proceedings

MDPI

Proceeding Paper

Monitoring, Inspection and Early Warning System in Electrical Distribution Networks Using Satellite Images †

Erick Armando Sedeño Bueno [1,*], José Luis Capote Fernández [1], René González Rodríguez [2] and Nelson Ivan Escalona Macides [2]

[1] Volttus Inc., Camagüey 70100, Cuba; capote@volttus.com
[2] Volttus Inc., Hamilton, ON L8P 3J2, Canada; rene@volttus.com (R.G.R.); nelson@volttus.com (N.I.E.M.)
* Correspondence: erick.bueno@volttus.com
† Presented at the 31st International Conference on Geoinformatics, Toronto, ON, Canada, 14–16 August 2024.

Abstract: Timely identification of problems in electrical distribution networks is crucial to preventing major failures, reducing costs, and ensuring a reliable power supply. This paper presents a monitoring, inspection, and early warning system designed specifically for electrical networks, utilizing satellite imagery to complement traditional inspections. The system uses spectral indices derived from satellite images to monitor environmental factors such as humidity, vegetation, snow cover, and burned areas, offering a comprehensive view of the grid's surroundings. Collected daily, this information detects changes that may pose risks to power lines and infrastructure. The system also allows users to include custom indices, ensuring flexibility in various environmental and network contexts. An integrated AI model estimates vegetation height from Sentinel-2 images, identifying potential risk areas where vegetation could threaten power lines. One key advantage of the system is the reduced reliance on costly, frequent manual inspections, lowering operational expenses compared to other methods like aerial photography or LiDAR scanners. Additionally, it provides early alerts to grid operators when potential issues are detected, enabling timely intervention and proactive maintenance. This improves network efficiency and reliability by enhancing the response to critical situations and facilitating preventive risk management.

Keywords: inspection of electrical networks; remote sensing; early warning; deep learning

check for updates

Citation: Bueno, E.A.S.; Fernández, J.L.C.; Rodríguez, R.G.; Macides, N.I.E. Monitoring, Inspection and Early Warning System in Electrical Distribution Networks Using Satellite Images. *Proceedings* **2024**, *110*, 27. https://doi.org/10.3390/proceedings2024110027

Academic Editors: Dongmei Chen, Yuhong He and Songnian Li

Published: 11 December 2024

Copyright: © 2024 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

1. Introduction

The total mileage of transmission lines has gradually increased with the continuous expansion of power grid construction coverage. These lines have the characteristics of being of large scale, long distance, and wide distribution, and are often distributed in remote areas with a relatively harsh operating environment. Normal vegetation growth can interfere with the normal operation of transmission lines, causing frequent failures [1,2].

With timely information, businesses can take concrete, opportune actions that can help increase safety, availability, and cost savings. Efficient reporting means the difference between uptime and downtime, customer cost savings, margins, and even life-and-death lost profits.

Vegetation encroachment near high-voltage power lines poses a risk of power outages. Trees falling or growing on transmission lines can cause power outages or start a fire in surrounding vegetation [3]. Ineffective vegetation management was identified as a major cause of the 2003 Northeast blackout, which affected around 55 million people in the US and Canada. In turn, it has been a causal factor in 290 automatic blackouts in North America in the last few years [4]. There are multiple strategies to manage the invasion of vegetation in high-voltage electrical line corridors, like visual field inspection, aerial video surveillance, aerial multispectral imaging, and LiDAR scanning. All these methods are not reliable due to their high cost, non-accuracy, and higher time complexity [5]. Removing all vegetation

in the vicinity of transmission lines is only viable in the short term. Information on surrounding vegetation is primarily collected using aerial data acquisition tools, although there are a number of studies that investigate the possibility of using satellite images [6–8], which are the source of the images used in this work.

The first version of NERC's Transmission Vegetation Management Program Standard, FAC-003-1, became mandatory and enforceable in 2007. The current version of FAC-003-4 requires applicability transmission and generation owners to have a vegetation management program to be able to manage it [4].

