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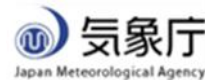
ENHANCED ESTIMATION OF BACKGROUND TEMPERATURE FOR FIRE DETECTION USING NEW GEOSTATIONARY SENSORS

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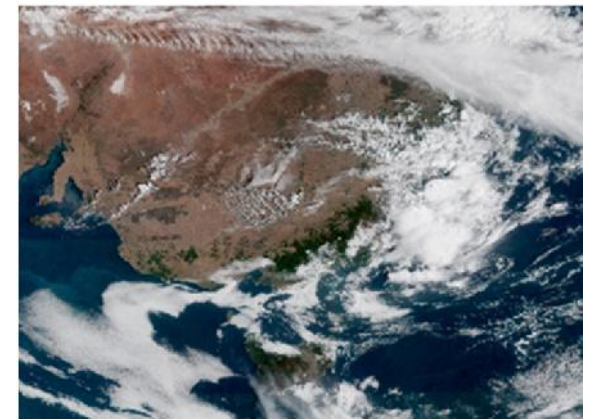
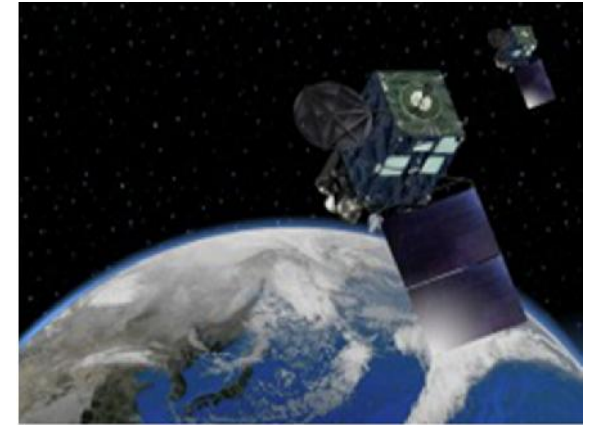
AIM

To provide more accurate background temperature information at landscape scales to improve the time of first detection of fire events.

- Utilisation of new **geostationary** sensors to provide relevant data about landscape surface temperature behaviour
- Temperature estimation achieved using **multi-temporal** image techniques, rather than from pixel context

