Hyperlocal disaster damage assessment using bi-temporal street-view imagery and pre-trained vision models

Yifan Yang, Ph.D. Student
Advisor: Dr. Lei Zou (lzou@tamu.edu)
Department of Geography, Texas A&M University
GEAR Lab Website: https://www.geoearlab.com

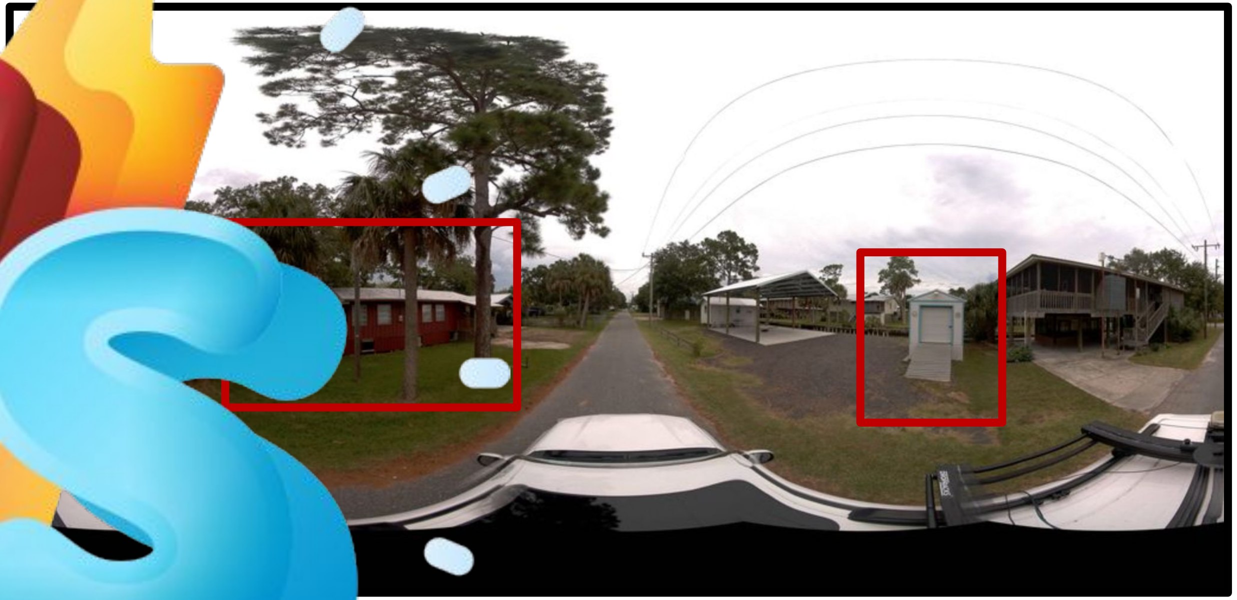
Introduction

Post-Hurricane Street View

Yifan Yang | Ph.d. Student@Texas A&M University | Email: yyang295@tamu.edu | Lab Website: https://www.geoearlab.com

