RECENT ADVANCEMENTS IN DERIVING NO_x EMISSION ESTIMATES FROM SATELLITE DATA

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DERIVING NO_X EMISSIONS FROM SATELLITE INFORMATION OVER LONG TIMESCALES

Using a methodology first pioneered by Beirle et al., 2011, and enhanced by Valin et al., 2013, de Foy et al., 2015 and Lu et al., 2015, we can derive NO_x emissions from OMI.

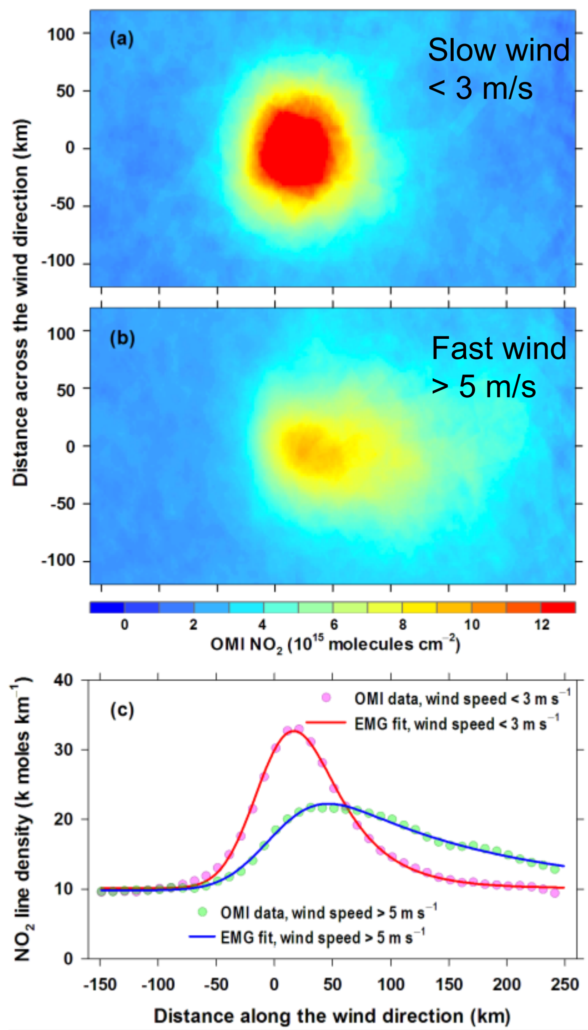
<u>Using an exponentially modified Gaussian function fit:</u>

$$NO_x\ Emissions = 1.33\left(\frac{\alpha}{\tau_{effective}}\right)$$

$$\text{where } \tau_{effective} = \frac{x_o}{w}$$

1.33 = NO_X/NO_2 ratio
α = observed OMI NO_2 burden
$\tau_{effective}$ = effective lifetime
x_o = e-folding distance
w = wind speed

*α and x_o are derived from the exponentially modified Gaussian fit



Urban areas	NEI emissions 2005–2014 (Mg h^{-1})	OMI-derived emissions (Mg h^{-1})
Atlanta, GA	12.7	6.7 ± 2.8
Boston, MA	10.3	10.9 ± 4.5
Charlotte, NC	3.3	2.7 ± 1.1
Chicago, IL	30.7	23.3 ± 9.7
Cincinnati, OH	7.9	4.9 ± 2.0
Dallas, TX	14.8	8.1 ± 3.4
Denver, CO	10.0	12.1 ± 5.0
Detroit, MI	26.1	18.7 ± 7.8
El Paso, TX	2.2	3.2 ± 1.3
Houston, TX	13.5	11.3 ± 4.7
Indianapolis, IN	4.3	3.1 ± 1.3
Jacksonville, FL	5.2	4.7 ± 2.0
Kansas City, MO	10.2	5.1 ± 2.1
Las Vegas, NV	6.1	6.7 ± 2.8
Los Angeles, CA	40.1	40.0 ± 16.6
Louisville, KY	6.3	2.5 ± 1.0
Memphis, TN	4.4	1.5 ± 0.6
Miami, FL	13.4	5.6 ± 2.3
Minneapolis, MN	12.8	9.3 ± 3.9
Nashville, TN	2.9	2.0 ± 0.8
New Orleans, LA	7.2	3.6 ± 1.5
New York, NY	43.2	50.7 ± 21.1
Philadelphia, PA	17.8	23.3 ± 9.8
Phoenix, AZ	10.8	12.2 ± 5.1
Portland, OR	6.9	9.9 ± 4.1
Richmond, VA	3.6	1.8 ± 0.7
Salt Lake City, U	3.6	8.2 ± 3.5
San Antonio, TX	5.4	3.2 ± 1.4
San Diego, CA	6.0	8.8 ± 3.7
Seattle, WA	13.0	13.3 ± 5.7
St. Louis, MO	11.0	4.9 ± 2.0
Tampa, FL	8.5	6.9 ± 2.9
Tucson, AZ	3.1	1.5 ± 0.6
Virginia Beach, V	6.1	4.6 ± 1.9
Washington, DC	18.5	13.0 ± 5.5

