Availability, outage, and capacity of spatially correlated, Australasian free-space optical networks

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Network capacity and reliability for free space optical communication (FSOC) is strongly driven by ground station availability, which is dominated by local cloud cover causing an outage. Here, we combine remote sensing data and novel methods to provide a generalized framework for assessing and optimizing optical ground station networks. This work is guided by an example network of eight Australian and New Zealand optical communication ground stations that span approximately 60° in longitude and 20° in latitude. Utilizing time-dependent cloud cover data from five satellites, we present a detailed analysis that determines the network availability and diversity, which showed that the Australasian region is well-suited for an optical network with a 69% average site availability and low spatial cloud cover correlations. Employing methods from computational neuroscience, we provide a Monte Carlo method for sampling the joint probability distribution of site availabilities for an arbitrarily sized and point-wise correlated network of ground stations. Furthermore, we develop a general heuristic for site selection under availability and correlation optimizations and combine it with orbital propagation simulations to compare the data capacity between optimized networks and the example network. We show that the example network may be capable of providing tens of terabits per day to a low Earth orbit satellite and up to 99.97% reliability to geostationary satellites. We therefore used the Australasian region to demonstrate, to the best of our knowledge, novel, generalized tools for assessing and optimizing FSOC ground station networks, as well as the suitability of the region for hosting such a network. © 2023 Optica Publishing Group

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1. INTRODUCTION

Australia and New Zealand are pursuing a network of optical ground stations (OGS) to support the future of optical communication in the region [1]. Free space optical communication (FSOC) offers myriad advantages over existing radio frequency technologies, but outages due to clouds are a long-acknowledged barrier to its widespread adoption and reliability [2]. For satellite operators seeking to transfer large quantities of data in a timely manner, an extensive and reliable ground segment is critical. The typical solution to cloud-induced outages is operating a network of OGS and introducing redundancy into the system by providing site diversity such that it is improbable that all OGS are obscured by clouds [3–6]. This paper aimed to develop a means of evaluating the capability of an FSOC network, including availability, diversity, and ultimately data capacity, alongside a general framework for network optimization.

A well-optimized FSOC network has high availability at each site and minimal correlation of cloud cover between sites for maximizing diversity. Low Earth orbit (LEO) satellites can improve data throughput by engaging with a well-optimized network, thus increasing the number of possible links. For geostationary orbit (GEO) satellites and deep space, where mutual visibility can be simultaneously maintained to multiple OGS,
a well-optimized network boosts reliability, i.e. the probability that at least one OGS is available.

We approach this issue by using the proposed Australasian Optical Ground Station Network (AOGSN) as an example [1]. The AOGSN will include at least the Australian National University’s Optical Communication Ground Station at Mount Stromlo Observatory, the Australian Defence Science & Technology Group OGS in Edinburgh, South Australia, and the University of Western Australia’s OGS in Perth [1,7–9]. All three are in a state of commissioning and aim to enter operation in 2023. To create a robust model network to study, we propose an additional five sites at Mt. Kent Observatory in Queensland, Mt. John Observatory in New Zealand, Alice Springs in the Northern Territory, Mildura in Victoria, and Dongara in central Western Australia. These additional sites are chosen as places with existing observatories or satellite ground segment infrastructure and represent realistic OGS placements. The base and extended AOGSN will be used henceforth for reference to the initial three OGS as a network or all eight OGS, respectively. Figure 1 shows the sites of the proposed network. We use the example of the extended AOGSN throughout this paper to compare it with a network chosen from an optimization model and to test methods for availability, diversity, and capacity estimation.

Complex theoretical models have been developed for determining and predicting outages, including factors such as fading of the atmospheric channel due to turbulence [3]. An experimental campaign to measure atmospheric turbulence at selected sites is considered in Section 8; however, this paper focuses on a spatial availability model without prior site selection. Therefore, as with earlier literature, we adopt a simple model for site outages: an OGS experiences an outage only due to cloud cover, which prevents the ground station from linking with the orbiting satellite [10,11].

Unlike clouds, where associated outages are a generic issue for any network, turbulence-induced outages are strongly system specific. They may depend on the orbital height of the satellite, details of the telescope, and ground station specifications, e.g., adaptive optics and uplink or downlink capabilities, and so forth [12–15]. This means that our generic, cloud-based outage model will require careful comparison with a real system, on a case-by-case basis. For example, an adaptive optics-compensated downlink from a GEO, at a high-quality site, is unlikely to experience many turbulent outages and will therefore have availability close to the cloud availability. Alternatively, uplinking to a LEO satellite in the same atmospheric conditions could suffer turbulent degradation that prevents the AO system from closing the loop for long periods of time, causing an outage. The difficulties of predicting turbulence conditions and how this could be expanded into a rigorous turbulent and cloud availability model are discussed further in Section 8. Our current model therefore encapsulates availability as the probability that a site is not cloudy at any given time. Given atmospheric turbulence might create additional outages, our model provides an upper bound on a realistic availability, which may be required for a detailed system-specific network performance analysis, which is beyond the study’s scope.

We provide a more rigorous definition of this cloud model based on the Bernoulli distribution in Section 2. Remote-sensing satellites measure cloud cover in different ways and with different issues, prompting us to adopt an approach that incorporates numerous satellites at different temporal and spatial resolutions, with decades of data in time. Deriving network

Fig. 1. Australasian optical ground stations currently being commissioned (green circles, “the base network”) and proposed for this study (red circles, “the extended network”), comprising the Australasian Optical Ground Station Network (AOGSN). Throughout our analysis, we use both these networks as case studies for availability, correlation, and network optimization in the Australasian region.
diversity requires knowledge of the point-wise cloud correlation between sites. Simultaneous cloud cover measurements of the entire Australasian region are only possible with GEOs given their coverage; therefore, this study places emphasis on data acquired from Himawari-8, a GEO weather satellite operated by the Japan Meteorological Agency, throughout our analysis [16].

We develop a general method for computing outage probabilities for an arbitrary sized network with arbitrary point-wise correlations between each node, analogous to a network of spiking biological neurons with a specified covariance structure [17]. We sample our model using the availability and point-wise correlation from the base and extended AOGSN to provide robust outage statistics, extending the analysis performed in [10]. Furthermore, utilizing our availability and diversity statistics, we compare the base and extended AOGSN outage probabilities with a network optimized to maximize availability and minimize point-wise correlation for every ground station (node). Diversity optimization methods have been developed recently [3,6,11,18]. However, to the best of our knowledge, we present a novel model for network optimization that is spatially resolved, not requiring pre-selected site locations.