Introduction

Post-Hurricane Street View

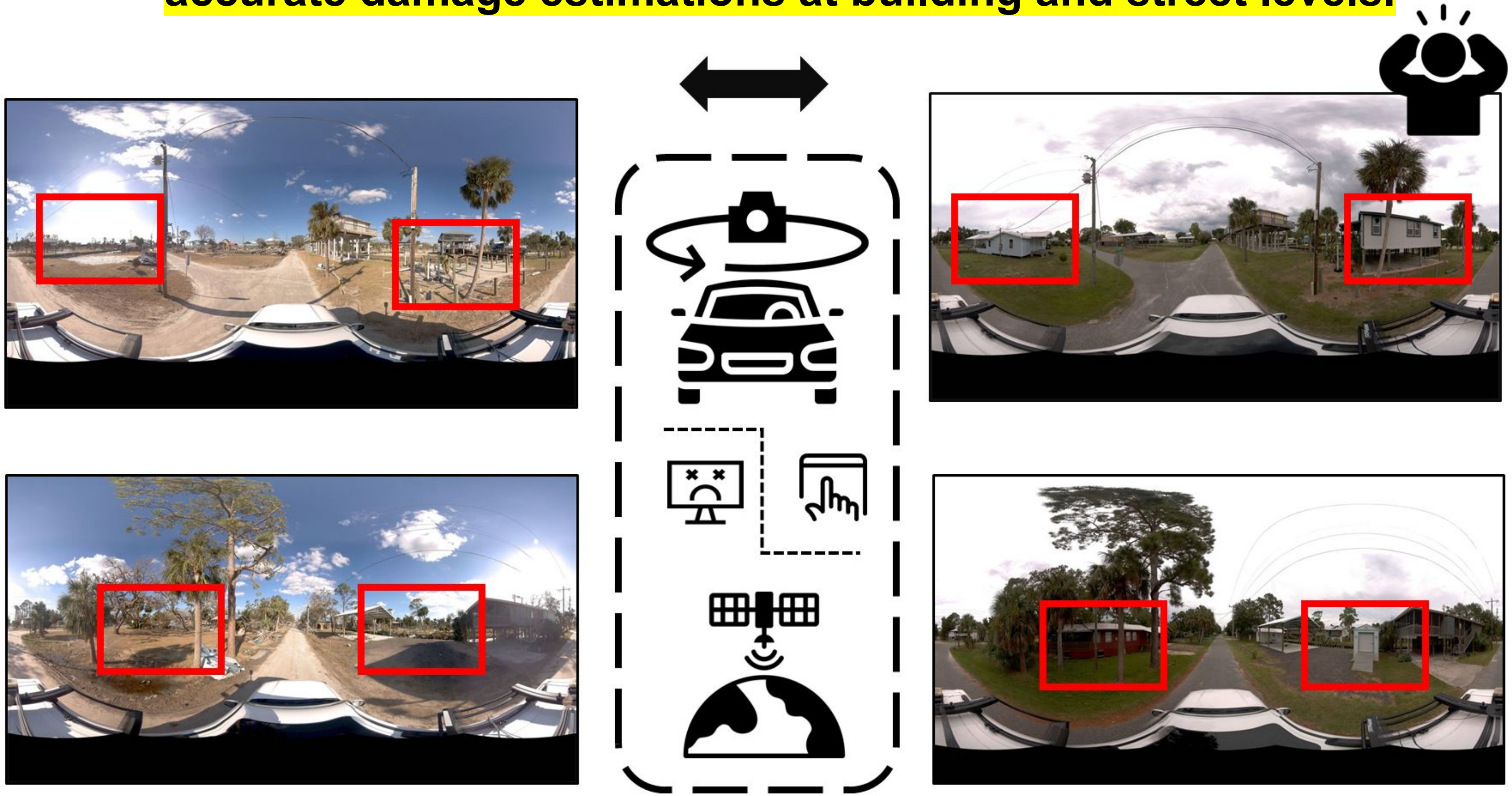


Pre-Hurricane Street View

Yifan Yang | Ph.d. Student@Texas A&M University | Email: yyang295@tamu.edu | Lab Website: https://www.geoearlab.com

Introduction

Pre-disaster images provide valuable benchmarks for accurate damage estimations at building and street levels.



After Hurricane Milton

Before Hurricane Milton

Figure 1. Pre- and Post-Hurricane Street View Comparison for Disaster Impact Assessment.

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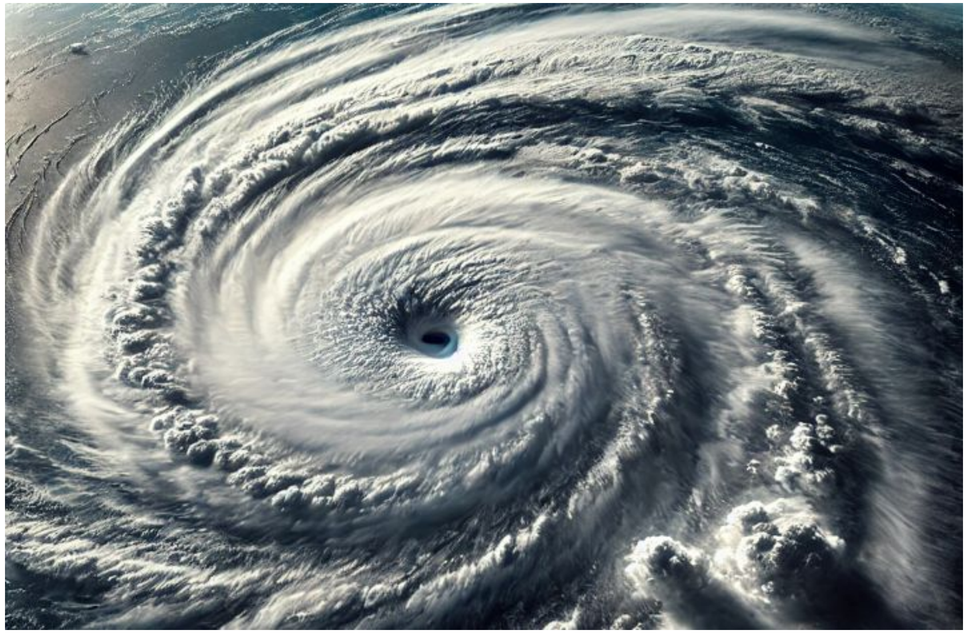
Research Objectives



(1) to assess the performance gains of incorporating pre-disaster street-view images

(2) to design and evaluate a dual-channel algorithm that reads pair-wise pre- and post-disaster street-view images for hyperlocal damage assessment.

