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AI-DRIVEN GEOSPATIAL ANALYSIS IN ECOSYSTEM MANAGEMENT: INTEGRATION OF MACHINE LEARNING METHODS

Can SAYGINER[1,*], Engin NURLU[2.]

[1]Department of Management Information Systems, Faculty of Economics and Administrative Sciences, Izmir Democracy University, Izmir
[2]Department of Landscape Architecture, Faculty of Agriculture, Ege University, Izmir

[*]Corresponding author: can.sayginer@idu.edu.tr

Can SAYGINER: https://orcid.org/0000-0002-1680-392X
Engin NURLU: https://orcid.org/0000-0001-5458-7749

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ABSTRACT: The escalating complexity of environmental pressures, including climate change, loss of biodiversity, and land degradation, demands new and integrated, science-based solutions for managing ecosystems. In this study, it is explored how the integration of machine learning (ML) and geospatial analysis is a truly transformative approach to understand, monitor, and manage ecosystems. Through reviewing a wide spectrum of recent research and cases, the paper evaluates the integration of ML processes—e.g., Random Forest, Support Vector Machines, Artificial Neural Networks, and deep learning models—alongside geospatial technologies like GIS, remote sensing, and satellite image technology. Importantly, the research focuses on Python and R as strong programming platforms for developing ecological AI solutions and underscores their importance for data preprocessing, predictive models, visualization, and decision support. A select group of fifteen case studies illustrates successful applications across various ecological scenarios, including assessments of deforestation, biodiversity conservation, land use and land cover classification, and evaluation of ecosystem services. These articles were selected to illustrate methodological variety, geographic coverage, and applied relevance of advances in ecosystem management. Furthermore, the review covers significant methodological progress, toolkits, and platform integration (such as Google Earth Engine and TensorFlow), which are used across geospatial AI workflows. It also highlights ongoing issues—e.g., data quality, computational demand, model interpretability, and ethical considerations—and possible avenues for future research and interdisciplinary collaboration and outlines future directions to foster cross-disciplinary research and sustainable AI application. This synthesis illustrates the promise of the consolidation of AI and geospatial analysis to support adaptive, transparent, and efficient ecosystem management amid the rapid global change.

Keywords: Geospatial analysis, machine learning, ecosystem management, remote sensing, land use and cover change

EKOSİSTEM YÖNETİMİNDE YAPAY ZEKÂ DESTEKLİ COĞRAFİ MEKÂN ANALİZİ: MAKİNE ÖĞRENİMİ YÖNTEMLERİNİN ENTEGRASYONU

ÖZET: Artan çevresel baskıların – özellikle iklim değişikliği, biyoçeşitlilik kaybı ve arazi bozulmasının – yarattığı karmaşıklık, ekosistem yönetiminde daha bütüncül ve bilimsel yaklaşımları zorunlu kılmaktadır. Bu çalışma, makine öğrenimi ile coğrafi mekân analizlerin bütüncül bir şekilde bir araya getirilmesinin, ekosistemlerin anlaşılması, izlenmesi ve etkin bir şekilde yönetilmesi açısından yenilikçi ve dönüştürücü bir yaklaşım sunduğunu ortaya koymaktadır. Makale, yakın dönemli araştırmalar ve örnek uygulamalar üzerinden, Rastgele Orman, Destek Vektör Makineleri, Yapay Sinir Ağları ve Derin Öğrenme modelleri gibi makine öğrenimi yöntemlerinin, CBS (Coğrafi Bilgi Sistemleri), uzaktan algılama ve uydu görüntüleme teknolojileriyle nasıl entegre edildiğini değerlendirmektedir. Ayrıca, yapay zekâ temelli ekolojik çözümler geliştirmede güçlü platformlar olan Python ve R dillerininin; veri ön işleme, tahmine dayalı modelleme, görselleştirme ve karar destek sistemlerindeki rollerine dikkat çekilmektedir. Seçilen on beş örnek uygulama, ormansızlaşma değerlendirilmeleri, biyoçeşitliliğin korunması, arazi kullanımı ve arazi örtüsü sınıflandırması ile ekosistem hizmetlerinin değerlendirilmesi gibi çeşitli ekolojik senaryolarda bu teknolojilerin başarılı kullanımını ortaya koymaktadır. Bu çalışmalar, ekosistem yönetiminde yöntemsel çeşitlilik, coğrafi kapsam ve uygulamaya dönük değer açısından örnek teşkil etmektedir. Ayrıca, inceleme; Google Earth Engine, TensorFlow gibi platformların entegrasyonunu, coğrafi mekân yapay zekâ iş akışlarında kullanılan araç setlerini ve yöntemsel gelişmeleri kapsamaktadır. Veri kalitesi, hesaplama yükü, model yorumlanabilirliği ve etik kaygılar gibi süregelen sorunlara dikkat çekilmekte; gelecekteki araştırma alanları ve disiplinlerarası iş birlikleri için olası yönelimler sunulmaktadır. Bu sentez, yapay zekâ ile coğrafi mekân analizlerinin birleşiminin, hızla değişen küresel koşullar karşısında uyarlanabilir, şeffaf ve etkin bir ekosistem yönetimini destekleme potansiyelini ortaya koymaktadır.

Anahtar Kelimeler: Coğrafi mekân analizi, makine öğrenimi, ekosistem yönetimi, uzaktan algılama, alan kullanımı ve arazi örtüsü değişimi

INTRODUCTION

Human action has many effects on the global environment, which affect the biosphere in turn, including the ocean, the atmosphere, and the earth's surface and the impact is both direct and indirect on these ecosystems. The goal of ecosystem management is to maintain or improve the functional quality of ecosystems that underlie their ability to sustain biodiversity and the ecosystem services that are the foundation of human well-being. It is a science in and of itself: The application of the science of ecology to the management of natural resources in order to create and sustain opportunities for future generations. Through application of ecological concepts in resource management, ecosystem management contributes to resilience of ecosystems and human well-being. Given the increasingly complex and multi-scalar challenges posed by global environmental pressures such as climate change, biodiversity loss, and land degradation, it requires adaptive, integrative approaches that can respond effectively to dynamic environmental conditions (Chapin et al., 2011). As these challenges accelerate, ecosystem management has become a pressing global priority. Effective strategies must balance ecological integrity with human development, ensuring that ecosystems continue to deliver critical services such as clean water, carbon sequestration, soil fertility, and climate regulation (Millennium Ecosystem Assessment, 2005). These approaches have been increasingly advocated by international organizations and frameworks. Ecosystem management, for example, is characterized by the development of measures intended to incorporate ecological models and considerations into the use of environmental and natural resources, such as use of the land and management of water resources, and of global environmental change (UNEP, n.d.). Ecosystem management is also a key commitment for the current period of the IUCN's Commission on Ecosystem Management (IUCN CEM, 2025).

