Land Use and Land Cover Segmentation in Central Phoenix (2022–2025)

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Abstract

This project performs semantic segmentation of satellite images for the Central Phoenix region using Sentinel-2 multispectral data and the Dynamic World V1 land cover dataset. A U-Net deep learning model is trained to classify pixels into one of nine land cover classes, achieving high accuracy and generalization. The work highlights the use of Earth observation data for regional planning and geospatial analysis.

1 Introduction

Land Use and Land Cover (LULC) mapping is crucial for environmental monitoring, urban planning, and resource management. With advancements in remote sensing and deep learning, it has become feasible to automate large-scale segmentation tasks using satellite imagery. This project leverages Sentinel-2 imagery and the Dynamic World dataset to perform multi-class semantic segmentation for the Central Phoenix area between 2022 and 2025.

2 Study Area and Dataset

Region of Interest

- **Location**: Central Phoenix, Arizona, USA
- **Time Period**: January 2022 to January 2025
- **Resolution**: 10 meters

Input Data

- **Imagery Source**: Sentinel-2 (Bands: B2, B3, B4, B8)
- **Label Source**: Google Dynamic World V1
- **Classes (9)**: Water, Trees, Grass, Flooded Vegetation, Crops, Shrub & Scrub, Built Area, Bare Ground, Snow & Ice

3 Data Preprocessing

- Sentinel-2 values were scaled from raw reflectance to [0, 1]
- Missing values were handled with zero-filling
- Patches of size 256×256 were created for both images and labels
- A stratified 80/20 split was used for training and validation

4 Model Architecture

A custom U-Net architecture was implemented in TensorFlow/Keras:

- 3 downsampling layers (encoder)
- Bottleneck layer with 256 filters
- 3 upsampling layers (decoder)
- Skip connections between encoder and decoder
- Softmax output for 9-class pixel-wise classification

5 Training Setup

- **Loss Function**: Categorical Crossentropy
- **Optimizer**: Adam
- **Metrics**: Accuracy
- **Batch Size**: 8
- **Epochs**: 50
- **Callbacks**: ModelCheckpoint, ReduceLROnPlateau, EarlyStopping

6 Results and Evaluation

The model achieved strong segmentation performance:

- **Pixel-wise Accuracy**: 95.95%
- **Weighted F1 Score**: 95.50%
- **Mean IoU**: 92.79%

Underrepresented classes like Crops and Flooded Vegetation had lower recall. This is expected due to their class imbalance in the dataset.

