

HyperLEAVES: A Proposal for a Paired Hyperspectral and Lidar Satellite Constellation

Jack Reid

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List of Acronyms

ATLAS	Advanced Topographic Laser Altimeter System
DSM	Digital Surface Model
DTM	Digital Terrain Model
COTS	commercial off-the-shelf
EO	Earth Observation
EO-1	Earth Observing-1
FOV	field-of-view
GLAS	Geoscience Laser Altimeter System
HyperLEAVES	Hyperspectral-Lidar Elevation and Vegetation Satellites
HsypIRI	Hyperspectral Infrared Imager
ICESat-2	Ice, Cloud, and land Elevation Satellite 2
LEO	Low Earth Orbit
lidar	light detection and ranging
MWIR	mid-wave infrared
NASA	National Aeronautics and Space Administration
NASEM	National Academies of Science, Engineering, and Medicine
NDVI	Normalized Difference Vegetation Index
NIR	near-infrared
SWaP-C	Size, Weight, Power, and Cost
SAR	synthetic aperture radar
SRTM	Shuttle Radar Topography Mission
SWIR	short-wave infrared
TIR	thermal infrared

1 Forestry Mapping Methods, Progress, and Direction

Forests play a critical role in regulating the carbon cycle on our planet. Many have argued that one of the most cost-effective means of mitigating climate change available to us is to conserve our remaining forest stock and actively plant new trees [1]. Mangroves are particularly important, having a significantly higher rate of carbon storage and sequestration than most terrestrial ecosystems [2]. These same forests, mangrove and otherwise, have faced significant deforestation risks over the past several decades and we are increasingly using space-based platforms to both monitor [3] and

respond [4] to deforestation changes. With this increasing need has come the increasing availability of sensing technologies. After decades of being limited to in-situ surveys (which are adept at capturing numerous details of forests, but difficult to scale) and multispectral imagery (which are adept at measuring large areas regularly, but only can be used for some classification and health proxy measurements), we have light detection and ranging (lidar), synthetic aperture radar (SAR), and hyperspectral tools available to us. Airborne lidar can generate detailed point clouds providing information about the vertical structure and understory of forests [5]. Space-based methods for studying mangrove structure typically use SAR, such as that on TanDEM-X [6]; a combination of the Shuttle Radar Topography Mission (SRTM) and ICESat's Geoscience Laser Altimeter System (GLAS) [7], with the former reliant on an assumption of a flat surface (water) under the canopy, limiting its applications to only mangroves and similar aquatic vegetation; or very high resolution stereophotogrammetry [8]. Though no one method has emerged as clearly dominant, with each exhibiting different error characteristics [8], these tools collectively have enabled better estimates of global mangrove heights [9] and stored carbon [10].

One limitation with the above referenced studies of mangroves using visual and infrared imagery is the assumption of uniform distribution of different mangrove species within the study area. Different mangrove species have different spectral responses and different phenological trajectories [11]. The Normalized Difference Vegetation Index (NDVI), one of the more commonly used metrics for tracking mangrove health, varies significantly enough between mangrove species that it has been used for species classification, particularly at higher spatial resolutions [12]. There is thus room for improving mangrove health assessments for forest management purposes by incorporating more detailed species classifications. This is achievable through textural and object-based analysis of high resolution images, such as those from airborne sensors or Worldview satellites [12, 13, 14]. These, however, are not consistently available over time for either local or global mangrove change-over-time analyses. Similar species differentiation can also be achieved via pixel-based analysis of hyperspectral data [15, 16], opening the door for a global species mapping using a space-based hyperspectral sensor, particularly if used in conjunction with existing mangrove spectral libraries [17]. The National Academies of Science, Engineering, and Medicine (NASEM) 2018 Earth Science Decadal Survey specifically cites the importance of species identification (including the use of hyperspectral data) for understanding ecosystem functioning (pg. 375 of [18]).

There is also room for improvement with canopy and vertical structure mapping of forests. In addition to the aforementioned space-based vegetation height measurement methods, there has been the recent addition of Advanced Topographic Laser Altimeter System (ATLAS) on the Ice, Cloud, and land Elevation Satellite 2 (ICESat-2). As its name suggests, ICESat-2 was not primarily designed for vegetation mapping and global biomass estimates, though this use was envisioned from early in its development and vegetation data products were designed even prior to launch [19]. ATLAS and its associated data products have promised significant improvements compared to its GLAS predecessor [19, 20, 21]. That said, a more recent evaluation of these capabilities found significant limitations, particularly over dense vegetation, even at the county scale (hundreds of square kilometers) [22]. Ultimately it looks like space-based lidar systems are still not in a position to either supplant SAR in tree height mapping or to meaningfully contribute to measurements of vertical structure as their airborne counterparts do.