To more effectively address contemporary environmental problems, new technologies are becoming increasingly important for current ecosystem management. Of these, the combination of machine learning (ML) with geospatial analysis has enabled the emergence of new frontiers in pattern discovery, predictive modeling, and real-time monitoring. This article examines the ways in which emerging modes of spatial knowledge, e.g. satellite imagery, Geographic Information Systsems (GIS), and remote sensing (RS), can reconfigure ecosystem management as a more anticipatory, ICT-enhanced, and evidence-based enterprise. These technological advances greatly enrich the scope of our analyses of ecosystems at larger scales with a higher resolution that in turn facilitate more informed and effective decisions and responses to emergent environmental concerns.

Geospatial Artificial Intelligence (GeoAI) is characterized by the confluence of artificial intelligence techniques, primarily machine learning and deep learning, with geospatial technologies, including geographic information systems (GIS), remote sensing (RS), and global positioning systems (GPS). This integration allows for the sophisticated analysis of spatial data, facilitating the extraction of actionable insights (Chen et al., 2023; Song et al., 2023). The advent of this hybrid discipline significantly enhances conventional spatial analysis by fostering capabilities such as automated pattern recognition, extensive environmental modeling, and ongoing monitoring of ecosystems in real-time (Abadi et al., 2016; Bivand et al., 2013; Alshari et al., 2023). In the scope of this paper, GeoAI is framed as an overarching concept that incorporates the collaborative application of AI methodologies alongside geospatial techniques for the management of ecosystems (Dritsas & Trigka, 2025; Liu et al., 2024).

Geospatial analysis is the analysis of data with a geospatial context and the representation of this analysis. The use of GIS and RS technologies have allowed such researchers to process large amounts of spatial information for the tracking of ecosystems over varying scales and geographic locations (Patterson & Hoalst-Pullen, 2010; Sample, 2013; Zhang et al., 2023). These technologies are particularly valuable for assessing land use and land cover (LULC), tracking habitat distribution, and detecting environmental changes over time.

Complementing these spatial tools, machine learning (ML)-defined by Mitchell (1997) as the study of algorithms that improve automatically through experience offers powerful capabilities for analysing large and complex datasets. The incorporation of RS data has significantly strengthened its capability of environmental monitoring. Some of the ML algorithms (e.g., supervised/unsupervised learning) can be applied to spatial data and used in finding pattern and prediction of ecological trends or region classification based on environmental traits

(Gutiérrez Caloir et al., 2023). For instance, deep learning models have demonstrated high accuracy in classifying particular LULC types by analyzing satellite images. DIVERGY can also be used to project the effects of a changing climate on biodiversity through a variety of ecological zones.

Geospatial analysis and machine learning (ML) are mutually exclusive, especially related to the analysis and interpretation of spatial data. Together, they facilitate smarter, faster and more automated prediction of geographic patterns and trends. ML is responsible for the major breakthroughs in RS and geospatial analysis by allowing rapid data processing, feature extraction and predictive modeling. With the expansion of geospatial data in terms of size, dimension and diversity, ML has gradually shown its strengths in decoding them for useful information and knowledge in related (Lary et al., 2016; Yuan et al., 2020; Pandey et al., 2023; Dritsas and Trigka, 2025). The fusion of geospatial approaches with ML represents a promising synergy where strong computer computational power is coupled with spatial perspective which serve to further the understanding of change in space and time, enhance predictive power and, ultimately, informed decision-making. This has ranged widely including LULC (Talukdar et al., 2020; Wang et al., 2022; Yu et al., 2022; Alshari et al., 2023; Mahmoud et al., 2023; Bojer et al., 2024; Liu et al., 2024; Şenay et al., 2024; Ersoy Tonyaloğlu, 2025), vegetation monitoring (Li et al., 2021; Ma et al., 2022), wildlife (Tuia et al., 2022), deforestation (Dominguez et al., 2022; Dias et al., 2024), biodiversity modeling (Silvestro et al., 2022; Shivaprakash et al., 2022; Raihan, 2023; Pettorelli et al., 2024), nature-based solutions (Gutiérrez Caloir et al., 2023; Prodanovic et al., 2024) and urban development (Haripavan et al., 2025). By linking various data sources such as satellite images and GIS data, this interdisciplinary approach can provide us with more accurate and large-scale ways for monitoring and managing ecosystems.

Areas of application for this integration are widening. For example, real-time land cover classification can now be conducted with supervised learning models and deep learning is often used to detect changes in habitats and forecast impacts of land use policy (Gutiérrez Caloir, et al., 2023). New technologies like the Earth Engine Automated Geospatial Elements Recognition (EEAGER) algorithm have even allowed for satellite detection of beaver dams, redefining the boundaries of ecosystem restoration for water-stressed areas (EEAGER Project, 2023).

Despite these advancements, there remain challenges in mitigating spatial biases, generalizing ML models to various other geographical areas, and interpreting ML outputs (Koldasbayeva et al., 2023). In this paper, the convergence of geospatial analytics was explored with ML in ecosystem management. It reviews state-of-the-art methodologies, real-world applications, and current/ongoing research gaps, emphasizing how integrated approaches can enhance ecosystem resilience and guide adaptive environmental policymaking.

Geospatial Analysis: A Crucial Component

Geospatial analysis is an essential instrument in ecosystem monitoring and management. Geographical data are managed, analyzed and visualized with the use of emerging technologies such as GIS, RS and spatial analysis methods. Such tools facilitate needful evidence-based decision making for the sustainable management of ecosystems (Obiorah et al., 2025) This section outlines the key components of geospatial analysis and its applications in ecosystem conservation and restoration. It also highlights recent advancements, current challenges, and emerging research directions, supported by examples from academic literature.

