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ARTICLE

Trends of recent data, AI/ML approaches for geospatial AI in Earth observation towards sustainable development goals

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The integration of data science and Artificial Intelligence (AI) into geospatial analysis has revolutionized Earth observation, driving progress towards the Sustainable Development Goals (SDGs). Recent developments in data acquisition technologies like high-resolution satellites and sensors have generated vast and diverse datasets for monitoring environmental changes and managing natural resources. Concurrently, innovations in Machine Learning (ML) and AI have significantly enhanced the processing, analysis and interpretation of this geospatial data. Techniques such as deep learning, spatial data mining and automated feature extraction are now essential to deriving actionable insights from complex geospatial datasets. This paper reviews the latest trends and breakthroughs in the application of AI/ML to geospatial data for Earth observation, emphasizing their role in advancing the SDGs. Key areas of focus include improved algorithms for land cover classification, disaster prediction and climate monitoring. These technologies enable more precise and timely responses to environmental challenges, such as deforestation, urbanization and natural disasters, thereby supporting sustainable management and policymaking. Furthermore, the integration of AI with geospatial data enhances predictive modelling, scenario planning and decision support systems, which are critical for achieving SDG targets related to environmental sustainability and resilience. The synthesis of recent research and technological developments highlights the potential of AI/ML approaches for geospatial analysis and their alignment with global sustainability goals. The outcomes underline the requirement for continued innovation and collaboration across disciplines to fully leverage these advancements for effective Earth observation and sustainable development.

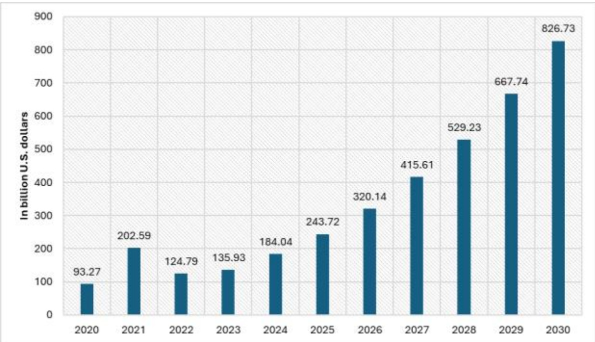
Keywords – *Climate change, data science, Earth observation, geospatial AI, spatial data mining, sustainability analytics, Sustainable Development Goals (SDGs)*

1. INTRODUCTION

Recent years have seen an evolution of new space technologies that are capturing the planet in multiple modalities (EO, SAR, LiDAR, RF, etc.) and in multiple dimensions (spectral, spatial and temporal) that can help nations with the successful implementation of a strong national geospatial infrastructure [1], [2]. New space developments include technology advances in the field of rocket launches, miniaturization of payloads and sensors resulting in reduced costs of satellites, Inter-satellite Links (ISLs), satellite on-board processing technologies, increasing network of ground stations, and others [3], [4]. However, the key aspect of national geospatial infrastructures is the foundational data. Aerial technologies have also advanced in the last few years with commercial companies collecting imagery at ultra-high spatial resolutions (<-15cm) as well as LiDAR data at high densities (10-20 points per sq. m) for the creation of Digital Elevation Models (DEMs) as well as 3D mesh models. Drone technology has also rapidly evolved in recent years allowing for ultra-high-resolution capture of imagery and 3D data for local areas, and their ability to rapidly mobilize allows for frequent map updates [5]–[7].

Rapid advances in autonomous driving vehicles resulted in HD mapping technology from terrestrial vehicles that includes street views and detailed 3D surface maps to capture road furniture such as traffic signs, stop signs, lane markings, etc. Public agencies such as NASA and ESA have continued their scientific satellite missions, Landsat and Copernicus missions respectively, providing global imagery datasets at medium spatial resolution. Several Non-Governmental Organizations (NGOs), such as Open Street Map (OSM), Google.Org and others, have developed global map/vector datasets such as building footprints, road networks, etc. that can be leveraged for national mapping [8]–[10]. Nowadays, any national mapping agency can leverage multiple datasets available in the commercial industry, as well as from public sector agencies to execute their mapping missions.

The last few years have also seen the increasing adoption of AI/ML technologies for a variety of applications including Generative AI (GenAI), Large Language Models (LLMs), Deep Learning (DL) and Machine Learning (ML) models. The invention of transformers by Google coupled with increased computational infrastructure has drastically increased the adoption of AI/ML technologies in our daily lives [11]–[14].



Source: http://www.statista.com/statistics/1474143/global-ai-market-size/

Figure 1 – Artificial intelligence (AI) market size worldwide from 2020 to 2030 (in billion U.S. dollars)

Fig. 1 tells us about the global market size of AI (for 2020 to 2030) in U.S. dollars. The global market size of AI seems to increase progressively each year, suggesting a projection of economic growth or investment over time. In the context of the global market size of Artificial Intelligence (AI), the bar chart likely illustrates projected growth in AI investment, spending or overall market size over the next decade. The chart clearly shows exponential growth in AI market size, which aligns with industry forecasts. In 2020, the market was valued at $93.27 billion but by 2030 it is projected to reach $826.73 billion, almost nine times the size in a decade. This reflects rapid advancements and adoption of AI across various sectors, including healthcare, finance, manufacturing, and more. Increasing computational power, improvements in AI algorithms (e.g., deep learning, neural networks) and the availability of large datasets are driving AI development. AI is being integrated into almost every industry. From autonomous vehicles and smart healthcare systems to finance, retail and logistics, the ability of AI to enhance productivity, accuracy and decision-making makes it highly valuable. Governments and companies are heavily investing in AI, both to gain competitive advantages and to address global challenges like climate change, healthcare and economic inequality. This increase in investment is reflected in the projected figures shown in the chart. AI is expected to contribute trillions of dollars to the global economy. According to some estimates, AI could add $15.7 trillion to the global economy by 2030, with productivity and product improvements. The chart aligns with projections for the global AI market, showing a significant growth trajectory from 2020 to 2030. This trend is driven by technological advancements, cross-industry adoption and increasing investment. As AI transforms industries, the global market size will continue expanding, with key sectors such as healthcare, autonomous vehicles and AI as a service being primary drivers of this growth.

Further, improvements in the classification technologies/platforms, as well as segmentation technologies have enhanced the use of AI/ML technology. The geospatial industry has seen an increased adoption of AI/ML (GeoAI) for object and feature extraction, change detection, and other mapping applications. GeoAI is poised to become integral to the geospatial community and national mapping agencies should embrace GeoAI for national mapping and maintenance in 2D, as well as 3D [12], [15], [16]. The major focus of the work is on “AI/ML Approaches+Geospatial AI+ Earth Observation+Sustainable Development Goals”.

Geospatial datasets, such as imagery, elevation models, road vectors and others, can be leveraged for a variety of applications beyond traditional mapping. EO imagery can be used for a variety of missions including agriculture, environment, transportation, natural resources management, atmospheric monitoring, census, etc [1], [17]. One of the key applications of EO imagery is Satellite-Derived Shallow water Bathymetry (SDSB) which allows for mapping and updating shallow water bathymetry in open oceans, as well as for inland waterways. DEMs play a critical role in flood plain/watershed modelling, transportation, insurance, topographic maps, and others [18], [19]. 3D texture models are becoming important for various missions including digital twins for smart cities, modelling and simulation, autonomous driving and other applications. A coordinated geospatial data acquisition mission will benefit national mapping agencies in efficiently leveraging various geospatial datasets for multi-purpose missions.

2. VARIOUS DATASETS AVAILABLE FOR NATIONAL MAP UPDATES

There are several datasets publicly available, as well as those from the private sector, for national mapping. The main datasets used for mapping include Electro-Optical (EO) imagery, Synthetic Aperture RADAR (SAR), digital elevation models including Digital Surface Models (DSMs) and Digital Terrain Models (DTMs), LiDAR and other 3D point clouds, 3D textured models, bathymetry, Ground Control Points (GCPs), image control points and various vector datasets including roads, buildings, coastlines, field/parcel boundaries, and others (Bui et al. 2021).

