remote sensing

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Review

Remote Sensing and GIS in Natural Resource Management: Comparing Tools and Emphasizing the Importance of In-Situ Data

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Abstract: Remote sensing (RS) and Geographic Information Systems (GISs) provide significant opportunities for monitoring and managing natural resources across various temporal, spectral, and spatial resolutions. There is a critical need for natural resource managers to understand the expanding capabilities of image sources, analysis techniques, and in situ validation methods. This article reviews key image analysis tools in natural resource management, highlighting their unique strengths across diverse applications such as agriculture, forestry, water resources, soil management, and natural hazard monitoring. Google Earth Engine (GEE), a cloud-based platform introduced in 2010, stands out for its vast geospatial data catalog and scalability, making it ideal for global-scale analysis and algorithm development. ENVI, known for advanced multi- and hyperspectral image processing, excels in vegetation monitoring, environmental analysis, and feature extraction. ERDAS IMAGINE specializes in radar data analysis and LiDAR processing, offering robust classification and terrain analysis capabilities. Global Mapper is recognized for its versatility, supporting over 300 data formats and excelling in 3D visualization and point cloud processing, especially in UAV applications. eCognition leverages object-based image analysis (OBIA) to enhance classification accuracy by grouping pixels into meaningful objects, making it effective in environmental monitoring and urban planning. Lastly, QGIS integrates these remote sensing tools with powerful spatial analysis functions, supporting decision-making in sustainable resource management. Together, these tools when paired with in situ data provide comprehensive solutions for managing and analyzing natural resources across scales.

Keywords: remote sensing; artificial intelligence; neural network; machine learning; in situ validation

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1. Introduction

The field of Smart Technology is a rapidly evolving amalgamation of hot topic technologies, including big data, cloud computing, remote sensing (RS), machine learning (ML), artificial intelligence (AI), the Internet of Things, and low-cost sensors, all of which are currently being used in some capacity to enhance agricultural and forest management across

the world [1,2]. However, the pace of advancement has often created disparities between the application of these technologies and the accessibility of the data products by end users, especially the broader public outside the scientific community [3]. While increased access to on-farm, in-forest, and in-city data products has the potential to revolutionize agriculture and forestry, understanding the current state of RS, image processing tools, the role of AI, and the value of in situ validation data will be critical to successful application of Smart Technology [4].

At the core of contemporary natural resource management is the Geographic Information System (GIS), a powerful tool that facilitates the integration and spatial analysis of various datasets. The GIS is a computer-based system designed to handle georeferenced data, including graphic and attribute data, as well as input from the Global Positioning System (GPS), plotters, network connections, CD-ROM drives, printers, and other software. This system proves invaluable for information analysis, automated mapping, and data integration, offering user-friendly access to extensive data. The GIS enables natural resource managers to interactively analyze large datasets and present results in formats that are directly relevant and useful for decision-making processes.

The layering capabilities of the GIS allows for multiple types of data to occupy the same geographic space. Integrated layers, such as remotely sensed imagery and georeferenced datasets, can then be analyzed to identify spatial relationships. A key objective of the GIS is to assist decision-making processes for the management of natural resources. In the past decade, RS has rapidly developed alongside the GIS, offering abundant information, faster processing times, increased availability, and a wide variety of product types, making it an indispensable tool for researchers across multiple disciplines [5]. Currently, land use and land cover (LULC) information obtained through RS technology have become crucial data products in natural resource management [6]. Accurate analysis and interpretation of RS images are vital for the sustainable management of natural resources. LULC serve as key indicators of the earth's surface, reflecting changes in spatial patterns that are closely linked to global ecological evolution, climate change, and ecological sustainability [7]. Furthermore, these factors significantly impact land–ocean interactions, the ecological environment, and atmospheric conditions [8].

In the last decade, we have seen a marked increase in the symbiotic use of RS tools and emerging AI and ML technologies. AI refers to systems that mimic human intelligence by perceiving their environment, analyzing data, and making decisions or taking actions autonomously to achieve specific goals. This definition encompasses both basic algorithms and advanced techniques like ML and deep learning (DL), highlighting AI's adaptability and goal-oriented nature [9]. ML is a subset of AI that involves algorithms enabling systems to learn from data, identify patterns, and make decisions or predictions with minimal human intervention. ML focuses on improving performance over time by adapting to new information, making it crucial for tasks like data analysis, image recognition, and natural language processing [9]. Within AI, a key subcategory is ML, which focuses on the ability of systems to learn from data patterns and improve their performance over time without being explicitly programmed for each task [10]. The potential of the technology is clear; large and complex datasets can be processed rapidly and autonomously, minimizing the need for direct human intervention [11]. In the field of natural resource management, integrated approaches that combine RS with AI have proven effective in applications ranging from yield prediction in agricultural fields [12,13] to the quantification of urban forest fragmentation [14].

While the integration of RS and AI offers a promising future for natural resource managers, there remains a critical need for in situ validation measurements to build and train image processing models [15]. Though the increase in the abundance and quality of remotely sensed data products and the methods for image processing have greatly improved research in the fields of forestry and agriculture, there are still limits with this technology. For example, recent studies have noted that satellite revisit time often presents a substantial challenge for land use classification [16,17], underlining the need for high-

quality in situ validation data. An accounting of available in situ validation data would improve accessibility and foster further growth within the field of RS and natural resource management.

