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Formalizing a Two-Step Decision-Making Process in Land Use: Evidence from Controlling Forest Clearcutting Using Spatial Information

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Abstract: In this paper, we examine a particular case of land use pattern: forest management activities facing an uncertainty related to spatial information signals received. We investigate the combination of two well-known theoretical approaches, the Blackwell theorem and entropy analysis, in providing a decision support framework for decision makers. We examine the uncertainty related to the information signals received within a decision support context and compute the optimal actions. Drawing on satellite imagery as an additional source of information provided by French spatial data infrastructure (SDI), we illustrate our approach through a clear-cutting control case study. The control of clear-cutting is a central issue in forest management. In order to perform an efficient control operation, uncertainty regarding the decisions to be taken needs to be minimized. Reducing uncertainty in a decision-making context related to forest management provides greater opportunities for improving productivity and for saving time and money. The results show that the information structure through the SDI signals has the most significant information power. Moreover, a maximum of two information structures can be compared when applying the Blackwell theorem. However, while using the entropy approach, a comparison of several information structures can be performed.

Keywords: Blackwell; decision-making; entropy; forest clear-cut; geospatial information; land use; spatial data infrastructure; sustainable development; value of information

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1. Introduction

The control of clear-cutting occupies a center place in land use, and particularly, forest management activities. Designing sustainable management plans in forest activity needs to be coupled with precise inspection control, to be sure that the clear-cuts meet the standards. The purpose of this paper is to examine the combination of two well-known theoretic concepts, Blackwell's theorem and entropy analysis, in providing a decision support framework for decision makers in forest management activities. We outline their association in a unified framework. We present an original approach to study the uncertainty related to information signals received and examine the optimal actions in a decision support context related to clear-cut controls.

1.1. Literature Overview

1.1.1. Standard Decision-Making Methods

There exist several approaches addressing the decision-making processes in the field of forest management. From the initial models developed [1] to more recent techniques

[2], the research works in this area are numerous. The authors in [3] present in their well-known paper, a review of some of the most used decision-making methods and their contribution to the field of forest management. As an example, the multi-objective programming (MOP) method describes how decision makers address the multiple objectives optimization issue linked to a predefined set of constraints. Through the multi-attribute utility theory (MAUT), a cardinal utility function is defined and optimized with respect to each respective constraint. Other methods such as the analytic hierarchy process (AHP) illustrate the decision-maker preferences based on linguistic and hierarchical scales. Other approaches using discrete multi-criteria methods, i.e., ELECTRE and PROMETHEE, were also largely deployed to better select afforestation alternatives when it comes to practices, locations and length of the afforestation period. While most of these methods are based on multi-criteria decision making (MCDM) [4], group decision making (GDM) and goal programming (GP) [5], new approaches are needed in order to respond to the emerging forest management problems, such as risk allocation efficiency, uncertainty under complex environments, multiple-purpose forestry decisions, etc. [6].

1.1.2. Blackwell Contribution to Decision Making

In this context, the robustness of Blackwell's theorem responds to the efficiency issue of risk allocation. Ref. [7] demonstrates that Blackwell equivalence, unlike analytic network processes (ANP) methods, holds for all convex and strongly monotone preferences. In a recent study, Ref. [8] showed that Blackwell's theorem could also be extended to overpass some optimization problems present in the multiple criteria decision support (MCDS) methods, in order to better estimate the maximum expected utility preferences. Unlike the simple multi-attribute rating technique (SMART) focusing on individual preferences, Blackwell's theorem properties can also target the decision-making classes, extending the equivalence results to variational preferences. Moreover, the usefulness of Blackwell's method needs to be highlighted for overcoming the eigenvalue techniques that may be found in some convex preference functions of the data envelopment analysis (DEA). Although decision making under uncertainty is closely related to information and its availability over time, the decision makers facing uncertainty are positioned in a situation without any initial information available, except for prior probabilities of states of nature [9,10]. These latter are characterized by subjective probabilistic distributions, founded by the economic agents and the decision makers [11].

In his seminal contribution, Ref. [12] showed more precise information results in higher welfare. This was called the Blackwell effect, where more information has positive impact on the economic welfare. Later on, Ref. [13] demonstrated that the more accurate the information revealed by the signals, the more limited the risk sharing opportunities in the economy. Intuitively, the more informative the signals are, the less risks that can be shared and the lower the welfare attained by risk-averse agents. On the other hand, many research studies have pointed out that more information could be harmful and the value of information may be negative [14]. In an economy with risk-sharing mechanisms, the release of more information may eliminate opportunities to reallocate risk through trade [15]. While several works highlight Blackwell's comparison of experiments, Ref. [16] investigates the expected value of information using a Bayesian learning link between periods. He underlines the fact that actions taken today under uncertainty determine not only the reward today but also the information available tomorrow In his work [17], he states that the negative relationship between more public information in the sense of Blackwell and the economic welfare is somehow a general case. He considers that Blackwell's ordering is necessary and sufficient, but under certain conditions, and provides equivalent characterization of this ordering. However, Ref. [18] suggests that many pairs of information structures that cannot be ranked by the Blackwell's criterion may still be ranked in investment problems independently of their prior distributions. Following the work of [19], who extends the Blackwell's partial order through restricting the attention to a certain class of decision-making problems, Ref. [20] considers different classes of decision problems and derived a complete order represented by the expected decrease in entropy from the prior to posteriors periods.

