Chapter 12
Actionable AI for Climate and Environment

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Contents

1 Introduction

AI has gained immense popularity and showcased its power across various domains and societies. Its successful applications have revolutionized industries, transformed the way we live, and enabled groundbreaking advancements (Marr 2019). Within the realm of healthcare, AI finds utility in early disease detection, crafting personalized treatment regimens, and facilitating drug discovery (Johnson et al. 2021). In the

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financial sector, AI algorithms are instrumental for tasks such as fraud detection, risk evaluation, and algorithmic trading (Nuti et al. 2011). In the domain of transportation, AI fuels the capabilities of autonomous vehicles, optimizes traffic management systems, and enhances predictive maintenance (Iyer 2021). AI has also made significant contributions to entertainment, with recommendation systems, virtual assistants, and immersive experiences (Ali et al. 2022). Moreover, AI has also made an impact in addressing societal challenges. For example, AI-based platforms facilitate personalized learning experiences and intelligent tutoring (Chaipidech et al. 2022). In agriculture, AI facilitates precision farming, monitors crop health (Sun et al. 2020), and optimizes crop yields (Sharma et al. 2022). Additionally, AI algorithms are deployed in the realm of cybersecurity to swiftly identify and mitigate real-time threats (Ali et al. 2022). Besides, maybe the most popular application, ChatGPT (Biswas 2023), is based on the progress of AI in natural language processing, machine translation, and speech recognition, improving communication and accessibility (Hirschberg and Manning 2015). AI has transformed our daily lives through virtual assistants like ChatGPT, Siri and Alexa, smart home automation systems, and personalized digital experiences. It has made significant strides in computer vision, enabling facial recognition, object detection, and augmented reality applications. The popularity and power of AI are reflected in its integration into our everyday devices and services.

AI is considered powerful and highly desired in climate and environment science. Climate and environmental research generate vast amounts of complex data from various sources such as satellite imagery, weather stations, and sensor networks (Sun et al. 2019). AI techniques, such as machine learning (ML) and deep learning, excel at processing and analyzing large datasets, identifying patterns, and extracting valuable insights (Janiesch et al. 2021). AI can help researchers uncover hidden relationships and correlations, enabling a deeper understanding of climate dynamics, ecosystem behavior, and environmental impacts. Another major reason is that AI algorithms can be trained on historical climate and environmental data to develop sophisticated models for predicting future scenarios (Sun et al. 2022, 2023). These models can simulate climate change impacts, forecast extreme weather events, predict species distribution shifts, and assess the effectiveness of mitigation strategies. AI-based prediction models provide decision-makers with valuable information to plan and implement adaptive measures to minimize risks and protect vulnerable ecosystems (Barzegar et al. 2018). Also, AI algorithms can optimize resource allocation and management in climate and environmental domains. They can assist in designing efficient energy systems, optimizing water resource allocation (Sun and Scanlon 2019), and managing waste and pollution. AI techniques enable real-time monitoring, data-driven decision-making, and automated control systems, leading to more sustainable and environmentally friendly practices (Cunningham 2021). AI-powered image and pattern recognition can aid in biodiversity conservation efforts. Meanwhile, AI can analyze images from remote sensing devices, cameras, or drones to identify and monitor endangered species, detect illegal logging or poaching activities, and assess the health of ecosystems (Dauvergne 2020). This helps researchers and conservationists make informed decisions and implement targeted conservation strategies. AI can handle complex tasks with speed and efficiency, allowing for scalable and automated processes. They can process large datasets and perform repetitive tasks more quickly than human experts, saving time and resources. Besides, AI also can facilitate real-time monitoring and decision-making, facilitating rapid response to climate events and environmental emergencies (Chowdhury et al. 2012).

One recent successful example is the use of AI in deforestation monitoring (Shivaprakash et al. 2022). Deforestation is a major environmental issue that contributes to climate change, loss of biodiversity, and other ecological imbalances. AI can detect deforestation by analyzing satellite imagery and other data sources to identify areas at risk and monitor changes in forest cover. Global Forest Watch, a partnership led by the World Resources Institute, utilizes AI algorithms to analyze satellite data and identify forest cover changes in near real-time (Perbet et al. 2019). This information helps governments, organizations, and local communities to take proactive measures to prevent further deforestation by sending enforcement teams to the identified locations, imposing penalties on illegal activities, and engaging local communities in sustainable land management practices. By harnessing the power of AI and ML, we can improve the efficiency and effectiveness of deforestation monitoring and prevention efforts, leading to better conservation outcomes and the preservation of valuable ecosystems.

While AI research has made significant advancements in various fields, there are several reasons why many AI research outputs are not always practical or actionable in real-world decision-making due to a number of restrictions and bottlenecks. First, AI researchers usually lack deep understanding and expertise in specific domains like climate and environment science. This can lead to a disconnect between the AI models developed and the practical needs of decision-makers. For example, an AI model trained to predict climate patterns may produce accurate results, but if it fails to consider the specific needs and constraints of stakeholders, it may not provide actionable insights. In addition, the current AI models heavily rely on data for training and inference. In the context of climate and environment, data may be limited, incomplete, or biased, leading to inaccurate or unreliable predictions. If an AI model is trained on historical climate data that does not reflect recent changes or emerging patterns, its predictions may not be applicable to the current climate scenario. Also, ethical and societal aspects must be comprehensively considered and dealt with before using AI to make any decisions. In climate and environment, decisions often involve trade-offs and value judgments. For instance, an AI model that recommends land-use changes for carbon sequestration may not account for the socioeconomic impacts on local communities or indigenous rights. This lack of ethical considerations can hinder the practicality and acceptability of AI research outputs. Another major challenge is that many AI models, such as deep neural networks, are often considered black boxes, making it challenging to understand and interpret their decision-making processes. This lack of interpretability raises concerns about accountability and trust. Decision-makers may be reluctant to adopt AI solutions if they cannot understand how the models arrive at their recommendations. Addressing these challenges requires close collaboration between AI researchers and domain experts in climate and environment science, policy, and decision-making. By incorporating domain-specific knowledge, ensuring diverse and representative datasets, addressing ethical considerations, and developing interpretable AI models, researchers can bridge the gap between AI research and practical decision-making in climate and environment.

This section basically sets the stage and we will start to explore the role of AI in climate and environmental applications. It highlights the increasing popularity and power of AI technologies in various sectors of society, including climate and environment. It acknowledges the successful applications of AI in areas such as weather forecasting, renewable energy optimization, and biodiversity conservation. However, it also acknowledges that many AI research outputs in this field are not always practical or actionable in real-world decision-making. In the following sections, we will delve into the reasons behind the gap between AI research and practical decision-making in climate and environment. It will discuss the challenges posed by the lack of domain-specific knowledge, data limitations and biases, ethical considerations, and interpretability of AI models. The focus will be on providing insights and strategies to make AI research more actionable and applicable in real-world climate and environmental decision-making. The cutting-edge AI technologies will be introduced, showcasing their potential in addressing climate and environmental challenges. Use cases will be discussed, illustrating how AI has been utilized in areas such as climate modeling, natural disaster prediction and management, environmental monitoring, and sustainable resource management. The chapter will emphasize the need for actionable AI strategies that incorporate domain expertise, ethical considerations, interpretable models, and stakeholder engagement. We will also provide detailed analyses, case studies, and practical recommendations to bridge the gap between AI research and real-world decision-making. It aims to guide researchers, practitioners, and policymakers in harnessing the power of AI to tackle climate and environmental issues effectively and implement actionable solutions.

