Reconstructing savannah wildfires using deep learning

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Introduction

Savannahs are the most fire prone terrestrial biome, accounting for over 70% of global burned area[1] and 62% of biomass burning emissions[2]. Reconstructing savannah fire events, by isolating points of ignition and mapping spread direction, requires frequent sampling at a high spatial resolution. The opposing strengths and weaknesses of geostationary and low earth orbit satellites makes data fusion approaches highly suitable.

This research combines geostationary observations from Himawari-9 with a low earth orbit active fire product (VIIRS AFIMG) to produce synthetic active fire detections every 10 minutes with the spatial resolution of a low earth orbit satellite.

Aims

- Produce high spatial and temporal resolution reconstructions of savannah wildfire activity by combining geostationary and low earth orbit observations.
- Improve localisation of fire activity within geostationary observations using the higher resolution solar reflective channels and auxiliary environmental and terrain variables.
- Determine how false negatives (undetected fire presence) can be differentiated from true negatives (fire absence) in a time series of active fire observations to identify data gaps.

Methods

- Train a deep learning model, based on a U-Net[3], using pairs of geostationary observations and low earth orbit active fire detections.
- Reconstruct fire activity by segmenting downscaled geostationary observations to produce isochrones of fire spread every 10 minutes.

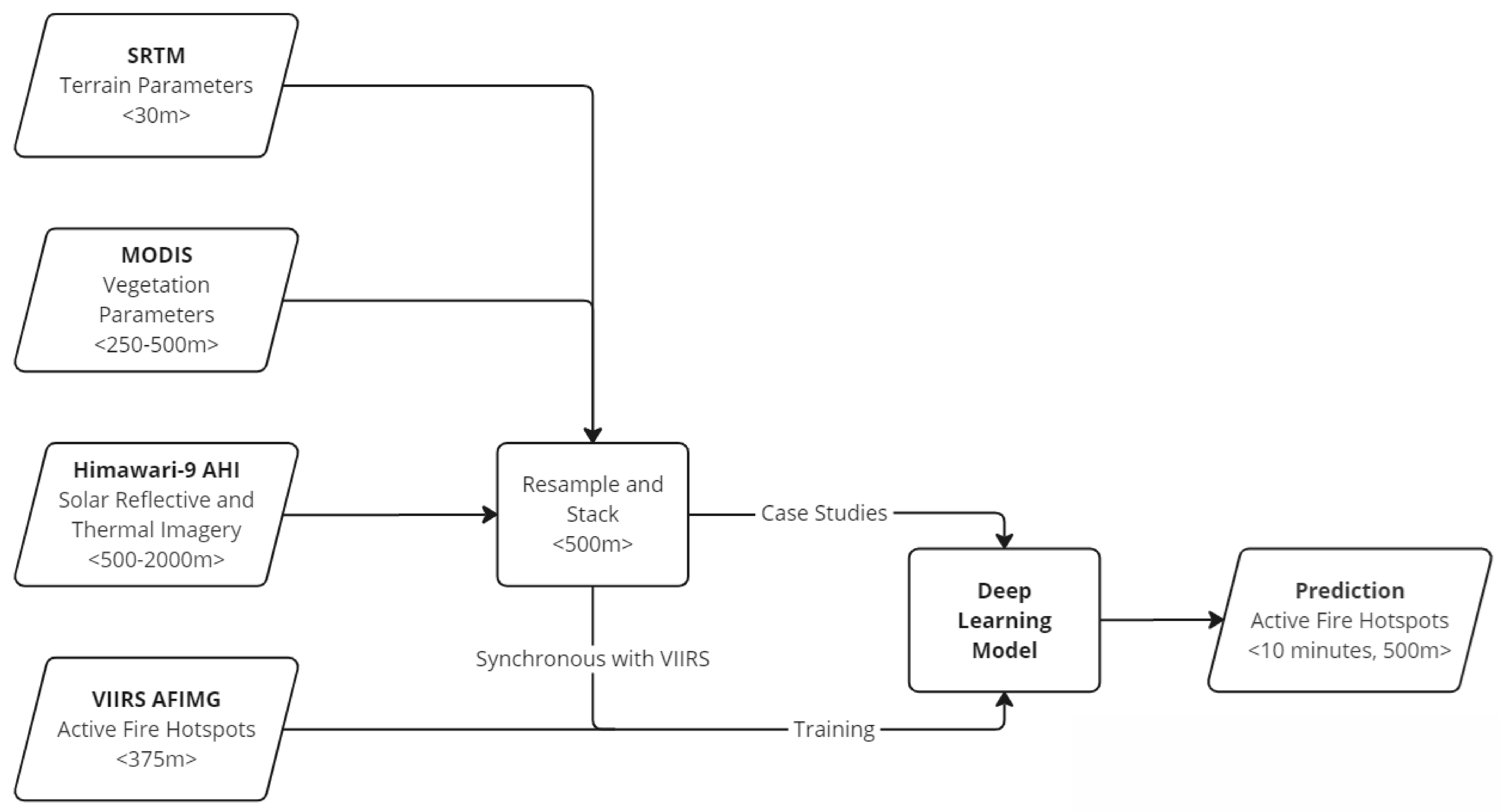
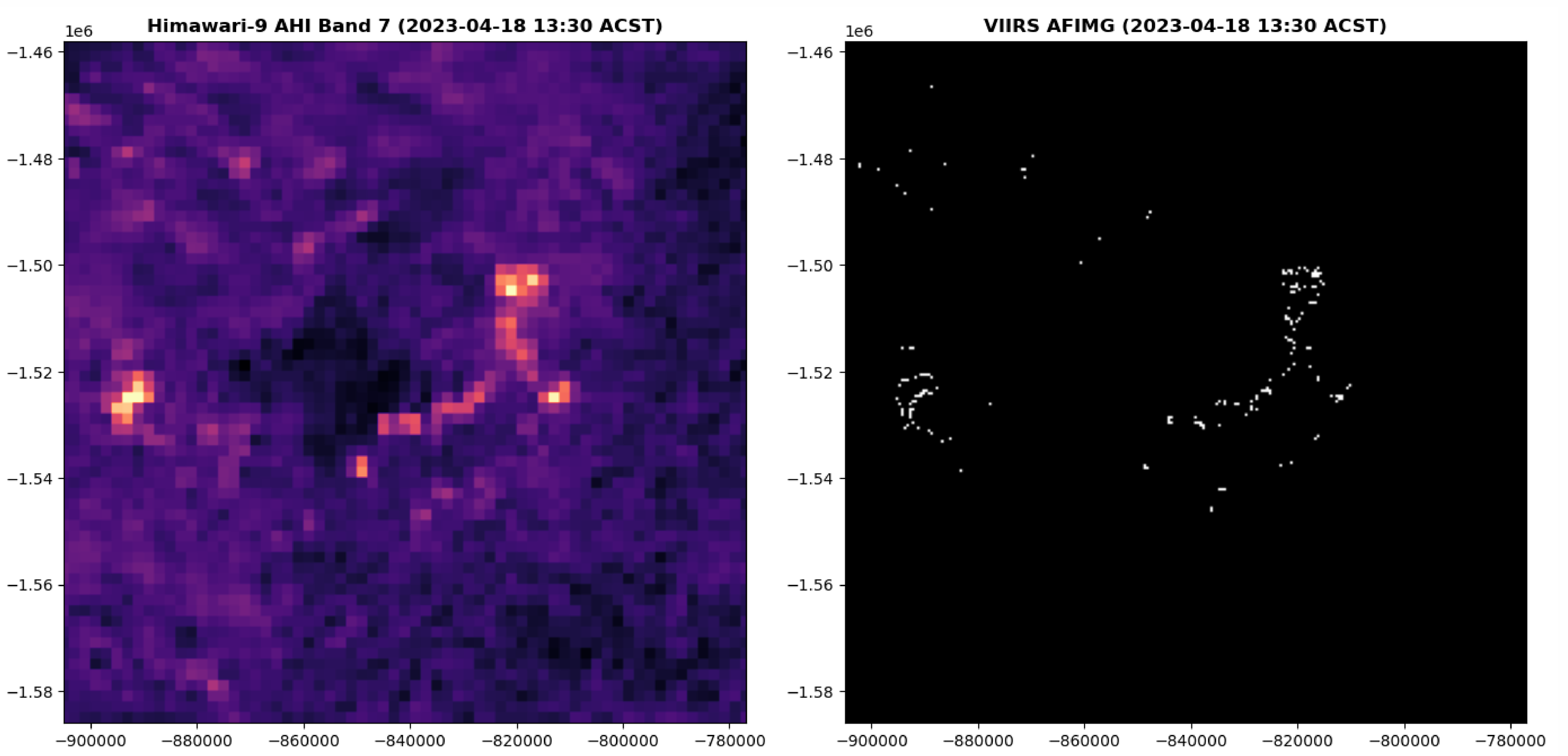


