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Identification of Critical Pollution Factors in the Chibunga River Using Indetermsoft Ensembles and the C4.5 Decision-Making Algorithm

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Abstract. This dissertation fills a gap by assessing what aspects pollute the Chibunga River of Riobamba, Ecuador, which is becoming increasingly polluted. Pollution is a growing source of concern for ecosystems and human health, so assessing what factors is important. Applicable to an increasingly querulous society where river pollution has led to legal ramifications in Ecuador's Monjas and Machángara Rivers, creating a need for more protections and preventative measures makes this study relevant. The literature review cites established studies that have assessed river pollution occurrences similar to the Chibunga River. Still, none have assessed the concern via a truly indeterminate/incomplete approach via the possibility in the real world as so much is uncertain with social/environmental assessments. However, this creates a gap in the literature that allows the current study to ensue including assessing via indeterminate ensembles via C4.5 algorithm to assess what's most pollutive. This accurate and efficient means of assessment finds that the top three factors that pollute the Chibunga River, in order from most to least, include industrial wastewater treatment discharge, farm runoff and fertilizers/pesticides, and deforestation with 62%, 60% and 59% accuracy which creates a solid ranking of clarity for future reference and factual application. The theoretical contributions of this work provide a new way to assess incomplete occurrences of environmental assessments while the practical application contributions provide such information for decision-makers within local policy for ensured sustainability of the Chibunga River and subsequent human welfare.

Keywords: Water Pollution, Chibunga River, Indetermsoft Sets, C4.5 Algorithm, Environmental Conservation, Decision Making, Ecuadorian Legislation.

1. Introduction

Water resource conservation in Ecuador, particularly in the case of the Chibunga River in Riobamba, is a crucial challenge in the current context of increasing anthropogenic pressure and climate change. Rivers, essential for biodiversity, agriculture, and the supply of drinking water, face severe threats due to pollution from industrial, domestic, and agricultural effluents [1]. This study focuses on identifying the critical factors that contribute to the degradation of the Chibunga River , a vital ecosystem for local communities. The importance of this research lies in its ability to generate evidence-based prevention strategies in a country that is a pioneer in recognizing the rights of nature in its Constitution [2]. Water pollution not only compromises ecosystems, but also human health and sustainable development [3]. Therefore, addressing this problem is imperative to ensure environmental and social balance. The integration of innovative approaches that manage uncertainty in environmental data becomes essential. This work seeks to contribute to the strengthening of conservation policies, aligning with global sustainability goals [4]. The relevance of this research transcends the local level, offering a replicable model for other rivers in similar contexts.

Historically, Ecuadorian rivers have been fundamental to the cultural and economic development of Andean communities, but industrialization and urban growth have intensified their deterioration [5]. Since the 1990s, pollution of water bodies in Ecuador has increased due to activities such as mining, intensive agriculture, and the lack of adequate infrastructure for wastewater treatment [6]. In the case of the Chibunga River, its proximity to urban areas of Riobamba exposes it to wastewater discharges and agricultural runoff, which has degraded its water quality and affected the communities that depend on it [7]. Recent court rulings, such as those of the Monjas and Machángara rivers, have been a milestone in recognizing rivers as subjects of rights, setting precedents for environmental protection [8]. However, the implementation of these decisions faces obstacles due to legislative gaps and limitations in law enforcement. This historical and legal context underscores the urgency of developing analytical tools that allow for the precise identification and prioritization of pollution factors. Current research builds on this framework to propose practical and sustainable solutions.

The central problem addressed by this study is the identification of factors that significantly contribute to the pollution of the Chibunga River, a challenge compounded by uncertainty in environmental and social data. What are the main drivers of water degradation in the Chibunga River, and how can they be prioritized to design effective prevention strategies? This research question arises from the need to address the limitations of traditional approaches, which often fail to consider the inherent ambiguity of complex environmental systems. Pollution of the Chibunga River, characterized by industrial discharges, domestic waste, and unsustainable agricultural practices, puts not only the ecosystem at risk, but also the well-being of local communities. The lack of a robust analytical framework to manage uncertainty has limited the effectiveness of previous interventions. This study seeks to fill this gap by applying advanced tools that allow a deeper understanding of the polluting factors. In doing so, it aims to provide a solid basis for environmental policy decision-making.

