SUSTAINABLE DEVELOPPEMENT IN MOROCCO: A BAYESIEN NETWORKS APPROACH

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**ABSTRACT**

The Bayesian networks approach is one of the main decision-making support systems (DMSS). For some applications, the Bayesian networks are preferable to other models (neural networks, multi-agent models, optimization models, macro-econometric models....). Moreover, the Bayesian networks are often used in conjunction with other decision-making support models. The number and the fields of applications of Bayesian networks are still limited. However, the Bayesian networks approach is very replied in the field of risk analysis, natural stock management, medical diagnoses ...; and it can be used in several other fields in order to give perfect analysis. This paper aims to present the methods that were used to develop decision-making support systems that apply Bayesian networks in the field of cephalopod fisheries management. This approach can be considered as a basic model in order to study the cephalopod fisheries sustainable developpement. This study has as an ambition to create and apply a Bayesian network to the cephalopod fishery management in Morocco.



## INTRODUCTION

Fishery management is a complex process which requires the adoption of a dynamic modeling approach of resource. Among the various modeling approaches used in decision-making support, bioeconomic models are the most used in the field of fishery management (Gupta *et al.,* 2006). These bioeconomic models of fisheries are an optimization models used to assess the impact of policies fishery management. The optimization models developed on the basis of technical relationships between biological and economic indicators are used to find fishing effort that maximizes the economic performance of the fishery. Maximizing the value derived from the sea is subject to biological constraints on natural limits of fish stock recovery. Thus, bioeconomic models of fisheries consider fishing activity as the only responsible for the degradation of the fish stock. However, degradation of fish stocks has due to several factors other than fishing (environment, conflicts between fleets, price ...). To model all these factors, Bayesian networks are a promising approach.

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The Bayesian networks approach, combined with optimization models is used in this work to understand the characteristics of sustainable development of the cephalopod fishery in Morocco. It allows the integration of socio-economic and institutional state of the fishery the biology and ecology of resources. This approach aims to estimate the bioeconomic impact of fishing.

### Bayesian networks: A decision-making support model

A Bayesian network is a graphic probabilistic model through which one can acquire, capitalize on and exploit knowledge. Bayesian networks are the natural successors and heirs to symbolic, connectionist and statistical approaches to Artificial Intelligence and Data Mining. The Bayesian network approach is a modeling approach based on the axioms of probability. It allows to study the causal relationships between variables and to calculate the probability of a variable when the other variables are known in the model. Bayesian network modeling aims to find the most likely cause of a phenomenon observed with more or less precision and accuracy. It allows, on the basis of Bayes' theorem to calculate the probabilities of a variable knowing the state of one or more other variables.

### *A. The Bayesian network method*

Bayesian network is a directed acyclic graph that represents various dependencies between variables represented by this network. In this graph, the vertices (nodes) represent variables (states, events ...) interconnected causal relationships represented by arcs. At each node of the Bayesian network is associated with a probability table. The set of nodes and arcs form the structure of Bayesian network (qualitative representation of knowledge), while all probability distributions is the parameters of the Bayesian network. An arc connects one and only one variable at a time and one another. An arc connecting the variable "A" to the variable "B" means that "A" is a cause of "B" (or "A" influences "B"). The variable "A" is said to be a "parent" of "B". The same variable "B" can have multiple parents A1, A2, ... An. In addition, a variable "A" may be a parent of several other variables, B1, B2, ... Bn. The relationship is transitive. All direct and indirect parents of a variable is called its "ancestors".

Thus, a Bayesian network consists of two main components:

- *The causal graph:* that is the network structure. This causal graph, directed and acyclic, is composed of nodes and arcs. Nodes represent variables, and arcs represent dependency relationships between these variables.

- *The distribution of probabilities :* that is the parameters of the Bayesian network. It allows to evaluate the conditional probabilities of each variable knowing his parents P(Variable/Parent). (where P means probability)

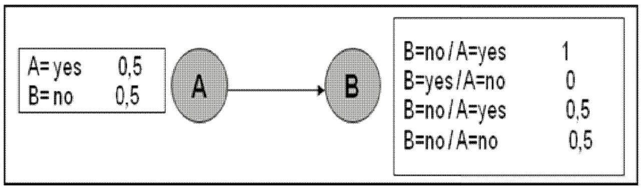



**Fig. 1. Bayesian network with two events**

### *B. Bayesian networks: An approach based on Bayes' rule*

Bayesian networks are an approach for handling uncertain knowledge that developed in the artificial intelligence community beginning in the middle of the 1980s (Tessem, *et al.,* 2009). The Bayes' rule, originally named "Conditional probability' rule" which had considerable applications, is a powerful tool for decision-making support. Indeed, the development of Bayesian networks, due to the computer revolution, has allowed the Bayes' rule to be at the heart of artificial intelligence approaches. According to the of total probability' rule, it is possible to determine the probability of an event "A" given the a priori probabilities of the causes Ci (C1, C2,..... Cn), and the conditional probability of event "A" for each event Ci (GILLE Balmisse, 2002). However, the question that arises is: if the event "A" occurs, what is the probability that the event Ci is the cause of the realization of "A"?