2.1 EO imagery

EO imagery is one of the main data sources used for mapping missions by national mapping agencies. EO imagery sources include satellites, planes, drones and terrestrial sensors [20], [21]. Key dimensions for the selection of EO imagery include spatial resolution (pixel resolution/Ground Sampling Distance (GSD) that defines the finest object that can be extracted from an image, spectral resolution (number of spectral bands, wavelengths of the spectrum, width of spectral bands to capture spectral signature of interest) and temporal resolution (revisit frequency over area of interest) [22], [23]. Spatial resolution can vary from 5cm for applications such as planimetric mapping to 3-meter-15-meter GSD for nationwide change detection. A standardized schema such as the National Imagery Interpretation Scale (NIIRS) [24], [25] describes the objects that can be detected at multiple pixel resolutions and helps agencies select the right spatial resolution for a specific mission. Also, it is important to keep in mind that image quality for the same spatial resolution can vary from one data source to another based on image quality parameters like Signal Noise Ratio (SNR), radiometric resolution (preferred >10 bits of data per pixel), and others that influence the overall usability of EO images [26]–[28]. National mapping agencies should also be aware of techniques such as pan sharpening, super-resolution and resampling that simulate a spatial resolution that is much finer than the native GSD in selecting an imagery source [29]–[31]. The spectral resolution is an indicator of the number of spectral bands captured by the EO sensor [1], [32], [33]. Typical sensors used for mapping missions include a minimum of four bands spanning across the Visible and Near-Infrared (VNIR) part of the Electromagnetic (EM) spectrum of sunlight. Depending on the number of bands, EO imagery can be classified as Multi-spectral (MS) bands (2-10 bands), Super-spectral (SS) (10-20 bands) and Hyper-spectral (HS) (>20 bands). Most of the AI/ML applications use multi-spectral visible bands (Red, Green, Blue (RGB)) for object detection, while applications like land use/land cover, agriculture, etc. require additional information from the NIR band, which contain unique spectral information for feature extraction. Few sensors in the market collect imagery in the Short Wave Infrared (SWIR) part of the EM spectrum [34], [35]. SWIR imagery can be used for specialized applications such as mineral mapping, methane detection in the atmosphere, soil and canopy moisture detection, and others. Mid-wave Infrared (MWIR) and Long Wave Infrared (LWIR) bands transmit information about thermal responses of land features that can be leveraged for unique missions comprising energy efficiency measurements of buildings, monitoring emissions in the oil and gas industry, and other applications [36]–[39].

Several commercial companies provide aerial and drone imagery and a few companies such as NearMap and Aerometrix are collecting imagery globally [40]–[42]. There are a select few companies including NCTech that are offering street view terrestrial imagery as an alternative to HD datasets from companies such as Google, Apple, HERE, and others. Table 1 shows a partial list of companies that provide global satellite imagery that can be used for national mapping.

Table 1 – Source of satellite EO imagery

Source / Data Type/ EM Spectrum/ GSD	Public / Private
Landsat 8 (MS) VNIR, SWIR, MWIR	Public (NASA)
Sentinel 5 (MS)	Public (ESA)
Maxar (SS), VNIR-SWIR	Private (USA)
Airbus (MS), VNIR	Private (Europe)
Planet (MS), VNIR	Private (USA)
Satellogic (MS), VNIR	Private (Argentina)
BlackSky (MS), VNIR	Private (USA)
SIIS (MS), VNIR	Private (S. Korea)
ISI (MS), VNIR	Private (Israel)
Superview (MS), VNIR	Private (China)
Jilin (MS), VNIR	Private (China)
Satlantis (MS), VNIR	Private (Europe)
SatelliteVu (MS), MWIR	Private (UK)
Albedo (MS), VNIR	Private (USA)
Pixxel (HS), VNIR	Private (India)
Orbital Sidekick (HS), VNIR, SWIR	Private (USA)
Earth Daily Analytics (VNIR, SWIR, MWIR)	Private (Canada)
Axelspace (MS), VNIR	Private (Japan)

National mapping agencies can also take advantage of Commercial Off The Shelf (COTS) global/national/regional image mosaic products offered by companies such as Maxar, Airbus, NearMap, and others [43], [44]. These datasets are typically built on global specification (e.g. UTM WGS84) and agencies can leverage these COTS products to rapidly create imagery base maps of their nation [45], [46].

Commercial companies offer various business models to access their imagery and products, as well as offering sovereign access to satellites to nations [47], [48]. Agencies can acquire new images for their areas of interest by tasking the satellites as well as accessing older data from the image archives, with the latter being a relatively cheaper option compared to tasking [49]–[51]. Several commercial companies have built platforms and Application Programming Interfaces (APIs) to provide access to new tasked imagery and archive imagery, as well as COTS products. For scientific applications, some companies are offering Analytics Ready Data (ARD or Data Cube) that is spectrally, spatially and temporally corrected imagery, from both public and private sources of imagery [52], [53]. Further, there are several data aggregators such as EUSI, UP42, SkyWatch, SkyFi, Appollo Mapping and others that provide access to multiple sources of EO imagery using one platform.

The positional accuracy of the EO imagery is a significant reason to consider the map scale of national maps. Satellite image accuracy is dependent on the pointing accuracy of the satellites as well as spatial errors propagated through various image processing steps [54]. Supplementary data like the Digital Terrain Model (DTM) with Ground Control Points (GCPs) play an essential role in the absolute accuracy of processed images. Also, positional accuracy of mosaic image products involves error propagation from bundle adjustment aerial triangulation of tie points from multiple images [55], [56]. National agencies require positional accuracies of EO imagery and associated products before using them for national map generations.

2.2 Synthetic Aperture RADAR (SAR)

SAR imagery can see through clouds and day/night and all-weather imaging is useful for national mapping in several pursuits involving geology, maritime, surface deformation, infrastructure maintenance, disaster response, and others (Arai et al. 2019; Perez et al. 2022). SAR imagery requires considering other dimensions like spatial resolution, wavelength (X, C, L), polarization and imaging modes (Spot, Strip, Scan) for mapping. SAR satellites acquire imagery by scanning the ground in two dimensions and the associated spatial resolution of SAR data is defined by Impulse Response (IPR) (Abe et al. 2020; Ghorbanian et al. 2021). The IPR is a two-dimensional entity that is characterized by the range-dimension width (the width of the IPR in the ranging dimension) and the cross-range (or azimuth) dimension width. An image is built up from the reflected signals in both dimensions (Dungan et al. 2002; Motwani, Shukla, and Pawar 2021) and a typical SAR sensor resolution is defined by the slant-range plane. L, C and X-bands are the most widely employed in SAR instruments with variable microwave pulses for different mapping missions. Table 2 summarizes the missions supported by variable microwave bands.