This study is organized by primarily using the AOGSN model network as an example to drive methods and provide realistic outputs and is structured as follows. In Section 2, we measure cloud cover over the entire Australasian region and for sites of the AOGSN. Section 3 covers the use of high temporal resolution and simultaneous cloud measurements to directly measure spatial correlation of cloud cover, as well as correlations between selected sites. We then present, to the best of our knowledge, a novel Monte Carlo method in Section 4 for determining the outage probabilities of a network based on the availabilities and correlations between ground stations. A simple heuristic model for site selection to maximize availability and diversity is presented in Section 5 and then used to estimate an optimized network that is compared with the AOGSN across a number of metrics. Finally, in Section 6, we use orbital simulations to estimate the coverage of the network and statistical link duration per day with LEO satellites. Estimates of network-wide link duration from simulation are combined with availabilities to estimate network capacity. For GEOs, we use our outage probability model to determine the network outage probability as a function of orbital longitude in Section 7. Finally, in Section 8, we summarize and list the key study findings.

2. CLOUD COVER AND SITE AVAILABILITY

Cloud cover, $C$, is the major factor in degrading an FSOC network’s availability, $A$ [2,19]. Although satellites measure $C$ in different ways, and many data products we use have already undergone spatial or time averaging, they are all capable of producing a binary cloud mask that flags $C$ for each pixel, $(x_j, y_j)$, and time, $t_n$, in a satellite image. We consider that $C$ is instantaneously measured as 0 (no cloud detection) or 1 (cloud detection) for each $(x_j, y_j)$ and $t_n$. Hence, over a time interval, $t \in [t_1, t_2]$, the cloud cover is a vector $C$ of $(0, 1)$, with length $n$. Each component of $C = (C_1, C_2, \ldots, C_n)$ follows a Bernoulli distribution, $C_n \sim \text{Bernoulli}(\Omega)$, where $p(C_n = 1) = \Omega$, and $p(C_n = 0) = 1 - \Omega = A$; hence,

$$p(C; \Omega) = \Omega^C A^{1-C} \tag{1}$$

is the probability distribution function for $C$. This is true for each $(x_j, y_j)$ on the grid.

Let us consider a network $N$ with $N$ nodes or sites. We call the $k$th site $S_k$, and hence $N \equiv \{S_1, S_2, \ldots, S_N\}$ is the set of $N$ sites, each with grid coordinates $(x_j, y_j)$. We may choose to index the sites themselves, rather than the grid coordinates, e.g., the probability distribution function at site $k$ is $p_k(C_k; \Omega_k)$. We avoid a subscript of $C$ for the time vector component index, $n$, which would interfere with our $k$ site index for simplicity. Because at any point in time each grid coordinate follows a Bernoulli distribution for $C$, so does each site. Therefore, the probability density function for each $k$ site is $p_k(C; \Omega_k) = \Omega_{k}^{C_k} A_k^{1-C_k}$. Note, directly from Eq. (1), we can immediately estimate the availability $A$ at site $k$ through the time-average $C_k = \Omega_k = 1 - A_k$. We use the ensemble $(X)$ notation for the time-average of the quantity $X$.

$A$ has the most intuitive interpretation for FSOC ground stations as it corresponds to the probability a site is available for communications. We conduct an extensive study of $C$ from numerous satellites to determine $A$ for each ground station of the AOGSN. Five separate remote sensing satellites and instruments are used to determine $A$, and long time spans are used to minimize climatic variation. Table 1 summarizes the satellites and instruments used for this study and the relevant time span of data associated with each. We use derived cloud retrieval products, with a focus on Sun-synchronous LEO satellites, and Himawari-8, which has been the prime GEO for use over the Australasian region since 2015 [16].

Although Earth observation LEO satellites can produce cloud mask swatches with $<100$ m spatial resolution, we find working with low-resolution global averages easier given the decades-long time spans involved and subsequent quantity of data. Comparisons with higher resolution data products, e.g., from Himawari-8, found reasonable agreement, likely from the large time span of data involved and the relatively homogeneous terrain of Australia (Appendix B). New Zealand is naturally more impacted by spatial averaging; Subsection 2.B outlines how $Aqua$/AIRS and MERRA-2 data are discarded for the Mt. John node in the AOGSN. Therefore, for the LEO satellites: $Terra + Aqua$/MODIS, $Aqua$/AIRS, and Suomi-NPP/VIIRS data, we use $1^\circ \times 1^\circ$ global grids with monthly $\Omega$ instead of raw $C$ measurements at high resolution [21–24].

| Satellite     | Instrument      | Time Span | Spatial Resolution |
|---------------|-----------------|-----------|--------------------|
| Himawari-8    | AHI             | 2015–      | 5 km               |
| Terra/Aqua    | MODIS           | 2002–      | 1°                 |
| Aqua          | AIRS            | 2003–      | 1°                 |
| Suomi NPP     | VIIRS           | 2012–      | 1°                 |
| MERRA-2°      | Assimilation    | 1980–      | 0.5°               |

*MERRA-2 is a historical assimilation of data from numerous sources provided by the NASA Global Modeling and Assimilation Office [20].

The remote sensing satellites used in this paper and the spatial resolution of the relevant cloud retrieval data products used are outlined in Table 1.
Spatial averaging for terrain more diverse than the Australian continent is likely to induce more errors, so doing the full computation on individual swatches is preferred. MERRA-2, a modern retrospective analysis of assimilated satellite data since 1980, is able to provide a uniquely long time span with daily cloud information at 0.5° × 0.6° spatial resolution [20]. However, MERRA-2’s reliance on older satellite data and large scale spatial averaging and interpolation can produce erroneous results. MERRA-2 is analyzed before being included in any statistical means (e.g., for the Mt. Stromlo and Alice Springs station it produces outlier results compared with other data). Long-time-span data, such as MERRA-2, is important for reducing uncertainty from periodic climatological phenomena such as the El Niño Southern Oscillation and Indian Ocean Dipole [25]. However, anthropogenic climate change is a non-periodic climatological effect that can induce significant error on long-time-span data, e.g., MERRA-2, as the effect on clouds and their circulation has been studied extensively [26–29].

A. Spatially Resolved Himawari-8 Maps

Himawari-8 is used for establishing an initial, spatially resolved picture of $A$ over the Australasian region, given it is a GEO satellite that produces a cloud mask of the entire region every 10 minutes at a 5 km resolution [16]. Due to the large quantity of data produced by Himawari-8 since 2015, images at 9 am and 3 pm Australian Eastern Standard Time (UTC + 10) are used, which is an Australian convention established by the Bureau of Meteorology. Figure 2 shows $A$ over eight years of Himawari-8 daytime cloud product provided by the Japan Aerospace Exploration Agency’s Earth Observation Research Center (JAXA/EORC) and the Japan Meteorological Agency [30,31]. Cirrus cloud identified by Himawari-8 is considered to be clear sky for Fig. 2 given its low 1.55 µm attenuation [32]. Himawari-8 can produce misleading results for pixels with high altitude areas that typically sit above cloud height, seen for the Alps down the length of New Zealand’s South Island in Fig. 2 [31], but this does not affect any region of Australia.

