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Evaluating the effects of spatial resolution on hyperspectral fire detection and temperature retrieval

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ABSTRACT

Hyperspectral data covering a wavelength range of 1.2–2.5 μm can be used to detect fires and model fire temperature and background land cover. Previous work has used hyperspectral data acquired from airborne platforms, limiting spatial resolution to finer than 20 m. The Hyperspectral InfraRed Imager (HyspIRI), a proposed hyperspectral/thermal infrared mission, will provide hyperspectral data over a spectral range of 0.35–2.5 μm at a spatial resolution of 60 m. This study uses airborne hyperspectral data to investigate changes in modeled fire temperature and area as spatial resolution is varied from 5 m to coarser than 60 m. Four images containing active fires were acquired by the Airborne Visible Infrared Imaging Spectrometer (AVIRIS), with spatial resolutions ranging from ~5 to ~20 m. Gaussian and aggregation resampling methods were compared for one scene containing fire, and both resampling methods were found to produce similar radiance values. As spatial resolution coarsened, the area flagged as having fire by the hyperspectral fire detection index (HFDI) increased. Fire temperature modeled using a multiple endmember spectral mixing model decreased at coarser spatial resolutions, while the modeled fire fractional area increased. Coarser spatial resolution hyperspectral data, including data collected by HyspIRI, are likely to provide increased fire area and lower temperatures when compared against simultaneously acquired higher spatial resolution data. Saturation in shortwave infrared (SWIR) bands was found in all four images, and increasing SWIR saturation thresholds could lead to improvements in fire characterization.

1. Introduction

Wildfire is a globally important process, affecting a wide variety of ecosystems and often endangering human life and settlement. The impacts of wildfires add to growing concerns regarding atmospheric pollutants, the carbon cycle and global climate change. Remote sensing has appropriately become an essential tool for examining and evaluating the effects of wildfires on the environment due to its ability to map fires and fire impacts over large areas (Lentile et al., 2006). Measurement of reflected and emitted shortwave electromagnetic radiation at high spectral resolutions can provide valuable information on fuels (Dennison et al., 2003; Varga & Asner, 2008), active fires (Dennison & Matheson, 2011; Dennison et al., 2006) and the impacts of fire on vegetation and soils (Kokaly et al., 2007; Lewis et al., 2007). Although remotely sensed information represents a snapshot in time, repeat acquisitions can allow detection of change over time, such as the regeneration of vegetation in a burned area (Riaño et al., 2002).

Hyperspectral sensors utilize a large number of contiguous bands, each with a narrow wavelength range (typically ≤10 nm). Previous work using Airborne Visible Infrared Imaging Spectrometer (AVIRIS) data has demonstrated that hyperspectral data can be used to detect fire (Dennison & Roberts, 2009) and model fire temperature (Dennison & Matheson, 2011; Dennison et al., 2006). Yet AVIRIS, like all airborne sensors, faces issues of varying spatial resolutions and has limited spatial and temporal coverage. The National Research Council Decadal Survey on NASA Earth Science Applications recommended the development of a hyperspectral/thermal infrared satellite mission (National Research Council, 2007). The proposed Hyperspectral InfraRed Imager (HyspIRI) would carry a visible-shortwave infrared (VSWIR) hyperspectral sensor with AVIRIS-like spectral range (0.38–2.5 μm) and resolution (10 nm), but data would be acquired at a spatial resolution of 60.0 m. Fire detection and temperature modeling algorithms that have been developed for higher spatial resolution AVIRIS data have not been tested at coarser spatial resolutions. Spectral mixing of fire emitted radiance may change modeled fire temperature and area as spatial resolution is altered.

By resampling AVIRIS images to coarser spatial resolutions and applying fire detection and temperature modeling algorithms, the impacts of spatial resolution on retrieved fire parameters can be simulated. This study has three main objectives: (1) assess whether simple averaging of adjacent pixels (aggregation) can be used as a substitute for a less flexible, but more realistic Gaussian resampling approach; (2) assess the performance of fire detection and temperature modeling algorithms applied to images resampled to coarser

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spatial resolutions; and (3) find a maximum shortwave infrared (SWIR) emitted radiance for 60.0 m spatial resolution data. By addressing each of these objectives, the abilities of HyspIRI VSWIR data for characterizing fire can be estimated.

2. Background

Hyperspectral sensors measure radiance reflected from or emitted by a surface. Cooler temperature objects (i.e., temperatures up to 500 K) emit most of their radiance in the thermal infrared (8–12 μm) and middle infrared (3–5 μm) regions of the electromagnetic spectrum. Hotter temperature objects (e.g., smoldering and flaming combustion above temperatures of 500 K) emit more of their radiance in the SWIR (1.4–2.5 μm). Planck's equation specifies emitted blackbody radiance at a specific wavelength and temperature. If radiance is known and blackbody emissivity is assumed, the radiative temperature of the object can be estimated by inverting Planck's equation.

