

1 Observation operator and detection limits for MODIS and VIIRS Fire Radiative
2 Power products
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7 **Abstract**

8 We analyze the MODIS and VIIRS active-fire Fire Radiative Power (FRP) products and suggest an
9 approximation for the FRP detection limit as a linear function of a pixel area and develop analytical
10 observation operators for both pixel-level and gridded FRP products. We have shown that the collection-
11 6.1 of MODIS has the FRP detection limit at 3.7 MW in case of a nadir retrieval at a clear-sky night. For a
12 daytime sideview, it reaches as high as 40 MW. For VIIRS, the smallest fire reliably detected at night is
13 0.5 MW. Application of the developed operators for the cross-mapping the MODIS and VIIRS datasets at
14 the pixel/granule level confirmed their consistency. Applying the grid-level operators alongside satellite
15 overpass and weather data, we generated global maps of fire detection probabilities, revealing regional
16 variations. As a global average, probability of detection of powerful fires is 78% for MODIS (88% for
17 VIIRS). Variations between regions are large: in some equatorial areas this probability is less than 30%
18 for MODIS (40% for VIIRS).

19

20 **Key words:** Fire Radiative Power, MODIS, VIIRS, observation operator, sensitivity, detection limit

21

22 1. Introduction

23 Vegetation fires have long been recognized as one of the most-powerful phenomena affecting the
24 lifecycle of forest and grassland ecosystems, a strong source of atmospheric pollutants, and a significant
25 climate factor (Crutzen et al., 1979; Kollanus et al., 2017; Buchholz et al., 2022; Khabarov et al., 2016;
26 Chowdhury et al., 2025). Since fires are a global phenomenon, satellite observations are the natural way
27 of their systematic monitoring. Two types of products are the most-important in this respect: burnt-area
28 scars left by recently occurred fires (Chuvieco et al., 2019) and active-fire products, such as Fire
29 Radiative Power (FRP) and Temperature Anomaly (TA), which rely on a thermal fingerprint of active fires
30 (Ichoku and Kaufman, 2005; Kaiser et al., 2012; Kaufman et al., 1998; Parrington et al., 2025). Both types
31 of products have their strong and weak points (Archibald and Roy, 2009; Roy et al., 2008; Schroeder et
32 al., 2014a; Vilar et al., 2015; Zubkova et al., 2023). This work concentrates on active-fire products.

33 Observations of active fires produce two types of data: hot spot counts (Arino et al., 2012; Li et al., 2001)
34 and fire radiative power FRP (Kaufman et al., 1998; Ichoku and Kaufman, 2005; Schroeder et al., 2014b;
35 Giglio et al., 2016, 2021; Schroeder, 2020a, 2020b; Xu and Wooster, 2023). The key strength of the FRP -
36 based approach is that the data characterizes the fire intensity at the moment of the observations. It
37 allows to construct operational global fire information systems (Kaiser et al., 2012; Wiedinmyer et al.,
38 2011; Sofiev et al., 2009; Chen et al., 2022), build injection-height models (Freitas et al., 2007; Sofiev et
39 al., 2013, 2012; Rémy et al., 2017; Li et al., 2022), and estimate characteristic diurnal cycle of the fire
40 activity (Soares et al., 2015; Sofiev et al., 2013).

41 A limitation of the active-fire data is a tendency to miss a substantial fraction of fires – a so-called
42 omission error. Thus, Schroeder et al. (2008) used Advanced Spaceborne Thermal Emission and
43 Reflection Radiometer (ASTER) and the Landsat 7 Enhanced Thematic Mapper Plus (ETM+) at 30 m
44 spatial resolution to provide a “ground truth” dataset for the MODIS algorithm. They produced summary

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48 statistics indicating that 50 to 100 ASTER fire pixels (corresponding to 5%-10% of area of a 1 km pixel)
49 are necessary to trigger the MODIS fire detection with >80% probability. The uncertainty in the estimate
50 was associated with the fraction of the pixel area covered by trees. No quantitative estimation of the
51 FRP detection limit was provided.

52 A fire can be missed if its radiative power is below the detection limit of a given instrument/algorithm.
53 This threshold, in turn, depends on the overall contrast of the scene, i.e., the size of the burning area,
54 the size of the pixel, background temperature of non-burning areas around the burning pixel. A larger
55 pixel means stronger averaging and lower contrast. We are aware about only one study so far that
56 quantified the dependence of the minimum strength of the observable fire on the pixel size (Maier et
57 al., 2013), which considered MODIS Collection 5 for Australia.

58 Among the key reasons for omission error of low-orbit satellites is a cloud obscuration during the
59 satellite overpass. This error is milder for geostationary-based instruments, such as SEVIRI, GOES, and
60 HIMAWARI (Roberts and Wooster, 2008; Schroeder et al., 2007; Schultz et al., 2008; Xu et al., 2017)
61 because they can provide information for a specific location several times per hour, thus avoiding some
62 clouds. However, the problem still exists: the effect of cloud obscuration was studied for Brazilian
63 Amazon (Schroeder et al., 2007) showing the GOES omission error of 11% of fire counts during the
64 considered episode.

65 Utilization of any observational data in numerical models requires a procedure that relates the observed
66 quantities and the ones computed by the model. It has been shown (Bocquet et al., 2015) that the
67 model-measurement comparison should be performed in the observational space, i.e., the modelled
68 quantities should be converted to the observed ones using an Observation Operator, hereinafter OOp
69 (Bocquet et al., 2015; Carrassi et al., 2018). In principle, every type of observation requires its own OOp,
70 but in many cases the modelled quantities are considered to be close enough to the observed ones for

71 assuming the identity OOp. For satellite data, this is practically never the case, therefore sophisticated
72 operators have been developed targeting radiance as one of the primary remote-sensing variables
73 (Evans, 2007; Greenwald et al., 2004, 2002; Kostka et al., 2014). Such operators involve radiative
74 transfer models and provide a sufficiently accurate mapping of the model data to variables observed by
75 the satellite instrument. It is also possible to construct simpler operators converting the model output to
76 an intermediate remote-sensing variable, which is deemed accurate. For instance, (Banks et al., 2012)
77 developed an OOp for the remote-sensing ocean color synthetic measurement at the water surface,
78 whereas the key step in the OOp for OMI NO₂ column data is accounting for the instrument averaging
79 kernel (Boersma et al., 2011).

80 For the FRP data, an identity operator has been used till today (Kaiser et al., 2012), and we are not
81 aware about any non-trivial OOp developed for the FRP retrievals.

82 The objectives of the current work are: (i) to quantify the detection limit of individual MODIS (collection
83 6.1) and VIIRS (collections 2 and 2.1) retrievals of FRP and to suggest a unified analytical approximation
84 as a function of pixel size; (ii) to suggest an observation operator for gridded MODIS and VIIRS FRP
85 products; (iii) to apply the developed OOp to quantify the omission error over the globe and estimate
86 the probability of fire detection by MODIS and VIIRS during the fire season as a function of the location,
87 (iv) to demonstrate the OOp application to mapping the level-2 MODIS and VIIRS FRP products.

88 The paper is organized as follows. The next section 2 describes the input data of the assessment, section
89 3 introduces the study methodology, derives the sensitivity of the FRP products, detection limit, and
90 OOp formulations; section 4 presents the results of the OOp application: global maps of the MODIS and
91 VIIRS omission error and application of pixel-level OOp to cross-mapping the MODIS and VIIRS pixel-
92 /granule-level FRP retrievals. These results are discussed in section 5.

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95 2. Input data

96 2.1. MODIS Fire Radiative Power and supplementary products

97 The MODIS dataset used in this study consists of the level-2 (L2) Fire Radiative Power retrievals MOD14
98 and MYD14 from the instrument onboard Terra (2000-2023) and Aqua (2002-2023) satellites
99 respectively. Hereinafter, the common notation will be MxD14. The L2 products were downloaded from
100 Atmosphere Archive & Distribution System (LAADS) Distributed Active Archive Center (DAAC)
101 (<https://ladsweb.nascom.nasa.gov/>, visited 12.10.2025, (Giglio and Justice, 2021a, 2021b). The data
102 after 2023 were not used to avoid impact of the TERRA constellation exit maneuvers.

103 The MODIS L2 products are organized in granules, i.e., chunks of data collected during 5 minute
104 intervals. Each MxD14 granule contains a field of flags for every pixel in a granule indicating if a
105 detection was possible or not (cloud obscuration, failed retrieval, sun glint, water surface etc.) and a list
106 of overheated pixels with FRP, geolocation, position in the swath, pixel size, etc. The geolocation of non-
107 overheated pixels was picked from the MODIS cloud products MxD35 collection 6.1 (MODIS Atmosphere
108 Science Team, 2017a, 2017b).