B. Seasonal Variation with Collated Data

To provide a more robust estimate of $A$, we then calculate $A$ from all five satellites and decades of data for all sites of the extended AOGSN. All sources of remote-sensing data outlined in Table 1 were used except for the Mt. John OGS where the Aqua/AIRS and MERRA-2 cloud retrieval algorithms produced erroneous results, likely due to nearby snow and ice or low resolution pixels including high-altitude mountains. For low-spatial-resolution images, the closest pixel to the site is used to represent the site cloud cover. Given Himawari-8’s 500 m/pixel spatial resolution, a region-of-interest (ROI) is drawn around the sites, and pixels within that ROI are averaged per frame. We model the spatial extent of these ROIs to correspond with a projected horizontal distance from a single layer of cloud at some height when observed at $\theta_{\text{elevation}} = 30^\circ$. ($\theta_{\text{elevation}} = 30^\circ$ is considered the minimum elevation angle for space-to-ground links throughout this paper.) Himawari-8 is capable of detecting cloud height, so we measure 5 km as the mean cloud height over the entire Australasian region from 2015 to 2022, such that our ROI for Himawari-8 is approximately 9 km in radius, or ±2 pixels.

Fig. 2. Availability of the Australasian region as detected by AHI/Himawari-8, averaged from using twice-daily cloud cover masks from 2015 to 2022. White dots correspond to the geographical position of all OGS of the extended AOGSN, and green outlines indicate base AOGSN sites. Annotated availabilities are shown for each site. Data provided by the Earth Observation Research Center (Japan Aerospace Exploration Agency).
affected by the same weather. An effective FSOC network should be designed such that its OGS do not have strongly correlated cloud cover. For the case of GEO or deep-space communication where visibility is maintained to an entire network, diversity corresponds directly to the likelihood that a link can be established with said network.

We use Himawari-8 for all cloud correlation analysis as it has made simultaneous \( C \) measurements of the entire region over the last eight years. Each pixel is flagged as 0 if no cloud or only cirrus cloud is present; otherwise it is flagged as 1, as described in Section 2. Therefore, we have the vector \( C_k \) (throughout this study, we use the subscripts \( X \) for function \( X(x_i, y_j) \) evaluated at grid coordinates \( (x_i, y_j) \) of length \( n \), where \( n \) is the number of daily images from 2015 to 2022, for each 5 km \( \times \) 5 km pixel \((x_i, y_j)\) in Himawari-8 frames of Australasia. We calculate the point-wise Pearson (linear) correlation coefficient, \( r_{ij} \), between site \( k \), \( C_k \), and every other pixel in Australasia, \( C_j \):

\[
r_{ij}(C_k, C_j) = \frac{\langle (C_k - \Omega_k)(C_j - \Omega_j) \rangle}{\left[ \langle (C_k - \Omega_k)^2 \rangle \langle (C_j - \Omega_j)^2 \rangle \right]^{1/2}},
\]

where \(-1 \leq r_{ij} \leq 1\). For \( r_{ij} = 1 \), the cloud cover between two pixels is perfectly linearly correlated (note that this type of correlation only captures linear correlations, and more complex, non-linear correlations may exist but will not be accounted for with this statistic; see, e.g., [33]) in time; hence, when one pixel is cloudy, so is the other. Conversely, when \( r_{ij} = -1 \) the pixels have perfect linear negative correlation, and when one pixel is cloudy, the other is not. Finally, \( r_{ij} = 0 \) corresponds to the case where two pixels are not linearly correlated in time. \( r_{ij}(C_k, C_j) \) is therefore a two-dimensional surface describing how \( C \) throughout the region is spatially correlated around site \( k \). The length scale and shape of \( r_{ij} \) is driven by localized and global weather dynamics, e.g., atmospheric circulation cells on the global scale and rain shadow more locally.

Figure 4 shows \( r_{ij}(C_k, C_j) \) for each site in the extended AOGSN. We find contours of equal \( r_{ij} \) around sites that represent the weather dynamics driving \( C \), e.g., elongation along the east–west axis for southern sites due to prevailing westerlies across Australia. Figure 4 shows that Alice Springs experiences correlated \( C \) over an extremely large area, the result of how pressure systems and fronts traverse the desert without coastal or topological effects. It is also evident that Dongara and Perth are located within each others \( r_{ij} = 0.4 \) contour, implying they will be strongly correlated, as shown in Subsection 3.B. The Mt. John site highlights the effect of rain shadow, as the correlation scale is stretched along the length of the New Zealand Southern Alps. Mt. John correlations also show misleading results on the Alps, due to those pixels sitting above the cloud height. Negative correlation between northern Australia and southwestern Australia is also clear in Fig. 4, which occurs because northern Australia has a tropical seasonality, i.e., a winter dry season, unlike the rest of the continent.

This method of computing \( r_{ij}(C_k, C_j) \) for \( k \) sites is an extension of earlier work [10]; i.e., we compute \( r_{ij} \) against \( C_k \) for the whole grid \((x_i, y_j)\) and not just point-wise between preselected site locations. This spatially resolved approach, despite being more computationally expensive, allows us to

Figure 3 shows \( A \) across all satellites and the annual average of \( A \pm \sigma \), with \( \sigma \) from satellite and seasonal variation. Figure 3 shows that most sites have high availability with an average of \( A = 0.69 \), particularly the arid sites such as Alice Springs (\( A = 0.83 \)) and Dongara (\( A = 0.77 \)). Most sites exhibit a drop in \( A \) during winter months, except for the northern sites of Alice Springs (23.8°S) and Mt. Kent (27.8°S), which experience a partial dry and wet seasonal cycle. Mt. John is an outlier due to its low availability and pattern of clearer skies in the winter despite its southern latitude (44°S). Appendix B demonstrates the independent results of \( A \) from the different datasets used.

3. NETWORK DIVERSITY

A. Spatial Correlation of Cloud Cover

Correlation of cloud cover between sites is the primary impact on network diversity, as two or more network nodes may be
construct a two-dimensional surface of \( r_{ij} \) for each site. In Section 5, we show how this quantity can be used to generate a network of maximally diverse ground stations.

### B. Site-Specific Correlations

To probe the pair-wise correlations between sites, we calculate

\[
r(\mathbf{C}_k, \mathbf{C}_l)
\]

between all sites of the extended AOGSN, where \( k, l \in \{1, \ldots, N\} \) for a network of \( N \) sites. We show the results with a correlation matrix in Fig. 5, which shows typically low, \( r \approx 0.1 \), between sites. However, we do note the Mildura–Edinburgh \((r = 0.51)\) and Perth–Dongara \((r = 0.5)\) sites show relatively strong, positive correlations. For example, this corresponds to half of all outages at Perth or Dongara affecting both sites. Negative correlation between Alice Springs and Perth/Dongara is due to the winter dry season of northern Australia, visible in Fig. 4.