Temperature modeling for wildfires is complicated by the fact that pixels can contain mixed radiance that includes multiple combusting and non-combusting areas. The effective temperature and subpixel area of a fire within a pixel can be modeled using a spectral mixing model, which models pixel radiance as a combination of endmember radiances multiplied by their fractional area. Endmembers are spectrally pure signatures of a given land cover type (or radiance emitted at a specific fire temperature, in the case of wildfires), gathered from either field-measured spectra, relatively pure pixels in the image, or modeled radiance that accounts for atmospheric effects through radiative transfer modeling (Eckmann et al., 2008). The general equation for spectral mixing is:

$$L_\lambda = \sum_{i=1}^{N} f_i L_{i\lambda} + \varepsilon_\lambda \tag{1}$$

where L_λ is the total mixed spectral radiance for the pixel, $L_{i\lambda}$ is the radiance of endmember i at wavelength λ, f_i is the fraction of endmember i, N is the number of endmembers, and ε_λ is the residual error. In the case of modeling fire in SWIR wavelengths, the fraction and radiance terms can represent reflected solar radiance or emitted radiance from a fire. The first spectral mixing model applied to temperature retrieval of wildfires was developed by Dozier (1981) for the Advanced Very High Resolution Radiometer (AVHRR). This method uses a two endmember model which employs two broadband AVHRR channels at 4 μm and 11 μm to spectrally discriminate between fire and nonfire (cool background) endmembers. The method uses the following equation:

$$L_\lambda = f_f \beta\left(\lambda, T_f\right) + f_b \beta(\lambda, T_b) \tag{2}$$

where f_f is the fire fractional area, f_b is the background fractional area, T_f is the fire temperature, T_b is the background temperature, and β is Planck's equation. Giglio and Kendall (2001) note that the method is based on the following assumptions: all objects and background emit as blackbodies, a hot object has a single, uniform temperature, atmospheric effects are minimal, and that nearby pixels may be used to estimate radiance for nonfire portions of a fire pixel.

2.1. Fire detection in hyperspectral data

Hyperspectral fire detection indices based on three spectral features have been proposed. Vodacek et al. (2002) and Amici et al. (2011) examined fire detection based on near infrared bands that capture potassium emission found in burning vegetation. Dennison (2006) introduced a carbon dioxide absorption index using a combination of three bands to indicate reduced carbon dioxide absorption caused by the limited path length of emitted radiance. Dennison and Roberts (2009) used kappa matrices to compare all potential paired combinations of AVIRIS bands, and termed the most accurate pair the Hyperspectral Fire Detection Index (HFDI):

$$\mathrm{HFDI} = \frac{\left(L_{2.43\mu m} - L_{2.06\mu m}\right)}{\left(L_{2.43\mu m} + L_{2.06\mu m}\right)}. \tag{3}$$

HFDI is based on both trace gas absorption and differences in the spectral shapes of reflected solar radiance and fire emitted radiance caused by Plank's equation. The value increases as the emitted radiance contribution to total radiance increases. Dennison and Roberts (2009) evaluated the performance of HFDI against the potassium emission index (Vodacek et al., 2002) and the carbon dioxide index (Dennison, 2006) on AVIRIS scenes of the 2007 Zaca Fire and the 2008 Indians Fire in California. They found that HFDI outperformed the other indices, with less sensitivity to smoke than the potassium emission index and less background noise than the carbon dioxide index. However, simulations did show that HFDI has decreased sensitivity to fire at modeled temperatures below 750 K and above 1400 K.

2.2. Hyperspectral fire temperature modeling

Modeling of fire temperature using hyperspectral data has built upon the mixing model approach of Dozier (1981). Green (1996) used observable spectral differences between emitted radiance and reflected solar radiance to model fire temperature. Dennison et al. (2006) improved upon the Green (1996) methods by applying multiple endmember spectral mixture analysis (MESMA; Roberts et al., 1998) to modeling fire temperatures. This method uses a spectral library of endmembers, and establishes the best fit combination of endmembers for each image spectrum. Dennison et al. (2006) used MESMA to compare and select the best fit combination of a reflected solar radiance endmember (from a spectral library of selected image endmembers), an emitted radiance endmember (from a spectral library of modeled emitted radiance endmembers for temperatures ranging from 500 to 1500 K), and a shade (no measured radiance) endmember. While the method was computationally intensive and produced some errors due to smoke and sensor saturation in the SWIR, it effectively combined temperature modeling and fire fractional area estimation with background land cover classification. Dennison and Matheson (2011) improved upon the Dennison et al. (2006) fire temperature algorithm by using HFDI for fire detection, as well as separate spectral libraries of background endmembers for smoke, nonsmoke, and fire pixels. The algorithm was applied to both AVIRIS data and coarser spatial resolution data from the MODIS/ASTER Airborne Simulator (MASTER), but differences in modeled temperature due to spatial resolution were not examined.

2.3. Spatial rescaling

A primary limitation on the ability to characterize land cover or model temperature in remotely sensed imagery is the spatial resolution of the imagery itself. Coarser spatial resolutions can result in a loss of spatial and spectral information. Multiple studies have examined the impact of spatial resolution on mapping of vegetation. Bian (1997) showed that variability in the values of a Landsat TM reflectance/absorptance biomass index decreased with coarsening spatial resolution. Walsh et al. (1997) also demonstrated that biomass variation was scale dependent, noting a smoothing of NDVI values at coarser resolutions. Nelson et al. (2009) coarsened Landsat TM and ETM+ imagery to facilitate forest boundary detection, but found that different thresholds must be set depending on the spatial resolution to avoid under- and over-detection of a boundary. Rahman et al. (2003) used spatial upscaling (coarsening of spatial