1.1.3. Entropy Analysis under Uncertainty

entropy analysis, initially developed by [21], occupied a central place in studying the uncertainty problems linked to information processing. While its related applications reached a large amount of scholarly literature (physics, chemistry, computer science, information theory, etc.), increasing attention has been given on its use within forest management activities. The allocation of resources, the planning activities and the policy development are therefore present in forestry entropy decisions, through questions of values, uncertainty and efficiency measures. While compared to standard multiple criteria decision support methods, entropy provides simple tools for in-depth uncertainty data analysis. In parallel with other methods requiring ratio or interval scale, such as the AHP and its diverse extensions, entropy is a useful tool for complementing the uncertainty analysis, covering both probabilistic and fuzzy cases. It meets the needs for studying ordinal and cardinal information, often present in decision-making case studies. Hence, by better structuring a decision-making context and achieving an optimal inter-temporal allocation of resources, entropy method pushes toward better balancing between present and future welfare [22].

Additional research studies assumed the relevance of entropy in creating interactions between the economy and the environment models, through analyzing various sustainability indicators [2]. As stated in [23], entropy could provide a theoretical basis, unifying the ecological and economics sciences. Consequently, information measures such as conditional entropy and mutual information have been largely applied to the analysis of ecological networks [24]. In such contexts, by taking the difference between the prior and the posterior entropy, the use of entropy does not only highlight the most informative power of an information structure. It also becomes possible to compare the informative power of several information structures in order to classify them according to their informative input. Hence, compared to a group decision-making model (GDM), entropy can establish comprehensive use of various kinds of information coming from diverse sources. Moreover, entropy can be applicable by solely knowing the prior and posterior probabilities, compared to other probabilistic methods (SWOT) and discrete models (DM), where complex numeric simulation and long-term memory models are required, somehow decreasing the accuracy of the results obtained. A recent review of entropy methods used in diverse research works can be found in [25].

1.2. Article Objective

Although the academic literature extensively explores the use of Blackwell's theorem in studying the value of information (VoI), little attention has been put on its combination with entropy analysis. Both theories, whether deployed in disparate context or associated with other concepts, were largely used in analyzing situations under uncertainty. The interest of our research is in understanding to which extent the combination of the two theories, the Blackwell's theorem and entropy analysis, affects the decision-making process. Reducing uncertainty through improving information quality makes it possible to make better decisions, in the sense of increasing social or individual welfare. While the decision making under uncertainty was largely examined under the option or quasi-option theories [9,26,27], the link between the decision analysis and the value of information concepts was explicitly addressed. Refs. [9,26] used a stochastic dynamic programming approach, which takes into consideration the inter-period information gain, in order to characterize the effect of irreversibility. The result fits the classical definition of the value of information (VoI), which is as follows [28]:

$$\begin{aligned}\text{VoI} &= \text{E (Maximum pay-offs)} - \text{Max (Initial expectations)},\\ &= \text{Optimal expected profit under additional information} - \text{Optimal initial expected profit}\end{aligned} \tag{1}$$

Through their work, they illustrated a hypothetical situation in which delaying some decisions in the hope of receiving more precise information on actual returns in the near future could be considered a way to make better choices. Later on, Ref. [29] integrated the uncertainty factor in determining the value of information about returns of uncertain future environmental damages. Ref. [30] brought additional development to the option value concept, highlighting the uncertainty linked to irreversible investments and the value of options when postponing the investment decision. This concept was extended later to situations where decision makers face hard uncertainty, represented by a non-additive measure over events.

While the decision makers are faced with information signals linked to the state of nature prior to their choice of action, the probability distribution may change before the optimal action is chosen. These changes in the information structures could not be captured by classical methods, hence the importance of going beyond the bounds of perfect information contexts. Despite the large attention devoted to studying informational decision making, the existing literature still lacks in responses concerning the role of additional information continuously available over time [31], the way it may influence the prior probabilities in a Bayesian way, and consequently, the decisions related. Our study concerns environments where information arrives over time, as examined previously by [32], similar to the concept of garbling, i.e., (the transformation between information structures) examined by [33]. Through the integration of a common information structure within both theories, we provide a decision support framework which integrates the multiple constraints of a decision-making exercise in terms of investment and expected return elements. This allows one to better understand the complex choices the decision makers may face, and therefore interprets their consequences. To the authors' best knowledge, integrating a common "information structure" to both entropy and Blackwell analysis into a unified framework has not been studied yet. Note that in our research, these concepts are applied for the first time with a particular focus on the satellite imagery as an additional source of information.

1.3. Why Choosing a Forest Clear-Cut Control

In order to give a more explicit view and develop concrete arguments, we will consider the forest management case study, and more particularly, the clear-cutting control. The control of clear-cutting lies at the heart of forest management activities, due to the large economic and environmental consequences it may have [34]. Clear-cutting is a forestry management practice in which most or all trees in a certain area are cut down [35]. It is used by foresters to create certain types of forest ecosystems and to promote selected species [36,37]. It responds to the environmental regulations initiatives elaborated by the FAO in 2016 [38] on promoting sustainable practices in the exploitation and preservation of the forests. Designing sustainable management plans in forest activity needs to be coupled with precise inspection control, to be sure that the clear-cuts meet the standards [39,40]. In general, a forest clear-cut control entity responsible for the control operations decides whether the control units should perform parcel inspections or not, based on received information. Decisions are made based on several "information signals" provided by different sources. Therefore, based on an entire "information structure", an action has to be taken with regard to the situation of clear-cut that emerges. Hence, in order to perform an efficient control operation, uncertainty regarding the decisions to be taken needs to be minimized [41]. As a consequence, the problem to be solved can be summarized as follows:

i. Find the most powerful information structures.

ii. Determine the optimal action in terms of payoffs.

