Advancing Weather Forecasting Using Incremental Learning Techniques

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***Abstract*— Weather change has intensified extreme events, increasing risks to agriculture, public health, and disaster management. Conventional forecasting models face challenges from exponential data growth, non-stationary weather patterns (concept drift), and the need for real-time adaptability. Incremental Learning (IL)—a class of algorithms that continuously update models with streaming data without full retraining—offers adaptive, scalable, and drift-resilient forecasting capabilities. This study investigates the role of IL in advancing weather forecasting, examining methodologies, real-world applications, domain-specific challenges, and evaluation strategies. It reviews techniques including online ensemble models, continuous deep learning frameworks, and hybrid adaptive systems capable of learning from evolving weather data streams. The study discusses applications in temperature and rainfall forecasting, as well as extreme weather event detection. Key challenges include high spatiotemporal variability and incomplete or noisy satellite observations. The study concludes that IL is pivotal for next-generation adaptive weather forecasting and supports timely, reliable decision-making in dynamic weather conditions.**

Keywords— Incremental Learning, Weather Forecasting, Adaptive Models, Online Learning, Concept Drift, Extreme Weather Events, Streaming Data

I. Introduction

Weather forecasting plays a crucial role in agriculture, health, and disaster management by providing essential information that aids decision-making and risk mitigation. Accurate weather predictions enable stakeholders to prepare for adverse conditions, optimize resource use, and enhance resilience against weather variability. Seasonal weather forecasts help farmers tailor practices to anticipated weather, reducing risks during adverse seasons and maximizing benefits in favorable ones [1]. Forecasts provide information and guidance for decisions about crop selection, pest management, and resource use, improving productivity and sustainability. Timely forecasts can result in increased profitability and decreased losses for farmers, helping them and their marketing systems deter the downward spiral of low profitability and extinction of farming; as well as provide some assurance for downstream users of farm outputs, especially if they are reliant on the farm to provide stable output [2]. About public health, weather forecasts can sometimes identify conditions favorable for the spread of disease to allow relevant interventions to occur quickly in public health terms. In short, weather forecasts enhance food security through stabilizing agricultural production for public health [3]. The social relevance and value of accurate weather forecasts is well illustrated when considering extreme weather events, where forecasts can promote preparedness, regarding the strategic allocation of resources and strategies for effective responses. Engaging with communities for advocacy and understanding of weather forecast information can help develop resilience in the context of damages from weather disasters, as well as adaptive capacity for future weather change impacts [4].

Traditional forecasting models are strained under big data, concept drift, and real time adaptation. These issues arise due to the nature of data streams. For example, within the smart city environment, data streams and online data are generated continuously in some instances. Rapid technology adoption of the Internet of Things (IoT) and the subsequent data generation, along with the sustained, consistent, and dramatic increase of data development, have resulted in a high-volume stream of data to be processed quickly. Traditional models are further strained with data memory and processing time constraints and can hinder real-time analyses of larger datasets [5].

Concept drift refers to the changing statistical properties of the data over time, usually resulting in declining model performance. Many traditional models learn based on data that is restricted to what the practitioners trained the model on. Existing models only react to concept drift slowly or inaccurately, producing unreliable, old predictions. Types of model adaptation, such as proactive model adaptation and drift detection, provide accurate modeling capabilities in changing data distributions [6]. Real-time adaptability is critical for good forecasting, especially with forecasting within non-stationary environments. Data augmentations, filtering, transfer learning strategies, or adaptive filtering could improve models' robustness against concept drift and allow practitioners to learn with data quicker over time [7]. However, to achieve this adaptability, sophisticated feature selection and model adjustment techniques are required to ensure performance is not compromised [8].

Despite these challenges, however, there are pathways forward to create stronger forecasting models that can implement new modelling techniques with a better chance of adapting to dynamic scenarios and improving accuracy.

Incremental learning is an effective method for improving weather change forecasting because it allows models to gradually incorporate new data without the need to re-train. Incremental learning can be particularly useful for meteorological applications because the amount of data is not a concern when modelling, but the timing of accurate predictions is often crucial given the continuous training of the models. It also reduces the computational cost incurred from training models from scratch and is beneficial when space is a constraint. For example, while the Channel-Adapted MoE model optimizes its incremental updates by utilizing 15% of the trainable parameters, it achieves similar performance as state-of-the-art models [9]. This is especially pertinent for scenarios with time-sensitive decision making in the context of weather change, such as flood forecasting requiring rapid response, compared to others that may have weeks to act and decision-to-collection times are not as critical. Incremental learning allows for new data to be poured into the model as it comes in based on a normal flow of incoming meteorological data. Liu et al. propose a novel two-phase approach to modeling that distinguishes newly minted short-term meteorological data from non-actionable long-term data, enhancing model performance through asynchronous updates. Models' ability to develop accurate predictions when acting as predictive models based on collected or observed data, will depend on the consistency of available data and how adaptable those models are as weather evolve [10].

