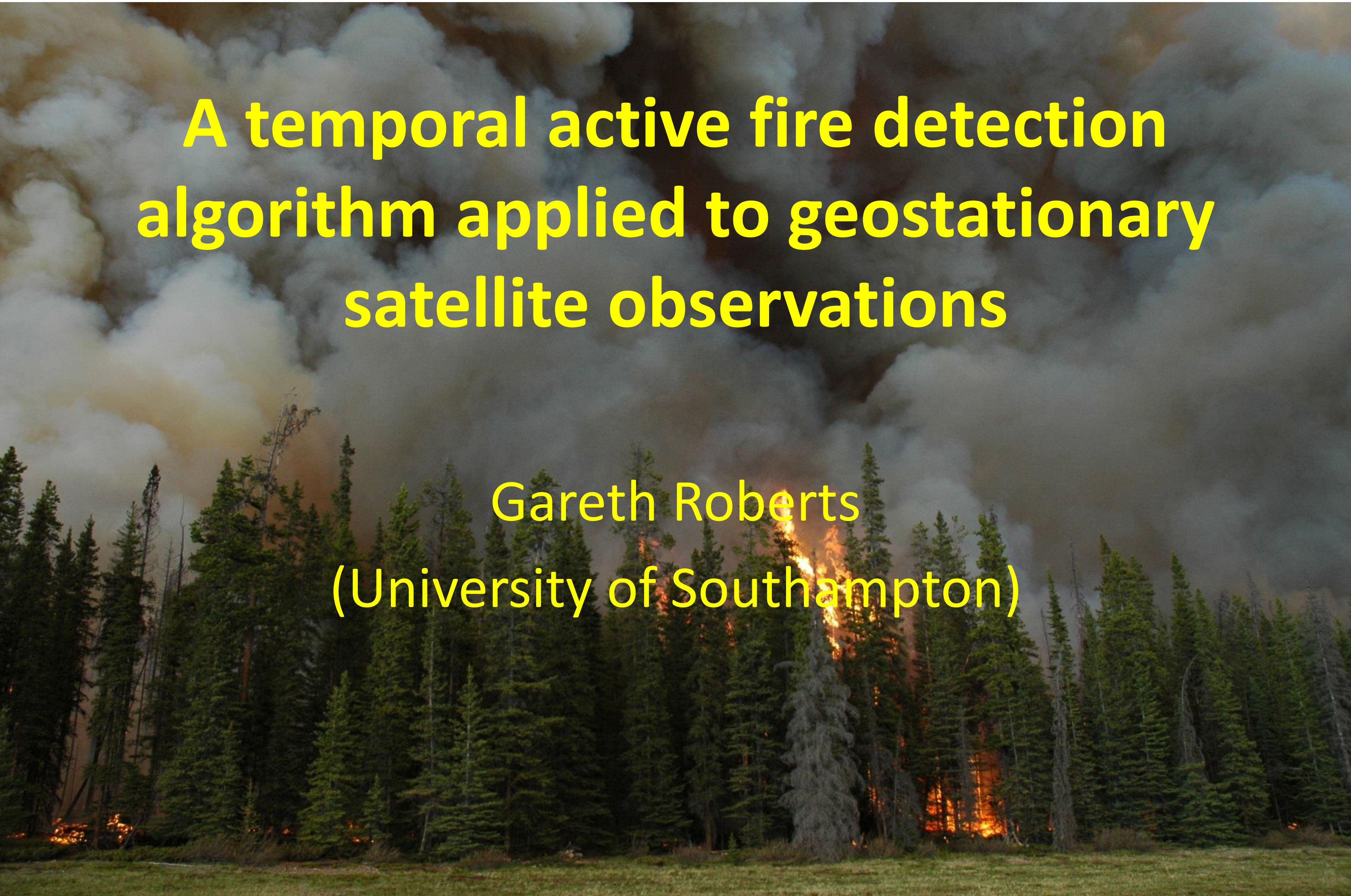
8th – 10th June

# LSA-SAF Workshop 2015



# A temporal active fire detection algorithm applied to geostationary satellite observations

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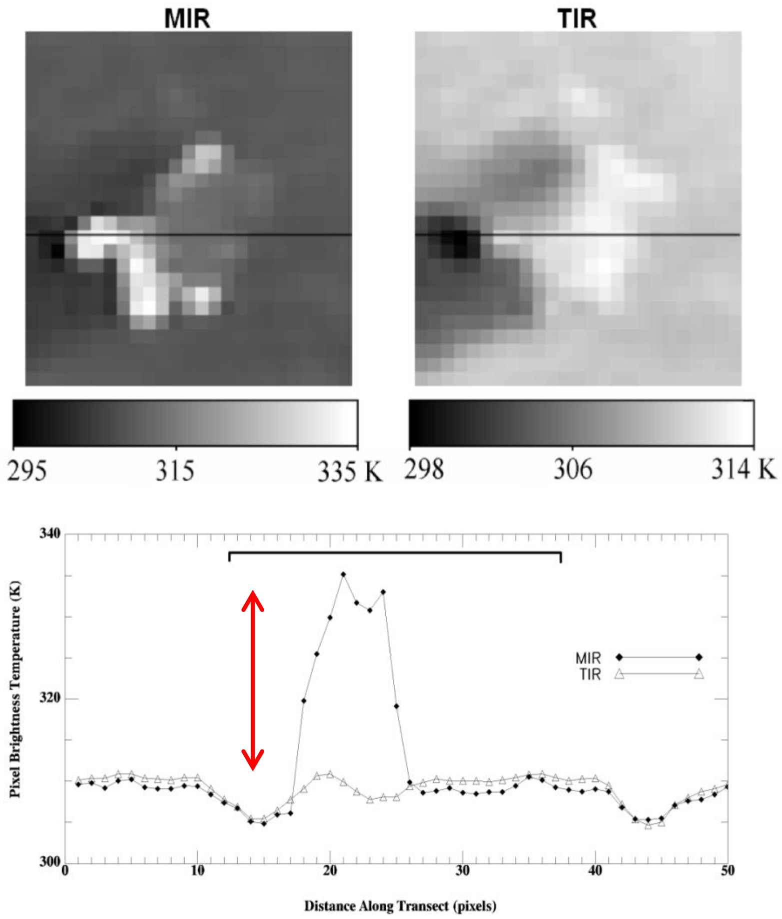
# Outline

- Active fire detection
  - Geostationary active fire detection
- Multi-temporal active fire detection approach
  - Modelling diurnal temperature cycle
  - Background characterisation
  - Active fire detections
  - Comparison to MODIS
- Conclusion

