

Unleashing the Potential of Artificial Intelligence (AI) Tools in**Phytogeographical studies**Chauhan, Nisha¹¹Assistant Professor, Department of Geography, S D (P G) College Muzaffarnagar, U.P.Kumar, Manoj²²Lecturer in Biology, Govt. I. College, Kunda, U.S. Nagar, U.K., Ex coordinator in UOU,
Haldwani, Nainital, Uttarakhand**Abstract**

Phytogeography, the study of the geographic distribution of plants, is important for understanding ecosystem dynamics, biodiversity, and ecological processes. Over the past few years, advances in technology, especially artificial intelligence (AI), have revolutionized various scientific fields, including ecology and environmental science. In recent years, AI techniques have been increasingly applied in phytogeography, providing new opportunities to increase our understanding of plant distribution patterns and improve conservation efforts. The study of the role of artificial intelligence in phytogeography focuses on how AI techniques such as machine learning, remote sensing, and spatial analysis are being used to analyse large-scale plant distribution data. By leveraging AI, researchers can gain valuable insights from vast and complex datasets, identify patterns and predict future changes in plant distributions with greater accuracy. Furthermore, AI-driven approaches have the potential to address important challenges in phytogeography, such as species distribution modelling, habitat mapping, and biodiversity conservation. By integrating AI with traditional ecological methods, more effective strategies can be developed to manage and conserve plant species and their habitats. AI-driven phytogeography research, provides an overview of recent progress, discusses potential applications of AI techniques in ecological studies, and the opportunities and challenges associated with the use of AI in understanding and conserving plant biodiversity. Ultimately, the integration of AI with phytogeography has the potential to revolutionize our understanding of plant distributions and inform more sustainable conservation practices in the face of global environmental change.

Keywords: Phytogeography, Ecosystem Dynamics, Remote Sensing, Modelling, Revolutionizing, Machine learning.

Materials and methods:

AI technology plays a very important role in exploring phytogeographical research in various ways. These techniques are helpful in the collection, processing, development, evaluation of various data and formulation of future plans for the conservation of various species as well as their ecosystem. Using AI techniques, environmental data can be easily collected from various sources such as herbarium records, field surveys, climate, topography, soil characteristics and topography. AI techniques also help in data cleaning, data processing, removing duplicates, fixing errors, and standardizing data formats. Geographic Information System (GIS), remote sensing data and satellite imagery provide information on vegetation index, land surface temperature and other relevant characteristics. GIS analysis to calculate spatial metrics such as habitat fragmentation, landscape connectivity and habitat suitability. Machine Learning Algorithms- AI based software and tools are very useful in phytogeographic studies to develop predictive models using

supervised learning algorithms like Random Forest, Support Vector Machine (SVM), and gradient boosting machine (GBM). Geographic Information System (GIS) – Software like Arc GIS, Q GIS can be used for spatial data analysis and visualization. Machine learning libraries of plant geosciences – Machine learning using libraries like scikit-learn, tensor flow and porch Can make models. Remote Sensing Software like ENVI, Erdas Imagine are used to process satellite imagery and extract vegetation indices.

Review of literature-

Recent advances in artificial intelligence (AI) have revolutionized various scientific fields, including ecology and environmental science. In the field of phytogeography, the application of AI techniques has attracted significant attention due to its potential to increase our understanding of plant distribution patterns and improve conservation efforts. This review builds on existing research on the role of AI in phytogeography.

AI techniques in phytogeography like Machine learning Several studies have demonstrated the effectiveness of machine learning algorithms such as random forests, support vector machines (SVMs), and gradient boosting machines (GBMs) in modelling species distributions and predicting habitat suitability. The use of deep learning models, especially convolutional neural networks (CNNs), has played an important role in analysing remote sensing data and extracting relevant features for plant distribution modelling. Applications of AI in phytogeography, AI-driven approaches to species distribution modelling have been widely used, allowing researchers to predict species ranges, identify suitable habitats, and assess the impact of environmental variables on plant distributions. Habitat mapping AI techniques enable accurate mapping of habitats and vegetation types using remote sensing data, thereby improving habitat classification and monitoring. Conservation Planning AI based analysis helps identify priority conservation areas, assess the effectiveness of protected areas, and develop strategies for habitat restoration and conservation interventions. Future research should integrate AI techniques with

traditional ecological methods to improve the accuracy and reliability of plant distribution models.

Observations

AI techniques in phytogeography

Artificial intelligence (AI) technology has emerged as a powerful tool to advance our understanding of plant distribution patterns and improve conservation efforts in the field of phytogeography. In recent years, AI has been applied to various aspects of phytogeography, offering innovative solutions to long-standing challenges. Phytogeographic studies involve analyzing the distribution patterns of plants in relation to environmental factors. Artificial intelligence (AI) technologies have begun to play an important role in such studies, aiding in data analysis, pattern recognition, and predictive modeling. Some of the commonly used techniques here are as follows.

A- Machine Learning (ML)-

Machine learning plays an important role in phytogeographical studies by enabling the analysis of large datasets and prediction of plant species distributions based on environmental factors. Here are several ways in which ML techniques are applied.

1. Species Distribution Modeling (SDM) –

ML algorithms such as Random Forest, Support Vector Machine, and MaxEnt are commonly used to model the relationships between plant species occurrences and environmental components such as climate, soil, and topography. These models predict the potential distribution of species in different landscapes and can help identify suitable habitats, conservation priorities, and areas vulnerable to climate change.

