Improving Wildfire Prevention: Combining FWI Components, Historical Burn Probabilities, and Multi-Sensor Satellite Data for Better Early Warning Systems in Los Angeles, CA

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EGU General Assembly 2025, Vienna, Austria

Introduction

Wildfires are a growing threat in fire-prone regions like Southern California, as seen in the severe 2024/25 fire season. Rapid climate shifts, prolonged drought, and expanding urban-wildland boundaries are intensifying both the frequency and severity of wildfire events. Despite advances in modelling and monitoring, current early warning systems often lack the spatial granularity and dynamic responsiveness needed for localised risk assessment.

This study introduces an innovative, data-driven approach that integrates Fire Weather Index (FWI) components, historical burn probabilities, and multi-sensor satellite observations (e.g., Landsat 8-9, ERA5, MODIS) and other data.

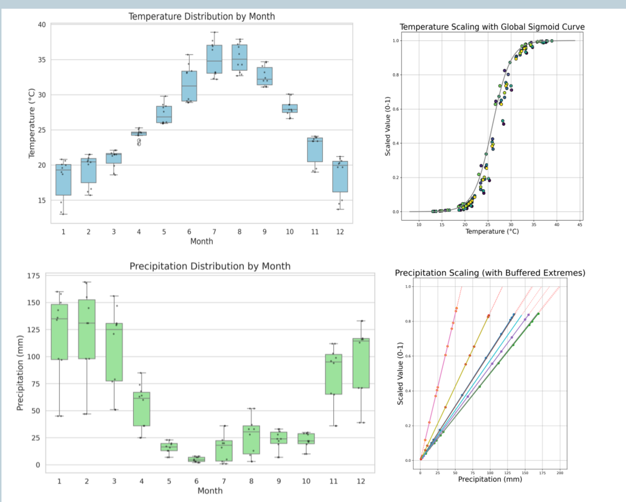
By automating risk weighting using Shannon entropy within an Analytic Hierarchy Process (AHP), our method reduces subjective bias and adapts to local conditions. The goal is to support the development of a real-time early warning dashboard for proactive wildfire risk management in, for example, the Los Angeles region or other challenging (dry/sparsely vegetated) landscapes.

Initially, we explored cross-validating MODIS and ERA5 Land Surface Temperature (LST) trends. However, significant microclimatic variability across landscapes revealed limitations in applying a single validation model region-wide. This insight led to a refined focus on local-scale analysis and automated, data-driven prioritisation to better capture wildfire risk in heterogeneous environments.

Background (Local Weather)

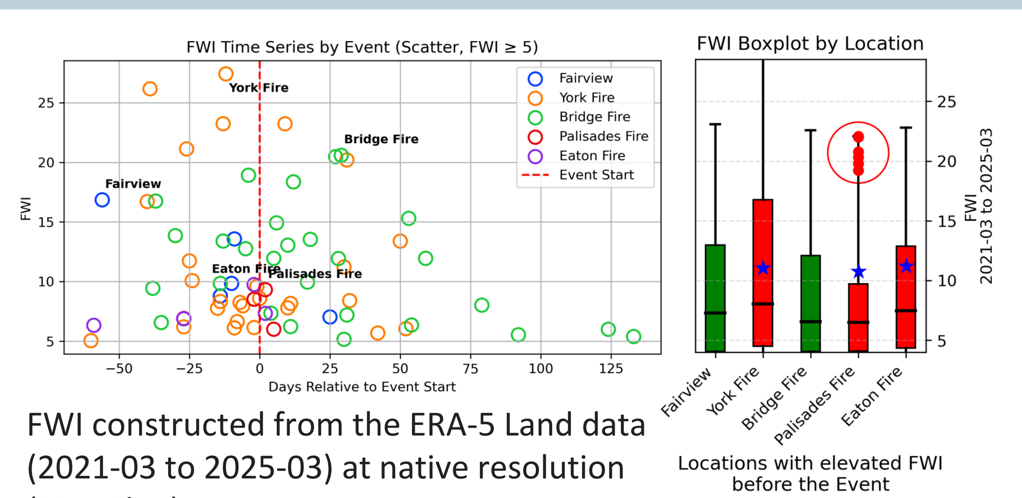
Historical Weather

To evaluate the role of climatic conditions in wildfire dynamics and recovery, we extracted monthly precipitation, temperature, and wind speed data from WorldClim v2.1, which provides long-term climate normals (1970–2000) at a spatial resolution of 30 arc-seconds.
For every month, pixel values were extracted and used to compute key summary statistics, like mean, median, minimum, maximum, and standard deviation.