That said, there is significant promise on this front. Lidar technology is advancing rapidly (discussed later in this proposal) and the NASEM 2018 Earth Science Decadal Survey listed space-based lidar as either *the* preferred measurement approach or one option among several for seven of their fourteen targeted observables [18]. Additionally, there is promise in combining space-based lidar data from ICESat-2 with other data sources, such as SAR and visual imagery, to essentially upscale canopy height and other lidar-observed vegetation attributes. [23].

This proposal builds upon these identified opportunities to develop a satellite mission concept, called Hyperspectral-Lidar Elevation and Vegetation Satellites (HyperLEAVES), aimed at answering the following questions:

1. Can a space-based hyperspectral imager provide sufficient spatial and spectral resolution to enable forestry species differentiation?

2. Can a space-based lidar system provide information on the understory, vertical forest structure, or even on individual trees, including height and tree crown shape?
3. Can hyperspectral and lidar data be combined to generate high-resolution mapping of forest canopy height?

Section 2 will layout the high level design parameters of HyperLEAVES along with their technical justification. Section 3 will then discuss potential data products and applications, including those beyond mangrove forest monitoring.

2 HyperLEAVES Mission Concept

The HyperLEAVES concept involves two satellites in sun-synchronous, Low Earth Orbit (LEO) orbits such that one lags the other by approximately 12 hours. The first of these satellites, hereafter referred to as HyperSat, would carry as its primary instruments hyperspectral visual and infrared imagers with a spatial resolution of 30m in the visual to short-wave infrared (SWIR) regime and 60m resolution in the thermal infrared (TIR) regime. The NASA-proposed Hyperspectral Infrared Imager (HsyPIRI) mission [24] is used in this proposal as a baseline reference for HyperSat. The second satellite, hereafter referred to as LEAVES, would carry a single photon near-infrared (NIR) lidar instrument. ICESat-2 is used as a baseline reference for LEAVES in this proposal.

The orbital lag between these two satellites is not dissimilar to 3 hour lag between that of AM/PM constellations which includes the Aqua and Terra satellites [25], and is intended to result in LEAVES imaging some of the same areas as HyperSat, but at night in order to reduce noise for the lidar system.

The specifications of the imaging systems, the satellites as a whole, and their orbits are described in more detail throughout this section.

2.1 HyperSat

The objective of HyperSat is to enable species differentiation in mangroves and other forests. The feasibility of this has already been demonstrated using the now defunct Hyperion imager, which had a 10nm spectral resolution ranging from 357nm to 2.576 μ m (visible through NIR) and a spatial resolution of 30m [15]. Fortunately, National Aeronautics and Space Administration (NASA) has already pursued the design of a full-scale followup to the Hyperion technology demonstration mission, called HsyPIRI [24]. It should be noted that the HsyPIRI design has gone through multiple revisions since it was initially proposed in the 2007 Earth Science Decadal Survey [26]. Unless otherwise stated, this proposal will be referring to the 2018 design parameters as specified in the *HsyPIRI Final Report* [24]. The general sensing parameters of this version of HsyPIRI can be seen in Table 1.

The HyperSat concept maintains virtually all of the HsyPIRI design parameters, only opting to reduce its orbital altitude from 504km to 480km. This is done primarily to accommodate the stricter design constraints of LEAVES, as explained further in Section 2.2. The reduced altitude results in a slightly improved spatial resolution, decreased swath width, and a slightly increased revisit period, assuming other design parameters, such as field-of-view (FOV) are kept constant. The change in resolution can be calculated from basic trigonometry, assuming a curved Earth and nadir-looking sensor. This results in a reduction of approximately 4.8% in both resolution and swath width, though the imagery would probably be resampled back to its original values for interoperability ease with other datasets. The reduction in swath width also impacts the revisit period, though this is somewhat offset but the change in orbital period due to the reduced altitude. In general, the revisit period scales according to Equation 1 [27]:

$$R \propto \frac{\sin(\lambda)}{T} \quad (1)$$

where R is the revisit period, λ is the earth central angle of the swath width, and T is the orbital period. Using this equation suggests that the revisit period will increase by approximately 3.9% and 4.0% for the hyperspectral component and the multispectral IR components, respectively.

The reduced altitude does come at another cost: reduced satellite lifetime. Atmospheric drag (still non-negligible in LEO, particularly $<1000\text{km}^2$) scales with atmospheric density, which in turn scales with the negative exponential of altitude at low altitudes ($<40\text{km}$), but has more complicated behavior in the LEO regime. Referring to the NRLMSISE-00 model of atmospheric density [28] suggests that the atmospheric density between 504km and 480km differs by a factor of approximately 200%, effectively halving the lifetime of HyperSat relative to HyspIRI, assuming equal orbital maintenance fuel capacity. While the HyspIRI Final Report does not contain mass estimates of the entire spacecraft, it is probable that fuel reserves could be increased to return the lifespan to at least the 2-4 year range.

