# Supplementary Material

## 'Artificial Intelligence for Modeling and Understanding Extreme Weather and Climate Events' by Gustau Camps-Valls et al. Nature Communications, 2024.

**Table S1.** Description of the statistical and artificial intelligence methods mentioned throughout the review for modeling and understanding weather and climate extreme events.

| Term | Definition |
|---|---|
| Artificial Intelligence (AI) | Simulation of human intelligence in machines that can perform tasks such as learning, reasoning, and problem-solving. |
| Attention Mechanism | A technique that enables machine learning models to focus on the most relevant parts of input data when making predictions, enhancing performance in tasks like language processing and image recognition by selectively weighting certain elements over others. |
| Autoencoder | A type of neural network that learns to encode input data into a smaller representation and then reconstruct it, used for tasks like dimensionality reduction and noise removal. |
| Backpropagation | A method for training neural networks by adjusting weights through the gradient descent of errors propagated backward from the output layer. |
| Characterization of Events | Methods employed to describe and understand the characteristics of extreme weather events. |
| Chatbot | AI-powered conversational agent that interacts with users via text or voice interfaces, providing information and assistance. |
| Causal Feature Selection | Identification of features with causal relationships to a target variable, enhancing model interpretability and robustness. |
| Causal Inference | Techniques used to identify cause-and-effect relationships from data, crucial for understanding underlying mechanisms. |
| Causal Representation Learning | Learning representations that encode causal relationships between variables, facilitating interpretable and robust predictions. |
| Class-imbalanced Learning | Techniques for handling datasets where some classes are underrepresented, improving model accuracy across all classes. |
| Clustering | Unsupervised learning methods that group similar data points based on features, often used in data analysis and pattern recognition. |
| Communication of risk using AI | Tools and strategies for conveying information about extreme weather events to stakeholders and the public. This includes chatbots, large language models, semantics, ontologies for organizing and understanding data, and situation rooms for real-time monitoring and decision-making. |
| Computer Vision (CV) | Field of artificial intelligence that enables machines to interpret and understand visual information from the world, including images and videos, through techniques such as image processing, pattern recognition, and deep learning. |
| Continual Machine Learning | A learning paradigm where models continuously adapt to new data over time without forgetting previous knowledge. |

**Table S1.** (cont.) Description of the statistical and artificial intelligence methods mentioned throughout the review for modeling and understanding weather and climate extreme events.

| Term | Definition |
|---|---|
| Convolutional Neural Network | Deep learning model designed for processing structured grid data, such as images, by applying convolutional layers that automatically learn spatial hierarchies of features, making it particularly effective for tasks like image recognition and classification. |
| Counterfactual Explanations | Explanations of model predictions that indicate how slight changes in input data could yield different outcomes, enhancing interpretability. |
| Data Denoising | Techniques that remove noise or irrelevant information from data, improving data quality and model accuracy. |
| Data Fusion | Methods that combine data from multiple sources to create a more comprehensive dataset, enhancing analysis and decision-making. |
| Data Gap-Filling | Methods for estimating missing data points in datasets, crucial for maintaining dataset completeness and consistency. |
| Decision-making | The process of selecting the best course of action among multiple alternatives based on available information and preferences. |
| Decision Tree | A model that makes decisions by splitting data into subsets based on feature values, often visualized as a tree structure. |
| Deep Learning (DL) | A subset of machine learning methods that utilize neural networks with multiple layers to extract features and learn patterns from data. |
| Deterministic Model | A model that provides a specific output for a given input without incorporating randomness. |
| Dimensionality Reduction | Techniques that reduce the number of input variables while preserving significant information, simplifying data analysis. |
| Distributed Solution | Methods that use multiple computing resources to parallelize tasks, enabling faster and scalable processing of large datasets. |
| Domain Adaptation | Techniques that allow models trained on one domain to generalize effectively in a different but related domain. |
| Early Warning System (EWS) | A system designed to monitor environmental conditions and issue alerts or warnings about impending extreme weather events or disasters. |
| Echo State Network (ESN) | A type of recurrent neural network that uses a sparsely connected hidden layer to efficiently model time series data. |