The information structure specifies the distribution of signals that the control entity receives about the different states of nature. While the application of entropy evaluates the rate of decrease in uncertainty following a reception of additional information, the

Blackwell approach determines the optimal action to be taken. Decomposing the decision-making process into many steps, more consistent with one another, provides a basis for bringing multiple decision elements together. The process is defined through the comparison of information structures based on the informative power and the optimal actions they induce. The contribution comes in presenting an original framework that articulates the two theories, in order to lead decision makers to model their decision in light of received information. Based on the empirical facts and on the existing theory, this paper seeks to fill a gap between the previous research in the field of value of information and the decision-making problems in land use under uncertainty.

1.4. Article Outline

The remainder of the paper is organized as follows: Section 2 presents the model, followed by a comparison of the informative power of the information structures using the Blackwell and entropy approaches. We then present the empirical context of a forest's clear-cutting decision-making problem. Section 3 lays out the findings from each of the two approaches. Section 4 offers a discussion based on the empirical analysis coupled with the existent literature. Finally, Section 5closes the paper.

2. Materials and Methods

2.1. Theoretical Model

We consider an economy that extends over two periods. Let $\boldsymbol{A} = \{\boldsymbol{a_1}, \boldsymbol{a_2}, \dots, \boldsymbol{a_n}\}$ be the set of available initial actions (at the beginning of the first period) and $\boldsymbol{B} = \{\boldsymbol{b_1}, \boldsymbol{b_2}, \dots, \boldsymbol{b_m}\}$ be the set of available actions at the beginning of the second period after receiving the additional information. $\boldsymbol{S} = \{\boldsymbol{s_1}, \boldsymbol{s_2}, \dots, \boldsymbol{s_L}\}$ is the set of possible states of nature and $\boldsymbol{Y} = \{\boldsymbol{y_1}, \boldsymbol{y_2}, \dots, \boldsymbol{y_K}\}$ is the set of messages/signals (additional information) received at the end of period one.

$\boldsymbol{L}$ and $\boldsymbol{K}$ respectively denote the number of possible states of nature and the number of available signals. The vectors $\boldsymbol{\pi} = (\boldsymbol{\pi_1}, \boldsymbol{\pi_2}, \dots, \boldsymbol{\pi_L})$ and $\boldsymbol{q} = (\boldsymbol{q_1}, \boldsymbol{q_2}, \dots, \boldsymbol{q_K})$ are defined as the prior probability distributions respectively associated with $\boldsymbol{S}$ and $\boldsymbol{Y}$ (i.e., $\boldsymbol{\pi_i} = \mathbb{P}[\boldsymbol{S} = \boldsymbol{s_i}]$; $\boldsymbol{1 \le i \le L}$ and $\boldsymbol{q_j} = \mathbb{P}[\boldsymbol{Y} = \boldsymbol{y_j}]$; $\boldsymbol{1 \le j \le K}$) with $\sum_{i=1}^{L} \boldsymbol{\pi_i} = \sum_{j=1}^{K} \boldsymbol{q_j} = \boldsymbol{1}$. The matrix $\boldsymbol{P} = (\boldsymbol{p_{ij}})_{\substack{1 \le i \le L \\ 1 \le j \le K}}$ represents the set of conditional probabilities of $\boldsymbol{s_i}$ given $\boldsymbol{y_j}$ $\left(\boldsymbol{p_{ij}} = \mathbb{P}[\boldsymbol{S} = \boldsymbol{s_i} | \boldsymbol{Y} = \boldsymbol{y_j}]\right)$. Each column of the matrix $\boldsymbol{P}$ represents the posterior probability distribution of $\boldsymbol{S}$ for a given received signal from the set $\boldsymbol{Y}$, e.g., the $\boldsymbol{j}$**th** column of $\boldsymbol{P}$ will be denoted by $\boldsymbol{\pi}(\boldsymbol{y_j}) = (\boldsymbol{p_{1j}}, \boldsymbol{p_{2j}}, \dots, \boldsymbol{p_{Lj}})$. In the sequel, the couple $(\boldsymbol{P}, \boldsymbol{q})$ will be denoted by "information structure". In addition, $(\boldsymbol{P}, \boldsymbol{q})$ will be used later to rank the information structures according to their informative power. In order to rank the initial actions, the payoff and cost functions for switching from one action in the first period to another one in the second period should be well defined.

Let

$$\boldsymbol{F}(\boldsymbol{a_i}, \boldsymbol{b_j}; \boldsymbol{s_l}) = \boldsymbol{R}(\boldsymbol{a_i}; \boldsymbol{s_l}) + \boldsymbol{U}(\boldsymbol{b_j}; \boldsymbol{s_l}) - \boldsymbol{C}(\boldsymbol{a_i}, \boldsymbol{b_j}; \boldsymbol{s_l}), \quad (2)$$

represent the total payoff produced by switching from $\boldsymbol{a_i}$ to $\boldsymbol{b_j}$ under state $\boldsymbol{s_l}$. $\boldsymbol{R}(\boldsymbol{a_i}; \boldsymbol{s_l})$ and $\boldsymbol{U}(\boldsymbol{b_j}; \boldsymbol{s_l})$ stand for the returns generated during the first and second period actions respectively under the state $\boldsymbol{s_l}$, while $\boldsymbol{C}(\boldsymbol{a_i}, \boldsymbol{b_j}; \boldsymbol{s_l})$ denotes the switching cost from $\boldsymbol{a_i}$ to $\boldsymbol{b_j}$ under the state $\boldsymbol{s_l}$.

In our context consisting of a decision-making problem, we will try to compare, on one hand, the informative power of two or more information structures, i.e., the amount to be learned from future information. On the other hand, we will seek to find the optimal actions to undertake. In order to perform this, two approaches will be used: the Blackwell theorem and the probabilistic entropy principle.

