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Challenges in remote sensing based climate and crop monitoring: navigating the complexities using AI

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Abstract
The fast human climate change we are witnessing in the early twenty-first century is inextricably linked to the health and function of the biosphere. Climate change is affecting ecosystems through changes in mean conditions and variability, as well as other related changes such as increased ocean acidification and atmospheric CO_2 concentrations. It also interacts with other ecological stresses like as degradation, defaunation, and fragmentation. Ecology and climate monitoring are critical to understanding the complicated interactions between ecosystems and changing climate trends. This review paper dives into the issues of ecological and climate monitoring, emphasizing the complications caused by technical limits, data integration, scale differences, and the critical requirement for accurate and timely information. Understanding the ecological dynamics of these climatic impacts, identifying hotspots of susceptibility and resistance, and identifying management measures that may aid biosphere resilience to climate change are all necessary. At the same time, ecosystems can help with climate change mitigation and adaptation. The processes, possibilities, and constraints of such nature-based climate change solutions must be investigated and assessed. Addressing these issues is critical for developing successful policies and strategies for mitigating the effects of climate change and promoting sustainable ecosystem management. Human actions inscribe their stamp in the big narrative of our planet's story, affecting the very substance of the global atmosphere. This transformation goes beyond chemistry, casting a spell on the physical characteristics that choreograph Earth's brilliant dance. These qualities, like heavenly notes, create a song that echoes deep into the biosphere. We go on a journey via recorded tales of ecological transformation as they respond to the ever-shifting environment in this text. We peek into the rich fabric of change, drawing insight from interconnected observatories. Nonetheless, this growing symphony is set to unleash additional transformational stories - narratives of natural riches and rhythms that are both economically and environmentally essential. Understanding these stories is essential for navigating this developing epic. A roadmap for sustainable development necessitates the ability to comprehend these stories, a problem that resonates across the breadth of monitoring programs, particularly in the infancy of integrated sites.

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Introduction

Good monitoring is essential for sustainable ecological management, the recovery of vulnerable species, and environmental reporting [1, 2]. Monitoring is especially vital in a changing environment, particularly in reaction to climate change and increased human use of natural resources [3, 4]. There are five important reasons to monitor: Understanding the way a system operates (including the efficacy of management actions); increasing awareness about a problem; engaging the public and leveraging effort; and identifying dangers or opportunities [5]. Monitoring is regarded as an essential component of global initiatives such as the Convention on Biological Diversity [6], national-level biodiversity management directives [7], the preservation of specific ecosystem integrity (e.g. [8]), and the protection of specific endangered species [9]. The interconnectedness between ecological systems and climate dynamics is well-established, with ecological processes being significantly influenced by climate variations. Monitoring these interactions is crucial for predicting and responding to environmental changes, but it comes with a set of intricate challenges that necessitate comprehensive investigation. In the intricate tale of our planet, human activities etch their mark across the global canvas. The composition of Earth's atmosphere is no exception, undergoing a transformation shaped by anthropogenic endeavours. A crescendo of increasing carbon dioxide, methane, nitrous oxide, HFCs, and perfluorocarbons resonates through the air, heralding this change. Moreover, the chemistry of precipitation in regions like North America, Europe, and Asia has been redefined by the touch of sulphur and nitrogen compounds [10]. These shifts ripple beyond chemistry, altering the very physiognomy of the atmosphere. From the depletion of stratospheric ozone to the birth of ground-level ozone [11, 12] and the nuanced dance of the radiation balance, these metamorphoses script a new narrative. As the radiation balance sways, it whispers of a warming world, with the promise of local and regional temperature changes as diverse as nature's palette. As we peer into these changing verses, environmental monitoring emerges as the sentinel, watching over Earth's pulse and melody. Environmental monitoring is a maestro conducting a symphony of objectives: unveiling problems, fashioning solutions, appraising the efficacy of control actions, and highlighting emerging concerns. A star in this performance is the integrated monitoring site – the ecological observatory. Nestled within this realm are long-term endeavors characterized by multidisciplinary scrutiny, united with meticulous research. In the pursuit of understanding, these sites dare to manipulate ecosystems as expansive as lakes or wetlands. This grand endeavor of integrated monitoring is driven by a purpose: to distill a tapestry of data that not only paints change but also deciphers its origins. This revelation of cause and effect is the bedrock of designing pollution control strategies. In the Canadian saga, the story of acid rain's impact unfurled through the lens of integrated monitoring, with sites like Dorset, Ontario, revealing its narrative. A symphony of data from 15 sites across Canada and the United States united to compose a target loading of 20 kg wet sulphate ha^{-1} yr^{-1}, a cornerstone adopted as Canadian policy in 1984. But these sites offer more than snapshots – they share epics. As the human population surges relentlessly forward, an ever-mounting strain is placed upon the delicate equilibrium of food demand. This imperative crescendo necessitates resolute action to safeguard food security for both the present and the unfolding tapestry of generations to come [13, 14, 15]. Within the pages of scholarly discourse, a legion of visionary researchers has proffered an array of inventive pathways, orchestrating a symphony of methodologies to perpetually surreal agricultural processes and fortify the bastions of food security. Here in lie some of their distinguished contributions:

A prelude to the agricultural harvest, yield estimation statistics stand as a sagacious guide for farmers, informing pivotal decisions such as the judicious application of fertilizers. Moreover, these statistics serve as sentinels, forewarning of potential threats like the encroachment of insects and the specter of drought, affording the opportunity for pre-emptive countermeasures [16]. The harmonious supply of major crops to meet demand requires an ongoing sonnet, a monitoring of crops throughout their growth. To avert the dissonance of scarcity and surplus, a global classification of crops during their seasonal crescendo becomes imperative [17]. A view of land transformation unfolds, extending the frontiers of effective croplands by repurposing fallow expanses. Yet, this ballet is not without consequences—abrupt land conversion, a metaphorical thunderclap, amplifies greenhouse gas emissions, casting a shadow over climate and local ecosystems. Enter land cover mapping, a cartographic aria, offering insights into the topography of interest, unravelling the sustainability and aptitude of the land for specific crop ballets [18]. The symphony of cultivation faces climatic crescendos in the form of drought and flood. To harmonize with these tempests, it is imperative to identify cultivars resilient to the strains of unfavourable weather, orchestrating a resilient response to minimize the discordant notes of crop loss [19].

The monitoring of these agricultural opuses has been relegated to the human touch, a laborious, costly, and error-prone ballet. Inspectors pirouette within a confined farmland, examining but a fragment within a specific temporal cadence. Expertise is a constraint; multiple inspectors may broaden the stage but at the cost of an opulent production [20]. The quality of the inspection

is a symphony directed by the knowledge and skill of the conductor. Yet, the outcome may falter, a potential discord echoing through the agricultural composition [21]. To liberate this agrarian way from its earthly constraints, remote sensing emerges as a celestial maestro, conducting agricultural symphonies with ethereal precision. Amidst the cosmic advantages of this technological overtone. Remote sensing unfurls its celestial cloak, enveloping vast expanses in its watchful gaze. The data, a celestial heartbeat, repeats within short intervals, creating a cosmic time-series database for an opulent monitoring spectacle [22]. The approach of remote sensing knows no boundaries, collecting data across myriad scales and resolutions. Its purpose is cosmic, unfettered by earthly constraints, a versatile spectacle for myriad applications [23, 24]. Remotely sensed data ascend to the astral realms of laboratories, where high-processing computers conduct celestial analyses for multiple applications simultaneously. No longer tethered to earthly confines, the need for physical presence or processing of modest data samples becomes a relic of the past [25]. Remote sensing devices, cosmic minstrels, record the celestial ballet of electromagnetic radiation absorption and reflection from plants. This cosmic melody unveils the biotic intrigues of insects and pesticides, alongside the abiotic echoes of drought and flood—celestial stresses upon the earthly stage [26].

A challenge enshrouds the realm of ecological variables: how to distil the essence of intricate ecological systems into measures that encapsulate the whole yet remain manageable and effective for scrutiny and modelling. Fluctuations in weather conditions, particularly abrupt changes, can induce stress in crops, with repercussions that are intricate, interwoven, and often specific to certain crops, growth stages, and genetic varieties. The quest for precise crop condition monitoring necessitates the identification of an optimal baseline product and a compatible remote sensing product at a spatial resolution conducive to minimizing uncertainties [27]. For example, discerning between irrigated and rainfed crops becomes crucial, particularly in dry seasons, allowing for location-specific monitoring tailored to individual irrigation conditions. Nevertheless, prevailing crop condition monitoring methods predominantly rely on low-resolution satellite data, which, with their coarse pixels, seldom reflect the conditions of individual crops unless within expansive parcels [28].

The advent of Sentinel-2–like satellite data brings promise to medium- to high-resolution crop condition monitoring, albeit requiring substantial data processing. However, the pursuit of high spatial resolution introduces challenges such as geolocation mismatch and impacts from soil backgrounds. The call is for users to wield the freedom to choose the spatial scale data that aligns with their unique monitoring targets, recognizing the potential limitations in detecting crop stress driven by drought [29].

Drought emerges as a formidable natural disaster, inflicting extensive stress and yield losses, with drought assessments integral to Crop Monitoring Systems (CMSs). The transition from meteorological drought to agricultural drought, spurred by a dearth of precipitation and heightened evaporation rates, precipitates reductions in crop yield or even complete failures. Various drought indices, including the Standardized Precipitation Index (SPI) [30]. Despite these advances, challenges persist in comprehensively determining the impacts of nutrients, diseases, and pests on crop stress.

