The Classification of Land Use and Land Cover Conducted Using the Manual Method in Arcgis and Using AI / Ml in Google Earth Engine for Salem District, Tamil Nadu, India

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Abstract

This study compares two methods for Land Use and Land Cover (LULC) change detection in Salem District, Tamil Nadu using manual mapping with ArcGIS and automated analysis using Google Earth Engine (GEE). ArcGIS provides high spatial accuracy, making it suitable for small-scale, detailed studies, but is resource-intensive and time-consuming. GEE leverages cloud computing for efficient, scalable analysis, enabling broader regional and temporal assessments. The comparison reveals ArcGIS is better suited for localized, precision studies, while GEE excels in rapid processing of large datasets. The study highlights each method's strengths and limitations, offering insights for applications in environmental monitoring and urban planning.

Keywords: LULC, Salem, ArcGIS - Google Earth Engine, AI, Remote Sensing, Classification Methods, Environmental Monitoring, Urban Planning, Geospatial Analysis, Conclusion, Future Scopes

Introduction

Land Use and Land Cover (LULC) classification is a critical aspect of understanding and managing natural resources, urban development, and environmental sustainability. Accurate LULC classification is essential for informed decision-making in areas such as agriculture, forestry, urban planning, and environmental conservation.

Traditionally, LULC classification has been conducted using manual methods, which, although effective, are often time-consuming and prone to human error. With the advent of advanced geospatial technologies, integrating Artificial Intelligence (AI) in platforms like Google Earth Engine (GEE) has revolutionized the process, offering faster, more precise, and scalable solutions.

This study focuses on classifying Land Use and Land Cover in Salem District, Tamil Nadu, India, comparing the traditional manual method in ArcGIS with the AI-powered approach in Google Earth Engine. Salem District, located in southern India, is characterized by a diverse landscape, including agricultural lands, forests, and urban areas. The region's varied topography and land use patterns present a unique challenge for accurate LULC classification.

The manual method in ArcGIS involves the visual interpretation of satellite imagery, relying heavily on the expertise of the analyst. This approach, while detailed, can be labor-intensive and subject to subjective bias. On the other hand, Google Earth Engine leverages cloud computing and machine learning algorithms to automate the classification process, providing a more objective and efficient solution.

This study aims to compare the effectiveness, accuracy, and efficiency of these two methods in classifying LULC in Salem District. The outcomes of this comparison will offer valuable insights into the advantages and limitations of traditional versus AI-driven approaches, contributing to the broader discourse on the modernization of geospatial analysis in environmental and urban studies.

Salem district is located in Tamil Nadu state, South India. Geographically, it lies between 11°10' and 12°10'N latitudes and 77°35' and 78°55'E longitudes. The study area is considered the largest district in Tamil Nadu and covers an area of 6016 km2. Isolated hills mark the boundaries of the study area, Nagaramalai in the northern part, Jarugumalai in the southern part, Kanjamalai in the western part, Godumalai in the eastern part, Shevaroy in the NE part and Kariyaperumal hill ranges in the south-western part.

Sarabanga, Thirumanimuthar, Sweta and Vasista are the main river systems in the Salem district. The major river in South India, Cauvery, passes through the study area and supplies water for domestic and agricultural purposes of the district. The study area is one of the fast-developing cities because of its favorable climate and plenty of natural resources. According to census data, the population in 2001 was 30.16 lakhs and that in 2011 was 34.82 lakhs, which indicate the rapid rate of urbanization in the study area.
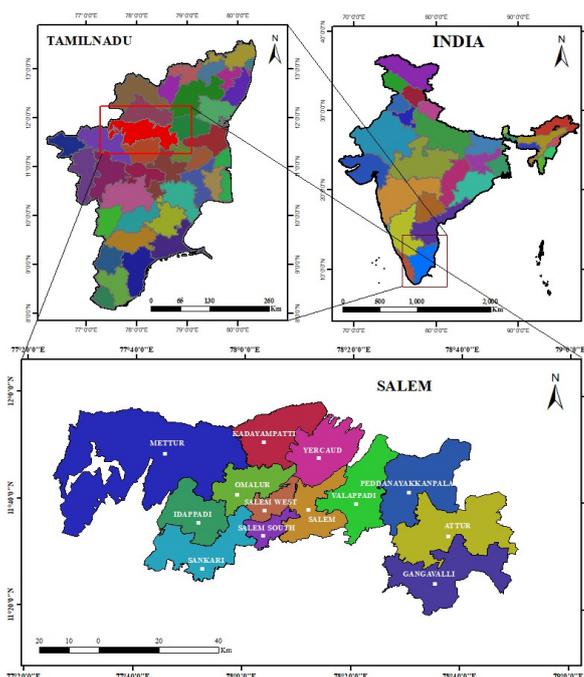
Figure 1.1: Study Area - Salem