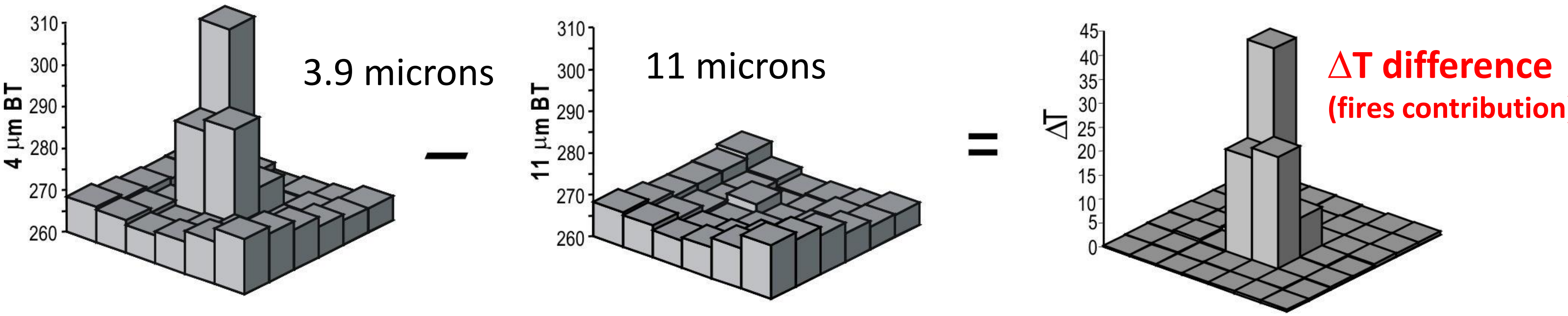
# Active Fire Detection

- ❑ Strong heritage
  - 1st demonstrated in 1981 using NOAA AVHRR
- ❑ Detect location of 'actively' burning fires
  - uses MIR & TIR wavebands
  - exploits high sensitivity of MIR channel to fire thermal emissions
- ❑ Thermal measurements used to 'characterise' fire
  - effective fire temperature and area
  - Fire Radiative Power (FRP)



# 'Contextual' active fire detection

- ❑ Uses MIR & TIR observations
  - exploits high & low sensitivity of MIR & TIR channels to fire thermal emissions




- ❑ Potential fire pixel (PFP) if $\Delta T$ > chosen threshold

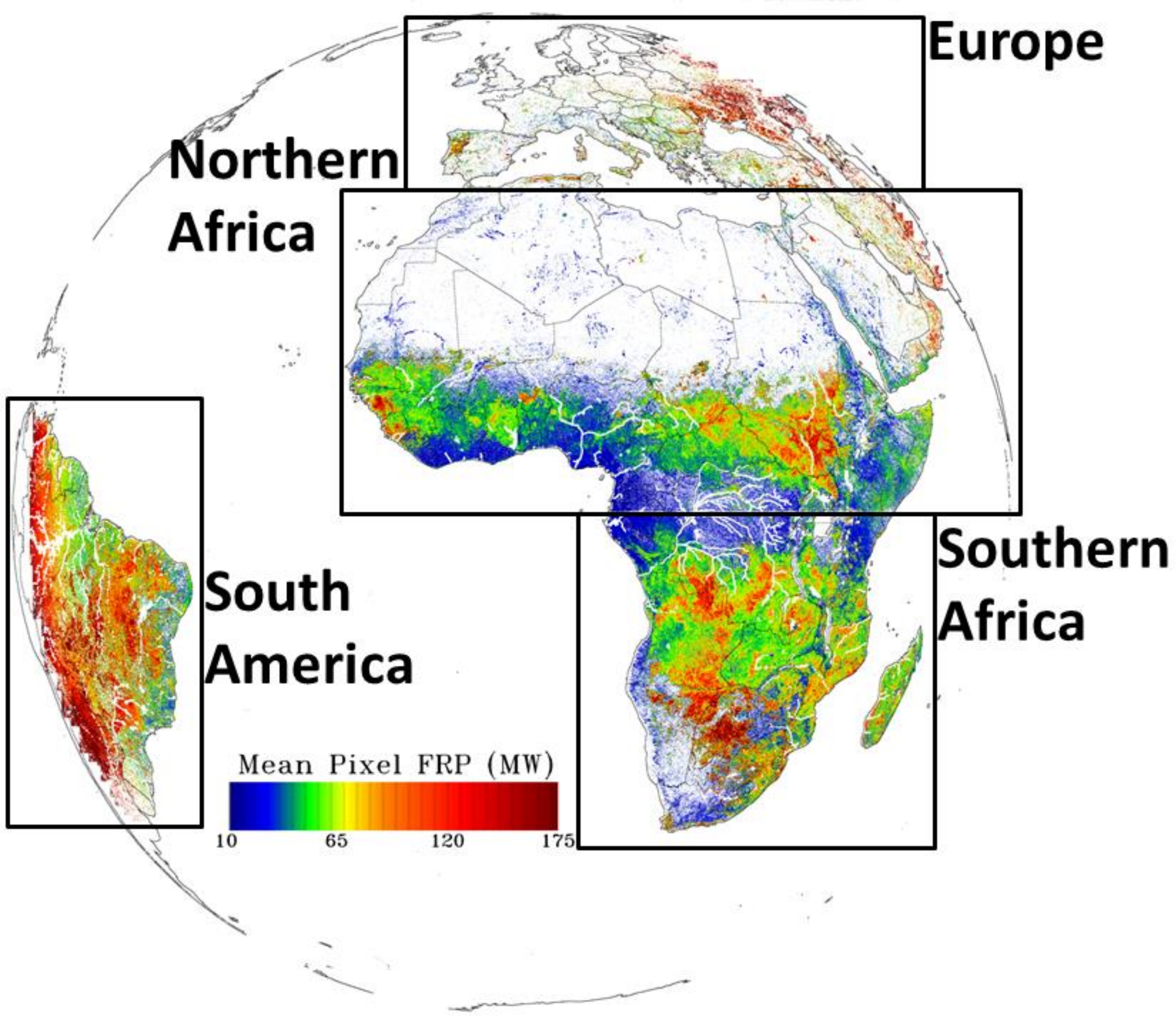
- ❑ Apply neighbourhood operations to surrounding pixels
  - assess PFP temperature elevation against surrounding pixels
  - dynamically adjust thresholds -> more scene dependent

- ❑ Most operational fire detection algorithms are contextual
  - applied to both polar and geostationary instruments

# Geostationary active fire detection

- ✓ Geostationary instruments
  - Operational
    - Longer time-series
- ✓ High temporal resolution
  - observes diurnal fire cycle
    - NRT application
- ✗ Low spatial resolution
  - omission of small/low intensity fires
- ✗ Pixel saturation issues
  - ~335K most GEO

SEVIRI MIR channel timeseries :
Fires are white/bright


Europe
Northern Africa
Southern Africa
South America
Mean Pixel FRP (MW)
10
65
120
175

# Multi-temporal active fire algorithm

- exploit geostationary temporal information
  - leverages off contextual active fire detections

- Improve :
  1. active fire detection sensitivity
  2. background characterisation
     - characterises of the fire (e.g FRP)
       - est. fuel consumption
     - confirms '*true*' fire detection

