Detection and impacts of tiling artifacts in MODIS burned area classification

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Abstract

Since 2000, observations from the Moderate Resolution Imaging Spectroradiometer (MODIS) instrument, aboard the Terra and Aqua satellites, have been used to monitor global burned area and its trends. The FireCCI and MCD64A1 products classify burned area using algorithms that detect change in surface reflectance and separately process each ∼10° × 10° MODIS tile. We find that artifacts arise in both products from this tiling procedure. In particular, we find severe tiling artifacts in FireCCI, version 5.1 (FireCCI51) in northwest India and Pakistan, where the classified burned area is disjointed at the latitudinal boundary of two tiles that largely separates the Indian states of Punjab and Haryana. In contrast, this tiling effect is less noticeable in MCD64A1, Collection 6 (C6). As a result, while the average 2003–2019 October–November burned area in Haryana is of similar magnitude across the two products, that for Punjab is 13,381 km² for MCD64A1 and just 1,486 km² for FireCCI. We find moderate tiling artifacts in Southeast Asia and Eastern Europe. Our results highlight that additional processing is needed to ensure the continuity of burned area classification in FireCCI and MCD64A1, as well as other products relying on tile-dependent algorithms.

1. Introduction

Accurate mapping of global burned area is necessary for informing fire management strategies and understanding the role of fire in land cover and land–use change, aerosol and greenhouse gas emissions, air pollution and public health, climate-chemistry interactions, and ecosystem dynamics (Johnston et al 2012, Andela et al 2017, van der Werf et al 2017). Burned area algorithms rely on change detection in near-infrared (NIR) and short-wave infrared (SWIR) surface reflectance in pre-fire and post-fire composites (Hawbaker et al 2017, Giglio et al 2018, Lizundia-Loiola et al 2020). To reduce the high computational expense in data processing, burned area algorithms are often applied to individual tiles (e.g. MODIS) or scenes (e.g. Landsat). However, this approach may introduce data artifacts at the tile boundaries, visually evident after the tile-dependent burned area maps are mosaicked together (Humber et al 2019, Liu et al 2020, Lizundia-Loiola et al 2020).

With the advent of Google Earth Engine, a cloud computing platform for geospatial analysis with a petabyte-scale public data catalog, end-users have immediate access and capability to analyze widely used global datasets, including many derived from MODIS (Gorelick et al 2017). As more end-users include high-level satellite products in analyses, this ease in data access demands better communication of caveats in their use to avoid erroneous assumptions or biased results (Humber et al 2019). To ameliorate such biases, it may be tenable to use a hybrid approach with multiple satellite products for regional fire studies (e.g. Liu et al 2019, Crowley et al 2019a, 2019b).

As planetary-scale studies have increased, the use of tiling, or splitting data processing into arbitrary geographical chunks, has become necessary to efficiently manage large geospatial datasets and limited computational resources (Giglio et al 2018, Lizundia-Loiola et al 2020). In this study, we identify and analyze...
the tiling artifacts in two MODIS-derived global burned area products: MCD64A1 and FireCCI. We develop methods to pinpoint tiling artifacts at both upscaled and pixel-level spatial resolutions. Then, we quantify the impacts of severe tiling artifacts on burned area analyses in affected regions, such as northwest India.

2. Methods

2.1. Satellite fire datasets

MCD64A1 C6 is the current version of NASA’s gridded, Level-3 MODIS burned area product at 500 m spatial resolution (Giglio et al 2018). MCD64A1 uses 1 km MODIS active fire hotspots to select training pixels and define thresholds to classify burned area with pre-fire and post-fire composites. MCD64A1 uses a burn-sensitive index calculated from MODIS surface reflectance in the NIR (1.24 μm) and SWIR (2.13 μm) bands.

FireCCI5 is the 250 m MODIS burned area product from the European Space Agency for its Climate Change Initiative (CCI) (Chuvieco et al 2018, Lizundia-Loiola et al 2020). FireCCI uses a two-phase ‘seed’ and ‘growing’ method, where the spatial patterns of initial high confidence ‘seed’ burn pixels are modified in the ‘growing’ phase. Like MCD64A1, FireCCI uses MODIS active fires as input. Because SWIR is only available only at 500 m resolution, FireCCI primarily relies on the 250 m NIR band at 0.86 μm.

MOD14A1 and MYD14A1 C6 are the gridded, Level-3 active fire products derived from MODIS observations of 1 km thermal anomalies (Giglio et al 2016, 2018). In contrast to tile-dependent burned area algorithm, the active fire algorithm uses Level-1B MODIS brightness temperatures, which are on unprojected swath, and defines classification thresholds using a moving window centered on the sample location.

2.2. Identifying tiling artifacts

2.2.1. Method 1: normalized difference of burned area and active fire

Liu et al (2020) introduced a metric to quantify the relative discrepancy between MODIS burned area and active fire products, inadvertently revealing large-scale tiling artifacts in MCD64A1. This metric relies on the normalized difference of monthly burned area and MOD/MYD14A1 active fire area on a grid with an upscaled spatial resolution of 0.25° × 0.25°. We further simplify the metric φ as follows:

\[ \phi_{ij} = \frac{BA_{ij} - AFA_{ij}}{BA_{ij} + AFA_{ij}} \]  

(1)

where BA is burned area and AFA is ‘active fire area,’ or the area of active fire pixels, in each grid cell located at longitude i and latitude j. A value of φ ~ −1 indicates dominance of AFA over BA, while φ ~ 1 suggests the opposite. However, the exact value of φ is less important than its relative value, because we visually examine spatial patterns in φ — that is, abrupt changes in φ across different tiles — to search for regions with large-scale tiling artifacts.