Local Fire Weather

The Fire Weather Index (FWI) shows substantial daily variation in fire conditions across study areas, emphasising the dynamic nature of wildfire risk, and these graphs are highlighting the importance of monitoring short-term fluctuations, as well as the necessity of localised forecasting to distinguish between high-risk but non-fire days and actual wildfire events.



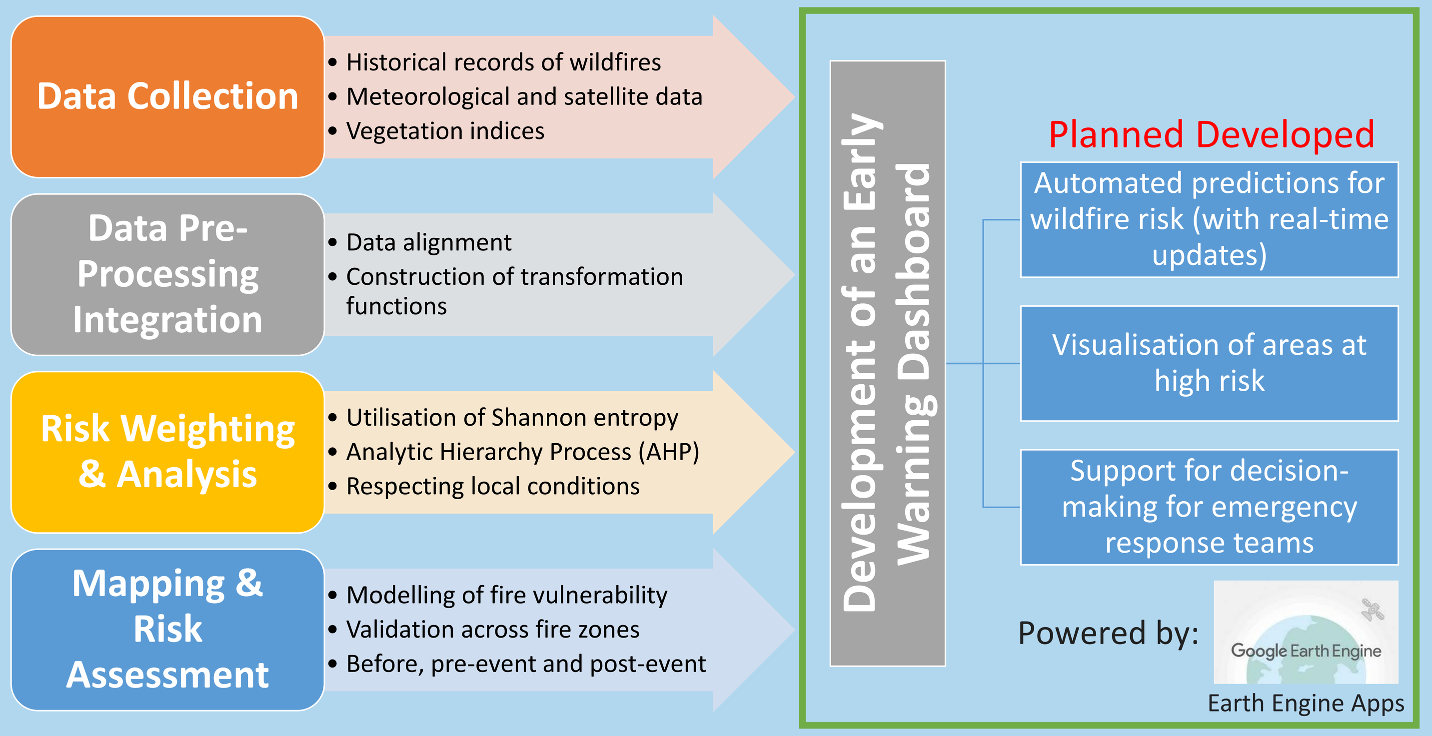
FWI constructed from the ERA-5 Land data (2021-03 to 2025-03) at native resolution (10x10km).