Fundamentals of geospatial analysis: Geospatial analysis is the examination of data that has a geographic or spatial aspect and potential to identify patterns, relationships, and trends. The essential geospatial analysis work consists of data collection, data manipulation, spatial analysis and data visualization. Data gathering comprises a range of inputs ranging from satellite images, aerial photographs, GPS devices, sensor networks and field work. RS technology: space satellite, drone equipment etc., provide high resolution image data (temperature, vegetation index, topography etc.), provide the accuracy and support to data analysis in GIS systems. Stals et al. (2023) emphasizes that RS techniques play a key role in climatic change mitigation by providing accurate estimations of biomass and carbon sequestration thanks to their precision and widespread monitoring. Data processing is the process of converting raw data into a more usable format by cleaning, transforming and integrating it. Geospatial data usually needs transformation, re-projection, and merging of disparate sources; off-the-shelf GIS software (e.g. ArcGIS, QGIS, Google Earth Engine) has built-in functions to accomplish these tasks and operate on the spatial data. Kosherbay et al. (2022) analyze urban heat island effect with satellite data, describe the challenges and methods of preprocessing satellite data and stress on the importance of precise satellite data preprocessing. Zhang and Yu (2022) highlight the increasing need for high-quality geospatial data for various applications such as environmental monitoring and urban development. It is believed how advanced processing techniques can significantly improve DEM quality, which is essential for accurate terrain analysis and modelling in landscape planning. It provides insights into the processing of time series data to assess change. Ersoy Tonyaloğlu et al. (2021) compare LULC classification methods by assessing the classification performances for object-based and pixel-based classifications on RapidEye satellite image.

Spatial analysis employs methods such as overlay analysis, buffer analysis, and hotspot analysis to explore spatial relationships and patterns. These techniques are used to pinpoint points of interest, like rich biodiversity points, deforestation zones, or locations vulnerable to natural disasters. Mapping, charting and 3D modeling are examples of techniques that are used to communicate information about locations. More complex visualization capabilities like interactive mapping and virtual reality improve the possibilities for the user to explore and understand geospatial information. Szczepanska et al. (2021) demonstrate that virtual reality can serve as a useful tool for public consultation in spatial planning and management by bringing a more engaging and realistic perspective to stakeholders and an opportunity to better know the spatial structure and decision-making implications. Similarly, Hochschild et al. (2020) explore the use of geospatial visualisation for landscape visualisation and argues how they can communicate complex spatial information and make sense of it. Furthermore, Chen et al. (2023) consider the confluence of artificial intelligence and visual analytics, focusing on the potential for enhancing spatial data interpretation in both geographic and virtual space.

Applications in ecosystem management: The field of ecosystem management is an important application domain of geospatial analysis and helps understanding various dimensions of ecosystems. It has applications in LULC monitoring and biodiversity assessment to conservation action planning and natural resource management. LULC pattern knowledge is essential for ecosystem management. Geospatial analysis enables the identification and surveillance of LULC typologies (i.e., forest, grassland, wetland, urban). Additionally, spatial analysis of environmental factors (eg temperature, precipitation, elevation, and plant cover) can be employed to model alkaloid habitat suitability and distribution. Liu et al. (2021) indicate the relative performance of ML algorithms in predicting site-level net ecological change in different biome groups, and show that geospatial and AI can be combined for enhancing ecosystem models.

Advances in geospatial technology: Recent geospatial technology enhancements have improved our ability to conduct spatial analysis of ecosystems at multiple scales of resolution. Lowell and Calder (2022) were also investigated the power of combined intensity-based and clustering-based techniques to derive bathymetric returns from LiDAR point clouds, highlighting the versatility and accuracy of LiDAR in various environmental applications. Maxwell et al. (2018) provided an overview of the uses of ML in ecological modeling and discussed the use of ML in modeling and how these can be used to increase the accuracy and efficiency of spatial predictions. Song et al. (2023) provide an overview of recent developments in geocomputing and GeoAI for mapping and stress the disruptive potential of these technologies in promoting the accuracy of geospatial data analysis and mapping. Developments of ML and image analysis illustrate the increasing ability of these technologies to improve the interpretation and utility of associated imagery for geospatial applications. Temporal and spatial evolutionary pattern of terrestrial ecosystems based on ML algorithms are reviewed by Wang (2022) with an AI-assisted prospect on enhancing temporal analysis of ecological change.

Geospatial analyses is an integral part of sustainable ecosystem management, offering insights pertinent for spatial patterns, environmental changes and resource management. The application of more advanced technologies such as RS, cloud computing (CC) and AI have enabled more robust geospatial analysis, thus delivering higher precision and better coverage. By tackling those problems limiting data accessibility, technical capacity and harmonization, Geospatial analysis will become a major player in environmental restoration and conservation efforts. Academic research findings on the other hand provide strong evidence of the far-reaching influence of geospatial analysis on our understanding and management of nature.

Leveraging R For Geospatial Analysis

R, a powerful statistical programming language, is widely used for geospatial analysis (Pebesma & Bivand, 2023; Lovelace et al., 2025). Its extensive libraries and packages make it a versatile tool for processing, analysing and visualizing spatial data, and researchers can use R for geospatial analysis to process large datasets, perform complex spatial operations and produce high-quality visualizations. This chapter presents different uses of R in geospatial analysis with examples from academic research and introduces the main packages and their applications.

Introduction to R for geospatial analysis: R offers a comprehensive suite of tools for geospatial analysis, from data import and manipulation to advanced spatial modelling and visualization. Due to its open-source nature and active community support, a number of packages have been developed specifically for geospatial tasks. Key packages include *sf* for working with spatial data, raster for raster data manipulation, *sp* for spatial objects, and *ggplot2* for visualization. Bivand et al. (2013) provide a broad overview of spatial data analysis in R and highlight the evolution and functionality of spatial packages.

Main packages and their applications: The *sf* package simplifies the manipulation of spatial data by using simple specifications (SFs) defined by the Open Geospatial Consortium (OGC) to read and write spatial data, perform geometric operations, and perform spatial compositing. Supporting spatial operations, Pebesma (2018) demonstrates the ability of the *sf* package to efficiently process large spatial datasets. Hijmans (2025) presents the use of the raster package in applications such as LULC classification and environmental monitoring for processing and reading raster data, such as satellite imagery and digital elevation models. The *sp* package provides classes and methods for spatial data, both vector and raster. It supports data types and allows integration with other R packages for advanced spatial modelling and analysis (Bivand et al., 2013).

Application of R in geospatial analysis: LULC classification classifies land surface features from satellite imagery. R packages such as *raster* and *randomForest* can perform supervised classification and produce detailed LULC maps. The *terra* package offers high-performance processing for multi-layer raster data and time-series analysis, especially useful in dynamic ecosystem modeling (Hijmans, 2025). The leaflet provides tools for creating dynamic, web-based visualizations. It is especially useful for stakeholder engagement and participatory mapping, enabling real-time interaction with spatial data (Cheng et al., 2018). The *landscapemetrics* is an advanced tool designed for calculating landscape metrics from raster data. These metrics, such as patch area, edge density, and shape complexity, are critical for assessing habitat fragmentation and ecological connectivity (Hesselbarth et al., 2019). Maxwell et al. (2018) used these packages for land cover classification and provided insights into land use patterns. Species Distribution Modeling (SDM) predicts the potential distribution of species based on environmental variables. Packages such as *dismo* and *MaxEnt* use species occurrence data and environmental predictors to produce distribution maps. Elith et al. (2006) used *dismo* to implement the *MaxEnt* algorithm and demonstrated its effectiveness in predicting distributions. Hydrological modelling simulates the movement and distribution of water over land; R packages such as *hydroTSM* and *SWAT* support hydrological analysis and study water resources and watershed management. Borrelli et al. (2018) provided data on water availability and the impact of land use change using *SWAT* for hydrological modelling of the Mediterranean region.