109 The key variables used in the assessment are: (i) the pixel-wise FRP expressed in megawatts throughout
110 the paper; (ii) quality flags of MxD14, (iii) geolocation information of individual pixels of MxD35.

111 The FRP retrievals were censored by removing ~0.6% of pixels with unphysically strong FRP, $P_p >$
112 500 MW . Secondly, the first months of MODIS Terra operations, until November 2000, were removed
113 entirely due to known problems with the sensor (Giglio et al., 2021). No other filtering was applied.

114 2.2. VIIRS Fire Radiative Power products

115 The VIIRS data from the instruments onboard SUOMI-NPP (2012-2024) and NOAA-20 (2018-2024)
116 satellites were obtained from the same NASA LAADS DAAC Earth Data server as the MODIS products.

117 We used VNP14IMG and VJ114IMG (Giglio, 2024a, 2024b) for FRP, locations of detected overheated
 118 pixels, and the detection mask, and VNP03IMG and VJ103IMG products (VIIRS Calibration Support Team
 119 (VCST), 2021a, 2021b) for pixel geolocation. The corresponding common notations hereinafter are
 120 Vxx14 and Vxx03. The data before February 2012 were discarded to avoid suspiciously large number of
 121 fires reported in the first days of the instrument operation. No other filtering was applied.

122 3. Methodology

123 3.1. Size of a MODIS and VIIRS pixel

124 An approximate formula for the pixel size calculations for both MODIS and VIIRS has been suggested by
 125 Ichoku and Kaufman (2005) with a reference to Masahiro Nishihama (pers. comm. 2004) and the MODIS
 126 Algorithm Technical Basis Document ATBD (Nishihama et al., 1997). A ground pixel size along the scan
 127 ΔS and the satellite track ΔT directions are functions of the scanning angle θ and orbit parameters:

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$$(1) \quad \Delta S = R_e s \left[\frac{\cos \theta}{\sqrt{(R_e/r)^2 - \sin^2 \theta}} - 1 \right]$$

$$(2) \quad \Delta T = r s \left[\cos \theta - \sqrt{(R_e/r)^2 - \sin^2 \theta} \right]$$

128 where $R_e=6378.137$ km is radius of Earth, $r=R_e+h$, h is altitude of the orbit (705 km for MODIS), p is pixel
 129 nadir size (1 km for MODIS), $s=p/h=0.0014184397$ (MODIS), and scanning angle θ is determined by the
 130 pixel number i in the scan line consisting for MODIS of totally $N=2030$ pixels:

$$(3) \quad \theta_i = s \left(i - \frac{N+1}{2} \right)$$

131 These formulas can also be applied to VIIRS with $h=825.2$ km, $N=6400$ non-aggregated pixels, $s=0.375$
 132 km (Schroeder et al., 2014b; Wolfe et al., 2013). Accuracy of this approximation has been verified

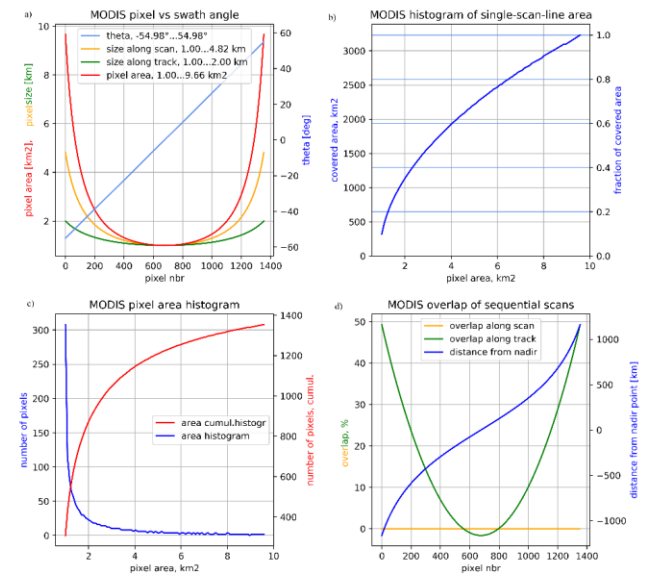
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140 against the instrument look-up table (W. Schroeder, pers.comm., 2022) and showed the error not
141 exceeding 0.2% for all variables of (1) - (3).

142 3.2. Swath geometry

143 Formulas (1) - (3) are illustrated in Figure 1 for MODIS and Figure 2 for VIIRS. The total width of the
144 MODIS scan over the Earth surface is ~2063 km, and the pixel area varies from 1 km² in nadir view at $\theta=$
145 0 up to 9.66 km² at the edge of the swath at $\theta=55^\circ$ (Figure 1 a). About 40% of the swath is covered by
146 pixels with $A_p < 2$ km² and only 20% - by pixels with $A_p > 6$ km² (Figure 1 b,c). MODIS swath has 10
147 detectors in the track direction (Nishihama et al., 1997). The growing size of the pixels towards the edge
148 of the swath means that the neighboring swaths partly overlap along the track direction (Figure 1 d, see
149 also Figure 3-1 of Nishihama et al. (1997) for MODIS).

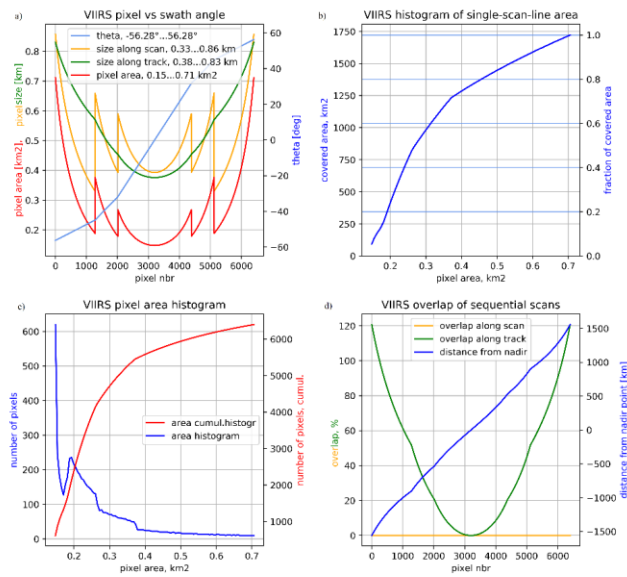


151 **Figure 1. MODIS swath geometry.** Panels: a) linear sizes, area, and viewing angle along the scan; b) fraction of swath covered
152 by pixels smaller than the given area; c) distribution of pixel area; d) overlap of pixels along the track and along the scan.

153

168 The VIIRS swath geometry (Figure 2) is generally similar but with peculiarities. To limit the pixel size
 169 growth along the scan direction, individual pixels of both I- and M-bands are aggregated as 3×1 (three
 170 scan-direction samples by one track-direction sample), 2×1 , and 1×1 for the scan angles of 0° - 30° , 30° -
 171 45° and 45° - 55° , respectively (Figure 1 in Schroeder et al. (2014b)).

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173 **Figure 2. VIIRS swath geometry.** Panels: a) linear sizes, area, and viewing angle along the scan; b) fraction of swath covered by
 174 pixels smaller than the given area; c) distribution of pixel area; d) overlap of pixels along the track and along the scan.

176 A single VIIRS sensor has 32 I-band sensors in the track direction, and subsequent scans substantially
 177 overlap at high scan angles leading to up to a triple coverage at the edge of the swath. To reduce the
 178 redundancy and to limit the amount of data to transfer, data readings from two and four I-detectors
 179 from the top and bottom of the arrays (the largest scan angles) are not transmitted in the 2×1 and 1×1
 180 aggregations zones, respectively (a “bow-tie deletion”). The current study used data of the higher-

182 [resolution](#) I-band detectors, which provide ~375m nadir pixel size (Wolfe et al., 2013), and explicitly
183 accounted for the pixel aggregation and the bow-tie deletion ([Error! Reference source not found.](#)).

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184 3.3. Pixel-wise and gridded statistics of retrievals

185 Since all considered satellites are on sun-synchronous orbits and because the fires are heavily influenced
186 by the local diurnal cycle, the analysis was performed in local solar time (LST). Two types of statistics
187 were computed: for individual pixels and for gridded data.

188 3.3.1. Pixel-wise detection limit

189 The pixel-wise assessment was performed independently for MODIS and VIIRS. Since it was made with
190 regard to the pixel area (not viewing angle), there was no difference between the procedures, only
191 numerical constants were instrument-specific. For individual pixels, the following classification flags
192 were adopted throughout the computations: missing data, cloud, sun glint, non-fire, fire. Areas outside
193 the swath were considered missing.