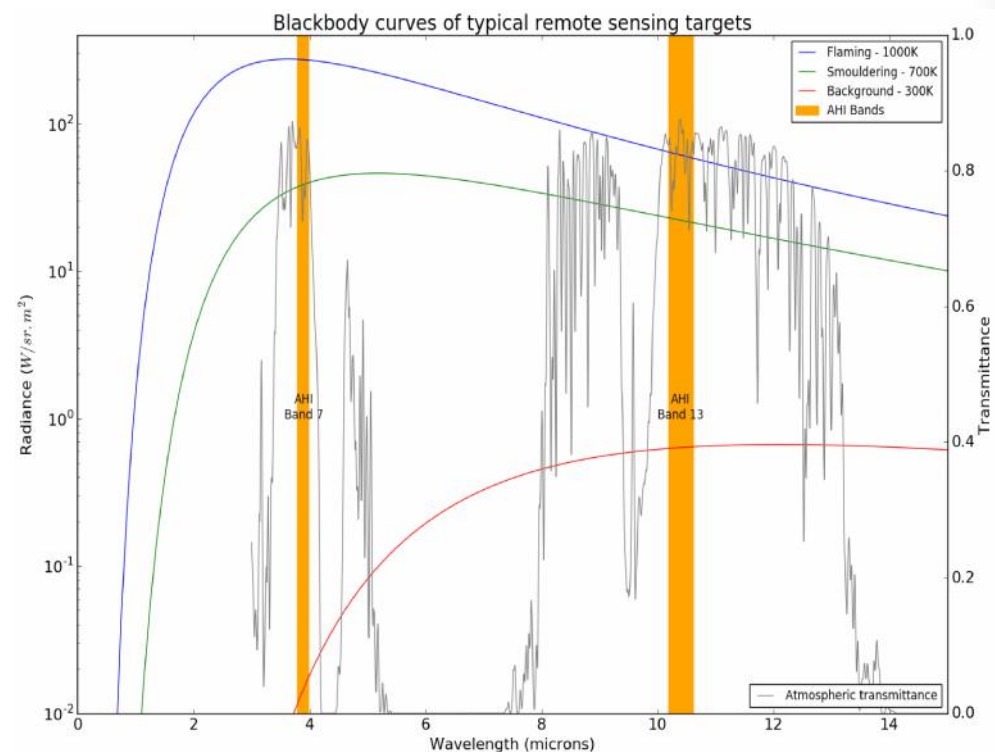
HIMAWARI-8 AND ENHANCED CAPABILITY

- Geostationary sensor with higher temporal and spatial resolution than previous geostationary sensors
- Full disk images every 10 min for all bands
- Enhanced forecasting capabilities
- Massive volumes of data for use in multi-temporal analysis



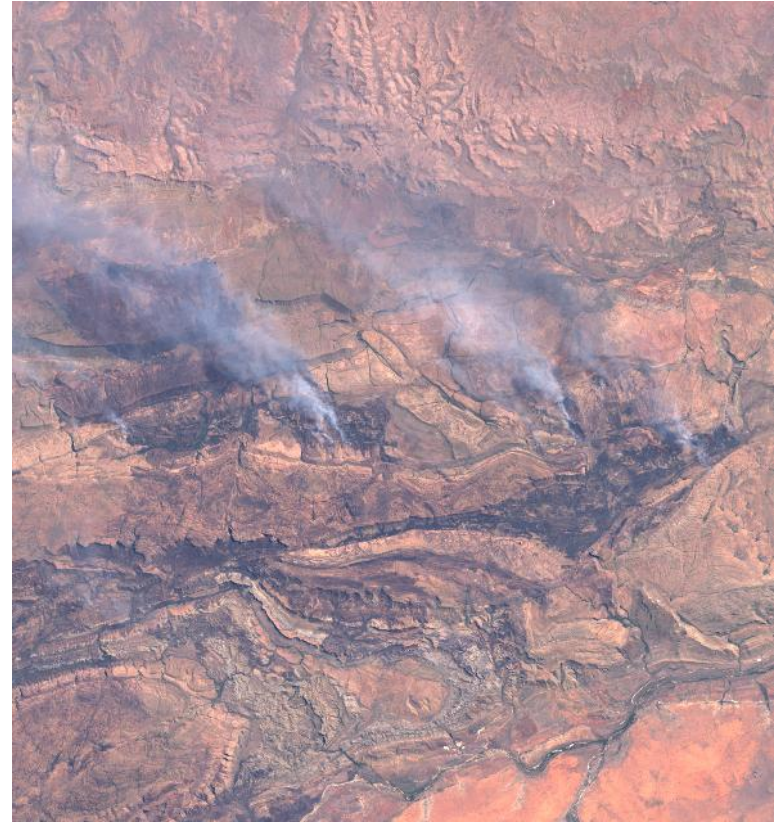
REMOTE SENSING OF FIRE

- Fires emit large amounts of radiation in the medium wave infrared (MWIR)
- Even small fires raise this radiation significantly – 10ppm can be detectable
- Confirming fire detection requires knowledge of a target pixel's background state



THE PROBLEM OF CONTEXT

- Single image algorithms rely on surrounding areas being uniform and unperturbed during fire
- Problematic in areas of high landcover variability
- Occlusion caused by clouds, smoke in fire events
- Small variance in background temperatures cause large errors in fire attributes



TEMPERATURE ESTIMATION FROM CONTEXT

Uniform landscape

20	21	20	20	21
20	20	20	21	22
19	20	20	21	22
18	18	20	21	21
17	18	19	20	21

- Average of pixel temps ~ pixel temp
- Target pixel temperature closely resembles the contextual surrounds
 - Surface temperature is usually spatially autocorrelated to surrounding pixels