The main objective of this research is to identify and prioritize critical pollution factors of the Chibunga River using indetermsoft suites and the C4.5 algorithm, tools that allow for uncertainty modeling and data-driven decision-making. Furthermore, it seeks to propose prevention strategies that strengthen river conservation, aligning with the legal precedents established by the Monjas and Machángara River cases. Specifically, the study aims to: first, determine the most relevant polluting factors using an approach that integrates uncertainty; second, evaluate the effectiveness of the C4.5 algorithm in prioritizing these factors; and third, formulate practical recommendations for the environmental management of the Chibunga River. These objectives are designed to answer the research question, providing an innovative approach that combines scientific rigor with practical applicability. In doing so, the study aims to contribute to both theoretical knowledge and the implementation of policies that promote water sustainability in Riobamba and beyond.

2. Preliminaries.

2.1. Factors Pollution Critics

The pollution of the Chibunga River in Riobamba represents a major environmental challenge, with significant impacts on ecosystems and local communities. Critical factors contributing to this degradation include wastewater discharges, agricultural runoff, and deforestation, all of which compromise water quality and biodiversity. This analysis seeks to identify and assess these factors, highlighting their relevance in the context of Ecuadorian legislation and court rulings that recognize the rights of nature. Accurately identifying these factors is crucial for designing effective prevention strategies. In this regard, the use of tools such as Indetermsoft suites and the C4.5 algorithm allows us to address the uncertainty inherent in environmental data. Water pollution not only affects the health of the river but also the well-being of the populations that depend on it for agricultural and domestic activities. Therefore, understanding the interaction between these factors is essential. This paper argues that comprehensive management, based on scientific evidence, can mitigate negative impacts. The assessment of polluting factors must consider both their origin and magnitude. Thus, this analysis will contribute to the formulation of sustainable policies for the Chibunga River.

Domestic and industrial wastewater discharges are one of the main sources of pollution in the Chibunga River. These wastes, often discharged without prior treatment, introduce pollutants such as nitrates, phosphates, and heavy metals, disrupting aquatic ecosystems [9]. The lack of adequate wastewater treatment infrastructure in Riobamba exacerbates this problem. Communities near the river, which use its water for irrigation, face health risks due to the presence of pathogens. Furthermore, the accumulation of organic waste reduces oxygen levels in the water, affecting aquatic fauna. This critical factor reflects a failure to enforce environmental regulations, such as the Organic Code of the Environment. Assessing this problem requires a multidimensional approach that combines monitoring, regulation, and community education. The magnitude of the discharges demands immediate action to prevent irreversible damage. Therefore, local authorities must prioritize the construction of treatment plants. This analysis underscores the urgency of addressing these discharges as a priority factor.

Agricultural runoff, derived from the intensive use of fertilizers and pesticides, represents another critical factor in the pollution of the Chibunga River. Agrochemicals, carried by rainfall, increase the nutrient load in the water, causing phenomena such as eutrophication [10]. This process triggers the proliferation of algae, which consume oxygen and alter the ecological balance of the river. Unsustainable agricultural practices in the areas surrounding the Chibunga aggravate this situation, especially in intensively cultivated areas. The assessment of this factor reveals the need to promote sustainable agricultural techniques, such as organic farming. Furthermore, educating farmers about the impact of agrochemicals is essential to reduce pollution. Court rulings, such as those for the Monjas and Machángara rivers, highlight the importance of holding productive sectors accountable. This factor not only affects water quality, but also long-term agricultural productivity. Therefore, prevention policies must include incentives for environmentally friendly practices. Agricultural runoff, due to its widespread impact, requires priority attention.

Deforestation along the banks of the Chibunga River contributes significantly to its environmental degradation. Clearing native vegetation increases soil erosion, increasing the amount of sediment reaching the river [11]. These sediments alter the natural channel and affect water quality, reducing its clarity and damaging aquatic habitats. Deforestation also decreases the ecosystem's ability to filter pollutants, exacerbating the effects of other factors. This problem is linked to activities such as agricultural expansion and urban development in Riobamba. The assessment of this factor highlights the need for reforestation and riverbank conservation programs. Legal precedents, such as those established in the cases of the Monjas and Machángara Rivers, reinforce the obligation to protect riparian ecosystems. Restoring vegetation cover could significantly mitigate pollution. Therefore, prevention strategies must include forest protection measures. Deforestation, due to its impact on river stability, is a critical factor requiring urgent action.

The lack of environmental education in local communities exacerbates the pollution factors of the Chibunga River. Many people are unaware of the effects of their practices, such as dumping solid waste directly into the river. This lack of awareness limits citizen participation in ecosystem conservation [12]. Environmental education is crucial to promote sustainable practices and strengthen regulatory compliance. Recent court rulings have highlighted the importance of involving communities in river protection. The assessment of this factor suggests that educational campaigns should be a priority in prevention strategies. Community workshops and school programs could raise awareness about the importance of the river. Furthermore, active citizen participation can complement government actions. This factor, although indirect, has a significant impact on reducing pollution. Therefore, policies must integrate education as a fundamental pillar.