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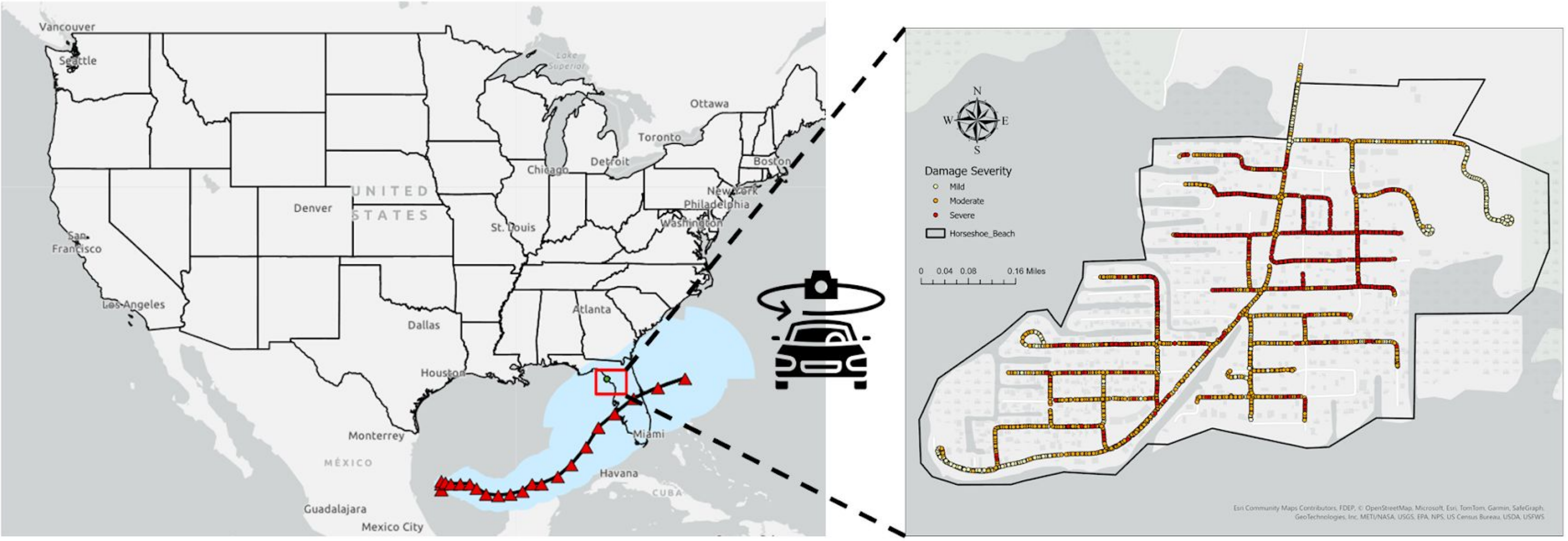
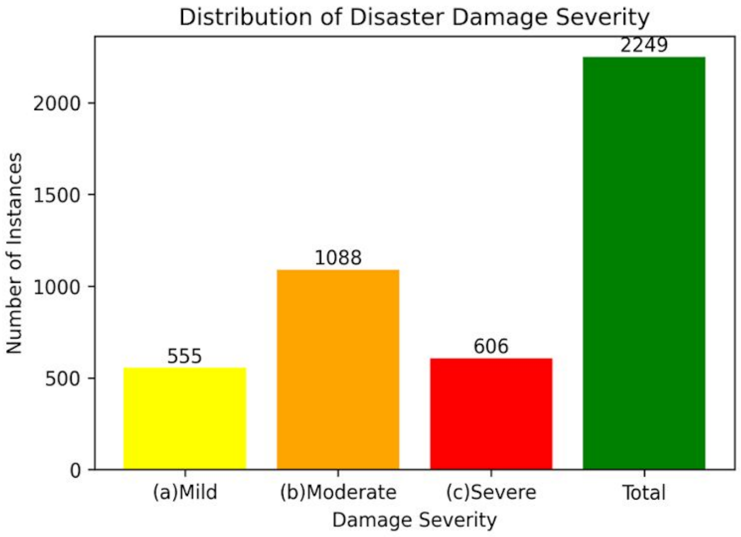
Data Collection and Preparation





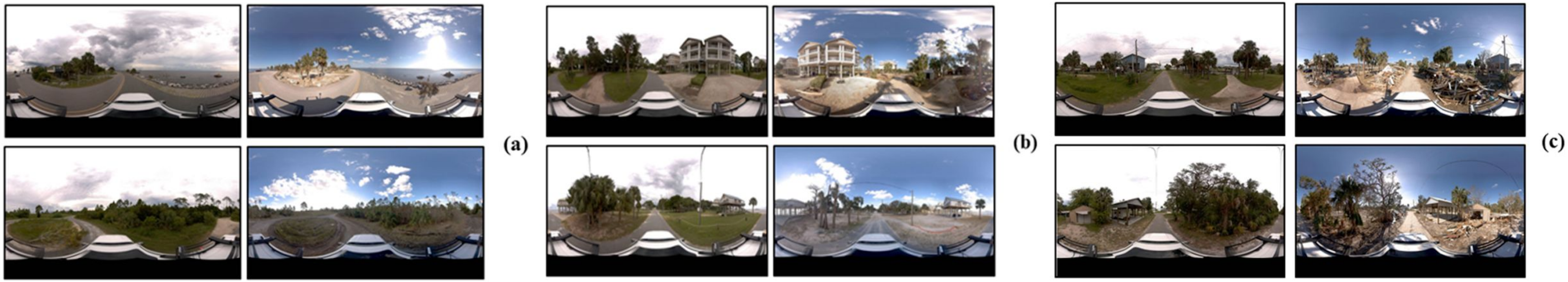


Figure 2. Study area and samples of street-view image pairs in Horseshoe Beach area of Florida.