The absence of in situ validation data poses a significant challenge in many RS applications, as algorithms and models typically need such data for accurate calibration and validation. While land cover mapping can sometimes overcome this hurdle by manually selecting in situ validation data from high-resolution satellite imagery, distinguishing between harvested and unharvested fields, for example, can be much more challenging. For mapping harvest dates, both phenological curve analysis and interferometric coherence analysis depend on in situ validation data. However, existing research often relies on census data, which, as previously mentioned, has notable limitations and lacks scalability. In the United States, the Department of Agriculture (USDA) conducts regular field surveys with a large team of approximately 4000 personnel and publishes weekly Crop Progress Reports [18]. Unfortunately, these data are only available at an aggregated state level [19]. In many other countries, even state-level aggregated harvest date data are not publicly accessible. This scarcity of field-level in situ validation data has significantly hindered the RS of harvest dates.

In situ images can serve as valuable validation data for assessing field conditions [20]. In recent years, DL methods, particularly those utilizing various convolutional neural networks (CNNs), have been applied to classify land cover types using crowd-sourced georeferenced field photos and images from Google Street View vehicles [21,22]. Although these studies have produced encouraging outcomes, the uncontrolled nature of image collection can result in biased sampling of in situ validation data, particularly concerning spatial and temporal coverage. To mitigate this issue, we need a better in situ validation data to predict the model with better accuracy.

The field of natural resource management is increasingly adopting various Smart Technology innovations; however, the rapid advancement in hardware and software have outpaced the study in the efficacy of the tools for the efficient and accurate study of image classification. To ameliorate this need, we conducted a literature review to identify the growth of image processing tools and emerging uses between 1990 and 2010 and from 2010 to 2024 based upon the peer reviewed articles published. We then highlighted three case studies demonstrating the use of AI and ML to process remotely sensed images in the field of natural resource management. In addition, we conducted a systematic review of available field data and developed a user-friendly database which can be queried to identify them based on need.

The integration of advanced software platforms for geospatial analysis, RS, validation, and image processing is necessary for the advancement and improvement of natural resource management. This paper (1) will highlight five platforms with unique strengths that are instrumental in processing the complex and diverse datasets emerging from modern natural resource management efforts (see Table 1), and (2) provide a reliable in situ validation data source for better prediction and accuracy. Google Earth Engine (GEE) version 7.3 offers cloud-based processing capabilities, enabling large-scale environmental data analysis. ENVI version 6.0 provides advanced tools for spectral analysis and image classification, widely used in RS. ERDAS IMAGINE version 16.8 supports comprehensive raster data processing and photogrammetry. Global Mapper version 23.1 is valued for its versatility in GIS data management mostly UAVs, LIDAR, while eCognition version 10.4 specializes in object-based image analysis, allowing for detailed feature extraction. These platforms were the five most employed platforms identified in the systematic review.

Table 1. The overview of different tools for image analysis.

Tool	Overview	Key Features	Applications
GEE	Cloud-based platform for planetary-scale environmental analysis	Access to petabytes of satellite imagery, powerful API, cloud computing, time-series analysis	Environmental monitoring, climate research, disaster response, land cover change detection
ENVI	Comprehensive image processing and analysis software for RS data	Advanced image processing tools, spectral analysis, integration with GIS, support for multispectral and hyperspectral data	RS, environmental monitoring, defense and intelligence, urban planning
ERDAS IMAGINE	Geospatial data authoring system for preparing, displaying, and analyzing raster data	Image classification, radar processing, photogrammetry, 3D modeling, terrain analysis	RS, geospatial analysis, environmental management, defense, and agriculture
Global Mapper	GIS application providing access to a wide range of spatial datasets with processing and visualization tools	Support for many file formats, terrain analysis, 3D visualization, user-friendly interface	GIS data management, terrain analysis, environmental modeling, civil engineering
eCognition	Software platform for object-based image analysis (OBIA), enabling advance classification and feature extraction	Rule-based image segmentation and classification, multiresolution segmentation, customizable workflows	Forestry, agriculture, urban planning, environmental modeling, disaster management

2. Google Earth Engine (GEE)

GEE, introduced in 2010, is a cloud-based platform designed to handle large-scale geospatial data processing using Google's infrastructure. It is accessible for free to those in education and research fields. GEE aims to offer a robust platform for large-scale algorithm development, support impactful research by providing unrestricted access to data and tools, and contribute to the global challenges of managing and analyzing big data effectively [23,24].

GEE has a vast catalog on the petabyte scale, including information from Landsat, Sentinel, and MODIS satellites and data on climate models, temperature, and geophysical characteristics [24,25]. The intuitive interface includes a code editor, or integrated development environment (IDE), for the JavaScript programming language [26,27]. A graphics window is built into the user interface to allow for ready interpretation of the processes conducted. Programs can also be written in Python, available through the Earth Engine library [28,29], and R [30,31]. For users with limited programming experience, GEE offers a simplistic interface known as "Explorer". Both platforms enable the import of local data and the export of information for further processing or visualization in GIS software like QGIS (Version 3.28) and ArcGIS Pro (Version 3.1.2), among others [32,33].

In geoscience and RS, GEE has emerged as a valuable tool for handling large datasets and facilitating various applications, such as monitoring agricultural productivity [34], tracking vegetation changes [35,36], mapping mangroves [37], analyzing LULC [38,39], and assessing forest fires [40]. These applications highlight GEE's capacity to support large-scale data management and foster scientific research [41]. Conducting a bibliometric

analysis can help identify research gaps and future directions within a field [42], providing an objective overview of the impact and influence of the research area and tracking the evolution of scholarly publications [43].