Unmanned aerial vehicles (UAVs) with light detection and ranging (LiDAR) techniques or digital cameras have been widely applied to improve the efficiency and accuracy of vegetation encroachment ferreting out [9]. However, inspection using the UAV with LiDAR is an expensive process, due to both logistics and its components, and must deal with a large number of calculations for data processing [10].

In this work, two monitoring strategies for electrical networks are mixed; the first is the use of spectral indices from satellite images to identify changes in nearby areas, and the other is the use of an artificial intelligence model to estimate the height of the vegetation and thus be able to include this important variable.

2. Methodology

The system for inspecting electric distribution networks enables the digitalization and georeferencing of inspection elements, ensuring comprehensive data collection for all network assets, including associated photographs and videos. This facilitates the generation of detailed reports on these assets. A maintenance module allows for the scheduling of maintenance activities and the management of associated human and material resources. Additionally, information from remote sensors enhances maintenance scheduling by providing critical insights.

The system is integrated with a geospatial ERP, which ensures that all elements of the electrical infrastructure can be managed holistically. Within the ERP, tasks are scheduled to collect indices related to the areas surrounding the electrical network. These indices may include expressions derived from the bands of Sentinel-2 multispectral images, commonly referred to as multispectral indices in the literature, or the height of vegetation, which is obtained using a modified deep learning model. Although originally developed for other purposes, this model has been adapted to support operational decision-making.

2.1. Monitoring Infrastructure on the Earth's Surface Using Remote Sensors

Monitoring infrastructure on the Earth's surface using remote sensors is a key application of Earth observation technology [11]. By using satellite images and other data collected by remote sensors, infrastructure such as roads, bridges, buildings, transmission lines, and pipelines can be accurately monitored and assessed. Satellite images and remote sensing data cover large areas, allowing a panoramic view of infrastructure and detecting potential problems over a large territory [1].

The European Space Agency under the Copernicus program for Global Environment and Security Monitoring provides advanced satellites and space sensors to collect data about the Earth from space [12]. These satellites offer observations on the atmosphere, oceans, Earth's surface, biodiversity, and other elements of the earth [13]. This agency has created a portal to access the products of the different missions it develops, including the Sentinel-2 satellite.

This satellite carries a high-resolution multispectral camera that captures high-resolution images of the Earth's surface in 13 different spectral bands, allowing detailed information on vegetation, water bodies, land cover, and other parameters related to the environment. Sentinel-2's multispectral camera is especially useful for monitoring land cover changes, conducting agricultural analysis, assessing water quality, and supporting decision-making in areas such as natural disaster management and urban planning [14,15].

More detailed reviews and extensive databases on the most useful spectral regions for agricultural monitoring are suggested to provide more comprehensive coverage of spectral indices in general [14,16]. These databases, initially developed for agriculture, today cover a wide range of applications ranging from geology, forest management, and fires to water management [17].

Some of the widely used indices that can be calculated from Sentinel-2 bands include:

- NDVI (Normalized Difference Vegetation Index): used to assess and monitor vegetation health.
- NDWI (Normalized Difference Water Index): used to map and monitor water bodies.
- NDSI (Normalized Difference Snow Index): used to detect and map snow and ice.
- SAVI (Soil Adjusted Vegetation Index): used to correct overestimation of the NDVI in areas with bare soil.
- BAIS (Burnt Area Index): used to detect areas damaged by fire.

Google Earth Engine (GEE) provides free access to Sentinel-2 data, allowing users to perform large-scale geospatial analysis without downloading the data. The Google Earth Engine (GEE) API is a powerful platform designed to perform large-scale analysis of satellite imagery and other geospatial data. It allows users to access a vast collection of data, perform complex calculations, and export results without the need for local processing infrastructure. In our project, the API is the way to perform the analysis without downloading the images for processing.