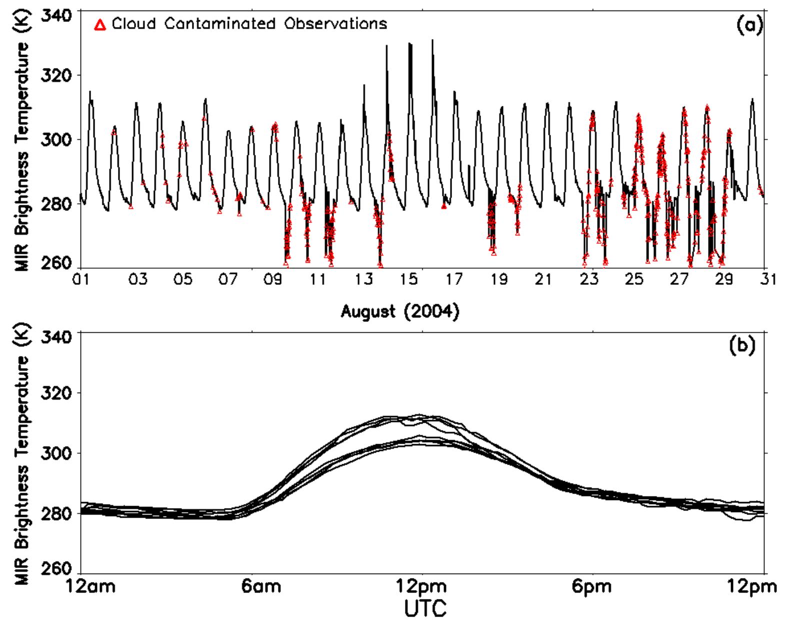
uncertainty increased by :
landcover heterogeneity
instrument characteristics
PSF, FIR
Can lead to large differences in FRP
up to 82% (Schroeder *et al*., 2010 JGR)

- Two components :
  1. model diurnal cycle MIR brightness temperature (BT)
     - non-fire affected obs.
  2. Standard Kalman Filter
     - account for errors in modelled DTC BT

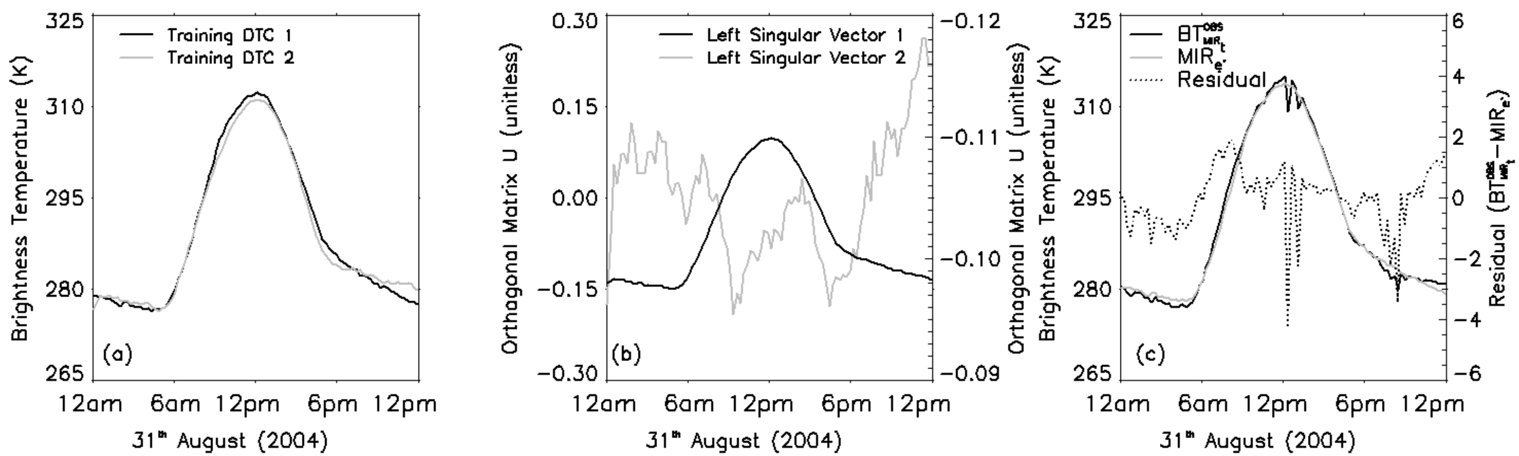
Roberts and Wooster (2014) RSE

# Multi-temporal active fire algorithm : Modelling DTC

- DTC modelled using 'training' dataset
  - 10 input DTCs from current pixel
    - ~cloud and fire free
      - '*contextual*' detections to identify active fire
      - <8 cloudy pixels