Fire landscape

20	21	20	20	21
20	20	20	21	22
19	20	🔥	21	22
18	18	20	21	21
17	18	19	20	21

- Fire obscures the temperature of the ground
- Actual temperature of the ground in the pixel is unknown, but is easily estimated from the surrounds

FACTORS THAT LEAD TO LOSS OF ACCURACY

Coastline

	20	20	21
20	20	21	22
20		21	22
	20	21	21
	19	20	21


Smoke

20	21	20	16	17
20	20	15	17	22
19	20		21	22
18	18	20	21	21
17	18	19	20	21

Cloud

-5	-3	0	20	21
20	-1	20	21	22
19	20		21	22
3	18	20	21	21
4	18	19	11	12

Landcover type

20	21	20	20	25
20	20	26	27	26
19	20		27	28
18	25	26	27	27
24	24	25	25	26

SOMETIMES IT'S ALL TOO MUCH

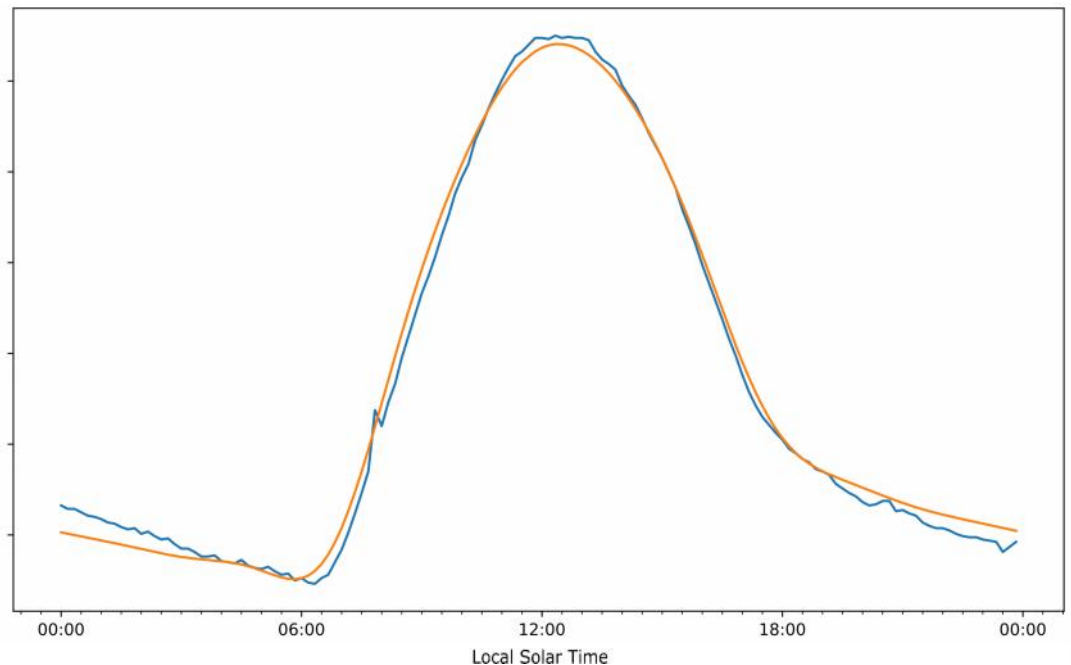


In complex situations, accurate estimation of ground conditions is impractical using the pixel surrounds

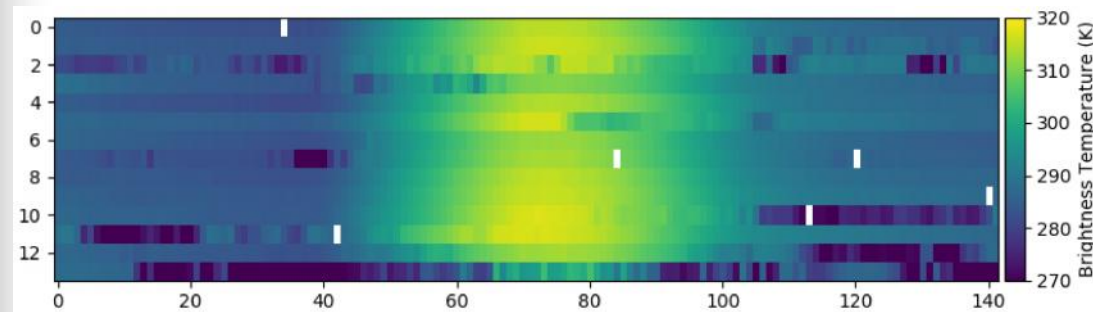
- Obscuration conceals data points
- Validity of surrounding temperatures difficult to determine
- To find valid pixels, we have to grow our search zone, leading to greater error
- Adjoining fires complicate this further

