MVeLMA: Multimodal Vegetation Loss Modeling Architecture for Predicting Post-fire Vegetation Loss

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Why Post-Fire Vegetation Matters



Source: https://mountainjournal.org/unified-wildfire-service-plan-stalls-after-congress-demands-answers/

Significance

Understanding post-fire vegetation loss is critical for:

- Developing effective ecological recovery strategies
- Helping resource allocation decisions
- Wildlife recovery efforts

Challenges

- Many wildfire contributing factors remain uncaptured in existing data
    - Their modalities
    - And relationships
- Not as interpretable

Background

Public and corporate administrations trying to update how they manage data that represents territorial attributes

Why?

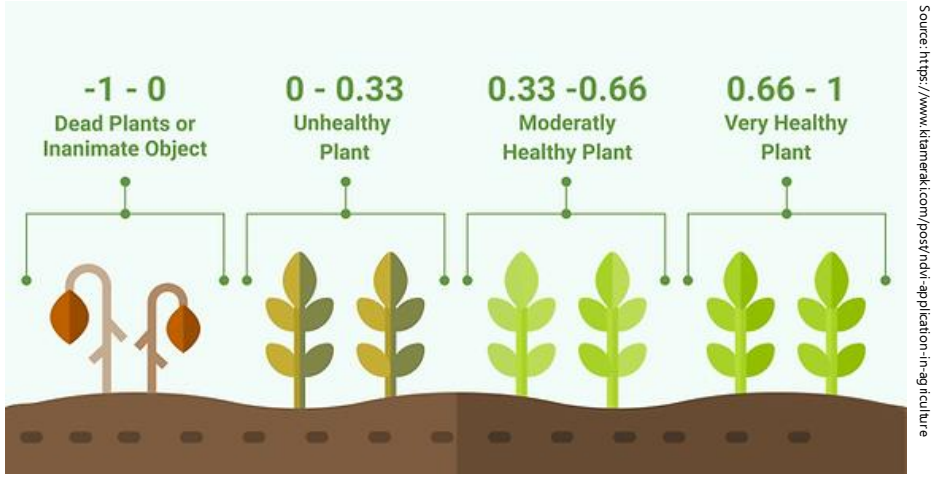
- Need for fundamental, trustworthy information
- **Remote sensing** - able to monitor the earth's surface at local, regional, and global scales.
- This has been used for science, education, and technological globally (accessible)

Normalized Difference Vegetation Index (NDVI)

- Surface reflectance measurement that reflects the level biomass and vegetation growth
- Uses stratum's red and near-infrared wavelengths
- Widely used agricultural production and biomass forecasts, crop health prediction, and agricultural productivity studies

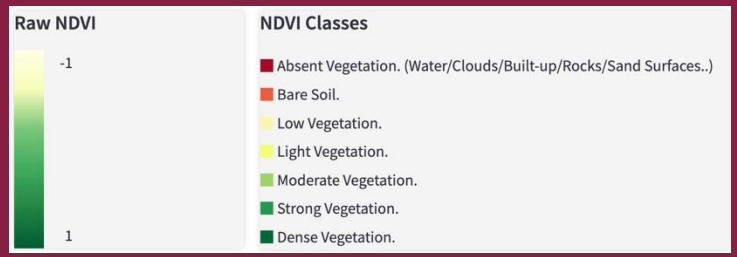
How do we define vegetation loss?

Change in NDVI values



Source: https://www.kitamerak.com/post/ndvi-application-in-agriculture

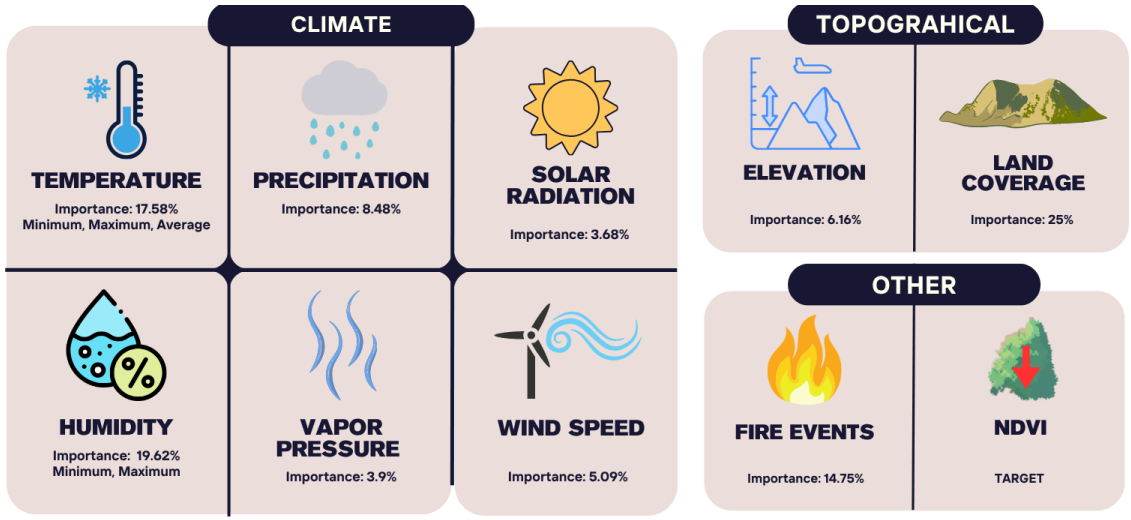
Satellite NDVI composite of Northern California (MODIS 250m resolution) displaying vegetation health gradients. Values range from low NDVI (red, <0.2) in barren and burned areas to high NDVI (green, >0.6) in healthy forested ecosystems.