Locations with elevated FWI before the Event

FWI classification:

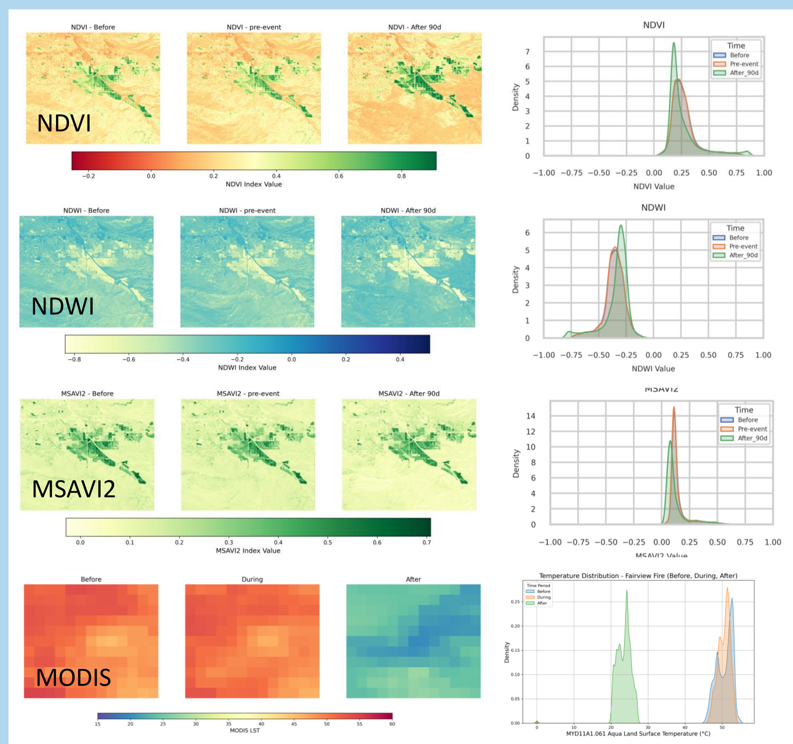
Very low danger:	< 5.2	High danger	21.3 and <38.0
Low danger:	5.2 and <11.2	Very high danger	38.0 and 50
Moderate danger:	11.2 and <21.3	Extreme danger:	>50