2 Latest AI Technologies in Daily Practice

2.1 Convolutional Neural Network (CNN)

Convolutional neural networks (CNNs) are a class of deep learning models commonly used for computer vision tasks such as image classification, object detection, and image segmentation (O'Shea et al. 2015). They consist of multiple layers of interconnected neurons that perform convolution and pooling operations to extract relevant features from images. Specifically, a typical CNN usually consists of input layers, hidden convolutional layers, activation and pooling layers, fully connected layers, and a dense layer as output (Fig. 12.1). The input to a CNN is usually an image represented as a grid of pixels with red, green, and blue (RGB) color channels (or more channels if the image is hyperspectral or multi-spectral). The middle

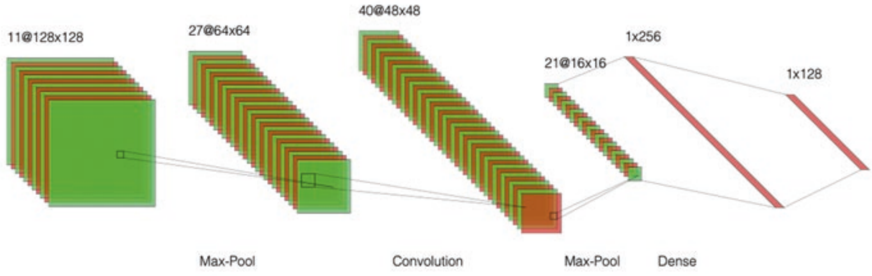

Fig. 12.1 An example CNN

layers of a CNN are convolutional layers that apply a set of filters to the input image. Each filter performs a convolution operation by sliding across the image, extracting local features by computing dot products between the filter weights and the pixel values in the receptive field. The output of this layer is a set of feature maps that capture different aspects of the input image. After each convolutional layer, a non-linear activation function, typically ReLU (Rectified Linear Unit) (Agarap 2018), is applied element-wise to introduce non-linearity and enhance the model's representational power. Pooling layers are then used to downsample the feature maps, reducing their spatial dimensions while retaining important information (Gholamalinezhad et al. 2020). Max pooling is a common pooling operation that selects the maximum value within a pooling window and discards the rest. Once the image features are extracted through convolutional and pooling layers, they are flattened into a 1-dimensional vector. The flattened vector is then connected to one or more fully connected layers, which are traditional artificial neural network layers where each neuron is connected to every neuron in the previous layer. The fully connected layers learn to combine the extracted features to make predictions on the input image, such as classifying it into specific categories. The final layer of the CNN is the output layer, which typically uses a softmax activation function for multi-class classification to produce class probabilities.

During training, the network learns the optimal weights for the filters and fully connected layers by minimizing a loss function, such as categorical cross-entropy, using gradient descent optimization algorithms like backpropagation. Once trained, the CNN can make predictions on new unseen images by forwarding them through the network, and the output with the highest probability corresponds to the predicted class.

CNNs have been successfully used in applications such as image classification, object detection, facial recognition, and medical image analysis. One of the most famous CNN architectures is the VGGNet (Wang et al. 2015), which achieved breakthrough performance in the ImageNet Large-Scale Visual Recognition Challenge (Russakovsky et al. 2015). The VGGNet consists of 16 convolutional layers, 5 max pooling layers, and 3 fully connected layers, with a total of 138 million parameters. It demonstrated the power of CNNs in image classification tasks by achieving state-of-the-art accuracy rates.

2.2 RNN

Recurrent neural networks (RNNs) are a class of neural networks commonly used for sequential data processing tasks (Sun et al. 2019). They have a unique ability to capture dependencies and patterns over time by using recurrent connections within the network. RNNs are particularly effective in tasks involving natural language processing and time series analysis.

Typical RNN include the following components. The input to an RNN is a sequence of data, such as a sentence or a time series. At each time step t, the RNN receives an input x(t) and a hidden state h(t-1) from the previous time step, which captures information from previous steps. At the initial step, h(0) is usually set to zero or initialized randomly. The hidden state h(t-1) is combined with the input x(t) and passed through a non-linear activation function, such as the hyperbolic tangent or the rectified linear unit (ReLU). The output of this activation function becomes the hidden state h(t) at the current time step. It represents a summary of the input sequence up to that point. The hidden state h(t) is then used as the input for the next time step, creating a recurrent connection that allows the RNN to process the sequence iteratively. At each time step, the RNN can produce an output based on the hidden state h(t). For example, in a language model, the output could be a probability distribution over the next word in the sequence. In sequence-to-sequence tasks, such as machine translation, the RNN can produce an output sequence by feeding the output at each time step as the input for the next step. While training, the RNN learns the optimal weights that maximize its predictive performance. This is done by comparing the predicted output with the ground truth labels and adjusting the weights using gradient descent optimization. Backpropagation through time (BPTT) is normally used to calculate the gradients of the loss function with respect to the weights over multiple time steps. It extends the standard backpropagation algorithm to account for the recurrence in the network. The gradients are then used to update the weights using an optimization algorithm such as stochastic gradient descent (SGD).

RNNs have been very successfully used in many applications, including language modeling, sentiment analysis, speech recognition, and machine translation. One popular variant of RNNs is the long short-term memory (LSTM) network (Hochreiter et al. 1997), which addresses the issue of vanishing gradients and allows the network to capture long-term dependencies. LSTM has achieved impressive results in various tasks, such as language translation and speech recognition, and is one of the industry-proven techniques. LSTM networks have been successfully used for language modeling tasks, where the goal is to predict the next word in a sequence of words. A prominent example is Google's Smart Reply feature, which suggests short responses to incoming emails. LSTM models are employed to understand the context and generate relevant replies. LSTM-based language models have also been applied in machine translation systems, improving the accuracy and fluency of generated translations. An example is the listen, attend, and spell (LAS) model (Chan et al. 2016), which uses LSTMs to convert acoustic features of speech into text. LAS has shown remarkable results in automatic speech recognition systems, enhancing transcription accuracy. Also in finance, LSTM models have been used for stock price prediction, enabling traders to make informed decisions. As for art and music, LSTM networks have been used to generate music sequences and compose new melodies. By training on large music datasets, LSTM models can learn musical patterns and create original compositions in various genres. This has led to the development of AI-generated music platforms and tools, such as Jukedeck and Amper Music.

2.3 Transformers

Transformers are a type of neural network architecture that has revolutionized natural language processing tasks (Tunstall et al. 2022). They use attention mechanisms to process sequences of data, such as sentences or paragraphs, by attending to different parts of the input. The self-attention mechanism captures dependencies between different words in a sentence or sequence. Each word in the input sequence is represented as a vector, and attention weights are calculated between all pairs of words. These attention weights determine the importance of each word in relation to the others, allowing the model to focus on relevant information. Transformers also consist of an encoder and a decoder. The encoder processes the input sequence, while the decoder generates the output sequence. The encoder's self-attention mechanism captures contextual information from the input sequence, creating rich representations for each word. The decoder's self-attention mechanism helps it attend to previously generated words, ensuring coherence in the generated output. Transformers incorporate positional encoding to account for the sequential order of words in the input sequence. Positional encodings are added to the word embeddings, providing the model with information about the relative positions of words. Transformers employ multi-head attention, where multiple attention heads are used to capture different aspects of the input sequence. Each attention head attends to different parts of the input sequence, allowing the model to capture diverse relationships. Transformers include feed-forward networks to transform the representations obtained from the self-attention mechanism. These networks consist of multiple layers of fully connected neural networks, introducing non-linearity and enabling complex transformations.