2.1.1. Blackwell Approach

We consider an information structure (P, q). Let $\Delta = (\delta_{ij})_{\substack{1\le i\le L\\1\le j\le K}}$ a Markov matrix of conditional probabilities, such that $\delta_{ij} = \mathbb{P}[Y = y_j | S = s_i]$. (P', q') represents another information structure, built on the same sets Y and S with $\Delta' = (\delta'_{ij})_{\substack{1\le i\le L\\1\le j\le K}}$ being the corresponding Markov matrix. Using Blackwell's terminology [42], the structure (P, q) is said to be more informative than (P', q'), and we denote $(P, q) \gtrsim (P', q')$, in the sense that it offers a greater amount of information at the end of the first period, which takes an optimal choice of actions at the beginning of period two. It is applicable if and only if there exists a Markov matrix M with appropriate dimensions such that $\Delta M = \Delta'$. This result is known in the literature as Blackwell's Theorem.

In order to avoid a high level of complexity resulting from the direct application of Blackwell′s theorem, equivalent results obtained in [12] (which simplify the procedure of ordering the information structures) will be introduced. First, some mathematical objects need to be defined. Recall that, for a given information structure (P, q) defined on the sets A, B, Y and S, an optimal decision consists of a precising first period action a_i then a second period b_j depending on the observed message/signal y_k at the end of the first period in order to maximize the total expected payoff. This maximization procedure can be represented by the following expression:

$$\Phi(P, q) = \max_{a_i \in A} \sum_{y_k \in Y} q_k \max_{b_j \in B} \sum_{s_l \in S} p_{lk}\ F(a_i, b_j; s_l). \tag{3}$$

Additionally, the prior probability distribution of the states of nature (i.e., probabilities before observing any signal) defined previously by the vector π will be fixed in a way to verify:

$$\pi_i = \sum_{j=1}^{K} q_j p_{ij}\ with\ 1 \le i \le L, \tag{4}$$

and will be noted as the mean of the structure (P, q). Thus, the main results of [12] are represented as follows:

Theorem 1. *Let (P, q) and (P', q') be two information structures defined on the same sets A, B, Y and S. Then, $(P, q) \gtrsim (P', q')$ if and only if for all convex function ψ: $[0,1]^L \to \mathbb{R}$,*

$$\sum_{j=1}^{K} q_j \psi\left(\pi(y_j)\right) \ge \sum_{j=1}^{K} q'_j \psi\left(\pi'(y_j)\right).$$

Remark 1. *In order to compare two information structures (P, q) and (P', q') in the sense of Blackwell, they must have the same prior probability distribution related to the states of nature, i.e.,*

$$\sum_{j=1}^{K} q_j p_{ij} = \sum_{j=1}^{K} q'_j p'_{ij}\ \forall i,$$

Remember the effect of the additional information on the posterior probabilities, i.e., the states of nature's probabilities at the beginning of period two.

The complexity of Theorem 1 relies on the universal quantifier that manages the choice of the convex function. A more practical and simpler method to be used in comparing information structures was introduced by [43].

Let B be a finite set of second period actions and $U(.,.)$ be the second period payoff function defined on $B \times S$. Ref. [43] showed that if (P, q) and (P', q') are two information structures defined on the same sets A, B, Y and S, then $(P,q) \gtrsim (P',q')$ if and only if

$$\sum_{y_k \in Y} q_k \max_{b_j \in B} \sum_{s_l \in S} p_{lk}\ U(b_j, s_l) \geq \sum_{y_k \in Y} q'_k \max_{b_j \in B} \sum_{s_l \in S} p'_{lk}\ U(b_j, s_l) \tag{5}$$

Hence, by applying Equation (5) under the constraint of Remark 1, it is possible to detect which information structure is more informative about the states of nature's posterior distribution.

2.1.2. Entropy Approach

Shannon's probabilistic entropy is used in the field of information theory, to measure the reduction of uncertainty in a decision-making context caused by an additional amount of information. This approach is defined as follows:

Definition 1. *The Shannon entropy, denoted by* H*, of a probability distribution* $\mathbb{P} = (\mathbb{P}[X = x_1], \dots, \mathbb{P}[X = x_n])$ *on a finite random variable* $X = \{x_1, \dots, x_n\}$ *is defined as a degree of uncertainty of a system composed of* n *outcomes.*

The mathematical expression of entropy is:

$$H(X) = -\sum_{i=1}^{n} \mathbb{P}[X = x_i] \log \mathbb{P}[X = x_i],$$

where log represents the binary logarithm function and entropy is expressed in bits [25]. By convention, we consider *0log0 = 0*. Note that when $H(X)$ is close to zero, the random variable X represents a very slight uncertainty. Consequently, the level of uncertainty increases with the increase in the value of entropy to reach a maximum of $\log n$ in the case of a uniform discrete probability distribution *(i.e.,* $\mathbb{P}[X = x_i] = \frac{1}{n}\ \forall i$*).* In general, entropy is useful to compute the level of uncertainty before (based on the prior probabilities) and after (based on the posterior probabilities) receiving additional information about the states of nature. Therefore, by using these measures in our context, it becomes feasible to evaluate the quality of an information structure at the level of the power of information received and compare it to other information structures. We start by computing the prior entropy:

$$H(S) = -\sum_{i=1}^{L} \pi_i \log \pi_i, \tag{6}$$

where $\pi_i;\ 1 \leq i \leq L$ denotes the prior probabilities of the states of nature and L the number of these states. Using Equation (6), we can measure the uncertainty at the beginning of period one.