194 The pixel detection limit was computed as follows ([Figure 32](#), [Figure 43](#)). The retrievals of each
195 instrument were aggregated to four 2-D distribution density functions: for daytime, nighttime, and
196 whole-day FRP $\pi_f(A_p, P_f)$, and for the whole-day number of fire pixels $\pi_n(A_p, P_f)$. Here, A_p is pixel
197 area, P_f is fire radiative power registered by an individual pixel at a single overpass. The obtained
198 distributions are shown in [Figure 32](#) and [Figure 43](#) for MODIS and VIIRS, respectively.

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FRP range, MODIS, 0 MW - 75 MW, 2000-2024

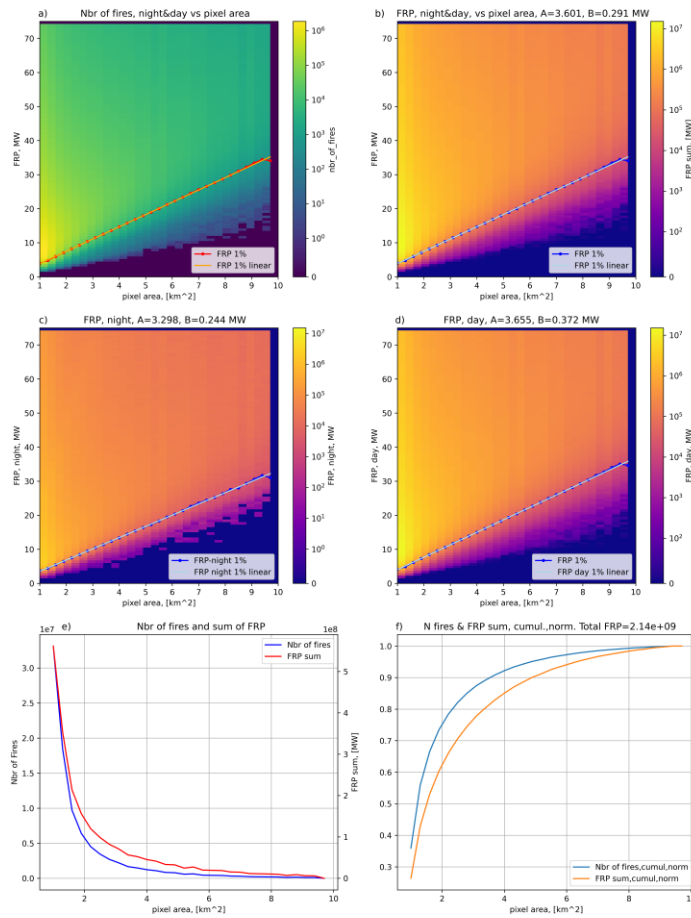
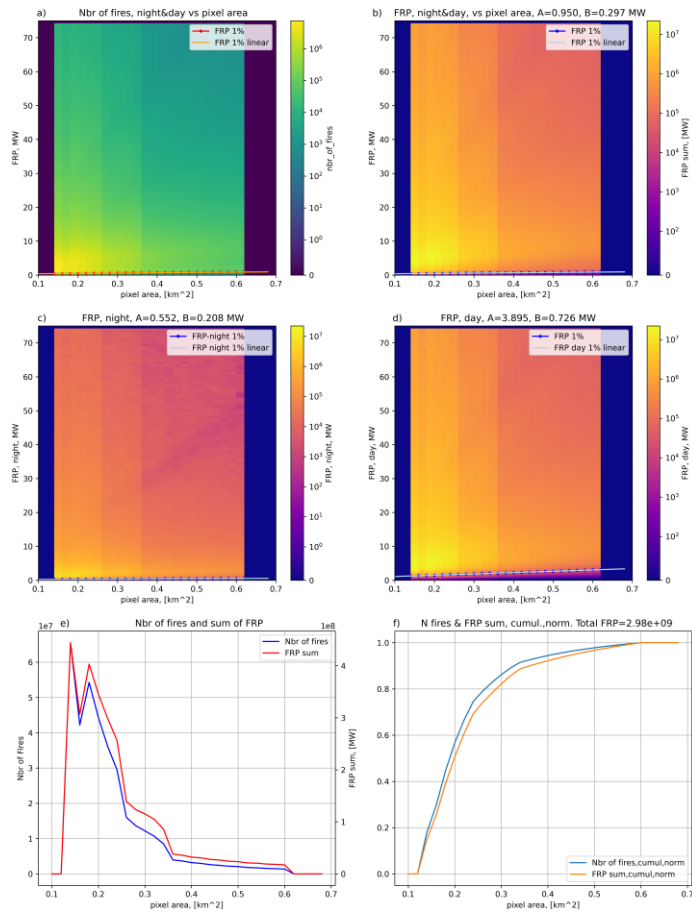


Figure 3. Distribution of the fire pixels detected by MODIS below 75 MW (arbitrarily taken cut-off allowing to see the peaks of the distributions and detection limits) as a function of a pixel size and FRP. Panel a) Total number of fire pixels for all overpasses, b) Total FRP of all overpasses, c) Total FRP registered by night-time overpasses; d) Total FRP registered by day-time overpasses; e) Total FRP and number of fire pixels of the specific area, all FRP values counted (no upper limit); f) same as e) but cumulative. Panels a)-d): red dots represent the 1%-tile for each pixel area whereas the orange lines on top of them represent the corresponding linear approximations, which slope A and intercept B are shown in the panel titles.

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FRP range, VIIRS, 0 MW - 75 MW, 2012-2024



213

214 **Figure 4.** Distribution of the fire pixels detected by VIIRS as a function of the pixel area and detected FRP. Same panels as for
 215 **Figure 32.** Panel a) Total number of fires for all overpasses, b) Total FRP of all overpasses, c) Total FRP registered by night-time
 216 overpasses; d) Total FRP registered by day-time overpasses; e) Total FRP and the number of fires registered by the pixels of the
 217 specific size, all FRP values counted (no upper limit); f) same as e) but cumulative. Panels a)-d): red dots represent the 1%-tile
 218 for each pixel area whereas the orange lines on top of them represent the corresponding linear approximations, which slope A
 219 and intercept B are shown at the panel titles.

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222 Detection limit identification was based on the vertical cross-sections of the FRP distribution densities

223 $\pi_f(A_p, P_f)$ (panels c and d in Figure 32 and Figure 43) for each specific pixel size (Figure 54 for MODIS
224 and Figure 65 for VIIRS). The noise in the curves for large FRP is due to the low number of fires falling
225 into the corresponding FRP ranges. The left sides of the curves in panels a) and b) of Figure 54 and
226 Figure 65 can be approximated by a rising logistic function, shifted downward and cut at zero to remove
227 the very small FRP values from the fit and then rescaled to reach max of 1.0:

$$(4) \quad P_{tot}(P_f) = P_0 + \frac{1}{a - c_o} \max \left(0, \frac{a}{1 + e^{-r_p(P_f - D_p)}} - c_o \right)$$

228 Here, P_{tot} is total FRP registered for the corresponding range of P_f , P_0 and a are coefficients of the fit, D_p
229 is the mid-point of the rising sigmoid curve, [MW], and r_p is rate of the function rise, [MW⁻¹], c_o is cut-off.
230 Their values are given under each panel of Figure 54 and Figure 65. As one can see, the shifted logistic-
231 function approximations turned very accurate for all curves (if the noise is smoothed, $r^2 > 0.95$ in all
232 cases and normalized RMSE < ~0.1%).

233 From the Eq. (4), the definition of the detection limit naturally comes as the position of the midpoint D_p
234 of the rising logistic function. For fires of such power, the total FRP registered by the instrument with the
235 pixels of the corresponding size is half of the histogram max value for that size. It corresponds to ~50%
236 of fires of this intensity missed by the instrument. Dependence of D_p and r on the pixel area A (panel c),
237 $D_p(A_p)$, is a linear function of the pixel area (correlation coefficient > 0.999):

$$(5) \quad D_p = \begin{cases} \infty & \text{for pixel flagged as missing} \\ \lambda_{lst} A_p + \mu_{lst} & \text{for pixel with a valid retrieval} \end{cases}$$

238 The coefficients λ_{lst}, μ_{lst} of the Eq. (5) are shown in Figure 54c and Figure 65c and summarized in Table
239 1 for MODIS and Table 2 for VIIRS. The dependencies of the sigmoid max slope on pixel size are well
240 approximated by hyperbolas.

