Mining Earth's Digital Strata for Geospatial AI: Bridging Data Collection, Synthesis, and Self-Training for Intelligent Earth Observation

THE OHIO STATE UNIVERSITY

Aswathnarayan "Ash" Radhakrishnan, Advisors: Dr. Jim Davis, Dr. Hari Subramoni
{radhakrishnan.39, davis.1719, subramoni.1}@osu.edu

ICICLE DEMOCRATIZING AI
CVL

FRAMEWORK OBJECTIVES

Develop a comprehensive framework spanning data collection, synthesis, and model adaptation for Earth observation tasks

1. How can we efficiently extract task-specific geospatial data from crowd-sourced resources?
2. Can generative models bridge distribution gaps with minimal computational resources?
3. How do we design self-training techniques specific to geospatial data uncertainties?

Impact:

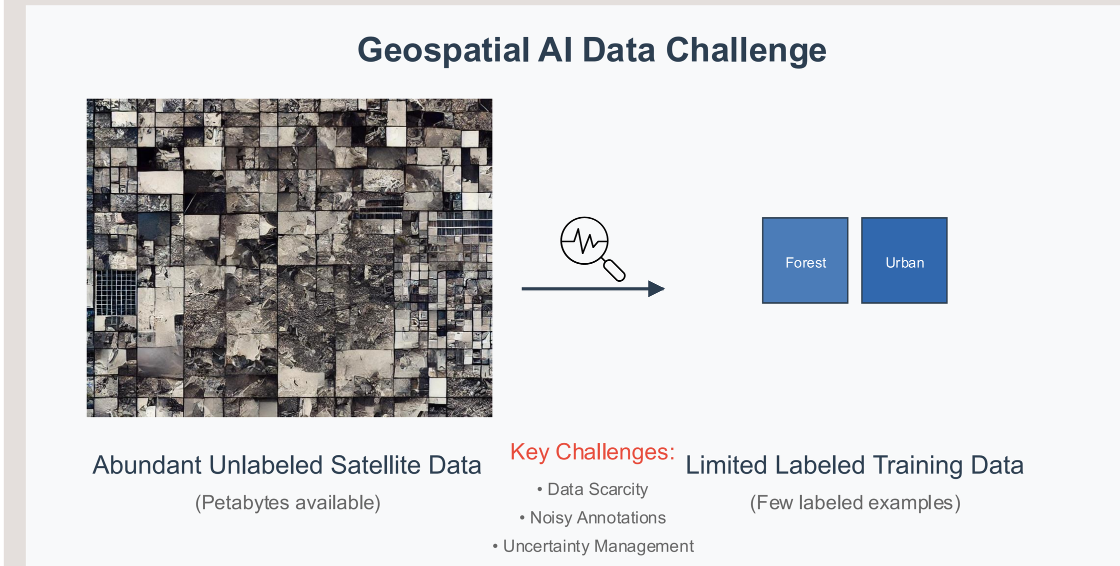
Advancing Intelligent and Automated Environmental monitoring pipelines for applications in agriculture, urban planning, disaster response, and climate research

MOTIVATION

Challenges in Geospatial AI

- **Task Data Scarcity:** Abundant raw imagery but limited task-specific labeled data
- **Annotation Noise:** Crowd-sourced mapping data contains inconsistencies, gaps, and temporal misalignments.
- **Distribution Gap:** Foundation models trained on web data fail to capture the features of real-world satellite imagery distributions
- **Multi-modal Integration:** Diverse data types (optical, radar, vector) lack unified analysis frameworks and pipelines for scientific analysis

KEY CHALLENGES



The Paradox of Earth Observation:
Petabytes of data collected daily yet limited actionable intelligence. *"Today's petabyte-scale data collection infrastructure has outpaced our manual analytical capabilities"*