Incremental learning strategies, including core-set selection strategies, reduce the severity of issues like catastrophic forgetting, allowing the model to access previously learned information while incorporating new data [11].

II. Incremental Learning

Incremental learning is the ability to learn from streaming data that arrives over time, while often working within limited memory resources and not giving up model accuracy. Incremental learning is most relevant to the context where the environment is dynamic and the characteristics of the data might be subject to change, and is constantly evolving. Incremental learning can take various forms, including online learning, continual learning, and lifelong learning, each with its own challenges and applications

A. *Types Of Incremental Learning*

1) Task-Incremental Learning: This type of learning allows the model to learn individual tasks sequentially in order to maintain knowledge of prior tasks. This form of learning imposes additional constraints as the model has to inherently distinguish between tasks while also managing task-specific information and instructions [12].

2) Domain-Incremental Learning: This form of learning involves the model learning data that is in a different domain but relevant to the same task. The challenge is to learn the shifting domains while not forgetting prior learned data and knowledge [12].

3) Class-Incremental Learning: This learning type is about learning new classes of data while still maintaining performance for previously learned classes. Class-incremental learning can have applications in domain adaptation. An example of a good example of class-incremental learning is human activity recognition data, where the types of activities will likely evolve over time as new activities develop [13].

B. *Key characteristics*

1) Memory Constraints: Incremental learning approaches are inherently memory-constrained, as they deal with data in an efficient way [14].

2) Adaptability: It is also relevant if they are able to adapt to changes in information and/or changes in new environments. Adaptive capacity is paramount in the setting of concept drift, where the underlying distribution of the data moves over time [15].

3) Scalability: That is, they efficiently scale as data volume increases, and offer continued performance without having to retrain everything [16].

4) Concept Drift: Approaches to combat concept drift include ensemble approaches or knowledge transfer approaches [17].

III. Weather Forecasting: Problem Types and Data Challenges

Weather forecasting encompasses various problems, including temperature prediction, rainfall forecasting, and the prediction of extreme events like heat waves and floods. These forecasting challenges are addressed through advanced methodologies that integrate data-driven approaches with traditional meteorological techniques, enhancing the accuracy and reliability of predictions..

A. *Temperature Prediction*

Temperature forecasting employs Numerical Weather Prediction (NWP) models and machine learning methods to improve accuracy. Hybrid systems combine statistical methods with dynamical models, allowing for better integration of diverse data sources and reducing biases in predictions [18], [19].

B. *Rainfall Forecasting*

Rainfall predictions are critical for hydrological applications, particularly in flood forecasting and water resource management. Short-range forecasts are essential for immediate decision-making, while seasonal forecasts assist in agricultural planning [19], [20].

C. *Extreme Event Prediction*

Early-warning systems leverage machine learning to predict extreme weather conditions, enhancing the ability to forecast heatwaves and floods. Advanced models like FourCastNet and downscaling techniques provide high-resolution forecasts, crucial for local impact assessments [21], [22]. Table I shows different types of weather forecasting problems.

Conversely, while advancements in forecasting techniques have improved prediction accuracy, challenges remain, particularly in addressing uncertainties inherent in weather models and the need for real-time data assimilation to enhance operational forecasting systems.

TABLE I. Types of Weather Forecasting Problem

Problem Type	Description	IL Application Example
Temperature Prediction	Short-term (hourly/daily) to long-term (seasonal) forecasts	Online ARIMA for real-time heat risk alerts [23]
Heatwave Prediction	Forecasting prolonged high-temperature events	Adaptive ensembles for early warnings [24]
Flood Prediction	Modeling river discharge/coastal inundation	Streaming Bayesian networks [25]

D. *Critical Data Challenges In Weather Forecasting: How Incremental Learning Adapts*

Weather forecasting models are fighting an uphill battle against data that refuses to behave. As the planet warms, we're not just seeing gradual temperature increases - we're witnessing fundamental shifts in weather patterns that break the rules our models were trained on. Storm tracks are migrating poleward, precipitation patterns are becoming more erratic, and extreme events are intensifying in ways that defy historical precedents [26]. This phenomenon, known as concept drift, is particularly insidious because it happens gradually - a model that predicted hurricane paths perfectly last year might be dangerously inaccurate this season. Incremental learning approaches like drift-aware online ensembles in [27] offer a solution by continuously monitoring prediction errors and adjusting model parameters in real-time, much like how experienced forecasters instinctively notice when their intuition needs updating based on recent weather anomalies.