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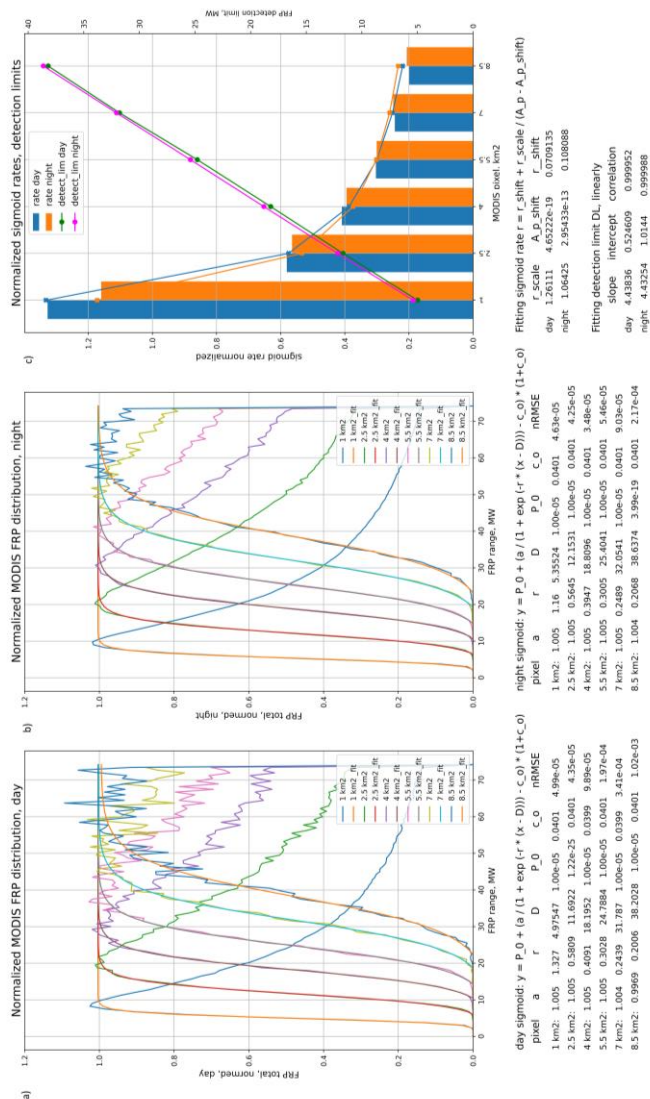
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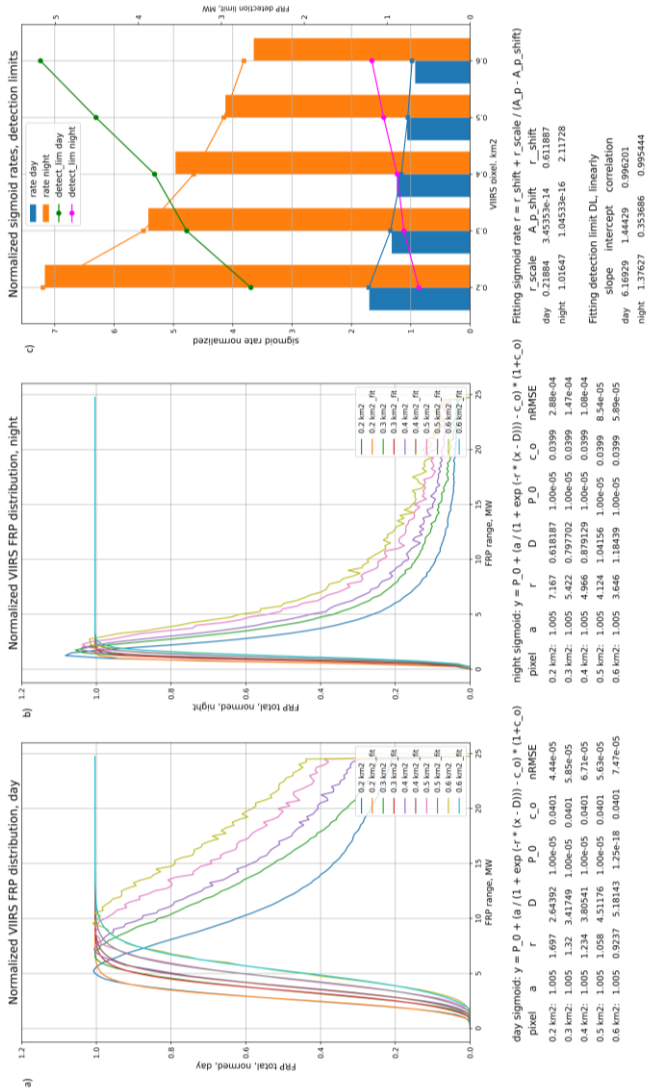


Figure 6. Definition of the FRP detection limit as a function of pixel size via the normalized FRP distribution for VIIRS. Panels are the same as in Figure 54. Colored broken lines at panels a), b) are the normalized vertical cross-sections of the panels c) and d) of the Figure 43 for day and night retrievals, respectively. All curves have been normalized to their smoothed max values. The rising part of each curve is approximated by a sigmoid function with parameters shown under the panel. Panel c) broken lines: FRP values corresponding to 0.5 levels of the corresponding sigmoid function of panels a) and b) – the detection limit for the specific pixel size; bars: slope of the sigmoid at those points

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272 Table 1. Coefficients for the pixel-wise MODIS Observation Operator, Eqs. (5) - (7)

	Day: $\phi < 90^\circ$	Night: $\phi \geq 90^\circ$
λ_{lst} (slope), [MW km ⁻²]	4.44	4.43
μ_{lst} (intercept), [MW]	0.52	1.01
r_0 (shift), [MW ⁻¹]	0.07	0.11
r_1 (scale), [km ² MW ⁻¹]	1.26	1.06
c_0 (cut-off)	0.045	0.045

273

274 Table 2. Coefficients for the VIIRS pixel-wise Observation Operator, Eqs. (5) - (7)

	Day: $\phi < 90^\circ$	Night: $\phi \geq 90^\circ$
λ_{lst} (slope), [MW km ⁻²]	6.17	1.38
μ_{lst} (intercept), [MW]	1.44	0.35
r_0 (shift), [MW ⁻¹]	0.61	2.12
r_1 (scale), [km ² MW ⁻¹]	0.21	1.02
c_0 (cut-off)	0.05	0.05

275

276 Figure 54c and Figure 65c show that the slope of the rising sigmoid of the Eq. (4) is a hyperbolic function
277 of the pixel size:

$$(6) \quad r_p = r_0 + \frac{r_1}{A_p - A_0}$$

278 For other coefficients, as follows from the fitting coefficients in Figure 54a,b and Figure 65a,b, the very
279 small value of P_0 can be neglected, and the coefficient a set to 1.0.

280 Finally, replacing P_f with a model-predicted P_{mdl} , we obtain the observed FRP P_{obs} as a function of

281 predicted P_{mdl} , thus concluding the pixel-wise observation operator $\Xi_{pix}(P_{mdl})$:

$$(7) \quad P_{obs}(P_{mdl}) \triangleq \Xi_{pix}(P_{mdl}) = \frac{P_{mdl} * 1}{1 - c_0} \max \left(0, \frac{1}{1 + e^{-r_p(P_{mdl} - D_p)}} - c_0 \right)$$

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3.3.2. Grid-cell-wise detection limit

This section introduces the OOp for models operating on a regular grid and with a regular time step. The grid cell size d is assumed to be significantly larger than the MODIS or VIIRS pixels. The grid-cell FRP $P(i,j)$ is a sum of FRPs of pixels in this cell: $P(i,j) = \sum_{(i,j)} P_f$. Evidently, the grid-cell fire detection is determined by the highest P_f – that very pixel has the highest chances to be noticed by the satellite. A mean fraction of the strongest fire pixel in the grid cell, $\gamma(d, P) = \overline{P_f}/P$, can be found from MODIS and VIIRS statistics as a function of $d \wedge P$ (Figure 76).

As seen from Figure 76, for grids coarser than 0.5° , γ depends only on total FRP $P(i,j)$: the curves corresponding to different d coincide. For fine grids, γ is larger reaching unity when grid cell size becomes similar to that of individual pixels. We approximated this 2-D dependency as follows:

$$(8) \quad \gamma = 1 - \left[1 - \left(\frac{P_2 - P_1}{P(i,j) - P_1} \exp\left(\frac{d_1}{d}\right) \right)^{k_1} \right]^{k_2}$$

Here, d is grid resolution, d_1 is its empirical scaling, P_1, P_2 , are FRP scaling constants, [MW], k_1, k_2 are dimensionless empirical constants. Both MODIS and VIIRS FRP retrievals can be approximated with this formula (Figure 76). The only difference is that VIIRS detects almost four times more small fires than MODIS, thus reducing the contribution of the strongest fire pixel by approximately 50%.