2. Remote sensing data analysis –

ML algorithms process satellite imagery, surface data, and aerial photographs to extract vegetation characteristics, classify land cover types, and monitor changes in plant communities over time. Techniques such as Convolutional Neural Networks (CNN) and Random Forests are used for image classification, object detection and vegetation mapping.

3. Community structure analysis –

ML clustering algorithms, such as k-means and hierarchical clustering, group similar vegetation types based on species composition and environmental characteristics. These techniques help to identify specific plant communities,

ecological gradients, and transitional areas within landscapes.

4. Ecological niche modelling (ENM) –

ML algorithms estimate the ecological needs of plant species from occurrence records and environmental data layers. These models estimate species' original and actual ranges, predict potential range shifts under different climate scenarios, and assess the impact of land-use changes on species distributions.

5. Data fusion and integration—

ML techniques integrate diverse data sources, including field surveys, herbarium records, climate models, and soil maps, to create comprehensive databases for phytogeographical analyses. Methods such as deep learning and Bayesian networks handle heterogeneous data types and capture complex relationships between variables.

6. Feature selection and dimensionality reduction –

ML algorithms identify relevant predictors and reduce data dimensionality to improve model interpretability and efficiency. Techniques such as recursive feature elimination (RFE), principal component analysis (PCA), and t-distributed stochastic neighbor embedding (t-SNE) prioritize informative variables and visualize

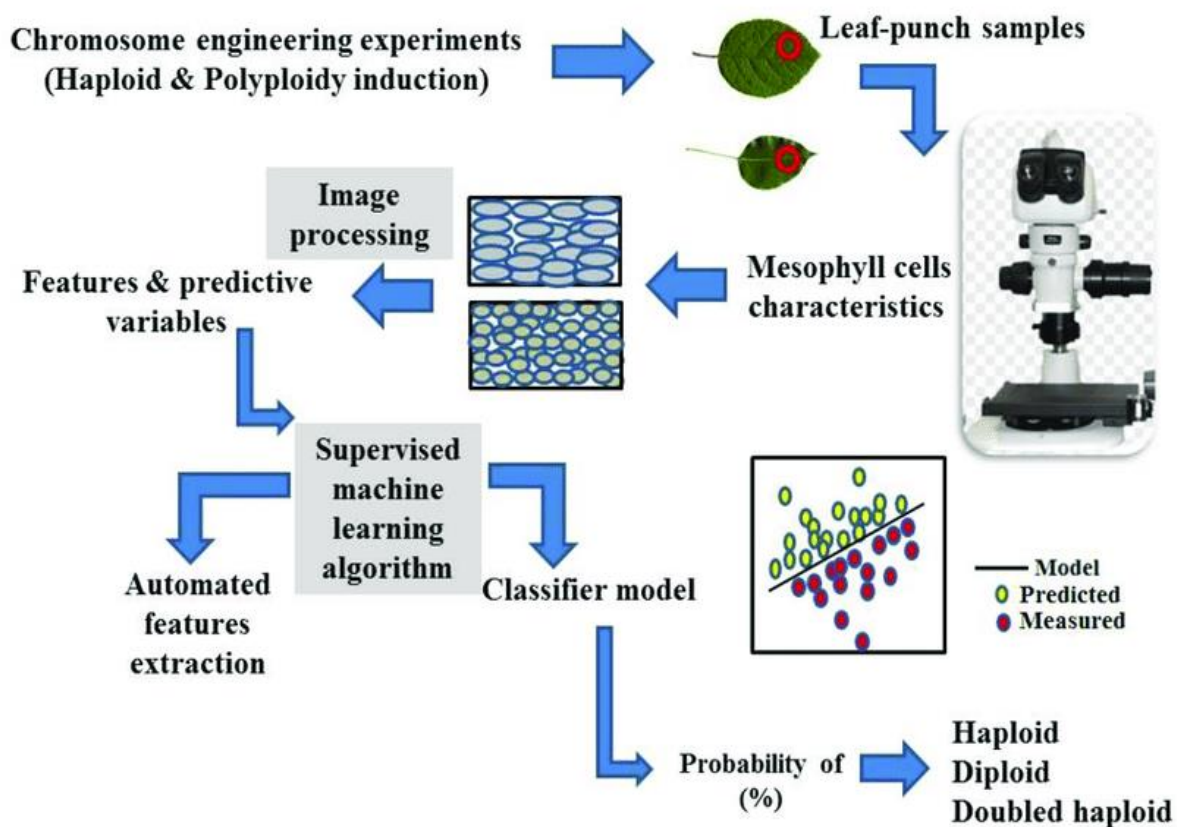
high-dimensional data in lower-dimensional spaces.

7. Model Evaluation and Uncertainty Analysis – ML frameworks assess model performance, validate predictions, and evaluate model robustness, and provide confidence intervals for ecological predictions.