By supposing that at the end of period one, additional information is being received in the form of signal/message y_k about the states of nature, we can compute the posterior entropy:

$$H(S|y_k) = -\sum_{i=1}^{L} p_{ik} \log p_{ik}, \tag{7}$$

where $p_{ik} = \mathbb{P}[S = s_i | Y = y_k]$. Using Equation (7), defined as the conditional entropy, the effect of the signal y_k on reducing the initial uncertainty can be measured. By considering all the possible signals with their probability distribution, the expected posterior entropy given below will be evaluated:

$$H(S|Y) = \sum_{k=1}^{K} q_k \, H(S|y_k), \tag{8}$$

where $q_k;\ 1 \leq k \leq K$ denotes the probability distribution of the received signals and K the number of available signals. Based on (8), the global expected effect of additional information on reducing uncertainty can be computed. In order to combine and compare the prior situation (Equation (6)) and the posterior ones (Equations (7) and (8)), the mutual information is defined as follows:

Definition 2. *The mutual information of two random variables X and Y, denoted as $I(X,Y)$ is defined as the change in information after observing Y, given the prior information on X. It is given by the following expression:*

$$I(X,Y) = H(X) - H(X|Y).$$

$I(X,Y)$ represents the difference between the prior and posterior entropies. Note that $I(X,Y) \geq 0$, because additional information can never increase the level of uncertainty of a random variable *(i.e.,* $H(X) \geq H(X|Y)$*)*. In the worst case, when Y is with no added information value, the level of uncertainty remains unchanged. Accordingly, a high $I(X,Y)$ implies that the amount of information about the variable X obtained from the variable Y is significant. Otherwise, Y is not helpful in obtaining information about X. If $I(X,Y) = 0$, then X and Y are independent.

In the context of a decision-making problem, the mutual information of the states of nature and the received signals are defined as follows:

$$\begin{aligned} I(S,Y) &= H(S) - H(S|Y) \\ &= -\sum_{i=1}^{L} \pi_i \, log \, \pi_i + \sum_{k=1}^{K} q_k \sum_{i=1}^{L} p_{ik} \, log \, p_{ik}. \end{aligned} \tag{9}$$

Based on Equation (9), the utility of a set of signals on the reduction of the level of posterior uncertainty can be evaluated. In other words, the mutual information can also be used to classify different information structures in terms of their informative power.

2.2. Case Study

Our analysis will be applied to a specific case study: the clear-cutting in France, where forests occupy 30% of the territory, i.e., 16.5 million hectares [44]. Forest clear-cut control is carried out by the regional and local technical authorities of the French ministry of agriculture. By performing land visits, the authorities are not able to carry out an exhaustive control. Additional information should be required. To achieve this process, the satellite images with their related applications are considered a very useful tool for the mapping and the detection of changes in the forests. The GEOSUD spatial data infrastructure (SDI) was selected to undergo the study, because of its significant positive effect on the availability of the geospatial data in France, more particularly, with its developed method for systematic mapping of the clear-cuts through high resolution (HR) satellite imagery. The operational applications of remote sensing in the field of forest management have remained limited for a long time. Several reasons are of influence: the high cost of available data, the insufficient image resolution and the difficult access to geo-spatial information [45]. Recently, several methods for the detection and mapping of clear-cuts have emerged [46]. Upon the request of the French ministry of agriculture and in order to face operational difficulties, the GEOSUD SDI has developed an algorithm for the systematic mapping of the clear-cuts, based on HR satellite imagery. The satellite images are available free of charge for the state services already registered on the GEOSUD SDI platform.

2.2.1. Data Collection and Analysis

Data were collected during a seven-month period, from May until November 2019. We conducted interviews with 116 respondents, representing a total of 23 control entities (Table 1). Representativeness of the control entities was found to be relevant to the whole French territory:

Table 1. Data collection.

Date (2019)	Region (France)	Number of People Interviewed
May	Occitanie/Nouvelle Aquitaine	26
June	Île de France/Centre Val de Loire	17
July	Pays de la Loire/Bretagne–Normandie	25
September	Hauts de France/Grand Est	22
October	Bourgogne–Franche–Compté	12
November	Auvergne–Rhône–Alpes/Provence–Alpes Côte d'Azur	14

In addition, we referred to technical documents and on-site mission reports, in order to enrich our observations. As our interviews progressed, we tried to collect information from different sources, which we fully integrated into our methodological application as follows.

2.2.2. Case Description

In order to apply Blackwell's theorem and entropy principle in a practical way, we considered the French administrative entities "DDT" and "DRAAF" (direction départementale des Térritoires, direction régionale de l'alimentation, de l'agriculture et de la forêt) responsible of the clear-cutting operations in France. The aim of these entities is to detect cheat cases, using the information provided by different sources. Based on an entire "information structure", a control entity has to take action with regard to the situation of the clear-cut that emerges. The representation of our case, as a two period's decision-making problem, is as follows:

Suppose that, without any information at the beginning of period one, the entity must choose between two actions: a_1 = control and a_2 = no control, with $A = \{a_1, a_2\}$. At the end of period one, further information would have been received. Based on these signals, another action should be taken at the beginning of period two. We considered four possible states of nature: s_1 = absence of cheating, s_2 = partially cheating inside management plan, s_3 = partially cheating outside management plan and s_4 = strong cheating (clearing). $S = \{s_1, s_2, s_3, s_4\}$ with $L = 4$.

In the first place, the state of nature denoted by s_1 represents an absence of cheating in the land plots. This is the case where the clear-cuts meet the standards. Secondly, within the management plans "plans simples de gestion (PSG)", there exist forest areas in which a number of forest practices are achieved. Cheating in such a context may take place in the sense of non-compliance with the intended area to be cut. This situation represents the second state of nature s_2. On the other hand, there are areas that are not subject to management plans, essentially unexploited forests where the cuts are still applied. Despite the fact that these areas regenerate into forests, it is considered as a superior level of cheating with respect to the preceding case and presents the third state of nature denoted by s_3. Finally, the highest cheating level that totally changes the plot assignment will be denoted by s_4. Due to this situation, the forests are permanently removed. Unlike clearing, which has an effect of destroying the wooded state and leading to a change in the use of the soil, the clear-cuts are accompanied by an obligation for a natural reconstitution or replanting of the cut surfaces [47]. It is the responsibility of the owner or the operator to ensure the renewal of the stands within a period after cutting, either through natural regeneration or replanting. Infringements of these obligations are sanctioned with fines, either for non-reconstitution of cuts or for unauthorized cuts considered as illegal and abusive.