Table 2 – SAR applications

Band	Mission
L (15-30 cm)	Geophysical monitoring, biomass and vegetation mapping, InSAR
C (3.8-7.5 cm)	Global mapping, change detection and monitoring of areas with low to moderate vegetation; ice, ocean, and maritime navigation
X (2.4-3.8 cm)	Urban monitoring

Most SAR systems provide dual and quad-polarized images, essentially giving multiple images of the same scene. Quad-polarized SAR, also referred to as Polarimetric SAR (PolSAR), captures diverse structural and texture information and allows the recognition of different scattering mechanisms [57]–[59]. The specific frequency, look angle, polarization and illuminated area of a SAR dataset determine which applications the dataset is appropriate for where several commercial companies offer a range of image capture modes that define the spatial resolution and the area captured in an SAR scan [60]. SPOT modes typically offer the highest resolution with a relatively small area (5 km × 5 km to 10 km × 10 km at sub-1-meter resolution), Strip mode offers 1–2-meter GSD and a larger footprint than the spot model, and the scan model at >2 m GSD with large areas ranging in thousands of sq km [61], [62]. Commercial SAR satellite companies offer various business models for tasking SAR satellites, as well as for accessing their image archives. Like EO companies, customers can access tasking and imagery via a platform and associated APIs. There are several public and private sources of SAR imagery and Table 3 provides a partial list of SAR sources:

Table 3 – Sources of SAR imagery

Company / Region	Public/Private
Sentinel 1/Europe	Public
ALOS/Japan	Public
Airbus (Tandem-X)/Europe	Private
MDA (Radarsat-2)/Canada	Private
eGeos (COSMOS-SkyMed)/Europe	Private
ICEYE/Europe	Private
Capella Space/USA	Private
Umbra/USA	Private
Synspective/Japan	Private

Few aerial companies are providing SAR imaging services that can be also leveraged by national mapping agencies.

2.3 Elevation data

Elevation is one of the key foundational pieces of data for national geospatial infrastructure. Elevation data types comprise Digital Terrain Models (DTMs), Digital Surface Models (DSMs), 3D texture models and point clouds (Bui et al. 2021; Roca and Arellano 2021). Sources of elevation data can range from sensors in space to aerial as well as terrestrial platforms. Key dimensions for the selection of DEM (DTM and DSM) data sources include spatial resolution of gridded data or density for point clouds for LiDAR and associated positional accuracy in X, Y and Z dimensions.

Shuttle RADAR Topographic Mission (SRTM) global elevation datasets, at 90-meter or 30-meter resolution, have been the commonly used elevation data around the globe (Ramírez et al. 2020; Zeng et al. 2020). National elevation programs have been in place in several countries that have collected DTM data at 10-meter spatial resolution and in the last few years, programs such as the 3D Elevation Program (3DEP) in the United States of America (USA) have captured the entire nation at 1-meter postings. These programs are primarily using aerial LiDAR technology with satellite and Interferometric SAR (IfSAR)-based elevation models complementing the LiDAR datasets (Katz, Batterman, and Brines 2020; Qabaqaba et al. 2023). Metropolitan areas in select countries across the globe have been mapped at much higher spatial resolution/ postings using aerial stereo photogrammetric, as well as LiDAR, technologies. Aerial oblique photography has been one of the commonly used technologies for creating photo-realistic 3D textured models of cities (Praticò, Di Fazio, and Modica 2021; Z. Sun, Deal, and Pallathucheril 2009; L. Yao et al. 2021). Terrestrial street view photogrammetry for HD mapping for autonomous vehicles has also been used to create 3D data.

Table 4 – Sources of DEM data

Elevation Source / Product / Posting / Technology	Public/private
SRTM (NASA)/DTM/30 m or 90 m (SAR)	Public
Airbus/DTM/10 m (SAR)	Private
Maxar/DSM-DTM-3D/<=1 m (EO)	Private
NTT Data/DTM/3 m (EO)	Private

There are several efforts, research and commercial, to combine the terrestrial and aerial 3D datasets to create a cohesive 3D dataset with photo-realistic representation of an area. Table 4 details some of the global sources of DEM data. Few companies are providing global satellite-derived shallow water bathymetry data including EOMAP and TCarta. Other technologies used for high-accuracy bathymetry maps include SONAR and LiDAR techniques and there are several companies offering services for maritime mapping of shallow waters and littoral zones [63], [64].

2.4 Ground Control Points (GCPs)

GCPs are an important aspect of ancillary data for enhancing and validating the positional accuracy of 2D images as well as 3D data. Surveying technologies such as Real-Time Kinematic (RTK) GPS provide centimetre-level accuracy GCPs in real-time (Dongsheng Liu et al. 2021; Petrocchi et al. 2024; Pierdicca and Paolanti 2022). Traditionally GCPs were collected on the ground for precisely geolocating 2D datasets, they can also be leveraged to validate the Z dimension of 3D datasets. Photo Identifiable Features (PIFs) of GCPs can be existing known points of interest and some nations have created a nationwide network of PIFs, like surveying monuments, that can serve multiple missions including georeferencing, cadaster creation and maintenance, transportation planning, and others. Few companies such as CompassData from the USA offer global GCPs from an archive (Araújo et al. 2019; Woo et al. 2018).

National agencies requiring GCPs only for georeferencing of imagery and datasets can use other alternatives to RTK GPS surveying, which can be resource-intensive and costly (Hagenaars et al. 2018; Zular et al. 2012). There are GPS technologies available on the market that can achieve sub-50 cm accuracy at much lower costs than RTK GPS. Similarly, image chips from high-accuracy imagery sources, both 2D and 3D, can also serve as sources for GCPs.

2.5 Open-source datasets

There are several open-source vector datasets that national agencies can leverage for national maps. Open Street Map (OSM) is a free open-source vector dataset with global coverage of roads, buildings and other features, and it is updated by millions of volunteers daily (Forghani and Delavar 2014; T. Zhang and Tang 2018). Humanitarian Open Street Map (HOT) is a non-profit organization that supports disaster response across the globe and produces vector datasets that agencies can use to respond to disasters (Aung 2021; Dias et al. 2023; Henderson 2010). Microsoft has released millions of building footprint data it has derived from its global aerial imagery missions and these datasets are available using Bing Maps API and have been also integrated into OSM (Asif, Naeem, and Khalid 2024; Dou et al. 2018; Huidong Li et al. 2018). Few entities have created global population density estimates including Oak Ridge National Laboratory (ORNL), WorldPop and Columbia University, NY USA that could be of help to national mapping agencies (Campbell-Lendrum and Corvalán 2007; Garshasbi et al. 2020; L. Yang et al. 2022).

Many public as well as private sources, now addressing climate change and are providing global datasets for trace gases and atmospheric pollutants. ESA, NASA, JAXA and a few other public agencies have scientific missions that provide information about greenhouse gases such as methane, nitrous oxide, formaldehyde and others, using satellites in Low Earth Orbit (LEO) and Geostationary Earth Orbit (GEO) (Ho et al. 2007; H Li et al. 2018; Segovia, Gaso, and Armienta 2007). Various NGOs such as the Environmental Defense Fund (EDF), Carbon Mapper and others, are now providing/planning to provide free access to methane and carbon dioxide data, on a global scale. Further, several private entities are now launching satellites for atmospheric mapping as well.

3. USE OF TECHNOLOGY FOR MAP MAINTENANCE AND UPDATE

3.1 AI/ML overview

AI/ML technologies are ready to transform map making and national agencies would prepare the current and future workforce to adopt these technologies (Casali, Aydin, and Comes 2022; Shahab et al. 2024). AI/ML is a rapidly evolving technology that is transforming our way of life (Joshi et al. 2016; Odu et al. 2022; Y. Yang et al. 2024). Multibillion-dollar AI/ML investments from Microsoft, Google, Meta OpenAI and other technology enterprises, are contributing to increased technological advances in this field. While techniques like ML/DL have been around for decades, it was the invention of transformers by Google engineers that resulted in the rapid evolution of the technology in the last few years (Dhedia et al. 2021; Pamela Flores, Gaudiano, and Gamba 2017; Scharien and Nasonova 2020). Computing technology from companies like NVIDIA, AMD, Intel, Google, Alibaba and others played a key role in the development of large AI/ML models (Chugh, Kumar, and Singh 2021; Perčić, Zelenika, and Mezić 2021).