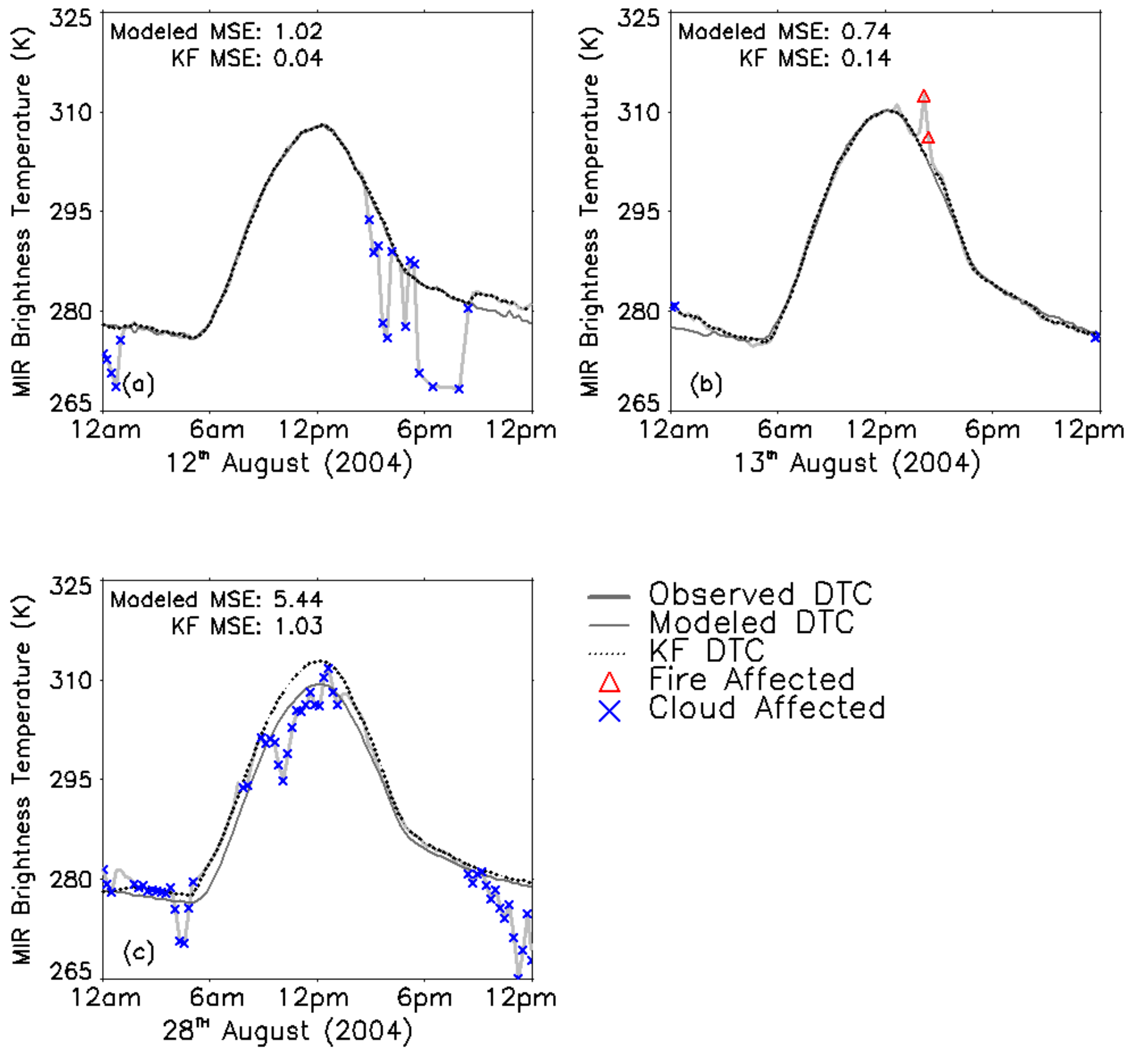

- Singular Value Decomposition
  - characterise temporal variation of pixel DTC $\rightarrow$ least squares estimate of obs. DTC



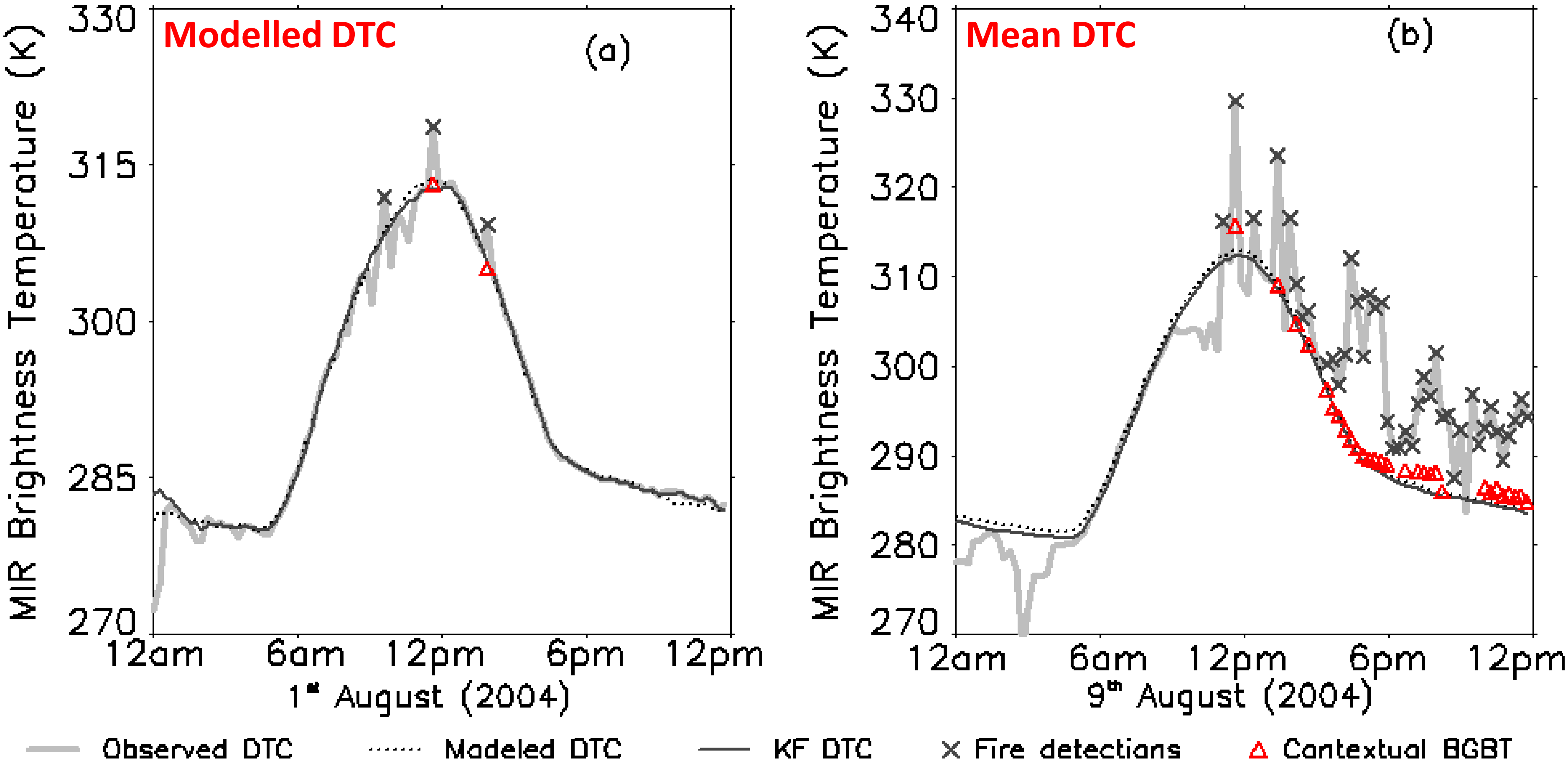

Udahemuka *et al.*, (2007), van den Bergh and Frost (2007); van den Bergh *et al.* (2009), IEEE TGRS

# Multi-temporal active fire algorithm : Kalman Filter

- **Standard Kalman Filter**
  - modelled DTC is the *process* model
- **Kalman Gain → 0**
  - fire or cloud affected observations
    - propagated using modelled DTC only
- **Fire detection**
  - $MIR_{obs}$-$MIR_{mod}$
    - 1K BT threshold
    - varies with MSE