2.2. Vegetation Height with Artificial Intelligence

Canopy height model (CHM) estimation has a long history, but advances in computer vision and satellite sensing technologies have opened new opportunities in this area. The height can be used effectively in different applications and extends the two-dimensional representation of the surface in the visible spectrum. LiDAR instruments have expanded the possibilities of this field and have also had a positive impact on the development of other methods, considerably improving their results [9].

The Global Ecosystem Dynamics Investigation (GEDI) is a joint mission between NASA and the University of Maryland, with the instrument installed aboard the International Space Station. Data acquired using the instrument's three lasers are used to construct detailed three-dimensional (3D) maps of forest canopy height and the distribution of branches and leaves. By accurately measuring forests in 3D, GEDI data play an important role in understanding how much biomass and carbon forests store and how much they lose when they are disturbed—vital information for understanding the Earth's carbon cycle and how it is changing. These data are being used to train artificial intelligence models to estimate the height of vegetation based on different satellites [18,19].

In this work, a deep learning model developed by Nico Lang et al. was used to obtain estimates of vegetation height from Sentinel-2 images. With their method, it was possible to produce a globally consistent and dense map of tree canopy heights for the entire Earth, with a ground sampling distance of 10 m. Other advantages of the model used are that, compared to other models, the overall underestimation bias for the high canopy is substantially reduced. Furthermore, the model used does not require local calibration and can therefore be implemented anywhere on Earth, including regions outside the GEDI coverage. The model also provides spatially explicit estimates of the predictive uncertainties of the retrieved canopy heights [20]. An important aspect of the work developed by Lang et al. is that both the source code used and the trained model are public on the Internet for use. As a result of the work mentioned above, annual canopy height maps are obtained for environmental purposes. These maps obtained are not useful for making operational decisions due to the dynamics of the vegetation itself. On the other hand, the process of classifying complete images, although very useful for the purposes of the project, is not feasible to carry out operationally.

3. Results

3.1. Monitoring of Spectral Indices in the Environment of Power Lines

The spectral indices are managed within the system itself, from the selection of the satellite, the mathematical expression for its calculation, and its representation. It is possible to create views with custom maps with the desired indices, offering a better perspective when making comparisons between network components (see Figure 1).

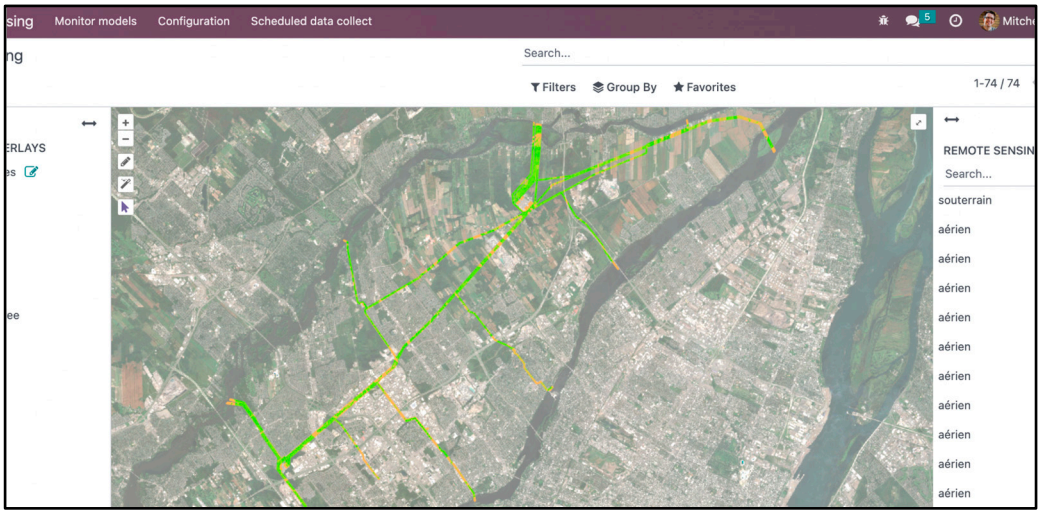


Figure 1. Layer with the vegetation index in the area of influence of the electrical grid.