ML/DL value chain is comprised of different levels like the data value chain. Most of the applications like object detection, feature extraction and image classification fall into the descriptive category (Motwake et al. 2024). Change detection between two or more temporal sequences of imagery or geospatial datasets falls into the descriptive category. Few services companies provide diagnostic services but they typically leverage human analysts to diagnose the information derived from imagery/geospatial sources (Gašparovič and Klobučar 2021; W. Li et al. 2023; S. Wang and Li 2021). The diagnostic phase typically requires the use of multiple data sources (multi-INT) to understand the image (Chakraborty et al. 2020; Mendoza et al. 2015; Vanama et al. 2021). An example of a diagnostic step can be understanding the agricultural output of a nation and correlating excess, or shortage of food supplies based on weather conditions. Patterns of life, both natural and human, can be predictable most of the time and mobile phone companies can predict the daily behaviours of people and recommend traffic situations along a route routinely taken by an individual. A GeoAI example of a predictive step could be the predictive socio-economic recovery of a neighbourhood, post-disaster, by observing traffic patterns on streets (Hou et al. 2024; H. Lee and Li 2024; Vitale, Salvo, and Lamonaca 2024). The prescriptive segment of DL/ML is presently used in the aircraft industry where the technology is being used to prescribe when maintenance is required for an aircraft engine. Likewise, a geospatial mission of the national agencies uses predictive recommendations from ML/DL including recommendations for pesticide applications based on potential pest infestations in agriculture (Hou et al. 2024; Randhawa et al. 2023; Qianheng Zhang, Kang, and Roth 2023). The diagnostic, predictive and prescriptive stages of the ML/DL value chain of GeoAI offer tremendous opportunities for new research for various national mapping missions (Cornara et al. 2019; Jayaraman, Srivastava, and Gowrisankar 2009; Lin et al. 2020).

The AI/ML methods can be categorized into two discrete categories descriptive and generative. ML and DL techniques typically are descriptive while generative AI methods and algorithms are used to generate new data or content which resembles, and often extends beyond, the original training data (Matakanye and van der Poll 2021; H. Wang 2024). Unlike traditional AI methods with a focus on recognizing patterns in data or making predictions based on existing data, generative AI can create entirely new data instances for explicitly unseen scenarios.

There are several methods for generative AI like Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), autoregressive models, and transformer models including OpenAI's Generative Pre-trained Transformer (GPT) series Generative Adversarial Networks (Chen et al. 2024; X Li et al. 2021). Generative AI has a wide range of applications for GeoAI. Large Language Models (LLMs) overlap with generative AI models and are designed to understand and generate human-like text. These models are built upon deep learning architectures, particularly transformer architectures, and are trained on vast amounts of text data (Wei, Gao, and Zhang 2023). Some of the key characteristics and features of large language models include scale, transformer architecture, pre-training and fine-tuning, generative and predictive capabilities, contextual understanding, and versatility. Examples of large language models comprise Generative Pre-trained Transformer (GPT) models developed by OpenAI, Bidirectional Encoder Representations from Transformers (BERT) developed by Google, and T5 (Text-To-Text Transfer Transformer) developed by Google Brain (Bosco, Wang, and Hategekimana 2021; Hastings et al. 2020). There are a few examples in the geospatial industry today where GeoAI professionals are starting to take advantage of GenAI and LLMs to address geospatial applications. These models have the potential to completely transform national mapping workflows in the future (H. Lee and Li 2024; Scorza, Corrado, and Muzzillo 2024).

3.2 AI/ML workflows

The first step in a typical AI/ML workflow includes data preparation which consumes a large volume of resources and time. Data preparation includes the creation of labels for training, testing and validation of the model performance. Labels for features of interest include image tiles with fixed dimensions (e.g. 64x64 pixels, 128x128 pixels, …) and involve drawing bounding boxes and/or polygons around features of interest. In many machine learning tasks, fixed image sizes for label images are not strictly required but they can be beneficial depending on the specific requirements of the model and the nature of the task. Convolutional Neural Networks (CNNs) commonly used for tasks like image classification, object detection and segmentation, typically require fixed-size input images (Guard and Budihal 2022; Song et al. 2021). This is because the convolutional layers in CNNs have fixed-size filters that slide over the input image, and the size of the output feature maps depends on the size of the input image (Guard and Budihal 2022; Yan Xie et al. 2019; Zhu, He, and He 2019). Therefore, using fixed-size images ensures consistency in the input size across different samples and allows for efficient processing in the network. In data preprocessing, even if the model does not strictly require fixed-size images, it's often beneficial to preprocess your data to have fixed-size inputs (Kogilavani et al. 2022; Komathy 2022; T. Sun et al. 2021). Resizing images to a common size can simplify data preprocessing and model training pipelines. Moreover, it can improve computational efficiency and memory usage during training. Some models, such as certain types of recurrent neural networks (RNNs) or attention-based models, can handle variable-length inputs more naturally (Manasa, Shukla, and Saranya 2021; Motwake et al. 2024; Shoaei et al. 2024). The choice of model architecture may also influence whether fixed image sizes are required. Some architectures, such as fully connected networks, may require fixed-size inputs, while others, like convolutional and recurrent networks, can handle variable-size inputs more flexibly (Motwake et al. 2024; Pandey and Janghel 2019; S. Sharma et al. 2020). There are several commercial companies and open-source tools that offer labelling technologies that can be leveraged by national agencies. There are ongoing efforts at global standards organizations such as the Open Geospatial Consortium (OGC) to establish standards for labelling. The bounding boxes or polygons are saved in predefined formats and directories, depending on the AI/ML model used for analysis (V. K. Sharma et al. 2017; Truong et al. 2017; Walker Johnson et al. 2011).

Table 5 – Free label sources for EO and SAR imagery

Label Sources
SSDD (EO and SAR ship detection)
SSDD+
SAR SHIP Dataset
AIR-SARShip-1.0/2.0 Dataset
HRSID
LS-SSDD-V1.0
Official SSDD
SRSD-V 1.0
RSDD-SAR
iVision MRSSD
xView3

Synthetic label generation has been employed in GeoAI to simulate various geographic backgrounds, varying atmospheric conditions, varying spatial resolution and other image artefacts (Iabchoon, Wongsai, and Chankon 2017; Loukanov et al. 2020). Synthetic label generation practices leveraging CAD models of objects of interest and insert them into imagery with varying backgrounds. Synthetic data labels could be of interest to national agencies for specific objects/features that might not have enough real-world geospatial data labels. There are several open sources for labels for EO and SAR imagery datasets (Table 5) for national mapping agencies to get started with GeoAI applications (Jian et al. 2020; Nasarian et al. 2020; Pereira et al. 2018).

There are evolving new developments in the AI/ML industry that are driving towards reducing manual labelling efforts (Dinesh and Rahul Prasad 2024; Waqar 2024). Zero-shot training and Segment Me Anything (SAM) are some of the examples of these developments that will help national agencies in their mapping efforts. There is also research being conducted to extend the LLMs to recognize various types of semantic objects in an image with techniques such as Vision Language Models (VLMs) that eventually minimize the need for large-label dataset creation.

Once the labels are created, the next step in AI/ML workflow is to create a subset of the labels into 3 categories i.e. 1. Training 2. Testing and 3. Validating the models. The next step includes selecting and running an AI/ML of choice (discussed in the next section) and validating the results. The training, testing and validation of the model are reiterated by modifying various parameters (e.g. epochs, label editing, etc.) and post-processing steps (e.g. lower probability objects) until the desired accuracy of object/feature detection is achieved. The final version of the models can be deployed to support real-time operations by the national mapping agencies. Reinforcement techniques are another technique that involves continuous training and validation of the models by using the new datasets to account for varying imaging artefacts.

