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An Ensemble-based approach for Continuous Monitoring and Attribution of Vegetation Loss Agents at Regional to National scale using Landsat imagery

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Background

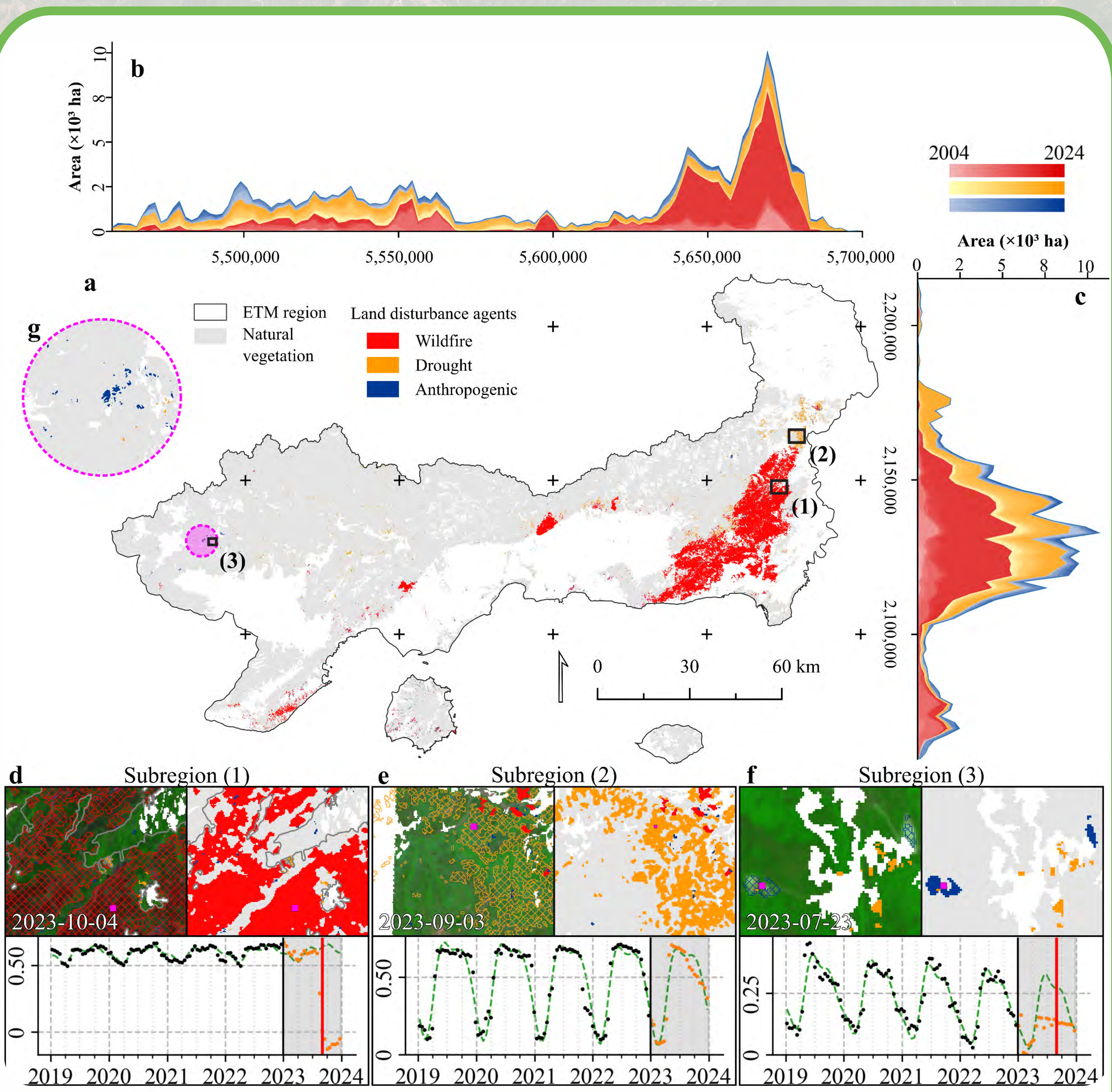
Vegetation loss from **wildfire**, **drought**, and **anthropogenic activities** is accelerating across Mediterranean landscapes, yet attribution of disturbance agents at sub-annual timescales remains an open problem. Offline algorithms lack the timely delivery of monitoring incoming observations that operational monitoring demands, and no study has tested whether an ensemble built *exclusively* from online algorithms can achieve reliable agent attribution.

