TerraVIV: The Platform for High-Fidelity Biomass Verification and Climate Resilience of Smallholder Farming.

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Introduction

Managing Climate Change and Variability (CCV) and Disaster Risk Reduction (DRR) in small farming communities requires high-precision, real-time biomass and risk mapping.

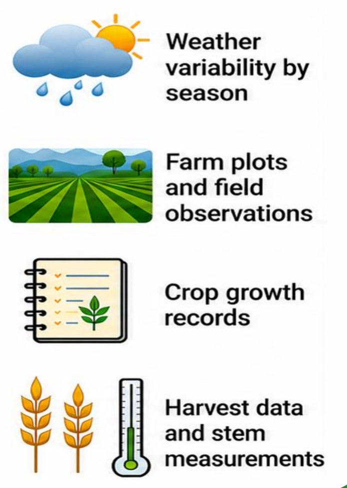
However, vital local and regional datasets remain largely inaccessible to local stakeholders. This data gap hinders proactive planning, underscoring an urgent need for a more integrated, systematic approach.

Integrating bottom-up participatory data with top-down drone imagery couples on-the-ground realities with scientific modeling. Concurrently, artificial intelligence (AI) drives advanced biomass analysis and climate-informed decision support.

TerraVIV addresses these challenges, enabling accurate biomass verification by blending participatory and drone datasets. Built to expand and adapt, the platform fosters climate-resilient farming communities capable of maintaining productivity alongside effective disaster risk management.

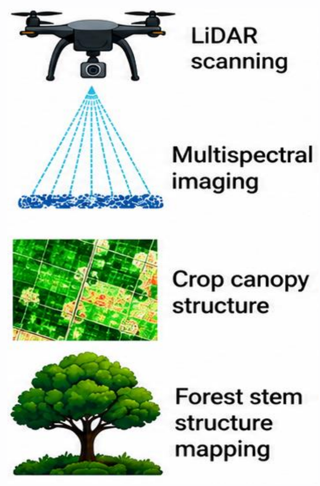
Methodology

1 Climate & Field Data acquisition



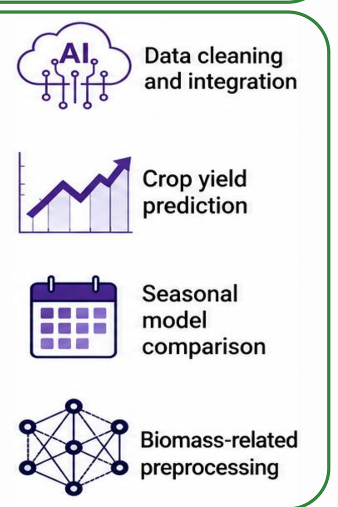
- TerraVIV begins by collecting climate and field data to capture seasonal climate variability and its effects on crop and forest systems.
- Climate data include rainfall, temperature, and seasonal conditions, while field data include plot characteristics, crop observations, harvest samples, and tree-related measurements.

2 Drone Sensing & Remote Observation



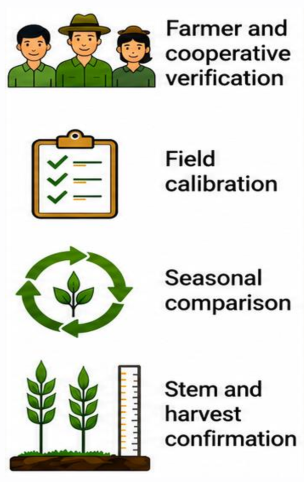
- Drone-based LiDAR and multispectral imagery are used to monitor crops and forests at much finer resolution than satellite-only monitoring.
- This step confirms and extends field observations by capturing canopy structure, crop vigor, and tree-level spatial patterns.

3 AI / Model Analysis



- The multi-source data are cleaned, organized, and analyzed using AI-based workflows.
- This stage includes data harmonization, feature extraction, model comparison, and seasonal evaluation.
- In the crop case, TerraVIV compares model behavior across seasons; in the forest case, it prepares point-cloud data for stem segmentation and biomass-related analysis.

4 Local Validation & Ground Truth



- TerraVIV uses local validation to ensure that model outputs remain consistent with on-the-ground reality.
- Farmers, cooperatives, and field collaborators participate in checking and interpreting the outputs, which builds shared ownership and trust in the platform.

5 Partnership & Decision Support

- Validated results are translated into practical outputs for climate adaptation and disaster risk reduction.
- The platform supports collaboration among researchers and local users, making it possible to develop shared roadmaps for crop management, risk reduction, and future biomass/carbon applications.
- TerraVIV therefore functions as both a scientific tool and a social platform for co-creating CCV/DRR solutions.