These changes are summarized in Table 1 and do not compromise the objectives of HyperSat. Obviously these estimations should be considered provisional, and more detailed numerical analyses should be conducted to confirm the results shown here.

Table 1: HyspIRI and Hypersat specifications [24]

		HyspIRI	HyperSat
Orbit	Altitude	504km	480km
	Lifetime	3-5 years	2-4 years
Optical Hyperspectral	Range	400-2500nm	
	Spectral Resolution	10nm	
	Spatial Resolution	30m	~28.5m
	Swath Width	185km	~176m
	Revisit Period	16 days	~16.6 days
	Mass	~130 kg	
IR Multispectral	Range	7-13 μm	7-13um
	# of Bands	7	
	Spatial Resolution	50	~47.5m
	Swath Width	518km	~493km
	Revisit Period	4 days	~4.2 days
	Mass	~100kg	

2.2 LEAVES

The objective of LEAVES is to increase the received photon spatial density, relative to ICESat-2, to the level required for high resolution canopy mapping, while staying within practical design limitations, particularly with regards to power and laser performance. For simplicity, this preliminary concept for LEAVES will keep ICESat-2's six beam geometry, including three strong beams and three weak beams, allowing for slope detection without incurring undue power requirements [29]. Similarly, the laser footprint will be maintained. This footprint, in conjunction with the six beam configuration, means that gridded data products for the globe should be available on an annual basis, as is planned for ICESat-2 [19], with near-real-time releases of along-track data. The remainder of this section will focus on the novel design elements required to reach the LEAVES objective.

There are several different factors which affect the precision of lidar data and derived data products, including point/pulse density of the laser, height thresholds, laser footprint size, and sample size (for bulk metrics such as average tree height in an area). While point density is not usually the limiting factor in airborne lidar systems, either for generating Digital Terrain Models (DTMs) or for estimating bulk biomass estimates [30, 31, 32, 33], ICESat-2 is point density limited in areas of dense vegetation, even at the 100m scale [22]. Individual tree crowns can be detected and measured at 4-5 points/m² and individual tree heights can be measured with 1 point/m² [34]. More detailed analysis of the understory, particularly in dense forests, requires densities of at least 12 points/m² and sometimes up to 170 points/m² [35]. These upper ranges are likely still infeasible for a space-based lidar system, but densities in the range of 1-10 points/m² are likely achievable. This means that the signal photons received per square meter must be increased 1-2 orders of magnitude from

the ICESat-2 ATLAS design, as seen in Table 2. Such a performance increase is not unprecedented. ICESat’s GLAS was a traditional multi-photon lidar system using a NIR laser. ICESat-2’s ATLAS, meanwhile, was able to achieve higher resolutions while using only about 1% the power [36].

In order to increase the spatial density to the requisite levels, LEAVES has several noticeable design changes. First is its use of a 1050nm NIR laser rather than a 532nm green laser. This change has several benefits. The atmospheric transmittance of 1050 nm light is approximately 10% higher than that of 532nm green light [37, 38], meaning that, assuming equal sensor sensitivity, more signal photons will be received per pulse of equal strength. Additionally, due to their lower frequency, 1050nm photons carry approximately half the energy of 532nm photons, reducing the power requirements of the LEAVES laser. A NIR laser was used by ICESat’s GLAS but the switch to a single photon design with ATLAS meant that higher sensitivity detectors were required. These were practical in green but not in NIR [39]. In the intervening decade, however, there have been advancements on this front. The first large-scale deployment of an airborne single photon lidar system occurred in 2016, using green light [40]. Commercial development of such instruments has since advanced [41, 42] and recent studies have demonstrated the feasibility of single photon NIR [43] and mid-wave infrared (MWIR) [44] lidar systems. While these systems are not at the commercial off-the-shelf (COTS) level yet, they are within reach of a dedicated development effort, similar to the state of single photon lidar systems when development of ATLAS began.

The other primary changes are to the laser pulse repetition frequency and the pulse energy, increasing the former to 40kHz and the latter to 0.4 - 2.4 mJ. Both of these increases are well within the reach of currently available technology. There is a green single photon COTS airborne lidar system available from Leica Geosystems that uses a pulse repetition frequency of 60kHz [45], while the previously referenced experimental single photon NIR system used a repetition frequency of 100kHz [43]. Many traditional COTS lidar systems have repetition frequencies of 150kHz to 2MHz [46]. All of these together suggest that 40kHz is readily achievable. Regarding increasing the pulse energy, commercial lidar providers do not typically publish the pulse energy of their products, but basic estimates based on the published pulse frequency and total power consumption of the products suggest that ATLAS is in line with standard COTS systems with regards to pulse energy. A custom, high-end sensor for space applications can be hoped to exceed this.

