Forest-Chat: Adopting Vision-Language Models for Interactive Forest Change Analysis

James Brock, Ce Zhang, Nantheera Anantrasirichai
University of Bristol
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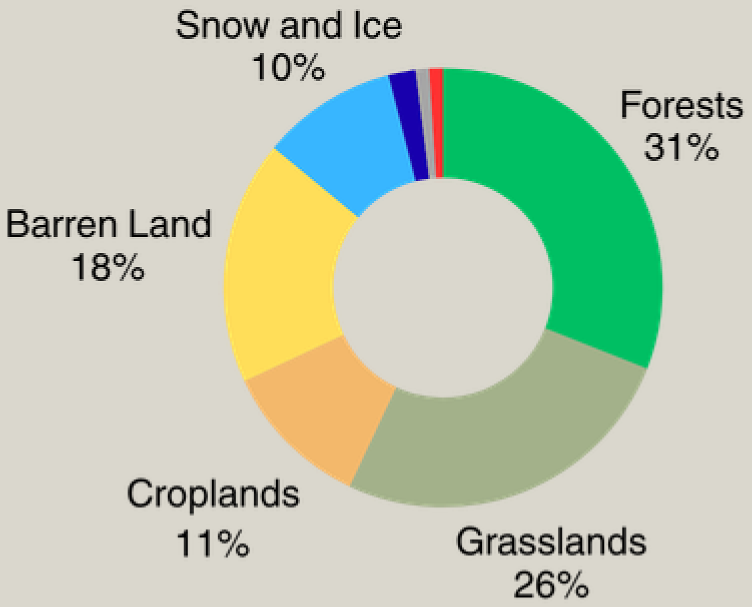
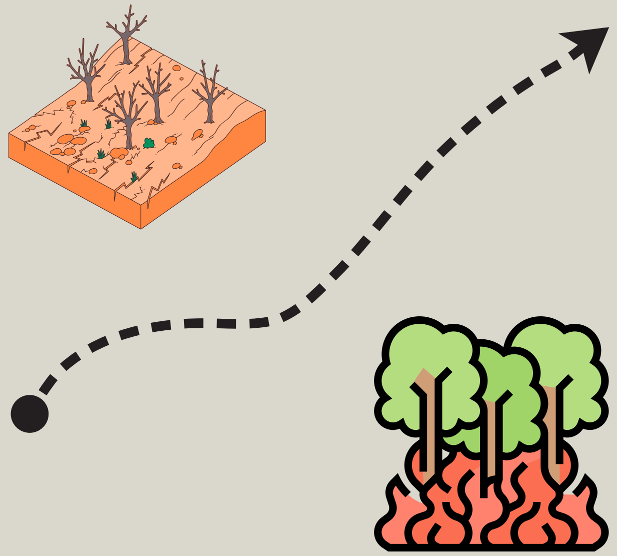
Forest monitoring increasingly relies on AI and remote sensing