Problem Statement

We formulate **post-fire vegetation loss** supervised regression problem over a multiscale feature space
Captures temporal dynamics and spatial features



Input:

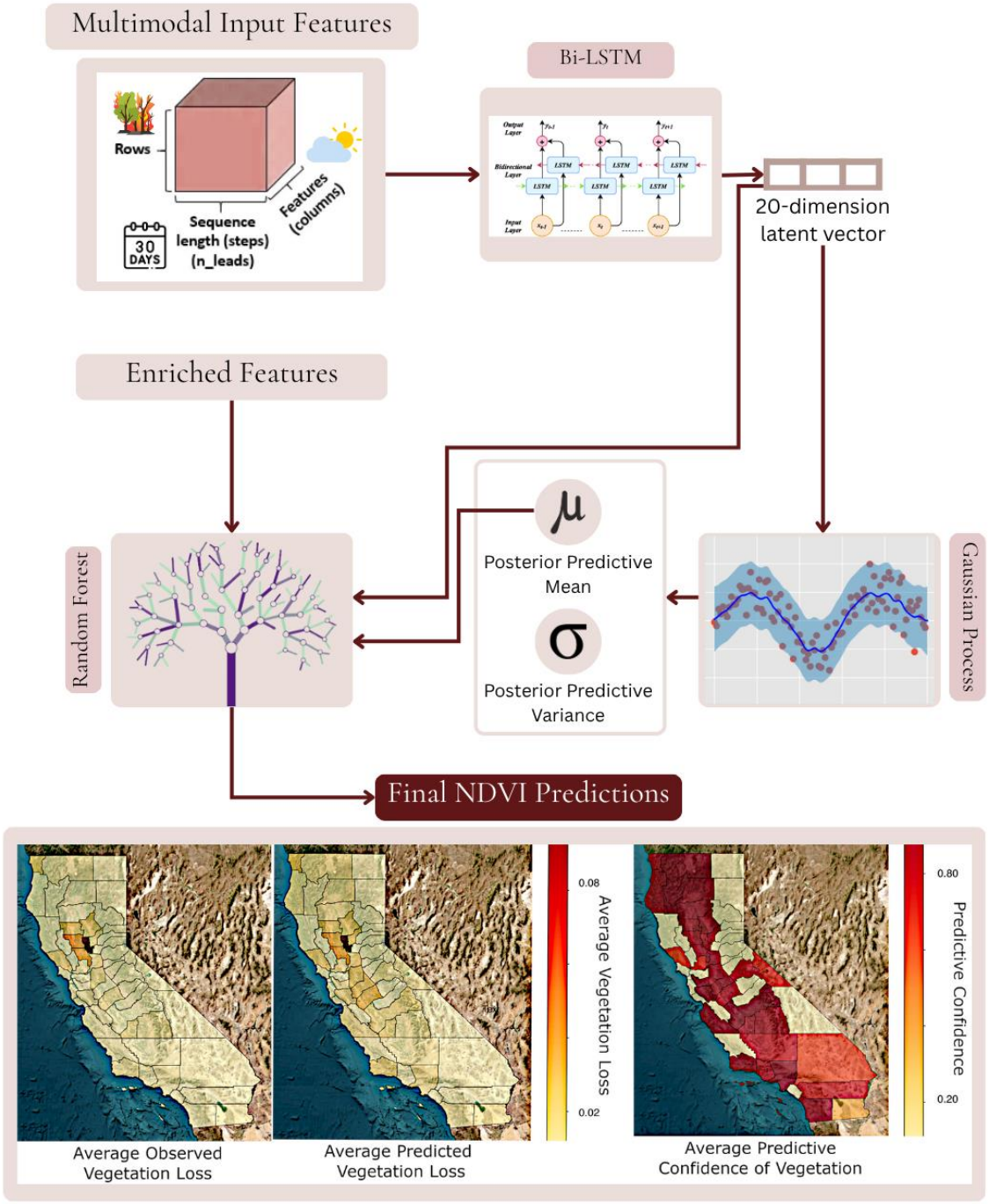
- Spatial information of 30-day pre-fire weather topographical features for each fire event

Output:

- NDVI loss

Maximize the **accuracy** and **precision** of predictions
Calculate and aggregate clear **uncertainty measures** at **county** level
Visualize regions to support identification of at-risk and **vulnerable regions**

