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PERFORMANCE OF FIRE DETECTION ALGORITHMS USING HIMAWARI-8

non-peer reviewed research proceedings from the Bushfire and Natural Hazards CRC & AFAC conference
Perth, 5 – 8 September 2018

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Version	Release history	Date
1.0	Initial release of document	05/09/2018

Publisher:
Bushfire and Natural Hazards CRC

September 2018

TABLE OF CONTENTS

ABSTRACT

A fire-hotspot detection algorithm tuned for Australian bio-geographical regions

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Accuracy is an important aspect of fire hotspot detection. Errors in the H8-AHI WF-ABBA fire hotspot detection can lead to a loss of trust in a fire hotspot detection product. Compared to MODIS and VIIRS polar-orbiting satellites hotspot detections, the WF-ABBA hotspot detection product over Australia 0400 UTC had minimum commission error rates of 31% (Winter), 35% (Summer), 48% (Spring) and 54% Autumn over 1 Dec 2015 – 30 Nov 2016. The WF-ABBA algorithm was originally developed for America and was not tuned specifically for the Australian continent. Here we create a new Himawari fire-hotspot algorithm tuned dynamically for 419 Australian bioregions. The new algorithm 0400 UTC had minimum commission error rates, in comparison to MODIS/VIIR hotspot detections, of 6% (Summer), 8% (Spring), 20% (Winter) and 41% (Autumn) over 1 Dec 2015 – 30 Nov 2016. These commission rates are a considerable improvement over the currently available (WF-ABBA) fire hotspot product.

INTRODUCTION

Fires when viewed from space produce positive anomalies in middle Infrared (MIR) satellite channel data. But, in order to correctly and accurately identify if a MIR value is a positive "anomaly", researchers try to capture the "normal", or "background" MIR value. Capturing a "normal" clear-sky MIR distribution is non-trivial because MIR values are sensitive to *both* thermal radiation *and* solar radiation reflected from clouds. Therefore, to capture a "normal" clear-sky MIR distribution it is important to remove data containing clouds.

Detecting clouds in geostationary satellite data is a complicated process. Clouds vary in form from Cumulonimbus through to Cirrus. And clouds change in properties such as height, optical thickness and amounts of water, graupel, ice, etc. As such, accurate cloud-detection using geostationary satellite information is an active area of research. Attempts to estimate clouds using simple techniques for active fire applications[1] use experimentally determined thresholds that delineate clear-sky from cloudy sky[2]. While simple thresholds hold in temperate areas such as the Brazilian Amazon where they were originally developed, the thresholds do not hold over all of Australia.

Imprecise assumptions regarding thresholds that delineate clear- from cloudy-sky can lead to either clouds getting into the dataset or more than necessary clear-sky or fire pixels being left out of the dataset. Cloud-contaminated datasets have the potential to have lower the "background" TIR and higher "background" MIR expected values. A lowered background TIR value could lead to more pixels being deemed as fires, and an increased background MIR could lead to more fire-pixels being treated as clear-sky pixels. Therefore, it is important to pre-process the dataset for cloud as accurately as possible.

This work asks: what are the "clear-sky" conditions for biogeographic sub-regions over Australia. And, can simple clear-sky statistics be used to detect fires in each of the biogeographical sub-regions?

BACKGROUND

Clear-sky satellite observations are linked to variables such as daytime radiation, atmospheric conditions and the underlying landscape characteristics. The amount of incoming radiation and hence heating of the ground can vary with time of day, season, proximity to the equator or pole and weather conditions. Landscape conditions can vary greatly across the Australian-continent. Hence not all areas of Australia can be representative of each other.

Statistical estimations increase in accuracy when the errors are small or the sample size is larger. The Himawari sensor has fixed accuracy specifications, and Himawari started archiving data in 2015. These cannot be changed. So, to increase the accuracy of the active fire detection we can only increase the sample area upon which the statistics are based. Normally-distributed populations have samples that are drawn from one single population. Variations in the underlying population can lead to a non-normal statistics and therefore inaccurate statistical estimations. To increase the sample size without distorting the statistic, we can group regions in terms of pixels that are representative of each other.

Biogeographic regions are regions of land that are representative of each other in terms of certain biological, ecological and climatic conditions. Version 7 of the Interim Biogeographic Regionalization for Australia has broken up Australia in 89 regions and 419 sub-regions[3,4]. These 419 sub-regions can be used to group representative areas of Satellite data.

METHOD

In this work, we created IBRA sub-region specific dynamically-varying definitions of clear-sky albedo, MIR and TIR. We used these "clear-sky" albedo, MIR and TIR definitions to detect potential fires in Himawari data.

