

Cadastral Boundary Delineation Using Transfer Learning Approach

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ABSTRACT

The adoption of Fit-for-Purpose Land Administration aims at providing a flexible and low-cost alternative for cadastral boundary delineation that emphasizes visible boundaries derived from earth observation imagery. Recent advances show that deep learning can support the automatic delineation of visible cadastral boundaries. However, applications remain constrained by limited, small-scale datasets and weak understanding of which cadastral characteristics are identifiable. This study investigates the use of a transfer learning-based U-Net model to extract visible cadastral boundaries from high-resolution UAV imagery in a study area covering 200 hectares in Banepa Municipality, Nepal. The U-shaped model, pre-trained on agricultural field boundaries in Cambodia and Vietnam, and fine-tuned on 30 cm satellite imagery of the Terai region, was applied as a fixed classifier to UAV orthophotos at 3 cm, 15 cm, and 30 cm resolutions. A patch-based pipeline splits imagery into 512 X 512 tiles, predicts boundary masks, and converts them into vector polylines via morphological operations, skeletonization, and graph-based line extraction. Results indicate that coarser resolutions produce more generalized and cadastral-like parcel shapes, while finer resolutions capture detailed man-made features but suffer from over-segmentation. The 15 cm resolution yields the best overall performance, particularly in sub-urban areas, though the model struggles to form closed and complete polylines. Predicted boundaries align closely with visible features such as roads, fences, and cultivation edges. The outcomes suggest that deep learning-based workflows can generate preliminary boundary maps that can assist image-based cadastral mapping, reducing reliance on manual digitization and field visits, thus supporting the concept of fit-for-purpose approach in countries with incomplete and outdated cadastres.

1. INTRODUCTION

Land tenure security is fundamental to achieving the Sustainable Development Goals (SDGs) related to poverty reduction, food security, and gender equality (Unger et al., 2021). Despite its importance, approximately 75% of the world's population lacks access to formal land administration systems, a gap

most prevalent in developing nations where traditional systems remain unaffordable (Enemark et al., 2014; Zevenbergen et al., 2013). The absence of formal recognition to land leads to increased tenure insecurity, reduced investment, and stagnant economic development (Brasselle et al., 2002; Lawry et al., 2014).

Traditionally, cadastre—the central component of land administration—has relied on ground-based surveying using Total Stations (TS) and Global Navigation Satellite Systems (GNSS) to capture high-precision coordinates (UNECE, 1996; Williamson, 2002). While accurate, these methods are labor-intensive, expensive, and slow. Estimates suggest that at current rates, achieving full cadastral coverage in many countries would take centuries (Zevenbergen et al., 2013). Consequently, land administration experts advocate for Fit-for-Purpose Land Administration (FFPLA), a shift in focus from high-precision mapping to flexible, affordable, and scalable coverage (Enemark et al., 2014; Williamson, 2008).

The spatial framework of FFPLA emphasizes image-based mapping, leveraging the fact that many cadastral boundaries coincide with visible features like roads, fences, and cultivation edges (Luo et al., 2017). The broader adoption of FFPLA has encouraged innovative technologies, such as the use of Unmanned Aerial Vehicles (UAVs) to accelerate the mapping processes. The fit for purpose approach to map cadastral boundaries predominantly included participatory mapping using on-screen visual interpretation approaches, which despite being a viable alternative to fieldwork, is often tedious and prone to human inconsistencies (Crommelinck et al., 2018). To improve efficiency, researchers initially explored Object-Based Image Analysis (OBIA) and rule-based workflows, such as Multi-Resolution Segmentation (MRS) and Mean-Shift segmentation (Kohli et al., 2017; Y. A. Wassie et al., 2018). However, these methods often struggle with parameter selection and varying geographic terrains (Hossain & Chen, 2019).

Recent studies demonstrate that the fusion of earth observation and deep learning algorithms provides promising opportunities in automated visible parcel boundary delineation where the study areas are large and a large amount of datasets have to be processed (Crommelinck et al., 2019; Fetai et al., 2021; Grift et al., 2023). Among deep learning techniques,

Convolutional Neural Networks (CNNs) are popularly used in image interpretation tasks and object detection and offer higher accuracy in delineating cadastral boundaries than traditional edge detection and image segmentation approaches (Xia et al., 2019; Fetai et al., 2022).