ChatGPT is probably the most well-known product of Transformers. It has been trained on a large corpus of text data and can generate coherent and contextually relevant responses in conversational settings. ChatGPT has been used in chatbots, virtual assistants, and other applications that require generating human-like text responses. Transformers also have significantly improved machine translation performance, surpassing traditional approaches. Google's Neural Machine Translation (GNMT) system (Wu et al. 2016) utilizes the Transformer model for high-quality translation between different languages. Transformers have shown effectiveness in capturing long-range dependencies and context, leading to more accurate translations. Other applications include extractive and abstractive text summarization tasks which means selecting important sentences from a document, while abstractive summarization generates concise and coherent summaries. Transformers have shown improvements in generating informative and coherent summaries by leveraging the attention mechanism. Sentiment analysis tasks are another type of work that Transformers can fulfill. They can capture contextual information and dependencies between words, improving sentiment analysis accuracy. Promising results for social media analysis, customer reviews, and other text classification tasks have been successfully obtained via transformers.

2.4 Reinforcement Learning

Reinforcement learning (RL) is a branch of AI that focuses on an agent learning to make decisions in an environment to maximize a reward signal (Arulkumaran et al. 2017). It uses trial and error learning through interactions with the environment. The RL process starts with defining an environment that the agent interacts with. The environment can be a simulated environment, a physical system, or a game. It provides feedback to the agent in the form of states, actions, and rewards. The agent is the learner or decision-maker that interacts with the environment. The environment presents the agent with a state, which represents the current situation or observation. The state can be a raw sensory input, a numerical representation, or a combination of various features. Based on the current state, the agent selects an action from a set of available actions. The action determines the agent's behavior or response to the environment. The agent follows a policy, which is a strategy that maps states to actions. After taking an action, the agent receives feedback from the environment in the form of a reward. The reward indicates the desirability or quality of the agent's action. The agent's objective is to learn a policy that maximizes the cumulative reward over time. The agent learns from experience by iteratively interacting with the environment. It updates its policy based on the received rewards to improve its decision-making. The RL algorithms, such as Q-learning and Deep Q-Networks (DQN) (Hester et al. 2018), use different approaches to update the policy and estimate the value of actions.

Reinforcement learning has found success in various applications, including game playing (e.g., AlphaGo), robotics, autonomous vehicles, and recommendation systems. ChatGPT actually used RL in its training extensively. AlphaGo, developed by DeepMind, demonstrated the power of RL in the game of Go (Silver et al. 2016). It defeated the world champion Go player, Lee Sedol, in a five-game match in 2016. AlphaGo used RL techniques, including Monte Carlo Tree Search and deep neural networks, to learn from self-play and make strategic decisions in the game. Another big application field of RL is robotics and RL has been employed to train robots for complex tasks, such as grasping objects and locomotion. For example, OpenAI's robot hand, Dactyl (Akkaya et al. 2019), learned to manipulate objects using RL algorithms. By interacting with the environment and receiving rewards or penalties based on task completion, the robot learned to perform dexterous manipulation tasks. Autonomous vehicles are another major user of RL and it helped the vehicle computers to make decisions in complex driving scenarios. Researchers have applied RL algorithms to optimize driving policies, including lane keeping, decision-making at intersections, and adaptive cruise control. The RL agents learn from simulated or real-world driving experiences and improve their driving performance over time. Another typical use case is training an agent to play the game of Atari Breakout. The agent observes the game screen as the state, selects actions (move paddle left or right), and receives rewards based on its performance (e.g., points for breaking bricks). By interacting with the game environment and receiving rewards, the agent learns to improve its policy and eventually becomes skilled at playing the game.

2.5 Generative Adversarial Networks (GANs)

The idea of GANs is highly ingenious (Goodfellow et al. 2020). It consists of two neural networks, a generator and a discriminator, that compete against each other. The generator aims to create realistic data samples, while the discriminator tries to distinguish between real and generated data. The generator takes random noise as input and generates synthetic data samples. The discriminator takes either real or generated data samples as input and predicts their authenticity. The generator generates a batch of synthetic samples by passing random noise through its network. The discriminator is trained on both real and generated samples, learning to classify them correctly. The generator aims to generate samples that are classified as real by the discriminator, fooling it. The discriminator aims to correctly classify real samples as real and generated samples as fake. The training process involves updating the weights of the generator and discriminator using gradient descent. The generator and discriminator are trained iteratively, with the generator trying to improve its generated samples based on the feedback from the discriminator. The goal is to reach a point where the generator can generate highly realistic samples that can fool the discriminator. Deep convolutional GANs (DCGANs) (Radford et al. 2015) are a popular variant of GANs used for image generation. The generator network consists of transposed convolutions that upsample the noise into a realistic image. The discriminator network is a convolutional neural network that classifies between real and generated images. The GAN is trained on a dataset of real images, and the generator learns to generate images that resemble the real ones. Table 12.1 shows the code of a simple version of GAN. If you continue to increase the layer numbers of hidden layers, it will eventually turn into a new DCGAN.

GANs have been successfully used in generating realistic images, synthesizing voice and music, creating deepfakes, and data augmentation for training other models. GANs have been used to generate realistic images that resemble real-world examples. Examples include generating high-resolution images from low-resolution inputs (e.g., super-resolution GANs) and generating new images based on existing

Table 12.1 A simple example of GAN

```
# Import required libraries
import tensorflow as tf
from tensorflow.keras import layers

# Define the generator model
generator = tf.keras.Sequential([
    layers.Dense(7*7*256, input_shape=(100,), use_bias=False),
    layers.BatchNormalization(),
    layers.LeakyReLU(),

    layers.Reshape((7, 7, 256)),
    layers.Conv2DTranspose(128, (5, 5), strides=(1, 1), padding='same', use_bias=False),
    layers.BatchNormalization(),
    layers.LeakyReLU(),

    layers.Conv2DTranspose(64, (5, 5), strides=(2, 2), padding='same', use_bias=False),
    layers.BatchNormalization(),
    layers.LeakyReLU(),

    layers.Conv2DTranspose(1, (5, 5), strides=(2, 2), padding='same', use_bias=False,
activation='tanh')
])

# Define the discriminator model
discriminator = tf.keras.Sequential([
    layers.Conv2D(64, (5, 5), strides=(2, 2), padding='same', input_shape=[28, 28, 1]),
    layers.LeakyReLU(),
    layers.Dropout(0.3),

    layers.Conv2D(128, (5, 5), strides=(2, 2), padding='same'),
    layers.LeakyReLU(),
    layers.Dropout(0.3),

    layers.Flatten(),
    layers.Dense(1)
])

# Compile the discriminator
discriminator.compile(optimizer='adam',
loss=tf.keras.losses.BinaryCrossentropy(from_logits=True))

# Compile the GAN
gan = tf.keras.Sequential([generator, discriminator])
gan.compile(optimizer='adam',
loss=tf.keras.losses.BinaryCrossentropy(from_logits=True))
```

ones (e.g., Pix2Pix). GANs have been employed for style transfer, allowing users to apply the style of one image to another, for example, CycleGAN (Chu et al. 2017) can transfer the style of one domain (e.g., horses) to another (e.g., zebras), and DeepArt enables users to apply artistic styles to their images. GANs have been used to generate images from textual descriptions. GANs is also being experimented to generate synthetic medical images, aiding in data augmentation and addressing privacy concerns, such as generating realistic brain MRI scans, retinal images, and skin lesion images, etc., for image enhancement.

