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Intelligent Hazard Assessment of Mangrove Degradation

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Abstract: Mangrove ecosystems are crucial for mitigating climate change by sequestering significant amounts of carbon, providing habitat for diverse species, and protecting coastal areas. Their sustainability is vital for global environmental balance and human welfare. Analysis using the Eidos system reveals the threats to mangrove forest health, considering both negative and positive factors and analyzing the strength and direction of each threat's influence. The Eidos system facilitated the development of a statistical model and cognitive system, demonstrating effectiveness in identifying and classifying degradation risks based on empirical data, allowing for early predictions at relatively low operational costs. These findings can be leveraged by coastal protection organizations worldwide, as the Eidos system is freely accessible online in multiple languages. The results have the potential to inform targeted mangrove conservation policies and enhance environmental protection initiatives in various regions.

Keywords: Mangrove, Degradation, Eidos System, SWOT Analysis, Hazard Assessment

INTRODUCTION

Mangrove forests thrive in the salty shallow waters of coastal areas, enduring conditions that most other trees cannot tolerate. Some species possess vertical roots that extend into the air, giving the trees a distinctive "walking on stilts" appearance. These forests are particularly valuable to coastal populations (Carugati et al., 2018). The vegetation acts as a buffer against soil erosion in the intertidal zone and serves as a protective barrier during destructive weather events such as tsunamis, tropical cyclones, and tidal waves. The supporting roots, submerged in silt and brackish water, provide shelter for juvenile fish and crustaceans, while a variety of birds, primates, and felines inhabit the mangrove branches. Furthermore, mangrove forests are significant carbon sinks, absorbing greenhouse gases more efficiently than mainland rainforests (Rizal, 2018). They also purify coastal waters, supply organic detritus and nutrients, and create habitats for economically important fish and crustaceans (Arifanti et al., 2022).

Despite their importance, mangrove forests in Indonesia face numerous threats from human activities. These areas are intensively exploited for timber, charcoal, tannins, building materials, household items, medicines, and raw materials for the pulp and paper industry (Arifanti et al., 2021). According to the Indonesian Ministry of Environment and Forestry, mangrove loss totaled 182,091 hectares between 2009 and 2019, primarily driven by coastal development, aquaculture deforestation, and agricultural land expansion. The deforestation of mangrove forests could potentially release 182.6 million tons of CO2-equivalent over a decade. Additionally, tin mining significantly impacts land quality and the environment (Rahmadi et al., 2023). The view of the coastal mangroves is shown in Figure 1.

Over time, these activities contribute to ecosystem damage, resulting in soil degradation and water quality deterioration, which diminishes vegetation diversity and necessitates land reclamation (Moriizumi et al., 2010). Increasing tin mining and salt production hinder mangroves' ability to support coastal ecosystems. Sedimentation from these activities can smother mangroves and coral reefs, ultimately leading to their death (Nurtjahya et al., 2017). Consequently, fish are forced to relocate further from the coast, while land-based mining reduces biodiversity and damages infrastructure by creating lakes from mining runoff.

Water pollution from fertilizer runoff, industrial and domestic waste, and oil spills further degrades water quality in mangrove forests, threatening biodiversity. Accumulations of rubbish, domestic waste disposal, vehicle emissions, and shipping activities pose significant risks to this ecosystem (Wattimena et al., 2021). Marine debris—particularly plastics, heavy metals, organic pollutants, and pathogens—enters the marine environment through improper disposal, accidental loss, and natural disasters. Plastic entangled in mangrove roots blocks oxygen, creating anoxic conditions that can lead to mangrove suffocation and deformities in pneumatophores (Nunoo & Agyekumhene, 2022).

Figure 1. *Ryzophora apiculate.*

Urban expansion and infrastructure development on coastlines, including ports and roads, further contribute to mangrove destruction. Mangroves are often cleared for shrimp farms and other aquaculture without modern waste treatment facilities, damaging surrounding marine habitats by depleting oxygen levels and altering species distributions (Sari & Rosalina, 2016). Efforts to preserve and restore mangrove ecosystems include planting seedlings along riverbanks and dispersing seeds via drones, achieving a success rate of 48%. Additionally, cleanup initiatives address plastic pollution (Rahmawati et al., 2023). However, pest infestations, such as weevils and pathogens, threaten the long-term survival of these forests.

Mangroves flourish where there is ample freshwater runoff and tidal waters. However, damming or siltation in estuaries restricts tidal flow into mangrove swamps. The construction of dams upstream for irrigation purposes limits freshwater supply to mangrove forests and leads to salinization of these swamps (Osorio et al., 2017). It is crucial to regulate human activities associated with mangrove wood processing, as the establishment of new paper mills and chipboard factories in Indonesia is detrimental (Sulistyowati & Astuti, 2018). Legal measures against those violating regulations regarding mangrove land use include administrative sanctions, reprimands, and revocation of business licenses in mangrove zones. Strict enforcement of conservation laws contributes to the sustainable management of mangrove forests (Li et al., 2021).

Indonesia's mangrove forests, covering over 3 million hectares, represent one of the largest mangrove ecosystems globally (Karimah, 2017). These forests are vital for maintaining coastal ecosystem balance, protecting shorelines from erosion, and providing habitats for various marine and terrestrial species. Furthermore, they store five times more carbon per hectare than tropical forests, playing a key role in climate change mitigation. Nonetheless, challenges such as deforestation, land conversion for aquaculture and agriculture, and urbanization threaten their sustainability (Risa et al., 2021). Data from the Ministry of Environment and Forestry indicate that approximately 40% of Indonesia's mangrove forests have been damaged.

While methods for assessing sustainable mangrove management exist, they often consider a limited number of factors or focus solely on economic assessments of mangrove ecosystems. Comprehensive software development is necessary to evaluate the state of mangrove forests under various growth conditions, especially given that many factors are expressed as linguistic variables. The Eidos intellectual system, operational for over 30 years, offers a universal solution (Lutsenko, 2020). Available online without a license, Eidos can generate ten mathematical models and perform diverse research tasks across various fields. It allows for the quantitative assessment of management forecasts and recommendations and evaluates the influence of various factors, suggesting alternatives to costly or inaccessible methods that yield similar results.

Assessing sustainable mangrove management has faced challenges, including a lack of comprehensive risk assessment tools for mangrove degradation. Many prior studies have limited their scope or focused solely on economic aspects, hindering a holistic understanding of the complex interactions among environmental and social factors affecting mangrove health. This work aims to employ automated system-cognitive analysis (ASC-analysis) through the Eidos system to evaluate the risks associated with mangrove forest degradation. Eidos is particularly suited for this research due to its capacity to model complex relationships between environmental and social factors influencing mangrove degradation. It was selected over other methods for its superiority in integrating cognitive and spatial data, facilitating thorough analysis of mangrove degradation hazards.

The use of systems like Eidos addresses gaps by thoroughly integrating cognitive and spatial data. Eidos not only offers comprehensive analysis but also provides mathematical models for an in-depth numerical evaluation of various aspects of mangrove degradation. To achieve this goal, the following tasks must be completed (Lutsenko, 2022):

First, a training database will be compiled based on empirical data, which will allow for evaluating the reliability of models generated by Eidos and selecting the most reliable one. This step is crucial for ensuring the validity of the analytical outcomes. Second, the training database will be reworked to ensure a sufficient level of data quality. High-quality data is essential for accurate modeling and reliable results, thus enhancing the overall effectiveness of the assessment process. Third, a study of the simulated subject area will be conducted, which will include information-semantic analysis and cluster analysis of classes and features for object recognition. This analytical approach will aid in comprehensively understanding the factors influencing mangrove health and degradation.

The Eidos system is a software package implementing mathematical models and methodologies for numerical ASC analysis, offering functions such as the synthesis and adaptation of the semantic information model of the subject area, including the active control object and its environment. It also identifies and predicts the state of active controls, developing control actions to transition the object to specified target states. Through in-depth analysis of the semantic information model, the system allows for selecting control factors that can effectively mitigate the danger of mangrove forest degradation.

Eidos distinguishes itself from existing systems by being developed in a universal format, making it applicable across various subject areas. It transforms initial empirical data into information and subsequently into knowledge, facilitating classification, decision support, and subject area research through its system-cognitive model while generating extensive tabular and graphical outputs. The system ensures stable identification of cause-and-effect relationships in large dimensions of incomplete, noisy, interdependent data, accommodating various types of scales and measurement units. Furthermore, it is freely accessible (http://lc.kubagro.ru/aidos/_Aidos-X.htm), with up-to-date source materials.

The primary aim of this study is to utilize the Eidos system for assessing the hazards of mangrove degradation through automated system-cognitive analysis. By integrating cognitive and spatial data, the research seeks to develop a comprehensive risk assessment tool that considers multiple environmental and social factors influencing mangrove health.

This study is significant as it addresses critical gaps in existing methods for assessing mangrove ecosystems. By leveraging the Eidos system, it aims to provide a more holistic understanding of the relationships between various factors affecting mangrove health and degradation. The findings will contribute to the development of effective management strategies and policies aimed at preserving and restoring mangrove forests, thereby enhancing their ecological and economic value.

METHOD

Data Collection

To obtain an integral assessment of the state of mangrove forests in Indonesia, we utilized a comprehensive model that incorporates various factors contributing to mangrove degradation. The model is represented as follows:

$$\mathrm{HAD} = \langle \mathrm{VMD}, \mathrm{OTSP}, \mathrm{SPV}, \mathrm{MDP}, \mathrm{VMM}, \mathrm{GUA}, \mathrm{EAA}, \mathrm{NMP}, \mathrm{MC}, \mathrm{PDSS}, \mathrm{RHA}, \mathrm{MCLR} \rangle, \tag{1}$$

where:
HAD – Hazard assessment of degradation
VMD – Volume of mangrove deforestation
OTSP – Offshore tin and salt production
SPV – Sewage pollution volume
MDP – Marine debris pollution
VMM – Volume of mud from mines
GUA – Growth of urban areas and associated infrastructure such as ports, marinas, roads, and buildings
EAA – Expansion of aquaculture activities
NMP – Number of mangroves planted
MC – Mangrove cleaning
PDSS – Pest and disease control costs
RHA – Restriction of human economic activity
MCLR – Monitoring compliance with laws and regulations

To evaluate the hazard assessment, we defined the output variable using the term set:

$$Y1 = \{\mathrm{high}, \mathrm{medium}, \mathrm{low}\} \tag{2}$$

The input variables are characterized by fuzzy term sets, allowing for nuanced interpretations of various factors impacting mangrove health:

$$\forall i, Xi = \{\mathrm{big}, \mathrm{average}, \mathrm{small}\} \tag{3}$$

A training database was created based on empirical data sourced from a combination of satellite imagery, field surveys, and existing environmental reports. This database includes quantitative data on mangrove cover changes, pollution levels, and human activities affecting mangrove ecosystems. A fragment of this training database is illustrated in Figure 2.