3.3 AI/ML approaches for image characterization

AI/ML models for image characterization fall into 5 categories: a) Image Classification, b) Object Detection, c) Oriented Bounding Box Detection, d) Semantic Segmentation and e) Pose Detection. Image classification models are designed to identify image tiles with one or more features of interest such as image tiles with agricultural fields (J. Liu et al. 2014; Oliphant et al. 2019). Image classification techniques are also ideal for area reduction for broad area search missions as well as for change detection (Anupama et al. 2021; Stibig et al. 2014; K. Wang et al. 2010). Object detection is the most common application in GeoAI and is used to identify objects such as buildings, cars, ships, planes, etc. in images (H. Lee and Li 2024; Petrocchi et al. 2024; Swietek 2024). Objects in the image tile are identified by bounding boxes and each bounding box is associated with a confidence of prediction for one or more labels/ classes. Oriented Bounding Box object detection is an improvement over object detection where the bounding boxes are oriented in the direction of the object of interest (Peng et al. 2021; Q Zhang et al. 2016). This technique leverages the Segment Me Anything (SAM) model to determine the size and direction of the objects of interest. Image Segmentation identifies the outlines of various objects in an image and is useful for various GeoAI applications including extraction of building footprints, agricultural field boundaries, flood extent, and others. Pose detection in the field of AI/ML involves estimating the pose (object position and orientation) of an object from an image or video (Nadian-Ghomsheh, Farahani, and Kavian 2021; Zaman et al. 2023). It aims to identify the spatial locations of key object joints (also known as key points). The relative positions of these key points can be used to distinguish one pose from another. GeoAI can leverage pose detection for object tracking missions such as MTI (Moving Target Indicator) of objects in 2D and 3D space and could be an area of interest to national mapping agencies in the future.

3.4 AI/ML techniques

Like the remote sensing image classification techniques, AI/ML techniques follow two approaches for image classification including supervised and unsupervised. Supervised classification approaches require priority training datasets that the GeoAI models leverage to characterize objects/features in an image (Chugh, Kumar, and Singh 2021; Seh et al. 2021). Unsupervised classification is gaining ground for object detection, outside the GeoAI field, and does not need any training datasets for image classification (Jian et al. 2020; Oetter et al. 2001; Praticò, Di Fazio, and Modica 2021). A combination of open-source labelling datasets such as Microsoft Common Objects in Context (Microsoft COCO), large-scale object detection, segmentation, key-point detection, and captioning datasets and the emergence of LLM for semantic correlation are driving the use of unsupervised classification approaches (Gallwey et al. 2019; Hao Li et al. 2023; Potnis et al. 2023). We will focus on supervised AI/ML model training which is commonly used in GeoAI.

There are two approaches in supervised AI/ML classification. Each approach has its strengths and weaknesses. An example of two-stage detection is You Only Look Once (YOLO) where a pre-trained model with pre-assigned weights can be adjusted to predict objects of interest in new images (Praticò, Di Fazio, and Modica 2021; Yeiser et al. 2020). Two-stage detectors are the most used technique in GeoAI. A Single Shot Detector (SSD) is a single-stage detector where a pre-trained model for image classification is used as the backbone network. The model can be tweaked for a specific detection task. One key distinction between YOLO and SSD is that the SSD model attempts to directly predict the probability of a class present in each bounding box whereas the YOLO model predicts the probability of multiple potential label classes (Berganzo-Besga et al. 2021; Deng, Lu, and Xu 2024). Another method for AI/ML classification is anchor-free object detection which has gained attention due to its speed and generalizability. Anchor-free methods directly predict object locations without predefined anchors/ boxes. Instead of bounding boxes predict points or key points associated with objects. They are more generalizable and can extend to tasks like key-point detection and 3D object detection (Hake et al. 2023; Ma et al. 2022). Anchor-free object detection offers advantages in terms of simplicity, generalizability and speed, making it a promising approach for improving small-size object detection models. Object training from scratch is another approach suitable for GeoAI for features that are not commonly used in pre-trained models. There are several tools available for this approach. National agencies may start with two-stage models such as YOLO and keep track of new trends that can improve GeoAI workflows in the future (Petrocchi et al. 2024; Wei, Gao, and Zhang 2023).

3.5 AI/ML frameworks

Frameworks are the backbone of AI/ML models. With the advancements in the field of AI/ML, its complexity grows, emphasizing the significance of frameworks in simplifying its processes. Conventionally, successful technologies have leveraged frameworks for efficient development (Martín et al. 2022; Swain et al. 2022). Acquiring proficiency in AI/ML frameworks not only saves time but also optimizes the development process. Some of the common frameworks used in the industry today include:

1. TensorFlow: TensorFlow is a free end-to-end open-source platform that has a wide variety of tools, libraries and resources for AI/ML. It was developed by the Google Brain team and initially released on November 9, 2015. You can easily build and train machine learning models with high-level APIs such as Keras using TensorFlow. It also provides multiple levels of abstraction so you can choose the option you need for your model (Xin Li and Su 2024; Martín et al. 2022).

2. CAFFE, Convolutional Architecture for Fast Feature Embedding, was originally developed at the Berkeley Vision and Learning Center at the University of California and released on 18 April 2017 (Guignard, Amato, and Kanevski 2021; K. 2022; Mani et al. 2020). It is a deep learning framework written in C++ that has an expression architecture that easily allows you to switch between the CPU and GPU. Caffe also has a MATLAB and Python interface. Caffe is the perfect framework for image classification and segmentation as it supports various GPU and CPU-based libraries such as NVIDIA, cuDNN, Intel MKL, etc (Capasso, Lauria, and Veneri 2018; She, Dong, and Liu 2022). Caffe can currently process over 60M images in a day with a single NVIDIA K40 GPU which makes it one of the fastest options today. Because of all these reasons, CAFEE is extremely popular in startups, academic research projects and even multinational industrial applications in the domains of computer vision, speech and multimedia (Aswani and Menaka 2021; Bathla, Aggarwal, and Rani 2019; Hijazi, Faris, and Aljarah 2021; S. Zhao et al. 2022).

3. Apache Spark: Apache Spark is an open-source cluster-computing framework that can provide programming interfaces for entire clusters. It was developed at Berkeley's AMPLab at the University of California and initially released on May 26, 2014. Spark Core is the foundation of Apache Spark which is centred on RDD abstraction (Campana and Delmastro 2021; Sarumi and Leung 2022; Sujitha and Seenivasagam 2021; Thirumal, Thangakumar, and Venkata Subramanian 2019).

4. PyTorch: PyTorch is a machine-learning library that is based on the earlier open-source Torch library. It was initially released in October 2016 and is in primary use now that Torch is not actively in development anymore (Laaber, Basmaci, and Salza 2021; Schoonderwoerd et al. 2021; Tamiminia et al. 2020). PyTorch provides TorchScript, which facilitates a seamless transition between the eager mode and graph mode. Moreover, the PyTorch distributed backend provides scalable distributed training for machine learning and optimized performance (D Liu et al. 2021; Sato et al. 2021).

5. Amazon SageMaker: Amazon SageMaker is a fully integrated development environment (IDE) for machine learning that was initially released on 29 November 2017. Amazon Web Services provides this machine learning service for applications such as computer vision, recommendations, image and video analysis, forecasting, text analytics, etc. Amazon SageMaker allows you to build, train and deploy machine learning models on the cloud (Ball, Anderson, and Chan 2018; Gaigg et al. 2020; Perez et al. 2022). Amazon SageMaker Autopilot also has an automated machine-learning capability that allows you to do all this automatically. Amazon SageMaker also allows you to create machine learning algorithms from scratch because of its connections to TensorFlow and Apache MXNet (Gao et al. 2021; Kozak et al. 2021; Surianarayanan and Chelliah 2021).