As a complement to the information associated with the inspection of electrical networks captured by technicians, the system collects statistics on the selected indices. In this way, pronounced changes in the index are sought that show alterations in the line environment and generate alerts to carry out more detailed inspections (see Figure 2).

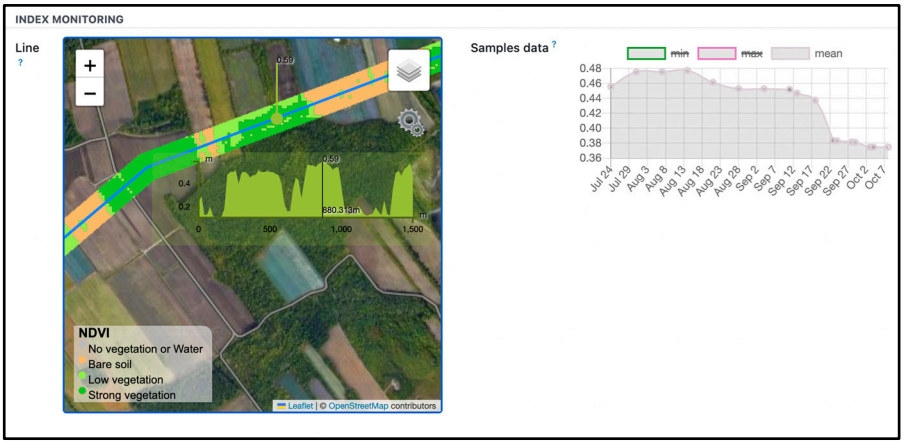


Figure 2. Visualization of the behavior of the indices in the detailed inspection of a line.

3.2. Monitoring of Spectral Indices in the Environment of Power Lines

In a recent study by Lang et al., a global map of vegetation canopy height at a 10 m resolution was obtained for the year 2020, providing essential information on the role of vegetation height in global carbon cycling and ecosystem biodiversity. The map was generated using a probabilistic deep learning model that combines sparse height data from the Global Ecosystem Dynamics Investigation (GEDI) LiDAR mission with dense optical satellite imagery from Sentinel-2. This model accurately recovers vegetation canopy height and quantifies uncertainty in these estimates, particularly improving the assessment of tall vegetation canopies with high carbon stocks [18,20].

In the aforementioned work by Lang et al., complete Sentinel-2 images are classified, being very effective in cloud-free areas. The method uses a combination of bands from the Sentinel-2 satellite, adding information related to the geographic area to estimate the height of the vegetation, and the output is an estimate of the variance, in addition to the height. Figure 3 shows the model training process for the proposed method.

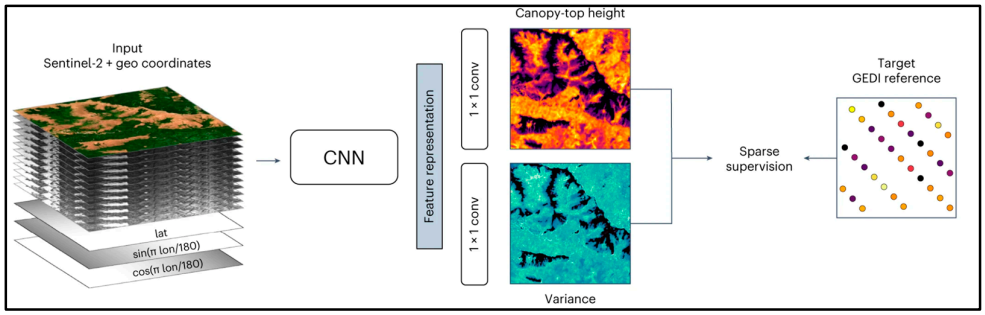


Figure 3. Illustration of the model training process with sparse GEDI LiDAR supervision. The CNN takes the Sentinel-2 image (S2) and the encoded geographic coordinates (lat, lon) as input to estimate the height of the dense canopy top and its predictive uncertainty (variance) [20].