Forests dominate land cover and are critical for climate regulation



Increasing changes: deforestation, agriculture, wildfires, regeneration



Remote sensing enables large-scale monitoring

Challenge: interpreting what changed and why is still difficult at scale

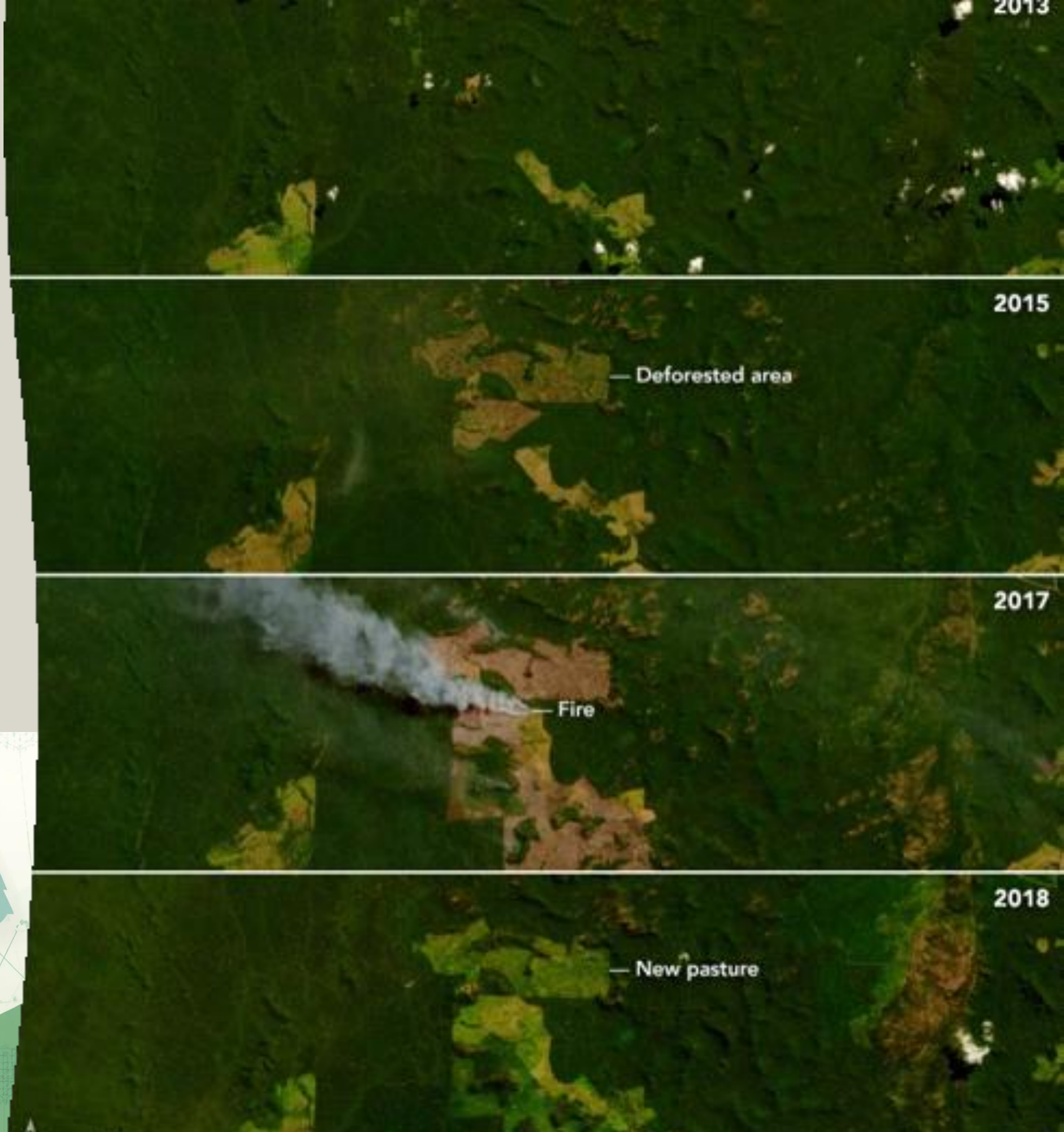
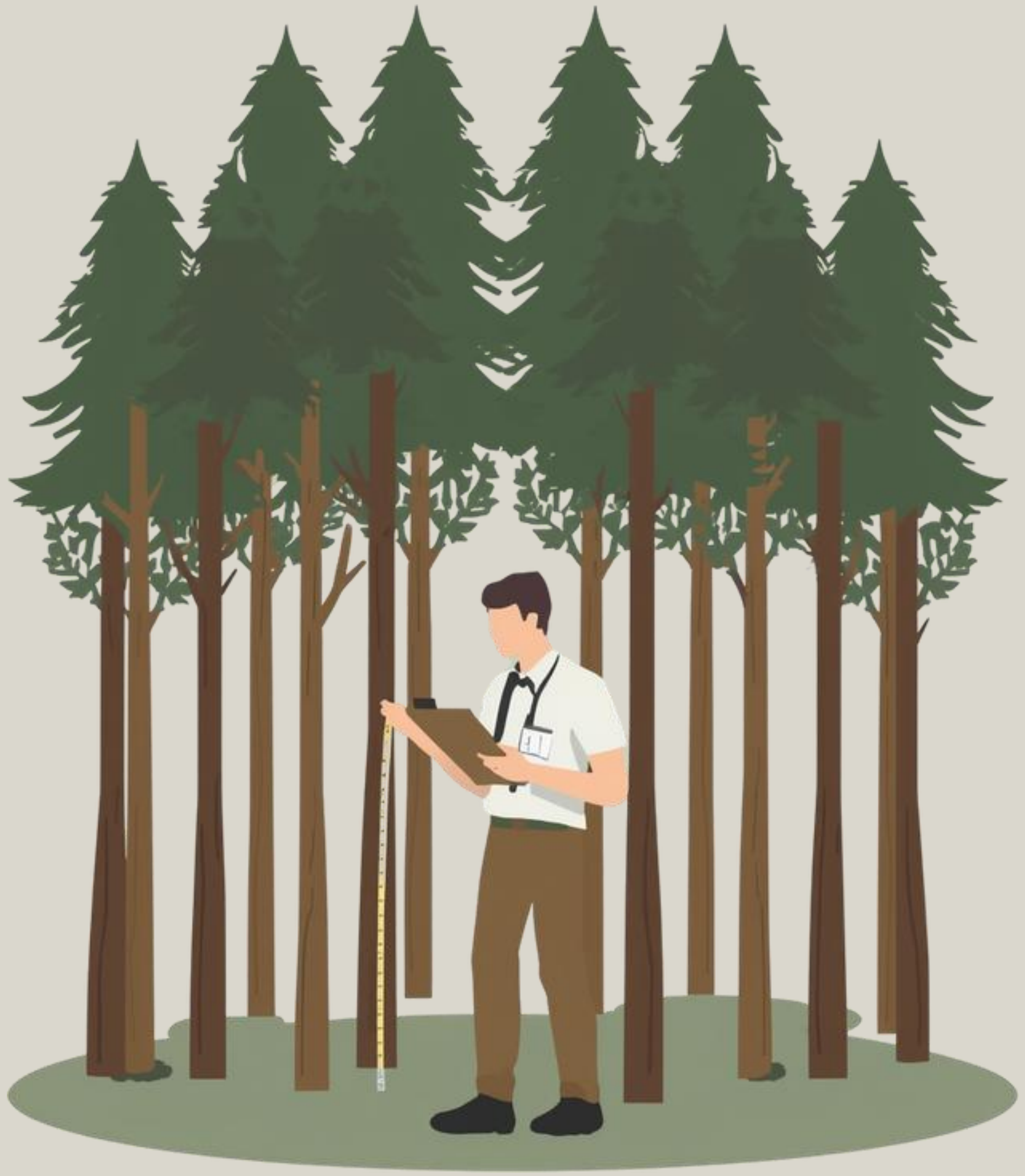