Inp_data

	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1	Version	HAD	VMD	OTSP	SPV	MDP	GUA	EAA	VMM	NMP	MC	PDSS	RHA	MCLR
2	1	high	big	big	big	big	big	big	big	small	small	small	small	small
3	2	high	big	big	big	big	big	big	big	small	small	small	small	average
4	3	high	big	big	big	big	big	big	big	small	small	small	average	small
5	4	high	big	big	big	big	big	big	big	small	small	average	small	small
6	5	high	big	big	big	big	big	big	big	small	average	small	small	small
7	6	high	big	big	big	big	big	big	big	average	small	small	small	small
8	7	high	big	big	big	big	big	average	big	small	small	small	small	small
9	8	high	big	big	big	average	big	big	big	small	small	small	small	small

Figure 2. Fragment of the training database.

The hazard assessment of mangrove forest degradation was informed by the collective knowledge of researchers, integrating ecological expertise with local environmental conditions. This comprehensive approach enables a better understanding of the multifaceted interactions between human activities and mangrove health. Data were gathered through collaboration with local communities, government agencies, and environmental organizations to ensure the assessment reflects both scientific and community insights.

Synthesis and Verification of Models

Mathematical models for Automated System-Cognitive (ASC) analysis within the Eidos system leverage fuzzy interval mathematics. This approach allows for the processing of large volumes of disparate and noisy interdependent data presented in various scales (nominal, ordinal, and numerical) and measurement units (Strielkowski et al., 2021). The essence of these modeling methods lies in calculating the information value of factors, which influence the state of the modeling object, leading it into a specific class.

The Eidos system facilitates the resolution of identification problems—such as classification, recognition, diagnostics, and forecasting—as well as decision support. It provides a framework for studying the modeled subject area through its system-cognitive model. Notably, the Eidos system can simultaneously operate with three statistical models and seven knowledge models, enabling comprehensive identification, decision-making, and research across various models according to two integral criteria. Furthermore, the system evaluates the effectiveness of different partial and integral criteria in addressing these challenges.

Models in the Eidos system are constructed using a matrix of absolute frequencies, reflecting the occurrences of gradations of descriptive scales against classification scale gradations (facts). To address the complexities of the problems, the system utilizes matrices of conditional and unconditional percentage distributions derived from the absolute frequency matrix. The calculation of the absolute frequency matrix is illustrated in Figure 3.

5.5. Модель: "1. ABS - a particular criterion: the number of occurrences of combinations: "class-attribute" for objects of the training sample"

Код признака	Наименование описательной шкалы и градации	1. HAD HIGH	2. HAD LOW	3. HAD MEDIUM	Сумма	Среднее	Средн. квадр.
1.0	VMD-average	2.0		35.0	37.0	12.33	19.66
2.0	VMD-big	21.0		6.0	27.0	9.00	10.82
3.0	VMD-small		35.0	2.0	37.0	12.33	19.66
4.0	OTSP-average	3.0	5.0	39.0	47.0	15.67	20.23
5.0	OTSP-big	20.0			20.0	6.67	11.55
6.0	OTSP-small		30.0	4.0	34.0	11.33	16.29
7.0	SPV-average	3.0		39.0	42.0	14.00	21.70
8.0	SPV-big	20.0			20.0	6.67	11.55
9.0	SPV-small		35.0	4.0	39.0	13.00	19.16
10.0	MDP-average	3.0	2.0	40.0	45.0	15.00	21.66
11.0	MDP-big	20.0			20.0	6.67	11.55
12.0	MDP-small		33.0	3.0	36.0	12.00	18.25
13.0	GUA-average	1.0	1.0	36.0	38.0	12.67	20.21
14.0	GUA-big	22.0		1.0	23.0	7.67	12.42
15.0	GUA-no		33.0	6.0	39.0	13.00	17.58
16.0	GUA-small		1.0		1.0	0.33	0.58
17.0	EAA-average	1.0	1.0	41.0	43.0	14.33	23.09
18.0	EAA-big	22.0			22.0	7.33	12.70
19.0	EAA-small		34.0	2.0	36.0	12.00	19.08
20.0	VMM-average	1.0		39.0	40.0	13.33	22.23
21.0	VMM-big	22.0		1.0	23.0	7.67	12.42
22.0	VMM-small		35.0	3.0	38.0	12.67	19.40
23.0	NMP-average	1.0		38.0	39.0	13.00	21.66
24.0	NMP-big		35.0	3.0	38.0	12.67	19.40
25.0	NMP-small	22.0		2.0	24.0	8.00	12.17

Figure 3. Matrix of absolute frequencies.

Subsequently, based on the matrices of conditional and unconditional percentage distributions, matrices of system-cognitive models are derived using specific knowledge criteria. Figures 4 and 5 illustrate the conditional and unconditional percentage distribution matrices, respectively.

The resulting system-cognitive models, as shown in Figure 6, demonstrate very high reliability, indicating their suitability for solving problems within this subject area. The reliability assessment of these models was conducted using 100 observation examples from the training sample, reinforcing the validity of the Eidos system's application in this context.

RESULTS AND DISCUSSION

Outcomes of Mangrove Degradation Risk Recognition

Recognition involves comparing the degree of similarity between a specific object and other objects or generalized class images, resulting in a ranked assessment of objects based on similarity. This approach aligns with the findings of Lutsenko (2020). The outcomes of this model are derived through the following steps:

5.5. Модель: "2. PRC1 - particular criterion: arb. probability of the i-th feature among the features of objects of the j-th class"

Код признака	Наименование описательной шкалы и градации	1. HAD HIGH	2. HAD LOW	3. HAD MEDIUM	Безусл. вероятн.	Среднее	Средн. квадр.
1.0	VMD-average	0.725		6.783	3.053	2.503	3.725
2.0	VMD-big	7.609		1.163	2.228	2.924	4.099
3.0	VMD-small		8.333	0.388	3.053	2.907	4.703
4.0	OTSP-average	1.087	1.190	7.558	3.878	3.279	3.707
5.0	OTSP-big	7.246			1.650	2.415	4.184
6.0	OTSP-small		7.143	0.775	2.805	2.639	3.919
7.0	SPV-average	1.087		7.558	3.465	2.882	4.086
8.0	SPV-big	7.246			1.650	2.415	4.184
9.0	SPV-small		8.333	0.775	3.218	3.036	4.604
10.0	MDP-average	1.087	0.476	7.752	3.713	3.105	4.036
11.0	MDP-big	7.246			1.650	2.415	4.184
12.0	MDP-small		7.857	0.581	2.970	2.813	4.378
13.0	GUA-average	0.362	0.238	6.977	3.135	2.526	3.855
14.0	GUA-big	7.971		0.194	1.898	2.722	4.547
15.0	GUA-no		7.857	1.163	3.218	3.007	4.241
16.0	GUA-small		0.238		0.083	0.079	0.137
17.0	EAA-average	0.362	0.238	7.946	3.548	2.849	4.415
18.0	EAA-big	7.971			1.815	2.657	4.602
19.0	EAA-small		8.095	0.388	2.970	2.828	4.566
20.0	VMM-average	0.362		7.558	3.300	2.640	4.263
21.0	VMM-big	7.971		0.194	1.898	2.722	4.547
22.0	VMM-small		8.333	0.581	3.135	2.972	4.653
23.0	NMP-average	0.362		7.364	3.218	2.576	4.151
24.0	NMP-big		8.333	0.581	3.135	2.972	4.653
25.0	NMP-small	7.971		0.388	1.980	2.786	4.494

Figure 4. Conditional Percentage Distribution Matrix.

5.5. Модель: "3. PRC2 - particular criterion: conditional probability of the i-th feature in objects of the j-th class"

Код признака	Наименование описательной шкалы и градации	1. HAD HIGH	2. HAD LOW	3. HAD MEDIUM	Безусл. вероятн.	Среднее	Средн. квадр.
1.0	VMD-average	8.696		81.395	36.634	30.030	44.716
2.0	VMD-big	91.304		13.953	26.733	35.086	49.205
3.0	VMD-small		100.000	4.651	36.634	34.884	56.461
4.0	OTSP-average	13.043	14.286	90.698	46.535	39.342	44.500
5.0	OTSP-big	86.957			19.802	28.986	50.225
6.0	OTSP-small		85.714	9.302	33.663	31.672	47.053
7.0	SPV-average	13.043		90.698	41.584	34.580	49.055
8.0	SPV-big	86.957			19.802	28.986	50.225
9.0	SPV-small		100.000	9.302	38.614	36.434	55.267
10.0	MDP-average	13.043	5.714	93.023	44.554	37.260	48.452
11.0	MDP-big	86.957			19.802	28.986	50.225
12.0	MDP-small		94.286	6.977	35.644	33.754	52.559
13.0	GUA-average	4.348	2.857	83.721	37.624	30.309	46.283
14.0	GUA-big	95.652		2.326	22.772	32.659	54.587
15.0	GUA-no		94.286	13.953	38.614	36.080	50.909
16.0	GUA-small		2.857		0.990	0.952	1.670
17.0	EAA-average	4.348	2.857	95.349	42.574	34.185	52.996
18.0	EAA-big	95.652			21.782	31.884	55.246
19.0	EAA-small		97.143	4.651	35.644	33.931	54.813
20.0	VMM-average	4.348		90.698	39.604	31.682	51.176
21.0	VMM-big	95.652		2.326	22.772	32.659	54.587
22.0	VMM-small		100.000	6.977	37.624	35.659	55.851
23.0	NMP-average	4.348		88.372	38.614	30.907	49.835
24.0	NMP-big		100.000	6.977	37.624	35.659	55.851
25.0	NMP-small	95.652		4.651	23.762	33.434	53.953

Figure 5. Matrix of unconditional percentage distributions.