Methodology

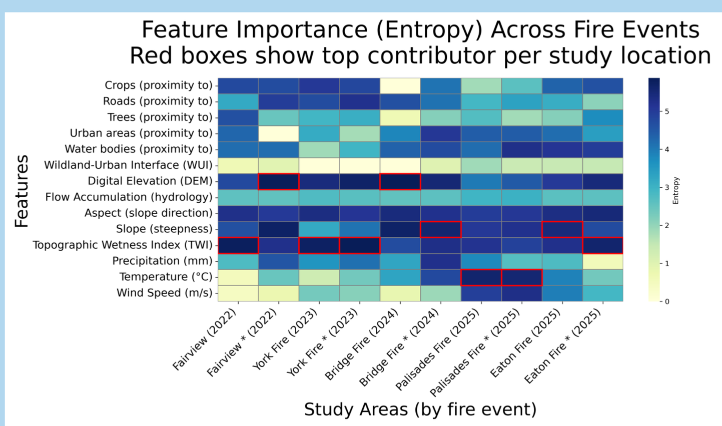


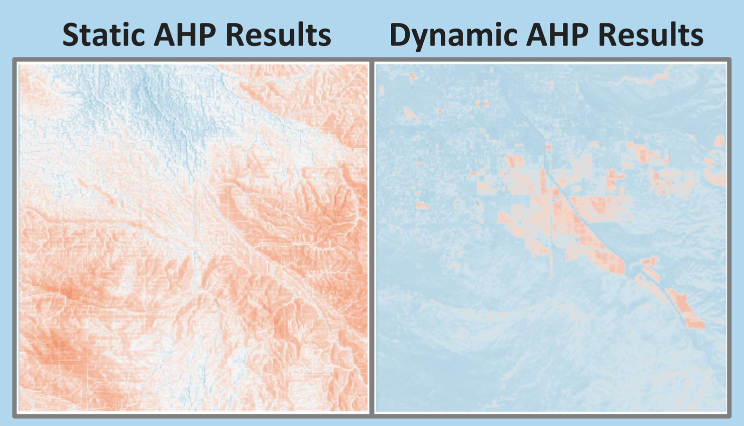
Local Conditions

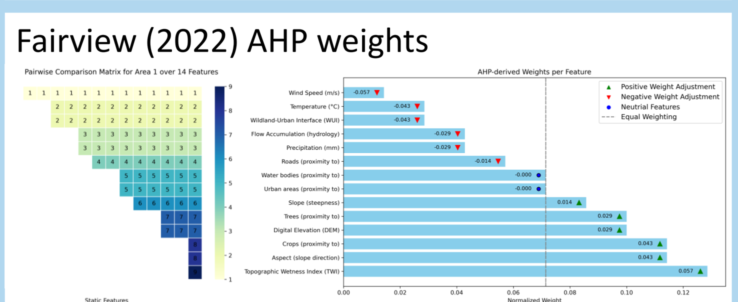
In this analysis, NDVI, NDWI, and MSAVI2 indices were employed to assess vegetation condition and moisture dynamics across wildfire-impacted areas. NDVI provided a robust measure of vegetation greenness for evaluating burn severity and recovery trajectories, while NDWI offered insights into vegetation water content and surface moisture — critical in fire-prone arid environments. MSAVI2 proved especially effective in low-vegetation or exposed-soil conditions common after fires, where it minimised soil background influence on vegetation signals.
MODIS 8-day average Land Surface Temperature (LST) is the fourth dynamic parameter to describe the local conditions.



Analytical Hierarchical Process





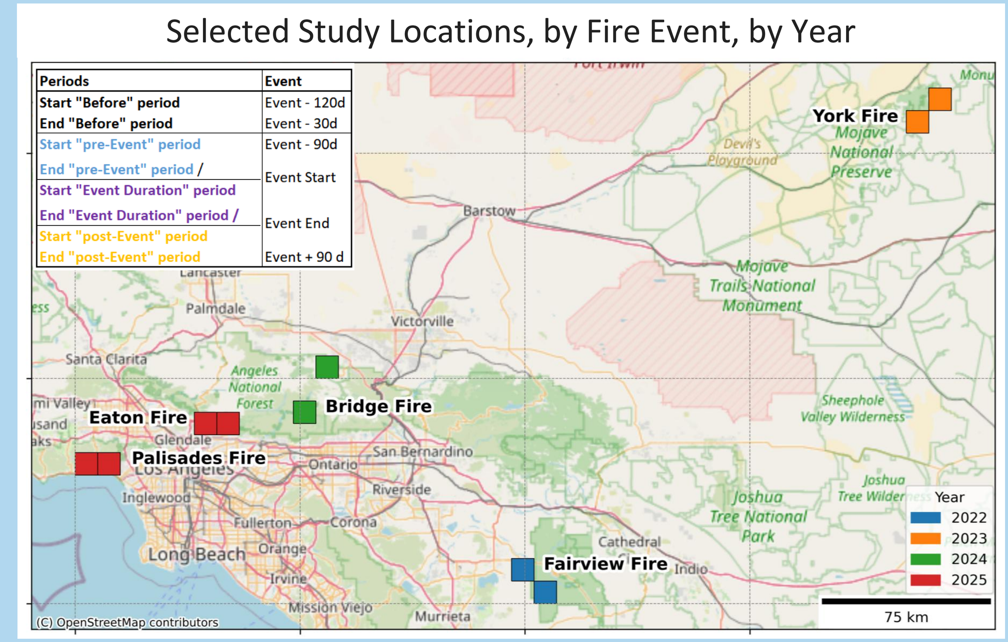


The heatmap ranks feature importance (Shannon SDI) by event, AHP calculates weights, and combined static-dynamic layers form an equally weighted risk map (for Fairview), by reporting period (before, pre-event, and post-event) integrating spatial-temporal data for wildfire risk assessment.