3 AI Research in Climate and Environmental Sciences

3.1 AI for Climate Modeling and Prediction and Impact Assessment

This section overviewed some latest research about using AI in climate modeling and prediction, as well as the climate impact assessment. For example, Kaack et al. (2022) provide a comprehensive framework for understanding the impacts of ML on greenhouse gas (GHG) emissions in the context of climate change mitigation. It emphasizes the need for further research, policy interventions, and organizational actions to ensure that ML is aligned with climate strategies and contributes positively to addressing climate challenges. They introduce a systematic framework for understanding the effects of ML on GHG emissions in the context of climate change mitigation. The framework encompasses three categories: computing-related impacts, immediate impacts of ML applications, and system-level impacts. It addresses the need to holistically account for ML in long-term climate projections and policy design. The article highlights that measuring macro-scale effects of ML is challenging and emphasizes the importance of estimating impacts, understanding dynamics, and prioritizing actions to align ML with climate strategies. The framework provides a comprehensive overview of the different mechanisms through which ML may impact emissions, offering a starting point for research, policymaking, and organizational action. Allawi et al. (2018) explained the importance of accurate simulation models for the effective operation of dam and reservoir systems in water resource management. It emphasizes the role of AI techniques in developing robust models to handle the stochastic nature of hydrological parameters and optimize reservoir operations. The review explores the application of AI in reservoir inflow forecasting, evaporation prediction, and the integration of AI with optimization methods. It also discusses future research directions and proposes a new mathematical procedure for evaluating the performance of optimization models in terms of reliability, resilience, and vulnerability indices. Haupt et al. (2021) discussed the application of artificial intelligence (AI) in post-processing weather and climate model output. It provides a historical overview and highlights the potential of AI in improving numerical weather prediction (NWP) forecasts and climate projections. The article emphasizes the need for trustworthy and interpretable algorithms, adherence to FAIR data practices, and the development of techniques that leverage our physical knowledge of the atmosphere. It also proposes the creation of a repository for datasets and methods to facilitate testing and intercomparison of AI approaches.

Huntingford et al. (2019) discuss the challenges in climate modeling, including the discrepancies between ESMs and the parameterization of sub-grid processes. ML and AI methods are proposed as potential solutions to reduce inter-ESM uncertainty and improve climate projections. The authors also highlight the importance of advanced algorithms in analyzing the increasing amount of climate-related data collected through satellite monitoring. They emphasized the untapped potential of ML and AI in addressing climate change challenges, advocating for their integration into climate research and adaptation planning processes. Crane-Droesch (2018) presents a ML-based approach to modeling crop yields, specifically focusing on corn yield in the US Midwest. The approach combines a semiparametric variant of a deep neural network, which can capture complex nonlinear relationships, with known parametric structures and unobserved cross-sectional heterogeneity. The results demonstrate that this approach outperforms classical statistical methods and fully nonparametric neural networks in predicting yields of withheld years. The study also reveals that the projected impacts of climate change on corn yield are large but less severe than those projected using traditional statistical methods, with a more optimistic outlook for the warmest regions and scenarios. Schultz et al. (2021) investigated the potential of deep learning (DL) methods in the field of meteorology, specifically for weather forecasting. While there is interest in applying DL techniques to improve weather prediction, the authors argue that fundamental breakthroughs are needed before completely replacing current numerical weather models. They highlight challenges such as the lack of explainability of deep neural networks and the need to incorporate physical constraints into DL approaches. Vo et al. (2023) developed a hybrid model, LSTM-CM, for drought prediction by combining long short-term memory (LSTM) and a climate model (CM). The performance of LSTM-CM is compared to standalone LSTM and the climate prediction model GloSea5 (GS5). LSTM-CM demonstrates improved drought predictions by combining the low bias of LSTM-SA and the physical process simulation ability of GS5, resulting in accurate detection of drought events with reduced uncertainty compared to LSTM-SA and GS5. Regarding the general use of AI in the more broad Earth science, Sun et al. (2022) provide an overview of the current status, technology, use cases, challenges, and opportunities of artificial intelligence (AI) in Earth sciences. Led by NASA Earth Science Data Systems Working Groups and Earth science information partners (ESIP) ML cluster, the study aims to improve accuracy, enhance model intelligence, scale up operations, and reduce costs in various subdomains. The paper covers major spheres in the Earth system, investigates representative AI research in each domain, and discusses the challenges and opportunities for Earth AI practitioners.

These AI studies demonstrate the increasing integration of ML and artificial intelligence techniques in various domains of climate and Earth sciences. These studies emphasize the potential benefits and challenges of applying AI in addressing climate change, improving weather forecasting, optimizing reservoir operations, enhancing drought prediction, and advancing crop yield modeling. The research highlights the need for further investigations, policy interventions, and organizational actions to ensure that AI is aligned with climate strategies and contributes positively to tackling climate challenges. The studies also underline the importance of interpretability, data practices, physical knowledge integration, and the development of reliable and scalable AI algorithms in Earth science applications.

3.2 AI for Environmental Monitoring and Conservation

Lamba et al. (2019) looked into the transformative impact of deep learning in the field of artificial intelligence and its potential applications in environmental conservation. It highlights the ability of deep learning to automate the classification of visual, spatial, and acoustic information, thereby enabling large-scale and real-time environmental monitoring. The article also addresses the challenges of resource requirements and data annotation that can hinder the widespread adoption of deep learning in conservation programs. Yang et al. (2021) developed an autonomous indoor environment management approach for smart homes, aiming to ensure a healthy indoor environment with minimized energy costs. The approach formulates the problem as a Markov decision process and proposes a deep reinforcement learning control strategy to make adaptive control decisions based on current observations, without requiring forecast information. Comparative results demonstrate that the proposed approach achieves improved control performance, reducing average daily energy costs while maintaining optimal indoor air quality and temperature. Borowiec et al. (2022) synthesize 818 deep learning studies and highlight the widespread adoption of deep learning in these disciplines since 2019. They discuss the applications, limitations, and future potential of deep learning in ecology and evolution, emphasizing its role in automated species identification, environmental monitoring, genetic analysis, and more. The review also suggests that deep learning will continue to be integrated into biodiversity monitoring, genetic inference, and training programs in the near future. Tuia et al.'s (2022) review work found that advancements in sensor technologies are revolutionizing data acquisition in animal ecology, offering opportunities for large-scale ecological understanding. However, the current processing approaches struggle to efficiently extract relevant information from the vast amount of data collected. Integrating ML with domain knowledge has the potential to enhance ecological models and create hybrid modeling tools, but interdisciplinary collaboration and training are essential for successful implementation in ecology and conservation research. These technological advancements in data collection can address the limitations of conventional methods, providing insights into wildlife diversity, population dynamics, and conservation needs at various spatial and temporal scales.

