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Visible Cadastral Boundary Delineation in Data-Scarce Countries using Data from Neighboring Data-Rich Countries

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Abstract

Accurate cadastral maps are essential for effective land administration, supporting tenure security, land management, and socio-economic planning. Automating cadastral boundary extraction can accelerate mapping in regions with incomplete or absent cadastral information, but deploying pretrained models in data-scarce areas is challenging due to limited reference data and heterogeneous landscapes. In this study, we investigate cross-region transfer learning for delineating cadastral boundaries using high-resolution aerial imagery. We employ *CadNet*, a U-shaped deep learning model with a Swin Transformer backbone pretrained on the Dutch *CadastreVision* dataset, and fine-tune it using Polish cadastral reference data selected for landscape similarity to a data-scarce region in northern Moldova. Evaluation on Moldovan test tiles demonstrates substantial quantitative improvements: recall for visually discernible boundaries increases from 0.310 to 0.624, total vector-based discrepancy via Normalized Discrepant Area decreases from 7.898 to 7.051. Qualitatively, fine-tuning produces more continuous and coherent boundaries, recovers interior parcel divisions, and better aligns predicted parcel structures with ground truth, compared to the pretrained model, which generates fragmented and incomplete boundaries. These results highlight the importance of landscape similarity and reference data quality for transfer learning and demonstrate a scalable framework for automated cadastral mapping in regions with similar landscape characteristics.

1. Introduction

Cadastral mapping, the documentation of land parcels and property rights, is a cornerstone of land administration, supporting tenure security, land management, and socio-economic planning (UN-Habitat, 2012). Traditional field-based surveying methods, while accurate, are time-consuming and resource-intensive, particularly across large or remote areas (Zevenbergen et al., 2015). High-resolution aerial imagery, combined with automated methods, offers a scalable alternative, enabling the extraction of visible cadastral boundaries and the production of up-to-date initial cadastral maps with reduced reliance on extensive ground surveys (Enemark et al., 2014, 2016). Recent advances in deep learning have further enhanced automated cadastral boundary delineation, achieving relatively high accuracy in extracting both raster and vector representations from aerial imagery (Crommelinck et al., 2019; Xia et al., 2019; Grift et al., 2023; Hosseini et al., 2025; Tareke et al., 2023). However, the applicability of such models is often constrained by the availability of labeled training data and differences in landscape morphology or cadastral systems, which limit transferability to new regions. Transfer learning presents a promising solution, allowing models trained in one geographic context to be adapted to others where annotated data are scarce or unavailable (Nowakowski et al., 2024; Ji and Tang, 2025).

In this study, we use the deep learning model *CadNet* (Grift et al., 2025) to investigate cross-region transfer learning for delineating cadastral boundaries. Specifically, we assess: (i) the ability of a model pretrained on the Dutch *CadastreVision* dataset (Grift et al., 2024) to transfer to a data-scarce region in northern Moldova, and (ii) the effect of fine-tuning using Polish cadastral data selected for landscape similarity. For this research, the Moldovan region was selected because, although reference cadastral data exist, the area still contains unmapped or inconsistently mapped boundaries, providing a realistic setting in which to evaluate model transferability. Importantly, no annotated data from the Moldovan test area is used for training, enabling an unbiased assessment of cross-region transferability. To our knowledge, this is the first study that evaluates transfer learning for cadastral mapping across multiple European regions.

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2. Study areas

The test study area comprises the Donduseni district in northern Moldova, which borders Ukraine directly. The region is dominated by extensive agricultural land, supported by fertile soils that cover approximately 75% of the national territory (World Bank, 2010; Shaker, 2018). Its cultural landscape features large consolidated fields, linear and gridded rural settlements, a well-developed local road network, and small, fragmented forest patches along drainage lines and field margins. In a broader European context, the area belongs to the *Continental Hills / Sediment / Arable Land* landscape class (Mücher et al., 2010), extending across central and eastern Poland, western Ukraine, Romania, and Moldova (Figure 1). This type of landscape is characterized by rolling hills formed on sedimentary deposits within the *Continental* bioclimatic zone, where warm summers and cold winters favor intensive crop production.