The forecasting of crop production involves a delicate interplay of crop area estimates and yield predictions within specific agro-ecological regions, administrative units, and crop types. Two methodological approaches, crop type mapping and geostatistical methods, converge to derive crop area estimations, with the former not only contributing to crop area estimation but also furnishing foundational data for crop condition assessment and yield prediction [31]. Despite strides in crop-mapping studies, most are confined to local areas heavily reliant on field data, lacking transferability to broader regions. Additionally, methodologies often depend on local knowledge of management practices, phenology, and prior insights into cropping patterns [32]. Geostatistical methods for deriving crop areas hinge on field survey information, satellite data, and statistical inference. The uncertainties and time lags associated with these methods render them impractical for precise crop area estimation. Conversely, remote sensing emerges as a beacon, easily distinguishing between cropped and non-cropped arable lands, allowing for the estimation of cropped areas with relatively low error rates [33]. Four satellite-driven methods for predicting crop yields ahead of harvest face uncertainties, particularly in extreme climatic conditions, highlighting the frailty of the yield prediction component in current crop monitoring models and vegetation indices (VIs) [34]. Understanding the determinants of crop yields, especially in challenging climates, remains a pressing frontier in the realm of crop monitoring.

Deep learning methods for Crop and Remote Sensing:

Convolutional Neural Networks (CNNs):

Image Classification: CNNs are a fundamental deep learning architecture used for image classification tasks in both climate and ecology. In climate research, they are applied to satellite and weather radar images to classify cloud patterns, detect cyclones, or identify land cover types. In ecology, CNNs are used to classify species based on camera trap images or analyze satellite imagery

to monitor deforestation or changes in vegetation cover [35].

Recurrent Neural Networks (RNNs): Time-Series Analysis: RNNs, including LSTM networks, are crucial for analyzing time-series data in climate and ecology. In climate science, RNNs can model and predict temperature trends, precipitation patterns, and sea-level rise. In ecology, they can capture temporal dependencies in wildlife migration, breeding, or population dynamics.

Generative Adversarial Networks (GANs): Data Augmentation: GANs are employed to generate synthetic data that can augment limited datasets in both fields. In climate research, GANs can generate additional climate data points to improve model training. In ecology, GANs can create synthetic images of rare species to balance training datasets.

Transfer Learning: Fine-Tuning Pretrained Models: Transfer learning is especially valuable in scenarios where labeled data is scarce. Researchers can take pretrained deep learning models, such as CNNs trained on large image datasets like ImageNet, and fine-tune them for specific climate and ecology tasks. This approach reduces the amount of data required for training and speeds up model development.

Spatial-Temporal Models: Capturing Complex Patterns: In both climate and ecology, complex patterns often emerge from the interaction of spatial and temporal factors. Specialized deep learning architectures like 3D CNNs or spatiotemporal CNNs are used to capture these dependencies. They can be applied to climate modeling for simulating weather patterns and ecosystem dynamics in ecological research.

Attention Mechanisms: Long-Range Dependencies: Attention mechanisms, popularized by Transformer models, are used to capture long-range dependencies in ecological and climate data. They enable models to focus on relevant information across time and space. In ecology, attention mechanisms can be applied to analyze species distribution patterns influenced by various environmental factors.

Graph Neural Networks (GNNs): Modeling Ecological Networks: GNNs are vital in ecology for modeling complex ecological networks, such as food webs, mutualistic interactions, or habitat connectivity. They allow researchers to understand the structure and dynamics of ecosystems and predict the consequences of species loss or habitat fragmentation.

Deep Reinforcement Learning (DRL): Optimizing Decision-Making: DRL techniques can optimize decision-making processes in climate adaptation and ecosystem management. For example, they can be used to find optimal resource allocation strategies for conservation efforts or determine the best time for planting crops based on climate conditions.

Time-Series Forecasting: Predictive Modeling: Deep learning models like Prophet or WaveNet are applied to climate and ecological time-series data for accurate forecasting. In climate science, they can predict temperature and precipitation trends. In ecology, they can forecast population dynamics or disease outbreaks in wildlife populations.

Anomaly Detection: Identifying Unusual Patterns: Deep learning-based anomaly detection methods, such as autoencoders, are used to identify unusual patterns or outliers in environmental data. For instance, they can detect pollution events in water bodies or abnormal climate conditions that may signify climate change-related anomalies.

Natural Language Processing (NLP): Text Data Analysis: In addition to numerical data, climate and ecology research often involves textual data from research papers, climate reports, and environmental policies. NLP techniques can be applied to extract insights, summarize findings, and aid in data integration and information retrieval.

Multi-Modal Fusion: Comprehensive Data Integration: Deep learning models can combine data from various sources, such as satellite imagery, climate data, and sensor readings. By fusing multi-modal data, researchers gain a holistic understanding of environmental changes and their impacts, allowing for more informed decision-making [36, 37].

Figure 1 shows structure of deep learning models, deep learning methods play a vital role in advancing climate and ecology research by enabling the analysis of complex, multi-dimensional data, leading to better climate predictions, more effective conservation efforts, and a deeper understanding of our planet's ecosystems. These techniques continue to evolve and offer exciting opportunities for addressing pressing environmental challenges.