As a simple metric to understand how diverse a network of \( N \) sites is, we compute the mean absolute correlation in the network:

\[
|\bar{r}| = \left( \begin{array}{c}
N \\
2
\end{array} \right)^{-1} \sum_{k=1}^{N-1} \sum_{l=k+1}^{N} |r(\mathbf{C}_k, \mathbf{C}_l)|,
\]

introduced earlier [10]. Note that, compared to the value of \( \bar{r} \) in [10], we choose to take the mean of the absolute value, \(|\bar{r}|\), which means we are probing the average magnitude of the correlation over the network as opposed to the average correlation. The latter may be zero for a network that has both strong positive and negative correlations; hence \( \bar{r} = 0 \) does not imply that the network, as a whole, has weak correlations, but \(|\bar{r}| \approx 0 \) does. We find \(|\bar{r}| = 0.088 \pm 0.11\) and \(|\bar{r}| = 0.073 \pm 0.076\) for the extended and base AOGSNs, respectively, which is reasonably low despite being skewed by a number of strongly correlated sites (e.g., Mildura–Edinburgh) shown in Fig. 5. Negatively correlated sites contribute given the absolute approach of Eq. (3), and the detrimental effects of negative correlations between network sites is explored in Appendix C. Nonetheless, \(|\bar{r}| = 0.088\) is a representative of a well-diversified network, owing to the large area of the Australasian region. This highlights the unique position for Australia and New Zealand to offer a robust, highly diverse FSOC ground segment, when combined with the high availabilities estimated in Section 2.

### 4. NETWORK RELIABILITY AND OUTAGE PROBABILITY

The diversity and availability of a network can be used to estimate the network reliability and outage probability. To understand the outage probability, we construct \( p_{\text{avail}}(k \leq M) \), the probability that at least \( M \) sites in the network of \( N \) nodes
(M ≤ N) are available in a network (the cumulative distribution function of the network availabilities). The case of M = 0 provides the network-wide outage probability, pavail(M = 0). For GEOs and deep-space targets, which can maintain visibility with an entire hemisphere 1 − pavail(M = 0) corresponds directly to the network reliability. Figure 5 shows that some significant correlations exist between AOGSN nodes, as do the networks proposed in [10]. Therefore, it is necessary to construct pavail(k ≤ M) including point-wise correlations between sites.

Constructing a closed-form analytical expression for pavail(k ≤ M) with correlation maintained between greater than three sites is impossible [34]. An earlier study provided an expression for uncorrelated sites and empirically measured the outage probabilities from C data for the correlated case [10]. Empirically estimating pavail(k ≤ M) can be compromised by the length of time required to determine low probability events such as network-wide outages [10]. For our case, we use only twice-daily images and find only one instance of a network-wide outage over the 2015–2022 time span for the extended AOGSN. This empirically means that, similar to [10], we cannot provide a robust estimate of pavail(M = 0) and require a better method to estimate these low-probability, correlated events. A robust method can also be used to estimate from correlated weather data built up over a relatively short amount of time.

Because there is no closed-form analytical expression for the probability function of a correlated network of Bernoulli events, we opt for a Monte Carlo sampling approach. Our goal is to construct pavail(k ≤ M) from a distribution that we are able to randomly draw events from. As per Section 2, each event is a time realization of the cloud cover at each site, Ck. We, therefore, have to construct the joint availability distribution (a multivariate Bernoulli distribution of dimension N) with correlations between each Ck marginal distribution. Again, k, l ∈ {1, . . . , N} for a network of N sites. We do this by utilizing a neuronal spike model [17], noting that a ground station network described by a correlated network of Bernoulli events is directly analogous to the correlated network of firing neurons [17].

Following [17], the method of constructing and sampling from the joint availability distribution is as follows. Consider x ∈ RN, with components xk. Let x follow a multivariate Gaussian distribution (i.e., each xk, admits to a Gaussian distribution),

\[
f(x; \mu, \Lambda) = (2\pi)^{-\frac{N}{2}} |\Lambda|^{-\frac{1}{2}} \exp \left\{ -\frac{1}{2} (x - \mu)^T \Lambda^{-1} (x - \mu) \right\},
\]

with mean \( \mu \in \mathbb{R}^N \) and covariance \( \Lambda \in \mathbb{R}^{N \times N} \), a symmetric and positive-definite matrix and det(\( \Lambda \)) is the matrix determinant. Reference [17] showed that if we are able to sample \( f(x; \mu, \Lambda) \) and pick a threshold,

\[
C_k = 1, \quad \text{if} \quad x_k > 0,
\]

then we are able to simulate a correlated multivariate Bernoulli process, with \( \Omega_k \) determined by \( \mu_k \) and the covariance \( \Gamma_{kl} \) between each ground station determined by \( \Lambda_{kl} \). Assuming that \( \Lambda_{kl} = 1 \), the relations between these quantities are as follows:

\[
\Omega_k = \phi(\mu_k),
\]

\[
\Gamma_{kk} = \phi(\mu_k) \phi(-\mu_k),
\]

\[
\Gamma_{kl} = \phi_2(\mu_k, \mu_l; \Lambda_{kl}) - \phi(\mu_k) \phi(\mu_l), \quad k \neq l,
\]

where

\[
\phi(\mu) = \frac{1}{2} \left[ 1 + \text{erf} \left( \frac{\mu}{\sqrt{2}} \right) \right]
\]

is the cumulative distribution function for a univariate, standardized (\( \mu = 0; \Gamma = 1 \)) Gaussian distribution and \( \phi_2(\mu_k, \mu_l; \Sigma_{kl}) \) is the two-dimensional counterpart. \( \mu_k \) is determined simply by inverting Eq. (9), which can then be used to generate \( \Gamma_{kk} \) employing Eq. (7). For the off-diagonal elements of \( \Lambda \), we perform a root-finding algorithm to determine what values of \( \Lambda_{kl} \) satisfy

\[
\Gamma_{kl} - [\phi_2(\mu_k, \mu_l; \Lambda_{kl}) - \phi(\mu_k) \phi(\mu_l)] = 0,
\]

noting that \( -1 ≤ \Lambda_{kl} ≤ 1 \) (this is true for Bernoulli events—see Appendix A in [17]—but not generally true for other random processes) and that \( \Gamma_{kl} \) is determined directly from the data (i.e., we compute the covariance between ground stations of the network; from Eq. (2), one can see that it is \( \left[ ((C_k - \Omega_k)^2) ((C_l - \Omega_l)^2) \right] \left[ 1 + \text{erf} \left( \frac{\mu}{\sqrt{2}} \right) \right] \)). \( \Gamma_{kl} \) and \( \Lambda_{kl} \) are monotonic functions of one another. Therefore, Eq. (10) has a single root between -1 and 1, which we determine using scipy [35]. This method differs from [5] by numerically solving Eq. (10) instead of obtaining an analytical expression by approximation.

