Enhancing Weather Prediction and Climate Modeling: A Multi-Criteria Decision-Making Approach to Artificial Intelligence Techniques

Ayat-Allah Bouramdane

Laboratory of Renewable Energies and Advanced Materials (LERMA), College of Engineering and Architecture, International University of Rabat (IUR), IUR Campus, Technopolis Park, Rocade Rabat-Salé, Sala Al Jadida, 11103, Morocco

Email: ayatallah.bouramdane@uir.ac.ma

Artificial Intelligence (AI) is increasingly being used in weather prediction and climate modeling, leading to improvements in accuracy, speed, and the handling of complex data.
This paper evaluates the major types of AI based on several criteria using Multi-Criteria Decision-Making (MCDM), particularly the Analytic Hierarchy Process (AHP) **[1, Section 2.2]**, which organizes decision problems into a hierarchy, facilitates pairwise comparisons to assign weights to criteria **(Figure 1)**, and identifies the best alternative based on overall scores **(Figure 2)**.

To understand AI's role in atmospheric sciences, it is crucial to first distinguish between **weather prediction** and **climate modeling**, as each serves a unique purpose within this field.
Weather Prediction involves short-term forecasts that can range from minutes to a few days. Traditional methods rely heavily on subjective assessments, personal intuition, and expert knowledge of similar past events. However, modern **weather forecasting** employs statistical models that analyze extensive datasets from satellite imagery, radar, and ground-based observations. These models enhance accuracy by projecting short- to medium-term trends, typically up to 15 days **[2]**.
Climate modeling, on the other hand, focuses on long-term changes in climate conditions over months, seasons, or years. This variability is driven by various processes within Earth's systems, including atmospheric patterns and ocean currents. A prominent example is the El Niño-Southern Oscillation (ENSO), characterized by periodic warming (El Niño) and cooling (La Niña) of sea surface temperatures in the Pacific Ocean, significantly impacting global weather patterns. ENSO events occur irregularly every two to seven years. The Earth's axial tilt of about 23.5° also significantly influences seasonal climate variability by causing different regions to receive varying sunlight amounts throughout the year. In summer, the tilted hemisphere faces the sun, resulting in longer days and more direct sunlight, while in winter, it tilts away, leading to shorter days and less sunlight. Although the distance from the sun varies slightly during the year, its impact on seasonal temperatures is less significant than that of axial tilt.
While **climate variability** refers to natural fluctuations in climate conditions over shorter timescales, **climate change** denotes long-term alterations in Earth's climate persisting over decades to centuries. These changes are often simulated using climate models that help predict future conditions under various greenhouse gas emission and socio-economic pathways. Climate change results from both natural processes and human activities, particularly emissions from fossil fuel combustion and deforestation **[3, 4]**.

Key AI techniques that can be applied in weather prediction and climate modeling include **[5]**:

Machine Learning (ML)