Methodology

Land Use Land Cover (LULC) mapping is essential for understanding environmental changes and land management. Traditional manual LULC mapping involves expert interpretation of satellite images and field surveys, ensuring high accuracy but requiring significant time and effort. In contrast, modern techniques utilize Google Earth Engine (GEE) combined with Artificial Intelligence (AI) and Machine Learning (ML) to automate and scale the mapping process. This approach leverages cloud-based processing and advanced algorithms to quickly classify large areas with improved consistency and accuracy. The following sections will delve into these methodologies, comparing their processes, advantages, and limitations.

For Manual Method

First, you start by collecting satellite images from the USGS (United States Geological Survey). For this project, you choose data from the Landsat 8 and 9 satellites, which are well-known for capturing detailed images of the Earth's surface. After selecting the right satellite images, the next step is to download this data to your computer.

Once you have the data, it needs to be preprocessed. Preprocessing involves getting the data ready for analysis, which might include cleaning up the images, correcting any distortions, and ensuring everything is lined up correctly. After preprocessing, you narrow down your focus to a specific Area of Interest (AOI) by using ArcGIS software. This means you'll be working with just the part of the satellite image that covers the area you're interested in studying.

The next important step is selecting training sets. This involves manually identifying and marking different types of land cover in your AOI, such as forests, water bodies, or urban areas. These training sets are used in the supervised classification process. Here, a machine learning algorithm, specifically the Maximum Likelihood Algorithm, is applied to the entire image.

It uses the training sets to categorize every part of the AOI into different land cover types. After running the classification, you get an output map that shows the LULC of your area. This map is initially in a raster format, which is grid-based. For further analysis, you convert this raster data into vector format, where the land cover types are represented as shapes like polygons.

Next, you calculate the area covered by each type of land cover. This helps you understand the extent of different land covers within your AOI. To ensure the results are reliable, you perform an accuracy assessment. This involves comparing the classified map with actual ground data or higher-resolution images to see how accurate your classification is. Finally, if you're interested in how the land cover has changed over time, you can perform a change detection analysis. This step involves comparing your current LULC map with maps from previous years to identify any significant changes, such as deforestation, urban expansion, or changes in water bodies.

