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Short contribution – Fire Management

Out of context: fire background temperature and methods for its calculation

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Abstract

Background temperature is an important component of any fire detection and monitoring method; the use of the contrast between the expected brightness temperature of a location and the brightness temperature associated with fire activity is the basis for most fire detection algorithms. The commonly used method for calculation of fire background temperature involves estimation of the surface characteristics using the immediately adjacent, non-occluded surrounds of the target pixel, in order to provide a contextually – based estimate of temperature. Depending upon conditions such as cloud, smoke, surface water and heterogeneity of land cover, this derivation of background temperature from the surrounding landscape can be vastly different from the measured brightness temperature of a pixel in a non-fire context. This paper examines the relationship between pixel brightness temperature and pixel context, to identify situations where the currently used contextual methods are most likely to perform below the required level of accuracy for fire detection. Initial results show that in many cases the ideal candidate pixels for estimating temperature at any one location may not be those that sit immediately adjacent spatially.

Keywords: diurnal modelling, land surface temperature, fire detection, spatial context, multi-temporal estimation

1. Introduction

Remote sensing techniques for detecting and attributing fire activity require the calculation of a pixel's nominal background – the temperature a pixel would display without the influence of fire – in order to determine whether a fire exists, and the magnitude of fire activity. Without the ability to directly measure this background temperature, most methods currently derive their background temperature from the image context, the area immediately surrounding the pixel spatially. This technique leverages the tendency of nearby pixels to display relatively similar characteristics due to spatial auto-correlation.

Problems arise with contextual methods when the area examined is not relatively homogeneous for surface temperature examination. Factors such as slope and aspect, weather effects, surface water, undetected cloud and smoke, and land cover changes can all affect the accuracy of results derived from the pixel context. This work looks to examine the efficacy of context for providing temperature estimation, and especially looks at the effects that occur when using contextual pixels that are further away than the immediate surrounds of a target pixel.

2. Method

This paper uses data from the AHI-8 sensor onboard the Japan Meterological Agency's Himawari 8 geostationary satellite. Band 7 MWIR (4µm) images were selected over a section of central Thailand for a period of 31 days, with the central day based upon the VNP14IMGLL (Schroeder et al., 2014) maximum fire occurrence for 2016. Images were selected for coincidence with the VIIRS overpass time for the area, which roughly corresponds to 0630 UTC. The area covered by the study in shown in Figure 1. Cloud areas were discarded using a cloud mask based upon Xu et al. (2010), and a land mask was used to eliminate lakes and oceans from examination based upon ancillary data provided by the Australian Bureau of Meteorology.

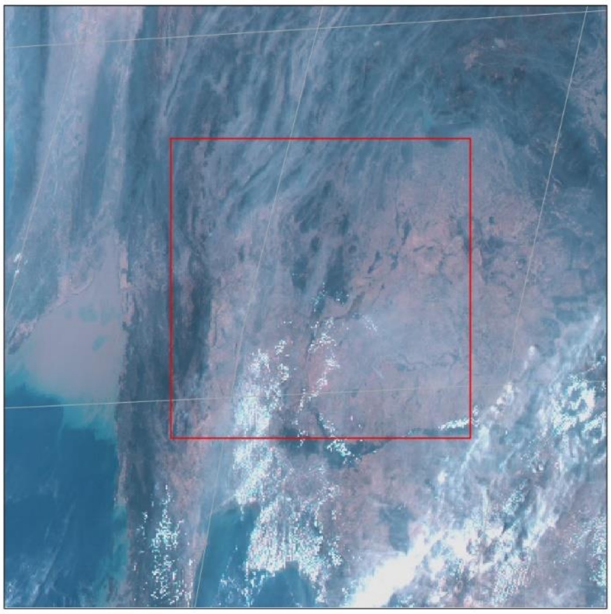

Figure 1 - The study area in central Thailand, as seen from AHI-8.

The study calculated the mean temperature of the surrounding pixel context in the area of examination for pixels in various configurations around the central pixel. Firstly estimation was based upon all available non-masked pixels in the 5 × 5 area surrounding the central pixel, then this area was increased to 7 × 7, 9×9 and finally 11×11 pixels. Means from these areas were then compared to the central pixel value to determine their error, and the means and variances of these differences were recorded for analysis.

The study also looks at use of pixel temporal information in comparison to pixels in the study area to provide a prediction of pixel brightness temperature. One pixel was randomly selected from the study area shown, then the root mean square error was calculated between this pixel and all other pixels in the first thirty days of the study period. The best 24 pixels for RMSE were then used as a predictive set for temperature in the target pixel for the 31st day of the study, and comparison was made to contextual pixel estimation in the 5 × 5 window for the same day.