For this exploratory study, we gathered 0400 UTC data from 1 Dec 2015 up to and including 30 Nov 2016. We defined sub-seasons for: early-summer, late-summer, early-autumn, late-Autumn, early-winter, late-winter, early spring and late-spring. For each IBRA sub-region, sub-season (and time-point) we did the following for albedo, MIR and TIR data:

1. Grouped the regional data for each individual day.
2. Filtered out all values where albedo was greater than 0.4 if albedo, or greater the 50th percentile clear-sky albedo value (as defined in step 8) + 0.05 if MIR or TIR.
3. Clipped each individual day sample at its 5% and 98% percentile values.
4. Calculated the median values of the clipped day samples.
5. Calculated the sub-seasonal mean and standard deviation across all daily median values.
6. Discarded any daily samples where the daily median was lower than the sub-seasonal median mean – sub-seasonal median standard deviation.
7. Collated all remaining values into a single sub-seasonal sample.
8. Calculated the sub-seasonal 1%, 50% and 99% percentile value from the "clear-sky" data.

We then reprocessed the unfiltered grouped (from step 1) dataset and identified suspect fire-detection spots where:

a. MIR > 99% clear-sky MIR,
b. TIR > 50% clear-sky TIR and,
c. albedo < (50% clear-sky albedo + 99% clear-sky albedo)/2.

Lastly, we characterized our confidence in these "suspect" points by analyzing their MIR- 99th percentile MIR clear-sky value.

We compared these "suspect" points and the WF-ABBA hotspots against MODIS and VIIRS hotspots available from Sentinel, where the confidence estimate was greater than 50.

RESULTS

The albedo, MIR and TIR clear-sky values differed greatly between IBRA sub-regions, and within individual sub-region sub-seasons. For example, the maps on figure 1 show the spatial variation in clear-sky 99th percentile MIR values.

Suspected hotspots identified using IBRA method had spatial patterns that varied with sub-season. The hotspot spatial patterns were similar to MODIS and VIIRS hotspot detections over each sub-season (not shown).