CONTEXT IS HARD – WHAT ELSE CAN WE USE FOR ESTIMATES OF TEMPERATURE?

- MWIR signals have reflectivity and thermal components that vary in a consistent fashion
- Local solar time at a location dictates how much MWIR radiation is present
- This can be used as a predictor of surface temperature when modelled accurately



EXAMINING THE TIME SERIES OF A PIXEL

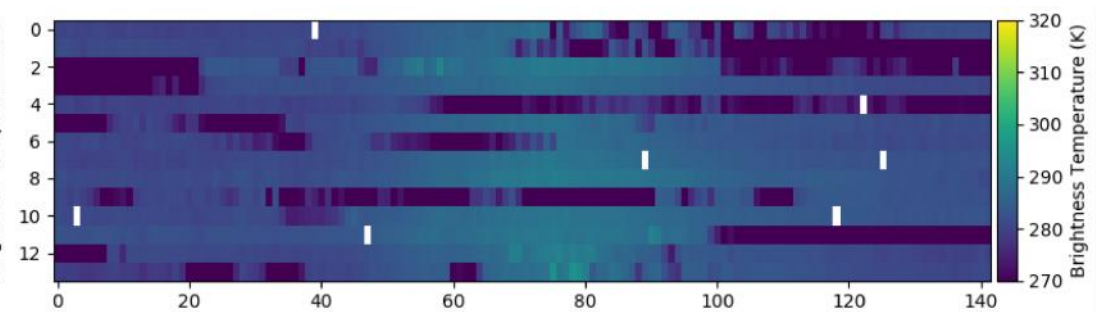


Inland pixel

Little cloud activity

Clear diurnal signal

High likelihood of generating
a good diurnal fit



Coastal pixel

High cloud activity

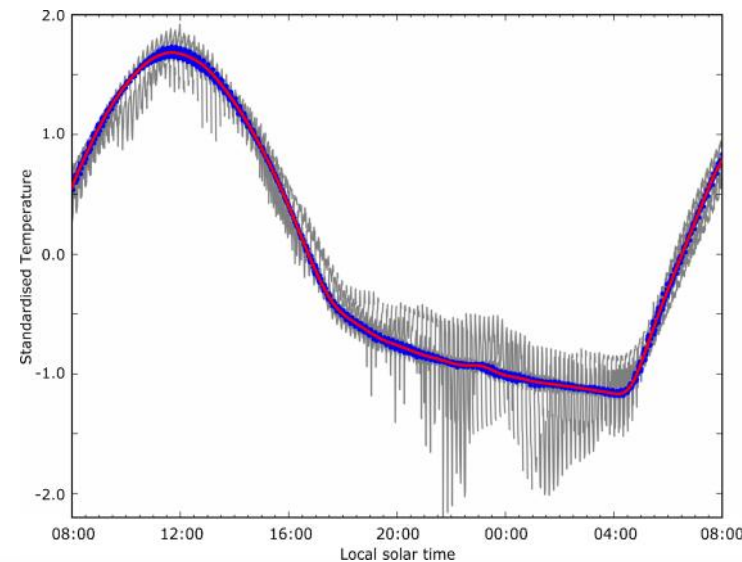
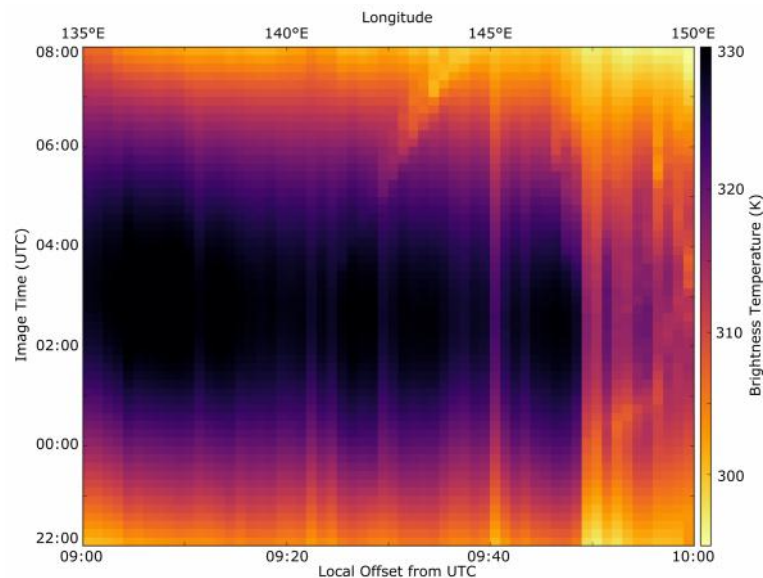
Weak diurnal signal