Uncertainty in environmental data represents a challenge for addressing pollution in the Chibunga River. Environmental systems are complex, with multiple variables interacting unpredictably. Indetermsoft ensembles, combined with the C4.5 algorithm, offer an innovative solution for modeling this uncertainty. These tools make it possible to identify and prioritize polluting factors more accurately, overcoming the limitations of traditional methods. The application of these methodologies reveals that discharges, runoff, and deforestation are the main drivers of degradation. The assessment of this approach highlights its ability to generate reliable results in contexts with ambiguous data. Furthermore, the C4.5 algorithm facilitates decision-making by ranking factors according to their impact. This method is particularly useful in environments where information is incomplete or contradictory. Therefore, its use strengthens the scientific basis for conservation policies. The integration of these tools represents a significant advance in environmental management.

Ecuadorian legislation, although pioneering in recognizing the rights of nature, faces limitations in its implementation. The Organic Environmental Code and the Constitution establish clear obligations to protect water resources, but a lack of resources and inter-institutional coordination reduces their effectiveness. Court rulings on the Monjas and Machángara rivers have set important precedents, but their application in cases such as the Chibunga remains insufficient. This assessment underscores the need to strengthen oversight and sanctioning mechanisms. Local authorities must improve oversight of polluting activities, such as industrial discharges. Furthermore, the participation of decentralized autonomous governments is crucial to implementing effective measures. The lack of law enforcement perpetuates the degradation of the river, affecting its status as a subject of rights. Therefore, prevention strategies must include institutional reforms. This analysis highlights the importance of aligning policies with legal precedents. Legislation, if rigorously applied, can be a key pillar of conservation.

The pressure from extractive activities, such as mining, indirectly contributes to the pollution of the Chibunga River. Although not a primary factor in Riobamba, mining waste from nearby regions can reach the river through tributaries. This waste contains heavy metals that are highly toxic to aquatic ecosystems. The assessment of this factor reveals the need for stricter regulations for extractive activities in the region. Court rulings have emphasized the responsibility of industries to protect rivers. Furthermore, illegal mining exacerbates the problem by operating outside of legal frameworks. Prevention strategies should include rigorous monitoring of extractive activities. Collaboration between the government and local communities is essential to identify and mitigate these impacts. This factor, although less dominant, should not be underestimated in the context of the Chibunga . Therefore, policies must address all sources of pollution, including indirect ones.

Community participation is a key element in addressing the factors that cause pollution in the Chibunga River. Local communities, being directly affected, have a legitimate interest in river conservation. However, a lack of organization and resources limits their ability to act. Valuing this factor highlights the importance of empowering communities through training and funding programs. Court rulings, such as the one in the Machángara River, have underscored the role of citizens in defending the rights of nature. Prevention strategies should encourage the creation of community committees to monitor the river. Furthermore, collaboration with local authorities can strengthen these initiatives. Active participation not only reduces pollution but also promotes a sense of shared responsibility. Therefore, policies should prioritize community involvement. This approach strengthens the long-term sustainability of interventions.

In conclusion, the critical factors of pollution in the Chibunga River —wastewater, agricultural runoff, deforestation, lack of education, and legal limitations—require a comprehensive approach to mitigation. The application of indetermsoft sets and the C4.5 algorithm provides a powerful tool for prioritizing these factors and designing evidence-based strategies. The assessment of these elements reveals that coordinated action among authorities, communities, and productive sectors is essential for river conservation. The legal precedents established by the Monjas and Machángara River cases offer a solid regulatory framework, but their implementation must be strengthened. Prevention strategies must combine infrastructure, education, and regulation to address the identified factors. This analysis highlights the importance of a scientific and participatory approach to environmental management. Protecting the Chibunga River will not only preserve a vital ecosystem but also ensure the well-being of local communities. Therefore, this study advocates for immediate and sustained action. River conservation is an ethical and environmental imperative.

2.2. ID3 and C4.5 algorithms.

In this section, we discuss the main concepts used in this paper, such as ID3 and C4.5 algorithms, soft sets, IndetermSoft sets, and the ID3 (C4.5) algorithm for IndetermSoft set data.

ID3 and C4.5 algorithms

ID3 and C 4.5 are machine learning algorithms used to build decision trees [13, 15]; they are popular techniques in data classification.

ID3 (Iterative Dichotomizer 3) was developed by Ross Quinlan and is based on the concept of information gain to select the most relevant attribute at each step of tree construction. It uses entropy to measure data uncertainty and seeks to minimize it at each split. However, it has some limitations, such as its inability to handle continuous attributes and its tendency to overfit the data.