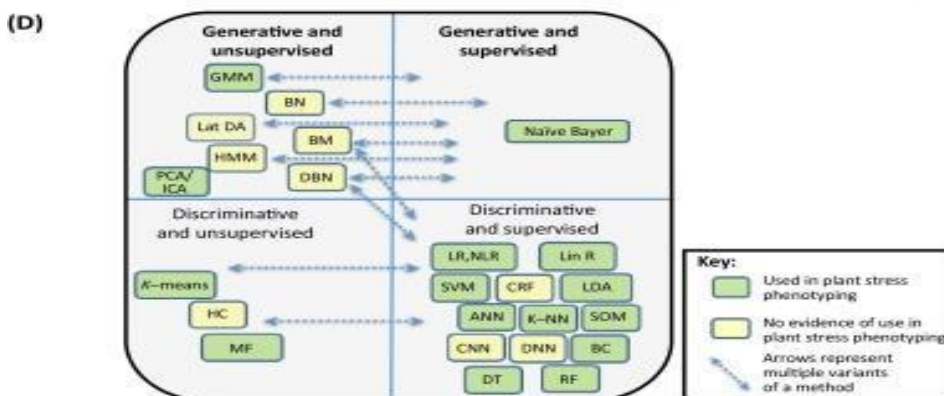
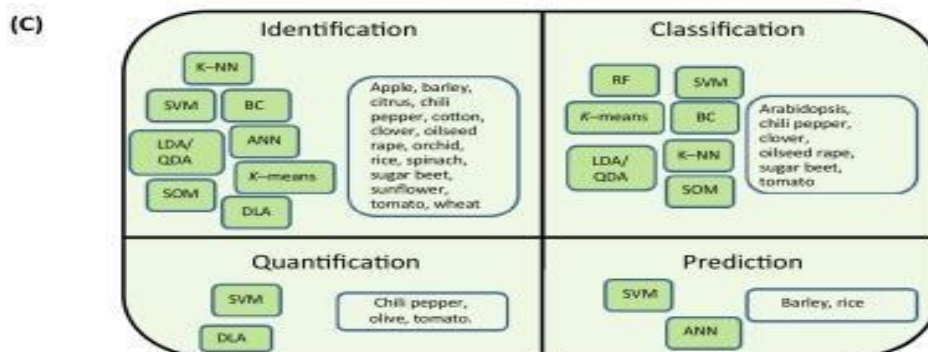
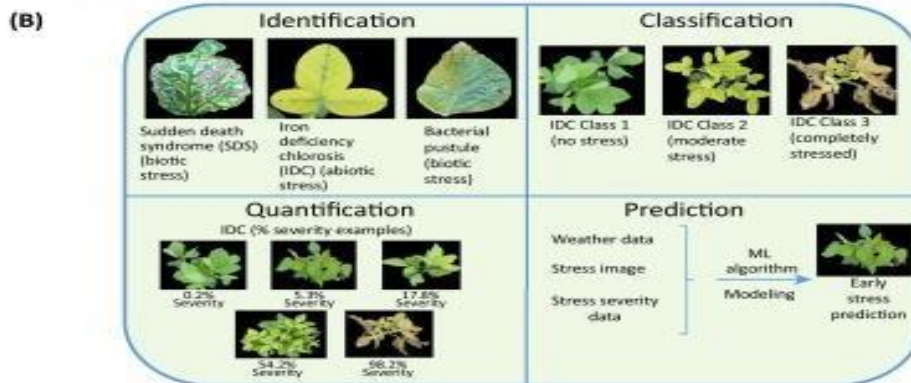
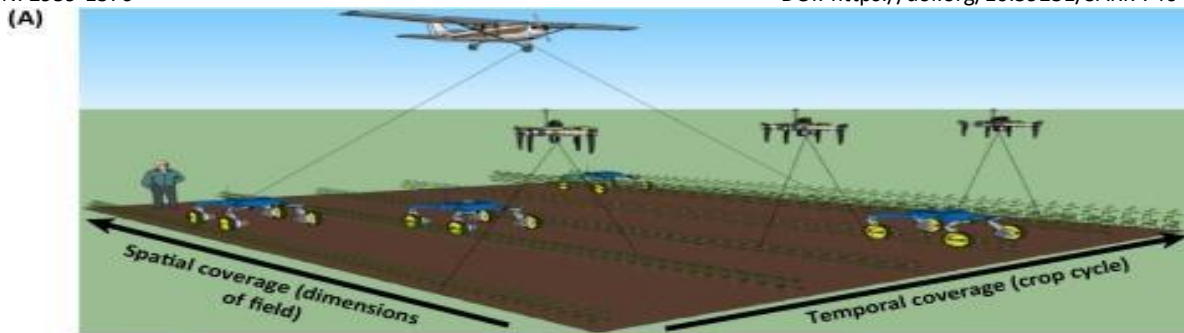
By leveraging these ML techniques, Phyto geographers can gain insight into the

quantify uncertainty in species distribution models. Cross-validation techniques, ensemble approaches, and probabilistic models estimate prediction errors,

