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Neutrosophic Sets and Systems, {Special Issue: Artificial Intelligence, Neutrosophy, and Latin American Worldviews: Toward a Sustainable Future (Workshop – March 18–21, 2025, Universidad Tecnológica de El Salvador, San Salvador, El Salvador)}, Vol. 84, 2025

University of New Mexico

Study of the impact of emerging technologies on the conservation of protective forests through the plithogenic hypothesis and neutrosophic stance detection

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Abstract. This paper investigates the efficacy of emerging technologies in protective forest conservation—artificial intelligence, drones, remote sensing, and blockchain—and whether such tools foster threat detection and enhanced biodiversity and human interaction. As deforestation and climate change continue to plague the planet, protected areas become more critical, and although successful conservation efforts exist, traditional tools fail to adequately provide the granularity and scalability required for nuanced action such as illegal logging or forest fires. The emerging abilities of these innovations have been published in scientific literature. However, there exists a translational gap in a systematic determination of their efficacy since levels of uncertainty and constraints are discussed upon implementation across varying ecological and socioeconomic spectrums. Therefore, this paper seeks to fill the void utilizing the plithogenic hypothesis—a neutrosophic application of modeling uncertainty through the probability of truth, indeterminacy, and falsity. 125 articles were examined for feasibility with the use of the Consensus Meter. Results denote a 48% probability of actualness that such technologies do work—74.3% that they increasingly foster early detection of threats, 72% that they help monitor biodiversity; yet 32% indeterminacy suggests challenges to success including expense and absent infrastructure. This is a unique form of assessment of efficacy in uncertain, complicated environments. Ultimately, implementation suggestions can include need vs. idea vs. environmental implementation and feasibility of financing and community support/inclusivity to realize what would theoretically contribute to forest conservation and policy proposals that use emerging technologies yet acknowledge ecological and socioeconomic realities.

Keywords: Plithogenic Hypothesis, Neutrosophic Stance Detection, Emerging Technologies, Forest Conservation, Threat Detection, Biodiversity Monitoring, Community Participation, Sustainability.

1. Introduction

Defensive forests that assist with climate mitigation and biodiversity are being lost through increased deforestation, forest fires, and illegal logging [1]. This article investigates the application of emerging technologies—artificial intelligence (AI), drones, remote sensing, and blockchain—to protect forest management and conservation. This is a relevant topic because these sensitive ecosystems are responsible for approximately 30% of the world's carbon dioxide emissions, and with increasing anthropogenic activities, emerging technologies have the potential to scan large areas with tremendous accuracy and enlist communities to aid in detection and subsequent conservation efforts. Therefore, knowing their efficacy is essential for the justification of conservation efforts [2]. What once were rudimentary practices for forest conservation have transformed into high-tech operations. For example, for the last few decades, human predictability and human patrols were the best adjustments for forest mismanagement. The first technological game changer occurred when satellite imaging was developed in the 1990s to comprehend forests. More recently, heightened data collection efforts, thanks to inexpensive drone ownership and IoT sensors within the population have allowed universities with environmental science/forestry programs to compile ahead-of-time resolution [3]. However, complications exist for developing nations that experience high-tech costs and no technology ownership due to infrastructural deficits. Therefore, awareness must be spread about access. Looking at the progression of technological advancements in forest management and conservation helps put today's potential for transformative protective forest conservation technology into perspective.

Forests are under more threat than ever due to climate change, with wildfires increasing by 11% between 2001 and 2022; illegal logging contributes to the deforestation of thousands of hectares of the Amazon each year [4]. However, means of technological development offer hope for new solutions; situational and socioeconomic location provides a basis for emerging technology assistance. For example, past literature indicates that AI and blockchain help to foresee wildfires and trace the traceability of forest-associated products, respectively. However, little is understood about universal application across governance systems or sustained success over time. Thus, a subservient research question emerged: To what extent do emerging technologies improve threat forecasting, biodiversity estimation, illegal deforestation prevention, and stakeholder support for conservation forests given relative situational limitations? This question emerged as only partially answered—as articles discuss the importance of emerging technology use for specific purposes—but few note how their potential use may be uncertain [5-6]. In addition, this is a widespread problem; forests are disappearing faster than suspected—without them, ecosystem services will be lost, and the climate of the world will be disrupted[5,6].

