Uncertainty in burned area (BA) products

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Outline

1. 101 burnt area detection
2. BA products: past
3. BA products: present
4. BA products: future/next generation
Burned area detection 101
What is in a burnt area algorithm?

→ Output: burnt/unburnt binary mask w/ estimate of day of burn (DOB)

Surface reflectance, active fire observations → “pre-processing” → “classification” → Pixel product → CMG product
What is in a burnt area algorithm?

Surface reflectance, active fire observations

“pre-processing”

“classification”

Pixel product

CMG product
Considerations

Pre-processing

1. Sparsity of the data
   a. Do we “observe” the fire (impact)?
      i. Enough observations + well timed observations

2. Auxiliary signal
   a. How do we deal with BRDF effect?
   b. Atmospheric conditions

3. Noise:
   a. Observation uncertainty
   b. Non-normal (atmospheric corr/cloud shadow)
Considerations

Detection
1. **Key**: how *separable* are burnt and unburnt pixels:
   a. Pre-processing *errors*
   b. Signal *space*
2. What are our *expectations* of burnt and unburnt pixels:
   a. What is our “likelihood” function…
   b. How do we parameterise it?
      i. empirically?

Pre-processing decisions

Likelihood issues

Signal issues
separability
Past UQ
No/poor uncertainty

**General:** Binary yes/no burnt + Day of Burn (DOB)

**MODIS BA 1 MCD64 (best):**
1. Burn date uncertainty (unc in DOB)
2. No burnt confidence/uncertainty, instead QA layer:
   a. Insufficient spectral separability between burnt and unburnt classes
   b. Too few observations in time series

→*useful hints at uncertainty...* BUT which are more/less important? Quantification?

**MODIS BA 2 MCD45 (good):**
1. BA pixel confidence QA
   a. 4 levels: (ordered: 1 Highest, 4 Lowest)

2. Other useful information:
   a. **Gap Range:** biggest gap in days between observations → algorithm performs better with shorter gaps
No/poor uncertainty

FireCCI v4 (good):
1. Confidence level: probability that burnt pixel is actually burnt
   a. → but what about unburnt pixels...? no information on omission from this
2. No DOB uncertainty?
But... underneath

1. No *uncertainties* on observations
2. No *uncertainty* in model

→ No *real* uncertainty propagation...

WHY: thresholds, complex temporal/spatial filtering... algs are _**VERY**_ non-linear

*Pixel:* “How certain are you a fire happened on day t at pixel p”?

*Grid:* “On day t what is the pdf of burnt area km²”? 
Present: FireCCI
Focus in FireCCI

1. Definition of uncertainty estimate
2. Error characterisation exercise (CERC)
3. Grid scaling
Uncertainty estimate in FireCCI: pixel level

Probability of burn $P_b$: Probability that a pixel has burnt

Features:
1. Defined for *all pixels* (not just alg labelled burnt)
   a. → Gives information on possible omission/commission errors
2. $P_u = 1 - P_b$
3. Should be related to classification uncertainty and data quality

So products are:
1. Binary DOB mask
2. Probability of burn (all pixels)
Error characterisation exercise

Developed a sampling framework for validating Pb estimates.

1. Generate N realisations of the data (adding noise, sparsity etc)
   a. → represent the uncertainty in the data (approximate distribution)
2. Run algorithm on the N realisations
3. Output N burnt/unburnt masks
4. An approximation to Pb is

\[ P_b|D = \frac{B}{B + U} \]

→ A better estimated based on limited N is

\[ \frac{B(b + 2, n - b + 2)}{B(b + 1, n - b + 1)} \]
**Results:**

**Algorithm Pb is too conservative**

1. **Under-estimates Pb over fires**
   a. (detected every run)

2. **Overestimates Pb over non-fires**
   a. (never detects a fire across N runs)

**Expected Pb:**

1. Very high in middle of fires
2. Lower at edges
3. Very low in non-fire areas
Aggregation to Climate Model Grid

- Pb assumed **independent** for each pixel
- Distribution of Pb over CMG given by **Poisson Binomial** distribution
  - Sum up independent bernoulli trials each described by Pb
- Can be approximated by a **normal distribution**
- **Grey line**: sum of pixels where $p_b > 0.3$
How do we process BA data for climate?

Training dataset of $s$ with $F$ indicated as dark areas

$p_0$ with $F$ indicated as dark areas

"Threshold + sum"

Probabilistic aggregation

Threshold \( \rightarrow \) 1916

PDF \( \rightarrow \) $N(2764.00, \text{var}=892.22, \text{skew}=0.01)$
Reconciling p\_b approach with sum of p\_xls

- Presently Pb:
  - Not accurate (validation)
  - Not used in algorithms (not propagated)
  - Alg developers trust their pixel BA more than Pb

→ For now rescale distribution

Sum of burned pixels: 1916
Pdf -> N(2764.00, var=892.22, skew=0.01)
But...

Questions remain:

*How to do full uncertainty propagation?*

**Problem:** thresholds, complex temporal/spatial filtering... algs are *VERY* non-linear
Next generation BA algs
Want to encapsulate uncertainty in output products:

Pixel level:

1. Observation errors + model errors:
2. *pdf* at pixel level (not point estimate of Pb?)

Grid level:

1. unc in pxl level → unc in BA km$^2$
An example “toy” algorithm

Criteria:

Propagate uncertainty in observations through to posterior estimate

Steps:

1. Edge preserving smoothing BRDF correction
2. Derivative + uncertainty
3. Uncertainty propagation through a classifier
BRDF correction (processing)

Correct to NBAR

Estimate derivative of f:
Challenge: uncertainty propagation requires either:
1. Analytic joint distribution (difficult)
2. Numerical integration method (mcmc etc)
3. Or some gaussian approximation method

…more advanced classifiers: naive bayes → gaussian process classifier
Posterior estimate

DOB

No fire
Issues

1. Ok *not* a great algorithm... but not the point....

Opportunities

1. Reduction in uncertainty from the data → *quantifies* how good the estimate is...
   *transparency*!

2. *Probabilistic* algorithms
   a. Easier to include *a priori* information e.g. active fires can be a *prior for* $P(B)$
   b. Makes developer decisions more transparent

3. *Grid scaling should be more straightforward* with full posterior pds (though assume independence?)
Conclusions

1. Improvement in UQ over time
   a. → still not there
2. Present algorithms have **no to poor UQ (no propagation too)**
3. Thinking about simple toy algorithms *provides insight* on new approaches to UQ + propagation
Thanks!

Questions, comments?
Spares
Retrieved white sky albedo

Fit to observations

Retrieved reflectance with uncertainty
Siberia
Visualising uncertainty
Uncertainty on input signal space

Uncertainty mapped into $p_b$
(likely non normal)