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Review Article

Exploring Applications, Datasets, Algorithms, and Technologies in Satellite Image Processing

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Abstract: Amidst an era filled with complex local and global problems, satellite data presents itself as a revolutionary tool with unmatched potential to tackle practical problems in a variety of fields. This article investigates how satellite imagery, which is available through open data programs and repositories, is a valuable tool for applications including wildlife conservation, urban planning, precision agriculture, and disaster management. It highlights the unique perspective that satellite data offers. Various sources for data acquisition, the applications that are suitable for a chosen satellite data and commonly used algorithms and techniques are discussed. Through case studies, the paper demonstrates how quick and reliable data provided by satellites can be used to solve complex real-world problems. The benefits of satellite data are emphasized, including its affordability, ability to monitor in real-time, and ability to support sustainable behaviours and policy-making. The study explores cutting-edge technologies, highlighting cloud computing and GIS integration as well as machine learning algorithms to build robust solutions using satellite data. The immense potential of satellite data is accompanied by challenges, including data integration, computational complexity, and ethical considerations. These challenges underscore the need for standardization and continuous efforts to fully realize the potential of satellite data in sustainable development and informed decision-making.

Keywords: Satellite Data, Remote Sensing, Classification, Deep Learning

Introduction

The utilization of satellite data has become a revolutionary force in an era where global concerns are becoming more complicated and offer a unique perspective that cuts across traditional borders. This research aims to explore the complex meaning of satellite data by examining its availability, variety of uses, ability to solve problems, benefits, cutting-edge technology, and associated difficulties. The unique perspective that satellite imaging offers, which can record information in real-time on a worldwide basis, highlights how valuable it is when it comes to solving important problems in a variety of fields. In the face of complex issues in urban planning, agriculture, disaster relief, and environmental preservation, this paper explores the field of satellite data and clarifies how its collection, use, and interpretation support well-informed choices and long-term solutions. The following sections will examine how satellite data is obtained, examine important applications, analyse how satellite images are used to solve complicated problems, highlight the benefits of using them, highlight innovative technologies, and discuss the difficulties in realizing the full potential of this invaluable resource. By doing this, this study aims to add to the expanding corpus of research that highlights the critical role that satellite data plays in forming a more sustainable and informed future.

The complex science of satellite imaging, which unearths a plethora of data essential for comprehending our dynamic planet, is entwined with the vast domain of satellite data. Fundamentally, the study of satellite imaging uses cutting-edge equipment and sensors in orbit to record electromagnetic radiation that is reflected or emitted from the surface of the Earth. In addition to revealing visible features, these multiwavelength photographs also explore the infrared, microwave, and other spectrums, providing deep insights into atmospheric, geological, and environmental processes. Because of the accuracy of this imaging science and the progress made in remote sensing technologies, it is possible to extract detailed geographical and temporal information that contributes to a greater understanding of Earth's processes. The investigation of satellite data will be intrinsically linked to the scientific complexities of imaging as this research progresses, revealing the subtleties that make satellite imagery a powerful

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instrument for revealing the complexities of our constantly changing world as reported by Ambrosetti (1984) and Garcia-del Real and Alcaráz (2024).

An extensive, narrative review of satellite image processing methods and their uses in several fields is provided in this paper. As opposed to concentrating on in-depth technical specifics or experimental comparisons, the goal is to give a broad picture of the discipline by summarizing important concepts, approaches, and developments. For researchers, practitioners, and policymakers interested in using satellite data for a variety of purposes, this review provides insights into the state and future prospects of satellite image processing.

In order to give a comprehensive overview of satellite image processing methods and their various applications, this study takes a narrative approach. Peer-reviewed journals, conference proceedings, and reliable online repositories were specifically searched using keywords like ”satellite image processing,” ”remote sensing applications,” ”feature extraction techniques,” and ”classification methods” to find pertinent literature. Recent studies, foundational publications, and research showcasing practical applications in a range of fields were prioritized. The selection process was guided by the studies' impact on the field, inventiveness, and relevancy, however it was not all-inclusive. A comprehensive awareness of the subject matter was made possible by the inclusion of many approaches and applications through the use of the narrative review method.

It is crucial to recognize the limitations of this narrative study, even if it offers a thorough summary of satellite image processing methods and their uses. This method does not entail a thorough, methodical search or a formal evaluation of the quality of the sources used, in contrast to systematic reviews. As a result, the literature selection process might have been biased, and some pertinent research might not have been included. This restriction emphasizes the necessity of systematic reviews in future studies to provide a more thorough and organized examination of particular facets of this field.

Satellite Data

In an age of rapid technological innovation, satellite data is becoming essential to our understanding and management of numerous issues that the world faces. Satellites with cutting-edge sensors and imaging capabilities that are in high Earth orbit gather a multitude of data in a variety of spectral bands. This extremely precise data provides a unique and all-encompassing view of the Earth's surface, atmosphere, and oceans. Applications for satellite data are numerous and include areas including agriculture, urban planning, disaster relief, environmental monitoring, and more. This overview explores the different kinds of satellite data and where they come from, revealing the wide range of information that these space observers offer. Satellite image processing uses a variety of publicly available domain-specific datasets for a range of applications. Sentinel-2, Sentinel-3, Landsat, and OpenStreetMap databases are used in urban planning and development to provide precise imaging, land use mapping, and geospatial data for effective urban management. Sentinel-2 and Landsat's multispectral imagery is useful for precision agriculture, helping with vegetation indices, large-scale agricultural assessments, and crop health monitoring. High-resolution photos from Sentinel-2, PlanetScope, and Landsat are used in forest and biodiversity monitoring, together with tools like Global Forest Watch and the Global Biodiversity Information Facility, to track species distribution, fires, and deforestation. While water resource management uses information from GRACE, Sentinel-1, and Landsat to monitor water bodies, floods, and changes in water quality, disaster management depends on Copernicus Sentinel-1 and Sentinel-2, NASA's EOS, and commercial suppliers for pre- and post-disaster evaluations.

High-resolution imagery from WorldView, GeoEye, and Pleiades is used in infrastructure monitoring, while InSAR datasets are utilised for ground deformation analysis. While wildlife conservation benefits from WorldView, PlanetScope, and tracking data from Movebank and the IUCN Red List, cultural heritage preservation uses WorldView, GeoEye, and LiDAR information for precise site mapping. Sentinel-5P, Aura, and TROPOMI databases are used in air quality monitoring to assess atmospheric pollutants, and Sentinel-2, OpenStreetMap, and Sentinel-1 imagery is used in smart city planning and traffic control. The foundation of satellite image processing is made up of these varied datasets, which are made accessible through open-access platforms and space agencies. They allow for creative applications in a variety of fields, facilitating well-informed decision-making and sustainable development.

Types of Satellite Data

Satellite data comes in various types, each serving distinct information requirements and analytical goals. Different types of satellite data are discussed along with their usefulness in various applications. Figure 1 shows a few sample satellite images from some of the popular satellites.

1. Optical Imagery: Optical imagery, which is recorded in the visible and near-infrared ranges, offers detailed, high-resolution pictures of the surface of the Earth. Applications like urban planning, environmental monitoring, and land cover classification greatly benefit from its use.
2. Radar Imagery: Radar imagery, which uses microwave frequencies to see through clouds and darkness, is essential for monitoring all weather conditions. Disaster relief, agriculture, and landscape mapping are a few examples of applications.

3. Infrared Imagery: By detecting thermal radiation, infrared sensors provide information on surface temperature differences. Applications such as monitoring volcanic activity, determining land surface temperatures, and recognising heat anomalies depend on this.
4. Multispectral Imagery: Combining data from multiple spectral bands, multispectral imagery allows for a more nuanced analysis of vegetation health, soil composition, and environmental changes over time.
5. Hyperspectral Imagery: In comparison to multispectral photography, hyperspectral data offers a wider range of spectral bands and more precise information about the materials and ambient conditions. Environmental studies, mineral prospecting, and precision agriculture can all benefit from this.

Sources of Satellite Data

Satellite data can be collected from a variety of online sources as a free product or on demand by the researchers.

It is often a challenge of the researchers to identify the appropriate source and the list of data sets available in the online portals. Most prominent satellite data sources are the following entities.

Open Data Programs: Global cooperation and research are encouraged by programmes such as the European Space Agency's Copernicus and the United States Geological Survey and NASA's Landsat, which offer free and unrestricted access to an abundance of satellite data.

1. Commercial Satellite Providers: High-resolution satellite imagery is available from private firms like DigitalGlobe (Maxar), Airbus, and Planet for a variety of uses, such as infrastructure monitoring, urban planning, and disaster response.
2. Government Agencies: National space agencies, like NASA, provide a wealth of satellite data for scientific research and global monitoring efforts.
3. International Collaborations: Satellite missions like the Joint Polar Satellite System (JPSS) and the Sentinel series of the European Space Agency are the result of cooperative efforts between nations.
4. Data Repositories and Platforms: Scholars and practitioners can access, analyse, and visualise satellite data through online platforms such as Google Earth Engine and NASA Earthdata, which offer an intuitive interface.