6. Accord.NET: Accord.NET is a machine learning framework that is completely written in C#. It was developed by César Roberto de Souza and was initially released on May 20, 2010. Accord.NET provides coverage on various topics like statistics, machine learning and artificial neural networks with various machine learning algorithms, like classification, regression, clustering etc. along with audio and image processing libraries (Bassuk et al. 2015; Kumar 2020). Accord.NET libraries are available as source code, executable installers, as well as NuGet packages (wherein NuGet is a free and open-source package manager that was created for the Microsoft development platform) (Bassuk et al. 2015; Huang, Mendis, and Xu 2019; Manos et al. 2023).

7. Microsoft Cognitive Toolkit: Microsoft Cognitive Toolkit is a machine learning or specifically, deep learning framework that was developed by Microsoft Research and initially released on 25 January 2016 (Bhalodia et al. 2021; G. Yang, Huang, and Zhao 2020). You can easily develop popular deep learning models such as feed-forward DNNs, convolutional neural networks and recurrent neural networks using the Microsoft Cognitive Toolkit. This toolkit uses multiple GPUs and servers providing parallelization across the backend. You can use the Microsoft Cognitive Toolkit in a customizable manner as per your requirements with your metrics, networks, and algorithms (Bai, Mas, and Koshimura 2018). You can use it as a library in your Python, C++, or C# programs or you can use BrainScript, its model description language.

Machine learning is a rapidly evolving field that has seen a significant surge in adoption by companies seeking to revolutionize industries (Bassuk et al. 2015; J. Kim and Song 2021; F. Zhao et al. 2021). As this technology progresses, the need for frameworks becomes increasingly important to simplify processes and ensure efficient development. These frameworks provide the necessary resources to create advanced machine-learning models tailored to specific requirements.

3.6 AI/ML models

AI/ML models use a mathematical formula to make predictions about future events. They are trained on a set of data and then used to make predictions about new data. Some common examples of ML models include regression models and classification models. A deep learning model, or a DL model, is a neural network that has been trained to learn how to perform a task, such as recognizing objects in digital images and videos or understanding human speech. Deep learning models are trained by using large sets of data and algorithms that enable the model to learn how to perform the task. The more data the model is trained on, the better it can learn to perform the task. DL models are composed of multiple layers of neurons or processing nodes. The deeper the model, the more layers of neurons it contains (Ansari and Akhoondzadeh 2020; McNorton et al. 2021). This allows the model to learn more complex tasks by breaking them down into smaller and smaller pieces. For example, ResNet is a deep learning model for computer vision tasks such as image recognition. It is one of the deepest models currently available, with a version that contains 152 layers (ResNet-152). Visual Geometry Group (VGG) deep convolutional neural network architecture YOLO, or "You Only Look Once," is a deep learning model for real-time object detection (Bassuk et al. 2015; Fan et al. 2021; Gallwey et al. 2019; J. S. H. Lee et al. 2016). Surpassing YOLOv4 and YOLOR, the latest versions, YOLOv7 and YOLOv8, are super-fast and very accurate, the current state of the art for several AI vision tasks. Some of the most popular open-source AI models include You Only Look Once (YOLO), Segment Me Anything (SAM), Regional-Convolution Neural Networks (R-CNN), and others (Bassuk et al. 2015; Smerdu, Kanjir, and Kokalj 2020).

AI/ML models are typically optimized for speed vs accuracy. An example of various model sizes available for YOLOV810 range from nano (YOLOv8n) to extra-large (YOLOv8x) with nano being the fastest and smallest, while extra-large is the most accurate yet the slowest among them (Berganzo-Besga et al. 2021; Ou et al. 2019; dos Santos et al. 2019). In addition, YOLO model iterations are managed by epochs. By trial and error and associated model performance statistics for the best and last epochs, analysts can identify the right number of epochs to be used to extract objects of interest. While most of the national mapping efforts need accuracy and can leverage extra-large size models, situations such as disaster management can leverage small models for faster response. Python is a commonly used programming language for running AI/ML models with several open-source tutorials on how to run the models with custom datasets of interest to national mapping agencies and several open-source tools are available for analysts to test different model sizes for GeoAI (Canty et al. 2020; Reichert et al. 2017; Yiqun Xie et al. 2023).

Post-processing is one of the last steps in analyzing an AI/ML model performance that can improve the object detection accuracy. Some of the commonly used post-processing steps include filtering the model results by size (absolute vs relative size to image tile), intersection and unions of various bounding boxes identifying objects of interest, confidence threshold of various labels, and others. The last few years have seen increasing adoption of AI/ML in the geospatial industry and there are examples of using AI/ML object/feature extraction at national/global scales. The following examples show the use of GeoAI for geospatial applications.

3.7 GeoAI composition

Combining generative AI with spatial reasoning and analysis techniques is the new frontier for automating authoritative and trustworthy spatial queries. Knowledge-based AI techniques have been around in geospatial sciences for decades while machine learning techniques and LLMs identify patterns from data, knowledge-based techniques rely on automated reasoning with symbolic representations of data. GeoAI orchestration combines multiple AI and analytical tools into workflows. Knowledge-based reasoners and authoritative data repositories are used to generate reliable and trustworthy responses to questions. AI "orchestration" is emerging as a foundational approach to combining the exceptional text-extruding capabilities of LLMs with reliable knowledge-based spatial reasoning and analysis.

3.8 Applications in national maps beyond traditional mapping

Several of the datasets, such as imagery, elevation models, GCPs, transportation networks and others, can be used for multiple missions within national agencies ranging from agriculture, census, transportation, environment, natural resources management, coastal management, disaster response, and others. Countries such as the USA have created federal geospatial programs such as the 3D Elevation Program (3DEP), National Agriculture Imagery Program (NAIP), US Census TIGER Road Network, and others that are leveraged by a combination of agencies across state/local/federal, as well as by military agencies. Some of the agencies in the USA were able to save hundreds of millions of dollars by leveraging the national geospatial programs. Table 6 shows various national missions and data requirements that can be leveraged for a unified nationwide geospatial program.

Table 6 – Various national missions and data requirements for EO and SAR imagery

Mission	Data	GeoAI application	Requirements
Census	EO Imagery	Building footprints, change detection	Blds: EO - RGB - 50 cm Change: 2 m-5 m MS
Agriculture	EO Imagery	Field Boundaries, Crop Type, Change Detection	Field Boundaries: EO RGB 50 cm Crop Type: EO Imagery, MS, 50 cm Change Detection: EO Imagery MS 2 m-5 m
Forestry	EO Imagery, DEM	Tree Identification, Tree Height/width, De/ Reforestation	Deforestation: EO MS 2-5 m Tree Height: DEM, 50 cm postings Change Detection: EO Imagery MS 2 m-5 m
Cadastre	EO Imagery, GCPs	Agriculture Parcels, Urban Parcels, Change Detection	Ag Parcels: EO RGB 50 cm; GCP's <1 meter accuracy. Urban Parcels: EO RGB 5-15 cm. GCP's: 5 cm accuracy Change Detection: EO 1-2 meters
Disaster Planning/ Response	EO/SAR Imagery, DEM	Flood plain mapping, Damage assessment	Flood plain: DTM, 1 m postings Disaster: EO Imagery, SAR Imagery, 50 cm
Water Resources Management	EO Imagery, DEMs	Watershed Modeling	EO Imagery: MS 1-5 meters DTM: 1-2 meters
Mineral Resources	EO Imagery, DEM	Mineral Deposits, Mining	Mineral: EO Imagery; HS: 1-2 meters Mining: DSM's <1 m
Atmospheric Monitoring	EO Imagery	Methane, Particulate Matter	EO Imagery: MS or HS: 5-50 meters
Coastal Monitoring	EO Imagery	Coastlines, Bathymetry	Coastlines: EO RGB <1 meter Bathymetry: EO MS, <1 meter
Transportation	EO Imagery, DEM	Road/Rail Mapping, Road furniture for Autonomous Vehicles	Road Rail: EO Imagery: <=50 cm Autonomous: EO Imagery <=15 cm; StreetViews: 3D <=30 cm
Telecommunications	EO Imagery, 3D	Cell tower detection	EO Imagery: MS <50 cm 3D: <= 30cm
Oil & Gas	EO Imagery, DEM	Detect roads, infrastructure	EO Imagery: MS: <50 cm DTM: <=50 cm

4. RECENT TRENDS WITH CASES

Recent trends in geospatial AI for Earth observation comprise the use of AI/ML for precision agriculture, climate change monitoring and disaster management. Table 7 explains the worldwide adoption of Artificial Intelligence (AI) by 2022 across various industries and functions. It reports that human resources, manufacturing including marketing and sales significantly adopted AI.