Image Credit: [1]

Existing systems don't effectively serve foresting monitoring workflows

Current Limitations

- Fragmented & task-specific
- Weak semantic understanding and lack of reasoning
- Data limitations
- Poor generalisation to domain shifts



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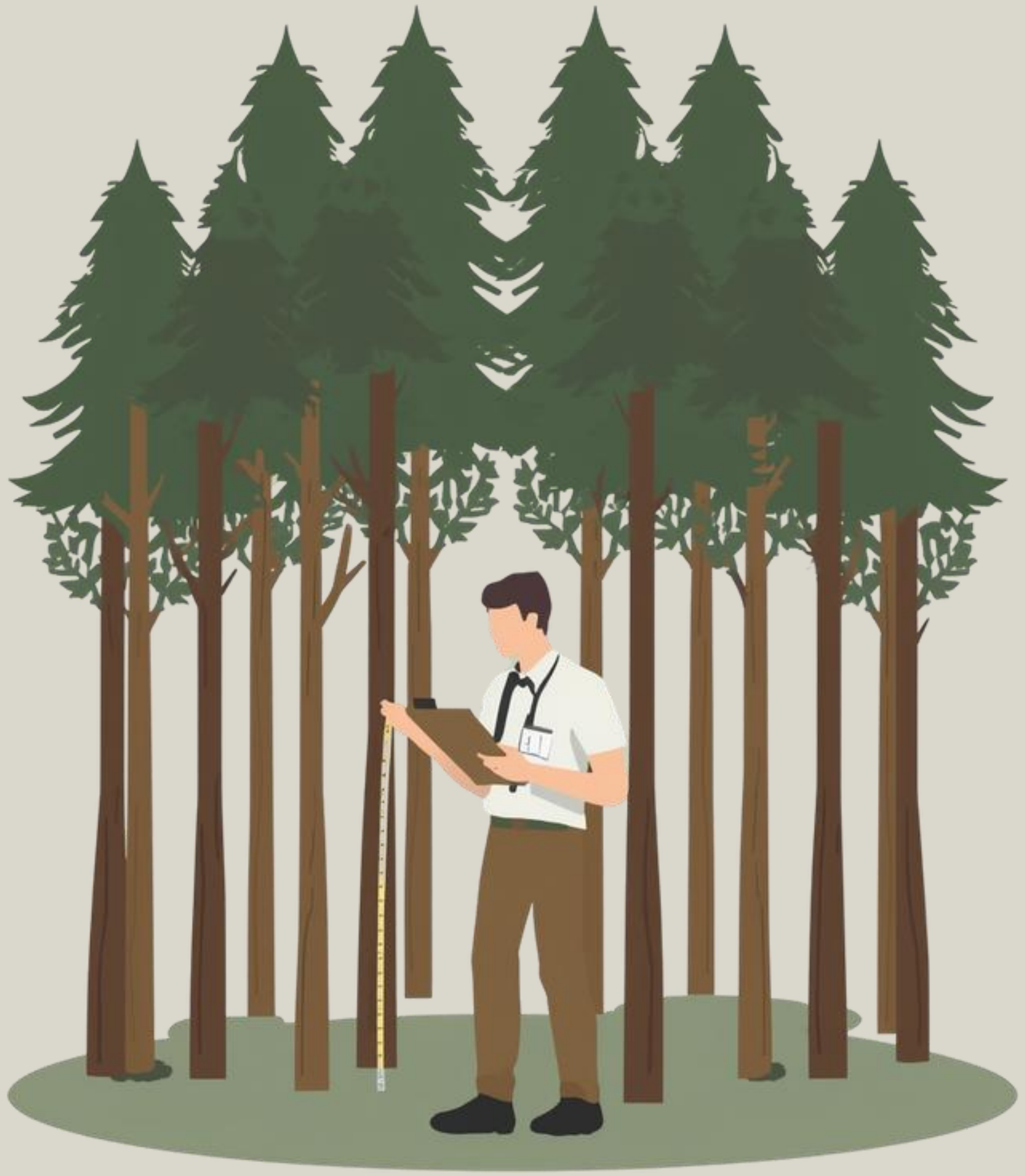