This entire process (shown in Figure 1.2), from data collection to change detection, provides a comprehensive way to map and analyze the land use and cover of an area, which is crucial for environmental management, urban planning, and resource monitoring.
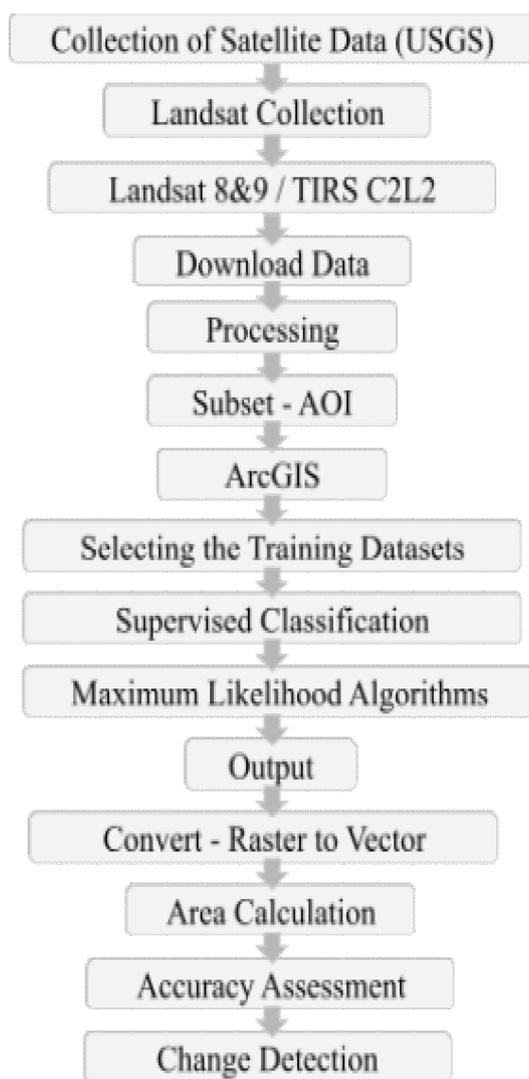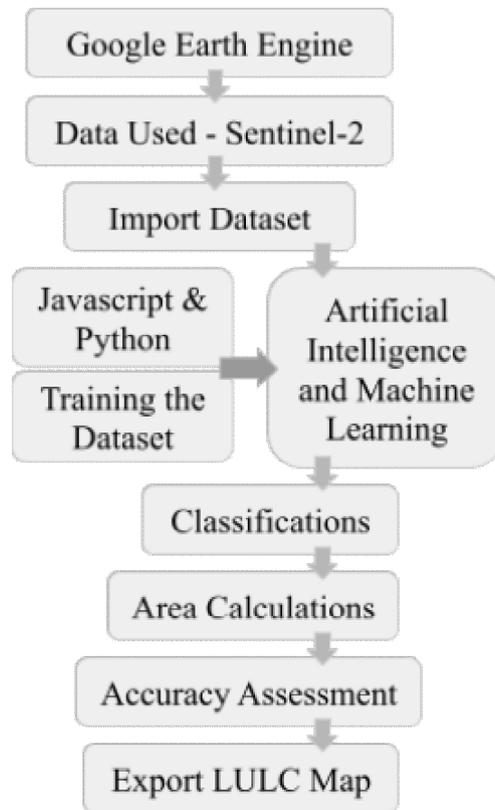

Figure 1.2: Flowchart

For Generated using Google Earth Engine with AI & ML

The process of creating a Land Use Land Cover (LULC) map using AI methods begins with utilizing Google Earth Engine to analyze Sentinel-2 satellite imagery. This high-resolution data is imported into the platform, where artificial intelligence and machine learning techniques are applied to classify the land into different cover types.

The classification process involves training models using JavaScript and Python, ensuring the algorithms accurately categorize the land cover. Once the classification is complete, the area covered by each land type is calculated, followed by an accuracy assessment to validate the results. Finally, the LULC map, which visually represents the different land cover types, is exported for further use. This approach leverages advanced AI techniques to create precise and efficient land cover maps.

Figure 1.3: Flowchart

Advantages
ArcGIS with Manually Trained Data
ArcGIS, when used with manually trained data, offers several advantages that make it highly suitable for smaller and medium-sized projects. Its primary strength lies in the high accuracy that comes from leveraging local expertise and user knowledge. This allows for the creation of a classification system tailored to specific needs, providing users with detailed control over the entire classification process. It is particularly effective for areas that require hands-on management and precision, especially when conducting temporal analysis, where it excels at delivering high accuracy for specific periods.

GEE with AI-Generated Scripts
Google Earth Engine (GEE) with AI-generated scripts is highly scalable, making it suitable for large-scale and even global projects. Its AI-driven automation significantly enhances efficiency, reducing the time needed for land use and land cover (LULC) mapping. One of the key advantages of this approach is the consistency in classification across extensive datasets, which helps minimize subjectivity. Additionally, GEE is accessible, offering free access to vast amounts of satellite imagery and geospatial tools, and simplifies the classification process. This reduces the need for deep GIS expertise, making it easier to use for a wider audience. It also excels in dynamic mapping and near real-time temporal analysis, making it ideal for monitoring rapidly changing environments.