Cases like AI-driven deforestation tracking in the Amazon and ML-based urban growth prediction showcase how these technologies are advancing the Sustainable Development Goals by providing actionable insights for environmental and resource management. Some of these are listed below:

Table 7 – Worldwide adoption of Artificial intelligence (AI) by 2022 (with industry and function)

Characteristic	Human resources	Manufacturing	Marketing & Sales	Product/service development	Risk
All industries	11%	8%	5%	10%	19 %
Business, legal, and professional services	11%	10%	9%	8%	16 %
Consumer goods/retail	14%	4%	3%	4%	15 %
Financial services	1%	8%	7%	31%	17 %
Healthcare/Pharma	15%	7%	2%	4%	22 %
High-tech/telecom	6%	6%	4%	7%	38 %

Source: http://www.statista.com/statistics/1112982/ai-adoption-worldwide-industry-function/

a) Climate change monitoring

Satellite data is extensively used to monitor climate change impacts. Several space agencies utilize satellites like RADARSAT to observe ice cover, forest changes and climate patterns. Integrating satellite data with ground-based observations helps in tracking temperature changes, the rise in sea levels and permafrost thawing.

b) Biodiversity and ecosystem health

The forest service and other agencies use remote sensing to monitor forest health and biodiversity. This includes tracking deforestation rates and habitat changes. Data on wetland changes and health is gathered through satellites, which is crucial for conservation efforts.

c) Land cover classification

AI-driven image classification techniques process satellite imagery to classify land cover types and monitor changes over time. This helps in land use planning and environmental management. Machine learning algorithms detect changes in land cover and vegetation, which is useful for tracking deforestation and urban expansion.

d) Disaster management

Several nations frequently experience natural disasters like hurricanes and earthquakes. Remote sensing data helps in disaster preparedness and response, including monitoring flood risks and earthquake impacts. Satellite imagery and data are used to assess damage and coordinate emergency response efforts in disaster-stricken areas. Machine learning models analyse weather forecasts, satellite imagery and historical flood data to predict and manage flood risks. AI algorithms assess damage from natural disasters by analysing satellite and aerial imagery, aiding in quick and accurate responses.

e) Urbanization and land use

Remote sensing data tracks urban expansion and land use changes in rapidly growing cities. This helps in planning and managing urban development. Satellite data supports agricultural monitoring, including crop health and land use efficiency. AI techniques classify and monitor land use patterns, helping in sustainable urban planning and managing urban sprawl. AI-driven analysis of geospatial data helps in optimizing traffic flow and reducing congestion in major cities.

f) Agricultural optimization

Machine learning models analyse satellite data to monitor crop health and predict yields, which supports precision agriculture and improves food security to help optimize the use of resources such as water and fertilizers by analysing soil and crop data.

g) AI/ML approaches - predictive modelling

Machine learning models predict climate impact, including extreme weather events and ecosystem changes. These models analyse historical climate data and current trends to forecast future scenarios. AI algorithms predict forest fire risks by analysing satellite imagery, weather data and historical fire patterns.

h) Data integration and visualization

AI tools integrate diverse datasets (e.g., satellite imagery and ground data) into geospatial platforms to allow for more comprehensive analysis. Visualization tools help in presenting complex data in an accessible format. It leverages geospatial AI and machine learning to address a range of environmental and developmental challenges. Their efforts align with various Sustainable Development Goals by utilizing recent data trends and advanced technologies to monitor climate change, manage natural resources and enhance disaster response. The integration of AI/ML with Earth observation data enhances the ability to make informed decisions and take timely actions towards achieving sustainability.

i) Sustainable Development Goals (SDGs)

Monitoring and forecasting climate impact (SDG 13-Climate Action) contribute to understanding and mitigating climate change. Tracking forest health, biodiversity and land use supports sustainable land management and conservation efforts (SDG 15-Life on Land). Urban planning and disaster management efforts contribute to more resilient and sustainable cities (SDG 11 Sustainable Cities and Communities). Monitoring agricultural productivity and optimizing resource use supports food security and sustainable agriculture (SDG 2-Zero Hunger).

5. CHALLENGES AND LIMITATIONS

The integration of recent data trends and AI/ML approaches in geospatial AI for Earth observation brings significant advancements towards achieving the Sustainable Development Goals (SDGs). The need for robust validation processes for critical considerations is crucial for ensuring the reliability, accuracy and relevance of AI/ML approaches in geospatial analysis, particularly in Earth observation for Sustainable Development Goals (SDGs). AI models should be validated to ensure that their use in decision-making, especially regarding environmental justice and conservation, is ethical and equitable. Poorly validated models could lead to unintended consequences, such as misallocation of resources or displacement of communities. Validation processes enhance trust among stakeholders (governments, NGOs, local communities) who rely on geospatial AI for policy and decision-making in the pursuit of SDGs. Rigorous validation ensures that the data and insights provided are trusted and respected. Nevertheless, these technologies also face several challenges and limitations and some key issues include:

5.1 Data quality and availability

a) Resolution and accuracy

High-resolution satellite data is often expensive and not always available for all regions. Lower-resolution data might not provide the detail needed for precise analysis. Limited resolution can affect the accuracy of models used for monitoring and managing resources, impacting decision-making processes.

b) Data gaps

Incomplete or inconsistent data coverage in some regions, especially in developing countries or remote areas, can hinder comprehensive analysis. Data gaps can lead to biased or incomplete insights, affecting the effectiveness of interventions and policy decisions.

5.2 Computational and technical constraints

a) Processing power

AI and ML models dealing with large-scale geospatial data require substantial computational resources. This can be a barrier for organizations with limited access to high-performance computing. Inadequate processing power can slow down data analysis and model development, delaying critical insights and actions.

b) Algorithm complexity

Developing and fine-tuning complex algorithms for geospatial data can be resource-intensive and requires expertise in both AI and geospatial sciences. The complexity of algorithms may limit their applicability and scalability, especially in regions with fewer technical resources.

5.3 Integration and interoperability

a) Data integration

Combining data from different sources (e.g., satellite imagery, ground-based observations, historical data) can be challenging due to differences in formats, scales and resolutions. Ineffective integration can result in incomplete or inaccurate analyses, reducing the reliability of the insights generated.

b) System interoperability

Different organizations and systems may use varying standards and protocols for geospatial data, complicating collaboration and data sharing. Lack of interoperability can hinder the seamless exchange of information and collaborative efforts, impacting the overall effectiveness of projects.

5.4 Ethical and privacy concerns

a) Data privacy

Geospatial data can sometimes reveal sensitive information about individuals or communities, raising privacy concerns. Ensuring data privacy and adhering to ethical standards is crucial to maintaining public trust and avoiding misuse of information.

b) Bias and fairness

AI models can inherit biases present in training data, leading to unfair or skewed outcomes. Biases in models can perpetuate inequalities and affect the fairness of interventions, especially in marginalized communities.