The answer to this question is given by the the use of Bayes' rule, which in its simplest form, can be stated as:

$$P(C_i / A) = \frac{P(A / C_i) \times P(C_i)}{P(A)} \quad \text{......................... (1.1)}$$

Where:
P (Ci / A): a posteriori probability of "C" knowing "A"
P (A / Ci): "A" likelihood function (For Ci known)
P (Ci): Ci a posteriori Probability
P (A): a priori probability (constant for each Ci)
In the general case of a Bayesian network consisting of n nodes A1, A2, .... An, the joint probability of all variables which are the nodes of this network is the product of the probabilities of each variable knowing his parents. It can be written as:

$$P(A_1....A_n) = \prod_{i=1}^{n} P(A_i / \mathrm{Parents}(A_i)) \quad \text{.................. (1.2)}$$

### *C. Construction and using of Bayesian network*

In the realization of a Bayesian network, there are two phases:
*The construction of the Bayesian network:* The construction of a Bayesian network is to draw causality between the variables of a Bayesian model. It identifies the dependencies between variables and assigns a probability distribution for each variable. It is therefore to create the structure and parameters of the Bayesian network. Dependency relationships between variables in a Bayesian model is developed using an expert or by the use of learning methods. Indeed, learning the structure and parameters of a Bayesian network can be done from existing data. Thus, the most important step in creating a Bayesian network is that of providing all the necessary parameters for inference in a graph. The use of machine learning methods allows using existing database, to determine the probability distribution associated with each variable and therefore to perform Bayesian inference. Learning techniques can perform learning causal relationships. They allow you to specify both learning the structure as parameters. Indeed, learning the structure of a Bayesian network is to find a graph that has the same skeleton as a model that represents the same conditional independencies. Moreover, the parameter learning is to estimate the conditional probabilities and specify the probability tables.

- *The using of Bayesian network:* This phase involves a very interesting property of Bayesian networks: inference. Indeed, the use of a Bayesian network based on the propagation of information within the network, which is used to calculate the a posteriori probability of the realization of a number of events. Bayesian inference is the result of the spread of information in the Bayesian network (Pearl, 1997).

## Fishery bieconomic model management: theoretical study and resolution

In the field of marine fisheries, management of fishing consists in the implementation of a rational exploitation of fisheries resources. Indeed, the rational exploitation of a renewable natural resource is defined as "the management of a stock on which man may take to meet its needs without jeopardizing the renewal of this stock." Bioeconomic models of fisheries are multi-criteria optimization models used for a long time to assess the impact of policies fishery management. These bioeconomic models prioritize overfishing and consider human intervention as the only responsible for the degradation of fishery resources. However, fishing is not the only factor responsible for the overexploitation of a fishery. Indeed, a fish population depends primarily on its size and its environment. It also depends on factors related to markets, changes in demand, prices ... etc.. In addition, changes in the marine environment could also be taken into account in the analysis of a fishery. Thus, bioeconomic models of fisheries neglect several factors that influence fish stocks. To model all of these factors, the use of Bayesian networks is necessary.

### *A. Theoretical Study of bioeconomic models*

Bioeconomic models of fisheries management are multi-criteria optimization models integrating both biological and economic variables of the fishing activity (Pearl, 1997). Bioeconomic models of fisheries are based on the optimal control theory allows to determine the balance of biomass and the level of fishing effort that maximizes the sustainable yield of the fishery. Bioeconomic models of fisheries can accurately describe the optimal policy of exploitation of a fishery. They describe the change in stock biomass over time and take into account not only the growth of the population, but also the removal of the resource. A bioeconomic model of the fishery has an economic component and a biological component. While the economic component assesses the impact of the measures implemented, the biological component is to estimate the evolution of the stock of the fishery over time.

### *Economic variables*

The economic component of a bioeconomic model of the fishery catch is to transform revenue (outputs) and fishing effort in production costs (inputs). Value added (VA) is the net result of the economic activity of fishing. It is equal to the difference between total revenue from catches (RT) and intermediate consumption expressed by the production costs of fishing effort (CT):

$$VA = RT - CT \quad \text{……………………………………. (2.1)}$$

Total revenue is equal to the capture (Y) multiplied by the price level (P) of species caught:

$$RT = P \times Y \quad \text{……… (2.2)}$$

The total cost (TC) is estimated by multiplying the average cost per unit of effort (c) the number of units that make up the fishing effort (E):

$$CT = c \times E \quad \text{…………………………………….. (2.3)}$$

Thus, value added (net revenue) from fishing VA can be written:

$$VA = P\times Y - c\times E \quad \text{……………………………………. (2.4)}$$

### *Biological variables*

The biological component of the bioeconomic model is to estimate the evolution of the stock of the fishery over time. Indeed, a fish population believes as a function of first increasing and then decreasing the size of this population. The population level corresponding to a zero growth rate is called the "carrying capacity" of the resource. This level of population is a stable equilibrium, since beyond this threshold, an additional unit of fishery resources implies a mortality rate higher than the birth rate, and thus a reduction of the population returns to its capacity (K). On the mathematical growth of a fish population is based on the following mathematical expression called logistic equation following the work of Verhulst and Pearl:

$$\frac{dB}{dt} = rB(t)[1 - \frac{B(t)}{K}] \quad \text{……………………………. (3.1)}$$

Where

B (t): the biomass population in time t,
r: intrinsic rate of population growth,
K: the load capacity of the environment.