Limitations
ArcGIS with Manually Trained Data
Despite its accuracy and customization capabilities, ArcGIS with manually trained data has limitations. The method's accuracy can be subjective, as it heavily relies on the user's expertise, which may introduce bias. It is also time-consuming and labor-intensive, making it impractical for large-scale projects. Scalability is another challenge, as expanding to larger areas requires considerable additional effort. Furthermore, the low level of automation means that the process is inefficient for managing large datasets or repetitive tasks. Lastly, the steep learning curve for those unfamiliar with GIS software can make ArcGIS less accessible to beginners.

GEE with AI-Generated Scripts
While GEE with AI-generated scripts is powerful, it has some limitations. Its performance is dependent on the quality of the training data, and inaccuracies can arise if the data is not representative or flawed. The "black-box" nature of AI models can also make it difficult to interpret results, posing challenges for users who prefer transparent processes. Customization options are more limited compared to manual classification methods, which can be a drawback for users needing specific outputs. Additionally, expertise in AI and machine learning is required to fully utilize the platform, making it less accessible to users without such knowledge. Internet dependency can be problematic in areas with poor connectivity, and free-tier users may face usage quotas and computational limits. Finally, AI models may require ongoing maintenance, as they might need retraining when new data becomes available.

Results & Discussions
Area Calculation for ArcGIS Generated Maps:
Water Bodies
- **Increase in Area:** The area of water bodies increased from 74.14 hectares in 2018 to 100.74 hectares in 2023, marking an increase of approximately 26.6 hectares (or 0.44% of the total land cover). This growth might be attributed to the development of artificial reservoirs, improved water management practices, or the expansion of natural water bodies due to climatic factors such as increased precipitation.
- **Implications:** The increase in water bodies is generally a positive development, as it may contribute to better water availability for agriculture and urban uses. However, it may also indicate potential issues like waterlogging or flooding in certain areas.

Trees
- **Slight Increase in Tree Cover:** The area covered by trees increased from 1312.62 hectares in 2018 to 1367.45 hectares in 2023, representing a growth of 54.83 hectares (0.91% of the total land cover). This increase is a positive sign, possibly resulting from afforestation efforts, conservation policies, or natural regrowth.
- **Sustainability:** The increase in tree cover contributes positively to biodiversity, carbon sequestration, and the overall ecological balance. It reflects a move towards more sustainable land management practices, which is essential for long-term environmental health.

Crop and Vegetation
- **Significant Decrease:** The most notable change is the decrease in crop and vegetation cover, which dropped from 3520.21 hectares in 2018 to 2949.46 hectares in 2023, a reduction of 570.75 hectares (9.48% of the total land cover). This substantial decrease could be due to several factors, including urban expansion, land degradation, or a shift in land use practices (e.g., conversion of agricultural land to built-up areas).
- **Agricultural Impact:** The reduction in crop and vegetation cover may have significant implications for food security, local agriculture, and the economy. It might also lead to a decrease in natural habitats for wildlife, increased soil erosion, and loss of biodiversity.

Buildup Area
- **Substantial Increase:** The buildup area saw a significant increase, growing from 1110.39 hectares in 2018 to 1599.10 hectares in 2023, an expansion of 488.71 hectares (8.12% of the total land cover). This reflects ongoing urbanization and infrastructure development.
- **Urbanization:** The increase in built-up areas is often associated with economic development, population growth, and increased demand for housing and infrastructure. However, this expansion can also lead to the loss of agricultural land, increased surface runoff, and potential urban sprawl, contributing to environmental degradation and a higher urban heat island effect.

