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Application of Artificial Intelligence in the Evaluation of Land Use and Land Cover Changes in the Ilo-Moquegua Hydrographic Basin

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This study evaluates land use and land cover change (LULCC) in the Moquegua River basin in Peru over 51 years, from 1972 to 2023. Aerial photographs, Landsat images, geoprocessing tools from ArcGIS, and intelligence software were used. Artificial GPT chat to analyze the past dynamics of LULCC in the region comprehensively. The results revealed significant impacts in six LULCC categories: agriculture, water, wetlands, urban areas, mining, and natural infrastructure. The degradation of wetland coverage is of particular concern, with a reduction from 1,646.80 hectares in 1972 to 1,404.45 hectares in 2023. In addition, we observed significant changes in the LULC categories, from natural to mining coverage with 6,226.51 hectares, from natural to agricultural with 5369.25 hectares, and from natural to urban infrastructure with 2108.15 hectares during the study period. This analysis has practical implications for spatial planning and environmental planning in the Moquegua River basin. The findings highlight the need to implement sustainable development strategies that address wetland degradation and adequately manage land use in this region. In addition, it provides valuable knowledge for making informed decisions within the framework of the 2030 Agenda and the search for environmental justice in Latin America.

Keywords: Artificial Intelligence, Ilo-Moquegua Hydrographic Basins, Land use and land cover, Change detection.

1. Introduction

Specialized studies of land use and land cover (LULC) focused on land changes have names such as Land Use Land Cover Change (LULCC), Land Cover and Land Use Change (LCLUC) and Land Use/Land Cover Change (LUCC). They are the primary result of the activities and alterations carried out by humanity [1][2]; they are part of the widespread and significant dynamic processes that drive environmental change and the degradation of natural ecosystems worldwide [3][4], occurring at various spatial and temporal scales [4], in an accelerated manner in recent decades [5], managing to significantly impact ecosystem services, biophysical surfaces and functioning of the planet's natural systems [6], having a detrimental effect on the sustainable development of the local, regional and global environment.

The assessment of land use and land cover change is one of the most precise methods that allow us to understand land use and cover in past times and estimate the typologies of changes [7]; it provides us with a perspective to model and predict possible future scenarios so that decision-makers can propose future planning and development strategies [8]. The evaluation and prediction of LULCC in hydrographic basins is a crucial component that directly influences hydrology and water resources [9][10] and is essential for optimized planning and management of water resources [11], including the regulation of climate and biodiversity that is in danger due to high deforestation rates [12].

The reports of land use statistics and indicators on global, regional and national trends from 1990 to 2019, carried out by FAO through the analytical summaries of FAOSTAT Analytical Brief, report that in the classification of agricultural land between 1990 and 2019, cropland increased by 5% and prairie and permanent pasture land decreased by 4%.. [13]. Other research on LULC worldwide carried out by Potapov et al. (2022) proves that during the period 2000-2020, there was a decrease in global tree cover of 1 million km2, and the highest rate of net forest loss was in South America, with 5%, that is, 0.44 million km2 of forest area.

At the national level of Peru, the report of the Ministry of Agrarian Development and Irrigation (MIDAGRI) and the National Institute of Statistics and Informatics (INEI) on the National Agricultural Survey between the years 2014 to 2019 and 2021 to 2022 regarding the uses of land, reports that there is a growing trend in the agricultural area, showing that in 2015 the agriculture area represented 36.1%, increasing 7.9 percentage points to 2022, where the agriculture area represents 44,9%. Likewise, it reports a decreasing trend of non-agricultural surfaces (forest, mountain, natural pasture, among other uses), showing that in 2015 it represented 63,9%, and in 2022, it represented 55,1% [15]. The deforestation process is the leading cause of forest loss in Peruvian [16]; on the other hand, MINAM (2023), with the results obtained from the National Inventory of Greenhouse Gases from 2000 to 2019, indicates that the primary emissions are due to land use, land use change and forestry, representing 47,90% of the total GHG generated in Peru.

Peru has an area of 129.2 million hectares (Mha); between the years 1985 and 2022, natural vegetation (forest, dry forest, flooded forest, grassland, scrubland and other covers) decreased by 4.1 Mha and the anthropic use (Mining, infrastructure, mining, agriculture, agriculture among others), highlighting that the mining surface increased by 165,5 thousand hectares (MHA), from 3,8 Mha in 1985 to 169,3 Mha in 2022, presenting an increase from 1 618 ha/year to 2009 and from 2009 to 2022 it presents a rate of 9 160 ha/year; The infrastructure area increased by 218,4 Mha, from 106,7 Mha in 1985 to 325,1 Mha in 2022, delivering a constant increase of 5,4 thousand hectares per year and the agricultural use area increased by 3,8 Mha from 10 000 hectares per year—7 Mha in 1985 to 14,5 Mha in 2022 [18].