Thus, the biomass over time is equal to the population biomass itself, depending on the capacity of the environment, multiplied by the intrinsic rate of population growth and reduced catch rates.

$$\frac{dB}{dt} = rB(t)[1 - \frac{B(t)}{K}] - Y \quad \text{…………………. (3.2)}$$

Where:

r: the population growth rate,
K: the load capacity of the environment,
Y: the value of the catch.

Thus, the value of the initial biomass in year t ($B_t$) depends on the natural growth rate of the fish population (r) and the value of the catch ($Y_t$). The latter, also called fishing mortality depends on the fishing effort is an endogenous variable determined by the bioeconomic model, and to calculate the corresponding production structure for each fishing by multiplying the initial population biomass ($B_0$) by fishing effort and catchability coefficient (q) defined as the fraction of the population per unit of fishing effort.

The Graham-Schaefer model has the catch rate Y(t) as follows:

$$Y(t) = qE(t)B(t) \quad \text{……………………………………. (3.3)}$$

Where:

B (t): the biomass population in time t, E
(t): the fishing effort
q: the catchability coefficient: defined as the fraction of the population per unit of fishing.

### *B. The Mathematical formulation and resolution of bioeconomic model*

The mathematical formulation of the bioeconomic model is to transform the objective function and the constraints in different equations and in equations that can form a system optimization that can be solved using a computer tool. The resolution of this model is based on maximizing the discounted sum of value added in time. This maximization of economic returns from the fishery is subject to biological constraints on natural limits of fish stock recovery. There are generally three main parts to provide optimization software:

***Decision variables:*** These relate to the fishing effort of different fishing patterns.

**Constraints:** These limits relate to the recovery of biological resources. These constraints are related to the management of fisheries access and limitation of fishing effort through the temporary ban on the fishing of endangered species, control taken by the definition of a threshold of maximum production (quotas) and the regulation of fishing gear.

***The objective function:*** The objective function is to maximize the discounted sum of value added in time. It is expressed as follows:

$$\sum_{t=0}^{T} \frac{VA_t}{(1+\alpha)^t} \qquad \text{…………………. (3.4)}$$

Where:

α: The discount rate
T: time horizon

The resolution of the model in a simulation scenario of a management system based on the total allowable catch (TAC) where the population biomass of 125000 tons, a growth rate r=0,20, and when taken are capped for the whole fleet to 50000 tons of octopus (exploitable potential in the South Atlantic area according to the National Institute for Fisheries Research) gives the following results:

**Table 1. Simulation results by the bioeconomic model of fishery management**

| | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 |
|---|---|---|---|---|---|---|
| **Boats** | | | | | | |
| High-sea fish | 62 | 63 | 65 | 67 | 68 | 68 |
| Inshore fish | 154 | 157 | 161 | 167 | 176 | 188 |
| Artisanal fish | 2277 | 2318 | 2377 | 2466 | 2597 | 2781 |
| **Production** | 49717 | 49697 | 49840 | 49683 | 48867 | 47385 |
| High-sea fish | 22778 | 22735 | 22876 | 22726 | 21900 | 20455 |
| Inshore fish | 16940 | 16963 | 16965 | 16959 | 16970 | 16931 |
| Artisanal fish | 9998 | 9998 | 9998 | 9997 | 9996 | 9998 |
| **VA (8%)*** | 1424 | 1305 | 1694 | 1081 | 941,87 | 785,99 |
| High-sea fish | 1114 | 1027 | 1077 | 873,4 | 773,7 | 662 |
| Inshore fishh | 183,2 | 208,2 | 338,9 | 161,4 | 135,6 | 107,3 |
| Artisanal fis | 79,49 | 69,41 | 278,60 | 46,56 | 32,50 | 16,36 |
| **Average VA** | 1223,8 | 1223,8 | 1223,8 | 1223,8 | 1223,8 | 1223,8 |

The resolution of the bioeconomic model optimization to determine fishing effort that maximizes the value added from a fishery while preserving the resource. However, this model does not determine the factors that most influence the stock. Indeed, fishing is not the only factor responsible for the overexploitation of a fishery. In addition, the resolution of the bioeconomic model estimates depends on prices and production costs which are considered exogenous variables. To consider these parameters as endogenous variables, it is necessary to use a model that allows Bayesian networks, using a learning method to determine these parameters.