This study proposes a **feature-level stacking ensemble** of nine base learners — three online algorithms (**BFM**, **EWMACD**, **CCD**) each applied to three spectral indices (**kNDVI**, **NBR**, **NDMI**) — trained on a 24-year Landsat dense time series over northeastern Greece. Attribution is performed in a single step, without prior disturbance mapping.

> **Objective:** Could combining online change detection algorithms outperform any single one — without a single offline step?

Methods

1. **Data & Study Area:** Landsat ARD (2000–2024) over Eastern Macedonia & Thrace — **3,122 scenes**, 30 m resolution, co-registered and NBAR-corrected. Time series regularized to **16-day intervals** via weighted RBF convolution.
2. **Nine Base Learners:** Each of three spectral indices (kNDVI, NBR, NDMI) is monitored independently by BFM, EWMACD, and CCD — giving **9 base learners**, each sensitive to a different facet of vegetation change. A **4-year historical window** was selected by ablation experiment.
3. **Feature Extraction:** Per base learner, breakpoint presence (binary), change magnitude, trend, intercept, and fitting error, were concatenated into a unified **pixel-level feature vector**.
4. **Meta-Learner:** A **CatBoost classifier** performs direct four-class attribution (wildfire / drought / anthropogenic / no disturbance) without a prior detection step. Hyperparameters optimized via Bayesian search with 10-fold cross-validation. Class imbalance handled by inverse-frequency weighting.
5. **Accuracy Assessment: 796 stratified validation samples** for 2023 — stratified random design employing proportionate allocation. Metrics: OA, UA, PA, macro-F1, commission and omission error.



Spatiotemporal distribution and agent attribution of vegetation loss (2004–2024). (a) Spatial distribution of loss agents for 2023. (b–c) Longitudinal profiles of disturbance frequency and area (ha) aggregated at 1,200-m intervals. (d–f) Case studies for wildfire, drought, and anthropogenic disturbances, including Landsat OLI imagery and BFM-NBR time-series profiles with detected breakpoints. (g) Detailed anthropogenic attribution for quarrying activities

Results

75.6%
Overall Attribution Accuracy
Across all four classes

+6.2%
Gain over best single
CCD-kNDVI

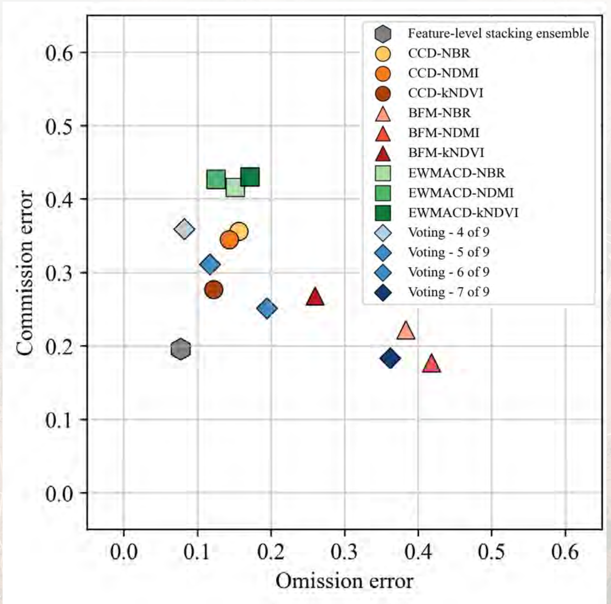
14.8%
Overall Detection Error
Lowest of all models