Lu et al., Atmos. Chem. Phys., 2015 from AQAST

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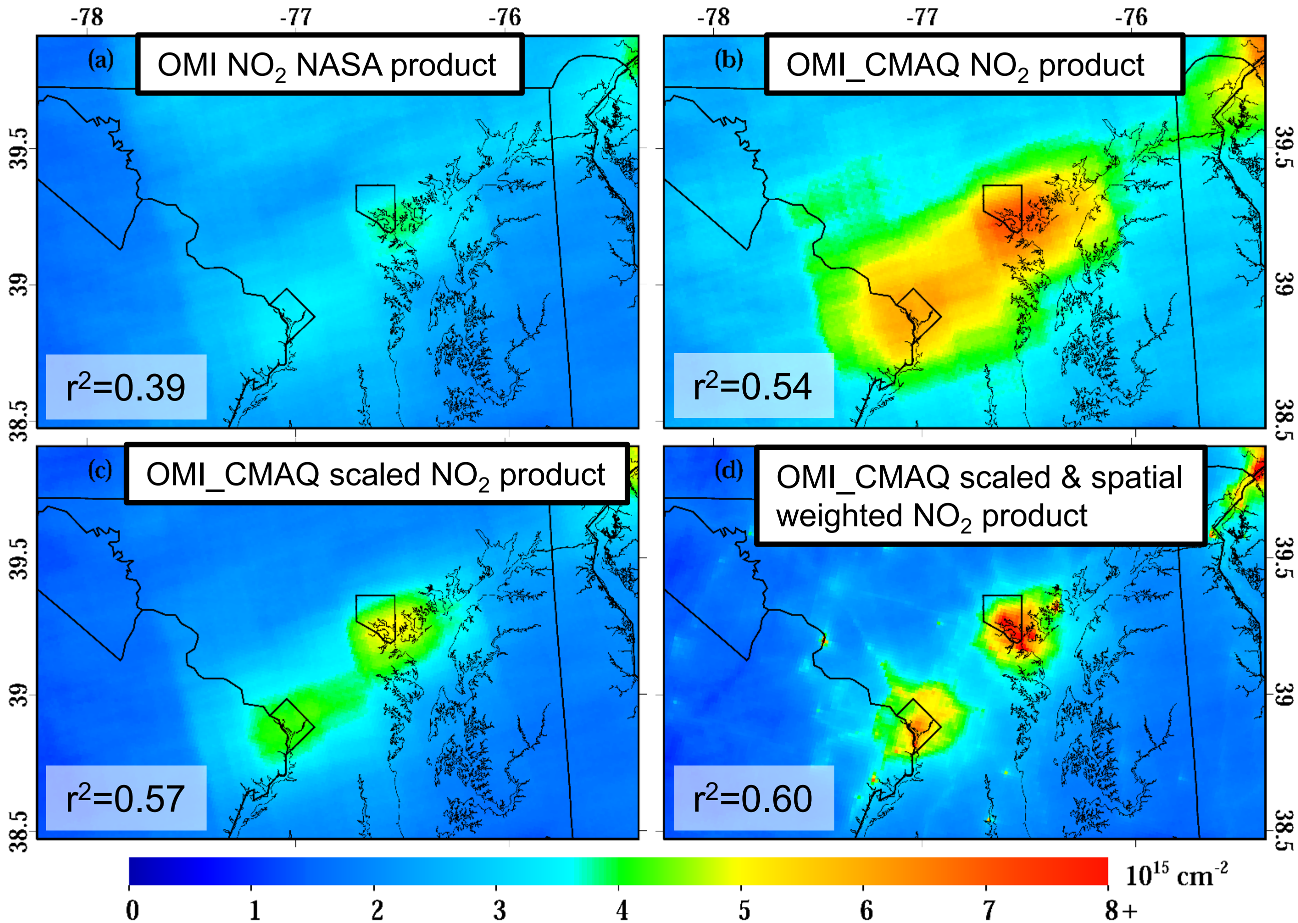
ENHANCED OMI NO_2 PRODUCTS