Rapid advancements in AI are poised to further enhance GEE's capabilities. We focus on AI: computer vision (CV), ML, and DL, a subset of ML. These technologies are crucial for harnessing big data across various domains and have driven significant progress in applications with substantial social impact, such as damage assessment and natural disaster prediction (e.g., automated flood damage assessment [23] and wildfire prediction [44,45], as well as healthcare [40,46,47]. Geospatial artificial intelligence (GeoAI) integrates techniques from spatial science (e.g., GIScience and RS), AI, data mining, and high-performance computing to derive valuable insights from geospatial big data [48]. While GeoAI builds on GIScience methods applied to RS data, it has expanded the capabilities of AI to address geospatial-specific big data challenges and issues.

Recent literature reviews have extensively covered the advancements and research applications of GEE. Key reviews include (i) an examination of the platform's usage, trends, and potential since its inception [24], (ii) a review focusing on GEE's applications in geographic big data [49], and (iii) an analysis of the development of scientific output related to Google Earth (GE) and GEE through a scientometric approach [50]. These studies provide valuable insights by offering systematic and scientometric reviews of various GEE applications.

3. The Environment for Visualizing Images (ENVI)

The Environment for Visualizing Images (ENVI) tool was launched in 1994. ENVI image analysis and processing software is designed to be accessible to a broad range of users, from beginners to experts in the field. Its user-friendly interface and intuitive tools allow users to obtain actionable results without requiring extensive training in RS. ENVI offers a comprehensive range of data visualization, processing, and analysis tools, organized into distinct tasks that guide users through the image processing workflow [51]. These tools cover various functions, including data calibration, pre-processing, atmospheric correction, pan sharpening, orthorectification, and image registration. ENVI workflows enable users to detect changes and anomalies, measure and extract features, and model topographic characteristics. The software also facilitates the generation and sharing of reports, enhancing its efficiency and effectiveness for a wide range of applications [51].

ENVI accommodates a broad spectrum of data formats, including scientific formats like HDF and CDF, as well as image types such as GeoTIFF and JITC-compliant NITF. The software excels in integrating diverse data types—radar, LiDAR, SAR, optical, hyperspectral, multispectral, stereo, thermal, and acoustic data—to leverage the strengths of different sensors and produce comprehensive geospatial products. ENVI is compatible with imagery from contemporary satellite and airborne systems, including Sentinel, Landsat, AVIRIS Hyperspectral, Planet Dove and SkySat, NPP VIIRS, GOES, Pleiades, SPOT, WorldView, RADARSAT, TerraSAR-X, and commercial LiDAR sensors. Its advanced spectral image processing and analysis capabilities, grounded in established scientific methods, enable users to detect targets, assess vegetation health, map materials of interest, and conduct various environmental and defense-related analyses [51].

Recent studies highlight the capabilities of ENVI in handling diverse geospatial data formats to enhance image analysis; for example, ref. [6] developed a prediction model for Chinese pear quality using hyperspectral imaging and artificial neural network (ANN). Also, ref. [52] employed hyperspectral imagery to detect subtle bruises on apples, while [53–55] used hyperspectral laser-induced fluorescence imaging to non-destructively assess soluble solids content and surface contamination on navel oranges. Additionally, Refs. [56–58] detected fecal contamination on apple cantaloupes using hyperspectral fluorescence imagery. Ref. [59] applied hyperspectral imaging to identify surface defects on tomatoes. These studies highlight ENVI's strong capabilities in hyperspectral image analysis.

ENVI supports various processes including data calibration, pre-processing, atmospheric correction, pan sharpening, orthorectification, and image registration. Its workflows are useful for detecting changes and anomalies, measuring and extracting features, modeling topographic characteristics, and more. A typical spectral workflow in ENVI includes data preparation, creating spectral libraries, target detection, mapping unique materials, and visualization.

4. ERDAS IMAGINE

Launched in 1978, ERDAS IMAGINE provides an extensive suite of tools for displaying, editing, and analyzing point clouds from LiDAR or stereo pair correlations [60]. Its user-friendly interface streamlines workflows, enhancing efficiency by allowing users to focus on analysis rather than data processing. The software's robust algorithms and data processing functions operate in the background, reducing manual correlation efforts by offering quick display capabilities and supporting multiple datasets in geographically linked viewers.

ERDAS IMAGINE excels in editing and classifying hyperspectral and LiDAR datasets and features modules for 3D viewing and vector display. It uses the ERDAS IMAGINE Macro Language (EML) for programming. The software also includes a ribbon layout designed for ML and DL workflows, which supports AI-based feature extraction from imagery. This feature enables users to collect training samples, train algorithms, and extract information from new images within a unified interface [61].

ERDAS IMAGINE is designed to be user-friendly, catering to both beginners and experienced users, and enables professional-level imagery processing. The software supports a range of workflows, including data conversion, orthorectification, color balancing, mosaicking, land cover mapping, terrain categorization, and LiDAR editing and classification. It also provides tools for map and report generation, feature capture and update, spatial modeling, and terrain analysis. For instance, it has been used for monitoring natural resources in conflict areas through object-based multiscale image analysis [62].

ERDAS IMAGINE Advantage enhances the capabilities of IMAGINE Essentials by offering more precise mapping, support for sensor models, and advanced geospatial data processing functions, such as point cloud editing, surface interpolation, radar analysis, and advanced image interpretation [61]. This version includes extended features from IMAGINE modules, facilitating more detailed mapping and advanced geospatial data processing [60,61].

The ERDAS IMAGINE Image tool performs image classification to identify terrestrial features based on spectral analysis. It employs two primary methods: supervised and unsupervised classification. In unsupervised classification, the software automatically clusters pixels based on their spectral properties without predefined categories. These clusters are then analyzed to identify terrestrial objects [63]. In supervised classification, users select representative samples or "training areas" for each category they wish to identify, guiding the classification process accordingly. Recent studies highlight the capabilities of ERDAS IMAGINE in handling diverse geospatial data formats to enhance image analysis, like Ref. [64], utilizing remotely sensed and elevation data in ERDAS IMAGINE to identify and classify bare soil erosion risk areas in Hatila Valley Natural Protected Area in northeastern Turkey. Additionally, high-resolution IKONOS imagery was used in ERDAS IMAGINE 9.0 for land use classification [64].