Visualization and communication: Visualization is an important component of geospatial analysis, enabling complex spatial data to be communicated effectively. R's visualization capabilities, especially *ggplot2*, allow researchers to create detailed and informative maps. It is widely used for creating high-quality geographic visualizations. Wickham (2016) describes the ability of *ggplot2* to integrate with spatial data packages to create detailed maps and sophisticated data visualizations. The *tmap* package is particularly effective for creating static and interactive thematic maps. It supports flexible layer-based mapping similar to *ggplot2* and is widely used in policy communication and spatial planning scenarios (Tennekes, 2018).

Challenges and future direction: The use of R for geospatial analysis presents challenges in terms of data complexity, computational burden and the need for expertise. The ongoing development of the R package and the integration of R with other geospatial tools aims to overcome these challenges. Processing large and complex spatial datasets is challenging. Efficient data processing and storage techniques are crucial. Geospatial analysis can be computationally intensive. Code optimization and the use of high-performance computing resources can meet these requirements. Effective use of R for geospatial analysis requires expertise in both R programming and geospatial concepts. Continuing education and training resources are essential; using R, researchers can perform complex geospatial analyses, produce high-quality visualizations, and gain valuable insights into spatial patterns and processes. Examples from academic research illustrate R's significant impact on advancing geospatial analysis and understanding and managing terrestrial ecosystems.

Harnessing Python For AI-Driven Solutions

Python is considered as the best programming language for AI professionals due to its simplicity and versatility, which makes it a popular language for creating AI products. Its libraries and frameworks also support machine learning, deep learning, and analytics applications. This chapter introduces the core libraries and their use, including methodology examples from academic literature on the various options available for making use of Python for AI-driven solutions in the context of sustainable land ecosystems.

Python for AI: Python has become a go-to choice in the world of AI and ML for several reasons, mainly as a result of the availability of libraries and frameworks which make it easier to develop and deploy AI models. Key libraries are *TensorFlow, Keras, Scikit-learn*, and *PyTorch*; these libraries also have their unique selling point in tackling the various aspects of AI and ML. Chollet (2017) gives a comprehensive overview on *Keras* and details on why to use *Keras* and how *Keras* simplifies for the implementation of DL models.

Main packages and applications: *Tensorflow* is an open-source library for ML and DL applications as developed by Google. It runs many types of NNs and is a front end for building and running ML models. Abadi et al. (2016) who also introduce *TensorFlow* and have shown how to use it for a large-scale ML projects *Keras*, a high-level neural network API running on top of *TensorFlow* allowing a faster development of DL models. *Keras* was utilised in the implementation of CNNs for image classification tasks by Chollet (2017). It is one of the most useful libraries for ML in Python and provides very simple and efficient tools for data mining and data analysis. Pedregosa et al. (2011) provides a comprehensive of *Scikit-learn* for ML. *PyTorch* is a popular open-source DL library developed by Facebook's Artificial Intelligence Research lab and provides an introduction and focuses on its applications in natural language processing and computer vision (Paszke et al., 2019).

Python application in AI-driven solutions: One of the basic tasks in computer vision is to perform image classification and object detection where AI models recognise and classify the object based on the given image. Convolutional Neural Networks (CNNs) are developed for these tasks using python libraries like *TensorFlow* and *Keras*. Redmon et al. (2016) introduced YOLO (You Only Look Once), a real-time object recognition method using *TensorFlow*. Natural Language Processing (NLP) is a field with its main focus on the interaction between computer and human language that allows computers on the one hand to understand, interpret and generate human language and on the other to generate language that can be easily processed by computers Python packages, such as *NLTK*, *spaCy* and transformers make it easy to build NLP applications. Devlin et al. (2019) presented BERT (Bidirectional Encoder Representations from Transformers), an NLP model, achieving SOTA results and it was introduced in the *PyTorch* platform. Time series analysis is concerned with data points taken or recorded at equally spaced intervals of time Python libraries like *Pandas*, *statsmodels*, and *Prophet* provides support for time series or time-based data analysis and forecasting. Taylor and Letham (2018) used time series analysis with the Prophet library for time series forecasting. A method in this category is reinforcement Learning, which can be used to train agents to act optimally with respect to some reward, by rewarding good behavior; Python libraries such as *OpenAI Gym* and *Stable Baselines* provide a collection of environments and algorithms to develop this type of models (Mnih et al., 2015); He introduced Deep Q-Networks (DQN) which applies reinforcement learning to the Atari game Python geospatial libraries that support analysis and visualization: *GeoPandas*, *rasterio* and *folium* GeoPandas Development Team (2014) released *GeoPandas*, an extension to the well-known *Pandas* library in Python that work with spatial data. Building on *Pandas*, *GeoPandas* adds support for powerful spatial operations to *Pandas* objects, thereby making it very easy to work with and analyze spatial data.

Visualization and communication: Visualization is very important for AI solutions, where complex data and model results need to be communicated effectively. There are Python visualization libraries that allow researchers to make beautiful and informative visualizations like *Matplotlib*, *Seaborn*, *Plotly* etc. Hunter (2007) introduced *Matplotlib*, a Python library for static, interactive, and animated visualization.

Challenges and Future Directions: Using Python for AI-based applications brings challenges with data and computations complexity, and the need for expertise, where the evolution of Python library and Python integration with other technologies attempts to meet these challenges. Processing large and complex datasets is challenging. Large, complex data sets are difficult to process. Efficient data processing and storage techniques are crucial; AI-driven solutions can be computationally intensive. Code optimization and the use of high-performance computing resources can meet these demands Effective use of Python for AI-driven solutions requires expertise in Python programming and AI concepts. Resources for ongoing education and training are very important to mountain farmers. Data processing and analysis AI-driven solutions Python is great in AI-driven projects because it brings a collection of libraries and frameworks for applying a variety of data processing, analyzing and modeling. By using Python, data scientists and analysts is able to work on advanced AI applications, high quality visualization, to extract amazing data trends and insights. Some examples from academic work show the importance of Python for implementation of such AI-based systems and in learning how to model and manage ecosystems.