# Multi-temporal active fire algorithm : Modelling DTC

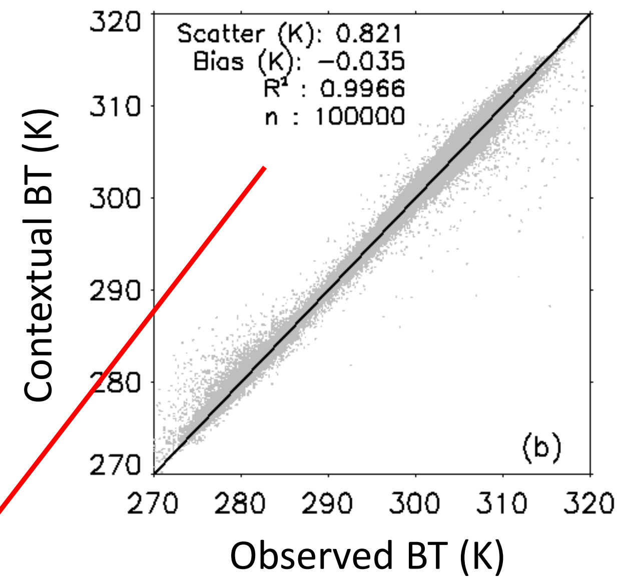


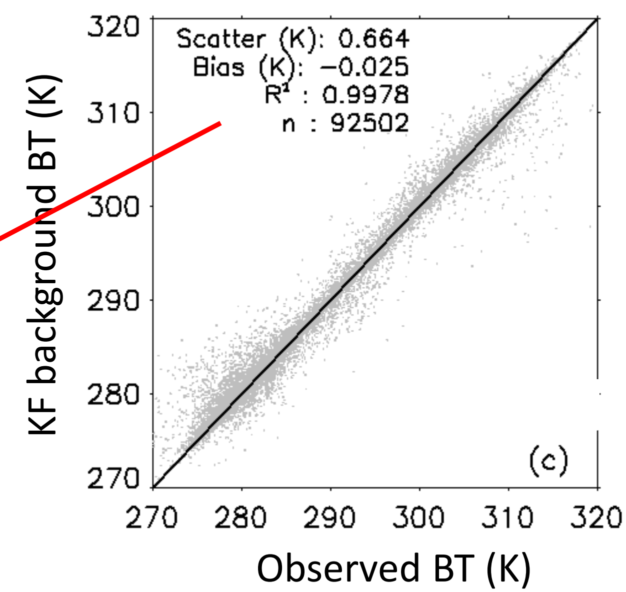

- ❑ DTC modelled only when :
  - <8 fire affected obs. & <40 cloudy obs.
  - ➢ Mean or previous modelled DTC used
    - based on training dataset

# Multi-temporal active fire algorithm : Background Characterisation

- Applied to 1 month SEVIRI data
  - August (2004)
  - 15 min resolution
  - southern hemisphere Africa

- Compared to
  - MIR observations
  - contextual fire detection algorithm
    - background BT estimates
    - fire detections & FRP

