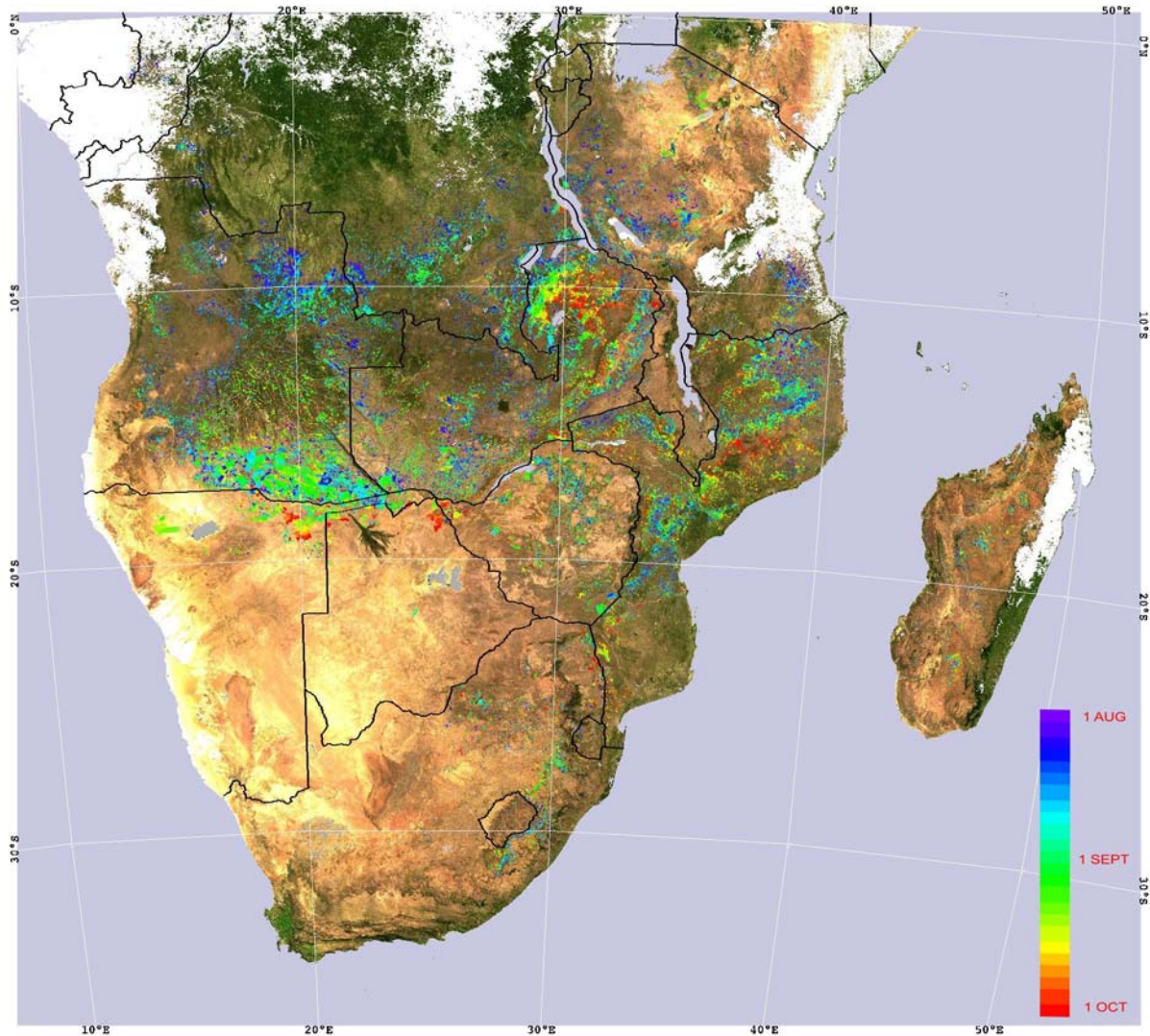


MODIS Collection 5 Burned Area Product MCD45 User's Guide

Version 1.1, September 2008

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1. Introduction

This document provides practical information about the Moderate Resolution Imaging Spectrometer (MODIS) Burned Area Product (MCD45), including product description, ordering procedures, data layer descriptions, and known problems.

