INSTRUMENTATION PHYSICS LABORATORY

SINCE 1983

Physics 305- White Noise Analysis

Black Marble

nighttime lights

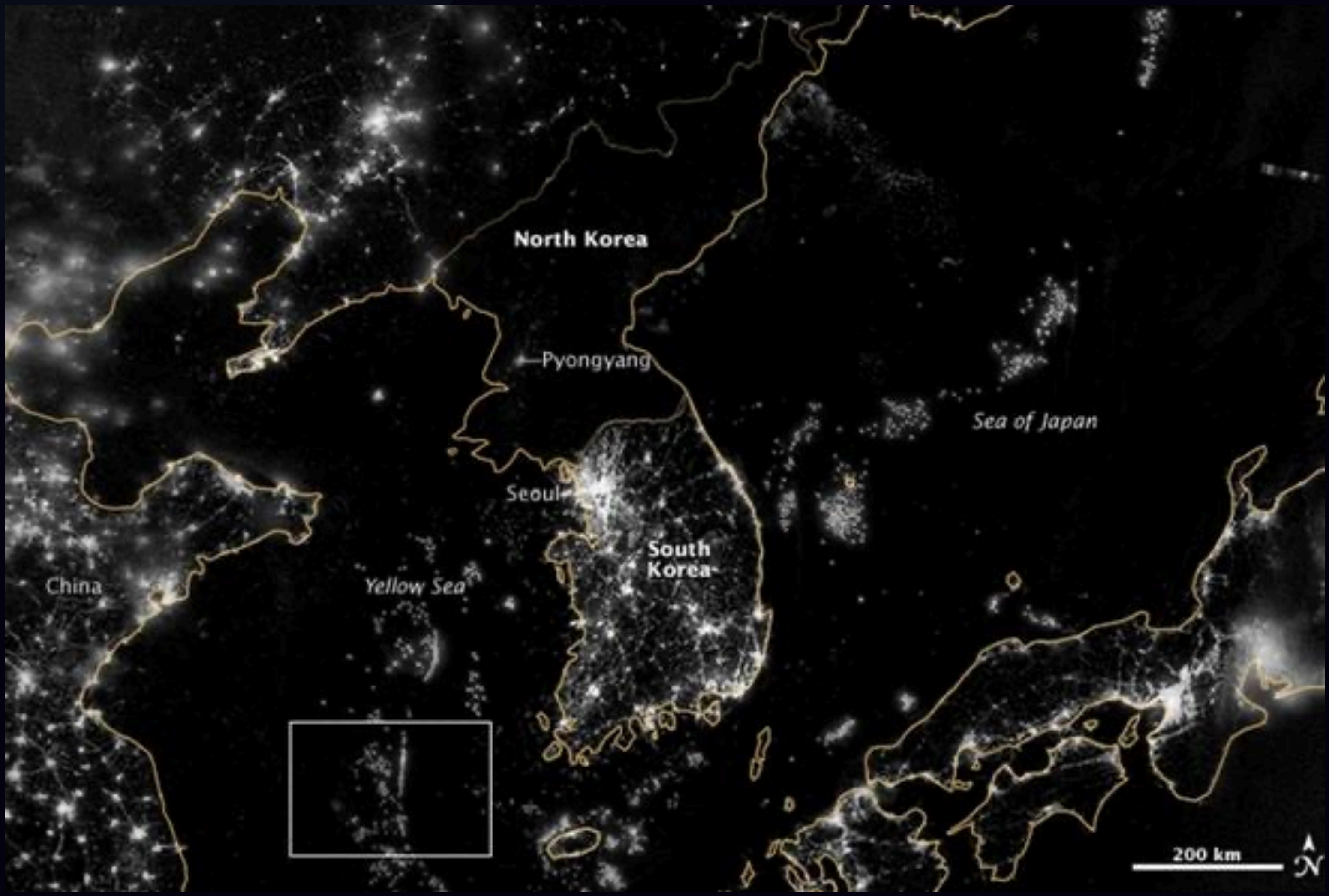
Final Project by **Rene L. Principe Jr.**

National Institute of Physics, University of the Philippines Diliman

rprincipe@nip.upd.edu.ph | rlprincipe@up.edu.ph

rlprincipe.wixisite.com/reneprincipejr

North/South Korea divide



NASA EARTH OBSERVATORY IMAGE BY JESSE ALLEN AND ROBERT SIMMON
https://www.cbsnews.com/pictures/north-korea-hermit-country-space-photos/3/

Berlin, Germany (2020)

https://twitter.com/NorbertElekes/status/1325892921590210560/photo/1

Crisis in Syria (83% NTL reduction)

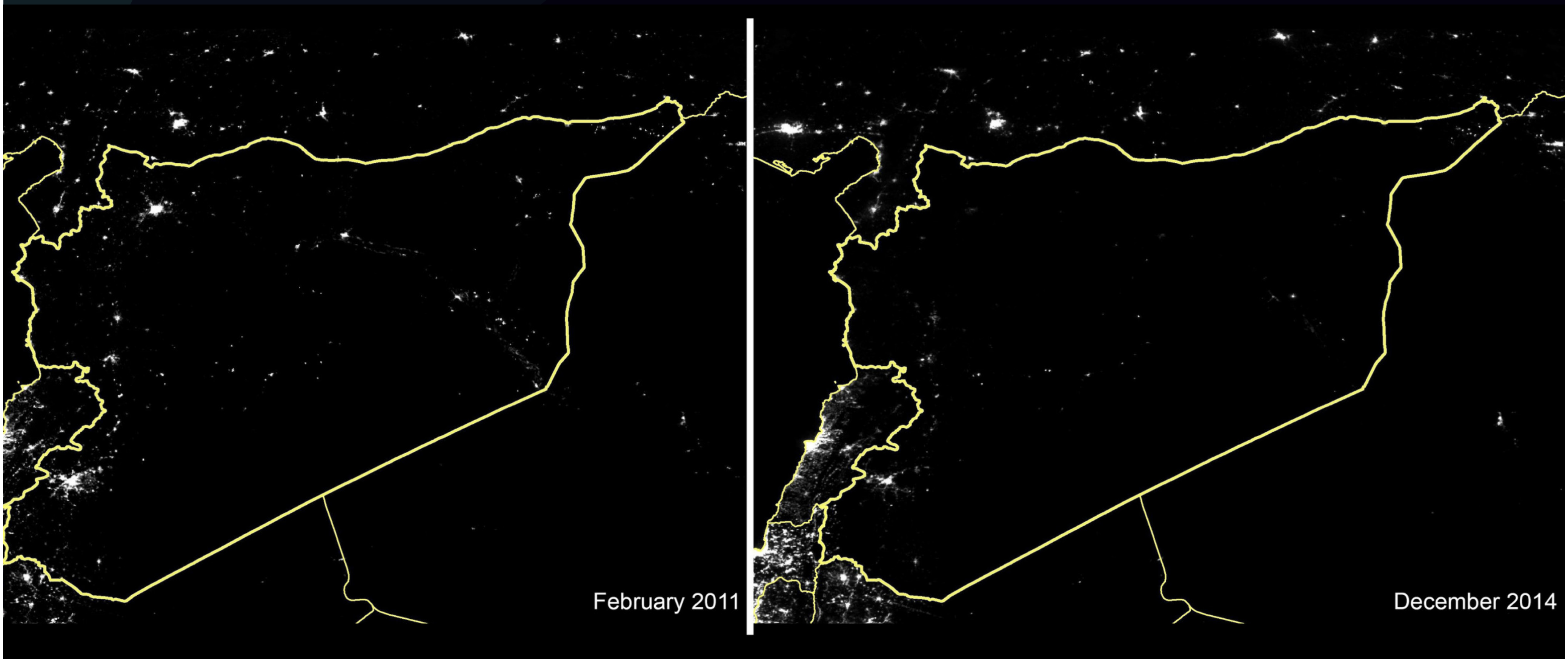
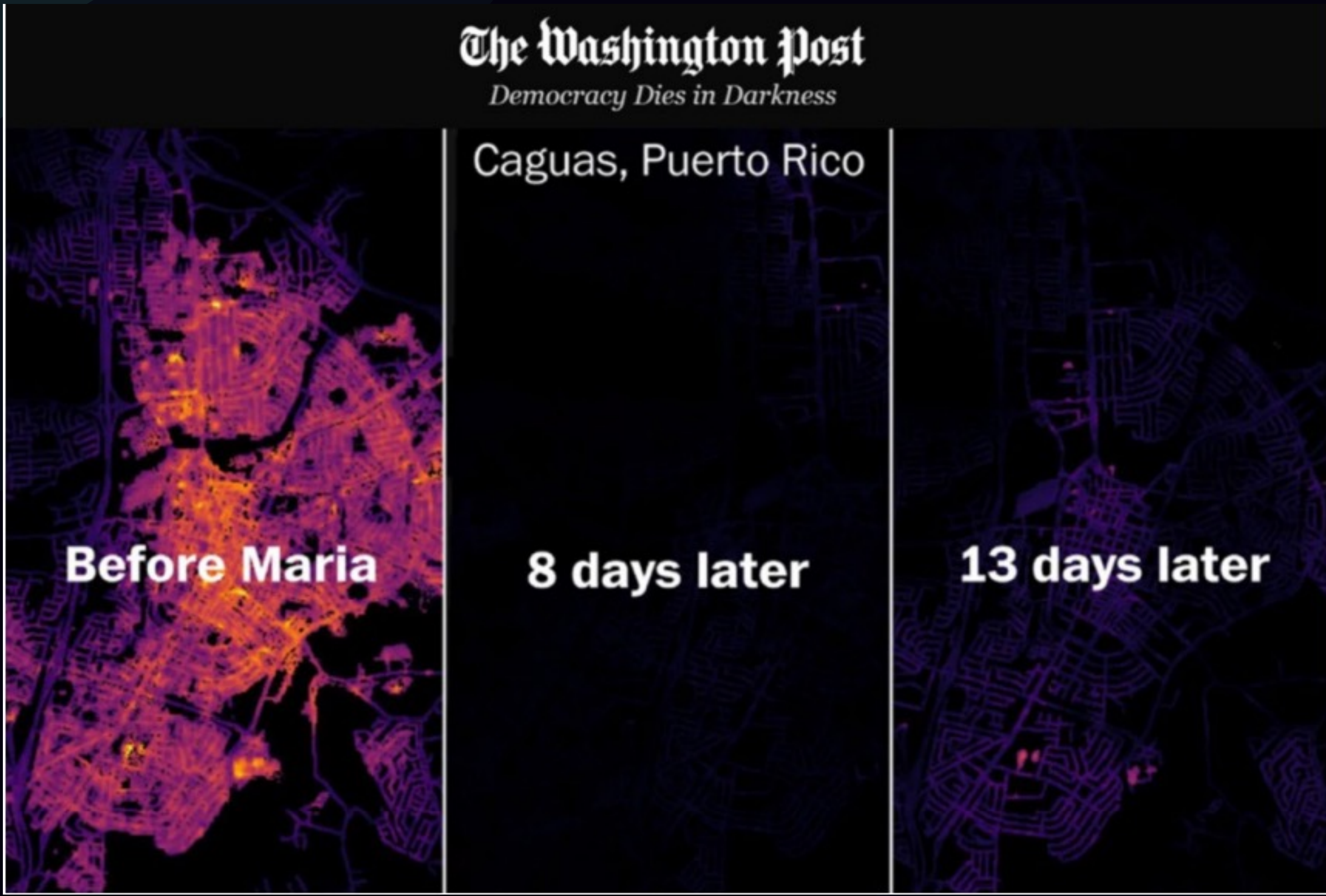
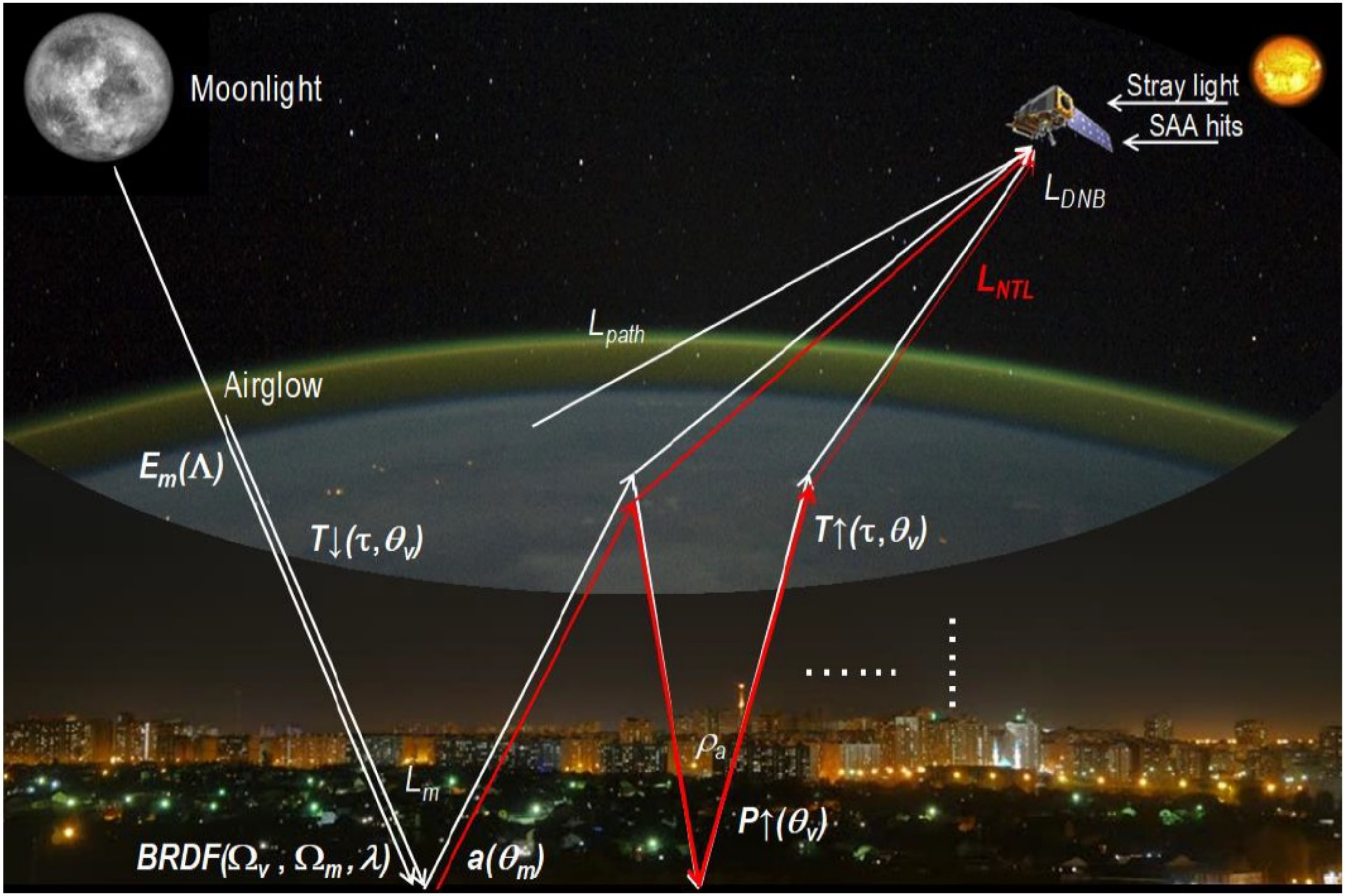


Photo: Satellite images showing night time light levels across Syria in February 2011 and December 2014 © #WithSyria and Wuhan University
https://www.amnesty.org/en/latest/news/2015/03/syria-goes-dark-83-of-lights-out-after-four-years-of-crisis/

Puerto Rico after Maria

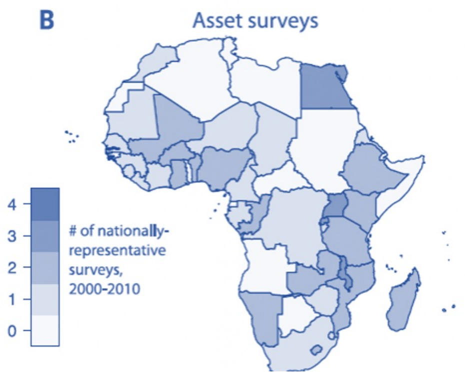


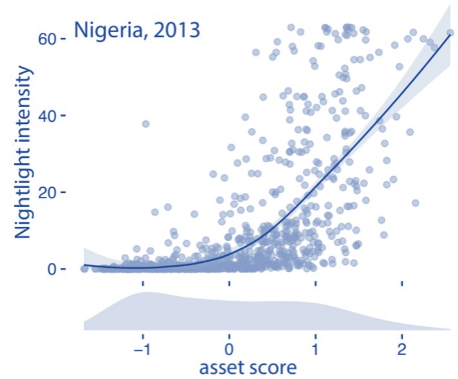


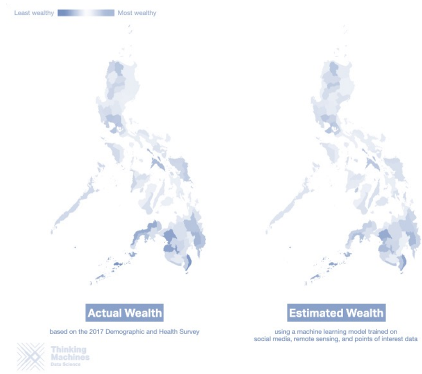
Principles of nighttime lights |

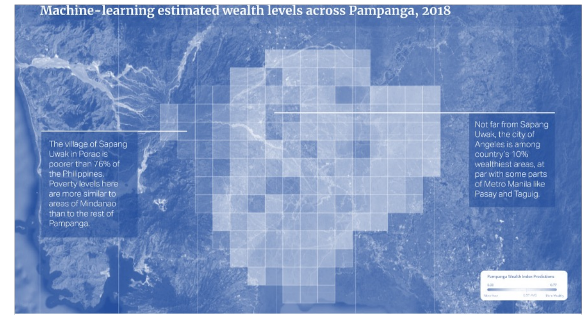
Miguel O. Roman et al. ***NASA's Black Marble nighttime lights product suite***. *Remote Sensing of Environment, 210:113–143, 7 2018.*

Relevant studies using NTL



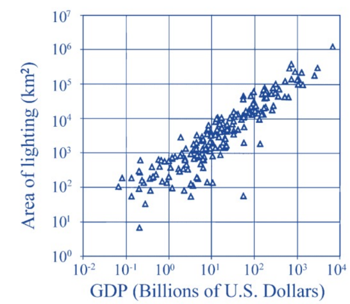


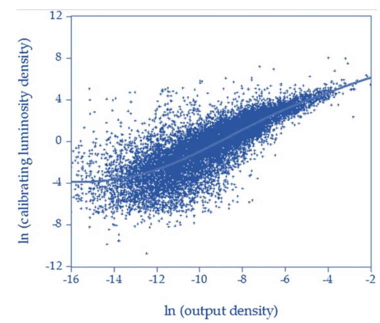




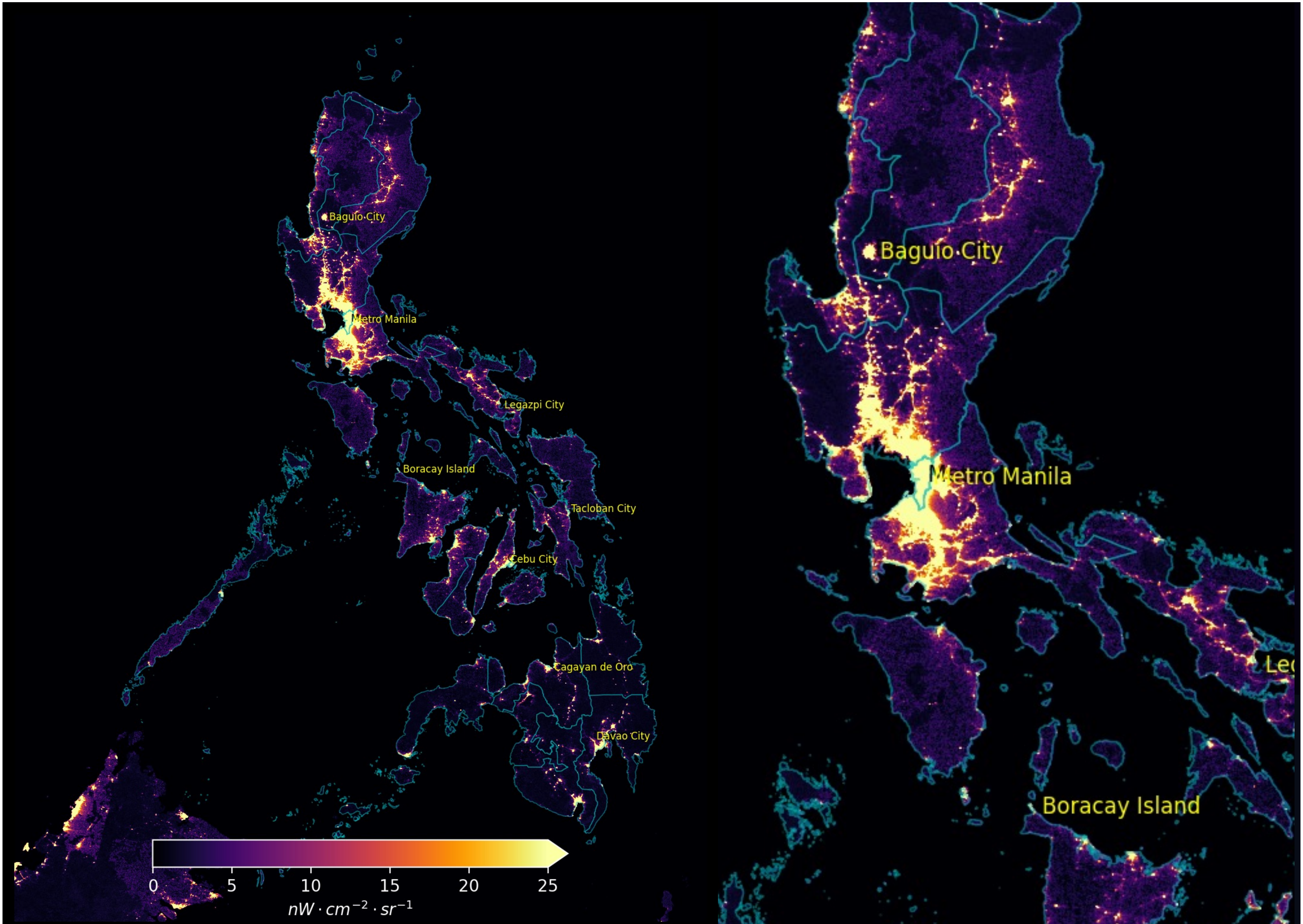
Why use nighttime lights?

1. NTL provides **improved accessibility** to information difficult to obtain by other means.
2. NTL is **consistent**, has a wide geographic coverage and **high spatiotemporal resolution**.
3. NTL are especially useful for a variety of **socio-economic research and applications**.

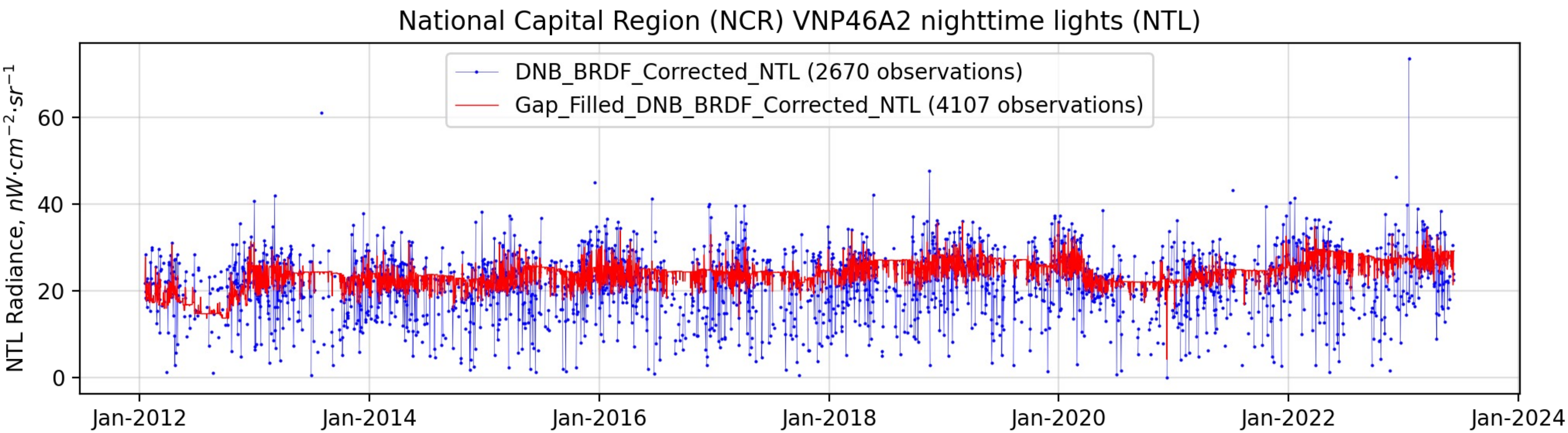


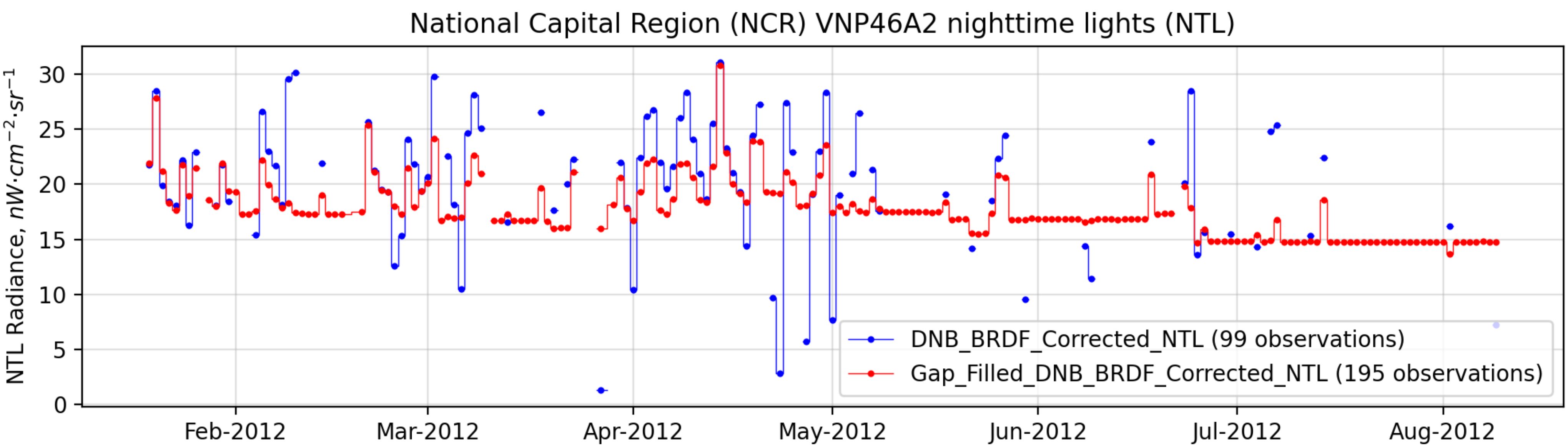


- *Neal Jean et al.* ***Combining satellite imagery and machine learning to predict poverty****. Science, 353:790–794, 2016.*
- *Isabelle Tingzon et al.* ***Mapping Poverty in the Philippines Using Machine Learning, Satellite Imagery, and Crowd-sourced Geospatial Information****. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, XLII:14–15, 2019.*
- *Xi Chen and William D. Nordhaus.* ***Using luminosity data as a proxy for economic statistics.*** *Proceedings of the National Academy of Sciences of the United States of America, 108:8589–8594, 2011.*
- *Christopher D Elvidge et al.* ***Night-time lights of the world: 1994–1995****. ISPRS Journal of Photogrammetry and Remote Sensing, 56(2):81–99, 2001.*

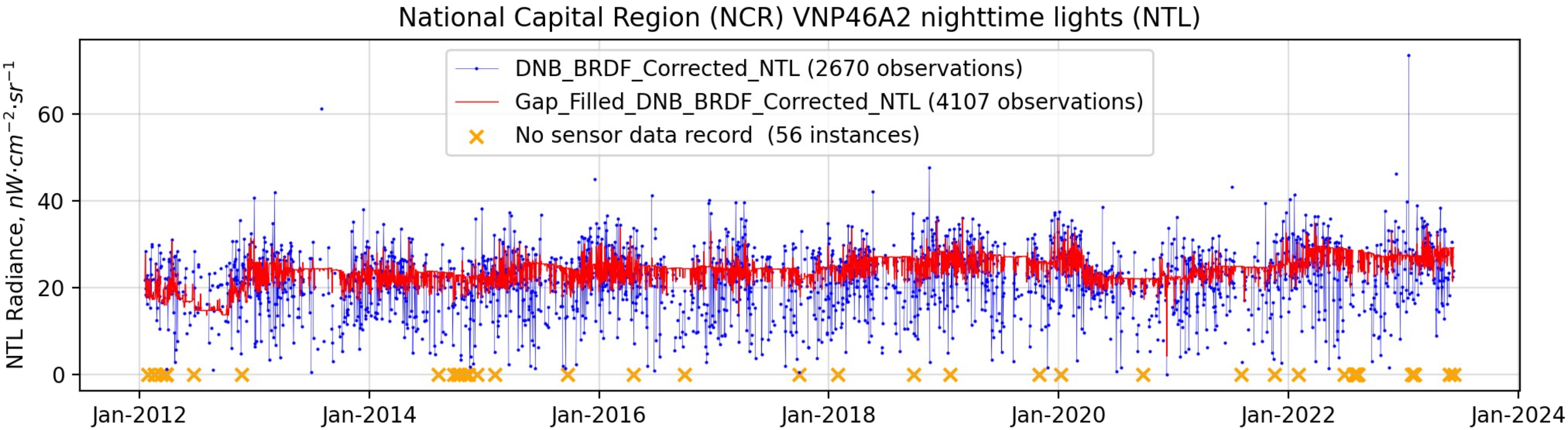

Baguio City
Metro Manila
Legazpi City
Boracay Island
Tacloban City
Cebu City
Cagayan de Oro
Davao City
0
5
10
15
20
25
$nW \cdot cm^{-2} \cdot sr^{-1}$
Baguio City
Metro Manila
Boracay Island