Concerns and challenges

Although leveraging remote sensing in agriculture holds the potential to revolutionize farming practices in the face of diverse challenges, offering valuable insights into crop conditions across different scales throughout the entire growing season. Armed with information on crop status, farmers can make informed decisions using cutting-edge technologies such as geospatial technology, the Internet of Things (IoT), Big Data analysis, and artificial intelligence (AI). Precision agriculture (PA) strategically employs these emerging technologies to optimize agricultural inputs, enhance production efficiency, and minimize input losses [38, 39]. The utilization of remote sensing technology in precision agriculture has witnessed a significant surge over the past few decades. However, to unlock its full potential, it is imperative to develop an accessible yet reliable workflow for real-time

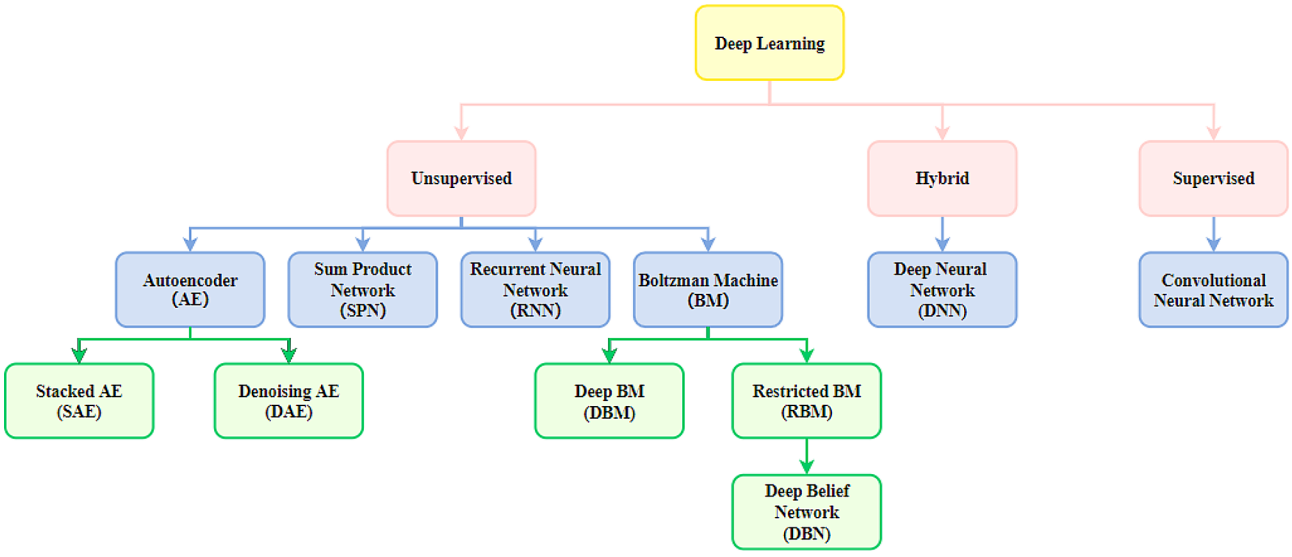

Fig. 1 Structure of deep learning models

remote sensing applications in precision agriculture. This undertaking is essential given the intricacies of image processing and the substantial technical knowledge and skills required. The realization of accurate yet user-friendly systems is anticipated to drive broader adoption of remote sensing technologies in both commercial and non-commercial precision agriculture applications.

Monitoring depends on a small number of indicators

By limiting the number of variables to one or two, the emphasis of the ecological management program is narrowed, and an oversimplified understanding of spatial and temporal relationships is fostered. This simplification frequently results in bad management judgments. To successfully monitor the numerous degrees of complexity within an ecological system, variables should be chosen from multiple levels of the ecological hierarchy. As a result, a fundamental problem is to identify a set of measurements that provide interpretable signals, can be used to track ecological conditions at a reasonable cost, and cover the whole range of ecological variation.

Choice of ecological variables

Goals and objectives that are unclear or ambiguous might result in "the wrong variables being measured in the wrong place at the wrong time with poor precision or reliability" [40]. To focus monitoring on present and future management concerns, primary goals and objectives should be established early in the process. The variables that are most closely related to those management issues can then be chosen to assess system attributes. However, society has traditionally chosen resource management goals that are purely concerned with short-term profit (for example, maximum crop output in agricultural systems or maximum lumber production in forests). These objectives may threaten the long-term viability of healthy ecological systems [41]. Management objectives, and therefore variable selection, should be linked to an awareness of the short-term and long-term implications of resource management decisions.

Lack of scientific rigor

The lack of comprehensive techniques for identifying ecological variables makes validating the information supplied by such factors problematic. Until conventional techniques for choosing and utilizing variables are developed, interpretation of their change through place and time remains uncertain [24]. The development and application of standard processes for the selection of ecological variables allows for repeatability, eliminates bias, and imposes discipline on the selection process, ensuring that the variables chosen address management issues.

Technological limitations

One of the major difficulties for climate monitoring will be to integrate passive sensor data directly from smartphones or wearables, as well as human perception data, into official data streams while completely respecting privacy and complying with the EU's GDPR. Data donation for science is becoming a new trend, with organizations like Open Humans providing academics, enterprises, NGOs, and policymakers with unparalleled access to new data sources and amounts. Standard smartphones and wearables now give, among other things, location, movement, individual carbon mobility footprints, health data, and much more. Advances in technology have undeniably improved monitoring capabilities, yet certain ecological and climate processes remain challenging to

observe accurately. Remote sensing tools, for instance, provide valuable insights, but they may not capture fine-scale ecological interactions. Additionally, technological limitations hinder real-time data acquisition, hindering our ability to grasp rapidly occurring changes [42, 43].