The Polish study area is located in the Lublin region of eastern Poland and was selected for its strong landscape similarity to the Moldovan test area. Agriculture is dominated by small, highly fragmented farms, with an average farm size of 7.7–7.8 ha, below the national average (Baran-Zgłobicka and Zgłobicki, 2012; Zgłobicki et al., 2020). Permanent crops, particularly apple orchards and berry plantations, are widespread, while forests occur mainly in the southern and eastern parts as large continuous complexes. Dispersed villages, linear and gridded

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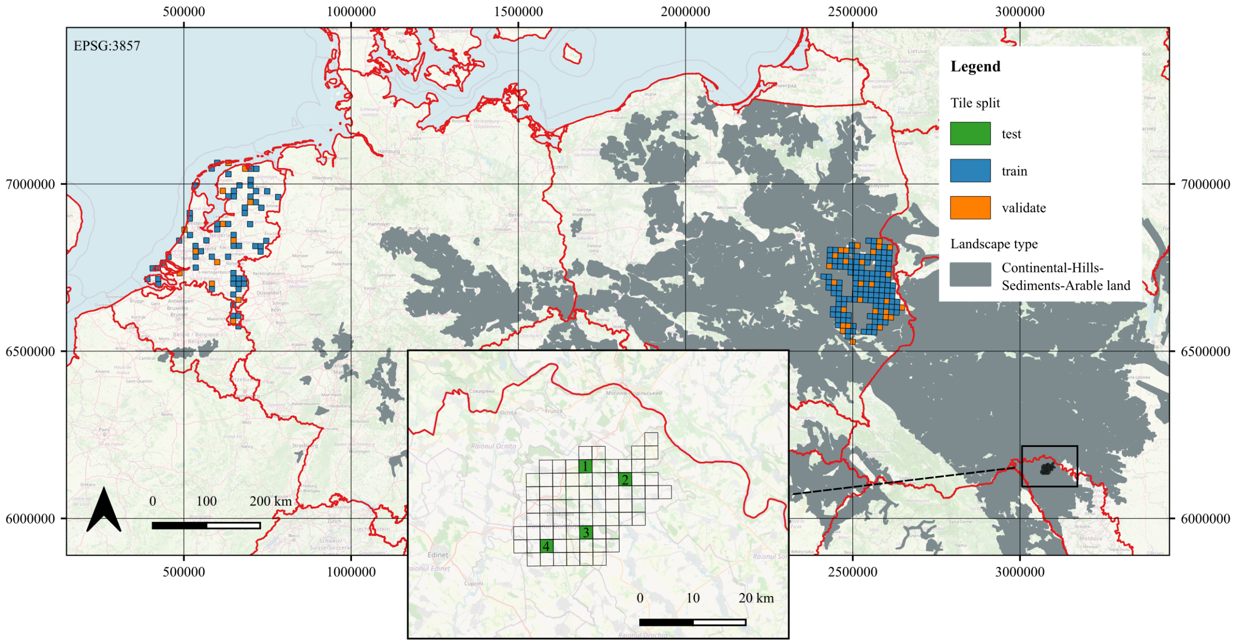

Figure 1. Study areas (the Netherlands, Moldova, and Poland) and dataset splits. The landscape type *Continental Hills / Sediment / Arable Land* (shown in grey) covers large parts of eastern Poland and northern Moldova. The Moldavan test set contains 4 tiles of 2.5 x 2.5 km (shown in green).

rural settlements, and an extensive network of local roads define the cultural landscape. In the broader European context, this region also falls within the *Continental Hills / Sediment / Arable Land* landscape class, making it comparable to the Moldovan study area.

The Dutch *CadastreVision* dataset covers 19 different cultural landscapes in the Netherlands, providing a benchmark with substantial variability in settlement, forest, road, water, and agricultural structures (Haartsen, 2010). Settlements include dispersed farmsteads, linear villages, and compact towns, while forests comprise small copses, linear wooded banks, and larger continuous blocks. Road networks range from dense urban grids to rural tracks, and water management features such as dikes, canals, and drainage channels are widespread. Agricultural fields range from small, irregular plots in reclaimed peat and clay regions to large rectangular polder fields, often bounded by hedgerows or ditches.

