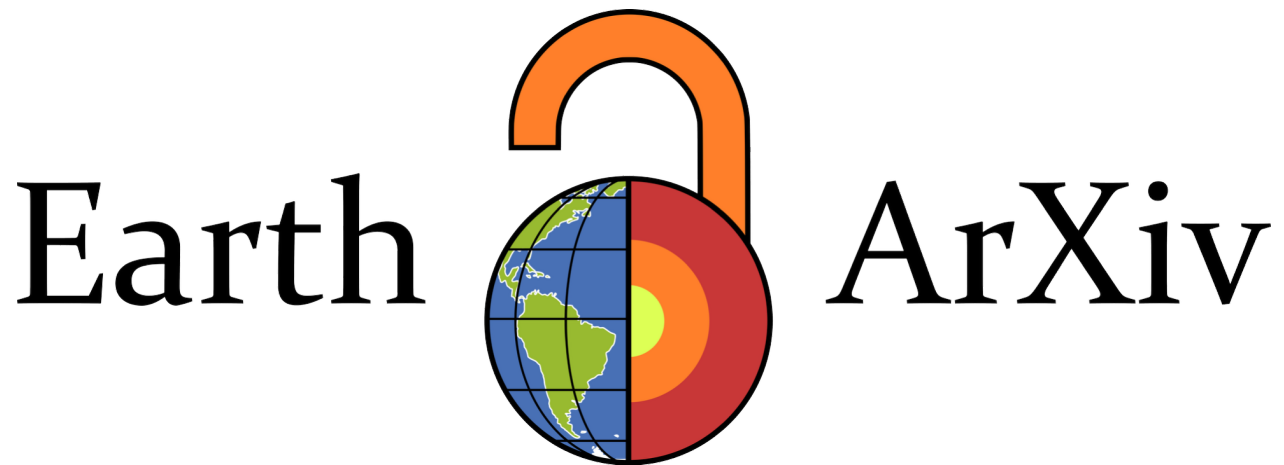




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Global Power Outage Detection at the Kilometer Scale from Satellite Nighttime Lights

Julian Rice^{*}, Ning Sun, Karthik Balaguru, Tse-Chun Chen, Brent Daniel, and Drew Suarez

Pacific Northwest National Laboratory, Richland WA

^{*}Corresponding author: julian.rice@pnnl.gov

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Abstract

Satellite nighttime light observations show great promise for remote sensing of power outages, yet have only been utilized in limited case studies to date. Here, we present generalized detection of power outages across the globe at ~ 1 -kilometer resolution. Our method, the **Outage Framework for Luminosity Interruptions (OWL-I)**, reveals the power outages can be reliably detected from VIIRS/Black Marble nighttime light observations with no knowledge of the driver event or infrastructural records. Confounding factors that have complicated past nighttime light outage detection efforts—including lunar illumination, satellite viewing geometry, snow albedo, and temporal factors—are, for the first time, jointly corrected in a unified framework. While conventional outage detection methods from the literature are shown to be prone to false positive detections, our method exhibits dramatically improved detection skill and remains well calibrated and skillful even for extreme events it was never trained on. When applied to the complete satellite nighttime light observational record 2012–2024, the structure, extent, and time-evolution of power outages are revealed with unprecedented fidelity. These results enable spatially detailed analyses of the drivers and impacts of power disruptions, supporting power grid resilience planning, hazard impact assessment, and emergency management research.

1 Introduction

Reliable electric power is foundational to modern economies and public health [18]. Accurate characterization of historical power disruptions, encompassing the spatial distribution, frequency, and magnitude of power outages, is essential for understanding grid resilience and safeguarding against future outages.

Despite this importance, publicly available high-resolution outage records are scarce. In the United States, the most comprehensive national dataset is EAGLE-I [6], which tracks electricity customers without power at 15-minute intervals for nearly all counties in the continental United States (CONUS). While invaluable, datasets such as EAGLE-I are inherently limited in spatial resolution: they cannot distinguish where outages occur within a county, nor whether outages are widespread and diffuse or local and intense, features that may significantly modulate impacts. Since counties vary greatly in size across the CONUS, with some comparable in area to e.g. mid-sized European nations, sub-county resolution is critical for hazard attribution and impact analysis. However, current power outage modeling and analysis efforts are fundamentally limited by this resolution gap, with most efforts operating at county or service-area scales [3, 11, 15, 36, 40, 42].



Figure 1: Confounding factors influencing satellite nighttime light retrievals: obscuration by (a) vegetation, (c) urban structures, and (f) clouds, the effects of which may be dependent on (e) viewing angle; enhancement due to (b) moonlight reflection and (d) snow albedo. Not pictured: weekly, seasonal, and long-term temporal effects.

Proprietary sub-county scale data acquired in partnership with utility companies has occasionally been analyzed in the literature [46, 47], but is geographically limited to the utility’s service region and cannot be shared publicly. Many other nations lack publicly-available high quality power outage records at any spatial resolution.

Satellite observations of nighttime light offer a physically motivated alternative for detecting power outages with much greater spatial fidelity [23]. When electricity goes out, nighttime brightness retrievals drop measurably in imagery acquired by satellite sensors such as the Visible Infrared Imaging Radiometer Suite (VIIRS) Day-Night Band (DNB). The widely-used Black Marble product [37, 45], a post-processed and quality-controlled dataset produced by NASA, makes these deviations even clearer. The conventional method of detecting outages in this data—which nevertheless provides serviceable results and has been utilized by most studies to date [14, 16, 24, 25, 38, 43, 50, 51, 53]—is to simply compute the ratio of nightly observed brightness to some baseline (usually a pre-event or long-term mean), with ratios below 100% indicative of an outage. However, VIIRS-derived brightness products are not designed exclusively with power outage detection in mind [45], and a growing body of research [20, 21, 41, 44] has identified a number of non-outage factors—including satellite viewing geometry, seasonal effects, snow albedo, and lunar illumination—that cause substantial variability in nighttime brightness (Figure 1). These confounding factors have been an unrecognized limitation of a disconcertingly large number of past studies, and while one or two confounding factors (usually viewing geometry) have been corrected for in a handful of event-specific outage detection works [7, 9, 17, 48, 50, 52], no study has developed and validated a method to systematically correct for all known factors, nor apply such a method at a national or global scale across a wide range of places, times, and events. The lack of a standardized, calibrated, and high-quality outage method and dataset derived from nighttime satellite observations is thus a glaring gap in the literature, and its establishment would be of obvious benefit to future research.

Here we address this gap with the **O**utage **F**ramework for **L**uminosity **I**nterruptions (OWL-I), the first generalized, standardized, and validated method for detecting power outages from satellite nighttime light observations at a global scale. OWL-I consists of a two-stage pipeline, in which known confounding factors in the nighttime light observation signal are first accounted for with a conceptual model, and then calibrated against county-scale outage observations with a robust and validated artificial intelligence approach while preserving kilometer-scale fidelity. This approach is found to drastically outperform common methods from the literature across a wide range of conditions, including extreme events for which it was never trained. With OWL-I, we produce a complete ~ 1 km daily power outage dataset for the entire CONUS spanning 2012–2024, and demonstrate promising generalizability to any region on the globe. This method and the resulting publicly available dataset represent a significant advance in high-resolution outage detection, enabling a range of previously difficult analyses including power grid structure discovery, high-resolution outage risk modeling, and sub-neighborhood scale vulnerability assessment.

2 Results

OWL-I is a two-stage framework which predicts outages given satellite nighttime light data, by (1) correcting for confounding factors at the scale of individual pixels (Methods 4.3) and (2) converting the corrected brightness to outage level with a robust machine learning method (Methods 4.4). These stages are evaluated individually and together in the following sections.

2.1 Correcting confounding sources of brightness variability

Nighttime light radiance, even after the NASA Black Marble post-processing, varies substantially due to known factors unrelated to power outages, including: satellite viewing angle [21, 41, 44], snow cover (Figure S2b and [44]), moonlight (Figure S2c and [8, 44]), and temporal factors on weekly (Figure S3 and [22]), seasonal [20, 22, 44], and long-term scales [20, 22]. These confounding factors have largely been identified individually in the literature, but not yet been corrected together in a unified framework. This is perhaps because many of these factors are too complex to model from a process perspective, since they are the result of interactions between viewing conditions, terrain, urban morphology, human behaviors, and natural processes (see, for example, the heterogeneous response of brightness to satellite viewing angle in Figure 2). We instead derive empirical relationships for these factors directly from the observational record with a “deconfounding” linear model grounded in physical understanding of the problem (Methods 4.3).

A surprising amount of variance is captured by this deconfounding model. As visible in Figure 3, the confounding factors represented in this simple model can explain up to 94.1% of the variance in a pixel’s nighttime light observations. They explain 35.4% of the variance in the average pixel, 35.1% in the median pixel, and 35.0% when taking the average weighted per-pixel by population. The skill is widespread, but particularly noticeable in the urban-rural boundaries surrounding sprawling metro areas, such as in the vicinity of Dallas, Texas. Put plainly, this result suggest that on average at least one third of the variability in surface nighttime brightness is due to confounding factors entirely unrelated to power outages.

This deconfounding model enables a new and more robust method of detecting outages. Instead of the conventional approach often used in the literature (Methods 4.2)—which identifies deviations between an observation and some long-term mean—we identify deviations between the observation and the corresponding value predicted by the deconfounding linear model, which serves as a more accurate “expected brightness baseline” that takes into account viewing geometry, lunar conditions, etc. (Methods 4.3). Still, a number of uncertainties remain. Chief among them is whether true power

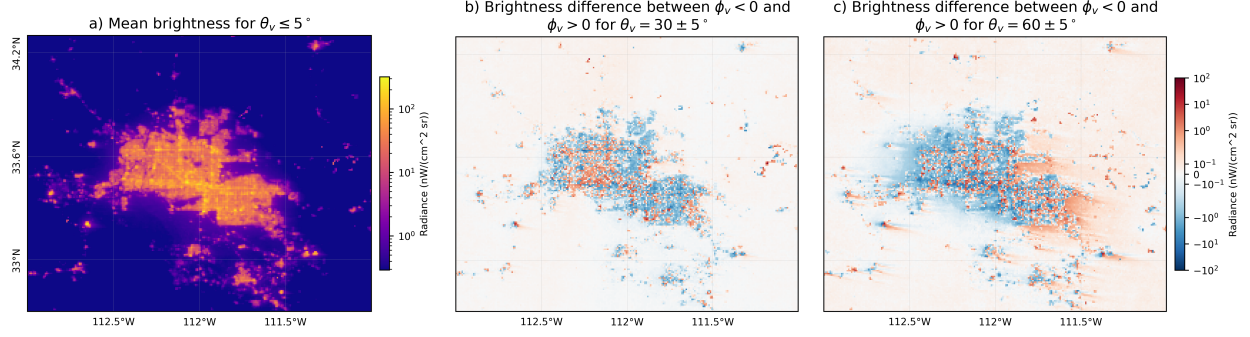


Figure 2: Dependence of nighttime light brightness on interactions between viewing zenith angle (θ_v) and viewing azimuth angle (ϕ_v). (a) Composite 2012-2024 mean brightness for the Phoenix, Arizona metropolitan area when viewed from overhead ($\theta_v \leq 5^\circ$). (b) The city’s brightness shows a moderate and heterogeneous response when viewed from the west ($\phi_v < 0^\circ$) as opposed to the east ($\phi_v > 0^\circ$) at moderate zenith angles ($\theta_v \approx 30^\circ$). (c) When the satellite is substantially off-nadir ($\theta_v \approx 60^\circ$) viewing azimuth angle has a much stronger effect, with urban glow casting a brightening effect on the side of the urban center opposite the satellite.

outage fraction varies linearly with brightness reduction (i.e., does a 25% reduction indicate 25% of customers are without power, or greater or fewer?) and whether that relation is stable across different population densities (i.e., is a 25% brightness reduction in rural Wyoming as indicative of power outage as a 25% reduction in downtown New York City?). Additionally, there may be confounding factor inter-relationships which are too complex to be included in the simple deconfounding model, yet may be learnable from the data directly in a more generalized model. In the next section, we address these concerns with the development of an artificial neural network model which corrects and calibrates against observed county-level outage totals while preserving pixel-level structure.