2. Overview of the MODIS Burned Area Product

2.1 MODIS Terminology

Processing Levels (from the EOS data products handbook):

Level 0 - Reconstructed unprocessed instrument/payload data at full resolution; any and all communications artifacts (e.g., synchronization frames, communications headers) removed.

Level 1A - Reconstructed unprocessed instrument data at full resolution, time-referenced, and annotated with ancillary information, including radiometric and geometric calibration coefficients and georeferencing parameters (e.g., platform ephemeris) computed and appended, but not applied, to the Level 0 data.

Level 1B - Level 1A data that have been processed to sensor units (not all instruments have a Level 1B equivalent).

Level 2 - Derived geophysical variables at the same resolution and location as the Level 1 source data.

Level 3 - Variables mapped on uniform space-time grid scales, usually with some completeness and consistency.

Level 4 - Model output or results from analyses of lower level data (e.g., variables derived from multiple measurements).

Tiles:

MODIS Level 2 and higher products are defined on a global 250 m, 500 m, or 1 km sinusoidal grid where spatial resolution is defined by the individual products. Grids are divided into fixed-area tiles of approximately 10 degrees x 10 degrees in size. Each tile is assigned a horizontal (h) and vertical (v) coordinate ranging from 0 to 35 and 0 to 17 respectively (Figure 1). The tile in the upper left corner is designated as h0,v0.

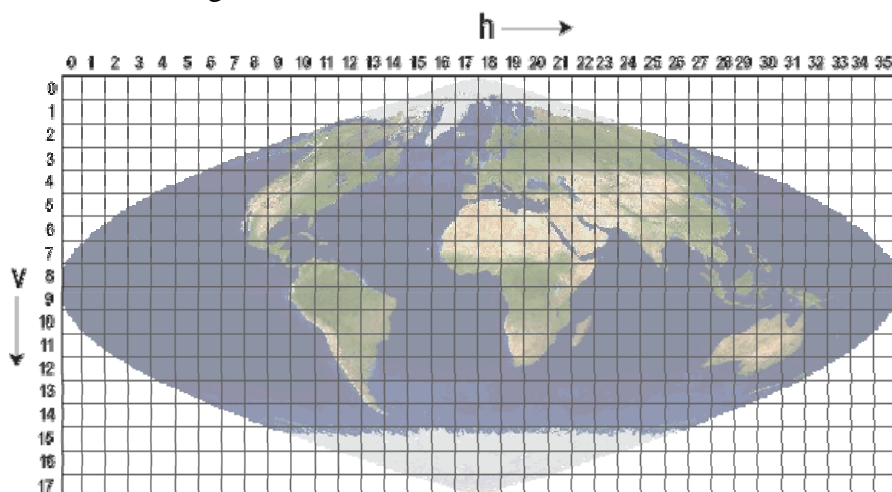


Figure 1. MODIS tile coordinates.

Collections:

Reprocessing of the entire MODIS data archive is performed periodically so as to incorporate better calibration, algorithm refinements, and improved upstream products into all MODIS products. The updated MODIS data archive resulting from each reprocessing is referred to as a collection. Later collections supersede all earlier collections.

The MCD45 MODIS Burned Area Product was not produced in Collections 1 through 4. It was produced for the first time as part of Collection 5, and it is available for the whole MODIS record (2000 to present).

2.2 MCD45 Product Suite

2.2.1 Level 3 Monthly Tiled Product: MCD45A1 (Terra and Aqua)

The MCD45A1 Burned Area Product is a monthly Level 3 gridded 500 m product containing per-pixel burning and quality information, and tile-level metadata. Product users are provided with a variety of quality assessment information and a single summary quality assessment score for each pixel. A detailed description of the product is provided in paragraph 4.2.1.

2.2.2 Level 3 Yearly Synthesis Product

This product is currently under development.

2.2.3 Climate Model Grid (CMG) Aggregated Product

This product is currently under development.