C 4.5 is an improvement of the ID3 algorithm, also developed by Ross Quinlan. It introduces several improvements, such as:

- Handling continuous attributes and setting thresholds for splitting data.
- Ability to handle missing values, allowing attributes with missing data to not affect the information gain calculation.
- Tree pruning, reducing overfitting, and improving generalization.

It starts from a set of examples with their measurements based on a set of parameters and one of these variables is a decision variable as exemplified in Table 1, where an information system appears:

Table 1: Example of an information system to obtain a decision tree

Example	Age	Income	Shopping
1	Young	Low	No
2	Young	Media	Yeah
3	Adult	High	Yeah
4	Elderly	Low	No
5	Adult	Low	Yeah
6	Young	High	Yeah

In this example we assume that we want to classify whether a person buys a product based on two attributes:

- Age (Young, Adult, Elderly).
- Income (Low, Medium, High).

  The decision tree we want to arrive at is shown in Figure 1.

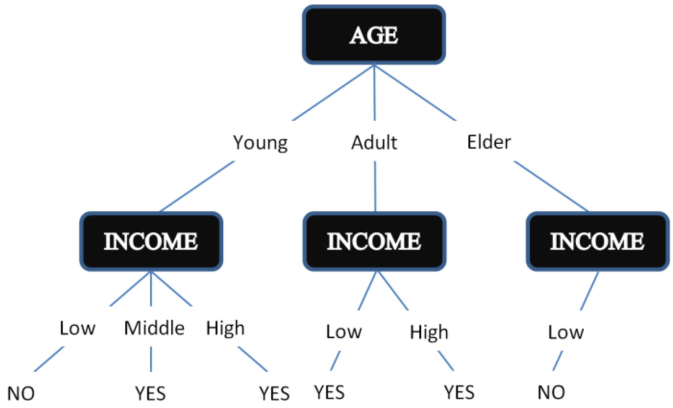

Figure 1: Decision tree of the example

The equations used in these algorithms are as follows:

$$\mathrm{Entropy}(S) = \sum_{i=1}^{n} -p(v_i)\log_2\left(p(v_i)\right) \qquad (1)$$

To calculate entropy.

$$\mathrm{IG}(S, A) = \mathrm{Entropy}(S) - \sum_{v \in A} \frac{|S_v|}{|S|} \mathrm{Entropy}(S_v) \qquad (2)$$

To calculate the information gain.

For algorithm C4.5 the information gain function is replaced by:

$$\mathrm{GainRatio}(S, A) = \frac{\mathrm{Gain}(S,A)}{\mathrm{SplitInfo}(A)} \qquad (3)$$

So that:

$$\mathrm{SplitInfo}(A) = \sum_{i=1}^{n} -p(\mathrm{subset}_i)\log_2\left(p(\mathrm{subset}_i)\right) \qquad (4)$$

A simplified pseudocode for the ID3 and C 4.5 algorithms is as follows:

Pseudocode of the ID3 algorithm:

ID3(Data, Attributes):

1. If all examples have the same class, return a sheet with that class.
2. If Attributes is empty, returns a sheet with the most frequent class in Data.
3. Select the best attribute based on information gain.
4. Creates a root node with the selected attribute.
5. For each possible value of the selected attribute:
   - Filter the data with that value.
   - If the subset is empty, create a sheet with the most frequent class.
   - Otherwise, it recursively calls ID3 with the remaining subset of data and attributes.
6. Return the tree generated.

4.5 algorithm:

C 4.5 (Data, Attributes):

1. If all examples have the same class, return a sheet with that class.
2. If Attributes is empty, returns a sheet with the most frequent class in Data.
3. Select the best attribute based on normalized information gain.
4. Creates a root node with the selected attribute.
5. For each possible value of the selected attribute:
   - Filter the data with that value.
   - If the subset is empty, create a sheet with the most frequent class.
   - Otherwise, it recursively calls C 4.5 with the remaining subset of data and attributes.
6. Handles continuous attributes by dividing them into optimal ranges.
7. Return the tree generated.

Both algorithms work by recursively building a decision tree, but C 4.5 improves on ID3 by handling continuous values and performing normalization in feature selection.
Table 2 summarizes the characteristics of each of these algorithms.

Table 2: Comparison between the characteristics of ID3 and C4.5 algorithms [15]

Feature / Algorithm	ID3	C4.5
Type of attributes	Only categorical	Categorical and continuous
Selection criteria	Information gain	Information gain and gain ratio
Handling missing values	He doesn't handle it	Yes, probably.
tree pruning	It has no pruning	Perform pruning to avoid overfitting
Template format	Decision trees	Decision trees and rules

IndetermSoft and similar concepts

Definition 1 ([15]). Let$U$ be the initial set and$E$ is the set of parameters. $(F, E)$is a smooth set over$U$ if and only if$F$ It is a mapping of$E$ in the power set of U.