For a clear-sky grid cell, it is natural to use an area-weighted spatial average of detection limits over the pixels in the cell and account for the fraction of the largest fire in the total FRP:

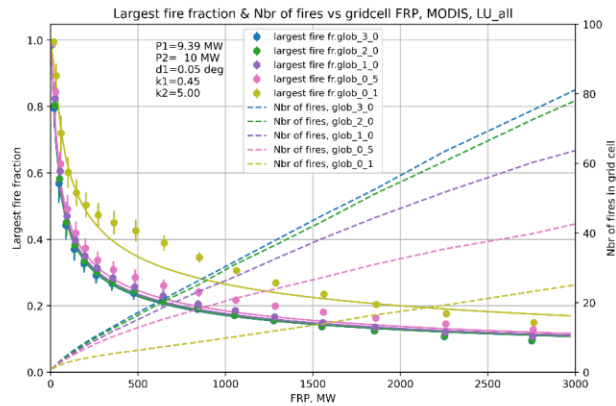
$$(9) \quad D_{clr_sky}(i,j) = \frac{\sum_{p \in (i,j)} D_p A_p}{\gamma \sum_{p \in (i,j)} A_p}$$

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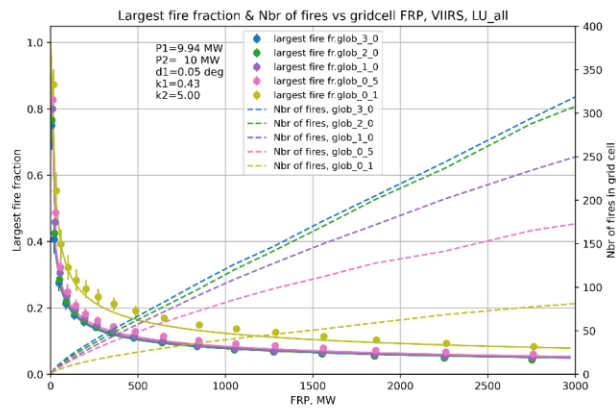
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a)



b)



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307 Figure 4. A mean fraction γ of the largest fire pixel in the total grid-cell FRP P , as a function of P . Calculated from MODIS 2000-
 308 2023 time series (panel a) and VIIRS 2018-2024 (panel b) as a function of grid-cell FRP for different grid resolutions dx . Fitting
 309 curves are computed from the Eq. (8) with the coefficients shown at the plot. Charts and dots are slightly shifted horizontally to
 310 reduce overlapping.

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312 For accounting for the partial obscuration of the grid cells, the following rules have been applied:

313 - for a grid cell (i,j) , the gridded fire radiative power is $P(i,j) = \sum P_f$ – a sum of all pixels within
 314 the grid cell (i,j) ;

315 - a fraction of the grid cell retrieved area, β_{ret} , is calculated from the pixel state flags as a fraction
 316 of the cell covered with pixels flagged as fire or non-fire, (i.e. not missing, cloudy, or sun-glint)

317 The grid-cell detection limit D_g is computed as a sum of the clear-sky detection limit D_{clr_sky} (9) and a

318 term inversely proportional to β_{ret} , thus approaching infinity for a fully cloudy grid cell. Formally, it can

319 be written as follows:

$$(10) \quad D_g(i,j) = \frac{\sum_{p \in (i,j)} D_p A_p}{\gamma \sum_{p \in (i,j)} A_p} + P_{max} \left(1 + \exp \left(\frac{\beta_{ret}(i,j)}{\sigma_{ret}} \right) \right)^{-1}$$

320 The summation in the first term is taken over all non-missing MODIS pixels p of the grid cell (i,j) , P_{max} is a

321 large FRP value, e.g., 10 GW, and σ_{ret} is a width of the transition range of the logistic function, e.g., 0.1.

322 With such parameters, the second term is practically zero for $\beta_{ret} > 0.3$ but quickly grows approaching 5

323 GW if the grid cell has fewer valid pixels. The very high but still finite detection limit for cloudy scenes is

324 taken to avoid numerical problems at the implementation stage.

325 With D_g from (10), the observed grid-cell FRP $P_{obs}(i,j)$ can be computed similarly to the pixel-wise OOp:

$$(11) \quad P_{obs}(P_{mdl}(i,j)) \triangleq \mathcal{E}_{grd}(P_{mdl}(i,j)) = \frac{P_{mdl}(i,j)}{1 + e^{-r_g(P_{mdl}(i,j) - D_g(i,j))}}$$

326 The sigmoid slope r_g can be calculated as an area-weighted mean value for the pixels in the grid cell or

327 simply taken as a prescribed instrument-specific constant representing a “typical” swath geometry

328 (Table 3). Additional uncertainties due to this simplification are much smaller than those of the cloud-

329 related term in the Eq. (10).

330

Table 3. Suggested “typical” slope r_g for Eq. (11)

	Day: $\phi < 90^\circ$	Night: $\phi \geq 90^\circ$
r_g MODIS, [MW km ⁻²]	0.5	1.2
r_g VIIRS, [MW km ⁻²]	1.5	15

3.4. Thin clouds and smoke obscuration

In the above derivations, it is assumed that fire is either obscured by a cloud or not. However, the cloud can be thin, or a fire can be dimmed by its own smoke or other aerosols. The satellite would then process the pixel like a non-obscured one, but the signal strength would be lower. Denoting aerosol column optical depth (AOD) at the wavelength of the fire detection (4 μ m for MODIS and VIIRS, Eq. (6) in (Giglio et al., 2016)) as τ_a , one should replace the model-predicted FRP P_{mdl} with $P_{mdl}^\sim$ in (7) and (11):

(12)
$$P_{mdl}^\sim = P_{mdl} \exp(-\tau_a)$$

All other terms remain the same. This approach should be considered as indicative because aerosol obscuration will impact the retrieval at other wavelengths too, thus influencing the fire detection / rejection procedure and indirectly affecting the gridded FRP (see Table 1, (Giglio et al., 2016) and Section 3 of (Schroeder et al., 2014b)).

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3.5. Application of the OOp for comparison of the satellite datasets

The OOp has been developed for projecting a model-predicted FRP onto the observational space, but it can also be used for projecting one FRP dataset onto another. A complexity, however, is that the OOp implies a space-time co-location of the datasets, which is impossible for the low-orbit satellites. For instance, the accurate spatial co-location of MODIS AQUA and VIIRS Suomi NPP retrievals is straightforward, but their retrieval times differ by 1-2 hours, leading to different cloud obscuration and fire stages. The imperfect temporal co-location can be accounted for by symmetric OOp application:

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352 For a given day, select overlapping granules of MYD14 & MYD35 of MODIS Aqua and VNP14 &
 353 VNP03 of VIIRS Suomi NPP
 354 Scan the overlapping areas picking MODIS active-fire pixels and VIIRS active-fire pixels
 355 Project each MODIS fire pixel to the corresponding VIIRS granule, collect VIIRS fire observations
 356 and missing cell fractions corresponding to this MODIS fire pixel
 357 Project each VIIRS fire pixel to the corresponding MODIS granule, collect MODIS fire
 358 observations and missing cell fractions corresponding to this VIIRS pixel
 359 Apply MODIS pixel-wise OOp, Eq. (7) Table 1, to each active fire of VIIRS accounting for the
 360 MODIS missing pixels, thus obtaining $\Xi_{pixMODIS}(P_{VIIRS})$
 361 Apply VIIRS pixel-wise OOp, Eq. (7), Table 2, to each active fire of MODIS accounting for the
 362 VIIRS missing pixels, thus obtaining $\Xi_{pixVIIRS}(P_{MODIS})$
 363 compare the obtained datasets;

$$(13) \quad \Xi_{pixMODIS}(P_{VIIRS}) \quad \text{vs} \quad \Xi_{pixVIIRS}(P_{MODIS})$$

364 Here, $\Xi_{pix}(P)$ is the pixel-wise OOp, Eq. (7).

365 4. Examples of the OOp applications

366 4.1. Application of grid OOp to retrieve cloud obscuration statistics

367 The cloud-related term in Eq. (10) leads to a space-dependent probability of missing a fire regardless of
 368 its intensity. A rough estimate of such probability is a mean of $(1 - \beta_{ret})$ for a particular region (see Eq.
 369 (10) for definition of β_{ret}), averaged over the satellite overpasses (Figure 87a, mean fraction of missing
 370 pixels in the MODIS granules). This fraction is computed from MxD35 and Vxx03 products for MODIS and
 371 VIIRS, respectively. Pixels with “sunglint” or “cloud” flags are considered missing. However, this fraction

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381 should be considered as the upper estimate of $(1 - \beta_{ret})$ because fires tend to occur in dry periods
 382 when the cloud cover (the main reason for missing observations) is lower than the annual mean.

383 A way to account for the mutual anticorrelation of clouds and fire occurrences is to calculate the mean
 384 cloud cover only during a fire season in the region. A quantitative criterion can be the non-zero sum of
 385 FRP for the surrounding area of, for instance, $1^\circ \times 1^\circ$ (Figure 87b for MODIS and Figure 87c for VIIRS).