On the other hand, the information signals that can be received by the control entity are as follows: y_1 = individual denunciation, y_2 = report from the « Centre national de la propriété forestière » (CRPF (the public institution in charge of developing the sustainable management of private forests in France. https://www.cnpf.fr/)), y_3 ="DDT" and "DRAAF" report, y_4 = GEOSUD SDI image demonstrating a cheat and y_5 = GEOSUD SDI image demonstrating a conformity with the law. $Y = \{y_1, y_2, y_3, y_4, y_5\}$ with $K = 5$.

Concerning the information signals that a control entity could receive, the first signal comes out in the form of an individual denunciation and will be denoted by y_1. The second case, y_2, is a report from the forest professionals, people who are used to the forest management activities and are legitimate to send information reports to the control entities. The third case, y_3, is represented by the state services who, through their various missions on the grounds, discover illegal cuts; this will enable a control procedure to be initiated later. Finally, the signals y_4 and y_5 represent the HR satellite images coming from the GEOSUD SDI. These images are additional elements for respectively demonstrating a cheat or a compliance with the law. Previously, the denouncement was considered a primary factor for executing a control operation. Actually, before starting a regularization phase and even after receiving a control signal, the authorities check out this information through the GEOSUD satellite imagery support.

We assume that the available actions at the beginning of period two, after receiving the information signals, are the same as those actions available initially, i.e., $b_1 = a_1$ and $b_2 = a_2$ with $B = \{b_1, b_2\}$. Note that the initial action a_1 is considered irreversible. Once a_1 is applied, no other actions can be taken in the second period.

Let the information structure (P, q) be described by the following:

$$P = (p_{ij})_{\substack{1 \le i \le 4 \\ 1 \le j \le 5}} = \begin{pmatrix} 0.05 & 0 & 0 & 0.20 & 0.80 \\ 0.05 & 0.20 & 0.20 & 0.05 & 0.10 \\ 0.70 & 0.70 & 0.70 & 0.75 & 0.05 \\ 0.20 & 0.10 & 0.10 & 0 & 0.05 \end{pmatrix}$$

and $q = (0.066, 0.066, 0.066, 0.04, 0.76)$.

The Matrix P results from the interviews and discussions with the experts, already mentioned above. Then, using this information structure, we can compute the prior distribution of the states of nature by applying Equation (4):

$$\pi = (0.619, 0.108, 0.208, 0.065).$$

As shown in matrix P, we respectively define four states of nature in rows and five signals in columns. We assume that the probability of a state of nature conditioned by receiving a signal will vary in each scenario in order to establish an information structure called P. A more explicit presentation of the matrix can clarify the logic behind some probabilities. As an example, announcing an individual denunciation, while having a state of nature indicating an absence of cheating is affected by a probability of 5% (row 1, column 1). The control entities reveal that similar cases exist with a low frequency. This is mainly due to the fact that some people prefer denouncing clear-cuts activities, even without being well informed of the whole situation. These denunciations are often related to environmental concerns that people have and their preference of being assured that the control services are aware of similar situations. Moreover, the zero probabilities (row 1, columns 2 and 3), represent a report case from the forest professionals or the state services announcing a cheating, without this being true in reality—an almost impossible situation.

Apparently, what was interesting to look at and unexpected before conducting our interviews, is that even though satellite imagery is supposed to give a high level of confidence about the state of the forests, some factors can lead to a misinterpretation of the images. Various entities noted that during particular seasons, by analyzing the satellite images from the GEOSUD SDI, some images provided facts that can be interpreted as cases of cheating; by performing field checks, these results appear to be wrong. This is due to factors such as drought, season change, etc. After discussing with the professionals, a probability of 20% was assigned for such situations (row 1, column 4). It is noted that in 80% of the cases, a satellite image showing compliance with the law sticks with the case of absence of cheating (row 1, column 5). Usually, the control entities hold the forest management plans in each department. In parallel, the GEOSUD SDI carries out detection work of the land plots via the satellite images coupled with the necessary applications. In general, if these plots are located within the PSGs, they will not be inspected by the control entities, because this was planned for in the PSGs. Thus, the attention will be mainly turned toward the lands located outside the PSGs. A report provided by the CRPF indicating a partial cheating outside PSG is represented in our matrix by a probability of 70% (column 2, row 3), compared to 20% when cheating is located inside the PSGs (column 2, row 2). Likewise, announcing an individual cheat denunciation in a management plan with the fact to be true remains a rare case, given the lack of ability in measuring the precise changes. Thus, a probability of 5% was affected (row 2, column 1). On the other hand, making an individual denunciation with a cheat out of the management plans represents a probability much higher than that of a clearing. This is due to the absence of very frequent cases of clearing and what it represents as illegal situations with very serious consequences. As a result, a probability of 70% (row 3, column 1) was assigned, compared to 20% for the state of nature s_4 (row 4, column 1).

3. Results

3.1. Entropy Results

Based solely on the probability distributions, we can apply an entropy approach to assess the effectiveness of the information structure in terms of reducing uncertainty. Starting with prior entropy, we obtain:

$$H(S) = 1.5\ bits.$$

After receiving the additional information, we can compute the posterior entropy:

$$H(S|Y) = 1.054\ bits.$$

Hence, the mutual information generated by the structure (P, q) is:

$$I(S,Y) = H(S) - H(S|Y) = 0.446\ bits.$$

Thus, the information structure has an information power of 0.446 bits. Therefore, without any assumptions about the payoffs of the first and second period actions, the reduction of uncertainty can be measured. Due to the additional signals received at the end of the first period, this reduction is equal to: $\frac{1.5-1.054}{1.5} \times 100 = 29.73\%$.