The study's general objective is to evaluate spatial trends of land use and land cover changes in the Ilo-Moquegua hydrographic basin by applying artificial intelligence between the years 1972 and 2023, identifying critical areas for conservation and implementing sustainable management strategies.

2. Materials and Methods

2.1. Study Area

The Ilo-Moquegua hydrographic basin is located in southern Peru, in the department of Moquegua, mainly occupying the province of Mariscal Nieto. Geographically, it is between 250000 to 350000 meters East and 8040000 to 8135000 meters to the North in the Universal Transverse Mercator (UTM) projection of the WGS 84 world geodetic system[19], as can be seen in Fig. 1.

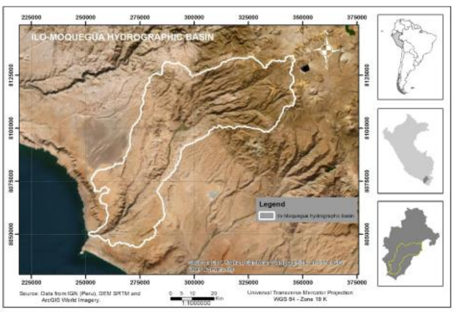

Fig. 1. Location of Ilo-Moquegua hydrographic basin.

The region's climate is temperate on the coast and is characterized by its uniformity throughout the year, with the average temperature varying between 14°C (August) and 25°C (February). In the intermediate zone near the coast and close to the mountain range, there is a dry, desert climate that extends into the Andean region. In the mountain area in the inter-Andean valleys, the climate is temperate; In the Punas, the climate is glacial cold, reaching several degrees below zero. Rain is scarce on the coast and in the lower parts of the Andean region. In the upper parts, rainfall does not exceed 500mm annually [20].

2.2. Methodology

Data Collection

To meet the research objectives, we employed observational methods and reviewed documentation from the study area [21]. This approach enabled us to gather and organize specific geographical spatial information for the years 1972 and 2023, which included:

a) For the period of 1972, the information collected was from Landsat 1 satellite images dated 1972-11-02 with location WRS 002, 072 (Path, Row) downloaded from USGS Earth Explorer https://earthexplorer.usgs.gov/ and aerial photographs from MINAGRI.

b) For the period 2023, used Sentinel-2 A images for optical remote sensing, dated 2023-08-2 with location WRS 002, 072 (Path, Row) downloaded from Copernicus browser https://browser.dataspace.copernicus.eu/. They have a spatial resolution of 4 bands at 10 m: band 2, band 3, band 4 and band 8, 6 bands at 20 m: band 5, band 6, band 7, band 8a, band 11 and band 12 and 3 bands at 60 m: band 1, band 9 and band 10 [22].

Data Processing

a) For the period of 1972. For the identification and mapping of the categories as well as the spatial distribution of land use and cover for the year 1972, using aerial photographs, which were scanned with a resolution of 600 DPI and georeferenced in ArcMap (Align aerial photography with control points, the transformation of the aerial photography by seven methods selecting the spline method and interpreting the mean square error) and Georectification of the aerial photography, continued the photointerpretation and mapping of the aerial photography was continued to build the database in the geographic information system with ArcMap tools.

b) For the period 2023, the steps followed for the management and processing of Sentinel-2 A optical images from the preprocessing stage, such as radiometric calibration, geometric calibration, atmospheric correction and validation of satellite images, using the SNAP Desktop software and the Arcgis 10,8 Geographic Information Systems software. The methods applied during the processing stage for classifying land use and land cover followed the techniques outlined in the book "Algorithms for Image Processing using Satellites" from the European Union's COPERNICUS program [23]. For distinguishing different land uses and covers, we utilized the band composition from Sentinel 2, including natural colour (4,3,2), agriculture (11,8A,2), land/water (5,6,4), and urban areas (12,11,4).

Land Cover Classification

The classification of land use and land cover types for the Ilo-Moquegua hydrographic basin are:

1. Agriculture: This class includes areas used for growing crops and raising livestock. It covers different agriculture practices, such as farming, mixed farming, plantations, orchards and pastures.