Depending on the application domains in which they are used, publicly accessible datasets for satellite image processing have different salient features. Spatial resolutions of 30 cm to 1.5 m are commonly available for high-resolution optical images from sources such as Pleiades, WorldView, and GeoEye. This enables precise feature identification for applications such as infrastructure monitoring, cultural heritage protection, and urban planning. In contrast, applications like water resource management, forest monitoring, and precision agriculture can benefit from the 10 to 30 m spatial resolution provided by medium-resolution satellites like Sentinel-2 and Landsat. Applications like infrastructure monitoring and disaster management can benefit from Synthetic Aperture Radar (SAR) data, which is available at spatial resolutions of 5 to 40 metres and provides an advantage in all-weather circumstances. Satellites such as Sentinel-1 provide this type of data. Different missions have different temporal resolutions; Sentinel-2 and PlanetScope, for example, have daily or frequent revisit times, which enable dynamic monitoring of changes over time. Utilization considerations include taking into account the possibility of cloud cover in optical imaging and comprehending the trade-offs between spatial and temporal resolution based on the particular requirements of each application. When picking datasets for satellite image processing applications, researchers and practitioners also need to take into account the availability of data, processing capabilities, and the precise spectral bands needed for their investigations. Table 1 presents the spectral information, satellite source and appropriate applications for each of the type of satellite data and Table 2 provides the online sources where these data can be acquired from.

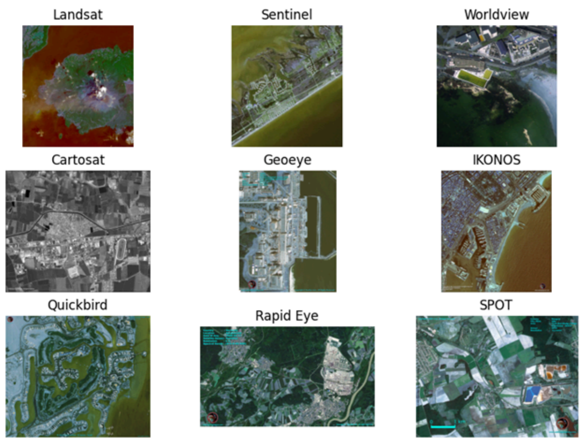

Fig. 1: Sample satellite images

Understanding the nuances of these satellite data types and their diverse sources lays the foundation for harnessing the full potential of these orbiting observatories in addressing the challenges and opportunities that our dynamic planet presents.

Applications of Satellite Image Processing

At the nexus of technology and Earth observation, satellite image processing is a revolutionary force that provides hitherto unattainable insights into our dynamic planet. Applications of satellite image processing are becoming more and more important as the globe struggles with urgent issues including urbanization, climate change, sustainable agriculture, and disaster relief. This study examines several fields, such as environmental monitoring, disaster management, urban planning, and precision agriculture, where satellite imaging is essential. Through the use of sophisticated algorithms, researchers and decision-makers can extract valuable information from large datasets. These algorithms range from conventional image processing approaches to state-of-the-art artificial intelligence and machine learning models. Through an exploration of applications, datasets, algorithms, and upcoming technologies, this study aims to clarify the complex role that satellite image processing plays in resolving practical issues and influencing Earth observation in the future.

Table 1: Types of Staellite Data and Spectral Range

Type	Spectral Range	Prominent Satellite Sources	Suitable Applications
Optical Imagery	Visible and near-infrared spectrum (0.4 to 2.5 μm)	Landsat Series, Sentinel-2A and Sentinel-2B, WorldView-1, WorldView-2, and WorldView-4, Pleiades-1A and Pleiades-1B	Land cover classification, Environmental monitoring, Urban planning
Radar Imagery	Microwave spectrum (1 mm to 1 m)	Sentinel-1A and Sentinel-1B, TerraSAR- X and TanDEM-X, RADARSAT-2	Terrain mapping, Agriculture, Disaster response
Infrared Imagery	Far-infrared (thermal) spectrum (3 to 14 μm)	NASA's Terra and Aqua satellites, Suomi NPP, GOES (Geostationary Operational Environmental Satellite) Series	Heat anomaly detection, Volcanic activity monitoring, Land surface temperature analysis
Multispectral Imagery	Combination of several discrete spectral bands, typically including visible, near-infrared, and sometimes shortwave infrared	WorldView-3, RapidEye, Landsat Series, QuickBird, IKONOS	Vegetation health assessment, Soil composition mapping, Environmental changes over time
Hyperspectral Imagery	Numerous contiguous and narrow spectral bands covering a broad range of wavelengths	HyspIRI (Hyperspectral Infrared Imager), EnMAP (Environmental Mapping and Analysis Program), Hyperion on EO-1 (Earth Observing- 1), Proba-V	Precision agriculture, Mineral exploration, Environmental studies

Table 2: Satellite Data and Online Sources

Satellite Data	Online Source for Data Download	Type
Landsat Data	USGS Earth Explorer	Optical, Multispectral
Sentinel-1 & 2 Data	Copernicus Open Access Hub	Optical, Radar
RADARSAT-2 Data	RADARSAT Geobrowse	Radar
NASA's Terra and Aqua data	NASA Earthdata Search	Infrared
WorldView Data	DigitalGlobe (Maxar) SecureWatch	Multispectral
HyspIRI (Future Mission)	NASA Earthdata Search.	Hyperspectral
EnMAP Data	EnMAP Data Portal	Hyperspectral
RapidEye Data	Planet Explorer	Multispectral
Pleiades-1A and Pleiades-1B	Airbus OneAtlas	Optical
TerraSAR-X and TanDEM-X	DLR Earth Observation Center (EOC)	Radar
QuickBird	DigitalGlobe (Maxar) SecureWatch	Multispectral
IKONOS	DigitalGlobe (Maxar) SecureWatch	Multispectral
Hyperion on EO-1	USGS Earth Explorer	Hyperspectral
Proba-V	ESA Earth Online	Hyperspectral
Suomi NPP	NASA Earthdata Search	Infrared
GOES Series	NOAA Comprehensive Large Array-data Stewardship System (CLASS)	Optical, Multispectral

Urban Planning and Development

Urban planning and development use satellite information to analyze, create, and manage urban regions' complex landscapes in a very detailed way. Kadhim *et al.* (2016) and Hoffman and Lemper (2018) claims that When it comes to charting land use patterns, keeping an eye on urban growth, and determining the demands for infrastructure, high-resolution optical and multispectral data are essential. When combined with environmental impact assessments, ongoing population density monitoring gives planners the capacity to make well-informed decisions about resource allocation and sustainable practices. Furthermore, the use of satellite images facilitates the execution of smart city projects, historical urban studies, and disaster risk management. Incorporating satellite data into urban planning not only improves accessibility, zoning, and transportation networks, but it also helps build smart, resilient communities that change sustainably over time.

Future planning decisions are informed by a thorough grasp of the past development of metropolitan areas made possible by satellite data. It is essential to land management, zoning, and the enforcement of laws to guarantee that urban planning policies are followed. Mobility and connectivity are further improved through the development of accessible spaces and the streamlining of public transport routes. Urban planning and development become multifaceted processes that

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take into account spatial dynamics, environmental effects, and demographic trends by utilising satellite imagery. This eventually helps to create interconnected, sustainable urban ecosystems.

Large-scale development initiatives sometimes call for the selection of cities for urban growth, a procedure that has historically been impacted by human judgment. This manual method could result in biased or inappropriate conclusions by ignoring important socioeconomic and environmental elements. In Libya, a satellite data driven solution was developed that integrated Fuzzy Overlay (FO) and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) to rank cities based on key criteria of urban development Kalantar *et al.* (2019). A dataset comprising 17 evaluation criteria across five urban conditioning factors was utilized as input for the FO model to determine the weights of each criterion. These weights were refined using a Support Vector Machine (SVM) classifier, ensuring greater accuracy and adaptability of the model. TOPSIS was subsequently applied to rank cities based on the refined criteria. Experimental results demonstrated the tool's effectiveness, achieving high overall accuracy and kappa statistics. Success rates ranged from 0.79 to 0.94, while prediction rates varied between 0.673 and 0.884. This case study highlights the potential of integrating advanced geospatial and machine learning techniques to enable equitable, efficient, and data-driven urban planning and development in Libya.

Precision Agriculture

With the use of satellite technology, precision agriculture transforms conventional farming methods by offering focused and data-driven methods for crop management as established by Choudhury (2024) and Jindo *et al.* (2021). Farmers may monitor crop health, growth trends, and resource usage more precisely with the help of high-resolution, aerial imagery of their fields provided by satellite imaging, which is often sourced from Sentinel-2 and Landsat. This information is crucial for maximising the use of water, insecticides, and fertilisers, ensuring that resources are used effectively and that environmental effect is kept to a minimum. Fields may be precisely mapped thanks to the integration of satellite data and GPS technology, which enables farmers to apply site-specific management plans that are customised to the particular requirements of various sections within a field.