Low chance of generating
accurate diurnal fit

LEVERAGING GEOSTATIONARY DATA TO ENHANCE INDIVIDUAL PIXEL OUTCOMES

Individual pixels are challenging to assess accurately, but we know they all behave similarly

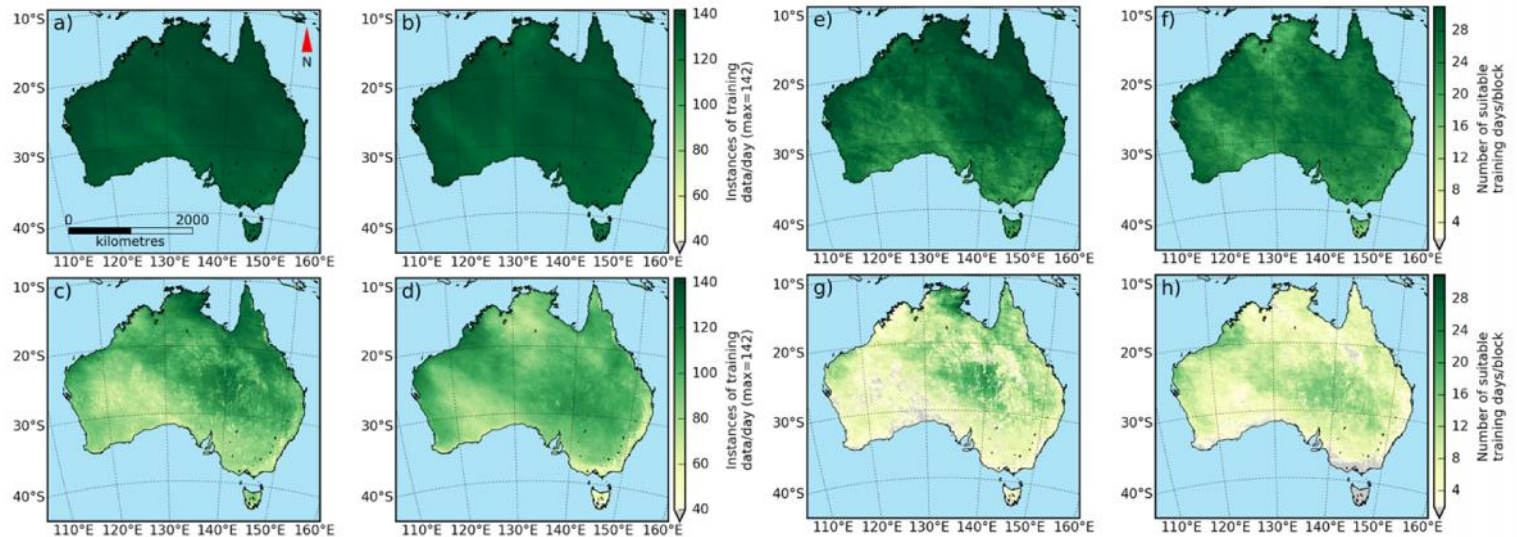
By aggregating temperatures over larger areas, we can bridge the gaps that occur at pixel level