5.5 Cost and accessibility

a) High costs

The cost of acquiring high-quality satellite imagery and maintaining advanced AI infrastructure can be prohibitive for many organizations, particularly in developing countries. High costs can limit access to essential data and tools, affecting the ability to leverage geospatial AI for sustainable development.

b) Limited access

Access to advanced geospatial AI tools and expertise can be limited in certain regions, hindering their effective use. Limited access can reduce the ability to implement and benefit from AI-driven solutions, affecting overall development outcomes.

5.6 Data interpretation and usability

a) Complexity of interpretation

Interpreting complex AI-generated insights requires specialized knowledge and skills, which may not be readily available in all regions. Difficulty in interpreting results can limit the actionable value of the data and reduce the effectiveness of decision-making processes.

b) Decision-making support

AI tools and models must be designed to provide clear, actionable insights rather than overwhelming users with complex data. Inadequate support for decision-making can undermine the practical utility of AI solutions, impacting their successful implementation.

5.7 Sustainability and long-term viability

a) Maintenance and updates

AI models and geospatial tools require regular maintenance and updates to remain effective and accurate. Lack of ongoing support and updates can lead to obsolescence, reducing the long-term viability of AI solutions.

b) Scalability

Scaling AI solutions to cover larger areas or additional applications can be technically challenging and resource-intensive. Challenges in scaling can limit the widespread adoption and impact of AI-driven geospatial tools.

While recent trends in data and advancements in AI/ML approaches for geospatial AI offer significant potential for advancing the Sustainable Development Goals, addressing these challenges is crucial for realizing their full benefits. Overcoming these limitations involves improving data quality and availability, enhancing computational resources, ensuring ethical standards and fostering collaboration and accessibility. The stakeholders can better leverage geospatial AI to address critical global challenges and support sustainable development effectively.

6. FUTURE DIRECTIONS

The future of trends in recent data and AI/ML approaches for geospatial AI in Earth observation is poised to significantly enhance efforts toward achieving the Sustainable Development Goals (SDGs). Here’s a look at some promising future directions and trends in this field.

6.1 Enhanced data integration and fusion

a) Multi-source data fusion

Integrating data from diverse sources, including satellites, drones, ground sensors and crowdsourced data, will become more sophisticated. Advanced fusion techniques will combine these datasets to provide more comprehensive and accurate insights. Improved integration will enhance the accuracy and completeness of geospatial analyses, supporting better decision-making and more effective management of resources.

b) Real-time data processing

With advancements in streaming technologies and edge computing, real-time processing of geospatial data will become more feasible. This will allow for immediate analysis and response to dynamic changes. Real-time data will enable quicker responses to environmental changes, disasters and other urgent situations, improving overall resilience and adaptability.

6.2 Advances in AI and machine learning techniques

a) Deep learning innovations

Continued advancements in deep learning, including the development of more sophisticated neural networks and algorithms, will enhance the ability to extract features, detect anomalies and classify land cover from satellite imagery. These innovations will lead to more precise and nuanced analyses, improving the monitoring of environmental changes, urban growth and resource management.

b) Explainable AI (XAI)

The development of explainable AI will make complex AI models more transparent and interpretable. This is crucial for understanding model predictions and gaining the trust of stakeholders. Explainable AI will facilitate better decision-making by providing clear insights into how predictions are made, supporting more informed and accountable actions.

6.3 Improved accessibility and inclusivity

a) Democratization of tools

Efforts will focus on making geospatial AI tools and data more accessible to a broader audience, including smaller organizations and developing countries. This includes open-source platforms and affordable data solutions. Increased accessibility will enable a wider range of stakeholders to utilize geospatial AI for sustainable development, fostering inclusive and collaborative efforts.

b) Capacity building

Training and capacity-building programs will be expanded to equip individuals and organizations with the skills needed to effectively leverage geospatial AI. This includes educational initiatives and technical support. Enhanced skills and knowledge will empower more communities to apply geospatial AI to local challenges, contributing to more effective and sustainable development outcomes.

6.4 Integration with emerging technologies

a) Internet of Things (IoT)

Integrating geospatial AI with IoT devices will enable continuous monitoring and real-time data collection from various sensors and devices embedded in the environment. This integration will provide more granular and timely data, enhancing monitoring capabilities and supporting proactive management of resources and infrastructure.

b) Blockchain for data integrity

Blockchain technology will be explored to ensure data integrity and security in geospatial data management. Blockchain can provide a transparent and tamper-proof record of data collection and processing. Improved data security and transparency will enhance trust in geospatial data, supporting more reliable and accountable decision-making.

6.5 Focus on specific sustainable development goals

a) Climate change mitigation and adaptation

Geospatial AI may play a crucial role in monitoring and mitigating climate change impact, including tracking greenhouse gas emissions, deforestation and land-use changes. Enhanced modelling will predict climate impact and support adaptation strategies. More accurate climate data and predictive models will inform policies and actions to mitigate and adapt to climate change, supporting SDG 13 (Climate Action).

b) Biodiversity and conservation

AI-driven approaches will improve the monitoring of biodiversity, wildlife habitats and conservation efforts. Enhanced species detection and habitat mapping will support biodiversity conservation strategies. Improved biodiversity monitoring will aid in the protection of ecosystems and species, contributing to SDG 15 (Life on Land).

c) Urban development and sustainability

Geospatial AI will assist in sustainable urban planning by providing insights into land use, infrastructure development and urban sprawl. Advanced analytics will support smart city initiatives and sustainable urban growth. Better urban planning and management will promote sustainable cities and communities, aligning with SDG 11 (Sustainable Cities and Communities).

6.6 Ethical and regulatory considerations

a) Ethical AI practices

There will be an increased focus on developing ethical guidelines and standards for the use of AI in geospatial applications. This includes addressing biases, ensuring privacy and promoting transparency. Ethical practices will ensure that AI applications are used responsibly, reducing potential negative impacts and fostering trust among users and stakeholders.

b) Regulatory frameworks

The development of regulatory frameworks to govern the use of geospatial data and AI technologies will become more critical. These frameworks will address data privacy, security and usage rights. Clear regulations will support the responsible use of geospatial AI, ensuring compliance with legal and ethical standards and protecting individuals' rights.

The future of geospatial AI in Earth observation holds tremendous potential for advancing the Sustainable Development Goals (SDGs). With the emphasis on enhanced data integration, advances in AI techniques, improved accessibility, integration with emerging technologies and ethical considerations, stakeholders can harness the power of geospatial AI to address global challenges effectively. Innovation and collaboration will be key to maximizing the benefits and achieving sustainable development outcomes.

7. CONCLUSION

The integration of data, Artificial Intelligence (AI) and Machine Learning (ML) approaches in geospatial AI for Earth observation represents a significant leap toward achieving the Sustainable Development Goals (SDGs). Recent trends indicate a growing sophistication in the use of AI/ML techniques to analyse and interpret vast amounts of geospatial data. These advancements are enabling more precise and timely insights into environmental changes, resource management and societal impacts, directly contributing to sustainable development efforts. The key theme for this work focuses on "AI/ML Approaches+Geospatial AI+ Earth Observation+Sustainable Development Goals". One notable trend is the increasing accessibility and democratization of geospatial data, which is being driven by open data initiatives and advancements in cloud computing. This has empowered a broader range of stakeholders, from governments to NGOs, to harness AI/ML tools for environmental monitoring and decision-making. Moreover, the development of more robust and scalable AI models has enhanced the accuracy of predictions in critical areas such as climate change, urbanization and disaster management. However, challenges remain, including the need for better data quality, integration of diverse data sources and addressing ethical concerns related to AI usage. As these technologies continue to evolve, fostering interdisciplinary collaborations and ensuring the inclusion of local knowledge and expertise will be crucial. The synergy between AI/ML and geospatial data in Earth observation is increasingly pivotal in driving progress toward the SDGs. By leveraging these technological advancements, we can enhance our ability to monitor, predict and respond to global challenges, ultimately fostering a more sustainable and resilient future.

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