

How do we fuse multi-sensor remote sensing data to precisely detect active fires in near real-time?



Natural
Hazards
Research
Australia

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Advanced Data Fusion for Near Real-Time Active Fire Detection

Polar-orbiting satellites provide fine spatial resolution, while geostationary satellites offer frequent observations. By fusing multiple Earth observation sensors via data assimilation, we harness these complementary strengths to deliver near real-time (under 10 minutes) active fire detection.

Data Sources and Fusion

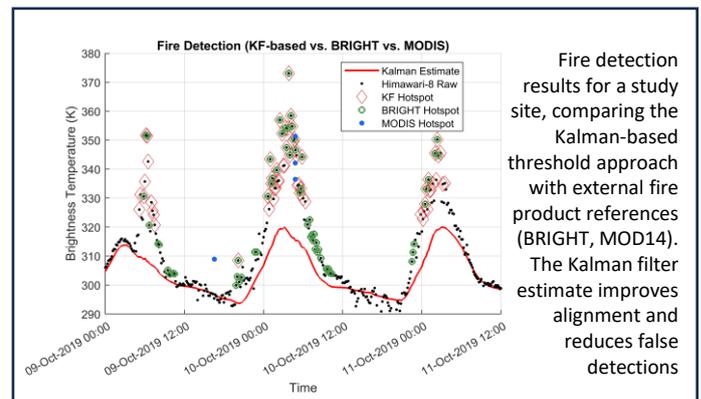
Geostationary sensors (Himawari-8/9, GeoKompsat-2A) provide frequent snapshots that reveal short-term temperature spikes, while polar-orbiting sensors (Sentinel-3) capture finer detail but revisit less often. By **fusing these data**, each sensor's limitations are offset by another's strengths, creating a continuously updated background temperature for rapid fire detection. The framework is **sensor-agnostic**, so future satellites can be integrated if they provide thermal infrared observations. Because sensors differ in resolution, revisit time, and spectral response, straightforward averaging can bias the background temperature. We address this using a **spatio-temporal weighting scheme** that accounts for time offsets, spatial footprints, and spectral closeness to the reference wavelength.

Kalman Filter and Data Assimilation

A **Diurnal Temperature Cycle** model estimates baseline thermal fluctuations. Observed satellite brightness temperatures are then assimilated to refine the background estimate. **Ensemble Kalman Filtering** adjusts for sensor discrepancies and noise, producing accurate background temperatures used for fire detection.

Why Not a Machine Learning Approach?

While deep learning shows promise, it demands extensive labeled data that cleanly separates fire from non-fire under diverse conditions. This challenge grows when fusing satellites with different resolutions, noise, and cloud contamination. A Kalman Filter approach is more **transparent**, **adaptive**, and **robust** for near real-time data streams, without retraining when new sensors or regions are introduced.



Stratified Study Case for Australia

A continent-wide experiment was conducted using carefully selected pixels that span various **climate zones**, **land cover types**, and **bioregions**. This stratified approach ensures that the chosen sites are representative of the diverse environmental conditions across Australia, demonstrating that our method is effective across the entire continent.

Three Kalman Filter Iteration Approach

Our Ensemble Kalman Filter performs **three assimilation-and-detection** passes. The first pass uses a strict threshold for major fires, minimizing false positives but missing smaller ignitions. The second lowers the threshold, capturing more fires at a slight risk of false alarms. The final pass is least restrictive, flagging subtle anomalies that could be early-stage fires, albeit with higher false detection. Together, these iterations **balance** conservative confirmation of large fires with broad coverage of smaller potential ignitions, **all within 10 minutes**.



Further information

For additional information scan the QR code or contact:
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