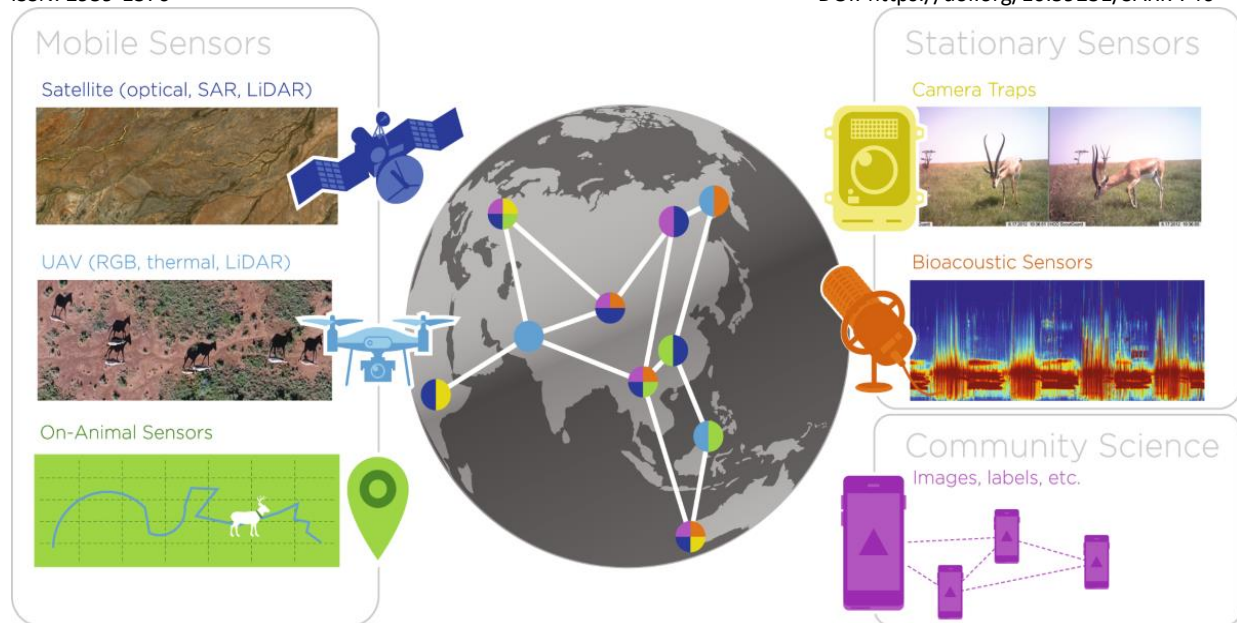
factors shaping plant distributions, predict ecosystem responses to environmental changes, and inform conservation strategies to conserve biodiversity.



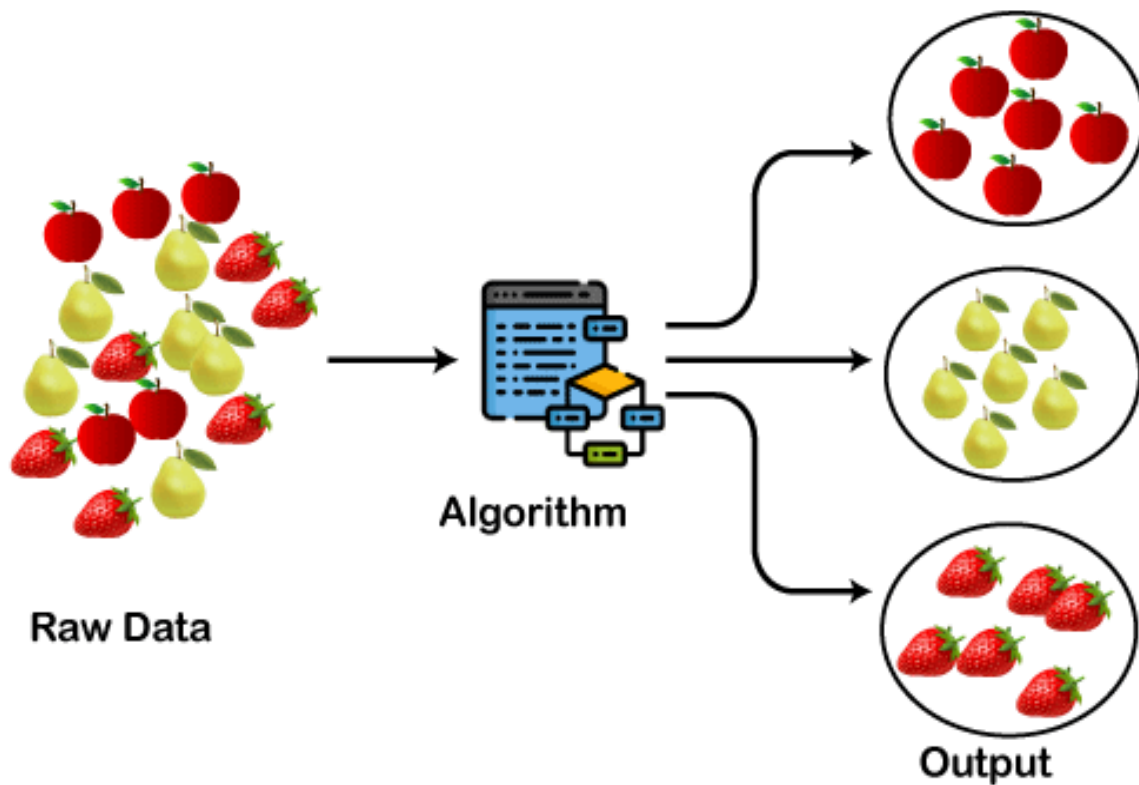
The proposed coupled image processing-supervised machine learning to determine the different plant species through cellular patterning