386 Due to anticorrelation between cloud cover and detection probability, the missing fractions in Figure
 387 87b,c, being more realistic than the mean cloud cover of Figure 87a, probably underestimate the
 388 omission error, thus being the lower estimate of the omission probability.

389 The results in Figure 87 depend on the arbitrarily selected size of the inspected area around the cloudy
 390 grid cell. Impact of this area has been quantified via a sensitivity study by varying it from 0.1° up to 20°
 391 (Figure 9). Calculations showed low sensitivity, e.g., doubling the area from $1^\circ \times 1^\circ$ to $2^\circ \times 2^\circ$ adds less
 392 than 10% to the omission probability of Figure 87b, c (see also Figure 9). Further expansion eventually
 393 leads to the same map as that of Figure 87a (for MODIS). A wider inspected area generally leads to less
 394 steep curves and smoother patterns (Figure 9). However, a wide search is not justified: already 200 km is
 395 too large as a correlation distance for regional fires. A smaller area leads to a patchy non-representative
 396 map.

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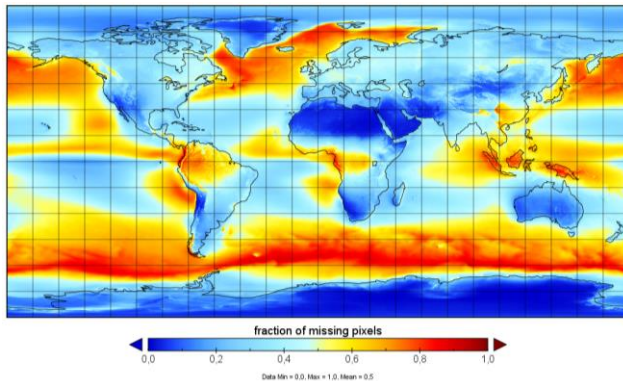
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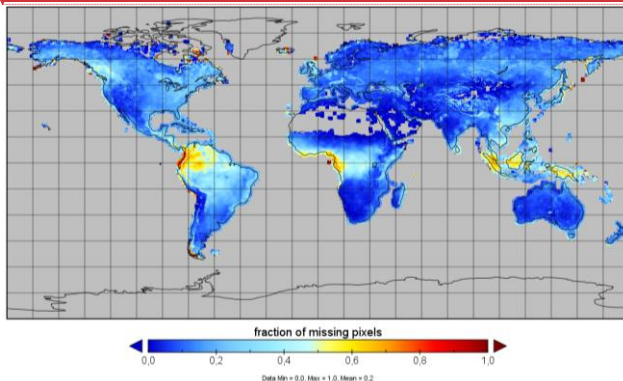
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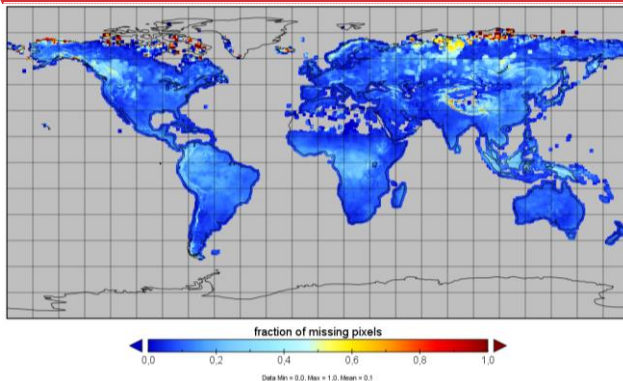
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a)



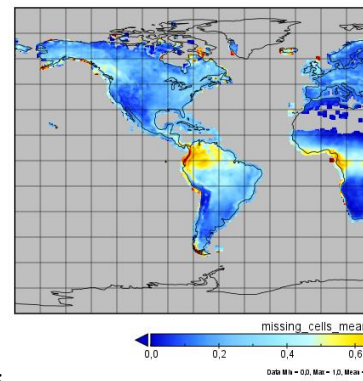
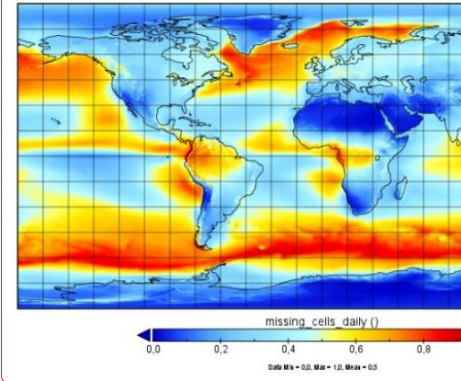
b)



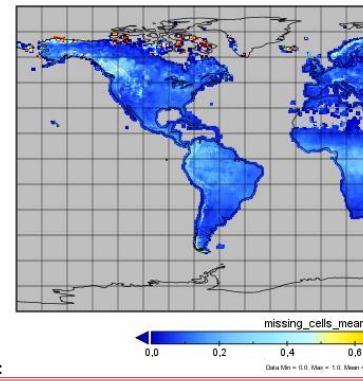
c)

Figure 8. Mean fraction of missing pixels due to cloud obscuration of MODIS, 2000-2020, and VIIRS, 2018-2024.10. Panel a) mean over all MODIS overpass times, b) mean over hours when non-zero FRP registered by MODIS anywhere in $1^\circ \times 1^\circ$ square centered around the grid cell, c) mean over hours when non-zero FRP registered by VIIRS anywhere in $1^\circ \times 1^\circ$ square centered around the grid cell.

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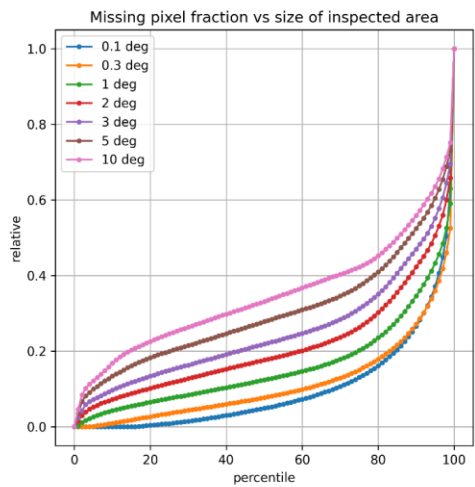
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427 *Figure 9. Distribution of mean fraction of MODIS missing pixels for different sizes of area around the detected fire inspected for*
428 *presence of other fires. The green curve (1 deg area size) corresponds to panel b) of Figure 87. The curve 0.1 deg corresponds to*
429 *no season checking, whereas the curve “10 deg” is practically equivalent to mean could fraction (panel a) in Figure 87).*
430 *Distribution is calculated only over land and regions with fires (Figure 87, panels b, c)*

431

432 The maps of [Figure 87](#) suggests that, even during the fire seasons, the omission error of low-orbit
433 satellite instrument like MODIS or VIIRS is typically within 20-40% for most fire-prone regions, with VIIRS
434 showing 10-20% lower omission error than MODIS. In equatorial regions, omissions can be much higher:
435 the fraction of missed fires can exceed 60% for MODIS and 40% for VIIRS.

436 The lower omission error of VIIRS may be due to (i) higher resolution, (ii) higher sensitivity, as shown in
437 the discussion below, (iii) [overpass time](#) in the middle of day when cloudiness may be at its daily lowest
438 level. Another peculiarity of VIIRS is a very high omission in Arctic, where MODIS shows the “usual” 40%.

439 This is caused by the high sensitivity of VIIRS: it detects more fire [pixels](#) in partly cloudy conditions and

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443 outside the main fire season. Clouds during these periods then contribute to the VIIRS omission error,
444 whereas MODIS misses them altogether and thus does not consider these times as fire-prone at all.

445 4.2. Application of OOp to relate VIIRS and MODIS observations

446 The pixel-wise OOp was applied to the MODIS AQUA and VIIRS SNP FRP retrievals for a full year of 2020,
447 taken as an example. The procedure followed the symmetric approach (13). The outcome (example in
448 [Figure 108](#)) expectedly showed that VIIRS registered ~30% more FRP than MODIS (panels a), b) [Figure](#)
449 [108](#)) due to its lower detection limit. Application of MODIS-based OOp zeroed pixels with small FRP
450 resulting in a 1.5 times lower granule total (panel d). Accounting for the differences in cloudiness via
451 application of VIIRS OOp to the MODIS fire pixels led to ~30% reduction of the total FRP, thus leaving
452 only those locations that were visible for both satellites (panel c).