3 Stage Multimodal Process

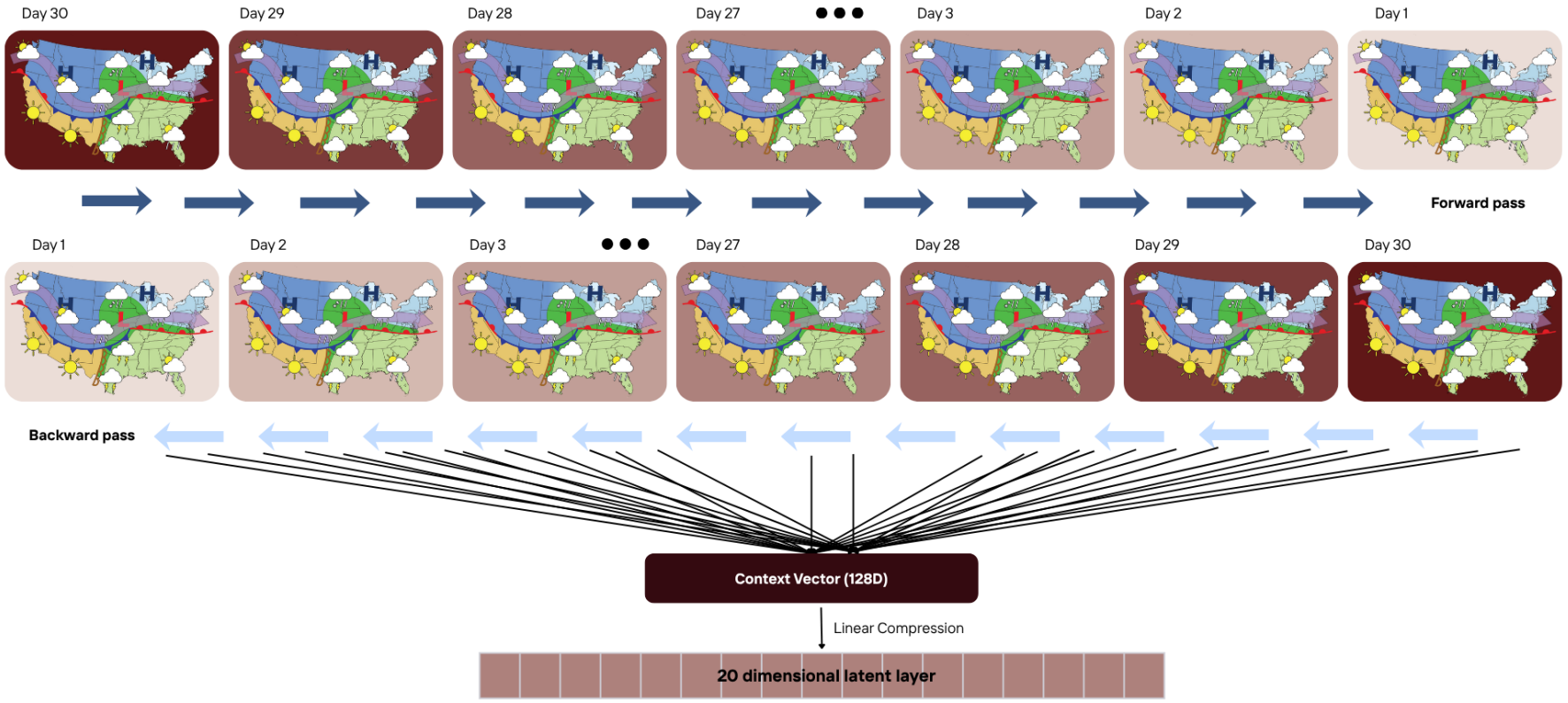


Each stage has strong points:

- **BiLSTM:** Strong at temporal pattern recognition that can take weather patterns and predict vegetation stress
- **GPR:** Strong at uncertainty quantification
- **RF:** Strong at feature integration and adjusting

Better vegetation loss predictions than any single method and has built-in uncertainty estimates for ecology management