Instead of processing full images, in this work the images are accessed through the Google Earth Engine (GEE) platform, which implies a variation of the original proposed model. In this case, exact samples are not obtained from a downloaded image, but rather, using the methods provided by the GEE API, the image is sampled in an area with dimensions that guarantee a resolution close to the needs of the deep learning classification model.

Cloud cover is a problem that can affect multispectral images. In this work, a mosaic of images is used using a mask over the clouds and sorted from the most recent. The polygon with the area of interest and the date range are used as analysis parameters in search of a cloud-free mosaic. This is an important variation of the original method proposed by Lang et al. that is validated in this work.

A service that allows the vegetation height raster to be obtained for a given polygon and date is implemented as a system module. Figure 4 shows an image obtained and the legend associated with the values that are in the range between 0 and 19.188377 m.

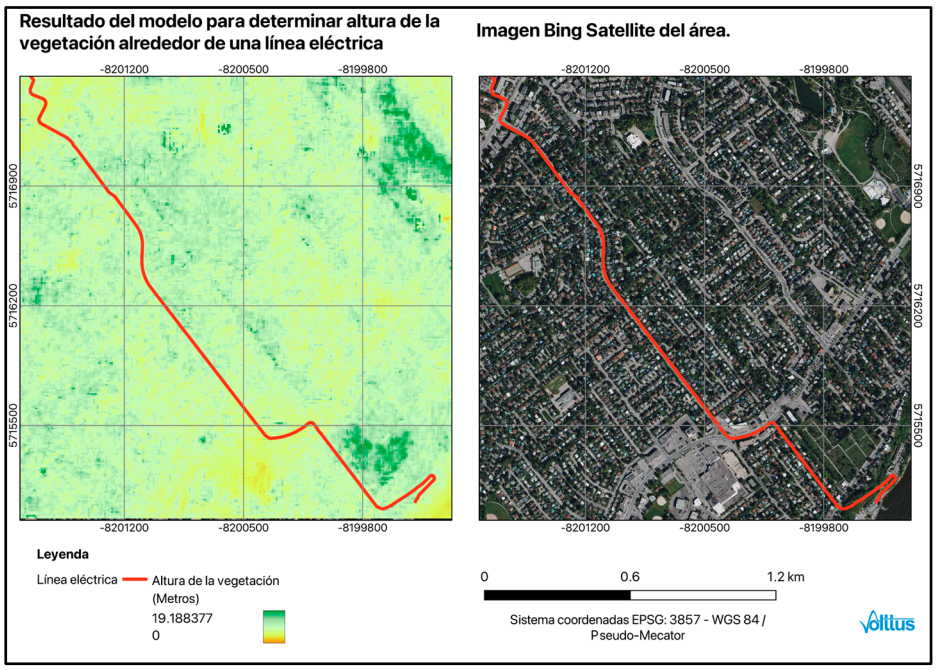


Figure 4. Vegetation height raster under a high-voltage line.

3.3. Validation of the Method Used

The area of interest for the experiment was selected taking into account the existence of power lines and recent GEDI data available, in this case for the Montreal area in Canada. To validate the method used, the GEDI data for the area were downloaded and a canopy height raster was generated using Sentinel-2 images from the approximate dates of the GEDI data (see Figure 5).