2.2.2. Method 2: adjacent burned pixel pairs across tile edges

Additionally, we develop a method to detect classification discontinuities across tile edges at the native spatial resolution. Figure 1 shows a schematic detailing our approach. First, we segment MODIS tile polygons into lines that represent the north–south or east–west edge of two tiles, which we generalize here as Tile 1 (T1), and Tile 2 (T2). We then apply a buffer around the tile edge equal to the nominal scale of the burned area product (FireCCI: ~250 m, MCD64A1: ~500 m) and isolate burned pixels adjacent to the tile edge. Next, we convert the burned pixels into centroids. We use gBA to denote burned pixel centroids adjacent to the shared T1–T2 tile edge.

Finally, we search for T2 centroids located within T1 buffer zones and use γBA_{T1,T2} to denote pixel pairs where the two pixels are directly adjacent to each other across the tile edge.

For each month and tile edge, we assign ‘priority’ classes based on gBA: none (gBA = 0), low (0 < gBA ≤ 10), medium (10 < gBA ≤ 50), and high (gBA > 50). Specifically, we place higher priority on tile edge artifacts where many burned pixels are potentially affected. To account for the coarser spatial scale of MCD64A1, we scale gBA by 2. For low to high priority cases, we define the fraction of adjacent pixels, ε_{T1,T2}, as an indicator of classification continuity across tile edges:

\[ \varepsilon_{T1,T2} = \frac{2(\gamma_{BA_{T1,T2}})}{gBA_{T1} + gBA_{T2}} \]  

(2)

Low ε (~ 0) indicates high likelihood of tile edge effects.

Additional details on the φ and ε metrics, including limitations, are contained in Supplementary section S1 (available online at stacks.iop.org/IOPSN/2/014003/imedia).
3. Results and discussion

By visually inspecting $\phi$, we find large-scale tiling artifacts in MCD64A1 and FireCCI in three regions: R1, northwest India and Pakistan (tiles h24v05 and h24v06); R2, Myanmar and Thailand (h26v06, h27v06, h26v07, and h27v07); and R3, Ukraine and southwest Russia (h19v03, h20v03, h19v04, and h20v04) (figure S1). MCD64A1 contains tiling artifacts in R1 (April-May) and R3 (March-April), and FireCCI in all three regions (R1: May, October-November; R2: January-April; R3: April). We find the most severe tiling artifacts in FireCCI in northwest India (R1) in October-November (figure 2). While FireCCI and MCD64A1 largely agree in Haryana (h24v06), FireCCI is almost entirely absent in Punjab (h24v05). The sharp discontinuity in $\phi$ across the h24v05-h24v06 tile edge highlights this discrepancy; while $\phi \approx 0$ for MCD64A1 in h24v05, $\phi \approx -1$ for FireCCI, indicating here the dominance of AFA over BA. At the pixel scale, the $\varepsilon$ metric confirms tile edge artifacts in FireCCI: on average, $\varepsilon = 0$ for FireCCI and $\varepsilon = 0.5$ for MCD64A1 (table S1). As a result, in Punjab, MCD64A1 averages ~9 times the burned area (13,381 km$^2$) of FireCCI (1,486 km$^2$) during the post-monsoon (October-November). In contrast, total post-monsoon burned area in Haryana is of similar magnitude (MCD64A1: 2,361 km$^2$, FireCCI: 2,717 km$^2$). FireCCI erroneously suggests that the burned area distribution in h24v05 is unimodal and not bimodal like in h24v06 (figure 3).

Though not as severe as FireCCI, MCD64A1 exhibits moderate tiling effects in earlier years (e.g. 2003–2004) (figures 2(b)–(c)). In the pre-monsoon (April-May), when fire activity is lower than in the post-monsoon, the $\phi$ and $\varepsilon$ metrics indicate tiling artifacts in both MCD64A1 and FireCCI (table S1).

Moderate tiling artifacts are present in FireCCI in Myanmar (R2) in January-April and in both MCD64A1 and FireCCI in Ukraine and southwest Russia (R3) in March-April and July-October (table S1, figures S2–S3).

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**Figure 1.** Pictorial depiction of the pixel-level approach to identify burned area artifacts at tile edges, as described in section 2.2.1.
In R3, the $\phi$ and $\varepsilon$ metrics do not always agree, indicating that the artifacts are more subtle. Specifically, gradients in $\phi$ across tiles may not be clear, and there may not be enough observations at the tile edge to confidently interpret $\varepsilon$. We recommend using the $\phi$ and $\varepsilon$ metrics to guide further visual inspection of the burned area products at monthly and native spatial resolution.

In summary, we propose two simple metrics to identify tiling artifacts in FireCCI and MCD64A1. As we show for northwest India, tiling artifacts can introduce large errors in burned area analyses. End-users can generate and use these metrics to compare biases in burned area datasets and identify the most appropriate data source for their region and burned area analysis. Our results suggest that additional processing in tile-based burned area products is necessary to ensure data quality in terms of spatial continuity, either through future algorithm updates or further post-processing by end-users.
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Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

Data availability

Results from this study can be visualized online with our Earth Engine App at https://globalfires.earthengine.app/view/ba-tiling. All data used in this study are publicly available. MODIS burned area and active fire datasets are distributed via NASA Earthdata (https://earthdata.nasa.gov/), and FireCCI is distributed via the European Space Agency’s Climate Change Initiative (https://climate.esa.int/en/projects/fire/data/). These datasets are also accessible through Google Earth Engine (http://earthengine.google.com/).

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