3.4. Generalized form for valid models at different int.crit. Current Model: "INF3"

Model name and private criterion	Integral criterion	S-precision models	S-Completeness models	L1-measure prof. E.V.Lutsenko	Average module similarity levels true-positive decisions
1. ABS - a particular criterion: the number of occurrences of combinati...	Correlation of abs.frequencies wit...	1.000	1.000	1.000	0.881
1. ABS - a particular criterion: the number of occurrences of combinati...	The sum of the absolute frequen...	0.955	1.000	0.977	0.781
2. PRC1 - particular criterion: arb. probability of the i-th feature among t...	Correlation of conditional relative ...	1.000	1.000	1.000	0.881
2. PRC1 - particular criterion: arb. probability of the i-th feature among t...	The sum of the conditional relativ...	0.958	1.000	0.978	0.906
3. PRC2 - particular criterion: conditional probability of the i-th feature i...	Correlation of conditional relative ...	1.000	1.000	1.000	0.881
3. PRC2 - particular criterion: conditional probability of the i-th feature i...	The sum of the conditional relativ...	0.958	1.000	0.978	0.906
4. INF1 - particular criterion: the amount of knowledge according to A. ...	Semantic resonance of knowledge	0.999	1.000	0.999	0.732
4. INF1 - particular criterion: the amount of knowledge according to A. ...	Sum of knowledge	1.000	1.000	1.000	0.401
5. INF2 - particular criterion: the amount of knowledge according to A. ...	Semantic resonance of knowledge	0.999	1.000	0.999	0.732
5. INF2 - particular criterion: the amount of knowledge according to A. ...	Sum of knowledge	1.000	1.000	1.000	0.401
6. INF3 - partial criterion: Xi-square, differences between actual and ex...	Semantic resonance of knowledge	1.000	1.000	1.000	0.866
6. INF3 - partial criterion: Xi-square, differences between actual and ex...	Sum of knowledge	1.000	1.000	1.000	0.829
7. INF4 - particular criterion: ROI (Return On Investment); probabilities f...	Semantic resonance of knowledge	1.000	1.000	1.000	0.816
7. INF4 - particular criterion: ROI (Return On Investment); probabilities f...	Sum of knowledge	1.000	1.000	1.000	0.502
8. INF5 - particular criterion: ROI (Return On Investment); probabilities f...	Semantic resonance of knowledge	1.000	1.000	1.000	0.816
8. INF5 - particular criterion: ROI (Return On Investment); probabilities f...	Sum of knowledge	1.000	1.000	1.000	0.502

Figure 6. Model Reliability Evaluation Results.

a) Empirical Data Collection and Processing

Empirical data on mangrove growing conditions was collected and processed into a training database suitable for input into the Eidos system. This dataset encompasses various factors influencing mangrove conditions, including both positive and negative influences.

b) Model Establishment

Using the processed data, the Eidos system constructs a mathematical model capable of predicting the risk of mangrove degradation. In this study, three statistical models and seven cognitive system models were developed to describe different scenarios and conditions of mangrove growth.

c) Determining the Level of Similarity

The Eidos model executes recognition operations by comparing new empirical data against generalized historical data. The degree of similarity between current and historical conditions informs the predictions of degradation risk.

d) Risk Variability Analysis

The analysis revealed variability in degradation risk based on different growing conditions. The calculated similarity levels categorized the risk into high (HAD-high), medium (HAD-medium), and low (HAD-low) classes, illustrating the potential extent of degradation under varying circumstances.

e) Use of Predictions for Conservation Action

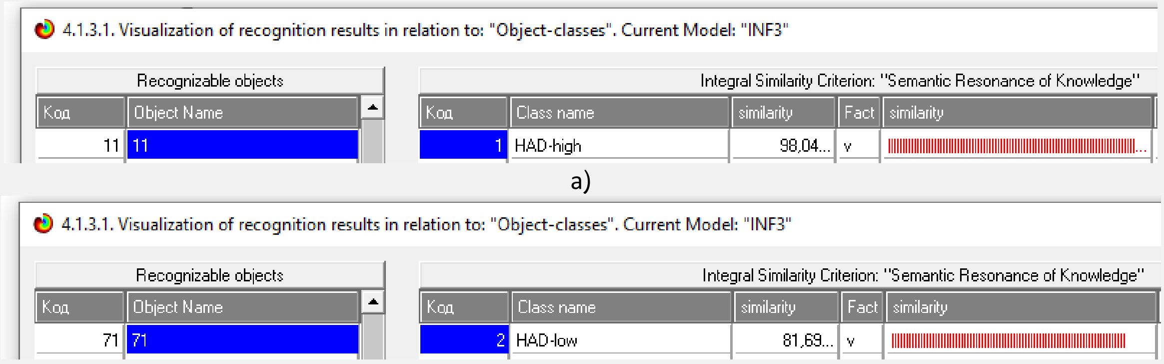
Risk predictions generated by the model inform conservation strategies. For instance, if the model indicates a high risk of degradation, proactive measures can be implemented to mitigate potential damage.

Figure 7 illustrates examples of high and low-risk predictions of mangrove degradation using the INF3 model, based on growth history observations.

The information portrait of a class is a comprehensive collection of data and characteristics analyzed by the Eidos system. This portrait highlights the strength and direction of various factors influencing mangrove forest degradation risk. Identifying the most impactful features enables researchers to focus on critical elements that require attention. An information portrait of the HAD-high class is depicted in Figure 8.

The HAD-high class information snapshot (Figure 8) provides insights into key factors influencing degradation risk. Each factor is evaluated for its influence on mangrove forest conditions, with the most significant factors prioritized. This streamlining enhances data collection efficiency and accuracy in conservation decision-making. This approach is supported by the findings of Friess et al. (2016), emphasizing the effectiveness of targeted management strategies for vulnerable mangrove ecosystems.

The information portrait begins with factors that positively influence the transition to a given state, followed by neutral factors and those that hinder this transition. An information portrait of the HAD-low class is shown in Figure 9.



4.1.3.1. Visualization of recognition results in relation to: "Object-classes". Current Model: "INF3"

Recognizable objects

Код	Object Name
11	11

Integral Similarity Criterion: "Semantic Resonance of Knowledge"

Код	Class name	similarity	Fact	similarity
1	HAD-high	98,04...	v	

a)

4.1.3.1. Visualization of recognition results in relation to: "Object-classes". Current Model: "INF3"

Recognizable objects

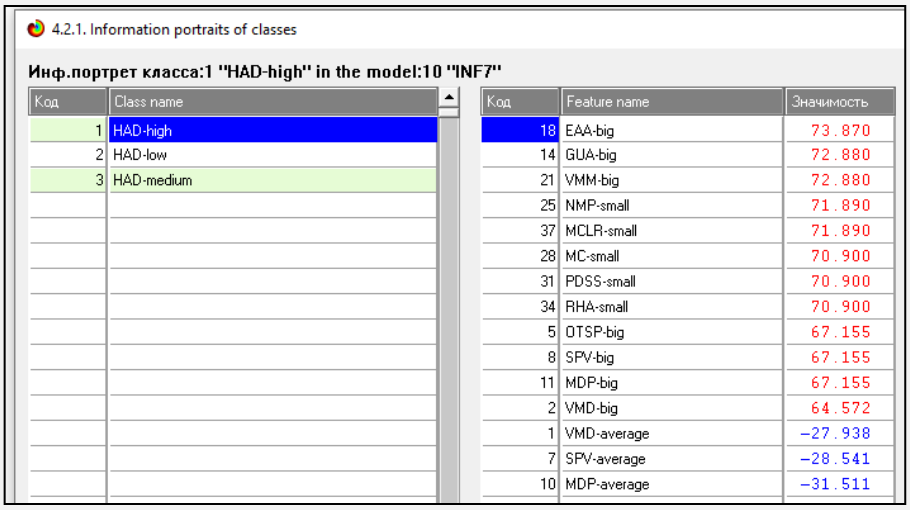
Код	Object Name
71	71

Integral Similarity Criterion: "Semantic Resonance of Knowledge"

Код	Class name	similarity	Fact	similarity
2	HAD-low	81,69...	v	

b)

Figure 7. Examples of mangrove degradation hazard predictions:
a) high risk; b) low risk.



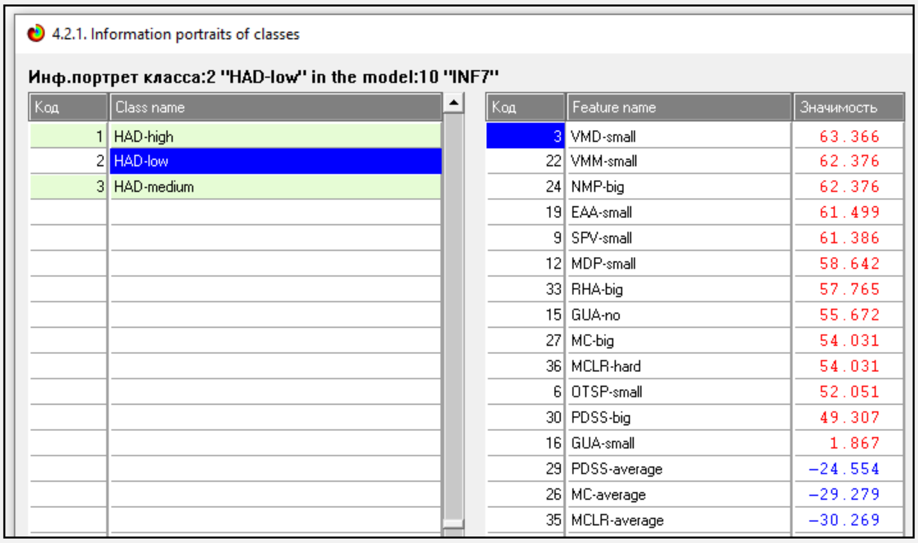
4.2.1. Information portraits of classes

Инф.портрет класса:1 "HAD-high" in the model:10 "INF7"

Код	Class name
1	HAD-high
2	HAD-low
3	HAD-medium

Код	Feature name	Значимость
18	EAA-big	73.870
14	GUA-big	72.880
21	VMM-big	72.880
25	NMP-small	71.890
37	MCLR-small	71.890
28	MC-small	70.900
31	PDSS-small	70.900
34	RHA-small	70.900
5	OTSP-big	67.155
8	SPV-big	67.155
11	MDP-big	67.155
2	VMD-big	64.572
1	VMD-average	-27.938
7	SPV-average	-28.541
10	MDP-average	-31.511

Figure 8. Information portrait of the HAD-high class.