+7.8%
CE/OE balance
Improvement across classes

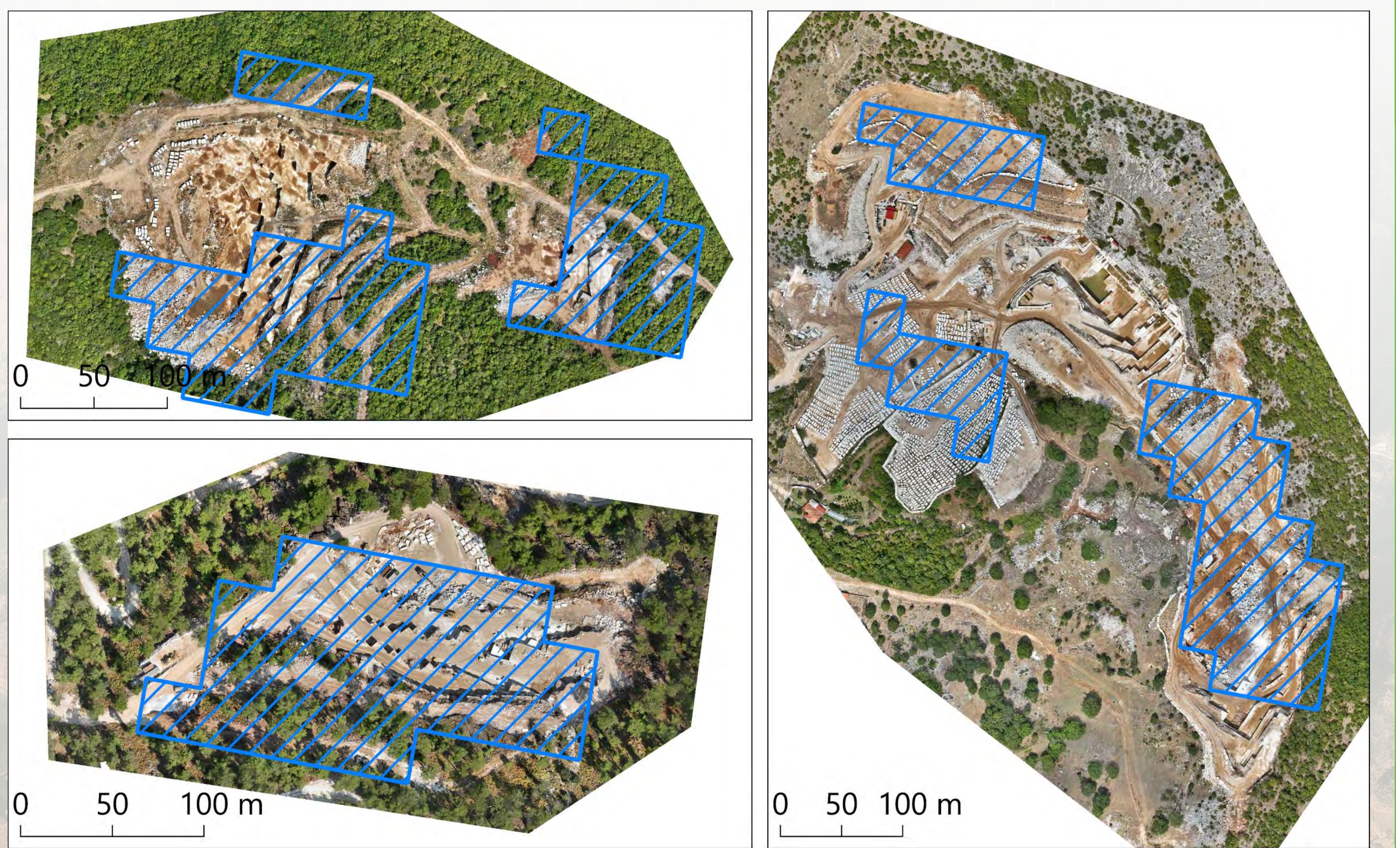
Wildfire — F1: 79.9%
Highest class F1. Supported primarily by **BFM and CCD** through large negative magnitudes in NBR and NDMI.

Drought — F1: 62.8%
Relied on absence of BFM breakpoints and intermediate-negative **EWMACD** magnitudes — separating it from wildfire when both co-occur.

Anthropogenic — F1: 55.5%
Distinguished by **kNDVI trend decline** across all algorithms, reflecting permanent land cover conversion.