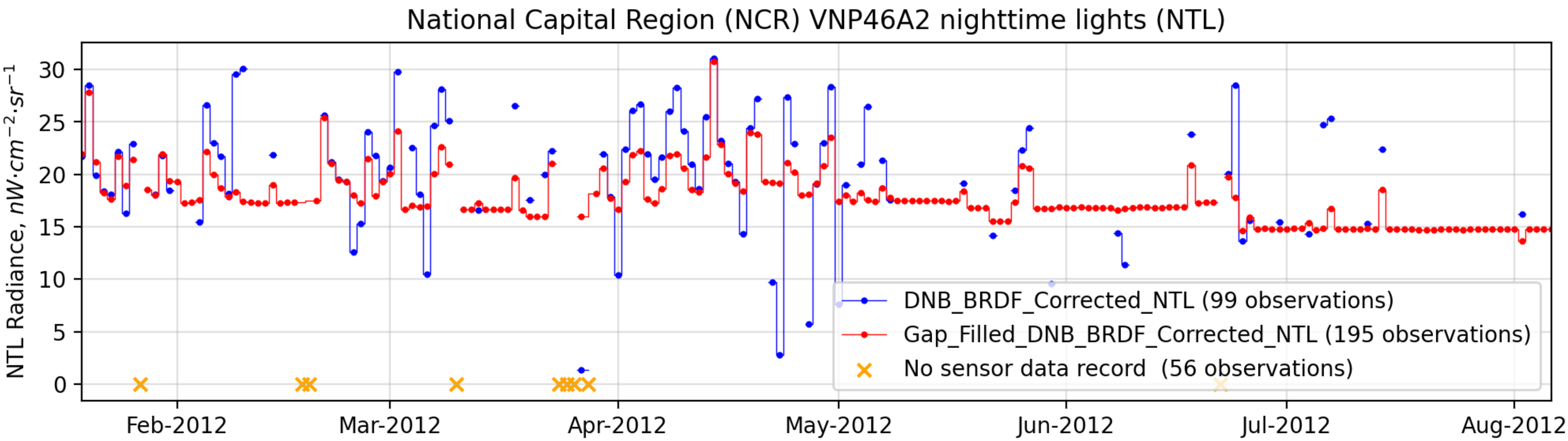
Regional NTL Data



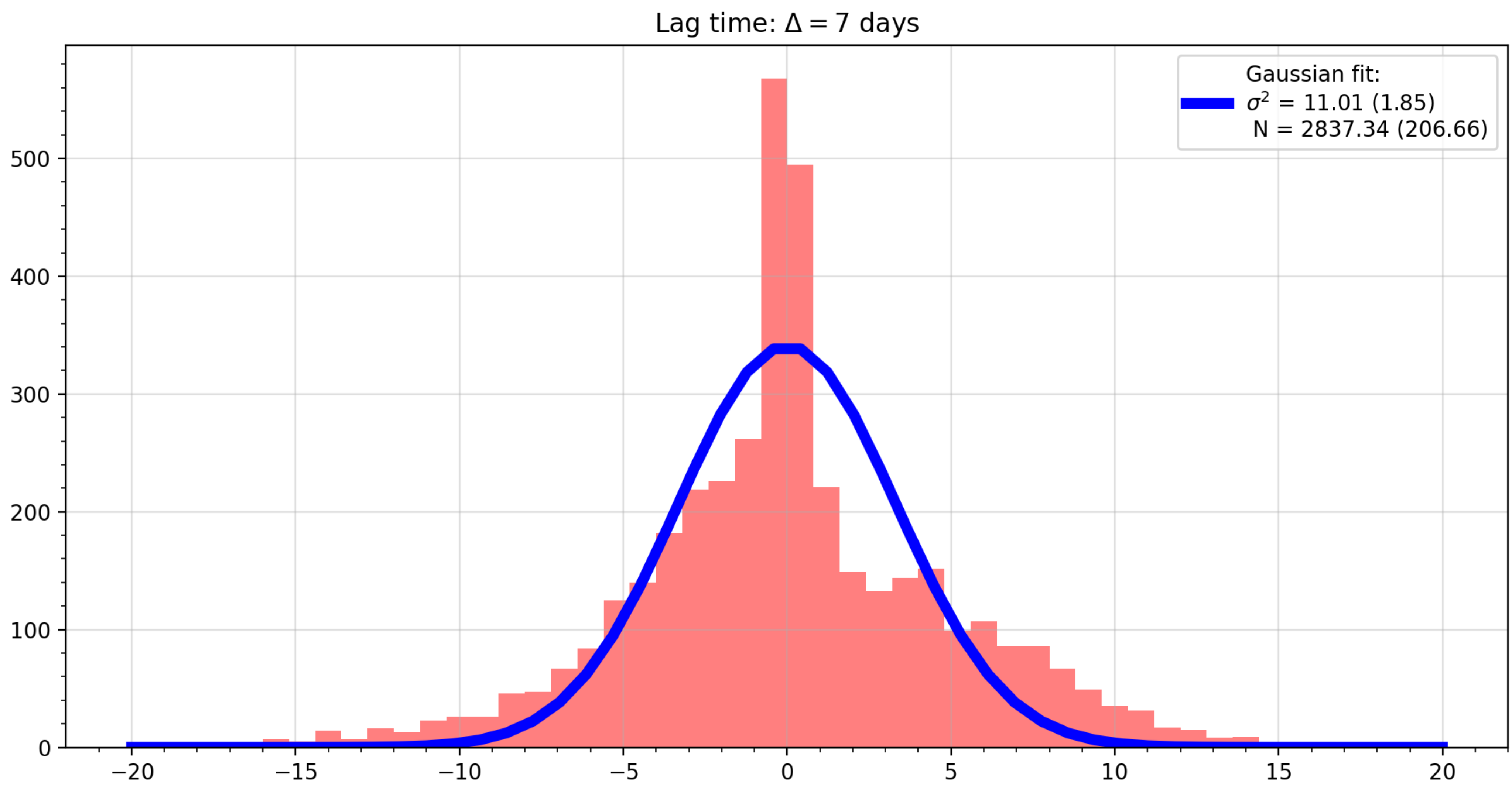


Regional NTL Data

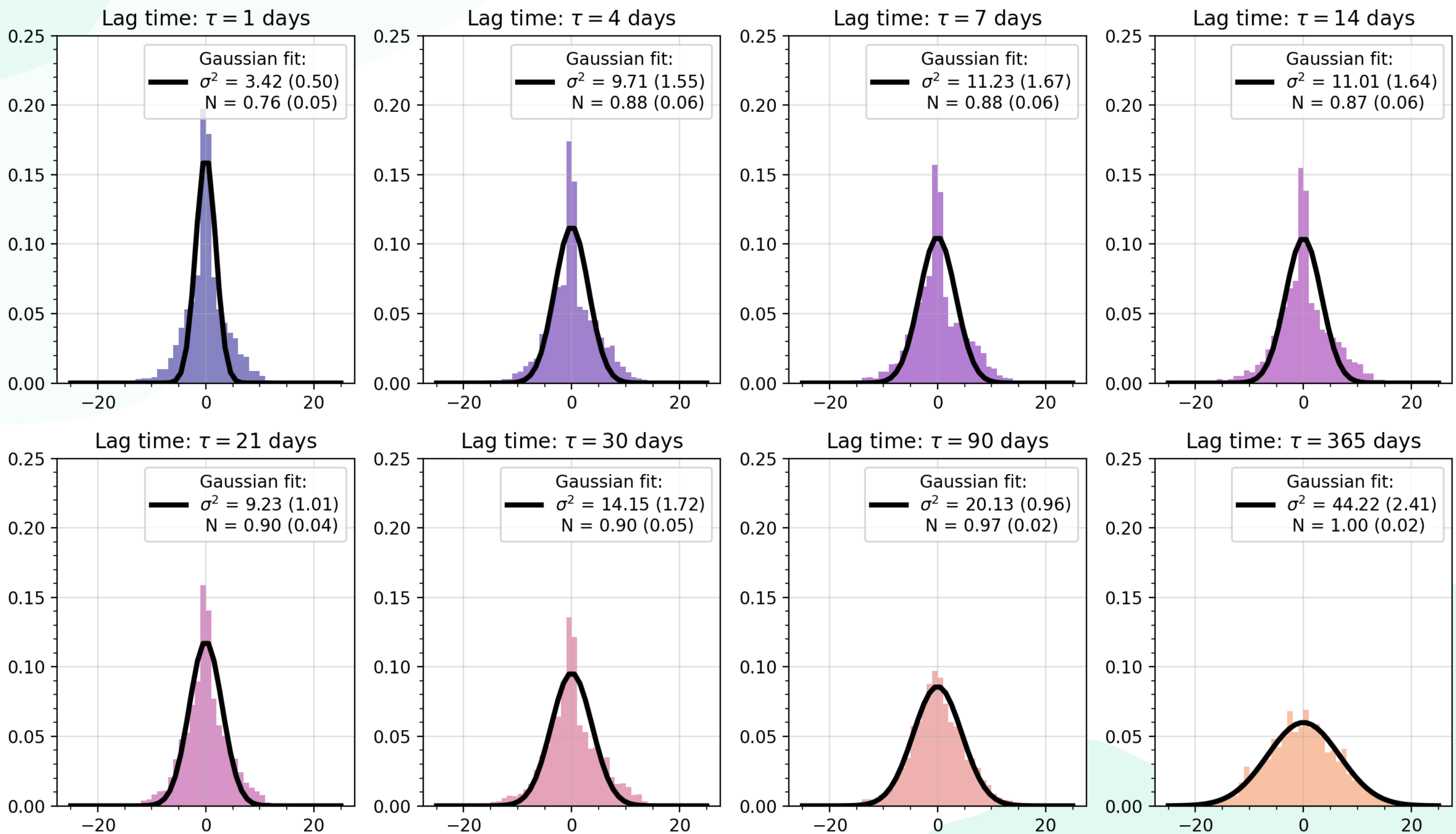




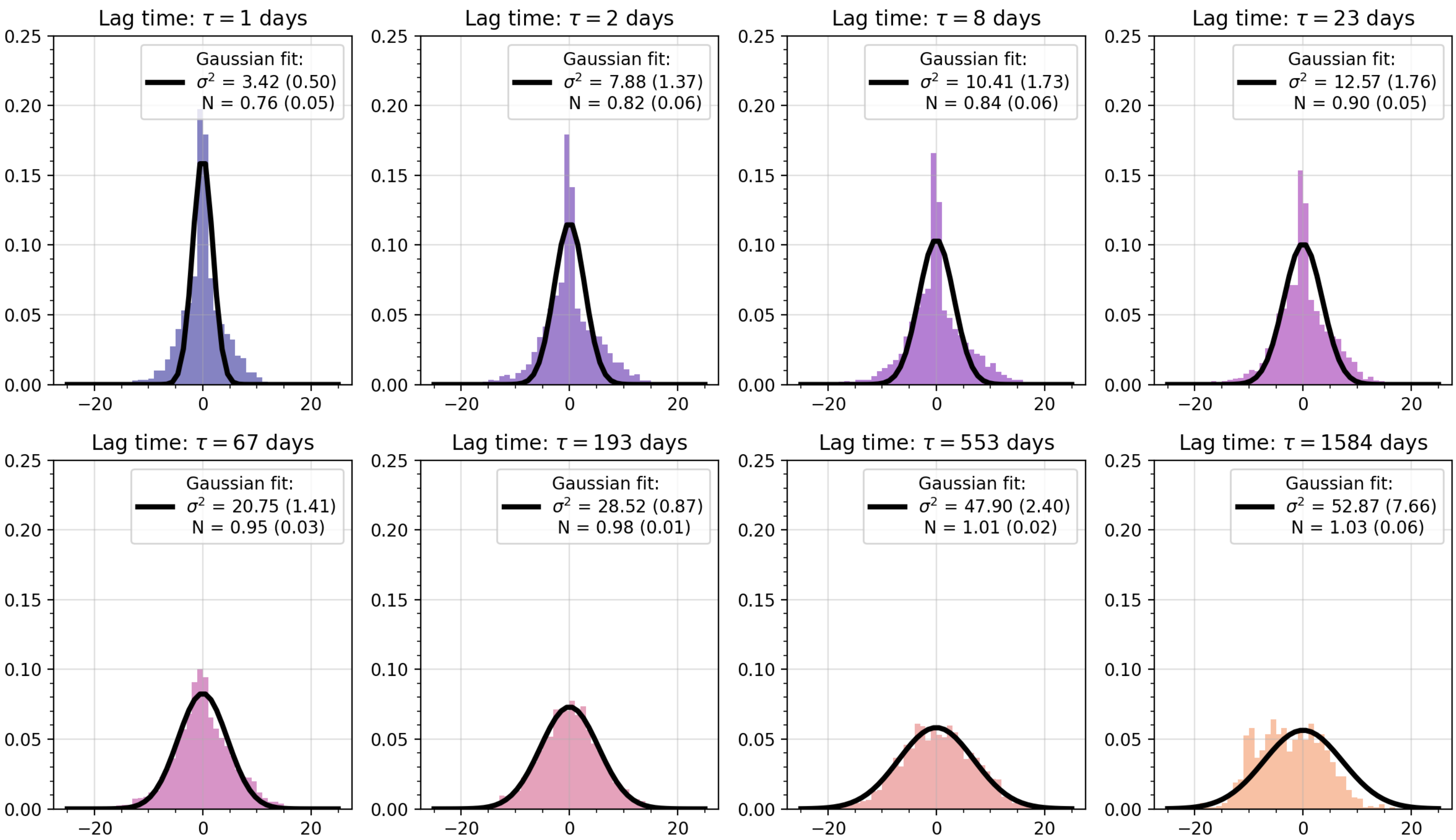
[PDF] Gaussian Fitting



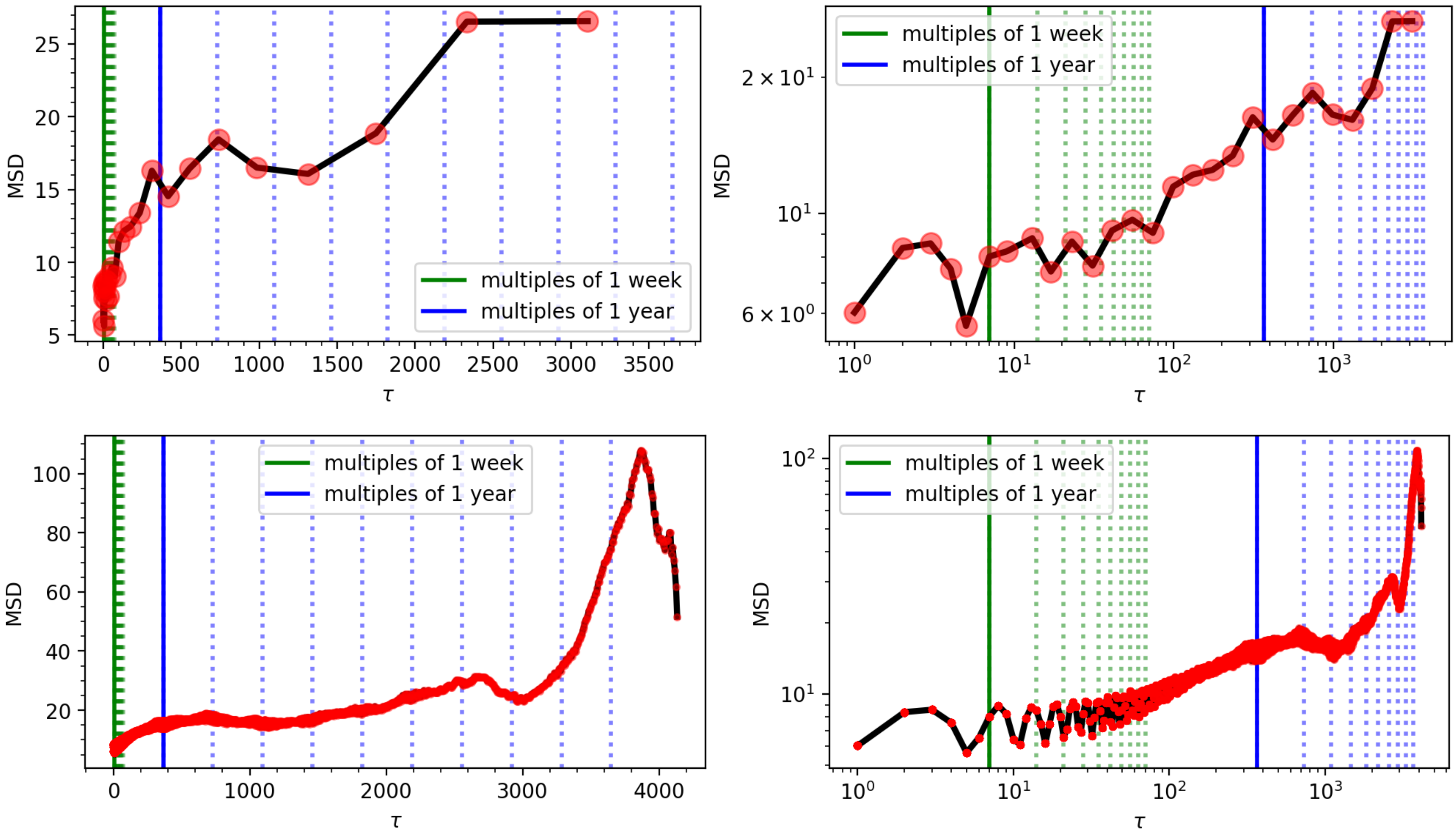
[PDF] Relevant Lag Times



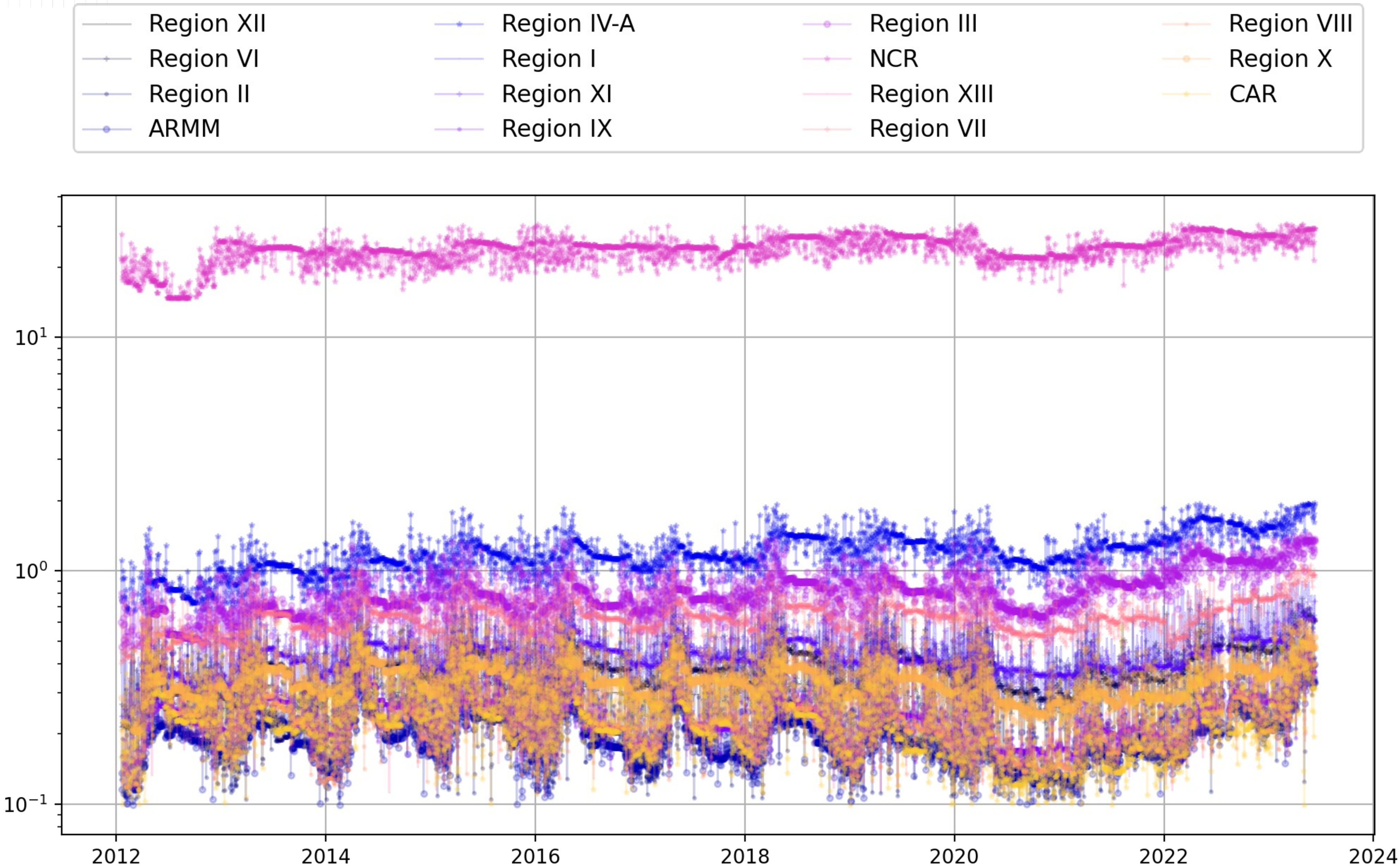
[PDF] Log-spaced Lag Times



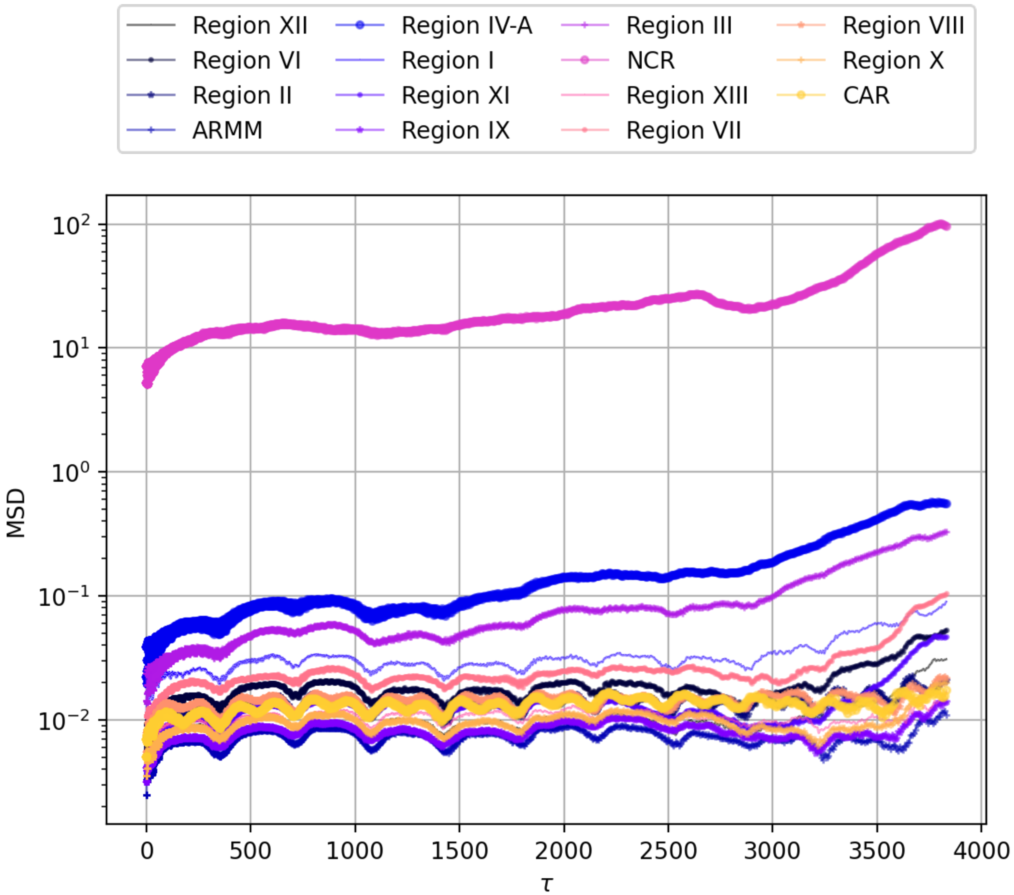
[MSD] Discrete and Continuous

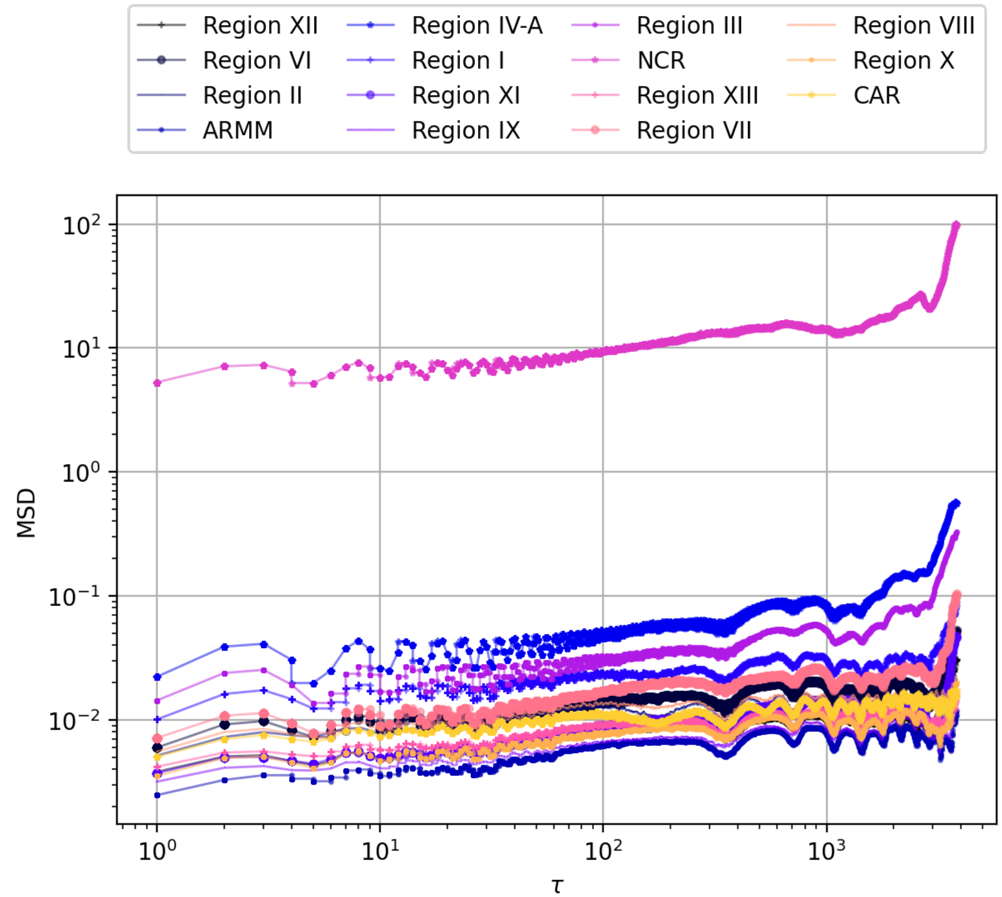


[NTL] Regional Monthly NTL

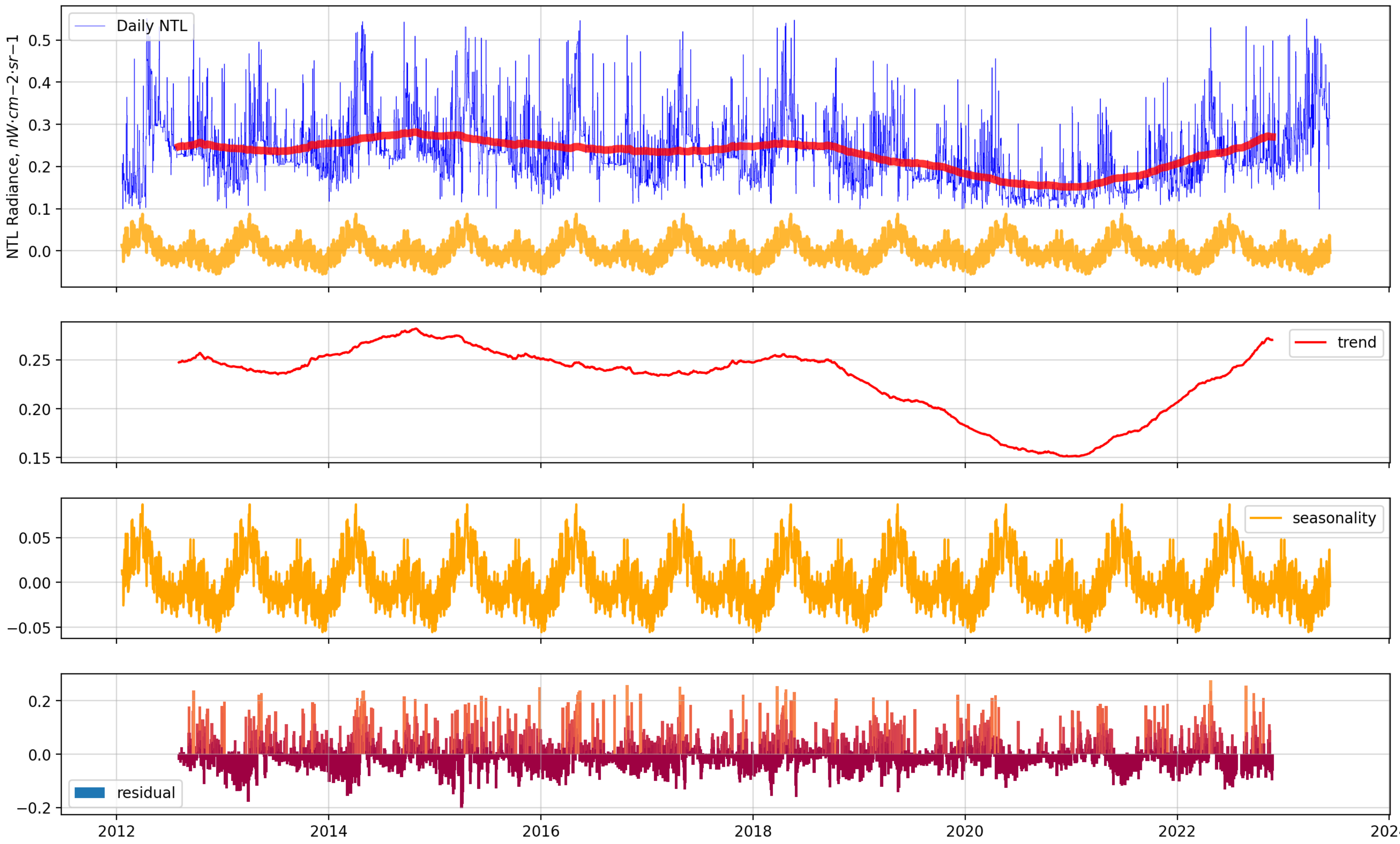