SATELLITE DATA COLLECTION AND GENERATION FRAMEWORKS

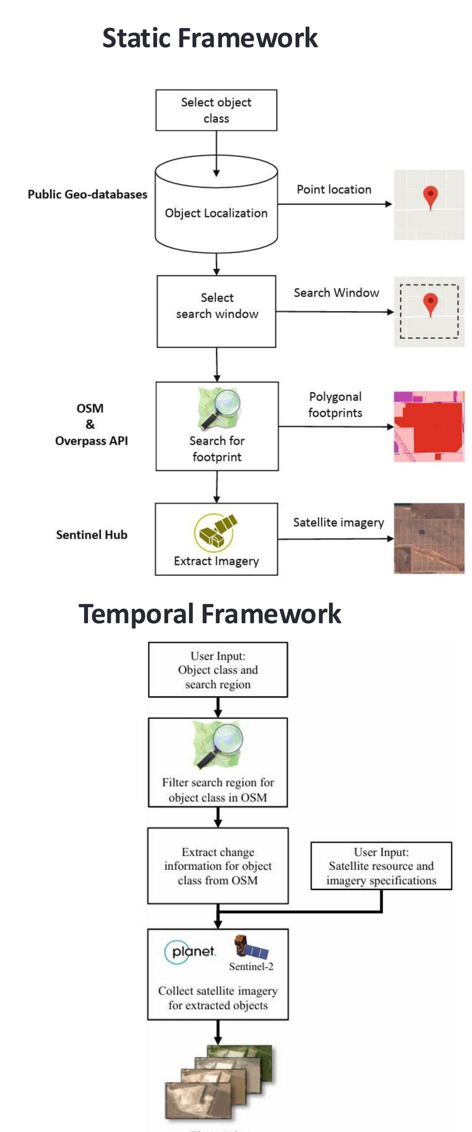
Data Collection Frameworks

Static Object Collection Framework:

- Leverages **OpenStreetMap** + **Satellite Imagery APIs**
- Extracts **Vectorized Geometries** of mapped objects

Temporal Framework for Dynamic Regions:

- Historical OSM data analysis for **Change Detection**
- **Spatio-Temporal Bounds Evolution tracking** with configurable sampling frequencies
- Customizable Pre-Processing Pipelines for **Time-Series Alignment and GeoRegistration**



Data Generation Frameworks

FewSatDiff:

Enhanced zero to few-shot image generation pipelines to bridge geospatial data distribution gaps in diffusion models with minimal task data for Domain Adaptation

Resource Adaptable Generation Pipelines:

1. **Enhanced Zero-Shot Synthesis: Prompt-Augmentation** for domain-specific characteristics + **CLIP Similarity filtering**
2. **Few-Shot Domain Adaptation:** Class-specific + ReferenceImage-Guided **InPainting Pipelines**
3. **Domain-Targeted Pretraining:** Pretraining pipelines with **VLM Autolabeling** for captioning Geospatial data properties for usage in high compute resource scenarios

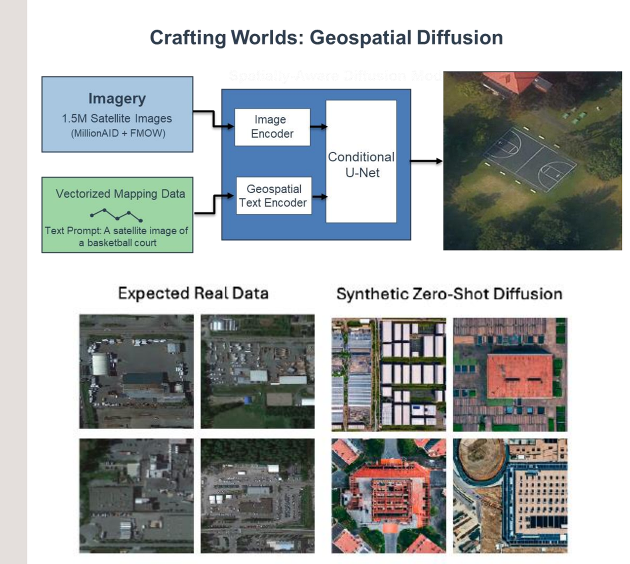
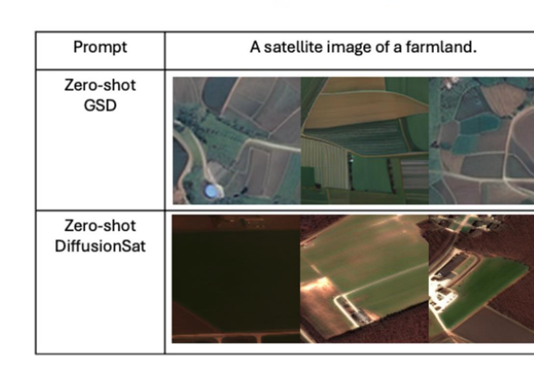