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Experimental Design

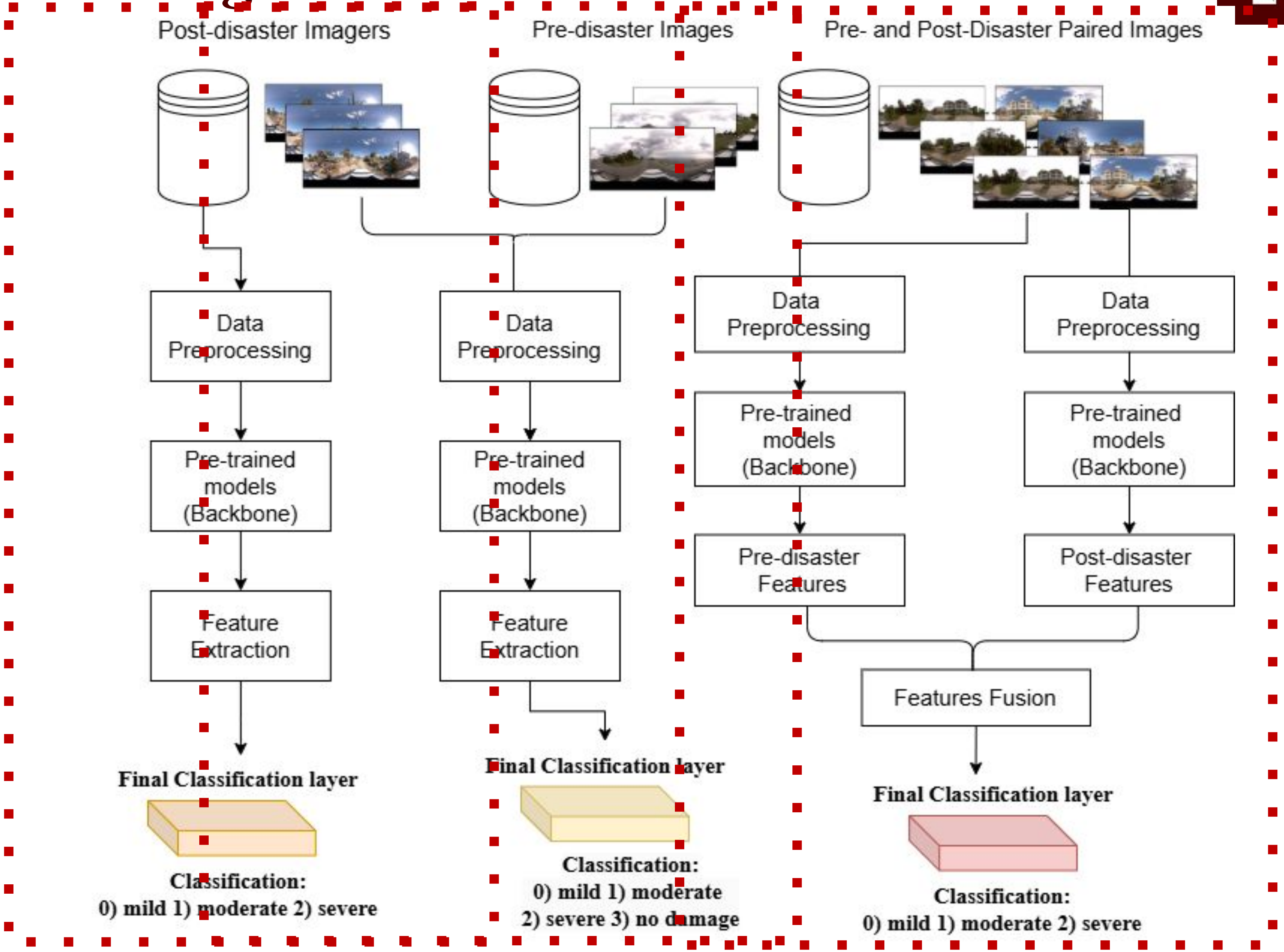

Figure 3. Comparison of Single-Phase and Bi-Temporal Disaster Classification

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Pre-Trained Vision Models with Disaster Images

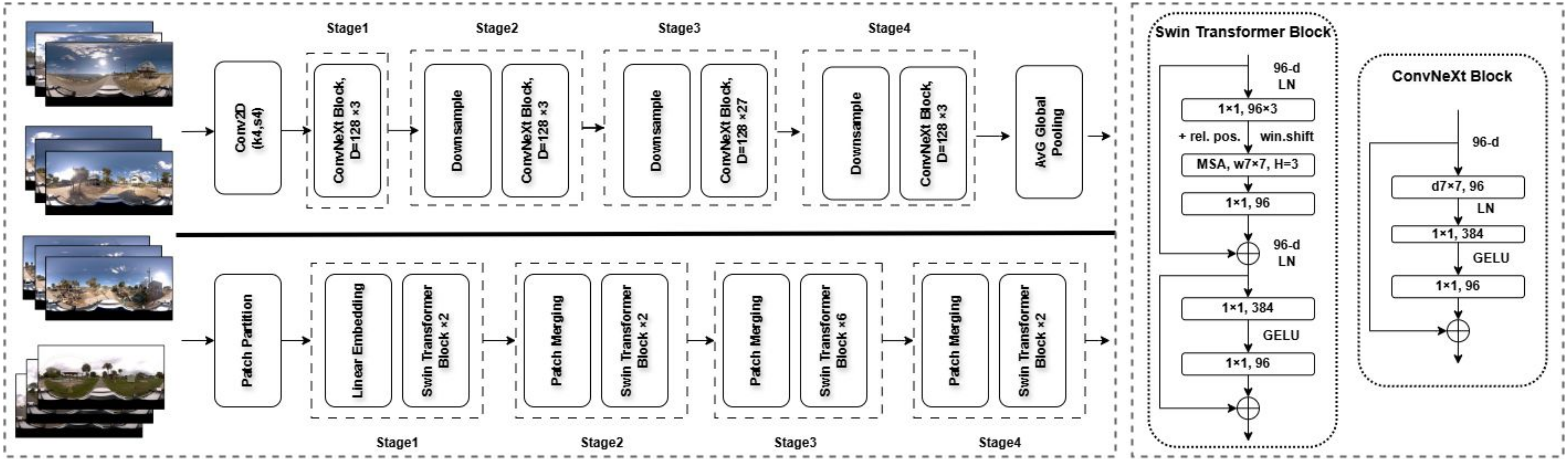

Figure 4. ConvNeXt and Swin Transformer for multi-stage feature extraction architecture of disaster perception.