4.2.1. Information portraits of classes

Инф.портрет класса:2 "HAD-low" in the model:10 "INF7"

Код	Class name
1	HAD-high
2	HAD-low
3	HAD-medium

Код	Feature name	Значимость
3	VMD-small	63.366
22	VMM-small	62.376
24	NMP-big	62.376
19	EAA-small	61.499
9	SPV-small	61.386
12	MDP-small	58.642
33	RHA-big	57.765
15	GUA-no	55.672
27	MC-big	54.031
36	MCLR-hard	54.031
6	OTSP-small	52.051
30	PDSS-big	49.307
16	GUA-small	1.867
29	PDSS-average	-24.554
26	MC-average	-29.279
35	MCLR-average	-30.269

Figure 9. Information portrait of the HAD-low class.

Figure 10 illustrates the Pareto curve depicting the significance of descriptive scales (features). Notably, 44% of the most significant features account for 50% of the total significance, while 50% of the most significant features represent 57% of the total significance. The monotonically increasing curve indicates no redundant features.

Figure 10. Pareto curve for the significance of descriptive scales.

The results of this study provide critical insights into the risk factors associated with mangrove degradation, emphasizing the need for tailored conservation strategies. The use of the Eidos system for modeling offers a robust framework for analyzing complex, interdependent data. By integrating diverse datasets, the model effectively captures the multifaceted nature of environmental threats to mangroves, such as urban development, pollution, and climate change.

The findings underscore the importance of empirical data in shaping effective conservation actions. The high-risk scenarios identified can serve as early warning signals, prompting immediate protective measures. For instance, areas predicted to be at high risk may benefit from enhanced monitoring and stricter enforcement of environmental regulations to curb deforestation and pollution.

Moreover, the identification of key factors influencing degradation risk allows for focused resource allocation. Understanding which variables exert the most significant impact on mangrove health can guide stakeholders in prioritizing interventions. This targeted approach not only improves the efficiency of conservation efforts but also fosters stakeholder engagement by highlighting the direct benefits of addressing specific risk factors.

The variability in risk levels across different growing conditions suggests that localized strategies may be necessary. Conservation plans should be adaptable, taking into account the unique ecological and socio-economic contexts of each region. This adaptability is crucial, especially in the face of climate change, which introduces further uncertainty into mangrove ecosystems.

Additionally, the development of information portraits enhances the decision-making process by simplifying complex data into actionable insights. By presenting the strengths and weaknesses of various factors influencing degradation risk, these portraits can facilitate discussions among policymakers, conservationists, and local communities.

The results align with previous studies highlighting the critical role of mangroves in coastal protection and biodiversity preservation (Friess et al., 2016; Lutsenko, 2020). As mangroves face increasing pressures, innovative modeling approaches like the Eidos system provide valuable tools for understanding and mitigating degradation risks. This research contributes to the growing body of knowledge aimed at preserving these vital ecosystems.

The integration of advanced modeling techniques with empirical data offers a promising pathway for enhancing mangrove conservation efforts. Future research should focus on refining these models and exploring the long-term effectiveness of implemented conservation strategies. Collaborative efforts among researchers, policymakers, and local communities will be essential to safeguard mangrove ecosystems for future generations.

Results of SWOT Analysis of Mangrove Growth Conditions

SWOT analysis is a widely recognized method for strategic planning, providing a framework to evaluate strengths, weaknesses, opportunities, and threats related to a specific situation. Despite its popularity, SWOT analysis has faced criticism for its reliance on expert judgment to assess the influence of various factors. Experts often base their evaluations on intuition and professional experience, which can introduce subjectivity and variability. This reliance on human assessment limits the robustness of the analysis, as experts may be unavailable or unwilling to engage.

To address these limitations, the Eidos system automates the expert functions by quantifying the strength and direction of factors influencing mangrove conditions directly from empirical data. This approach enhances objectivity and reliability, allowing for a more comprehensive SWOT analysis without the constraints of human bias.

The data preparation process for the SWOT analysis of the HAD-high class is illustrated in Figure 11. This figure showcases how empirical data was organized and analyzed to identify critical factors affecting mangrove degradation risk.

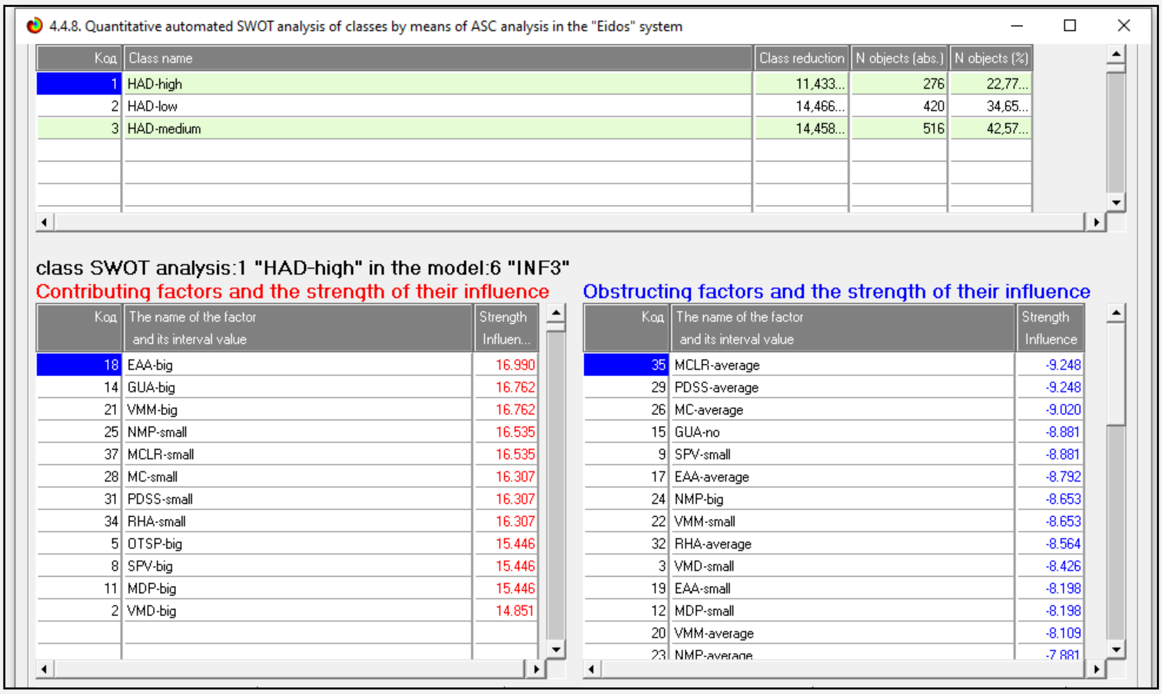


Figure 11. Preparing data for the HAD-high class SWOT analysis.

Figure 12 presents the SWOT diagram for the HAD-high class, which highlights the factors influencing the risk of mangrove forest degradation. The diagram includes 14 significant links, with the nature of each link indicated by color (red for positive influences, blue for negative influences). The thickness of the lines reflects the strength of these connections. This visual representation aids in understanding the intricate relationships between various factors affecting mangrove health.

The SWOT analysis reveals a nuanced picture of the problem landscape surrounding mangrove ecosystems. By examining the interplay between strengths and weaknesses alongside threats and opportunities, the analysis delineates a comprehensive problem field. This problem field encompasses the issues present within the modeled ecosystem and its external environment, providing insights into their interrelationships.

Having such detailed information is crucial for setting development goals, identifying pathways to achieve these goals, and formulating effective implementation strategies.

Similarly, the preparation of data for the SWOT analysis of the HAD-low class is depicted in Figure 13, showcasing the systematic organization of empirical data relevant to lower-risk scenarios.

The SWOT diagram for the HAD-low class, shown in Figure 14, provides a contrasting perspective on the factors influencing mangrove health in lower-risk scenarios. This diagram highlights the distinct strengths and opportunities available to support mangrove conservation, as well as potential weaknesses and threats that may hinder progress.

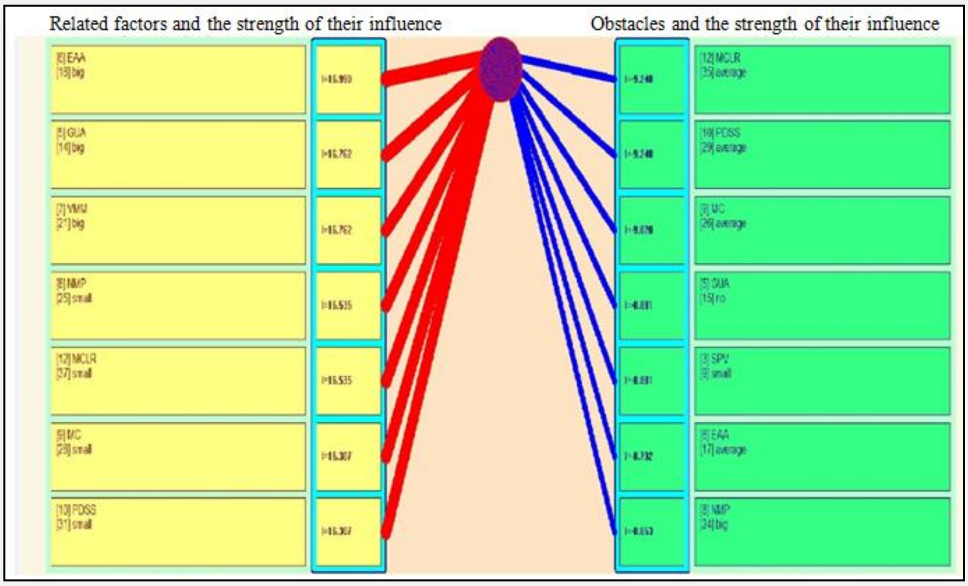


Figure 12. SWOT diagram of the HAD-high class.