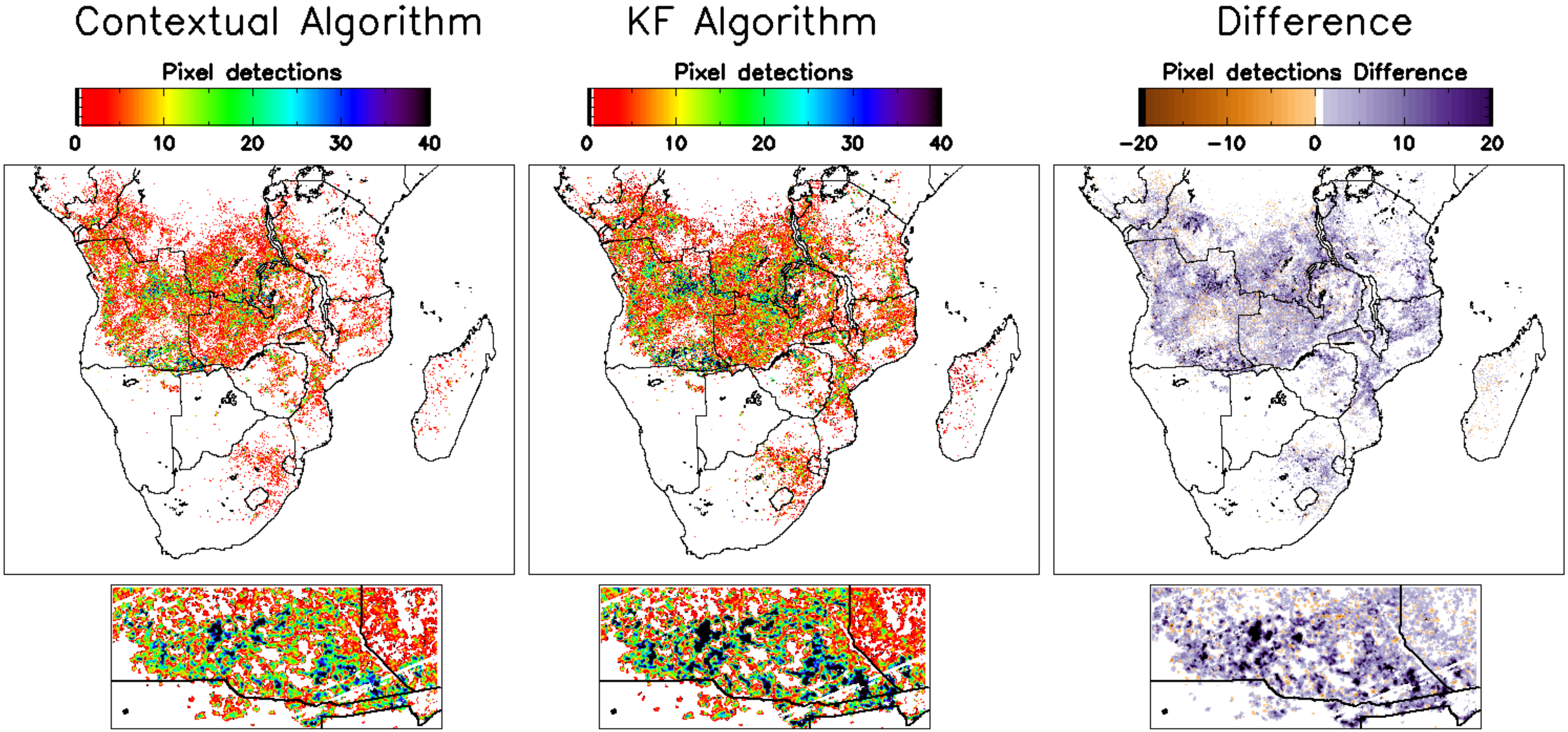


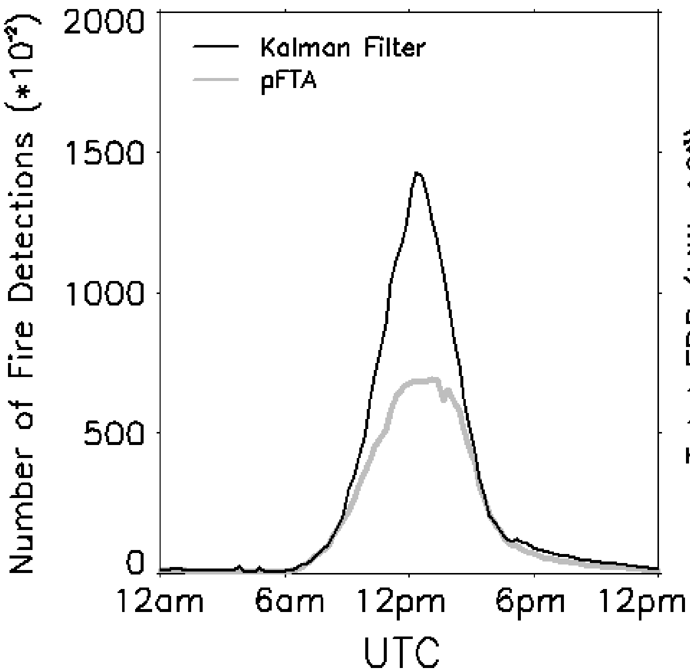

Both have low bias & scatter

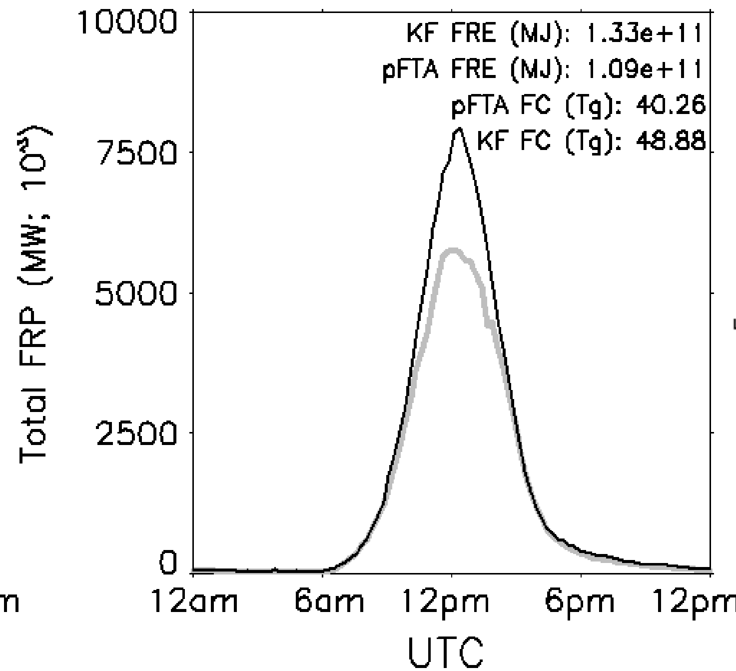
KF marginal improvement

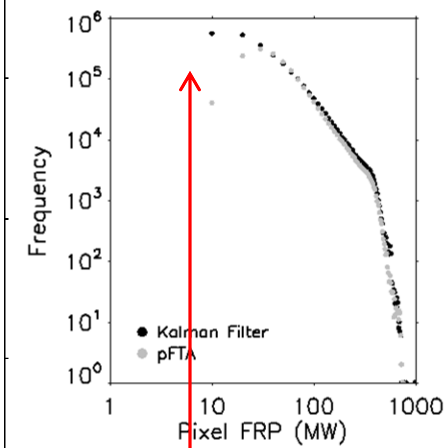
# Multi-temporal active fire algorithm : Fire detections



# Multi-temporal active fire algorithm : Fire detections



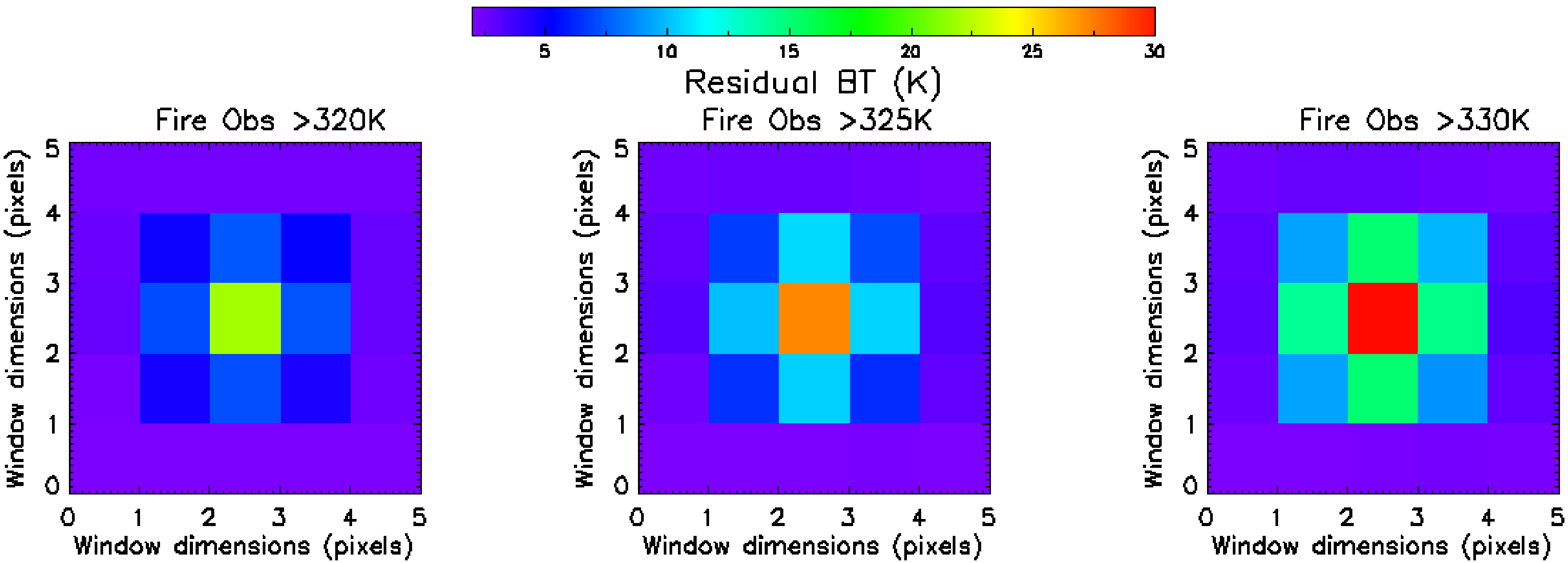




- ❑ KF detects > number of fires (~1 million fire obs.)
  - mostly low intensity fires (<30MW)
- ❑ Lower relative improvement in fuel consumption
  - ~20% (8Tg)
    - **BUT** in a month where fires occur in locations where SEVIRI pixel area is large