BROAD AREA TRAINING (BAT) TEMPERATURE FITTINGS

Increased availability of fitting data, especially in coastal areas and south eastern Australia

BAT Fitting



Per pixel fitting

From Hally, B., Wallace, L., Reinke, K., Jones, S., 2017. *A Broad-Area Method for the Diurnal Characterisation of Upwelling Medium Wave Infrared Radiation*. *Remote Sens.* 9, 167. doi:10.3390/rs9020167

BROAD AREA TRAINING (BAT) TEMPERATURE FITTINGS

Lower noise in the fitted estimates of temperatures, especially with increasing cloud

Provides background data at times and locations where the contextual techniques fail

Fitting technique	RMS Error (K)					
	Incidences of CSP < 1	≤ 10	11 – 30	31 – 50	51 – 70	> 70
Pixel-based training		0.78	1.01	2.28	3.25	10.40
BAT (30 days)		0.94	0.94	1.11	1.48	4.19
BAT (10 days)		1.15	1.21	1.40	2.10	6.31
Contextual temperature		0.33	0.42	0.41	0.40	0.42
<i>Number of samples</i>		903	741	768	851	2345

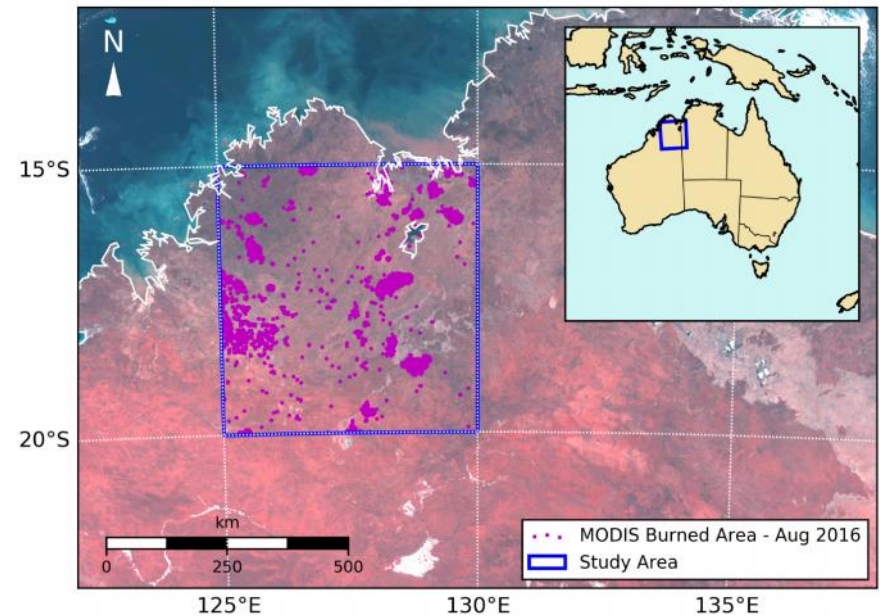
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PERFORMANCE IN COMPARISON TO LOW EARTH ORBIT (LEO) FIRE PRODUCTS

August 2016 over Kimberley region of WA
Fires in 2675 AHI pixels (~4% of area) over time period

Thresholds for fire (Δ temp between fit and measurement) were examined for suitability

Evaluation against Auscover MODIS burned area product, along with VIIRS and MODIS active fire products



DETECTION CAPABILITIES AGAINST LEO PRODUCTS

Significant correlation between detections from LEO and AHI
 AHI performs well when dealing with smaller fires (VIIRS product)
 Higher temporal resolution outweighs the coarser spatial resolution for fire detections