6. Results and Discussion

Figure 2 demonstrates the spatial distribution of errors in contextual temperature estimation in the area selected. The first map shows the variation in means at the 5 × 5 window, which highlights areas of relief and land cover changes as edge effects. Bodies of water that have not been properly eliminated also demonstrate temperature over-estimation. As the window of examination increases, these variations in the landscape become more prominent as drivers of error for background temperature.

The distributions shown to the right of the maps describe the statistical distribution of temperature estimates. There is no skew to the results - globally the mean tends to zero, but as the window size grows the distribution of points flattens and the variance of the calculated values increases markedly.

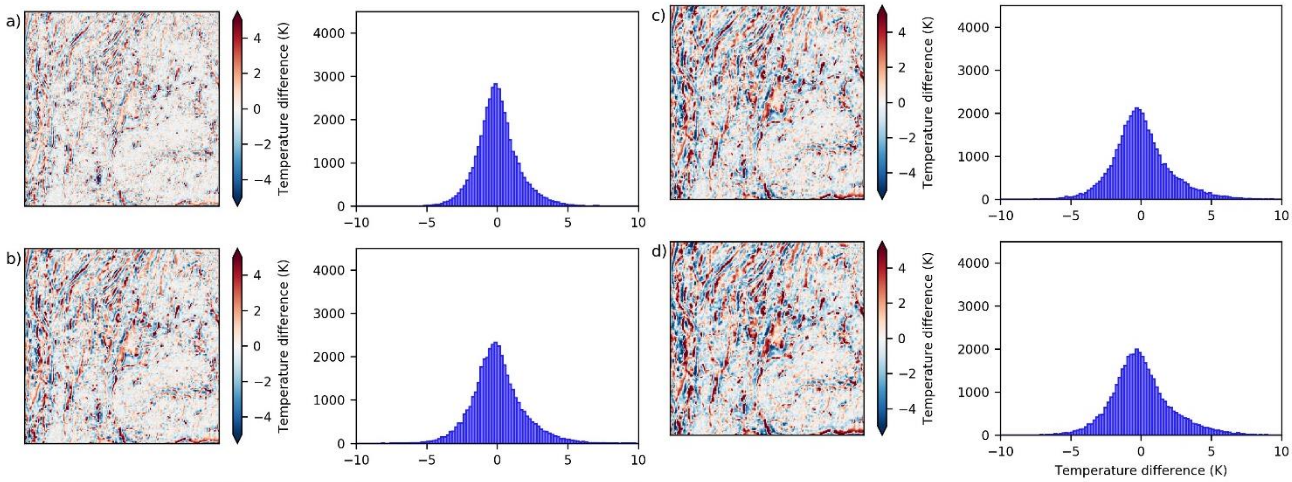

Figure 2 - Effect of expanding the contextual area of analysis on brightness temperature estimation for part of central Thailand. The spatial and statistical distributions for pixel differences from the context are shown for a) 5×5, b) 7×7, c) 9×9, and d) 11×11 contextual windows.

Figure 3 shows the spatial distribution of pixels that have the lowest root mean square error compared to the selected pixel (AHI 1836, 977). The lowest 24 RMSE values were then selected as a training series for estimation of pixel values on the 31st day of the study period. As can be seen here, using the pixel histories in this way can provide data even when a large portion of the pixel history is cloud affected, and the resulting mean value from the selected pixels provides a better estimate of the target pixel temperature than the context in this case.

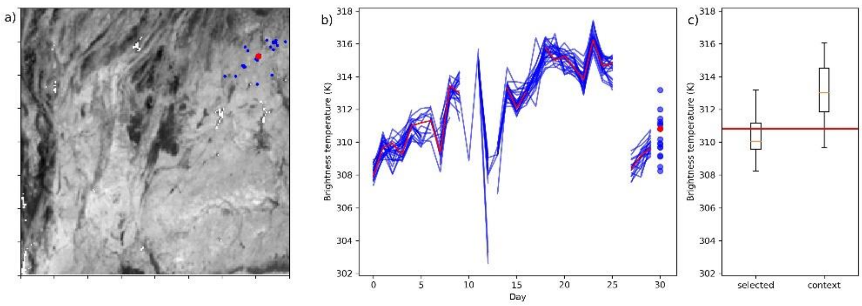

Figure 3 - Using selected pixels from the study area to provide background estimates. a) Location of pixels with lowest RMS error compared to the examined (red) pixel; b) diagram of temperatures over the thirty day period; c) plot of selected pixel values versus the pixel context.

This work shows a small sample of some of the issues that can occur with use of contextual temperature estimation. Land cover change is a particular driver of error in this area, but there are several other factors that can cause increased variance in calculated temperature values. Any method using contextual information for estimating temperature values should be aware of the specific sources of error that exist in the region of examination, as the errors seen here can easily result in misattribution of fire characteristics, and errors in both omission and commission of fire products.

3. References

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