We can combine these proposed design parameters to scale from ATLAS to LEAVES. Equation 2 does this for spatial density of received signal photons and Equation 3 does this for power consumption, with the results seen in Table 2:

$$\rho_L = \frac{\rho_A f p}{t e} \quad (2)$$

where ρ_L and ρ_A are the spatial density of received signal photons for LEAVES and ATLAS, respectively; f is the proposed factor of increase in pulse frequency (4); p is the proposed factor of increase in pulse power (2); t is the ratio of atmospheric transmittance of 532nm to that of 1050nm light (0.9); and e is the ratio of energy per photon of 532nm and 1050nm light (0.507).

$$P_L = P_A f p \quad (3)$$

where P_L and P_A are the power consumption of the LEAVES lidar instrument and of ATLAS, respectively. While the power increase is significant, it is not out of line with other Earth Observation (EO) satellites. While ICESat-2 has an overall power consumption of about 1.2kW, Aqua is around 4.9kW [47] and Landsat-8 is around 4.3kW [48]. This suggests that a 1440kW instrument is not all together infeasible. Mass of imaging systems generally scales with power consumption [27], so the estimated LEAVES instrument mass (not the full satellite mass) is 1400 kg. Once again, ICESat-2 is relatively light compared to Aqua and Landsat-8, so this increase should be manageable.

Table 2: LEAVES and ICESat-2 lidar specifications [29, 49]

	ICESat-2 ATLAS	LEAVES
Footprint size	13m	13m
Laser wavelength	532nm	1050nm
Pulse repetition frequency	10kHz	40kHz
Laser divergence	20 μ rad	20 μ rad
Pulse Energy	0.2-1.2 mJ	0.4 - 2.4 mJ
Power Consumption	300W	1440W
Instrument Mass	298kg	1400kg
Point Density	\sim 0.01-0.1 pts/m ²	\sim 0.1 - 1 pts/m ²

It should be noted that the above estimates assume no technological advances beyond those specifically stated, leaving room for further improvement. For instance, if a single photon lidar system is developed for 1550nm instead of 1050nm, further gains could be had in either signal photon density or power consumption, without sacrificing transmissivity of the atmosphere.

2.3 Size, Weight, Power, and Cost (SWaP-C)

As stated earlier, the HyperLEAVES concept calls for a sunsynchronous, circular or near circular orbit, at an altitude of 480km. This is similar to ICESat-2, though ICESat-2 is not in a sunsynchronous orbit precisely. This orbit is able to accommodate the objectives of both HyperSat, whose passive imagers are best suited to the irradiance consistency of a sunsynchronous orbit, and LEAVES, whose active sensor does not require a consistent solar overpass time but does require a relatively low altitude, while also enabling a joint mission. The ideal US launch site is Vandenberg Space Force Base due to its relatively northern latitude (34°43'N) and its ability to accommodate northerly/westerly launches. The former is preferable as, unlike with most orbital insertions, sunsynchronous orbits are a form of polar orbit that require the launch vehicle to counter most of Earth's rotational velocity rather than be assisted by it. A launch site farther from the equator reduces this extra effort. Similarly, launching directly into a polar orbit requires the rocket to launch either directly north or even somewhat westerly, which is more difficult to safely do from the the Florida and Texas launchsites.

In terms of mass of the satellites, it is expected that HyperSat will likely weigh approximately 1kg, as both of its instruments are approximately 100kg and the Earth Observing-1 (EO-1)-1, which bore the Hyperion predecessor, had a mass of 573kg. This is relatively light compared to other civil scientific EO satellites and may be surprising, considering that the high data generation rate of a hyperspectral sensor may necessitate more on-satellite storage and/or heavier communications components. Such components are more than offset by the limited cooling requirements of the HyperSat instruments when compared to the more sensitive, high precision infrared sensors found on many major scientific satellites. LEAVES, meanwhile, owing to the higher power requirements and the resultant likely higher complexity of the lidar instrument overall (including stricter thermal constraints owing to its use of a NIR laser rather than a green one), will likely have a higher mass, in the 2-3.5kg range. This is still within the feasible range as many active sensing satellites weigh more than 3-4 kg (e.g. Aqua [47] and Terra [50]).

These combinations of masses and orbital trajectory are well within the abilities of many medium-lift launch vehicles, including SpaceX's Falcon 9, Northrop Grumman's Antares, and Rocket Lab's upcoming Neutron, particularly if the the two satellites are launched separately from one another, as they almost certainly will be.