Within the deep learning domain, the task of cadastral boundary delineation is formulated as a semantic segmentation problem, as it requires the assignment of class labels at the pixel level to identify boundary regions. Fully Convolutional Network (FCN), first introduced by Long et al. (2015), adapts CNN architectures by replacing fully connected layers with convolutional layers, enabling dense, pixel-wise predictions for inputs of arbitrary size. The encoder–decoder structure, combined with skip connections, facilitates the preservation and recovery of spatial information, making FCNs particularly effective for semantic segmentation tasks.

Among FCN architectures, U-Net, proposed by Ronneberger et al. (2015), has been extensively adopted in cadastral and field boundary extraction studies. U-Net offers a good balance between segmentation accuracy and computational efficiency. Its symmetric encoder–decoder design with skip connections supports precise spatial localization, which is critical for accurate pixel-level delineation of cadastral boundaries.

Despite the significance of such architectures, challenges in widespread application remains. High-quality cadastral benchmark datasets are scarce, and the performance of these algorithms across different geographic locations is not well understood (Grift et al., 2023). Transfer learning—the process of taking a model trained on a data-rich source and fine-tuning it for a new task—offers a way to overcome data scarcity and speed up automation (Bashath et al., 2022).

Building upon this paradigm, this study employs a U-Net architecture previously trained on a large agricultural benchmark dataset AI4Small Farms created by Persello

et al. (2023), and fine-tuned on a visible boundary dataset from the Terai region of Nepal. This transfer-learning based model is utilized to extract visible cadastral boundaries in Banepa Municipality using UAV imagery at three resolutions—3 cm, 15 cm, and 30 cm. By testing these different resolutions, the study investigates how varying image resolutions and local geographic characteristics influence the transferability and accuracy of deep learning models, while qualitatively assessing their ability to identify visible boundaries in urban and sub-urban areas.

2. MATERIALS AND METHODS

2.1. Image data

Literature indicates that deep learning methods exhibit higher performance in regions with visible cadastral boundaries, which are predominantly found in rural and semi-urban settings. For this study, we have selected a 200-hectare site (Figure 1) within ward 10 of Banepa Municipality of Kavrepalanchok District. This area encompasses diverse topographic variations such as low land, gentle slopes to steep hills, and mixed land use types including residential, agricultural and forested zones.

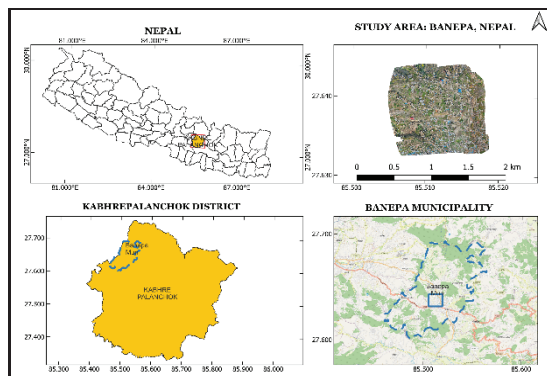


Figure 1. Study area

The UAV images were captured using a DJI Mavic Pro drone at a flight altitude of 100 m, with 70% overlap between images. The data were processed in Pix4D mapper to create an ortho-mosaic (with a spatial resolution of 3 cm and a digital elevation model (DEM) at 10 cm resolution derived from a photogrammetric point cloud. An ortho-mosaic was produced

using the DEM. Horizontal and vertical accuracies were assessed by comparing coordinates of five ground control points (GCPs) and three independent checkpoints, surveyed via static differential global positioning system (DGPS) observations with Trimble R 7 receivers. Raw GNSS data were post-processed in Trimble Business Center software, yielding a root mean square error (RMSE) of 0.006 m during ortho-mosaic georeferencing.

The UAV orthophoto was further down-sampled to 30 cm and 15 cm resolutions using average resampling, as the original model was trained on 30cm imagery. This allowed testing transfer learning performance on resolutions differing from the training data; 15 cm was selected as an intermediate value between the original resolution 3 cm and 30 cm.