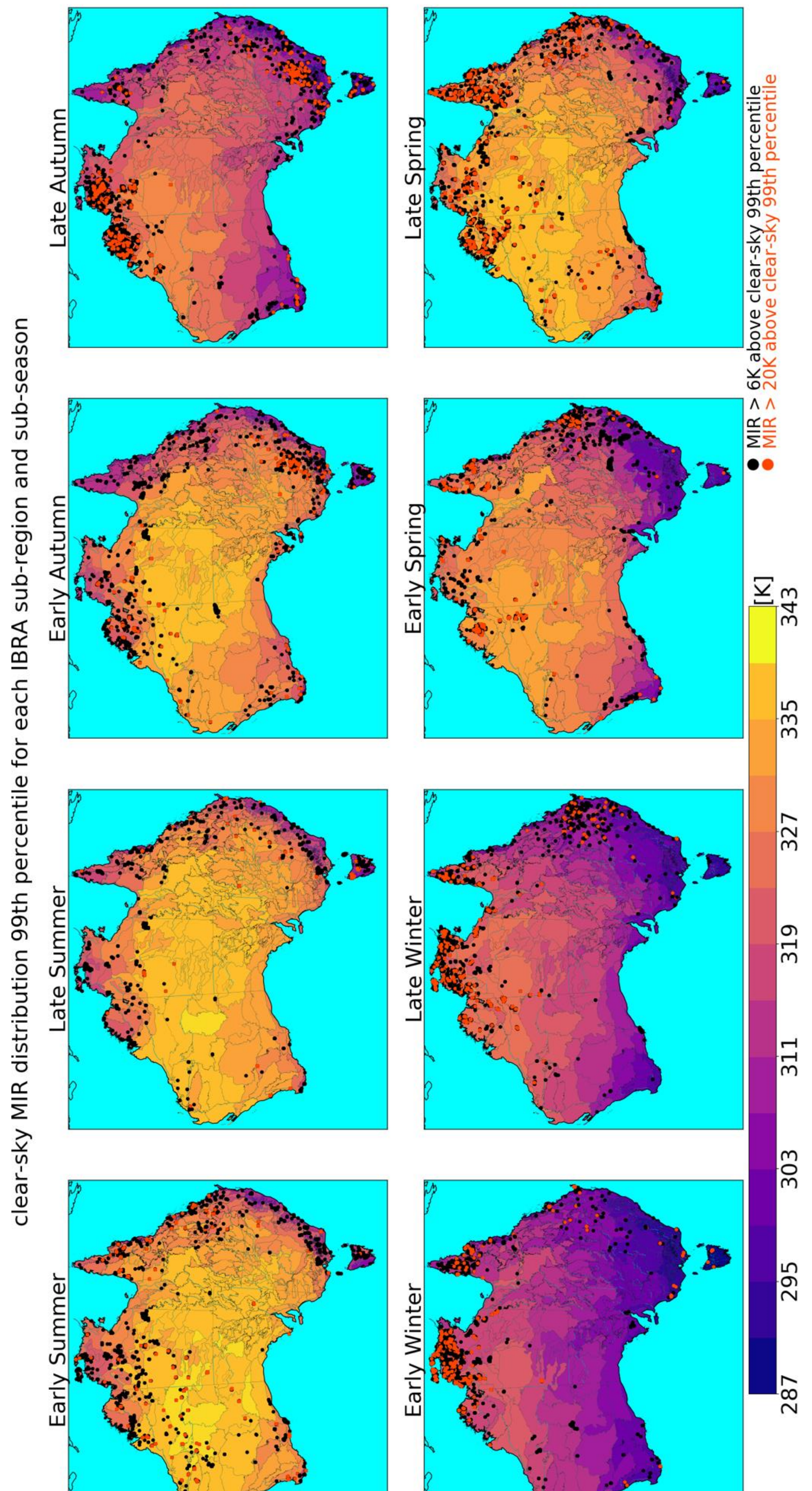

FIGURE 1 SUB-SEASONAL AND IBRA REGION CLEAR-SKY MIR DISTRIBUTION 99TH PERCENTILE VALUES ON BACKGROUND PLOT, WITH SUSPECT HOTSPOTS WITH MIR VALUES 6K AND 20K ABOVE THE CLEAR-SKY MIR 99TH DISTRIBUTION VALUE.

The percentage of IBRA hotspots that occurred within 20km of a MODIS/VIIRS hotspot (with MODIS/VIIRS confidence greater than 50% *and* on the same date) was highest in Summer (up to 94%) and Spring (up to 92%), and lowest in Winter (up to 80%) and Autumn (up to 59%) (figure 2). These statistics were encouraging in comparison to the WF-ABBA hotspots that had greatest matches for Winter (up to 69%) and Summer (up to 65%), and lower Spring (up to 52% -- with a peak in lower fire radiative power) and Autumn (up to 46%) (figure 3).

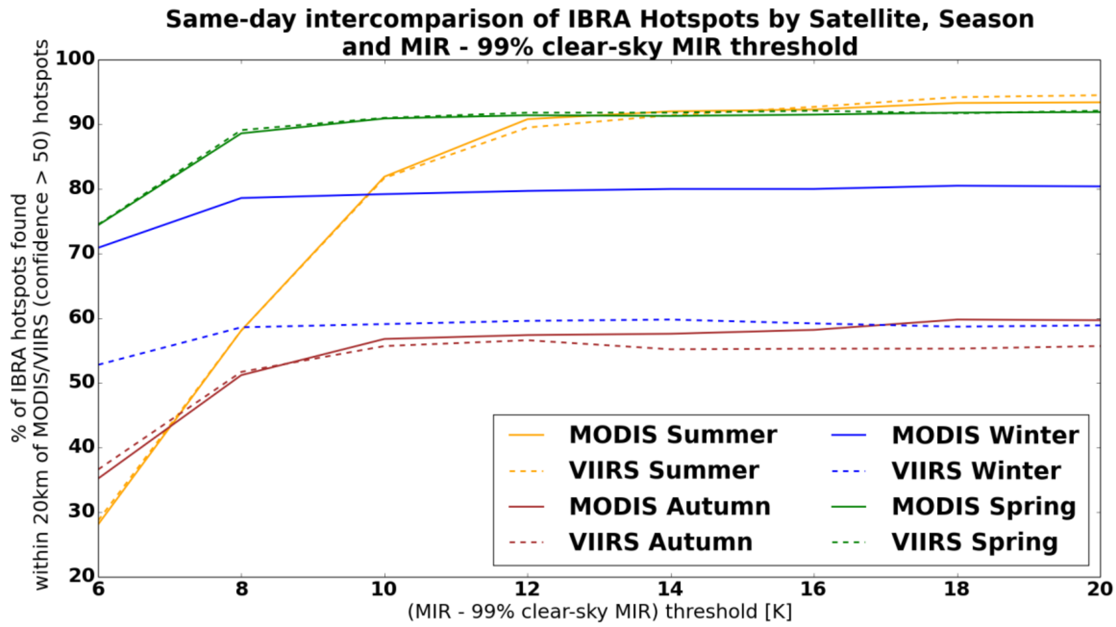

FIGURE 2 PERCENTAGE OF IBRA HOTSPOTS FOUND WITHIN 20KM OF MODIS/VIIRS (CONFIDENCE > 50) HOTSPOTS, FOR EACH SEASON AND MIR – CLEAR-SKY 99TH PERCENTILE THRESHOLD.