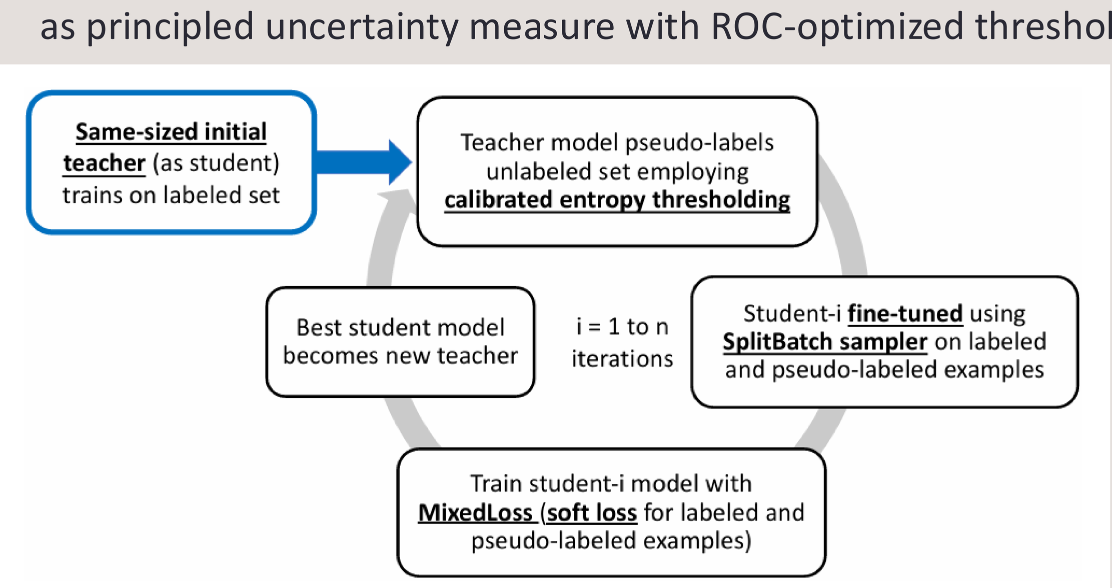
Figure 1. Distribution shifts between real-world satellite imagery vs. Stable Diffusion generated synthetic images.



ENHANCED SELF-TRAINING FRAMEWORK

Enhanced Self-Training (EST)

- **Weighted SplitBatch Sampler:** Separates mini-batches with configurable ratios of labeled vs. pseudo-labeled data
- **Dataset-Adaptive Model Calibration:** Temperature-scaling optimization to ensure confidence scores reflect true reliability
- **Entropy-Based Pseudo-Label Selection:** Uses normalized entropy as principled uncertainty measure with ROC-optimized thresholds



OVERVIEW OF KEY RESULTS & CONTRIBUTIONS

- End-to-end Satellite imagery Autolabeling Pipeline reducing annotation burden
- Vector-format Deep Learning Pipelines enabling easy GIS integrations
- **Licensed Invention** available on **GitHub (github.com/osu-cvl/Construction-Site-Satellite-Imagery-Collection)**
- Resource-efficient generative modeling techniques **achieving 3.5× lower FID for satellite imagery domains (84.45 → 27.77 ↓)**
- Modular, plug-and-play **Pseudo-labeling Teacher-Student Training Pipelines**
- **Dataset-adaptive Parameter Tuning & Open-Set Filtering** to handle noise in both real-world and synthetic data

Table 5.1: Key design choices (with selected options) and their impact on accuracy.

Design Component (Selected Choice)	Impact on Accuracy
Loss Function (Soft Loss)	SVHN: +0.3%, CIFAR-10: +1.7%, CIFAR-100: +3.0%
Student Initialization (Fine-Tuning)	SVHN: +0.3%, CIFAR-10: +0.6%, CIFAR-100: +3.6%
Mini-Batch Composition (SplitBatch Sampler)	Minor improvement (up to +0.1%)
Sampling Technique (Weighted Split-Batch)	CIFAR-10: +1.4%, CIFAR-100: +1.1%
Pseudo-Label Selection (Calibrated Entropy Thresholding)	SVHN: +1.0%, CIFAR-10: +2.0%, CIFAR-100: +1.4%
Teacher Size (Larger Same-Sized Models)	SVHN: +2.4%, CIFAR-10: +0.6%, CIFAR-100: +1.2%

Table 5.1: Performance comparison between related work NoisyStudent (NS) [32] and our Enhanced Self-Training (EST) approach across different datasets.

Datasets	Best Accuracy (%) NS [32]	EST
SVHN	91.65	**93.00**
CIFAR-10	89.15	**94.21**
CIFAR-100	70.53	**76.42**
CINIC-10	83.47	**88.59**
TinyImageNet	49.32	**52.23**

Table 4.2: Comparison of different pipelines across few-shot settings on EuroSat and UC Merced.