Goldberg et al., 2017; ACP



(a)→(b): Use CMAQ instead of GMI to calculate the Air Mass Factor (AMF)

(b)→(c): Scale CMAQ based on D-AQ aircraft observations, and then calculate AMF

(c)→(d): Spatial weighting based on the variability within CMAQ [Kim et al., 2016; GMD]

Showing a June & July 2008 – 2012 average; r^2 denotes correlation with ground monitors

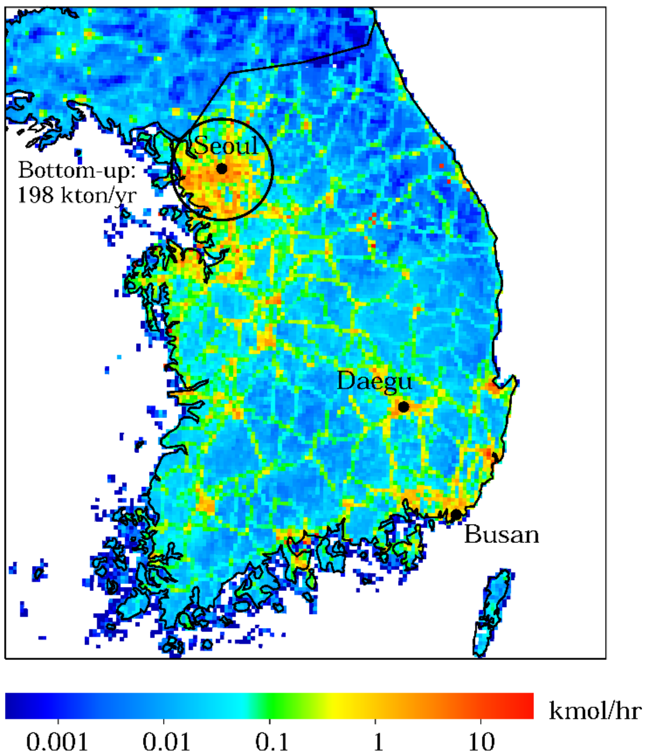
(d) Is much better than (a) when compared to in situ observations!

Key takeaways:

- Model resolution plays a significant role in the calculation of air mass factors (high resolution = better)
- Accuracy of model simulation is critical in generating robust satellite observations
    - If model emissions or chemistry are way off, satellite will be unrealistic
- Spatial weighting helps satellite match urban-scale variability better