[MSD] Regional Monthly NTL

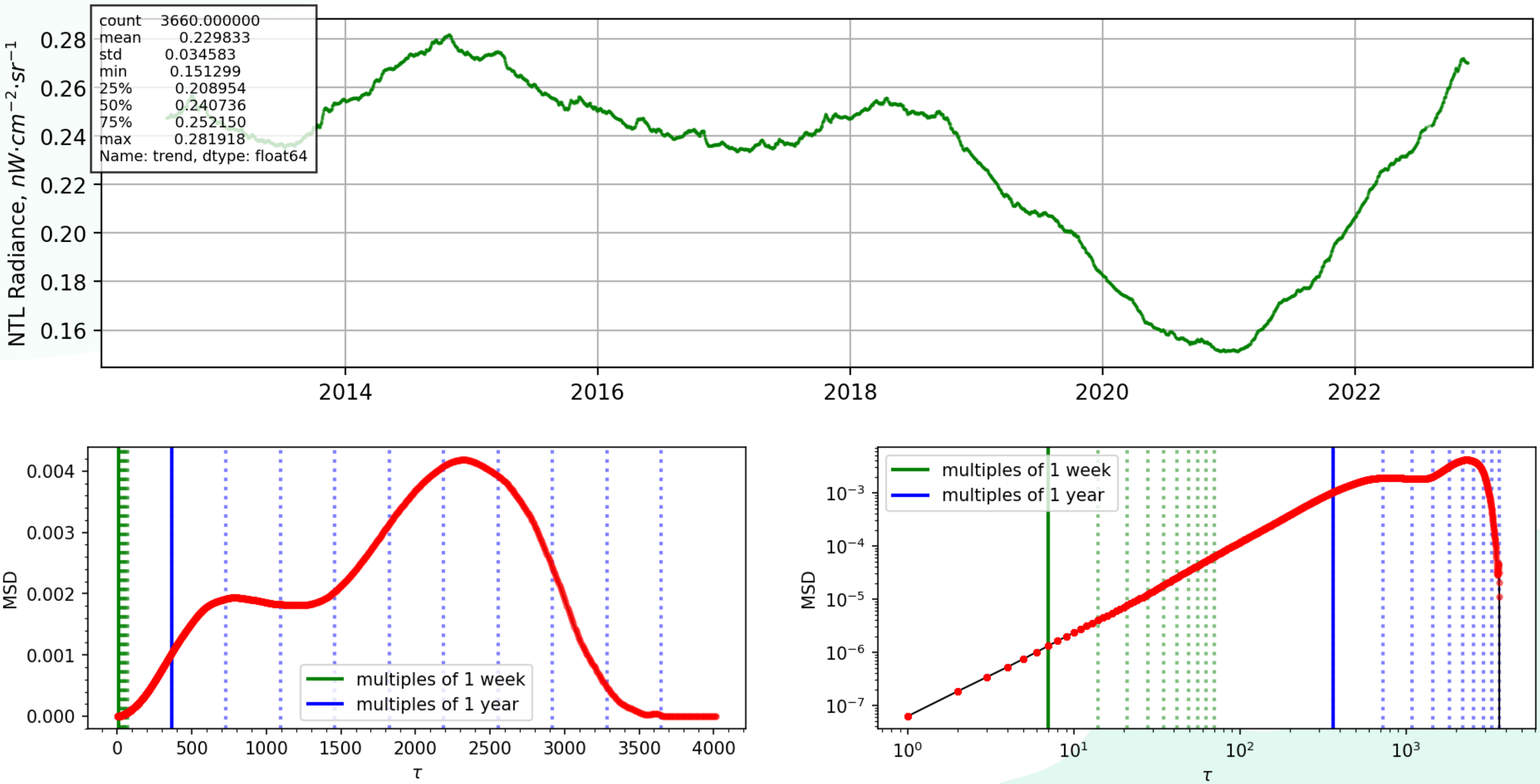




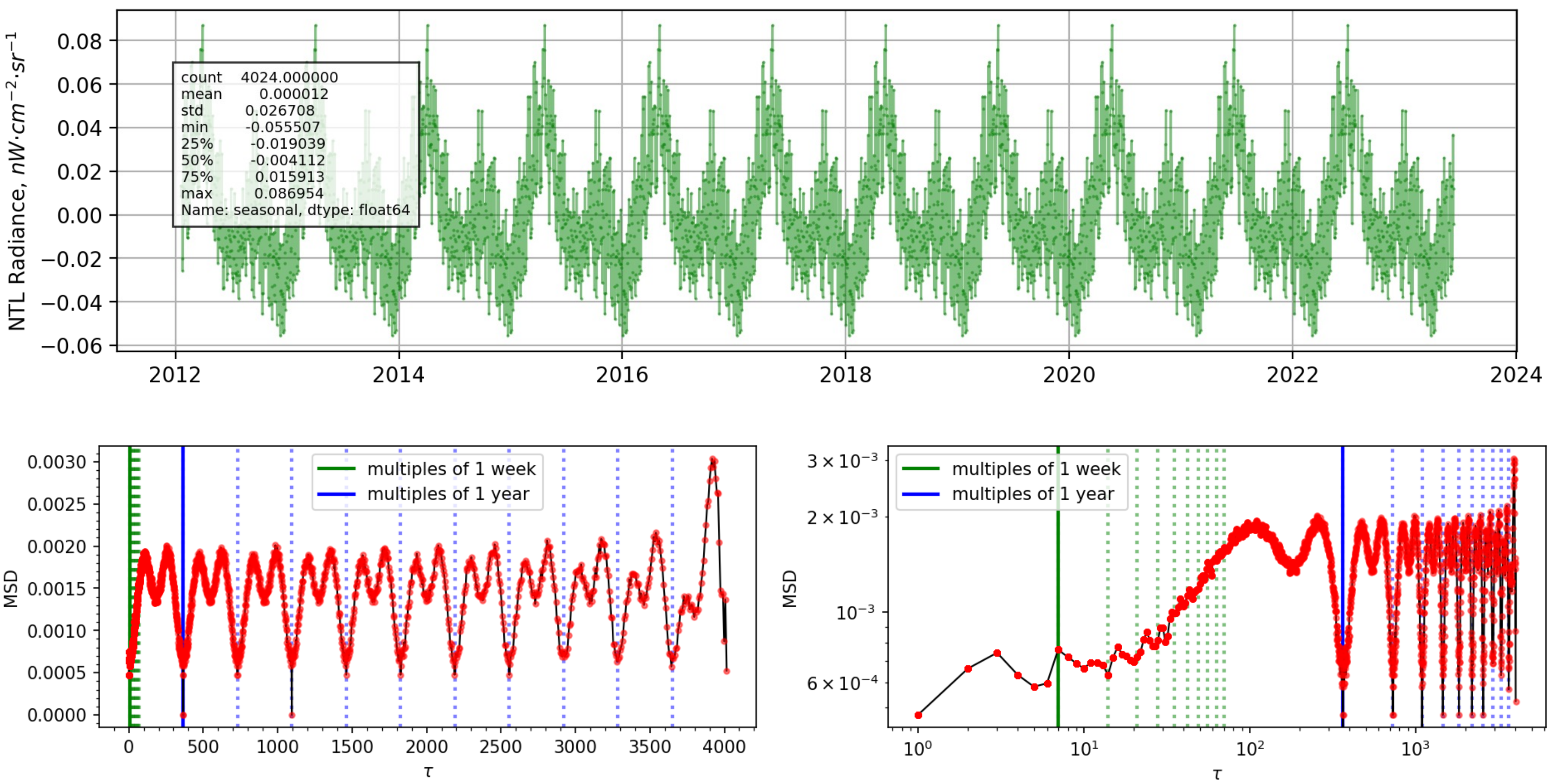
[STL] Decomposing NTL using LOESS



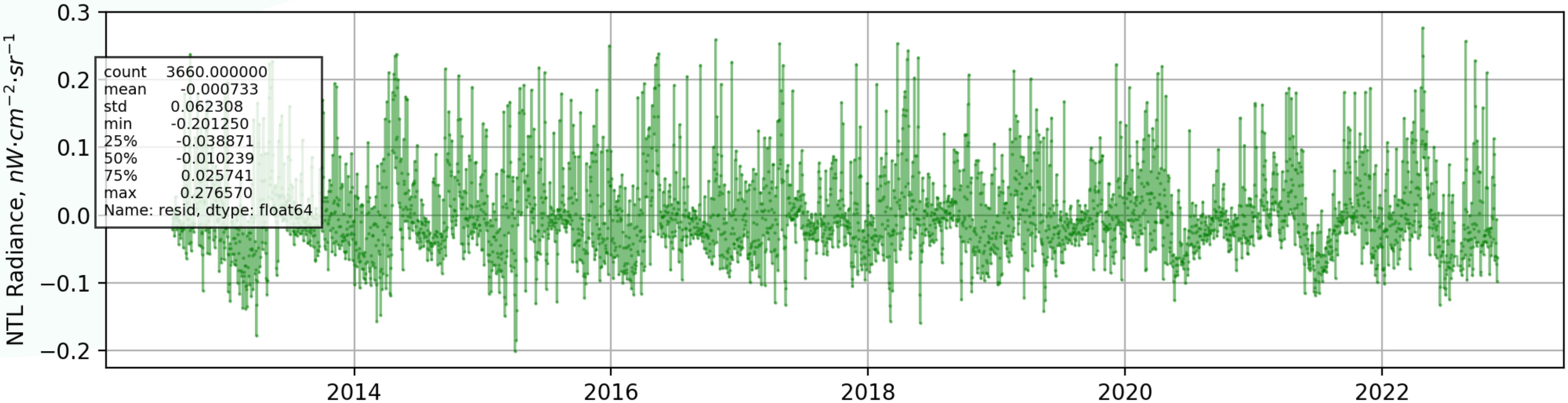
[MSD] NTL Trend of NCR

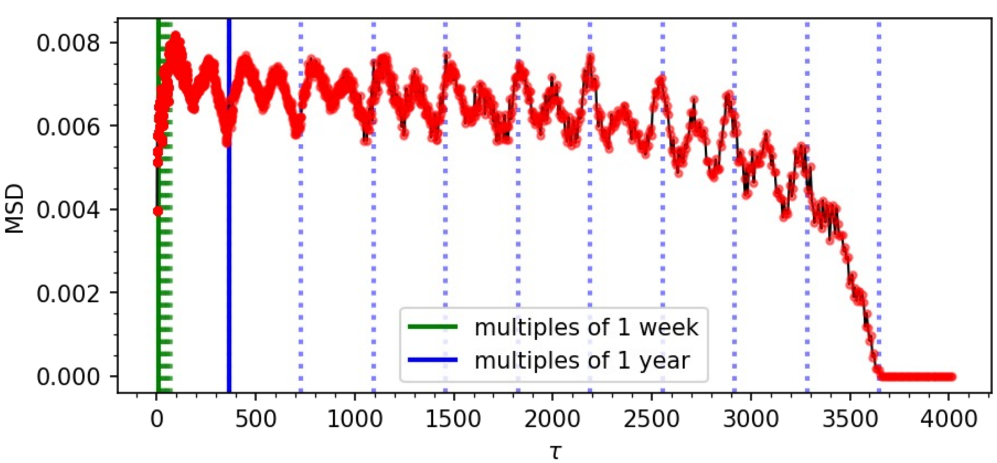


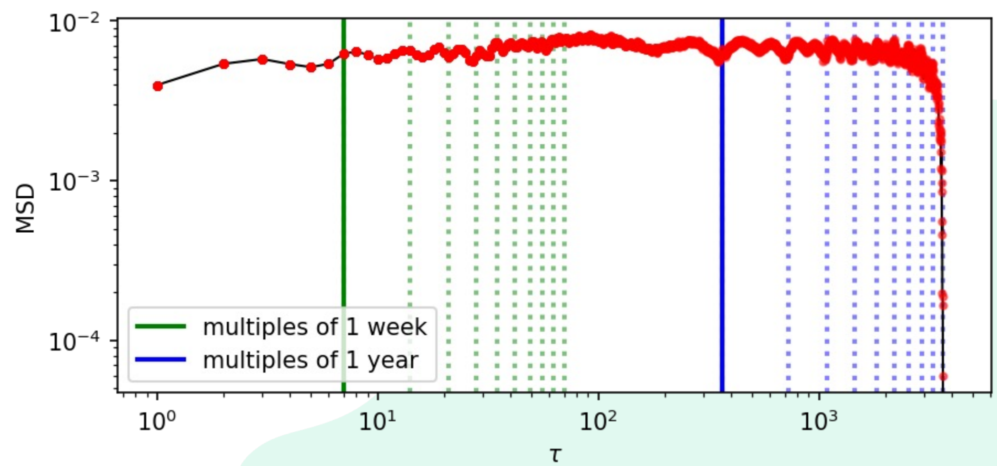
[MSD] NTL Seasonality of NCR



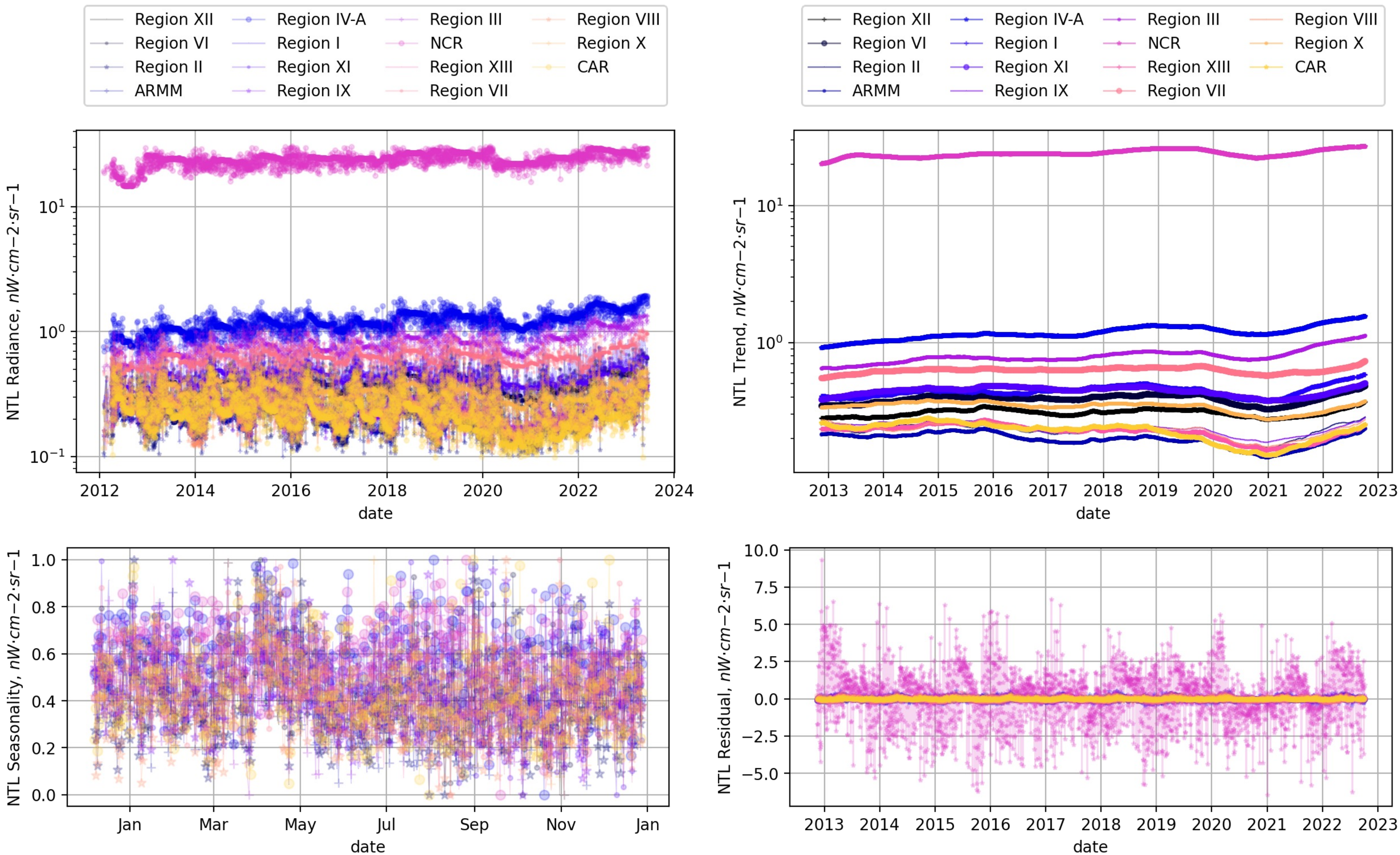
[MSD] NTL Residual of NCR



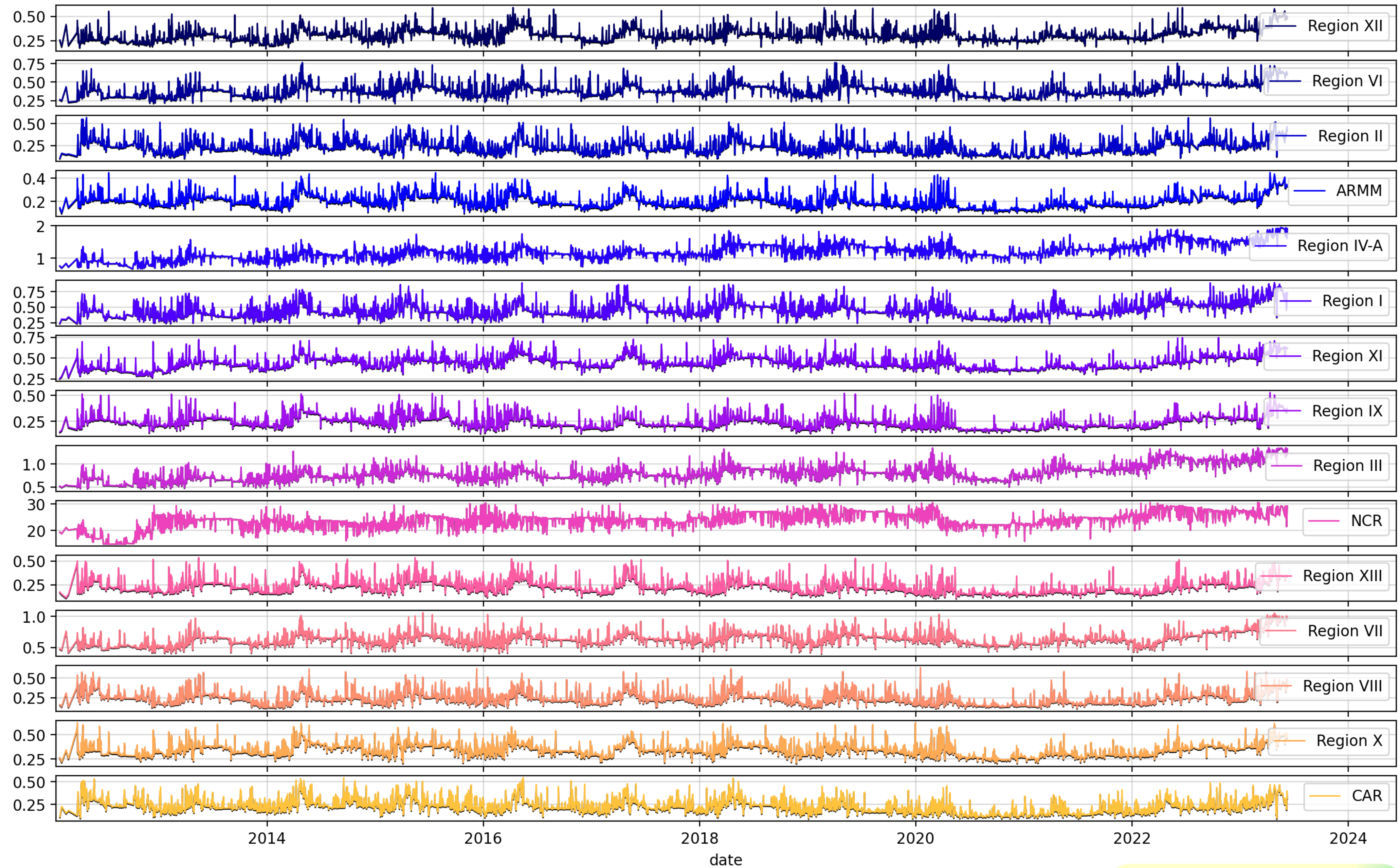




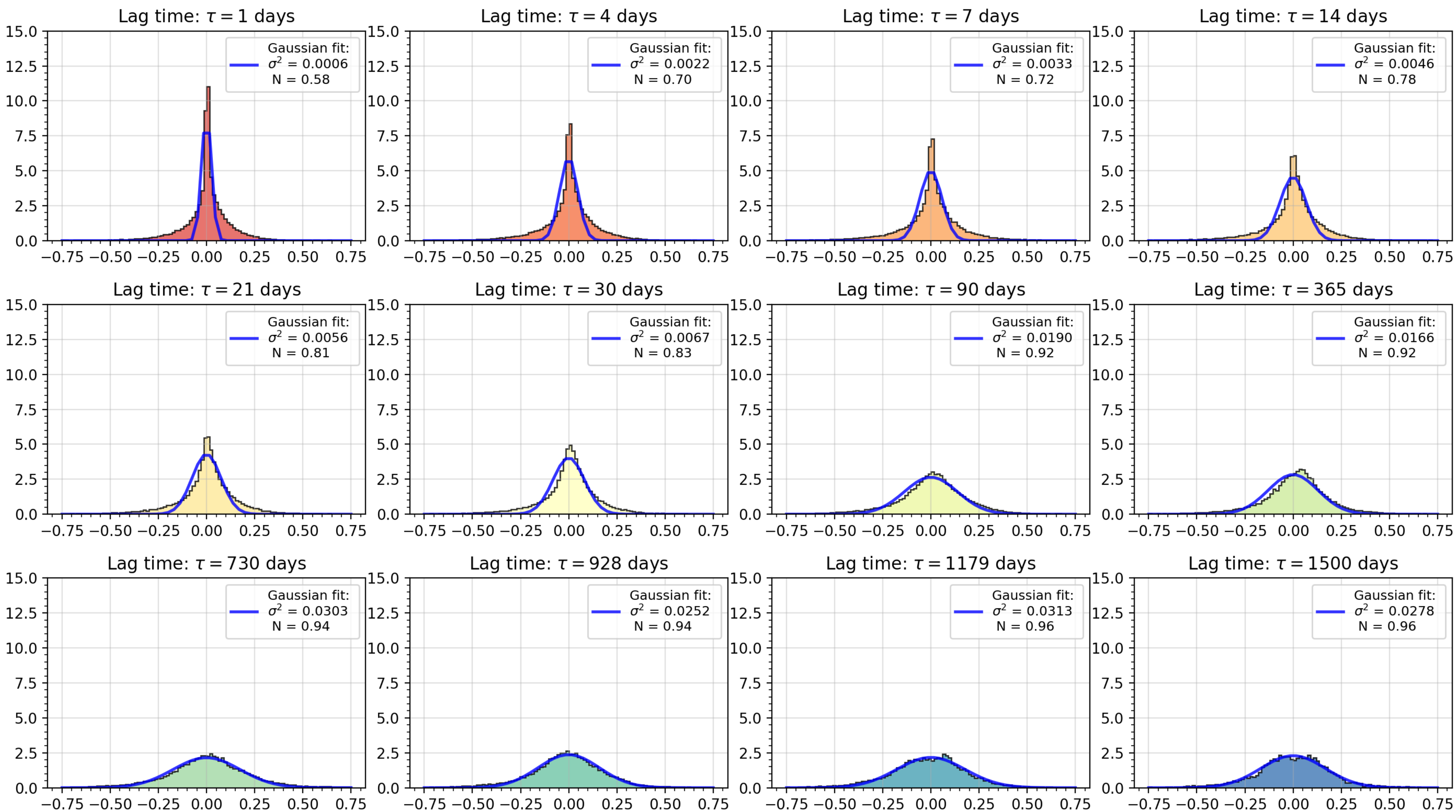
Regional NTL (STL disaggregated)