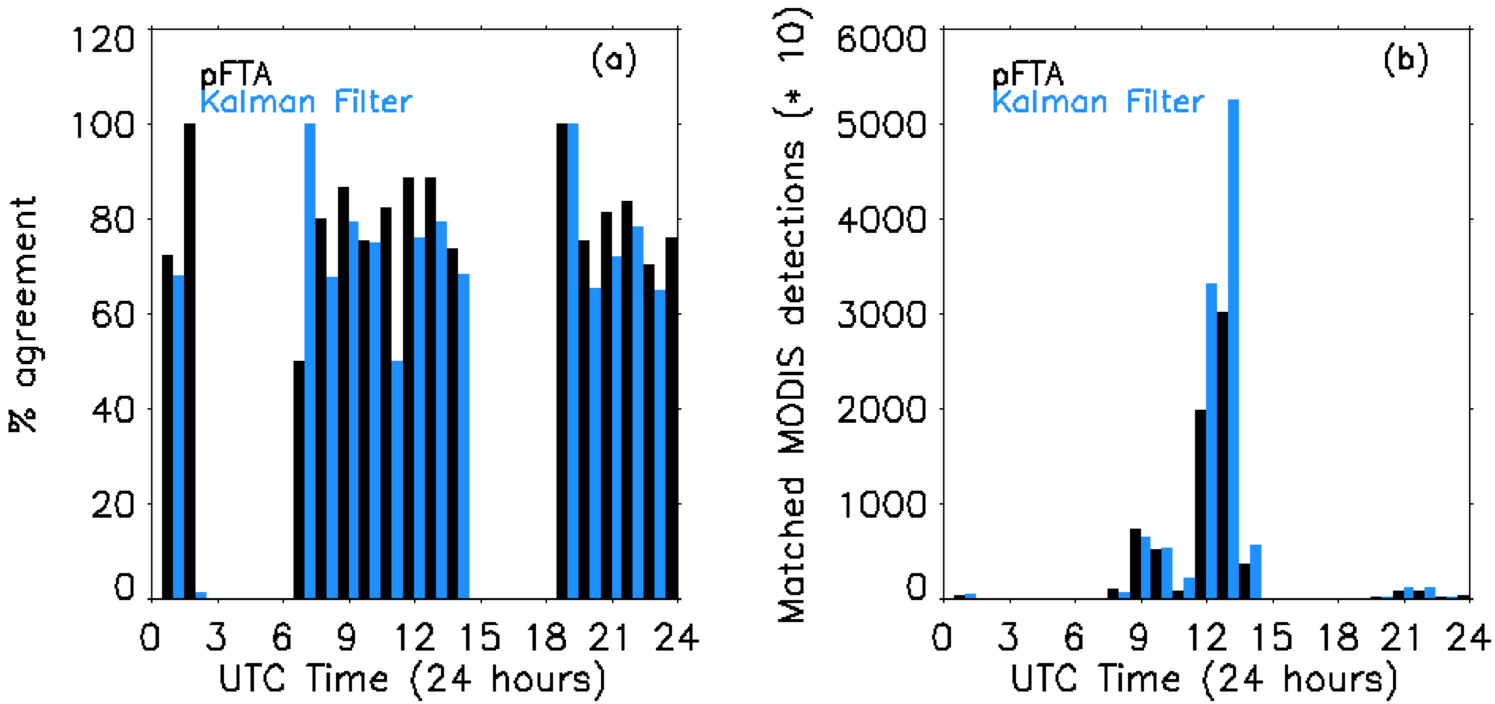
# Background Characterisation : SEVIRI PSF impact

- Background characterisation important for fire detection and FRP measurement




Note : 3×3 pixel window surrounding active fire pixel not used for background characterisation in LSA-SAF FRP product

# Multi-temporal active fire algorithm : Comparison to MODIS




- ❑ Kalman Filter detects many more MODIS detections than contextual algorithm
  - 73,000 & 41,000
- ❑ BUT much higher 'false alarm' rate (16% compared to 8%)

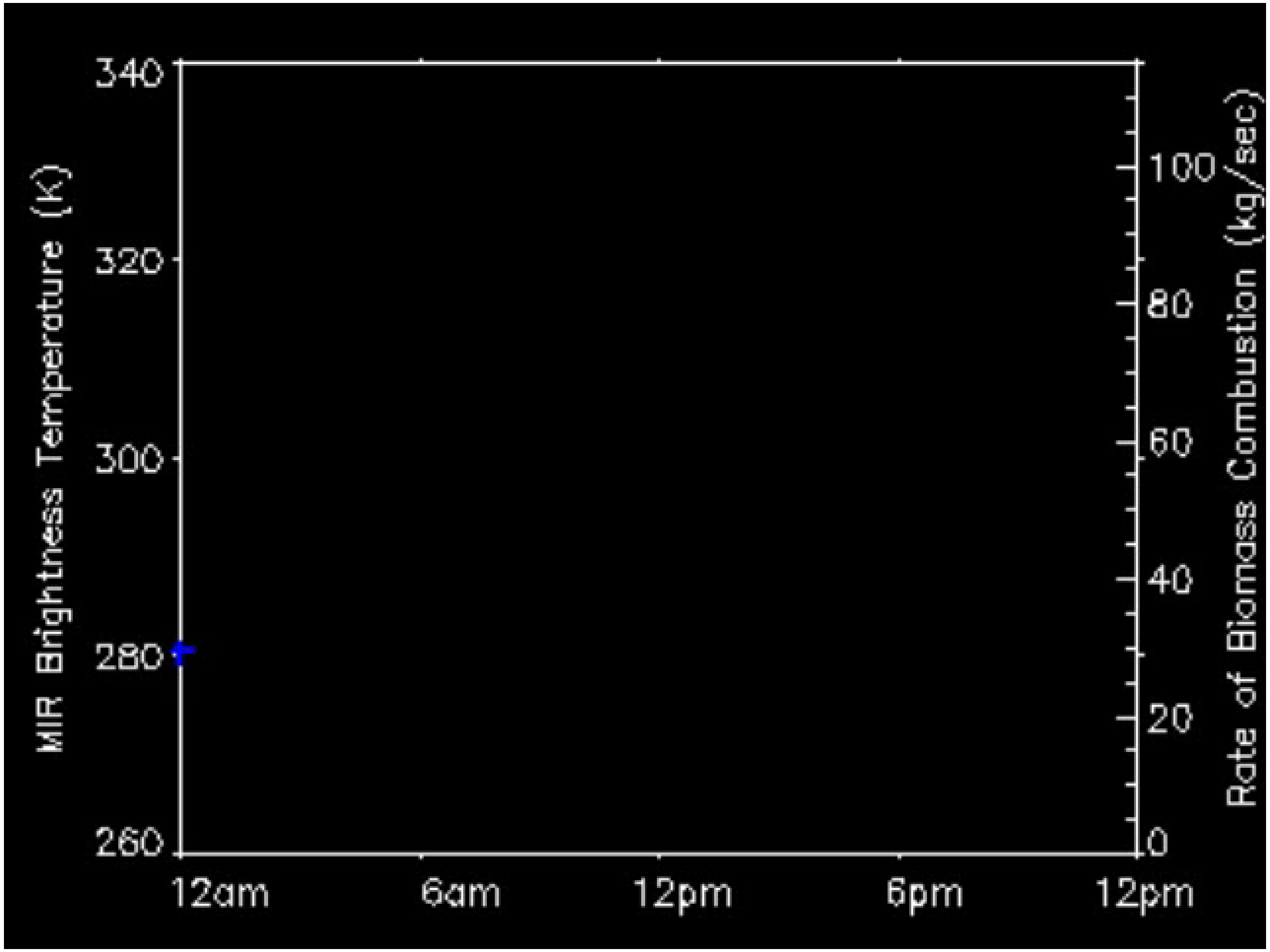
# Multi-temporal active fire algorithm : conclusion