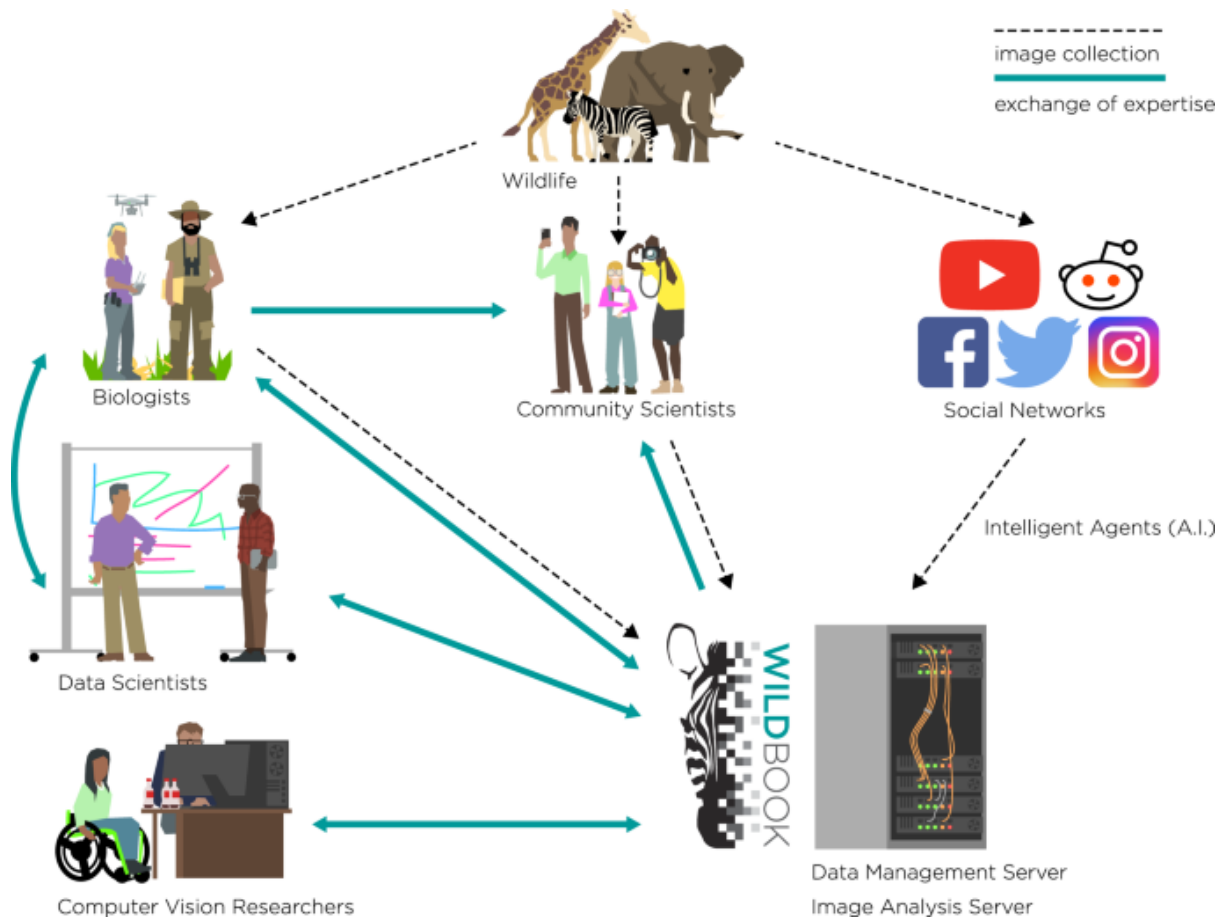
Machine learning for high thoughts



Perspectives for machine learning for wild life



Machine learning in cluster data separation



B. Deep Learning

Deep learning is a subset of machine learning that has emerged as a powerful tool in phytogeographical studies due to its ability to extract complex patterns from complex data, particularly in image analysis and spatial modeling. Deep learning plays an important role in the study of areas related to phytogeography. In which the main areas are as follows.

1. Vegetation Classification – Deep learning models, particularly Convolutional Neural Networks (CNN), are used to classify vegetation types based on satellite imagery or high-resolution aerial photographs. These models automatically learn features from raw pixel data, enabling accurate mapping of different plant communities and land cover types.

2. Object Detection and Segmentation– CNN architectures such as Mask R-CNN and

U-Net are employed for object detection and semantic segmentation of vegetation in remote sensing imagery. These models identify the crowns of individual plants or trees within the landscape, facilitating detailed analysis of vegetation structure and spatial patterns.

3. Change detection and monitoring – Deep learning models analyze multi-temporal satellite images to detect changes in vegetation cover, land use, and habitat fragmentation over time. By comparing image pairs or time-series data, these models identify areas undergoing deforestation, urbanization, or ecological succession, thereby aiding long-term monitoring of landscape dynamics.

4. Species distribution modelling – Deep learning algorithms predict environmental preferences of plant species from occurrence records and remote sensing data. Models such as deep belief networks (DBN) and recurrent neural networks (RNN) capture complex relationships between species distributions and environmental variables, allowing accurate prediction of species habitat suitability and range shifts under climate change scenarios.

5. Ecological Phenology – Deep learning models analyse time-series satellite imagery to track vegetation phenology, including leaf initiation, flowering, and senescence. By extracting phenological metrics from satellite data such as NDVI time series, these models quantify seasonal changes in plant productivity, detect anomalies in phenological patterns, and assess the impact of climate variability on ecosystem dynamics.

6. Habitat Connectivity Modelling – Deep learning techniques, combined with graph theory and spatial analysis, model habitat connectivity networks and ecological corridors for plant dispersal. Graph convolutional networks (GCNs) analyse landscape connectivity patterns, identify key habitat nodes and linkages, and prioritize conservation actions to enhance landscape connectivity and species resilience.