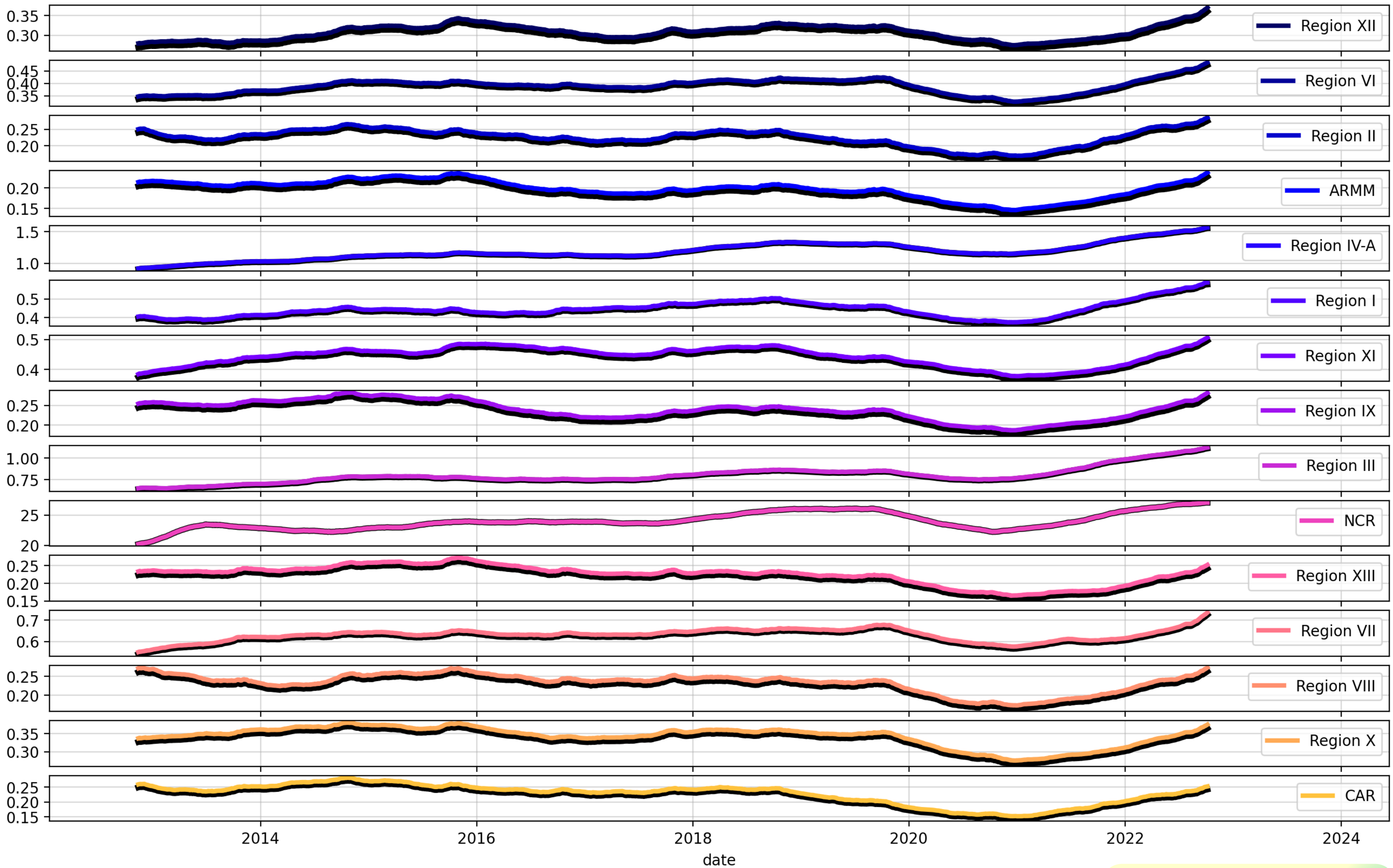
Regional Monthly Average NTL



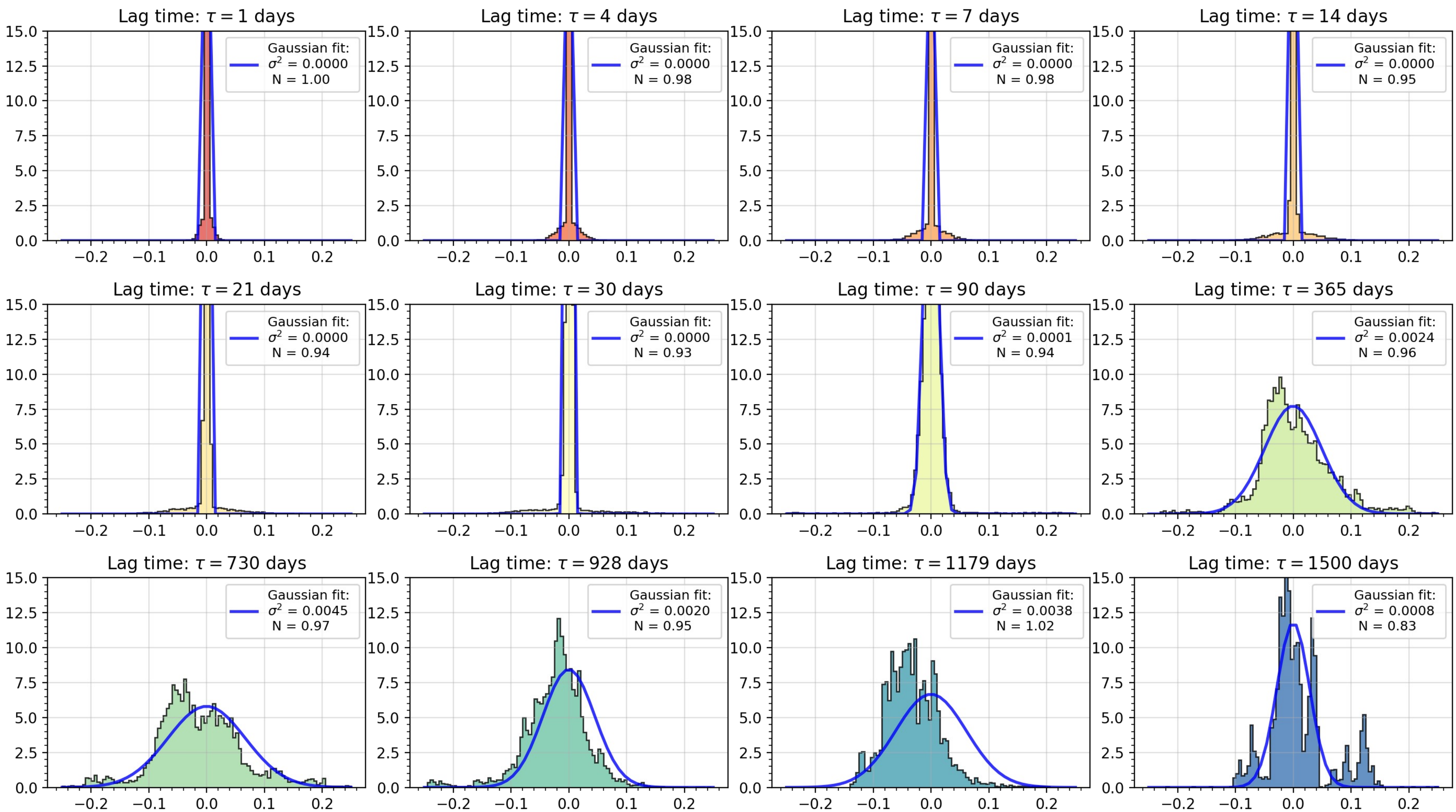
[PDF] Regional NTL raw values



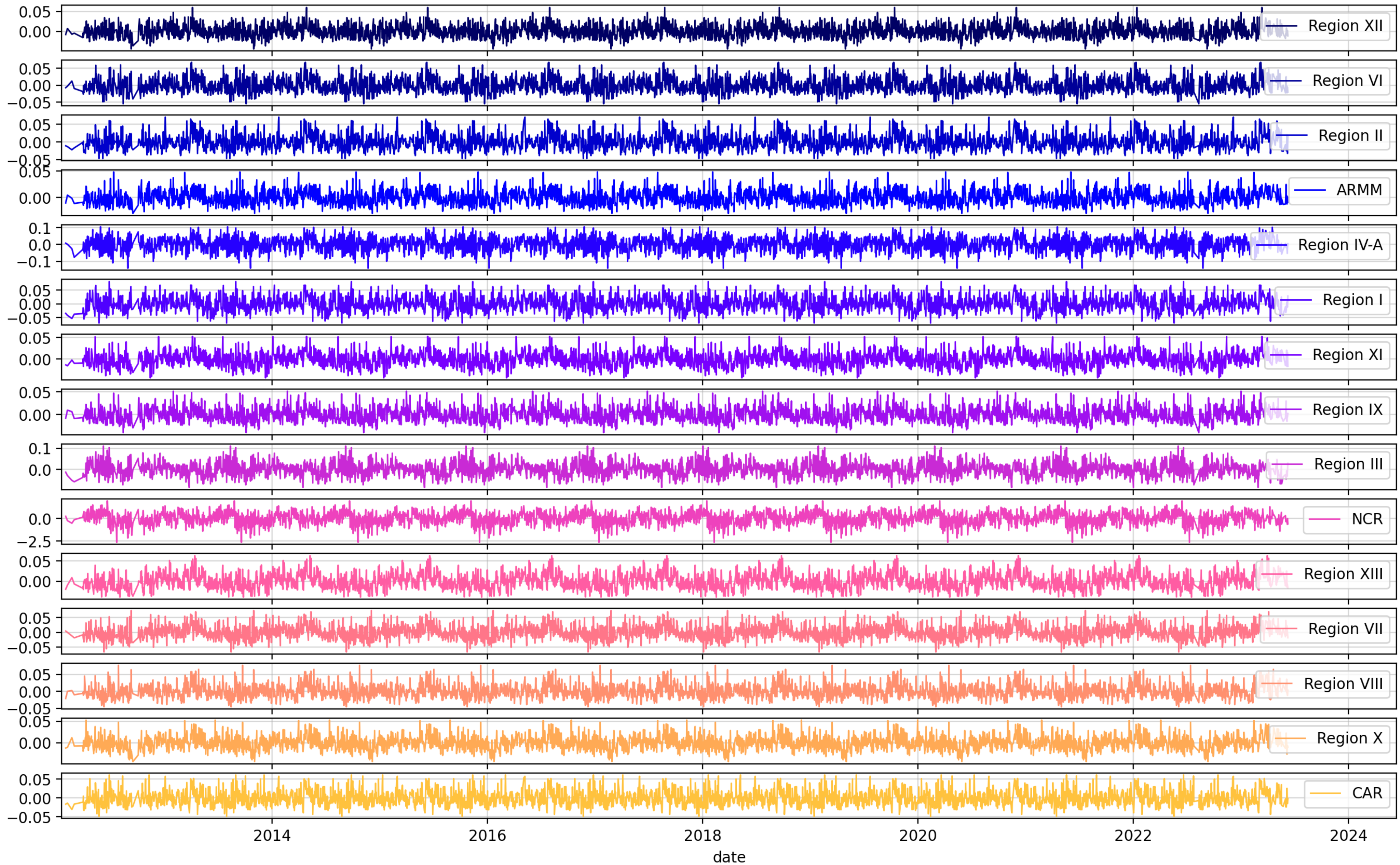
Regional NTL Trends



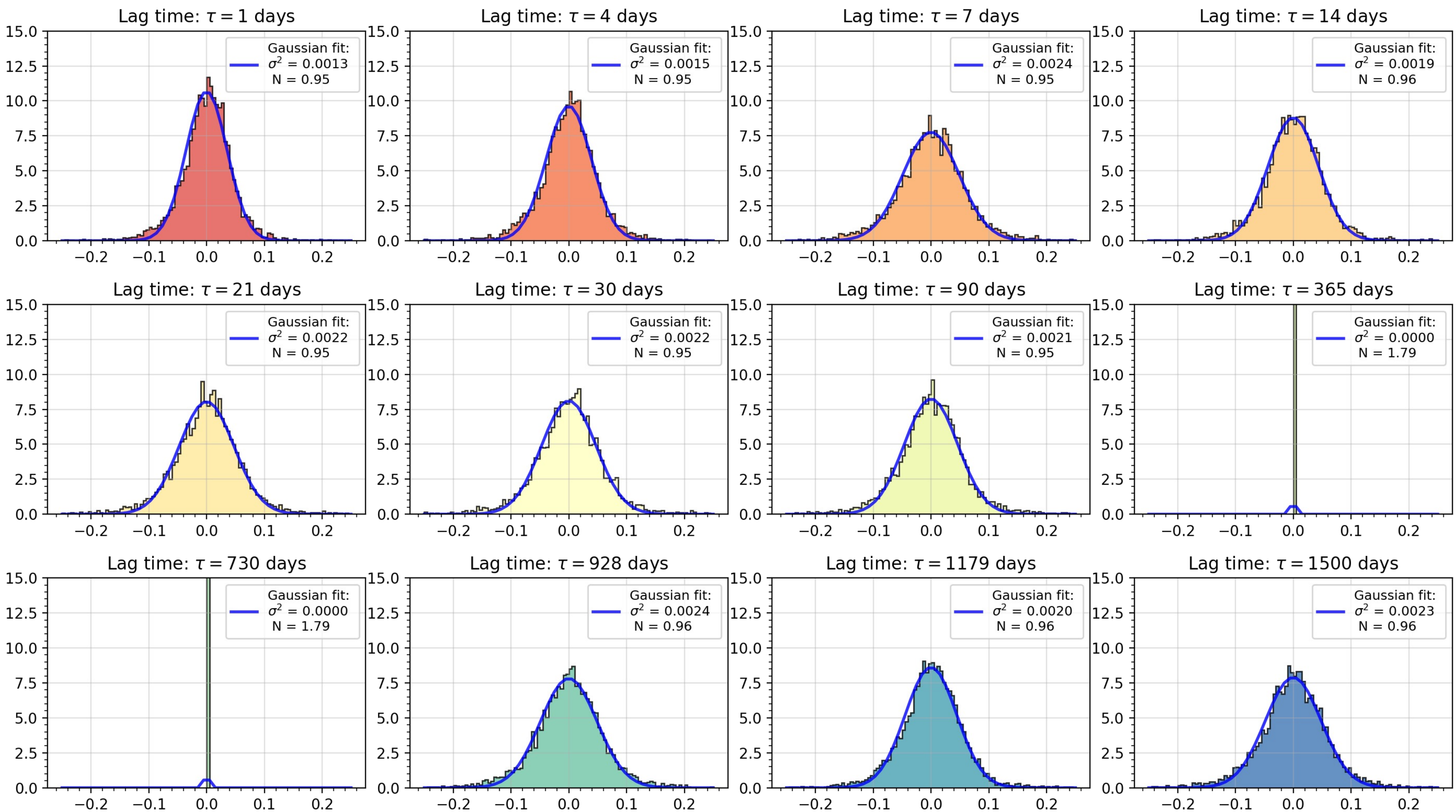
[PDF] Regional NTL Trends



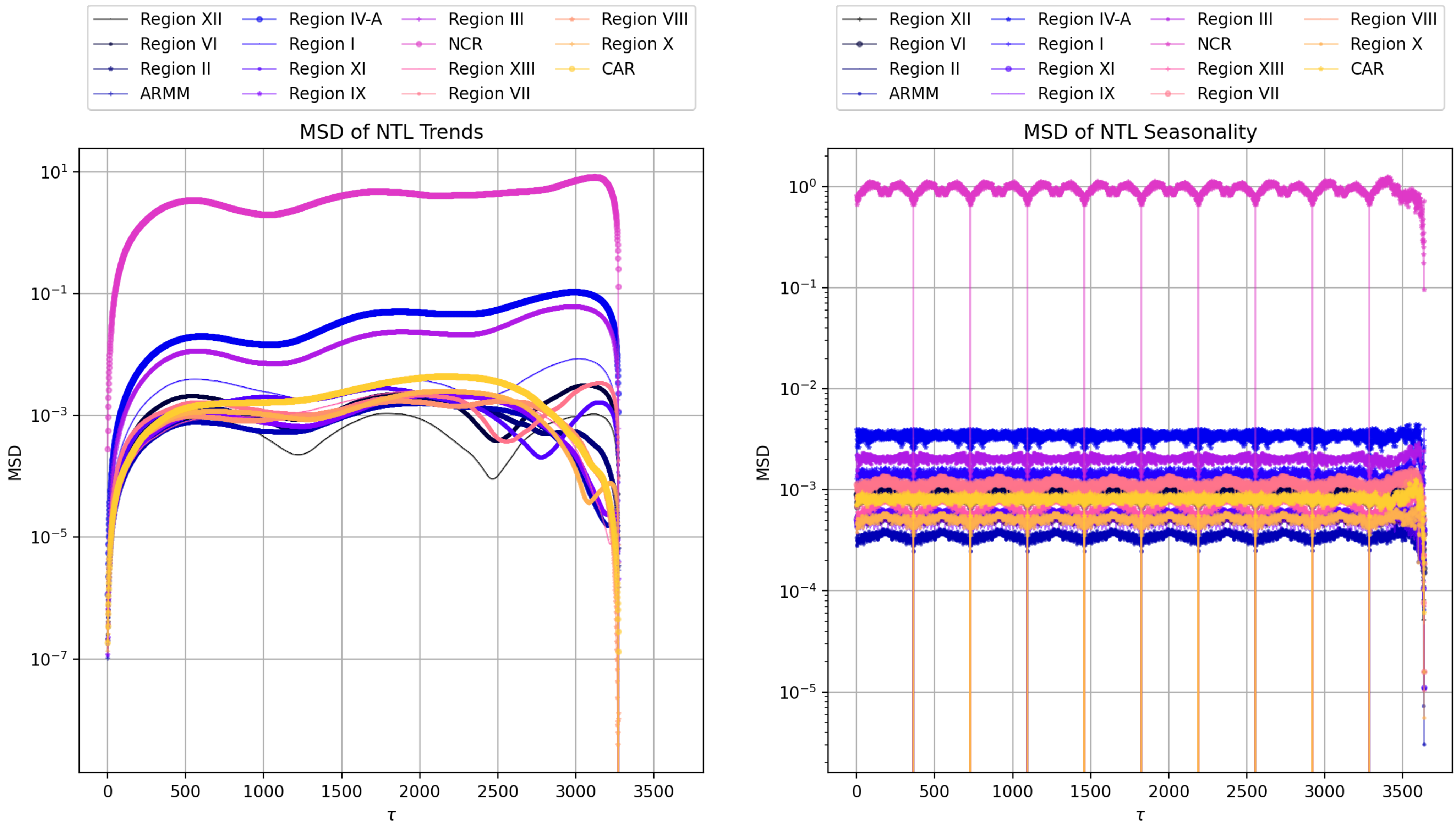
Regional NTL Seasonality



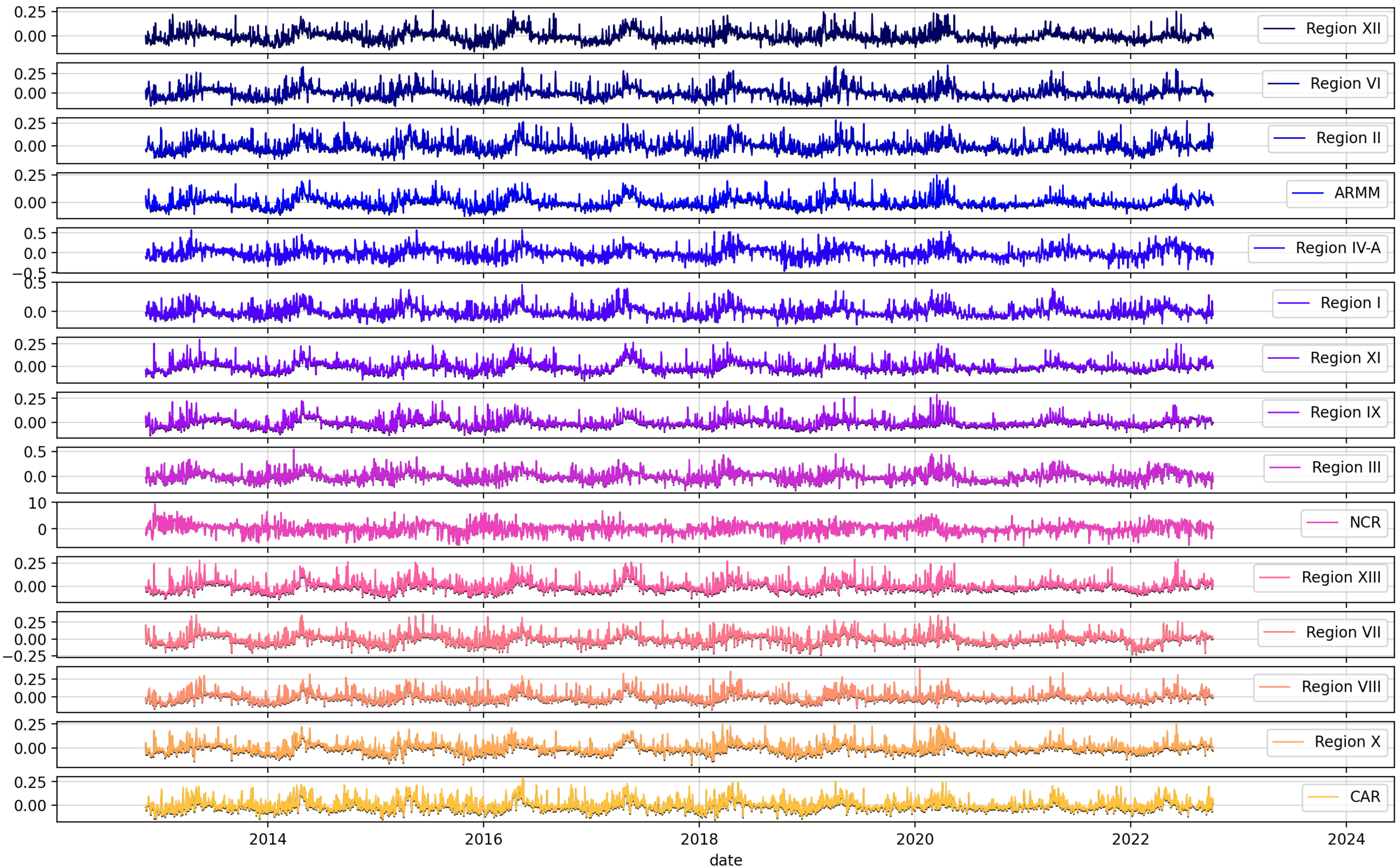
[PDF] Regional NTL Seasonality



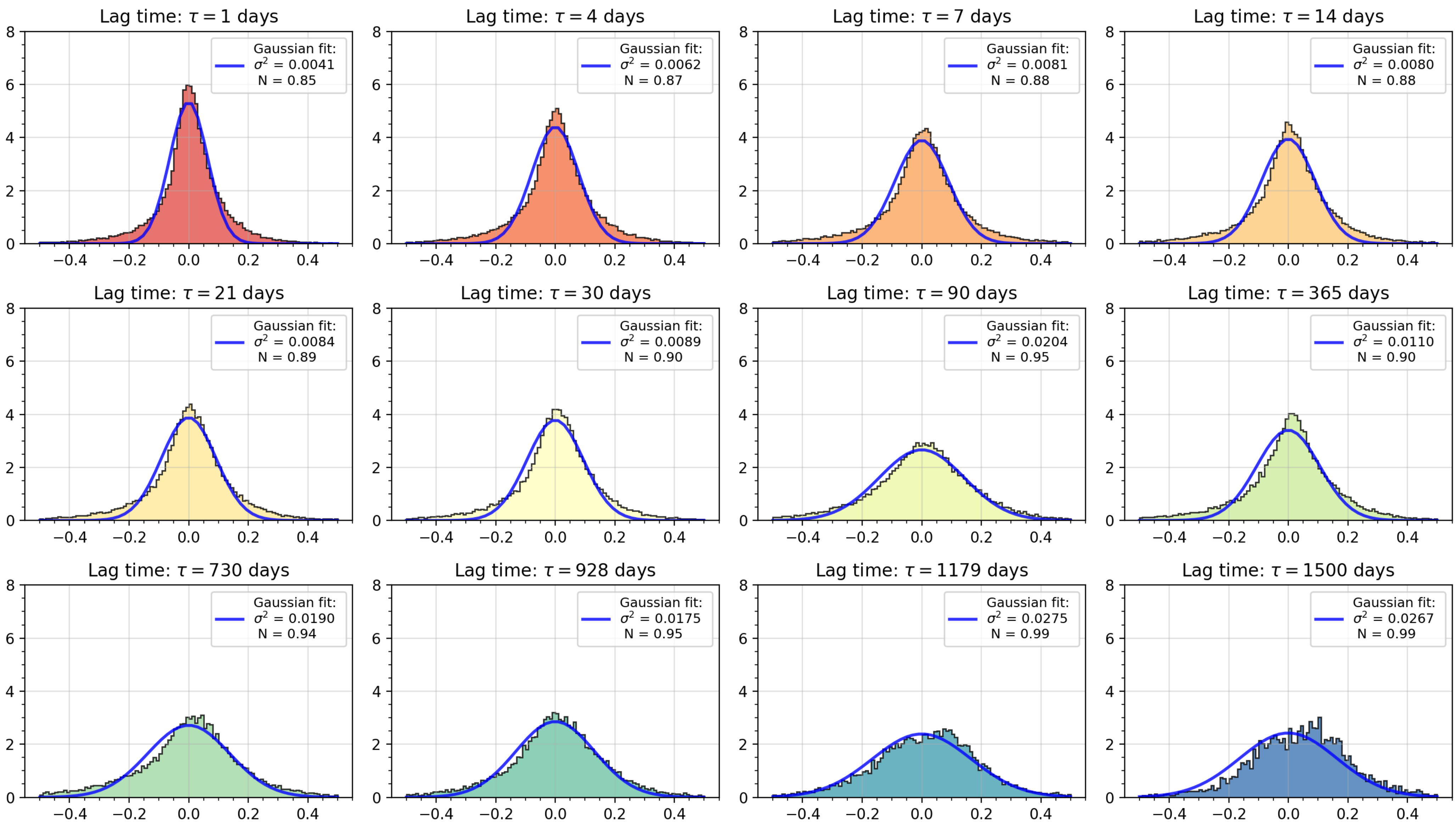
[MSD] NTL Trend and Seasonality



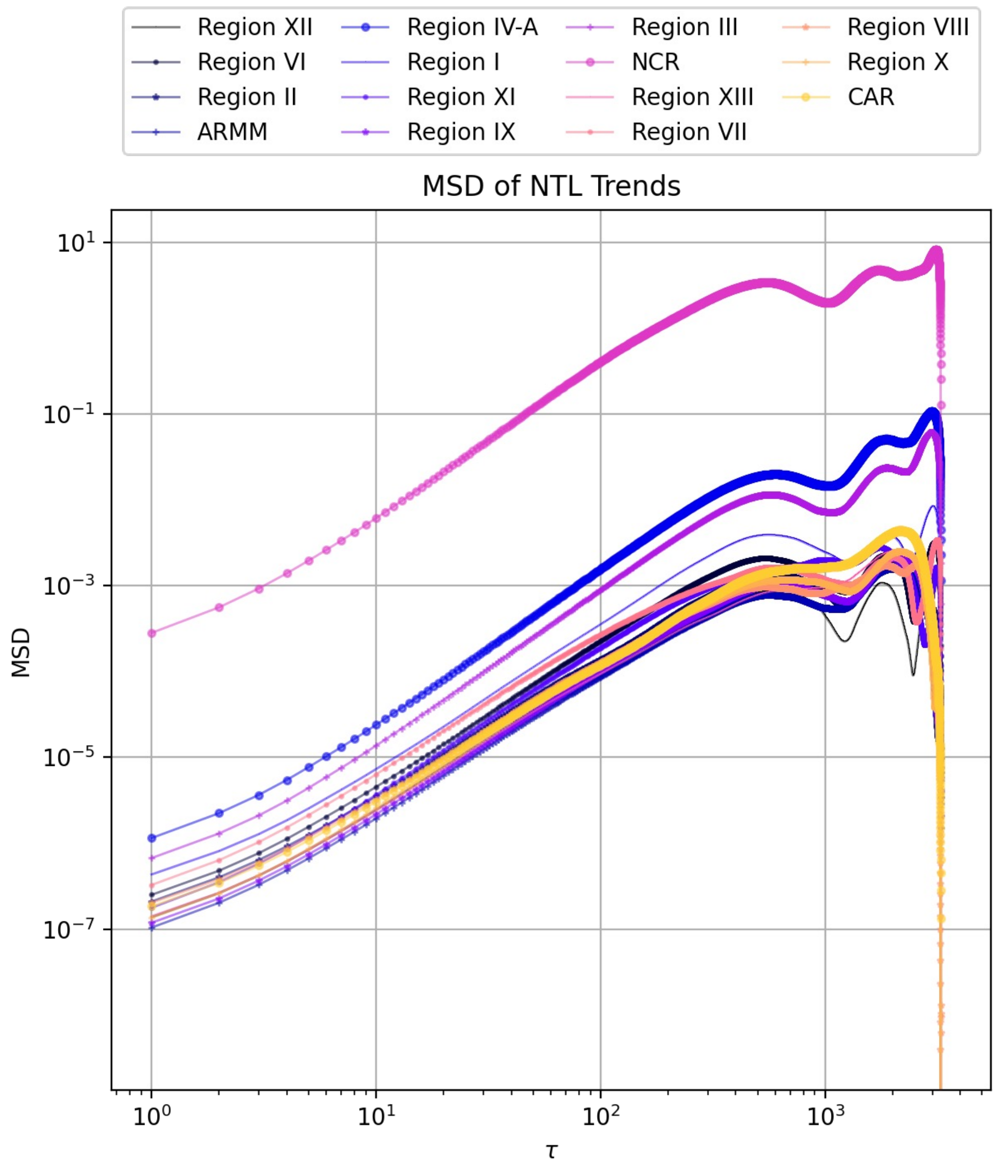
Regional NTL Residuals

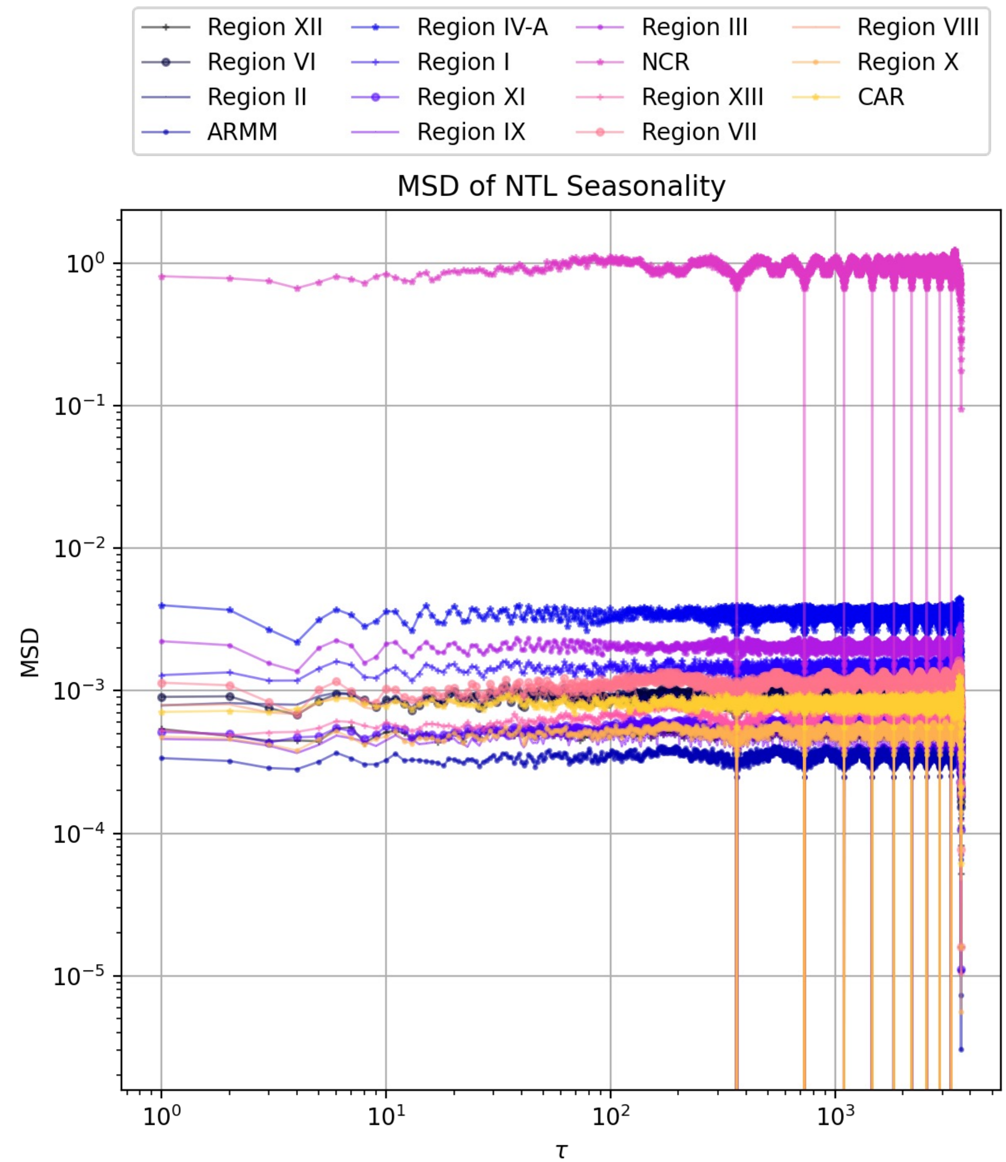


[PDF] Regional NTL Residuals



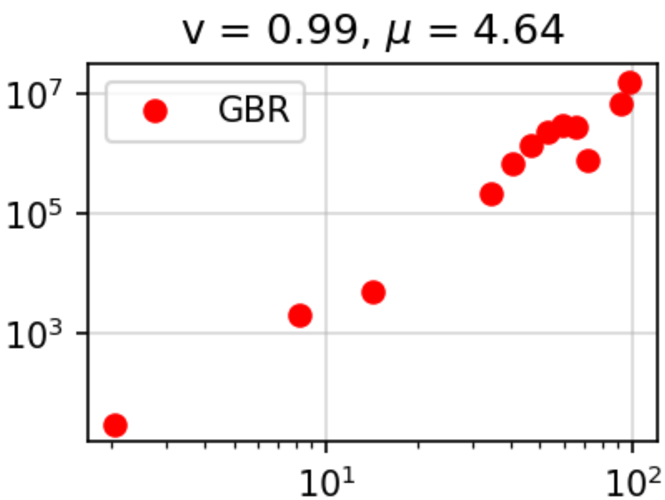
[MSD] NTL Trend and Seasonality

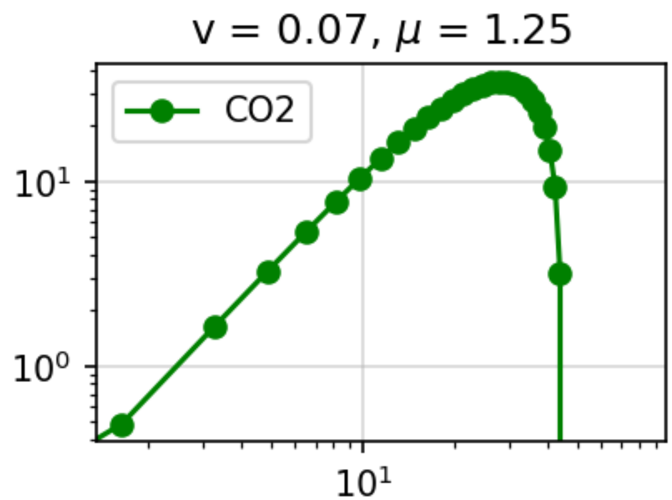


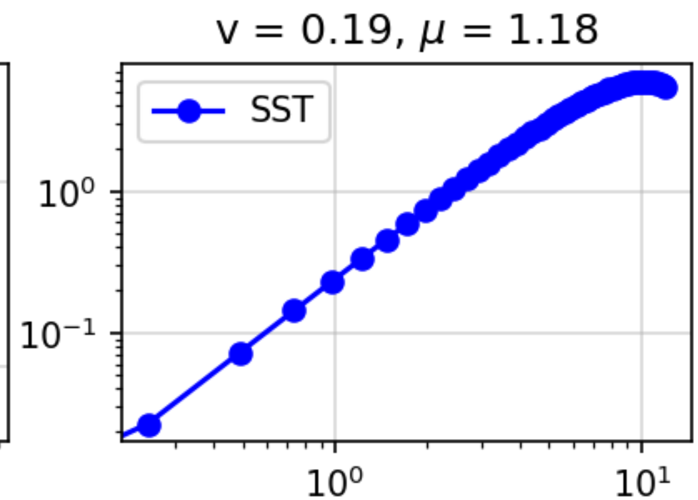


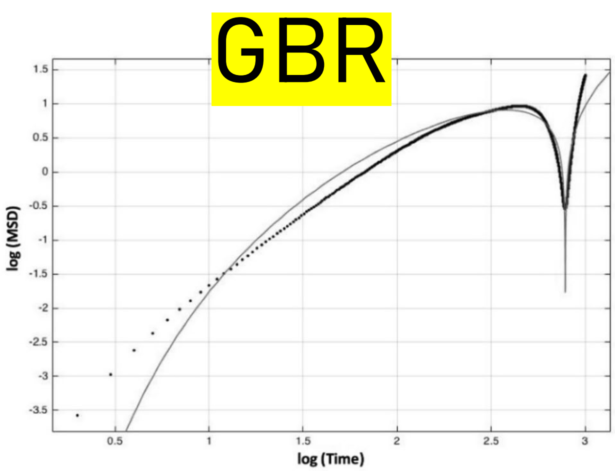
[MSD] Candidate MSD

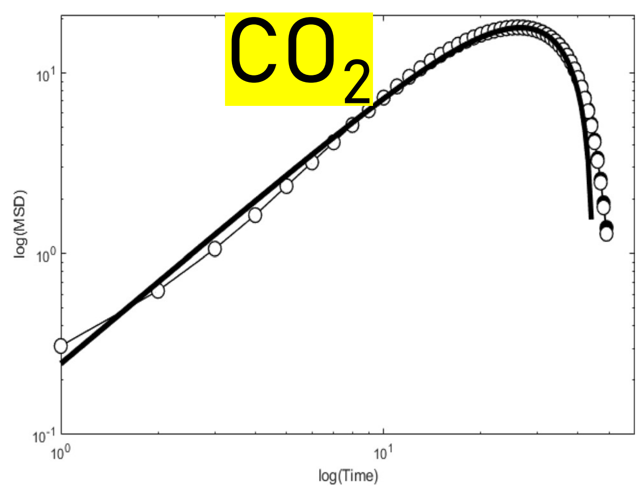
$$MSD = \frac{\Gamma(\mu)\cdot\cos(vT/2)\cdot J_{\mu-\frac{1}{2}}(vT/2)}{\pi^{-\frac{1}{2}}\cdot T^{\frac{1}{2}-\mu}\cdot v^{\mu-\frac{1}{2}}}$$

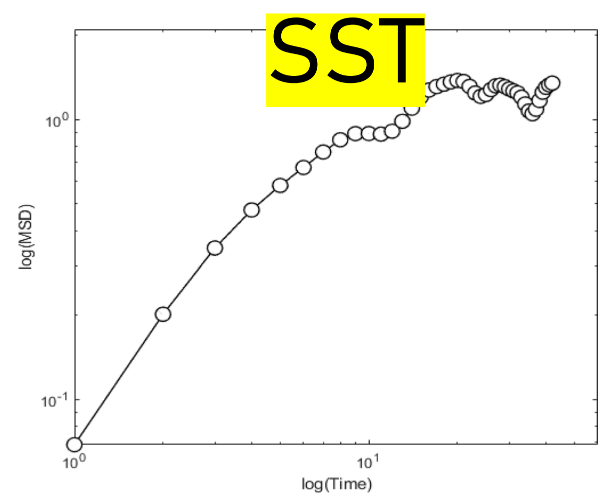












[MSD] Replicating Figures

- $$MSD = \frac{\Gamma(\mu)\cdot\cos(vT/2)\cdot J_{\mu-\frac{1}{2}}(vT/2)}{\pi^{-\frac{1}{2}}\cdot T^{\frac{1}{2}-\mu}\cdot v^{\mu-\frac{1}{2}}}$$

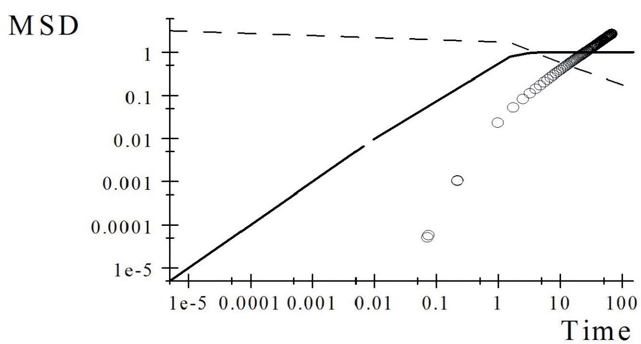
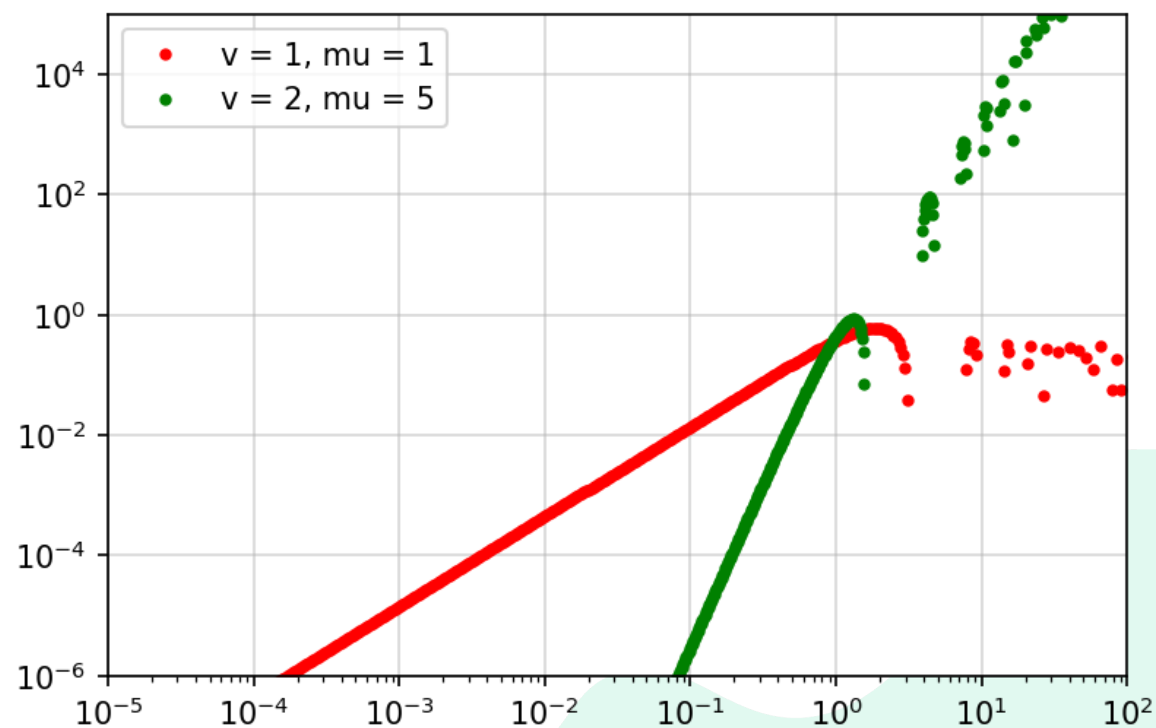


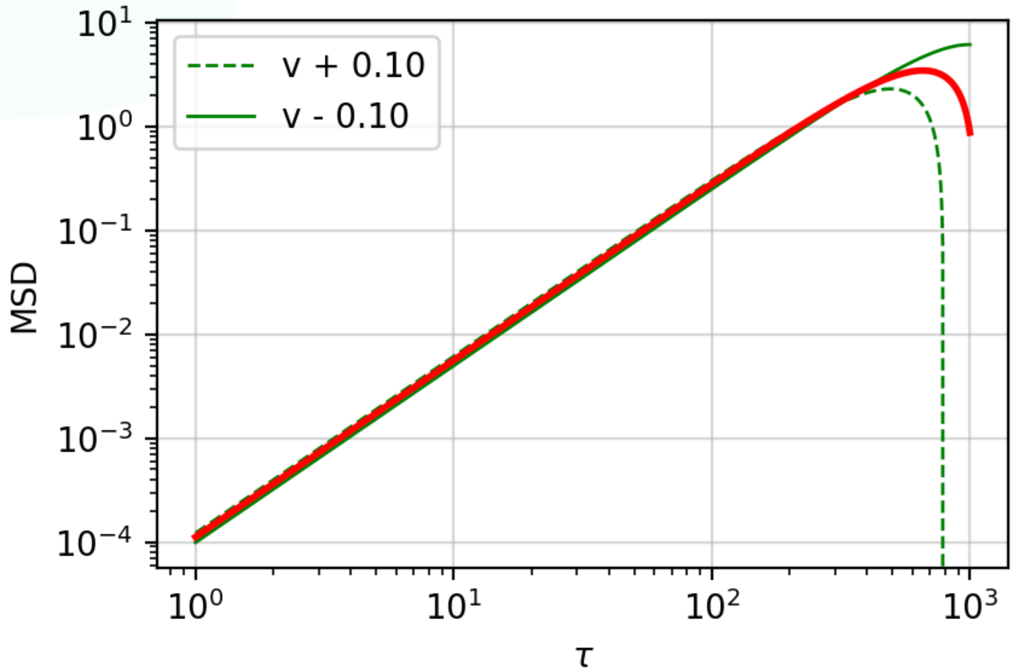
Fig. 5.3. Log-log graph of MSD_{eB} versus time for $\mu = 1$, $\nu = 1$ (solid line); $\mu = 1$, $\nu = 1/2$ (dashed line); and $\mu = 5$, $\nu = 2$ (circle).