2.2. Transfer learning approach

In the context of transfer learning, pre-trained models are trained on benchmark datasets that combine images with corresponding labels. This strategy is used extensively to address two major requirements of deep learning models—1) vast amounts of labeled datasets and 2) resource-intensive computational resources—to train models effectively. Common approaches include using the pre-trained model directly as a classifier (no retraining needed); as a feature extractor (freezing convolutional layers while retraining the classifier); or via fine-tuning (retraining some or all layers for the new task) (Elgendy, 2020). In this study, we used the pre-trained model solely as a classifier to delineate visible boundary features in UAV imagery that potentially correspond to cadastral boundaries.

2.3 Model and weights

The model architecture employed in this study is a modified U-Net designed specifically for satellite image segmentation. The model was pre-trained on the AI4SmallFarms dataset by Persello et al. (2023), which comprises high-resolution Google Maps imagery and 439,001 agricultural field polygons spanning diverse agricultural landscapes in Vietnam

and Cambodia. The network was fine-tuned on a 30 cm resolution satellite imagery dataset of visible cadastral boundaries, digitized by experts to represent cadastral features in Nepal's Terai region.

2.4 Model pipeline

The processing pipeline consists of four key steps implemented via dedicated Python modules (Table 1).

Table 1. Pipeline modules and description

Step	Module	Description
1	patch.py	Split study area image into 512 * 512 pixel patches
2	data_generator.py	Load images/masks with on-the-fly augmentation (flip, rotate)
3	georeferenced_predictions.py	Generate geo-referenced raster predictions
4	polygonize.py	Skeletonize → graph extraction → vector polylines

Key components:

Config.py manages central configuration including data paths, hyperparameters (BATCH_SIZE=2, EPOCHS=100, LEARNING_RATE=0.0001), and training models (FROM SCRATCH or PRETRAINED_WEIGHTS).

data_generator.py implements a DataGenerator class extending tf.keras.utils.Sequence for efficient batch loading, with augmentations: horizontal/vertical flips, 0-360° rotations) and normalization options (min-max, z-score, or log).

models/satellite_unet.py deploys keras_unet.models.satellite_unet, supporting training from scratch or fine-tuning, optimized with Jaccard Loss and metrics (Recall, Precision, F1 score, IoU)

2.5 Vectorization pipeline

The polygonize.py module converts binary segmentation masks into GIS-compatible

vectors through morphological operations (dilation to connect fragments, erosion to remove artifacts), skeletonization to one-pixel lines, graph-based extraction using sknw (pixels as nodes, adjacency as edges), and Douglas-Peucker simplification (0.6 m tolerance).