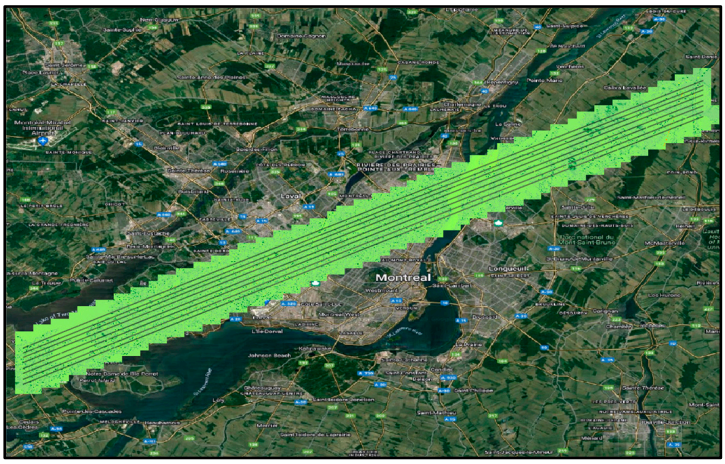


Figure 5. GEDI data of the area of interest next to the height estimation raster obtained using the model defined by Lang 2023 [20].

Using the actual height values obtained by the GEDI LiDAR and the values estimated by the trained model, the error values were calculated and compared with those obtained by Lang et al.

The same statistics used in the reference literature were calculated: the root mean square error (RMSE) (Equation (1)) of the predicted heights, their arithmetic mean error (MAE) (Equation (2)), and their mean error (ME, Equation (3)). The latter quantifies the systematic height bias, where a negative ME indicates underestimation, that is, predictions that are systematically lower than the reference values.

$$RMSE = \sqrt{\frac{1}{N}\sum_{1}^{N}(\hat{y}_i - y_i)^2} \quad (1)$$

$$IS = \frac{1}{N}\sum_{1}^{N}|\hat{y}_i - y_i| \quad (2)$$

$$ME = \frac{1}{N}\sum_{1}^{N}(\hat{y}_i - y_i) \quad (3)$$

N: number of sample points.
$\hat{y}_i$: vegetation height values obtained from the model.
y_i: vegetation height value obtained from GEDI.

Figure 6 shows the results obtained from the aforementioned statisticians in the preparation of the global canopy height map.

Table 1 shows a comparison between the results obtained by Lang et al. (2023) [20] and the values obtained when evaluating the results of our method, showing that lower error values are obtained and therefore the method is feasible to apply in the area of interest. By obtaining lower error values than those obtained in the original publication, it is assumed that the changes introduced in the method when composing the image as a mosaic of images in a range of dates, with a resampling to obtain the resolution closest to that necessary for the model, were successful.

Table 1. Comparison of results obtained with those of Lang et al. (2023) [20].

Metrics Analyzed by Lang et al. (2023) [20]	Values Obtained by Lang et al. (2023) [20]	Values Obtained in the Evaluation Carried Out
aRMSE	7.3	6.51
aMAE	5.5	4.71
aME	−1.8	−1.72