3. Data

Building on the study areas described above, this section details the imagery and reference data used for each region. This study draws on three primary datasets: the Moldovan, Polish, and Dutch *CadastreVision* dataset (Grift et al., 2024). The Moldovan dataset consists of orthophotos acquired between 2016 and 2021 at an original spatial resolution of 20 cm, resampled to 25 cm to ensure consistency across datasets (AGCC, 2021). The Corresponding cadastral reference data was collected from 2001 onward (AGCC, 2025). From this region, four 2.5 × 2.5 km tiles in the Donduseni district were selected as the test set (green numbered tiles in Figure 1). These tiles encompass a mixture of semi-urban and rural landscapes and were chosen for their complete cadastral coverage. In contrast, several surrounding tiles (shown as transparent in Figure 1) lack full boundary coverage, reflecting the broader data scarcity in the region and highlighting areas where automated boundary extraction could support future cadastral mapping efforts. Within the four selected tiles, the cadastral reference data include both boundaries that are visually observable in the imagery and boundaries that are not. To enable a quantitative evaluation of visible boundary extraction, all reference boundaries were manually classified as visible or invisible by direct comparison with orthophotos.

The Polish dataset comprises high-resolution orthophotography acquired in 2024 at 25 cm resolution, paired with openly available cadastral boundaries (GUGiK, 2024, 2025). It spans 185 tiles of 10 × 10 km, providing extensive coverage of the Lublin region. For model development, the dataset was split into 129 training tiles, 28 validation tiles, and 28 test tiles.

The *CadastreVision* dataset consists of 25 cm aerial imagery and cadastral boundary annotations collected in 2022, covering 90 tiles of 10 × 10 km (Grift et al., 2024). The sampling strategy captured a diverse range of cultural landscapes, including both visually clear physical boundaries and more ambiguous legal boundaries that lack explicit markers. For this study, 63 tiles were used for training, 13 for validation, and 14 for testing.

To facilitate deep learning model training, all tiles were subdivided into 512 × 512 pixel patches, sampled across the tiles to reduce computational costs. Table 1 summarizes the final patch counts used for training, validation, and testing.

Country	pixel size (cm)	train patches	validation patches	test patches
The Netherlands	25	48599	10002	-
Poland	25	12076	2621	-
Moldova	25	-	-	6084

Table 1. Imagery specifications and patch counts. For the Netherlands and Poland, the table reports the training and validation patches used for pretraining. For Moldova, only test patches are listed, as this dataset was used solely to evaluate model transferability.

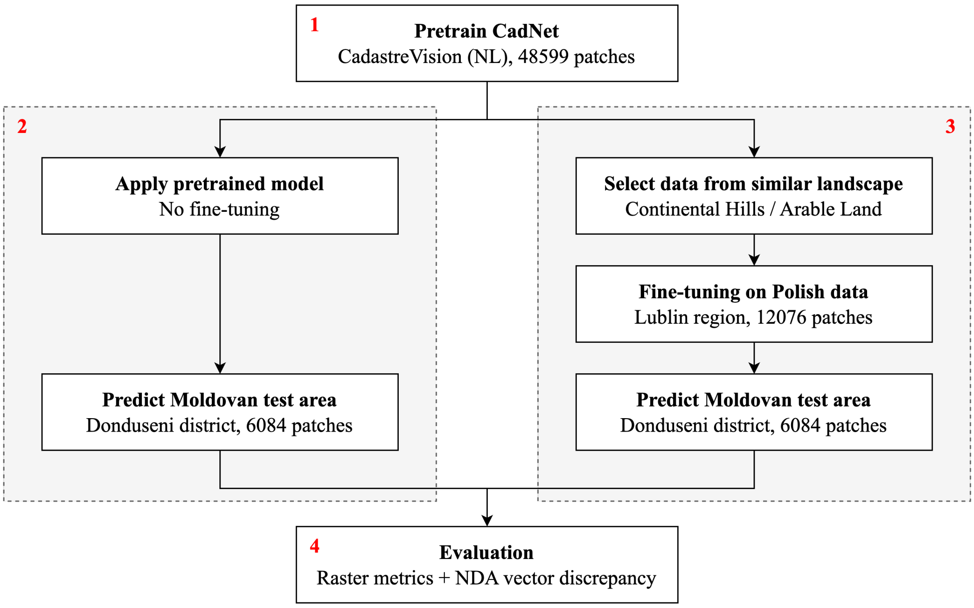

Figure 2. Proposed workflow: (1) pre-training *CadNet* on *CadastreVision*; (2) direct transfer to the Moldovan test area without fine-tuning; (3) fine-tuning with data from the Lublin region (similar landscape) before making predictions; and (4) evaluation on the Donduseni district using raster metrics and vector discrepancy measures.