Ultimately, to alleviate this issue, this paper uses a plithogenic method, relative to neutrosophic theory, as it allows uncertainty to exist with probable truths, indeterminate and falsities. This study processed 125 scientific articles and further assessed them with the Consensus Meter tool [7] relative to five categories: early detection, biodiversity assessment, deforestation awareness, public knowledge, and future sustainability. Such a method supports a collective approach necessary to approach a complicated problem where variables are necessarily hazy or even contradictory [8].

Typically, deforestation awareness comes from governmental policies and community activism—but to little or no effect. In the last decade, various innovative systems have been introduced like LiDAR for superior forest mapping [9], and blockchain networks for timber resource tracking [10]. Yet without the synergism of such innovations with prior expectations or community knowledge, the integrations fell short. Therefore, the gap in the literature would be filled with an assessment of how innovations coincide with old ones.

The research problem engages with emergent technologies that could be used to sustainably transform forest preservation. By answering this question, not only does she fill a gap in the research, but she also attempts to satisfy the global need to preserve forests, which serve as carbon sequestration sources and biodiversity hotspots. Findings impact matters of legislation and forest management due to impending climate change. The research seeks three objectives: to determine whether emergent technologies effectively preserve protection forests through a plithogenic assessment; to discern technical, financial, and socio-cultural limitations that preclude the use of such technologies; to provide a course of action to incorporate such technologies with traditional means of preservation to avoid any equity gaps in sustainable forest preservation. These objectives give a reason behind the research while situating the study as an effective and welcomed addition to ongoing scholarship.

2. Theoretical Framework

Neutrosophic (or indeterminate) data are characterized by inherent vagueness, lack of clarity, incompleteness, partial unknowns, and conflicting information [11,12]. Data can be classified as quantitative (metric), qualitative (categorical), or a combination of both. Plithogenic variable data [14] describe the connections or correlations between neutrosophic variables. A neutrosophic variable [15], which can be a function or operator, treats neutrosophic data in its arguments, its values, or both. Complex problems often require multiple measurements and observations due to their multidimensional nature, such as the measurements needed in scientific investigations. Neutrosophic variables may exhibit dependence, independence, partial dependence, partial independence, or partial indeterminacy as in science [16].

A Plithogenic Set [20, 21] is a non-empty set P whose elements within the domain of discourse U ($P \subseteq U$) are characterized by one or more attributes $A_1, A_2, \cdots, A_m$, where m is at least 1. where each attribute can have a set of possible values within the spectrum S of values (states), such that S can be a finite, infinite, discrete, continuous, open, or closed set.[17]

Each element $x \in P$ is characterized by all possible values of the attributes within the set $V = \{v_1, v_2, \cdots, v_n\}$. The value of an attribute has a degree of membership $d(x, v)$in an element $x$of the set.P, based on a specific criterion. The degree of membership can be diffuse, diffuse intuitionist or neutrosophic, among others [18].

That means,

$$\forall x \in P, d: P \times V \rightarrow \mathcal{P}([0,1]^z) \quad (1)$$

Where$d(x, v) \subseteq [0,1]^z$ and $\mathcal{P}([0,1]^z)$is the power set of $[0,1]^z$.$z = 1$ (the fuzzy degree of menbership), $z = 2$(the intuitionist fuzzy degree of membership) or $z = 3$ (the neutrosophic degree of memnership).

plithogenic [17], derived from the analysis of plithogenic variables, represents a multidimensional probability (" plitho " meaning "many" and synonym of "multi"). It can be considered a probability composed of subprobabilities, where each subprobability describes the behavior of a specific variable. The event under study is assumed to be influenced by one or more variables, each represented by a probability distribution (density) function (PDF) [19].

Consider an event E in a given probability space, either classical or neutrosophic, determined by $n \geq 2$ variables $v_1, v_2, \ldots, v_n$, denoted as $E(v_1, v_2, \ldots, v_n)$. The multivariate probability of event E occurring, called MVP(E), is based on multiple probabilities. Specifically, it depends on the probability of event E occurring with respect to each variable: $P1(E(v_1))$for variable v_1, $P2(E(v_2))$for variable v_2, etc. Therefore, $MVP(E(v_1, v_2, \ldots, v_n))$ is represented as $\left(P1(E(v_1)), P2(E(v_2)), \ldots, Pn(E(v_n))\right)$. The variables $v_1, v_2, \ldots, v_n$, and probabilities $P_1, P_2, \ldots, P_n$, can be classical or have some degree of indeterminacy [20].

