FOREST COVER TYPE PREDICTION
Chaos-Aware Machine Learning Arquitecture

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Environment & Objectives

Looking forward a tool to predict how seven types of trees should naturally distribute in a comprehend cell of 30x30 meters, we plan on build a reliable machine learning model that learns how variable ecology influents.

We'll build a prediction system that adapts the large data resource around 56 features that combines height, slope, aspect and soil labels.

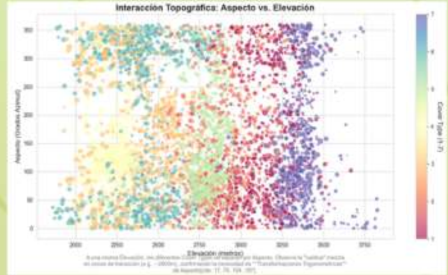
In summary, our main objectives rely on:

- Chaos-aware validation: elevation bands at 2,400 / 2,800 / 3,200 m.
- Uncertainty: aleatoric (entropy) + epistemic (model variance) with threshold amplification.
- Weighted ensemble (RF + XGBoost + LightGBM) for robust, calibrated predictions.

Approach & Planning

Classical ecological linear models fail to capture abrupt regime shifts in montane ecosystems. We adopt ensemble tree methods (RF, XGBoost, LightGBM) + domain feature engineering for robustness and interpretability.

Elevation × aspect coupling produces phase-transition zones (mid-elevation most chaotic). We encode aspect trigonometrically and stratify evaluation by elevation bands (2,400 / 2,800 / 3,200 m).



Data: Roosevelt NF – 15,120 samples, 56 cartographic features at 30 m resolution. Results are region-bound; multi-region validation reserved for future work.

Winning a competition ≠ deployable system, so we must design for reliability, observability and operational recovery. Operational focus: modular pipeline, experiment tracking (MLflow), low-latency serving (FastAPI/Kubernetes), and continuous drift monitoring (PSI, KL).

Gap proposal: prior work rarely treats regime-specific chaos as a design requirement. We look forward to contribute with chaos-aware pipeline + dual uncertainty + elevation-banded validation to manage sensitivity.

Methodology & Progress

<u>Requirements Specification</u>:

Functional requirements include: multi-class prediction (7 classes) with full probability vector; domain-aware features (sin/cos aspect, elevation bands, soil consolidation); uncertainty quantification (aleatoric, epistemic, combined); monitoring & drift detection; dual serving modes (real-time REST + batch GeoTIFF export). Non-functional requirements emphasize modularity, loose-coupling, high cohesion, interpretability, reproducibility (MLflow), availability and MTTR targets.

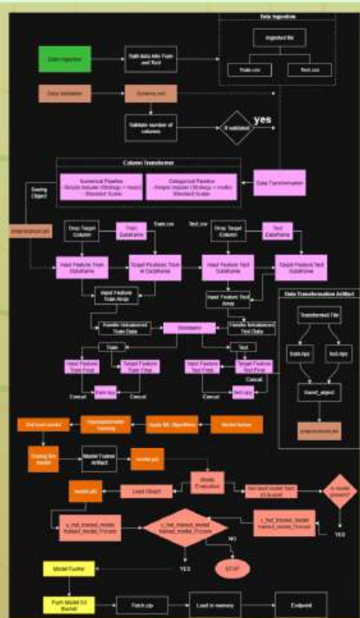
<u>Systems Analysis Summary</u>:

The data mix continuous topo inputs and many rare soil categories – mountains create fragile zones where tiny changes can flip labels, 56 features (topography, distances, 40 soil one-hots with 73% sparsity, wilderness binaries). Vulnerabilities: soil sparsity, threshold chaos (±50m around 2,400/2,800/3,200 m), geographic/time brittleness, aspect-elevation nonlinear coupling

<u>High-Level Architecture Design</u>:

The architecture follows separation of concerns, loose coupling (data contracts), high cohesion, scalability and maintainability. A modular, auditable pipeline from raw GIS to predictions, designed so any layer can be replaced without breaking the system, these layers are:

- 1) Data Ingestion
- 2) Validation
- 3)Feature engineering {sin/cos aspect, elevation bins, soil consolidation}
- 4) Model training {spatially blocked 5-fold CV, Optuna, weighted ensemble}
- 5) Prediction & uncertainty {aleatoric entropy + epistemic variance, threshold amplification}
- 6) Monitoring {PSI, KL, band-wise metrics}
- 7) Serving {FastAPI/Kubernetes, real-time & batch}



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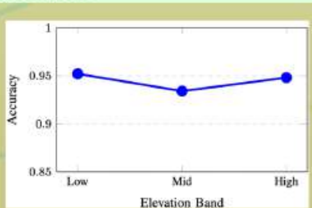
Validation and Experimentation Plan:
We validated not only overall accuracy but also resilience: blocked CV prevents leakage across elevation regimes, planning on stress-test the model with realistic noise/drift scenarios, and we will quantify uncertainty so the system can defer to humans where predictions are unreliable

Results

Baseline and Ensemble Performance: Weighted ensemble (RF + XGBoost + LightGBM) – Accuracy 95.2%; ensemble improves calibration vs single models

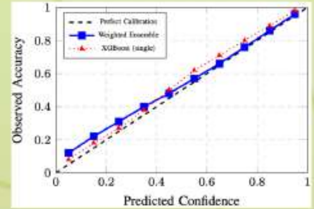
Band-Wise Performance Analysis: shows mid-elevation (2,400–2,800 m) as the most error-prone regime – motivates banded validation and uncertainty amplification.



Threshold Proximity Effects: proximity policy: ×2 uncertainty amplification in ±50 m windows → 19.6% of patches flagged for manual review.

Robustness Under Perturbations: perturbation tests (±25 m elevation, ±5° aspect, 5% noise) produce ⩽3 pp accuracy degradation – meets acceptance criteria.

Uncertainty Calibration: weighted ensemble yields near-diagonal reliability – probabilities align with observed accuracy



Overall Findings & Interpretations: Chaos-aware ensemble delivers high accuracy (95.2%), reliable calibration and perturbation robustness. ~19.6% of area flagged for manual review – supports a human-in-the-loop deployment model

Conclusions & Future Work

Mid-elevation transition zones drive most errors; uncertainty amplification and banded validation reduce silent failures and enable an auditable manual-review workflow.

Combining ecological domain knowledge with systems engineering produced interpretable, maintainable predictions ready for operational validation.

A chaos-aware, production-oriented pipeline (domain features + weighted ensemble + uncertainty & monitoring) achieves 95.2% accuracy while providing auditable decision support in transition zones.

Next steps: test the approach in other regions, improve uncertainty modeling, and integrate live sensors and retraining to handle seasonal and climate-driven shifts