What's Needed Next

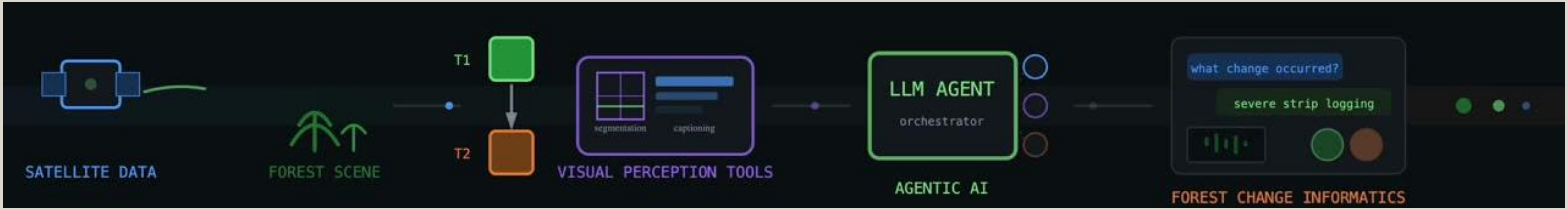
- Unified systems for detection + interpretation
- Richer multimodal understanding
- Increased dataset quantity + quality
- Robust, adaptable, interactive workflows with flexible orchestration

"Not just better models - but systems that reason, interact, and coordinate."

Idea: An agentic approach to interactive forest change analysis

Input: Bi-temporal satellite imagery of forest scenes

Reasoning & coordination: decompose user queries into executable tasks



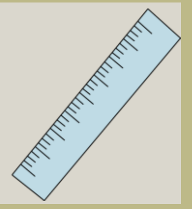
Perception: Vision-language understanding of change dynamics incorporating what, where, and why?

Output: Flexible, interpretable understanding of forest change dynamics

→ **Generating bespoke forest scene insights from satellite imagery**

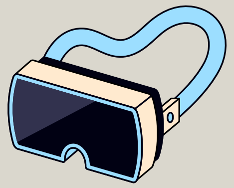
Research objective: Assess VLM-based agent capabilities for interactive forest change analysis