2.6 Experimental setup

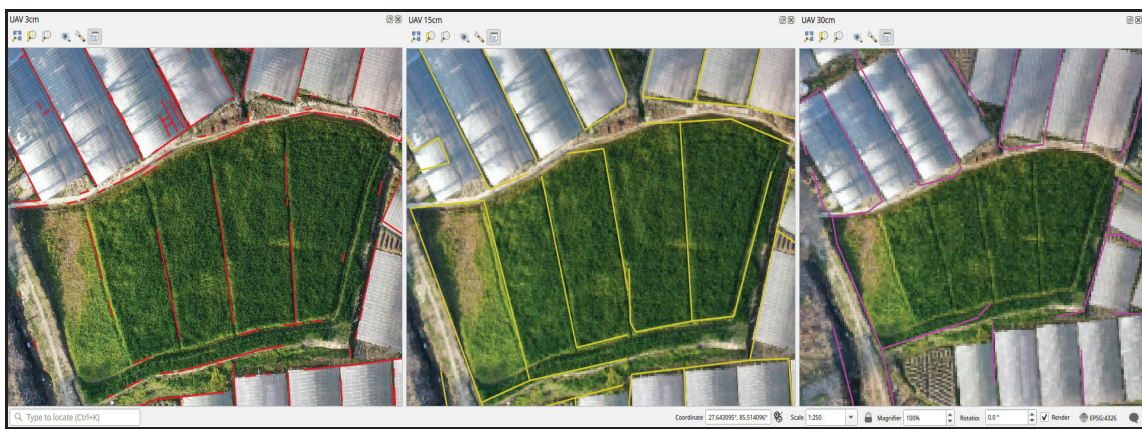
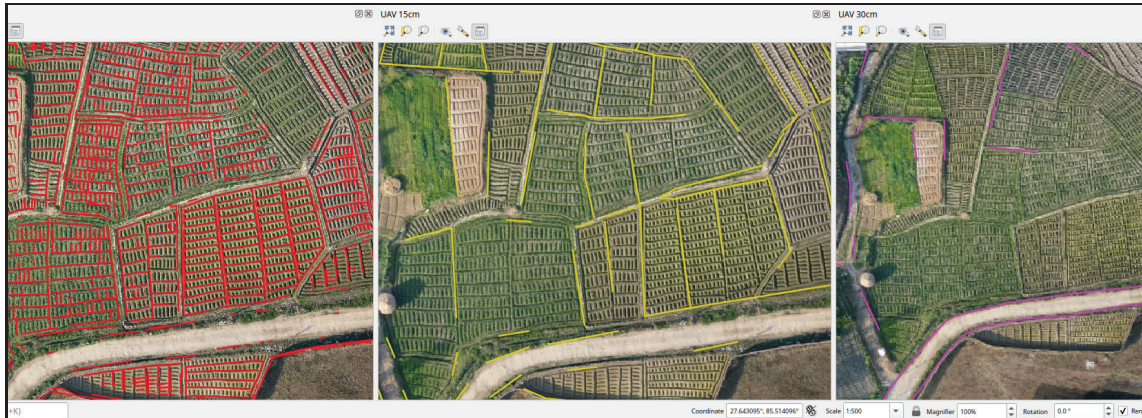
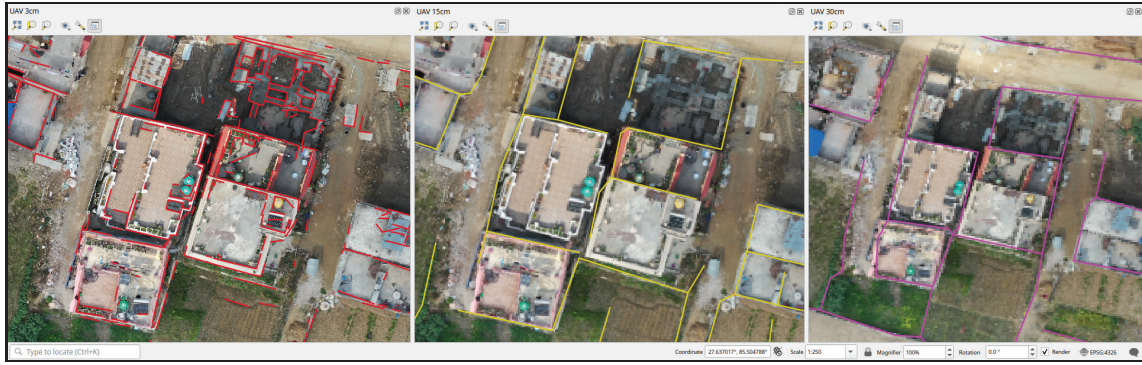
The model was implemented using a robust hardware and software stack. The hardware configuration includes a high-performance computing system equipped with an **Intel Core i7-13700H CPU** (13th Gen, 20 threads, 2.4GHz) and **32 GB of RAM**. To handle the intensive computational requirements of the transfer learning model, an **NVIDIA GeForce RTX 4060 GPU** was utilized.

The model inference was performed on **Windows 11** operating system using Python 3.10.1 in a **virtual environment (venv)**, with **TensorFlow 2.10.1**. To leverage the GPU capabilities, **CUDA 11.2** and **cuDNN 8** were configured as the parallel computing platform and deep neural network library, respectively.

TensorFlow 2.10.1
virtual environment (venv) for dependency management
Python 3.10.1
Windows 11 operating system
cuDNN 8
CUDA 11.2
NVIDIA GeForce RTX 4060 GPU and 13th Gen Intel Core i7-13700H CPU (20 threads, 2.4GHz) and 32 GB of RAM.

3. RESULTS AND DISCUSSION

The classifier generated georeferenced vector polylines from binary masks. Figure 2 shows predicted boundaries overlaid on UAV orthophotos at 3 cm, 15 cm, and 30 cm resolutions across 17 representative tiles. Due to unavailable reference cadastral data, evaluation relied on qualitative visual assessment focusing on boundary alignment, completeness, and processing efficiency.