Power consumption can similarly be extrapolated from the instrument consumptions to around 1kW and 3-4kW for HyperSat and LEAVES respectively. Both of these are within common levels for satellites of their class and thus should be able to be accommodated with a reasonably sized solar array.

The cost of HyperSat is likely to be relatively cheap, owing to it not relying on novel or even particularly cutting-edge technology. The experimental EO-1 cost only around 200M\$ at the

time (around 290M\$ in 2021 dollars) and HsypIRI was only estimated to cost around 500M\$ [51]. LEAVES will likely be more expensive, in the 1-2B\$ that many large civil scientific satellites cost, including ICESat-2. It is possible that this price tag will be somewhat reduced by falling launch costs, but the significant effort required to develop and test a single photon NIR lidar system of sufficient power and precision will likely outweigh any such savings. These estimates are summarized below in Table 3.

Table 3: HyperLEAVES power, mass, cost, and launch estimations.

	HyperSat	LEAVES
Power	1kW	3-4kW
Mass	1-2kg	2-3.5kg
Cost	500M\$	1-2B\$
Launch Site	Vandenberg Space Force Base	
Launch Vehicle	Medium-left launch vehicle (e.g. SpaceX Falcon 9, Rocket Lab Neutron, Northrop Grumman Antares)	

3 Data Products and Applications

The data generated by the HyperLEAVES mission would have numerous uses, both scientific and applied. The HyperSat sensors would enable vegetation species identification at a global scale through spectral unmixing, enabling the determination of the mixture of species in particular area. Such identification reduces error in vegetation health measurements (by taking into account differing phenological trajectories and spectral responses of different species), allows for tracking of invasive species of vegetation among native species, and assists forest management decisions by helping to ascertain the exact contents of forest stocks without expensive and cumbersome in-situ surveys.

While achieving detailed, dense, three dimensional points of our planets forests from space may still be beyond our reach, LEAVES represents a significant step towards this goal, significantly increasing point density without sacrificing resolution. This will enable more detailed vertical structure measurements of even dense vegetation, allowing for improved estimates of regional and global carbon storage and biomass. Furthermore, when the two satellites of HyperLEAVES are used in conjunction, there is the promising possibility of using HyperSat’s imagery to upscale the LEAVES data, thereby filling in the gaps between the lidar tracks with estimates of tree height [23].

Beyond these forestry-specific objectives, the HyperLEAVES design also addresses, in full or in part, several other objectives of the earth science community, as seen in Table 4. Both hyperspectral imagery and more detailed space-based lidar systems are in high demand at the moment. As multispectral imagery in both visible and IR ranges become increasingly available at <10 m resolutions and sub daily revisits, new scientific and application gains are to be found in other sensor types.

Table 4: HyperLEAVES power, mass, cost, and launch estimations.

Observing System Priorities	HyperSat	LEAVES
Aerosols Vertical Profiles		Partial (NIR laser may not be sensitive enough to aerosals)
Aquatic-Coastal Biogeochemistry	Partial (does not meet specified revisit rate)	
Greenhouse Gases	Addresses	Addresses
Ice Elevation		Addresses
Ocean Ecosystem Structure		Partial (is not multifrequency, NIR rather than green limits bathymetric applications)
Snow Depth and Snow Water Equivalent		Addresses
Surface Biology and Geology	Addresses	
Terrestrial Ecosystem Structure		Addresses

It should be noted that both of these satellites are likely to have high rates of data production, particularly compared to their current generation counterparts. The data generation rate of each of HyperSat’s sensors can be estimated using Equation 4:

$$B = \frac{SnLv}{r^2} \quad (4)$$

where B is the data production rate, S is the swath width of the image, n is the number of bands, L is the luminosity levels per bands in bits, v is the ground track velocity of the satellite, and r is the spatial resolution of the image. Based on this, HyperSat is likely to generate approximately 50MB/s across its two sensors, compared to Aqua’s approximately 1MB across its sensors [47]. This could be compressed significantly prior to transmission (which would require yet more computing power available onboard the spacecraft) but is still likely to be high. Fortunately, by the time that HyperLEAVES would launch, it is likely that a variety of commercial space-based data transmission systems will be in place that will be able to accomodate this load (as evidenced by NASA’s stated intention to switch over to such systems by 2030 [52]).