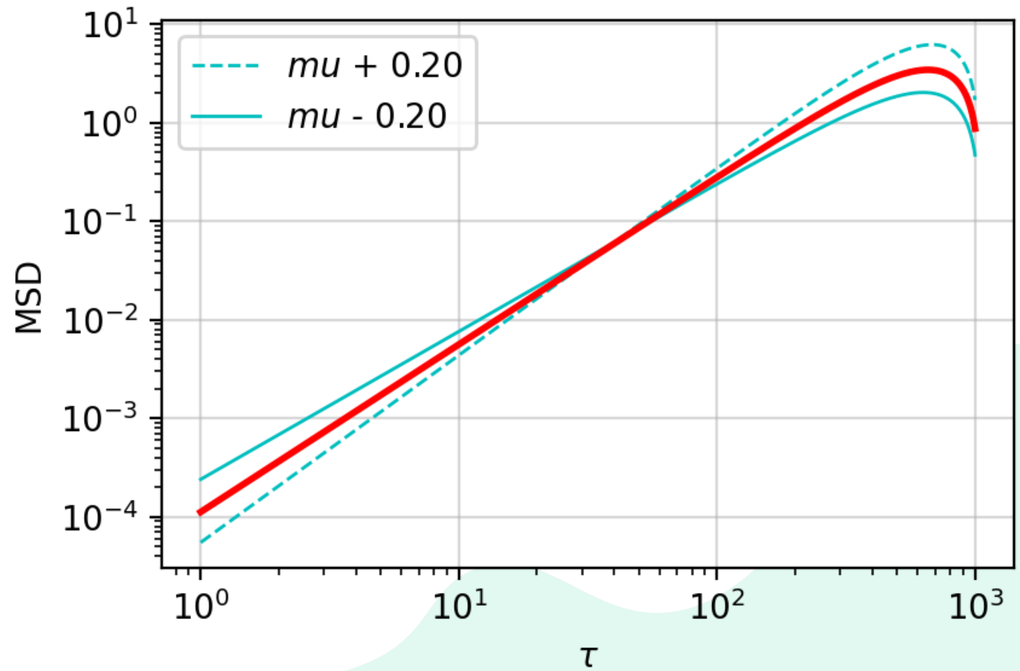


[MSD] Fitting Theoretical MSDs

$$x(T) = x_0 + \int_0^T (T-t)^{\frac{\mu-1}{2}} t^{\frac{\mu-1}{2}} \sqrt{\cos(vt)\, dB(t)}$$

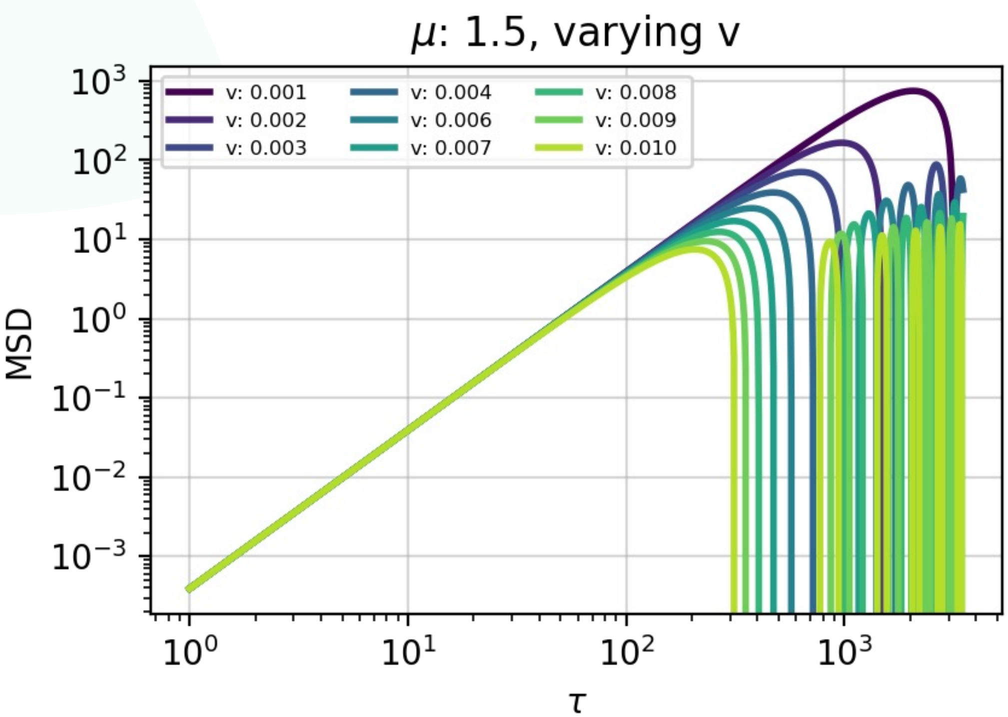
$$MSD = \frac{\Gamma(\mu) \cdot \cos(vT/2) \cdot J_{\mu-\frac{1}{2}}(vT/2)}{\pi^{-\frac{1}{2}} \cdot T^{\frac{1}{2}-\mu} \cdot v^{\mu-\frac{1}{2}}}$$

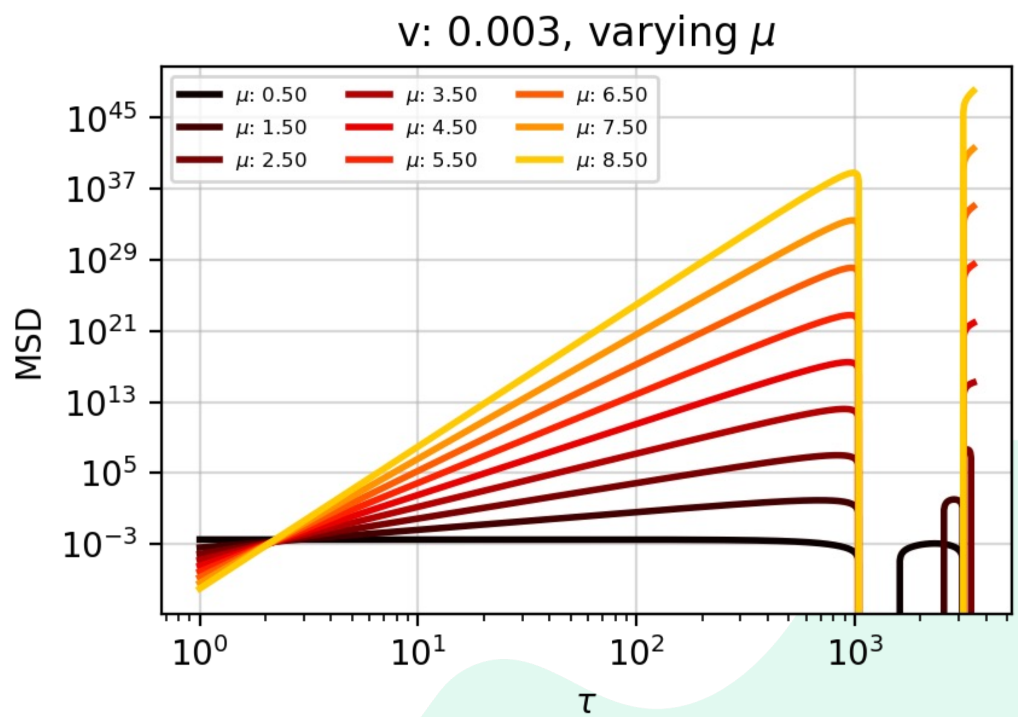




[MSD] Parameter Variations

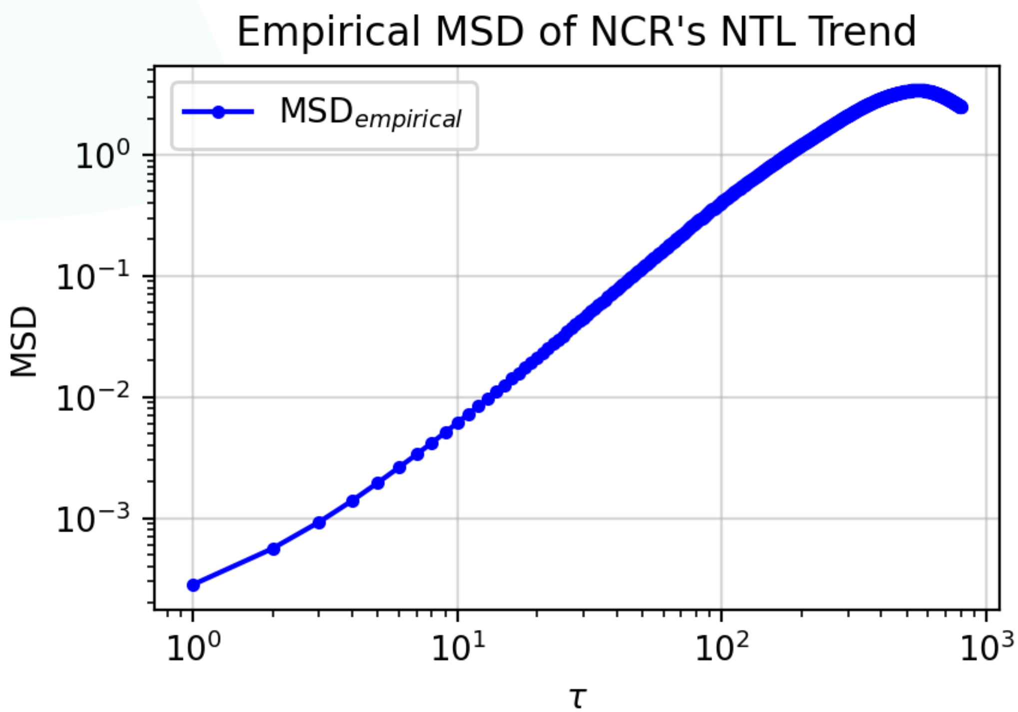
$$MSD = \frac{\Gamma(\mu) \cdot \cos(vT/2) \cdot J_{\mu-\frac{1}{2}}(vT/2)}{\pi^{-\frac{1}{2}} \cdot\ T^{\frac{1}{2}-\mu} \cdot v^{\mu-\frac{1}{2}}}$$

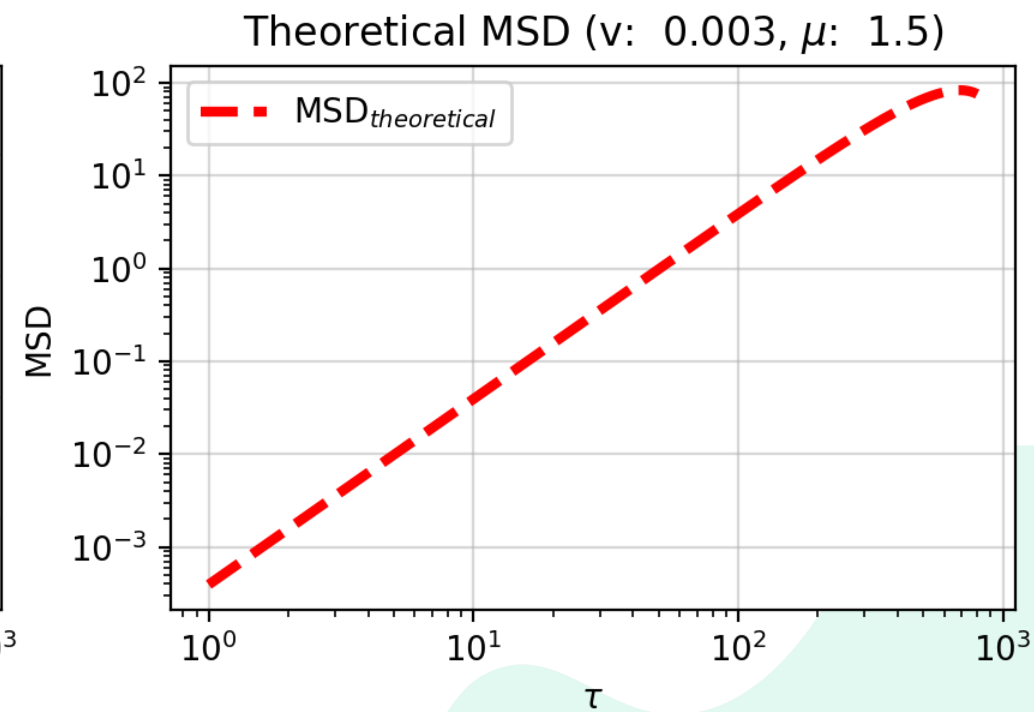




[MSD] Empirical vs Theoretical MSD

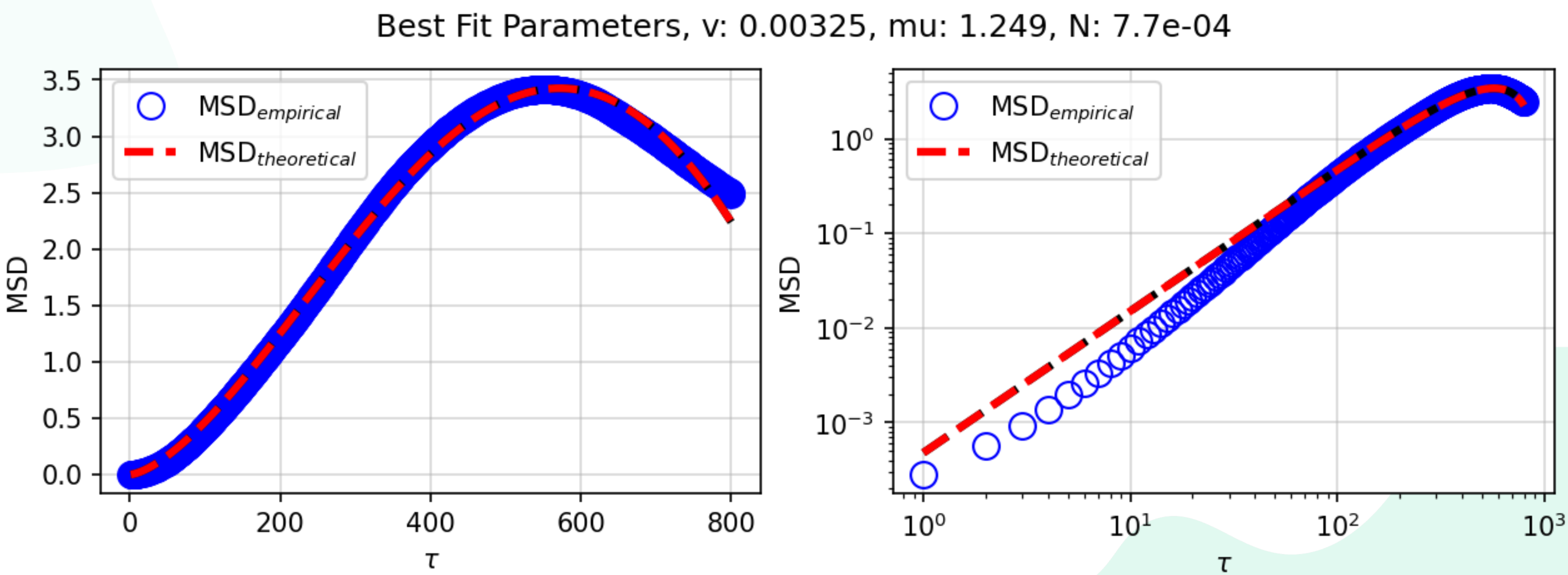
$$MSD = \frac{\Gamma(\mu) \cdot \cos(vT/2) \cdot J_{\mu-\frac{1}{2}}(vT/2)}{\pi^{-\frac{1}{2}} \cdot \; T^{\frac{1}{2}-\mu} \cdot v^{\mu-\frac{1}{2}}}$$



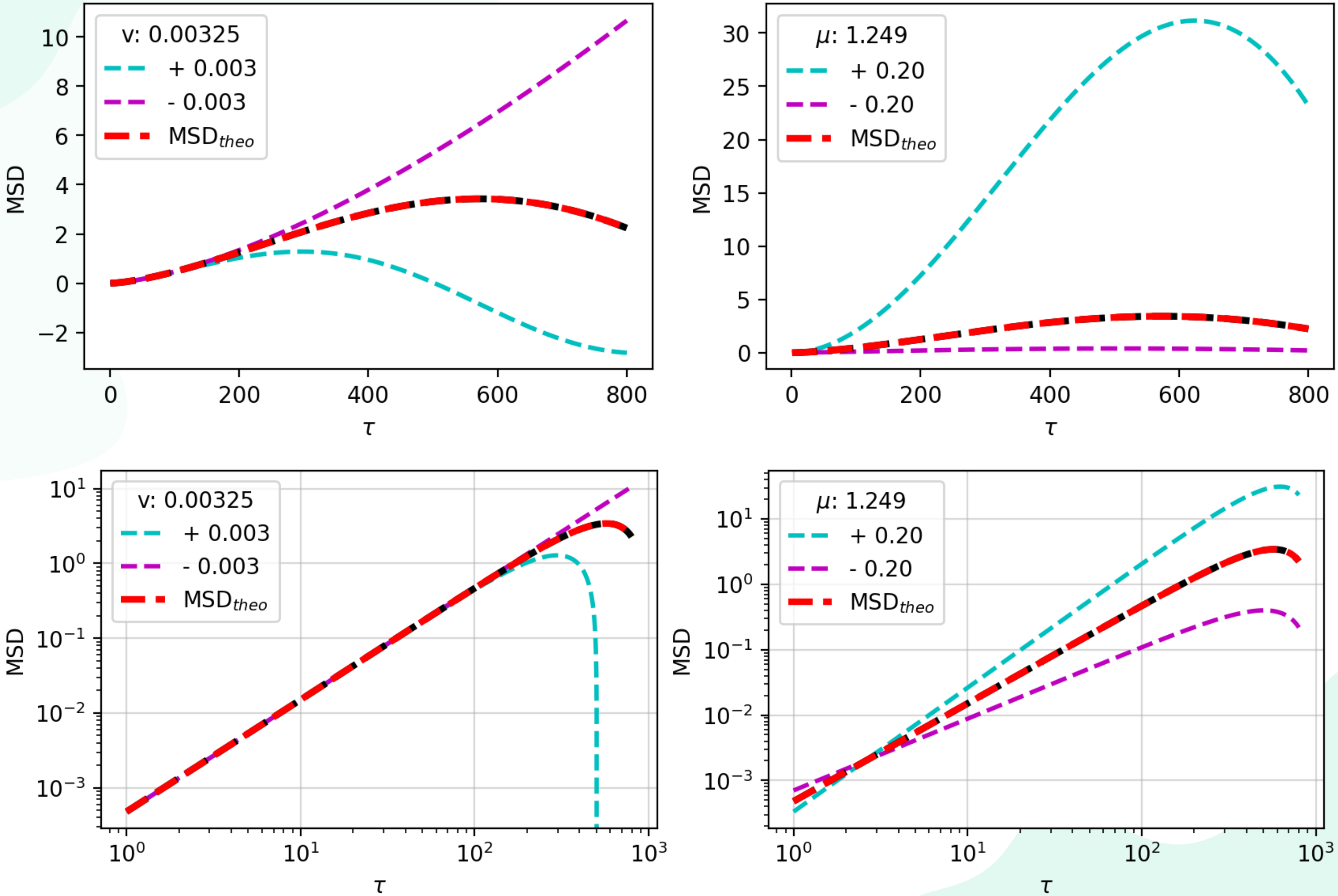


[MSD] Fitting Theoretical MSD

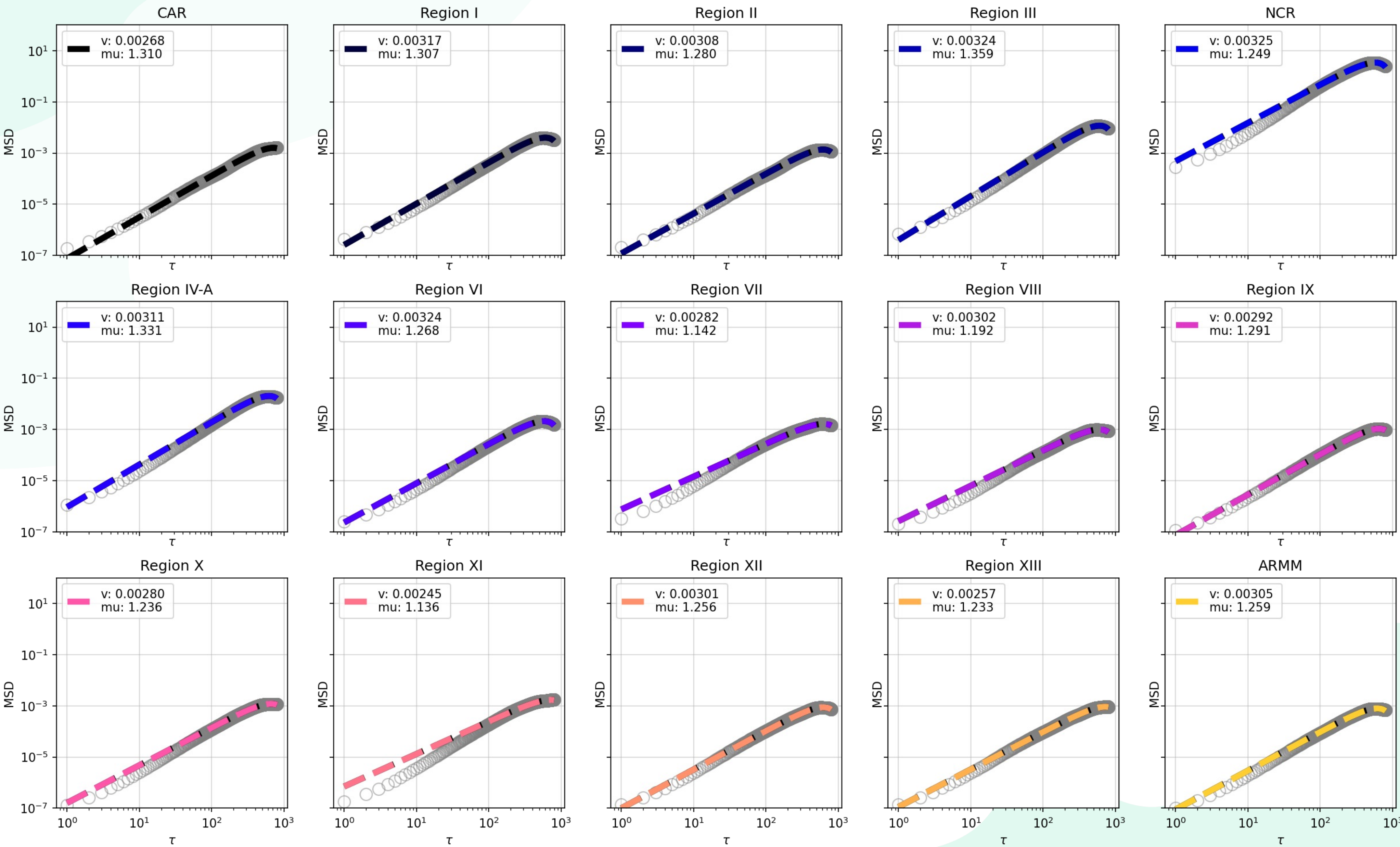
$$MSD = \frac{\Gamma(\mu) \cdot \cos(vT/2) \cdot J_{\mu-\frac{1}{2}}(vT/2)}{\pi^{-\frac{1}{2}} \cdot \ T^{\frac{1}{2}-\mu} \cdot v^{\mu-\frac{1}{2}}}$$