2.2 Generalized outage detection with OWL-I

Our method, which we term OWL-I, is a robust neural network that relies primarily on the corrected brightness signal derived from the deconfounding linear model, but learns to further correct and calibrate it against EAGLE-I power outage observations. However, to properly calibrate kilometer-scale predictions against county-level targets requires an unorthodox modeling approach. This many-to-one (pixels-to-county) optimization problem would be challenging or impossible with traditional regression or machine learning techniques, and even many standard computer vision methods are ill-suited for this task. While window-based techniques such as convolutional networks and vision transformers are state-of-the-art in many image-to-image tasks, they are naturally inclined to blurriness even when trained on pixel-level targets [12]; when only aggregated targets are available, they are by nature incapable of preserving pixel-scale output fidelity (as illustrated in Figure S4). In contrast, OWL-I utilizes a novel framework which operates only on single pixels—thus intrinsically preserving kilometer-scale fidelity—while being trained to accurately reconstruct county-level EAGLE-I outage totals by summing outages over county areas (Methods 4.4).

To robustly test the generalizability of the OWL-I method, we train an ensemble of models with eight-fold cross validation, and assess their skill across the entire period of EAGLE-I coverage by evaluating ensemble members on years which they were never trained on. We compare OWL-I with the uncorrected and uncalibrated “conventional method” (Methods 4.2) often found in the literature,

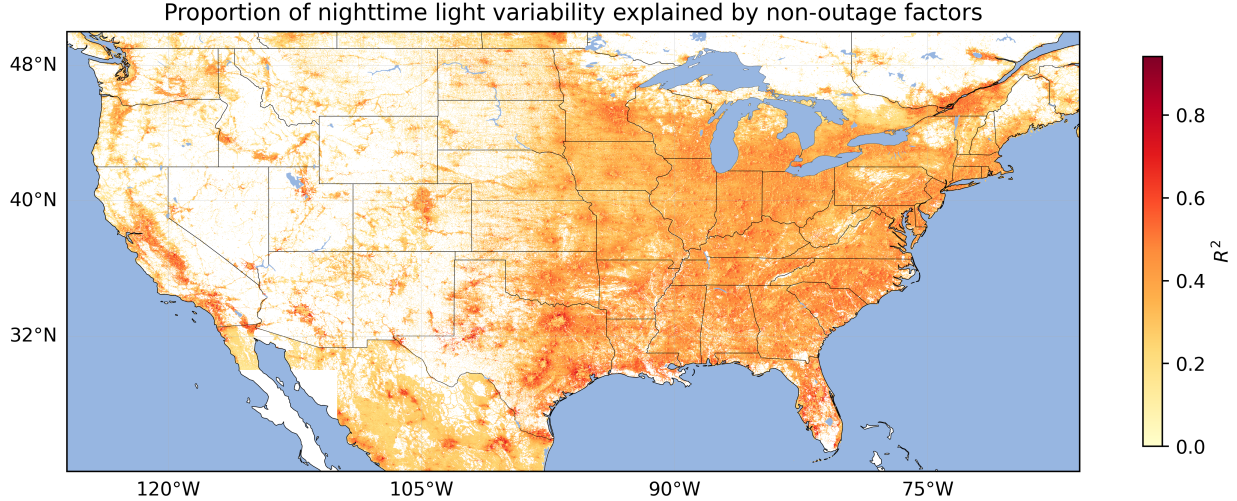


Figure 3: Proportion of variance in Black Marble BRDF-corrected log-nighttime light observations explained by confounding factors, 2012-2024.

and corrected but still uncalibrated “deconfounded outage method” (Methods 4.3). R^2 is used as the primary assessment metric, with linear-space R^2 primarily indicative of a method’s ability to capture major outages, and log-space R^2 indicative of a method’s ability to discern outage magnitude across all event and county sizes. Pearson and Spearman correlation provide additional context for the comparisons, indicating whether a method captures the correct relative magnitudes and ordering of outage events.

By all metrics in Table 1, OWL-I significantly outperforms both of these baselines in predicting EAGLE-I outages at test time. Although the baselines have moderate Pearson correlations and Spearman rank correlations with the EAGLE-I targets, they both exhibit negative R^2 indicating a mean bias. OWL-I has substantially better performance in both linear- and log-space R^2 , suggesting good calibration and skill across a wide range of outage events, as well as substantially better correlation in both the Pearson and Spearman sense (with a Pearson correlation of more than double that of the conventional method). The deconfounded outage method exhibits generally better performance than the conventional method, though by a much smaller margin.

Table 1: Performance of three nighttime light outage detection methods in predicting 2014-2024 county-level EAGLE-I outage observations. OWL-I ensemble members were evaluated only for samples that they were never trained on. R^2 s and Pearson correlations are provided in both linear space and log space. Bolded values indicate best performance among the three methods; OWL-I achieves the best score in all cases.

Method	R^2		Pearson r		Spearman ρ
	Lin.	Log.	Lin.	Log.	
OWL-I (ours)	0.489	0.431	0.720	0.657	0.507
Deconfounded outage	-3.128	-1.789	0.388	0.365	0.327
Conventional outage	-4.628	-1.673	0.358	0.341	0.300

Given the state-of-the-art skill achieved by OWL-I, we apply the framework to the complete nighttime light record for the continental United States 2012-2024 (Methods 4.5) and make the result-

ing outage dataset publicly available on Zenodo at <https://doi.org/10.5281/zenodo.20433558> [35].

2.3 Case studies

For deeper understanding of OWL-I’s abilities, we evaluate the method’s skill on notable outage events within the record, using the ensemble member which was never trained on that event for an unbiased characterization of model generalization skill.

2.3.1 Hurricane Michael, 2018

Hurricane Michael was a Category 5 hurricane which made landfall on the Florida panhandle near Panama City around 1:30pm local time on October 10th, 2018, with winds of approximately 160 miles per hour [5]. It caused widespread damage, with an estimated \$25 billion in direct losses throughout Florida, Georgia, and Alabama [5]. As a recent major power outage event, it has been analyzed using satellite outage detection methods in the literature, both with the conventional method (Zhang et al. [50] and Mitsova et al. [24]) and partially-deconfounded methods (Zheng et al. [52] apply a quadratic correction for satellite viewing zenith angle only). We use the conventional method (with L_{ref} established as March-September 2018 mean nighttime brightness, following Mitsova et al. [24]) and our deconfounded outage method (as it is a superset of the corrections applied by Zheng et al. [52]) as representative baselines to compare against, and analyze the period of October 10th-31st to capture the onset of outage and restoration of power over time. Pixel-level predictions are generated with all three methods, and aggregated to county levels as in Equation 6, with a minimum satellite population coverage (F_{cov}) of 75% for county-nights to be considered valid for inclusion.

Maximum predicted outage maps for all three methods for the period—at both pixel and county scales—as well as the EAGLE-I ground truth are shown in Figure 4. It is immediately apparent that both the conventional and deconfounded methods substantially overestimate the spatial extent of outages, predicting a significant outage in nearly every county in the region at least once during the period. OWL-I is much more accurate, slightly underestimating the extent of outages compared to EAGLE-I but capturing the localization of damage along the storm’s track quite well. When evaluated for all county-nights in the case study, OWL-I outperforms the two baselines by an obvious margin (Table 2a). When isolating only those counties where peak EAGLE-I outages exceeded 5,000 customers (counties labeled by name in Figure 4a), the margin is smaller though still in OWL-I’s favor, particularly for the log-space metrics which highlight skill for low and moderate outage levels (Table 2b). These results suggest that the simpler methods are relatively suitable for identifying major outage peaks, but are unskilled at identifying minor outages, non-outages, or the decaying tails of major outages.

These insights are bolstered by visualizing the temporal progression of outages from the three methods against nightly EAGLE-I observations (Figure S5). In Florida’s Leon and Bay counties, where outage totals approached 100,000 customers or more, all methods appear similar. In moderately-impacted counties (peak customers out <30,000), greater variability is evident: The conventional method is prone to large and anomalous fluctuations—sometimes in the opposite direction of the EAGLE-I trend, such as November 13th-15th in Houston County, AL—and rarely settles to a zero outage level following the event, thus overestimating outage durations. The deconfounded method is similar but smoother, though still exhibiting obvious anomalies (e.g., the end of the month in Houston County, GA). OWL-I tracks the overall shape of the observed outage curves much better, though often settles to zero sooner than observations, thus underestimating outage durations.

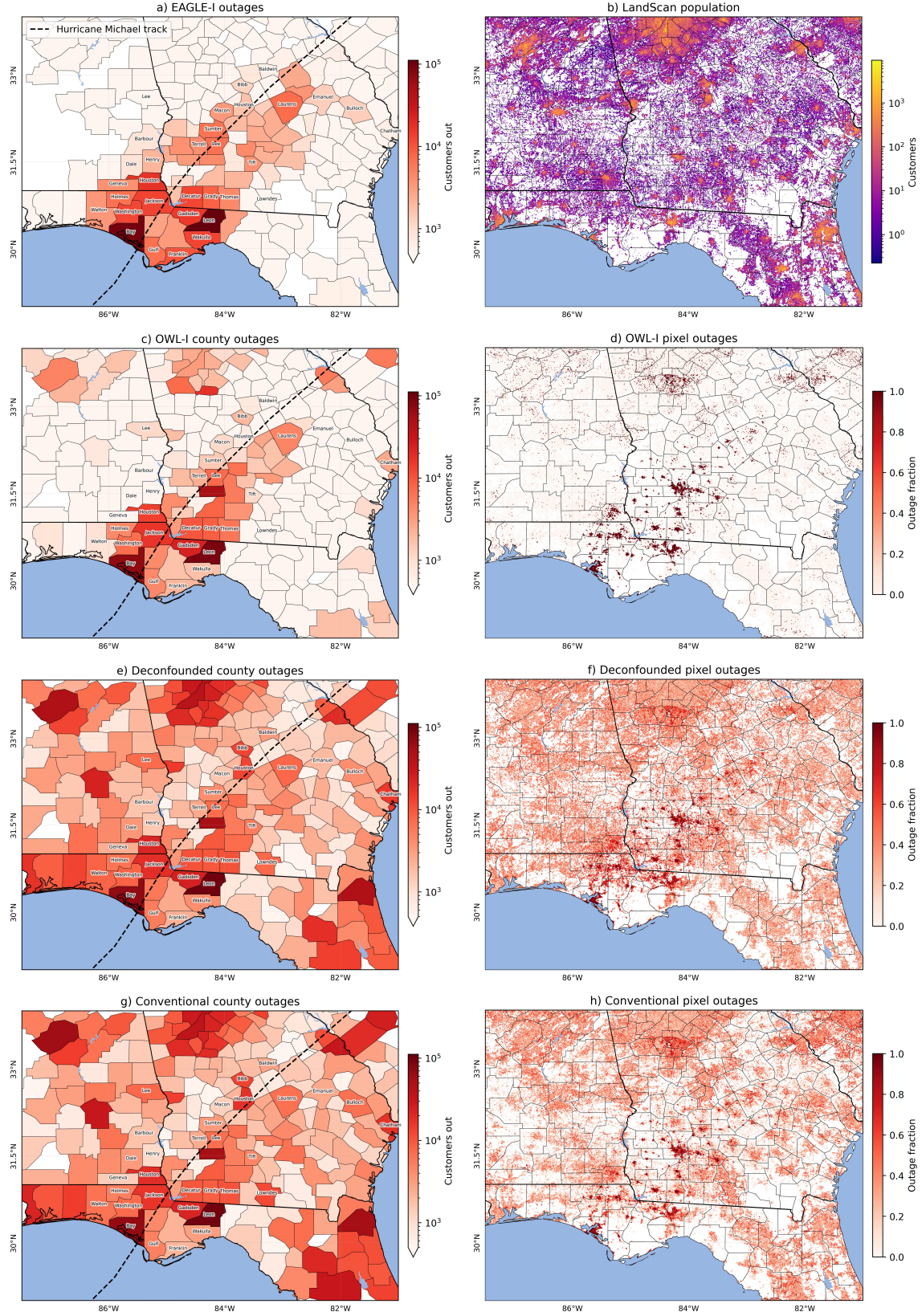


Figure 4: Maximum outages in the path of Hurricane Michael for October 10th-31st, 2018, from (a) nightly EAGLE-I and (c-h) three satellite outage detection methods at pixel and county-aggregated scales, with (b) LandScan population for reference. For OWL-I, the ensemble member that was never trained on 2018 is used.