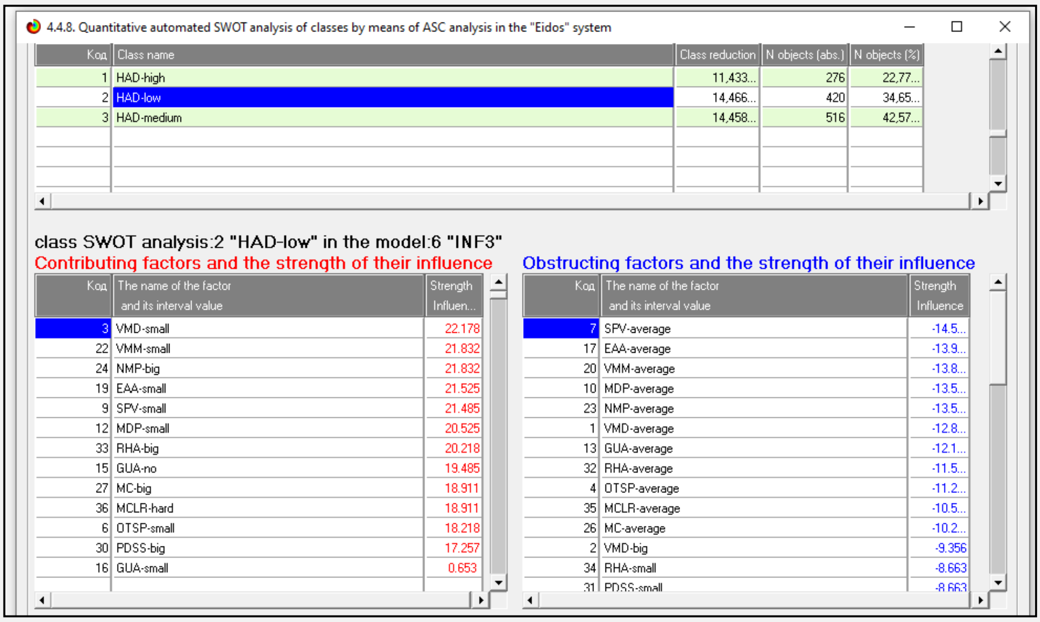


Figure 13. Preparing data for a SWOT analysis of the HAD-low class.

Through these analyses, the Eidos system facilitates a more data-driven approach to SWOT analysis, yielding actionable insights for conservation planning. By clearly visualizing the strengths and weaknesses of mangrove ecosystems, as well as the opportunities and threats they face, stakeholders can make informed decisions that enhance conservation efforts.

The automation of SWOT analysis using the Eidos system not only improves the accuracy of the evaluation but also broadens the accessibility of strategic planning for mangrove conservation. This approach represents a significant advancement in the field, ensuring that management strategies are grounded in empirical evidence and tailored to the specific conditions of mangrove environments.

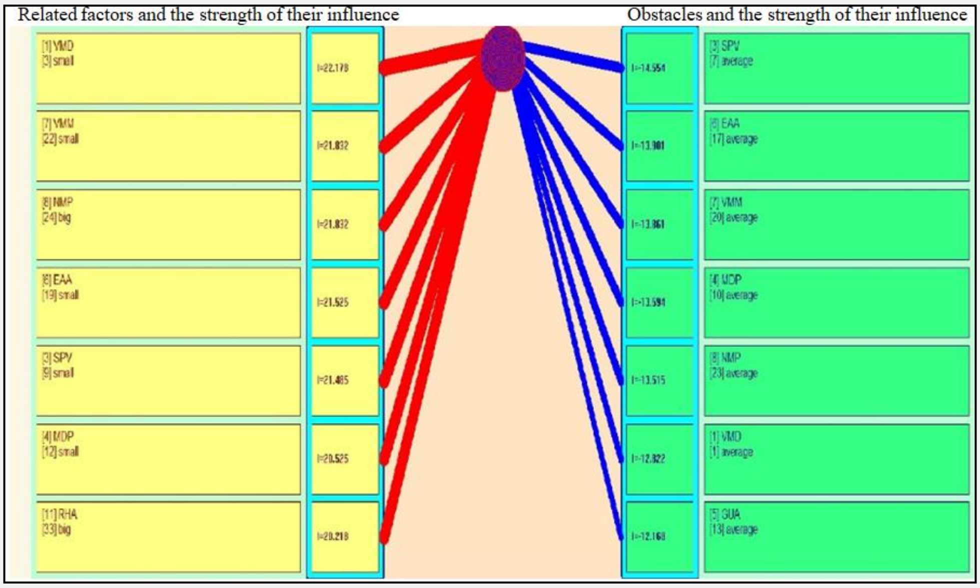


Figure 14. SWOT diagram of the HAD-low class.

Cognitive Class Clustering

Cognitive Class Clustering is an essential process for understanding the relationships among various classes within the Eidos system. As illustrated in Figure 15, the semantic 2D network of classes clearly indicates significant distinctions between them, which facilitates easy recognition by the Eidos system. Each class represents a unique set of characteristics and factors influencing mangrove conditions, allowing for nuanced analysis and understanding.

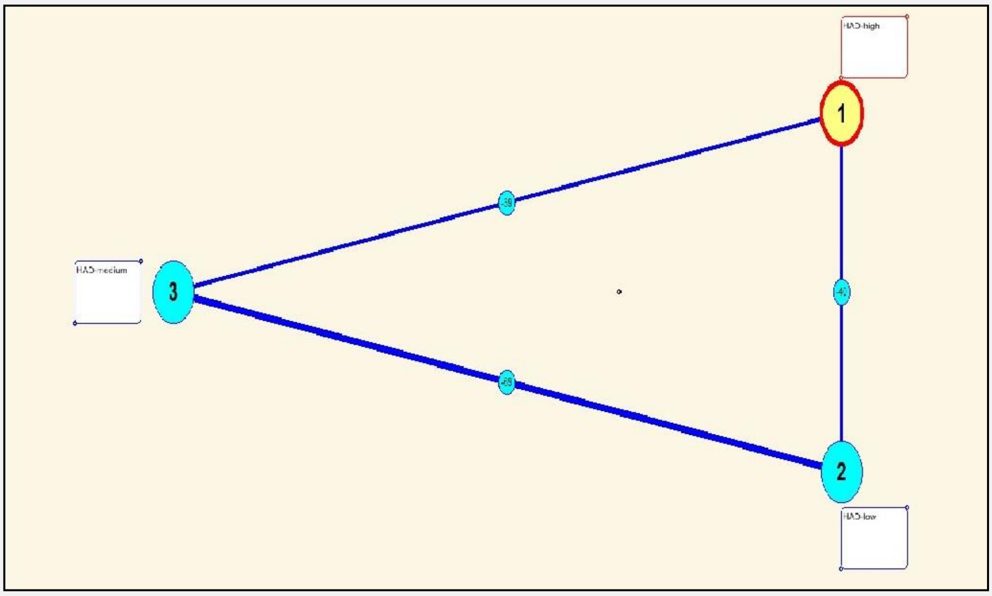


Figure 15. Semantic 2D class network.

It is important to note that while the system-cognitive models (SC-models) effectively highlight the dependencies between factor values and their resultant impacts, they do not elucidate the underlying causes or mechanisms driving these influences (Lutsenko, 2022). Thus, the interpretation of these SC models requires the expertise of specialists who possess a deep understanding of the subject matter. Their insights are crucial for unpacking the complexities embedded within the models and translating them into actionable strategies for mangrove conservation.

Figure 15 serves as a foundational visual representation of the cognitive relationships among different classes, setting the stage for a deeper exploration of class similarities and differences. This information is further enhanced through the similarity matrix, which can be visualized in various forms, including cognitive diagrams and agglomerative dendrograms. Agglomerative dendrograms are particularly useful in cognitive clustering, an automatic classification technique that groups objects based on their characteristics.

In the cognitive clustering process, objects are categorized into clusters where intra-cluster differences are minimized, while inter-cluster differences are maximized. This methodological approach ensures that the classification reflects the true nature of the relationships among classes. The outcomes of cluster and constructive analysis yield several key results: the calculation of the class similarity matrix, the generation of clusters and structures, and the capability to visualize and print these clusters.

Figure 16 presents the dendrogram of cognitive class clustering, showcasing the hierarchical relationships among classes. Each branch of the dendrogram represents a cluster, providing a clear visual understanding of how classes relate to one another. The dendrogram not only conveys the composition of the clusters but also delineates their boundaries, offering valuable insights into the structure of the data.

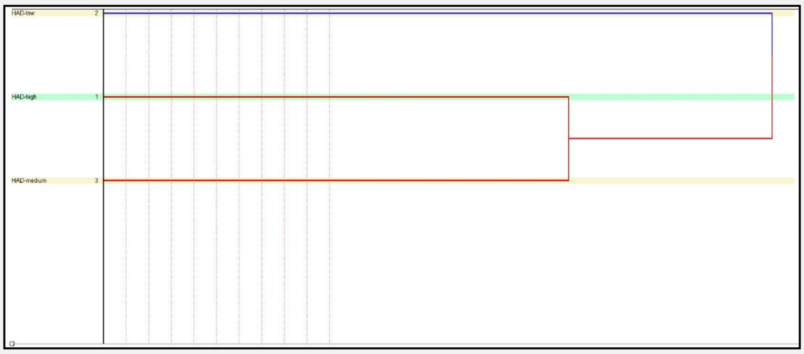


Figure 16. Dendrogram of cognitive class clustering.