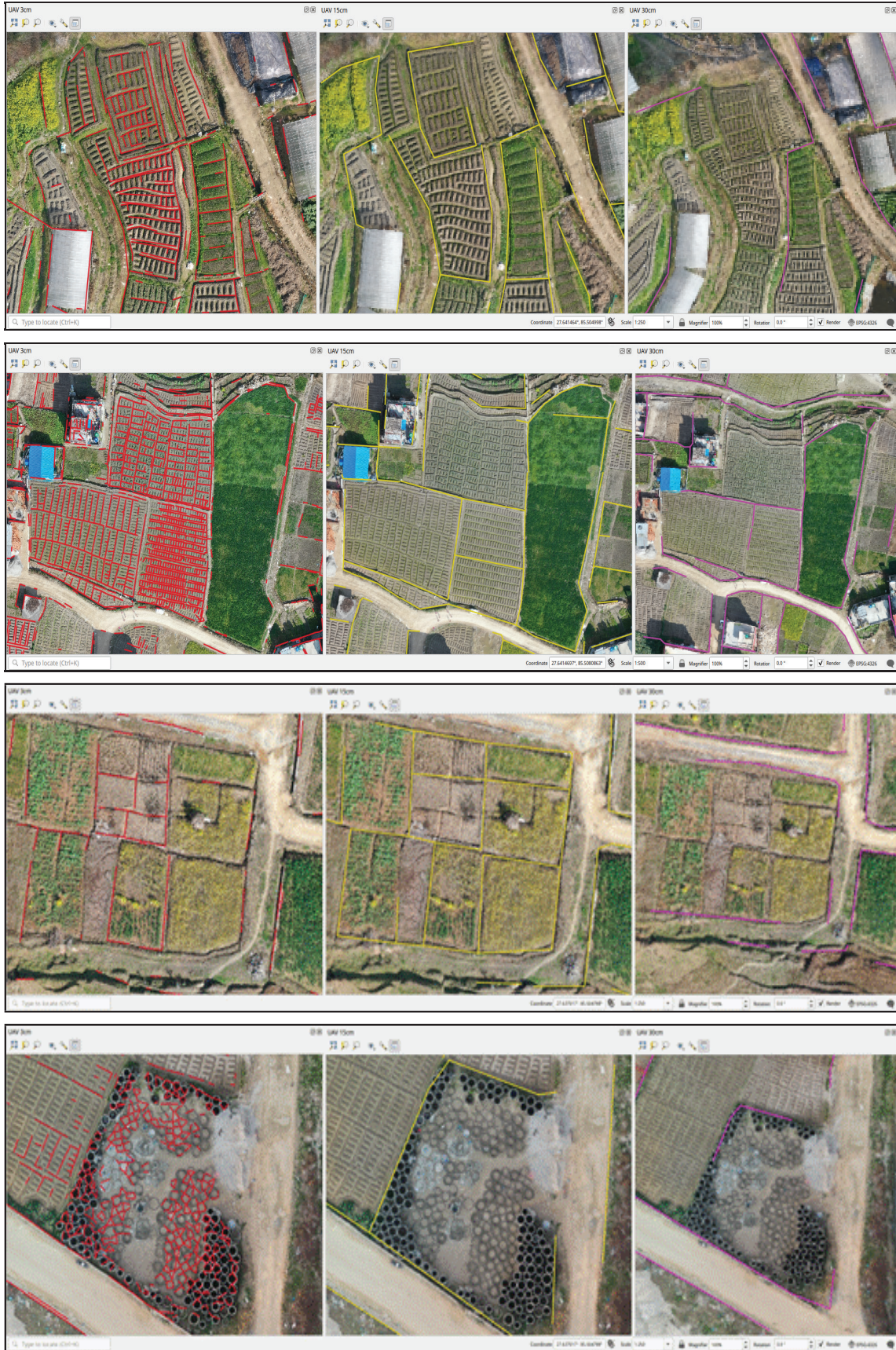






Figure 2. Predicted boundary polylines (colored overlays) generated by the classifier, shown overlaid on UAV orthophotos at 3 cm, 15 cm, and 30 cm resolutions

The 3 cm UAV imagery required the longest processing time, with the full pipeline completing in 2 hours and 55 seconds. At this resolution, the model predicted clear, man-made boundaries, such as fences and well-structured plots. However, a drawback of the model was that it frequently interpreted minor spatial variations such as temporary agricultural divisions and subtle textural changes as parcel boundaries. This resulted in over-segmentation, producing fragmented parcel divisions that deviated from real cadastral representations.