## Bayesian networks: application to fisheries management

Bayesian networks provide a modeling tool suitable to represent a fishing system. The creation of a Bayesian network for fisheries management can analyze data on production to highlight the causes of degradation of fish stocks. The Bayesian network approach allows modeling a system composed of different variables related to the fishery management. It allows to perform simulations with the aim of varying the model parameters to observe their influence on the other variables. (Quantity of catch, price species ....).

To implement this Bayesian network, we use the editing software and automatic learning of Bayesian networks "BayesiaLab." This software, which is part of the French company's products "Bayesia", allows the use of methods of decision-making support and artificial intelligence.

### *A. The fishery Bayesian network structure*

The fishery Bayesian network structure consists of various biological, economic and institutional variables of a fishery. It allows to find the causal relationships between these variables. Fishery Bayesian network structure is constituted by a graph consisting of nodes representing biological, economic and institutional factors that constitute the state of fisheries resources. These nodes are interconnected by causal relationships represented by arrows (edges). In a fishery, the system consists of a fish population that evolves according to a function of growth and fishermen seeking to maximize their profits. In addition, there is a maximum in the amount of fish that can be extracted steadily.

The amount of fish that can be harvested without compromising the normal recovery of stocks is equal to the change in the fish population. Indeed, the depletion of fish stocks is due firstly to the natural resource (natural growth rate that depends on the species studied). Overexploitation of these resources is another factor of marine resources degradation. This overexploitation is due to overinvestment in production capacity, which translates into an effort that exceeds the capabilities of resource renewal. The effort depends on the system of access to the fishery (free or regulated) prices, fishing technology used as well as production costs. In addition, marine pollution is an important other factor to consider in the fisheries resources management. In fact, the pollution has adverse effects on the preservation of fish stocks, since it hinders the reproduction of fish species, increased mortality, reduced productivity and affects the quality of these products.

The structure of the Bayesian network representing these variables is:

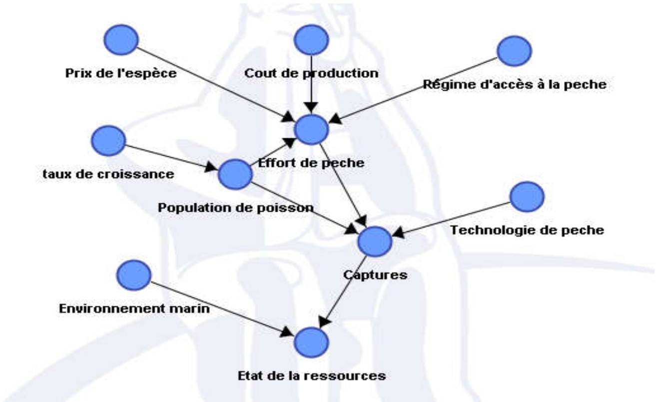



**Fig. 2. Cephalopod fisheries Bayesian network graph**

### B. *The fishery Bayesian network parameters*

Determining the fishery Bayesian network parameters is to assign a probability table for each node in the Bayesian network. This is done using either an expert or by using a learning method based on an existing database. On all nodes with incoming edges, we assign probabilities for each of the possible values, given all combination of values for the parents. For all nodes without parents, we assign a priori probabilities for each of the possible values for the variable. The probabilities associated with the nodes of the fishery Bayesian network allows to calculate the probability distributions of system states with time and management actions. The probabilities are given in Appendix 1.

## RESULTS AND DISCUSSION

The use of Bayesian networks is the most interesting phase in the modeling Bayesian networks. Indeed, once the network structure and probabilities distributions associated with different variables are defined, the simulations can be made in order to determine the impact of a change in the probability of the other variables in the Bayesian network. The use of Bayesian network consists of the simulation of management scenarios. This simulation is to assign a definite value to a variable (probability 100%) and to measure the impact of this change on the other variables in the Bayesian network. The simulation of each scenario is based on Bayesian inference and Monitoring. Bayesian inference is to propagate within a Bayesian network one or more known information for some nodes to infer their impact on information to other nodes. It allows updating the probabilities of each node due to a change in all observations and reflecting the new state of consciousness after each simulation. Bayesian inference is used to measure the probabilistic interactions between variables through simulations of management scenarios. It allows calculating the probability of each node by propagating of the conditional probabilities known. Methods of inference can be exact methods (method of message propagation, methods of grouping of nodes) or approximated. These methods use inference algorithms that are based on the notion of conditional probabilities and the Bayes' rule. Monitoring can view the probabilities of the various categories of a variable or assign a certain value to a variable. It allows to check the consistency of the Bayesian network. The simulation results are presented in the graphs in Appendix 2. These graphs show of results simulation of three scenarios:

The first scenario shows that overfishing is attributed primarily to catch that exceed the reproductive capacity of the fish stock. The problems of marine environment pollution come in second place. In addition, although the effort of fishing is optimal, the fishings technologies makes that the captures do not correspond to the optimal quantity which ensures a sustainable development of the cephalopod fishery. The second scenario is a scenario under-exploitation of fisheries resources. The simulation of this scenario shows that the under-exploitation of fishery resources resulting from a level of catches below the reproductive capacity of the fish stock. The third scenario involves the simulation of optimal conditions of fishery resources. This scenario shows that the optimal use of resources is the result of an optimal fishing effort and catch quantities optimum.