A new environmental science strategy to researching human emotions in cities has also been presented, which is linked to wearables. By identifying the relationship between stress and well-being, we may gain a deeper knowledge of urban stress. Wearables and other low-cost sensors have an untapped potential for expanding our understanding of aspects that can assist to enhance human well-being, access to green space, city planning, and implementing actions to reduce cities' carbon emissions [44, 45]. Environmental research has traditionally been a Global North activity, restricted to more wealthy nations where individuals have time for voluntary work and unpaid hobbies. Nonetheless, owing to digital technology, the Global South has jumped ahead of several critical stages of development, with mobile phone saturation high in many areas where there are no landlines. Environmental activities are far less popular in emerging countries, as evidenced by data from various open environmental science platforms, such as iNaturalist.

Data integration

The integration of diverse data sources, such as satellite imagery, ground-based measurements, and modelling outputs, is essential for a holistic understanding of ecosystems and climate. However, this integration poses challenges in terms of data compatibility, accuracy, and calibration. Effective data integration techniques must be developed to create comprehensive models that reflect the complex reality of these systems. Three key technological problems have been identified in reviews of ecological informatics: data dispersion, heterogeneity, and provenance [46, 47, 48]. Ecosystems and ecosystems differ across the world, and data is collected at thousands of sites. Although major research projects, institutes, and agencies typically manage large amounts of data representing relatively few data sets, most ecological data are difficult to discover and preserve because they are contained in relatively small data sets dispersed among tens of thousands of independent researchers. Due to the range of themes addressed by ecologists and the many experimental techniques utilized by different researchers, data heterogeneity poses problems. Data provenance—origins and history—is required when, as in ecological research, intriguing results emerge after complicated, multistep data collecting, modeling, and analysis procedures.

Scale disparities

Ecological processes operate at various spatial and temporal scales, which can pose challenges when attempting to draw meaningful conclusions. Upscaling observations from small plots to larger landscapes often leads to oversimplification, while downscaling global climate models to regional or local scales may result in loss of detail. Bridging these scale disparities requires sophisticated methodologies that consider multiscale interactions.

Interdisciplinary collaboration

Ecology and climate monitoring inherently demand interdisciplinary collaboration among scientists from diverse fields such as biology, climatology, geology, and sociology. Effective communication and collaboration can be challenging due to differences in terminology, methodologies, and research priorities. Establishing common ground and fostering interdisciplinary teamwork is essential to overcome these barriers. Another significant problem is the vital necessity to monitor the provenance of generated data objects and scientific conclusions from data collection to quality assurance, analysis, modelling, and, finally, publishing [49]. Provenance is especially crucial in supporting scientific conclusions used in policy and management decisions, because field experiments and procedures may be difficult to replicate due to the difficulties of recreating environmental circumstances. Computer scientists are making significant progress in creating methods to capture evidence information. Data processing and analysis information that led to a specific set of results may be documented using scripted analytic tools like R and scientific workflow platforms like Kepler and Taverna.

Data quality and uncertainty

The accuracy of monitoring data is pivotal for making informed decisions. However, ecological and climate data often contain uncertainties due to measurement errors, incomplete coverage, and modelling assumptions. Developing robust techniques for quantifying and communicating these uncertainties is crucial to ensure that policy decisions are based on a realistic understanding of potential outcomes. However, just a small percentage of the ecological data collected is easily discoverable and accessible, much alone valuable. Based on our personal experience in developing data archives for ecology, we estimate that less than 1% of the ecological data gathered is available following the publication of associated conclusions [50, 51]. We provide opinions of distilled data through presentations and publications rather than direct access to data. To reap the benefits of ecological and environmental synthesis, we must address the technological and sociocultural barriers that have impeded free access to data. While "open data" will improve and accelerate

scientific progress, there is also a need for "open science," which preserves not just data but also analyses and techniques, resulting in greater openness and repeatability of discoveries. It has been emphasized that environmental research programs should attempt to reach a bigger audience that more accurately represents society. Furthermore, scientists must be more open to engaging with the general public and communicating science in a clearer and simpler manner, such as by avoiding jargon and communicating in ways that are clearer and more intelligible to non-specialists. Scientists must leave their ivory towers and connect more broadly with society and people.

Access to resources and infrastructure

Monitoring initiatives require substantial resources, including funding, technology, and trained personnel. In some regions, especially developing countries, limited access to these resources can hinder effective monitoring efforts. Addressing this challenge involves international cooperation, capacity building, and technology transfer to ensure comprehensive global monitoring coverage.

Addressing Dynamic systems

Ecological and climate systems are inherently dynamic and subject to nonlinear behaviours. Traditional linear modelling approaches may fall short in capturing the complexity of these systems. Embracing dynamic modelling techniques, such as agent-based models and system dynamics, can provide a more accurate representation of the interactions between ecological processes and climate dynamics.