Additionally, Figure 17 illustrates the results of a step-by-step change in inter-cluster distance during the cognitive clustering process as derived from the Eidos system. This graphical representation highlights the progressive nature of clustering, where the distances between clusters are determined by the cumulative information within the feature system that defines an object's membership to a particular cluster. The ability to observe these changes over iterations allows researchers to assess the stability and reliability of the clustering outcomes.

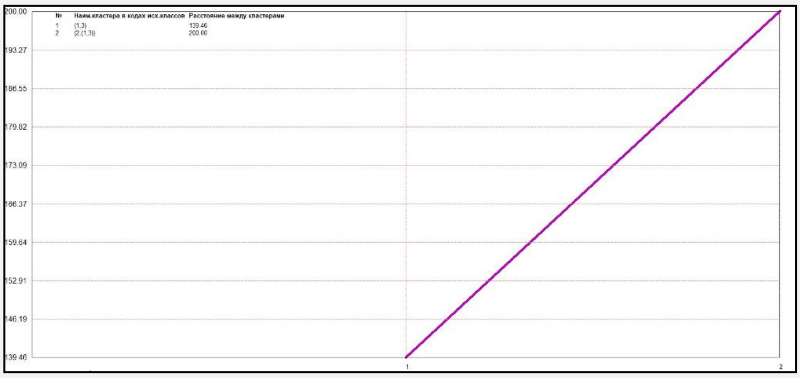


Figure 17. Change in intercluster distance during cognitive clustering.

Through cognitive class clustering, the Eidos system not only enhances the classification of mangrove conditions but also provides a robust framework for analyzing complex ecological data. By facilitating a deeper understanding of class relationships, this process contributes to more effective management and conservation strategies tailored to the specific needs of mangrove ecosystems.

Cognitive Feature Clustering

Cognitive Feature Clustering provides a valuable framework for understanding the relationships between various factor values influencing mangrove ecosystems. As illustrated in Figure 18, the semantic two-dimensional cognitive feature diagram reveals that all factor values can be organized into two significant clusters that are diametrically opposed in their meanings. These clusters represent the extremes of a conceptual continuum, highlighting the contrasting influences on mangrove conditions.

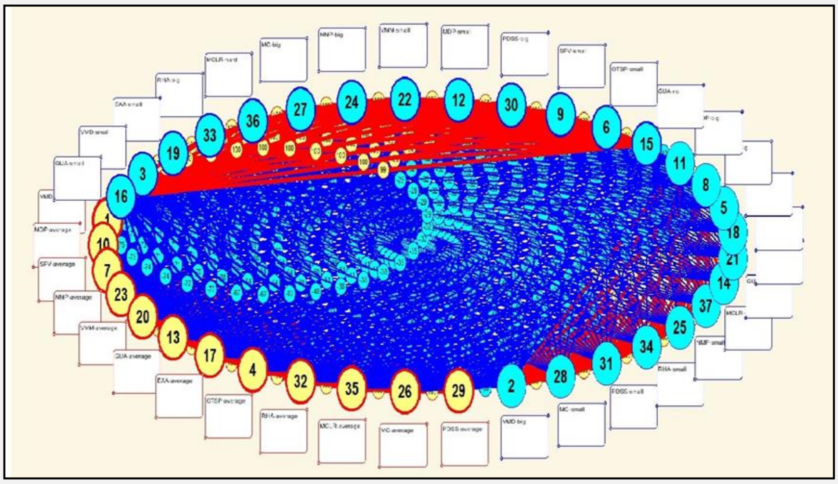


Figure 18. Semantic 2D Cognitive Feature Diagram.

This cognitive diagram is noteworthy for its reliance on quantitative estimates derived from a system-cognitive model based on empirical data, rather than traditional methods that often depend on subjective expert assessments grounded in experience and intuition. This objective approach enhances the reliability and validity of the clustering outcomes, providing a more robust understanding of the underlying factors at play.

Figure 19 presents the agglomerative dendrogram of cognitive clustering for the factor values, further elucidating the relationships among these factors. The dendrogram visually represents how various factors group together based on their similarities, offering insights into the dynamics of the mangrove ecosystem and the interactions between different influences.

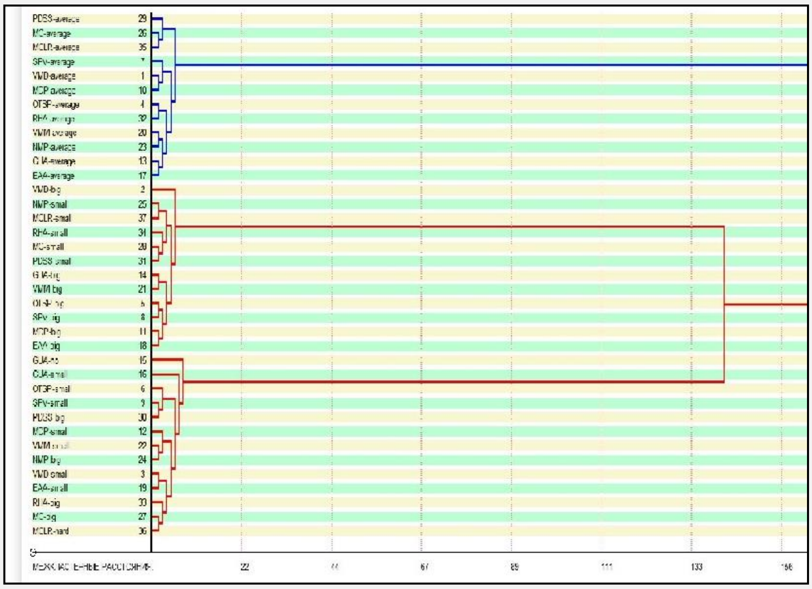


Figure 19. Dendrogram of cognitive clustering of factor values.

Additionally, Figure 20 depicts a graph of changes in intercluster distances, derived from the feature similarity matrix. This visualization parallels the information presented in the cognitive diagram and highlights how the distances between clusters evolve as more data is considered. Tracking these changes is crucial for understanding the stability and significance of the clusters, allowing researchers to identify which factors consistently influence mangrove health and resilience.

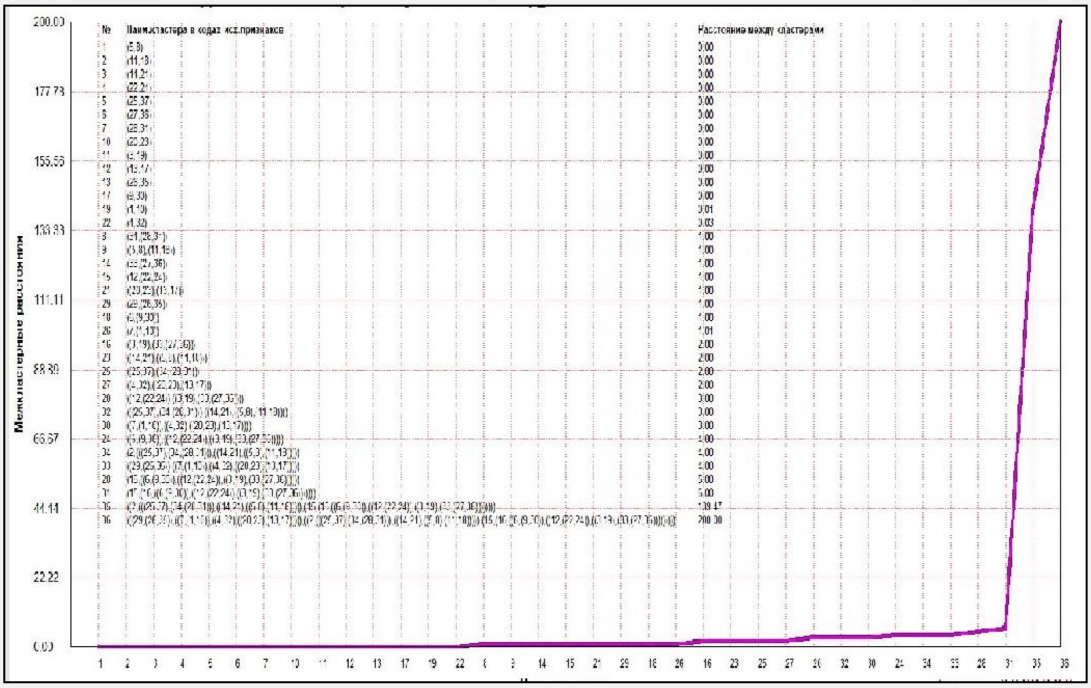


Figure 20. Plot of changes in intercluster distances.

Through cognitive feature clustering, researchers can systematically categorize and analyze the myriad influences on mangrove ecosystems. This method not only enhances the understanding of complex ecological interactions but also informs conservation strategies by pinpointing critical factors that need to be addressed to promote the sustainability of these vital environments.

Non-local Neuron and Neural Network

The concept of non-local neurons and their integration into neural networks represents a significant advancement in modeling the complex relationships influencing mangrove forest degradation. Figure 21 illustrates a non-local neuron, which serves as a fundamental building block within the neural network framework. Each neuron corresponds to specific growing conditions, while receptors are linked to various dangers of mangrove degradation. Notably, these neurons are arranged in descending order of their strength of determination; those on the left exhibit a more robust correlation with the influencing factors, whereas those on the right are influenced to a lesser degree.

In the Eidos system, non-local neurons are visually represented through specialized graphic forms that convey both the strength and direction of influence from receptor signals to neuron activation or inhibition. This visualization, expressed through variations in color and thickness of the dendrites, provides an intuitive understanding of how different conditions impact the degradation risk of mangrove forests.

Figure 22 presents a fragment of a non-local neural network, highlighting approximately 49% of its structure. This representation underscores the intricate interconnections within the network, where multiple neurons work collaboratively to evaluate the multifaceted factors contributing to mangrove degradation risks.

