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A Deep Learning Method for Cultivated Land Parcels (CLPs) delineation from high-resolution remote sensing images with high-generalization Capability

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Abstract

Accurate delineation of cultivated land parcels (CLPs) from high-resolution remote sensing images is vital for precision agriculture but faces challenges in detection accuracy, generalization, and parcel optimization. This study introduces a multitask deep learning network integrating region and boundary detection with distinct decoders, enhanced by color space transformations and attention mechanisms for generalization. A parcel optimization step repairs boundary breaks and fuses results for regular parcels. Tested on GaoFen-1 images from four Chinese regions, the method achieves high accuracy and stable spatiotemporal generalization.

Introduction

◆**Importance: CLPs are the essential unit of agricultural statistics, supporting parcel-level assessments and precision agriculture.**

◆**Existing methods (deep learning based):**

- **Region-based : MPSPNet, DeeplabV3+**
- **Edge-based: Segnet, ResU-Net, and R2UNet**
- **Hybrid methods (multi-task): ResUNet-a, BSiNet, SEANet, BFINet**

◆**Challenges:**

- **Struggles to predict high-quality region and boundary results simultaneously.**
- **Limited generalization performance of the model.**
- **Fail to effectively integrate boundary and region results into parcel results**

◆**Objective: Develop a high-accuracy, generalizable method with effective parcel optimization.**

Methodology

◆ **Multitask Detection Network:**

- **Shared encoder, separate decoders for region (semantic recognition) and boundary (fine-grained depiction) tasks.**
- **Region task: Predicts region and distance maps.**
- **Boundary task: Uses side architecture for multiscale prediction.**
- **Multitask balance: Modeling uncertainty to adaptively adjust task weights**

◆ **Generalization Enhancements:**

- **Color space transformations (e.g., hue adjustment).**
- **Spatial/hierarchical attention mechanisms.**

◆ **Parcel Optimization:**

- **Repairs long-distance boundary breaks via breakpoint detection/extension.**
- **Fuses region and boundary results at object level.**

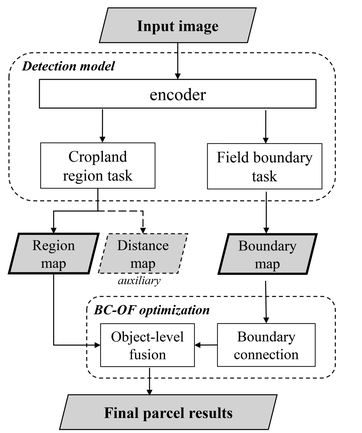

Fig.1 Workflow of our method

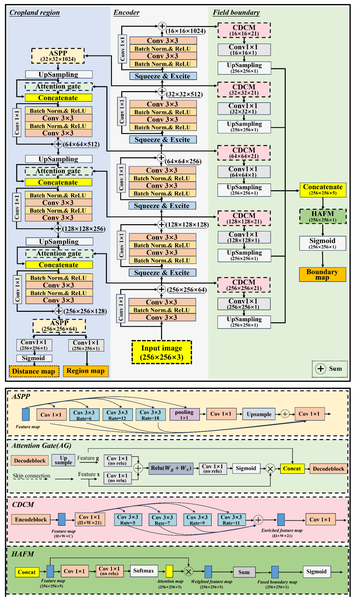

Fig.2 Architecture of our network

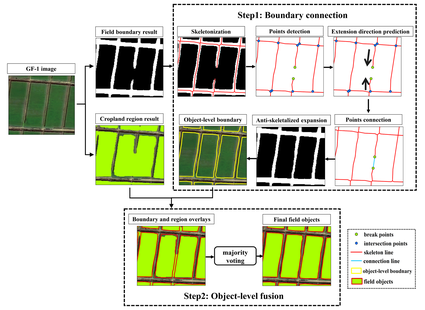

Fig.3 Workflow of our optimization method

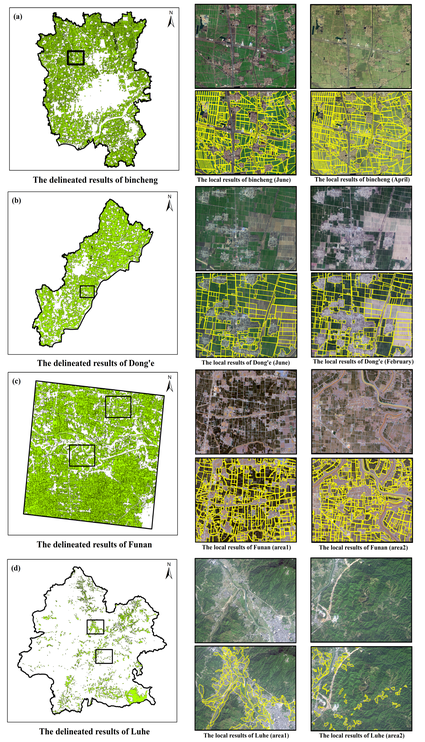

Fig.4 Delineated results in study areas

Experiments and Results

- **Datasets: GaoFen-1 images from four diverse regions in China.**
- **Findings: Superior delineation accuracy, stable generalization across regions/times.**
- **Comparisons: Outperforms methods like ResUNet-a, BSiNet, SEANet.**

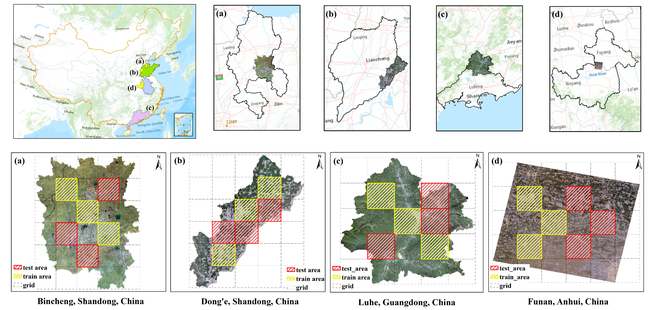

Fig.5 Geographic location of the study sites and their images

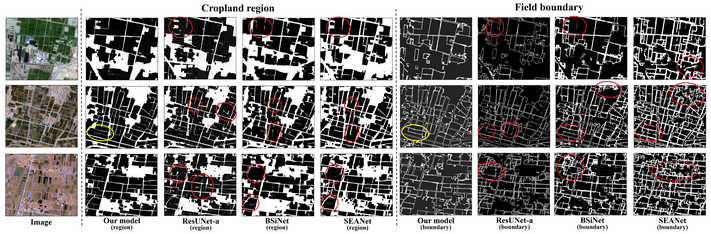

Fig.6 Comparison of our network and other recent multitask networks

Discussion and Conclusion

◆ **Discussion:**

- Advantages:
  - High accuracy (high-quality region and boundary result),
  - robust generalization (high transfer performance in unseen data),
  - regular parcels (close to manually outlined results).
- Limitations: May need fine-tune (transfer learning) for highly heterogeneous landscapes.

◆ **Conclusion:** Novel multitask network and optimization step achieve state-of-the-art CLP delineation with practical utility.