Deep learning has the potential to revolutionize environmental conservation by automating the classification of visual, spatial, and acoustic data, enabling large-scale and real-time monitoring. However, challenges such as resource requirements and data annotation need to be addressed for widespread adoption in conservation programs. In the context of smart homes, a deep reinforcement learning approach has been proposed for autonomous indoor environment management, reducing energy costs while maintaining optimal air quality and temperature. The adoption of deep learning in ecology and evolution has rapidly increased since 2019, with applications in species identification, environmental monitoring, genetic analysis, and more, and it is expected to continue integrating into biodiversity monitoring and genetic inference.

3.3 AI for Air Quality Prediction and Monitoring

It has been very popular in the past few years among scientists to use AI to monitor and predict air quality. Because of the lightweight and flexibility of AI models (compared to the heavy numerical models), and the availability of large long-time-series datasets, scientists are getting more used to utilizing ML algorithms to analyze various data sources and predict air quality levels in real-time. The training data is collected from air quality monitoring stations, satellite imagery, weather data, and additional environmental parameters and serves as input for training and validating AI models. For instance, the OpenAQ project (https://openaq.org/) collects global air quality data from various sources and makes it accessible for research and analysis. The collected data is then processed and cleaned to remove outliers, fill in missing values, and standardize the format to ensure data consistency and quality for further analysis. Relevant features are extracted from the collected data to represent different aspects of air quality, such as pollutant concentrations, meteorological conditions, geographical factors, and temporal patterns, which will be used as inputs for the AI models. Common target features include particulate matter (PM) concentrations, temperature, wind speed, and humidity from air quality sensor data. The next step is to train AI models, such as regression models, decision trees, support vector machines, or deep learning models, using the preprocessed data. The models will learn the relationships between the input features and the corresponding air quality levels. The trained models are then evaluated using validation data to assess their performance in predicting air quality. Metrics like mean absolute error, root mean square error, or correlation coefficients are commonly used to measure prediction accuracy. The collected data is usually split into training and validation sets, and evaluating the model's performance on the validation set. Once the models are trained and validated, they can be deployed to make real-time air quality predictions based on the latest input data to enable continuous monitoring and timely alerts for potential air quality issues.

There are many recent air quality studies focusing on AI. For example, Alnuaim et al. (2023) have developed a website using AI technology to improve the real time CMAQ ozone products and provide the public with more accurate and reliable ozone forecasting (Fig. 12.2). Indoor air quality monitoring has gained attention due to the COVID-19 pandemic, as indoor spaces can trap pollutants and potentially contribute to virus transmission. Existing monitoring systems lack predictive capabilities, prompting the development of an IoT-based solution that measures multiple pollutants and predicts air quality using ML algorithms. Mumtaz et al. (2021)

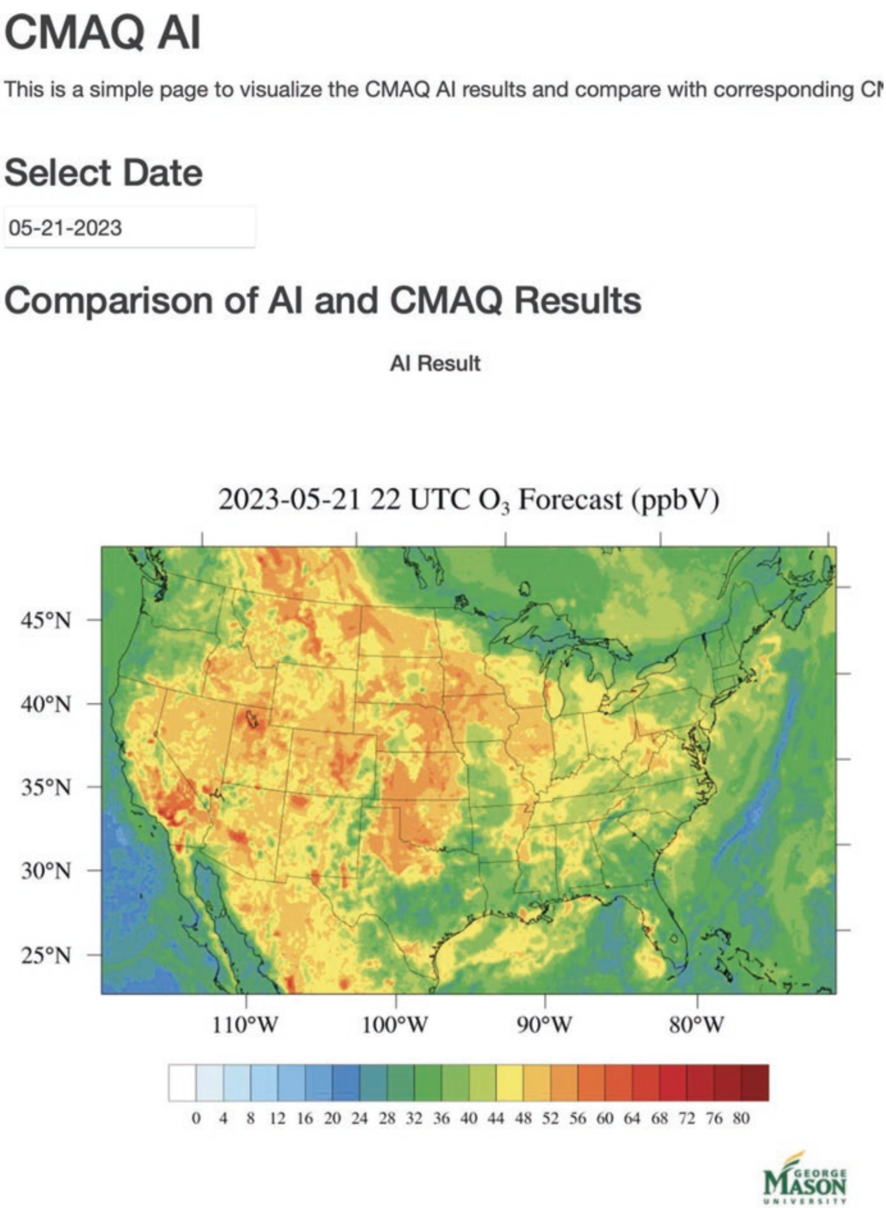

Fig. 12.2 The Community Multiscale Air Quality modeling system (CMAQ) AI website deployed (Alnuaim et al. 2023)

developed a system which can achieve high accuracy in classifying air quality using a neural network model and accurately predicted pollutant concentrations and overall air quality using an LSTM model, offering advantages such as remote monitoring, scalability, and real-time status updates. Kang et al. (2018) explored the use of big data analytics and ML techniques for air quality forecasting. Masih, A. (2019) did a similar study by using support vector regression (SVR) to forecast pollutant and particulate levels and to predict the air quality index (AQI). Vu et al. (2019) used random forest to assess the plan's effectiveness by separating the impact of meteorology on air quality and their results showed that meteorological conditions played a significant role in year-to-year variations in air quality, but the action plan still led to substantial reductions in air pollutants, primarily from coal combustion. Ameer et al. (2019) discussed the challenge of air pollution in city environments and the importance of real-time monitoring using IoT-based sensors. It compares four advanced regression techniques for predicting air quality and evaluates their performance based on Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and processing time. Lee et al. (2020) present a ML approach for predicting PM2.5 concentration in Taiwan and utilized a large-scale database from the Environmental Protection Administration and Central Weather Bureau, incorporating data from 77 air monitoring stations and 580 weather stations. The method shows promising results for 24-hour PM2.5 prediction at most air stations, and proved forecasting accuracy is improved by the method. Lim et al. (2019) used mobile sampling with low-cost air quality sensors to develop land use regression (LUR) models for street-level PM2.5 concentration in Seoul, South Korea. The study collects 169 hours of data from a 3-week campaign using smartphone-based particle counters and incorporates geospatial data from OpenStreetMap. Three statistical approaches are compared, with the stacked ensemble model achieving the highest cross-validation R2 value of 0.80, indicating the potential of mobile sampling and ML for characterizing urban street-level air quality with high spatial resolution, particularly in areas with limited air quality data.