Utilizing this construction and sampling method, we create three multivariate availability distributions for the extended AOGSN and three availability cumulative distribution functions by sampling the availability distribution 10^8 times (equivalent to 10^8 time realizations), all of which use \( \Omega_k \) directly determined from the data. The difference between the three distributions is as follows: (1) we construct a distribution with \( \Gamma \) directly from our data, encoding the real \( r(C_k, C_l) \) between sites; (2) we run a \( r(C_k, C_l) = 0 \) simulation, which enforces that there is no correlation between sites, comparable to the results in [10]; and (3) we choose a \( r(C_k, C_l) = 0.5 \), \( k \neq l \) to understand the outage probability for a network that is strongly correlated in \( C \).

Figure 6 shows the cumulative distribution function pavail(k ≤ M) for M = 0–8, with cases (1), (2), and (3) for the extended AOGSN and with only case (1) for the base AOGSN. We estimate network-wide outage probabilities of pavail(M = 0) = 2.4 × 10^-4 and pavail(M = 0) = 0.064 for the extended and base AOGSN configurations, respectively. From Fig. 6, we see that a small (N = 3) and well-separated network, e.g., the base AOGSN, can have (marginally) lower or comparable outage probability than a highly available but very correlated network of eight OGS. Figure 6 also shows that, while pavail(M = 0) = 2.4 × 10^-4 for measured \( r(C_k, C_l), \)

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Figure 4 indicates that correlation surfaces can be used for optimally planning an FSOC network. We expand this idea by considering a simple spatially resolved model for iteratively determining the coordinates $(x_i, y_j)$ of $N$ sites $S_k$, in the network $\mathcal{N}$ (the same notation as we used in Section 2). Our method for determining the optimal $(x_i, y_j)$ for each $S_k$ in the network relies on two site characteristics: the first is average cloud cover $0 \leq \Omega_k \leq 1$ at each $S_k$. The second is the temporal correlation $-1 \leq r_{ij}(C_k, C_j) \leq 1$. We discuss the exact procedure for generating the correlation in Section 3.

To maximize the connectivity of each $S_k$ and robustness of $\mathcal{N}$, we propose a simple heuristic: (1) the optimal site is one that minimizes the amount of cloud coverage, hence maximizing the time it may be available on the $\mathcal{N}$, and (2), the optimal $\mathcal{N}$ is one that supports a series of uncorrelated $S_k$ (supported by the lowest probability of an outage in Fig. 6), such that if any $S_k$ are unavailable due to cloud cover events, other sites in $\mathcal{N}$ will most likely not suffer the same deficiency.

Based on this simple heuristic, the first site $S_1$ we pick is located at

$$S_1(x_i, y_j) = \text{argmin}_j \{ \Omega_j \},$$

where $\text{argmin}_j$ returns the sites coordinates that minimize the time-average of $C_{ij}, \Omega_{ij}$, without any extra constraints. The second site we pick does not, however, have the same degrees of freedom, and we want to minimize both $\Omega_{ij}$ and the site–pair correlation with $S_1$. Hence, we define a new, quadratic (positive, semi-definite) function, $g$, as a function of spatial coordinates $(x_i, y_j)$ such that

$$g_{ij} = \|\omega_0 \Omega_{ij} + \omega_1 r_{ij}(C_1, C_j)\|^2,$$

where $\omega_0$ and $\omega_1$ are weights that determine what we deem more important—the cloud cover between sites or maintaining an uncorrelated network—and $\|a + b\|^2 = a^2 + b^2$ is the two-norm squared. Note that $g_{ij} = 0$ at its global minima, which corresponds to a site with no average cloud cover and no correlation with $S_1$, and $g_{ij} = \omega_0^2 + \omega_1^2$ at its maxima, describing a site that is on average always cloudy and strongly correlated (either positive or negative; note that we show that both types of correlations reduce the performance of the network in Appendix C) with $S_1$. Hence, $S_2$ is

$$S_2(x_i, y_j) = \text{argmin}_j \{ g_{ij} \}.$$

Now we must generalize Eq. (12) for a general $S_k(x_i, y_j)$, noting that we ought to always be able to minimize $g_{ij}$ to find any next site on the network. The procedure for $N$ sites is simply

$$g_{ij}(N) = \|\omega_0 \Omega_{ij} + \frac{1}{N} \sum_{k=1}^{N} \omega_k r_{ij}(C_k, C_j)\|^2,$$

$$= \|\omega_0 \Omega_{ij} + \frac{1}{N} [\omega_1 r_{ij}(C_1, C_j) + \omega_2 r_{ij}(C_2, C_j) + \cdots + \omega_N r_{ij}(C_N, C_j)]\|^2,$$

**5. GENERATING AN OPTIMAL NETWORK**

We are interested in developing a method for site selection in an FSOC network. An optimized network, produced without preselection, can also be compared with an existing network (our example AOGSN) to judge how well optimized the network is. In addition, this method can be adopted to select additional sites in an established network. Methods have been presented for how diversity can be optimized with varying channel and outage models, but their optimization relies on preselected sites in a network [3,6].
which describes our selection criteria, \( g_{ij}(N) \) as a linear combination of time-averaged cloud cover through the first term and pair-wise site correlations, each with a weighting \( \{\omega_1, \ldots, \omega_N\} \). This maintains \( g_{ij}(N) = 0 \) as a global minima, but now \( g_{ij}(N) = \omega_i^2 + \omega_j^2 + \cdots + \omega_N^2 / N^2 \) is the global maximum. Hence, to generate the first site in \( \mathcal{N} \), we use Eq. (11), and then to successively generate \( n \in N \) following sites, we use Eq. (14), that is,

\[
S_n(x_i, y_j) = \argmin_{c_i, C} \left\{ \Omega_{ij}, \text{if } n = 1, \right. \\
\left. \left\{ g_{ij}(n) \right\}, \text{if } n > 1, \right. 
\]

(16)

to populate \( \mathcal{N} \). Note that this simple method can be easily generalized for including any other site characteristics that may help determine a robust \( \mathcal{N} \). This method can also be used to optimally add OGS to an existing network, which is explored in Appendix A.

We initially set all \( \omega = 1 \); however, Subsection 6.C explores the use of a \( \omega \) function to further optimize for a given orbital inclination. The \( \omega \) terms can also be used to mask for regions-of-interest. The result of running this method with 8 years of daily cloud data from Himawari-8 over Australia is shown in Fig. 7 for \( N = 8 \). New Zealand is ignored for simplicity and to reduce computational demand given the number of correlation calculations.