Table 2: Hurricane Michael case study performance. Each method is evaluated for its skill in predicting nightly county outage totals compared to EAGLE-I ground-truth, for all county-nights with sufficient valid EAGLE-I and nighttime light data. Methods are evaluated for (a) all counties shown in Figure 4, and (b) only for those counties with peak EAGLE-I outages exceeding 5,000 customers. For OWL-I, the ensemble member that was never trained on 2018 is used. Bolded values indicate best performance among the three methods; OWL-I achieves the best score in all cases.

(a) All counties in region					
Method	R^2		Pearson r		Spearman ρ
	Lin.	Log.	Lin.	Log.	
OWL-I	0.826	0.386	0.910	0.664	0.509
Deconfounded outage	-0.295	-2.417	0.620	0.073	-0.016
Conventional outage	-0.242	-2.122	0.595	0.099	0.018

(b) Counties exceeding 5,000 peak customers out in EAGLE-I					
Method	R^2		Pearson r		Spearman ρ
	Lin.	Log.	Lin.	Log.	
OWL-I (ours)	0.904	0.582	0.969	0.775	0.776
Deconfounded outage	0.847	-0.424	0.933	0.372	0.331
Conventional outage	0.838	-0.349	0.925	0.353	0.320

2.3.2 2021 Texas winter storms

In February 2021, a series of winter storms brought record cold and snow to much of Texas, resulting in significant disruptions to power generation and distribution. Nearly 10 million people were left without power at the peak of the outages, and over 200 deaths are attributable to the event [29]. We evaluate OWL-I against the baselines methods for the period February 10th-28th, with the conventional method following a similar satellite outage detection study for this event (Xu et al. [48]).

OWL-I is again clearly the best method for capturing the spatiotemporal pattern of outages during this event (Table 3), although this event appears to be much more challenging for all satellite outage detection methods than the case of Hurricane Michael. The baseline methods again somewhat overestimate the extent of peak outages, while OWL-I slightly underestimates it (Figure S6); however, the temporal progression (Figure S7) reveals that the baseline methods often predict their peak well after the actual outages occurred, rendering the temporal-maximum maps misleading. Instead, plotting the relation between observed and predicted outages for all county-nights simultaneously (Figure S8) shows that the baseline methods frequently predict substantial (≥ 1000 customer) outages when the true outages are minimal (~ 10 customers or less). Although OWL-I is not immune to outlier predictions it follows EAGLE-I much more closely, with a log-space R^2 of 0.355 compared to less than -1.0 for the baseline methods.

Table 3: 2021 Texas winter storms case study performance, as in Table 2, for (a) all counties in the region, and (b) only those counties with peak EAGLE-I outages exceeding 20,000 customers. Bolded values indicate best performance.

(a) All counties in region					
Method	R^2		Pearson r		Spearman ρ
	Lin.	Log.	Lin.	Log.	
OWL-I (ours)	0.182	0.355	0.539	0.625	0.514
Deconfounded outage	-0.520	-1.339	0.514	0.194	0.127
Conventional outage	-0.527	-1.152	0.486	0.210	0.150

(b) Counties exceeding 20,000 peak customers out in EAGLE-I					
Method	R^2		Pearson r		Spearman ρ
	Lin.	Log.	Lin.	Log.	
OWL-I	0.141	0.469	0.528	0.689	0.539
Deconfounded outage	-0.585	-1.659	0.478	0.180	0.181
Conventional outage	-0.595	-1.512	0.448	0.161	0.141

2.4 Kilometer-scale outage dynamics

In addition to quantifying OWL-I’s skill against county-level targets, a closer investigation of how the framework operates at individual pixels is revealing of its capabilities and internal processes. We find that OWL-I learns a sigmoidal relationship between brightness anomalies and predicted pixel-level outages, depicted in the partial dependence plot of the two variables (Figure 5). The learned relationship between brightness anomaly and outage level is strongly non-linear, despite

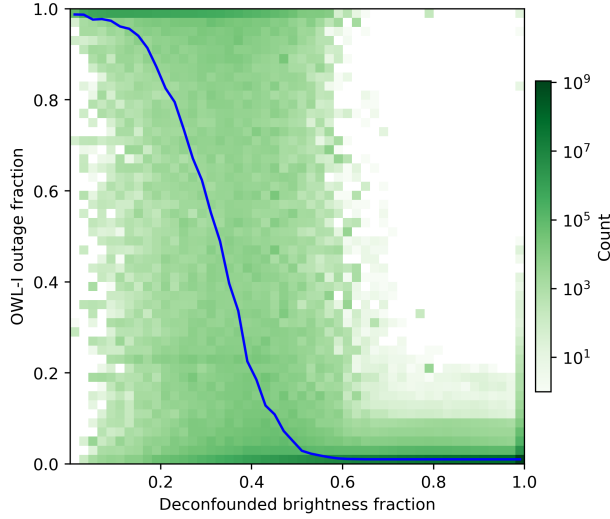


Figure 5: Partial dependence between (deconfounded) brightness anomaly and OWL-I outage predictions at the pixel level, weighted by per-pixel LandScan population. The blue line shows the mean response, while the green density scatterplot shows the underlying data.

the common assumption of linearity in the literature. On average, the model predicts outages when brightness dips below 50% of expected, and approaches total outage for brightnesses below 10% of expected. This curve highlights the importance of a trained and calibrated method such as OWL-I; the linear assumption is intuitive and easy to make, but seems to be the source of frequent overestimation by the conventional outage method as identified in our case studies. The density scatterplot backdrop in Figure 5 also shows that model outputs are not solely a function of brightness anomaly, but are modulated by learned corrections related to other confounding factors and conditions, though primarily only for brightnesses between 10% and 60% of expected.

Another important feature of our proposed method is that it preserved kilometer-scale fidelity while learning the proper calibration from county-level targets. To demonstrate this capability, we can return to the 2021 Texas winter storms case study, with a focus on the Houston metropolitan area. Houston (and broader Harris County) did not experience a total blackout during this event, but instead the localized failure of individual circuits [53], as is visible in the raw brightness maps (Figure 6a-b). OWL-I captures this spatially heterogeneous pattern of apparent outages qualitatively quite well (Figure 6c), and does not simply learn an average outage level applied to all pixels in the county. By design, OWL-I’s “pixel-independent” architecture (Methods 4.4) is not prone to the loss of fidelity that many alternate approaches would be susceptible to when trained on county-level targets.

2.5 Global outage detection

Although OWL-I is only trained on the continental United States where EAGLE-I is available, the framework is intentionally designed to rely only on globally-available data sources (primarily Black Marble and LandScan Global) at inference time, and is thus theoretically capable of generalizing to any location on Earth. While some specific aspects of United States brightness dynamics may not be applicable in other regions, we suspect the dominant relationships between population density, brightness, and outage will remain similar enough that OWL-I can serve as a reliable first-order estimate in global applications, where outage records of any kind (not to mention at 1 km resolution)

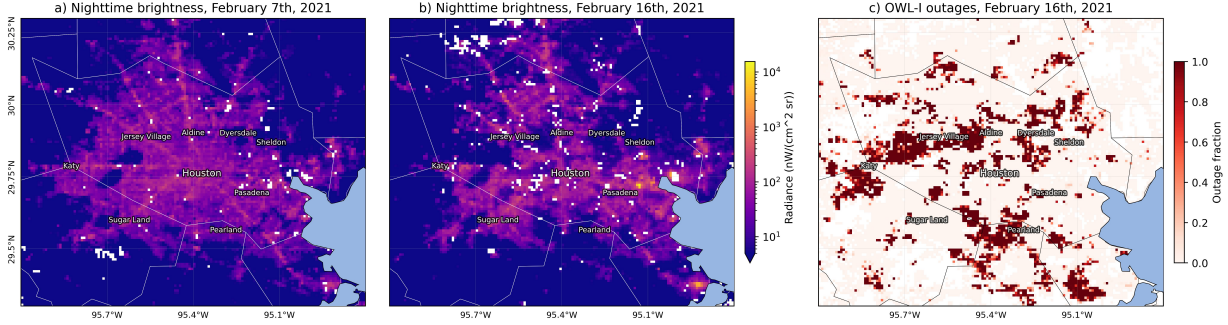


Figure 6: The Houston metropolitan area during the 2021 Texas winter storms. (a) NASA Black Marble nighttime brightness before the event and (b) near peak outage. (c) OWL-I outages for the same date demonstrate that kilometer-scale fidelity is preserved.

may otherwise be scarce. To investigate further, we analyze three such events across diverse regions and scales, and compare with contemporary news reports for a qualitative assessment of OWL-I’s global capabilities (Fig. 7).

2021 Pakistan blackout At 11:40pm local time on January 9th 2021, a power system failure plunged Pakistan into a nationwide blackout which was gradually restored over the following day. Although widespread use of backup generators in this region [39] makes it difficult to assess the exact proportion of people who were truly without access to power, NetBlocks estimated that internet connectivity in the country dropped by 38% in the immediate wake of the outage [28]. From the satellite nighttime brightness observations collected that night, OWL-I successfully detects a national-scale power outage event with an estimated 41.2 million people experiencing outage in cloudless regions (Fig. 7a). However, given that 47% of the nation’s population is obscured by clouds on this date (primarily in the densely-populated Punjab region), the true total is potentially far more; simple extrapolation suggests 77 million people out. OWL-I’s estimated percentage of the nation’s (satellite-visible) population experiencing outage is 32.3%, similar to NetBlocks’ estimate of 38% though consistent with OWL-I’s generally conservative tendencies found in preceding sections.

2023 Türkiye earthquakes On February 6th 2023, a M_w 7.8 earthquake struck northwest of Gaziantep, Türkiye, although the aftermath of this event was mostly obscured by clouds. A further M_w 6.3 aftershock (ISC 625728181) struck near the city of Antakya in the evening of February 20th, further damaging the already fragile infrastructure [10]. OWL-I successfully detects this localized outage in Antakya on that night, with severe outage across the city affecting at least 225,000 people (Fig. 7b). Specific reporting of the power outage impacts of this event are difficult to find, but this series of earthquakes is known to have damaged the entire city of Antakya [49].

2019 Java blackout Disruption to a critical East-West transmission line caused cascading power system failures across the Indonesian island of Java starting around noon local time on August 4th 2019, primarily impacting the western and to a lesser extent central parts of the island [32]. Although upwards of 100 million faced outages at the peak [1], power was restored to the capital Jakarta and some other areas in nine hours [33]. Still, many regions faced outages into the night, with OWL-I detecting a widespread outage impacting at least 6.9 million people (Fig. 7c). The framework correctly identifies the outages to be concentrated primarily on the western half of the island, while also accurately capturing the largely-restored conditions in Jakarta providence—although a clearer view of that region is precluded by cloud cover.