7 Visualizations

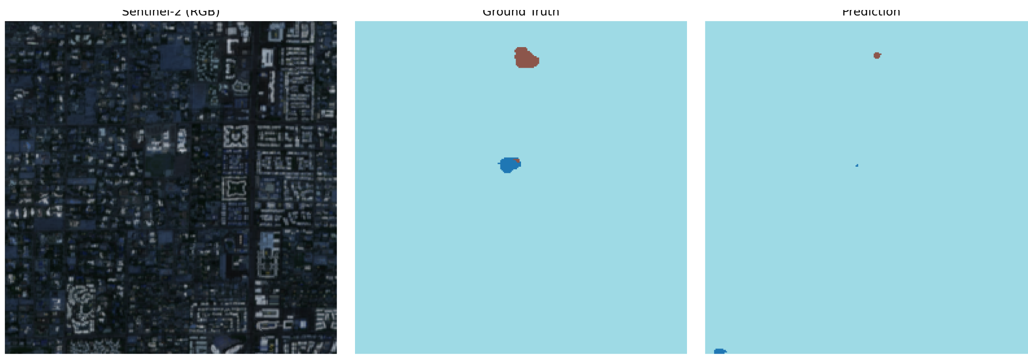

Figure 1: Comparison of Sentinel-2 RGB, Ground Truth, and Model Prediction

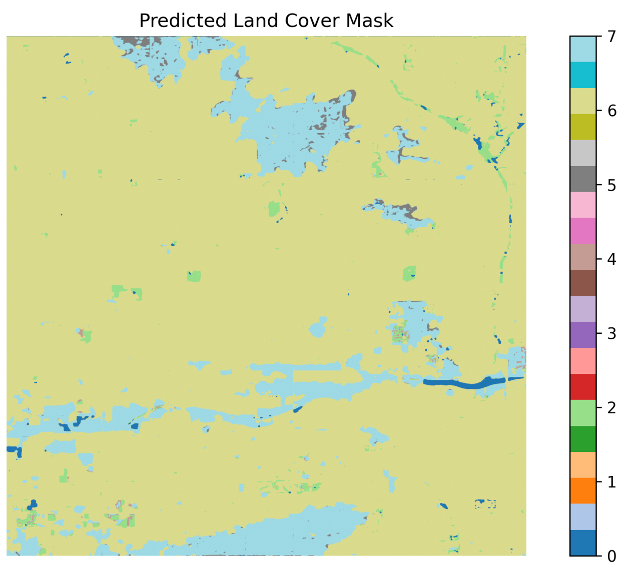

Figure 2: Stitched Full-Sized Prediction Map

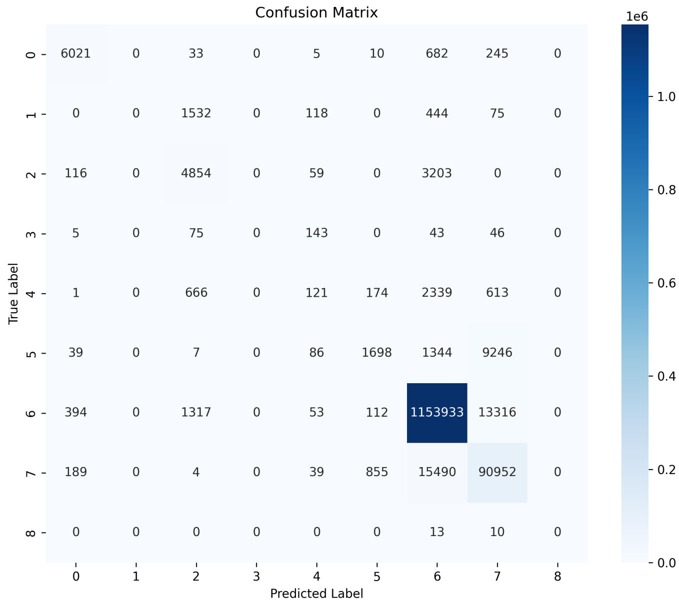

Figure 3: Confusion Matrix of Predicted vs True Classes

8 Conclusion

This project demonstrates the power of remote sensing combined with deep learning for accurate land cover segmentation. By leveraging openly available Sentinel-2 and Dynamic World datasets, we created a model capable of identifying urban and ecological features in Central Phoenix. Further improvements can include multi-temporal analysis and augmentation of underrepresented classes.

9 References

- Google Dynamic World: `https://dynamicworld.app`
- Sentinel-2 Data: `https://sentinel.esa.int`
- Ronneberger, O. et al., (2015). U-Net: Convolutional Networks for Biomedical Image Segmentation.

10 Model Architecture

The model is based on the U-Net architecture, a popular convolutional network design for biomedical and satellite image segmentation. It consists of an encoder (downsampling path), a bottleneck, and a decoder (upsampling path) with skip connections.

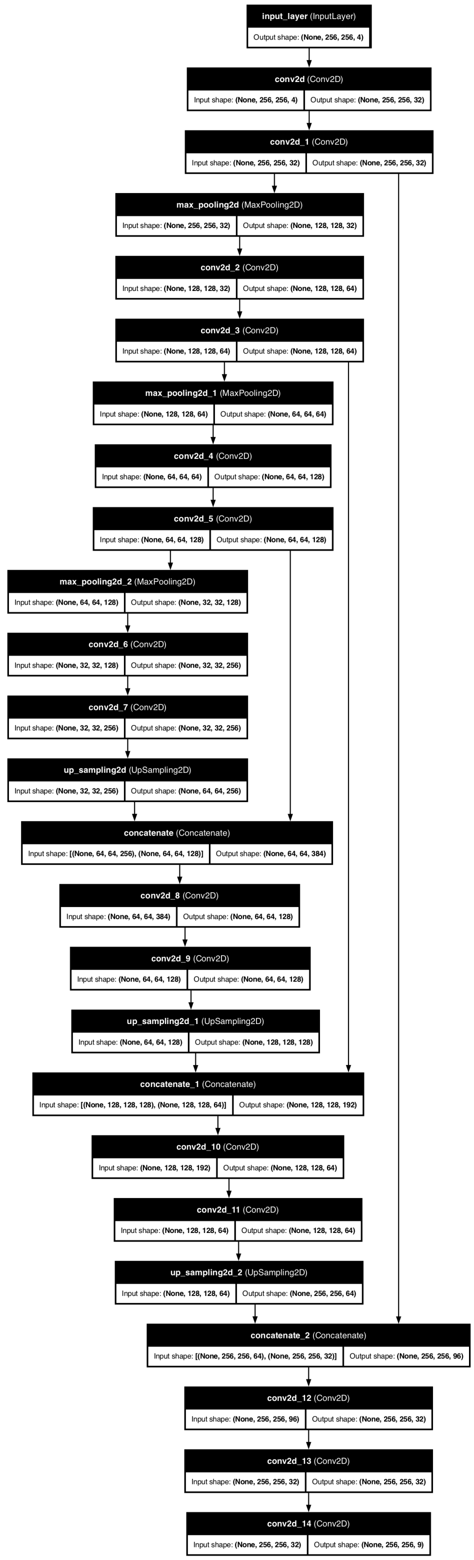

Figure 4: U-Net model architecture for 9-class land cover segmentation.

11 Future Work

While the current U-Net-based model achieves high overall performance in segmenting land use and land cover in Central Phoenix, there are several opportunities to extend and improve this work:

- **Multi-temporal Modeling:** Future versions can incorporate temporal sequences of Sentinel-2 imagery to capture seasonal or annual changes in vegetation, water bodies, and urban development. This may help improve classification in areas with dynamic land cover.
- **Class Imbalance Handling:** Some land cover types such as *crops* and *flooded vegetation* are underrepresented in the dataset. Applying techniques like focal loss, oversampling, or synthetic data augmentation could help improve the model's ability to generalize for rare classes.
- **Alternative Architectures:** More advanced architectures like ResUNet, DeepLabV3+, or Vision Transformers (ViTs) may offer improved segmentation accuracy, especially in complex urban settings.
- **Integration with GIS Systems:** Exporting predicted maps to vector formats or integrating with urban planning GIS tools could support real-world decision-making for sustainability and infrastructure planning.
- **Cross-region Generalization:** Testing the model's transferability to nearby cities or other desert urban regions could provide insights into its robustness and scalability.