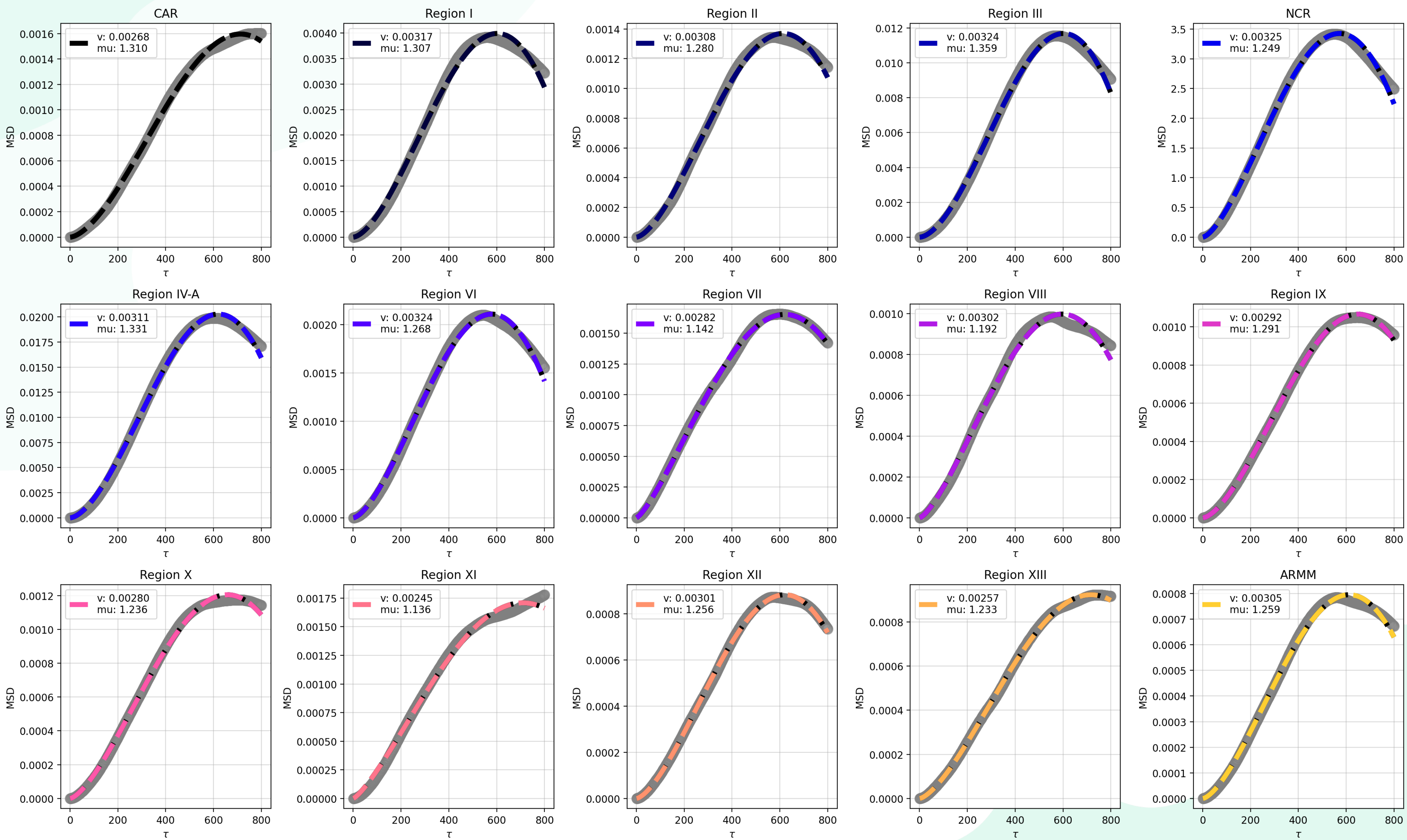
[MSD] Parameter Variations



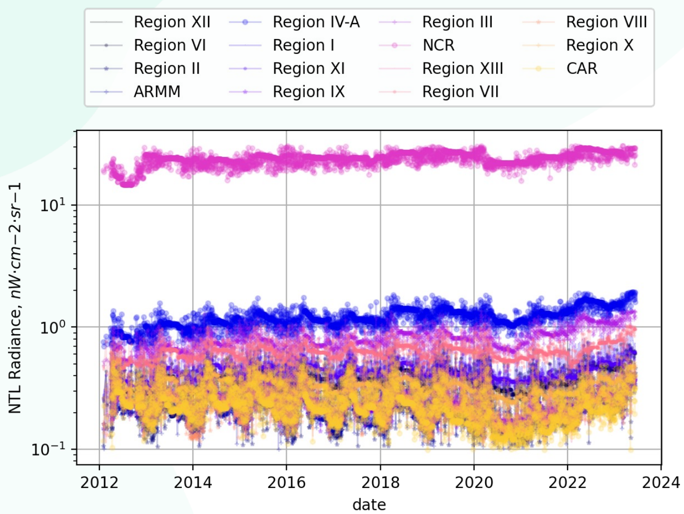
[MSD] Fitting for all NTL Trends

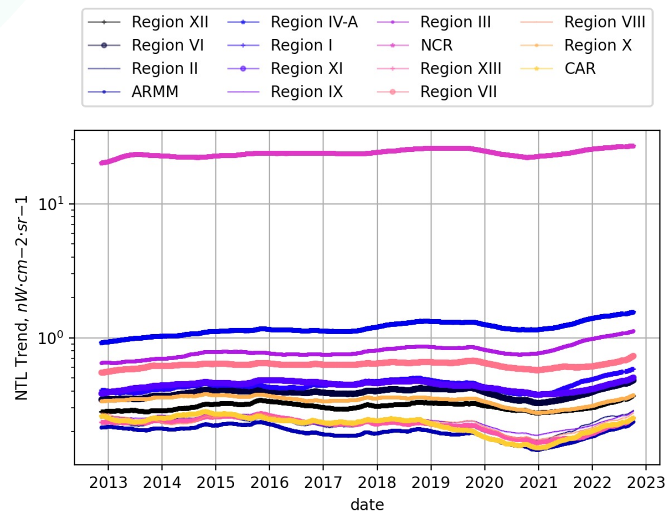


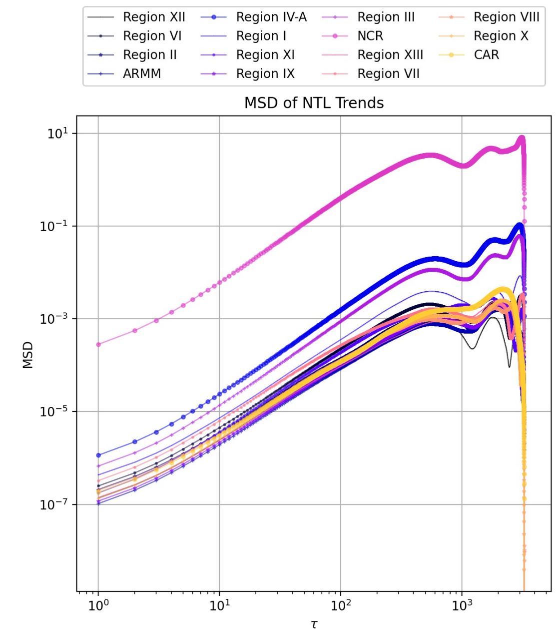
[MSD] Fitting for all NTL Trends

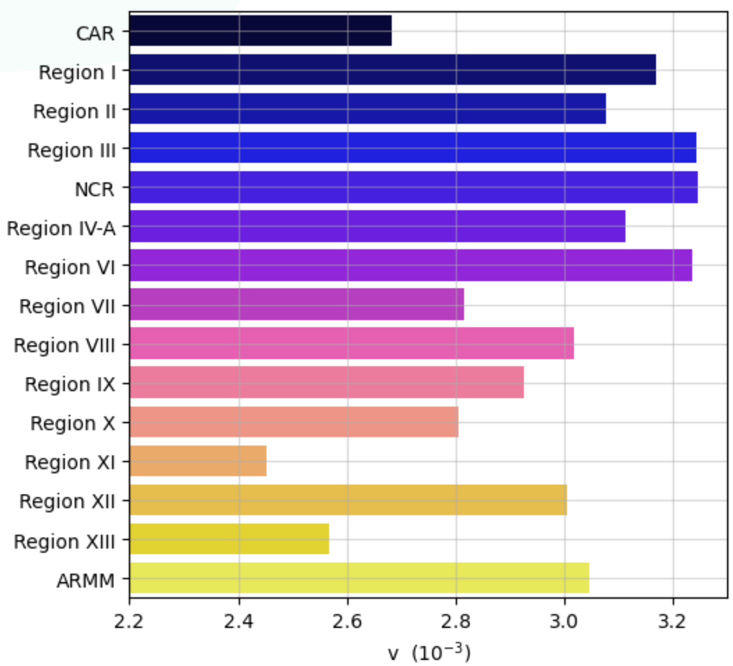


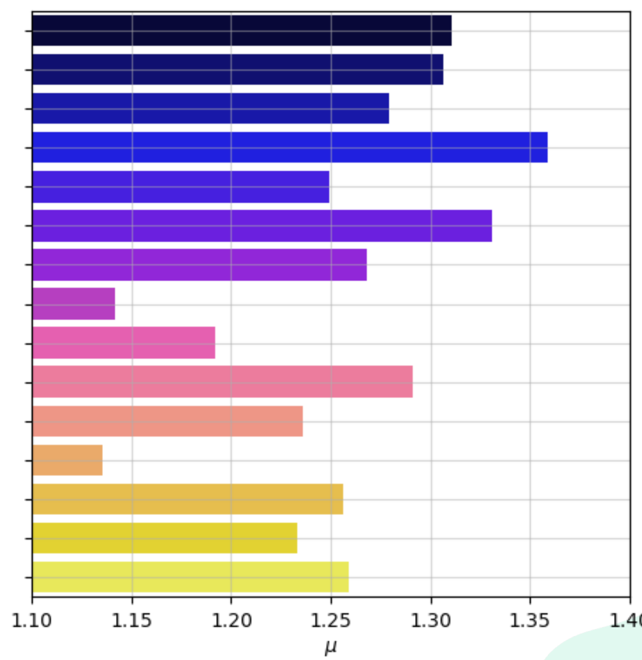
[MSD] Comparison of best-fit params

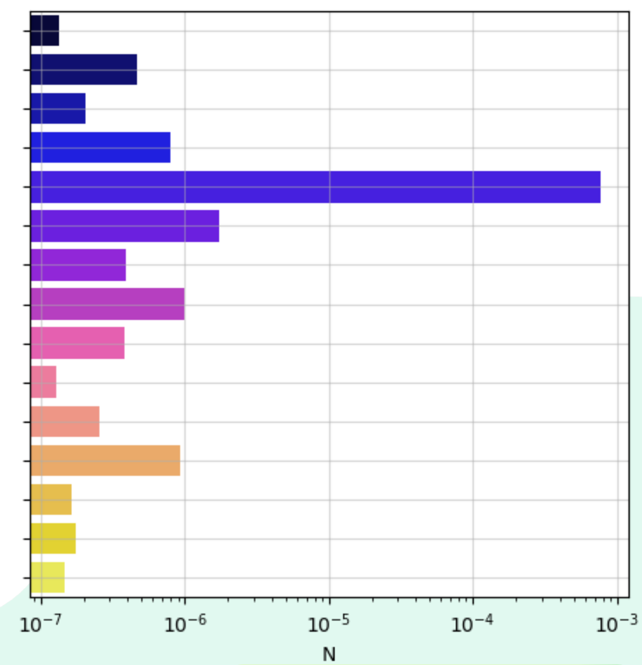








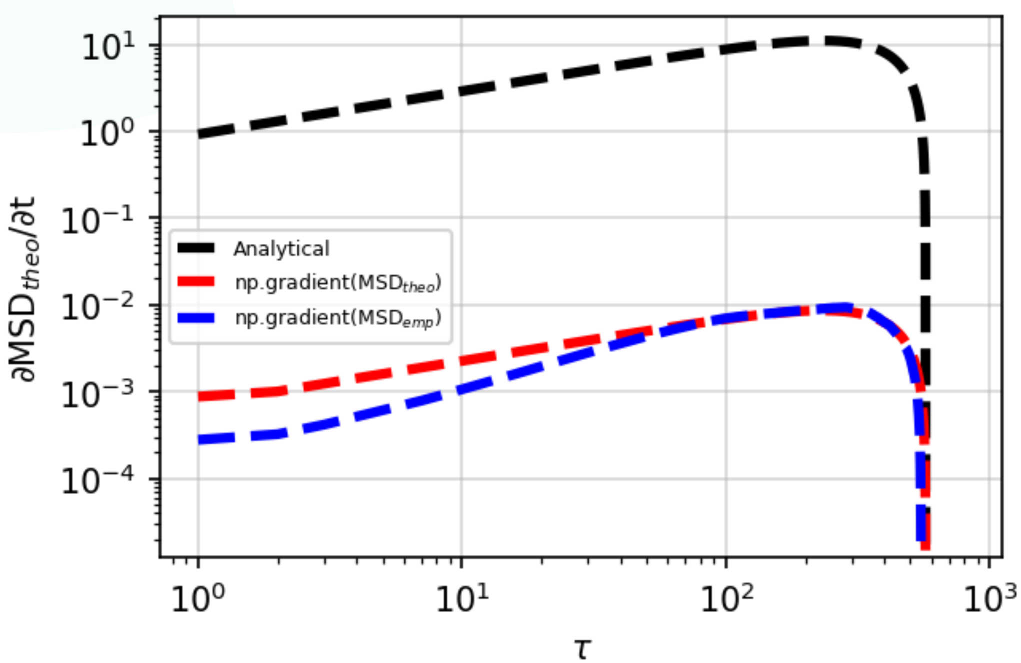


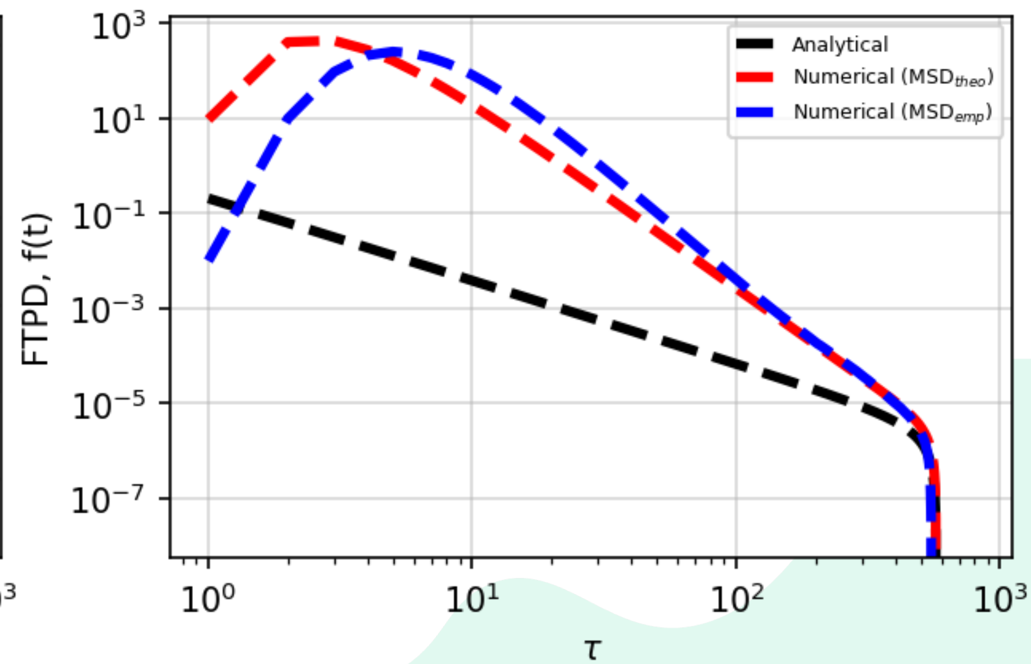


[FPTD] Analytical vs Numerical

$$MSD = \frac{\Gamma(\mu)\cdot\cos(vT/2)\cdot J_{\mu-\frac{1}{2}}(vT/2)}{\pi^{-\frac{1}{2}}\cdot\ T^{\frac{1}{2}-\mu}\cdot v^{\mu-\frac{1}{2}}}$$

$$f(t) = -\frac{(x_0-x_c)}{\sqrt{2\pi}[M(t)]^3}\frac{\partial M(t)}{\partial t}\ exp\left[-\frac{(x_0-x_c)^2}{2M(t)}\right]$$





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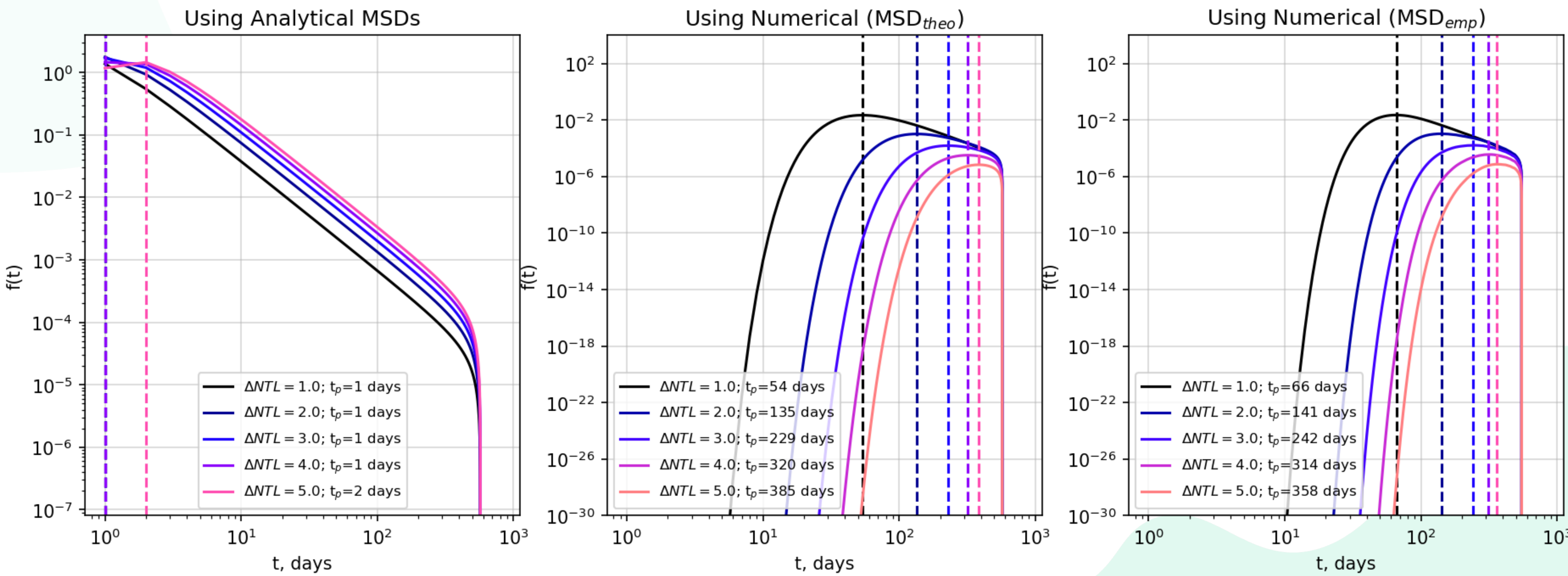
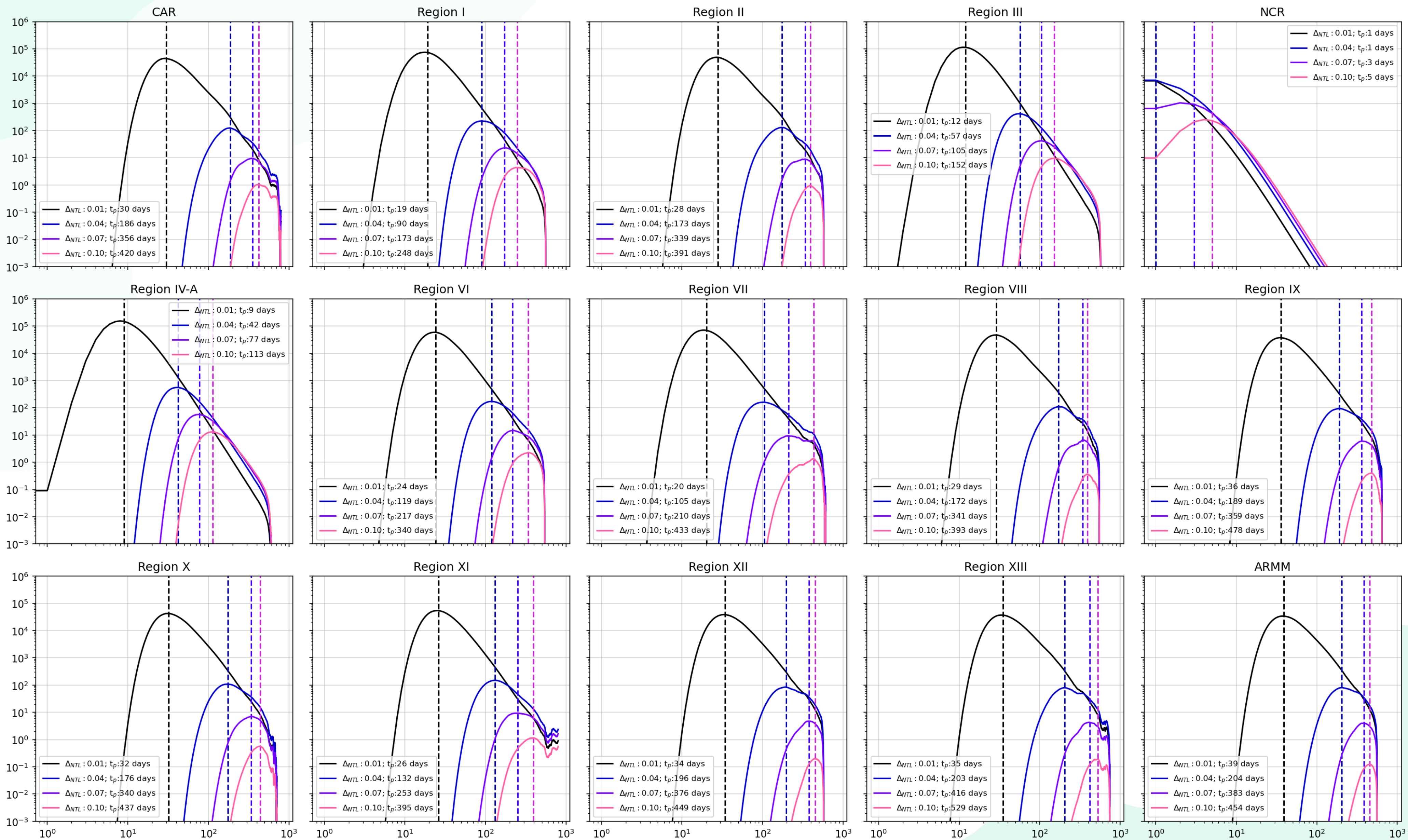
$$MSD = \frac{\Gamma(\mu)\cdot\cos(vT/2)\cdot J_{\mu-\frac{1}{2}}(vT/2)}{\pi^{-\frac{1}{2}}\cdot\ T^{\frac{1}{2}-\mu}\cdot v^{\mu-\frac{1}{2}}}$$

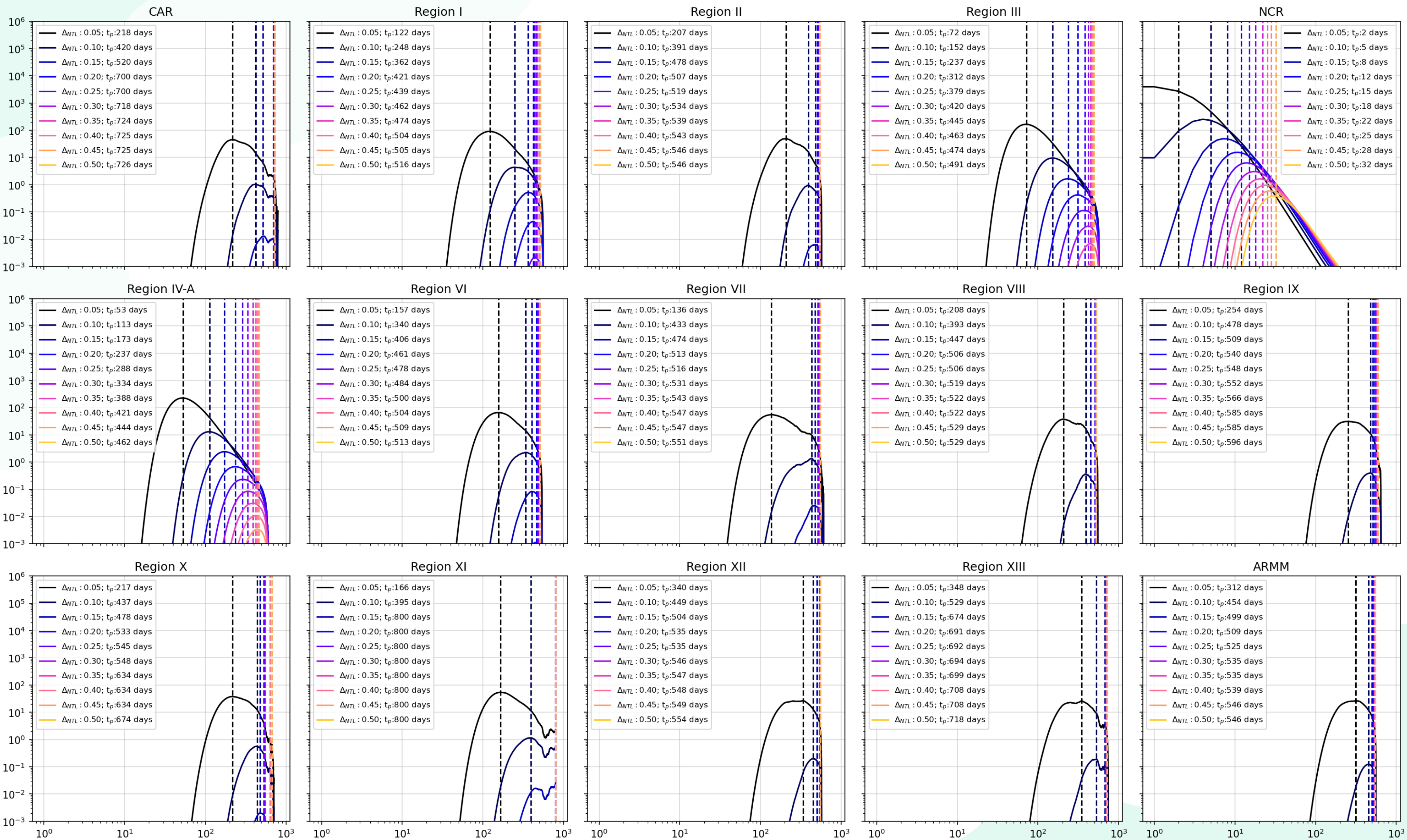
$$f(t) = -\frac{(x_0 - x_c)}{\sqrt{2\pi}[M(t)]^3}\frac{\partial M(t)}{\partial t}\, exp\left[-\frac{(x_0 - x_c)^2}{2M(t)}\right]$$



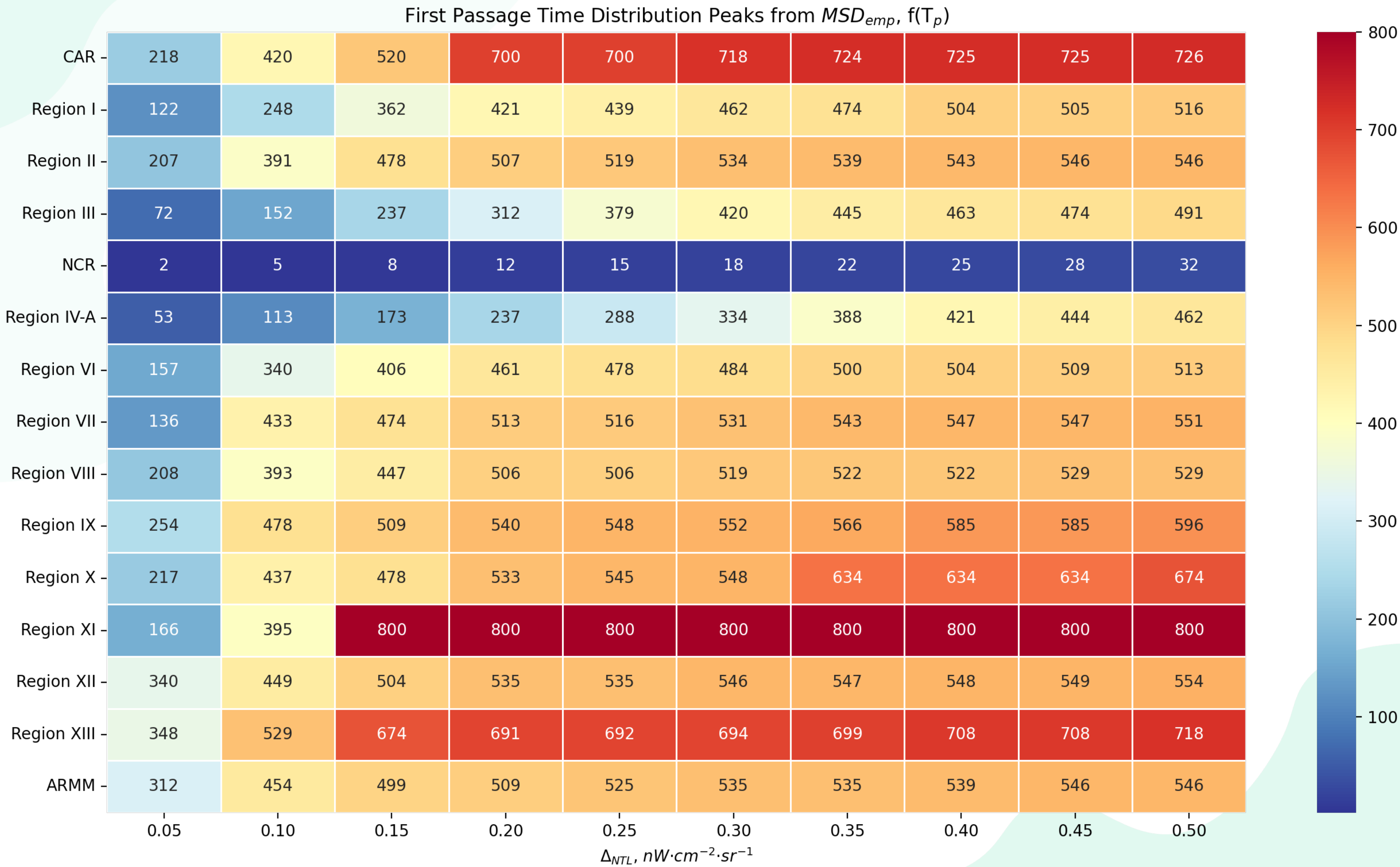
[Numerical FPTD] Using MSD_{emp}



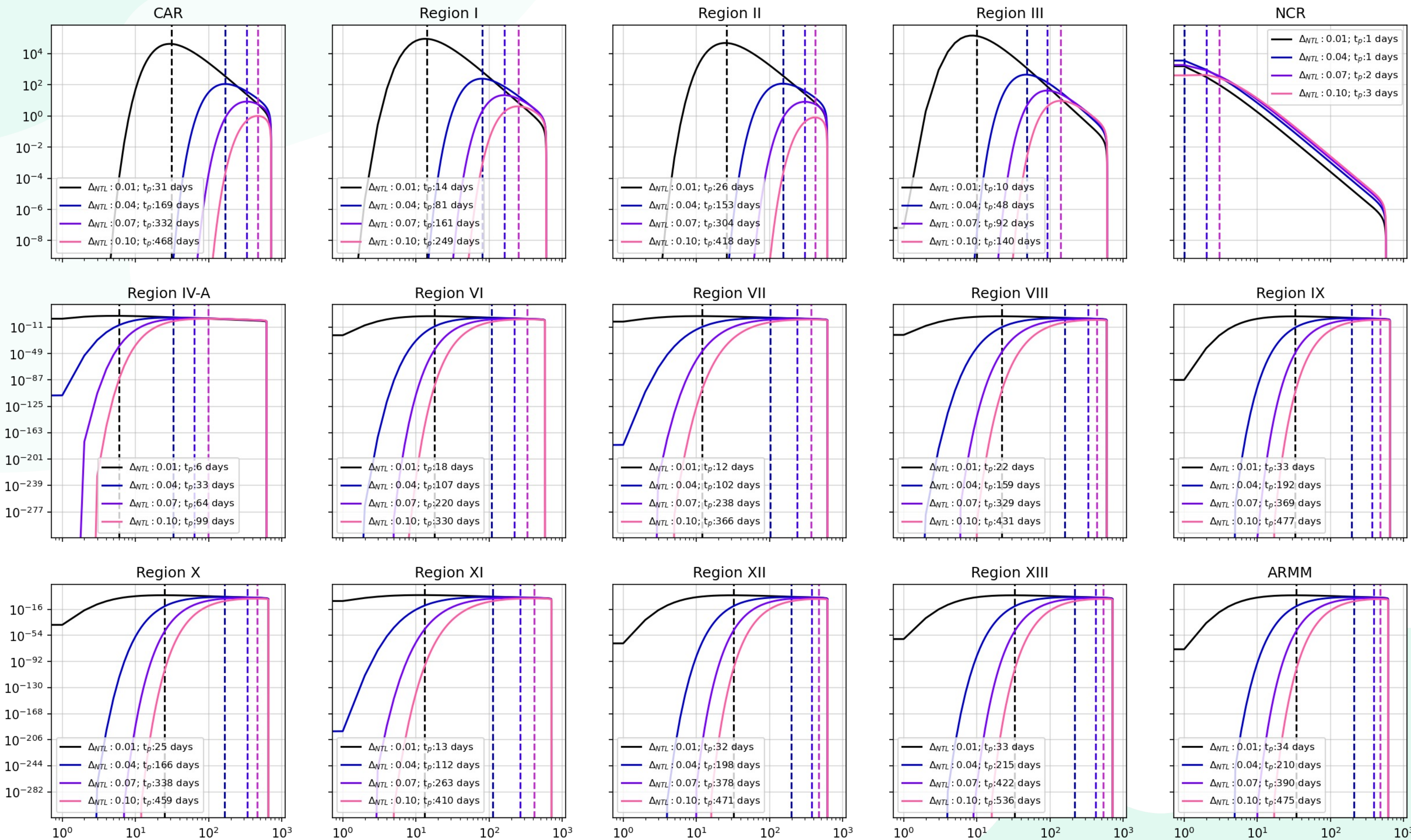
[Numerical FPTD] Using MSD_{emp}



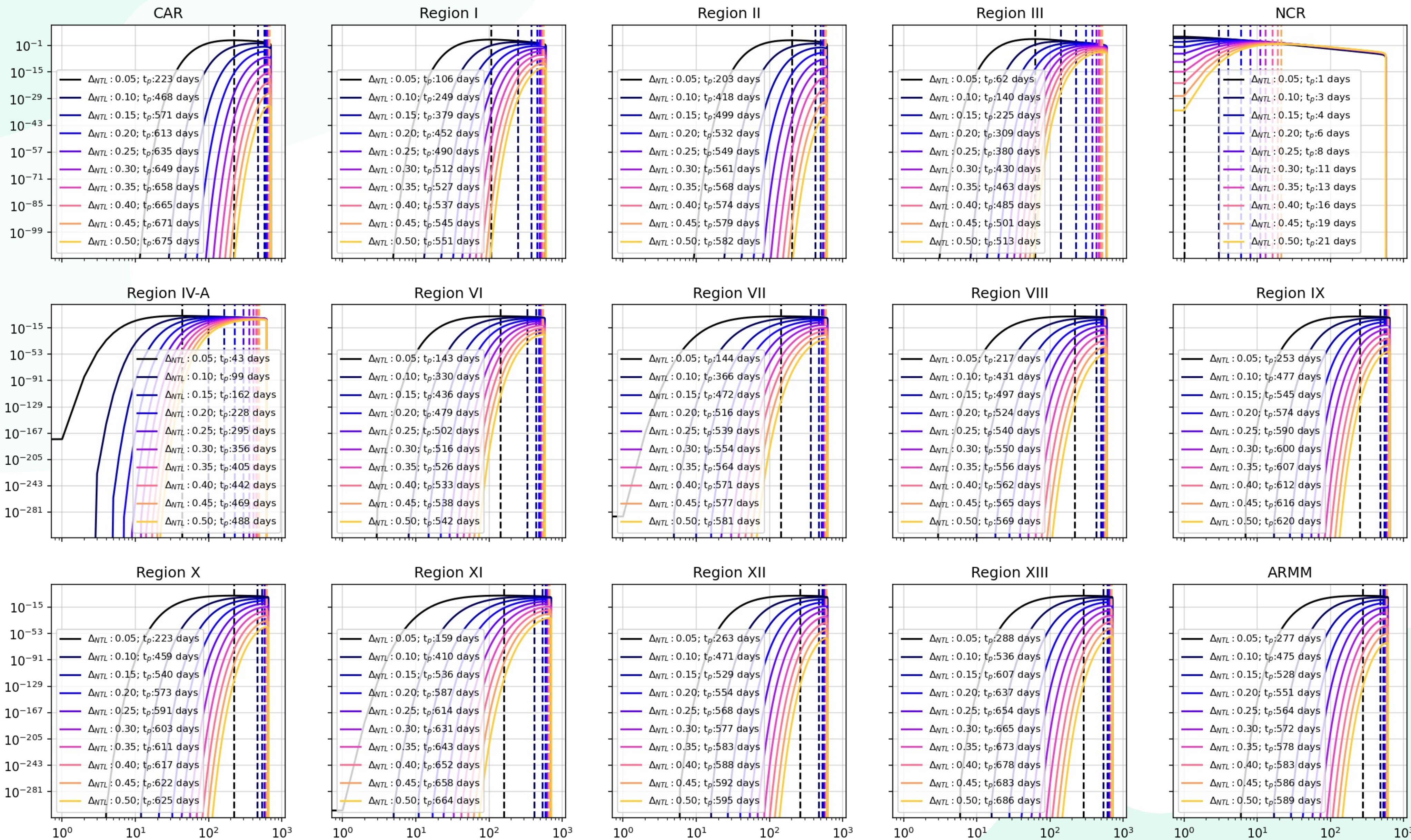
[Numerical FPTD] Using MSD_{emp}



[Numerical FPTD] using MSD_{theo}



[Numerical FPTD] using MSD_{theo}



[Numerical FPTD] using MSD_{theo}

First Passage Time Distribution Peaks from MSD_{theo}, $f(T_p)$

	0.05	0.10	0.15	0.20	0.25	0.30	0.35	0.40	0.45	0.50
CAR	223	468	571	613	635	649	658	665	671	675
Region I	106	249	379	452	490	512	527	537	545	551
Region II	203	418	499	532	549	561	568	574	579	582
Region III	62	140	225	309	380	430	463	485	501	513
NCR	1	3	4	6	8	11	13	16	19	21
Region IV-A	43	99	162	228	295	356	405	442	469	488
Region VI	143	330	436	479	502	516	526	533	538	542
Region VII	144	366	472	516	539	554	564	571	577	581
Region VIII	217	431	497	524	540	550	556	562	565	569
Region IX	253	477	545	574	590	600	607	612	616	620
Region X	223	459	540	573	591	603	611	617	622	625
Region XI	159	410	536	587	614	631	643	652	658	664
Region XII	263	471	529	554	568	577	583	588	592	595
Region XIII	288	536	607	637	654	665	673	678	683	686
ARMM	277	475	528	551	564	572	578	583	586	589