Machine Learning in Ecosystem Management

Machine learning (ML) is one of the technologies with the potential to transform data into valuable knowledge in large, complex datasets. Specifically, they can be implemented to facilitate ecosystem management for monitoring biodiversity, forecasting environmental dynamics, and optimizing resources, as well as enhancing conservation interventions. This chapter describes the applications of these technologies in ecosystem management, highlighting basic methods and examples of academic research.

Introduction to Machine Learning (ML): ML is the creation of algorithms that enable a computer to leam from data and make predictions and decisions. Data mining is the process of finding hidden patterns and knowledge from large amounts of data. DL is a type of ML which is based on multilayer neural networks (NNs) trained on big data. Sarker (2021) highlights that ML algorithms, particularly those within the realm of DL, possess the capability to intelligently analyze large-scale data sets. Jordan and Mitchell (2015) present a summary of the goals and uses of ML and its relevance to a variety of disciplines, including ecological and environmental sciences.

Main methods and applications: Supervised learning algorithms are applied on labeled data sets. These algorithms are able to predict new data given learned associations. Elith et al. (2006) applied a supervised learning approach to relate species distributions to the environment. Unsupervised learning algorithms discover patterns in labeled but non-responsive data and are applied to clustering, association, and dimensionality reduction. Mukherjee et al. (2023) employed unsupervised learning to define ecoregions from vegetation and climate information. Reinforcement learning usually learns to take action through rewarding the behaviors they desire; Silvestro et al. (2022) used reinforcement learning to maximize effectiveness of conservation actions. DL algorithms such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) are good at dealing with complex data such as images and time series. Wang et al. (2024) used deep learning to analyse satellite imagery and perform land use and land cover (LULC) classification.

Application in ecosystem management: ML and DL algorithms have been already employed in large dataset from camera traps, acoustic sensors and satellites to track the biodiversity (Pettorelli et al., 2024). Norouzzadeh et al. (2018) proposed a DL approach for wildlife species identification from camera trap images. ML models have the potential to predict enviornmental changes like climated impacts, LULC change and pollution levels to support proactive management and mitigation strategies among others. Rolnick et al. (2022) applied ML for predicting climate impacts. Machine learning and data mining can also optimize use of natural resources, including water and forest. Maxwell et al. (2018) employed ML techniques to balance and adjust irrigation schedules in agriculture. Conservation planning is assisted by ML and data mining which can indicate important habitats, evaluate threats and prioritize activities.

Visualization and communication: Effective visualization is crucial to communicate results from complex data and models to stakeholders, and Python and R machine learning and data mining tools have solid support for complex rendering of informative plots, for example, with *Matplotlib*, *Seaborn* and *ggplot2*. Hunter (2007) illustrates the power and flexibility of *Matplotlib* in the context of ecological data.

Challenges and future directions: The use of ML, data mining and DL for ecosystem management is subject to challenges in terms of data quality, computational demands and model interpretability. Ensuring data integrity, accuracy and consistency is essential for reliable model predictions; Giri et al. (2010) emphasize the importance of high-quality data in global land cover mapping. Training complex ML models requires significant computational resources. Abadi et al. (2016) discuss optimizing computational performance in large-scale ML projects. Understanding how ML models make decisions is important to gain trust and ensure transparency; Ribeiro et al. (2016) introduce the LIME framework, which provides insight into model predictions.

ML, data mining and DL are powerful tools for ecosystem management, enabling the analysis of complex ecological data and supporting informed decision-making. These technologies enable researchers to monitor biodiversity, predict environmental change, optimize resource use and effectively plan conservation actions. Examples from academic research demonstrate the significant impact of these technologies in advancing the understanding and management of ecosystems.

MATERIALS AND METHODS

This research adopts a conceptual synthesis approach to provide a coherent and integrative viewpoint on the integration of geospatial and machine learning techniques in ecosystem management. In light of the swift evolution of GeoAI applications across various ecological settings, a conceptual synthesis was chosen to effectively capture methodological trends, contextual differences, and practical outcomes, while avoiding the stringent inclusion criteria typical of systematic or scoping reviews. This paper aims to showcase the utility and methodological breadth of ML and geospatial analysis tools in ecosystem management through 15 illustrative case studies. These works span a wide variety of environmental applications, including deforestation, biodiversity loss, land use and land cover (LULC) changes, and climate-driven vegetation dynamics. They exemplify how different types of ML algorithms (e.g., RF, SVM, LR, ANNs, CNNs, and LSTM models) have been applied in diverse geographic and environmental contexts.

The selection of these case studies was guided by five principal criteria: (1) relevance to ecosystem management goals, which include conservation and climate adaptation objectives, (2) integration of AI with geospatial technologies including RS and GIS, (3) variety of analytical techniques and representing global scale, i.e., from Turkey and South Africa to China, India and the Amazon basin, (4) use of peer-reviewed literature for scientific rigor, and (5) illustrative ability to indicate the success as well as persistent methodological or ethical challenges in this domain.

RESULTS

Case Studies and Applications of Machine Learning

The integration of AI, particularly, ML and geospatial analytics into ecosystem management has significantly advanced the monitoring, prediction and overall management of natural environments. This chapter presents a range of case studies demonstrating how ML-based approaches have been successfully applied to address complex environmental issues. Subsequent sections examine key ML algorithms-including supervised learning, unsupervised learning, reinforcement learning, and deep learning (DL)-and their integration with geospatial tools in ecosystem management. These applications illustrate the practical use of various ML techniques in solving diverse environmental problems. Additionally, the fundamental principles of each machine learning approach are outlined, along with their relevance to real-world applications such as the monitoring and analysis of LULC changes and forest ecosystem dynamics. Each of the fifteen case studies in this section showcases how the integration of AI, ML, and geospatial technologies can effectively address diverse ecological and environmental management challenges.

A notable example of AI-driven geospatial analysis is the monitoring of forest cover and LULC changes. By combining satellite imagery with ML algorithms—such as Random Forest (RF), Logistic Regression (LR), Decision Tree (DT), Support Vector Machines (SVMs), Artificial Neural Networks (ANNs), Long Short-Term Memory (LSTM), and Convolutional Neural Networks (CNNs)—researchers can effectively detect and track environmental changes using these models. In particular, they enable the monitoring of LULC changes, as well as forest degradation and deforestation. Moreover, these models support the prediction and simulation of environmental dynamics, enhancing the spatial and temporal accuracy of ecosystem assessments.