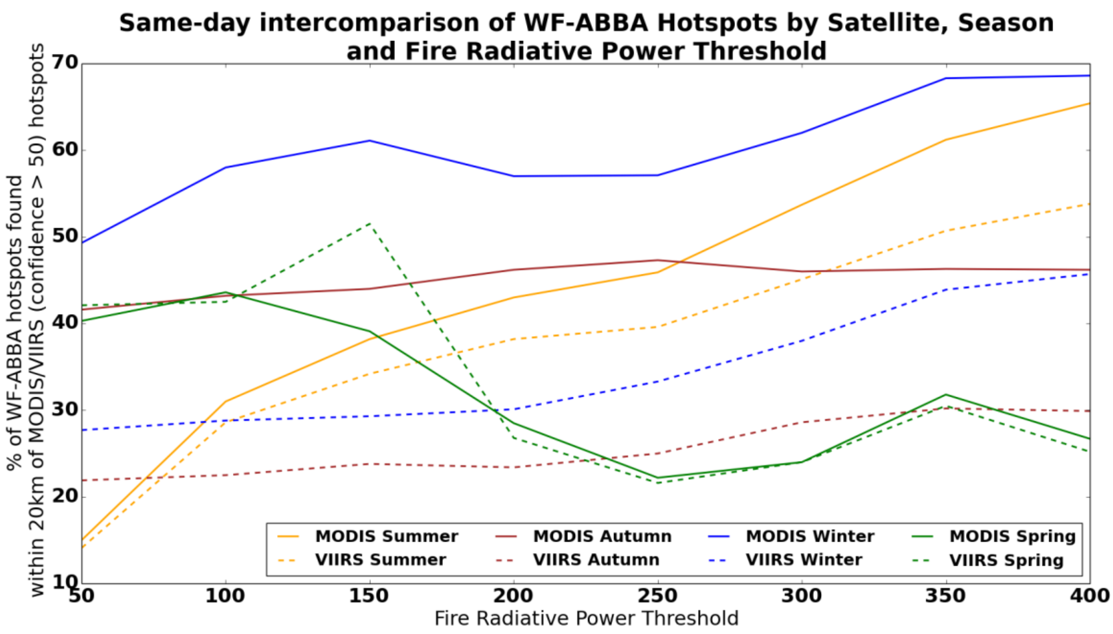

FIGURE 3 AS IN FIG.2, EXCEPT FOR WF-ABBA HOTSPOTS THRESHOLDED BY FIRE RADIATIVE POWER AS A MEASURE OF CONFIDENCE.

DISCUSSION

The MIR, TIR and albedo clear-sky characteristics varied between IBRA sub-regions. Individual IBRA sub-regions also varied between different sub-seasons. Preliminary results from 89 IBRA regions also showed significant variation over the diurnal cycle (not shown). These results indicate that a single "clear-sky" threshold across Australia is not appropriate either for an entire diurnal period or an individual time, (although some sub-regions may be more temperate).

The IBRA comparisons against MODIS and VIIRS were particularly encouraging during Summer and Spring. But, the results during Winter and Autumn indicate that our dynamic-threshold IBRA technique may be sensitive to raised MIR values against cooler background brightness temperature values. Whether or not these are valid fire-detections needs to be investigated further.

The inter-comparison was complicated by the higher temporal resolution data of the geostationary satellites and the higher spatial resolution of the polar-orbiting satellites. To make results ours more robust we need to increase the number of time-points analyzed. To do this we also need to expand the algorithm into the night-time period when albedo observations are not available. We also need to use the larger time-point dataset to investigate rates of omission errors. That will be included in the next phase of our study.

Lastly, this study uses sub-seasonal grouping of data. The next logical step would be to compute real-time hotspot statistics using a running window. Real-time dynamic IBRA based fire hotspot detection may have the potential to be fast, efficient and accurate and most important tuned specifically for Australia.

CONCLUSION

Clear-sky MIR, TIR and albedo differ significantly across between IBRA regions, and for individual IBRA sub-regions between sub-seasons. Australia-wide clear-sky MIR, TIR and albedo estimates cannot not reflect this level of variability. Dynamic characterization of clear-sky conditions for MIR, TIR and albedo can be achieved across IBRA sub-regions. These dynamic clear-sky statistics can be used to form a simple fire hotspot algorithm that has lower rates of commission errors than the currently available WF-ABBA algorithm.

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