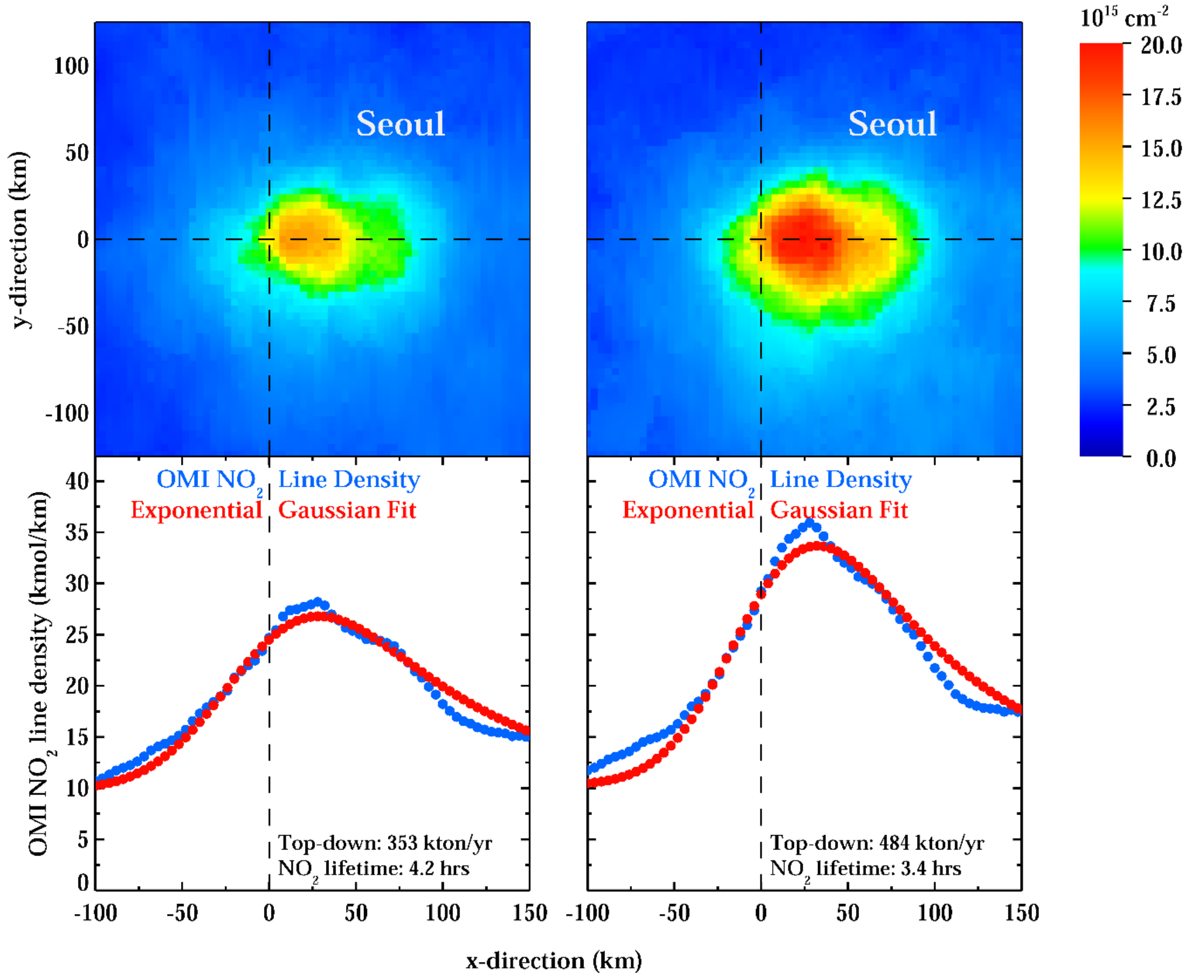
USING AN ENHANCED SATELLITE PRODUCT TO DERIVE NO_X EMISSIONS FROM SEOUL, SOUTH KOREA, MAY 2016

Bottom-up emissions inventory:



Top-down NO_X emission estimates:

Standard OMI NO_2 Enhanced OMI NO_2



Bottom-up NO_X emissions inventory appears to be underestimated by:

- 36% using standard product
- 53% by using the enhanced product

Atmos. Chem. Phys. Disc., In review.