Benchmarking



Joint change detection and captioning against SOTA models on two datasets

Zero-shot capabilities



Explore vision foundation model performance in zero-shot settings

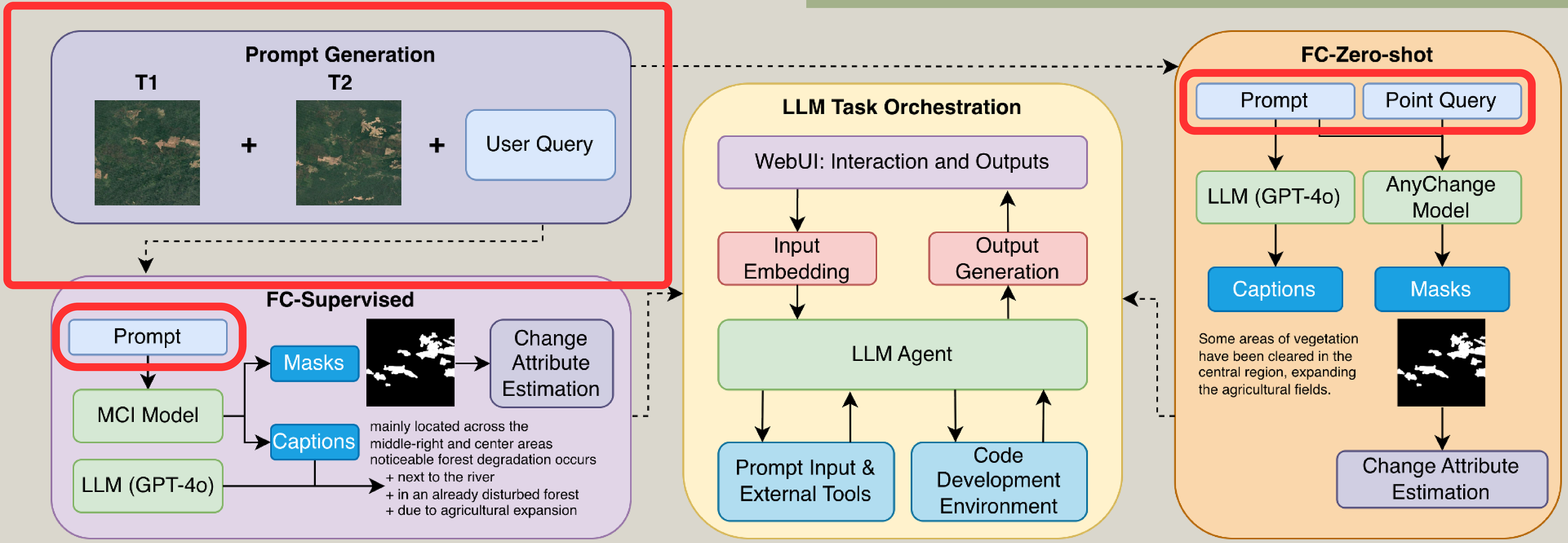
Cross-domain adaptation

Analyse how well learned features transfer across different data domains

Conversational utility

Validate vision-language agent robustness for forest change analysis

Forest-Chat agent overview



Input

- Bi-temporal satellite images
- Text-based user query
- Interactive UI

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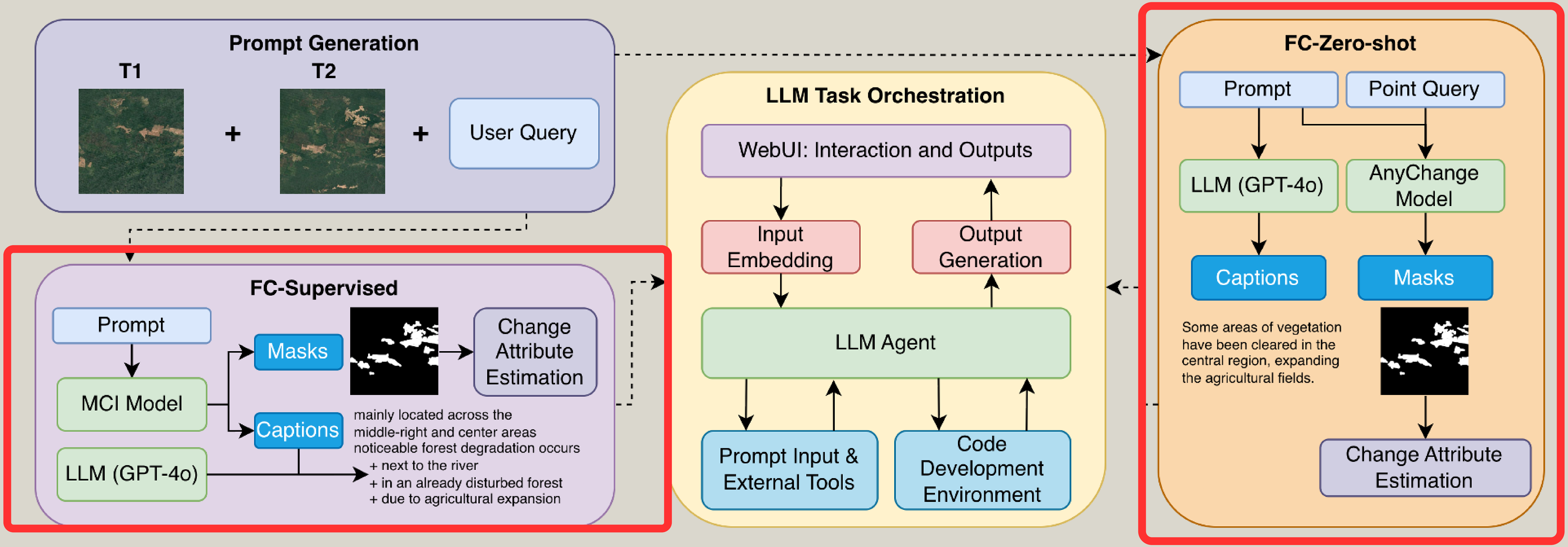

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Perception

- Unified CDC model (MCI[3])
- Zero-shot CD (AnyChange[4])
- Zero-shot CC and caption refinement (GPT-4o[5])