2. Water: This class refers to bodies of water, including lakes, rivers, reservoirs and wetlands covered with water throughout the year. It does not include seasonal water sources that could dry up at certain times of the year.

3. Wetlands (Bofedal) are areas where water is present at or near the soil surface for much or all of the year. Specifically, "Bofedales" refers to the high-altitude wetlands typical of the Andes, which are crucial for biodiversity and act as natural water regulators.

4. Urban Infrastructure: This class covers all land used for urban development, including residential, commercial and industrial areas. It includes buildings, roads, bridges and other infrastructure that supports urban activities.

5. Mining: This class encompasses areas allocated for extracting metallic and non-metallic natural resources from the earth. It includes open-pit mines, quarries, and other territorial alterations directly associated with the mining industry.

6. Natural: Natural areas are those relatively unaffected by human activities, where ecological processes are not significantly altered. These include high Andean forests, pajonal, cardonal, grasslands, coastal deserts, and natural parks preserved for biodiversity, recreation, and resource conservation.

Each land cover class plays a unique role in the landscape and has different implications for environmental management and policymaking.

The verification of the interpretation of the first period, 1972, using the Landsat 1 image was corroborated with the support of national maps from the National Geographic Institute 35u and 35v corresponding to the study area and the Ecological Map of Peru from ONERN. For the interpretation of the second period, 2023, the Sentinel images were assisted with 10 meters resolution images, carrying out a field visit, where the accuracy of the thematic interpretation was verified, placing emphasis on covering the most significant difficulty or doubt, finding 96% accuracy in the interpretation of 124 verified polygons, of which 96 were correct and five incorrect, to continue with calculating the percentage of areas.

Area Percentage for 1972 and 2023: Calculated by dividing the area for each category by the total area covered in each respective year, then multiplying by 100 to convert to a percentage.

Change Detection Analysis

To analyze the areas of land use and land cover change in the Ilo-Moquegua hydrographic basin between 1972 and 2023, the cross-tabulation matrix proposed by Pontius, Shusas, & Mceachern [24]; this matrix is also known as a transition matrix that determines a pattern of earth change. The matrix is presented in Table 2, where each row represents the category of the map at time 1 (T1) and each column the category of the map at time 2 (T2), observing that the main diagonal represents the spaces that remain between T1 and T2, and the other values represent the transitions that occurred during T1 and T2 for each of the categories. In the Total Time 2 row, the total number of employees in each of the categories in T2 is added (P+n), similar to that in the Total Time 2 column, the total number of employees in each of the categories in T1 (Pn+). The last row shows the expansion values that each category had between T1 and T2, and the last column shows the reduction values that each category had between T1 and T2.

Table 1. Cross tabulation matrix.

	Time 2				Total Time 1	Reduction
	Category 1	Category 2	Category 3	Category 4		
Time 1						
Category 1	P11	P12	P13	P14	P1+	P1+ - P11
Category 2	P21	P22	P23	P24	P2+	P2+ - P22
Category 3	P31	P32	P33	P34	P3+	P3+ - P33

Category 4	P41	P42	P43	P44	P4+	P4+ - P44
Total Time 2	P+1	P+2	P+3	P+4	1	
Expansion	P+1 - P11	P+2 - P22	P+3 - P33	P+4 - P44		

Source: Pontius, Shusas, & Mceachern [24]

Validation and accuracy assessment of land use and land cover change

Ground verification: AI model predictions were validated with accurate data on the ground through field visits or high-resolution images.

Error matrix and Kappa analysis: The confusion matrix was calculated to evaluate the accuracy of classification and change detection, and the Kappa statistic was calculated to measure reliability.

The Kappa Consistency Index (KIA), or Cohen's Kappa[25][26][27], is a statistical measure used to assess the agreement between two categorized observations. In the context of land use and cover changes, this index can evaluate how consistent the land use classifications are between two dates, considering both matches (main diagonal of the transition matrix) and discrepancies.

To calculate Cohen's Kappa from the transition matrix we have created, we follow these steps:

1. Calculate the Observed Agreement (Po): The proportion of areas that did not change between 1972 and 2023 (sum of the main diagonal) relative to the total observed area.

2. Calculate the Expected Agreement (Pe): The probability of agreement by chance, calculated from the marginal frequencies of the classes.