To make the transition from plithogenic neutrosophic probability (PNP) to univariate neutrosophic probability UNP, we use the conjunction operator [21]:

$$UNP(v_1, v_2, \ldots, v_n) = v_1 \wedge_{i=1}^{n} v_n \quad (2)$$

$\wedge$ In this context, it is a neutrosophic conjunction (t-norm). If we take$\wedge_p$ as the plithogenic conjunction between probabilities of the PNP type, where $(T_A, I_A, F_A) \wedge_p (T_B, I_B, F_B) = (T_A \wedge T_B, I_A \vee I_B, F_A \vee F_B)$, such that $\wedge$is the minimum t-norm of fuzzy logic and $\vee$the maximum t-norm [22].

3. Material and Methods

This section introduces a novel methodological framework that integrates neutrosophic logic and plithogenic theory into the scientific method to assess complex causal hypotheses under conditions of ambiguity and contradiction. It begins with the precise formulation of the hypothesis and the identification of independent and dependent variables. Using stance detection algorithms applied to scientific literature, each empirical statement is classified into neutrosophic triplets (Truth, Indeterminacy, Falsity). These are then aggregated through plithogenic conjunction to compute the Plithogenic Neutrosophic Probability (PNP), offering a holistic measure of support. Finally, the neutrosophic negation of the hypothesis provides a dual perspective, highlighting areas of clarity, ambiguity, and contradiction in the current state of knowledge.

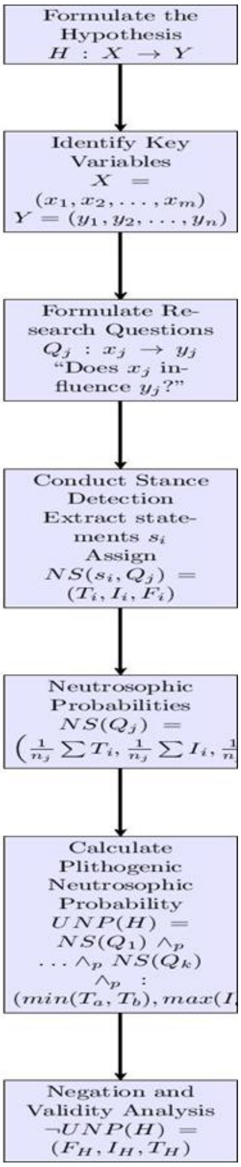

Figure 1. Step-by-step validation of hypotheses using Plithogenic Neutrosophic Probability (PNP)

3.1 Formulate the hypothesis

Let a scientific hypothesis H be defined as a causal relation between an independent variable X and a dependent variable Y such that

$$H: X \rightarrow Y \tag{3}$$

Here, X denotes a vector of technological interventions and Y denotes the outcomes related to forest conservation.

3.2 Identify key variables

The independent variable is denoted as $X = (x_1, x_2, \dots, x_m)$ and the dependent variable as $Y = (y_1, y_2, \dots, y_n)$. Each research question is modeled as $Q_j: x_j \rightarrow y_j$, with $j = 1, 2, \dots, k$.

3.3 Formulate specific research questions.

Each sub-hypothesis Q_j is reformulated as a research question of the type: "Does x_j significantly influence y_j under specific conditions?"

3.4 Conduct stance detection on scientific literature.

For each question Q_j, a set of statements $s_1, s_2, \dots, s_{n_j}$ is extracted from the literature. Each statement s_i is assigned a neutrosophic stance triplet [23]:

$$NS(s_i, Q_j) = (T_i, I_i, F_i), \tag{4}$$

where $T_i, I_i, F_i \in [0,1]$ and $T_i + I_i + F_i \leq 3$.