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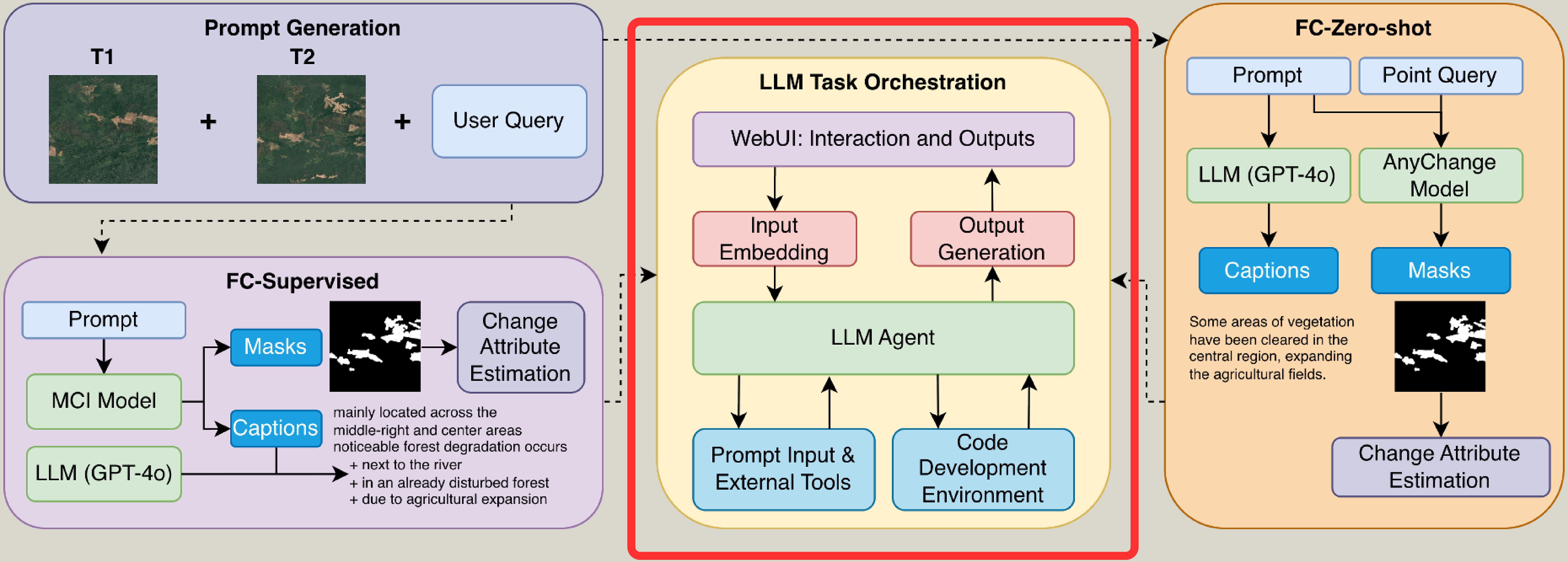

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Perception

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Orchestration

- LLM-agent task understanding
- Code orchestration framework
- External tool utilisation

Remote sensing image change interpretation lacks adequate benchmark datasets

Dataset	Main Task(s)	Key Characteristics	Labels Available	Resolution	Samples
Forest-Change[2, 7]	Change Detection + Captioning	Small, imbalanced, subtle deforestation, human + rule-based annotation	Masks + 1:4 Human to Rule-based Annotated Captions	30m	334
LEVIR-MCI-Trees[3]	Change Detection + Captioning	Urban object change masks, tree-focused captions, clearer structures	Masks + 5 Human Annotated Captions	0.5m	2305
JL1-CD-Trees[6]	Change Detection (domain transfer)	Tree cover gain + loss, domain shift, seasonal & atmospheric noise	Masks only	0.5 - 0.75m	408

- three noted areas of loss in the top left top right and centre on the edge of previous clearings new loss is moderate whilst overall loss is considerable
- slight forest degradation is noted mainly located in the top-left area
- concentrated in the top-left region small amounts of forest loss are apparent

Finding 1: Robust performance across multiple tasks in supervised and zero-shot settings