Case Study 1: Modeling Deforestation in the Bozdağ Mountains, Turkey: In the Bozdağ Mountains of western Turkey, long-term deforestation patterns were modeled using ML regression analysis integrated with GIS and the IDRISI Selva Land Change Modeler (LCM). The study employed logistic regression to assess deforestation risk, incorporating spatial variables such as altitude, slope, and proximity to roads, settlements, and agricultural areas. Results indicated that areas with lower slope gradients were particularly vulnerable to deforestation due to agricultural expansion. The resulting risk map provides a valuable tool for informing land-use planning and supporting targeted interventions to mitigate further deforestation (Malkoç & Nurlu, 2024). Hence, Case Study 1 demonstrates the use of logistic regression within a GIS framework and IDRISI Selva's Land Change Modeler to evaluate deforestation risk in Turkey's Bozdağ Mountains, highlighting the influence of topographic and proximity-based variables on forest degradation.

Case Study 2: Deep Learning-Based Prediction of Deforestation in the Brazilian Amazon: Deforestation in the Brazilian Amazon has been widely studied using advanced ML algorithms. One notable study developed a hybrid deep learning model that combined a Multi-Layer Perceptron (MLP) for analyzing static environmental variables with a Long Short-Term Memory (LSTM) network to capture temporal trends over a 20-year period (1999-2019). Following extensive model calibration and validation, the hybrid model demonstrated high predictive accuracy. Findings from the study revealed a significant projected increase in deforestation, with strong correlations observed between agricultural expansion and forest loss. Importantly, the results suggest that increased public investment in environmental governance could help mitigate these impacts. This case provides important insights into the human-induced factors influencing the ecological trajectory of the Amazon rainforest (Dominguez et al., 2022). Thus, Case Study 2 develops a hybrid deep learning architecture combining Multi-Layer Perceptrons (MLP) and Long Short-Term Memory (LSTM) networks to analyze long-term deforestation in the Brazilian Amazon, capturing both static and temporal drivers of forest loss.

Case Study 3: Explainable Machine Learning Models for Deforestation Prediction in the Brazilian Amazon: Building on previous research, another study investigated deforestation dynamics in the Brazilian Amazon between 1999 and 2020 using a suite of ML algorithms, including Decision Trees (DT), Random Forest (RF), Extra Trees (ET), Gradient Boosting, and Support Vector Machines (SVMs). The study applied explainable AI methods to assess the relative importance of sixteen environmental and socio-economic variables influencing deforestation. Among the tested models, tree-based algorithms-particularly Random Forest (RF)- demonstrated the highest classification accuracy and interpretability. The harvested area of temporary crops emerged as the most significant driver of deforestation. Furthermore, the analysis revealed a strong inverse relationship between public spending and deforestation rates. These findings contribute to a deeper understanding of human-driven deforestation processes and provide valuable guidance for designing policy-driven forest conservation strategies (Dias et al., 2024). As a result, Case Study 3 applies explainable ML techniques to identify key socio-environmental determinants of deforestation across the Amazon, utilizing algorithms such as RF and Gradient Boosting, and providing transparency in model decision-making.

Case Study 4: Modeling Land Use and Land Cover Changes for Ecosystem Service Prediction in Aydın, Turkey: This study examines the effects of LULC changes on ecosystem services in Aydın province, Turkey, with the goal of supporting sustainable development planning. Using the PLUS model and incorporating ML algorithms such as Random Forest (RF) for land use simulation, the study modeled future LULC patterns under three distinct development scenarios: natural development, ecosystem service-based development, and economy-driven development. The impacts of these changes on ecosystem services—specifically carbon storage and habitat quality—were assessed using the InVEST tool. Key drivers of LULC change included agricultural expansion, shifts in vegetation types, and urbanization. The results indicated that while the loss of shrubland and forests reduced ecosystem service capacity, converting open spaces into these land types improved carbon storage and habitat quality. Among the three scenarios, the ecosystem service-based approach demonstrated more effective management of land resources by balancing ecological and economic benefits (Ersoy Tonyaloğlu, 2025). In short, Case Study 4 integrates ML-based land use simulation via the PLUS model with ecosystem service assessment tools in Aydın, Turkey. This approach evaluates how alternative development trajectories affect carbon storage and habitat quality.

Case Study 5: Predictive Mapping of Land Use and Land Cover Using Multi-Spectral Satellite Imagery: This study develops a predictive model for mapping LULC using multi-spectral satellite imagery sourced from a 4-band PlanetScope satellite. To improve the spatial resolution of the extracted features, high-resolution images from Google Earth were also incorporated. A total of 105 geo-referenced images, categorized into eight LULC classes, were analyzed using various ML algorithms, including Support Vector Machines (SVMs), Decision Trees (DT), Random Forest (RF), Naive Bayes (NB), and Artificial Neural Networks (ANNs). Among these algorithms, the Artificial Neural Networks (ANNs) achieved the highest classification accuracy. Model performance was evaluated using standard metrics, including precision, recall, F-score, and kappa coefficient. This research represents a pioneering effort in utilizing 3-meter resolution satellite imagery for LULC monitoring in the northern part of Egypt's western region. The findings have promising implications for sustainable land use planning and enhanced geographic information services (Mahmoud et al., 2023). Case Study 5 leverages multi-spectral PlanetScope imagery and machine learning classifiers to produce high-resolution land cover maps in Egypt. Artificial Neural Networks (ANNs) yielded superior results, offering a practical solution for arid-zone monitoring.

Case Study 6: Cost-Free Automated Land Cover Mapping for Sustainable Management in Lesotho: This study presents a cost-free, fully automated land cover mapping framework aimed at assisting developing countries in monitoring LULC. Using open-access Sentinel-2 satellite imagery combined with machine learning techniques, the framework was applied at a national scale in the Kingdom of Lesotho, located in Southern Africa. Data processing and feature extraction were performed using google Earth Engine, while land cover data from the FAO was utilized to train Support Vector Machines (SVMs) and Bagged Trees (BT) classifiers. The results demonstrated that both models were effective in classifying urban and agricultural areas. This approach provides accurate land cover maps in a short time frame, offering a practical and cost-effective alternative to traditional GIS methods, which tend to be resource-intensive and expensive. The framework holds significant potential for supporting sustainable land management in resource-limited environments (Mardani et al., 2019). As a result, Case Study 6 introduces a low-cost, automated land cover mapping workflow using Sentinel-2 data and open-source platforms. The method proves effective for large-scale applications in resource-constrained regions like Lesotho, supporting sustainable land governance.

