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., 2015).
- 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**:

$$B = \mathbf{G}(D) \tag{1}$$

where the operator (BA algorithm) $\mathbf{G}$ 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 B_{True}
  - Scattering properties of the landsurface derived from a novel processing of MODIS surface reflectance (MOD09).
- **Step 2:** Simulate observations typically seen by EO sensors. This allows for the solution to the forward problem:

$$D = H(B_{\text{True}}) \tag{2}$$

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

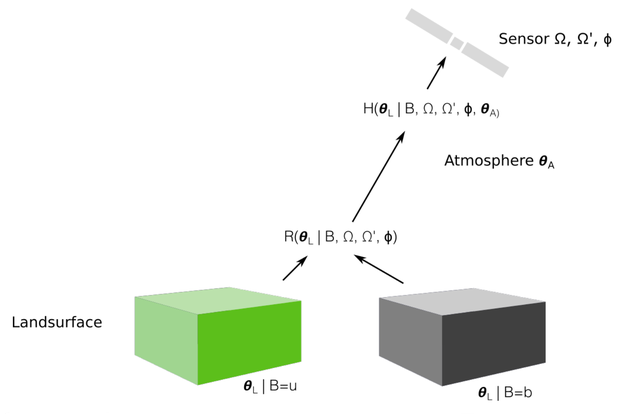

Figure 1: Approach for simulating sensor observations. First estimates of the landsurface state θ_L and their dependence on whether a fire has occurred are made. From these an RT model simulates the angular dependence of reflectance depending on view and illumination geometries. Finally the properties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

References

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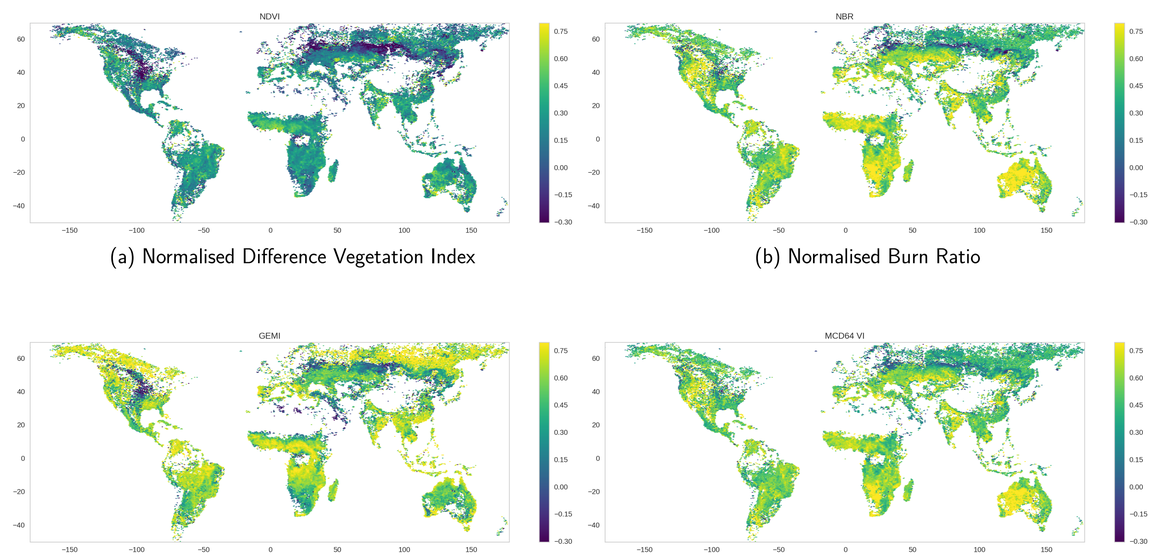
Summary

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.



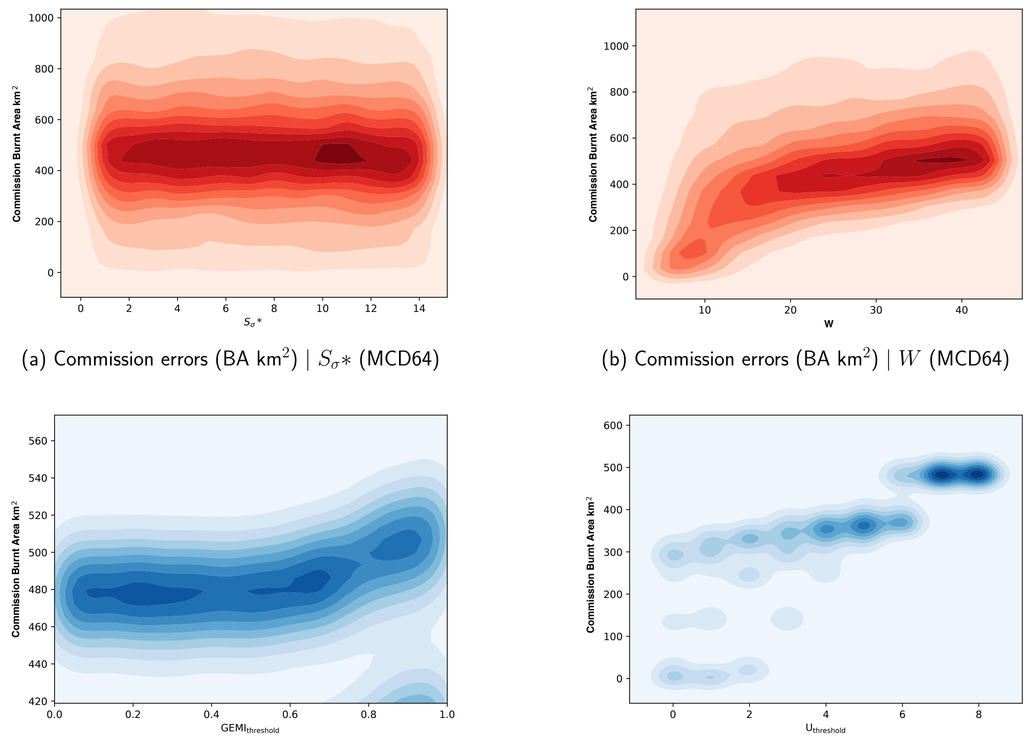
(a) Normalised Difference Vegetation Index (b) Normalised Burn Ratio

(c) Global Environment Monitoring Index (d) NIR/SWIR VI in MCD64.

Figure 2: Optimality ϕ 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 $\phi \to 0$ 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**.



(a) Commission errors (BA km^2) | $S_\sigma*$ (MCD64) (b) Commission errors (BA km^2) | W (MCD64)

(c) Commission errors (BA km^2) | GEMI$_{\text{threshold}}$ (Fire_cci) (d) Commission errors (BA km^2) | U$_{\text{threshold}}$ (Fire_cci)

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, $S_\sigma*$ 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$_{\text{threshold}}$ is a threshold in a decrease in the GEMI VI for a pixel to have burnt. U$_{\text{threshold}}$ 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.