ML models operate through a structured process involving data input, training, evaluation, and prediction.
The first step in building an ML model is **gathering relevant data**. This data can come from various sources, such as sensors, databases, or online repositories. Once collected, the data must be cleaned and preprocessed to ensure it is suitable for analysis. This involves cleaning (i.e., removing duplicates, correcting errors, and dealing with missing values), normalization (i.e., scaling numerical values to a common range, which helps improve model performance), feature selection (i.e., identifying and selecting the most relevant features "variables" that will be used for training the model).
After preparing the data, the next step is to **select a suitable ML algorithm**. Different algorithms are designed for various types of tasks, such as:
(i) Supervised Learning: is a type of AI that learns from examples.
Training with Examples: Think of it like teaching a friend to predict the weather by showing them many past weather data---including temperatures, humidity levels, and wind speeds, and whether it rained or was sunny on each day---along with the actual weather conditions that occurred on those days. You provide this data to the AI, telling it «Here is the temperature and humidity, and this is what the weather was like (sunny, rainy, etc.)".
Learning the Patterns: The AI looks for patterns in this data. For instance, it might notice that when the temperature is above 30°C and the humidity is low, it is usually a sunny day. The AI uses these patterns to create a model, which is like a set of rules or a recipe it can follow in the future.
Making Predictions: Once the AI has learned from the examples, you can give it new data, like today's temperature and humidity, and ask, "What will the weather be like tomorrow?". The AI uses the patterns it learned to make a prediction. For example, it might predict that if the temperature is 32°C and humidity is 25%, there's a good chance it will be sunny.
Checking Accuracy: After making a prediction, you can check how close the AI's guess was to the actual weather. Over time, the AI gets better and better at making accurate predictions by adjusting its model based on how well it did in the past.
(ii) Unsupervised Learning: is a type of AI where the machine tries to understand data and find patterns without being given specific instructions or labels. It helps find surprises, hidden connections, or unknown patterns in weather and climate data. Imagine you have lots of weather data (temperatures, wind speeds, rainfall, and more) from different cities and times. But instead of telling the AI what these numbers mean (like whether it is a sunny day or a rainy day), you just give it the raw data. The AI's job is to look at the data and find patterns or groups that you might not have noticed. Let's say you give the AI a year's worth of weather data from a region. It does not know what "summer" or "winter" is, or what type of weather belongs to each. It might still notice that: there is a group of days where the temperature is high, the air is dry, and there is little wind (this could be the summer months); there is another group where it is cooler, there is more wind, and it rains a lot (this might be the winter season). The AI is clustering or grouping similar types of weather together, even though it was not told what seasons are. It learns by finding these hidden patterns in the data. Scientists might use unsupervised learning to discover new types of weather patterns or climate systems that they did not know existed before. For example, it might discover a new pattern of storms that frequently happens before hurricanes, helping us better predict when hurricanes are coming; it could also find hidden relationships, like a connection between ocean temperatures and rainfall patterns, helping climate scientists understand long-term climate changes.
(iii) Reinforcement Learning is a type of AI that learns by trial and error, just like playing a game where you get rewarded (or get points) for making the right moves. Over time, the AI figures out what actions lead to the best results by trying different things and seeing how much reward it gets. Let's say we use reinforcement learning to help manage a water supply during unpredictable weather. The AI gets weather data (like temperature and rainfall predictions) and decides how much water to use for irrigation each day. On the first day, it might decide to use a lot of water, but later it finds out there is a drought coming, so it earns a low score because it should have saved some. The next time, the AI remembers that using too much water during a dry period results in a bad outcome, so it adjusts and decides to save more water the next time similar weather conditions appear. In summary, reinforcement learning is like teaching an AI through rewards and penalties. The AI learns by trying different actions and getting feedback in the form of points or rewards. Over time, it figures out the best way to act to get the highest reward. In the context of weather prediction, this could help AI systems decide how to manage resources or respond to changing weather in the smartest way possible.

Once an algorithm is selected, **the model is trained** using the prepared data. This process involves feeding the data into the model and adjusting its parameters to minimize the difference between the actual and predicted outputs. A loss function quantifies how far the model's predictions are from the actual outcomes. Common loss function includes Mean Squared Error for regression tasks. The model adjusts its parameters based on the loss calculated. This is done using optimization algorithms like Stochastic Gradient Descent (SGD), which help in minimizing the loss function by updating the weights of the model iteratively.
After training, **the model is evaluated** using a separate dataset known as the validation or test set.
Once the model is trained and evaluated, it can be used for **making predictions on new data**.

The advantages of ML are numerous. First, ML can **process vast amounts of data far more quickly and accurately than humans**, enabling it to **identify complex patterns that might otherwise go unnoticed**. This capability leads to improved accuracy in predictions and insights, particularly in dynamic fields like meteorology and climate science. Additionally, ML models can **adapt over time as they receive new data, ensuring that their predictions remain relevant even as conditions change**. However, there are notable disadvantages to ML as well. One primary concern is the **reliance on high-quality data**; ML models can produce inaccurate results if the data used for training is biased, incomplete, or of low quality. Additionally, **the complexity of some ML algorithms** can make them difficult to interpret, leading to a lack of transparency in decision-making processes. This "black box" nature can be problematic, especially in critical applications where understanding the rationale behind predictions is essential.

ML has made significant strides in the field of weather prediction, where it is used to improve forecasting accuracy. For instance, meteorologists employ ML algorithms to analyze historical weather data, satellite imagery, and real-time sensor data. These models can predict severe weather events such as hurricanes, tornadoes, or heavy rainfall by recognizing patterns that precede these occurrences. For example, the **European Centre for Medium-Range Weather Forecasts (ECMWF)** employs ML to enhance its numerical weather prediction models, allowing for improved short- and medium-term forecasting.
The **Intergovernmental Panel on Climate Change (IPCC)** has begun incorporating ML techniques to improve the accuracy of climate projections, assisting policymakers in making informed decisions about climate mitigation and adaptation strategies.