These examples suggest that OWL-I remains qualitatively skillful in global applications, and captures coherent patterns of outage consistent with reported impacts. These results further highlight

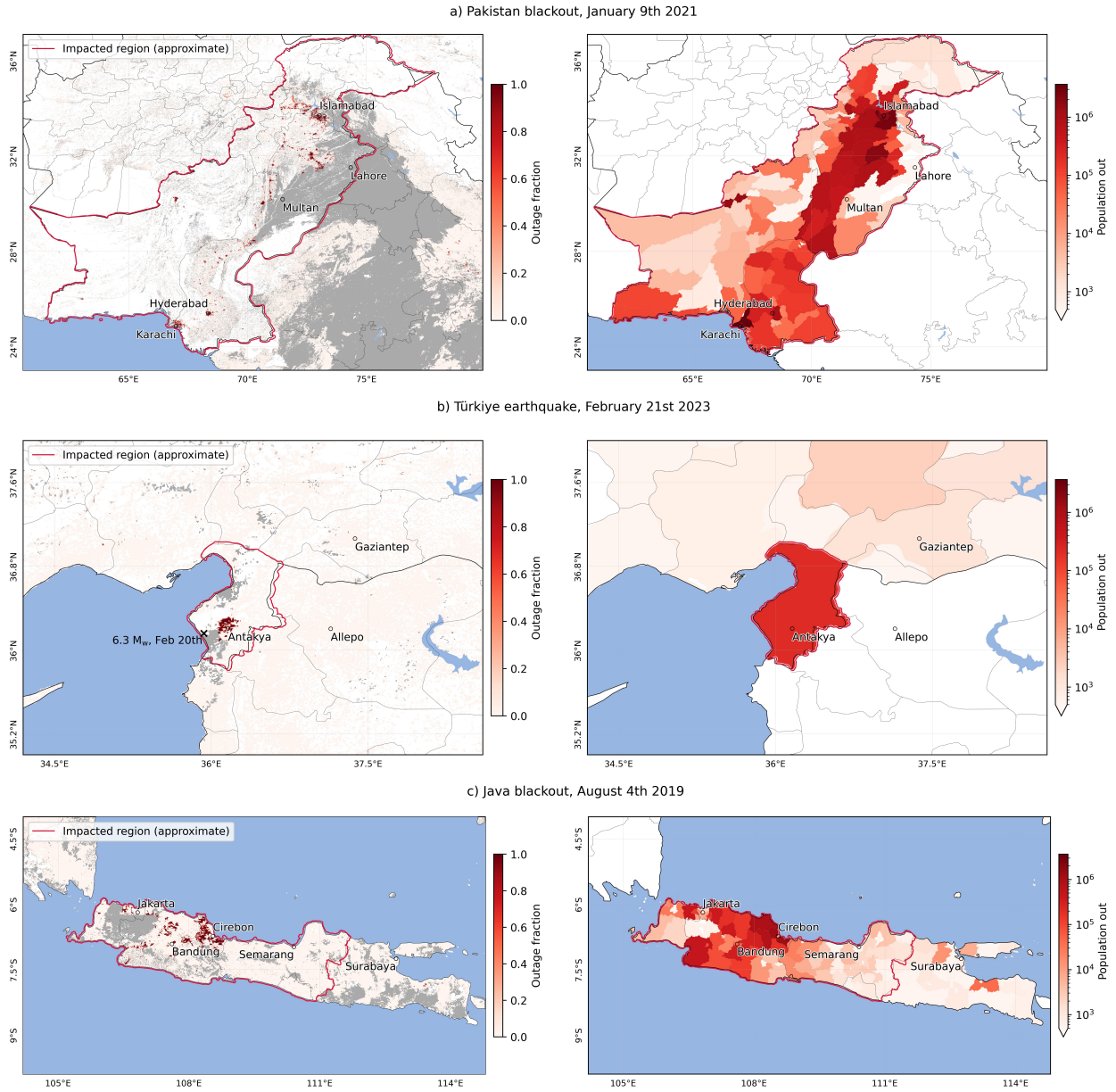


Figure 7: OWL-I outage detections at pixel (left) and district (right) levels for three major outage events globally: (a) the 2021 Pakistan blackout, (b) 2023 earthquake-induced outages in Türkiye, and (c) the 2019 blackout on the Indonesian island of Java. Grey patches indicate populated areas with invalid (i.e. cloudy) nighttime light observations on that date. Approximate impacted districts according contemporary news reports are outlined. Map boundaries from Cartopy’s defaults may be contested, and do not imply official endorsement by the authors.

the benefits of OWL-I’s “pixel-independent” architecture (Methods 4.4), which is naturally capable of generalizing to new regions whereas other methods that rely on pre-defined training domains would fail. Still, it remains very difficult to quantitatively validate these results, since local power outage records for these events are inaccessible, especially at sufficient spatiotemporal resolution to assess kilometer-scale accuracy and co-locate with exact satellite overpass times.

2.6 Suggestions for future outage detection studies

Our results reveal that power outage detection from satellite nighttime lights is greatly complicated by a number of factors that do not appear to be widely understood in the broader outage detection community. Although all of these factors have been individually identified in the literature, only a few works by the Black Marble developers themselves [44] have attempted a comprehensive survey of these issues. For the benefit of future researchers, we list the challenges and misconceptions known to us below:

1. Black Marble’s BRDF correction is imperfect, and further calibration is required to effectively remove the influence of both moonlight (particularly in rural regions) and snow albedo.
2. A number of other confounding factors cause substantial non-outage variability in nighttime brightness, namely: satellite viewing geometry (*both* zenith and azimuth angle), seasonality, day-of-week effects, and long term trends.
3. The fraction of customers experiencing outage is not, in general, linearly proportional to the fractional decrease in satellite observed brightness. Assuming so causes frequent false positive outage detections.
4. Black Marble satellite acquisitions do not occur at the same time every night, nor do the viewing times follow a strict 16-day cycle. Observation time effects should therefore be handled individually for each pixel on each night.

3 Discussion

This study introduces OWL-I, a globally-applicable framework for deriving daily, kilometer-scale power outage estimates from VIIRS/Black Marble nighttime light observations. The method combines two complementary components: (1) a physically motivated deconfounding model that removes major non-outage sources of surface brightness variability and (2) a neural calibration model that maps residual dimming to outage fraction, which enforces agreement with county outage totals while preserving pixel-scale spatial fidelity. Across held-out samples spanning the continental United States 2014–2024, OWL-I substantially outperforms two baselines representative of the most common satellite-based outage detection methods found in the literature. Case studies for 2018’s Hurricane Michael and the 2021 Texas winter storms showcase that OWL-I captures both the spatial localization and temporal evolution of outages better than the baselines. In particular, baseline methods frequently overestimate outage extent and duration, whereas OWL-I remains well-calibrated across both major and moderate events, even for years and conditions excluded from model training. Applying this framework to the full nighttime light record of the continental United States yields the first standardized, calibrated, and reproducible national-scale outage dataset at 1 km nightly resolution for 2012–2024, with pixel-level uncertainty estimates, and is made publicly available on Zenodo at <https://doi.org/10.5281/zenodo.20433558> [35]. This product helps close a persistent

gap between county-level outage reporting and the sub-county scale needed for hazard attribution, equity analysis, and resilience planning.

We further demonstrate that OWL-I maintains reasonable outage detection ability when generalizing globally, for events ranging from localized disaster-induced outages to national power system failures. OWL-I thus shows promise for serving as a globally-standardized high-resolution power outage detection system, a step toward closing persistent power outage data gaps in vulnerable regions across the globe. Given the large uncertainty bounds inherent in the global application of OWL-I as outlined here due to the scarcity of ground-truth outage records, we leave further quantitative validation and production of a complete global outage dataset for future work.

While OWL-I is a significant advance in satellite-based outage detection, it still faces a number of limitations, the most obvious and challenging of which are due to the physical realities of the problem. The task of measuring power outages from satellites is deeply confounded by many irregular sources of light emission and dampening, as well as frequent cloud obfuscation, such that even a “perfect” model would achieve far less than 100% detection accuracy. While validation suggests that OWL-I explains approximately 49% of the variation in the outage record—a significant advance over previous methods (Table 1)—the other half of outage variance remains unexplained due to some combination of model error and the insurmountable problems detailed above. Our approach’s model error generally manifests as conservative predictions, and thus may underestimate the extent and duration of outages. Avenues for reducing model error are ripe for future exploration, with improvements in training data (such as compiling outage data from multiple sources, or gathering more accurate county-level customer counts) and modeling procedures (such as identifying additional confounding factors or more advanced model architectures) being obvious candidates. For these reasons, OWL-I is ideally utilized in concert with complementary outage data sources such as local utility records; however, as it is often impossible to acquire such records (particularly in data-sparse regions), satellite-derived outage data may serve as a valuable estimate where no others exist.

4 Methods

We develop a well-calibrated dataset of kilometer-scale power outages derived from satellite nighttime light brightness observations, correcting for a number of known confounding factors that have been identified in the literature. Our methodology consists of: (1) nighttime light acquisition and quality screening, (2) per-pixel deconfounding regression, (3) training of a neural network outage model ensemble, and (4) nightly CONUS inference for the full observational period.

4.1 Data

OWL-I integrates data from various sources, summarized in Supplementary Table S1.

4.1.1 Nighttime light data

The day-night band (DNB) of the Visible Infrared Imaging Radiometer Suite (VIIRS) [13] is a sensor aboard a constellation of NOAA-operated satellites, which measures visible light radiance from the earth’s surface. These satellites observe every point on the earth at least once per night, usually between midnight and 4:00am local time. While VIIRS represents a significant improvement over the DMSP-OLS system it superceded, it is still subject to obfuscation by clouds and other challenges. Data from the VIIRS DNB is processed by NASA to produce the Black Marble dataset [37, 45], a suite of products which provides calibrated estimates of nighttime brightness of the earth’s surface once per night, and is made available to the public via the NASA LAADS DAAC API. Two Black Marble products are utilized in this study:

1. VNP46A1 [26] provides the raw brightness collected at the sensor, although we do not utilize that variable in this work. The more relevant fields are the viewing conditions, especially the time of observation and position of the satellite.
2. VNP46A2 [27] provides corrected and quality-controlled data derived from VNP46A1. The key resulting variable is `DNB_BRDF-Corrected_NTL`, nighttime light brightness corrected with a conceptual bidirectional reflectance distribution function (BRDF) model, which accounts for the expected influence of moonlight reflectance, snow albedo, atmospheric airglow, aurorae, and other factors (as described in [37]). All references to “brightness observations” herein refer to this variable. The product also provides quality flags which indicate possible interference by clouds, snow-cover, aurorae, or other data quality issues.

We download and save the relevant variables for the entire temporal coverage period and all locations intersecting the CONUS (Black Marble data is packaged in 10×10 -degree tiles) in NetCDF format optimized for fast machine readability, resulting in a store of approximately 550 GB. To ensure data quality, we only utilize those observations which have a “High” data quality flag which excludes pixels impacted by cloudiness, aurora, and other factors. Since LandScan gridded population estimates are provided at 30 arcsecond resolution, native VIIRS pixels at 15 arcsecond (~ 500 m) resolution were downsampled in 2×2 blocks to 30 arcseconds (~ 1 km). This aligned grid serves as the co-registration reference for all downstream products. In the event that any pixel in the downsampling block is labeled low-quality, the entire downsampled pixel is labeled low-quality and excluded as well. Given that the minimum reliably detectable brightness of the Black Marble product is estimated to be $0.29 \text{ nW} \cdot \text{cm}^{-2} \cdot \text{sr}^{-1}$ [37], we clip the nighttime light observations to that lower bound. Supplementary Figure S1 shows the heterogeneity and complexity inherent in this data. Cloud obfuscation can be widespread, and images may be stitched together from multiple satellite passes causing irregularities and discontinuities in collection time.