7. Data fusion and transfer learning – Deep learning architecture integrates multi-modal data sources, including satellite imagery, climate models, and species occurrence records, to improve model generalization and transferability. Transfer learning techniques fine-tune pre-trained deep neural networks on specific phytogeographic tasks, leveraging

knowledge learned from related domains to enhance model performance with limited training data.

8. Uncertainty quantification and model interpretation – Deep learning frameworks incorporate probabilistic models, Bayesian neural networks, and uncertainty estimation techniques to quantify prediction uncertainties and assess model reliability in phytogeographical applications. Explanatory methods, such as attention mechanisms and saliency maps, provide insight into model predictions and highlight important features that determine species distributions.

By harnessing the capabilities of deep learning, Phyto geographers can unravel complex ecological patterns, improve predictive models of species distributions, and make evidence-based decisions in rapidly changing environments.

C. Geographic Information System (GIS)

Phytogeography plays an important role in phytogeographic studies by providing tools to analyze, visualize, and interpret spatial data related to plant distribution and environmental factors. The use of GIS as geographical information systems can play an important role in phytogeographic research.

1. Spatial data integration – GIS integrates diverse geospatial datasets, including vegetation maps, soil surveys, climate data, topographic maps, and satellite imagery. By overlaying and combining these datasets, researchers can explore relationships between plant distributions and environmental variables at different spatial scales.

2. Species distribution mapping- GIS software is used to create species distribution maps based on field surveys, herbarium records and occurrence data. Researchers use spatial interpolation techniques, such as kriging and inverse distance weighting, to predict species abundance and visualize species richness patterns across landscapes.

3. Habitat suitability modelling – GIS-based habitat suitability models predict the potential distribution of plant species based on environmental conditions. Techniques such as logistic regression, Maxent, and Random Forest are applied to analyse species-environment relationships and identify suitable habitats for conservation planning and management.

4. Land Cover Classification- GIS tools classify land cover types and vegetation communities using remote sensing imagery.

Supervised and unsupervised classification algorithms, such as maximum likelihood classification and k-means clustering, classify pixels into vegetation classes, enabling accurate mapping of plant distributions and landscape patterns.

5. Ecological Niche Modeling (ENM) – GIS-based ENM techniques model the ecological niche of species and predict their potential distribution across geographic regions. These models predict species' habitat preferences based on environmental variables such as temperature, precipitation, altitude, and soil type, and identify suitable habitats for species conservation and restoration efforts.

6. Spatial analysis and modelling: GIS facilitates spatial analysis of phytogeographical data, including hotspot analysis, spatial auto correlation, and landscape connectivity analysis. Researchers use GIS tools to quantify landscape metrics, assess habitat fragmentation, and identify priority areas for biodiversity conservation and habitat restoration.

7. Ecological Corridor Planning – GIS-based corridor analysis identifies landscape linkages and connectivity pathways for plant dispersal and migration. Using least-cost path

analysis and circuit theory approaches, researchers delineate ecological corridors that promote gene flow and species movement, facilitating landscape-scale conservation planning and increased habitat connectivity. Is.

8. Visualization and communication – GIS software enables the creation of informative maps, figures, and visualizations to communicate phytogeographic findings to diverse audiences. Researchers use GIS tools to produce maps showing species distributions, habitat suitability models, and spatial patterns of biodiversity, raising public awareness, and increasing stakeholder participation in conservation initiatives.

D. Data Mining and Pattern Recognition-

By leveraging the capabilities of GIS technology, phytogeographers can analyze spatial patterns of plant distribution, assess environmental drivers of biodiversity and develop evidence-based conservation strategies to protect and manage ecosystems in a rapidly changing world. Can develop. Data mining and pattern recognition techniques play a vital role in phytogeography by extracting valuable insights from large datasets related to plant distribution, environmental variables and

ecological processes. The following methods can play an important role in data mining and pattern recognition.

1. Species occurrence data analysis – Data mining techniques, such as association rule mining and frequent pattern analysis, identify co-occurrence patterns of plant species within ecological communities. These methods reveal species associations, habitat preferences, and ecological interactions, providing insight into plant community structure and dynamics.

2. Environmental variable selection - Pattern recognition algorithms, including feature selection and dimensionality reduction techniques, identify relevant environmental variables that influence plant distributions. Methods such as principal component analysis (PCA), t-distributed stochastic neighbor embedding (t-SNE), and mutual information gain prioritize informative predictors and reduce data dimensionality for modeling species distributions.

3. Species distribution modeling (SDM)- Data mining algorithms, such as decision trees, random forests, and support vector machines, model the relationship between species occurrences and environmental

covariates. These models predict species distributions, estimate habitat suitability, and identify environmental limitations that influence species persistence and range dynamics.

4. Biogeographical Pattern Analysis- Data mining methods analyze spatial patterns of plant distribution to identify biogeographical regions, biodiversity hotspots and areas of endemism. Cluster analysis, spatial autocorrelation, and species network analysis: Pattern recognition techniques, such as network analysis and graph theory, characterize ecological networks of plant interactions, such as mutualisms, competition, and trophic relationships. These methods quantify network topology, identify key species, and assess the resilience of plant communities to environmental disturbances.

6. Temporal trend detection- Data mining algorithms detect temporal trends and anomalies in plant distribution data, such as range shifts, phenological changes, and the spread of invasive species. Time-series analysis, trend detection methods, and anomaly detection algorithms monitor long-term changes in plant populations and assess

the impact of climate change and anthropogenic activities.