3.5 Neutrosophic Probabilistic Hypotheses

For each Q_j , we compute the average neutrosophic probabilities as:

$$NS(Q_j) = \left(\frac{1}{n_j} \cdot \sum_{i=1}^{n_j} Ti, \frac{1}{n_j} \cdot \sum_{i=1}^{n_j} Ii, \frac{1}{n_j} \cdot \sum_{i=1}^{n_j} Fi\right) \tag{5}$$

Where n_j is the number of statements extracted for the question Q_j

3.6 Calculate the plithogenic neutrosophic probability (PNP)

The global hypothesis H is synthesized through plithogenic conjunction applied to the triplets of each sub-hypothesis:

$$UNP(H) = NS(Q_1) \wedge_p NS(Q_2) \wedge_p \dots \wedge_p NS(Q_k) \tag{6}$$

The plithogenic conjunction $\wedge_p$ is defined as:

$$(T_a, I_a, F_a) \wedge_p (T_b, I_b, F_b) = \left(min(T_a, T_b), max(I_a, I_b), max(F_a, F_b)\right) \tag{7}$$

3.7 Negation and Validity Analysis

To assess the strength of the hypothesis, we compute the neutrosophic negation:

$$\neg UNP(H) = (F_H, I_H, T_H) \tag{8}$$

This allows the interpretation of the hypothesis from both affirmation and denial perspectives, thereby clarifying the degree of support, ambiguity, and contradiction in the current scientific literature.

4. Case study.

The integration of emerging technologies such as artificial intelligence, remote sensing, drones, and blockchain into the management and conservation of protective forests offers transformative potential for improved monitoring, early threat detection, and data-driven decision-making. These technologies provide advanced capabilities for real-time biodiversity monitoring, wildfire detection, identification of illegal logging, and tracking changes in forest ecosystems with unprecedented accuracy.

IoT sensor networks facilitates the continuous collection of critical environmental data such as temperature, humidity, air quality, and precipitation levels, allowing forest scientists and managers to identify patterns and trends that might otherwise go undetected using traditional methods. Blockchain platforms improve transparency and traceability in the forest product supply chain, helping to combat illegal logging and promoting sustainable practices.

However, there are considerable limitations and challenges that create uncertainty regarding the universal effectiveness of these technologies. Implementation and maintenance costs represent significant barriers, especially for developing regions with limited resources and extensive forests. Infrastructural gaps, including limited connectivity and insufficient power supply in remote areas, can compromise the functionality of these technological solutions. Variability in technical capabilities and knowledge across different regions and organizations can result in disparities in the effective implementation and utilization of these technologies. Ethical challenges related to data privacy, the rights of Indigenous communities, and information sovereignty pose important considerations that must be adequately addressed. Furthermore, there is a risk that overreliance on technological solutions can divert attention and resources from established and proven conservation strategies. Effectively integrating these technologies with traditional conservation methods and local ecological knowledge represents another significant challenge that must be addressed to maximize their positive impact.

Hypothesis

The implementation of emerging technologies (artificial intelligence, remote sensing, drones, and blockchain) in protective forest management significantly improves early threat detection, biodiversity monitoring, prevention of illegal deforestation, and community engagement in conservation efforts.

To investigate this hypothesis, we follow a systematic research process based on the notion of "partial falsifiability of fuzzy and fuzzy extension hypotheses" proposed by Smarandache is detailed below along with the variable it is intended to measure:

Early threat detection

Q1: Does the implementation of emerging technologies in protective forests significantly improve early detection of threats such as wildfires, pests, and illegal activities?

Variable: Effectiveness in early detection of threats in protected forest areas.

Biodiversity monitoring

Q2: Do emerging technologies allow for more accurate and comprehensive monitoring of biodiversity in protective forests compared to traditional methods?

Variable: Accuracy and scope of biodiversity monitoring.

Deforestation prevention

Q3 : Does the integration of emerging technologies effectively reduce illegal deforestation rates in protected forest areas?

Variable: Illegal deforestation rates in areas where emerging technologies have been implemented.

Community participation

Q4: Do emerging technologies facilitate greater and more effective participation of local communities in forest conservation efforts?

Variable: Level of participation and contribution of local communities in conservation initiatives.

Long-term sustainability

Q5: Are emerging technology-based solutions for protective forest conservation sustainable in the long term considering economic, technical, and social factors?

Variable: Long-term sustainability of conservation technology initiatives.

These questions allow us to measure different aspects and outcomes of the implementation of emerging technologies in protective forest conservation and how they affect the effectiveness of protection efforts.