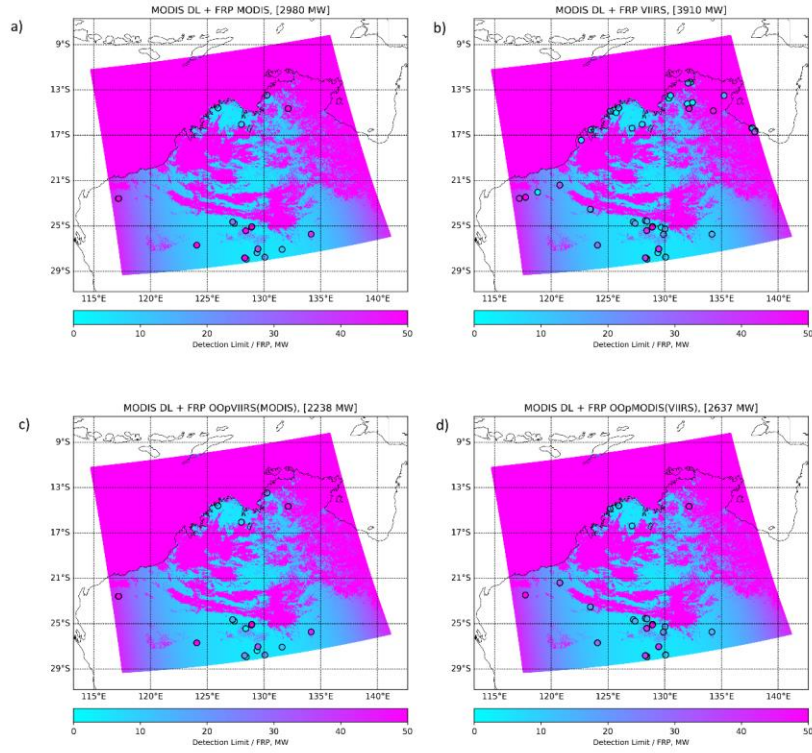
453 Analysis of the whole year 2020 brought over 40,000 MODIS AQUA granules with fire pixels registered
454 by at least one instrument. Total FRP retrieved by MODIS and VIIRS within these granules was 128 TW
455 and 177 TW, respectively. Symmetric application of $\mathcal{E}_{pixVIIRS}(P_{MODIS})$ and $\mathcal{E}_{pixMODIS}(P_{VIIRS})$ lead to 88
456 TW and 106 TW, respectively. This is illustrated in [Figure 119](#), which compares VIIRS retrievals before
457 and after the MODIS OOp application (P_{VIIRS} , blue dots and $\mathcal{E}_{pixMODIS}(P_{VIIRS})$, orange dots) with the
458 MODIS FRP processed by the VIIRS OOp ($\mathcal{E}_{pixVIIRS}(P_{MODIS})$, x-axis in [Figure 119](#)).

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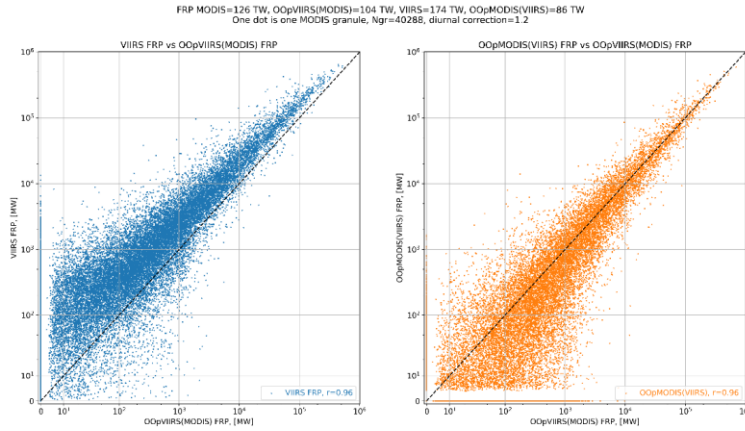


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464 Figure 10, MODIS and VIIRS fire retrievals for a MODIS AQUA granule over North-East Australia, 1.1.2020, 5:15 UTC, [MW].
 465 Background in all panels is MODIS detection limit accounting for larger pixels at the swath edges and cloudiness. Upper panels
 466 show MODIS and VIIRS FRP retrievals that fell into that granule, lower panels present the $\mathcal{E}_{pixVIIRS}(P_{MODIS})$ and
 467 $\mathcal{E}_{pixMODIS}(P_{VIIRS})$, respectively.

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471 Figure 11. Summary of P_{MODIS} (blue) and $\mathcal{E}_{pixMODIS}(P_{VIIRS})$ (orange) for 2020. Each dot represents the total FRP of fires that
 472 fell to a single MODIS AQUA granule. Granules that did not have VIIRS coverage (missing or corrupted VIIRS granules) and
 473 granules with no fires in both instruments are filtered out. A diurnal variation correction factor 1.2 is applied to VIIRS retrievals
 474 (see Discussion section).

475

476 The OOp-processed datasets match closely: the initial 38% difference, VIIRS registering more FRP, turns
 477 to 20% more OOp-processed FRP of MODIS. This 20% difference originates from different overpass
 478 times of the satellites (see the discussion section below), so accounting for it results in a close match of
 479 the OOp-processed datasets (Figure 119).

480 5. Discussion

481 5.1. Features of the pixel-wise detection limit and OOp of MODIS and VIIRS FRP retrievals

482 The first percentiles of the distribution densities $\pi_f(A_p, P_f)$ and $\pi_n(A_p, P_f)$ (Figure 32, Figure 43) (the
 483 red-dots and orange regression lines) are linear functions of the pixel area for both MODIS and VIIRS,
 484 with correlation coefficient >0.99 . For both satellites, the 1st percentile of the nighttime FRP is lower
 485 than that of daytime, for all pixel sizes, with the difference being larger for VIIRS than for MODIS.

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490 The panels e) and f) of the figures show that the smallest pixels register most of the FRP and the total
491 number of fires. For MODIS, 50% of fires are from 1 – 1.2 km² area pixels while the fraction of the swath
492 covered by such pixels is about 20% (see the swath geometry in [Figure 1b, c](#)). For VIIRS, pixels < 0.3 km²
493 occupy 60% of the swath area but provide ~90% of fire detections ([Figure 2b, c](#)).

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494 5.2. Previous assessments of the MODIS/VIIRS omission error and sensitivity to small fires

495 The results reported above can be compared with case studies presented in literature. For instance, the
496 cloud obscuration of fires in Brazilian Amazon (Schroeder et al., 2007) led to the omission error of 11%
497 for GOES geostationary fire products. This estimate expectedly differs from the MODIS / VIIRS statistics
498 ([Figure 87](#)): e.g., the mean cloud cover of MODIS overpasses over that area is 0.4 - 0.7. For fire seasons,
499 [Figure 87b](#) suggests the omission error from 0.2 - 0.6 for MODIS and 0.1-0.3 for VIIRS. The difference
500 from the value of (Schroeder et al., 2007) refers to the ability of geostationary satellites to follow the fire
501 over time thus avoiding some clouds. As follows from the comparison, it can about-half the omission
502 error, at a price of 16 times lower resolution (GOES sub-satellite pixel was 4km × 4km), with the
503 corresponding loss of small- and mid-sized fires.

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504 The only study reporting the dependence of the fire detection probability on the pixel size was made for
505 [MOD14 Collection 5 data](#) by (Maier et al., 2013) for Australia. The study suggested that fires with FRP <
506 3.6 MW are never detected (practically no fires were recorded up to 5 MW) whereas the frequency
507 distribution of FRP is significantly disturbed already at 15 MW. According to the FREEVAL study (Schultz
508 et al., 2008), the minimum-FRP detection threshold for MODIS Collection 4 was about 7 – 10 W m⁻² (7-10
509 MW for 1 km² pixel). This is in agreement with the predicted sensitivity limit of 10 – 20 W m⁻² of
510 (Kaufman et al., 1998). Finally, our earlier estimates made for Collection 5 (Soares et al., 2015) pointed
511 out that noticeable distortions of the FRP distribution start at 15 W m⁻². Except for (Maier et al., 2013),
512 none of these works referred to the pixel size and the overpass time, and should therefore be attributed

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518 to the smallest nadir pixel of MODIS, 1 km². These numbers are about-twice higher than the limit
 519 obtained above for Collection 6, which confirms the better detection of small fires in Collection 6 in
 520 comparison with the earlier Collections.