These studies demonstrate ERDAS IMAGINE's capability as a powerful tool for radar image analysis. In terms of pre-processing, ERDAS IMAGINE offers various enhancement techniques to improve image quality, including min-max filtering, Gaussian filtering, invert filtering, histogram equalization, and contrast stretching [60]. Among these, histogram equalization has been found to produce the best results by enhancing areas with low contrast. To achieve optimal image enhancement, a hybrid approach using multiple methods is often recommended.

5. Global Mapper

Global Mapper was launched in 2001. Global Mapper stands out as a versatile GIS software solution that caters to both beginners and experienced professionals in the geospatial field [65]. With its intuitive interface and extensive data processing capabilities, users can seamlessly work with over 300 file formats, covering vector, raster, elevation, and point cloud data types. The software's ability to reproject data on-the-fly and support various projections ensures compatibility and accuracy across datasets. Global Mapper also integrates with numerous online data services, providing access to aerial imagery, elevation data and satellite imagery, among others, making it a robust tool for comprehensive spatial analysis and visualization [65].

One of Global Mapper's key strengths lies in its advanced digitizing and editing tools for vector data. Users can create, edit, and manipulate vector features with precision, including specialized geometric features like range rings and grids. The software supports complex spatial operations such as Intersection, Union, and Difference, and offers robust attribute and geometry editing capabilities. Combined with its scripting and batch processing tools, Global Mapper allows for efficient automation of GIS tasks, enhancing productivity and workflow management in both small-scale projects and large-scale operations [65].

Global Mapper provides additional export options for web tile formats, creating a series of raster tiles from the loaded map data. These exports are compatible with popular online map formats like Google Maps and Bing Maps [66].The export process also generates an HTML file to display the tiles in the chosen web interface, complete with standard map navigation and layout tools. Additionally, through a partnership with Mango Map, users can upload map data directly from Global Mapper to a Mango-hosted map site, which facilitates easy sharing with end-users [66]. The Pixels-to-Points tool is particularly beneficial for Unmanned Aerial Vehicle (UAV) operators, as it converts simple drone-captured images into a 3D model of a project area. This tool provides foundational data for extensive classification, Digital Elevation Model (DEM) creation, and feature extraction capabilities [67]. The tool, currently in beta release, enables the transformation of overlapping aerial images, such as those from UAVs, into a high-density point cloud [67]. Using the principles of photogrammetry, which involve deriving measurements from photographs, the Pixels-to-Points tool analyzes the relationship between identifiable objects in consecutive images to establish the three-dimensional coordinates of points representing the surface. This tool generates a point cloud and can also create an orthorectified image, effectively stitching and adjusting images to match their three-dimensional coordinates [67]. It enhances the ground point detection process, particularly in areas with large buildings, introduces a new geographic point sorting option for faster rendering and analysis, supports reading and writing LAZ (LasZip) files with LAS 1.4 fields, provides the ability to grid a point cloud with RGB values into an image layer, and includes an improved noise point detection and classification tool [67].

Recent studies highlight the capabilities of Global Mapper in handling diverse geospatial data formats to enhance image analysis, like using ML to classify unique features in point cloud data, bridge infrastructure, identify utility corridor encroachment, modeling dam construction, road site planning, measuring and manipulating gold course terrain, and using spatial data in land management decisions [65]. These studies underscore the value of Global Mapper as a powerful tool for UAV LIDAR data analysis. It works better in a small area and for point cloud processing.

6. eCognition

eCognition, introduced by Trimble in 2000 [68], is a cutting-edge image analysis tool that has transformed the way geospatial data are [69] processed and interpreted. Specializing in object-based image analysis (OBIA), eCognition shifts from traditional pixel-by-pixel classification to grouping pixels into meaningful objects or segments. This method enhances classification accuracy by considering spatial relationships and contextual information within the imagery. As a result, eCognition is highly effective in various

applications, such as environmental monitoring, urban planning, and agriculture. By mimicking human cognitive processes, the software integrates diverse geospatial data through patented segmentation and classification techniques, allowing it to identify and analyze objects based on their color, shape, texture, size, and contextual relationships, like an experienced analyst [69].

This advanced approach enables eCognition to dynamically classify and analyze different types of geospatial data, including imagery, vectors, and point clouds. The iterative segmentation and classification process builds a powerful cognitive network, which significantly enhances the depth and value of the information extracted. Users can further customize their analysis by combining various steps, such as object creation, classification, and detection, into a Rule Set or a custom application. This flexibility allows for the transformation of raw geospatial data into actionable geoinformation, making eCognition a comprehensive and automated tool for geospatial data interpretation.

Recent studies have highlighted eCognition's ability to handle diverse geospatial data formats, demonstrating its effectiveness in fields such as surveying and mapping, transportation infrastructure, utilities, oil and gas, mining, and public safety. These studies emphasize eCognition's value as a powerful tool for hyperspectral image analysis, further solidifying its role as a leading solution in the geospatial data analysis landscape [69].