### Conclusion

The developments of this paper concern an application of Bayesian networks for making-decision support in cephalopod fishery management. In this work, we tried to create and apply a Bayesian network for the management of fisheries resources. This modeling approach has identified the causes of the fishery resources degradation among many parameters and highly correlated. The first results of this paper show that Bayesian networks are an ideal modeling tool to represent in a compact system of fishing. Indeed, the use of Bayesian networks mode has identified the factors that define a management strategy that ensures sustainability of fisheries resources. However, the results obtained by this method are dependent on with the structure and parameters of the fishery Bayesian network. In this work, the structure and parameters of the Bayesian network are defined on the basis of previous studies on the fishing industry. Thus, the definition of the structure and parameters of Bayesian network applied to the fisheries resources management is the main limitation of this method. To overcome this limitation, we have, in subsequent work, using a method for learning the structure and parameters of the fishery Bayesian network.

## REFERENCES

Gupta, J.N.D., G.A. Forgionne, and T. M. Mora, Eds., Intelligent Decision-making Support Systems. London: Springer-Verlag, 2006.

Tessem, B., J. Keyser, P.l Johe and S. Ulvatn, " Developing Decision Support with Bayesian Networks in Fisheries Surveillance ", in *The Open Information Systems Journal*, 2009, 3, 26-35

Daniel Charbonier "Fisheries and aquaculture in the Mediterranean", *Economica*, 1990.

Kadiri Abdelkader, E. L. "Sea and environment," the new century: Strategy Review No. 39, May 1998.

Finn Jensen, V. "Bayesian Networks and Decision Graphs", Springer, 2001.

Finn Jensenm V., and Olesen Lauritzen, S. K. "Bayesian updating in causal probabilistic networks by local computations," Computational Statistics Quarterly, 1990.

Gille Balmisse "Bayesian networks," in September, 2002.

Pearl, J. "Probabilistic reasoning in intelligent systems: Networks of plausible inference," Morgan Kaufmann, second edition, 1997.

Schaefer, M,.B. "Some aspects of the dynamics of populations important to the management of the commercial maritime fishing", Bull. Inter-Amer. Too. Tunna Comm, 1954.

Patrik Naim, Pierre-Henri Wuillmen, Philippe Leray, Olivier Pourret, ANNA Becker: "Bayesian Networks", Eyrolles, 3rd edition, 2004.

Gachet, A., and P. Haettenschwieler, Development processes of intelligent decision-making support systems: review and perspective. In: J.N.D. Gupta, G.A. Forgionne, and T. M. Mora, Eds., Intelligent Decision-making Support Systems. London: Springer-Verlag, 2006, pp. 97-121

Cowell, R. G., S. L. Lauritzen, A. P. David, and D. J. Spiegelhalter, Probabilistic Networks and Expert Systems. 2nd ed., New York: Springer-Verlag Inc., 2007

Pourret, O., P. Naïm, and B. Marcot, Eds., Bayesian Networks: A Practical Guide to Applications, Chichester, England: John Wiley and Sons Ltd., 2008

## APPENDICES

### Appendix 1:

| Normal | Elevé |
|---|---|
| 50,000 | 50,000 |

**Price of the species**

| Elevé | Faible |
|---|---|
| 50,000 | 50,000 |

**production cost**

| Libre | Réglementé |
|---|---|
| 50,000 | 50,000 |

**Mode of access to fishing**

| Normal | Faible |
|---|---|
| 50,000 | 50,000 |

**Growth rate**

| Taux de cro… | Renouvellement normal du stock | Dégradation |
|---|---|---|
| Normal | 100,000 | 0,000 |
| Faible | 0,000 | 100,000 |