Moreover, farmers can identify and act quickly in response to pest infestations, disease outbreaks, or modifications in crop conditions thanks to satellite imagery's real-time monitoring capabilities. In addition to reducing input costs and promoting sustainable agriculture practices, this proactive strategy increases overall crop output. Satellite technology is driving precision agriculture, which is revolutionising current farming by encouraging a more effective, sustainable, and commercially feasible method of crop management as discussed by Lobell *et al.* (2015). Son *et al.* (2024) explored the effectiveness of combining satellite data and AI algorithms to improve crop yield.

Satellite technology has made precision agriculture a global success story with a favourable impact on agricultural productivity. One example of an implementation is precision irrigation, which maximises water use and reduces waste by using data on soil moisture obtained from satellites. By customising fertiliser inputs to particular field regions, variable rate fertilisation improves nutrient uptake and crop health. This is made possible by satellite vegetation health maps. Crop losses can be decreased and early disease diagnosis can be facilitated by targeted actions made possible by satellite monitoring of crop health indicators. High-resolution field maps aid in precision planting, which maximises seed location for better crop uniformity and maximum yield potential. Additionally, satellite data helps farmers manage weather and climate risk by allowing them to foresee catastrophic events and take preventative action. Lastly, precision harvesting guarantees that crops are taken in their prime, reducing losses and raising total yield. It is aided by satellite insights. The sample satellite image specific to a chosen agricultural field presented in Figure 2 shows how traditional agricultural methods are transformed by satellite-driven precision agriculture, becoming more robust, efficient, and sustainable. Sahu *et al.* (2019) explored the ways in which satellite data can serve as a tool for precision agriculture. In the field of precision agriculture, Farmonaut is a remarkable success story that uses satellite-based crop monitoring to give farmers useful information. Farmonaut democratizes precision agriculture for farmers of all sizes by utilizing satellite imagery and sophisticated algorithms to replace expensive on-ground sensors and time-consuming hand inspections.

The cutting-edge technology from Farmonaut offers real-time insights into important agricultural parameters:

1. Crop Health: It provides timely information about the health of plants by enabling real-time monitoring of vegetative vigor.
2. Water Stress: By identifying regions impacted by insufficient irrigation or drought, the system enables timely remedial measures.
3. Soil Health: Optimizing crop development and productivity requires a thorough examination of the soil's characteristics.

By facilitating data-driven decision-making, this innovative method not only improves farming efficiency but also guarantees sustainability. Farmonaut is a prime example of how satellite technology may transform conventional farming methods and open the door to more intelligent and inclusive agricultural solutions.

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Fig. 2: Productivity map for a sample field using satellite data

Forest and Biodiversity Monitoring

With the use of satellite technology, forest and biodiversity monitoring offers a revolutionary method for managing and protecting ecosystems. Satellites using optical and radar sensors can monitor forest cover, identify deforestation, and evaluate biodiversity in real time by providing extensive and up-to-date data as discussed by Bochenek *et al.* (2018). With the use of these technologies, it is possible to map wooded regions precisely, track changes over time, and pinpoint locations that are susceptible to encroachment or illicit logging. Satellites also help in habitat monitoring, which enables researchers and environmentalists to monitor the diversity and health of ecosystems. Mapping wildlife migration patterns, determining biodiversity hotspots, and evaluating the effects of human activity on natural environments are all made easier with the use of high-resolution satellite imagery. Neumann *et al.* (2015) investigated the effectiveness of satellite data in studying the terrestrial animal movement. Through the provision of practical insights for sustainable forest management and biodiversity conservation, this all-encompassing monitoring strategy supports conservation efforts. Additionally, evaluating the effects of climate change on forests and biodiversity depends heavily on satellite data. A better knowledge of changes brought about by climate change can be attained through tracking alterations in the distribution of species, evaluating the health of ecosystems, and monitoring vegetation changes. Satellite technology makes it easier to adopt focused conservation methods, save endangered species, and advance sustainable land-use practices by giving a broad, bird's-eye perspective of forests and ecosystems. Satellite-based Forest and biodiversity monitoring is a vital component of the international effort to protect and maintain Earth's many ecosystems.

Satellite data can be used to compute vegetation indices like NDVI (Normalized Difference Vegetation Index) that can throw light on the health of the vegetation as presented in Figure 3. It is possible to determine "normal" growing conditions in a region for a specific time of year by averaging NDVI values over time. Subsequent examination will reveal how healthy the vegetation looks in comparison to average. When examined over a period of time, NDVI can show changes in vegetation brought on by phenological stage shifts in plants, natural disturbances like wildfires, and human activities like deforestation. It can also show where vegetation is thriving and where it is under stress.

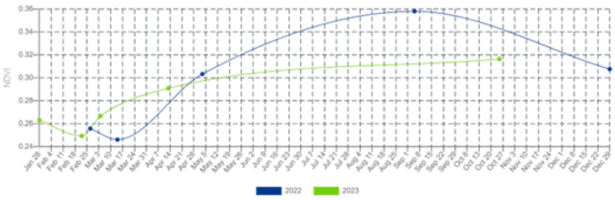

Fig. 3: NDVI timeseries analysis for Bangalore city for 2022 and 2023

Several cases of environmental protection have shown the value of satellite data. Satellites such as Sentinel-2 and Landsat are able to identify deforestation in the Amazon, allowing for quick action against illicit logging. Synthetic aperture radar-equipped satellites, such RADARSAT-2, help monitor oil spills by determining their extent and directing cleanup operations. Multispectral and hyperspectral sensors are used to evaluate the health of coral reefs, giving scientists the information, they need to identify stressors and put protective measures in place for these ecosystems. Nguyen *et al.* (2021) demonstrated the usefulness of satellite data in mapping coral reef and monitoring their health. Satellites can also be used to monitor vessel movements in the field of fisheries to identify instances of illicit fishing in marine protected areas as presented by Shanthi *et al.* (2022) and Fridman *et al.* (2019). Satellites also play a critical role in protecting the environment, biodiversity, and public health through their contributions to water resource management, air quality monitoring, and natural disaster response.

Disaster Management

Using satellite technology, disaster management improves readiness, response, and recovery for a range of natural and man-made calamities. Satellites fitted with a range of sensors, such as radar and optical equipment, offer vital real-time data for tracking and evaluating the effects of disasters. By providing high-resolution photos and identifying changes in affected areas, satellites provide crucial insights during calamities like hurricanes, wildfires, and earthquakes. Higuchi (2021) discusses the various ways in which satellite data along with computational techniques can be used for disaster management and risk mitigation. Emergency responders can use this information to better allocate resources, identify areas of immediate concern, and create evacuation plans. Furthermore, satellite technology supports early warning systems, which help authorities foresee and lessen the effects of disasters, particularly in areas that are exposed to risks like landslides or floods as investigated by Teodoro and Duarte (2022).

Additionally, satellite data is essential for post-disaster assessment and recovery. Satellites enable officials prioritise locations for quick assistance following natural disasters like floods and earthquakes by giving precise before-and-after imagery. Rebuilding infrastructure, allocating resources, and organising relief operations all depend on this knowledge. All things considered, the use of satellite technology into disaster management guarantees a better educated and coordinated reaction to lessen the effects of calamities on communities, enabling a quicker and more efficient healing process as Brown *et al.* (2010) and Duric *et al.´* (2017) highlighted in their research works.

In numerous notable occasions, satellite data has been essential to the reaction to and recovery from disasters. Satellites played a vital role in tracking Hurricane Katrina's path and determining the degree of flooding, which facilitated quick reactions and recovery operations. High-resolution satellite photography helped with damage assessment, search and rescue efforts, and effective resource deployment following the earthquake in Haiti. Similar to this, satellites helped with evacuation planning and worldwide relief coordination following the Japanese earthquake and tsunami by providing vital information on damage. Satellite images helped with infrastructure damage assessment and search and rescue efforts following the earthquake in Nepal. Satellites tracked the dynamics of the fire in real time during the California wildfires, which aided in planning for post-fire recovery and firefighting operations. Lastly, satellite data aided long-term recovery operations and directed humanitarian efforts in Puerto Rico following Hurricane Maria. These incidents highlight how crucial satellite technology is to improving disaster management and enabling efficient reaction and recovery efforts.

