



Project Proposal

Using Satellite Imagery and Geo AI for Long-Term Urban Growth: A Case Study of Riyadh

Prepared By

Name: **Waleed Ahmad AlSharif**

ID No.: **252001025**

Submitted in fulfillment of the requirements for the degree Master
of Science in Artificial Intelligence

At

Collage of Informatics

Midocean University

UAE

Supervisor Name: **Dr. Khaled Eskaf**

Collage of Informatics, Midocean University, Comoros

Email: 252001025@st.midocean.edu.km

alshareefw@yahoo.com

1. Project Overview

Problem Definition

Riyadh's rapid urban sprawl has brought a tangled mess of challenges, and it's starting to weigh heavily on how people live in the city. The city keeps growing fast, but without solid land-use planning, new developments pop up in scattered patches. Good land gets wasted, neighborhoods sprawl out, and infrastructure just can't keep up. Building roads, water lines, and other services gets pricier and a whole lot less efficient. At the same time, as new buildings go up, green spaces and natural vegetation keep shrinking. That's a problem, especially here, where trees and parks help cool the city, clean the air, and just make life better for everyone. When those green spots disappear, the city heats up, biodiversity drops, and it takes more energy to keep buildings cool — a real issue in Riyadh's harsh climate. On top of that, more people keep moving in, stretching the city's infrastructure to its limits. Roads get jammed, water and power supplies come under strain, and public services can't always keep up. Too often, the people in charge don't have up-to-date info, so planning falls behind. The result? More traffic, higher costs, and a city that struggles to function smoothly. Right now, most urban monitoring in Riyadh is still stuck in the past — slow, manual, and based on static reports. It's expensive, takes too long, and just can't keep up with how fast the city changes. Plus, it doesn't predict future trends, so city planners are always reacting instead of getting ahead of problems. There's a real need for smarter, automated ways to track urban growth — systems that use data to help leaders plan for a livable, sustainable future.

Motivation and Importance

Managing Riyadh's urban growth takes more than just good intentions—it needs real, up-to-date data and smart monitoring tools that work with the Riyadh Regional Plan and Saudi Vision 2030's push for smart cities. That's where this project steps in. We're blending multi-temporal satellite images with AI-powered Geo-AI models—think deep neural networks and advanced image recognition tech—to spot urban features, track how land use shifts over time, and measure sustainability in tough desert conditions. With this system, you can keep an eye on things like how fast the city's spreading, how much green space is left, how dense different neighborhoods are getting, and where the city's infrastructure feels the most strain. We're not just looking at what's happening now—we're

using spatiotemporal analysis and generative models to play out different “what if” scenarios for future growth, depending on how planners and policymakers steer things. Bottom line: this approach gives decision-makers the evidence they need to make smarter calls, plan better, and build a city that holds up over time. It fits right into the government’s strategy and helps make sure Riyadh grows in a way that’s both sustainable and resilient for years to come.

Project Contribution

Here’s what this project brings to the table: a Geo-AI framework that blends satellite images, deep learning, and generative AI. It digs into how cities have grown, checks out key sustainability markers, and even models what city growth might look like down the road. The idea is to give planners real, data-backed insights they can use—something that works for both research and day-to-day planning.

2. Project Goal

General Goal

General Goal Build an AI-powered geospatial system that tracks and predicts how cities expand, all by using satellite photos. Measurable Objectives 1. Pull out urban features—buildings, greenery, roads—from satellite images with solid accuracy. 2. Sort land-use types reliably with deep learning. 3. Measure sustainability numbers, like how much green space there is or how fast built-up areas spread. 4. Use generative AI to create realistic future scenarios for urban growth. 5. Show results with visuals that make sense, so planners and policymakers get what they need. 6. Test everything out with a real-world case—Riyadh.

3. Methodology

The approach sticks to solid academic research standards and matches what Midocean University expects. It's all about being clear, doable, and technically on point.

3.1 Data Collection

We'll use multi-temporal satellite images from open sources like Sentinel-2 and Landsat. These give us multispectral data that works well for analyzing city land use and vegetation. To keep everything in the right place, we'll add GIS layers like administrative boundaries.

3.2 Data Preprocessing

For preprocessing, we'll handle cloud masking, atmospheric correction, normalization, spatial alignment, and split the images into tiles. We'll also calculate vegetation indices like NDVI to boost how well we can classify vegetation. After that, we'll divide the data into training, validation, and test sets.

3.3 Model Design and Implementation

We'll use Convolutional Neural Networks (CNNs) to pull out important features from the data. For pixel-level land-use maps, U-Net and Deep Lab architectures come into play—they're solid choices for semantic segmentation. To get the best results, we'll fine-tune model parameters through validation experiments. On top of that, we're looking at generative AI models. Diffusion-based approaches let us simulate how cities might grow under different planning scenarios. This way, we can see possible futures, not just talk about them.

3.4 Evaluation Strategy

We'll measure how well the models do using accuracy, precision, recall, F1-score, and Intersection over Union (IoU). To check how well we catch land-use changes over time, we'll run temporal validation. Whenever possible, we'll stack our results up against what's out there in the literature.

4. Project Plan and Timeline

The project is structured over a 10-week period to ensure feasibility and timely completion.

