Developing best practice for Burnt Area products

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Introduction

• Detection of Burnt Area (BA) from optical Earth Observation (EO) data is challenging due to two features:
  • Data
    – Insufficient observations: sparse observations in time and space make it difficult to detect fires in fast recovery regions.
    – Insufficient spectral signal: small or low-intensity fires will have only a small impact on the reflectance properties of the land surface.
  • Algorithms
    – Incorrect models: algorithms contain models of fire properties which may be incomplete or incorrect.
    – Data ‘processing’ concerns: algorithms may not treat features of the data appropriately: e.g. treatment of BRDF, treatment of observation sparsity.
  • Global BA products still have considerable omission/commission errors due to these features (Padilla et al., 2017).
  • Teasing apart reasons for these errors requires a new framework for designing and evaluating BA algorithms.

Method

BA detection as an Inverse Problem

The BA detection can be phrased as an Inverse Problem:

\[ B - G(I, D) \]

where the operator (BA algorithm) G attempts to infer burnt area B from the observations D. Inverse theory provides a powerful mathematical framework within which to design new algorithms as well as evaluate present algorithms.

Modelling of EO observations

• ‘Virtual laboratories’ provide powerful testing frameworks in which algorithms can be compared and iteratively improved (Widlowski et al., 2007).
  • Step 1: Generate a model of the properties of the landsurface using:
    – Reference Burnt Area (e.g. Landsat BA maps or active fires) provide observations. An Monte-Carlo sensitivity analysis has indicated that these parameters may greatly affect the resulting BA estimates.
  • Step 2: Simulate observations typically seen by EO sensors. This allows for the solution to the forward problem:

\[ D = H(I_{\text{true}}) \]

which can then be used to test algorithms (see figure 1).

Figure 1: Approach for simulating sensor observations. First estimates of the landsurface state \( \phi \) and their dependence on whether a fire has occurred are made. These are an RT model simulates the angular dependence of reflectance depending on view and illumination geometries. Finally the properties of the atmosphere \( \phi_A \) are simulated. Varying these parameters can therefore generate apparent ‘sensors’ with different temporal and angular sampling regimes as well as observation opportunity.

References


Summary

1. Present BA algorithms show considerable commission/omission errors.
2. A systematic analysis of BA detection approaches remains an interesting challenge.
3. A framework for designing and evaluating BA algorithms is presented based upon the generation of ‘virtual laboratories’.
4. An analysis of some of the key BA algorithm issues indicates areas for improvement in the creation of next generation BA products.

Results

Burn signal

• An analysis of spectral burn signals indicates that presently used spectral indicies (VIs) perform poorly for global BA detection.

![Figure 2](https://via.placeholder.com/150)

Figure 2: Optimality \( \phi \) of presently used VIs for BA detection. When \( \phi = 1 \) the variation in the VI contains all the variation in the true spectral burn signal. As \( \phi \rightarrow 0 \) the VI includes no discernible information on the burn signal.

Algorithm parameterisations

• Ad-hoc parameterisations effect BA estimates. All BA algorithms contain parameters which control the eventual BA product. These parameters represent understandings of the fire process on the land-surface or properties for treatment of the observations. An Monte-Carlo sensitivity analysis has indicated that these parameters may greatly affect the resulting BA estimates.

![Figure 3](https://via.placeholder.com/150)

Figure 3: Top) Parameters in the MCD64 algorithm (Giglio et al., 2009) and commission error. W is the length of the compositing window in days, \( S_{\text{w}} \) is a spatial-temporal metric which determines whether nearby pixels show evidence for coincident burning. Bottom) Parameters in the Fire_cci algorithm (Alonso-Canas and Chuvieco, 2015) and commission error. GEMI\_threshold is a threshold in a decrease in the GEMI VI for a pixel to have burnt. U\_threshold is a threshold defining the unburnt class.

Next Steps

• Propose a set of best practice principles for next generation products.
• Make reference datasets public for algorithm developers to design and improve their algorithms.