Finding 2: MLLM's can be utilised for post-captioning domain knowledge injection

Generic prompting

- Capture key changes
- Generic LLM style
- Can hallucinate

Style-guide prompting

- Reflects original style
- Few-shot examples reduce hallucinations

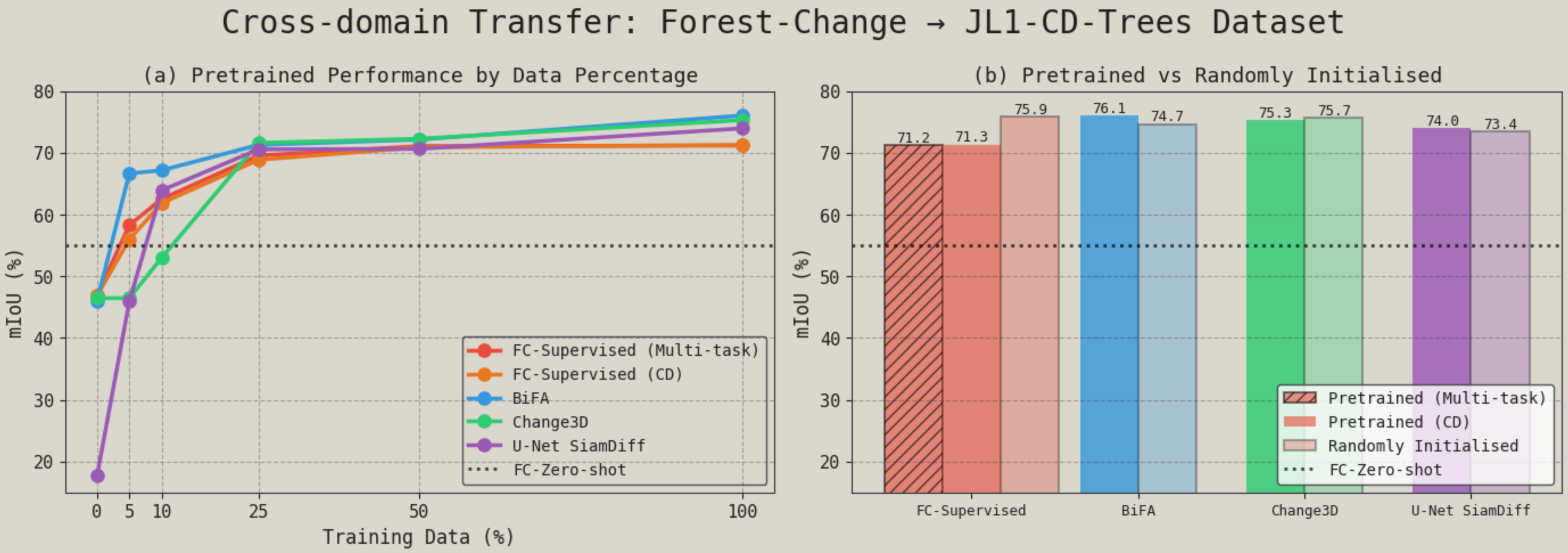
Refined captions

- Adds missing geographical info
- Can artificially reduce scores
- Corrects mistakes

Finding 3: Minimal data requirements for cross-domain adaptation

Zero-shot performance sensitive to object-specific ground truth masks

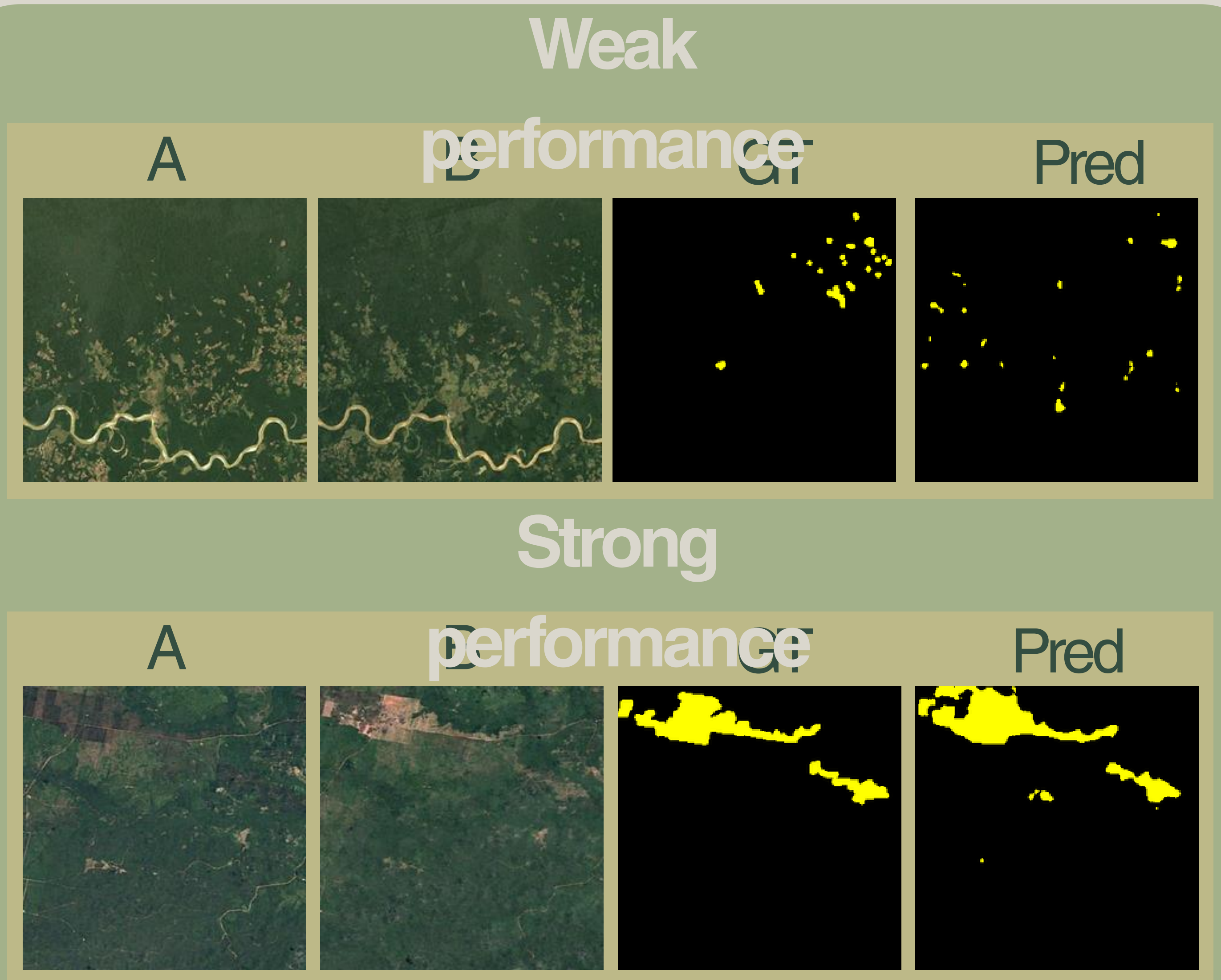
FC-Zero-shot Baselines	
Dataset	**MIoU**
Forest-Change	**60.15**
LEVIR-MCI-Trees	**47.32**
JL1-CD-Trees	**54.98**