**Fish Population**

| Normale | Sophistiquée |
|---|---|
| 50,000 | 50,000 |

**Echnology of fishing**

| Protégé | Pollution |
|---|---|
| 50,000 | 50,000 |

**Marine environment**

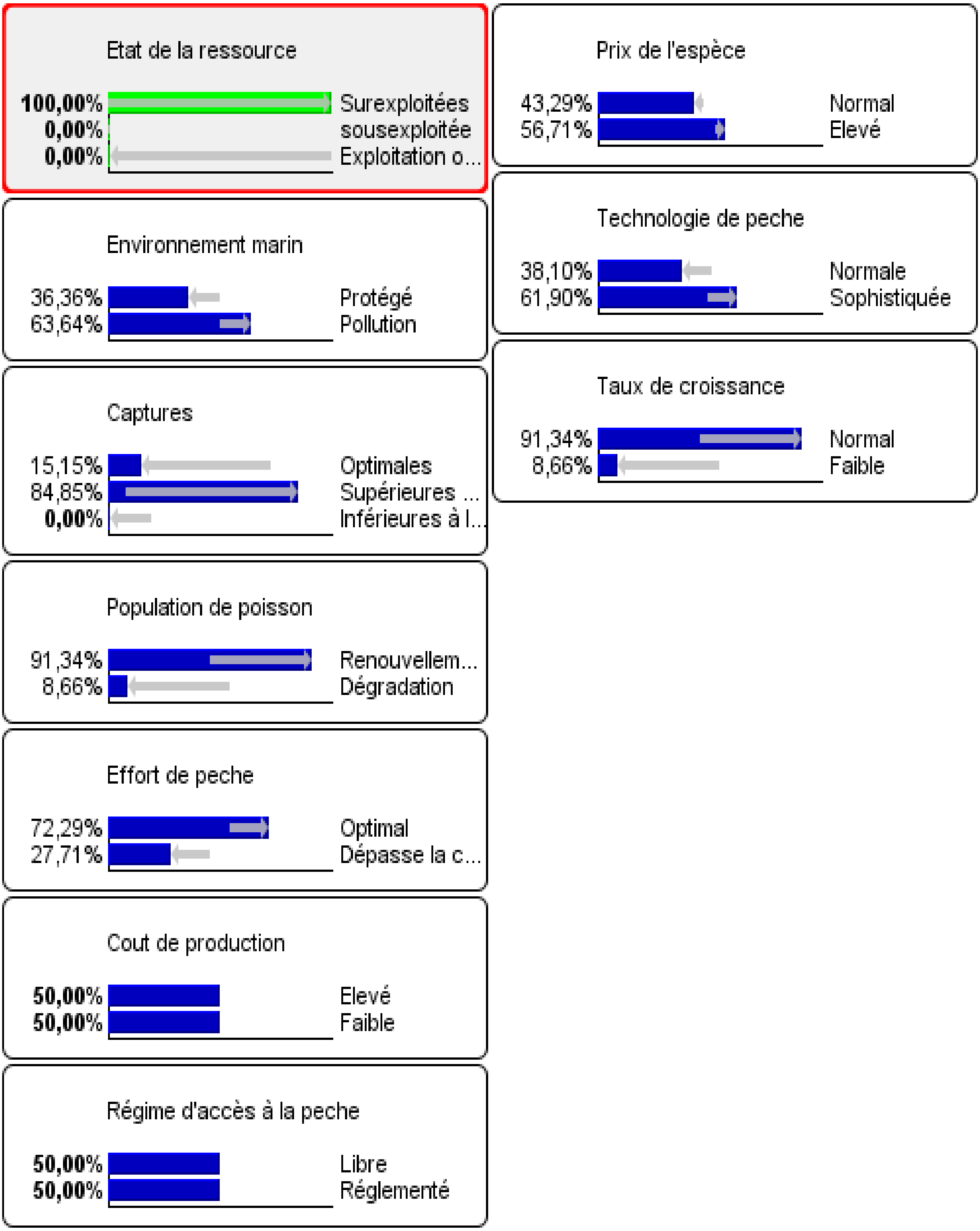
| Régime d'ac… | Cout de pro… | Prix de l'esp… | Population … | Optimal | Dépasse la capacité de renouvellement |
|---|---|---|---|---|---|
| Libre | Elevé | Normal | Renouvelle… | 100,000 | 0,000 |
| | | | Dégradation | 0,000 | 100,000 |
| | | Elevé | Renouvelle… | 75,000 | 25,000 |
| | | | Dégradation | 25,000 | 75,000 |
| | Faible | Normal | Renouvelle… | 100,000 | 0,000 |
| | | | Dégradation | 0,000 | 100,000 |
| | | Elevé | Renouvelle… | 75,000 | 25,000 |
| | | | Dégradation | 25,000 | 75,000 |
| Réglementé | Elevé | Normal | Renouvelle… | 100,000 | 0,000 |
| | | | Dégradation | 0,000 | 100,000 |
| | | Elevé | Renouvelle… | 75,000 | 25,000 |
| | | | Dégradation | 25,000 | 75,000 |
| | Faible | Normal | Renouvelle… | 100,000 | 0,000 |
| | | | Dégradation | 0,000 | 100,000 |
| | | Elevé | Renouvelle… | 75,000 | 25,000 |
| | | | Dégradation | 25,000 | 75,000 |