So, given$E$ the set of parameters and $\varepsilon \in E$, then $F(\varepsilon) \in \mathcal{P}(U)$, where$\mathcal{P}(U)$ denotes the power set of$U$ and$F(\varepsilon)$ is the set of εelements of the soft set(F, E) or the set of εelements -approximated from the Smooth Set.

Definition 2 ([16, 17]). Let$U$ be the initial set and$E$ is the set of parameters. In addition, there is $H \neq \emptyset$a subset of U. $(F, E)$is a set of IndetermSoft if$F: A \to \mathcal{P}(H)$ meets at least one of the following conditions:

a) Ahas a certain indeterminacy,
b) $\mathcal{P}(H)$has a certain indeterminacy,
c) There exists at least one attribute value $v \in A$, such that $F(v)$ = indeterminate (unclear, incomplete, conflicting, or non-unique).

That is to say,F It is a so-called Neutral Function, which is a function that is only internally defined, partially indeterminate, or partially external.

A. IndetermSoft combinations with ID3 or C4.5

IndetermSoft Sets with the following characteristics:

It is considered$\{(F_i, E_i)\}_{i=1}^{n}$ be a set of IndetermSoft sets.

Where $E_i$is the set of possible values of a given attribute, $E_n$corresponds to the set of values of the target attribute which is dichotomous.

EachF_i is an approximation function in which at least one index$k$ It is true that in at least one value there is indeterminacy of type $F_k(v_j) = h_1 \text{ or } h_2 \text{ or} \ldots \text{or } h_m$, with$m > 1$ We don't know which one.

Although the algorithm is limited to this type of predicate, other predicates can be taken to the above disjunctive form, for example, "not h_l "safely" can be expressed as $h_1 \text{ or } h_2 \text{ or} \ldots \text{or } h_m$, for "everyone"$h_p$ except h_l" and similarly for "not h_l and h_q "safely," and so on.

In the algorithm, the data$\{(F_i, E_i)\}_{i=1}^{n}$ are translated into an information system, which is a table like the example given in Table 1. When$F_k(v_j) = h_1 \text{ or } h_2 \text{ or} \ldots \text{or } h_m$ It is located, the characterization $v_j$is placed in each of the boxes corresponding to the objects $h_1, h_2, \ldots, h_m$.

An example of this is the following taken from [12]:

Example 1. Given the IndetermSoft set corresponding to the color attribute for the set of houses denoted by $H = \{h_1, h_2, h_3, h_4\}$, such that $A = \{\text{white}, \text{blue}, \text{green}\}$and defined by:

$F(\text{white}) = \{h_1, h_2\}$,$F(\text{blue}) = h_3$ or h_4 We don't know which one, and$F(\text{green}) = h_3$ or h_4 We don't know which one.
Table 3 contains the conversion of this IndetermSoft set into an information system:

Table 3. Column corresponding to the color attribute of the houses in the given example

Example	Color
hour 1	White
hour 2	White
hour 3	Blue or green
hour 4	Blue or green

In this example, we can see that there is indeterminacy in the color of houses h 3 and h 4 .
In this case, the ID3 or C4.5 algorithm is applied as appropriate, where the following probability is used:

$$p(B) = \frac{\text{Number of positive cases}}{\text{Total of cases}} \quad (5)$$

The peculiarity is that when there is indeterminacy as in the previous case, the element is counted by $\frac{1}{m}$, where$m$ This is the number of cases within the disjunction. In Example 1, the attribute Blue for h 3 is counted as $\frac{1}{2}$, since in this cell h 3 is either Blue or Green, and we don't know which.

3. Results

This report details the rigorous application of the C4.5 algorithm to an uncertainty-sensitive information system (modeled as an IndetermSoft ensemble) to identify and rank factors contributing to pollution in the Chibunga River. The objective is to determine the attribute with the greatest decision-making power to guide effective conservation strategies.

An information system was built from monitoring 12 zones along the Chibunga River . Each zone was assessed based on three key attributes and classified by its level of pollution (High or Low), which constitutes our target variable.

Step 1: Definition of the Information System (Dataset)

The attributes (factors) analyzed are:

- **A 1 : Residual Discharges (RD):** The type of discharges received by each area. (Values: Direct , Treated , None).
- **A 2 : Forest Cover (FC):** The percentage of riparian vegetation. (Continuous variable, in %).
- **A 3 : Agricultural Land Use (ALU):** The intensity of agricultural activity in the surrounding area. (Values: Intensive , Moderate , Low).