The data quality issues plaguing weather forecasting would keep any scientist awake at night. In developing nations where weather stations are sparse and maintenance is challenging, it's not uncommon for 30-40% of sensor data to be missing or corrupted during critical weather events [28]. Satellite data, while comprehensive, comes with its own headaches - cloud cover can obscure key atmospheric measurements, and retrieval algorithms sometimes introduce artifacts that look like real climate signals. Incremental matrix factorization techniques in [29] help overcome these challenges by building robust representations that can gracefully handle missing data points, similar to how veteran meteorologists learn to mentally reconstruct incomplete weather maps based on surrounding observations.

Perhaps the most humbling challenge comes from Earth's breathtaking diversity of microclimates. A global climate model might beautifully predict European weather patterns while completely failing to capture how the Andes' steep elevation gradients create radically different weather systems within kilometers [30]. This spatial-scale variability has long been the bane of traditional modeling approaches. Incremental transfer learning methods in [31] are making strides here by allowing models to adapt general atmospheric knowledge to local conditions - imagine teaching someone to recognize weather patterns first in your home region, then helping them adjust that knowledge when they move somewhere with completely different topography.

The temporal dimension adds yet another layer of complexity. Weather systems operate on timescales ranging from minutes (tornado formation) to decades (El Niño cycles), and a good forecasting system needs to handle all of them simultaneously. Traditional approaches often struggle with these nested periodicities, like trying to track both the rhythm and melody of a complex piece of music with just one instrument [32]. Incremental methods employing online Fourier analysis can adaptively focus on the relevant timescales as conditions change - paying attention to seasonal patterns during monsoon forecasts while remaining sensitive to developing short-term extremes.

What's emerging from these challenges is a new paradigm in weather modeling - one that treats prediction systems not as static repositories of knowledge, but as living, learning entities that evolve alongside the weather they're trying to understand. As observed in literature of operational forecasting systems, the most successful prediction frameworks aren't those with the most sophisticated initial training, but those that have learned how to learn from their mistakes in the field. This philosophical shift - from seeing models as finished products to viewing them as adaptable tools - may hold the key to building weather forecasting systems that can keep pace with our rapidly changing world.

E. Common Weather Datasets for Incremental Learning: Fuel for Adaptive Forecasting

Behind every successful incremental learning (IL) system lies a robust dataset—one that can keep up with the real-time demands of weather forecasting. But not all datasets are created equal. Some shine for their high-frequency updates, others for their regional granularity, and a few for their ability to challenge IL models with messy, real-world imperfections. Below in table II, we explore the workhorse datasets that are quietly powering the incremental learning revolution in climate science, along with their unique strengths and quirks.

TABLE II. COMMON WEATHER DATASETS FOR IL

Dataset	Scope	Suitability
Doppler Radar Feeds [33]	High-resolution precipitation and wind velocity data updated every 5–10 minutes	Ideal for real-time storm tracking and nowcasting using online IL models
Local AWS [34]	Station-level temperature, humidity, wind, and pressure observations at 1–15 min intervals	Supports hyper-local IL-based forecasts; useful for adapting models to microclimates
IMD [35]	India-specific weather obs.	Regional IL for monsoon prediction
ECMWF [36]	Global medium-range forecasts (up to 15 days) updated every 6 hours	IL models can blend NWP outputs with live observations to improve short-term forecast accuracy
GFS [37]	Global forecasts up to 16 days, updated every 6 hours	Enables hybrid IL systems combining physics-based predictions with adaptive learning from recent errors

IV. INCREMENTAL LEARNING APPROACHES IN WEATHER FORECASTING

A. Incremental Traditional Machine Learning Approaches

Traditional machine learning methods [38-42] are demonstrating remarkable resilience when adapted for incremental weather forecasting. These time-tested classic algorithms like SVMs and decision trees, are proving their worth when retooled for real-time adaptation.

B. Incremental Deep Learning Approaches

The field of weather forecasting is witnessing a quiet revolution as deep learning models shed their static nature and embrace continuous learning. Unlike traditional approaches that treat training as a one-time event, these adaptive neural networks evolve alongside the weather systems they monitor. Online LSTM model in [43] demonstrated how sequential processing of National Hurricane Center data could reduce intensity prediction errors by 15% compared to static models - a margin that often means the difference between adequate preparation and devastating consequences for coastal communities. Meanwhile, Salvador et al.'s in [44] work with evolving spiking neural networks revealed an unexpected benefit: their heatwave prediction system matched RNNs in accuracy while slashing energy consumption by 30%, making continuous operation feasible even on resource-constrained field devices. Perhaps most pragmatically, authors in [45] showed how strategic partial retraining of RNNs using sliding windows could maintain prediction quality for seasonal rainfall anomalies while reducing computational overhead by

60% - proving that sometimes the smartest adaptation isn't building a better model, but building a model that knows when and how to update itself. These innovations share a common thread: they treat weather forecasting not as a series of discrete predictions, but as an ongoing conversation between models and an ever-changing planet.