Water Resource Management

For the purpose of keeping an eye on bodies of water, evaluating their quality, and managing water resources worldwide, satellite data is essential. Satellites with a variety of sensors, such as optical and infrared instruments, help keep an eye on bodies of water like rivers, lakes, and reservoirs. They offer high-resolution imagery that makes it possible to monitor water levels, spot surface area changes, and evaluate the general well being of aquatic ecosystems. For the purpose of identifying fluctuations in the supply of water and guaranteeing the sustainable use of water resources, this information is especially helpful. Earth observing satellites like Landsat series have been extensively employed in detecting and mapping water bodies effectively as reported by Van Dijk and Renzullo (2011) and Sheffield *et al.* (2018). The availability of multi-temporal data also facilitate change detection studies that can lead to insightful outcomes for decision makers. Figure 4 and 5 present visualizations of temporal changes to two of the lakes in Bangalore, India during the period 1987 to 2020. This data was also be used to build forecast models to predict the future changes and to take appropriate actions for conserving the water bodies by Bijeesh and Narasimhamurthy (2021).

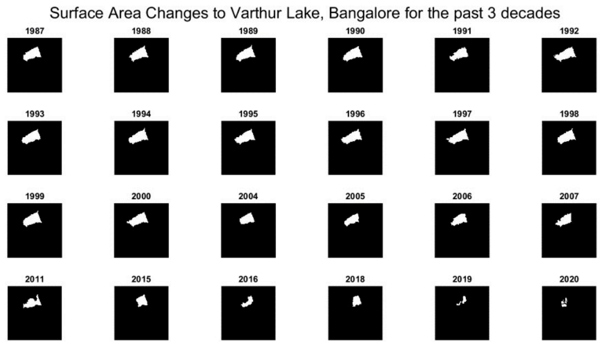

Fig. 4: Change visualization for Varthur Lake, Bangalore, India

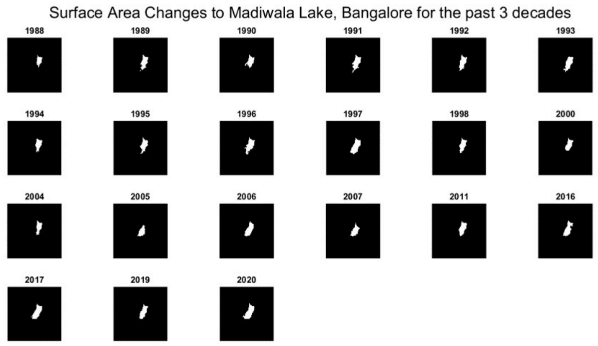

Fig. 5: Change visualization for Madiwala Lake, Bangalore, India

Apart from the observation of water bodies, satellites also aid in the evaluation of water quality by gathering information on characteristics such as sedimentation, chlorophyll content, and turbidity. With the use of remote sensing technologies, hazardous algal blooms and pollution incidents can be identified, giving authorities advance notice. Combining satellite data with in-situ measurements improves the precision of water quality evaluations, assisting in the detection of possible sources of contamination and enabling timely corrective action. Satellite data are essential for supporting efficient strategies for managing water resources, guaranteeing clean water supply for ecosystems and human use, and advancing sustainable practices to address the world's mounting water concerns. Swain and Sahoo (2017) and Lioumbas *et al.* (2023) have demonstrated the approaches in water quality analysis using satellite data.

Globally effective solutions for managing water resources have benefited greatly from the use of satellite photography. For example, satellites with remote sensing capabilities have been used in Australia's Murray-Darling Basin to track water levels and evaluate agricultural water consumption. Authorities can more effectively allocate water supplies, improve irrigation techniques, and lessen the effects of protracted droughts with the help of the data collected. Similarly, the United

States' Landsat programme has been essential in monitoring the Great Lakes region's water availability and quality.

Decision-makers are assisted in detecting problem regions, controlling causes of pollution, and guaranteeing the sustainability of water resources by the information obtained from satellites. These illustrations explain how satellite imagery supports large-scale, sustainable water resource use by improving monitoring and management initiatives.

Infrastructure Monitoring

Satellite imaging is essential for keeping an eye on vital infrastructure and assisting with maintenance initiatives in a variety of industries as reporeted by D'Amato *et al.* (2022). Power plants, pipelines, and electrical grids are among the things that satellites with synthetic aperture radar and high-resolution cameras help to monitor in the energy sector. These satellites offer precise imaging that may be used to evaluate the state of infrastructure, find any problems, and guarantee the dependability of energy systems. Satellites help with the upkeep and monitoring of railroads, bridges, and roadways in the transportation industry. Authorities can determine locations that are vulnerable to damage, evaluate the effects of natural disasters, and schedule timely maintenance tasks to improve efficiency and safety by taking precise pictures of transportation networks. Montillet *et al.* (2016) presents techniques for monitoring critical infrastructure using available satellites.

Moreover, satellite photography helps with the infrastructure monitoring for water and wastewater Andres *et al.* (2018). Pipeline leaks and variations in water quality can be detected by satellites fitted with multispectral sensors. Water authorities can use this information to ensure that clean water is delivered to communities efficiently, minimise losses, and preserve the integrity of water supply infrastructure. Satellites are essential for monitoring buildings, bridges, and other important structures in the context of urban planning. Authorities may evaluate structural integrity, spot possible dangers, and schedule maintenance tasks to guarantee the longevity and safety of vital infrastructure by routinely taking high-resolution photos. All things considered, there are many uses for satellite imaging in critical infrastructure monitoring, providing insightful information for preventive maintenance and long-term management of vital systems that are crucial to contemporary societies.

In a number of cases, satellite data has been a major factor in preventing infrastructure breakdowns. For instance, in order to avert catastrophic breakdowns in oil and gas pipelines, satellites fitted with Synthetic Aperture Radar (SAR) have been used in the field of pipeline monitoring to identify possible leaks and ground subsidence. Furthermore, satellites are essential for monitoring structural changes, detecting patterns of erosion, and determining reservoir levels in the context of dam safety. These functions allow for the early identification of possible problems and the timely maintenance necessary to prevent dam failures.

Furthermore, high-resolution satellite imagery has proven essential for monitoring the structural integrity of important infrastructure, such as bridges, buildings, and other structures in urban areas as presented by Spencer Jr *et al.* (2019). This has helped authorities proactively address maintenance needs and identify weak points, averting possible collapses or disruptions. These instances underscore the proactive role of satellite data in averting infrastructure failures and enhancing the resilience of key systems critical for societal well-being.

In order to successfully preserve cultural heritage and support the preservation and restoration of historical places around the world, satellite imagery has become essential. In the ancient Syrian city of Palmyra, where fighting posed serious hazards to cultural heritage, satellite data was utilised to track and evaluate damage from looting and vandalism. Documenting the condition of the archaeological site, directing conservation efforts, and increasing public understanding of the value of protecting cultural heritage were all made possible by the pictures. Similar to this, satellite technology was used in Machu Picchu, Peru, to control and monitor the impact of visitors to the UNESCO World Heritage site. The information made it easier to develop plans for sustainable tourism, which in turn helped to protect the historical site from any damage and ensured its long-term preservation. These initiatives highlight the impactful role of satellite imagery in cultural heritage preservation, offering valuable insights for informed decision-making and proactive conservation measures.

Wildlife Conservation

With the use of satellite technology, wildlife monitoring has been transformed, allowing scientists and environmentalists to monitor migratory patterns and stop poaching Wall *et al.* (2014). Satellites with GPS and remote sensing capabilities are useful for monitoring animal migration since they may gather important information about an animal's movement over great distances. For example, satellites follow the migration paths, nesting locations, and feeding areas of marine species such as sea turtles in the research presented by Yu *et al.* (2023). In a similar vein, satellite technology helps track the movements of land animals, such as the Serengeti wildebeests, in terrestrial ecosystems. Understanding biological dynamics, recognizing important habitats, and developing conservation plans that support the preservation of migratory species all depend on this knowledge.

Satellite data is also employed to identify sources of pollution, offering insights into the origin and distribution of contaminants. For example, satellites equipped with advanced sensors can detect emissions from industrial facilities, power plants, and transportation sources. This information is crucial for environmental authorities and policymakers to assess the impact of human activities on air quality, enforce regulations, and develop targeted strategies to mitigate pollution. The global perspective provided by satellite data enhances the understanding of air quality dynamics and supports efforts to address the challenges of urbanization, industrialization, and other factors contributing to air pollution. Banerjee and Palit (2023) discussed some of these pressing issues and possible interventions with the help of satellite data to mitigate them.

A number of notable examples of wildlife conservation success stories can be attributed to satellite image processing. Satellite imagery and image processing have been useful in tracking and safeguarding the tigers in Nepal's Bardia National Park, which are listed as endangered species. Conservationists have been able to detect changes in land cover and anticipate potential risks to tiger habitats by analysing satellite imagery. This has made patrolling and anti-poaching tactics more effective. In a similar vein, satellite image processing has made conservation efforts for elephants in Africa more successful. Through the utilisation of satellite data, researchers can track the movements of elephants, identify illicit activities like poaching, and devise strategies to preserve these remarkable animals. These achievements demonstrate how satellite image processing can significantly improve wildlife conservation efforts, allowing for proactive measures to protect endangered species and their habitats.