We also reduce the spatial resolution of Himawari-8 data for this analysis to 25 km from 5 km to further reduce computational effort. Figure 7 is dark where \( g_{ij} \) is close to 0, and the process of minimizing \( g_{ij} \) selects these areas. Each \( S_k \) also imposes a structure to the surface of \( g_{ij} \) related to the \( r_{ij}(C_k, C_g) \) functions in Fig. 4. We see from Fig. 7 that sequentially minimizing \( g_{ij}(N) \) picks locations for \( \mathcal{N}_{N=8} \), which are well spaced and in areas of low cloud cover, tending to be in extremely arid parts of Australia.

The effectiveness of our optimization technique can then be judged by comparing it with the extended AOGSN, a more realistic example network. Table 2 uses the mean of \( A \) across each of the sites, \( \bar{A} \), \( |\bar{r}| \) (Eq. (3)), and \( p_{\text{avail}}(M = 0) \) to compare the AOGSN with \( \mathcal{N}_{N=8} \). Table 2 shows that for all metrics, \( \mathcal{N}_{N=8} \) outperforms the extended AOGSN. We also see in Table 2 that \( \mathcal{N}_{N=8} \) has an order-of-magnitude lower chance of a network-wide outage. However, the metrics we employ in Table 2 do not properly represent network capability on comparison, e.g., outage probability for both \( \mathcal{N}_{N=8} \) and the extended AOGSN seem sufficient for a reliable network.

In the next sections, we use orbital simulations to provide a more detailed view of network capability.

### 6. LEO Satellite Link Modeling

We conduct orbital propagation simulations that can be combined with availability measurements to estimate the data capacity for different network configurations. We do this by using the a.i.-solutions FreeFlyer software to simulate LEO satellite links to the AOGSN. Coverage as a function of orbital height (\( h_{\text{orbit}} \)) and minimum OGS elevation angle (\( \theta_{\text{elevation}} \)) can be used to estimate the number and duration of passes a satellite has with the network. While GEO or deep-space applications are likely to maintain mutual visibility across the entire network, LEO satellites will typically only see one node at a time, so an increase in the number of passes directly corresponds to an increased number of links and average data capacity.

Figure 8 shows coverage for ground stations in the AOGSN with \( \theta_{\text{elevation}} \geq 30^\circ \) and \( \theta_{\text{elevation}} \geq 45^\circ \) to a satellite with \( h_{\text{orbit}} = 500 \text{ km} \). \( h_{\text{orbit}} = 500 \text{ km} \) is selected as a typical orbit for LEO satellites. The area covered by the network in Fig. 8 is large, highlighting how an Australasian network can provide ground segment support over a significant area, continuing a well-established role in radio ground segment operations [37]. However, the overlapping circles in Fig. 8 represent areas of mutual coverage, implying the proposed extended AOGSN has some redundancy not present in the optimized network, \( \mathcal{N}_{N=8} \).

### A. Link Duration Analysis

We conduct further orbital simulations to determine average link durations \( \tau(i) \) between LEO orbits and the extended AOGSN, i.e., the sum of passes and their duration. The parameter space of orbital inclination \( i \) is modeled by scaling a fiducial ISS orbit to 530 km (common height for LEO communication satellites), and then orienting it from

| Network | \( \bar{A} \) | \( |\bar{r}| \) | \( p_{\text{avail}}(M = 0) \) |
|---------|---------|---------|-----------------|
| AOGSN extended | 0.69 ± 0.09 | 0.08 ± 0.11 | 2.4 × 10^{-4} |
| AOGSN base | 0.67 ± 0.06 | 0.073 ± 0.076 | 0.064 |
| \( \mathcal{N}_{N=8} \) | 0.83 ± 0.04 | 0.069 ± 0.060 | 1.47 × 10^{-5} |

\( \bar{A} \) is the statistical mean of \( A \) across all sites in a given network. The uncertainties of \( A \), like in Fig. 3, represent seasonal variation and satellite-to-satellite variability.

\( |\bar{r}| \) is determined from Eq. (3) shown with ±σ from both calculations. The uncertainties of \( |\bar{r}| \) are the σ from all values in the matrix used to compute \( |\bar{r}| \) described in Eq. (3).

\( p_{\text{avail}}(M = 0) \) is from the Monte Carlo method for sampling the availability PDF described in Section 4.
with \( \theta \) because it includes short passes that glance at a robust statistical sample. This method may overestimate Single time step from Fig. 9.

Coverage for the ground stations in the extended AOGSN and satellites with inclination \( \tau \) from the extended AOGSN. We therefore record \( \tau \) due to the new correction term, \( \tau(\theta_{\text{elevation}}) \), which may not be ideal for maximizing \( \tau \) with a given satellite or constellation. We therefore adjust the method from Section 5 to produce an optimized network for a specific \( i = 90^\circ \) polar orbit satellite. Many current FSOC satellites are approximately in polar orbits, and Earth observation satellites, which may one day be supported by an FSOC ground segment for improved downlinks, typically use a Sun-synchronous near-polar orbit.

To optimize for an \( i = 90^\circ \) orbit, we look at the \( \tau(i = 90^\circ) \) values for each AOGSN site in Fig. 10 and deduce a relation empirically from our simulations. If \( L \) is far from \( i \), we can see that \( \tau(i) \) is asymptotic, which is satisfied for all sites in the extended AOGSN. We therefore record \( \tau(i = 90^\circ) \) as a function of \( L \) and normalize the results,

\[
\omega(L) = 0.00745L + 1, \tag{17}
\]

to create an expression that describes \( \tau(i = 90^\circ) \propto L \).

\( \omega(L) \) is normalized to the equator \( (L = 0) \) with a minimum of 0.33 at the south pole \( (L = -90) \). We can then use \( \omega(L) \) as a weighting function for all \( \omega_k \) in Eq. (12), which adds a linear north–south gradient for preferencing southern sites to the surface, \( g_{\text{f}}(N) \), being minimized by the algorithm in Section 5. We re-run the optimization to generate \( \mathcal{M}_{N_{\text{obs}}} \), the set of sites selected after applying this latitude-correction, which is shown in Fig. 11. We see very little difference between Fig. 11 \( (\mathcal{M}_{N_{\text{obs}}}) \) and Fig. 7 \( (\mathcal{N}_{N_{\text{s}}}) \) for \( S_7 \) to \( S_8 \), but with some southern shift for \( S_7 \) and \( S_8 \) due to the new correction term,
Therefore, the minor difference of $S_i$ for capacity compared with the extended AOGSN, respectively, the extended AOGSN and optimized networks, [38,39]. A general improvement can be seen in Fig. 12 between transfer per day with a LEO satellite and the current capability optimized networks can feasibly support many terabits of data degradation of bit rate due to turbulence, so it is only a guide of capacity in this manner does not consider potential outages or related to both, and the chance of both being available simultaneously is total link time by including scenarios where a LEO can main-

![Latitude correction for $i = 90^\circ$, $M_{N=8}$, $\omega(L) = 0.00745L + 1$](image)

**Fig. 11.** Optimized selection of eight sites, $M_{N=8}$, using the method from Section 5 with the linear latitude weighting function, Eq. (17), to optimize specifically for $i = 90^\circ$ orbits.