3. Obtaining the MODIS Burned Area Product

All MODIS products are available free of charge. The MODIS burned area product is available for download via ftp from the website <http://modis-fire.umd.edu/>.

The MODIS Burned Area Product will be eventually available for ordering from the Land Processes Distributed Active Archive Center (LP-DAAC) using the EOS Data Gateway web interface located at:

<http://edcimswww.cr.usgs.gov/pub/imswelcome/>

4. Detailed Product Description

4.1 Algorithm Background

Burned areas are characterized by deposits of charcoal and ash, removal of vegetation, and alteration of the vegetation structure (Roy et al. 1999). The MODIS algorithm to map burned areas takes advantage of these spectral, temporal, and structural changes. The algorithm detects the approximate date of burning at 500 m by locating the occurrence of rapid changes in daily surface reflectance time series data. It is an improvement on previous methods through the use of a bidirectional reflectance model to deal with angular variations found in satellite data and the use of a statistical measure to detect change probability from a previously observed state (Roy et al. 2005). The algorithm maps the spatial extent of recent fires only and excludes fires that occurred in previous seasons or years.

The bidirectional reflectance model-based change detection algorithm developed for the MCD45 product is a generic change detection method that is applied independently to geolocated pixels over a long time series (weeks to months) of reflectance observations (Roy et al. 2002, Roy et al. 2005). Reflectances sensed within a temporal window of a fixed number of days are used to predict the reflectance on a subsequent day. A statistical measure is used to determine if the difference between the predicted and observed reflectance is a significant change of interest. Rather than attempting to minimize the directional information present in wide field-of-view satellite data by compositing, or by the use of spectral indices, this information is used to model the directional dependence of reflectance. This provides a semi-physically based method to predict change in reflectance from the previous state.

The Bidirectional Reflectance Model-based Expectation Approach

Methods have been developed to model the BRDF with a limited number of parameters and then to estimate the model parameters from a finite set of remotely sensed observations (Lucht 2004). The semi-empirical RossThick-LiSparse reciprocal BRDF model is used for the MODIS global burned area product as it performs robustly in the global MODIS BRDF/albedo product (Schaaf et al. 2002). Like other linear kernel-driven models it allows analytical model inversion with an estimate of uncertainty in the model parameters and linear combinations thereof (Lucht and Roujean 2000, Lucht and Lewis 2000). At each geolocated pixel the three parameter RossThick-LiSparse reciprocal BRDF model is inverted against $m \geq 7$ reflectance observations sensed in a temporal window of $n (\geq 16)$ days duration. The BRDF model parameters are used to compute predicted reflectance and uncertainties for the viewing and illumination angles of a subsequent observation. A Z-score is used as a normalized measure related to the probability of the new observation belonging to the same set as that used in the BRDF model inversion:

$$Z_{\lambda} = \frac{\rho_{new}(\lambda, \Omega, \Omega') - \rho(\lambda, \Omega, \Omega')}{\varepsilon} \quad (1)$$
$$\varepsilon = \sqrt{\sigma_{\lambda}^2 + e^2 \frac{1}{w}}$$

where:

Z_λ is the Z-score value,

$\rho_{new}(\lambda, \Omega, \Omega')$ is the new reflectance observation,

$\rho(\lambda, \Omega, \Omega')$ is the model predicted reflectance at wavelength λ computed by analytical inversion of the BRDF model against previous reflectance observations,

Ω and Ω' are the viewing and illumination vectors respectively of the new reflectance observation,

σ_λ is a fixed pre-assigned estimate of the noise in $\rho_{new}(\lambda, \Omega, \Omega')$ defined by Vermote et al. (2002),

e is the root mean squared of the residuals of the BRDF inversion (used as an estimate of noise in the observations and the lack of ability of the model to fit the measurements), and

w is the 'weight of determination' of $\rho_{new}(\lambda, \Omega, \Omega')$ (Lucht and Lewis 2000).