On the other hand, in order to compute the reduction of uncertainty made possible just through the additional information due to the GEOSUD SDI satellite images (i.e., signals 4 and 5), it is necessary to compute the posterior entropy that is given by:

$$H\left(S|y_{\{4.5\}}\right) = 1.020 \text{ bits}.$$

with a reduction of uncertainty equal to: $\frac{1.5-1.020}{1.5} \times 100 = 32\%$.

In addition, after receiving the additional information provided by signals 1, 2 and 3, the posterior entropy is as follows:

$$H\left(S|y_{\{1,2,3\}}\right) = 1.190 \text{ bits}.$$

with a reduction of uncertainty equal to: $\frac{1.5-1.190}{1.5} \times 100 = 20.67\%$.

According to our data, the additional information received through GEOSUD SDI signals appears more valuable in terms of reduction of uncertainty than the signals 1, 2 and 3; $H(S|y_{\{4.5\}}) > H(S|y_{\{1,2,3\}})$. Thus, the GEOSUD SDI information structure has more significant information power.

3.2. Blackwell Results

In order to apply Blackwell's theorem, the payoffs of different actions under different states of nature should be defined. The necessary factors used to compute these payoffs are summarized in Tables 2 and 3.

Table 2. Unit amounts of different factors of payoffs.

Factors	Amount per Unit
Fuel	0.17 EUR/km
Technician salary	2700 EUR/month i.e., 150 EUR/day
Engineer salary	4750 EUR/month i.e., 250 EUR/day
Average number of working days	19 days/month
Fine due to $\boldsymbol{s_3}$	4000 EUR
Fine due to $\boldsymbol{s_4}$	160,000 EUR

Table 3. Elements constituting the payoffs of each action.

	Number of Days/Engineer	Number of Days/Technician	Average Distance (km)	Fine (€)
$(\boldsymbol{a_1}, \boldsymbol{s_1})$	0.5	0	150	0
$(\boldsymbol{a_1}, \boldsymbol{s_2})$	1	0	150	0
$(\boldsymbol{a_1}, \boldsymbol{s_3})$	15	15	300	4000
$(\boldsymbol{a_1}, \boldsymbol{s_4})$	15	15	300	160,000

As shown in Table 3, we present the elements that constitute the returns of the first action ($\boldsymbol{a_1}$) with respect to the four states of nature; the returns in EUR generated during the first and second period actions, under different states of nature, are summarized in Tables 4 and 5.

Table 4. Payoffs of the first period actions $(\boldsymbol{R}(\boldsymbol{a_i}; \boldsymbol{s_l}))$.

	$\boldsymbol{s_1}$	$\boldsymbol{s_2}$	$\boldsymbol{s_3}$	$\boldsymbol{s_4}$
$\boldsymbol{a_1}$	−150.5	−275.5	2051	153,949
$\boldsymbol{a_2}$	0	0	0	0

Table 5. Payoffs of the second period actions $(\boldsymbol{U}(\boldsymbol{b_j}; \boldsymbol{s_l}))$.

	$\boldsymbol{s_1}$	$\boldsymbol{s_2}$	$\boldsymbol{s_3}$	$\boldsymbol{s_4}$
$\boldsymbol{b_1} = \boldsymbol{a_1}$	−150.5	−275.5	2051	153,949
$\boldsymbol{b_2} = \boldsymbol{a_2}$	0	0	−4000	−160,000

In addition, the cost in EUR of switching from an action to another under different states of nature is considered to be zero because all these costs are financed by state services other than the "DDT" and "DRAAF". Recall that switching from a_1 to any other action in the second period in impossible.

To assess the informative power of the considered information structure in the sense of Blackwell, we apply Equation (5):

$$\sum_{y_k \in Y} q_k \max_{b_j \in B} \sum_{s_l \in S} p_{lk} \ U(b_j, s_l) = 7669.62.$$

The optimal action to be taken at the beginning of period one can be specified by maximizing the expected payoff (Equation (3)).

Based on all the previous cost and information assumptions, the best action to be initially taken is a_2 because it generates a maximum expected payoff of EUR 24,125.48, higher than the a_1 expected payoff equal to EUR -314.72.

Remark 2. *In this application, the comparative aspect of the two approaches (Blackwell and entropy) was not applied due to a unique information structure represented by* (P, q)*. The availability of another source of information, allows one to build another information structure in order to perform a comparison between the two.*

4. Discussion

First, in a situation where the decision maker is faced with several information structures, the application of entropy approach highlights the structure with the most informative power by taking the difference between the prior and the posterior entropy. The mutual information represents the level of uncertainty diminished by the received signals. Hence, it becomes possible to compare the informative power of several information structures with respect to their prior probability distribution, and compute the reduction in the uncertainty level through each of these structures. Thus, without any additional information, these structures can be classified according to their informative input. However, only two information structures can be compared at once in order to elaborate the informative power of each, through the Blackwell theorem. Herein, we can highlight the first advantage of entropy mutual information approach compared to the principle of Blackwell. Second, in order to apply the Blackwell comparison theorem, many assumptions should be taken about the payoff of the first and second period actions, under different states of nature. Additional considerations regarding the transition costs in response to a period change could also be present and may lower the accuracy of the decisions. However, the mutual information approach is applicable by solely knowing the prior and posterior probabilities. Thus, level one could be helpful in discriminating the information structures in order to pass to the second level concerning the action optimization.