This study employs four pre-trained vision models: ConvNeXt-Tiny, ConvNeXt-Base, Swin Small Patch Window7 224, and Swin Base Patch Window7 224.

Dual-Channel with Pairwise Bi-Temporal Images

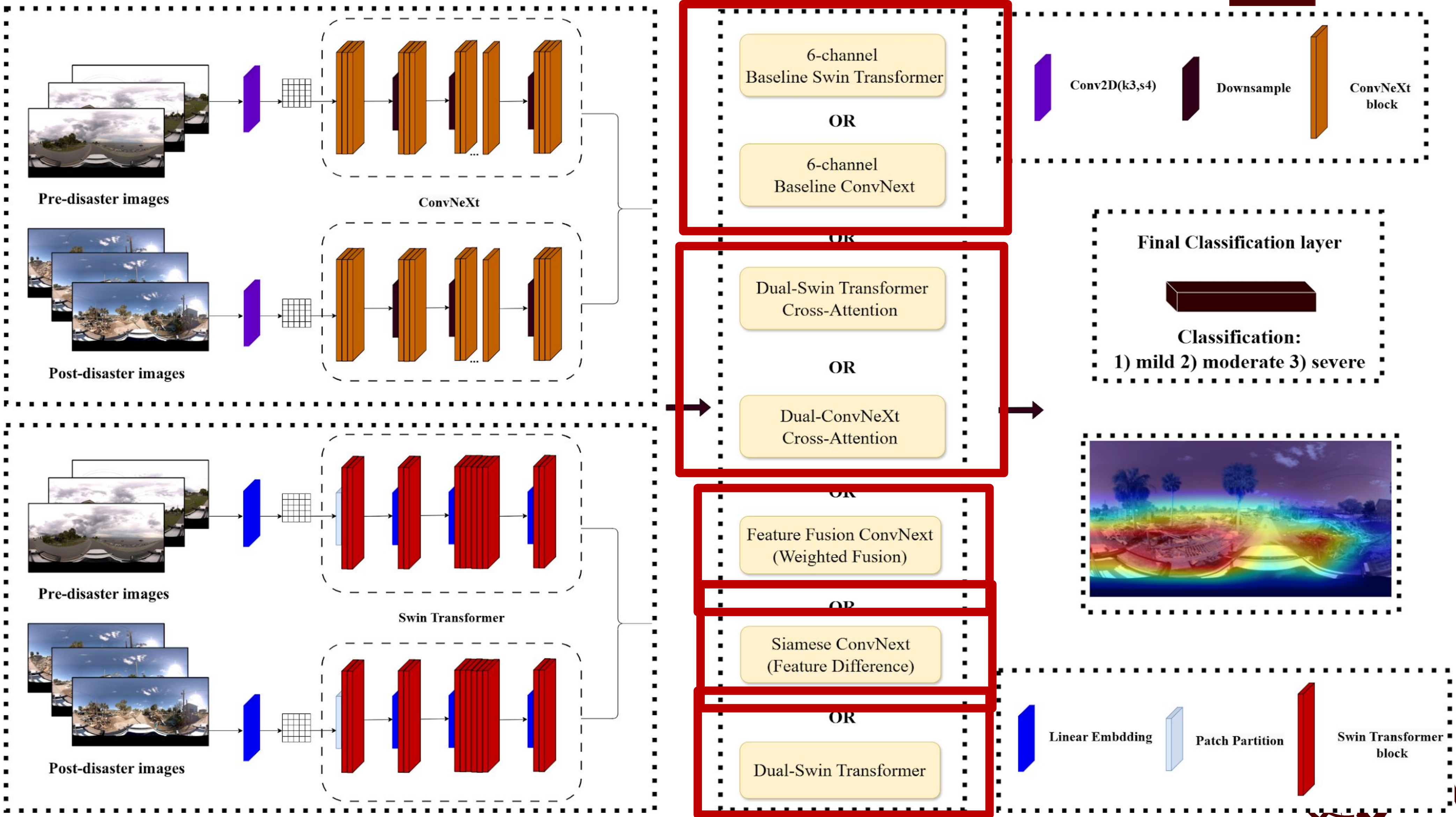

Figure 5. Dual-Channel training process for Bi-Temporal SVI Disaster Perception.

Results: Pre-Trained Models on Post-Disaster Images

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Table1 Performance of Pre-Trained Models on Post-Disaster Imagery Classification

Model name	Accuracy	P	R	F1	Class-Specific Accuracy		
					0-mild	**1-moderate**	**2-severe**
ConvNeXt_tiny	***72.15%***	***0.7313***	***0.7315***	***0.7179***	***55.0%***	82.37%	***68.82%***
ConvNeXt_base	70.22%	0.7256	0.7022	0.6961	50.93%	85.19%	61.05%
swin_small_patch_window7_224	70.00%	0.7301	0.70	0.6879	44.04%	***88.84%***	58.12%
swin_base_patch_window7_224	70.37%	0.714	0.7037	0.6954	46.88%	84.07%	65.34%

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Results: Pre-Trained Models with Bi-Temporal Images