Group\Threshold	2 K		3 K		4 K		5 K	
	Detected	Synchronous	Detected	Synchronous	Detected	Synchronous	Detected	Synchronous
<i>n=150 for all</i>								
Burned area only	75.3%	N/A	63.3%	N/A	56.0%	N/A	50.0%	N/A
VIIRS AF only	95.3%	38.7%	88.0%	27.3%	84.7%	22.0%	77.3%	17.3%
MODIS AF only	97.3%	60.7%	97.0%	58.0%	91.3%	52.7%	86.0%	48.0%
Both AF products	99.3%	68.0%	98.3%	58.7%	92.0%	51.3%	89.3%	46.0%

From Hally, B., Wallace, L., Reinke, K., Jones, S., Skidmore, A., 2017. *Advances in Active Fire Detection Rates and Times Using the Broad Area Training (BAT) Method for Geostationary Satellite Data*. (in review)

EARLY WARNING CAPABILITY INCREASES

With high detection rates, similar fires to those detected by LEO sensors can be found sooner

First detection improvements average around 6 hours, with bigger improvements for small fires

Detection occurs more accurately when less of the fitting is exposed to fire

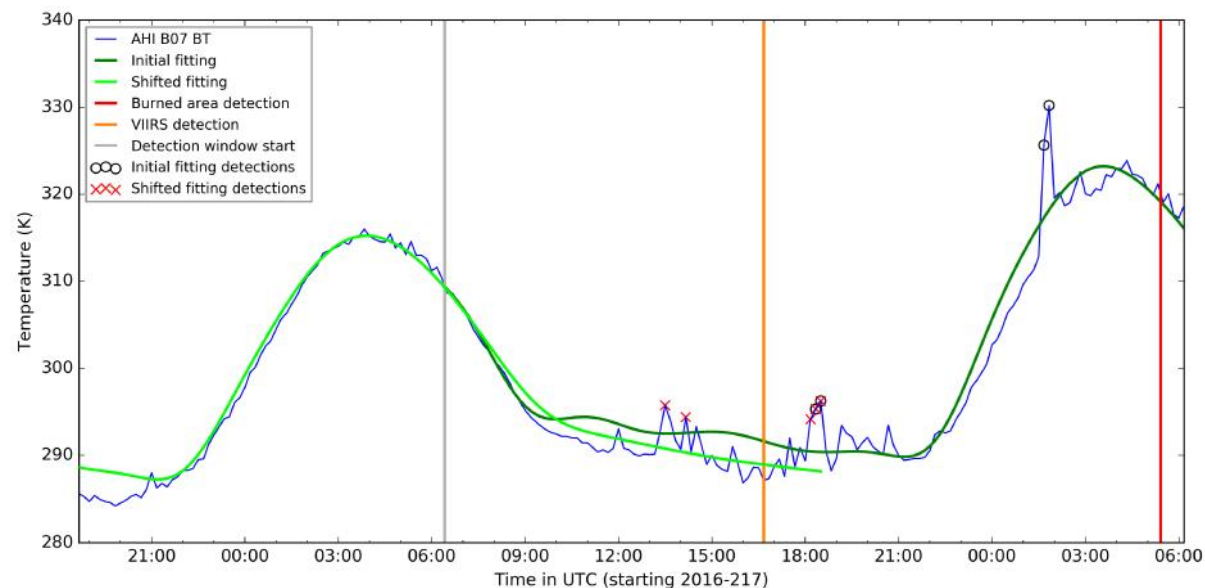
From Hally, B., Wallace, L., Reinke, K., Jones, S., Skidmore, A., 2017. *Advances in Active Fire Detection Rates and Times Using the Broad Area Training (BAT) Method for Geostationary Satellite Data.* (in review)