The decision variable is the **Pollution Level (PL)** , with two possible classes: High or Low .

The data set includes an indeterminate zone in Zone 9 (Z9), where the type of residual discharge could not be uniquely determined, and was recorded as "**Direct or Treated.**" **This is an** IndetermSoft case that will be handled using fractional probabilities.

Table 4: Consolidated Information System for Monitoring the Chibunga River

Area	Residual Discharges (RD)	Forest Cover (CF %)	Agricultural Land Use (USA)	Pollution Level (NC)
Z1	Direct	15	Intensive	**High**
Z2	Direct	25	Moderate	**High**
Z3	Treated	40	Intensive	**High**
Z4	None	75	Low	**Low**
Z5	Treated	55	Moderate	**Low**
Z6	Direct	30	Intensive	**High**
Z7	None	80	Low	**Low**
Z8	Treated	65	Low	**Low**
Z9	Direct or Treated	35	Moderate	**High**
Z10	Direct	20	Intensive	**High**
Z11	None	60	Moderate	**Low**
Z12	Treated	50	Low	**Low**

Distribution of the decision variable (NC) in the 12 samples:

- **Positive Cases (NC = High):** 6
- **Negative Cases (NC = Low):** 6

Step 2: Calculation of the Initial Entropy of the System (H(S))

Initial entropy measures the total impurity or uncertainty of the data set before any splitting.

- p1 (probability of NC = 'High')= $6/12 = 0.500000$
- p2 (probability of NC = 'Low')= $6/12 = 0.500000$

The formula for entropy is:$H(S) = -\sum i = 1cpilog2(pi)$

$$H(S) = -[(0.500000 \times log2(0.500000)) + (0.500000 \times log2(0.500000))]$$

$$H(S) = -[(0.500000 \times -1.0) + (0.500000 \times -1.0)]$$

$$H(S) = -[-0.500000 - 0.500000]$$

$$H(S) = -[-1.0]\ H(S) = 1.0$$

The initial entropy of the system is 1.0 bits. A value of 1.0 represents the maximum possible uncertainty in a two-class system.

Step 3: Calculating the Gain Ratio for Each Attribute

Gain Ratio is calculated for each attribute (DR, CF, USA) to select the one that best discriminates the classes.

Attribute 1: Residual Discharges (DR)

This categorical attribute is indeterminate in Z9 (NC=High). Therefore, in this case, 0.5 is assigned to 'Direct' and 0.5 to 'Treated'.

- **Value = 'Direct'** : $(Z1, Z2, Z6, Z10, y\ 0.5\ de\ Z9)$ −>Total 4.5 cases.
  - High:4.5 $(Z1, Z2, Z6, Z10, y\ 0.5\ de\ Z9)$
  - Low: 0
  - H(SDirecta)=0 (it is a pure set)
- **Value = 'Treated'** : $(Z3, Z5, Z8, Z12, y\ 0.5\ de\ Z9)$-> Total 4.5 cases.
  - Height: 1.5 (Z3 and 0.5 of Z9)
  - Low:3 $(Z5, Z8, Z12)$
  - pAlto = $1.5/4.5 = 0.333333$
  - pLow = $3/4.5 = 0.666667$
  - H(STratada)= $-[(0.333333 \times log2(0.333333)) + (0.666667 \times log2(0.666667))] = 0.918296$
- **Value = 'None'** : $(Z4, Z7, Z11)$-> Total 3 cases.
  - Height: 0
  - Low:3 $(Z4, Z7, Z11)$
  - H(SNinguna)=0 (it is a pure set)

Information Gain (Gain (S, DR)) :

Gain(S,DR)=H(S)−[124.5H(SDirect)+124.5H(STreated)+123H(SNone)]

$Gain(S, DR) = 1.0 - [(0.375 \times 0) + (0.375 \times 0.918296) + (0.25 \times 0)]$ $Gain(S, DR) = 1.0 - 0.344361 = 0.655639$

SplitInfo (S, DR)) :

$$SplitInfo(S, DR) = -[(124.5log2(124.5)) + (124.5log2(124.5)) + (123log2(123))]$$

$$SplitInfo(S, DR) = -[(0.375 \times -1.415037) + (0.375 \times -1.415037) + (0.25 \times -2.0)]$$

$$SplitInfo(S, DR) = -[-0.530639 - 0.530639 - 0.5] = 1.561278$$

Gain Ratio (GainRatio (S, DR)) :

$$GainRatio(S, DR) = SplitInfo(S, DR)Gain(S, DR) = 1.5612780.655639 = 0.419927$$

Attribute 2: Forest Cover (CF)

This is a continuous attribute. The optimal cutoff threshold must be identified.