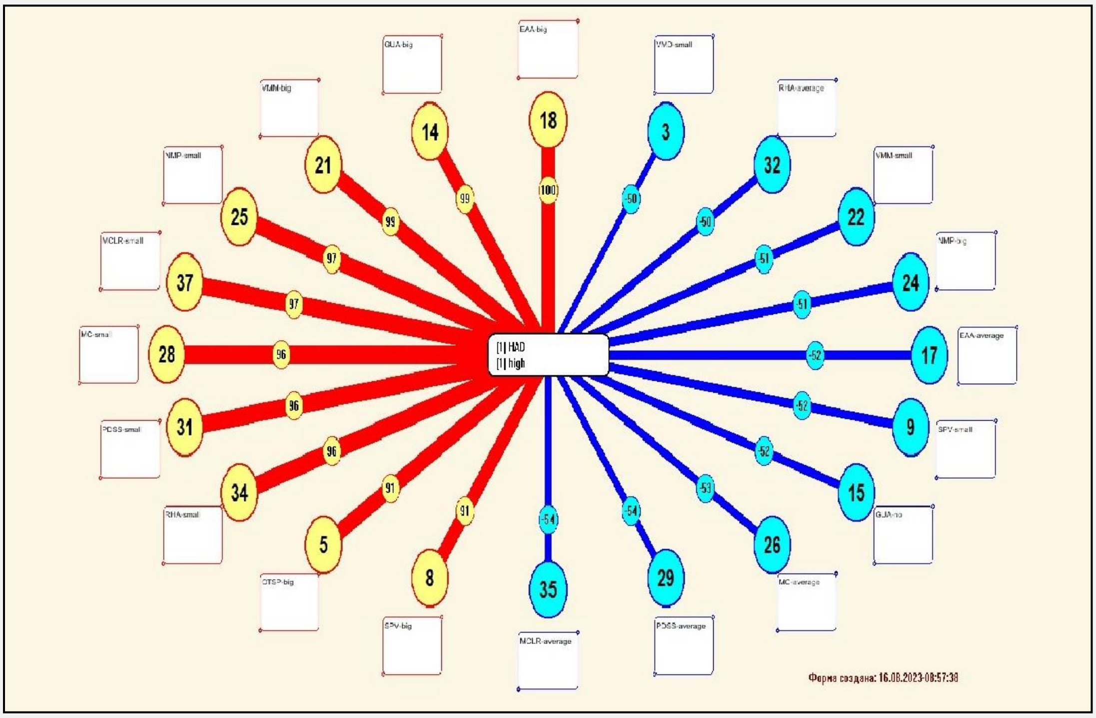


Figure 21. Non-local neuron reflecting the strength and direction of the influence of growing conditions on the danger of mangrove forest degradation.

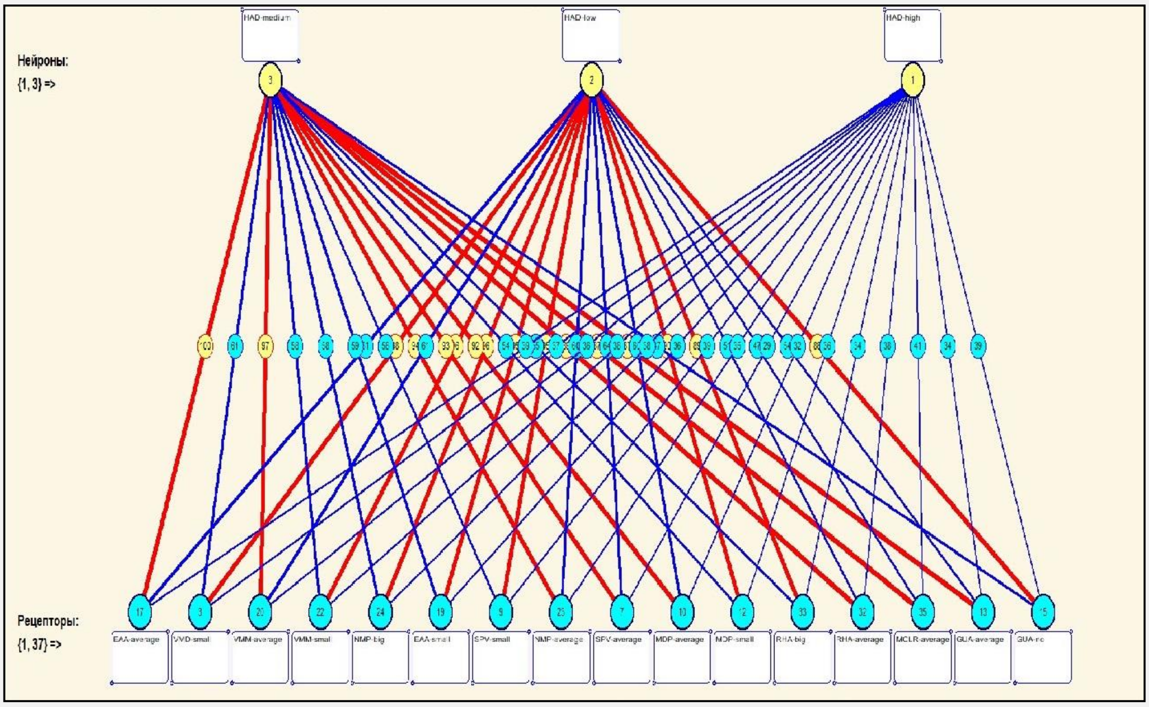


Figure 22. Non-local neural network reflecting the strength and direction of the influence of growing conditions on the danger of mangrove forest degradation (a fragment of about 49%).

Moreover, Figure 23 showcases a Pareto subset of the non-local neural network within the INF3 model, consisting of three neurons. Although this slide may appear complex at first glance, it encapsulates the challenges inherent in accurately classifying the dangers posed to mangrove ecosystems. The intricate interactions among the neurons illustrate the multifactorial nature of the problem, emphasizing the necessity for sophisticated modeling techniques to capture the nuances of ecological dynamics effectively.

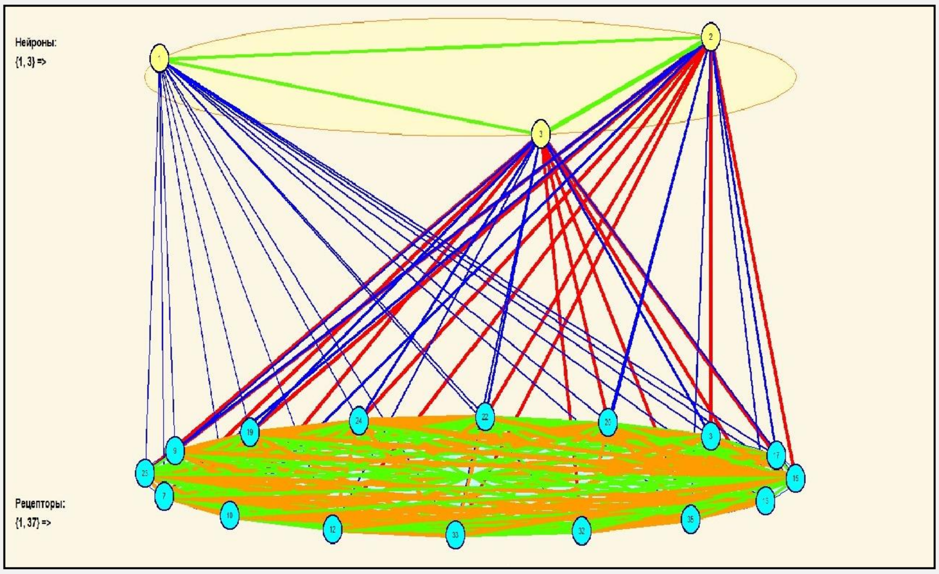


Figure 23. Pareto subset of a non-local neural network.

By leveraging non-local neurons within neural networks, researchers can better understand and predict the conditions leading to mangrove degradation. This innovative approach not only enhances predictive capabilities but also aids in developing targeted conservation strategies that address the specific threats facing these critical ecosystems.

Urgency of Assessing the Level of Danger of Mangrove Forest Degradation Using the Eidos System

Assessing the level of danger of mangrove forest degradation using the Eidos system is crucial for effective environmental conservation efforts. This system provides a comprehensive and measurable understanding of the health of mangrove ecosystems, enabling researchers and managers to pinpoint areas that are particularly vulnerable to degradation. Given the vital role of mangroves in maintaining coastal ecosystems and mitigating the impacts of natural disasters, such as storms and tidal waves, this assessment becomes increasingly significant.

The Eidos system employs rigorous data and analytical techniques, facilitating the design of more targeted and effective conservation strategies. By accurately identifying the specific levels of hazard, restoration and protection measures can be prioritized, optimizing the allocation of limited resources. Moreover, this system empowers decision-makers to base their strategies on solid evidence, enhancing the efficiency of conservation programs at local, national, and global scales.

Regular assessments using the Eidos system also contribute to long-term monitoring of mangrove conditions. By comparing data over time, stakeholders can evaluate the effectiveness of implemented actions and identify trends that may necessitate urgent responses. This ongoing evaluation is essential for ensuring the sustainability of mangrove ecosystems and the continued provision of ecosystem services to local communities dependent on these resources.

According to Corte et al. (2021), mangroves serve not only as habitats for diverse marine and terrestrial species but also as natural barriers against tidal waves, protecting coastlines from erosion while providing vital ecosystem services, such as food and biological resources. However, global mangrove forests are facing severe degradation due to human activities, including land encroachment for aquaculture, mining, and urban development. Hence, assessing the degradation risk is imperative for identifying vulnerable areas and developing timely protection strategies.

This perspective aligns with the findings of Vieira et al. (2021), which emphasize that a deep understanding of the factors driving degradation—such as declining water quality, changes in land use, and economic pressures—can inform the development of effective mitigation strategies. Such assessments should not only measure the loss of mangrove area but also evaluate the quality of the ecosystem and its regenerative capacity.

Furthermore, comprehensive and accurate assessments can provide a strong foundation for formulating improved environmental policies (Fraisl et al., 2020). These policies can encompass land use regulations, sustainable development initiatives, and the establishment of conservation zones tailored to local conditions. By integrating ecological, social, and economic considerations, such policies can prevent further degradation and support the restoration of impacted mangrove forests.