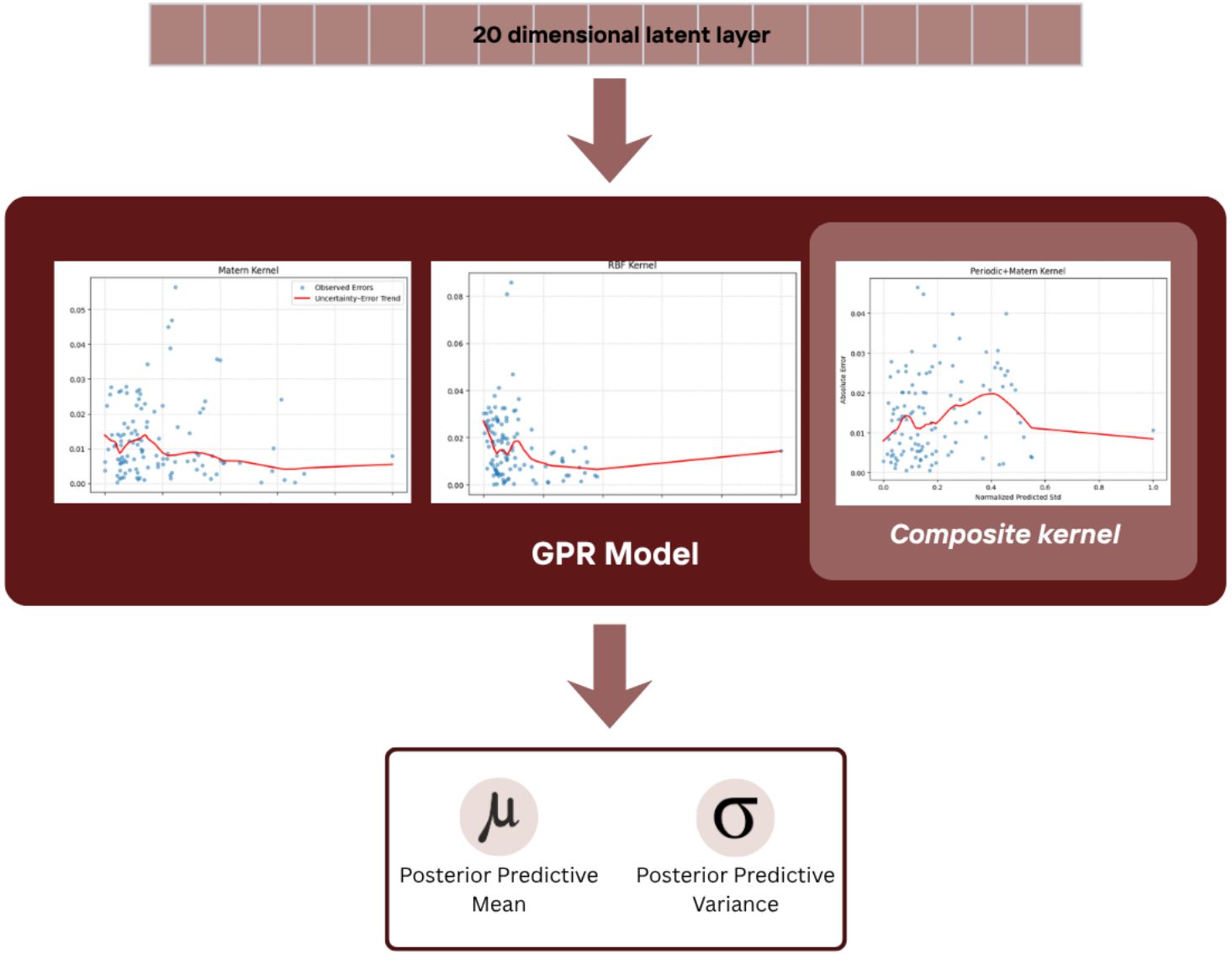
Stage 1: BiLSTM



Why BiLSTM + Attention?

- BiLSTM: Captures **temporal** patterns in **both** directions
- Attention: focuses on the **most important days (recent)**
- 20D Output: creates **compact** features of the GPR stage