Z_λ is adaptive to the viewing and illumination angles of the new observation, as well as the angular distribution, amount of noise, and number of observations used in the BRDF inversion. The Z-score is computed for MODIS bands 2 and 5 as these bands are both sensitive to burning and experience a decrease in reflectance post-fire. A new observation is considered as a burn candidate if:

$$(Z_{band2} < -Z_{thresh}) \text{ OR } (Z_{band5} < -Z_{thresh}) \quad (2)$$

where:

Z_{band} is the Z-score defined (1) and

Z_{thresh} is a fixed wavelength independent threshold

and if:

$$\rho(\lambda_{band5}, \Omega, \Omega') - \rho(\lambda_{band7}, \Omega, \Omega') > \rho_{new}(\lambda_{band5}, \Omega, \Omega') - \rho_{new}(\lambda_{band7}, \Omega, \Omega') \quad (3)$$

AND

$$\rho(\lambda_{band2}, \Omega, \Omega') - \rho(\lambda_{band7}, \Omega, \Omega') > \rho_{new}(\lambda_{band2}, \Omega, \Omega') - \rho_{new}(\lambda_{band7}, \Omega, \Omega')$$

where $\rho_{new}(\lambda, \Omega, \Omega')$ is the new reflectance observation and $\rho(\lambda, \Omega, \Omega')$ is the model predicted reflectance computed by analytical inversion of the BRDF model against $m \geq 7$ previous reflectance observations. The justification for equation (3) is that burning causes a reduction in band 2 and 5 reflectance but less change in band 7 reflectance, whereas persistent cloud, shadow, or soil moisture changes would have a similar effect in both bands. Band 2 helps to remove changes associated with increasing plant water content which is negatively related to band 5 and 7 reflectance but not band 2 reflectance (Zarco-Tejada et al. 2003). In this work $Z_{thresh} = 3.0$ to detect only those reflectance changes that fall outside of the expected reflectance variation modeled from previous values (the probability that $Z < -3.0$ is ~ 0.0013).

Temporal Implementation

The computation (equations 1-3) is repeated independently for each geolocated pixel, moving through the reflectance time series in daily steps to detect change. A temporal constraint is used to differentiate between temporary changes, such as shadows, undetected residual clouds, soil moisture changes and data artifacts, that pass (1) – (3) from fire-affected areas that have persistently lower post-fire reflectance.

Gaps in the reflectance time series, for example due to cloud cover or bad quality input data, reduce the temporal frequency of Z-score calculations as they reduce the number of observations available for prediction and the number of windows that have sufficient observations for BRDF inversion. To reduce the impact of gaps, the duration of the BRDF inversion window is allowed to increase and the Z-score is computed not just for the subsequent day but for several subsequent days. The duration of the BRDF inversion window is allowed to increase, from a minimum of $n = 16$ days up to a maximum of $(n + n_{\text{extra}})$ days, until there are at least 7 observations. When there are fewer than 7 observations no inversion is performed. In this way, more BRDF inversions may be performed in the presence of missing data, providing more opportunities for detecting burning events. At each window containing 7 or more observations the BRDF parameters are used to compute Z-scores for the non-missing observations sensed on the following S_{search} days. If within the following S_{search} days a burn candidate is found, i.e. criteria (1) - (3) are met, then the Z-scores continue to be computed for S_{test} days after the first burn candidate.

For each inversion window, the day that the first burn candidate was detected ($\text{Day}_{\text{first}}$), the maximum of its band 2 and 5 Z-scores (Z_{first}), and the total number of observations over the subsequent S_{test} days that were considered (N_{used}) and detected as burned (N_{pass}), are derived. Different $\text{Day}_{\text{first}}$ candidates may be detected due to sensitivity of the adaptive window duration and multi-date prediction to gaps in the time series. In addition, the same geolocated pixel may burn on separate dates. The results from the different inversion windows are ranked with respect to N_{pass} and then N_{used} to provide results in order of the most evidence of persistent burning. If there are results with equal N_{pass} and N_{used} values then the one with the greatest Z_{first} is ranked as more persistent. Searching both forward and backward in time allows burn candidates to be detected in the S_{search} days preceding or following periods of persistently missing data. This also allows burn candidates to be detected in the first and last S_{search} days of the time series. Results for the forward and backward directions are derived independently. When searching backward in time, an increase in reflectance in the appropriate MODIS bands is searched for rather than a decrease in reflectance.