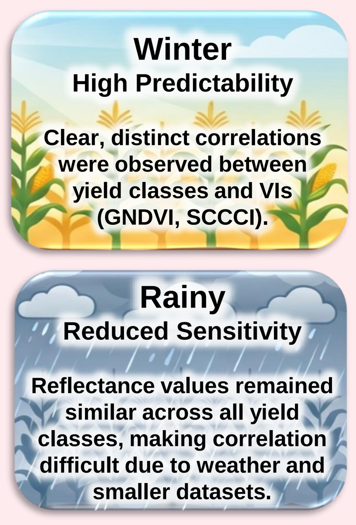
Results

TerraVIV presents two case studies showing how seasonal climate variability affects predictive modeling and forest data preprocessing.

Case 1: Sweet Corn – Biomass and Yield-Risk Assessment

- The prediction model produced plot-level yield estimates, but performance varied between winter and rainy seasons. This was supported by field observations and sampling procedures conducted at the study site in Chiang Dao, Chiang Mai, Thailand, as shown in Figures 1 and 2.
- The two most important vegetation indices, GNDVI and SCCCI, were compared across seasons, as shown in Figure 3.
- During the winter season, both indices showed a clear positive relationship with yield, where higher index values corresponded to higher yields.
- In contrast, the rainy season showed a flatter pattern, with similar reflectance values across yield levels and a weaker relationship with yield.

Figure 1. Study site
(Chiang Dao, Chiang Mai, Thailand)



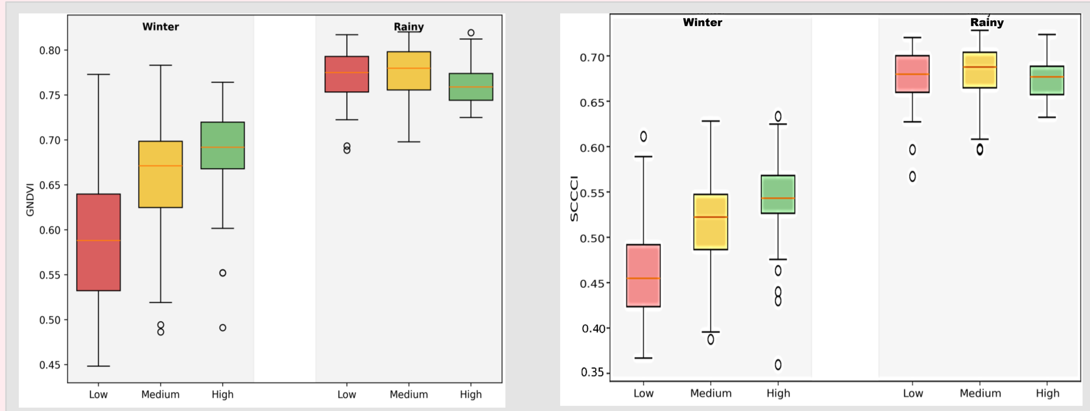


Figure 3. The box plots illustrate the distribution of the two most important vegetation indices, GNDVI (left) and SCCCI (right), categorized by yield levels (Low, Medium, High) and seasons.

Figure 2. Field sampling procedure involving GPS coordinate collection and sweet corn harvesting for biomass and yield evaluation.

- This difference was mainly influenced by variable weather conditions and the smaller rainy-season dataset, which limited model discrimination. Even so, the overall model accuracy remained above 80%, although the rainy season showed higher error and lower reliability than the winter season.