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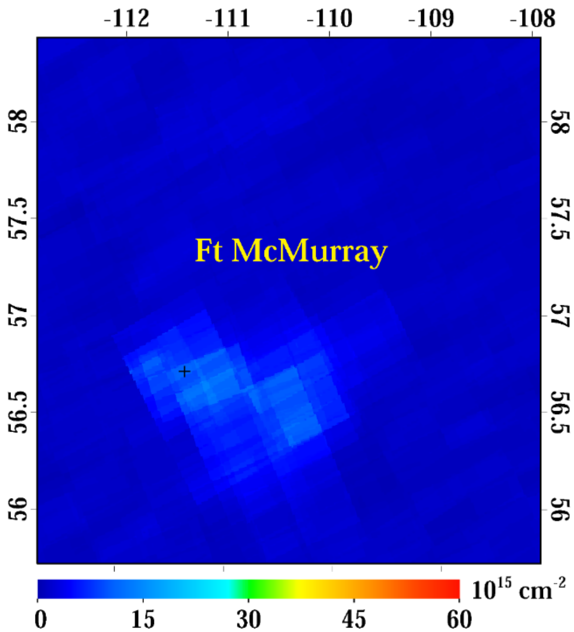
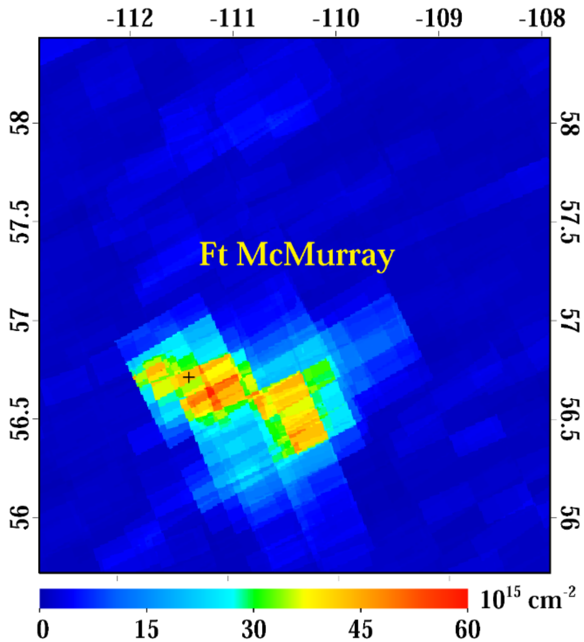
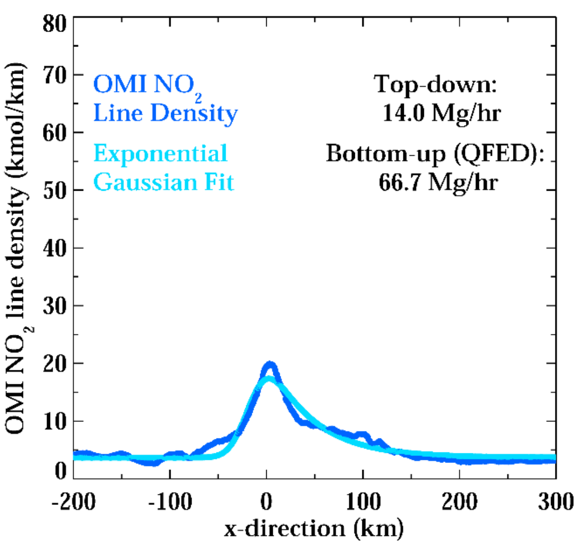
USING AN ENHANCED SATELLITE PRODUCT TO DERIVE NO_X EMISSIONS FROM THE FORT MCMURRAY WILDFIRE, MAY 2016

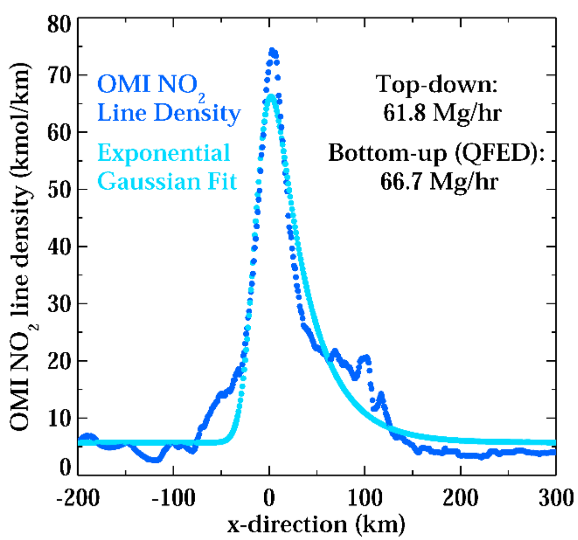
Standard OMI NO_2



Re-processed OMI NO_2







Use parameterization derived by Bousserez, 2014 to re-process OMI NO_2 retrieval:

$$CF_{NO2} = \log_e(3.4\ \Delta NO_2 + 2.2)$$

where CF = Correction factor and
$\Delta NO_2 = (NO_{2\ wildfire} - NO_{2\ background}) / NO_{2\ background}$

New OMI NO_2 top-down estimate shows better agreement with bottom-up inventory!

Biggest discrepancies will be for anomalous wildfires in rural regions.