7. Literature Review

The literature review was conducted using major online databases and library catalogs including Google Scholar and ResearchGate. The request and beautiful soup function were used in the Python version 3.11. The initial search started in January 2024 with query "Google Earth Engine Image Analysis for Natural Resources", "ENVI Image Analysis for Natural Resources", "ERDAS IMAGINE Image Analysis for Natural Resources", and "Global Mapper Image Analysis for Natural Resources", which yielded a total of almost 20,000 scientific articles. Using different keywords such as "RS", "GIS", "ERDAS IMAGING", "ENVI", "GEE", "eCognition", and "Global Mapper", many articles were retrieved from Google Scholar and ResearchGate. Due to the limited application programming interface (API) key, Google Scholar and ResearchGate were the only two databases accessed, and the articles were retrieved from them. A 0.5 s time was given to prevent getting blocked by the site. The next step involved identifying how many of the articles utilized each specific tool. To narrow down the results further, more specific search terms like "natural resources management using GEE" were employed, which specifically filtered for studies utilizing GEE. The steps were similar for other tools. This systematic approach allowed for the identification and analysis of a number of articles published using these tools, particularly in the field of natural resources management. Under this selection criteria, we identified 12,837 total articles related to all these tools. We divided the article publication date into two time intervals, the first from 1990 to 2010 and second from 2010 to2024 (see Figure 1). We then made a bar chart showing the change in use for each image processing tool between the two time intervals. The major limitation was the lack of an API key to access other databases like Zotero, Mendeley, and Libraries. This literature review gives a general idea of how the change in use of different tools occurred with the time interval.

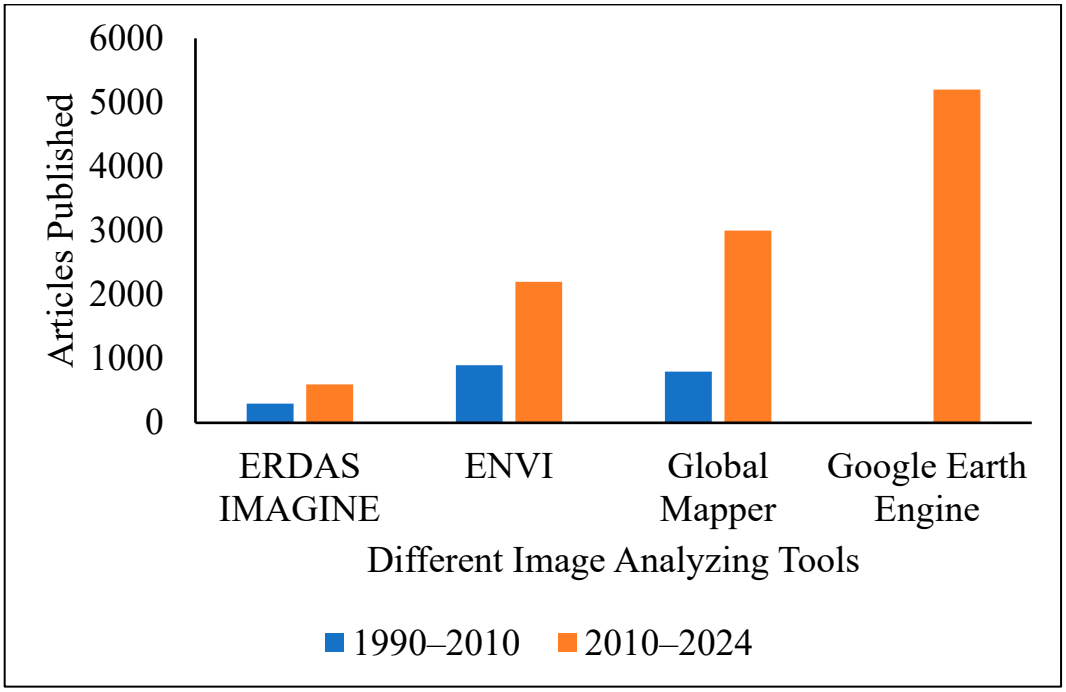


Figure 1. Articles published using different image analysis tools in different time intervals.

8. Case Studies of AI in RS Applications

8.1. Classification

Automated species identification of forest trees would save natural resource managers time and money when planning conservation actions and timber harvests. While spectral differences between tree species have repeatedly been proven in laboratory settings, the lack of high-resolution spatial and spectral imagery, ML algorithms, and robust in situ data has limited the applicability of these methods in the field. The most promising identification models currently available integrate hyperspectral imagery (i.e., images that cover a contiguous and continuous range of wavelengths) and Light Detection and Ranging (LiDAR), which has been defined as a data fusion approach [70].

ML can be applied to this data fusion approach through CNNs. This algorithm characterizes the hyperspectral signatures and places the pixel information within a spatial context using the LiDAR dataset. A CNN classifier developed by [71] was tested within the Teakettle Experimental Forest northeast of Freson, CA, using GPS-coordinated tree inventories collected via field surveys as the training dataset. Hyperspectral imagery, consisting of 426 bands ranging from 280 to 2510 nm, Red–Green–Blue imagery, and LiDAR was captured by manned aerial vehicles to obtain a spatial resolution of approximately 1 m. Two data fusion CNN models were then developed, the first using hyperspectral imagery, and the second using RGB imagery. Approximately 700 trees, consisting of seven different species, were used to train, test, and validate the custom CNNs, comparing the accuracy between the models.

In this analysis, the hyperspectral CNN model proved to be substantially more accurate, outperforming the Red–Green–Blue (RGB) CNN model by 23%. Species were correctly classified 87% of the time with some variation between the genera included in this study; for example, pine species were correctly classified with at least 90% precision, while the precision of fir and oak species fell below 80%. The framework presented by this study offers a repeatable method that should be improved over time, and in different regions.

Though classifying plant species via remotely sensed imagery remains challenging, CNNs have been successfully applied in several different settings [72]. Species identification from Wildlife Cameras with CNNs report 93% accuracy [73].