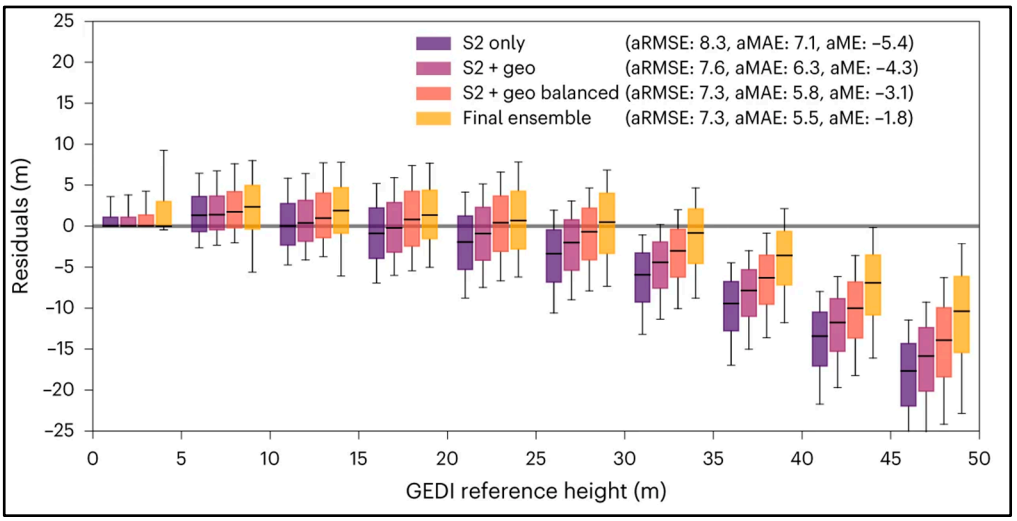


Figure 6. Residual analysis w.r.t. canopy height intervals and ablation study of the model components. Negative residuals indicate that the estimates are lower than the reference values [20].

4. Discussion

This work allowed the results to be shown for a monitoring, inspection, and early warning system for electrical distribution networks that complements the information collected by technical personnel through the use of satellite images.

It was possible to verify the system's capacity to collect daily spectral indices calculated from the bands of satellite images, which made it possible to maintain surveillance of the spatiotemporal behavior of phenomena that can cause failures in the electricity supply network.

The integration of the system with an artificial intelligence model allowed for the calculation of the height of the vegetation from the Sentinel-2 images, which helped identify risk areas based on the proximity of the vegetation to the power lines.

Taking into account the differences in the ways of acquiring samples for classification with artificial intelligence and their preprocessing, a validation of the results was carried out, showing the consistency of the proposed method.

This system can contribute to early warning by detecting in a timely manner failures that harm a reliable electricity supply, which favors cost reduction and guarantees the correct functioning of the electrical network.

Author Contributions: Conceptualization, E.A.S.B., J.L.C.F., R.G.R. and N.I.E.M.; methodology, E.A.S.B. and J.L.C.F.; software, E.A.S.B., J.L.C.F., R.G.R. and N.I.E.M.; validation: E.A.S.B.; formal analysis: R.G.R.; investigation: E.A.S.B. and J.L.C.F.; resources: N.I.E.M.; data curation: E.A.S.B.; writing—original draft preparation: E.A.S.B.; writing—review and editing: E.A.S.B.; visualization, J.L.C.F.; supervision, J.L.C.F.; project administration, R.G.R. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: Data are contained within the article.

Conflicts of Interest: All authors are employed by the company Volttus. All authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest. The [company Volttus in affiliation and funding] had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