References

- [1] R. Pomeroy, “One trillion trees - uniting the world to save forests and climate,” <https://www.weforum.org/agenda/2020/01/one-trillion-trees-world-economic-forum-launches-plan-to-help-nature-and-the-climate/>, Jan. 2020.
- [2] D. C. Donato, J. B. Kauffman, D. Murdiyarto, S. Kurnianto, M. Stidham, and M. Kanninen, “Mangroves among the most carbon-rich forests in the tropics,” *Nature Geoscience*, vol. 4, no. 5, pp. 293–297, May 2011.
- [3] L. Goldberg, D. Lagomasino, N. Thomas, and T. Fatoyinbo, “Global declines in human-driven mangrove loss,” *Global Change Biology*, vol. 26, no. 10, pp. 5844–5855, Jul. 2020.
- [4] M. Finer, S. Novoa, M. J. Weisse, R. Petersen, J. Mascaro, T. Souto, F. Stearns, and R. G. Martinez, “Combating deforestation: From satellite to intervention,” *Science*, vol. 6395, no. 360, pp. 1303–1305, 2018.
- [5] T. Fatoyinbo, E. A. Feliciano, D. Lagomasino, S. K. Lee, and C. Trettin, “Estimating mangrove above-ground biomass from airborne LiDAR data: A case study from the Zambezi River delta,” *Environmental Research Letters*, vol. 13, no. 2, p. 025012, Feb. 2018.
- [6] S.-K. Lee and T. E. Fatoyinbo, “TanDEM-X Pol-InSAR Inversion for Mangrove Canopy Height Estimation,” *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 8, no. 7, pp. 3608–3618, Jul. 2015.

- [7] T. E. Fatoyinbo and M. Simard, “Height and biomass of mangroves in Africa from ICESat/GLAS and SRTM,” *International Journal of Remote Sensing*, vol. 34, no. 2, pp. 668–681, Jan. 2013.
- [8] D. Lagomasino, T. Fatoyinbo, S. Lee, E. Feliciano, C. Trettin, and M. Simard, “A Comparison of Mangrove Canopy Height Using Multiple Independent Measurements from Land, Air, and Space,” *Remote Sensing*, vol. 8, no. 4, p. 327, Apr. 2016.
- [9] M. Simard, L. Fatoyinbo, C. Smetanka, V. H. Rivera-Monroy, E. Castañeda-Moya, N. Thomas, and T. Van der Stocken, “Mangrove canopy height globally related to precipitation, temperature and cyclone frequency,” *Nature Geoscience*, vol. 12, no. 1, pp. 40–45, Jan. 2019.
- [10] D. Lagomasino, T. Fatoyinbo, S. Lee, E. Feliciano, C. Trettin, A. Shapiro, and M. M. Mangora, “Measuring mangrove carbon loss and gain in deltas,” *Environmental Research Letters*, vol. 14, no. 2, p. 025002, Jan. 2019.
- [11] H. Li, M. Jia, R. Zhang, Y. Ren, and X. Wen, “Incorporating the Plant Phenological Trajectory into Mangrove Species Mapping with Dense Time Series Sentinel-2 Imagery and the Google Earth Engine Platform,” *Remote Sensing*, vol. 11, no. 21, p. 2479, Jan. 2019.
- [12] L. Valderrama-Landeros, F. Flores-de-Santiago, J. M. Kovacs, and F. Flores-Verdugo, “An assessment of commonly employed satellite-based remote sensors for mapping mangrove species in Mexico using an NDVI-based classification scheme,” *Environmental Monitoring and Assessment*, vol. 190, no. 1, p. 23, Dec. 2017.
- [13] J. Cao, W. Leng, K. Liu, L. Liu, Z. He, and Y. Zhu, “Object-Based Mangrove Species Classification Using Unmanned Aerial Vehicle Hyperspectral Images and Digital Surface Models,” *Remote Sensing*, vol. 10, no. 1, p. 89, Jan. 2018.
- [14] T. Wang, H. Zhang, H. Lin, and C. Fang, “Textural–Spectral Feature-Based Species Classification of Mangroves in Mai Po Nature Reserve from Worldview-3 Imagery,” *Remote Sensing*, vol. 8, no. 1, p. 24, Jan. 2016.
- [15] P. C. Pandey, A. Anand, and P. K. Srivastava, “Spatial distribution of mangrove forest species and biomass assessment using field inventory and earth observation hyperspectral data,” *Biodiversity and Conservation*, vol. 28, no. 8, pp. 2143–2162, Jul. 2019.
- [16] M. Kamal and S. Phinn, “Hyperspectral Data for Mangrove Species Mapping: A Comparison of Pixel-Based and Object-Based Approach,” *Remote Sensing*, vol. 3, no. 10, pp. 2222–2242, Oct. 2011.
- [17] K. A. Prasad, L. Gnanappazham, V. Selvam, R. Ramasubramanian, and C. S. Kar, “Developing a spectral library of mangrove species of Indian east coast using field spectroscopy,” *Geocarto International*, vol. 30, no. 5, pp. 580–599, May 2015.
- [18] Committee on the Decadal Survey for Earth Science and Applications from Space, *Thriving on Our Changing Planet: A Decadal Strategy for Earth Observation from Space*. Washington D.C.: National Academies Press, Jan. 2018.
- [19] A. Neuenschwander and K. Pitts, “Ice, Cloud, and Land Elevation Satellite 2 Algorithm Theoretical Basis Document for Land - Vegetation Along-Track Products,” Goddard Space Flight Center, Greenbelt, MD, Tech. Rep., Sep. 2019.
- [20] —, “The ATL08 land and vegetation product for the ICESat-2 Mission,” *Remote Sensing of Environment*, vol. 221, pp. 247–259, Feb. 2019.
- [21] A. L. Neuenschwander and L. A. Magruder, “Canopy and Terrain Height Retrievals with ICESat-2: A First Look,” *Remote Sensing*, vol. 11, no. 14, p. 1721, Jan. 2019.
- [22] X. Tian and J. Shan, “Comprehensive Evaluation of the ICESat-2 ATL08 Terrain Product,” *IEEE Transactions on Geoscience and Remote Sensing*, pp. 1–15, 2021.
- [23] W. Li, Z. Niu, R. Shang, Y. Qin, L. Wang, and H. Chen, “High-resolution mapping of forest canopy height using machine learning by coupling ICESat-2 LiDAR with Sentinel-1, Sentinel-2 and Landsat-8 data,” *International Journal of Applied Earth Observation and Geoinformation*, vol. 92, p. 102163, Oct. 2020.
- [24] HypSIRI Mission Concept Team, “HypSIRI Final Report,” Jet Propulsion Laboratory, Pasadena, CA, Tech. Rep., Sep. 2018.
- [25] X. Xiong, B. N. Wenny, and W. D. Barnes, “Overview of NASA Earth Observing Systems Terra and Aqua moderate resolution imaging spectroradiometer instrument calibration algorithms and on-orbit performance,” *Journal of Applied Remote Sensing*, vol. 3, no. 1, p. 032501, Jun. 2009.