Air Quality Monitoring

Satellite data provide useful information about pollutants and help identify sources of pollution; it is essential for monitoring air quality globally as claimed by Rowley and Karakus (2023). Sensor-equipped satellites, like those from the Copernicus program, can detect particulate matter, nitrogen dioxide, and sulphur dioxide concentrations, as well as other atmospheric characteristics. With the use of this data, comprehensive maps of air quality may be created, showing the amounts of pollution in various areas. Shelestov *et al.* (2018) claims that satellite data is especially useful in places where there is a lack of infrastructure for ground-based monitoring to keep an eye on air quality .

Additionally, satellite data is used to locate pollution sources, providing information about the origin and distribution of pollutants. For instance, satellites with cutting-edge sensors on board can identify pollution coming from vehicles, power plants, and industrial sectors. To evaluate how human activity affects air quality, implement laws, and create focused pollution mitigation plans, environmental authorities, and legislators need access to this data. Holloway *et al.* (2021) provides a worldwide perspective that satellite data can be used to improve our understanding of the dynamics of air quality and can help us tackle the problems caused by industry, urbanization, and other factors that contribute to air pollution .

By giving fast and thorough information on air pollution levels, satellite-based air quality monitoring significantly improves public health by assisting authorities and communities in taking preventive action to protect public health. The assessment of the health risks related to exposure to pollutants like nitrogen dioxide and particulate matter is aided by the data produced by satellites. With the use of this data, policymakers can target their interventions and reduce the negative effects of air pollution on vulnerable populations. Examples of these interventions include the implementation of emission regulations, the regulation of industrial operations, and the planning of urban development strategies. One example of a successful application of satellite data is the monitoring and management of air pollution in Beijing and New Delhi as presented by Witte *et al.* (2009). In these instances, satellite observations have aided in the understanding of the sources of pollution, the implementation of pollution control strategies, and the raising of public awareness, all of which have improved the quality of the air and consequently, the population's health. To create healthier and more sustainable urban environments, public health programs must use satellite-based air quality monitoring.

Smart Cities and Traffic Management

In the creation and optimisation of smart city applications, satellite imagery is essential, especially when it comes to public transit, parking space utilisation, and traffic control. High-resolution camera-equipped satellites offer real-time data on traffic patterns, road conditions, and congestion levels to optimise traffic flow. With the use of this data, automated traffic management systems may be put into place that can redirect cars, modify traffic signals on the fly, and give commuters real-time traffic reports. City planners can determine the efficacy of the current road infrastructure and make well-informed changes to increase traffic efficiency, lessen congestion, and improve overall mobility by using satellite imagery Bellini *et al.* (2021).

Satellites aid in the creation of intelligent parking solutions in the field of parking space utilisation. Mapping parking lots, determining available spaces, and estimating parking demand are made easier with the use of high-resolution satellite photography. By combining this data with smart city apps, drivers may find parking spots more quickly, which eases traffic and lessens the impact of needless vehicle movements on the environment.

Katrenko *et al.* (2020) explores the usefulness of satellite data in improving the traffic flow and parking system. Additionally, the planning and improvement of

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public transport timetables and routes is made possible by satellite data. Authorities can follow vehicle movements, analyze passenger demand, and optimize routes to enhance the effectiveness and accessibility of public transportation services by keeping an eye on public transportation networks from space. All things considered, the use of satellite imagery in smart city projects helps to build more livable, efficient, and sustainable urban environments Hulleman (2000) and Oskarbski *et al.* (2019).

In several cases, satellite image processing has greatly improved smart city programs. Barcelona, Spain, developed a smart mobility platform by utilizing satellite imagery to improve traffic management. Through the integration of satellite data, this program helps residents commute more efficiently by tracking traffic patterns, identifying regions of congestion, and providing real-time information. Singapore uses high-resolution imagery to evaluate land use and track construction activity, and it uses satellite image processing for urban planning and development. Furthermore, satellite data is used to assist smart transportation systems in Curitiba, Brazil. This allows the city to improve overall mobility, regulate traffic flow, and optimize public transit routes. These case studies show how the effectiveness of smart city projects is enhanced by satellite image processing, which offers insightful information on effective public transport, urban design, and traffic optimisation.

Algorithms for Satellite Image Processing

Image processing, feature extraction, and classification techniques are essential in the field of satellite image analysis because they convert unprocessed data into meaningful insights. Techniques for processing images, such as filtering, fusion, and geometric and radiometric adjustments, improve the quality of satellite data and set the stage for further analysis. A step further is feature extraction, which extracts specific data from satellite photos, like textures, vegetation indices, and distinguishing points, which are necessary for classifying objects and patterns within the imagery. Classification algorithms classify pixels in images, making it possible to do supervised and unsupervised tasks such as mapping land cover, and to detect changes over time. The fundamental components of satellite image analysis are image processing, classification, and feature extraction (Asokan and Anitha, 2019; Asokan *et al.*, 2020). These three processes enable the extraction of valuable information for a wide range of applications, from urban planning and disaster management to environmental monitoring. The satellite image processing pipeline presented in Figure 6 shows an organized flow of steps from gathering raw data to producing useful insights. Satellites are the first step in the process; they take raw images and send them to the image acquisition system. The data is gathered and formatted by this system for subsequent processing. Preprocessing, the following step, ensures that the data is clean and georeferenced by eliminating noise and fixing distortions. After that, the pipeline advances to Image Enhancement, where key features are highlighted using methods including filtering and contrast correction. After enhancement, feature extraction finds particular textures, structures, or patterns in the image that are essential to comprehending the data. Following the extraction of these attributes, the data is classified using statistical or machine learning techniques into predetermined classifications. After processing, the data is examined for Change Detection, which finds and measures changes over time, such deforestation or urban growth. Lastly, using the processed satellite images as a basis, the Decision-Making step compiles all of the findings into useful insights that direct strategic planning, monitoring, or intervention activities. This pipeline is an excellent example of how satellite data may be seamlessly integrated with computational procedures to tackle challenging real-world issues.

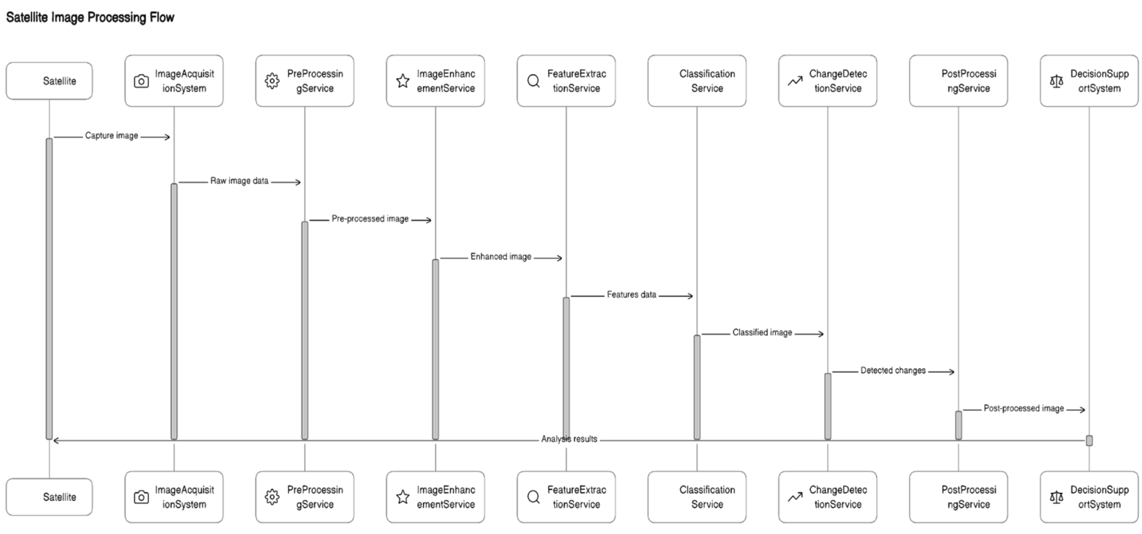

Fig. 6: Satellite Image Processing Pipeline

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A variety of methods are used in image processing to improve, adjust, and work with satellite images.

Radiometric corrections use techniques including contrast stretching, gamma correction, and histogram equalization to improve the overall visual quality by addressing pixel value concerns. Accurate spatial representation is ensured through geometric modifications like map projection and orthorectification. Satellite images can be made clearer and less noisy by using filtering techniques such as bilateral, median, and Gaussian filters. Principal Component Analysis (PCA) and the Brovey transform are two examples of image fusion methods that mix data from several spectral bands to improve the interpretability of the images. By combining these methods, raw satellite data is refined and made ready for additional examination and interpretation. Sharmila *et al.* (2013) presents various satellite image processing techniques along with their applications.