3. Apply Cohen's Kappa Formula:

$K = (Po - Pe)/(1 - Pe)$

Application of Artificial Intelligence in the evaluation of land use and land cover change

In the evaluation of land use and land cover change in the Ilo-Moquegua hydrographic basin, the advanced GPT-4 artificial intelligence technology was applied, which allowed for shortening processes and the use of various software for analysis and validation of the processes. Each methodological stage is generated after having annexed the information on the land use and cover classes for the years 1972 and 2023.

In the framework of Chat GPT and additional OpenAI language models, a "prompt" is defined as the text input given by the user to elicit a particular response from the model. It serves as a directive or stimulus that shapes how the model generates its response [28].

Based on data from the previously calculated Pontius cross-tabulation matrix, the table summarizing the areas of persistence, expansion, reduction and general change for each land cover category between 1972 and 2023 is obtained. Here's how we'll categorize and calculate each one:

Persistence: Area that remained the same for each category (diagonal elements of the matrix).

Expansion: The total increase in area for each category from 1972 to 2023.

Reduction: Total area decreases for each category from 1972 to 2023.

Change: Net change is the absolute difference between expansion and reduction.

We need to perform several steps to create a table that summarizes the areas of each land cover category for both 1972 and 2023, along with the percentage of change, rate of change per year, and other relevant calculations. Here's a step-by-step breakdown of the calculations:

Area (1972 and 2023): Directly taken from the sum of each row and column of the Pontius matrix for the respective years.

Percent of Change (%): Calculated as: ((Area 2023-Area 1972))/(Area 1972)×100

Rate of Change (ha/year): Calculated as ((Area 2023)-(Area 1972)) x Number of Years

where the number of years = 2023 - 1972 = 51 years.

Total Area Change (ha): Absolute change in area from 1972 to 2023.

3. Results and Discussion

3.1. Results with the Chat GPT-4 artificial intelligence application

Before continuing, we must note that we validated all the results generated by the Chat GPT-4 artificial intelligence application using ArcGIS tools and spreadsheets for the table reporting process. This validation process confirmed the accuracy of the results, as both methods work with map data in vector format.

The land use and coverage map of the Ilo-Moquegua hydrographic basin for the year 1972 with the six classes is presented in Fig. 2, and for the year 2023 in Fig. 3.

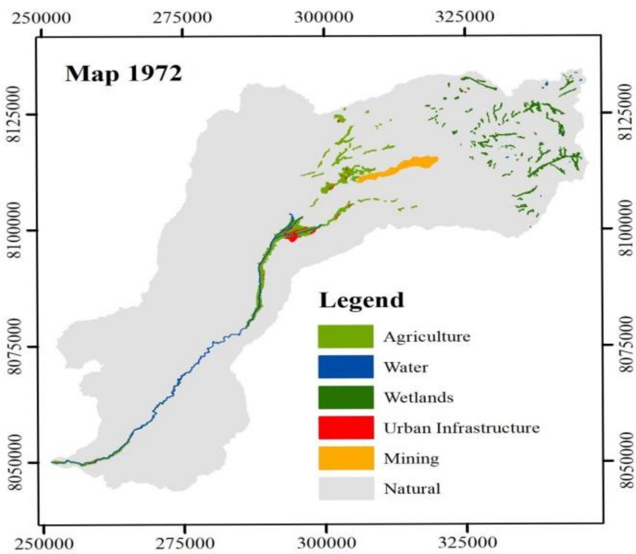

Fig. 2. Map of land use and coverage of the Ilo-Moquegua hydrographic basin for 1972.

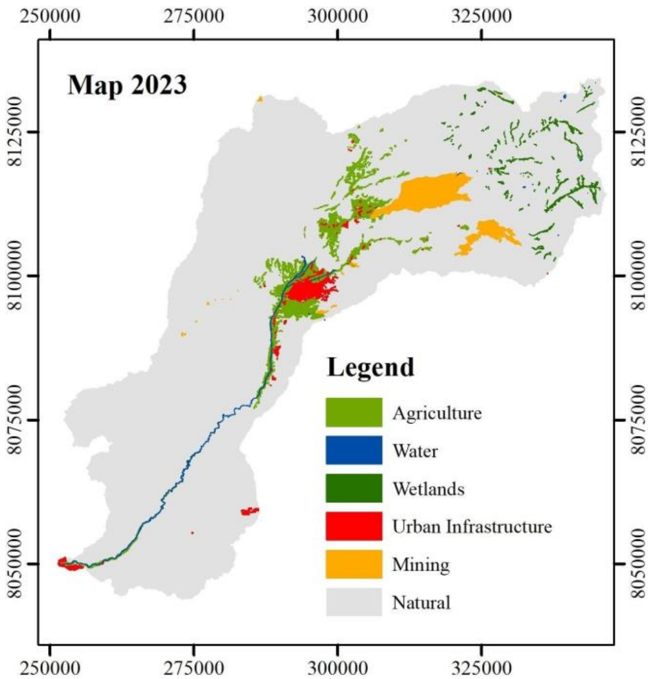

Fig. 3. Map of land use and coverage of the Ilo-Moquegua hydrographic basin for 1972.