4. Methodology

This section describes the model architecture, training procedure, and evaluation configurations used to assess cross-region transferability. To assess this, we employ *CadNet*, a transformer-based deep learning model designed for extracting cadastral boundaries from high-resolution aerial imagery (Grift et al., 2025). *CadNet* adopts a U-shaped encoder–decoder architecture with a Swin Transformer backbone pretrained on ImageNet-22k, providing strong high-level feature representations for boundary detection. Boundary continuity is supported through mechanisms that propagate predictions across decoder stages and integrate multi-scale contextual information. The network produces pixel-wise probability maps through dedicated segmentation and connectivity heads. These outputs are post-processed through thresholding, morphological filtering, and skeletonization to obtain one-pixel-wide boundary masks, which are subsequently converted into graph structures and vectorized using the Douglas–Peucker algorithm to generate sparse polyline representations.

The training and evaluation procedure consists of four main stages (Figure 2). First, *CadNet* is pretrained on the Dutch *CadastreVision* dataset using the Adam optimizer with a learning rate of 0.0001 and a batch size of 8. Second, the resulting pretrained model is applied directly to the Moldovan test area (NL configuration), enabling out-of-distribution performance assessment without local annotations. Third, to improve transferability, the pretrained model is fine-tuned using Polish cadastral data selected for its landscape similarity to northern Moldova (NL+PL configuration). Fine-tuning updates all model weights using the same optimization settings, a configuration that proved most effective, allowing the model to retain general feature representations while adapting to region-specific landscape patterns. Finally, the fine-tuned model is then evaluated on the same Moldovan test tiles, and its predictions are compared with those from the NL configuration to quantify the benefits of targeted domain adaptation.

Raster predictions are evaluated using standard classification metrics: precision, recall, and F1 score. Vector prediction quality is quantified using the Normalized Discrepant Area (NDA) metric (Shi et al., 2003), which measures geometric disagreement between predicted and reference boundaries. NDA performs a bidirectional comparison: first treating the reference data as the baseline, then treating the predictions as the baseline. In each direction, line sets are discretized at 10cm intervals, and for every sampled point, the nearest point on the opposing line set is identified. The connecting segments are buffered and merged to form a discrepant area, which is then normalized by the smaller of the total buffered areas. Summing the two normalized values produces a symmetric, scale-independent measure of geometric error. NDA is particularly suitable for sparse

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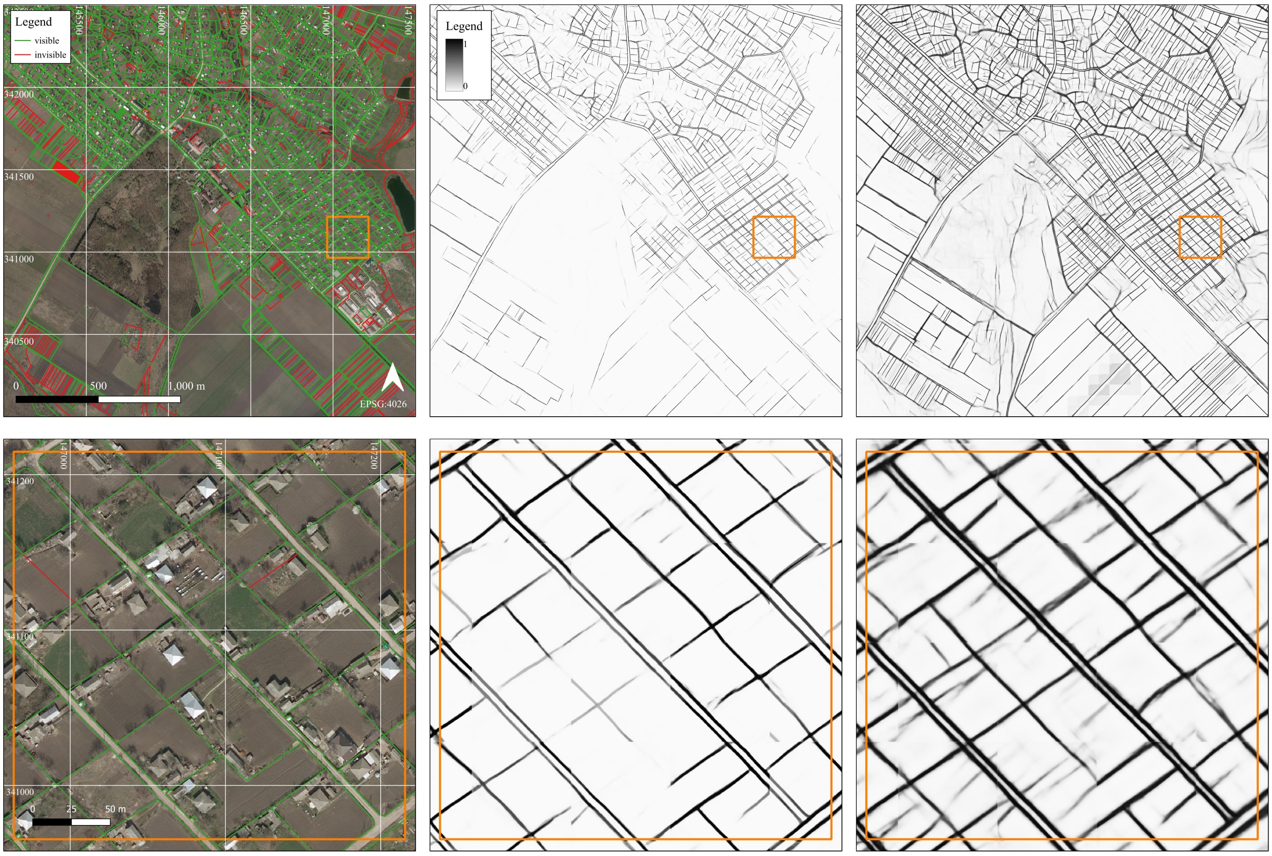
Configuration	Precision	Recall	F1	Recall visible
NL	0.349	0.201	0.255	0.310
NL+PL	0.213	0.415	0.282	0.624