$\omega(L)$. This similarity is likely because the first sites have such high availability that they remain optimal despite the orbital dynamics favoring southern locations. The method we have demonstrated could be generalized to any orbital parameters, not just $i$, and for an entire satellite constellation.

C. Network Capacity

Finally, we combine work on availability, $\tau(i)$ modeling, and optimization techniques by constructing a general network capacity for LEO satellites. The availability-corrected, network-wide link duration, $T(i)$, for a network of $N$ sites is

$$T(i) = \sum_{k=1}^{N} A_k \tau_k(i). \quad (18)$$

We calculate $T(i)$ for four networks: (1) the base AOGSN, (2) the extended AOGSN, (3) $\mathcal{N}_{N=8}$, and (4) $M_{N=8}$. Figure 12 shows $T(i)$ for these four networks and an estimate of the daily data capacity with a 5 Gbps bit rate, which will be possible with future on–off keying satellite terminals [38,39]. Note that this expression for $T(i)$ overestimates the total link time by including scenarios where a LEO can maintain mutual visibility with $>1$ available sites by including both links. In practice, the satellite must choose which OGS to link with, and the chance of both being available simultaneously is related to $r$ for that pair, e.g., from Fig. 5. Estimating network capacity in this manner does not consider potential outages or degradation of bit rate due to turbulence, so it is only a guide of system performance for a given bit rate.

![Network link duration, $T(i)$ [Eq. (18)], and data capacity estimates for the AOGSN (extended, solid; base, dashed) and two networks optimized for maximizing availability and diversity. Optimized networks $M_{N=8}$ (dashed-dotted, Subsection 6.B) and $\mathcal{N}_{N=8}$ (dotted with triangles, Section 5) are with and without latitude-correction for polar orbits, respectively. Data estimation uses 5 Gbps as the fiducial bit rate, multiplied by $T(i)$ for current on/off keying capability, assuming a uniform atmospheric channel for every site.](image)

**Fig. 12.** Network link duration, $T(i)$ [Eq. (18)], and data capacity estimates for the AOGSN (extended, solid; base, dashed) and two networks optimized for maximizing availability and diversity. Optimized networks $M_{N=8}$ (dashed-dotted, Subsection 6.B) and $\mathcal{N}_{N=8}$ (dotted with triangles, Section 5) are with and without latitude-correction for polar orbits, respectively. Data estimation uses 5 Gbps as the fiducial bit rate, multiplied by $T(i)$ for current on/off keying capability, assuming a uniform atmospheric channel for every site.

with the $\omega(L)$ weighting function, shows only a marginal improvement of 3% over $\mathcal{N}_{N=8}$ for highly inclined orbits.

We may be interested in the case of network capacity for a LEO constellation uniformly distributed in $i$. Integrating $T(i)$ over $i$ for all networks in Fig. 12 allows us to compare this general case. Upgrading from the $N = 3$ base AOGSN to the $N = 8$ extended AOGSN corresponds to a 293% increase of data capacity when integrating $T(i)$ for the uniform case. This also shows a 27% and 20% efficiency gain for $\mathcal{N}_{N=8}$ and $M_{N=8}$, respectively, compared to the extended AOGSN. The optimization from Section 5 therefore yields a network superior in data capacity to the more realistic AOGSN. We could also use this method to optimally select additional sites for a network and estimate the increased capacity from doing so.

7. GEO VISIBILITY ANALYSIS

While we have extensively studied the case of how the AOGSN can support LEO satellites, a large and diverse optical network can provide very high reliability to GEO or deep space if there is significant mutual visibility to numerous OGS. GEO optical feeder links to ground may become an important future application of FSOC networks, where ground segment reliability is critical [40,41]. The Asia-Pacific region may soon host a GEO satellite with an FSOC terminal to demonstrate this capability, which an Australasian network could reliably support [39,42].

We therefore use orbital simulations with *a.i.-solutions* FreeFlyer to determine GEO visibility to each ground station in the AOGSN with $\theta_{\text{elevation}} > 30^\circ$. For simplicity, GEO orbital placement is considered only a function of longitude with $h_{\text{orbit}} = 35,786$ km and $i \lesssim 1^\circ$. Hence, GEO longitude corresponds to visibility with $N \leq 8$ nodes, allowing estimates
of $p_{\text{avail}}(M = 0)$, described in Section 4, as a function of longitude. Figure 13 shows the number of nodes in the extended AOGSN visible to a GEO as a function of longitude. A portion of the AOGSN is therefore visible to a GEO between different longitude bounds. For each segment, e.g., $N = 8$ from 140° to 160°, Fig. 13 shows $p_{\text{avail}}(M = 0)$ for that set of sites. The extended AOGSN is three times longer in longitude than latitude, which helps maintain $p_{\text{avail}}(M = 0) < 0.01$ over $\approx 80°$ of longitude as shown in Fig. 13. This example network could then feasibly provide reliable support to GEO satellites over nearly one-fourth of the planet. The low number of visible nodes to the east and west of Australia in Fig. 13 indicates extensions in these directions are ideal if minimizing GEO communication outages are a high priority. Placing an OGS in the Polynesian region, e.g., Tahiti, could be an ideal extension by allowing visibility for North American GEO satellites such as the Laser Communications Relay Demonstration [43].

Figure 13 further highlights the improvements between the base and extended AOGSN.

8. CONCLUSION

A. Summary and Key Results

We have developed and shown use cases for a number of novel methods for assessing and optimizing FSOC ground segment networks, focusing, but not being limited to, the availability and site-wise correlations within the Australasian region. An example network called AOGSN is proposed as a realistic representation of an Australasian network, with base ($N = 3$) and extended ($N = 8$) variants. Furthermore, we perform detailed case studies on the base and extended AOGSN, which are highly relevant to the future of optical communications within the Australasian region, comparing them to theoretically optimized networks throughout the study.