4.1.2 EAGLE-I

EAGLE-I [6] collects the number of electric customers out at 15-minute intervals for CONUS counties scraped directly from utility company websites, and is one of the best publicly available source of broad-coverage power outage data. While immensely useful, this dataset still suffers from a few quality issues:

1. Coverage is imperfect (although improving over time), with some counties or service areas exhibiting gaps of days to years at a time.
2. The EAGLE-I database makes no distinction between “zero customers experiencing outage” and “missing observation” for any given timestep. Missing data can thus only be conclusively ruled out when a non-zero observation is present.
3. The total number of customers in each county is not known. For convenience, EAGLE-I provides modeled estimates of the total number of customers, but these estimates are imperfect and sometimes result in county outage levels well exceeding 100%. Note that *electric customers* is different from (although correlated with) *people*, and instead counts the number of electricity-consuming endpoints (which may be residential, commercial, or industrial sources).

4.1.3 Other sources

LandScan [19] provides gridded population estimates. We select the LandScan Global product, which represents an “ambient” population estimate (an average of daytime and nighttime population) to best align with the distribution of electric customers. Gridded average gross building height data is gathered from the Global Human Settlement Layer [31]. This measures building height averaged by area, suspected to be impactful to the way satellite viewing geometry modulates observed brightness. It also serves as a good proxy for level of urbanization. Moon position and brightness relative to locations on the earth’s surface are computed exactly with the PyEphem package [34].

4.2 Conventional outage detection method

The most common approach for detecting outages in nighttime light observations is to compute the fractional deviation below some reference brightness (usually a long-term or pre-event average), and assume that the deviation is equal to fraction of residents experiencing outage [14, 16, 24, 25, 38, 43, 50, 51, 53]. Following these methods, we define the “conventional outage method” as:

$$\hat{F}_{\text{out}} = 1 - \frac{L_{\text{obs}}}{L_{\text{ref}}} \quad \text{Conventional outage method} \quad (1)$$

where $\hat{F}_{\text{out}}$ is the pixelwise fraction of customers experiencing power outage (clipped to the range $[0, 1]$), L_{obs} is a single nighttime brightness observation, and for L_{ref} we use the annual median brightness in that pixel unless otherwise specified.

4.3 Deconfounding linear model

Nighttime light radiance at a given pixel, even after NASA’s BRDF correction, varies substantially due to known factors unrelated to power outages:

- Satellite viewing zenith (vertical angle relative to nadir, i.e., directly overhead) and azimuth (compass direction, clockwise from north) angle greatly influences sensed brightness, primarily

via their complex relationship to urban morphology (Figure 2) [21, 41, 44]. While the VIIRS satellites nominally operate on a repeating 16-day orbital cycle—leading some studies to assume observations captured every 16th day utilize a consistent viewing geometry [9, 17, 41]—this is not true due to irregularities caused by cloud cover (see Figure S1).

- Weekly patterns are apparent in nighttime brightness, with weekends generally brighter than weekdays in urban areas (see Figure S3 and [22]).
- Long-term trends due to population growth as well as land-use and development changes [20, 22].
- Seasonality affects both human behavior and environmental factors such as vegetation [20, 22, 44].
- Snow cover substantially increases surface albedo (see Figure S2b and [44]).
- Moonlight reflected off Earth’s surface impacts sensed brightness (see Figure S2c and [8, 44]).

The fact that these last two factors influence the data is perhaps surprising, as both lunar radiance and snow albedo are ostensibly controlled for by NASA’s BRDF correction in the Black Marble products; however, the imperfection of the BRDF correction in accounting for these factors is evident in the data (Figure S2) and an issue known to the Black Marble team [44]. In sparsely populated regions, we find that a simple linear correlation with moon brightness routinely explains up to 45% of the variability in Black Marble BRDF-corrected brightness data. Counterintuitively, this is due to Black Marble exhibiting anomalous dips in brightness for rural regions during full moons, suggesting that the BRDF formulation is actually *over-correcting* for the influence of the moon in these areas. In the northern latitudes of the CONUS, the presence of snow cover further explains up to 20% of the variability in BRDF-corrected brightness, most prominently in urban areas.

To isolate the outage-related dimming signal, we seek to find an empirical relation which captures the dominant components of these confounding factors while avoiding capture of any true outage signal. Crucially, a generalized model—one which operates the same for all pixels in the domain—is not possible, since a pixel’s brightness response to e.g. viewing conditions is an inherent attribute which can differ strongly from even nearby pixels (see Figure 2), and would be quite difficult to describe with a process-based approach. Instead, each pixel’s behavior must be learned empirically and independently, though with a consistent framework. To this end, we fit an ordinary least-squares regression model to the log-transformed radiance time series at each pixel individually. This formulation allows us to encode domain knowledge of the structure of the relationships while minimizing the potential for overfitting to other sources of variability (which may occur with the use of a model with more degrees of freedom, e.g., a neural network). Specifically, we fit the following

450 deconfounding linear model:

$$\begin{aligned}
\ln(L_{\text{obs}}) = & \beta_0 && \text{Intercept} \\
& + \beta_1 \theta_v + \beta_2 \theta_v^2 && \text{Zenith effect} \\
& + \beta_3 \sin(\phi_v) \theta_v + \beta_4 \cos(\phi_v) \theta_v && \text{Linear zenith-azimuth interaction} \\
& + \beta_5 \sin(\phi_v) \theta_v^2 + \beta_6 \cos(\phi_v) \theta_v^2 && \text{Nonlinear zenith-azimuth interaction} \\
& + \beta_7 L_{\text{moon}} && \text{Moonlight} \\
& + \beta_8 S && \text{Snow} \\
& + \beta_9 \lambda_Y && \text{Population growth} \\
& + \beta_{10} D && \text{Long-term trend} \\
& + \beta_{11} \sin(D_Y \frac{2\pi}{365}) + \beta_{12} \cos(D_Y \frac{2\pi}{365}) && \text{Seasonal effect} \\
& + \sum_{i=2}^7 \beta_{13+i} \left(\begin{cases} 1 & \text{if } D_{\text{week}} = i \\ 0 & \text{otherwise} \end{cases} \right) && \text{Day-of-week effects} \\
& + \epsilon && \text{Residual}
\end{aligned} \tag{2}$$

451 where L_{obs} is Black Marble’s BRDF-corrected observed nighttime light radiance, θ_v and ϕ_v are
452 viewing zenith and azimuth angles, S is the binary Black Marble snow flag, λ_Y is the annual
453 LandScan population estimate in that pixel, L_{moon} is lunar brightness, and D , D_Y , and D_{week} are
454 integer-incrementing day, day of year, and day of week respectively. Following Li et al. [21] and Tan
455 et al. [41], viewing zenith angle effects are modeled as a quadratic expression. Our correction for
456 azimuth angle (handled in circular coordinates) is more novel; since the influence of azimuth angle is
457 strongly dependent on some nonlinear function of zenith angle (see Figure 2), no standalone azimuth
458 terms are included, only linear and quadratic zenith-azimuth interactions. Seasonal effects are
459 estimated as a sinusoidal function with amplitude and phase defined by sine and cosine components,
460 and a temporal trend term is included to capture long-term changes, both following Li et al. [20]. Day-
461 of-week effects are modeled with indicator variables for Tuesday-Sunday, representing their difference
462 from Monday brightness. By jointly estimating all of these parameters in a single expression—as
463 opposed to estimating each in isolation and summing together later—we find the optimal coefficients
464 (in the least-squares sense) and avoid erroneously attributing the same variation to multiple sources.
465 The log transform of target radiance is motivated by multiplicative noise in nighttime light: variance
466 in raw radiance scales approximately with the radiance level, so log space homogenizes variance,
467 which better aligns with ordinary least-squares regression assumptions.

468 Outage fraction derived from this deconfounded brightness signal can be computed as follows,
469 by comparing the brightness observation (L_{obs}) with the corresponding “expected brightness” value
470 predicted by the deconfounding linear model ($\hat{L}_{\text{dec}}$):

$$\hat{F}_{\text{out}} = 1 - \frac{L_{\text{obs}}}{\hat{L}_{\text{dec}}} \quad \text{Deconfounded outage method} \tag{3}$$

471 4.4 OWL-I

472 4.4.1 Architecture

473 We train a “pixel-independent” multilayer perceptron (MLP) to map per-pixel nighttime light features
474 to per-pixel outage fractions. Each pixel is processed identically and independently, with no spatial

mixing. This design allows the model to handle counties with arbitrary shapes and sizes, and generalizes naturally to full CONUS inference. Formally, the model f with parameters θ maps:

$$f_{\theta} : \mathbb{R}^{P \times I} \rightarrow \underbrace{[0, 1]^P}_{\hat{F}_{\text{out}}} \quad \text{OWL-I outage model} \quad (4)$$

where P is the number of pixels in a county and I is the number of input features. The model follows a standard MLP architecture, with fully-connected hidden layers followed by normalization and activation, and optional dropout applied before the final output layer. Finally, sigmoid activation is applied so that the predicted pixel outage fractions ($\hat{F}_{\text{out}}$) are constrained to the range $[0, 1]$. The hidden layer sizes, input feature selection, and other architectural parameters are determined by robust hyperparameter optimization (Methods 4.4.4). The complete list of potential input features is provided in Supplementary Section S1. The model is implemented in PyTorch [30].

4.4.2 Optimization

Alignment of gridded and county data With predictions in the form of pixel-level outage fractions, but our training targets in the form of county-level totals of customers out, three alignment challenges present themselves: spatial, temporal, and unit of measure.

The spatial misalignment is most easily handled. The `exactextract` Python package [4] is used to compute exact fractional overlaps between county boundaries and pixel extents, and pixel-county membership is weighted accordingly. Pixel-level outages can then be summed over county areas.

Temporal misalignment is more complex. While satellite overpass time is sometimes assumed to always be 1:30am local time in the literature [51], this is not always the case, as observation time can vary from night to night by multiple hours [44]. Further, the nighttime light observations comprising a single county may be stitched together from multiple satellite passes (as in Figure S1). Since outage levels can change rapidly between satellite passes in the same night, a more careful and precise alignment is required. To this end, for each pixel within a county on a given night, we linearly interpolate between the nearest (15-minute) EAGLE-I observations according to that pixel’s exact viewing time, and then take the average of these values across all county pixels weighted by population density.

Lastly, a conversion factor is needed between population and electric customers. Since the true number of electric customers in each county is not known, EAGLE-I modeled customer totals are used. Thus for each CONUS county, we compute the county-specific customers-per-person (CPP) ratio, defined as:

$$\text{CPP}_c = \frac{N_c}{\sum_{p \in c} \lambda_p w_p} \quad (5)$$

where N_c is the modeled total customer count from EAGLE-I for county c , λ_p is the LandScan population in pixel p , and w_p is the fraction of the pixel’s area that falls within the county’s boundary. The vast majority (94%) of CPP_c values are larger than 0.3. However, a few outliers fall below this range, the most extreme being Wahkiakum County, WA where EAGLE-I estimates there to be just a single electric customer in a county of ~ 4500 people. In the absence of better estimates, we clip the range of CPP_c values to a minimum of 0.3 to eliminate these obviously erroneous outliers. This correction affects only 62 of 3186 CONUS counties.

Loss function The county-level predicted number of customers out ($\hat{N}_{\text{out}}$) is formed by aggregating predicted pixel outage fractions for all cloud-free pixels, weighted by pixelwise customer

count estimates, and scaled to extrapolate to missing (e.g. cloud obfuscated) pixels:

$$\hat{N}_{\text{out}} = \sum_{p \in c} \underbrace{(\hat{F}_{\text{out}})}_{\text{outage}} \cdot \underbrace{(\lambda_p \cdot w_p \cdot \text{CPP}_c)}_{\text{pixel customers}} \cdot \underbrace{\frac{1}{F_{\text{cov}}}}_{\text{missing data}} \quad (6)$$

where, for each pixel p in county c , λ_p is LandScan population, w_p is the fraction of the pixel’s area which lies within the county computed with `exactextract`, and CPP_c is the county’s customers per person ratio. F_{cov} is the fraction of the county’s total population covered by valid nighttime light observations, and acts as a simple scaling factor which assumes that missing pixels have the same outage level as the customer-weighted average of observable pixels. The training loss for a batch of B examples is then the mean squared logarithmic error (MSLE) between predicted and EAGLE-I-observed county customer counts:

$$\mathcal{L} = \frac{1}{B} \sum^B (\ln(\hat{N}_{\text{out}}) - \ln(N_{\text{out}}))^2 \quad (7)$$

Standard mean squared error was also explored, but because of the orders-of-magnitude range in county-level populations the model was found to heavily overfit to populous counties and effectively ignore rural areas. The MSLE target is found to correct for this bias while maintaining skillful predictions for major outage events.