Figure 1 (above): Processing flow chart for wildfire reconstructions



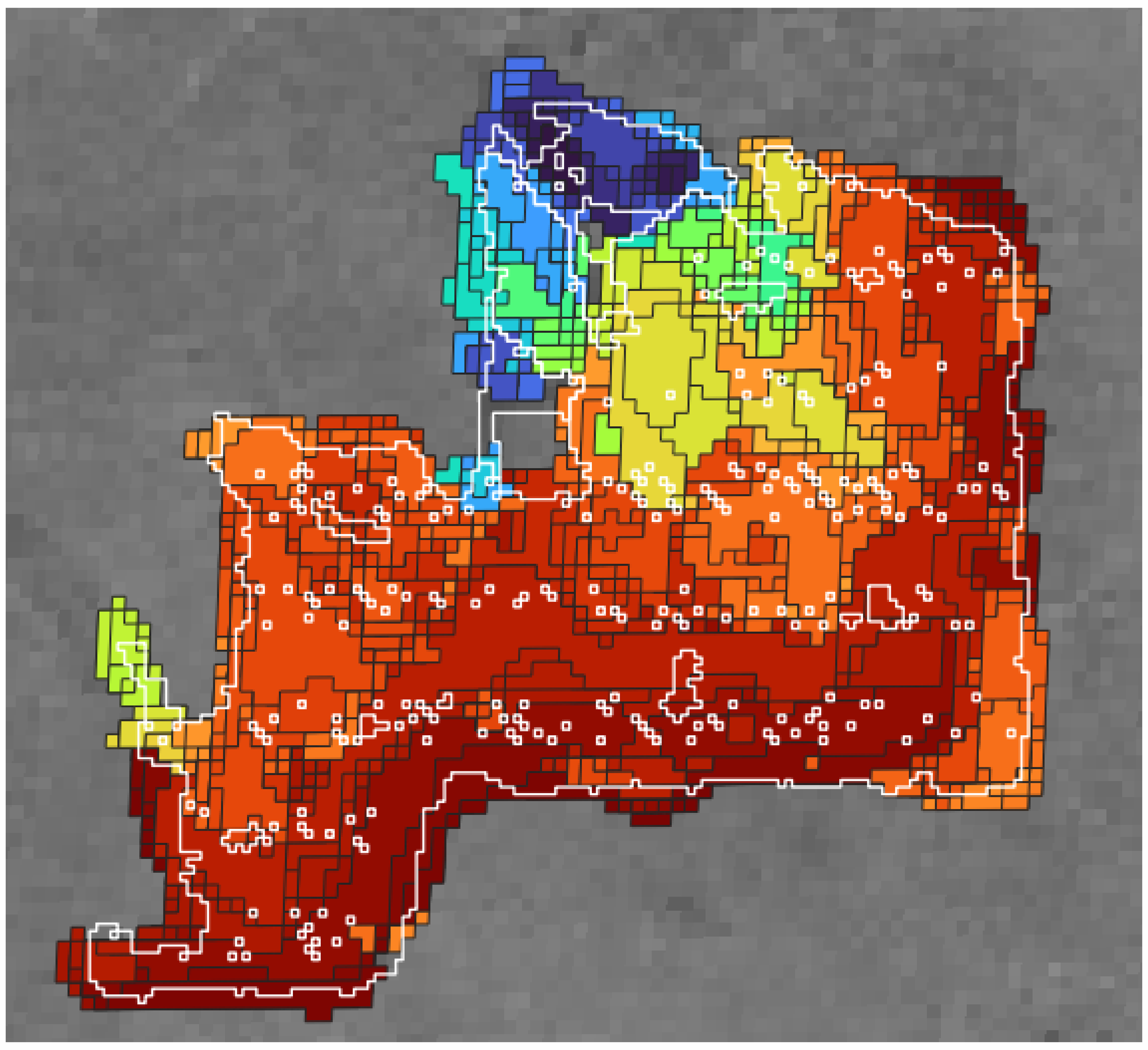


Figure 2 (Left): Training image pair of Himawari-9 AHI band 7 (3.9 μm) and VIIRS AFIMG hotspots.

Figure 3 (Right) – Day and night-time reconstruction of a case study fire. Fire spread mapped at 500m and 10-minute intervals. Earliest detections in red. White boundary represents the burn scar mapped by NAFI.

References

1 Giglio et al. 2018, “The Collection 6 MODIS burned area mapping algorithm and product.,” Remote sensing of environment, vol. 217, pp. 72–85.

2 Van Der Werf et al. 2017, “Global fire emissions estimates during 1997–2016,” Earth System Science Data, vol. 9, no. 2, pp. 697–720.

3 Ronneberger et al. 2015, “U-Net: Convolutional Networks for Biomedical Image Segmentation,” in N Navab, J Hornegger, WM Wells, & AF Frangi (eds), *Medical Image Computing and Computer-Assisted Intervention (MICCAI)*, Lecture notes in computer science, Springer International Publishing, Cham, pp. 234–241.

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