Stage 2: Gaussian Process Regression

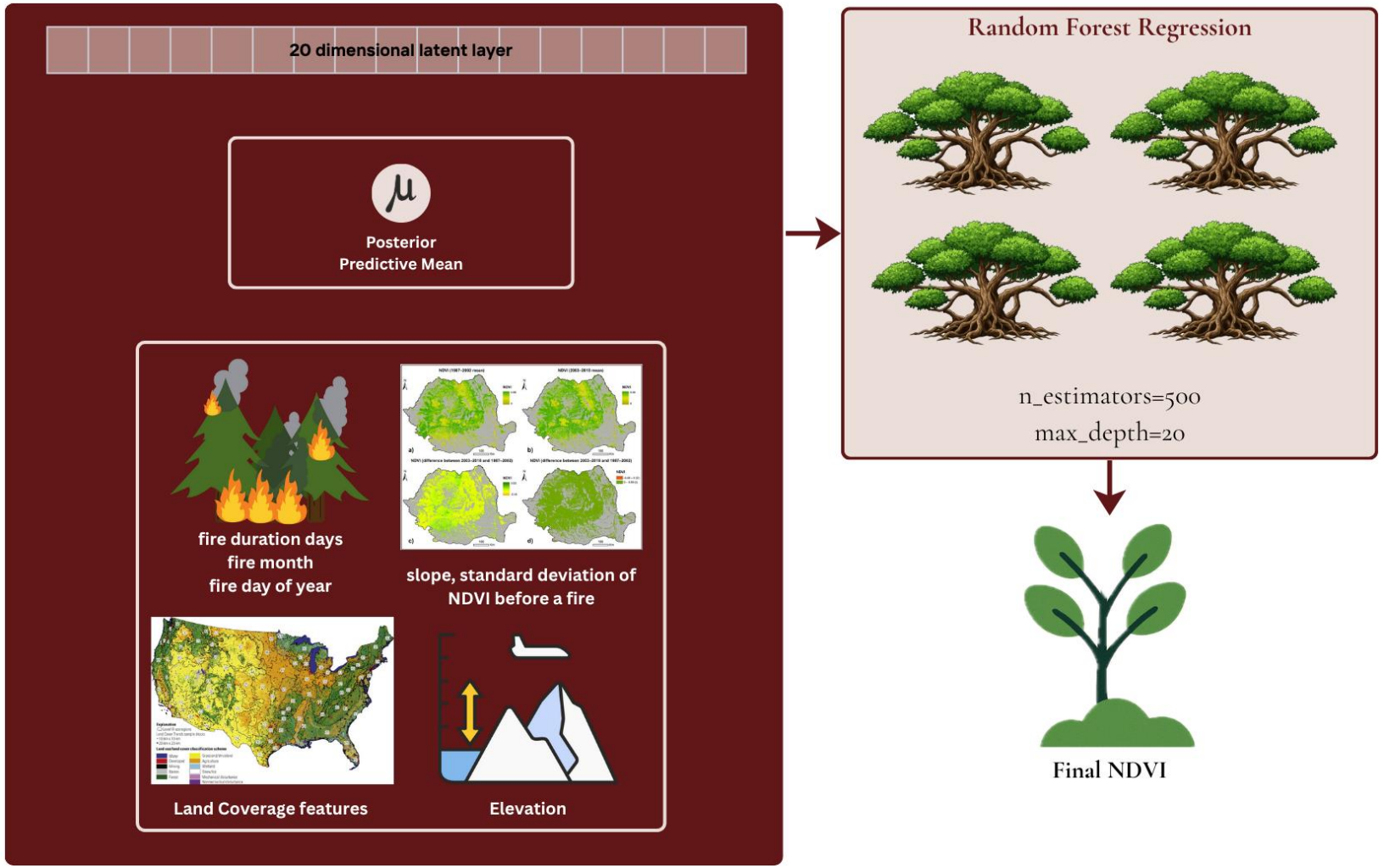


1. **Learns a smooth function** in the 20D latent space
- Similar weather patterns (close in latent space) should give similar vegetation loss predictions

2. **Uses kernel functions** to measure similarity
- The composite kernel, made up of periodic and matern kernels determines how "smooth" predictions should be
- *How similar are these two weather patterns?*

3. **Provides uncertainty quantification**
- Outputs two values: μ (mean prediction) and σ (uncertainty)

Stage 3: Random Forest Regression



Combines **temporal** patterns, **probabilistic** predictions, and **spatial** context for final vegetation loss prediction

1. Integrates Three Information Types
Temporal (latent) + Probabilistic (GP) + Spatial (environment)

- GP only sees weather patterns, not location/soil/elevation
- RF combines all contexts

2. Captures Complex Interactions

- **Example:** Same weather pattern, different outcomes:
- Low elevation + grassland → 32% loss
- High elevation + forest → 19% loss

3. Refines GP Predictions with Context

- **Without latent vector:** RF treats all GP predictions the same
- **With latent vector:** RF understands which weather patterns caused the prediction and adjusts based on local conditions

Experimental Performance

1. Multimodal Feature Integration
- Combines temporal weather patterns (BiLSTM)
- Probabilistic predictions (GP)
- Spatial context (RF)

MVeLMA integrates 40+ features from **multiple data** modalities

2. Addresses Probabilistic Method Limitations
- Probabilistic baselines struggle with limited data in sparse regions
- MVeLMA's GP provides **uncertainty quantification** while RF adds **robustness**

3. Addresses Deterministic Method Limitations
- Methods like LSTM-MC, GRU, 1D-CNN capture temporal patterns but ignore spatial dependencies
- Don't quantify prediction uncertainty