Deep Learning is a subset of ML that focuses on neural networks. **Neural Networks (NNs)** are like a web of connected nodes (or "neurons"), inspired by the brain. These neurons work together to process information. Each node takes in input (like temperature, humidity, or wind speed), processes it, and passes the result to the next layer of nodes. The final output could be a weather prediction, like "sunny" or "rainy." **Convolutional Neural Networks (CNNs)** are specialized for image recognition, making them effective at identifying weather patterns from satellite images. **Recurrent Neural Networks (RNNs)** are designed to work with sequential data, where the order of the information matters, like time series. **Long Short-Term Memory Networks (LSTMs)**, a more advanced type of RNN, excel at retaining important long-term information, making them ideal for tracking and predicting climate changes over extended periods. Lastly, **Graph Neural Networks (GNNs)** focus on understanding complex relationships in data, such as how different regions' weather systems interact with each other. Each of these neural networks has unique strengths depending on the nature of the data and the prediction goals.

Ensemble Learning is a powerful approach that combines multiple models to improve prediction accuracy and robustness. **Bagging (Bootstrap Aggregating)** works by training several models independently on random subsets of the data and then averaging their predictions, which helps reduce variance and avoid overfitting. **Boosting**, on the other hand, focuses on training models sequentially, where each new model learns from the mistakes of the previous ones, placing more emphasis on the data points that were mispredicted, thereby enhancing the overall predictive power. Finally, **Stacking** involves training multiple diverse models and then using another model to learn how to best combine their predictions, often resulting in improved performance by leveraging the strengths of different algorithms.

Hybrid models encompass a range of techniques that combine various approaches to tackle complex problems effectively. **Physics-Informed Neural Networks (PINNs)** integrate physical laws into neural networks, allowing them to learn from both data and fundamental physics, making them useful for modeling intricate climate phenomena such as heat transfer and fluid dynamics.

Evolutionary Algorithms (EAs) are like how nature finds solutions over time. Just like animals and plants adapt to survive, EAs help computers discover better ways to solve problems. One type of EA is called **Genetic Algorithms (GAs)**. Imagine you have a garden of plants. You choose the strongest plants and mix them together to grow even better ones. GAs do the same thing with ideas— they take the best solutions, combine them, and keep the ones that work best. This helps find the most efficient ways to use energy or manage resources in climate models. Another type is **Particle Swarm Optimization (PSO)**. Think of a flock of birds searching for food. Each bird helps the others by sharing information about where to find the best spots. PSO works similarly by having different potential solutions move around together, helping each other find the best answers for things like improving renewable energy systems. Finally, we have **Neural General Circulation Models (NeuralGCM)**. Imagine a weather map that shows what the weather will be like. Traditional models use complicated math to make predictions. NeuralGCM enhances these models by using a special kind of computer learning (like a brain) to improve accuracy. It learns from a lot of weather data, helping us understand climate patterns and make better forecasts.

Natural Language Processing (NLP) helps computers understand and work with words. For example, if someone asks a computer about the weather, NLP helps it understand the question and provide a good answer, like telling you if it will rain tomorrow.

Fuzzy Logic Systems help computers make decisions when things are not clear. Imagine trying to decide if it's warm enough to go swimming. Instead of just saying "yes" or "no," fuzzy logic lets the computer consider different temperatures and conditions, like "It feels a bit warm, but not too warm," which can help decide if it is a good day to swim.

Expert Systems are like having a super-smart weather expert. They use a lot of weather information to give advice, like what to do during a storm. If there is a chance of flooding, an expert system can recommend how to prepare.

Support Vector Machines (SVM) help computers sort different weather types. For instance, they can learn to separate sunny days from rainy days by looking at things like temperature and humidity, helping forecasters make better predictions.

Decision Trees and Random Forests help computers decide based on questions. A decision tree might ask, "Is it cloudy?" If the answer is yes, it might then ask, "Is the temperature below 60 degrees?" Random Forests use many of these trees together to improve predictions about weather patterns and climate changes.

Bayesian Networks show how different weather factors connect. For example, they can help a computer understand how the chance of rain is linked to temperature and humidity, making it easier to predict when a storm might happen.

By evaluating these different AI systems under different criteria, scientists can get better at predicting the weather and understanding our climate.