The urgency of these assessments extends to socio-economic dimensions as well. Firdaus et al. (2021) highlight the necessity of involving local communities—who rely on mangrove forests for their livelihoods and resources—in the assessment and decision-making processes. This inclusive approach ensures that protection strategies are not only environmentally effective but also socially and economically sustainable for the communities involved.

Limitations

To integrate converted source data into the Eidos system, users must utilize the universal programming interface and adhere to specific data format requirements, notably in Excel format. While the spring 2011 version of the Eidos system had a training sample size limit of 100,000 objects, the current version has eliminated this restriction, enabling the system to process millions of objects. However, limitations remain concerning knowledge bases, which cannot exceed 4,000 classes and 4,000 gradations of factors.

The Eidos system features a complex user interface with 55 operational modes, excluding the "Exit" mode. Navigating this system independently poses significant challenges; any errors can lead to system halts or inaccurate results. Users attempting to learn multiple operational modes simultaneously may require several months of training. To mitigate this learning curve, it is advisable to review presentations available at Patreon, which outline the principles of using automated system-cognitive analysis for solving complex problems.

CONCLUSION

The Eidos system facilitated the creation of three statistical models and seven cognitive system models to assess the hazard level of mangrove forest degradation based on empirical data. Its high reliability in identifying and classifying degradation risks has been validated through a comprehensive retrospective database. This study highlights the variability in degradation risk under different growing conditions, emphasizing the importance of early predictions to inform effective protection strategies while minimizing costs.

In contrast to traditional experimental methods, which are often costly and time-consuming, computer simulations with the Eidos system require significantly lower operational expenses and enhance prediction accuracy. This innovative methodology allows for a more efficient evaluation of coastal ecosystem safety, as the Eidos system can be operated by users with basic training and does not necessitate expensive equipment.

However, the Eidos system's application is constrained by its technical complexity and cumbersome user interface. While it can manage extensive datasets and offers numerous advanced modes, users must be proficient in the programming interface and adhere to specific data formats. Additionally, the limitations on the knowledge base dimensions (maximum of 4,000 classes and gradation factors) may hinder its capacity to address the complexity of ecological data. Errors in data organization can lead to inaccuracies in results.

Future research should explore several avenues to enhance the Eidos system's capabilities, such as expanding its capacity to manage more complex data and improving modeling techniques for variations in mangrove conditions. Integrating the system with sensor and remote sensing technologies could facilitate real-time monitoring of environmental changes in mangrove ecosystems. Additionally, developing more timely prediction methods and testing the Eidos system across diverse geographic locations would help validate and generalize its findings, ultimately contributing to more effective mangrove conservation efforts.

Acknowledgment

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REFERENCES

Arifanti, V. B., Novita, N., Subarno, & Tosiani, A. (2021). Mangrove Deforestation and CO2 Emissions in Indonesia. In *IOP Conference Series: Earth and Environmental Science, 874*(1), 1–15. https://doi.org/10.1088/1755-1315/874/1/012006

Arifanti, V. B., Sidik, F., Mulyanto, B., Susilowati, A., Wahyuni, T., Subarno, Yulianti, Yuniarti, N., Aminah, A., Suita, E., Karlina, E., Suharti, S., Pratiwi, Turjaman, M., Hidayat, A., Rachmat, H. H., Imanuddin, R., Yeny, I., Darwiati, W., Sari, N., Hakim, S. S., Slamet, W. Y., & Novita, N. (2022). Challenges and Strategies for Sustainable Mangrove Management in Indonesia: A Review. *Forests, 13*(5), 1–18. https://doi.org/10.3390/f13050695

Carugati, L., Gatto, B., Rastelli, E., Lo Martire, M., Coral, C., Greco, S., & Danovaro, R. (2018). Impact of Mangrove Forests Degradation on Biodiversity and ecEsystem Functioning. *Scientific Reports, 8*(1), 1–11. https://doi.org/10.1038/s41598-018-31683-0

Corte, G. N., Checon, H. H., Shah Esmaeili, Y., Lefcheck, J. S., & Amaral, A. C. Z. (2021). Mangrove Fragments as Key Coastal Reservoirs of Taxonomic and Functional Biodiversity. *Biodiversity and Conservation, 30*(5), 1573–1593. https://doi.org/10.1007/s10531-021-02158-y

Firdaus, M., Hatanaka, K., & Saville, R. (2021). Mangrove Forest Restoration by Fisheries Communities in Lampung Bay: A Study Based on Perceptions, Willingness to Pay, and Management Strategy*. Forest and Society, 5*(2), 224–244. https://doi.org/10.24259/fs.v5i2.12008

Fraisl, D., Campbell, J., See, L., Wehn, U., Wardlaw, J., Gold, M., Moorthy, I., Arias, R., Piera, J., Oliver, J. L., Masó, J., Penker, M., & Fritz, S. (2020). Mapping Citizen Science Contributions to the UN Sustainable Development Goals. *Sustainability Science, 15*(6), 1735–1751. https://doi.org/10.1007/s11625-020-00833-7

Friess, D. A., Thompson, B. S., Brown, B., Amir, A. A., Cameron, C., Koldewey, H. J., Sasmito, S. D., & Sidik, F. (2016). Policy Challenges and Approaches for the Conservation of Mangrove Forests in Southeast Asia. *Conservation Biology, 30*(5), 933–949. https://doi.org/10.1111/cobi.12784

Karimah, K. (2017). Peran Ekosistem Hutan Mangrove Sebagai Habitat Untuk Organisme Laut. *Jurnal Biologi Tropis, 17*(2), 51–57. https://doi.org/10.29303/jbt.v17i2.497

Li, D., Zhao, L., Guo, Z., Yang, X., Deng, W., Zhong, H., & Zhou, P. (2021). Marine Debris in the Beilun Estuary Mangrove Forest: Monitoring, Assessment and Implications. *International Journal of Environmental Research and Public Health, 18*(20), 1–16. https://doi.org/10.3390/ijerph182010826

Lutsenko, E. V. (2020). *Design and Development of Intelligent Information Systems*. Kuban State Agricultural University.

Lutsenko, E. V. (2022). Automated System-Cognitive Analysis of the Dependence of Agrophysical Indicators of the Soil on Its Processing, Fertilizers and the Phase of Wheat Vegetation. In *Polythematic Online Scientific Journal of Kuban State Agrarian University* (Issue 181). https://doi.org/10.21515/1990-4665-181-017

Moriizumi, Y., Matsui, N., & Hondo, H. (2010). Simplified Life Cycle Sustainability Assessment of Mangrove Management: A Case of Plantation on Wastelands in Thailand. *Journal of Cleaner Production, 18*(16–17), 1629–1638. https://doi.org/10.1016/j.jclepro.2010.07.017

Nunoo, F. K. E., & Agyekumhene, A. (2022). Mangrove Degradation and Management Practices along the Coast of Ghana. *Agricultural Sciences, 13*(10), 1057–1079. https://doi.org/10.4236/as.2022.1310065

Nurtjahya, E., Franklin, J., Umroh, & Agustina, F. (2017). The Impact of Tin Mining in Bangka Belitung and Its Reclamation Studies. *Sriwijaya International Conference on Engineering, Science and Technology (SICEST 2016), 1*(6), 1–7.

Osorio, J. A., Crous, C. J., Wingfield, M. J., De Beer, Z. W., & Roux, J. (2017). An Assessment of Mangrove Diseases and Pests in South Africa. *Forestry, 90*(3), 343–358. https://doi.org/10.1093/forestry/cpw063

Rahmadi, M. T., Yuniastuti, E., Suciani, A., Harefa, M. S., Persada, A. Y., & Tuhono, E. (2023). Threats to Mangrove Ecosystems and Their Impact on Coastal Biodiversity: A Study on Mangrove Management in Langsa City*. Indonesian Journal of Earth Sciences, 3*(2), A627. https://doi.org/10.52562/injoes.2023.627

Rahmawati, D., Fahrezy Sutikno, M. A., & Wulandari, H. U. (2023). Penanaman Mangrove Kawasan Pesisir Mangunharjo Bentuk Pelestarian Ekosistem Sebagai Upaya Penyelamatan Generasi. *Jurnal Dharma Indonesia, 1*(1), 13–19. https://doi.org/10.15294/jdi.v1i1.68445

Risa, N. E. W., Uspar, Alamsyah, R., Tenriwaruwaty, A., Wahyuni, A. P., & Liswahyuni, A. (2021). Peran Masyarakat Desa Pasimarannu Kabupaten Sinjai untuk Melindungi Pantai dari Ancaman Abrasi dengan Melakukan Penanaman Mangrove*. Tarjih : Agribusiness Development Journal, 1*(2), 32–40. https://doi.org/10.47030/tadj.v1i2.298

Rizal, A. (2018). Economic Value Estimation of Mangrove Ecosystems in Indonesia. *Biodiversity International Journal, 2*(1), 98–100. https://doi.org/10.15406/bij.2018.02.00051

Sari, S. P., & Rosalina, D. (2016). Mapping and Monitoring of Mangrove Density Changes on tin Mining Area. *Procedia Environmental Sciences, 33*, 436–442. https://doi.org/10.1016/j.proenv.2016.03.094

Strielkowski, W., Lutsenko, E., & Pavlov, D. (2021). Fossil Fuel Industry Development in the 21st Century: a Case of Coal. *SHS Web of Conferences, 128*(2), 1–7. https://doi.org/10.1051/shsconf/202112802004

Sulistyowati, E., & Astuti, P. (2018). Community Knowledge Related to Mangrove Conservation Law Products. *SHS Web of Conferences, 54*(201), 30–45. https://doi.org/10.1051/shsconf/20185403012

Vieira, L. R., Vieira, J. G., da Silva, I. M., Barbieri, E., & Morgado, F. (2021). GIS Models for Vulnerability of Coastal Erosion Assessment in a Tropical Protected Area. *ISPRS International Journal of Geo-Information, 10*(9), 598–612. https://doi.org/10.3390/ijgi10090598

Wattimena, R. M., Leatemia, W., & Tahamata, L. C. O. (2021). Perlindungan Hukum Terhadap Hutan Mangrove Pada Areal Pesisir Pantai. *Balobe Law Journal, 1*(2), 109. https://doi.org/10.47268/balobe.v1i2.652