Policy implications

Accurate ecological and climate monitoring data directly influence policy decisions aimed at mitigating climate change impacts and preserving biodiversity. The challenges in collecting, integrating, and interpreting this data necessitate policy frameworks that are adaptable, evidence-based, and incorporate feedback loops to account for evolving scientific understanding. When designing technical solutions for handling ecological information, the variability of ecological data must be considered. Ecology's multiplicity of subdisciplines (e.g., ecosystems/community ecology, marine/freshwater/terrestrial ecology, and plant/animal/microbial ecology) results in heterogeneous data. Furthermore, neighbouring disciplines in earth and life science, as well as important fields in the social sciences and humanities, have their own terminology, specific measurements, and experimental designs, all of which contribute to heterogeneity.

Another significant difficulty in climate monitoring is determining ways to motivate individuals to engage in science and answer the question, "What's in it for me?" Clear communication on how the data is being utilized and why the data is so vital is critical in this case. For example, a variety of incentives, such as prizes and co-authorship [52] and information nudges, such as the Earth Challenge (EARTHDAY.ORG, 2022), have been tried to increase engagement and retention, although Peoples are also intrigued in assisting science and challenging themselves intellectually [53].

Crop remote sensing Recognition algorithms

The fundamental process of crop remote sensing recognition involves judging and extracting category attribute information based on the characteristic differences displayed in remote sensing data. Essentially, it is a classification problem. In the field of crop remote sensing recognition, the development of classification algorithms can be summarized into three stages, early strong learning methods, ensemble learning methods based on weak learning, and deep learning methods represented by neural networks. In this paper, early strong learning methods and ensemble learning methods are collectively referred to as traditional machine learning methods, for contrast with the current research focus—deep learning methods.

Crop remote sensing Recognition based on traditional machine learning methods

Early strong learning methods involve constructing a single classifier using probabilistic statistical methods to complete the classification task Fig. 2 shows applications in different fields of ecology. Typical algorithms include the minimum distance method, maximum likelihood method, decision tree method, support vector machine, etc. The maximum likelihood method is one of the most commonly used supervised classification methods, assuming that the data approximately follows a normal distribution. It uses the training dataset to calculate features such as mean, variance, and covariance, establishing the prior probability density functions for each class. This enables the calculation of the membership probability for pixels to complete the classification. The maximum likelihood method is widely used in crop remote sensing classification due to its simplicity, ease of implementation, and integration of Bayesian theory and prior knowledge into the classification process. It performs optimally compared to other traditional classification methods. However, it is suitable for multispectral data with fewer bands, and its performance is less effective in hyperspectral image classification. Decision trees are a classification method based on inductive reasoning. They define and continuously update rules for dividing spectral, color, and spatial information in remote sensing images until no further division is possible. Decision tree algorithms are easy to understand, highly operational, capable of handling multi-output problems, and widely used in crop remote sensing recognition. However, their drawback is

Fig. 2 Applications of AI in different fields of ecology

poor generalization ability, especially when dealing with high-dimensional data. Support Vector Machine (SVM) is based on structural risk theory, quadratic optimization theory, and kernel space theory. It seeks the optimal classification hyperplane in a high-dimensional feature space, solving complex classification and regression problems. SVM shows stability and high classification accuracy in crop remote sensing, but its performance is poor in solving multi-class classification problems and high-dimensional feature spaces, and the correct selection of the kernel function lacks theoretical basis.

Ensemble learning algorithms integrate the results of a series of independent or non-independent weak learners using a certain strategy to obtain the final result, surpassing the performance of individual learners. The construction process includes generating basic classifiers and merging classification results. Common methods for generating basic classifiers include Bagging and Boosting. Bagging uses random sampling with replacement to construct different training datasets for classifier generation. Boosting initially assigns equal weights to different samples, then decreases the weights of correctly classified samples and increases the weights of misclassified samples during training. This focuses the learning algorithm on misclassified samples, and the final model is obtained through weighted combination. The advantages of ensemble learning are as follows: (1) Statistical aspect: multiple learners can obtain a relatively stable hypothesis space to reduce generalization errors (2). Computational complexity: ensemble learning can effectively reduce the possibility of the algorithm falling into local optima (3). Hypothesis space: multiple learners can expand the hypothesis space, facilitating the learning of better approximations. In crop remote sensing recognition, the most widely used machine learning methods are random forests, Adaboost, gradient boosting trees, etc. Although traditional machine learning methods can effectively recognize crops in different regions, their reliance on shallow direct observation features and manually designed features during the recognition process leads to

poor learning ability for deep-level features and the lack of co-learning ability for different types of features in remote sensing data.

Crop remote sensing Recognition based on deep learning

Deep learning, as a branch of machine learning, aims to establish neural networks that simulate human brain analysis and learning. It utilizes massive training data to drive deep neural networks to learn more useful deep-level features, ultimately improving classification accuracy. Deep neural network models have a large number of parameters, providing the model with sufficient complexity. On the one hand, the model has enough complexity, and on the other hand, it has the ability to learn features from end to end in the data, replacing manual feature engineering based on human experience and prior knowledge. In recent years, deep learning based on artificial neural networks has made breakthroughs in machine learning and data mining, including remote sensing, benefiting from the flexibility in feature representation, end-to-end feature learning without relying on expert knowledge, automation, and computational efficiency.