Iterative Procedure for Identification of Burned Candidates

The global algorithm attempts to reduce errors of commission by selecting only burned pixels where there are burn candidates that provide persistent evidence of fire occurrence. As the measured persistence varies depending on gaps in the reflectance time series and the timing of the fire relative to non-missing data, an iterative rather than simple thresholding approach is used. Burn candidates found in both the forward and backward directions are considered.

First, burned pixels are selected as occurring on $\text{Day}_{\text{first}}$ if:

$$N_{\text{pass}} \geq 3 \text{ AND } (N_{\text{pass}} / N_{\text{used}}) \geq 0.5 \text{ AND } N_{\text{inv}} \geq 3 \quad (4)$$

In this way only candidates are selected, regardless of the direction of the detection, where at least 50% of the observations considered over the subsequent S_{test} days are detected as burned and at least 3 inversions (N_{inv}) are used for the consistency test. If several burn candidates are found at a given pixel, then they are considered in order of decreasing evidence of persistent burning and the first one that passes condition (4) is selected. If forward and backward search results have equal persistence then the forward direction results are given precedence. In cloudy regions, even confidently detected burn candidates might have insufficient data for 3 inversions within the timeframe of the consistency test. As a consequence, if – and only if – backward and forward predict the same change, burned pixels are selected, regardless of N_{inv} using the less restrictive test:

$$N_{\text{pass}} \geq 3 \text{ AND } (N_{\text{pass}} / N_{\text{used}}) \geq 0.5 \quad (5)$$

Second, rather than discard burn candidates that are likely burned but do not pass conditions (4) and (5) due to insufficient observations, they are considered using less restrictive criteria than (4) or (5) in an iterative search method. This method is based on the principle that there is increasing expectation of a burn occurring in pixels neighboring confidently detected burns (Roy et al. 2002, Graetz et al. 2003). In this search procedure, the burn candidates selected by (4) and (5) are considered seed pixels.

In the first set of iterations, non-seed pixels where burn candidates were detected that did not pass conditions (4) or (5) are accepted as burned if they have two or more adjacent seed neighbors and if:

$$\text{Day}_{\text{first}} - \text{Day}_{\text{first_seed}} < N_{\text{gap}} \text{ AND } N_{\text{pass}} \geq 2 \text{ AND } (N_{\text{pass}} / N_{\text{used}}) \geq 0.25 \quad (6)$$

where $\text{Day}_{\text{first}}$, N_{pass} , and N_{used} are the values for the burn candidate that did not pass conditions (4) or (5) and $\text{Day}_{\text{first_seed}}$ is the mean $\text{Day}_{\text{first}}$ value of the two to eight adjacent seed pixels. The N_{gap} constraint ensures that only burn candidates that occur temporally as well as spatially close to the neighboring seed pixels are considered. This procedure is repeated in an exhaustive iterative manner with the pixels that passed condition (6) being considered as seeds for the next iteration until no more burn candidates that pass (6) can be included. As with condition (4), if several burn candidates are found at a given pixel then they are considered in order of decreasing evidence of persistent burning until (6) is met. Again, if forward and backward search results have equal persistence then the forward direction results are given precedence.

In the second part of the procedure, the residual burn candidates not selected in the previous steps are considered if at least three neighbors have been selected. The average day of burning of the neighbors is computed, and the pixel is accepted if the backward or forward day closest to the average day is less than N_{gap} days apart. No other thresholds are used, and this step is not iterated.

Pixels where there were insufficient observations throughout the time series to invert the BRDF model are labeled with a unique code (10000) so they are not subsequently mistaken as being unburned.

4.2 Data Format

4.2.1 MCD45A1 Monthly Tiled Burned Area Product

4.2.1.1 Science Data Sets (SDS)

The product is distributed in the standard MODIS land Hierarchical Data Format (HDF), and includes the following data layers, defining for each 500m pixel:

Burndate (2 bytes): Approximate Julian day of burning from eight days before the beginning of the month to eight days after the end of the month, or a code indicating unburned areas, snow, water, or lack of data.