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| Term | Definition |
| --- | --- |
| Emulation Model | A model that approximates complex simulations or processes, enabling faster analysis while retaining essential characteristics. |
| Ensemble Model | A model that combines predictions from multiple models to improve overall performance and accuracy. |
| Ethical Aspects | Concerns related to the moral implications and societal impact of artificial intelligence and climate science, including privacy, bias, transparency, accountability, and the equitable distribution of benefits and harms, particularly when addressing extreme events and their consequences. |
| Explainable AI (XAI) | Methods that aim to provide insights into artificial intelligence model predictions or decisions, making them interpretable and understandable to humans. |
| Extreme Event Attribution | The process of determining the extent to which human-induced climate change and natural variability contribute to specific extreme weather events. |
| Extreme Event Detection | Use of techniques and algorithms to identify and recognize patterns or anomalies in data related to extreme weather events. |
| Extreme Event Impact Assessment | Methods for evaluating the consequences of extreme weather events on various sectors, including infrastructure, economy, and ecosystems. |
| Extreme Event Prediction | Techniques for forecasting the likelihood and intensity of extreme weather events, leveraging statistical and machine learning models. |
| Extreme Value Theory (EVT) | A branch of statistics focusing on extreme deviations from the median of probability distributions; used in climate science to predict and understand the likelihood and characteristics of rare, extreme weather events. |
| Feature Attribution | Techniques that identify the contribution of individual features to the model's output, used to interpret model predictions. |
| Feature Engineering | Handcrafted process of transforming raw data into meaningful features that enhance model performance. |
| Federated Learning | A collaborative approach to training ML models across multiple devices or servers without centralizing the data, enhancing privacy. |
| Foundation Model | A large, pre-trained model that can be fine-tuned for a variety of downstream tasks, such as language generation or image classification. |
| Gaussian Process (GP) | A probabilistic model used for regression and classification that provides uncertainty estimates along with predictions. |

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| Term | Definition |
|---|---|
| Gaussianization | Techniques that transform data to approximate a Gaussian distribution. |
| General Circulation Model (GCM) | A mathematical model that simulates physical processes in the atmosphere, ocean, and land for climate predictions. |
| Generative Model | A model that generates new data samples similar to the training data, often used in applications like image synthesis. |
| Gradient-based Class Activation Map (Grad-CAM) | A visualization method that highlights regions in an input image that are important for the model's classification decision. |
| Graph Neural Network (GNN) | A type of neural network designed to work with data structured as graphs, capturing relationships between nodes. |
| Human-in-the-loop | Methods that incorporate human feedback during the model training or decision-making process, enhancing performance and trustworthiness. |
| Invariant Feature Representation | Techniques that ensure model representations remain stable across different conditions or environments, aiding in generalization. |
| Large Language Model (LLM) | Artificial intelligence models trained to generate human-like text based on given prompts or inputs, capable of providing information or answering questions. |
| Local Interpretable Model-Agnostic (LIME) Explanations | An interpretable artificial intelligence method that approximates complex model predictions locally with simpler interpretable models. |
| Long Short-Term Memory Networks (LSTMs) | A type of recurrent neural network architecture capable of learning long-term dependencies, making them suitable for sequential data like time series. |
| Long-tail Learning | Techniques that aim to improve model performance on rare or infrequent classes in a dataset, which often represent the "long tail" of a distribution, by addressing issues of class imbalance and ensuring that the model generalizes well across all classes, including those with limited training examples. |
| Low-shot Learning | Techniques that allow models to learn effectively from only a few training examples, enhancing generalization. |
| Machine Learning (ML) | Algorithms that enable computers to learn from and make predictions or decisions based on data without being explicitly programmed. |
| Model Calibration | Adjusting model predictions to improve accuracy and reliability, especially for probability-based models. |

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| Term | Definition |
| --- | --- |
| Monte Carlo (MC) Dropout | A technique in neural networks to approximate model uncertainty by using dropout during prediction. |
| Multimodal Learning | A method that integrates information from multiple data types, such as text and images, for improved prediction. |
| Natural Language Processing (NLP) | Artificial intelligence methods that enable computers to understand, interpret, and generate human language, facilitating text-based tasks. |
| Neuron Integrated Gradients (NIG) | An explanation method that provides feature attribution by integrating gradients along the path from a baseline to the input. |
| Numerical Weather Prediction (NWP) | A mathematical approach that uses physical models and observational data to forecast weather conditions. |
| One-Class Classification | Techniques for classifying data when only one class is well-represented, often used in anomaly detection. |
| Online Machine Learning | A method where models continuously update with new data, allowing adaptation to changing patterns over time. |
| Outlier Detection | Identification data points significantly different from others, useful for spotting anomalies or errors. |
| Parameter Estimation | Techniques for determining the values of model parameters that best explain the observed data. |
| Partial Dependence Plot (PDP) | A visualization tool that shows the relationship between a feature and the predicted outcome in a model. |
| Physical Models and Simulations | Mathematical and computational representations of physical systems, used to predict behaviors and outcomes. |
| Physics-based and Hybrid Machine Learning Models | Approaches that combine physical modeling with machine learning to capture both theoretical and data-driven insights. |
| Prototype-based Model | A model that represents each class with one or several prototypes, enabling interpretable machine learning based on similarity to these prototypes. |
| Quantile Regression | A method that estimates different quantiles of the response variable, useful for modeling uncertainty in predictions. |