Table 2. Raster-based performance metrics for both model configurations. Visible-boundary recall was computed exclusively for the visible boundary class.

Configuration	NDA reference	NDA prediction	Total NDA	NDA visible reference
NL	7.033	0.865	7.898	2.725
NL+PL	4.497	2.554	7.051	1.025

Table 3. Vector-based discrepancy metrics (NDA) for the NL and NL+PL configurations.



(a) Reference (b) NL (c) NL+PL

Figure 3. Raster predictions for the two model configurations on the test tile in Moldova (tile 3 in Figure 1). Top row: full tile comparison of (a) the annotated cadastral reference, with visible boundaries shown in green and invisible boundaries in red, (b) predictions from the NL configuration, and (c) predictions from the NL+PL configuration. Bottom row: enlarged views of the orange boxed area shown in the corresponding panels of the top row. The zoomed-in comparison highlights the denser, more continuous boundary predictions produced by the NL+PL configuration.

linear boundary networks, where polygon-based metrics are inapplicable.

Because all model configurations predict a single boundary class and do not distinguish between visible and invisible boundaries, completeness remains the primary metric for evaluating performance across these categories. In practice, this corresponds to the raster-based recall of visible boundaries and to the NDA component, which uses reference data as the baseline to quantify missed or partially captured boundaries.

5. Results

Raster-based evaluation (Table 2) reveals clear differences between the two model configurations. The fine-tuned model (NL+PL) achieves substantially higher recall (0.415) and visible-boundary recall (0.624), indicating improved detection

(a) Reference (b) NL (c) NL+PL

Figure 4. Vectorized boundary predictions of tile 1 (Figure 1) of the Moldovan test set. Top row: (a) cadastral reference with visible boundaries in green and invisible boundaries in red, (b) the NL configuration predictions (yellow), and (c) the NL+PL configuration predictions. Bottom row: enlarged views of the orange boxed area, showing that the NL+PL configuration produces denser, more coherent vector networks with improved recovery of interior parcel subdivisions, whereas the NL configuration yields sparse and fragmented polylines with frequent gaps.

of physically observable cadastral boundaries. This improvement comes at the cost of reduced precision (0.213), reflecting a higher number of false positives, whereas the Netherlands-pretrained model (NL) is more conservative, yielding higher precision (0.349) but substantially lower recall (0.201). These results suggest that fine-tuning enhances boundary completeness at the cost of additional detections, whereas the pretrained model captures only the most salient edges. Vector-based evaluation using the NDA metric (Table 3) confirms these trends. The NL+PL configuration achieves a lower total NDA (7.051) than the NL configuration (7.898), indicating a better alignment with the reference boundaries. For reference-based evaluation, the NL+PL configuration also outperforms the NL configuration (4.497/7.033), while visible-boundary discrepancies are similarly reduced (1.025/2.725). The NL configuration shows a slightly lower discrepancy when using predictions as the baseline (0.865/2.554), reflecting its conservative predictions. Overall, the NL+PL configuration demonstrates improved completeness and closer correspondence with ground truth geometry.