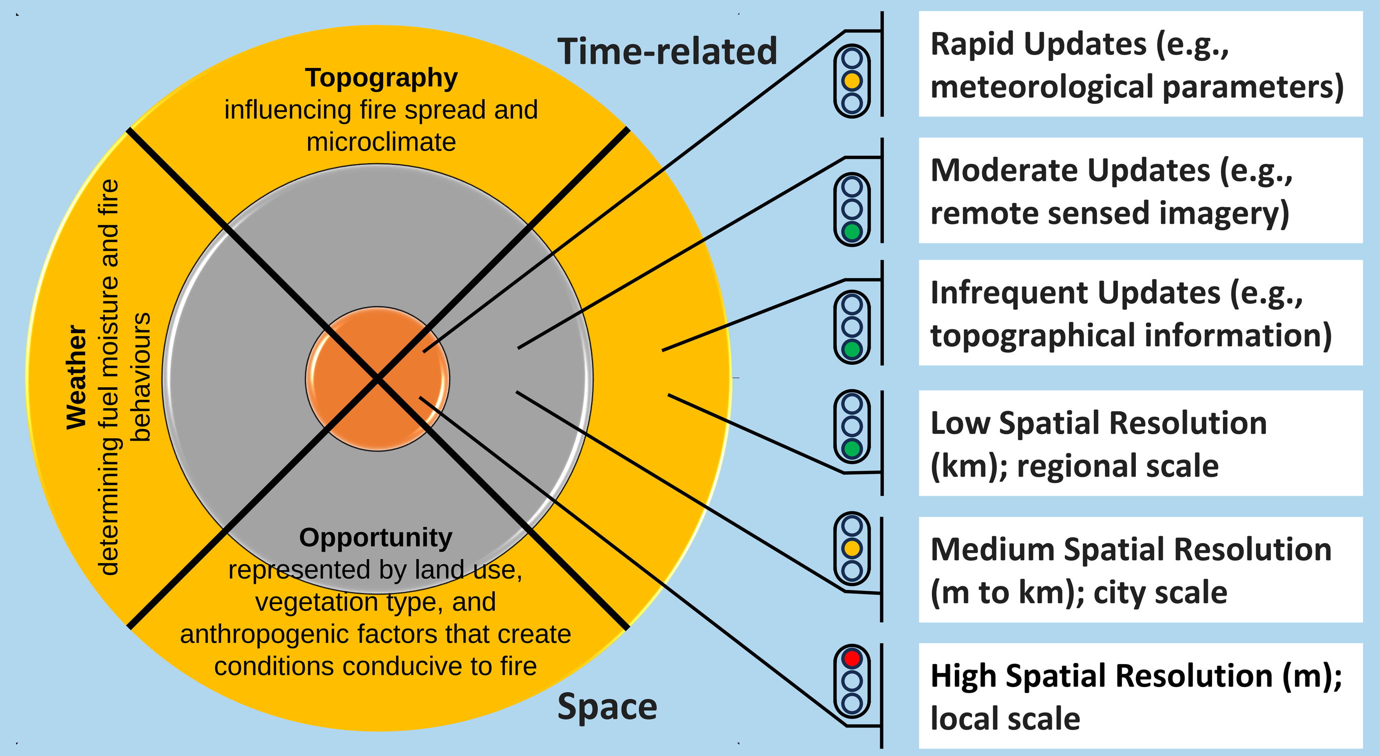
Study Areas

In this study, we investigated five wildfire events in California, selected for their timing and geographical relevance to the most recent wildfires in the greater Los Angeles area.