Case Study 7: Comparing Machine Learning Algorithms for Land Use and Land Cover (LLULC) Classification in West Bengal, India: This study compared six ML algorithms—Random Forest (RF), Support Vector Machines (SVMs), Artificial Neural Networks (ANNs), Fuzzy ARTMAP, Spectral Angle Mapper (SAM), and Mahalanobis Distance (MD)—to assess their effectiveness in LULC classification in West Bengal, India. The accuracy of each model was evaluated using multiple metrics, including the Kappa coefficient, receiver operating characteristic (RoC) curve, index-based validation, root mean square error (RMSE), and visual cross-validation. The results indicated that while all methods performed relatively well, Random Forest consistently achieved the highest classification accuracy. The study concludes that RF is the most suitable ML classifier for LULC modeling in the dynamic, charland-dominated landscapes of the region (Talukdar et al., 2020). Thus, Case Study 7 conducts a comparative evaluation of multiple classification algorithms for LULC mapping in West Bengal, identifying Random Forest (RF) as the most robust method in dynamic floodplain environments.

Case Study 8: Enhancing Land Use and Land Cover Classification with Hybrid Models: This study aimed to improve LULC classification by combining object-based analysis with neural network techniques, using satellite imagery from Sentinel and Landsat. A hybrid model, integrating Artificial Neural Networks (ANNs) with Random Forest (ANN_RF), was developed and applied to map the urban area of Sana'a city. The results showed that this combined approach outperformed the use of neural networks alone, offering superior classification accuracy. Additionally, the method enhanced conventional neural networks without the need for DL, making it a practical and efficient option for future research and applications (Alshari et al., 2023). In brief, Case Study 8 enhances urban land cover classification in Sana'a, Yemen, through a hybrid model that combines object-based image analysis with neural network techniques, improving classification reliability without relying on DL infrastructure.

Case Study 9: Modeling Ecosystem Services and Their Drivers in Zhejiang, China: Understanding the drivers of ecosystem services (ESs) and their interrelationships is crucial for effective ecosystem management. In this study, a modeling approach was applied in Zhejiang Province, China, to explore how these drivers influence ESs and the formation of ecosystem service bundles (ESBs). Random Forest (RF) was employed to model ESs and ESBs in regression and classification modes, respectively, while Shapley Additive Explanations (SHAP) were used to interpret the influence of each driver. Seven ESs were mapped at high spatial resolution, and K-means clustering identified four ESBs. The results indicated that each ES is shaped by distinct drivers, and that synergies or trade-offs among services are influenced by the direction and strength of these drivers. Effective management of these dominant factors is key to enhancing ecosystem service supply (Xu et al., 2022). In short, Case Study 9 models the relationships between ecosystem services and their drivers in Zhejiang Province using Random Forest (RF) and SHAP values. The study reveals distinct influence patterns and provides a nuanced understanding of service synergies and trade-offs.

Case Study 10: Predicting Vegetation Growth Using Extreme Gradient Boosting in China: This study developed a ML model based on the Extreme Gradient Boosting (XGBoost) method to predict vegetation growth during the growing season in China over a multi-year period. The model utilized satellite-based vegetation data from the beginning of each growing season, along with CO_2 levels and various meteorological factors, as input variables. The results showed that the model successfully captured both the spatial and temporal patterns of vegetation growth, aligning closely with satellite-observed NDVI data. It also performed well in representing seasonal variations and remained robust during extreme climate events, such as drought. This approach offers a promising tool for monitoring vegetation dynamics and supporting agricultural management strategies (Li et al., 2021). Therefore, Case Study 10 employs Extreme Gradient Boosting (XGBoost) to forecast vegetation growth across China, integrating early-season satellite indicators and climate variables to detect spatial-temporal patterns and drought sensitivity.

Case Study 11: GIS-Based Multi-Criteria Approach for Nature-Based Solutions in the Netherlands, Serbia, and Bolivia: This study develops new GIS-based tools to allocate large-scale Nature-Based Solutions (NBSs) using a multi-criteria approach. By integrating ML, spatial data analysis, and hydrodynamic modeling, the study focuses on rainwater harvesting, wetland restoration, and riverbank stabilization in the Netherlands, Serbia, and Bolivia. The Random Forest (RF) algorithm was employed for land cover classification due to its high accuracy in processing spatial data, particularly for wetland restoration and riverbank stabilization. The study emphasized the value of combining GIS, RS, and ML in NBSs planning, offering valuable insights for sustainable environmental management and climate change adaptation (Gutiérrez Caloir et al., 2023). Thus, Case Study 11 implements a GIS-based, multi-criteria framework for allocating NBSs across three continents. The inclusion of ML supports scenario analysis for wetland restoration, rainwater harvesting, and erosion control.

Case study 12: Deep Learning for Forecasting Vegetation Dynamics in South Afria's Fynbos Shrublands: Ma et al. (2022) demonstrated the power of integrating AI and environmental data to predict ecological change by combining DL and environmental variables to predict vegetation dynamics in open ecosystems. This study explores deep learning-based approaches for predicting vegetation dynamics in the fynbos shrublands of South Africa's Cape Floristic Region. Several deep learning models, including Vanilla Recurrent Neural Network (Vanilla RNN), Fully Connected Long Short-Term Memory (FC-LSTM), and Convolutional long short-term memory (ConvLSTM) were tested using thirteen environmental variables, such as precipitation and temperature, to improve forecasting accuracy. Among these models, the ConvLSTM model outperforms other approaches in predicting vegetation states, with July's mean precipitation providing the most significant performance boost (Ma et al., 2022). In brief, Case Study 12 uses advanced DL models, including ConvLSTM, to simulate vegetation dynamics in South Africa's fynbos biome. The model's accuracy underscores the capacity of temporal neural networks in capturing ecological responses to climatic variation.

Case Study 13: Monitoring Agricultural Land Use Change Using Machine Learning Approaches: This case study draws on the work of Oğuz and Yıldız (2023), who investigated the impacts of agricultural expansion on land use dynamics. By applying supervised machine learning algorithms, including Random Forest (RF) and Gradient Boosting, to satellite imagery from agricultural regions, the study revealed how intensifying agricultural activities influence spatial patterns over time. The approach provided a data-driven foundation for identifying unsustainable trends and informed the development of more resilient land management strategies within sensitive rural landscapes. Thus, Case Study 13 applies Random Forest (RF) and Support Vector Machine (SVM) algorithms to monitor agricultural land transformation, providing insights for sustainable rural land use planning.

Case Study 14: Biodiversity Conservation Through Remote Sensing and ML Integration: Based on the findings of Oğuz and Çınar (2023), this study applied a combination of RS data and ML classification techniques to assess biodiversity distribution across ecologically significant habitats. Using Sentinel-2 imagery alongside Support Vector Machines (SVMs) and K-Nearest Neighbors (KNN), the model successfully detected species-rich zones under threat from land conversion. The research demonstrated the role of integrated geospatial-ML frameworks in biodiversity mapping and emphasized the importance of technology-assisted monitoring for conservation planning. Hence, Case Study 14 utilizes Sentinel-2 imagery and ML classifiers such as K-Nearest Neighbors and SVM to detect and prioritize biodiversity hotspots for conservation management.