7. Predictive modelling and forecasting –

Pattern recognition models, such as autoregressive integrated moving average (ARIMA) and long short-term memory (LSTM) networks, predict future trends in plant distribution and ecosystem dynamics. These models incorporate historical data, environmental drivers, and predictive variables to estimate changes in species distributions under different scenarios.

8. Data fusion and integration-

Data mining techniques integrate heterogeneous datasets, including remote sensing imagery, ecological surveys, climate models, and genetic data, to enhance phytogeographical analyses. Multi-source data fusion, combination methods, and integration frameworks combine complementary information sources to improve model accuracy and robustness.

By applying data mining and pattern recognition techniques, phytogeographers can uncover hidden patterns in plant distribution data, elucidate the ecological processes driving biodiversity patterns, and make recommendations for the conservation of ecosystems in a changing world. can

inform evi m. Agent-Based Modeling (ABM) in Plant Geography-

E. Agent-Based Modelling (ABM) in Plant Geography-

Agent-based modelling (ABM) provides a powerful framework for simulating the behavior of individual plants and their interactions within their environment, making it particularly valuable in phytogeography for understanding complex ecological processes. ABM can be applied in the study of plant geography in the following ways.

1. Individual-based simulation -ABM represents plants as autonomous agents with specific characteristics and behaviors, such as growth, dispersal, and reproduction. By modeling individual-level processes, ABM captures emergent properties of plant populations, such as population dynamics, spatial patterns, and community structure.

2. Dispersal modelling – ABM simulates plant dispersal mechanisms, including seed dispersal by wind, water or animals, as well as vegetative propagation via rhizomes or runners. Agents interact with their environment, such as terrain characteristics, habitat suitability, and dispersal barriers, to

determine movement patterns and colony dynamics.

3. Habitat fragmentation and connectivity-

ABM assesses the impact of habitat fragmentation on plant populations and ecosystem connectivity. By modeling landscape features such as habitat patches, corridors, and barriers, ABM measures the effects of landscape structure on species persistence, gene flow, and metapopulation dynamics.

4. Species interactions – ABM simulates plant interactions, such as competition for resources, facilitation, and interactions with other species. Agents compete for light, water, nutrients, and space in their local neighborhoods, affecting individual growth rates, survival chances, and community structure.

5. Climate change adaptation – ABM examines plant responses to climate change, including changes in species distributions, phenological changes, and adaptation strategies. Agents change their behavior and life history in response to changing environmental conditions such as temperature, precipitation, and carbon dioxide levels. Agents adjust their behavior and life history traits in response to changing

environmental conditions such as temperature, precipitation, and carbon dioxide levels, which affect species range dynamics and ecosystem resilience.

6. Disturbance ecology – ABM models the effects of natural and anthropogenic disturbances such as fire, grazing, logging, and land-use change on plant communities. Agents experience mortality, regeneration and succession processes following disturbance, shaping vegetation dynamics, diversity patterns and ecosystem recovery trajectories.

7. Community Assembly Processes – ABM explores mechanisms of community assembly including niche-based processes, dispersal limitation, and stochasticity. By simulating species interactions and colonization events, ABM elucidates the relative importance of ecological processes in shaping plant community structure and biodiversity patterns.

8. Conservation planning and management – ABM evaluates alternative conservation strategies and land management practices to conserve plant diversity and ecosystem services. By simulating land-use scenarios, habitat restoration efforts, and conservation interventions, ABM informs

decision-making processes and identifies effective strategies for biodiversity conservation in dynamic landscapes.

By integrating these components, the ABM provides a comprehensive framework for studying plant ecology, understanding the mechanisms driving species distributions, and predicting ecosystem responses to environmental changes and human activities.

F. Natural Language Processing (NLP) in Plant Geography

Natural language processing (NLP) can enhance phytogeographical studies by extracting valuable information from textual sources such as research articles, ecological surveys, and botanical databases.

Data extraction – NLP algorithms extract plant species occurrence data, habitat descriptions, and environmental variables from unstructured text sources. Named entity recognition (NER) identifies mentions of plant species, geographical locations and ecological terms in text documents, enabling automated data extraction and annotation.

1. Species Occurrence Mining – NLP methods extract species occurrence records from textual sources such as field notes, herbarium labels, and ecological surveys. Text mining algorithms identify species

names, abundance numbers, and geographic coordinates mentioned in text documents, enriching species occurrence databases for phylogeographic analyses.

2. Taxonomic annotation—NLP tools classify plant species mentioned in text documents into taxonomic categories, such as family, genus, and species. Taxonomic NER algorithms recognize species names and link them to standardized taxonomic databases, facilitating species identification, data reconciliation, and taxonomic annotation in biodiversity databases.

3. Habitat description analysis – NLP techniques analyze habitat descriptions in ecological surveys and vegetation inventories to characterize plant communities and environmental conditions. Text analysis algorithms identify habitat keywords, vegetation characteristics and ecological indicators mentioned in text descriptions, providing insight into species-habitat relationships and community structure.

4. Ecological Trait Extraction – NLP methods extract ecological traits and functional traits of plant species from textual sources such as taxonomic descriptions and ecological studies. Trait extraction algorithm to extract morphological characteristics,

physiological characteristics and ecology of plant species mentioned in text documents.

5. Literature Review Automation – NLP tools automate literature review processes by summarizing relevant research articles, identifying key findings, and extracting scientific information related to phytogeography. Text summarization algorithms generate concise summaries of research papers, enabling researchers to quickly review and synthesize knowledge from large document collections.