The 30 cm UAV imagery achieved the fastest processing time, completing the entire pipeline in approximately 40 seconds. At this resolution, the model generated more generalized parcel representations, emphasizing the dominant land-cover classes. Linear features such as roads were identified more effectively compared to other resolution.

The 15 cm UAV imagery provided a balance between spatial detail and generalization, yielding the most promising overall results. The pipeline completed in 4 minutes and 6 seconds, significantly faster than the 3cm data while offering more details than the 30 cm imagery. Nevertheless, the model had some limitations. The model tended to generate extra segments around buildings, and while boundary segments were often detected, complete parcel polylines were not consistently formed. The extraction quality was also strongly influenced by land cover: green land cover patches were typically extracted as complete and closed polylines, whereas bare land cover patches were extracted only as partial segments.

Comparing the length of the extracted line segments, the model made more predictions on 3cm imagery. At 15 cm and 30 cm resolutions, longer and continuous line segments were produced. This suggests that higher imagery resolution limits the model's ability to delineate and connect linear features.

Table 2. Processing times and segment lengths by resolution

Resolution	Processing Time	Total Segment Length (km)
3 cm	2h 55m	258,447
15 cm	4m 6s	132,072
30 cm	40 s	74,163

3.1. Interpretation

The visual assessment reveals that predicted polylines align closely with physically visible features (fences, cultivation edges, roads, etc.) across resolutions. The authors interpret the model outputs as a reflection of current ground reality better than potentially outdated official records, which often include legal constructs without physical markers. A basic observation suggests that at different resolutions different granularity is observed.

3cm	15cm	30cm
Plots	Farms	Roads

The predicted boundaries can support Nepal's UAV-based cadastral mapping by automating the initial delineation of visible cadastral boundaries. Addition of an automated step in the pre-survey phase could offer several practical advantages.

1. First, it helps field teams start with a clearer visual reference, reducing uncertainty and speeding up the adjudication process.
2. Second, it allows technical staff to shift effort from drawing parcel boundaries by hand to verifying and adjusting model outputs, which is generally faster and less error-prone.
3. Third, it helps to maintain consistency across different survey areas and survey teams.

This approach aligns with contemporary research on cadastral data maintenance.

Fetai et al. (2022) suggest that automatically detected visible physical boundaries can serve as preliminary digital spatial boundaries, which field teams can subsequently refine through either manual adjustment using UAV imagery or ground surveys. However, it should be understood that deep learning excels where visible boundaries predominate but it cannot capture legal cadastral constructs lacking physical expression such as fragmented administrative divisions or outdated records without ground markers. Multiple studies confirm this fundamental limitation and suggest that deep learning is effective only for visible boundaries (Y. Wassie et al., 2016); there is a need to quantify visible vs. invisible boundary proportions in benchmarks, as legal cadastral data often diverges from topographical reality (Grift et al., 2023).

3.2 Limitations

1. Due to the lack of reference data for quantitative comparison, evaluation metrics namely, precision, recall and F-score are not computable.
2. This study used the pre-trained model as a classifier, fine-tuning with a locally representative dataset can enhance the output.
3. The UAV orthophoto contained shadowed areas caused by variations in illumination and object height. These shadows may have affected the spectral characteristics of certain features, leading to potential misclassification and reduced accuracy in shaded regions.
4. The model was trained on a representative dataset for flat terrain in Cambodia, Vietnam and fine-tuned in the dataset of Chitwan, so it is not able to detect terraces in hilly areas, although terrace features are visible features in UAV images. Fine-tuning the model on a representative terrace dataset should result in better model prediction.

4. CONCLUSION

The results show that the transfer learning-based U-Net model, used as a fixed classifier, can extract visible cadastral boundaries from UAV imagery. Resolutions of 3 cm, 15cm and 30 cm were tested, with 15 cm offering the best balance between detail and generalization. Processing times range from 40 seconds for 30 cm resolution to 2h55m for 3 cm resolution across the tested resolutions, offering substantial gain in terms of time consumed over manual digitization. These exploratory qualitative findings demonstrate the utility of automated preliminary mapping within Nepal's image-based cadastral re-surveying workflows, particularly by providing field teams with clear visual references and reduce manual digitization effort. This approach aligns with and supports the spatial framework of Fit-for-Purpose Land Administration for regions with incomplete/outdated cadastral coverage.

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