Feature extraction is the process of identifying pertinent details from satellite photos to describe particular patterns or objects. Algorithms for texture analysis, such as Gabor filters and the Grey Level Co-occurrence Matrix (GLCM), allow images to display fine features and spatial correlations. Based on spectral reflectance, vegetation indices, such as the Enhanced Vegetation Index (EVI) and Normalised Difference Vegetation Index (NDVI), measure the health of the vegetation. Algorithms for edge detection, such as the Canny edge detector, recognize the borders separating various areas within an image. The techniques of corner detection, line detection, and segmentation—which recognize unique points, linear features, and coherent regions, respectively—are also included in the feature extraction process. Algorithms for detecting interest points pinpoint prominent areas in a picture, which helps with further processing such as image registration and matching. These feature extraction techniques are essential for deriving patterns and relevant data from satellite photos, enabling a variety of uses from urban planning to environmental monitoring. Karim *et al.* (2017) performed a comparative study of commonly used feature extraction methods for satellite images.

Classification algorithms are used to divide up the pixels in a satellite picture into several groups, which helps with mapping land cover and identifying objects. Labelled training samples are used by supervised classification algorithms like Maximum Likelihood Classification (MLC) and Support Vector Machines (SVM) to allocate pixels to predetermined classes. Unsupervised techniques that group pixels based on spectral similarity without the need for prior class information include K-Means clustering and hierarchical clustering. When it comes to complex classification problems, Object-Based Image Analysis (OBIA) uses algorithms like Random Forest, taking into account contextual information and spatial relationships. Change detection algorithms are essential for tracking changes in the environment and land use dynamics because they can detect differences between two or more time periods or images. Ouchra and Belangour (2021) provides a comprehensive analysis of classification techniques in the context of satellite imagery. Tables 3 to 9 summarizes various satellite image processing tasks and commonly employed algorithms to achieve these tasks.

Software Tools

A plethora of open source and proprietary software tools are available for processing satellite data. A list of popular software tools is presented in this section.

1. ENVI (Environment for Visualizing Images): A comprehensive software for image processing, classification, and analysis of remote sensing data.
2. ERDAS IMAGINE: A geospatial data authoring system for preparing, displaying, and enhancing digital images in remote sensing applications.
3. QGIS (Quantum Geographic Information System): An open-source GIS software that supports satellite image processing, classification, and spatial analysis.
4. ArcGIS: A widely used GIS platform that includes tools for satellite image analysis, spatial statistics, and geoprocessing.
5. Google Earth Engine: A cloud-based platform for planetary-scale environmental data analysis, providing access to a vast amount of satellite imagery.
6. SNAP (Sentinel Application Platform): An open-source software for processing and analyzing Sentinel-1 and Sentinel-2 data.
7. MATLAB: A programming language and environment for numerical computing widely used for image processing, classification, and algorithm development.
8. R: A programming language and software environment for statistical computing and graphics, with packages for remote sensing and spatial analysis.

Programming Languages

A list of commonly used programming languages with libraries supporting satellite data processing is presented in this section.

1. Python: Widely used for its versatility, Python has numerous libraries such as NumPy, SciPy, OpenCV, and scikit-learn for image processing, classification, and feature extraction.
2. R: Apart from its use as a statistical computing language, R has packages like raster, rgdal, and caret for spatial analysis and machine learning.
3. Java: Java-based libraries like JAI (Java Advanced Imaging) and JTS (Java Topology Suite) are used for image processing and spatial data handling.

4. C++: Efficient for developing custom algorithms and applications, with libraries like OpenCV and ITK (Insight Segmentation and Registration Toolkit) for image processing.
5. IDL (Interactive Data Language): A programming language specifically designed for data analysis, signal processing, and image analysis.
6. GDAL (Geospatial Data Abstraction Library): A translator library for raster and vector geospatial data formats, often used in conjunction with other programming languages.

These tools and programming languages provide a robust ecosystem for implementing a wide range of algorithms in satellite image processing, classification, and feature extraction, catering to the diverse needs of remote sensing applications.

Table 3: Preprocessing Algorithms

Algorithm	Application	Strengths	Weaknesses
Histogram Equalization	Image enhancement	Improves contrast effectively	Can over-enhance noise
Contrast Stretching	Dynamic range adjustment	Simple and computationally efficient	Limited to low dynamic range images
Gamma Correction	Brightness adjustment	Good for fine-tuning brightness	Sensitive to gamma value selection
Gaussian Filter	Noise reduction	Effective for removing Gaussian noise	Can blur edges
Median Filter	Noise reduction	Preserves edges while removing noise	Computationally intensive
Bilateral Filter	Edge-preserving smoothing	Excellent edge preservation	Computationally expensive

Table 4: Geometric Correction and Projection Algorithms

Algorithm	Application	Strengths	Weaknesses
Orthorectification	Geometric correction	Corrects terrain distortions accurately	Requires DEM and precise metadata
Map Projection	Coordinate transformation	Necessary for geographic analysis	Potential distortions in reprojected images

Table 5: Segmentation Algorithms

Algorithm	Application	Strengths	Weaknesses
Watershed Segmentation	Object delineation	Handles overlapping objects well	Sensitive to noise
Region Growing	Region-based segmentation	Intuitive and simple	Can lead to over-segmentation
Mean Shift Segmentation	Clustering-based segmentation	No assumptions about shape	High computational cost
Felzenszwalb's Graph-Based	Hierarchical segmentation	Fast and efficient	Sensitive to parameters

Deep Learning in Satellite Image Processing

By utilising neural networks' capacity to automatically extract hierarchical features from data, deep learning algorithms have become extremely effective instruments in the rapidly evolving field of satellite image processing Soufi and Belouadha (2023). While recurrent neural networks (RNNs) are useful for sequential data analysis in time-series satellite photography, Convolutional Neural Networks (CNNs) are the industry standard for tasks like object detection and picture categorization. By collecting inherent features, autoencoders enable unsupervised learning, whereas Generative Adversarial Networks (GANs) produce artificial images for data augmentation.

Image processing is accelerated through transfer learning using pre-trained models such as VGG16 and ResNet, while sequential data is well-managed using Long Short-Term Memory Networks (LSTMs). Innovative methods for geometric transformations, image similarity analysis, and hierarchical feature learning are provided by Siamese networks, Capsule networks, and Spatial Transformer Networks (STNs). Performance and interpretability are increased by specialised designs such as Mask R-CNN, which improve object instance segmentation, and attention techniques, which sharpen focus on pertinent picture regions. This set of deep learning algorithms enables the analysis of satellite images for a variety of uses, such as object recognition and change detection, offering hitherto unseen potential for deriving significant insights from satellite data. Table 10 lists the deep learning algorithms used in various satellite data processing tasks.

Satellite image processing encompasses a wide range of algorithms, from conventional image processing methods to the state-of-the-art field of deep learning. When combined, these techniques allow for the useful insights to be extracted from large datasets that are collected by Earth observation satellites. These technologies enable scientists, researchers, and practitioners to address a wide range of problems, whether through sophisticated techniques like Generative Adversarial Networks (GANs) and Convolutional Neural Networks (CNNs) or traditional methods like geometric and radiometric adjustments. A new era of advanced satellite image analysis is being ushered in by the merging of classical and deep learning algorithms, which improves the efficiency and accuracy of tasks like land cover classification and dynamic change detection. These algorithms will surely be essential in utilising satellite data to its fullest extent for urban planning, disaster relief, environmental monitoring, and other purposes as technology develops, ultimately leading to a more thorough understanding of our changing planet.

Technologies in Satellite Image Processing

Advances in efficiency, scalability, and accessibility brought about by the integration of state-of-the-art technology have significantly advanced satellite image processing in recent years. Cloud computing and edge computing are two major trends in this field (Leyva-Mayorga *et al.*, 2023).