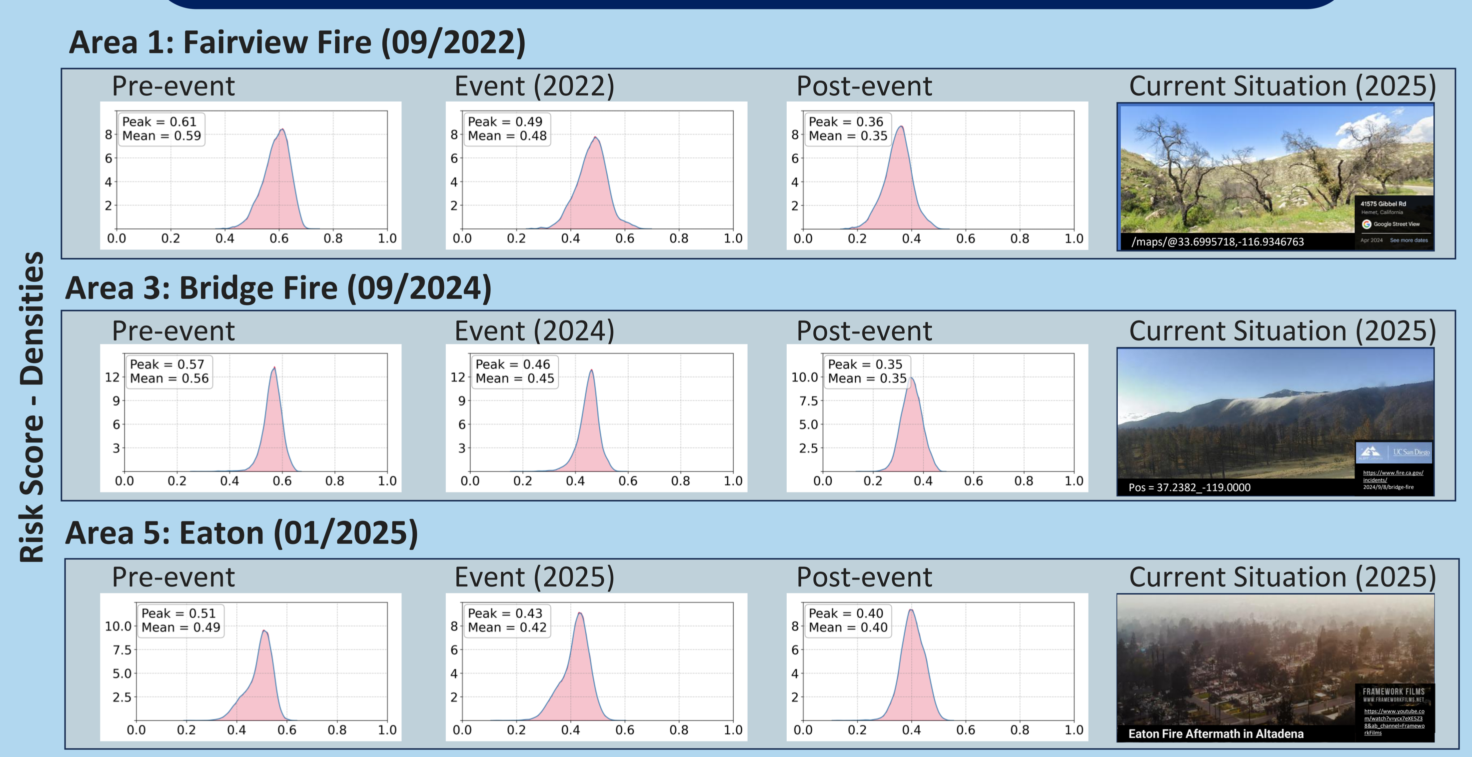
Each fire region, measuring 10x10 km, is derived from CAL FIRE incident reports. Furthermore, a second location within the same fire zone was included to enable blind testing of our methodology.



Temporal and Spatial Resolution of Risk



Risk Evaluation and Recovery



Discussion & Conclusion

- A key contribution of this study lies in addressing the limitations of expert-driven weighting in multi-criteria decision analysis at fine spatial scales.
- Traditional Analytic Hierarchy Process (AHP) applications rely on expert judgment, which becomes impractical or unreliable when applied to localized units, such as 10×10 km cells in this study, where no individual expert can feasibly possess site-specific knowledge.
- To overcome this, we propose a novel integration of the Shannon Diversity Index (SDI) as a proxy for localised expertise. By quantifying ecological heterogeneity, Shannon diversity provides a meaningful, data-driven surrogate for expert input, enabling context-sensitive weighting without requiring subjective intervention.
- The input for the SDI is a set of fuzzy functions to represent gradual transitions in environmental criteria; this approach creates a scalable, reproducible, and objective framework for environmental decision support.

Limitations & Future Work

Sparse Historical Fire Records:

In some of the 10×10km regions, historical burn data is limited or absent, leading to low sample sizes and potential biases in risk estimation.

Land Surface Temperature (LST) Cross-Validation:

MODIS vs ERA5 LST cross-validation was not yet implemented; future work will explore this for thermal anomaly verification.

Future Directions:

- Explore regional proxies for fire history
- Integrate synthetic burn probability models
- Conduct validation of early warning triggers using past fire events
- The results are preliminary, and the dynamic risk layer can be enhanced with downscaled temperature, precipitation, and wind data to create FWI, SPIE, and KBDI indices, which were unavailable at the time of presentation.

Data Sources

All input data layers (n = 21), including raw and composite indices, were sourced from the publicly available Google Earth Engine Data Catalogue. Detailed descriptions and links to each dataset are provided in the supplementary material and are available upon request.

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