- [26] N. R. Council, *Earth Science and Applications from Space: National Imperatives for the Next Decade and Beyond*, Jan. 2007.
- [27] J. Wertz, D. Everett, and J. Puschell, *Space Mission Engineering: The New SMAD*. Microcosm Press, 2011.
- [28] J. M. Picone, A. E. Hedin, D. P. Drob, and A. C. Aikin, “NRLMSISE-00 empirical model of the atmosphere: Statistical comparisons and scientific issues: TECHNIQUES,” *Journal of Geophysical Research: Space Physics*, vol. 107, no. A12, pp. SIA 15–1–SIA 15–16, Dec. 2002.
- [29] T. A. Neumann, A. J. Martino, T. Markus, S. Bae, M. R. Bock, A. C. Brenner, K. M. Brunt, J. Cavanaugh, S. T. Fernandes, D. W. Hancock, K. Harbeck, J. Lee, N. T. Kurtz, P. J. Luers, S. B. Luthcke, L. Magruder, T. A. Pennington, L. Ramos-Izquierdo, T. Rebold, J. Skoog, and T. C. Thomas, “The Ice, Cloud, and Land Elevation Satellite – 2 mission: A global geolocated photon product derived from the Advanced Topographic Laser Altimeter System,” *Remote Sensing of Environment*, vol. 233, p. 111325, Nov. 2019.
- [30] X. Liu, Z. Zhang, J. Peterson, and S. Chandra, “The effect of LiDAR data density on DEM accuracy,” in *Proceedings of the International Congress on Modelling and Simulation (MODSIM07)*, L. Oxley and D. Kulasiri, Eds. Canberra, Australia: Modelling and Simulation Society of Australia and New Zealand Inc., Dec. 2007, pp. 1363–1369.
- [31] S. Luo, J. M. Chen, C. Wang, X. Xi, H. Zeng, D. Peng, and D. Li, “Effects of LiDAR point density, sampling size and height threshold on estimation accuracy of crop biophysical parameters,” *Optics Express*, vol. 24, no. 11, pp. 11 578–11 593, May 2016.
- [32] J. Strunk, H. Temesgen, H.-E. Andersen, J. P. Flewelling, and L. Madsen, “Effects of lidar pulse density and sample size on a model-assisted approach to estimate forest inventory variables,” *Canadian Journal of Remote Sensing*, vol. 38, no. 5, pp. 644–654, Nov. 2012.
- [33] K. K. Singh, G. Chen, J. B. McCarter, and R. K. Meentemeyer, “Effects of LiDAR point density and landscape context on estimates of urban forest biomass,” *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 101, pp. 310–322, Mar. 2015.
- [34] S. E. Reutebuch, H.-E. Andersen, and R. J. McGaughey, “Light Detection and Ranging (LIDAR): An Emerging Tool for Multiple Resource Inventory,” *Journal of Forestry*, vol. 103, no. 6, pp. 286–292, Sep. 2005.
- [35] H. Hamraz, M. A. Contreras, and J. Zhang, “Forest understory trees can be segmented accurately within sufficiently dense airborne laser scanning point clouds,” *Scientific Reports*, vol. 7, no. 1, p. 6770, Jul. 2017.
- [36] NASA Technology Transfer Program, “Single-Photon Lidar Maps Ground Features Quickly, Efficiently,” https://spinoff.nasa.gov/Spinoff2016/ps_6.html, 2016.
- [37] Guth, Peter, “Atmospheric Transmittance,” https://www.usna.edu/Users/oceano/pguth/md_help/remote_sensing_course/atmos_transmit.htm, Sep. 2020.
- [38] Connell, Bernie, “CIRA/WMO VLab New Satellite Information,” <https://rammb.cira.colostate.edu/training/rmtc/newsat.asp>.
- [39] W. Abdalati, H. J. Zwally, R. Bindschadler, B. Csatho, S. L. Farrell, H. A. Fricker, D. Harding, R. Kwok, M. Lefsky, T. Markus, A. Marshak, T. Neumann, S. Palm, B. Schutz, B. Smith, J. Spinhirne, and C. Webb, “The ICESat-2 Laser Altimetry Mission,” *Proceedings of the IEEE*, vol. 98, no. 5, pp. 735–751, May 2010.
- [40] A. Swatantran, H. Tang, T. Barrett, P. DeCola, and R. Dubayah, “Rapid, High-Resolution Forest Structure and Terrain Mapping over Large Areas using Single Photon Lidar,” *Scientific Reports*, vol. 6, no. 1, p. 28277, Jun. 2016.
- [41] B. Jutzi, “Less Photons for More LiDAR? A Review from Multi-Photon Detection to Single Photon Detection,” *Proceedings of the 56th Photogrammetric Week (PhoWo)*, University of Stuttgart, Stuttgart, Germany, pp. 11–15, 2017.
- [42] M. Sirota and R. Roth, “The Evolution of Lidar,” <https://www.gim-international.com/content/article/the-evolution-of-lidar>, Feb. 2017.