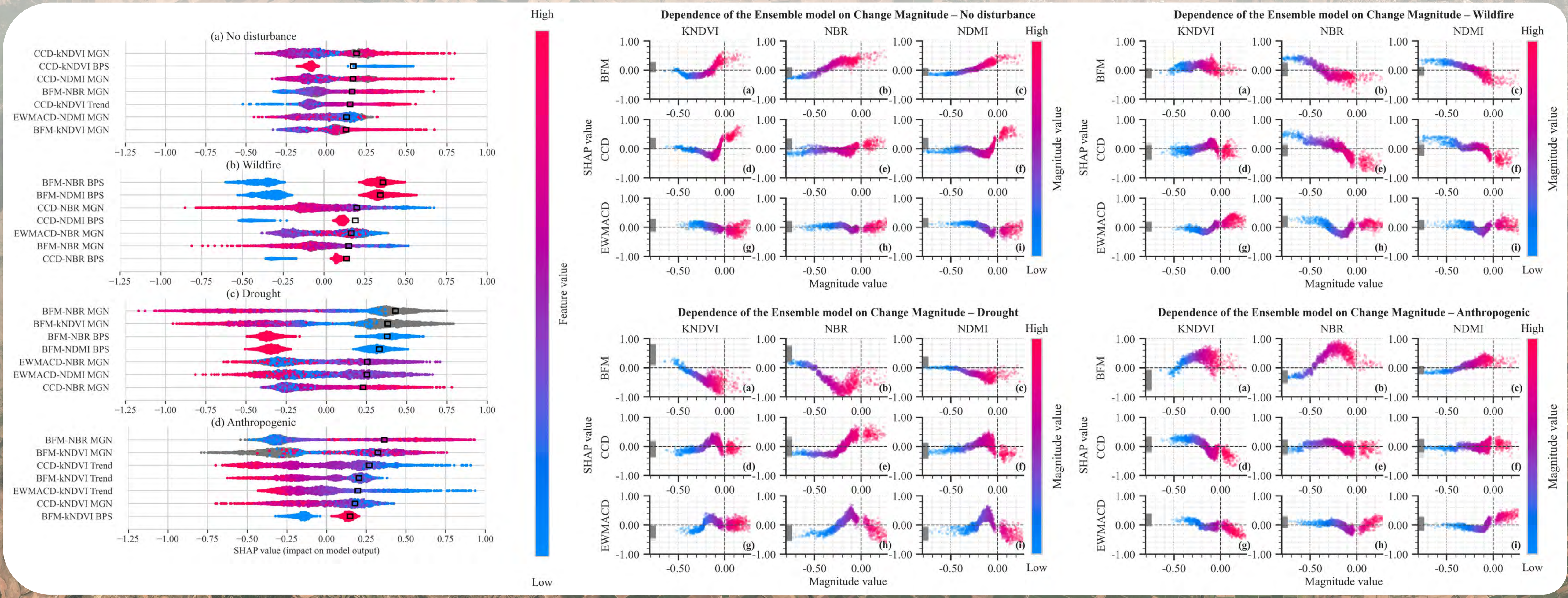


The feature-level stacking ensemble (grey hexagon) **outperformed all** nine individual base learners and all voting-aggregation approaches, achieving the best balance between commission and omission errors.



Comparison of anthropogenic disturbance attribution for three quarries. Blue hatched areas represent automated attribution results (2023) validated against UAV orthophotos (2025).

> **Change magnitude** was the single most important feature class across all four attribution categories, followed by breakpoint presence and trend.



Conclusion

An ensemble built *only* from online algorithms can attribute multiple vegetation loss agents **without offline analysis, annual composites, or a two-step detection pipeline**.

→ **Complementary Sensitivities**
Combining **BFM** (abrupt), **EWMACD** (gradual), and **CCD** (persistence) into a single meta-learner captures what no individual algorithm can alone

→ **Operationally Deployable**
Processing one 48 km² in ≈81 minutes – scalable from regional to national monitoring without cloud-platform lock-in.

→ **Remaining Challenges**
Attribution of diffuse anthropogenic disturbances and drought events with limited training samples.

> As pressures reshape these ecosystems, **real-time, agent-specific monitoring** is no longer a research goal but an operational necessity.

Acknowledgements

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