**Effort of fishing**

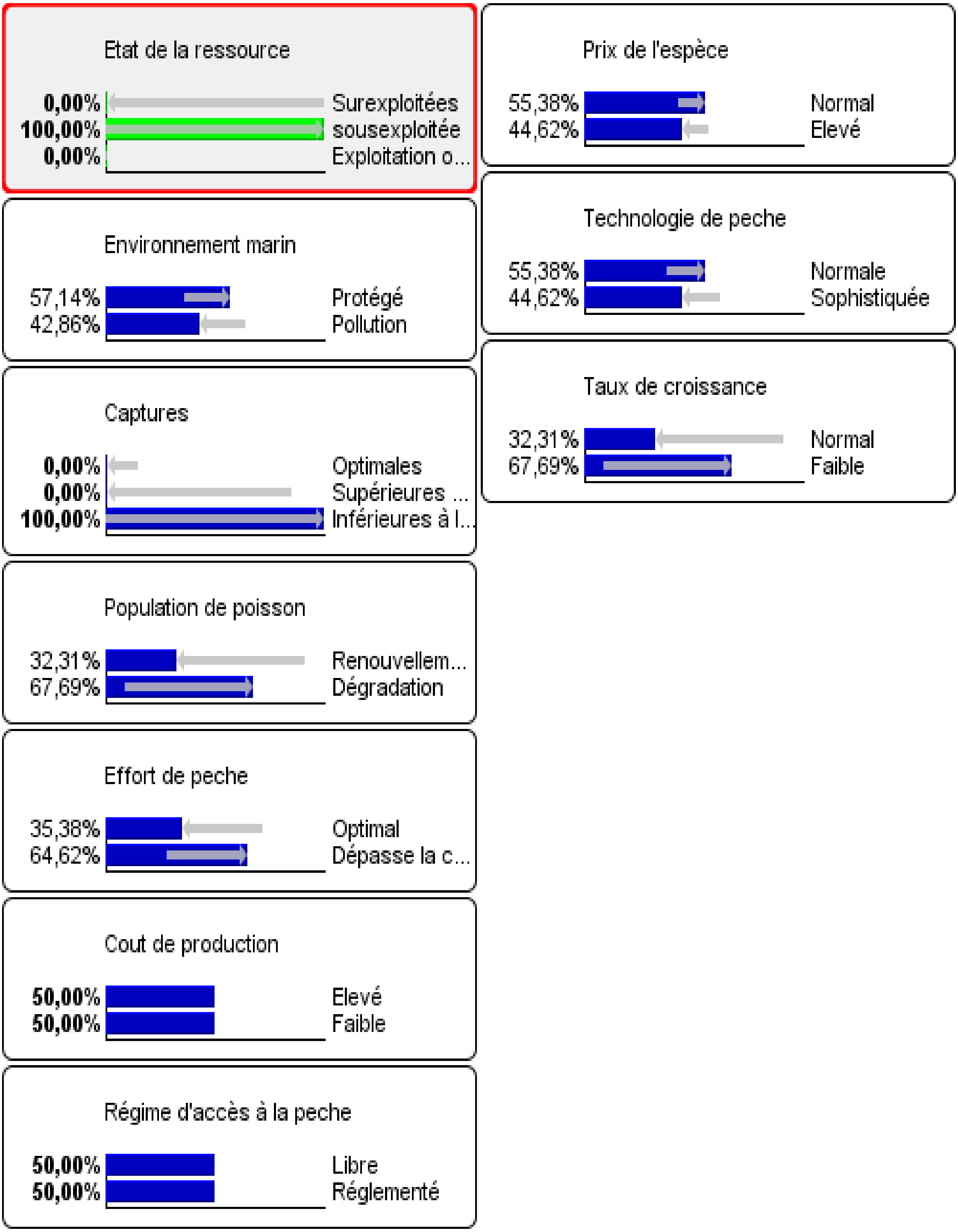
| Population … | Effort de p… | Technologie… | Optimales | Supérieures à l'optimum | Inférieures à l'optimum |
|---|---|---|---|---|---|
| Renouvelle… | Optimal | Normale | 25,000 | 25,000 | 50,000 |
| | | Sophistiquée | 25,000 | 50,000 | 25,000 |
| | Dépasse la … | Normale | 25,000 | 75,000 | 0,000 |
| | | Sophistiquée | 0,000 | 100,000 | 0,000 |
| Dégradation | Optimal | Normale | 75,000 | 0,000 | 25,000 |
| | | Sophistiquée | 75,000 | 0,000 | 25,000 |
| | Dépasse la … | Normale | 25,000 | 0,000 | 75,000 |
| | | Sophistiquée | 25,000 | 0,000 | 75,000 |