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Table 6: Classification Algorithms

Algorithm	Application	Strengths	Weaknesses
Maximum Likelihood Classification (MLC)	Statistical-based classification	Robust for Gaussian distributions	Assumes normal distribution of data
Support Vector Machines (SVM)	Binary and multi-class classification	Effective for high-dimensional spaces	Sensitive to kernel and parameter tuning
Decision Trees (e.g., CART, C4.5)	Simple rule-based classification	Easy to interpret	Prone to overfitting
Random Forest	Ensemble-based classification	Handles non-linear data effectively	Computationally intensive for large data
k-Nearest Neighbors (k-NN)	Proximity-based classification	Simple implementation	Computationally expensive for large data
Neural Networks	Complex pattern recognition	High accuracy with sufficient training	Requires large labeled datasets
Convolutional Neural Networks (CNNs)	Image-based classification	Excels in image processing tasks	Requires significant computational power
Recurrent Neural Networks (RNNs)	Sequence-based data classification	Handles temporal dependencies	Prone to vanishing gradient issues
Long Short-Term Memory (LSTM)	Sequential data (e.g., time series)	Mitigates vanishing gradient problem	Computationally expensive
Transformer Networks	Text and sequential data classification	Superior for large-scale datasets	Requires large computational resources
Deep Belief Networks (DBNs)	Unsupervised feature learning	Effective for high-dimensional data	Complex to train
Naive Bayes	Text and categorical data classification	Simple and fast	Assumes feature independence
Gradient Boosting (e.g., XGBoost, LightGBM)	Ensemble-based classification	High accuracy and efficiency	Sensitive to hyperparameter tuning
k-Means Clustering	Unsupervised classification (clustering)	Easy to implement	Assumes spherical clusters
Self-Organizing Maps (SOM)	Clustering and visualization of data	Handles non-linear data distributions	Sensitive to parameter initialization
Deep Convolutional Generative Adversarial Networks (DCGANs)	Data generation and classification tasks	Learns complex data distributions	Requires careful tuning of discriminator and generator
Autoencoders	Feature extraction and anomaly detection	Reduces dimensionality effectively	Limited for direct classification tasks
Capsule Networks	Image classification	Captures spatial hierarchies effectively	Computationally expensive
Ensemble Learning (e.g., Bagging)	Combines predictions of multiple models	Reduces overfitting	Computationally intensive
Probabilistic Neural Networks (PNN)	Statistical pattern recognition	Fast training	Requires large memory
Extreme Learning Machine (ELM)	Single-layer feedforward network	Fast training	Limited generalization capability
ResNet (Residual Networks)	Deep learning-based classification	Handles vanishing gradient in deep layers	High computational cost
Inception Networks (GoogleNet)	Multi-scale feature extraction	Excellent for image classification	Computationally demanding
U-Net	Segmentation and classification	Ideal for biomedical image processing	Requires large labeled datasets
YOLO (You Only Look Once)	Real-time object detection and classification	High-speed processing	Requires high GPU resources
EfficientNet	Scalable image classification	Balances performance and computational cost	Complex training process
VGGNet	Image classification	Simple and effective	High memory and computational requirements

Table 7: Feature Extraction Algorithms

Algorithm	Application	Strengths	Weaknesses
Principal Component Analysis (PCA)	Dimensionality reduction	Reduces data size without significant loss	Assumes linear relationships
Wavelet Transform	Multi-resolution analysis	Captures both spatial and frequency info	Complex to implement
Gray Level Co-occurrence Matrix (GLCM)	Texture analysis	Effective for texture-based classification	Computationally intensive
Local Binary Patterns (LBP)	Texture analysis	Simple and efficient	Limited to local textures

Table 8: Change Detection Algorithms

Algorithm	Application	Strengths	Weaknesses
Image Differencing	Detecting pixel-level changes	Simple and efficient	Sensitive to threshold selection
Change Vector Analysis (CVA)	Multispectral change detection	Handles multidimensional data	Computationally intensive
Binary Change Detection	Detecting binary changes (presence/absence)	Easy to interpret	Limited to specific types of changes
Principal Component Analysis (PCA)	Feature extraction for change detection	Reduces dimensionality effectively	Can miss subtle changes
Image Ratioing	Identifying spectral changes	Simple implementation	Cannot detect subtle changes
Minimum Noise Fraction (MNF)	Noise-reduction in change detection	Effective in noisy datasets	Requires careful preprocessing
Independent Component Analysis (ICA)	Change detection via signal separation	Handles mixed data sources	Computationally intensive
t-Distributed Stochastic Neighbor Embedding (t-SNE)	Feature reduction for change detection	Captures non-linear relationships	High computational cost
Gray-Level Change Detection	Identifying intensity-based changes	Works on grayscale data	Limited spectral detail
Time-Series Analysis	Multi-temporal change detection	Captures temporal trends	Requires multiple data acquisitions
Post-Classification Comparison	Comparing classified images	High accuracy for thematic changes	Requires accurate classification
Continuous Change Detection and Classification (CCDC)	Land cover change and trend analysis	Captures continuous trends	Computationally demanding
Multivariate Alteration Detection (MAD)	Multivariate data change detection	Robust against data variations	Requires expert knowledge
Deep Learning-Based Change Detection	Complex pattern recognition	High accuracy with sufficient training	Requires large labeled datasets
Optical Flow	Motion and temporal changes	Handles gradual changes	Computationally intensive
Spectral Angle Mapper (SAM)	Spectral similarity-based change detection	Insensitive to illumination differences	Limited to specific spectral changes
Cross-Correlation Analysis	Time-lagged change detection	Handles temporal lags effectively	Requires time-series data
Kullback-Leibler Divergence (KLD)	Statistical change detection	Effective for probabilistic changes	Sensitive to data distribution
Dynamic Time Warping (DTW)	Temporal change alignment	Effective for non-linear temporal changes	Computationally expensive

Table 9: Spectral Index Algorithms

Algorithm	Application	Strengths	Weaknesses
Normalized Difference Vegetation Index (NDVI)	Vegetation monitoring	Widely used, simple	Limited to vegetation-specific monitoring
Enhanced Vegetation Index (EVI)	Vegetation monitoring	Reduces atmospheric interference	More complex than NDVI
Soil Adjusted Vegetation Index (SAVI)	Vegetation monitoring	Mitigates soil brightness impact	Requires additional calibration
Green Normalized Difference Vegetation Index (GNDVI)	Chlorophyll content estimation	High sensitivity to vegetation health	Requires accurate reflectance data
Normalized Difference Water Index (NDWI)	Water body detection	Highlights water bodies effectively	Limited in areas with mixed vegetation and water
Modified NDWI (MNDWI)	Water body detection	Better separation of water from built-up areas	Sensitive to thresholds
Automated Water Extraction Index (AWEI)	Water body detection	Effective for automated water body mapping	May require regional calibration
Normalized Difference Moisture Index (NDMI)	Moisture content detection	Useful for monitoring soil moisture	May not work well in non-vegetative regions
Water Ratio Index (WRI)	Water content detection	Good for analyzing water reflectance	Less commonly used

Cloud Computing

Because cloud computing provides scalable and on-demand computer resources, it has completely changed the processing of satellite images. Cloud computing platforms such as Google Cloud Platform (GCP), Microsoft Azure, and Amazon Web Services (AWS) offer sophisticated infrastructures for processing, storing, and analysing vast amounts of satellite data. Cloud-based solutions make it possible to handle data in parallel, which speeds up the execution of complicated algorithms on large datasets. Customers can take advantage of cloud-based geospatial analytic services such as Google Earth Engine, AWS Lambda for serverless computation, and Amazon S3 for data storage. This method not only reduces processing times but also makes it possible for organizations and academics to use cutting-edge computing capabilities without requiring a sizable on-premises infrastructure.

Edge Computing

As a supplemental technology, edge computing has surfaced to meet the demand for processing and analysing satellite data in real-time. By processing data closer to the source, edge computing lowers latency and bandwidth needs compared to standard cloud computing. Edge computing in the context of satellite image processing allows for on-site analysis, which makes it appropriate for applications like disaster response and autonomous systems that call for quick reactions. With their potent CPUs and machine learning capabilities, edge devices can locally preprocess and filter satellite imagery before sending pertinent data to cloud-based or centralized systems. This method works especially well in situations when processing in close to real-time and with little latency is essential.

Table 10: Deep Learning Algorithms used for Satellite Image Processing

Deep Learning Algorithm	Application
Convolutional Neural Networks (CNNs)	Object detection Image classification Feature extraction
Recurrent Neural Networks (RNNs)	Sequential data analysis Time-series analysis and prediction
Autoencoders	Dimensionality reduction Feature learning
Generative Adversarial Networks (GANs)	Image synthesis Data augmentation
Transfer Learning (e.g., using pretrained models like VGG16, ResNet)	Image classification Feature extraction
Long Short-Term Memory Networks (LSTMs)	Sequence modelling Time-series analysis
Capsule Networks	Image understanding Hierarchical feature learning
Spatial Transformer Networks (STNs)	Geometric transformations Spatial localization
Siamese Networks	Image similarity Analysis Change detection
Mask R-CNN	Object instance segmentation
Attention Mechanisms	Focusing on relevant image regions Improving model interpretability

Machine Learning and AI Integration

In satellite image processing, the use of artificial intelligence (AI) and machine learning techniques has grown in popularity. For deep learning tasks including object recognition, change detection, and picture classification, Convolutional Neural Networks (CNNs) and recurrent neural networks (RNNs) are used. The computational power needed for training and implementing these sophisticated models is provided by cloud computing platforms. Furthermore, AI-capable edge devices may conduct real-time analysis locally, which speeds up the decision-making process.

Open-Source Tools and APIs

Access to satellite image processing capabilities has become more accessible due to the availability of open-source tools and APIs. The foundation for handling and modifying geographic data is provided by libraries such as scikit-image, rasterio, and GDAL (geographic Data Abstraction Library). Developers may effortlessly access and incorporate satellite data into their apps with the help of API services provided by satellite imagery suppliers like Sentinel Hub and Planet. Satellite image processing will advance in the future as a result of the convergence of edge, cloud, and artificial intelligence technologies. These developments open the door to fresh applications and insights in a variety of fields, including urban planning, disaster management, environmental monitoring, and data accessibility and efficiency.