- 0 - unburned
- 1-366 - approximate Julian day of burning
- 900 – snow or high aerosol
- 9998 - water bodies (internal)
- 9999 - water bodies (seas and oceans)
- 10000 - not enough data to perform inversion throughout the period

BA pixel QA (1 byte): Confidence of the detection (1 (most confident) to 4 (least confident)).

- 1 - most confidently detected pixels, regardless of direction in time (forward, backward or both), passing test (4) described in section 4.1
- 2 - pixels where backward and forward direction in time predict the same change, passing test (5) described in section 4.1
- 3 - pixels selected in the first stage of the contextual analysis
- 4 - pixels selected in the second stage of the contextual analysis

Number of Passes (1 byte): Number of observations where the temporal consistency test is passed.

Number Used (1 byte): Number of observations used in the temporal consistency test.

Direction (1 byte): Direction in time in which burning was detected (forward, backward or both).

- 1 - forward
- 2 - backward
- 3 - both

Surface Type (1 byte): Information describing the land cover type and properties. The information is stored in the individual bits of the layer.

- bit 0(1=yes, 0=no): - water ($NDVI < 0.1$ and $b7 < 0.04$)
- bit 1(1=yes, 0=no) - low NDVI ($NDVI < 0.1$)

- bit 2(1=yes, 0=no) - shallow, ephemeral, deep inland water (QA from MOD09 = 3, 4, 5 AND NDVI <0.1)
- bit 3(1=yes, 0=no) - cloud (from MOD09 internal cloud mask)
- bit 4(1=yes, 0=no) - cloud shadow (from MOD09 internal cloud mask)
- bit 5(1=yes, 0=no) - view and solar zenith angle mask ($Vz > 65$ threshold or $Sz > 65$)
- bit 6(1=yes, 0=no) - high view and solar zenith angle ($Vz > 50$ and $Sz > 55$)
- bit 7(1=yes, 0=no) - snow OR [high aerosol (from MOD09 QA) AND high view / solar zenith ($Vz > 55$ and $Sz > 55$)]

example: if the Surface Type value of a pixel is 18, the corresponding binary number is 01001000; as bits 1 and 4 are set to 1, it means low NDVI and cloud shadow detected.

Gap Range 1 (2 bytes): Information describing the largest number of consecutive missing/cloudy days (if any) in the time series and the start day of the missing/cloudy period.

bits 0-8 - Julian day of the start of the gap

bits 9-13 - number of missing days including the start day

example: if the pixel value is 3372, the corresponding binary number is 001101001011000. The first nine bits (001101001) represent the number 300, the four following bits (0110) represent the number 6. Hence a six day gap starting at julian day 300.

Gap Range 2 (2 bytes): Information describing the second largest number of consecutive missing/cloudy days (if any) in the time series and the start day of the missing period.

bits 0-8 - Julian day of the start of the gap

bits 9-13 - number of missing days including the start day

4.2.1.2 MCD45A1 Metadata

In addition to the mandatory metadata required by the EOS Data Information System (EOSDIS) Core System (ECS), a set of product specific, tile-level metadata are included to enable the burned area product to be archived and ordered via ECS DAAC ordering systems.

The metadata report for each tile includes:

1. The percentage of land pixels detected as burned.
2. The percentage of pixels not processed due to insufficient cloud-free data.
3. The percentage of pixels in each of the “BA pixel QA” categories.
4. The number of pixels detected in each direction in time (forward, backward or both).

4.2.2 MCD45 Yearly Synthesis Burned Area Product

This product is currently under development. Data format information will be included at the time of product release.

4.2.3 MCD45 Climate Model Grid (CMG) Aggregated Burned Area Product

This product is currently under development. Data format information will be included at the time of product release.

5. Caveats and Known Problems

A *provisional* version of the MCD45A1 product is available for evaluation purposes through the University of Maryland ftp server <ftp://ba1.geog.umd.edu>. We welcome users comments and feedback regarding this product. Users should be aware however that this is the first global generation of this product and it has a provisional product maturity status. Consequently:

- the product quality is not optimal;
- incremental algorithm refinements and product improvements are still occurring;
- users are encouraged to participate in the quality assessment (QA) and validation of the product but should be aware that product QA, validation and refinement are ongoing;
- the product will be replaced in the archive when the validated product becomes available;
- please contact science team representatives prior to use of the product in publications.