6. Biogeographic text analysis – NLP techniques analyze biogeographic texts, historical documents, and expedition reports to reconstruct past plant distributions and biogeographic patterns. Text mining algorithms extract geographical references, place names, and spatial information from historical texts, supporting biogeographic reconstructions and paleoecological studies.

7. Semantic search and information retrieval – NLP-based search engines enable semantic search and information retrieval in biodiversity databases and digital libraries. Semantic search algorithms understand user queries, match search terms to relevant concepts, and retrieve documents containing

relevant information on plant distributions, species traits, and ecological processes.

By leveraging NLP techniques, plant geographers can efficiently extract, analyze, and synthesize textual information from diverse sources, enriching biodiversity databases, supporting ecological research, and enhancing knowledge discovery in plant geography.

G. Remote sensing in geographical studies

Remote sensing is invaluable in photogeographic studies, providing a bird's-eye view of the Earth's surface through the use of sensors mounted on satellites or aircraft. Remote sensing techniques can help in geographical studies in the following ways.

1. Land cover classification- Remote sensing helps in classifying different land cover types like forests, urban areas, agricultural land, water bodies etc. This classification is important for understanding land use patterns, ecosystem health, and changes over time.

2. Vegetation analysis – This allows monitoring of vegetation health, biomass estimation, and detection of changes such as deforestation, or forest fires. This information assists in ecological studies,

biodiversity assessment and conservation efforts.

3. Terrain Mapping – Remote sensing technologies such as SPECT (Light Detection and Ranging) provide accurate elevation data, which is important for creating digital elevation models, slope analysis, and landform classification.

4. Environmental monitoring- Remote sensing helps in monitoring environmental parameters like water quality, air pollution and land degradation. It provides insight into the impact of human activities and natural processes on the environment.

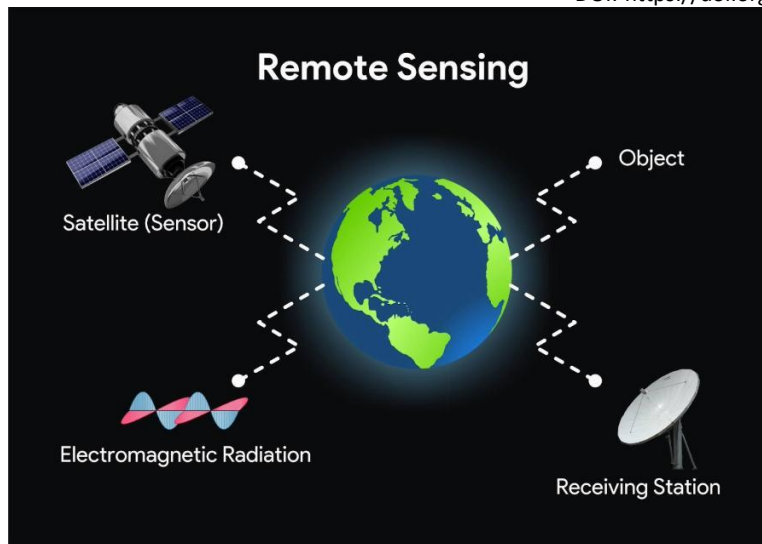
5. Natural Hazard Assessment- It helps in identifying and monitoring natural hazards like floods, earthquakes, landslides and volcanic eruptions. Remote sensing data enables better preparedness, response and mitigation strategies.

6. Urban Planning-Remote sensing supports urban planning by providing data on urban sprawl, infrastructure development and population distribution. It helps in optimizing resources, improving transportation networks and managing urban growth.

7. Archaeological studies – Remote sensing can detect buried archaeological features such as ancient ruins, burial sites and historical landscapes. This non-invasive technique helps archaeologists identify potential excavation sites and preserve cultural heritage.

8. Climate change studies- Remote sensing provides long-term data on climate change such as temperature, rainfall and sea level rise. It helps scientists understand climate change trends, assess its impact on ecosystems, and formulate adaptation strategies.

9. Disaster Management-Remote sensing facilitates rapid assessment and response during natural disasters such as hurricanes, wildfires and tsunamis. It assists in damage assessment, search and rescue operations and recovery efforts.



Remote sensing in phytogeographical studies

Conclusion

Artificial Intelligence (AI) has emerged as a powerful tool to advance our understanding of plant distributions and improve conservation efforts in phytogeography. By leveraging AI techniques, researchers can gain valuable insights into complex ecological processes, identify habitats important for conservation, and develop effective strategies for conserving biodiversity. In this paper, we explore the role of AI in phytogeography and its potential to enhance understanding and conservation efforts. We reviewed a variety of AI techniques used in phytogeography research, including machine learning algorithms, deep learning models, and spatial analysis techniques. We discussed applications of AI

in species distribution modelling, habitat mapping, landscape connectivity analysis, priority area identification, climate change impact assessment and conservation planning and management. Looking ahead, future research directions include improving data integration and sharing, developing explainable AI models, addressing data limitations and bias, improving model generalizability and transferability, capacity building and training, promoting ethical and responsible AI and enhancing validation and reproducibility. By addressing these challenges and pursuing these future directions, researchers can harness the full potential of AI to increase our understanding of plant distributions, inform conservation strategies, and promote sustainable

management of natural ecosystems. Through collaborative efforts and interdisciplinary research, AI-powered phyto-geography has the potential to revolutionize conservation efforts and contribute to the conservation of plant biodiversity around the world.

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