However, besides funding and opportunities, there are many other issues causing these studies to be not immediately actionable. Most of the studies focus on small-scale experiments or specific locations, which may not be easily scalable or replicable in larger areas or diverse contexts. For example, the study by Mumtaz et al. develops an IoT-based system for air quality monitoring and prediction, but its applicability in different indoor environments or regions with varying pollutant sources and characteristics may be limited. They rely on historical data or data collected during specific campaigns, which may not reflect real-time air quality conditions or enable timely interventions. For instance, the research by Ameer et al. (2019) compares regression techniques for air quality prediction but does not address the challenge of real-time monitoring and decision-making. While ML models show promise in predicting air quality, they often neglect external factors that influence pollution levels. For example, Vu et al. assess the effectiveness of an action plan using random forest, but the model's reliance on meteorological conditions alone may overlook other significant contributors to air pollution, such as industrial emissions or traffic patterns. Although some studies explore the effectiveness of air quality improvement measures, the translation of findings into actionable policies or interventions is often overlooked. For instance, while Lee et al. present a ML approach for predicting PM2.5 concentrations, they do not provide concrete recommendations for mitigating pollution or integrating the predictive models into air quality management strategies. Several studies rely on limited data sources or specific geographical locations, which may not represent the complexities and variations of air pollution in different regions or countries. For example, Lim et al.'s study on land use regression models for PM2.5 concentration focuses solely on Seoul, South Korea, making it challenging to generalize the findings to other urban areas with different characteristics and pollutant sources. To ensure the actionable nature of air quality research, it is important to acknowledge early and address these limitations and consider broader factors such as scalability, real-time data availability, policy integration, and generalizability to diverse contexts. Additionally, collaboration between researchers, policymakers, and stakeholders is essential to translate research findings into effective strategies for mitigating air pollution.

3.4 AI for Oceanographic Research

AI has a wide range of applications in oceanography, enabling advancements in various areas such as marine ecosystem monitoring, climate modeling, underwater exploration, and ocean data analysis. AI-powered image recognition algorithms can automate the identification of marine species based on images or video footage. This helps in assessing biodiversity and tracking species distributions. For example, the Fish4Knowledge project (https://homepages.inf.ed.ac.uk/rbf/fish4knowledge/) developed AI algorithms for automated fish species recognition using underwater videos. AI can also predict ocean currents, sea surface temperature anomalies, and harmful algal blooms. For autonomous underwater vehicles (AUVs) and robotics, AI enables them to autonomously navigate, collect data, and perform tasks such as seafloor mapping, oceanographic surveys, and ecosystem monitoring. The REMUS SharkCam (Hawkes et al. 2020), developed by Woods Hole Oceanographic Institution, utilizes AI to track and film sharks in their natural habitats. Ocean acoustic data analysis is another major area for AI to conduct marine mammal detection, underwater noise analysis, and mapping seafloor habitats. On large-scale climate modeling, AI-based models can enhance the accuracy and efficiency of ocean climate and weather predictions by assimilating data from multiple sources. These models can improve storm track predictions, sea surface temperature forecasts, and El Niño/Southern Oscillation (ENSO) predictions. In addition, ocean pollution detection and monitoring is another important application of AI, for example, the DeepSeaVision project developed an AI-based system to detect and track plastic debris in the ocean using satellite images.

In literature, there are waves of AI-related papers published in oceanography journals and conferences. Chen et al. (2019) focused on the remote estimation of surface seawater partial pressure of CO2 (pCO2) in the Gulf of Mexico (GOM) and found that the random forest-based regression ensemble (RFRE) model was the best approach among various modeling techniques. The RFRE model utilized extensive pCO2 datasets collected over 16 years, along with satellite-derived environmental variables such as sea surface temperature, salinity, chlorophyll concentration, and diffuse attenuation of downwelling irradiance. The model has high accuracy, with a root mean square difference (RMSD) of 9.1 μatm, coefficient of determination (R2) of 0.95, and satisfactory performance in both open GOM waters and coastal/river-dominated waters. Niu et al. (2017) used ML algorithms to study source localization in ocean acoustics, including feed-forward neural networks (FNN), support vector machines (SVM), and random forests (RF), to estimate source ranges based on observed acoustic data. Bianco et al. (2019). reviewed that deep learning (DL) has shown promising advancements in acoustics, particularly in tasks such as sound event detection and source localization, can outperform conventional methods, and offer a general framework for acoustics tasks, eliminating the need for specialized algorithms in different subfields. However, a major challenge is the availability of sufficient training data, although synthetic data or data augmentation can help address this limitation. Recent studies have demonstrated the effectiveness of DL architectures, such as convolutional recurrent neural networks (CNNs) and deep residual neural networks (ResNet), in achieving competitive results in sound event detection, direction of arrival (DOA) estimation, and ocean source localization tasks. Gregor et al. (2019) concluded that although advanced statistical inference and ML methods have been used to fill gaps in sparse surface ocean CO2 measurements and constrain the variability in sea-air CO2 fluxes, these methods are reaching their limitations, referred to as "the wall," where pCO2 estimates are constrained by data gaps and scale-sensitive observations. To enhance surface ocean pCO2 estimates, further improvements might be possible by incorporating additional variables, increasing sampling resolution, and integrating pCO2 estimates from alternate platforms. James et al. (2018) trained ML models on iterations of a physics-based wave model to predict ocean conditions. The models, tested on Monterey Bay, replicated wave heights with a root-mean-squared error of 9 cm and correctly identified over 90% of the characteristic periods, achieving efficient computation compared to the physics-based model. Fan et al. (2021) developed OC-SMART, a versatile platform for analyzing data obtained by satellite ocean color sensors, supporting multiple sensors and providing products such as reflectances, chlorophyll concentration, and optical properties. By utilizing extensive radiative transfer simulations and ML techniques, OC-SMART improves the quality of retrieved water products and resolves issues with negative water-leaving radiance. It is claimed to be faster than NASA's SeaDAS platform, includes advanced cloud screening, and can recover valuable data in coastal areas, making it a valuable tool for ocean color analysis. Sinha and Abernathey (2021) explored the use of ML algorithms to infer global surface currents from satellite observable quantities. The ML models are trained using simulated ocean data and show that a neural network (NN) outperforms linear regression models, accurately predicting surface currents over most of the global ocean. By incorporating geographic information and using convolutional filters, their research showed that NN can effectively learn spatial gradients and improve the accuracy of surface flow predictions. Gloege et al. (2022) produced The Lamont Doherty Earth Observatory-Hybrid Physics Data (LDEO-HPD) pCO2 product by using ML to merge observations with global ocean biogeochemical models

(GOBMs) to estimate surface ocean pCO2 and air-sea CO2 exchange. By training an eXtreme Gradient Boosting (XGB) algorithm to correct the model-data mismatch, LDEO-HPD provides a more accurate reconstruction of pCO2 compared to other observation-based products. The results show good agreement with independent pCO2 observations and are consistent with estimates from other products and the Global Carbon Budget.