(More information on maturity levels can be found [here](#))

6. Frequently Asked Questions

Frequently asked questions will be added when received.

7. Citation

The MODIS burned area product, and the details of the algorithm, are described in the following papers. They should be referenced when using the MODIS burned area product:

D.P. Roy, L. Boschetti, C.O. Justice, J. Ju, The Collection 5 MODIS Burned Area Product - Global Evaluation by Comparison with the MODIS Active Fire Product, 2008, *Remote Sensing of Environment*, 112, 3690-3707 ([PDF file, 4.5MB](#))

Roy, D.P., Jin, Y., Lewis, P.E., Justice, C.O. 2005. Prototyping a global algorithm for systematic fire-affected area mapping using MODIS time series data. *Remote Sensing of Environment*, 97:137-162. ([PDF file, 4MB](#))

Roy D.P., Lewis P.E., Justice C.O. 2002. Burned area mapping using multi-temporal moderate spatial resolution data - a bi-directional reflectance model-based expectation approach. *Remote Sensing of Environment*, 83:263-286. ([PDF file, 2.3 MB](#))

8. References

8.1 Journal Articles

W. Lucht, Viewing the Earth from multiple angles: Global change and the science of multiangular reflectance, *Reflection Properties of Vegetation and Soil with a BRDF Data base*, Eds. M. von Schonermarck, B. Geiger, and H.P. Roser, Wissenschaft und Technik Verlag, Berlin, 2004.

W. Lucht and P.E. Lewis, "Theoretical noise sensitivity of BRDF and albedo retrieval from the EOS-MODIS and MISR sensors with respect to angular sampling", *International Journal of Remote Sensing*, vol. 21, pp. 81-98, 2000.

W. Lucht and J.L. Roujean, "Consideration in parametric modeling of BRDF and albedo from multi-angular satellite sensor observations", *Remote Sensing Reviews*, vol. 18, pp. 343-379, 2000.

D.P. Roy, L. Giglio, J. Kendall and C.O. Justice, "Multitemporal active-fire based burn scar detection algorithm," *International Journal of Remote Sensing*, vol 20, pp. 1031-1038, 1999.

D.P. Roy, P.E. Lewis and C.O. Justice, "Burned area mapping using multi-temporal moderate spatial resolution data – a bi-directional reflectance model-based expectation approach," *Remote Sensing of Environment*, vol. 83, pp. 263-286, 2002.

D.P. Roy, Y. Jin, P.E. Lewis and C.O. Justice, "Prototyping a global algorithm for systematic fire affected area mapping using MODIS time series data," *Remote Sensing of Environment*, vol. 97, pp. 137-162, 2005.

C.B. Schaaf, F. Gao, A.H. Strahler, W. Lucht, X. Li, T. Tsang, N. Strugnell, X. Zhang, Y. Jin, J.-P. Muller, P.E. Lewis, M. Barnsley, P. Hobson, M. Disney, G. Roberts, M. Dunderdale, R.P. d'Entremont, B. Hu, S. Liang, J. Privette, and D.P. Roy, "First Operational BRDF, Albedo and Nadir Reflectance Products from MODIS," *Remote Sensing of Environment*, vol. 83, pp. 135-148, 2002.

E.F. Vermote, N.Z. El Saleous and C.O. Justice, "Operational atmospheric correction of the MODIS data in the visible to middle infrared: First results" *Remote Sensing of Environment*, vol. 83, pp. 97– 111, 2002.

P.J. Zarco-Tejada, C.A. Rueda and S.L. Ustin, "Water content estimation in vegetation with MODIS reflectance data and model inversion methods" *Remote Sensing of Environment*, vol. 85, pp. 109– 124, 2003.

7.2 Websites

URL 1: <http://edcimswww.cr.usgs.gov/pub/imswelcome/> (last accessed June 20, 2006)