Table2 Performance of Pre-Trained Models with Bi-Temporal Data

Model name	Accuracy	P	R	F1	**Class-Specific Accuracy**		
					0-mild	**1-moderate**	**2-severe**
ConvNeXt_tiny	86.42%	0.8698	0.8642	0.8617	46.41%	81.71%	71.50%
ConvNeXt_base	87.32%	0.8785	0.8732	0.87	47.62%	85.27%	71.90%
swin_small_patch_window7_224	87.94%	0.8924	0.8794	0.8732	40.68%	***91.82%***	***75.86%***
swin_base_patch_window7_224	***88.98%***	***0.8967***	***0.8898***	***0.8876***	***54.35%***	87.62%	67.24%

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Results: Dual-Channel Models

Table3 Performance of Pre-Trained Models with Dual-Channel Models

Model name	Accuracy	P	R	F1	Class-Specific Accuracy		
					0-mild	**1-moderate**	**2-severe**
Baseline-ConvNext	72.80%	0.7315	0.7280	0.7256	56.91%	79.12%	75.54%
Baseline-Swin Transformer	66.14%	0.6889	0.6614	0.6481	39.02%	84.34%	57.55%
Dual-ConvNeXt + Cross-Attention	76.91%	0.7704	0.7691	0.7672	***71.08%***	72.36%	***91.37%***
Dual-Swin Transformer + Cross-Attention	76.91%	***0.7970***	0.7691	0.7615	51.47%	***91.97%***	74.60%
Dual-Swin Transformer	74.17%	0.7420	0.7417	0.7408	62.69%	75.45%	81.33%
Feature-fusion ConvNext	***77.11%***	0.7751	***0.7710***	***0.7678***	59.39%	82.72%	84.44%
Siamese ConvNeXt	75.54%	0.7878	0.7554	0.7498	53.28%	90.79%	71.11%

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Grad-CAM for Performance Evaluation

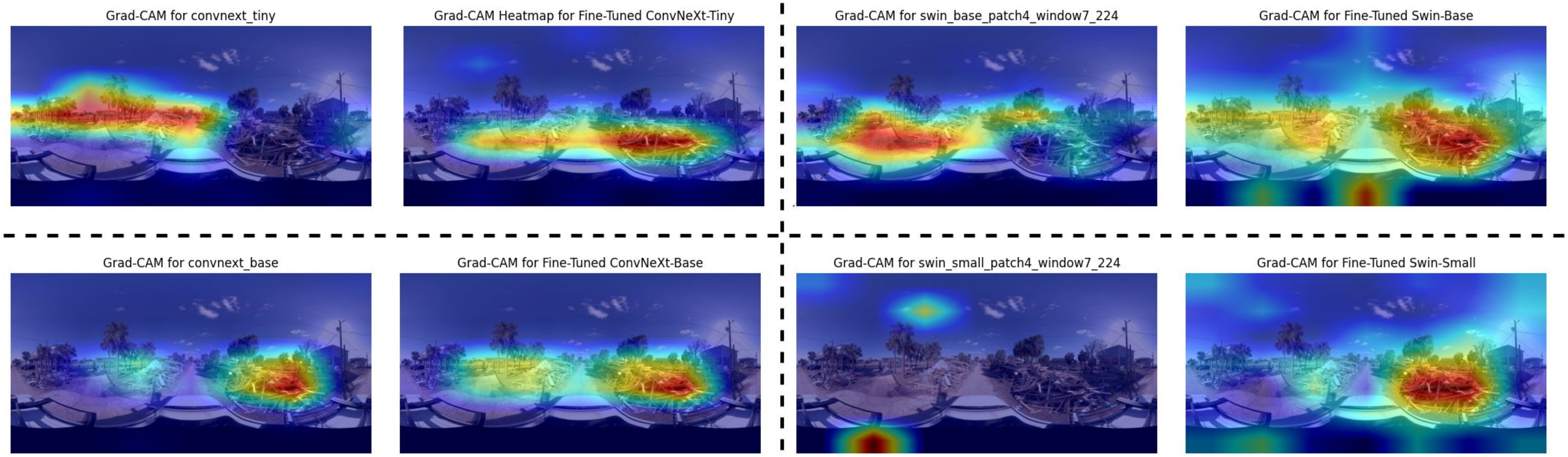

Figure 7. Grad-CAM Visualizations for Disaster Perception Using Pre-trained without fine-tuning and Fine-Tuned Models.

These heatmaps highlight the model's attention areas in the image, reflecting different models' perception of the disaster-affected areas. By visualizing the attention areas of different models, Grad-CAM helps explain why some models perform better in classifying disaster severity.

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Grad-CAM Performance Evaluation