The aforementioned maps in shapefile format were the primary data entered so that the CHAT GPT-4 Artificial Intelligence language model with practical and specific prompts according to the required methodologies can perform the analysis as performed by GIS software, obtaining as a first result of the table that summarizes the hectares and the percentage of each category of land use and coverage for the years 1972 and 2023 in Table 2.

Table 2. Land Use and Land Cover Areas and Percentages for 1972 and 2023

Land Cover Category	Area 1972 (ha)	% of Total 1972	Area 2023 (ha)	% of Total 2023
Agriculture	5 119,59	1,46%	10 287,61	3,03%
Water	582,08	0,17%	598,86	0,18%
Wetlands (Bofedal)	1 646,80	0,47%	1 404,45	0,41%
Urban Infrastructure	232,14	0,07%	2 541,54	0,75%
Mining	1 968,78	0,56%	8 195,29	2,41%
Natural	343 981,22	97,27%	330 502,87	93,12%
Total	353 530,61	100%	353 530,61	100%

Table 2 clearly illustrates how the land cover proportions have shifted over the 51 years, highlighting significant expansions in agriculture and mining, alongside a noticeable decrease in natural areas. The increases in urban infrastructure also reflect growing urbanization pressures. This change distribution is crucial for understanding the dynamic environmental and socioeconomic factors affecting the region.

The second result requested from CHAT GPT-4 is the cross-tabulation matrix by [24] presented in Table 3. This matrix displays the area in hectares that have transitioned from one land cover class in 1972 to another in 2023.

Table 3. Pontius Cross-tabulation Matrix

	2023					
From/To 1972	Agriculture	Water	Wetlands	Urban Infrastructure	Mining	Natural
Agriculture	4 918,36	0	0	201,24	0	0
Water	0	565,14	0	0	0	16,94
Wetlands	0	0	1 404,45	0	0	242,35
Urban Infrastructure	0	0	0	232,14	0	0
Mining	0	0	0	0	1968,78	0
Natural	5 369,25	33,73	0	2 108,15	6 226,51	330 244

In Table 3, each matrix cell shows the amount of area transformed from the land cover class of the row (a state in 1972) to the class of the column (a state in 2023). This provides a comprehensive view of how land cover classes have changed over time, allowing for the identification of specific patterns of change or stability in land use.

The third result requested from CHAT GPT-4 is the calculations of the Kappa Consistency Indices (KIA) for the cross-tabulation matrix of changes in land cover between 1972 and 2023:

Observed Agreement (Po): 95,98%

Expected Agreement (Pe): 91,02%

Cohen's Kappa Index (KIA): 0,55

Interpretation:

Po indicates that approximately 96% of the total land cover areas remained in the same category between 1972 and 2023.

Pe represents the agreement we expect by chance based on the marginal distributions of the classes on both dates.

KIA is a measure of agreement adjusted for chance. By [25][26][27], a value of 0,55 suggests moderate agreement between the land cover classifications in the two periods studied, beyond what chance would typically expect.

This index helps understand the stability of land use in the region over time, indicating that, although there have been significant changes, most areas have maintained their original classification with a reasonable level of consistency.

The fourth requested result of CHAT GPT-4 in Table 4, which summarizes the areas of persistence, expansion, reduction, and net change for each land cover category between 1972 and 2023, measured in hectares:

Table 4. Areas of persistence, expansion, reduction and general change for each LULC class between 1972 and 2023

LULC Class	Persistence (ha)	Expansion (ha)	Reduction (ha)	Net change (ha)
Agriculture	4 918,36	5 369,25	201,24	5 168,01
Water	565,14	33,73	16,94	16,78
Wetlands	1 404,45	0	242,35	-242,35
Urban Infrastructure	232,14	2 309,39	0	2 309,39
Mining	1 968,78	6 226,51	0	6 226,51
Natural	330 243,58	259,29	13 737,64	-13 478,35

Interpretation:

Persistence (ha): The area within the same land cover class that remained unchanged over the period.