Qualitative inspection (Figures 3 and 4) illustrates that the NL configuration captures general parcel layouts but produces fragmented boundaries, particularly in built-up areas and homogeneous agricultural fields. Physical features such as roads, hedgerows, and irrigation channels are often detected, whereas interior parcel divisions are often missed, leading to irregular, misaligned boundaries. Fine-tuning with Polish data substantially improves raster predictions: boundaries are more continuous and closely follow local parcel patterns, recovering numerous interior divisions absent in NL. In vector form, the NL configuration produces sparse, fragmented, and inconsistent predictions. Many parcels are merged or simplified, and segments in built-up areas often fail to form closed polygons. In contrast, the NL+PL configuration generates denser, more coherent vectors that better capture both large-scale block structures and finer interior subdivisions. Agricultural and residential parcels are extracted with improved alignment, continuity, and completeness.

6. Discussion

This study demonstrates the potential of cross-region transfer learning for automated cadastral boundary delineation in regions with limited reference data. The pretrained *CadNet* model captures general parcel layouts but produces fragmented and incomplete boundaries, particularly in densely built areas and homogeneous agricultural landscapes. Fine-tuning the pre-trained model on Polish cadastral data selected for landscape similarity substantially improves both raster and vector outputs, resulting in denser, more continuous boundaries, improved recovery of interior parcel divisions, and closer alignment with reference data. These findings suggest that landscape similarity plays an important role in enabling effective knowledge transfer between regions. However, absolute precision, recall, and F1 scores remain modest relative to typical remote sensing segmentation tasks. This reflects intrinsic challenges in cadastral boundary extraction: many boundaries are not visually represented in aerial imagery, visible boundaries exhibit high heterogeneity (e.g., ditches, buildings, waterways), and boundary pixels constitute a sparse, thin class relative to the background.

Quantitative evaluation also reveals a trade-off between completeness and precision. The fine-tuned model (NL+PL) achieves higher overall boundary recall (0.415/0.201) and markedly higher visible-boundary recall (0.624/0.310), indicating improved detection of physically observable cadastral limits, but at the cost of increased false positives relative to the pretrained baseline (NL). Nevertheless, the higher F1 score for the NL+PL configuration suggests that the improvement in completeness outweighs the reduction in precision, resulting in a better overall predictive performance. This pattern is also reflected in the vector-based evaluation, where the NL+PL configuration shows a closer overall correspondence with the reference geometry. The evaluation is partly constrained by the quality of the Moldovan reference data, which exhibits local geometric misalignments and incomplete cadastral coverage. Although these discrepancies introduce uncertainty into the reported metrics, they also demonstrate a practical advantage of the approach: automated boundary predictions can help identify inconsistencies and gaps in existing cadastral records.

These limitations point to several directions for future research. Future research should evaluate the implementation of this approach in other regions characterized by the same landscape class, such as the eastern part of Ukraine or other parts of Moldova. In addition, we plan to integrate the model into an iterative cadastral mapping framework, where the outputs serve as an initial baseline within a graphical user interface. Human corrections of boundary predictions can then be reintegrated to progressively refine model performance and improve cadastral map completeness and accuracy in data-scarce regions. A comparison between manual and AI-assisted cadastral mapping is an important part of this future research direction. Finally, a more systematic analysis of domain differences, including spectral, structural, and cadastral characteristics, across a wider set of target and candidate fine-tuning regions would further strengthen the robustness of the landscape similarity selection strategy and yield new insights into the conditions under which cross-region transfer is most effective.

7. Conclusion

Cross-region transfer learning provides an effective approach for automated cadastral boundary delineation in data-scarce regions. Applied to the Donduseni district in northern Moldova, fine-tuning *CadNet* with landscape-similar Polish cadastral data (NL+PL) markedly improved boundary continuity, completeness, and alignment with reference data compared to the pretrained baseline (NL). Visible-boundary recall increased from 0.310 to 0.624, and reference-based vector discrepancy decreased from 7.033 to 4.497, demonstrating that targeted domain adaptation substantially enhances both raster and vector prediction quality. The study highlights the importance of landscape similarity for model transferability, offering a scalable methodology for cross-border cadastral mapping. Iterative adaptation using local data offers a promising direction to progressively refine both model performance and cadastral map quality in regions with limited annotated data.

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