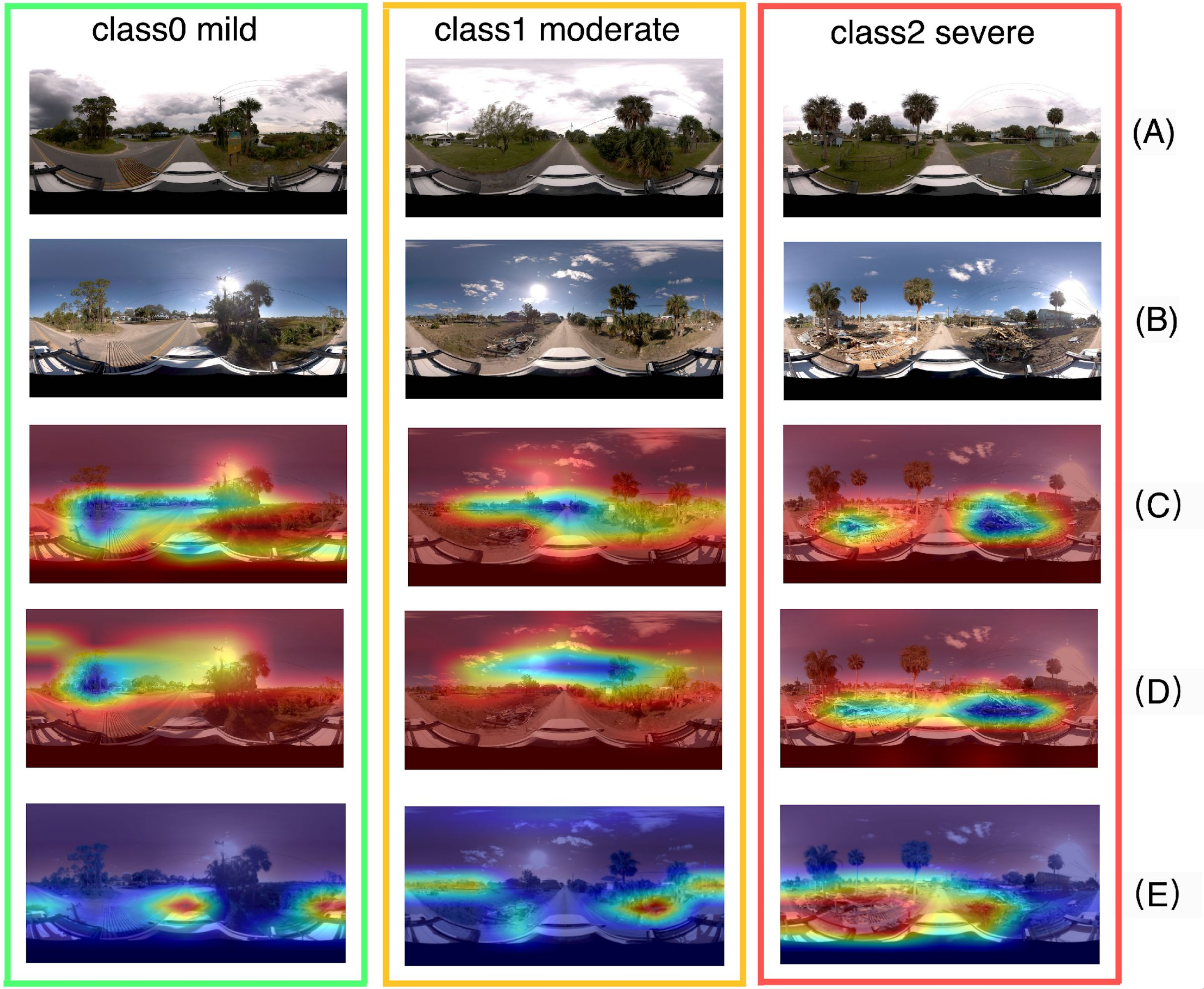
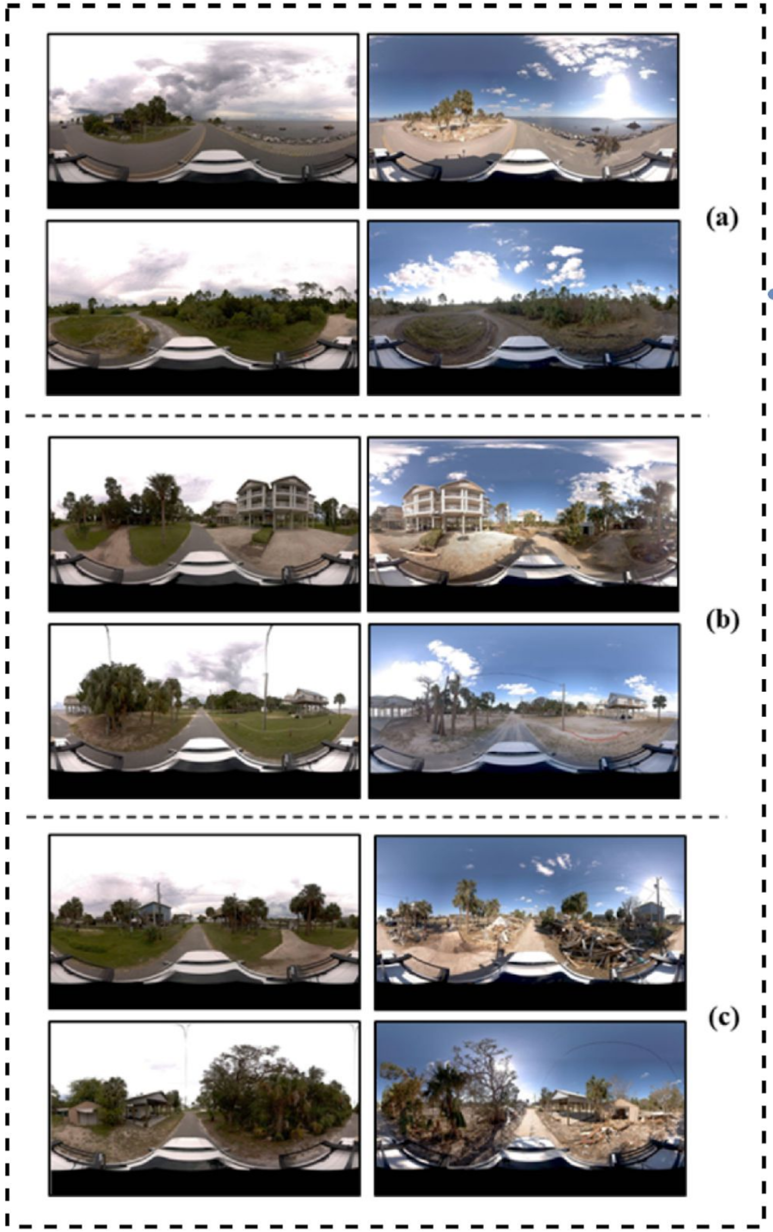


Figure 8. Results of Grad-CAM analysis of disaster perception using three different experiments.