4.4.3 Training data

Because non-outage nights are far more frequent than outage nights, data imbalance is a frequent problem in machine learning-driven outage modeling studies [54]. To gather a balanced, varied, and representative dataset for our task, we stratify samples by county, and then select 50 nights for each, comprising: 25 nights drawn at evenly-spaced quantiles of the EAGLE-I outage distribution for that county (ensuring coverage across a wide range of outage levels including non-event nights); and the 25 nights with the highest recorded outage counts (to capture the rarer but most important outage events). To isolate only high-quality data, training samples are limited to those for which $F_{\text{cov}} \geq 0.95$, limiting the impact of extrapolating missing pixels to $\pm 5\%$. This threshold balances data quality with quantity, allowing some slightly cloudy nights but limiting their impact. The aligned training dataset spans the EAGLE-I coverage period, late 2014 through 2024.

4.4.4 Hyperparameter optimization & ensemble generation

The model architecture and training hyperparameters are optimized using Optuna [2] with the tree-structured parzen estimator (TPE) algorithm over 250 trials. The hyperparameter search space consists of:

- Input feature set
- Hidden layer sizes and depth
- Dropout rate
- Learning rate
- Batch size
- Batch normalization
- Activation function
- Number of training epochs

Hyperoptimization trials were trained on data from 2014-2022, with 2023 used as the validation set. Validation log-space R^2 was used as the hyperparameter optimization metric. Data from 2024 was selected as the testing set, and put aside for evaluation only after the hyperoptimization process was complete. Models were trained with the Adam optimizer and a cosine learning rate annealing schedule, with parameters tuned by the hyperoptimization scheme.

To evaluate the framework’s generalization across all dataset years, an ensemble of eight models is created aligning with eight year-stratified dataset folds constructed to each contain at least 1000 dataset samples each: 2014-2016 (1451 samples), 2017-2018 (1702 samples), 2019 (1046 samples), 2020 (1160 samples), 2021 (1226 samples), 2022 (1478 samples), 2023 (1817 samples), and 2024 (1762 samples); note that annual sample size generally increases over time due to improving EAGLE-I coverage. The top eight hyperparameter configurations found during hyperoptimization (listed in Table S2) are used, to ensure a diversity of models. This ensemble of models enables out-of-sample skill evaluation across all dataset years and a convenient way to characterize pixel-level uncertainty via inter-model spread.

4.5 CONUS-scale inference

The trained ensemble is applied to the full CONUS daily nighttime light record to produce the OWL-I USA dataset, parallelized across spatial and temporal dimensions on DOE’s NERSC supercomputing system. The ensemble mean for each pixel-night is computed to represent OWL-I’s best estimate of the outage level, while the ensemble standard deviation provides a measure of pixel-level uncertainty. The full record (January 19th 2012 through December 31st 2025) covers nearly two years prior to the period training data availability (November 2014 through December 2024), providing an extended record. The dataset is available at, and further described in, Rice et al. [35].

Data Availability

The OWL-I USA dataset, covering the continental United States at 30-arcsecond (~ 1 km) nightly resolution for the period 2012-2024, is made publicly available on Zenodo: <https://doi.org/10.5281/zenodo.20433558> [35]. NASA Black Marble [26, 27, 37, 45], EAGLE-I [6], LandScan [19], GHSL [31] are all publicly accessible.

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Author Contributions

J.R.: Conceptualization, data curation, methodology, software, investigation, validation, visualization, writing - original draft, review & editing. T.C.C., D.S.: Methodology, writing - review & editing. K.B., B.D.: Conceptualization, methodology, supervision, writing - review & editing. N.S.: Conceptualization, methodology, supervision, project administration, writing - review & editing.

Competing Interests

The authors declare no competing interests.

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Supplementary Material for “Global Power Outage Detection at the Kilometer Scale from Satellite Nighttime Lights”

Julian Rice^{*}, Ning Sun, Karthik Balaguru, Tse-Chun Chen, Brent Daniel, and Drew Suarez

Pacific Northwest National Laboratory, Richland WA

^{*}Corresponding author: julian.rice@pnnl.gov

S1 Neural network hyperoptimization details

The following features were made available for selection by the hyperoptimization algorithm (+log indicates a log-scaled version was also made available): annual median brightness (+log), annual median deviation of brightness (+log), average gross building height (+log), cloud confidence, cloud mask quality, cloud flag, day of week, day of year (sine/cosine embedding), landscan population (+log), lunar azimuth angle (sine/cosine embedding), lunar zenith angle, lunar brightness, angle between moon and satellite, normalized brightness fraction ($\hat{F}_L$) (+log), normalized brightness z-score ($\hat{Z}_L$), satellite azimuth (sine/cosine embedding), sensor zenith angle, and snow flag. $\hat{F}_L$ and $\hat{Z}_L$ are derived from the deconfounding linear model’s outputs, defined as:

$$\hat{F}_L = \frac{L_{\text{obs}}}{\hat{L}_{\text{dec}}} \quad (1)$$

$$\hat{Z}_L = \frac{\hat{F}_L - 1}{k \cdot \text{MAD}(\hat{F}_L - 1)} \quad (2)$$

where $\hat{F}_L$ is the fraction observed nighttime light brightness relative to “expected”, and $\hat{Z}_L$ is the Z-score of $\hat{F}_L$ —i.e. normalizing $\hat{F}_L$ deviations by its usual variability—computed with the median absolute deviation (MAD) for robustness (the $k = 1.4826$ factor makes the MAD a consistent estimator of standard deviation). With this formulation, $\hat{F}_L < 1$ or $\hat{Z}_L < 0$ signifies anomalous dimming, possibly indicative a power outages.

Table S1: Summary of primary input data sources, and resulting output from the OWL-I framework.

Dataset	Resolution	Coverage	Variables
NASA Black Marble [3, 4, 7, 8]	15 arcseconds (~500 m), nightly	Global, 2012-01-19 to present	Nightly BRDF- corrected radiance, quality flags, snow & cloud cover, time of observation, sensor viewing angles
EAGLE-I [1]	County-level, 15-minute	USA, November 2014 – 2024	Ground-truth electric customer outage counts, estimated total customers
LandScan Global [2]	30 arcseconds (~1 km), yearly	Global, 2012 – 2024	Gridded ambient population
Global Human Settlement Layer [5]	3 arcseconds (~100 m)	Global, 2018	Average gross built-up height
PyEphem library [6]	Any	Any	Lunar position and brightness
Output			
OWL-I USA	30 arcseconds (~1 km), nightly	Continental USA, 2012-01-19 to 12-31-2024	Outage fraction (ensemble mean and standard deviation)

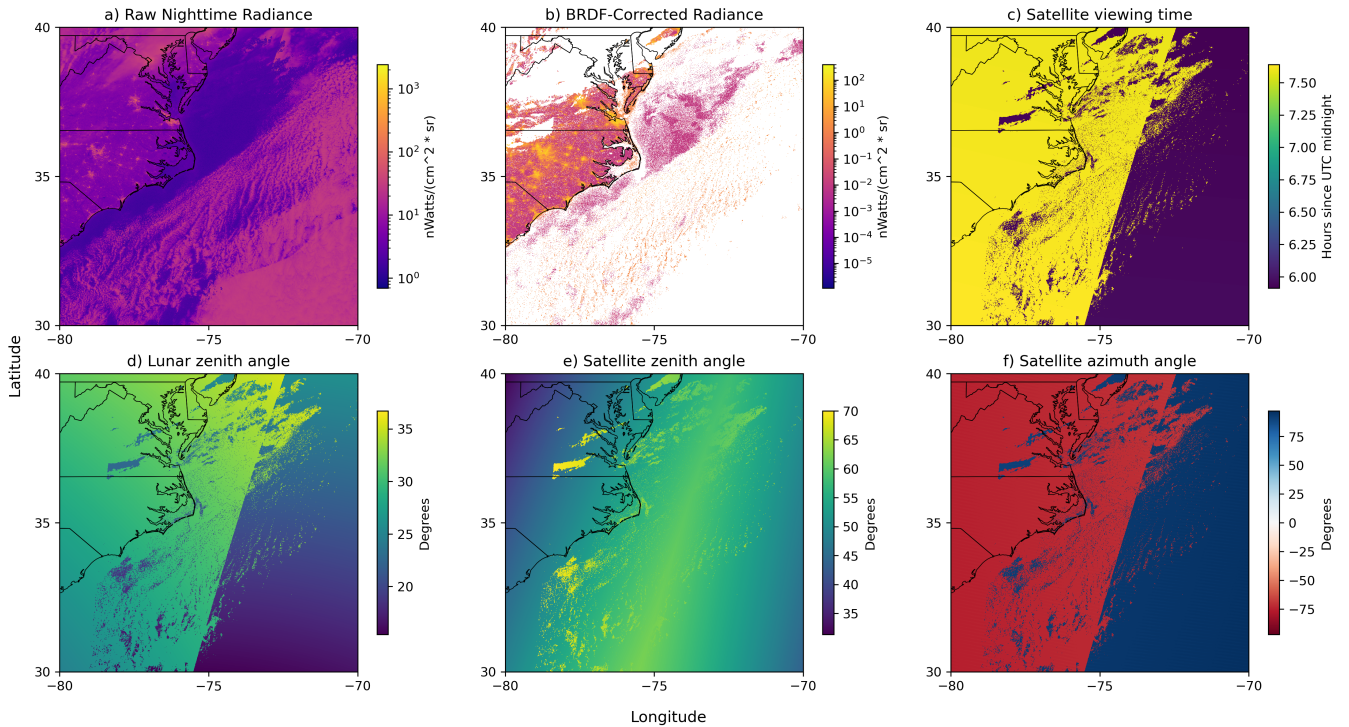


Figure S1: A sample snapshot of NASA Black Marble nighttime light data (a-b) and viewing conditions (c-f), for February 1st, 2018 over the mid-Atlantic coastline, illustrating data challenges related to cloud obfuscation and boundaries between adjacent satellite passes.

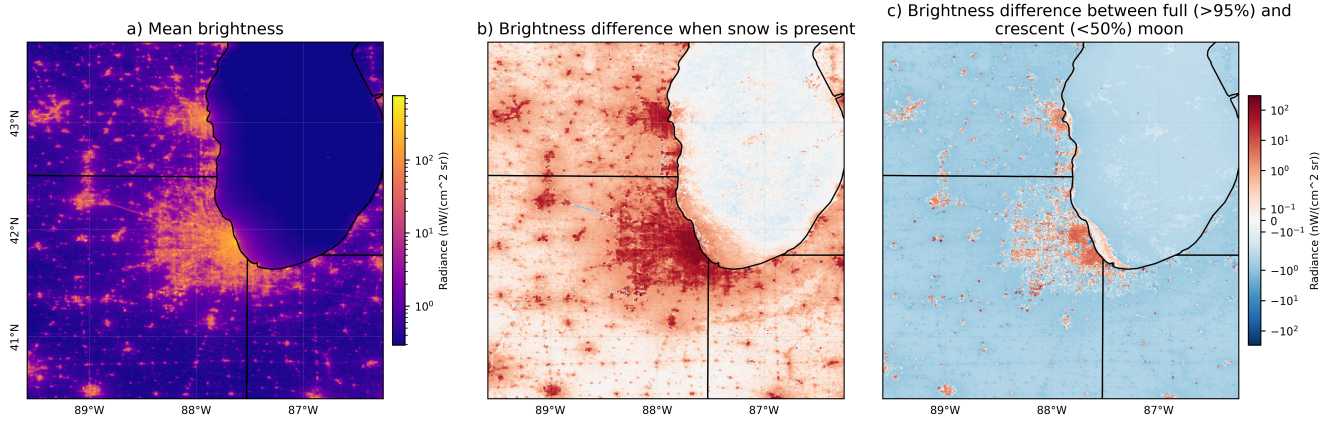


Figure S2: Moonlight and snow effects on BRDF-corrected nighttime brightness. (a) Composite 2012-2024 mean brightness centered on the Chicago, IL metropolitan area. (b) When snow is present, BRDF-corrected brightness increases. (c) During full moons, BRDF-corrected brightness decreases in urban areas, and increases in rural areas. This is despite NASA's BRDF correction model ostensibly accounting for both of these factors; it appears that snow albedo is under-corrected for, while moonlight is over-corrected for in rural areas.