**Table S1.** (cont.) Description of the statistical and artificial intelligence methods mentioned throughout the review for modeling and understanding weather and climate extreme events.

| Term | Definition |
|---|---|
| Random Forest | An ensemble learning method that builds multiple decision trees and aggregates their predictions for improved accuracy. |
| Reconstruction-based Model | Models that learn to reconstruct input data, often used in anomaly detection and image generation. |
| Recurrent Neural Network (RNN) | Neural network designed to process sequential data by maintaining a hidden state that captures information from previous time steps, allowing it to learn dependencies and patterns in time series or natural language data. |
| Reinforcement Learning | A machine learning paradigm where agents learn to make decisions by maximizing rewards through trial and error. |
| Robust AI | Artificial intelligence systems that maintain their performance and reliability under a wide range of conditions, including novel or adversarial conditions, ensure consistency in decision-making even when faced with uncertainties or unexpected data. |
| Semantics and Ontologies | Frameworks for organizing and understanding data by defining concepts and their relationships in a specific domain. |
| SHapley Additive exPlanations (SHAP) | An explainable artificial intelligence method used to attribute the importance of each feature to the model's output, offering insights into the factors driving predictions. |
| Situation Rooms | Dedicated spaces equipped with technology and tools for real-time monitoring, analysis, and decision-making during emergencies or critical events. |
| Storyline Approaches | Methods that construct plausible sequences of events or scenarios to illustrate potential outcomes, often used in risk communication. |
| Support Vector Machine | A supervised learning model that finds the optimal hyperplane to classify data points in feature space. |
| Transfer Learning | A method where models trained on one task are adapted to improve performance on a related task, often with limited data. |
| Transformer | A type of neural network architecture that has shown remarkable success in various natural language processing tasks by capturing dependencies across long distances. |
| Trustworthy AI | AI systems designed with reliability, safety, fairness, transparency, and accountability in mind, ensuring that they make decisions that align with ethical principles and societal values. |
| Uncertainty Quantification | Methods that assess the degree of uncertainty in model predictions, critical for risk-sensitive applications. |
| Variational Inference | A method that approximates complex probability distributions in Bayesian inference, making computations tractable. |
| Weather Forecasting | Predicting atmospheric conditions over a short or medium time horizon, using models based on meteorological data. |

**Table S2.** Strengths and weaknesses of artificial intelligence methods mentioned throughout the review for modeling weather and climate extreme events.

| Method | Strengths | Weaknesses |
|---|---|---|
| Decision Tree | - Simple to interpret<br>- Handles non-linear data well | - Prone to overfitting<br>- Sensitive to noisy data |
| Random Forest | - Reduces overfitting<br>- Robust to outliers | - Less interpretable<br>- May require tuning of parameters |
| Support Vector Machine | - Effective in high-dimensional spaces<br>- Robust to overfitting | - Requires careful kernel selection<br>- Can be computationally expensive |
| Gaussian Process | - Provides uncertainty estimates<br>- Flexible modeling | - Computationally intensive for large datasets<br>- Requires prior distribution choice |
| Autoencoder | - Good for dimensionality reduction<br>- Can capture complex patterns | - May not generalize well<br>- Sensitive to hyperparameters |
| Convolutional Neural Network | - Excellent for image data<br>- Captures spatial hierarchies | - Requires large datasets<br>- Complex architecture |
| Recurrent Neural Network | - Handles sequential data well<br>- Good for time series | - Prone to vanishing gradient<br>- Long training times |
| Long Short-Term Memory Network | - Overcomes vanishing gradient<br>- Captures long-range dependencies | - Computationally intensive<br>- Complex to tune |
| Attention Mechanism | - Focuses on important features<br>- Interpretable | - Can be complex to implement<br>- Requires significant data |
| Transformer | - State-of-the-art in many NLP tasks<br>- Handles long sequences well | - High computational resource requirements<br>- Requires large datasets |
| Echo State Network | - Efficient training<br>- Captures dynamic temporal patterns | - Requires careful initialization<br>- Less flexible |
| Graph Neural Network | - Effective for relational data<br>- Captures graph structure | - Complex architecture<br>- Scalability issues with large graphs |
| Large Language Model | - Captures language patterns effectively<br>- Strong performance on NLP tasks | - Requires massive datasets<br>- High computational cost |
| Foundation Model | - Generalizes across tasks<br>- Leverages large-scale training | - High resource requirements<br>- Less interpretable |