For determining availability statistics of networks, we compare among a range of remote sensing data from five Earth observation satellite sources, but particularly focus on the highly spatially and temporally resolved cloud cover data from the Himawari-8 GEO satellite. We model the cloud cover as a Bernoulli process, which provides us a mathematical formalism for the site availability, and joint availability probability distribution function, which we construct and sample to access outage probabilities. We provide a detailed analysis of the spatially resolved correlations between pair-wise ground stations and between ground stations and arbitrary sites. These statistics are combined with orbital simulations to estimate link duration and network capacity statistics. We list the key results below:

- We estimate a 69% average site availability and an average correlation of $|\bar{r}| = 0.088$ for the extended AOGSN (comparable correlations to an ideal, optimized network; see Table 2), demonstrating the large (spatially uncorrelated) and arid nature of the Australasian region.
- Using site availability and correlation measurements and the method outlined in [17], in Section 4, we construct the network availability probability distribution function for an arbitrary-sized Australasian network with arbitrary correlations between sites. The analysis of this correlated network shows that the extended AOGSN has $p_{\text{avail}}(M = 0) = 2.4 \times 10^{-4}$; i.e., at any given time there is close to a one-in-five-thousand chance of suffering a network-wide outage (shown in Fig. 6, alongside statistics for the AOGSN base and ideal, optimized networks). Hence a large and diversified network such as the AOGSN is reliable enough to overcome the reliability challenge for FSOC space-to-ground communication.
- We develop a spatially resolved method for optimizing the positions of ground stations based on the network availability and diversity without site preselection. This method
can be used to develop new or extend existing networks, which we show in Section 5 and Appendix A, respectively, and to generate an optimal network to provide an ideal reference for commissioned networks (e.g., for comparing with the preselected AOGSN).

- In Section 6, we combine orbital LEO simulations with previous availability models to estimate network capacity as a function of orbital inclination, showing that the extended AOGSN is close to optimal (compared to our ideal, optimized network) and both the AOGSN and optimal network are capable of supporting bit rates of $\geq 10$ Tb/day to a LEO.

B. Limitations of Our Study and Future Work

This study considered only a simple availability model based on time-averaged cloud cover. Clearly, as shown in Fig. 3, there is seasonal variation (which can lead up to a factor of $\approx 2$ variation in the availability) and temporal correlation that we do not account for in our study. We will leave a detailed analysis of how the performance of FSOC networks in the Australasian network will change with seasonal, climatic, and temporal correlations for future work. Cirrus and other thin icy clouds could be more rigorously discarded from the total cloud fraction, as they usually do not create an outage. A method for differentiating the liquid cloud fraction, i.e., approximately thick clouds, from the total cloud fraction is outlined in [44] and could be adapted in future studies striving to add additional complexity to the models we have presented.

Furthermore, the atmospheric channel will also constrain availability, which has been explored theoretically in other network diversity studies [3,11]. Very arid and flat sites with low cloud cover likely have strong and detrimental turbulence conditions; hence, the results presented in our study represent an upper bound of the site availabilities. This consideration may be especially important in the context of sensitive coherent protocols, which may require adaptive optics [45]. Network degradation due to turbulence is highly system specific, so estimating system performance should be done on a case-by-case basis. We plan to deploy atmospheric turbulence instruments in prospective sites as part of future investigations to explore OGS placement for the Australasian region, focusing on the suitability of low cloud cover desert and arid sites. However, for a network model that retains spatial freedom and without an experimental campaign at selected sites, there is no feasible or reasonable way to include turbulence in the present, spatially resolved outage model. Well-validated spatial estimates of daytime turbulence do not exist, and testing emerging models (e.g., [46,47]) will require extensive experimental data for future models that include these effects.

Our optimization method described in Section 5 relies on only two site characteristics: (1) the availability and (2) the spatially resolved cloud cover correlation, both of which are equally weighted and without any spatial (latitude, longitude, or altitude) constraints. The latitude-correction case studied in Subsection 6.B demonstrates the flexibility of this method by optimizing for a specific orbit. The theoretical outage model involving the atmospheric channel developed in [3] highlights that our cloud-only model, and proceeding literature, can only provide an upper bound of availability by not including turbulence-induced outages [10].

APPENDIX A: OPTIMIZATION FOR ADDITIONAL SITES AND REGIONS

Our optimization method described in Section 5 can be used to select additional sites for an existing network. This is done by first constructing the $g_{\beta}(N)$ function for the initial ground stations and then adding sites following the process used to construct $N_{\text{Nmb}}$ and $M_{\text{Nmb}}$. We test this using the AOGSN base network as the initial condition and run the algorithm until it reaches $N = 8$, as shown in Fig. 14. This method could be particularly useful when combined with the capacity estimation from Section 6, as the improvement from optimally adding a new OGS to an existing network can be quantified. This application could also be useful with additional ROI masking functions to guide site selection for extending a given network, such as the AOGSN. Figure 14 indicates that, for optimization, the best site to extend the base AOGSN with is located in northern Western Australia.

APPENDIX B: REMOTE-SENSING SATELLITE VARIABILITY

In Section 2, we outlined the method of using all five satellites from Table 1 to estimate $A$ (or $\Omega$) in a robust fashion. Figure 15 shows the different seasonal $A$ curves from all five data products. We can see clearly from the figure that there is reasonable agreement between all satellites despite different methods and resolution. However, Alice Springs suffered issues with Himawari and MERRA-2, while Mt. John had issues with $Aqual/AIRS$ and MERRA-2 due to snow and ice reflectance. In these cases, data streams were discarded as outliers. Furthermore, we can see that higher resolution data, Himawari-8, finds agreement with low resolution data, indicating that spatial averaging is often appropriate. The reliability of spatial averaging owes to Australia’s relatively homogeneous
have the same behavior for large $r$, as we showed previously
in Fig. 6 and discussed in Section 4. However, for $M = 0$ to $M \leq 4$, the networks show different availability statistics. For this range of $M$, the network without correlations performs the best, followed by the negatively correlated network, and then the positively correlated network. This shows that negatively correlated networks admit to better availability statistics than positively correlated ones, but networks without correlations between ground stations perform the best.

**APPENDIX C: A NETWORK WITH NEGATIVE CORRELATIONS BETWEEN GROUND STATIONS**

The most prominent negative correlations we observe in Fig. 5 are due to seasonal inversions. Negative correlations between network nodes intuitively boost diversity, i.e., in the $N = 2$ case, the minima of their availability curves are out of phase. We test how negative correlations influence the network statistics by constructing cumulative distribution functions, as in Section 4 for a negatively correlated network, and discussed in Section 4. However, for $M = 0$ to $M \leq 4$, the networks show different availability statistics. For this range of $M$, the network without correlations performs the best, followed by the negatively correlated network, and then the positively correlated network. This shows that negatively correlated networks admit to better availability statistics than positively correlated ones, but networks without correlations between ground stations perform the best.

**Figure 15.** Availability as a function of month for the Mildura AOGSN site, showing the seasonal variability and each separate cloud retrieval product (different colors) used in this paper, which are averaged over in Fig. 3.

**Figure 16.** Same as Fig. 6 but for three networks that admit to the AOGSN extended configuration with negative correlation (solid, $r = -0.2$), no correlation (dashed, $r = 0.0$) and positive correlation (dotted, $r = 0.2$) between ground stations.

terrain and could cause errors in other environments. High-resolution swathes from the Aqua, Terra, and Suomi NPP LEO satellites can be used if the extra resolution is required.

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