Stance detection and calculation of neutrosophic probabilities

Stance detection was conducted for each research question using a consensus-based tool that classifies scientific statements into three categories: affirmative (support), uncertain (indeterminate), and negative (refutation). This classification served as the basis for constructing neutrosophic probability triplets (T, I, F) for each hypothesis. The data were obtained through an extensive bibliographic analysis comprising 125 peer-reviewed scientific articles published between 2018 and 2024.**Details of articles analyzed by question:**

P1: Early threat detection

- Articles with a positive stance: 26 articles.
- Articles with indeterminate position: 6 articles.
- Articles with negative stances: 3 articles.
- Total items for P1: 35

P2: Biodiversity monitoring

- Articles with a positive stance: 18 articles.

- Articles with indeterminate position: 4 articles.
- Articles with a negative stance: 3 articles.
- Total items for P2: 25

P3: Deforestation prevention

- Articles with a positive stance: 15 articles.
- Articles with indeterminate position: 9 articles.
- Articles with negative stances: 6 articles.
- Total items for P3: 30

P4: Community Participation

- Articles with a positive stance: 12 articles.
- Articles with indeterminate position: 8 articles.
- Articles with negative stances: 5 articles.
- Total items for P4: 25

P5: Long-term sustainability

- Articles with a positive stance: 5 articles.
- Articles with indeterminate position: 3 articles.
- Articles with negative stances: 2 articles .
- Total items for P5: 10

Neutrosophic probability calculation

From this data, we calculate the neutrosophic probabilities for each question:

P1: Early threat detection

- Positive probability (T): 26/35 = 0.743
- Indeterminate probability (I): 6/35 = 0.171
- Negative probability (F): 3/35 = 0.086
- Neutrosophic probability P1: (0.743, 0.171, 0.086)

P2: Biodiversity monitoring

- Positive probability (T): 18/25 = 0.720
- Indeterminate probability (I): 4/25 = 0.160
- Negative probability (F): 3/25 = 0.120
- Neutrosophic probability P2: (0.720, 0.160, 0.120)

P3: Deforestation prevention

- Positive probability (T): 15/30 = 0.500
- Indeterminate probability (I): 9/30 = 0.300
- Negative probability (F): 6/30 = 0.200
- Neutrosophic probability P3: (0.500, 0.300, 0.200)

P4: Community Participation

- Positive probability (T): 12/25 = 0.480
- Indeterminate probability (I): 8/25 = 0.320
- Negative probability (F): 5/25 = 0.200
- Neutrosophic probability P4: (0.480, 0.320, 0.200)

P5: Long-term sustainability

- Positive probability (T): 5/10 = 0.500
- Indeterminate probability (I): 3/10 = 0.300
- Negative probability (F): 2/10 = 0.200
- Neutrosophic probability P5: (0.500, 0.300, 0.200)

The results are summarized in the following table:

Table 1. Stance assessment on research questions regarding the implementation of emerging technologies for protective forest conservation

Questions	Positive	Indeterminacy	Negative	Neutrosophic probability
P1	26 articles (74.3%)	6 articles (17.1%)	3 articles (8.6%)	(0.743, 0.171, 0.086)

Questions	Positive	Indeterminacy	Negative	Neutrosophic probability
P2	18 articles (72.0%)	4 articles (16.0%)	3 articles (12.0%)	(0.720, 0.160, 0.120)
P3	15 articles (50.0%)	9 articles (30.0%)	6 articles (20.0%)	(0.500, 0.300, 0.200)
P4	12 articles (48.0%)	8 articles (32.0%)	5 articles (20.0%)	(0.480, 0.320, 0.200)
P5	5 items (50.0%)	3 articles (30.0%)	2 articles (20.0%)	(0.500, 0.300, 0.200)

Univariate neutrosophic probability

Univariate neutrosophic probability is calculated using the plithogenic conjunction operator with the following considerations:

According to equation (2) provided in the plithogenic theory: $UNP(v_1, v_2, \ldots, v_n) = v_1 \wedge_p v_2 \wedge_p \ldots \wedge_p v_n$

Where $\wedge_p$ is the plithogenic conjunction between probabilities of the PNP type, such that: $(T_1, I_1, F_1) \wedge_p (T_2, I_2, F_2) = (T_1 \wedge T_2, I_1 \vee I_2, F_1 \vee F_2)$

Where ∧ is the minimum t-norm and ∨ is the maximum t-norm in fuzzy logic.