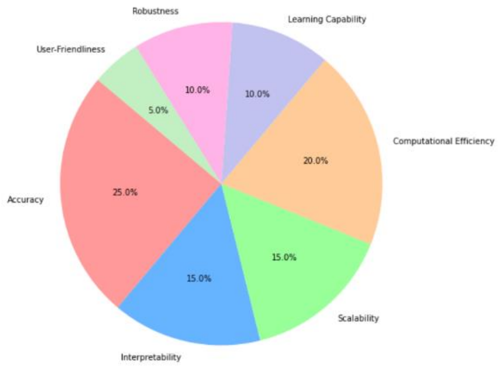

Figure 1: Relative weights of evaluation criteria for artificial intelligence techniques in weather prediction and climate modeling. The results indicate that **accuracy** (i.e., the ability of the model to correctly predict outcomes) is the most important criterion with a high weight of 25%, followed by **computational efficiency** (i.e., the resources required for training and inference) (20%) and medium weights for **interpretability** (i.e., how easily the model's decisions can be understood by humans) and **scalability** (i.e., the model's ability to handle increasing amounts of data or complexity) (15% each); **learning capability** (i.e., the model's ability to improve with more data) and **robustness** (i.e., the model's performance under varying conditions and data quality) are also considered important but receive a lower medium weight of 10% each, while **user-friendliness** (i.e., how accessible a model is to non-experts) is the least critical factor with a low weight of 5%. Source: Author's own elaboration.

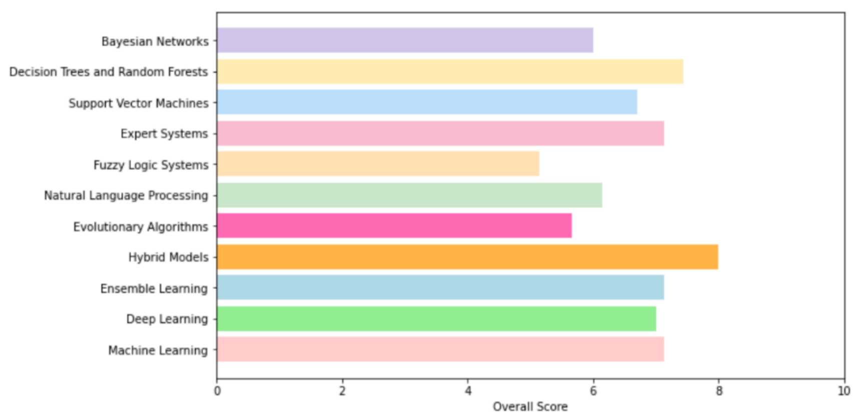

Figure 2: The comparative performance scores of artificial intelligence techniques for weather prediction and climate modeling, ranking them as follows: **Hybrid Models** lead with a score of 8.00, followed by **Decision Trees and Random Forests** at 7.43, and both **Machine Learning** and **Ensemble Learning** tied at 7.14. Next is **Expert Systems** also at 7.14, while **Support Vector Machines** score 6.71. **Deep Learning techniques** are slightly lower at 7.00, followed by **Natural Language Processing** at 6.14 and **Bayesian Networks** at 6.00. **Evolutionary Algorithm**s trail at 5.67, and **Fuzzy Logic Systems** have the lowest score of 5.14. Source: Author's own elaboration.

References

[1] Bouramdane, A.-A. (2023). Cyberattacks in Smart Grids: Challenges and Solving the Multi-Criteria Decision-Making for Cybersecurity Options, Including Ones That Incorporate Artificial Intelligence, Using an Analytical Hierarchy Process. Journal of Cybersecurity and Privacy (JCP), 3, 662-705. https://doi.org/10.3390/jcp3040031

[2] Plat.ai. (n.d.). Difference Between Prediction and Forecast. *Retrieved October 11, 2024, from* https://plat.ai/blog/difference-between-prediction-and-forecast/

[3] Bouramdane, A-A. (2021), "Scenarios of Large-Scale Solar Integration with Wind in Morocco: Impact of Storage, Cost, Spatio-Temporal Complementarity and Climate Change". *Institut Polytechnique de Paris, [PhD Thesis], Physics, Oct 2021*, https://tel.archives-ouvertes.fr/tel-03518906

[4] Bouramdane, A.-A (2022). Assessment of CMIP6 Multi-Model Projections Worldwide: Which Regions Are Getting Warmer and Are Going through a Drought in Africa and Morocco? What Changes from CMIP5 to CMIP6? *Sustainability, 15, 690*. https://doi.org/10.3390/su15010690

[5] Jeon, S., & Kim, J. (2024). Artificial Intelligence to Predict Climate and Weather Change. JMST Advances.