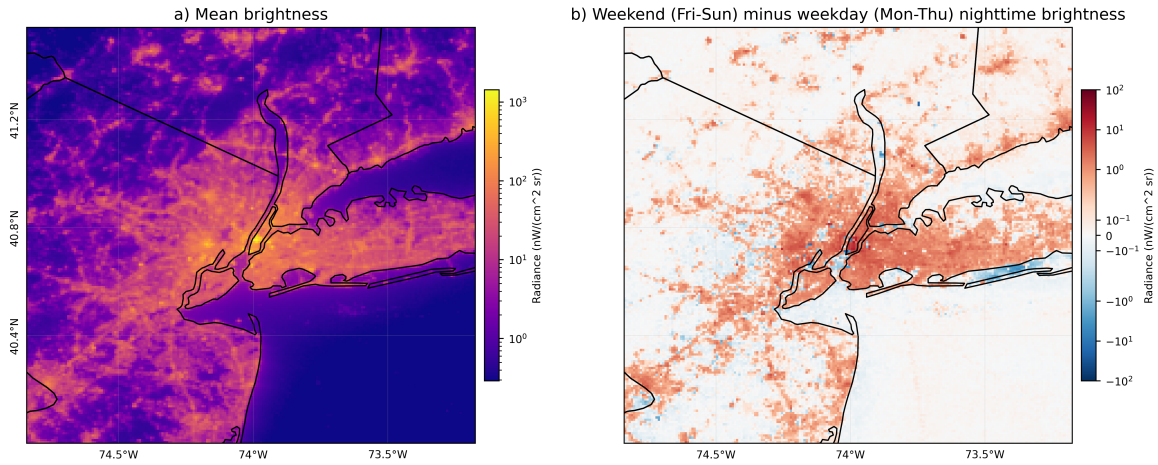


Figure S3: Day-of-week effects on nighttime brightness. (a) Composite 2012-2024 mean brightness for the greater New York, NY metropolitan area. (b) Weekends (Fri-Sun) tend to be brighter at night than weekdays (Mon-Thu) in urban regions.

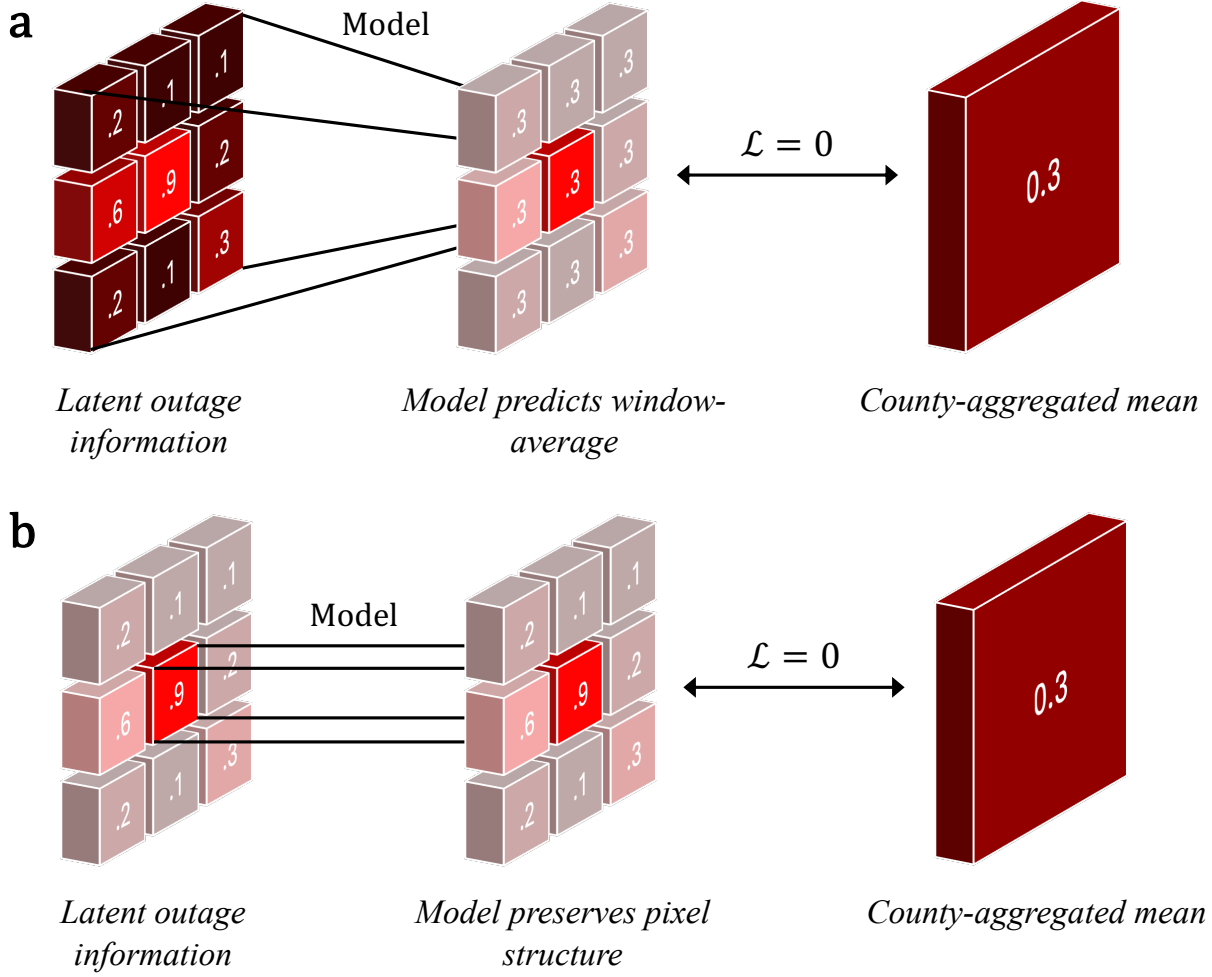


Figure S4: Conceptual comparison of possible model architectures, with gridded inputs (left), model predictions (center), and training targets (right) in a hypothetical 3x3 “county”. (a) When using a convolutional-style model with spatially-aggregated targets, loss is perfectly optimized ($\mathcal{L} = 0$) when the model outputs window-averages, and thus there is no incentive to preserve pixel-level fidelity. (b) When modeling each pixel independently (our approach), loss is perfectly optimized only when pixel structure is preserved, since the model cannot access information from neighboring pixels.

Table S2: Top eight neural network model configurations from hyperparameter optimization, by validation R^2 .

<i>Results</i>							
Trial number	225	123	217	198	199	158	170
Validation log-space R^2	0.3975	0.3972	0.3971	0.3935	0.3904	0.3852	0.3847
Training time (mm:ss)	07:22	13:31	06:25	14:19	13:40	11:48	09:50
<i>Hyperparameters</i>							
Activation	GELU	GELU	GELU	GELU	GELU	GELU	GELU
Batch size	16	8	8	32	8	64	16
Depth	5	7	2	2	2	4	6
Dropout	0.216	0.090	0.076	0.317	0.045	0.467	0.099
Epochs	13	33	19	32	40	36	40
Learning rate	5.13×10^{-3}	5.66×10^{-3}	2.78×10^{-3}	1.76×10^{-3}	5.61×10^{-3}	6.40×10^{-3}	3.92×10^{-3}
Maximum width	512	32	128	256	64	128	64
Normalization	None	None	None	None	None	None	None
Width factor	2.028	1.420	2.306	1.445	2.083	1.535	1.530
<i>Features</i>							
Angle between moon and satellite		✓				✓	
$\log_{10}$ Brightness annual median	✓	✓	✓	✓	✓	✓	✓
Brightness annual med. dev.		✓		✓	✓		
$\log_{10}$ Brightness annual med. dev.	✓	✓		✓	✓	✓	✓
Cloud flag	✓		✓	✓	✓	✓	✓
Cloud flag quality				✓	✓		
Day of week	✓	✓	✓	✓	✓	✓	✓
Day of year (cos)		✓				✓	✓
Deconvolved brightness fraction ($\hat{F}_L$)			✓	✓	✓		
$\log_{10}$ Deconvolved brightness fraction	✓	✓		✓	✓	✓	✓
Deconvolved brightness z-score ($\hat{Z}_L$)	✓	✓	✓	✓	✓	✓	✓
$\log_{10}$ LandScan population	✓		✓	✓	✓	✓	✓
Lunar brightness	✓	✓	✓	✓	✓	✓	✓
Lunar zenith	✓	✓				✓	✓
Satellite azimuth (cos)	✓	✓	✓	✓	✓	✓	✓
Satellite azimuth (sin)		✓	✓	✓	✓	✓	✓
Snow flag	✓	✓	✓	✓	✓	✓	✓