Convolutional Neural Network (CNN) is one of the most successful architectures in deep learning. CNN has high computational efficiency in the learning process and is sensitive to spatial relationships in image data, making it the most effective model for recognizing 2D features in image patterns. In the remote sensing domain, 2D CNN has been widely used for extracting spatial features, enabling target detection and semantic segmentation based on high-resolution images. Another major application of CNN is in the classification of hyperspectral images, where 1D, 2D, and 3D CNNs are used to extract spectral features, spatial features, and 'spectral-spatial' features, respectively. In crop remote sensing classification, research has shown that 2D convolutional operations in the spatial domain achieve better accuracy than 1D convolutional operations in the spectral domain. Concatenating multispectral images at different growth stages and applying 1D convolutional operations in the spectral domain also improves the accuracy of land cover classification. Although convolutional operations can effectively extract features in the spatial, spectral, or 'spectral-spatial' domains, CNNs are rarely used for extracting features in the temporal domain, i.e., they cannot effectively extract temporal change features in time series remote sensing data.

Recurrent Neural Network (RNN) is another type of deep learning network model specifically designed to handle time series data. Due to its ability to capture dependencies in long sequence data, RNNs have achieved success in various remote sensing applications. For example, RNNs have been successfully used to analyze spectral correlations and trends in time series of multispectral data. Combining CNNs and RNNs for image classification involves using CNNs to generate multi-level convolutional feature maps and then using RNNs as decoders to recursively collect multi-scale feature maps and aggregate them sequentially to form high-resolution semantic segmentation images. RNN networks have many improved models to enhance learning efficiency, with the most famous being the Long Short-Term Memory (LSTM) network, mainly designed to address the vanishing gradient and exploding gradient problems during long sequence training processes. Compared to ordinary RNNs, LSTMs perform better in tasks such as change detection based on long time series data and crop classification. Furthermore, combining CNNs and LSTMs, where 2D convolutional operations extract spatial feature information and LSTMs capture temporal dependencies in time series data, has achieved better results than traditional methods.

Represented by the LSTM, recurrent neural networks have significant advantages in extracting features from time series remote sensing data. However, RNNs based on threshold mechanisms tend to experience vanishing gradients and difficulties in capturing long-range information dependencies when dealing with long time series data as shown in Fig. 3. To address this, Transformer networks based on self-attention mechanisms have emerged. Currently, Transformer models and their variants have become the mainstream methods for solving sequence-related problems and have achieved success in crop classification recognition based on time series remote sensing data, becoming a hot research topic.

Issues and prospects

In general, current remote sensing models for crop yield estimation exhibit a variety of forms, but in practical applications, they often face challenges such as insufficient generalization ability, lagging monitoring timeliness, and insufficiently detailed mapping of yields. These issues make it difficult to meet the requirements of current precision agriculture for the timeliness and spatial resolution of crop yield estimation [54].

With the increase in high-resolution, hyperspectral resolution, and high temporal resolution remote sensing data, as well as the development of technologies such as deep learning, researching how to couple deep learning with crop growth models to construct scalable and efficient transplantable fine-scale crop yield remote sensing dynamic estimation models is a potential research direction [55]. Fully utilizing crop growth models to simulate crop growth under different point scales and environmental conditions, capturing crop growth patterns, and using deep learning methods to learn and model the capabilities of complex situations, completing spatial extrapolation, and achieving mechanistic constraints

Fig. 3 Remote sensing data collection sources

with deep learning is a promising avenue for future research.

Remote sensing-based climate and crop monitoring using AI offers tremendous potential for enhancing agricultural practices and understanding climate patterns. However, it also presents several challenges that need to be addressed for effective implementation. Here are some key issues and complexities:

Data quality and availability Inconsistent and low-quality data from remote sensors can lead to inaccuracies in climate and crop monitoring. Limited access to historical data and real-time information can hinder long-term analysis and decision-making.

Data integration Integrating data from various sources, including satellite imagery, weather stations, soil sensors, and drone surveys, can be complex and may require sophisticated data fusion techniques. Ensuring interoperability between different data formats and platforms is challenging.

Data Processing Processing large volumes of remote sensing data requires significant computational resources and may lead to scalability issues. Preprocessing tasks such as atmospheric correction and data calibration are crucial but computationally intensive.

Data interpretation Developing algorithms and models that can accurately interpret remote sensing data to monitor climate and crop conditions is a complex task. Different crops and regions may require customized approaches, making generalization difficult.

Machine learning and AI models Building robust AI models for climate and crop monitoring demands access to large and diverse datasets for training and validation. Ensuring the models' reliability and interpretability is essential for decision-making in agriculture.

Scalability Scaling up remote sensing and AI-based monitoring systems to cover large agricultural areas can be challenging, especially in resource-constrained regions.