Applying this formula to our neutrosophic probabilities :

$$UNP(H) = (0.743, 0.171, 0.086) \wedge_p (0.720, 0.160, 0.120) \wedge_p (0.500, 0.300, 0.200) \wedge_p (0.480, 0.320, 0.200) \wedge_p (0.500, 0.300, 0.200)$$

Breaking down the calculation step by step:

1. $(0.743, 0.171, 0.086) \wedge_p (0.720, 0.160, 0.120) = (min(0.743, 0.720), max(0.171, 0.160), max(0.086, 0.120)) = (0.720, 0.171, 0.120)$

2. $(0.720, 0.171, 0.120) \wedge_p (0.500, 0.300, 0.200) = (min(0.720, 0.500), max(0.171, 0.300), max(0.120, 0.200)) = (0.500, 0.300, 0.200)$

3. $(0.500, 0.300, 0.200) \wedge_p (0.480, 0.320, 0.200) = (min(0.500, 0.480), max(0.300, 0.320), max(0.200, 0.200)) = (0.480, 0.320, 0.200)$

4. $(0.480, 0.320, 0.200) \wedge_p (0.500, 0.300, 0.200) = (min(0.480, 0.500), max(0.320, 0.300), max(0.200, 0.200)) = (0.480, 0.320, 0.200)$

Therefore, $UNP(H) = (0.480, 0.320, 0.200)$

Interpretation of results

The value (0.480, 0.320, 0.200) for a neutrosophic probabilistic hypothesis indicates the following:

- **0.480** : There is a 48.0% probability that the hypothesis is true. This suggests moderate evidence that implementing emerging technologies in protective forest management significantly improves early threat detection, biodiversity monitoring, prevention of illegal deforestation, and community engagement.
- **0.320** : There is a 32.0% uncertainty, reflecting a considerable level of uncertainty or incomplete knowledge about the overall effectiveness of these technologies in all forest conservation contexts.
- **0.200** : There is a 20.0% probability that the hypothesis is false, indicating that there is some evidence that contradicts or does not support the proposed benefits of these emerging technologies.

Negation of the hypothesis

According to equation (4) of the plithogenic theory, the negation of the probabilistic neutrosophic hypothesis is calculated as:$\neg(T, I, F) = (F, I, T)$

Therefore, the negation of our hypothesis $UNP(H) = (0.480, 0.320, 0.200)$would be:$\neg UNP(H) = (0.200, 0.320, 0.480)$

This negation can be interpreted as follows:

- **0.200** : There is a 20.0% probability that the denial of the hypothesis is true. This means that there is a relatively low probability that the implementation of emerging technologies will NOT improve the conservation of protective forests.
- **0.320**: There is a 32.0% uncertainty, indicating a considerable level of uncertainty about the validity of the rejected hypothesis. This reflects the complexity of assessing these effects in various contexts.
- **0.480**: There is a 48.0% probability that the denial of the hypothesis is false. This suggests that there is moderate evidence against the idea that emerging technologies have no positive impact on conservation.

The results of the analysis of the neutrosophic probabilistic hypothesis, with a univariate neutrosophic probability $UNP(H) = (0.480, 0.320, 0.200)$,They offer a nuanced perspective on the impact of emerging technologies (artificial intelligence, remote sensing, drones, and blockchain) on protective forest conservation. The probability of truth of 48%, the probability of uncertainty of 32%, and the probability of falsity of 20% allow for meaningful conclusions and highlight opportunities for future research. The results are analyzed in detail below, considering the implications of each research question and the associated challenges.

The 48% probability of truth indicates moderate support for the hypothesis that emerging technologies improve the conservation of protective forests, with a particular emphasis on early threat detection ($P1: T = 0.743$)and biodiversity monitoring. ($P2: T = 0.720$).These values suggest that technologies such as drones equipped with thermal sensors and AI algorithms applied to satellite imagery are generating tangible positive results. For example, studies have shown that drones can detect forest fires with 95% accuracy in remote areas, while IoT sensor networks allow biodiversity monitoring with unprecedented resolution, identifying patterns in ecosystem health. These advances are particularly valuable in large forests where traditional methods, such as human patrols, are less efficient.