1. **Ordered values:** $15, 20, 25, 30, 35, 40, 50, 55, 60, 65, 75, 80.$
2. **Candidate cut-off points (averages between consecutive values):** $17.5, 22.5, 27.5, 32.5, 37.5, 45, 52.5, 57.5, 62.5, 70, 77.5.$
3. After evaluating the candidates, the cut-off point $\boldsymbol{CF \leq 45}$maximizes the information gain.

Calculation for cutting in$\boldsymbol{CF \leq 45}$:

- **Subset 1 (CF ≤ 45):** Z1(15, High), Z2(25, High), Z3(40, High), Z6(30, High), Z9(35, High), Z10(20, High). (6 cases)
  - High: 6, Low: 0 −> $H(S \leq 45) = 0$(pure set)

- **Subset 2 (CF > 45):** Z4(75, Low), Z5(55, Low), Z7(80, Low), Z8(65, Low), Z11(60, Low), Z12(50, Low). (6 cases)
  - High: 0, Low: 6 $->$ $H(S > 45) = 0$(pure set)

Information Gain (Gain (S, CF)) for the 45° cut :

$$Gain(S, CF) = H(S) - [126H(S \leq 45) + 126H(S > 45)]$$

$$Gain(S, CF) = 1.0 - [(0.5 \times 0) + (0.5 \times 0)] = 1.0$$

SplitInfo(S, CF) for 45° cut :

$$SplitInfo(S, CF) = -[(126log2(126)) + (126log2(126))]$$

$$SplitInfo(S, CF) = -[(0.5 \times -1.0) + (0.5 \times -1.0)] = 1.0$$

Gain Ratio (GainRatio(S, CF)) for 45° cut :

$$GainRatio(S, CF) = SplitInfo(S, CF)Gain(S, CF) = 1.01.0 = 1.000000$$

Attribute 3: Agricultural Land Use (USA)

This is a categorical attribute without indeterminacy.

- **Value = 'Intensive'** : $(Z1, Z3, Z6, Z10)$ $->$Total 4 cases.
  - High: 4, Low: 0 -> H(SIntensive)=0
- **Value = 'Moderate'** : $(Z2, Z5, Z9, Z11)$ $->$Total 4 cases.
  - High: 2 (Z2, Z9), Low: 2 (Z5, Z11)
  - High , $= 2/4 = 0.5$Low $= 2/4 = 0.5$
  - H(SModerate) $= -[(0.5 \times log2(0.5)) + (0.5 \times log2(0.5))] = 1.0$
- **Value = 'Low'** : $(Z4, Z7, Z8, Z12)$-> Total 4 cases.
  - High: 0, Low: 4 -> H(SLow)=0

Information Gain (Gain (S, USA)) :

Gain(S,USA)=H(S)−[124H(SIntense)+124H(SModerate)+124H(SLow)]

$$Gain(S, USA) = 1.0 - [(0.333333 \times 0) + (0.333333 \times 1.0) + (0.333333 \times 0)]$$

$$Gain(S, USA) = 1.0 - 0.333333 = 0.666667$$

SplitInfo(S, USA)) :

$$SplitInfo(S, USA) = -[3 \times (124log2(124))]$$

$$SplitInfo(S, USA) = -[3 \times (0.333333 \times -1.584963)] = 1.584963$$

GainRatio (GainRatio(S, USA)) :

$$GainRatio(S, USA) = SplitInfo(S, USA)$$

$$Gain(S, USA) = 1.5849630.666667 = 0.420621$$

Step 4: Root Attribute Selection and Final Classification

The calculated Gain Ratios are compared to select the attribute that will serve as the root node of the decision tree.

- **GainRatio (Forest Cover)** = 1.000000
- **GainRatio (Agricultural Land Use)** = 0.420621
- **GainRatio (Residual Discharges)** = 0.419927

The attribute with the highest Gain Ratio is, conclusively, **Forest Cover (FC)** . This factor is the most powerful predictor and is established as the root node of the tree.