Classes	2018	%	2023	%	⇑ / ⇓
Water Bodies	74.14	1.23	100.74	1.67	⇑
Trees	1312.62	21.81	1367.45	22.72	⇑
Crop and Veg	3520.21	58.50	2949.46	49.02	⇓
Buildup Area	1110.39	18.45	1599.1	26.57	⇑
Total	6016.38		6016.75		

Table 1: Change Detection
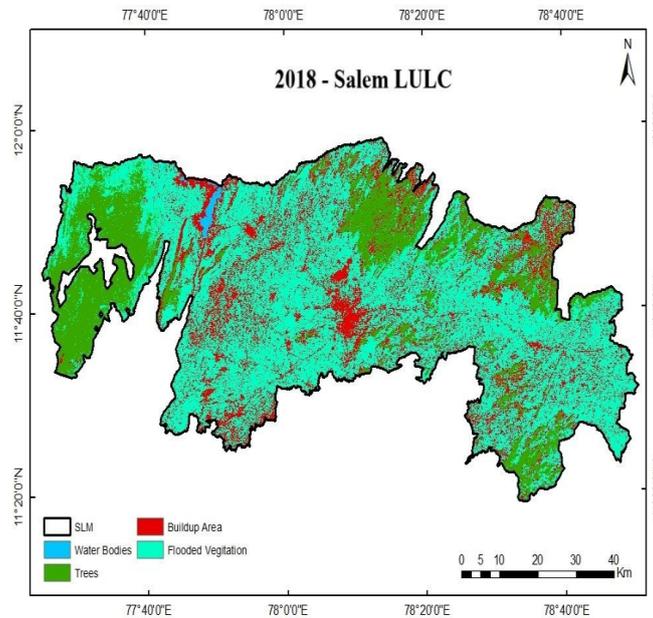
Figure 1.4: 2018 Salem LULC
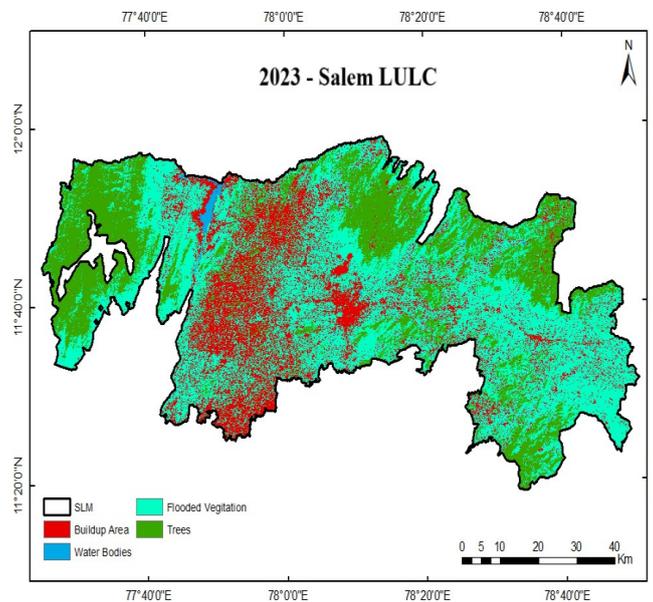
Figure 1.5: 2023 Salem LULC

Area Calculation for Google Earth Engine Generated Maps:
Water Bodies
- **Increase in Area:** The area under water bodies increased significantly from 57.149 hectares in 2018 to 123.21 hectares in 2023, marking an increase of 66.061 hectares (1.1% of the total land cover). This increase could be due to the expansion of water reservoirs, construction of new water bodies, or changes in water management practices.
- **Implications:** This growth in water bodies is beneficial for water resource management and could indicate better availability of water for agricultural and domestic purposes. However, it may also suggest increased precipitation or flooding, which may require further investigation.

Trees
- **Expansion of Tree Cover:** The area covered by trees increased from 1917.179 hectares in 2018 to 2136.77 hectares in 2023, reflecting a growth of 219.591 hectares (3.65% of the total land cover). This increase likely results from afforestation programs, natural forest regrowth, or improved forest management practices.
- **Environmental Benefits:** The Increase in tree cover is a positive sign for biodiversity conservation, carbon sequestration, and the overall health of the ecosystem. It suggests a move towards more sustainable land management, contributing to climate change mitigation and improved air quality.

Crops & Vegetation
- **Notable Decrease:** The most significant change observed is the reduction in crop and vegetation cover, which

decreased from 3257.791 hectares in 2018 to 2701.19 hectares in 2023, a decline of 556.601 hectares (9.25% of the total land cover). This reduction could be driven by urban expansion, conversion of agricultural land into other land uses, or changes in agricultural practices.