8.2. Early Detection

Early detection of pests and diseases afflicting agricultural commodities is critical to maintaining economic productivity. Orchards and nurseries are of particular interest in pest and disease management due to relatively large capital investments required for planting and maintenance. One of the most serious diseases afflicting orchards in the United States is citrus greening, or Huanglongbing (HLB), which has decreased citrus acreage and yield in Florida by 38% and 74%, respectively, between 2005 and 2018 [74]. Currently, there is no known cure for HLB, and the removal of all symptomatic trees is the most effective method to prevent the spread to healthy trees.

While mitigation practices have anecdotally shown to limit the spread of HLB in Florida nurseries, the need to rapidly test for, and then quarantine, impacted orchards remains a pressing concern. The most prevalent diagnostic methods for large scale orchards, field analysis, and laboratory biochemical analysis, are both time intensive and expensive, which limits the ability of agriculturalists to identify outbreaks and restock post removal. However, advancements in RS and ML algorithms have increased the accuracy in HLB detection and decreased costs and time in detecting the disease.

Recent studies, such as [75], have utilized drones outfitted with hyperspectral cameras to detect differences in reflectance between HLB-infected and healthy citrus trees. The pixel data from the images were fed through an ML algorithm which incorporated 62 vegetative indices (e.g., NDVI) as well as 15 canopy feature parameters (e.g., area features) resulting in a detection model based on multi-feature fusion. While more complex than other HLB detection models, the inclusion of the physiological characteristic of the citrus trees increased the accuracy to 99.72% for the verification dataset. Further research is required to address the prevalence of false positives.

This melding of ML algorithms and hyperspectral remotely sensed datasets has been demonstrated as a useful tool in the early detection of various plant diseases. Developing similar models to address similar emerging forest threats, such as Beech Leaf Disease, may improve our ability to quarantine infected stands and plan salvage operations to prevent wildfires. In agriculture, frequent drone missions can monitor crop health and aid in the application of fertilizers and pesticides.

8.3. Decision-Making

A growing component of the public policies aimed at mitigating and adapting to climate change include green infrastructure within urban spaces [76]. Urban forests can provide several ecosystem services which contribute to improved quality of life, reductions in surface water runoff, cooling effects, reductions in air pollution, and noise absorption [77–79]. However, tree plantings in urban areas must be made with careful planning to (i) avoid as much as possible damage to sidewalks, roofs, wirings, and drainage systems, (ii) mitigate potential risks of falling branches [80], and (iii) maximize ecosystem services [81]. Regardless of the level of care taken when planting the tree, it will eventually need to be removed to preemptively prevent collapse. Thus, monitoring the risk of falling is a critical component of green infrastructure management. AI can be employed through risk analysis protocols to prioritize investment from managers.

The urban trees of Itanhaém, São Paulo, Brazil, pose a considerable risk due to insufficient planning and neglect. To address this problem, a protocol was developed to classify urban trees by integrating three visual assessment methods. Key variables in this model included crown area, root injuries, and target frequency, among others. Data were collected from 230 urban trees, including *Terminalia catappa*, *Ficus benjamina*, and *Delonix regia*, using a smartphone and the ODK Collect app for data storage and processing. Using the decision tree algorithm (C4.5) in the WEKA software, the study identified 14 out of 36 variables as sufficient to determine tree risk, achieving a 73% accuracy rate.

The findings underscore the potential of AI to enhance urban forestry management by identifying and prioritizing high-risk trees more efficiently. The decision tree model demonstrated a significant reduction in the number of variables needed for accurate risk

classification. However, the model showed some limitations in classifying high-risk trees accurately, suggesting the need for further refinement and a larger dataset of high-risk trees. Overall, this research emphasizes the importance of incorporating AI and predictive models in urban tree management practices to improve the safety and sustainability of urban forests.

9. In Situ Validation Data Availability

Available in situ validation data were collected across the USDA FS Northeast Climate Hub in a wide variety of national research networks, regional cooperatives, and statewide mesonets, as well as several independent field stations (see Figure 2). As it stands, these data are spread out across dozens of data portals and user interfaces, complicating the process of acquiring necessary data for any research or management project. Here, we attempted to catalog the data available and develop an easy to use, data query platform to identify data products across the northeast in a single location. In this catalog, we included national research networks, statewide mesonets, and independent field stations.

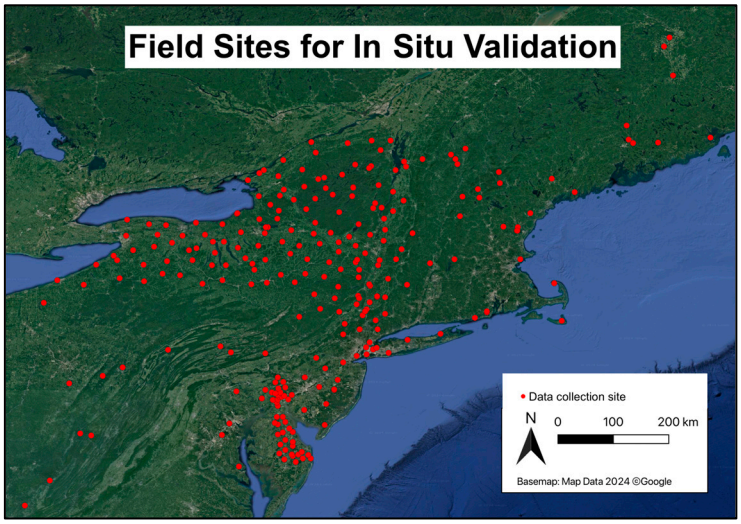


Figure 2. Map of sites identified and included in database.