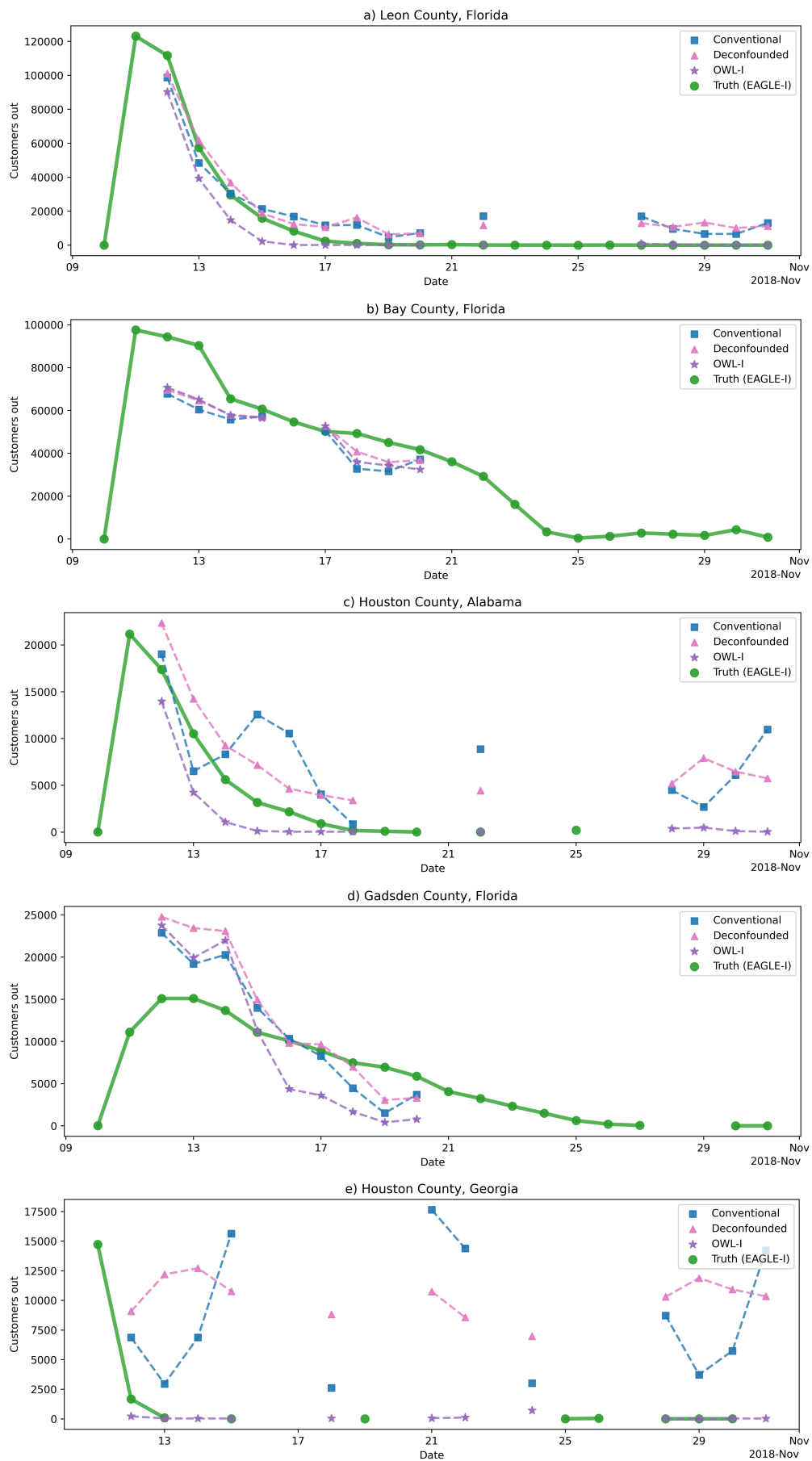


Figure S5: Hurricane Michael nightly outage timeseries for the five most impacted counties (by peak nightly EAGLE-I customer outage count). Missing data points indicate missing (possibly zero) outage for EAGLE-I, or insufficient satellite coverage for the satellite-based methods.

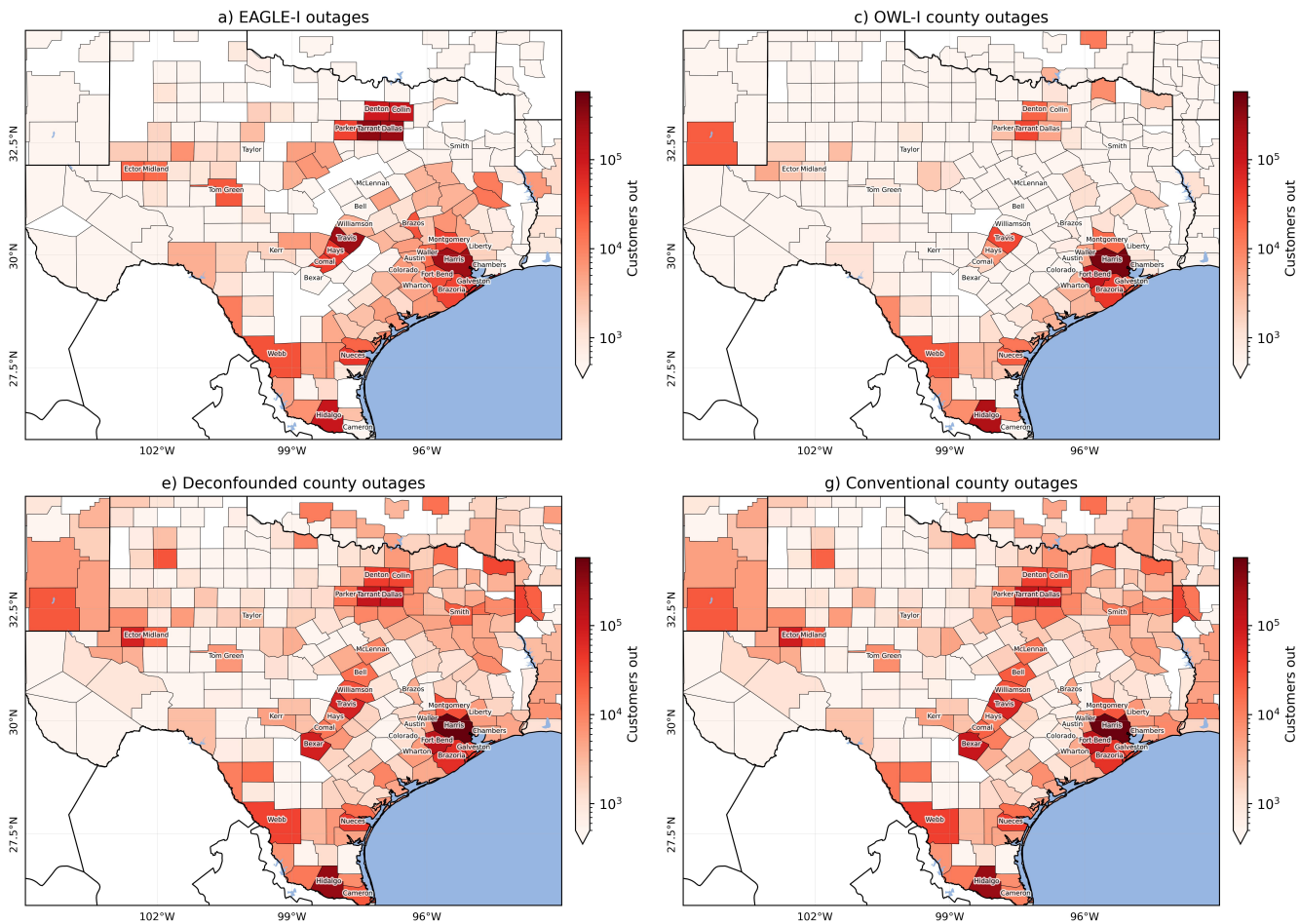


Figure S6: Maximum outages during the 2021 Texas winter storms, from (a) nightly EAGLE-I and (c-h) three satellite outage detection methods at county-aggregated scales.

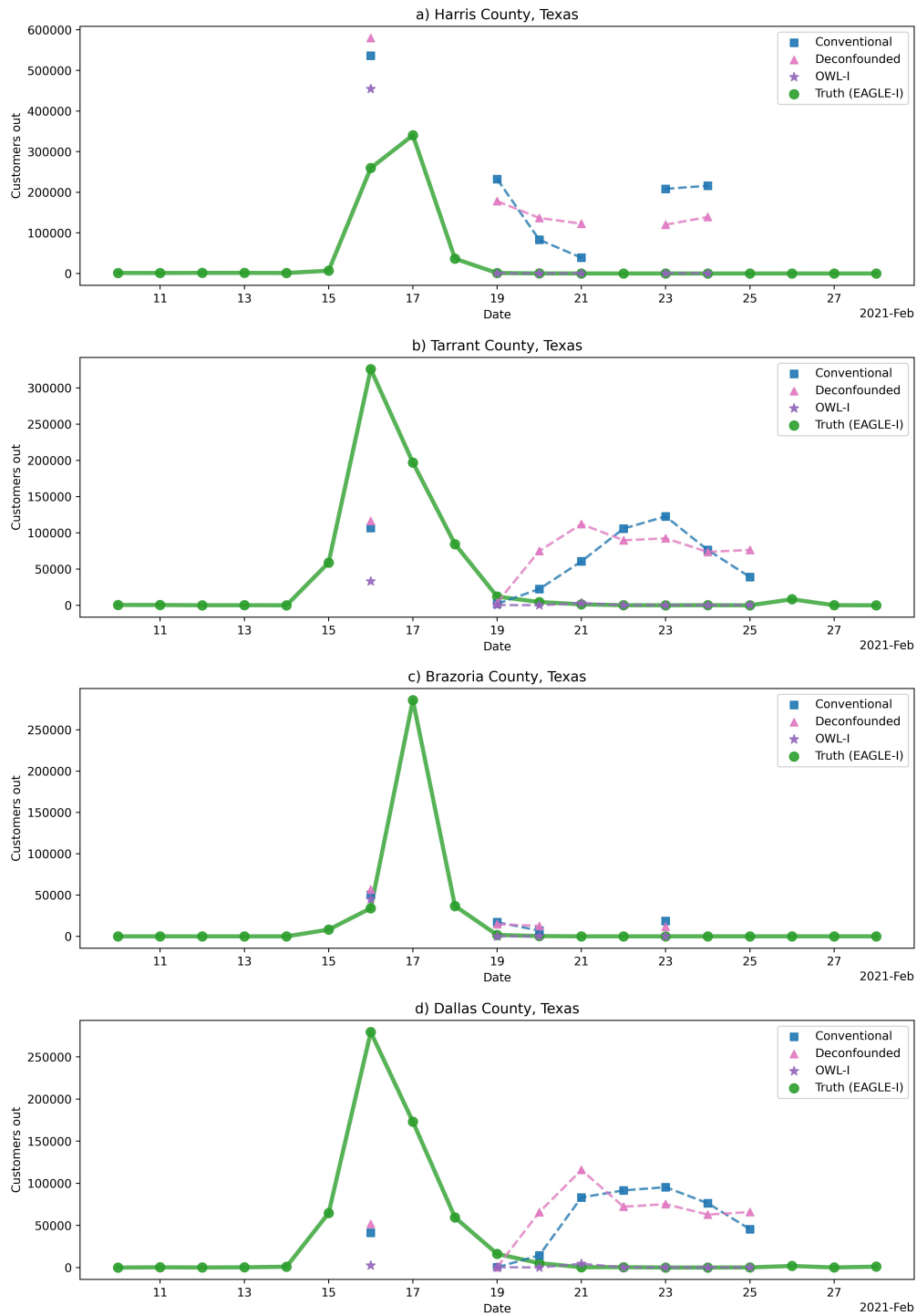


Figure S7: 2021 Texas winter storm outage timeseries for the four most impacted counties (by peak nightly EAGLE-I customer outage count). Missing data points indicate missing (possibly zero) outage for EAGLE-I, or insufficient satellite coverage for the satellite-based methods.

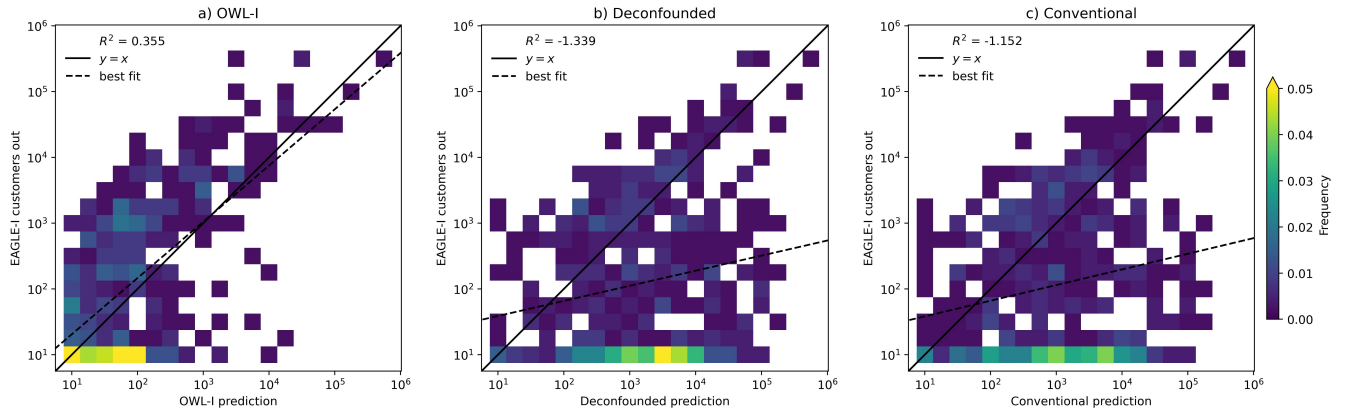


Figure S8: Density scatterplot of all county-night predictions and their associated ground truth customer outage totals for the 2021 Texas winter storms, with log-space R^2 and line of best fit.

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