- **Agricultural Impact:** The decline in crop and vegetation areas may negatively impact food production, local agriculture, and rural economies. Additionally, this reduction could lead to habitat loss, reduced biodiversity, and increased soil erosion, particularly in regions dependent on agriculture.

Built-Up Area

- **Significant Increase:** The built-up area expanded considerably, increasing from 784.713 hectares in 2018 to 1055.55 hectares in 2023, an increase of 270.837 hectares (4.5% of the total land cover). This reflects ongoing urbanization, infrastructure development, and population growth.
- **Urbanization Trends:** The increase in built-up areas is indicative of economic development, industrial growth, and increased housing demand. While this expansion supports economic growth, it also raises concerns about the loss of natural habitats, increased pollution, and the potential for urban Sprawl. Effective urban planning is necessary to mitigate these impacts and ensure sustainable development.

Classes	2018	%	2023	%	⇧ / ⇩
Water	57.14	0.94	123.21	2.04	⇧
Trees	1917.17	31.86	2136.77	35.51	⇧
Crops & veg	3257.79	54.14	2701.19	44.89	⇩
Built Area	784.71	13.04	1055.55	17.54	⇧
Total	6016.83		6016.83		

Table 2: Change Detection
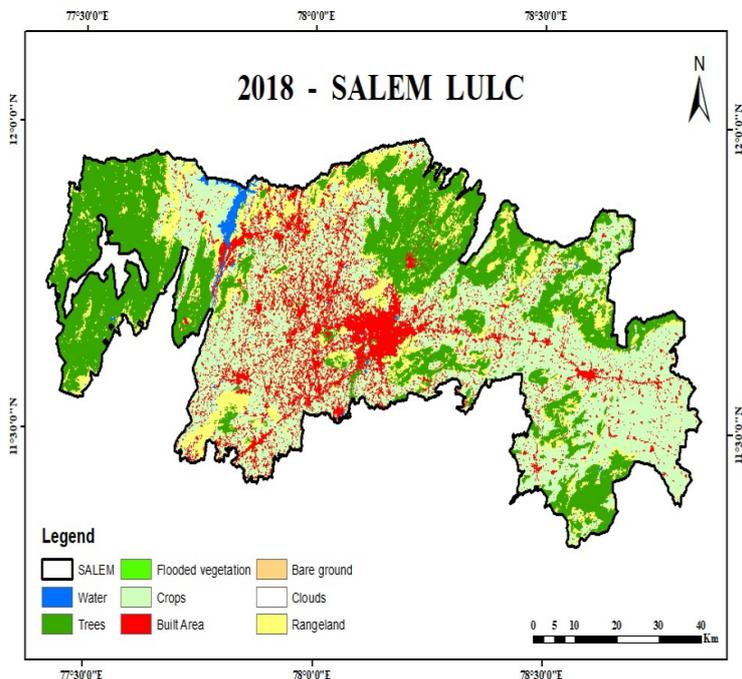
Figure 1.6: 2018 Salem LULC
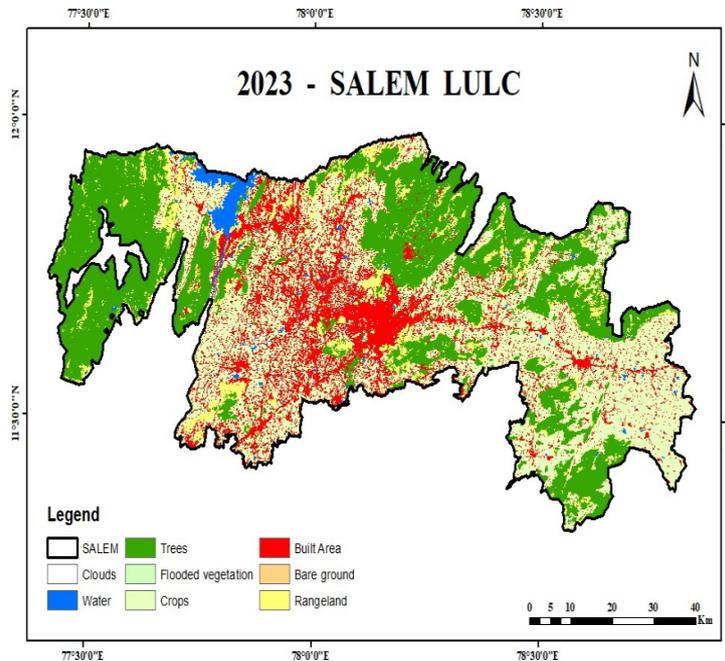
Figure 1.7: 2023 Salem LULC