National research networks, such as the Long-Term Ecological Research Network (LTER) and the United States Department of Agriculture Forest Service Experimental Forests and Ranges (EFRs), are located across the country in ecologically significant sites. The individual stations are often developed around a longstanding experiment, secured by stable funding commitments, and support numerous short-term auxiliary experiments [82]. Each station is typically equipped with a uniform sensor array to provide methodological standardization [83]. Though budgetary restrictions are always a concern, the national scale of these networks often allow for cutting-edge data collection, such as high-resolution airborne RS platforms and eddy covariance towers [84]. While these networks are critical to answering pressing research questions, such as the consequences of forestry management techniques or nutrient applications [85], there is often a lack of spatial scale to meet the pressing questions of global change [86].

Statewide mesonets, such as the New York State Mesonet and the Delaware Environmental Observing System, are generally planned as spatially intensive and uniform, and collect specific datasets for applications in agriculture and weather forecasting. The composition of statewide mesonets varies substantially from state to state. For example, the NYS mesonet contains 181 observing platforms, including 126 standard sites (collecting meteorological data), and several subnetworks, focused on snow water equivalent, flux measurements, and atmospheric profiles. This mesonet was initially founded following a

series of weather-related natural disasters that exposed the lack of intensive spatial data collection necessary for accurate meteorological modeling [87].

In addition to national, regional, and statewide data collection networks, there exist many independently operated field stations that collect valuable data, which may or may not be available to unaffiliated researchers or other interested parties. While the data products available at these stations may be focused on the research or outreach goals of the specific station, there remains a vast quantity of data that could be useful, if researchers and land managers are aware of their availability. To help address this issue, we have cataloged stations across the northeastern United States to identify potentially useful data products.

The northeastern United States was defined as the range covered by the USDA Forest Service Northeast Climate Hub (Maine, New Hampshire, Vermont, New York, Massachusetts, Connecticut, Rhode Island, New Jersey, Pennsylvania, Maryland, West Virginia, and Delaware). Field stations were identified by searching the databases of the USDA, USGS, NOAA, NEON, LTER, LTAR, AmeriFlux, and GLEON, as well as the Organization of Biological Field Stations and statewide mesonets (i.e., the Delaware Environmental Observing System). Of the 276 field stations cataloged in this search, 42 were operated by either a 501(c)(3) non-profit or academic institution, independent of any broader network of field stations. The remainder were associated with a statewide mesonet or larger national network (i.e., NEON).

Each field station included in the database collected some type of biotic or abiotic data, ranging from tree inventories and mammal surveys to complete meteorological stations with soil moisture data. Of the 276 field stations surveyed, 94 stations collected only abiotic data (i.e., meteorological data), 25 collected only biotic data (i.e., tree inventories), and 157 collected some form of both abiotic and biotic data. The availability of the data at the stations surveyed varied, with 236 stations offering real-time and historic data for download, 12 offering only historic data for download, 5 offering only real-time data for download, and 23 without open access to data. Of the stations without access to data, 21 were independently operated.

To allow for end users to better access these data, we created an open access geopackage which allows for queries of station locations and accessible datasets. The geopackage format is an open source SQLite database format with spatial integration [88]. The database, including associated metadata and tutorials for viewing and querying the database in QGIS, is available at https://github.com/petermanos/field_validation_data (accessed on 6 November 2024). In the database, field stations are organized such that users can query based on location, type of data collected, or timeframe of data collected (real-time or historical) using structured query language (SQL). The purpose of the database is to connect users to places where the data they require are collected. This database does not provide the data collected by these field stations but rather links to the field station or network sites where data can be downloaded.

10. Discussion

GEE is significantly advancing the field by allowing researchers, scientists, and developers to efficiently extract valuable insights from extensive RS datasets, mitigating the challenges associated with traditional data analysis methods [89]. It is also freely accessible. Despite these advantages, there are limitations, such as a maximum storage capacity of 250 GB per user and restricted memory for training ML algorithms, which can constrain users' ability to fully leverage the platform. Nevertheless, GEE represents a groundbreaking approach to processing geospatial data and addressing various big data challenges in RS. The growing publication trends related to GEE suggest its increasing popularity not only among RS researchers but also among natural resource managers [89].

ERDAS IMAGINE and ENVI are leading software systems for professional image processing in RS, each with their own strengths and weaknesses. While both systems offer similar functions, they complement each other effectively. ERDAS IMAGINE is particularly strong in geometry processing tasks, such as geometric correction, clipping, and mosaicking.

In contrast, ENVI excels in classification and spectral processing tasks [90]. For optimal use, ERDAS IMAGINE should be employed for geometry processing, and ENVI should be utilized for spectral analysis. Additionally, ENVI's quick mapping tool makes it more efficient than ERDAS IMAGINE. However, ERDAS IMAGINE requires manual insertion of annotations, which can be more time-consuming compared with ENVI. The ENVI works better with hyperspectral and multispectral image analysis, however ERDAS IMAGINE works better for radar, LIDAR data, and 3D models [90]. Due to its unique advantages and drawbacks, the workflow for thematic mapping in ENVI differs somewhat from the general design flow chart. For instance, in image fusion, Principal Components Analysis (PCA) is used to generate three components as RGB values for SPOT image fusion. Unlike ERDAS IMAGINE, where stacking techniques are commonly used for map display, PCA in ENVI also serves a classification function. This distinction influences how mosaic-based pixel mapping and other methodologies are employed in thematic mapping processes [90].

ENVI's display window includes a subject image window, a zoom window, and a scroll window, all of which can be resized, which can aid in the search for cognominal points. However, once selected, these cognominal points are not easily adjustable. Beginners often find it necessary to delete and reselect them to achieve an RMS error of less than 1 pixel, making the process time-consuming.