The 32% level of indeterminacy reflects the dependence of the success of these technologies on contextual factors. Variables such as available infrastructure, local technical capacities, socioeconomic conditions, and the ecological characteristics of forests influence the effectiveness of technological interventions. This high degree of indeterminacy is particularly evident in the areas of deforestation prevention ($P3: I = 0.300$), community engagement ($P4: I = 0.320$), and long-term sustainability ($P5: I = 0.300$). For example, implementing blockchain to track forest products requires reliable connectivity, which is often lacking in remote areas.

The lowest probabilities of veracity are observed in deforestation prevention ($P3: T = 0.500$), community engagement ($P4: T = 0.480$), and long-term sustainability ($P5: T = 0.500$). These results suggest that while emerging technologies show efficacy in pilot projects or controlled environments, their scalability faces significant hurdles. Deployment costs, which can exceed $100,000 per IoT monitoring system over large areas, represent a major barrier, especially in developing countries. Furthermore, the need for ongoing maintenance, technical training, and adaptation to complex forest environments (e.g., dense forests with high canopy cover) limits widespread adoption. In the case of deforestation prevention, institutional resistance and lack of coordination between actors (governments, NGOs , communities) reduce the effectiveness of tools like blockchain.

Community engagement analysis ($P4: T = 0.480, I = 0.320, F = 0.200$) reveals moderate potential for emerging technologies to strengthen local community engagement but also highlights limitations. The 32% uncertainty suggests that this potential is not being fully realized, possibly due to cultural barriers or a perception of the technologies as external. Research indicates that mobile applications that enable communities to report illegal activities, such as logging, are most effective when designed with the active participation of local users. Respectful integration with traditional ecological knowledge, such as the use of drones to complement community patrols, can improve the acceptance and effectiveness of these tools. However, a lack of training and equitable access to the technologies remains a challenge.

The distribution between certainty (48%) and indeterminacy (32%) points to the need for adaptive approaches that combine emerging technologies with traditional conservation methods. Rather than replacing established strategies, such as forest patrols or community governance systems, technologies should be integrated to enhance them. For example, the use of IoT sensors to alert local patrols of potential fires combines technological precision with human expertise, achieving better results . This hybrid approach is crucial to addressing indeterminacy and ensuring that solutions are contextually appropriate.

5. Conclusion

Ultimately, this study provides a plithogenic scenario in which emerging technologies—artificial intelligence, drones, remote sensing, and blockchain—moderately improve protective forest management with a 48% probability of occurrence. Findings suggest they assist with real-time threat detection and high-fidelity biodiversity assessments. However, with a 32% fluctuation, situational challenges like high expense and lack of infrastructure restrain their potential to engage in anti-deforestation efforts and community outreach. Ultimately, while they're promising developments, they need to be adjusted for varying situations. These results are practically applicable for they can revolutionize the way humans control forests. For instance, with drones and sensors, forest rangers will be notified of smoke via satellite imagery or chainsaws via air footage before too much damage is done, as ecosystems are vital.

Furthermore, using blockchain technology to authenticate the source of forest products can decrease efforts at sustainability as it decreases illegal sales. Such practical uses can not only improve management efforts but also sustain ecosystem service sustainability as threats from climate change will only increase.\

The main contribution of this study is the use of the plithogenic hypothesis, a novel predictive framework that evaluates uncertainty across multi-dimensional challenges. This novel evaluation supplements technology assessments used in this conservation project best suited for environments of uncertainty. By analyzing 125 peer-reviewed articles, the study renders an empirically based contribution to literature surrounding the intersection of new technological development and environmental conservation. Yet there are limitations. The Consensus Meter involved in the stance setection analysis has a 10% error margin which may distort results. Furthermore, the lack of longitudinal studies and studies across different regions offered a non-generalizable approach; however, this is representative of the multifaceted generalizability of such technologies worldwide. Future studies should include longitudinal analyses to determine whether such technologies can destabilize biodiversity efforts over time even if short-term economic efficiency exists. Generalizing over a longer time with better data collections should be undertaken with different methodologies—perhaps Bayesian networks or deep learning algorithms—to assess metaphorical applicability of plithogenic elsewhere. Furthermore, studies should assess feasibility with consideration of integrating these technologies with Indigenous knowledge systems for equity and community engagement. Finally, generalizing the assessment across ecosystems—assessing applicability in mangroves or boreal forests—would expand the generalizability. Ultimately, there is no one answer through technology or traditional practices; the balance between the two must be found for ecological and sociological equity.

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Received: December 26, 2024. Accepted: April 7, 2025.