Method	Dataset	1-shot	3-shot	5-shot	10-shot
Few-Shot Real only	EuroSat	21.62%	53.04%	68.28%	80.20%
	UC Merced	56.67%	78.10%	88.81%	93.33%
RG + GLIDE	EuroSat	52.60%	69.00%	73.02%	85.16%
	UC Merced	63.10%	85.95%	88.57%	94.76%
DB GSD	EuroSat	**53.60%**	**77.12%**	**85.92%**	**97.50%**
	UC Merced	**80.95%**	**88.33%**	**90.71%**	**96.43%**

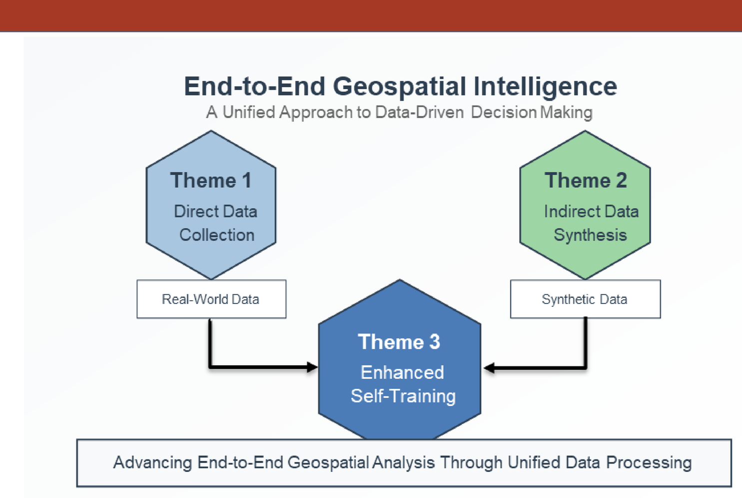
Table 4.3: Comparison with existing geospatial foundation models on 10-shot classification tasks.

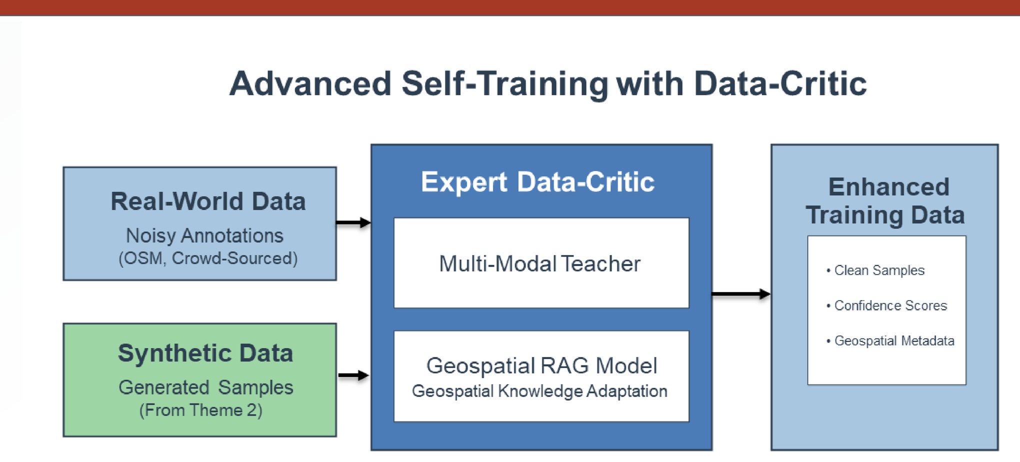
Method	EuroSat	UC Merced
DiffSat [13] + GeoRSCLIP [34]	**97.80%**	92.48%
(Our) DB GSD + CLIP	97.50%	**96.43%**

CURRENT WORK

Real-World Applications of Unified Frameworks

- **Crop Growth Stage Analysis:** Working on monocular depth estimation approaches from drone imagery using Image-conditioned Diffusion techniques
- **Digital-Twin Modeling:** Integrating multi-source multi-modal sensing information to simulate digital twins of real-world large areas of interest such as agricultural farms or solar power plants enabling experimentation on downstream domain-specific tasks in a simulated twin of the real-world environment
- **Shallow Water Bathymetry:** Working on geospatial physics constrained deep learning techniques for mapping the bottom of the seafloor depths along shallow water coastal regions from multi-modal remote sensing data





Publications

1. Ilin, R., Davis, J., Lerner, S., Cunningham, J., **Radhakrishnan, A.**, "Tracking with Context in Wide Area Motion Imagery," MSS Passive Sensors Symposium, 2019.
2. **Radhakrishnan, A.**, et al., "*A Framework for Collecting and Classifying Objects in Satellite Imagery*," ISVC 2019.
3. Motlagh, N.K., **Radhakrishnan, A.**, et al., "*A Framework for Semi-automatic Collection of Temporal Satellite Imagery for Analysis of Dynamic Regions*," ICCV Workshop: Learning to Understand Aerial Imagery 2021.
4. **Invention Disclosure:** *Automated Time-series Imagery Extraction of Construction Zones Using OpenStreetMap* (Ref. No. T2021-034).
5. **Radhakrishnan, A., et al.,** "*Design Choices for Enhancing Noisy Student Self-Training*," WACV 2024.