Case Study 15: Simulating Historical Landscape Change Using HLC and Regression-Based Modeling in the Göksu Valley, Turkey: This case study introduces an innovative methodology aimed to simulate historical landscape changes through the integration of Historic Landscape Characterization (HLC) data with a computational modeling framework (Erdoğan et al., 2020). Conducted in the Göksu Valley of southern Turkey, the research utilized regression-based modeling techniques, employing software tools such as ArcGIS, TerrSet, GRASS, R, and Dyna-CLUE. The primary objective of the model was to forecast future cultural landscape scenarios by analyzing historical transformations that occurred from the 1950s to the 2010s. The study identified twenty-two distinct HLC types, which were subsequently consolidated into eight-character classes to align with modeling requirements. Logistic Regression (LR) models were created using various spatial covariates, including elevation, slope, proximity to rivers, roads, and urban settlements. The findings illustrated the model's capability to accurately reflect the observed changes in the landscape while also projecting possible future trajectories of landscape transformation influenced by prevailing socio-economic trends. The research underscored the significance of integrating cultural and historical contexts into land change models and highlighted the value of interdisciplinary modeling approaches—particularly those that merge landscape ecology with historical geography—for fostering informed and participatory landscape planning.

Collectively, these studies reflect the growing capacity of AI and geospatial-enabled approaches to generate actionable insights for ecosystem conservation, land-use optimization, and resilience-building in the face of environmental change.

DISCUSSION

The merger of AI and geospatial analysis for ecosystem management offers great promise but also faces numerous challenges, such as scenarios involving data quality, computational costs, interpretability, ethical behavior, and collaboration (Giri et al., 2010; Zhao et al., 2022; Mardani et al., 2019; Strubell et al., 2019; Li et al., 2016; Ribeiro et al., 2016; Lundberg & Lee, 2017; Obermeyer et al., 2019; Floridi et al., 2018; Huang et al., 2020; Yin et al., 2018).

Data availability and quality: Efficient operation of AI models hinges on the availability of high-quality and complete datasets, yet there are many regions, especially in developing countries, where environmental data is incomplete and lacks standards for comparison (Giri et al., 2010). Python libraries like requests, *BeautifulSoup* and *Pandas* in addition to R libraries such as *rvest*, *httr*, *dplyr*, and *tidyr* can be valuable when scraping data and need to bring together a range of different environmental datasets. In addition, the inclusion of blockchains in geospatial data management might also secure the data and improve interoperability (Zhao et al., 2022). It is also critical to establish partnerships between governmental, academic and international bodies (Mardani et al., 2019).

Computation requirements: DL techniques are known to require significant computational power and energy. High-Performance Computing (HPC) resources can not be easily accessed, which limits their large-scale application (Strubell et al., 2019; Li et al., 2016). In order to perform parallel, scale-out, and power-efficient workflows, Python offers multiprocessing, threading, and GPU-compatible libraries such as *TensorFlow* and *CUDA*, while R includes tools like parallel, future, and profvis packages. Additionally, cloud platforms like *Google Colab* and *RStudio Cloud* improve accessibility for users.

Model interpretability: Trust in AI applications requires knowing how a model provides its output. Methods such as LIME (Ribeiro et al., 2016) and SHAP (Lundberg & Lee, 2017) are essential to make sense of complex black box models. Visualisation packages in Python (such as: *matplotlib, seaborn, plotly*) and R (*caret, iml*) can assist you to analyze the importance of the feature and the behaviour of your model.

Ethical and societal considerations: It is important to ensure the responsible use of AI so that biases are not perpetuated and negative consequences for marginalised groups are avoided (Obermeyer et al., 2019). Techniques like Fairlearn for Python and the *Fairness* package in R promote fairness outcomes, and frameworks like the European Union's Ethics guidelines for trustworthy AI provide structured direction (Floridi et al., 2018). It is also vital to involve local communities and consider cultural practices during the development.

Interdisciplinary collaboration: It is critical to forge bridges between ecology, data science, and policy. *Jupyter* notebooks in Python and *RMarkdown* in R support teamwork and iterative reporting. Yin et al. (2018) emphasize the semantic alignment of socio-economic and ecological data, and platforms like *CyberGIS-Jupyter* support reproducibility and collaborative geospatial analysis.

CONCLUSION

The fifteen case studies, in combination, demonstrate the emerging frontier of AI-geospatial integration in ecosystem management and point towards possible future directions for methodological improvement. While these works span geographically diverse contexts and types of algorithms, their analytical power can be strengthened by the consistent application of open-source programming environments such as Python and R, which offer rich suites conducive to manipulation of spatial data, development of ML methods, and visualization and support reproducing and sharing work between fields. Using Python libraries such as *TensorFlow, PyTorch* and *Scikit-learn*, or R packages like *sf and terra* in future work would make it possible to improve the scalability, interpretability and ethical clarity of our models. As such, these computing ecosystems are crucial not only for the development of more accessible and robust data science workflows, but also for supporting dynamic, data-driven decision-making required for the sustainable management of ecological systems in a changing world.

Together, the reviewed case studies demonstrate methodological diversity and applied potential for AI in conjunction with geospatial data for ecosystem management. Despite regional disparities and differences in technical emphasis both Python and R are seen as essential tools that strengthen model development, spatial analysis expertise and ethical accountability (Mardani et al., 2019, Zhao et al., 2022, Giri et al., 2010).

The successful application of GeoAI is predicated on improvements in data quality, computational power, model interpretability, ethical guidelines, and cross-sectoral convergence. As demonstrated in the examples discussed, transparent, collaborative programming workspaces not only facilitate reproducible and thereby scalable methodologies, but underpin inclusive, data-informed forms of governance, a major prerequisite for the sustainable management of ecosystems (Li et al., 2016; Strubell et al., 2019; Lundberg & Lee, 2017; Floridi et al., 2018).

By further incorporating these tools and principles, the global community can increase the speed of deployment of adaptive and resilient environmental management strategies suited to an age of rapid ecological change. Future research may focus on the creation of explainable and ethically aligned GeoAI models that foster transparency and build stakeholder trust in environmental decision-making processes. Additionally, the incorporation of real-time data streams from Internet of Things (IoT) devices and participatory sensing platforms has the potential to greatly enhance the responsiveness and flexibility of ecosystem management strategies.

AUTHOR CONTRIBUTIONS

Can Saygıner: Conceptualization, methodology, and writing. **Engin Nurlu:** Review and editing.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

ETHICS COMMITTEE STATEMENT

An ethics committee statement is not required for this study.

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