Week	Activity Title	Description
1	Data Collection	Acquire satellite and GIS data; set up development environment
2	Preprocessing	Cloud masking, normalization, labeling
3	Exploratory Analysis	Analyze urban and vegetation trends
4	Baseline Modeling	Implement CNN and segmentation models
5	Model Optimization	Tune hyperparameters and improve accuracy
6	Generative Modeling	Simulate future urban growth scenarios
7	Evaluation	Quantitative and qualitative evaluation
8	Case Study	Apply models to Riyadh
9	Visualization	Develop GIS-based visualization and decision-support tool
10	Reporting	Final report and presentation preparation

5. Expected Results and Evaluation Criteria

Here’s what the project delivers:

- Land-use classification maps pulled straight from satellite images, with a focus on accuracy.
- A solid, numbers-driven look at how cities are spreading out and how green spaces are changing.
- Simulations that show what future urban development might look like.
- A working Geo-AI prototype that proves these ideas work in practice.
- Academic review based on how sound the methods are, how clear the results come through, and whether all this matters for real-world urban planning.

6. Resources and Feasibility

Software and Tools

- Python programming language
- Jupyter Notebook
- TensorFlow or PyTorch
- Geospatial libraries (GDAL, Rasterio, GeoPandas)
- GIS software (QGIS or ArcGIS)

Data Resources

- Sentinel-2 and Landsat satellite imagery
- GIS shapefiles and administrative data

Computing Resources

- Personal workstation or laptop
- Optional cloud-based computing resources

The required resources are readily available, ensuring the project is feasible within the given timeframe.

7. Literature Review

Recent research—everything here is from the last five years—covers urban growth, satellite imagery, and Geo-AI methods. These studies lay out the latest approaches, and they make it clear where the gaps are. That’s exactly where this project jumps in.

No.	Year	Reference	Title	Authors	Summary	Methodologies	Key Findings / Limitations
1	2021	Yuan et al.	Urban Land-Use Classification Using Deep Learning	Yuan et al.	Applied deep learning models to classify urban land-use categories from high-resolution satellite imagery.	U-Net, CNNs	High classification accuracy; limited focus on sustainability indicators.
2	2021	Zhu et al.	Deep Learning for Remote Sensing Applications	Zhu et al.	Reviewed recent deep learning approaches for satellite image analysis and urban monitoring.	CNNs, Transformers	Strong performance reported; high computational cost and data requirements.
3	2022	Ibrahim et al.	Remote Sensing-Based Urban Growth Analysis in Arid Regions	Ibrahim et al.	Analyzed urban expansion in arid environments using multi-temporal satellite imagery.	Landsat, NDVI, change detection	Relevant to arid cities; lacks AI-based automation and prediction models.
4	2022	Li et al.	Urban Expansion Analysis Using	Li et al.	Studied urban growth trends using machine learning and multi-	Random Forest, time-	Effective for historical analysis; limited future growth simulation.

No.	Year	Reference	Title	Authors	Summary	Methodologies	Key Findings / Limitations
			Machine Learning		temporal satellite data.	series analysis	
5	2023	Chen et al.	Semantic Segmentation of Urban Areas Using Deep Learning	Chen et al.	Proposed improved deep learning models for accurate urban feature extraction.	DeepLabV3+, CNNs	High segmentation accuracy; requires large, labeled datasets.
6	2023	Zhao et al.	Urban Growth Prediction Using Deep Learning	Zhao et al.	Predicted future urban expansion using deep learning and historical satellite imagery.	CNN-LSTM, spatiotemporal modeling	Promising prediction results; limited integration of planning constraints.
7	2024	Hassan et al.	Geo-AI for Sustainable Urban Planning	Hassan et al.	Integrated Geo-AI techniques to assess sustainability indicators in urban environments.	Geo-AI, NDVI, GIS analysis	Strong sustainability focus; limited generative scenario simulation.
8	2024	Wang et al.	Generative Models for Urban Growth Simulation	Wang et al.	Explored generative AI models to simulate urban growth scenarios from satellite data.	Diffusion models, GANs	Novel approach; still at experimental stage.

7.1 Summary of Recent Research Trends

Lately, deep learning has taken urban land-use classification and growth analysis to another level—way ahead of the old-school methods. More and more, researchers are focusing on spatiotemporal modeling and digging deeper into sustainability.

7.2 Identified Research Gaps

- Limited Geo-AI studies focused on Middle Eastern and arid-region cities.
- Insufficient integration of sustainability indicators such as green-space ratios.
- Minimal use of generative AI for future urban growth simulation.
- Lack of decision-support tools designed for urban planners.

7.3 Research Contribution

This project tackles those issues head-on. By using advanced Geo-AI and generative AI in Riyadh, it offers solid data analysis and future growth simulations—giving urban planners the tools and insights they need for smarter, more sustainable decisions.

8. References

1. Ma, L., Liu, Y., Zhang, X., Ye, Y., Yin, G., & Johnson, B. A. (2019). Deep learning in remote sensing applications: A meta-analysis and review. *ISPRS Journal of Photogrammetry and Remote Sensing*, 152, 166–177.
2. Zhu, X. X., Tuia, D., Mou, L., Xia, G. S., Zhang, L., Xu, F., & Fraundorfer, F. (2017). Deep learning in remote sensing: A comprehensive review and list of resources. *IEEE Geoscience and Remote Sensing Magazine*, 5(4), 8–36.
3. Weng, Q. (2012). Remote sensing of impervious surfaces in the urban areas: Requirements, methods, and trends. *Remote Sensing of Environment*, 117, 34–49.
4. Chen, L. C., Zhu, Y., Papandreou, G., Schroff, F., & Adam, H. (2018). Encoder-decoder with atrous separable convolution for semantic image segmentation. *ECCV*.
5. Li, X., Zhou, Y., Asrar, G. R., Imhoff, M., & Li, X. (2020). The surface urban heat island response to urban expansion: A panel analysis for the conterminous United States. *Science of the Total Environment*, 605–606, 426–435.
6. European Space Agency (ESA). Sentinel-2 User Handbook.
7. United Nations (2019). *World Urbanization Prospects*.