Δ_{NTL}, $nW{\cdot}cm^{-2}{\cdot}sr^{-1}$

Colour scale: 100, 200, 300, 400, 500, 600, 700, 800

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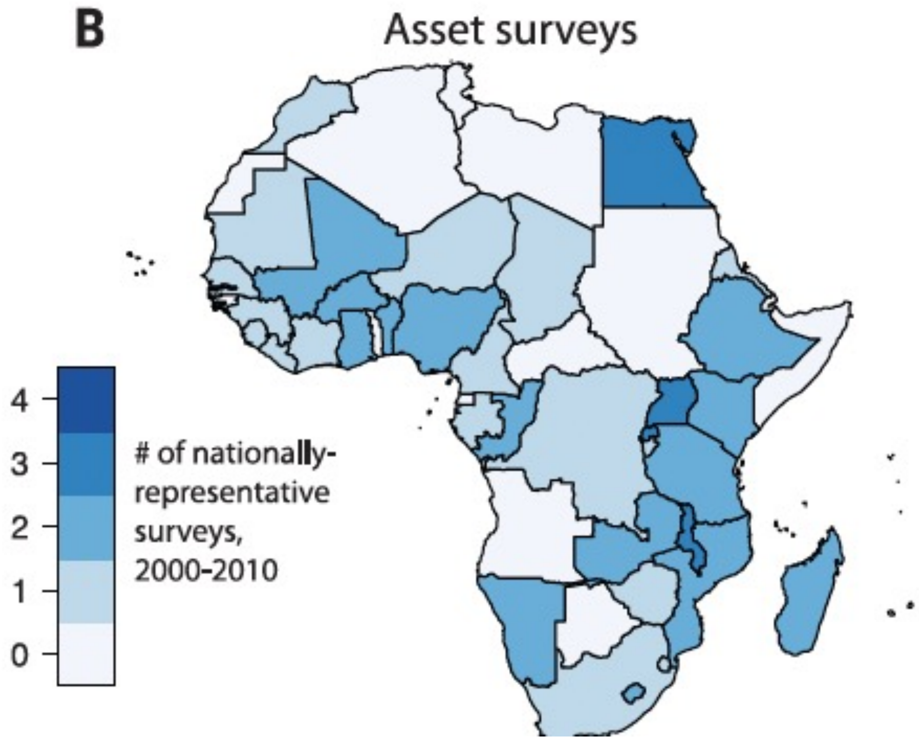
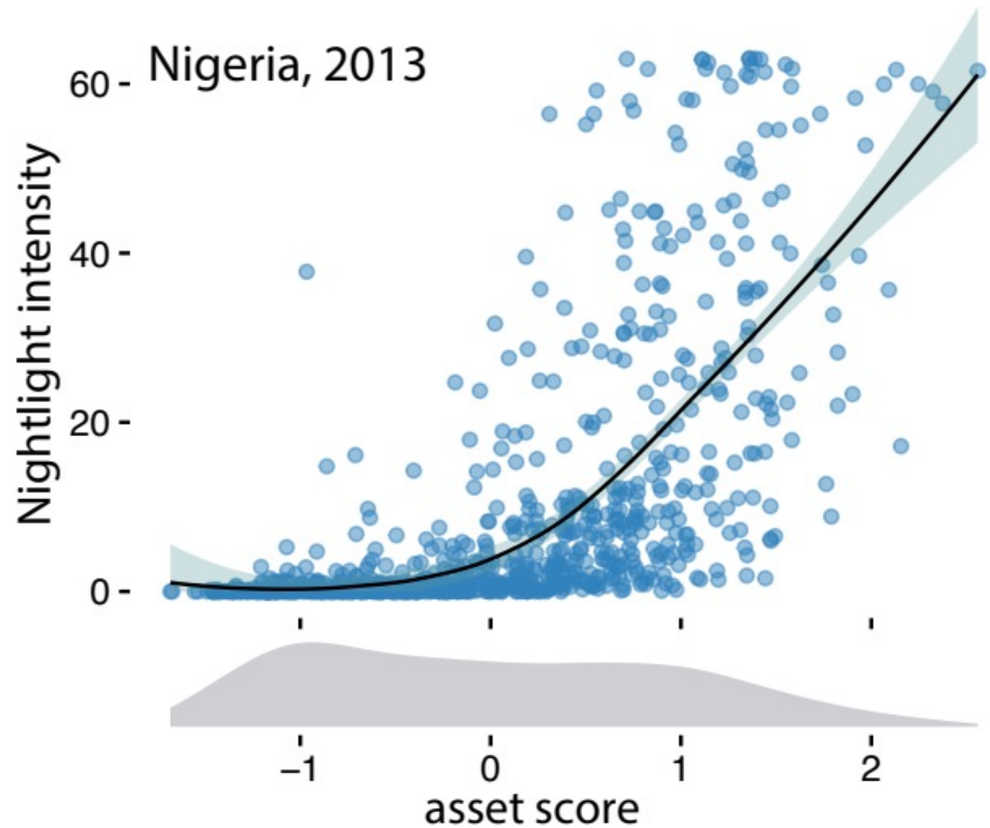
5. Japan International Cooperation Agency, **Republic of the Philippines Data Collection Survey on the Incentive Mechanism for Improving Disaster Resiliency of Electric Power Distribution Network Final Report**, October 2015.
6. M. V. S. Villanueva, **Challenges and opportunities for sustainable post- disaster resettlement in the Philippines** (2018), https://www.preventionweb.net/publication/challenges-and-opportunities-sustainable-post-disaster-resettlement-philippines.

Significance: NTL and Poverty

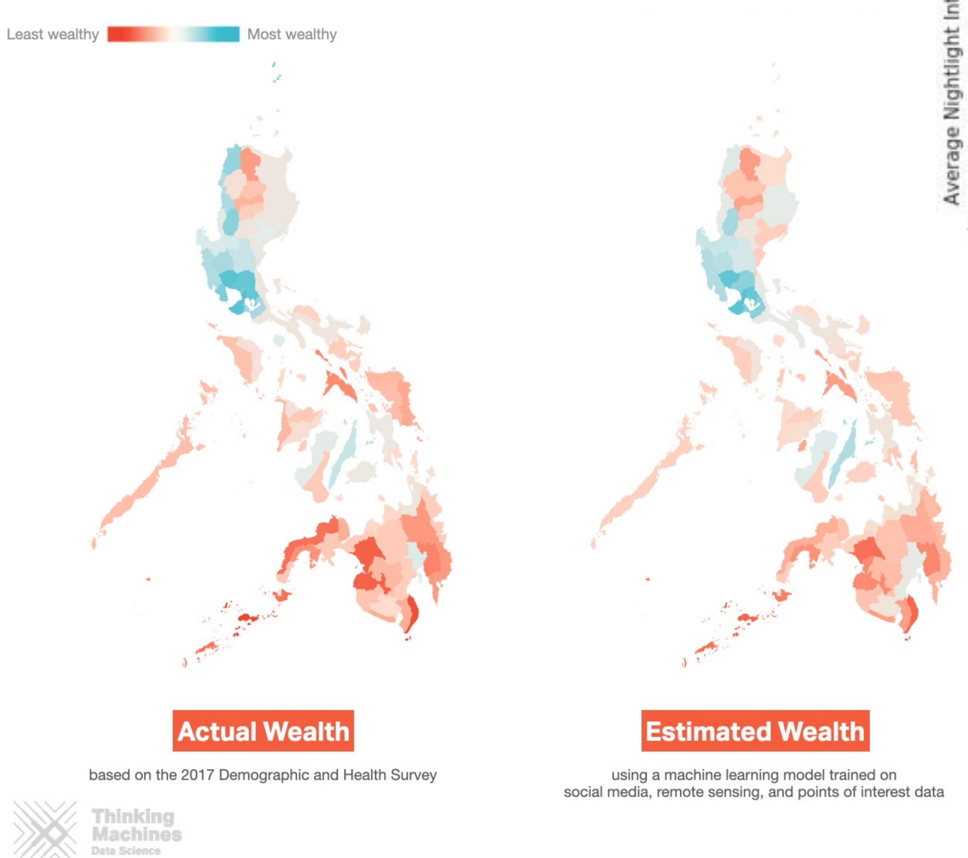


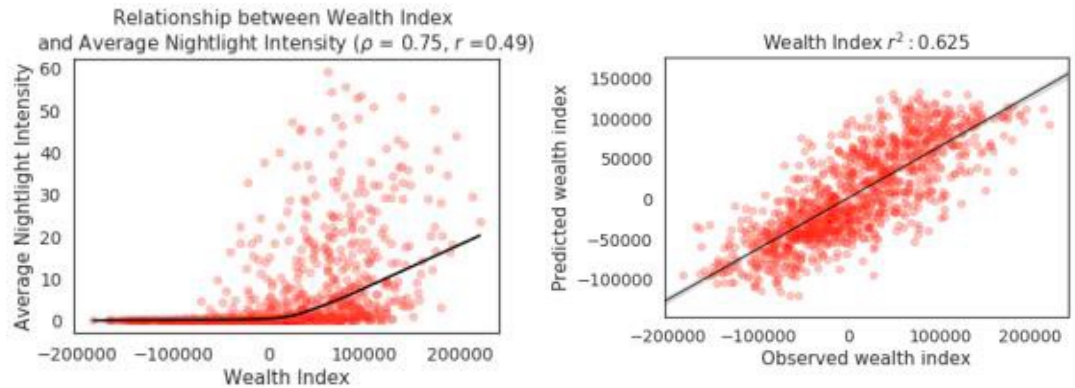


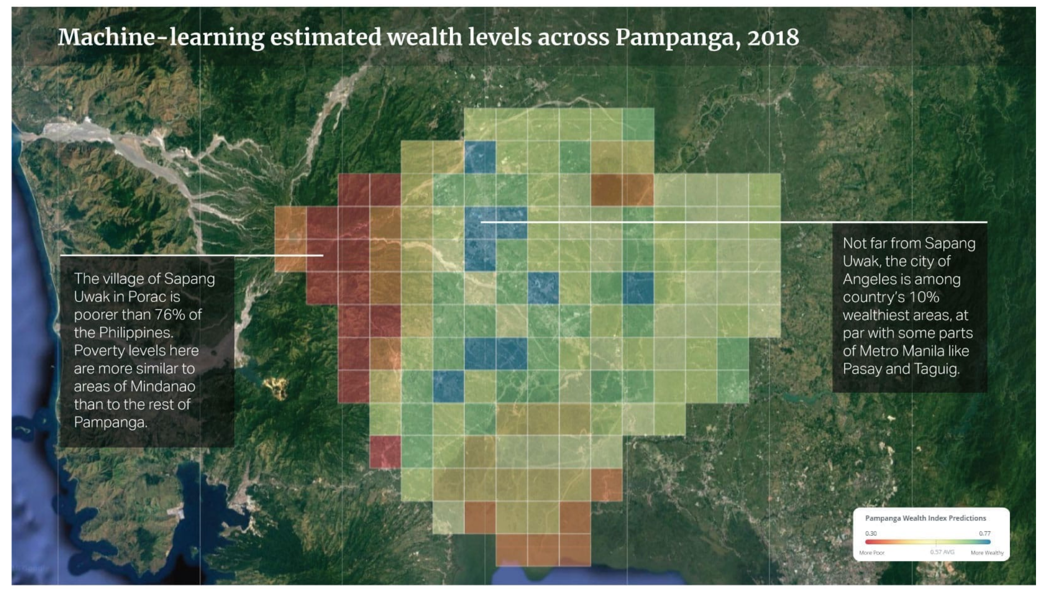
Asset vs Nighttime Lights

Neal Jean et al. ***Combining satellite imagery and machine learning to predict poverty***.
Science, 353:790–794, 2016.

Significance: NTL and Poverty







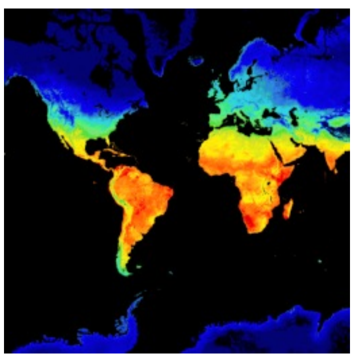
* Source: Philippine Poverty Census 2015

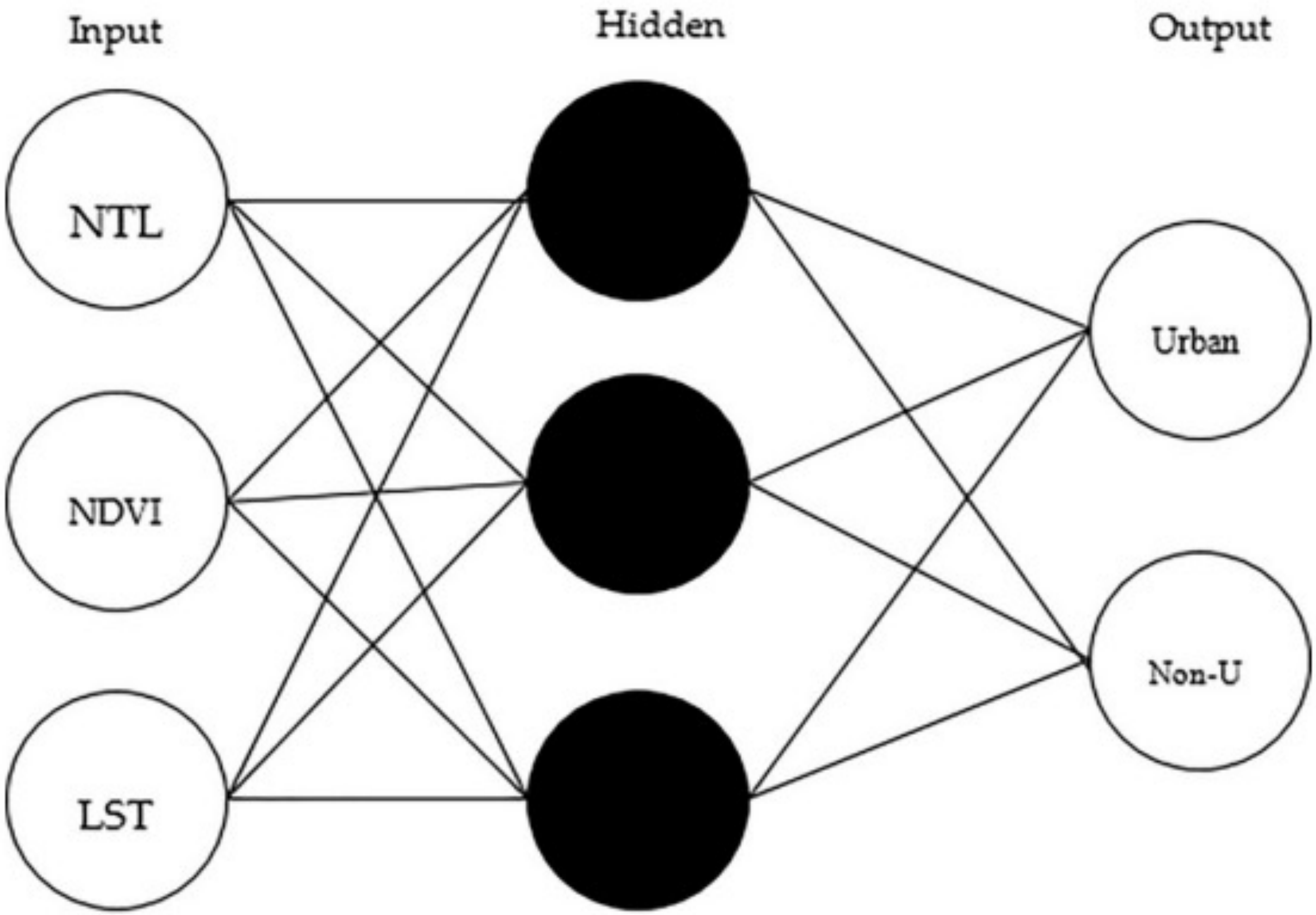
Thinking Machines Data Science

NTL-based Poverty Mapping in PH |

Isabelle Tingzon et al. ***Mapping Poverty in the Philippines Using Machine Learning, Satellite Imagery, and Crowd-sourced Geospatial Information****.*
The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, XLII:14–15, 2019.

Significance: NTL and Urbanization

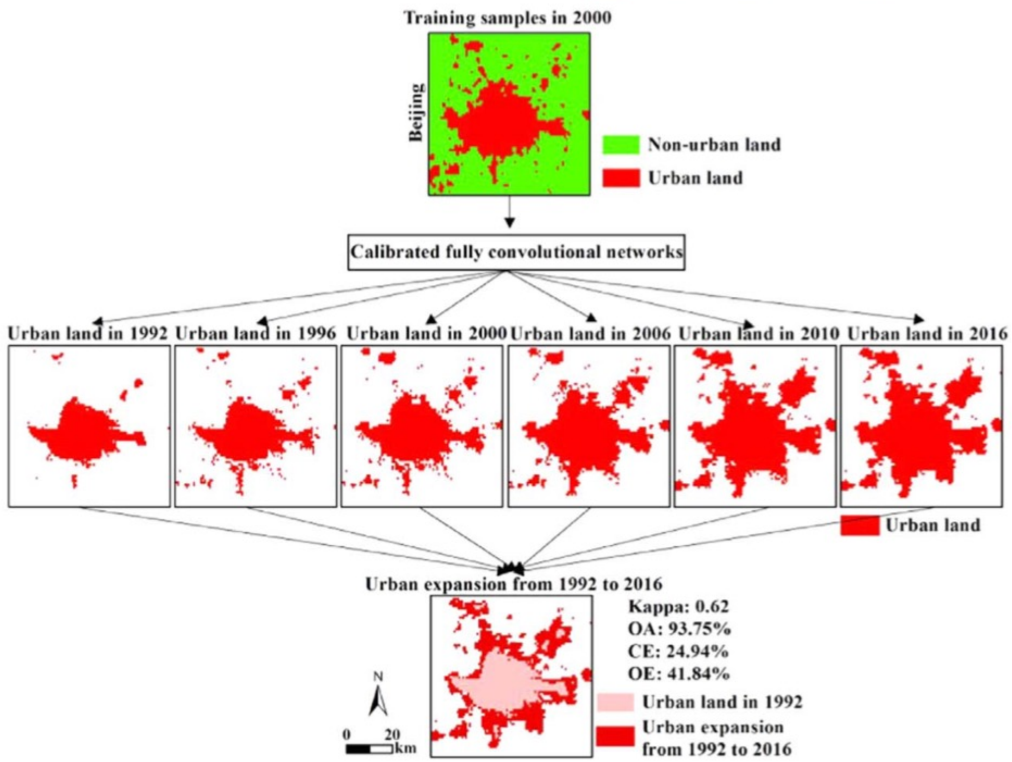


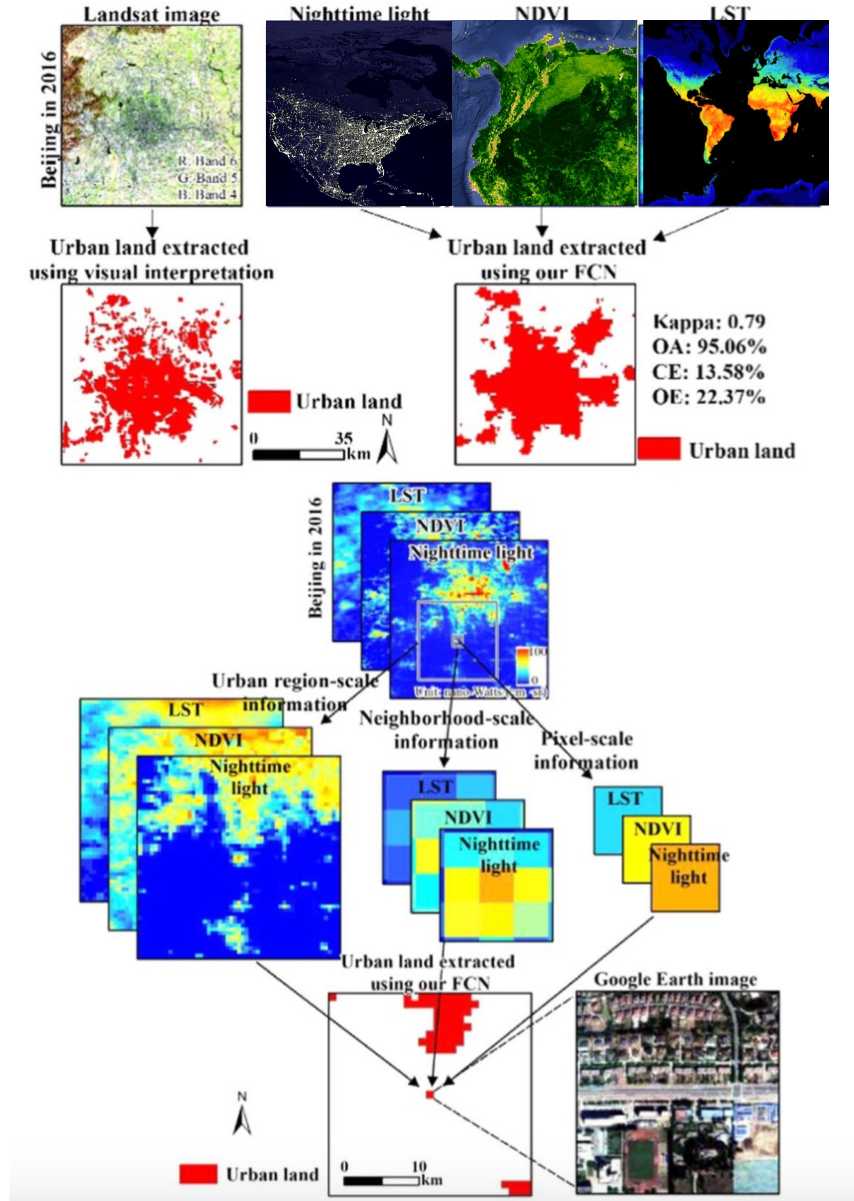


Urban Mapping using NTL and ancillary data

Xu, T., Coco, G., & Gao, J. **Extraction of urban built-up areas from nighttime lights using artificial neural network.** Geocarto International, 35(10), 1049–1066., 2020

Significance: NTL and Urbanization





CNN-based urban expansion mapping |

Chunyang He et al. ***Detecting global urban expansion over the last three decades using a fully convolutional network.*** *Environmental Research Letters, 14, 2019.*

Shift to LED Lighting

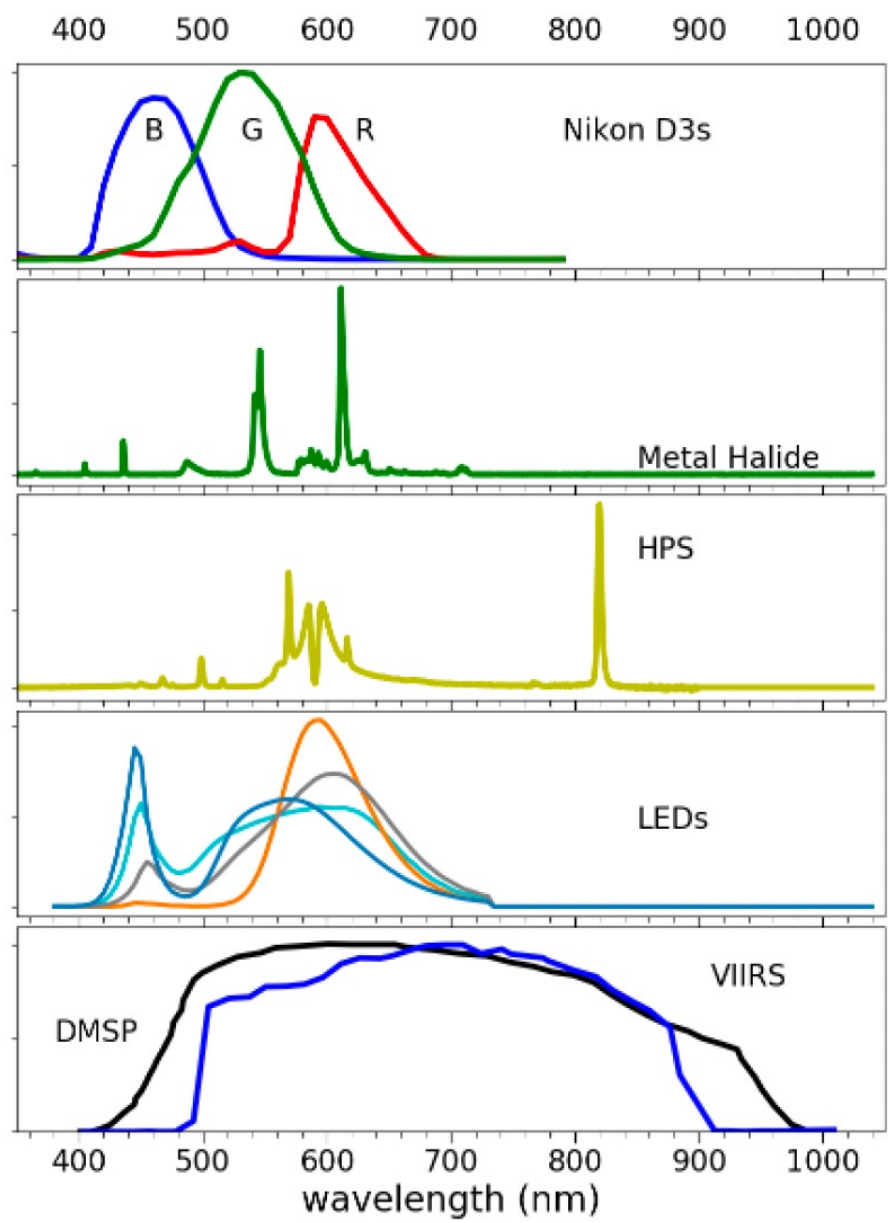
1. Integration of Level 3/4 Administrative Shape Files
2. Extending NDWE Analysis for Disaster Management:
3. Addressing the Impact of Spectral Shift in Street Lighting

The Berlin Divide (2020)

https://twitter.com/NorbertElekes/status/1325892921590210560/photo/1

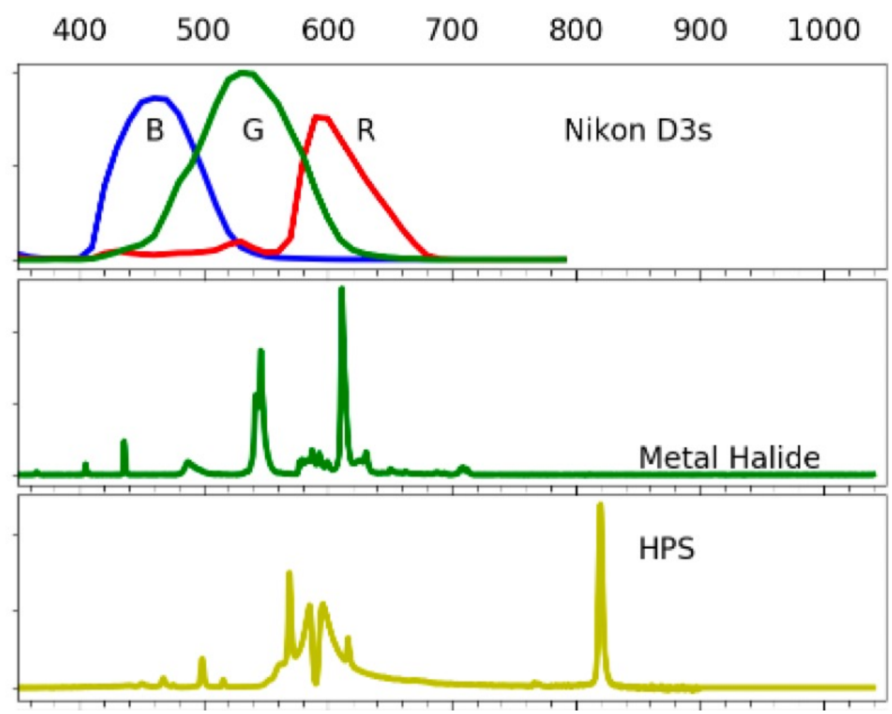
Spectral Response Functions

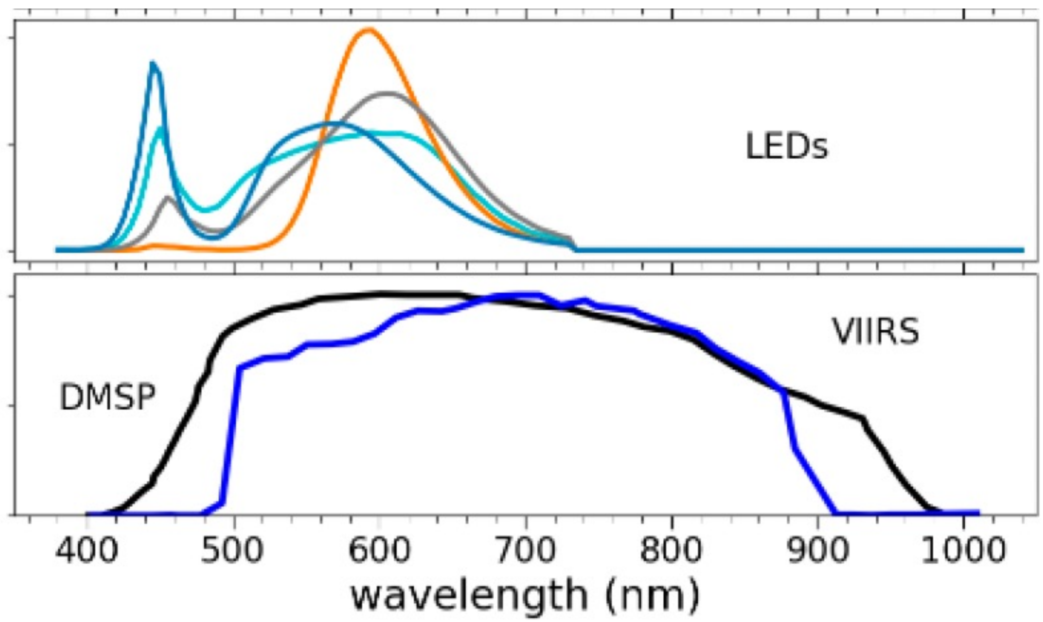
- **Nikon D3s Cameras** used by the astronauts at the ISS
- Metal Halide lamp, popular on architectural lights
- High pressure sodium (HPS) light, popular until 2014 on street lighting
- LEDs of 5000K (blue), 4000K (cyan), 2700K (grey), and PC-Amber (amber), popular on street lighting
- Representative spectral response of **DMSP/OLS(black) and Suomi-NPP/VIIRS/DNB(blue)**



Challenges of Spectral Shift

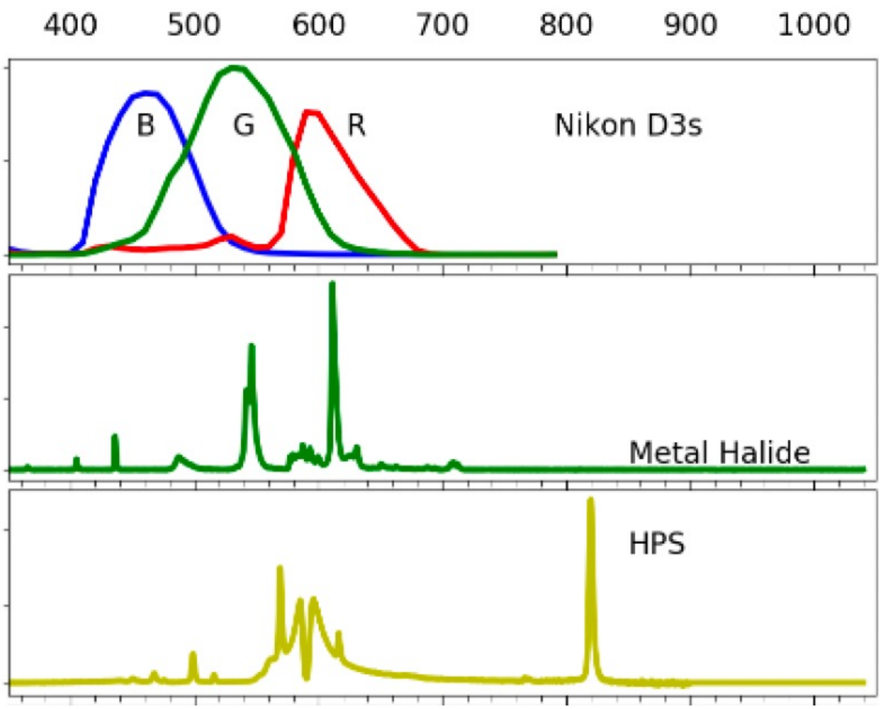
1. NTL sensors are panchromatic. Though the bandwidths have been broad, they have also been insensitive to the blue part of the visible spectrum (380 to 450 nm);

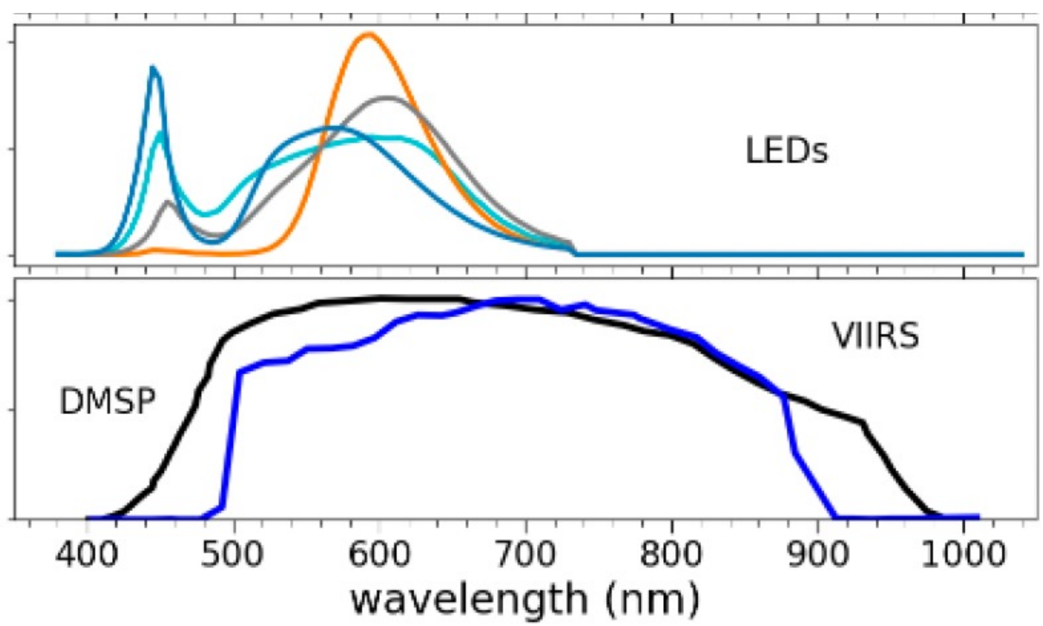




Challenges of Spectral Shift

2. Outdoor lighting is transitioning from low-pressure sodium (narrow spectrum) to LED lamps (broad-white spectrum), essentially increasing the blue-light emissions.