References

1. Yang, Z.; Deng, Y.; Li, M.; Liu, Y.; Zhao, B.; Chen, Z.; Liu, S.; Kong, L.; Zhao, B.; Wang, J. Monitoring and Early Warning of Transmission Line External Breakage Based on Satellite-Ground Coordination. *J. Phys. Conf. Ser.* **2021**, *2078*, 012071. [CrossRef]
2. Faster, R. Towards real-time object detection with region proposal networks. *Adv. Neural Inf. Process Syst.* **2015**, *9199*, 2969239–2969250.
3. Bandara, S.; Rajeev, P.; Gad, E. Power Distribution System Faults and Wildfires: Mechanisms and Prevention. *Forests* **2023**, *14*, 1146. [CrossRef]
4. Gugel, H.; Ekisheva, S.; Lauby, M.; Tafreshi, F. Vegetation-related outages on transmission lines in north america. In Proceedings of the 2018 IEEE Power & Energy Society General Meeting (PESGM), Portland, OR, USA, 5–10 August 2018; pp. 1–5.
5. Ahmad, J.; Malik, A.S.; Xia, L.; Ashikin, N. Vegetation encroachment monitoring for transmission lines right-of-ways: A survey. *Electr. Power Syst. Res* **2013**, *95*, 339–352. [CrossRef]
6. Di Benedetto, A.; Fiani, M.; Marsella, M. Remote sensing technologies for linear infrastructure monitoring. *Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci.* **2019**, *42*, 461–468.
7. Gazzea, M.; Pacevicius, M.; Dammann, D.O.; Sapronova, A.; Lunde, T.M.; Arghandeh, R. Automated Power Lines Vegetation Monitoring Using High-Resolution Satellite Imagery. *IEEE Trans. Power Deliv.* **2022**, *37*, 308–316. [CrossRef]
8. Qayyum, A.; Malik, A.S.; Saad, M.N.; Iqbal, M.; Ahmad, R.F.; Abdullah, T.A.; Ramli, A.Q. Monitoring of vegetation near power lines based on dynamic programming using satellite stereo images. In Proceedings of the 2014 IEEE International Conference on Smart Instrumentation, Measurement and Applications (ICSIMA), Kuala Lumpur, Malaysia, 25 November 2014; pp. 1–6.
9. Sikorska-Lukasiewicz, K. Methods of automatic vegetation encroachment detection for high voltage power lines. In Proceedings of the Radioelectronic Systems Conference 2019, Jachranka, Poland, 20–21 November 2019; pp. 481–486.
10. Sharifisoraki, Z.; Dey, A.; Selzler, R.; Amini, M.; Green, J.; Rajan, S. Monitoring Critical Infrastructure Using 3D LiDAR Point Clouds. *IEEE Access* **2022**, *11*, 314–336. [CrossRef]
11. Navalgund, R.R.; Jayaraman, V.; Roy, P.S. Remote sensing applications: An overview. *Curr. Sci.* **2007**, *93*, 1747–1766.
12. ESA El programa Copérnico [Internet]. 2017. Available online: https://www.esa.int/Space_in_Member_States/Spain/El_programa_Copernico (accessed on 21 April 2023).
13. Ottinger, C.K.S.D.M.; Wegmann, M.; Guo, H.; Wang, C.; Zhang, J.; Wikelski, M. Earth observation satellite sensors for biodiversity monitoring: potentials and bottlenecks. *Int. J. Remote Sens.* **2014**, *35*, 6599–6647. [CrossRef]
14. Segarra, J.; Buchaillot, M.L.; Araus, J.L.; Kefauver, S.C. Remote sensing for precision agriculture: Sentinel-2 improved features and applications. *Agronomy* **2020**, *10*, 641. [CrossRef]
15. ESA. ESA—Introducing Sentinel-2 [Internet]. 2017. Available online: https://www.esa.int/Applications/Observing_the_Earth/Copernicus/Sentinel-2/Introducing_Sentinel-2 (accessed on 5 July 2023).
16. Espinoza, G.E.; Siburian, I.M.; Masih, I.; Bastiaanssen, W. Remote Sensing Based Indices for Drought Monitoring on Paddy Fields. The Case Study of Lower Citarum-Indonesia. In Proceedings of the AGU Fall Meeting Abstracts, Washington, DC, USA, 10–14 December 2018; p. H51K-1442.
17. Chen, Z.; Zhao, S. Automatic monitoring of surface water dynamics using Sentinel-1 and Sentinel-2 data with Google Earth Engine. *Int. J. Appl. Earth Obs. Geoinf.* **2022**, *113*, 103010. [CrossRef]
18. Chen, L.; Ren, C.; Bao, G.; Zhang, B.; Wang, Z.; Liu, M.; Man, W.; Liu, J. Improved object-based estimation of forest aboveground biomass by integrating LiDAR data from GEDI and ICESat-2 with multi-sensor images in a heterogeneous mountainous region. *Remote Sens.* **2022**, *14*, 2743. [CrossRef]
19. Illarionova, S.; Shadrin, D.; Ignatiev, V.; Shayakhmetov, S.; Trekin, A.; Oseledets, I. Estimation of the Canopy Height Model from Multispectral Satellite Imagery with Convolutional Neural Networks. *IEEE Access* **2022**, *10*, 34116–34132. [CrossRef]
20. Lang, N.; Jetz, W.; Schindler, K.; Wegner, J.D. A high-resolution canopy height model of the Earth. *Nat. Ecol. Evol.* **2023**, *7*, 1778–1789. [CrossRef] [PubMed]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.