- [43] Z.-P. Li, Z.-P. Li, Z.-P. Li, X. Huang, X. Huang, X. Huang, Y. Cao, Y. Cao, Y. Cao, B. Wang, B. Wang, B. Wang, Y.-H. Li, Y.-H. Li, Y.-H. Li, W. Jin, W. Jin, W. Jin, C. Yu, C. Yu, C. Yu, J. Zhang, J. Zhang, J. Zhang, Q. Zhang, Q. Zhang, Q. Zhang, C.-Z. Peng, C.-Z. Peng, C.-Z. Peng, F. Xu, F. Xu, F. Xu, J.-W. Pan, J.-W. Pan, and J.-W. Pan, “Single-photon computational 3D imaging at 45 km,” *Photonics Research*, vol. 8, no. 9, pp. 1532–1540, Sep. 2020.
- [44] M. Widarsson, M. Henriksson, P. Mutter, C. Canalias, V. Pasiskevicius, and F. Laurell, “High resolution and sensitivity up-conversion mid-infrared photon-counting LIDAR,” *Applied Optics*, vol. 59, no. 8, pp. 2365–2369, Mar. 2020.
- [45] “Leica SPL100 Single Photon LiDAR Sensor,” <https://leica-geosystems.com/en-US/products/airborne-systems/topographic-lidar-sensors/leica-spl100>, 2021.
- [46] “RIEGL VQ-1560 II-S,” <http://www.riegl.com/nc/products/airborne-scanning/produktdetail/product/scanner/70/>, 2020.
- [47] Kramer, Herbert, “Aqua,” <https://earth.esa.int/web/eoportal/satellite-missions/a/aqua>, 2002.
- [48] —, “Landsat-8 / LDCM,” <https://earth.esa.int/web/eoportal/satellite-missions/1/landsat-8-ldcm>, 2012.
- [49] World Meteorological Organization, “Details for Instrument ATLAS,” <http://www.wmo-sat.info/oscar/instruments/view/atlas>, Mar. 2017.
- [50] Kramer, Herbert, “Terra,” <https://directory.eoportal.org/web/eoportal/satellite-missions/t/terra>, 2002.
- [51] D. Mandl, G. Crum, V. Ly, M. Handy, K. F. Huemrich, L. Ong, B. Holt, and R. Maharaja, “Hyperspectral Cubesat Constellation for Natural Hazard Response (Follow-on),” in *30th Annual AIAA/USU Conference on Small Satellites*, 2016, p. 4.
- [52] D. Baird, “NASA to Commercialize Near-Earth Communications Services,” <https://www.nasa.gov/feature/Goddard/2020/nasa-to-commercialize-near-earth-communications-services>, Oct. 2020.