Case 2: Forest – Biomass and Carbon Estimation

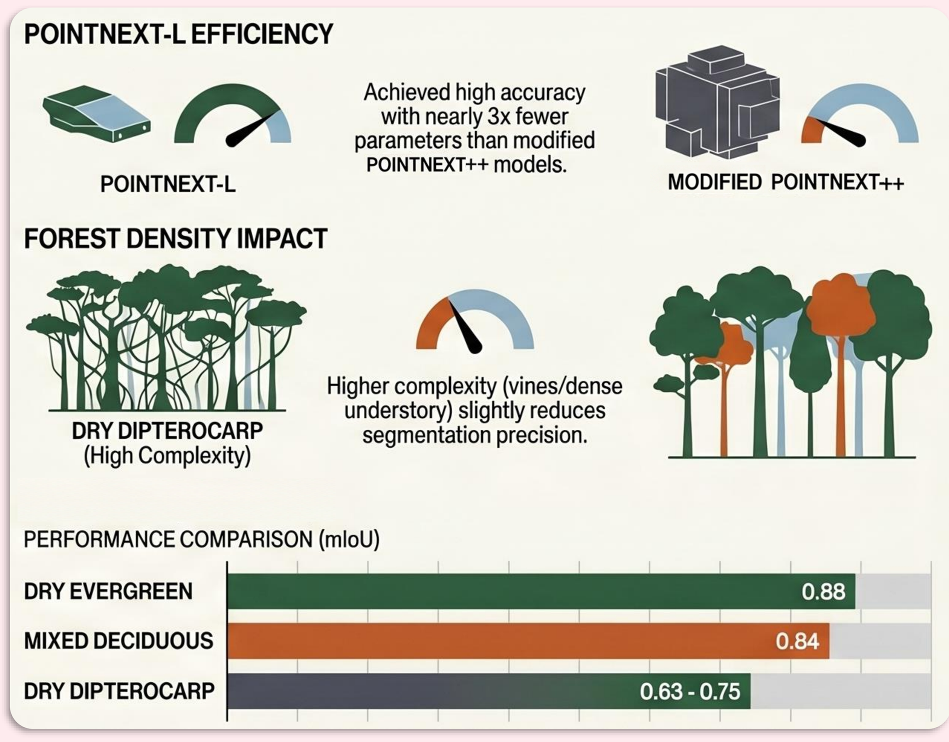


Figure 4. The forest stem segmentation model achieved high performance with fewer parameters than the modified PointNext++ baseline.

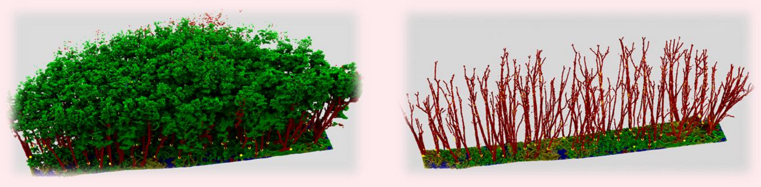
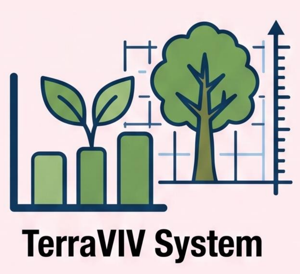


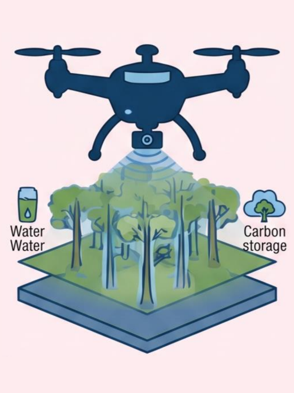
Figure 5. Semantic segmentation of forest point-cloud data into stem and non-stem components using AI models integrated into TerraVIV.

- TerraVIV demonstrates its ability to organize and preprocess tree-scale data for structural analysis, particularly the semantic segmentation of vegetation into stem and non-stem components, as shown in Figure 4. The forest stem segmentation model achieved high performance with fewer parameters than the modified PointNext++ baseline. Accuracy remained strong in simpler forest types, while denser forest structure slightly reduced segmentation precision.
- Figure 5 illustrates that individual tree stems can be identified from point-cloud data as a distinct structural layer beneath the canopy.
- This is an important technical step because stem delineation provides the foundation for reliable tree measurement, which is required before biomass estimation and carbon-stock calculation can be meaningfully undertaken.
- Although carbon credit estimation is still under development, the TerraVIV platform effectively supports upstream workflows, particularly through accurate stem segmentation, which serves as a crucial foundation for reliable biomass and carbon sequestration assessments.

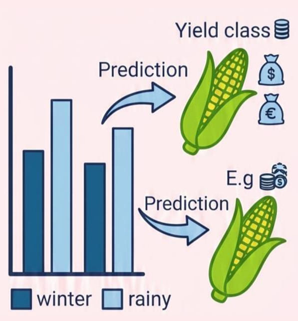
Conclusion



TerraVIV demonstrates that integrating climate data, participatory field observations, drone observations, and AI-based analysis can be used to examine the effects of climate variability on crops and to provide a systematic basis for collecting and analyzing forest structure.



In the forest case study, accurate stem segmentation improves biomass and carbon estimation by reducing measurement uncertainty. Reliable carbon information can support forest monitoring, climate mitigation planning, and sustainable forest management while reducing the risk of errors in carbon accounting and resource assessment.



Seasonal differences significantly influenced yield prediction performance, highlighting the impact of climate variability on crop response. Early yield estimation can help farmers identify production risks, anticipate potential income losses, and support climate-informed decision-making for CCV/DRR.

Overall, TerraVIV emphasizes local validation and the use of multiple data sources to support climate adaptation, disaster risk reduction, and the long-term development of credible biomass and carbon-related applications.

References / Footnotes

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Acknowledgments

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