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FUTURE WORK: LOOKING FORWARD TO USING TROPOMI DATA!

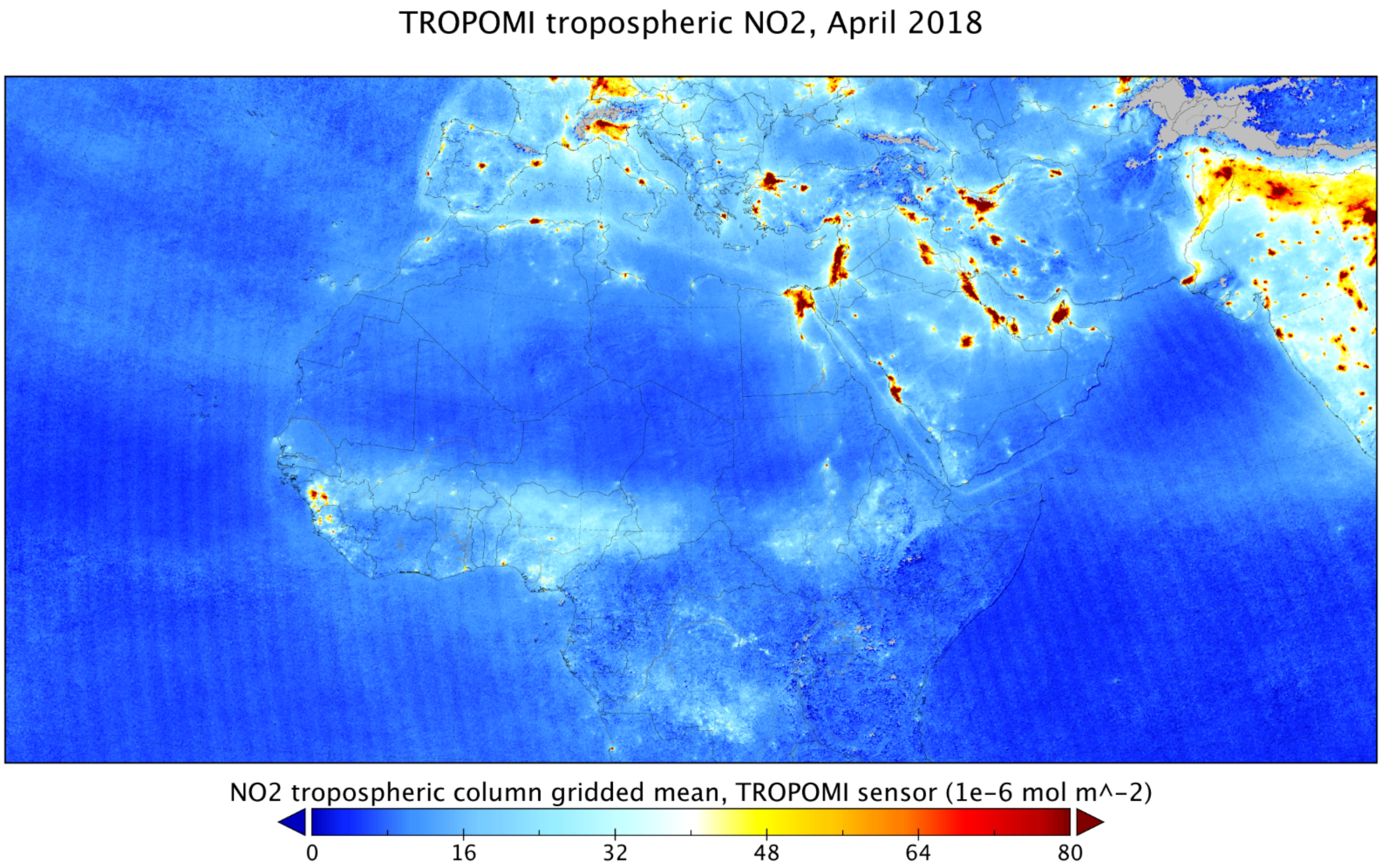

Image acquired from: http://www.esa.int/Our_Activities/Observing_the_Earth/Copernicus/Sentinel-5P/Copernicus_Sentinel-5P_releases_first_data

NO_X emission inventories data can be evaluated on much shorter timescales! Monthly, if not weekly!

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