Similar to other AI applications in climate sciences, while the mentioned research papers present valuable contributions to the field of oceanography and demonstrate the potential, there are certain limitations and challenges that restrict their immediate adoption. For example, the practical implementation of Chen et al.'s model requires extensive pCO2 datasets and satellite data, which may not be readily available or accessible in real-world scenarios. Additionally, the model's performance in different oceanic regions or under different environmental conditions needs to be further evaluated. Niu et al's study will be restricted by the applicability of these algorithms in real-world situations and may be limited by the availability of sufficient training data, which can be a challenge in ocean acoustics. The effectiveness of these algorithms needs to be validated in different acoustic environments and with diverse source characteristics. Although as Bianco et al.'s review revealed and emphasized on the promise of deep learning (DL) in acoustics for tasks such as sound event detection and source localization, the availability of large and diverse training datasets remains a challenge. The reliance on synthetic data or data augmentation techniques may introduce biases or limitations in the generalizability of the trained models. Further research is needed to address these challenges and improve the robustness of DL approaches in acoustics. Gregor et al.'s research acknowledged the "wall" phenomenon which indicates that pCO2 estimates are constrained by data gaps and scale-sensitive observations. The study explicitly suggests potential improvements such as incorporating additional variables, increasing sampling resolution, and integrating data from alternate platforms, practical implementation, and addressing the limitations of sparse data availability and observational constraints remain significant challenges. James et al.'s work focuses on a specific test site, Monterey Bay, and limits the generalizability of the models to different oceanic regions and conditions. Further validation and testing across diverse geographical locations are necessary to assess the models' robustness and applicability in practical oceanographic applications. For Fan et al.'s OC-SMART, the practical adoption may require addressing challenges related to data availability, integration with existing data processing systems, and validation across different sensor platforms and environmental conditions. Sinha et al.'s ML models' performance and generalizability need to be further evaluated across diverse oceanic regions and under different oceanographic conditions. Additionally, incorporating geographic information and using convolutional filters may introduce challenges in terms of data processing requirements and computational complexity. The practical implementation and utilization of the Gloege et al.'s product depend on the availability and accessibility of relevant observational data and the integration of the product into existing carbon cycle research and monitoring frameworks.

4 Analyzing Low Actionability of AI Projects

After reviewing the use cases in the previous section, most AI projects in climate and environmental science face challenges that limit their actionability and practical applicability in real-world decision-making. These challenges arise from the inherent complexities of climate and environmental systems, the presence of uncertainties and incomplete knowledge, limited data availability and quality, as well as the need for model validation and reliability. Additionally, real-world decision-making processes pose their own set of challenges, including policy and governance considerations, communication and stakeholder engagement, and ethical and equity considerations. Climate and environmental systems are characterized by intricate interdependencies and nonlinear dynamics, making them difficult to model accurately. Despite advancements in AI techniques, climate models still struggle to capture all the complexities of the Earth's climate system. Uncertainty and incomplete knowledge are prevalent in climate and environmental science. Predicting the long-term impacts of climate change on specific regions or ecosystems is a complex task due to uncertainties in data, model formulations, and future projections. This limits the reliability of AI-based predictions and decisions. A study by Knutti et al. (2017) emphasizes the importance of quantifying and communicating uncertainties in climate projections to improve decision-making processes.

Another critical challenge is the limited availability and quality of climate and environmental data. Data scarcity in remote or inaccessible regions hampers the development and training of robust AI models. Furthermore, the lack of long-term observations or sparse data for rare events or extreme conditions adds further complexity. Climate Data Records provided by research institutions help bridge the data gaps, but challenges persist in data coverage and quality (Eyring et al. 2016). Validating AI models and ensuring their reliability is crucial for real-world decision-making. The performance of AI models relies on the quality of validation datasets and the ability to reproduce past events accurately. However, validating AI models for future projections, where real-world observations are limited, poses challenges. Models used for long-term climate predictions or ecological forecasts require rigorous validation procedures. Real-world decision-making involves policy and governance considerations. AI projects in climate and environmental science must align with policy frameworks and governance structures to inform decision-making. However, integrating AI-derived information into policy processes and ensuring transparency and interpretability of AI models can be challenging. The United Nations Sustainable Development Goals provide a framework for integrating AI in climate change mitigation strategies and sustainable development initiatives (Lee et al. 2016). Effective communication and stakeholder engagement are essential for AI projects. Communicating complex AI-driven results and uncertainties to policymakers, scientists, and the general public can be challenging. Public perception and understanding of AI predictions related to extreme weather events or biodiversity loss play a crucial role in decision-making processes. Maibach et al. (2015) stress the importance of clear and accessible communication to bridge the gap between scientific findings and public understanding. Ethical considerations and equity concerns are also significant. AI projects should address potential biases, ensure fair distribution of benefits, and avoid excluding marginalized groups in decision-making processes. The impact of AI-driven climate models on vulnerable communities and the potential for AI technologies to reinforce existing inequalities need careful attention. The Climate Justice Research Centre addresses issues of equity and justice in climate and environmental decision-making (Climate Justice Research Centre, https://www.climatejusticecenter.org).

5 How to Make AI Practical?

We believe that every AI project has the potential to be practical and make its positive impacts on climate and environment. This section will list several key strategies that can be employed to make your AI research more action-oriented. However, there are many parties involved when any AI model is going online and making real impacts. The playbooks for each group will be different on how to develop, treat, adapt, utilize, and thrive on the AI application. This section will break down the strategies and give suggestions tailored for them.

5.1 Suggestion for AI Practitioners

AI practitioners should consider the following strategies. First, prioritize understanding the specific needs and context of end-users and stakeholders. This involves engaging with decision-makers, policymakers, and domain experts to identify the key challenges, uncertainties, and decision-making processes. By understanding the user's perspective, AI practitioners can tailor their models and outputs to provide actionable insights. For example, in flood risk management, AI models can be developed to provide real-time flood forecasting and early warning systems that are directly relevant to emergency response agencies and local communities. By aligning the AI models with user needs, the outputs become more actionable and relevant to decision-makers. Second, practitioners should build AI models with the integration of domain knowledge and constraints. This involves collaborating with domain experts to incorporate their insights and understanding of the underlying processes and factors influencing climate and environmental systems. Through combining domain knowledge with AI techniques, practitioners can develop models that are more accurate and reliable. For example, in carbon sequestration projects, AI models can be used to optimize land-use planning by considering ecological constraints, biodiversity conservation, and socioeconomic factors. By accounting for domain-specific knowledge and constraints, AI models become more realistic and feasible for real-world decision-making. Third, AI practitioners should focus on providing outputs that are not only accurate but also actionable and interpretable by end-users.