**Fish catches**

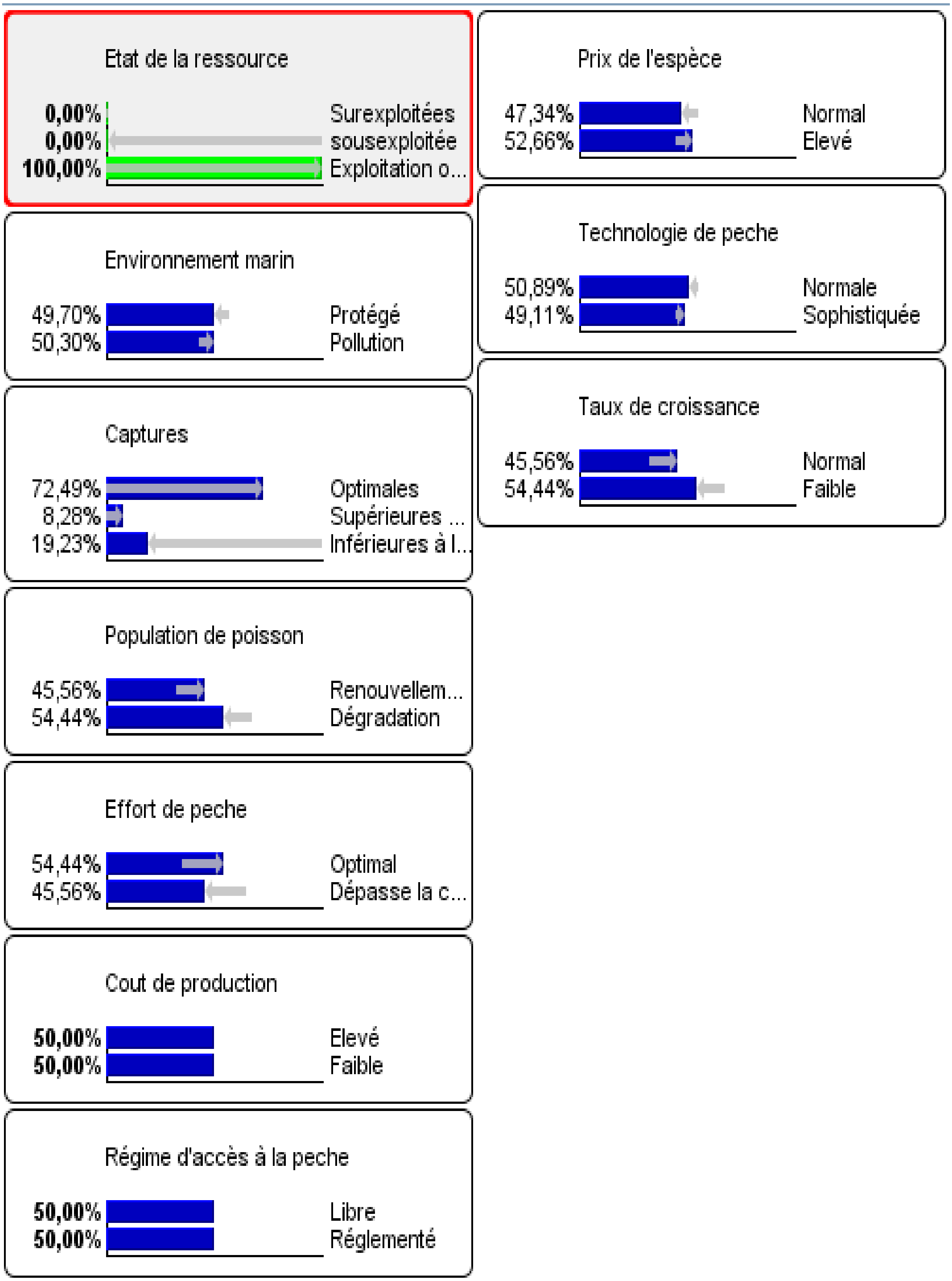
**Appendix 2:**




**Scenario 1**


Etat de la ressource
0,00% Surexploitées
100,00% sousexploitée
0,00% Exploitation o...
Environnement marin
57,14% Protégé
42,86% Pollution
Captures
0,00% Optimales
0,00% Supérieures ...
100,00% Inférieures à l...
Population de poisson
32,31% Renouvellem...
67,69% Dégradation
Effort de peche
35,38% Optimal
64,62% Dépasse la c...
Cout de production
50,00% Elevé
50,00% Faible
Régime d'accès à la peche
50,00% Libre
50,00% Réglementé
Prix de l'espèce
55,38% Normal
44,62% Elevé
Technologie de peche
55,38% Normale
44,62% Sophistiquée
Taux de croissance
32,31% Normal
67,69% Faible

**Scenario 2**


Etat de la ressource
0,00% Surexploitées
0,00% sousexploitée
100,00% Exploitation o...
Environnement marin
49,70% Protégé
50,30% Pollution
Captures
72,49% Optimales
8,28% Supérieures ...
19,23% Inférieures à l...
Population de poisson
45,56% Renouvellem...
54,44% Dégradation
Effort de peche
54,44% Optimal
45,56% Dépasse la c...
Cout de production
50,00% Elevé
50,00% Faible
Régime d'accès à la peche
50,00% Libre
50,00% Réglementé
Prix de l'espèce
47,34% Normal
52,66% Elevé
Technologie de peche
50,89% Normale
49,11% Sophistiquée
Taux de croissance
45,56% Normal
54,44% Faible

**Scenario 2**

*******