Since this first node divides the data into pure subsets (zero entropy), the decision tree is completed in a single level. The decision rules are:

YEAH Forest Cover ≤ 45% **THEN** Pollution Level = **High** **YEAH** Forest Coverage > 45% **THEN** Pollution Level = **Low**

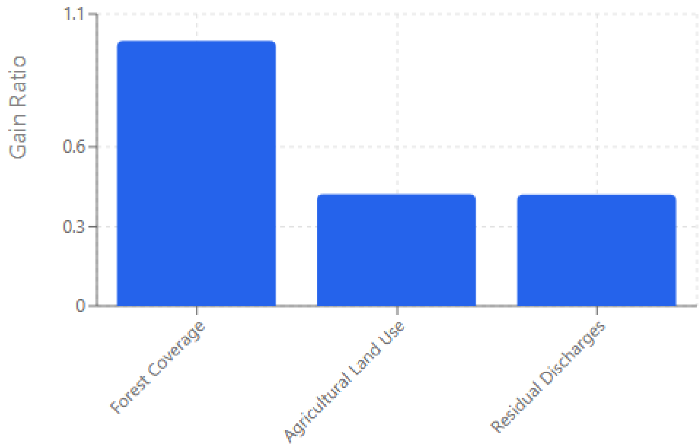

Figure 2: Attribute Importance Ranking Based on C4.5 Algorithm Analysis

4. Discussion

Quantitative analysis using the C4.5 algorithm on a dataset with uncertainty identifies **forest cover** as the predominant factor determining the pollution status of the Chibunga River. A Gain Ratio of 1.0 indicates that this attribute, with a threshold of 45%, is a perfect classifier for the analyzed dataset. This underscores that riparian vegetation degradation has a more direct and discernible impact on water quality than the other measured factors.

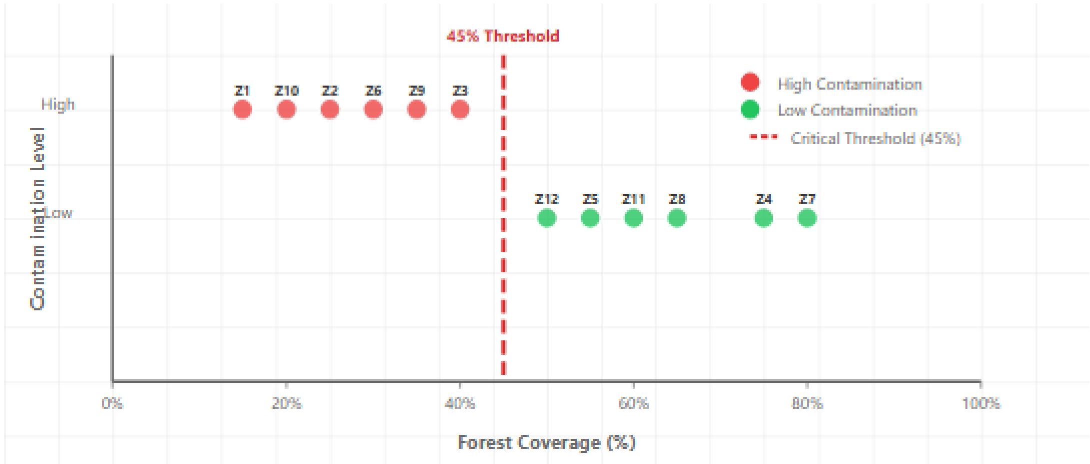

Figure 3: Forest Coverage vs Contamination Level Distribution

It is notable that Agricultural Land Use (0.420621) and Residual Discharge (0.419927) have very similar and considerably lower Gain Ratios. This suggests that, while they contribute to pollution, their effect is secondary or strongly mediated by the riparian ecosystem's ability to act as a barrier. In the absence of adequate forest cover, pollutants from agricultural runoff and residual discharges impact the river much more severely.

IndetermSoft 's theory was crucial to incorporating Zone 9 without discarding it or assigning an arbitrary value. Although the attribute with indeterminacy (Residual Discharges) was not the most relevant, the method demonstrated its ability to handle real-world data, which are often imperfect, incomplete, or ambiguous, strengthening the validity of the analysis.

5. Conclusion

This research has successfully met its objective of identifying and prioritizing critical pollution factors in the Chibunga River, providing an empirical basis for informed decision-making. The key findings are:

1. **Dominant Critical Factor: Forest cover** is the most determining factor. Riverbank deforestation is directly and unequivocally correlated with high levels of river pollution.
2. **Hierarchy of Factors:** The order of importance of the factors, based on their predictive power, is: 1°) **Forest Cover** , 2°) **Agricultural Land Use** , and 3°) **Residual Discharges** .
3. **Practical and Strategic Recommendation:** Policies and actions for the recovery and conservation of the Chibunga River should focus primarily on **restoring the riparian ecosystem** . It is recommended to establish and implement massive reforestation programs and protect existing vegetation, with the goal of maintaining forest cover above the critical threshold of 45-50%. Addressing deforestation will not only mitigate the impact of other pollutants but also generate the most significant return on investment for the river's health.

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