521 The dependence of the detection limit on the pixel size is dictated by the geometry of the instrument
 522 and the basic principle of the temperature-contrast based fire detection, leading to qualitatively similar
 523 dependencies obtained by (Maier et al., 2013) and in the current work. Among the differences, one can
 524 notice an almost-perfect linear relation of the detection limit in the current study in contrast to a
 525 “saturation” noticed for large viewing angles by Maier et al, who attributed it to the randomly selected
 526 1% threshold. However, in the current study, there is no saturation for 1% threshold either ([Figure 32](#),
 527 and [Figure 43](#)). A more probable reason is an insufficient number of fire detections in the large-pixel size
 528 range: only 57.2 thousand events were counted in the Maier et al analysis vs ~90 million cases for
 529 MODIS in this study. Should this saturation be ignored, the detection limit for the largest pixels at the
 530 edge of the swath would exceed 55 MW for Collection 5, compared to 42 MW / 39 MW for day/night
 531 overpasses for Collection 6 in this study.

532 5.3. Comparison with sensitivity and detection probability of SEVIRI

533 The sensitivity of SEVIRI has been evaluated within the FREEVAL project (Schultz et al., 2008). That study
 534 concluded that “SEVIRI should be able to confidently detect actively burning fires whose FRP reaches a
 535 minimum of around 100 MW, and in certain cases may be able to detect fires whose FRP is even lower
 536 than this, down to around 50 MW.” That generic conclusion was refined by the fire histogram of the
 537 sub-satellite pixels (Figure 4.2 in the FREEVAL report), whose size (3 km × 3 km) closely matches pixels at
 538 the edge of the MODIS swath. In the FREEVAL histogram, strong disturbances start from FRP of 43 MW,
 539 with detection limit being between 35 - 40 MW. This result corroborates very well with the current
 540 assessment because the 9 km² area corresponds to 40.5-40.9 MW detection limit (day-night) according

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558 to Eq. (5) and Table 1. Therefore, the lowest detection limit of SEVIRI (sub-satellite fires) is 10% lower
559 than the corresponding detection limit of MODIS near the edge of its swath. The difference can originate
560 from the differences in the instruments, the FRP retrieval algorithms, and the accumulated statistics (the
561 FREEVAL SEVIRI histogram is based on 3 months in 2004).

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562 Comparison with VIIRS is not unequivocal. Schroeder et al. (2014b) related the fire size and temperature
563 to the probability of VIIRS to detect it and concluded that a small (1.5m radius) but hot (1000K) fire can
564 be noticed at night. In a qualitative agreement with that prediction, a histogram of VIIRS FRP data
565 (Figure 43) suggests ~0.7 MW detection limit at night in the center of the swath.

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566 5.4. Comparison of MODIS and VIIRS

567 A direct comparison of the detection limit formulas and coefficients for MODIS and VIIRS (Table 1, Table
568 2, Figure 1210) reveals both the effect of the pixel size on the detection limit and the difference
569 between the instruments and processing algorithms: VIIRS is about 3x more sensitive than MODIS for
570 comparable pixel size of ~ 1km² at night, but about 25% less sensitive during day (within 5% for the first
571 percentile).

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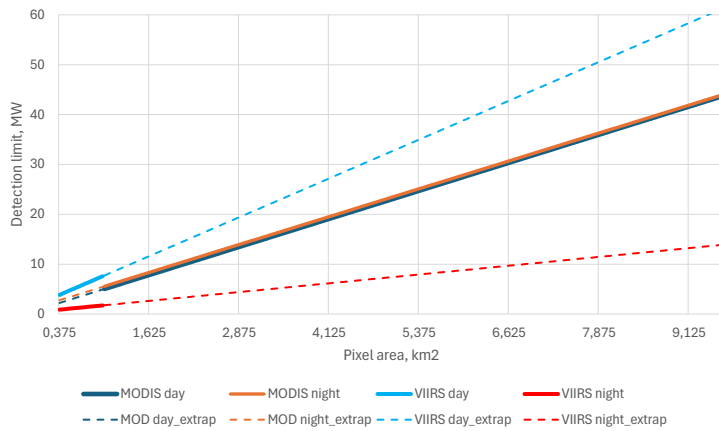


Figure 12, MODIS and VIIRS detection limits as functions of pixel sizes. Solid lines denote the actual pixel size range of the instruments, whereas dashed lines show their extrapolation to cover the whole size range 0.375 km² – 9.6 km².

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Application of the OOp-s matches the datasets (Figure 108, Figure 119): the remaining difference of 23% between the $\mathcal{E}_{pixMODIS}(P_{VIIRS})$ and $\mathcal{E}_{pixVIIRS}(P_{MODIS})$ is a result of the later overpasses of AQUA, which registers most fires around 13:00-14:00 local time, compared to 12:00-13:30 of SNP. The absolute peak of fire intensity, however, was estimated at 14:00-15:00 from the geostationary SEVIRI retrievals (Soares et al., 2015), practically independently from the land use type. According to those calculations (see Fig.5 there), the difference between SNP and AQUA observations corresponds to ~20% higher total FRP for MODIS AQUA (depending on actual retrieval times, the difference is within 0%-50% range), which closely matches the 23% difference between OOp-processed FRPs (this correction is applied to the scatterplots in Figure 119).

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5.5. Implications for atmospheric composition assessment

A substantial fraction of fires missed by MODIS and VIIRS, either due to cloud obscuration or finite detection limit, can lead to inconsistencies in the fire retrievals. The first problem is that the satellites

598 register more fires in centres of the swaths than at their edges. Moreover, the orbits shift every day with
599 revisit time of 16 days. As a result, application of an atmospheric composition model with such fires as
600 input would lead to appearing / disappearing fire detections, missing [smoke](#) plumes, and incorrectly
601 reproduced episodes.

602 The second issue is more general. The atmospheric models are calibrated and evaluated against a
603 variety of independent observations, and mean bias of predicted concentrations is one of critical
604 parameters. Many assessments of non-anthropogenic emissions rely on inverse problem solutions
605 (a.k.a. top-down emission inventories). Having a fraction of fires missing, the emission inversion
606 algorithm may tend to offset the bias due to missing fires by exaggerating the emission factors for the
607 observed ones. Such artificial increase might partly explain the factor of 3.4 between the top-down and
608 bottom-up approaches to PM emission from fires, as noted in earlier studies (Kaiser et al., 2012; Soares
609 et al., 2015). Conversely, missing fires lead to distorted pollution patterns and lower correlation with
610 observations. In the inverse problems context, lower model-measurement correlation leads to under-
611 estimation of optimized emission fluxes (Sofiev et al., 2024).

612 One of possible ways to [address](#) the problem of the omission error is to construct [a](#) fire prediction
613 model capable of assimilating the [active-fire products into the model](#) state [that exists regardless of](#)
614 [specific observations. Such a model would allow for fires](#) to the areas not observed due to clouds or
615 below-detection-limit. The vital part of such exercise would be the FRP observation operator
616 constructed in this paper.

617 6. Conclusions

618 Detection limits of Fire Radiative Power (FRP) products of two low-orbit satellites, MODIS and VIIRS,
619 have been identified and related to size of the observation pixels. Two types of observation operator
620 (OOp) for FRP retrievals have subsequently been constructed: for individual pixels of the satellite

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625 retrievals, and for gridded representation of the FRP fields. The key parameter for the pixel-level OOp is
626 the size of the observation pixel, which solely determines the detection limit as a linear function of the
627 pixel area, with different coefficients for day / night and MODIS / VIIRS retrievals [in clear-sky conditions](#).
628 For gridded representation, the fraction of the largest fire-pixel in the total grid-cell FRP and cloud cover
629 are also important. The probability of detecting even a powerful fire can be as low as 30% for regions
630 with a dense cloud cover. Fires can also be overshadowed by thin clouds or fire smoke attenuating the
631 irradiance and reducing the retrieved FRP.

632 Application of the OOp-s confirmed their internal consistency: OOp-processed MODIS and VIIRS
633 retrievals, with a correction to the different overpass times, showed a close match of the retrieved FRP.

634 The detection limits of the FRP products of MODIS Collection 6.1 are 5.7 MW / 3.7 MW for day- / night-
635 time overpasses for the smallest-size pixels in the middle of the swath (about-half of those earlier
636 reported for Collection 5). For VIIRS Collection 2, these are 3.7 MW and 0.7 MW, respectively. Finite
637 detection limit leads to an omission of small fires.

638 The suggested formulations were developed for MODIS and VIIRS, but can also be used, with refitted
639 coefficients, for other low-orbit and, potentially, geostationary instruments.

640 7. Code and data availability

641 Code of the observation operator and its coefficients identified for MODIS and VIIRS are available from
642 the GitHub public repository: https://github.com/fmidev/FRP_OOp and from Zenodo archive
643 <https://doi.org/10.5281/ZENODO.18339604> (Sofiev and Kouznetsov, 2026).

644 8. Author contribution

645 MS developed the concept, performed data analysis, and wrote the paper; RK participated in the
646 concept development, contributed to data analysis and edited the paper.

9. Competing interests

The authors declare that they have no competing interests

10. Acknowledgements

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