Challenges of Spectral Shift

From a biological perspective:

3. ALAN has been found to **affect individual physiology and behavior (including that of humans) to community structure and ecosystem function**. For example, melatonin suppression is particularly sensitive to those at blue wavelengths.

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journal homepage: www.elsevier.com/locate/scitotenv

ELSEVIER

Light pollution as a factor in breast and prostate cancer

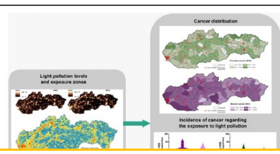
Héctor Lamphar [a,b], Miroslav Kocifaj [b,c], Jorge Limón-Romero [d], Jorge Paredes-Tavares [a], Safei Diba Chakameh [e], Michal Mego [f], Natalia Jorgelina Prado [g,h], Yolanda Angélica Baez-López [d], Emiliano Raúl Diez [g,h,*]

[a] Cátedras CONACYT, 08400 Ciudad de México, Mexico
[b] ICA, Slovak Academy of Sciences, 845 03 Bratislava, Slovakia
[c] Faculty of Mathematics, Physics, and Informatics, Comenius University, 842 48 Bratislava, Slovakia
[d] UABC, Facultad de Ingeniería Arquitectura y Diseño, 22860 Ensenada, Mexico
[e] National Health Information Center, 811 09 Bratislava, Slovakia
[f] 2nd Department of Oncology, Comenius University, Medical Faculty and National Cancer Institute, 833 10 Bratislava, Slovakia
[g] Facultad de Ciencias Médicas, Universidad Nacional de Cuyo, 5500 Mendoza, Argentina
[h] Institute of Medical and Experimental Biology of Cuyo, UNCuyo CONICET, 5500 Mendoza, Argentina

HIGHLIGHTS

- Light pollution is a global environmental issue that affects photosensitive organisms.
- Long-term exposure to light pollution can be a risk factor for breast cancer.
- Breast cancer incidence in Slovakia showed a positive relation with light pollution.
- Prostate cancer did not relate to light pollution.

GRAPHICAL ABSTRACT



frontiers in Ecology and Evolution

ORIGINAL RESEARCH
published: 18 January 2022
doi: 10.3389/fevo.2021.786557

Tracking Flights to Investigate Seabird Mortality Induced by Artificial Lights

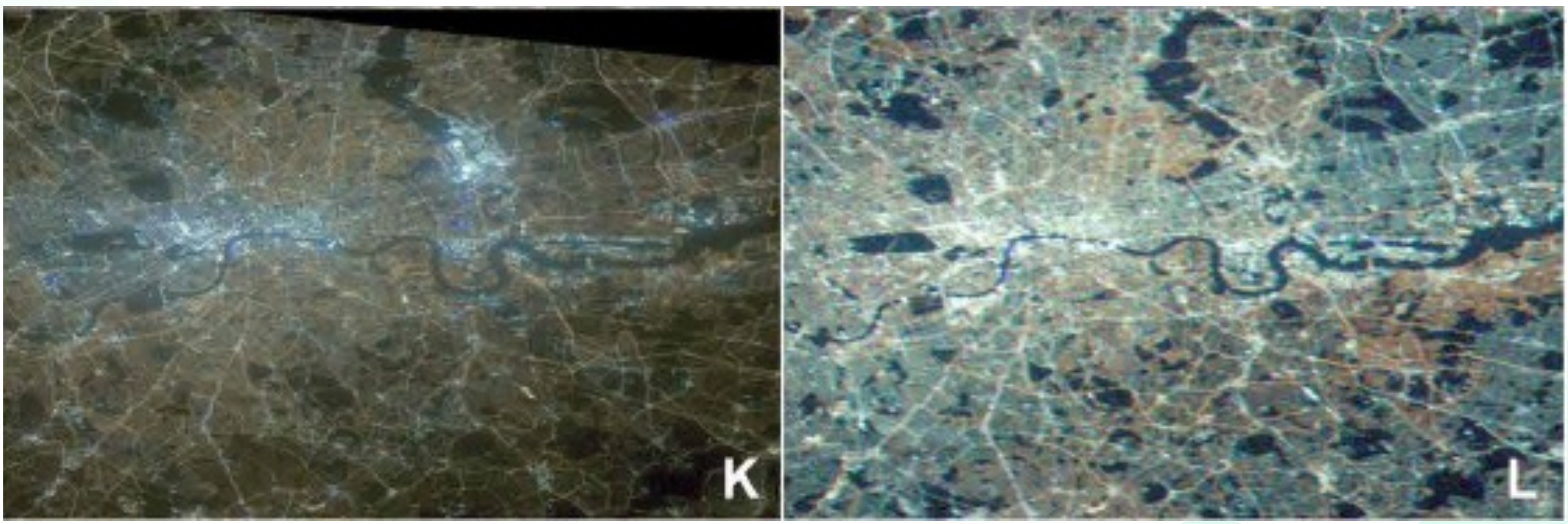
Airam Rodríguez [1,2,3*], Beneharo Rodríguez [1], Yarci Acosta [4] and Juan J. Negro [5]

[1] Canary Islands' Ornithology and Natural History Group (GOHNIC), Buenavista del Norte, Spain, [2] Terrestrial Ecology Group (TEG-UAM), Department of Ecology, Universidad Autónoma de Madrid, Madrid, Spain, [3] Centro de Investigación en Biodiversidad y Cambio Global (CIBC-UAM), Universidad Autónoma de Madrid, Madrid, Spain, [4] Sociedad Española de Ornitología (SEO/BirdLife), Delegación de Canarias, La Laguna, Spain, [5] Estación Biológica de Doñana, Department of Evolutionary Ecology, Consejo Superior de Investigaciones Científicas, Seville, Spain

Rebound effect (Jevon's Paradox)

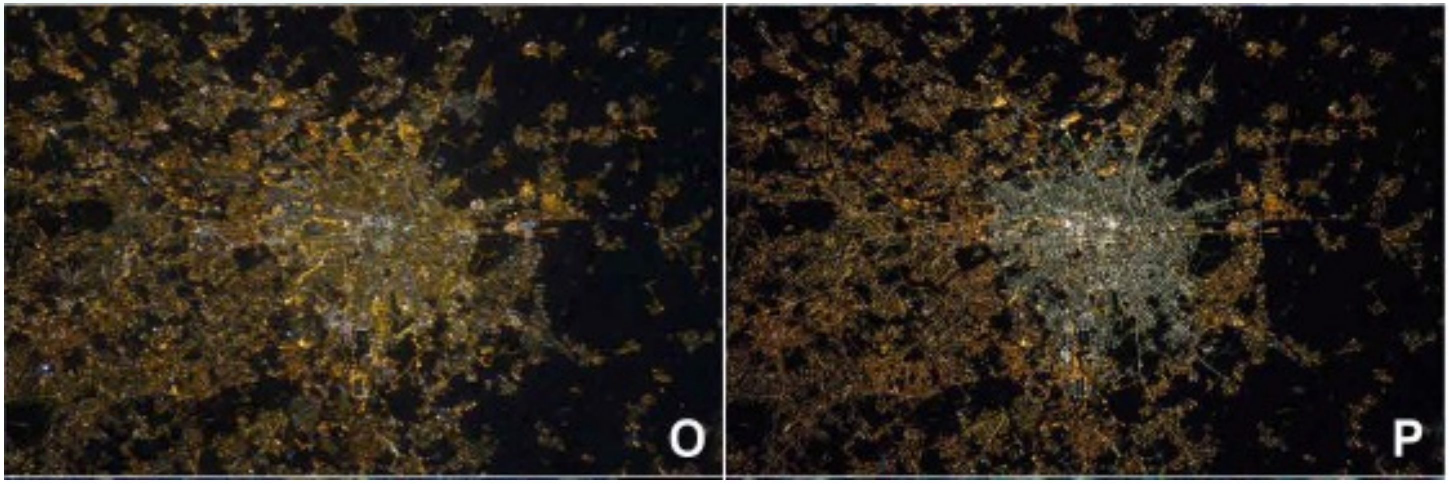
- Low cost and high-power efficiency of LED have driven increased demand for lighting, and hence, any efficiency gains have been counteracted by increased consumption of light.

London, UK: 51% conversion to LED by 2019

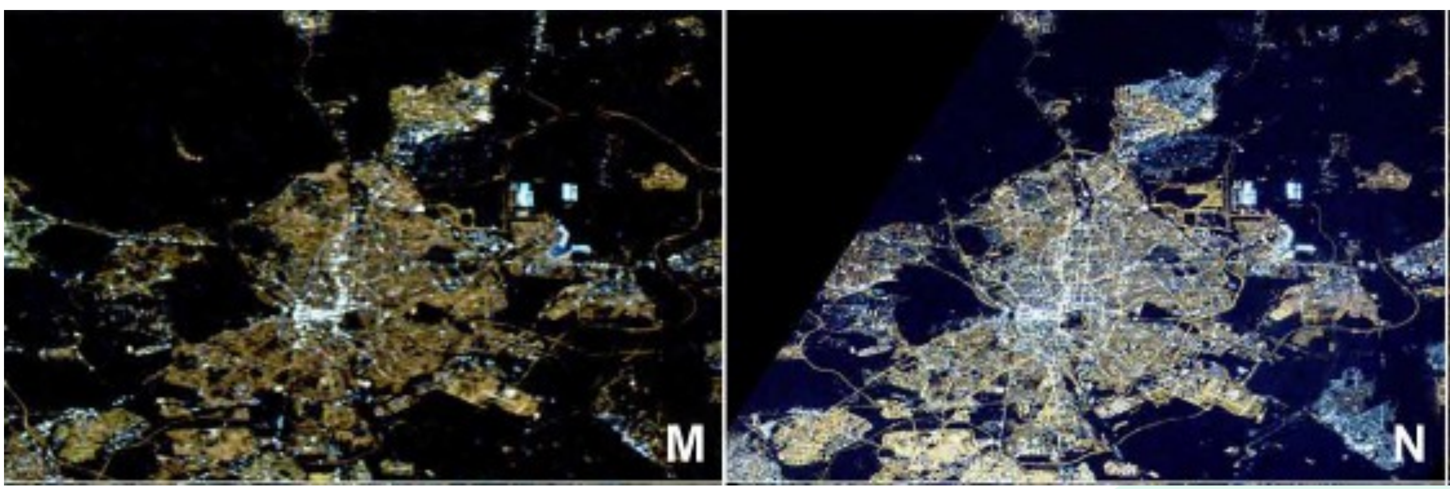


Transition to LED lighting

- Milan, Italy: first total conversion to white LED (2012 vs 2015)



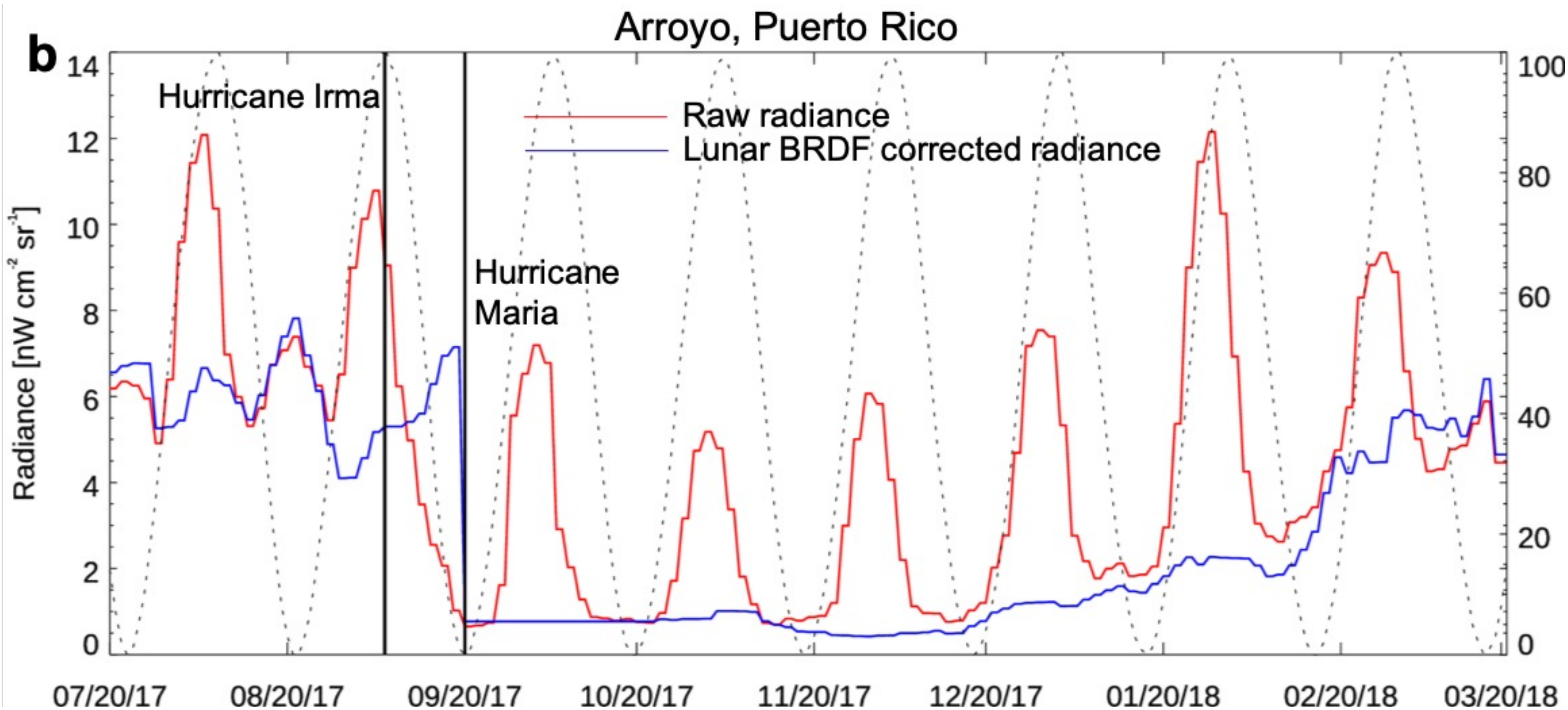
- Madrid, Spain: 56% conversion to LED (2012 vs 2017)



Appendix: VIIRS Boat Detection

https://www.mecreeled.com/wp-content/uploads/2019/03/fishing-light-led.jpg

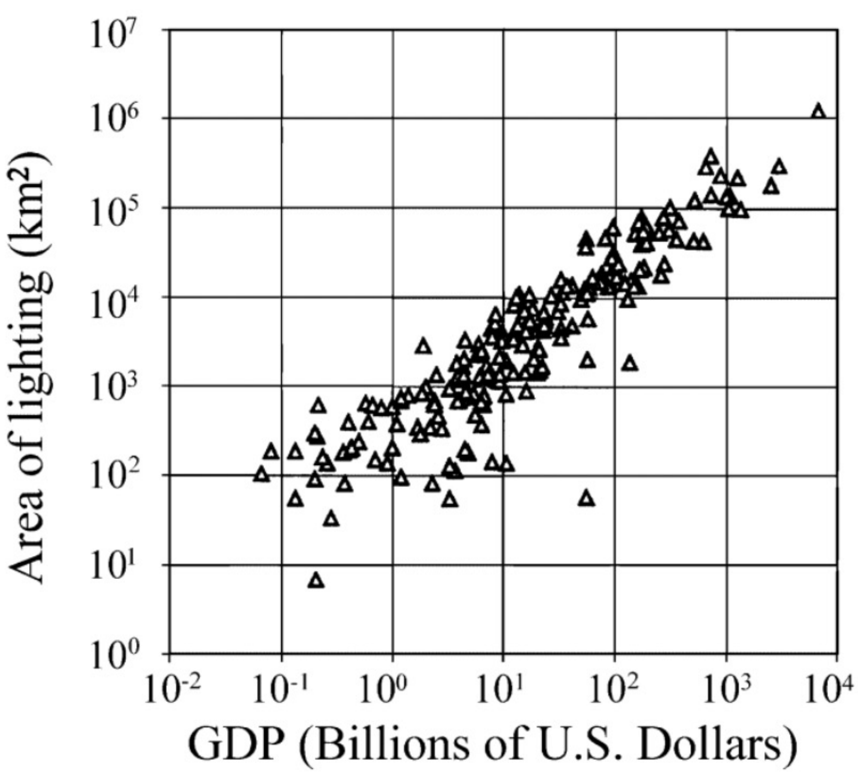
Lunar effects on NTL

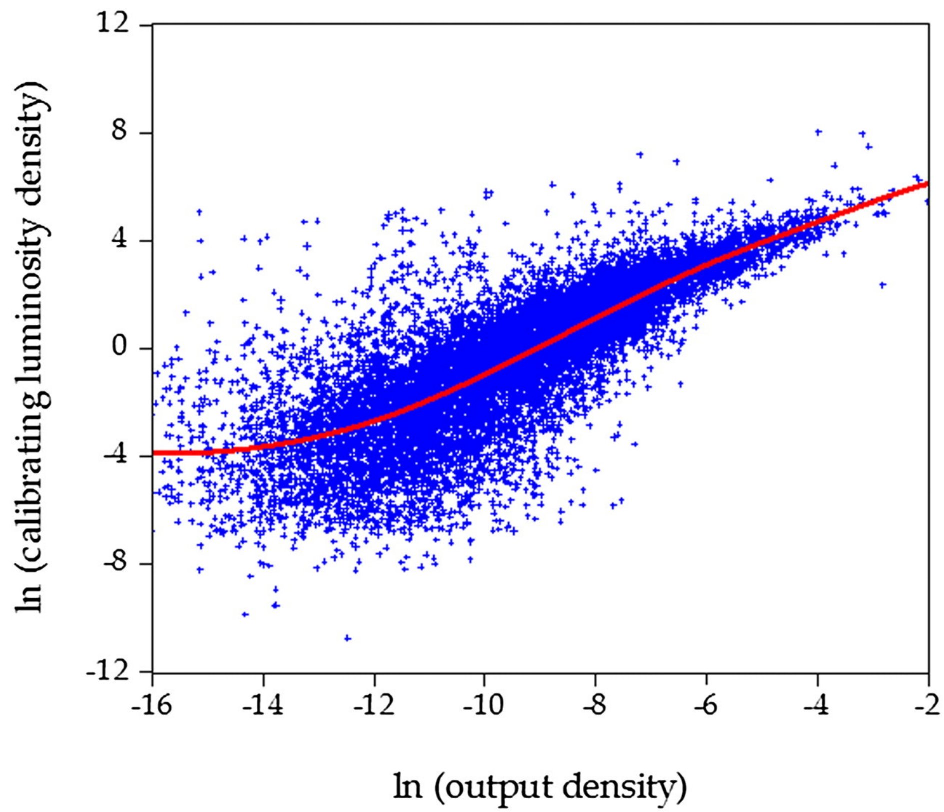


NTL and Economy

Lit Area at night vs GDP of 200 countries

Christopher D Elvidge et al. ***Night-time lights of the world: 1994–1995****.*
ISPRS Journal of Photogrammetry and Remote Sensing, 56(2):81–99, 2001.





Luminosity vs GDP

Xi Chen and William D. Nordhaus. ***Using luminosity data as a proxy for economic statistics.***
Proceedings of the National Academy of Sciences of the United States of America, 108:8589–8594, 2011.

NTL and Land Use

- Can we combine NTL with other data?
- What comprises NTL and by how much?
- Are there more granular NTL data?

Table 2. Essential urban land use classification schemes-Level 1.

Level 1	01	02	03	04	05
Categories	Residential	Commercial	Industrial	Transportation	Public management and service

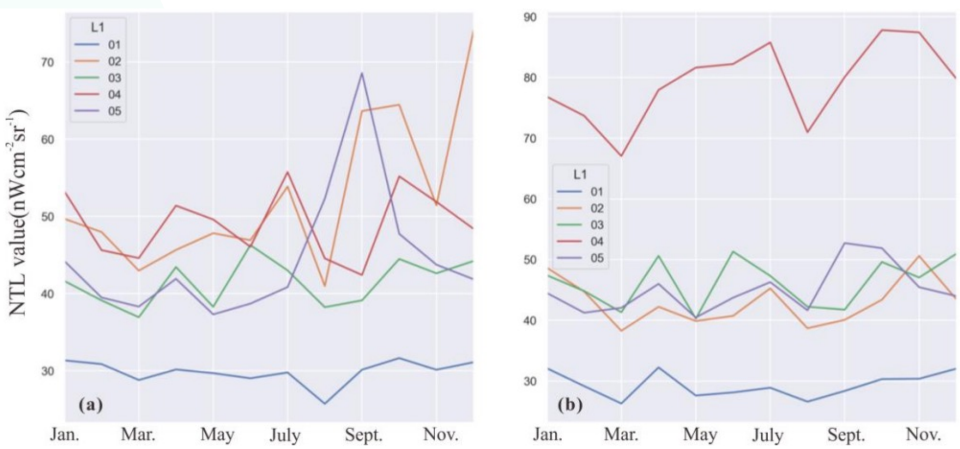
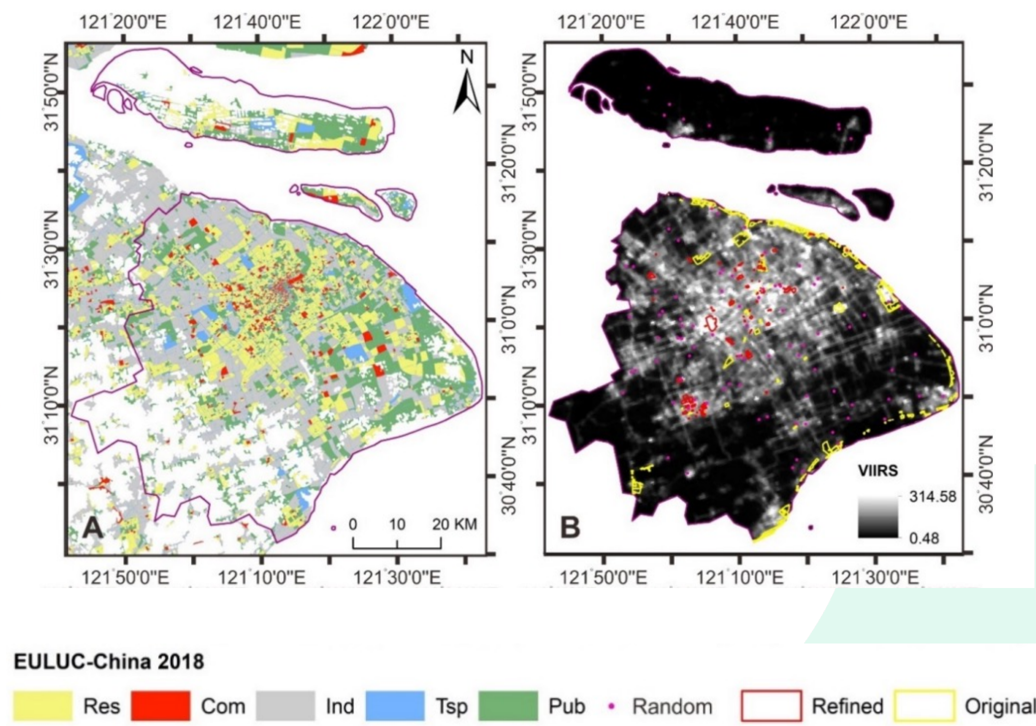
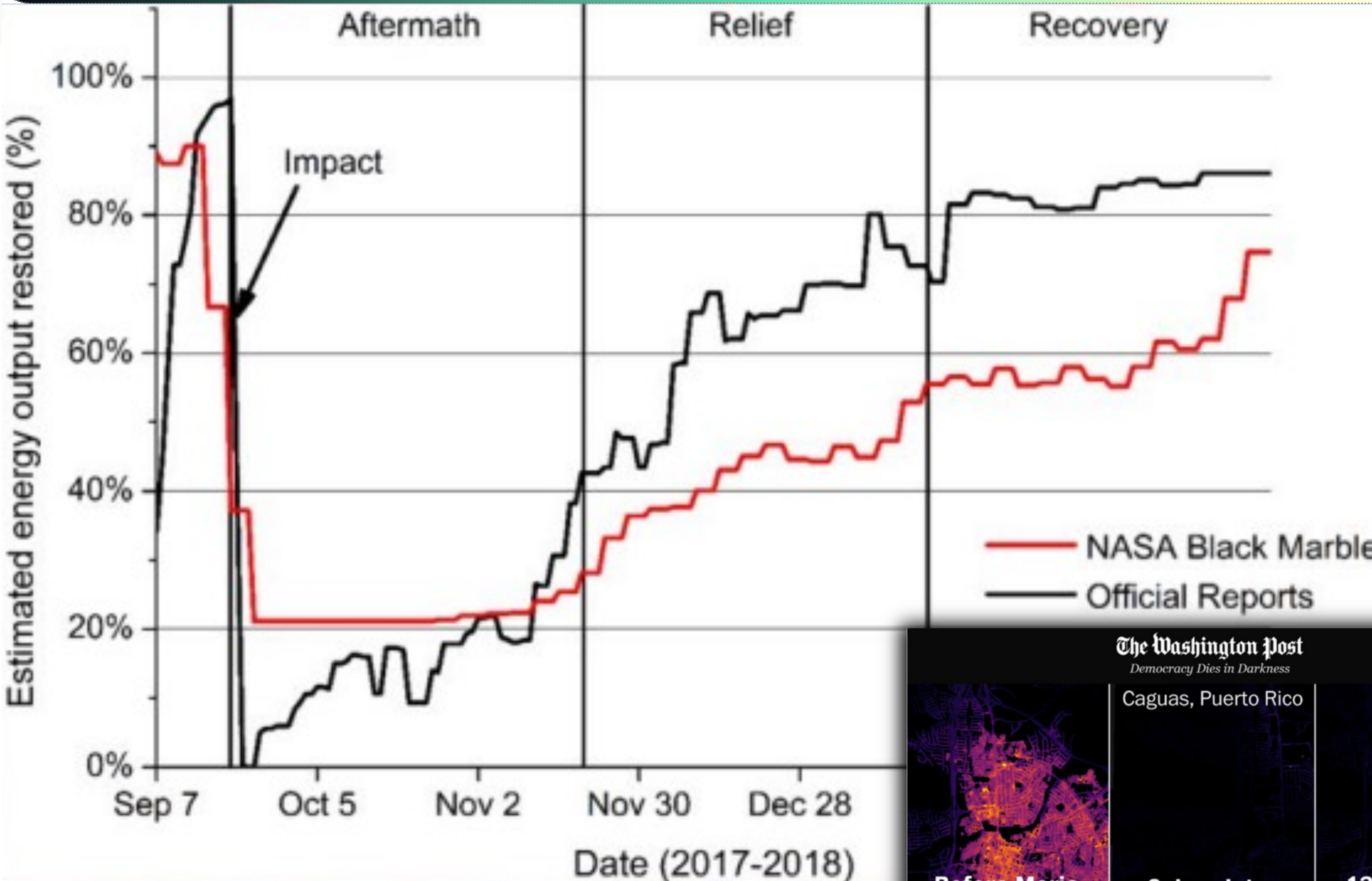


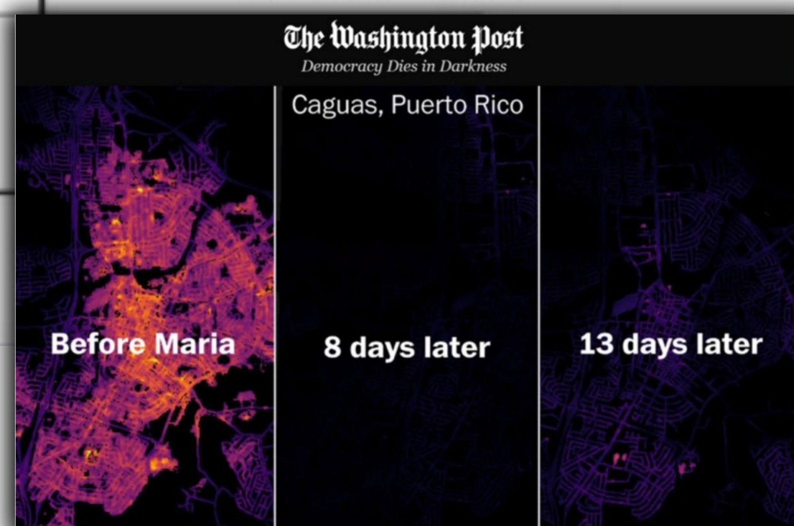
Figure S1. Temporal profile of original parcels (a) and refined parcels (b). Each line is plotted according to the temporal average nighttime light values of a certain type. 01 to 05 represents residential, commercial, industrial, transportation and public service land use types as Table 2 shows. L1 represents the Level 1 classification in EULUC-China.



Ren, Zhehao, Yufu Liu, Bin Chen, and Bing Xu. 2020. **"Where Does Nighttime Light Come From? Insights from Source Detection and Error Attribution"** *Remote Sensing* 12, no. 12: 1922. https://doi.org/10.3390/rs12121922

NTL and Disasters





NTL tracks electric restoration in Puerto Rico

Miguel O. Roman et al. ***Satellite-based assessment of electricity restoration efforts in Puerto Rico after Hurricane Maria***. PLoS ONE, 14(6), 2 2019.