Since Geographic Information Systems (GIS) provide the fundamental framework for managing, organizing, and analysing geospatial data, they are essential to satellite image analysis. GIS makes it easier to integrate various datasets, such as satellite photos and ground-based data, in the context of satellite photography. It gives users the fundamental tools they need to visualize and analyze satellite imagery, enabling them to make themed maps, run spatial queries, and spot patterns in the data. By allowing the comparison of temporal information, GIS facilitates change detection and monitoring by helping to identify changes in land use and environmental dynamics. In addition, GIS provides a framework for spatial modelling and decision support, enabling users to build models that integrate data from satellites to make well-informed decisions in areas like environmental management, urban planning, and disaster relief. GIS, in short, improves the efficacy of satellite image analysis by offering a contextual framework that is geographically informed for the interpretation and application of information derived from satellites.

The following recommendations are put forth to address issues with satellite image processing, namely those pertaining to processing speed, data storage, and computational complexity:

- Cloud computing: Scalable and reasonably priced methods for handling big datasets are provided by cloud platforms such as AWS, Google Cloud, and Microsoft Azure. With services like Amazon S3, Google Earth Engine, and Azure Maps, these platforms facilitate the processing and storing of satellite data. Real-time processing, worldwide collaboration, and the removal of the need for substantial local infrastructure are all made possible by cloud computing.
- Graphics processing units, or GPUs, are ideal for computationally demanding activities like feature extraction, classification, and picture enhancement because they are tuned for parallel processing. Processing times can be significantly decreased by implementing GPUs into workflows, particularly for deep learning algorithms used for tasks like object detection, segmentation, and change detection. To expedite the processing of satellite data, platforms such as TensorFlow and NVIDIA CUDA facilitate GPU acceleration.

- Distributed Computing: Processing massive datasets across numerous nodes is made possible by distributed computing frameworks like Apache Hadoop and Apache Spark. These frameworks guarantee effective use of resources, increase processing speed, and make it possible to handle datasets that are too big for a single system by distributing jobs across multiple workstations. In order to scale as required, distributed computing can also be integrated with cloud environments.
- Collaboration and Open Standards: Encouraging interoperability via APIs and open data standards guarantees the smooth integration of various platforms and solutions. This makes it possible for companies and researchers to efficiently work together on big projects and take advantage of common resources.
- Toolkits and Libraries: Using pre-existing frameworks like PyTorch and TensorFlow for

GPU-accelerated processing or libraries like Google Earth Engine for cloud-based analysis lowers the overhead of creating solutions from scratch and expedites experimentation.

Satellite image processing workflows can overcome current obstacles and provide more effective and scalable solutions to real-world issues by integrating these cutting-edge technology and methodologies.

Challenges and Future Directions

There are various obstacles to overcome in satellite image processing that affect the effectiveness, precision, and moral implications of using geospatial data. The diversity of datasets from many sources is the primary cause of the data integration challenge, which calls for the smooth integration of remote sensing, socioeconomic, and ground-based data. To overcome this obstacle,

standardized data interoperability protocols and advanced geographic information systems (GIS) are essential. They enable a comprehensive analysis that takes into account several aspects of geographical information. Another challenge is the computing complexity involved in processing large amounts of high-resolution satellite data. Feature extraction, change detection, and picture classification algorithms might need a lot of resources. Through the provision of on-demand resources, cloud computing platforms facilitate distributed computing and parallel processing, hence delivering a scalable solution. The management of computational complexity in large-scale satellite image processing is facilitated by the integration of Graphics Processing Units (GPUs), optimization of algorithms, and effective utilization of specialized hardware.

In satellite image processing, data correctness and quality are still recurring problems. Cloud cover, air interference, and sensor noise are a few examples of problems that can affect how reliable the data is. Improving data accuracy can be achieved by combining data from many sensors, using sophisticated image correction algorithms, and implementing quality evaluation protocols. Over time, preserving data quality requires regular validation and calibration procedures. Affordability and accessibility present additional difficulties, necessitating programmes like open data guidelines, unrestricted access to specific satellite datasets, and cooperative efforts to lower the price of data collection and processing. Lastly, because deep learning models' decision-making processes are frequently opaque, it might be difficult to interpret them. This issue is being addressed by ongoing attempts to create explainable AI (XAI) methodologies, which will improve comprehension and transparency of the characteristics that deep learning models in important applications learn. To ensure the appropriate and fair use of geospatial data in satellite image processing, researchers, governments, and industry stakeholders must work together to address these difficulties. A critical analysis of problems and challenges in satellite data processing is presented by Zhang and Zhang (2022) and Zhang *et al.* (2022).

When processing satellite images, ethical issues are crucial, particularly when it comes to security, privacy, and possible data exploitation. Because satellite imagery has a high resolution, there is a possibility that sensitive information will be captured. Therefore, strong data governance frameworks, regulatory requirements, and ethical standards are required. It's critical to strike a balance between preserving individual privacy rights and allowing unrestricted access to data for research purposes. Involving stakeholders in the creation of moral guidelines encourages the prudent application of satellite data. Greenland and Fabiani (2023) throws light on some of the pressing ethical issues in using satellite data for real world problems.

Dynamic trends and breakthroughs that have the potential to completely transform the area of satellite image processing characterise its future. With better temporal resolution and more frequent revisit times, high-resolution satellite constellations are expected to be deployed more frequently. This innovation improves monitoring capabilities for a wide range of applications, including disaster relief and agriculture. Artificial intelligence (AI) and machine learning (ML) continue to be closely related fields, with sophisticated algorithms handling issues related to the interpretability of deep learning models and automating image analysis tasks. A more thorough understanding of the Earth's surface is also aided by the merging of multi-sensor data and the emergence of edge computing for real-time analysis. Complex computations could be expedited by quantum computing, and more open data projects could lead to more accessibility and cooperation. Future uses could include the integration of augmented reality (AR), which would enable dynamic visualisations for disaster relief, urban planning, and navigation. The future of satellite image processing is multifaceted and will require worldwide collaboration, adherence to standards, and a heightened focus on sustainable development and climate monitoring.

In conclusion, technological advancements like high-resolution constellations, sophisticated AI and ML integration, edge computing, multi-sensor data fusion, quantum computing exploration, open data initiatives, and augmented reality applications are all part of the future direction of satellite image processing. All of these trends point to a direction towards utilising satellite data for a wide range of applications in ways that are more internationally collaborative, technologically advanced, and easily accessible.

Conclusion

A wide range of opportunities and challenges have been made solvable by the investigation of satellite image processing applications, datasets, methods, and technology. The wide range of uses, from air quality monitoring and disaster management to precision agriculture and urban planning, demonstrate the adaptability of satellite data. Research and applications in these fields are made easier by the abundance of commercial and open-source datasets available; systems such as Copernicus and Google Earth Engine provide invaluable resources. In order to extract useful insights from satellite imagery, advanced algorithms—which might range from conventional image processing techniques to cutting-edge deep learning models—are essential for tasks like feature extraction, change detection, and classification. Satellite image processing becomes more scalable and efficient when technologies like edge computing, cloud computing, and artificial intelligence are integrated. Cloud platforms offer resources for processing and storing data on demand, and edge computing allows real-time analysis for apps that need quick replies. Explainable AI (XAI) approaches have emerged to overcome issues with complicated models' interpretability. Data integration, computational complexity, ethical issues, and the ongoing need to guarantee data quality and accuracy are some of the field's challenges.

High-resolution satellite constellations are expected to become more common in the future, along with ongoing AI and ML integration, the investigation of quantum computing applications, and a greater emphasis on sustainable development and climate monitoring.

Essentially, this paper highlights the revolutionary influence of satellite image processing across several fields, propelled by sophisticated algorithms, developing technology, and an increasing focus on the conscientious and moral utilization of geospatial information. To fully utilize satellite data for tackling global concerns and expanding scientific understanding, this diverse sector demands constant collaboration, adherence to standards, and an optimistic outlook. Because satellite image processing offers a vital window into our dynamic globe, it continues to be of utmost relevance in addressing real-world problems. Applications are found in many different fields, such as environmental monitoring, disaster management, and urban planning. The abundance of data collected by satellites provides decision-makers, researchers, and policymakers with previously unheard-of insights into global issues including climate change, resource management, and disaster response. The processing of large amounts of geographic data is becoming more efficient and scalable thanks to continuous improvements in algorithms and technologies, such as the combination of cloud computing and artificial intelligence. Satellite image processing is a key component in the complex and linked concerns that our globe is facing today. It allows us to gain a better understanding of Earth's dynamics and provides us with useful information to tackle the many problems that characterize our day.

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Ethics

There are no ethical issues to report in this study.

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