Prompt: Disaster Damage Classification
The first image shows the scene before the disaster, while the second image shows the scene after the disaster. The task is to classify the damage in the second image into one of three categories based on visible changes:
1. Mild Damage: Clean scene with little or no damage, such as small areas of fallen trees or a few knocked-down road signs.
2. Moderate Damage: More cluttered scene, with larger areas of fallen trees, some standing water, and possibly more fallen road signs or road closures.
3. Severe Damage: Highly chaotic scene, with extensive areas of fallen trees, flooded roads, and visible housing trash.
Output Format:
•Fallen trees score: [score / 100]
•Housing trash score: [score / 100]
•Destroyed buildings score: [score / 100]
•Standing water in the street score: [score / 100]
•Damage degree score: [score / 100]
•Damage degree: [Mild Damage, Moderate Damage, Severe Damage]

Future Directions

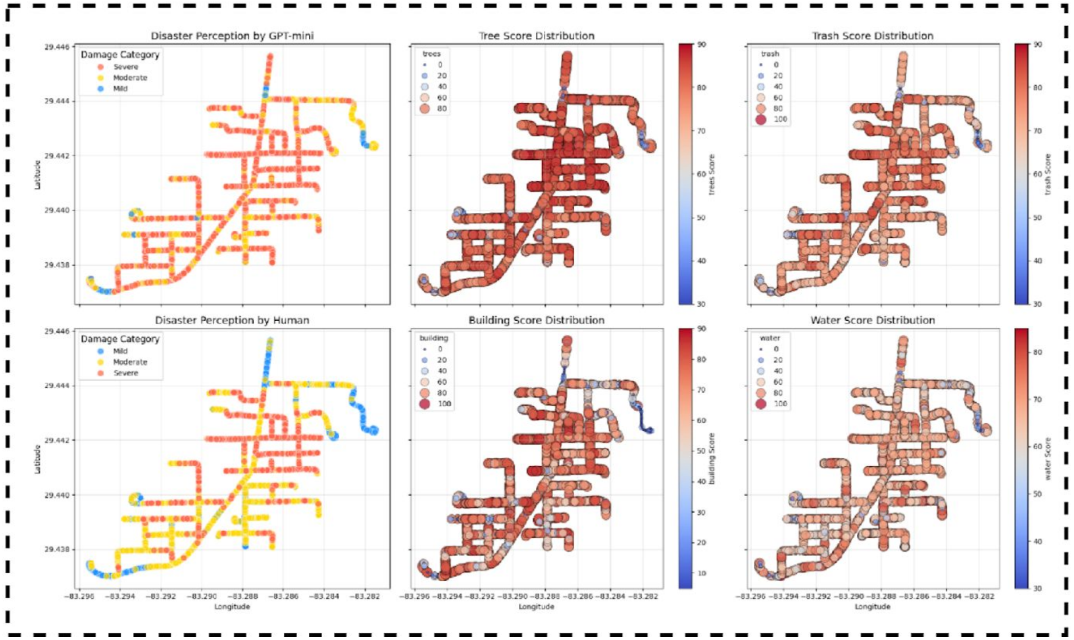
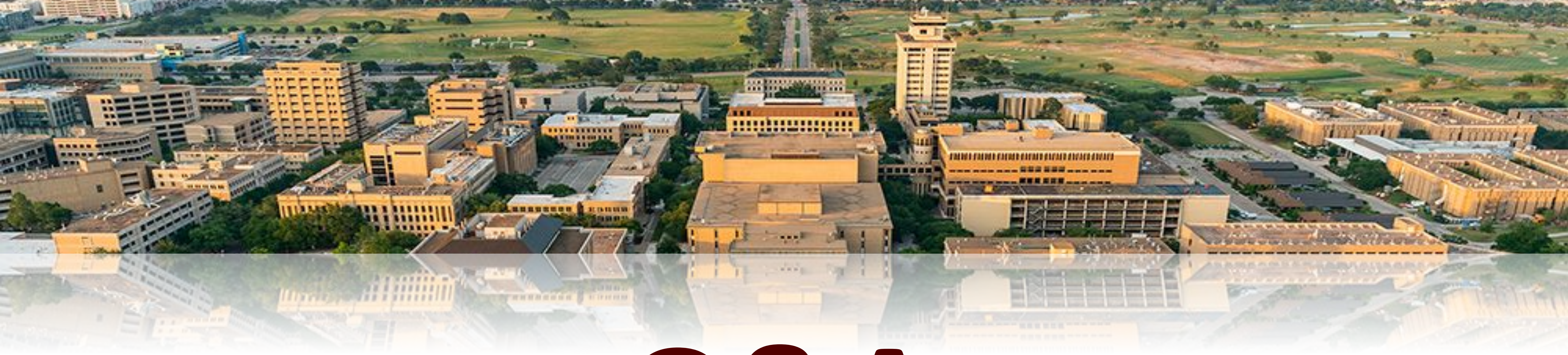


Figure 9. Exploring pre-disaster and post-disaster imagery using GPT-4o-mini.



Q&A

Welcome any comments/questions

yyang295@tamu.edu

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