VIIRS Detection only (n=150)	2 K	3 K	4 K	5 K
Original detection rate	95.3%	88.0%	84.7%	77.3%
Shifted detection rate	95.3%	88.0%	85.3%	76.0%
Mean detection time before first LEO AF with original window	4h 48m	2h 41m	2h 07m	1h 55m
Mean detection time before first LEO AF with shifted window	6h 47m	6h 08m	6h 06m	5h 43m
MODIS Detection only (n=150)	2 K	3 K	4 K	5 K
Original detection rate	97.3%	94.0%	91.3%	86.0%
Shifted detection rate	91.3%	84.0%	82.0%	82.7%
Mean detection time before first LEO AF with original window	8h 06m	6h 28m	5h 42m	4h 49m
Mean detection time before first LEO AF with shifted window	9h 36m	7h 34m	6h 34m	5h 39m
Both AF Detected (n=150)	2 K	3 K	4 K	5 K
Original detection rate	99.3%	95.3%	92.0%	89.3%
Shifted detection rate	95.3%	89.3%	88.0%	84.7%
Mean detection time before first LEO AF with original window	5h 25m	4h 27m	3h 54m	3h 31m
Mean detection time before first LEO AF with shifted window	7h 26m	6h 09m	5h 35m	5h 24m

HIGHER ACCURACY IN NEAR REAL TIME

Earlier fitting start times provide more accurate detection of earlier events

Less exposure of modelled brightness temperature to anomalies such as fire



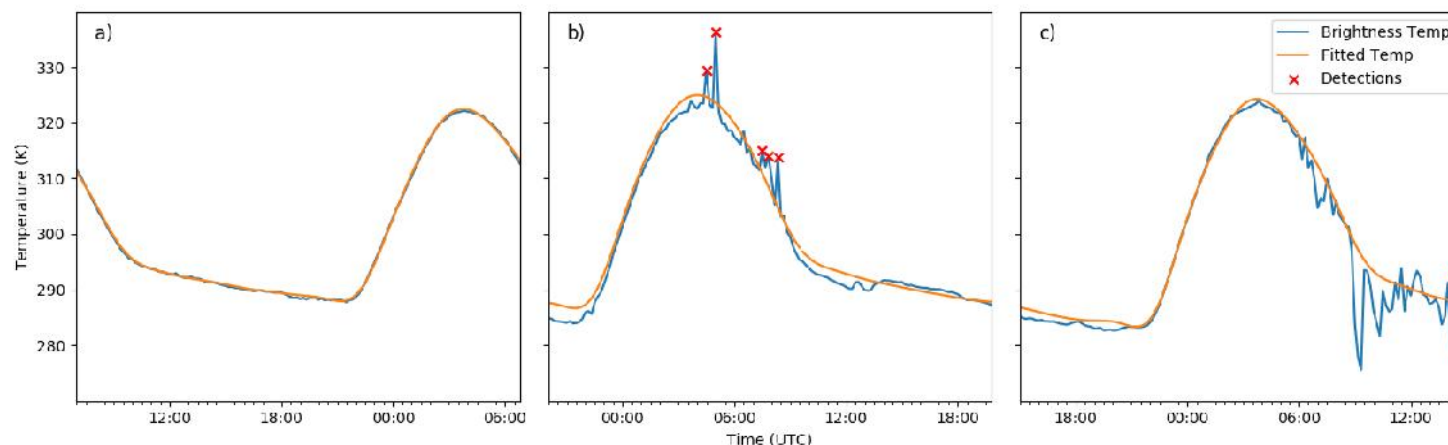
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DETECTION EVALUATION

Further analysis of detection causes for 4K threshold

79% of burned area detections had geostationary detections

Cloud caused most detections where no burned area was recorded



From Hally, B., Wallace, L., Reinke, K., Wickramasinghe, C., Jones, S., 2017. *Enhanced estimation of background temperature for fire detection using new geostationary sensors*. Proceedings of AFAC Conference, Sydney, 2017.

FIRST DETECTION OF FIRE

- Higher temporal resolution outweighs the lower spatial resolution of AHI for first detection
- BAT detects most fires visible from LEO sensors using AHI images
- Cloud remains the largest impediment to accurate modelling

FUTURE WORK

- Evaluation of modelling method over wider range of landcover, seasonality, latitude
- Determination of appropriate detection thresholds at full disk scale
- Integration of improved cloud masking in fitting routines

THANK YOU

ACKNOWLEDGEMENTS

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