Future Scope of This Study

The study of Land Use/Land Cover (LULC) changes using tools like ArcGIS and Google Earth Engine opens up several promising areas for future exploration:

- **Enhanced Environmental Monitoring:** Future research can build on this study to develop more advanced systems for real-time monitoring of environmental changes, helping to quickly identify and respond to issues like deforestation, urban sprawl, or natural disasters.
- **Improved Urban Planning:** The insights from LULC changes can guide smarter urban planning, ensuring that cities grow sustainably, with balanced development that minimizes environmental impact and preserves green spaces.
- **Climate Change Adaptation:** As climate change continues to alter landscapes, this study can be a foundation for developing strategies to adapt land use practices, such as planning for changing agricultural zones or protecting vulnerable ecosystems.
- **Integration with Emerging Technologies:** The methods used here can be integrated with emerging technologies like AI, machine learning, and big data analytics to create more precise and predictive models for land use and environmental management.
- **Policy Formulation and Assessment:** The study provides a basis for evaluating the effectiveness of current land use policies and can inform the creation of new policies that promote sustainable land management practices.
- **Biodiversity Conservation:** By understanding how land cover changes affect habitats, future research can contribute to strategies that protect biodiversity, particularly in regions experiencing rapid development or environmental stress.
- **Global and Regional Studies:** The methodologies can be scaled to global or regional studies, allowing for comparisons between different areas and the identification of global patterns in land use changes.
- **Educational and Capacity Building:** The findings and techniques from this study can be used to educate and train professionals and policymakers in effective land use management, fostering better practices at local, national, and international levels.
- **Cross-Sectoral Applications:** The study's results can be applied beyond environmental science to sectors like agriculture, water resources, disaster management, and urban development, supporting a wide range of societal needs.

Overall, this study has the potential to significantly impact how land use is managed and understood, leading to more sustainable and resilient communities in the face of ongoing environmental changes.

Conclusion

In comparing LULC map generation using ArcGIS with manually trained data and Google Earth Engine (GEE) with AI-generated scripts, both methods offer valuable insights and tools for land cover analysis, yet they differ significantly in their approach, strengths, and limitations.

Arcgis With Manually Trained Data

excels in providing highly accurate and customizable LULC maps, particularly for small to medium-sized areas. This method is ideal when local expertise is available, allowing for detailed adjustments and corrections based on specific

knowledge of the region. However, it is time-consuming, labor-intensive, and less scalable, making it less practical for large-scale or dynamic analyses. The accuracy of this method is highly dependent on the user's expertise, which can introduce subjectivity and potential biases.

Google Earth Engine with AI-generated scripts

offers a powerful, scalable solution for large-scale LULC mapping, particularly when working with extensive datasets or conducting temporal analyses. The integration of AI allows for consistent, automated classification across vast areas, making it highly efficient and suitable for dynamic monitoring. However, this method requires a solid understanding of coding and AI, and the results may be influenced by the quality and representativeness of the training data. Additionally, while it provides broad consistency, it may lack the fine-tuning and detailed customization possible with manual methods.

Overall, the choice between these methods should be guided by the specific requirements of the project. For detailed, small-scale studies requiring high accuracy and expert input, ArcGIS with manually trained data is preferable. For large-scale, time-sensitive, or regularly updated analyses, Google Earth Engine with AI-generated scripts offers unmatched scalability and efficiency [1-4]. A combination of both approaches might be the best strategy in some cases, leveraging the strengths of each method to achieve a comprehensive and accurate understanding of land use and land cover dynamics.

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