This can be achieved by translating complex AI outputs into intuitive and understandable formats, such as visualizations or decision-support tools. Additionally, AI models should provide explanations or justifications for their predictions or recommendations to enhance trust and understanding. For example, in climate change impact assessment, AI models can be used to analyze the vulnerability of different regions and provide visualizations that clearly highlight areas at high risk. Also interpretable outputs can help decision-makers better understand the implications of the AI models and make informed decisions. AI practitioners should consider the ethical implications and potential biases associated with their models. Bias in AI can lead to unfair outcomes and exclusion of certain groups or communities. AI practitioners should invest in diverse and representative training data, consider algorithmic fairness techniques, and conduct thorough evaluations for bias. For instance, in environmental justice, AI models can be used to analyze the distribution of environmental burdens and ensure equitable access to environmental resources. By addressing ethical and fairness considerations, AI models become more trustworthy and accountable for real-world decision-making.

AI practitioners should actively reach out to create partnerships for collaboration and interdisciplinary research between AI experts, climate scientists, environmental researchers, and policy stakeholders. This collaboration can help bridge the gap between technical advancements and real-world applications. By working together, different stakeholders can contribute their expertise, validate AI models, provide contextual knowledge, and ensure the relevance and practicality of the AI products. For example, in renewable energy planning, collaborative research between AI experts and energy policymakers can lead to the development of AI-driven tools that optimize renewable energy deployment based on spatial, economic, and environmental considerations. By fostering collaboration, AI practitioners can develop models that address the complex challenges of climate and environmental decision-making.

5.2 Suggestions for Decision-Makers and Stakeholders

Although most responsibilities of making AI practical are on AI researchers' shoulders, there is still a lot more that can be done from the user side to help them develop better AI products. AI users should first identify their specific challenges and goals related to climate and environmental issues, like understanding the areas where AI can provide valuable insights or solutions, such as improving resource management, optimizing energy efficiency, or enhancing environmental monitoring. Clearly defining their needs can make users better assess the relevance and potential impact of AI research products. Instead of being pitched by scientists, users with demands should actively reach out to academia. Collaborating with AI experts and researchers can be highly beneficial for users in climate and environment. AI experts can provide guidance on selecting appropriate AI models and methods, tailoring them to specific user requirements, and validating their effectiveness in addressing real-world challenges. This collaboration can involve partnerships with academic institutions, research organizations, or AI consulting firms. Meanwhile, before full-scale adoption, users should consider conducting pilot studies or demonstrations to evaluate the feasibility and benefits of AI research products, such as implementing AI models on a smaller scale or in controlled environments to assess their performance, reliability, and practicality. Pilot studies can help identify any potential limitations or adjustments needed for successful implementation.

As decision-makers and stakeholders often assess the cost-effectiveness and return on investment before adopting AI research products, they should perform a thorough cost-benefit analysis that takes into account the implementation costs, potential savings, improved decision-making capabilities, and long-term benefits. This analysis can help justify the adoption of AI and secure necessary resources. Also, there are a lot of things to consider from the user side besides science integrity. AI users should prioritize addressing privacy, security, and ethical considerations to gain trust and ensure compliance with regulations. This includes safeguarding sensitive data, implementing appropriate security measures, and adhering to ethical guidelines and standards. Users should be transparent about the data sources, model training methods, and potential biases to build confidence among stakeholders.

6 Vision for Earth AI in Future Environment Practice

Our shared vision for AI is very important for bringing scientists and the society together to address pressing issues. Earth AI represents the next generation of systems that can provide innovative solutions for tackling climate and environmental issues in an intelligent and unprecedented manner. This vision is unique in its approach to addressing climate challenges by harnessing advanced technologies and data-driven methodologies to offer actionable insights and innovative solutions for environmental monitoring, conservation, resource management, and climate change mitigation with unparalleled efficiency and capability. Unlike traditional technologies, Earth AI combines the power of artificial intelligence, ML, and big data analytics to unlock the full potential of available environmental data, enabling us to make more informed decisions and take proactive measures in addressing climate issues. Earth AI offers a transformative approach that can enhance our understanding of complex Earth systems, optimize resource allocation, support evidence-based decision-making, and foster collaboration among stakeholders. It is this integration of cutting-edge technologies with environmental stewardship that sets Earth AI apart, making it a crucial component of our future strategy to tackle climate challenges effectively and promote sustainable practices.

Earth AI is expected to provide actionable insights and innovative solutions for environmental monitoring, conservation, resource management, and climate change mitigation, for example, the use of AI technologies to revolutionize environmental monitoring and conservation efforts (Sun et al. 2022). For example, remote sensing data combined with ML algorithms can enable the automated detection and tracking of deforestation, illegal fishing activities, or wildlife poaching in real-time. This allows for more efficient and targeted interventions, such as timely enforcement actions or habitat protection measures. Organizations like Global Forest Watch and Wildlife Insights are already leveraging AI to monitor and protect forests and wildlife. AI can optimize the management of Earth's limited resources, and analyze large datasets from weather sensors, satellite imagery, and agricultural records to optimize water usage, crop yields, and irrigation practices. This helps in reducing water waste, improving food production, and ensuring sustainable resource allocation. It will support climate change mitigation and adaptation strategies by predicting extreme weather events, assessing the impact of climate change on ecosystems, and designing resilient infrastructure. AI-powered models will be able to optimize renewable energy deployment, developing carbon capture and storage technologies, and improving climate risk assessments for vulnerable communities. Projects like ClimateAI and Climate Corporation are actively working on AI-based climate solutions. Earth AI envisions the development of decision-support systems that facilitate collaborative and evidence-based decision-making processes. By integrating AI models, expert knowledge, and stakeholder inputs, these systems can provide policymakers with insights to design effective environmental policies, conservation strategies, and sustainable development plans. They can also simulate the potential outcomes of different policy scenarios to guide decision-makers in making informed choices. Initiatives like AI for Earth by Microsoft and the Earth System Prediction Capability are aiming to provide decision-support tools for environmental management.

7 Conclusion

This chapter listed the need for AI practitioners to bridge the gap between AI research and actionable science in the field of climate and environment, and revealed the challenges faced by AI models and products in terms of their limited actionability and adoption in real-world decision-making processes. It provides valuable insights and future outlooks for AI practitioners to make their products better positioned for actionable science like improving interpretability and transparency of AI models, integrating domain expertise in model development, leveraging interdisciplinary collaborations, focusing on scalability and transferability of models, and addressing data limitations and biases. Through implementing these strategies, AI practitioners can expect to enhance the practicality and relevance of their AI products, ensuring their effective use in addressing climate and environmental challenges and enabling informed decision-making processes.

In future, the guidance for actionable AI can better position our scientists for adoption from the public, by providing better AI products with interpretability and transparency of AI models to gain stakeholders' trust and facilitate understanding of model predictions. We expect this chapter will help Earth AI scientists thrive on integrating domain expertise and involving stakeholders in the model development process to ensure the relevance and applicability of AI solutions, actively reaching out to promoting interdisciplinary collaborations to leverage diverse perspectives and expertise, facilitating the development of holistic and actionable AI products, communicating the benefits and value of AI products effectively to decision-makers, policymakers, and the public, fostering trust, and promoting adoption. By incorporating these future outlooks into their practices, scientists in climate and environment domains can drive the transformation of AI research into actionable science, contributing to effective climate and environmental management and decision-making processes.

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