On the other hand, ERDAS IMAGINE excels in certain aspects, such as its capability to automatically update the RMS error after adding a pair of corresponding points. This feature makes it easier for users to adjust the point positions promptly based on the RMS error changes, thus enabling beginners to more accurately identify corresponding points [91]. In geometry correction, ERDAS IMAGINE often proves more efficient than ENVI due to its broader range of features and simpler interface [90]. While ENVI excels in visualization, which can be valuable for ERDAS IMAGINE users, ERDAS IMAGINE offers greater diversity in its tools. For example, in mosaic creation, ERDAS IMAGINE provides options for geographic reference-based mosaicking, direct mosaicking, and automatic edge detection using various algorithms or user-drawn lines. This flexibility offers users more choices [90]. Conversely, ENVI's mosaic capabilities are limited to pixel-based and geographic reference-based methods, lacking automatic edge detection algorithms, which can be challenging for beginners when dealing with images where edges are not clearly defined. In clipping tasks, ERDAS IMAGINE provides various tools like the Require Box and area of interest tools, whereas ENVI offers fewer options. For image fusion, ERDAS IMAGINE allows the direct merging of images with different sizes and geographic references, while ENVI requires resolution adjustment of one image to match the other before applying the fusion algorithm [92]. Global Mapper excels in 3D visualization, while eCognition is better suited for object-based image analysis. Selecting the appropriate software based on these strengths can optimize workflow and enhance results. In situ validation data have been critical to the development of effective remotely sensed data products, and with the recent expansion of AI applications in the RS field, the importance of in situ validation will continue to grow. The study by [93] uses TSS-RESTREND analysis, combining in situ vegetation data and MODIS remote sensing products to examine South Korea's vegetation response to rainfall variability. The findings emphasize the importance of integrating multi-source data for understanding ecological processes and highlight the need for continuous ground-based observations to complement satellite data. The study by [94] evaluates the accuracy of the OpenET system, which provides field-scale evapotranspiration (ET) data using an ensemble of six remote sensing models. Comparing OpenET outputs with data from 152 in situ stations, primarily eddy covariance flux towers, shows a mean absolute error of 15.8 mm per month (17% of observed ET) and r^2 of 0.9 for cropland sites. The findings by [94] highlight the utility of a model ensemble approach for improving ET data accuracy, especially for agricultural water management. The study by [95] presents a neural network classifier for detecting red tide blooms using MODIS-Aqua satellite data and in situ samples, demonstrating superior performance compared with existing methods. The model's innovations include depth normalization and a K-

nearest neighbor proximity weighting scheme, enhancing operational monitoring of algal blooms. Our hope is that the GIS database developed in this manuscript will provide researchers, land use managers, and other interested end-users with ready access to the necessary datasets to expand the role of Smart Technology in their respective fields. Though our database is somewhat limited in geographic range and functionality, it should serve as a baseline for future growth of similar systems to provide wider access.

11. Limitations and Recommendations

Despite the promising advancements in AI and ML applications in RS, several limitations persist. One major challenge is the requirement for large, high-quality training datasets, which can be difficult to obtain, particularly for specific environmental conditions or rare species. Additionally, many machine learning algorithms, such as CNNs, often operate as black boxes, making it challenging to interpret their predictions and understand the underlying factors driving the results. This lack of interpretability can hinder the adoption of these technologies by natural resource managers who require transparent and explainable decision-making tools. Moreover, issues related to data integration from diverse sources, varying spatial and temporal resolutions, and the potential for overfitting models to localized datasets can affect the generalizability of AI applications across different landscapes and ecosystems.

To enhance the effectiveness and applicability of AI and ML in remote sensing applications, several recommendations can be made. First, increasing collaboration among researchers, data providers, and practitioners is crucial to develop standardized protocols for data collection, processing, and sharing, thereby facilitating access to high-quality training datasets. Additionally, efforts should be directed toward improving the interpretability of AI models through the development of techniques that allow users to understand how predictions are made, such as explainable AI (XAI) methods. Regular validation and refinement of models using in situ data can help improve accuracy and generalizability. Furthermore, investing in training programs for natural resource managers on AI and ML applications will empower them to leverage these technologies effectively in their decision-making processes, ultimately leading to better conservation and management outcomes.

12. Conclusions

The increasing human population places significant pressure on natural resources, making effective management crucial. RS and GIS offer powerful tools to monitor and manage these finite resources efficiently. Geospatial information plays a vital role in identifying and analyzing factors that impact resource utilization, enabling informed decisions for sustainable management that benefits both current and future generations. Integrating image data with in situ validation is essential for enhancing the accuracy and reliability of RS models. The establishment of a Ground Truthing Database facilitates the creation of a comprehensive network of free, accessible data that connects ground observations with advanced analytical platforms.

Our study highlights that GEE has advanced significantly due to its extensive geographic coverage, easy access to satellite imagery, multispectral capabilities, user-friendly interface, and no cost. ENVI is effective for smaller geographic areas and hyperspectral imagery, offering a cost-effective alternative to ERDAS IMAGINE, which is specialized in radar, LIDAR, and photogrammetric data processing. ENVI's lower cost and ease of use make it suitable for users with minimal coding experience, whereas ERDAS IMAGINE is better suited for complex analyses requiring specialized skills. Global Mapper is increasingly used for analyzing UAV images and creating 3D models, while eCognition excels in object-based image analysis. The growing adoption of GEE in recent studies underscores its effectiveness in covering large areas, while advancements in UAV technology and 3D modeling have driven the increased use of Global Mapper. The integration of in situ validation with these tools is crucial for improving the precision of applications, ensuring that the data used for resource management is both accurate and actionable.

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