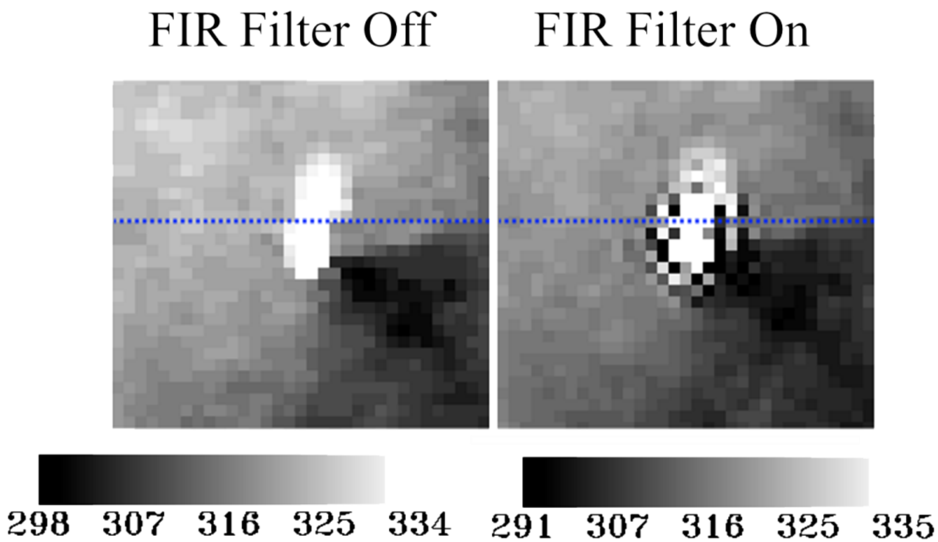
- ❑ Multi-temporal algorithms offer some benefits
  - ❑ Detects > of active fires
    - ❑ Lower intensity
    - ❑ 20% increase in monthly fuel consumption
  - ❑ Marginal improvement in background characterisation

- ❑ However :
  - high error of commission
    - limits of geostationary fire detection reached…….
  - future GEO satellites offer higher spatial & temporal resolution

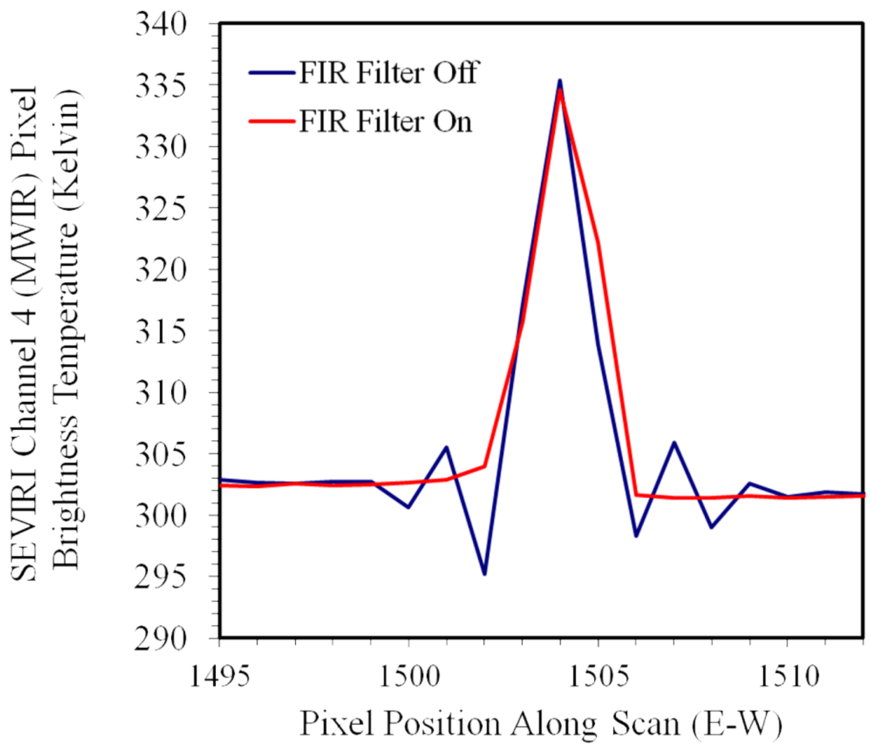
- ❑ Better integration with 'contextual' fire detection approach may yield best results

Thanks to EUMETSAT, LSA-SAF & NASA for providing data





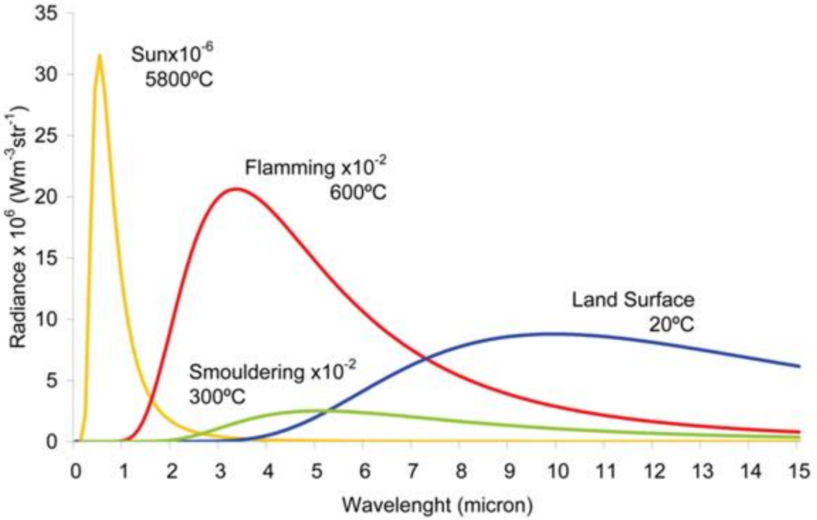

MWIR SEVIRI image over large fire

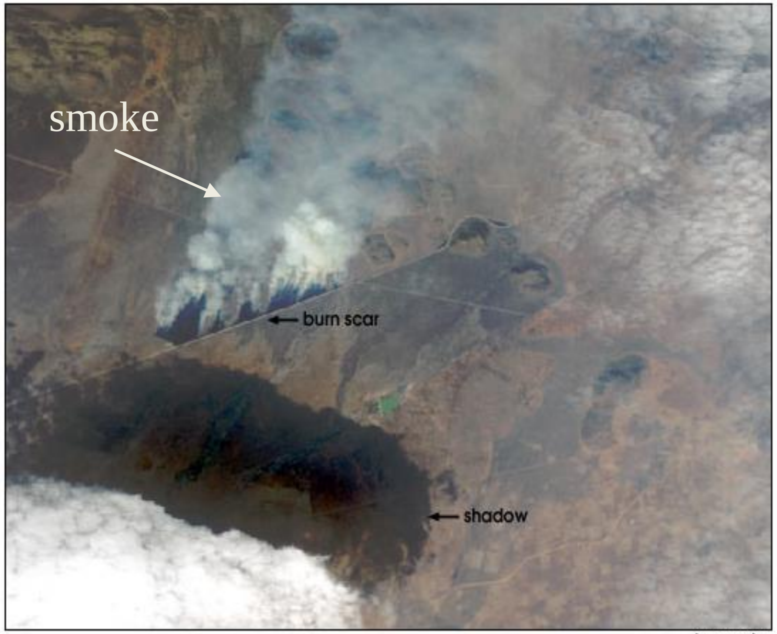



MWIR pixel BT transect across Active fire

# Wildfire

- Fires have high temperatures compared to ambient surroundings
- High temperatures result in very intense radiant energy emissions particularly in the middle IR (3-5 μm) spectral region.
- Fire MIR emission so strong that fires of $10^{-3} \rightarrow 10^{-4}$ pixel are detectable.




true color


infrared composite