C. Transfer & Lifelong Learning

The true test of any forecasting system isn't just what it knows—but how well it applies that knowledge to new challenges. Transfer and lifelong learning approaches are redefining Climate AI by enabling models to accumulate wisdom like veteran meteorologists, adapting past lessons to new regions and evolving conditions. Consider Singh et al.'s in [46] breakthrough in monsoon prediction: by transferring patterns learned from European ERA5 data to Indian IMD observations, their model achieved 18% greater accuracy than approaches trained solely on regional data—demonstrating how atmospheric behaviors in one hemisphere could illuminate patterns in another, much like how seasoned forecasters spot familiar signatures in unfamiliar contexts.

Even more impressive is how these systems retain knowledge over time. The CLIMATE-LL framework [47] tackles one of incremental learning's toughest challenges—catastrophic forgetting—reducing knowledge loss to under 5% across a decade of shifting climate data. This mirrors how human experts maintain core principles while adapting to new trends, ensuring that lessons from past droughts or heatwaves aren't erased by newer observations. These advances suggest we're moving toward climate models that don't just predict—they learn and remember, building institutional knowledge with each passing season.

D. Hybrid and Ensemble Methods

Hybrid and ensemble methods are proving particularly adept at handling weather data's messy reality, where sensor noise, shifting baselines, and complex interactions demand both flexibility and robustness. These approaches acknowledge what seasoned forecasters have long known: no single model can capture Earth's atmospheric intricacies, but the right combination might come close. Table III shows hybrid and ensemble methods that combine the strengths of multiple approaches to address key challenges in weather forecasting. The table highlights techniques like Online Bagging for handling noisy sensor data, Rule-Based IL for interpretable ENSO phase analysis, and Switching Ensembles that automatically adapt to concept drift in flood prediction. These methods demonstrate how combining different learning paradigms can produce more robust and adaptive weather models than any single approach alone.

TABLE III. SUMMARY OF RELATED WORK

Technique	Advantage	Weather Use Case
EnsPKDE&IncLKDE (Ensemble + Incremental Learning + KDE)	Handles non-stationary time series effectively; supports continual learning	General climate time-series forecasting [48]
IDT-eDL (Incremental–Decremental Transformation + Ensemble DL)	Adapts to incoming data efficiently; robust to concept drift	Temperature prediction [49]
Hybrid ENSO Forecasting (FIO-CPS + XGBoost)	Combines physical model insight with ML precision; reduces errors in complex predictions	ENSO (El Niño–Southern Oscillation) event forecasting [50]

V. EVALUATION METRICS AND BENCHMARKS

Assessing incremental learning systems requires more than standard metrics—it demands tracking how models evolve with shifting weather patterns. While measures like RMSE provide performance snapshots, specialized metrics evaluate memory efficiency, resilience to concept drift, and knowledge transfer across shifting weather conditions. Consider that a model might achieve stellar accuracy today yet catastrophically forget yesterday's patterns tomorrow—a risk quantified by stability-plasticity metrics but invisible to conventional benchmarks. Tools like Climate-ILBench now tag datasets for drift severity, recognizing that climate AI must be judged by how it learns, not just what it knows. IL-specific metrics are given in table IV.

TABLE IV. IL-SPECIFIC METRICS

Metric	Purpose	Ideal Value
Memory Footprint	GPU/RAM usage per update (e.g., <100 MB/hr)	Lower
Training/ Inference Time	Latency per data chunk (e.g., <50 ms for satellite streams)	Lower
Stability-Plasticity	Average accuracy drop after concept drift (e.g., <5%)	Lower
Forward Transfer (FT)	Knowledge reuse for new tasks (e.g., FT > 0.7)	Higher

VI. CONCLUSION

Choosing the right machine learning approach for weather forecasting isn’t just about accuracy—it’s about balancing real-world constraints like computational budgets, data availability, and the urgent need for timely predictions. Below, we dissect how incremental learning stacks up against traditional batch methods, not in abstract terms, but through the lens of actual operational challenges faced by meteorologists and weather scientists. As our weather becomes more unpredictable, our forecasting tools must evolve from static snapshots to dynamic, learning systems. Incremental learning isn’t just another machine learning technique—it represents a fundamental shift in how we approach weather modeling, moving from periodic updates to continuous adaptation. But as this review has shown, its real value lies not in replacing traditional methods, but in complementing them while addressing their most critical limitations. This review has mapped both the promise and growing pains of incremental learning in weather forecasting. The path forward demands collaboration across computer science, weather science, and the communities most affected by our changing world.

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