Privacy and Data Security Collecting and sharing remote sensing data, especially high-resolution imagery, can raise privacy concerns. Protecting sensitive information and complying with data privacy regulations are essential.

Accessibility Ensuring that remote sensing and AI-based tools are accessible to farmers, policymakers, and researchers globally can be a logistical challenge.

Infrastructure and connectivity Many remote agricultural areas lack reliable internet connectivity and infrastructure to support data transmission and access to AI-based tools.

Cost Implementing remote sensing and AI technologies can be expensive, both in terms of hardware and software requirements. Cost-effective solutions need to be developed to make these technologies accessible to a wider range of users.

Skill gap There may be a shortage of skilled professionals who can effectively utilize remote sensing and AI technologies for climate and crop monitoring. Capacity-building and training programs are necessary to bridge this gap.

Ethical considerations Ethical concerns, such as the use of AI in agriculture, data ownership, and the potential for technology-driven disparities, need to be addressed.

Addressing these challenges requires collaborative efforts from governments, research institutions, private companies, and local communities. Innovative solutions, increased data sharing, and ongoing research are essential to navigate the complexities of remote sensing-based climate and crop monitoring using AI and realize its full potential for sustainable agriculture and climate resilience.

Conclusion

The challenges in ecology and climate monitoring are multifaceted and intertwined, demanding collaborative efforts across scientific disciplines, technological innovation, and international cooperation. Overcoming these challenges is imperative to develop effective strategies for climate adaptation, ecosystem management, and the safeguarding of our planet's ecological and climatic equilibrium. As technology advances and our understanding deepens, it is crucial that the scientific community remains agile and proactive in addressing these challenges to ensure a sustainable future for all living beings. These instances of environmental change were chosen to highlight that long-term monitoring has already recorded various environmental reactions to changing atmospheric chemistry. In my opinion, there will be more sophisticated ecological reactions to the constantly changing chemical and physical features of the atmosphere. As a result of continued stratospheric ozone depletion, we may anticipate greater UV-B radiation reaching the earth's surface [56]. This has the potential to have a wide range of ecological consequences. Measuring biological impacts and understanding relationships with other stressors, such as acid rain, that may influence the same ecosystem will be challenging and would need integrated monitoring.

Some experts anticipate that the prevalence of insects and illnesses will rise as these creatures adapt to new ecological settings. The balsam woolly adelgid, for example, cannot endure a winter cold of −34 degrees Celsius. If this value is not attained as a result of climate change, the length and intensity of epidemics will rise [57]. The impact on forests may outweigh the physical impacts of climate change, such as drought. There is evidence that insects are already adjusting in the Canadian Boreal Shield. The time of the spruce bud worm life-cycle, for example, has been seen to alter by 3–7 days during the last 25 years [58]. The aquatic, forest, and agricultural resources that are being impacted by climate change constitute the foundation of many North American economies. Defining and comprehending changes will be critical for long-term resource management. Any cause-and-effect correlations utilized to justify pollution control and resource management initiatives must withstand thorough scrutiny. This poses a significant challenge for monitoring programs, particularly integrated monitoring sites that can give the long-term perspective backed by

process research and experimental data required for scientific defence of proposed management strategies.

The difficulties many people have in accessing relevant and timely quality-controlled data and information in formats that can be easily incorporated into specific analyses with other data sources are significant challenges to building stakeholders' capacity to use climate information in research and decision-making activities [59]. Many challenges exist in terms of data, services, practice, and policy (IRI 2006), which must be solved if climate and environmental information are to play an important role in decreasing climate-related hazards.

- **Multidisciplinary Maze**: The challenge of defining research's purpose resonates differently among diverse communities. The lack of a shared understanding often hinders the cohesive orchestration of multi-disciplinary endeavours.
- **Elusive Data**: The tapestry of evidence requires threads of relevant, accessible data, locally and globally. The absence of a seamless thread weaves gaps in policy-relevant evidence essential for decision-making.
- **Knowledge Generation Gap**: The canvas of new knowledge remains half-painted due to insufficient prowess in deciphering, assessing, and integrating climate information into the intricate weave of research questions.
- **Tools in Dearth**: The symphony of data requires tools that harmonize space and time, interfacing seamlessly with other research software. Yet, gaps exist in tools that can perform this complex dance.
- **Fenced Knowledge**: Policies and technological tangles lock knowledge within silos, inhibiting the creation of networks among researchers with common objectives, hindering the collective advancement.
- **Adapting Policies**: The environment of policies and practice often lags behind the dynamic pulse of new knowledge, failing to respond promptly to emerging insights into shifts in disease risk.

Amidst these hurdles, a clarion call emerges for actionable insights. The keystone to informed choices lies in the embrace of accurate, timely information that paints the climatic and environmental canvas. This information should not be an enigma but a beacon, accessible at the right time and place, illuminating the path of decision-makers. As we navigate these challenges, creativity must intertwine with commitment, steering us towards a landscape where climate information serves as a compass, guiding us to a more resilient and informed future.

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Data availability
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Declarations

Competing interests
The authors declare no competing interests.

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