Detection limits, data gaps, and system fragility constrain real-world impact

Remaining Challenges

- Struggles with small, subtle, and fragmented change patches
- Dataset size, quality, and task support limits model potential
- Scaling system to incorporate additional capabilities is non-trivial

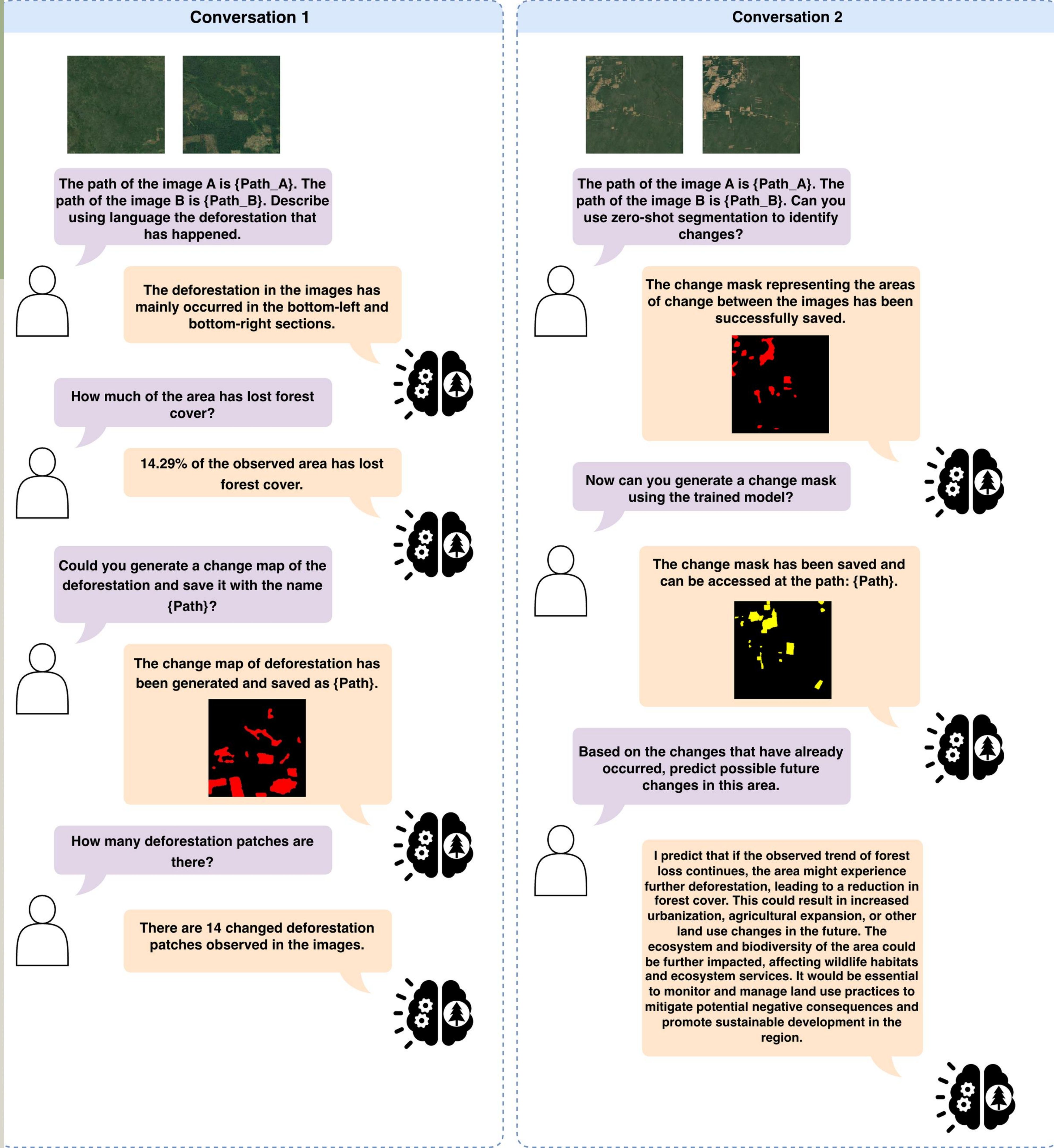


Promising Directions

- Auxiliary data and localisation architectures for small patches
- Larger, multi-modal datasets with richer annotations
- Task-aware retrieval and expanded toolsets

Forest-Chat: a practical integration study into interactive forest change analysis

- VLM and agentic integration yields a capable system for supervised and zero-shot forest change analysis
- Ecological RS exposes domain-specific challenges in detection, captioning, and agent reasoning
- Forest-Change and Forest-Chat provide a reproducible baseline for future work



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Acknowledgements

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