Herein, several steps should be applied. We enumerate these steps as follows, presenting a decision policy form:

Step 1. The choice of the two most powerful information structures, based on level one results. Once the information structure is ranked according to their informative input, the decision maker may eliminate the other possible alternatives, hence making the decision process easier.
Step 2. The assessment of the information power: the two structures should be assigned with their informative power in the sense of Blackwell.
Step 3. The computation of the optimal action: the action with the maximum expected payoff.

Applying the Blackwell method right after entropy theory and not as a first step, avoids integrating many factors to all the initial information structures available. Computing the information power of all the information structures while integrating the economic factors (such as the cost, the revenues, etc.) is a hard exercise. Once step 1 is complete, the Blackwell method applied to two structures simplifies the variables assignment and increases the precision and accuracy of the decision-making process.

While this study offers an articulation between two widely known theoretical approaches, it also reveals concrete results. The empirical research helps to better understand how the information is being used to support forest management activities. Understanding the impact of spatial data on decision-making processes makes it possible to offer answers to the evolution of devices carrying these types of data. The detailed description of the case study and the decision policy process help to better illustrate the choices to which the controlling entities are confronted with in regard to their actions within a common framework policy.

The case study analyzed in this paper can advance the general observations on how to shape the decisions and actions between different parties concerned in forest management activities. Although we were not able to apply, in our case study, steps 1 and 2, which represent the comparative aspect for information power, due to the absence of several information structures, we established a comparison between the signals y_1, y_2, y_3, on the one hand, and the spatial information denoted by the signals y_4, y_5, on the other hand. For a control entity, it was shown that the additional information received through the GEOSUD SDI is set to be the best scenario in reducing the uncertainty (32%) compared to a typical scenario with no spatial information (20.67%). Moreover, by applying step 3 to the unique information structure, we determined the optimal action (a_2 = No control). Not controlling in period one leaves the choice to perform a control under period two. Hence, the optimal action a_2 is the more flexible compared to a_1. The latter result is not necessarily always true. Several conditions and hypotheses should be verified, especially [4] considering that at the end of the first period, perfect information will be available in order to choose the optimal action. However, in our case, the information at the end of the first period is according to a probabilistic distribution, hence partial information.

Although not all control activities are similar nor the actions involved, this paper offers a useful description to put these concepts together and summarize their implications in a decision-making process. It offers a support tool where some analytical models do not capture the decision makers' intuitive preferences [48]. Moreover, it helps to overcome the complexity of group decision-making models [49,50], the unavailability of sufficient data or time constraints [51] and the aggregation of subjective and objective judgements in the evaluation processes [52]. An understanding of the value of information may rely in some cases on the decision makers themselves, whose actions tend to be too revealing of the value [53].

Despite the fact that our approach relies on the choice of probabilities in a subjective way, this procedure has been widely used in decision making because it requires no historical data [54,55]. Other studies such as binomial probabilities are commonly used as well in strategic decision fields, making the problem simpler by analyzing the possible outcomes as either occurring or not occurring [56].

5. Conclusions

This study provides a valuable tool in analyzing how the decision process can accompany the reflections of policy makers in land use patterns. Reducing the uncertainty in a decision-making context related to forest management can provide greater opportunities for making better decisions, improving productivity and saving time and money [57]. Our research shows that combining entropy and Blackwell methods is useful for defining a decision-making strategy. The main contribution of the paper is in presenting an innovative approach on how this articulation can influence the decision maker's strategy in land use. The usual problem relies on the set of decisions to take that logically determine future outcomes. By providing concrete elements on how forest control entities can model their actions in light of received information, this paper offers a framework through which these concepts are associated. A detailed description of the forest clear-cutting case study contributes to understanding the choices that the control entities face regarding their actions, as part of a global regulating policy.

The central issue of economics dealing with natural resource problems is the way to measure and respond to sustainability constraints related to decisional contexts. Our approach is particularly relevant in determining the way current or future decisions may impact decision-making processes. It could be easily adapted to several contexts. As in the multi-criteria approaches, where the decision makers' preferences are integrated into multiple analytical frameworks, this methodology could be very useful, especially as it provides a simple tool for analyzing complex managerial and marketing decision processes. Additionally, as the public concern for environmental issues is increasing, due to the lack of public participation in decision making, the results can be used in a more formalized manner. Environmental assessment, biodiversity issues, and climate change are examples of where decision makers are faced with long iterative decisions [58]. Thus, incorporating environmental and sustainability considerations into strategic decision-making processes could optimize the decision tasks related to project evaluation [59].

Finally, pursuing further research is needed as a next step, through case studies presenting several information structures. Applying this methodology in larger contexts can enrich the analysis and results of future works and case studies. Moreover, since participatory approaches have gained large acceptance in forest management practices, crossing this methodology with entropy theory could be of utility in measuring environmental performance. Despite the flexibility in weight generation for the economic agent or decision makers, this combination can have positive impacts on reinforcing community-based forest management. Another possibility for extending this work consists of combining non-parametric techniques known for their commonly used classification and ranking methods. Although Blackwell's theory allows for the incorporation of the quantitative information that exists in a two-step decision policy, its combination with other non-parametric techniques may increase its capability to accommodate multiple criteria in decision-making analyses. While increasing stakeholder engagement is needed in forest management and planning processes, non-parametric techniques can be useful in capturing behavioral patterns among decision makers, leading to better implementation of forest-management strategies in the future. Experiences gained from cognitive mapping applied to forest management can also pave the way into their effective integration into multi-step decision models such as entropy and Blackwell. Thus, with the awareness that decision support methods are contributing at various economic, management and organizational levels, it will be of interest to look closely at the repositioning of the different stakeholders in the forest sector, in a system tackled by continuous and challenging development.

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