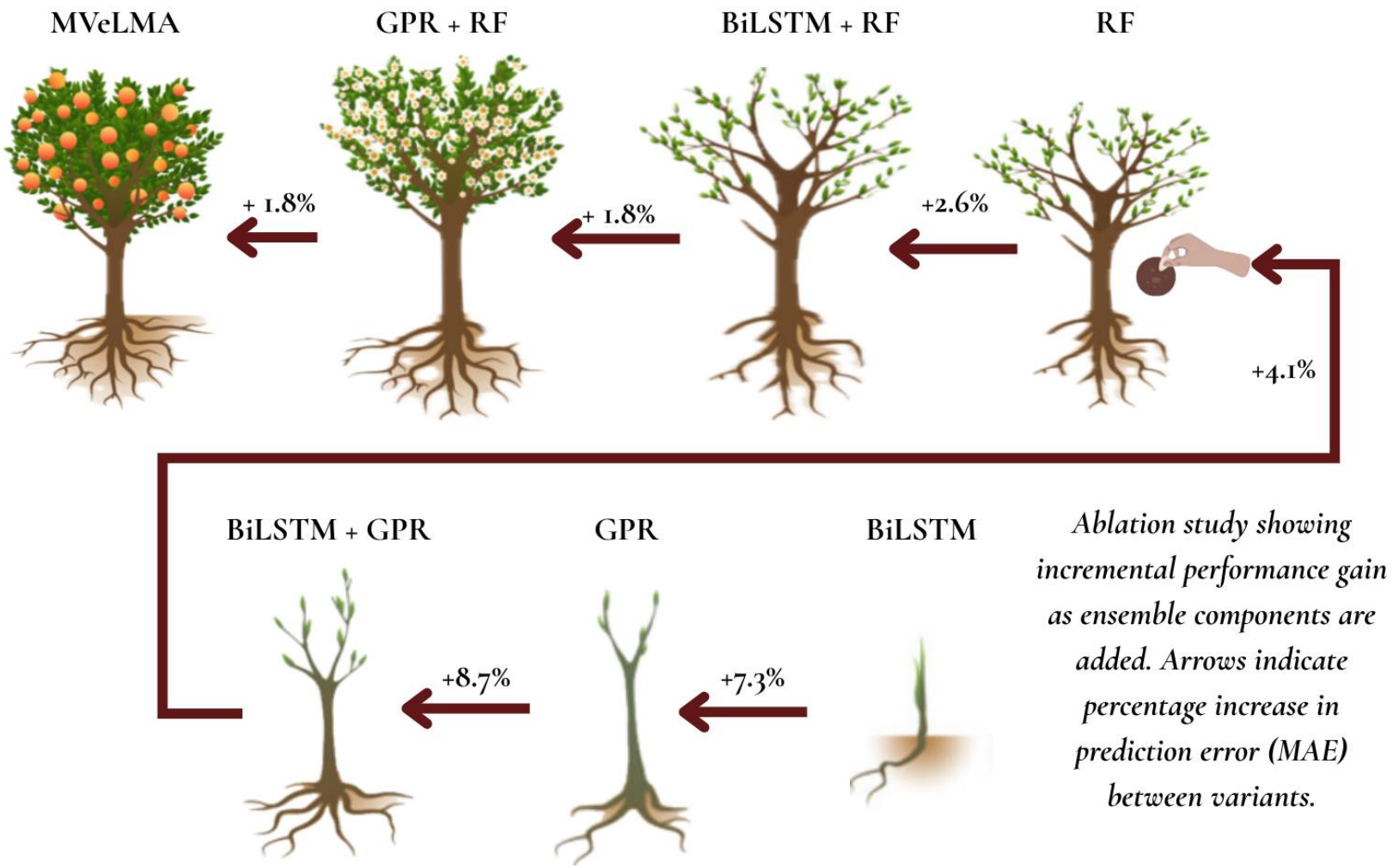
Performance Gap
- **15-35% improvement** in R^2 over next-best models (FFNN: 0.6175, 1D-CNN: 0.5382)
- **50-125% improvement** in MAPE over weakest baselines (LSTM-MC: 10.77%)
- Consistent advantage across all metrics demonstrates robustness

Model	MAE	R^2	MAPE (%)	NRMSE
MVeLMA	0.0109	0.7232	4.77	0.5261
FFNN	0.0126	0.6175	5.45	0.6185
UFSTP	0.0151	0.4815	9.77	0.7201
GRU	0.0133	0.485	5.15	0.7176
1D-CNN	0.0138	0.5382	6.87	0.6795
LSTM-MC	0.0159	0.441	10.77	0.7477



MVeLMA achieves best results in all 4 evaluation metrics
- Lowest MAE (0.0109) and MAPE (4.77%) among all models
- Highest R^2 (0.7232), indicating strongest **predictive** strength
- Best NRMSE (0.5261), showing most **accurate normalized** predictions

Ablation Study



Ablation study showing incremental performance gain as ensemble components are added. Arrows indicate percentage increase in prediction error (MAE) between variants.

1. **RF is Most Critical**
   - Final integration layer essential for combining all information types
   - Spatial context significantly improves predictions
2. **All Components Necessary**
   - Each removal degrades performance
   - No single component can be eliminated without performance loss
3. **Complementary Architecture**
   - BiLSTM: Temporal feature learning
   - GPR: Probabilistic smooth mapping
   - RF: Spatial integration and refinement

Combined effect is better than individual of parts

Case Study: Spatial & Temporal Analysis of California Wildfire Vegetation Loss

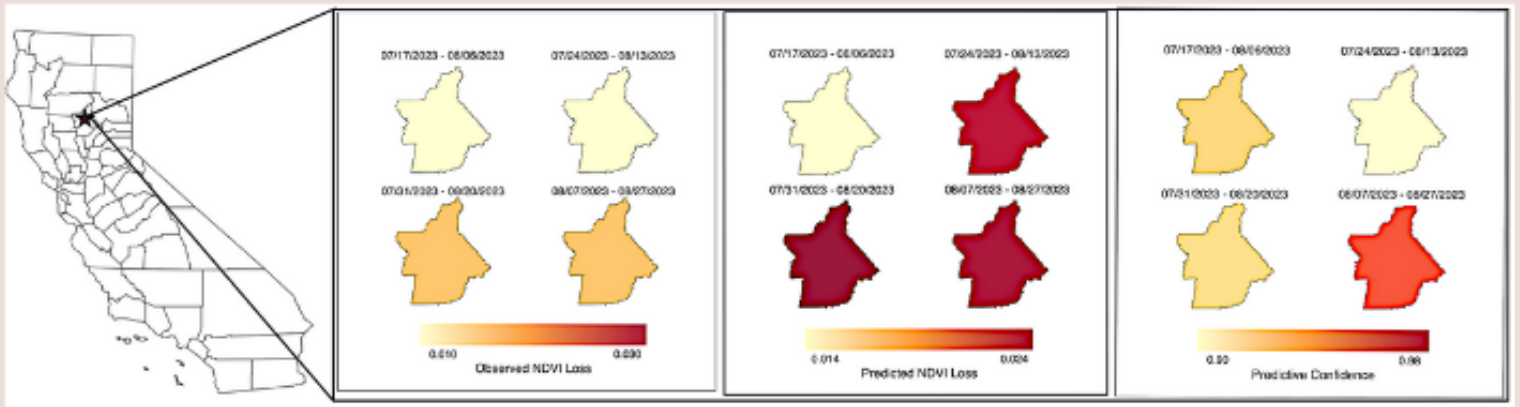
Spatial Analysis:

- Analyzed post-fire vegetation loss across **California** test counties
- OPFVL (Observed) ranged from 0.0006 to 0.0873
- PPVL (Predicted) ranged from 0.0092 to 0.0684
- MVeLMA maintained **high confidence** (0.87-0.98 APC) across all counties

Temporal Analysis:

- Selected Butte County due to high fire frequency and seasonal variability
- Analyzed fire events in overlapping 3-week periods (July-August)
- MVeLMA **captured progression**: OPFVL increased from 0.0123 to 0.0265
- Predictions **closely tracked** observations
- Confidence remained **consistently high** (>0.97) throughout season

Butte County Burns: Can MVeLMA Predict the Damage?



Results show MVeLMA successfully identifies high-risk counties with reliable confidence estimates and accurately tracks seasonal vegetation loss patterns, showing its practical utility for guiding post-wildfire recovery strategies and emergency resource allocation.

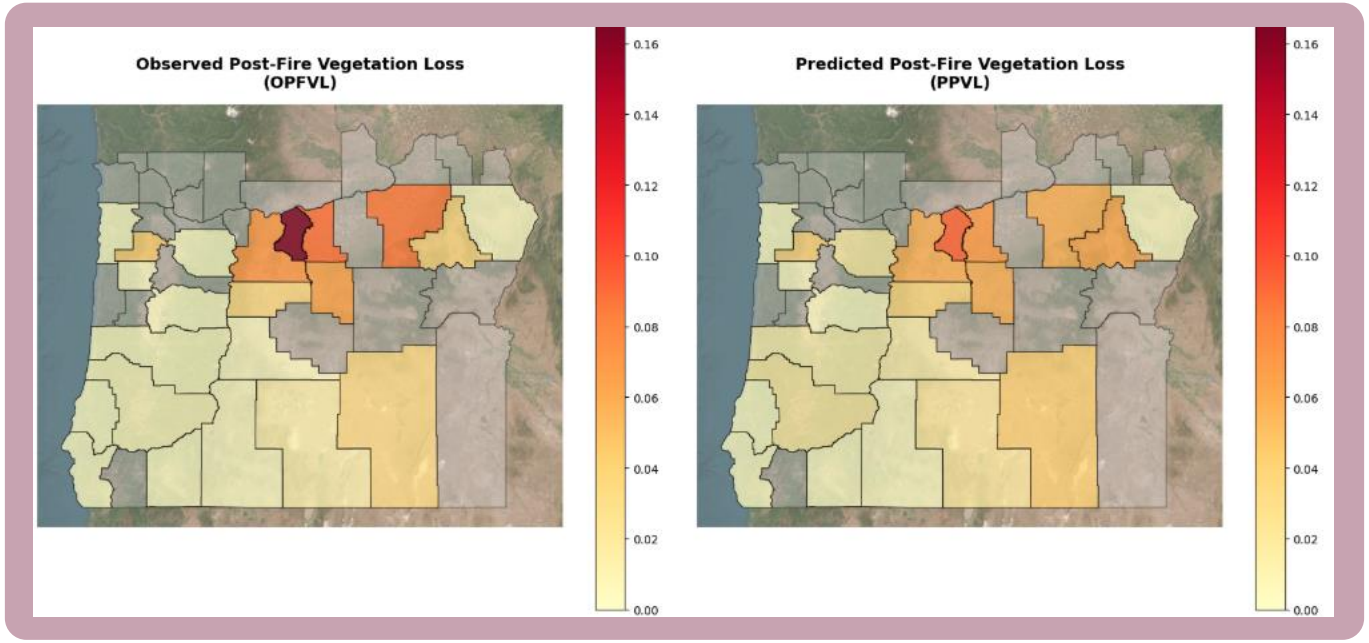
Cross-Regional Validation with Oregon

Model Performance on Oregon Data:

- R^2 = 0.7390 (Strong predictive accuracy)
- MAE = 0.0247
- MAPE = 1.51% (Lower than California)
- NRMSE = 0.5109
- More consistent predictions across Oregon counties

Findings:

- Model generalizes to new region
- New region has more wet and temperate climate
- Earlier fire season (May-July vs Jul-Sep) shows seasonal adaptability
- Comparable R^2 despite regional differences



Future Work

Broader Application:

- Validate on additional states (East coast)
- Test on extreme fire events
- Integrate real-time weather forecasting

Data Sparse Regions:

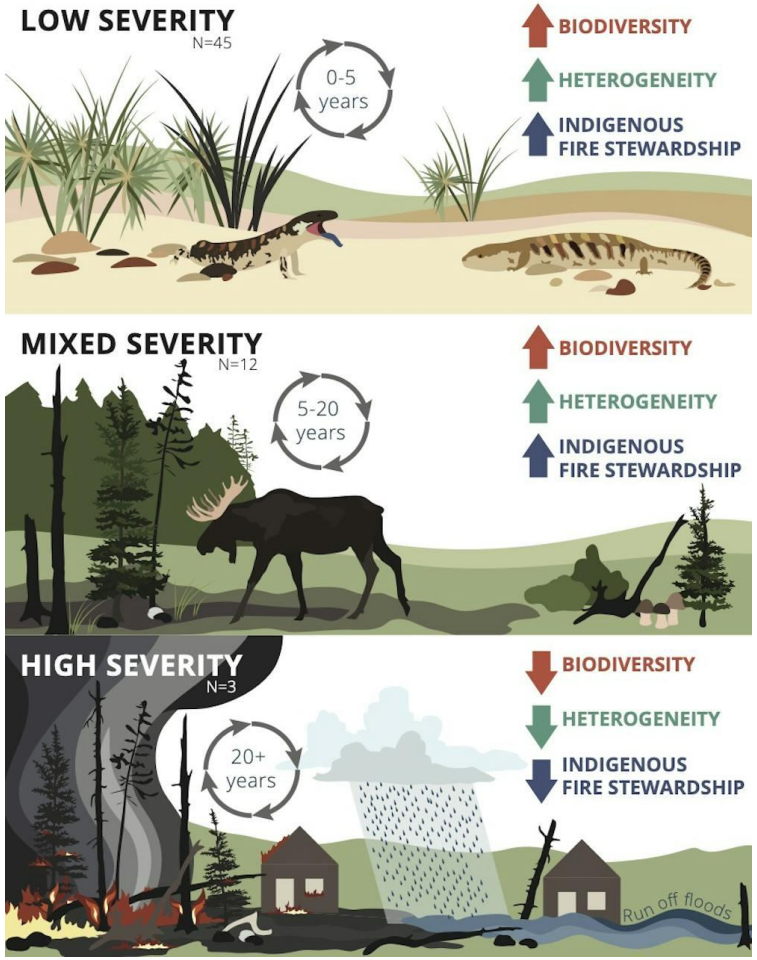
- Apply transfer learning where ground truth data is limited
- Which enriched features are most important?

Presentability:

- A User Interface (UI) to select attributes (e.g., vegetation, elevation, climate features) to see effect of each piece



Source: https://readyforwildfire.org/post-wildfire/after-a-wildfire/



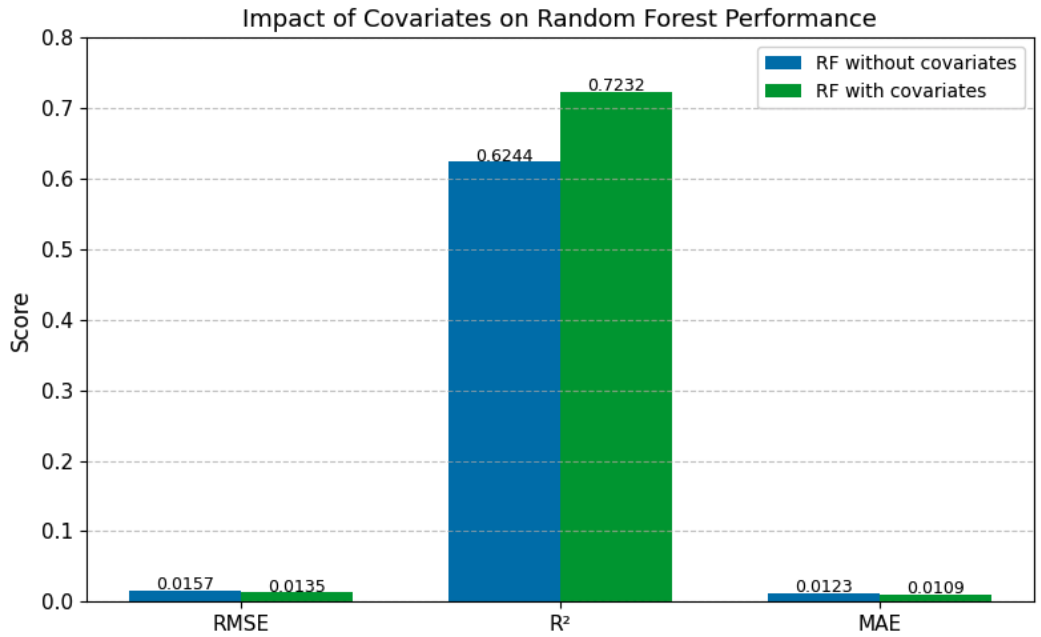
Source: https://theconversation.com/how-indigenous-burning-practices-can-help-curb-the-biodiversity-crisis-165422





Thank you!

Any Questions?


Impact of Covariates on Random Forest Performance
RF without covariates
RF with covariates
Score
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
0.0157
0.0135
0.6244
0.7232
0.0123
0.0109
RMSE
R²
MAE