Expansion (ha): Total area gained by each land cover class from other classes.

Reduction (ha): Total area lost by each land cover class to other classes.

Net change (ha): The difference between expansion and reduction, showing whether each class has generally increased or decreased in area.

Table 4 highlights how land use and coverage have evolved, indicating areas of environmental stability, pressure, or recovery.

The fifth requested result of CHAT GPT-4 is the detailed table summarizing the areas of each land cover category for both 1972 and 2023, along with the percent of change, rate of change per year, and total area change:

Table 5. LULC class areas for 1972 and 2023, total area change, percentage change and rate of change by year

Land Cover Class	Area 1972 (ha)	Area 2023 (ha)	Total Area Change (ha)	Percent of Change (%)	Rate of Change (ha/year)
Agriculture	5 119,59	10 287,61	5 168,01	100,95%	101,33
Water	582,08	598,86	16,78	2,88%	0,33
Wetlands	1 646,80	1 404,45	-242,35	-14,72%	-4,75
Urban Infrastructure	232,14	2 541,54	2 309,39	994,81%	45,28
Mining	1 968,78	8 195,29	6 226,51	316,26%	122,09
Natural	343 981,22	330 502,87	-13 478,35	-3,92%	-264,28

Interpretation:

Persistence and Change: The table reveals significant changes across land cover classes over the 51 years. For instance, "Urban Infrastructure" and "Mining" have grown tremendously, reflecting substantial developmental and extractive activities in these areas.

Percent of Change (%): This column indicates the relative change from 1972 to 2023, providing insights into how dramatic the changes have been in percentage terms. Urban infrastructure has nearly a tenfold increase, highlighting significant urban expansion.

Rate of Change (ha/year): This metric provides an annualized view of the change, which helps understand the rate at which land cover transformations have occurred annually.

3.2. Evaluation of results of quantitative changes of LULC

Based on the analysis of changes in land use and land cover (LULC) in the Ilo-Moquegua hydrographic basin between 1972 and 2023, we can extract and consolidate the results and discussion of the study:

Agriculture: Expanded significantly from 5,119.59 ha in 1972 to 10,287.61 ha in 2023, nearly doubling in area, with a percent increase of approximately 100.95%.

Urban Infrastructure: Showed the most dramatic increase, from 232.14 ha to 2 541.54 ha, indicating a growth of over 994%, which reflects intense urbanization.

Mining: Increased from 1 968,78 ha to 8 195,29 ha, marking a 316% increase, suggesting substantial growth in mining activities.

Natural Areas: Declined from 343,981.22 ha to 330,502.87 ha, a reduction of 3.92%, highlighting pressures from expanding agricultural, urban, and mining activities.

Water and Wetlands: More minor changes were made. Water areas slightly increased, while wetlands decreased by 14.72%, potentially reflecting changes in hydrological conditions and land management practices.

3.3. Discussion of the implications of land use and land cover changes.

According to the analysis and results of the data, we consider three aspects, which are:

1. Environmental impact: Reducing natural areas, particularly vegetation and wetlands, could significantly affect biodiversity, soil erosion and local climate regulation. Expanding mining areas, urban infrastructure, and agriculture could cause habitat fragmentation, affecting local flora and fauna.

2. Water resources: Changes in water bodies and wetlands can affect the quality and availability of water for agricultural and human consumption. The slight increase in water-covered areas may not fully offset the ecological impacts of reduced wetland areas.

3. Socioeconomic factors: Expanding agricultural land and mining activities have contributed to the region's economic development. However, this could also lead to conflicts over land use, especially where agriculture expansion encroaches on natural areas or mining activities impact environmental and community health.

4. Conclusion

The analysis clearly shows significant transformations in the land cover of the Ilo-Moquegua watershed over the last 51 years, driven by climate change and potentially socioeconomic developments. These findings highlight the urgent need for integrated land use planning and environmental conservation strategies to ensure the region's sustainable development.

The application of artificial intelligence, such as ChatGPT-4, represents a significant advancement in language processing models powered by AI. It facilitates streamlining geoprocessing software usage and simplifies the processes involved in analyzing and presenting results. However, it is crucial to recognize that the accuracy of the outcomes heavily depends on the user's ability to input precise and appropriate prompts. Correct and carefully crafted prompts are essential for generating reliable and accurate results.

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