Machine Learning for Climate Intelligence and Weather Forecasting in the Tropics

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Key Messages

- Factors such as convectional rainfall, dense vegetation, and hilly terrain decrease the accuracy of weather predictions in the tropics offered by traditional weather forecasting systems which provides about 39% accuracy in predicting weather conditions in the tropics compared to 84% accuracy from machine learning models.
- The effects of climate change on national economies, lives, and livelihoods, particularly for climate-vulnerable populations, are exacerbated as a result of inequities in access to weather information.
- Machine learning technology creates a green window of opportunity to support a just climate transition using predictive algorithms that optimize weather forecasting in tropical climates.
- Governments in the tropics should adopt machine learning for climate forecasting as part of their climate adaptation plans.

Climate change-amplified extreme weather events are causing increasingly devastating and unpredictable societal, economic, and natural ecosystem impacts. Accurate weather prediction is increasingly vital for communities and governments to deal with the rapidly changing climate.[12] Traditional weather forecasting models are based on physical equations that are implemented using numerical weather prediction (NWP).[2] This model does not work effectively in tropical zones, where it struggles to predict rain and other key influencing conditions. For example, weather prediction accuracy averages only 39% in West Africa, while in North America, prediction accuracy averages 80%.[5] In regions with tropical climates, where the effects of climate change are more pronounced, there is a demand for systems capable of predicting rainfall within distances of less than one kilometer.[3] However, achieving this accuracy level is expensive and many tropical countries fall within the low or middle-income brackets. Convectional rainfall, dense vegetation, and hilly terrain in tropical regions significantly influence local weather conditions.[3]

Lack of accurate weather forecasting in these regions has implications for food production, food security, and natural disaster responses

Landscape Analysis

The Potential for ML Technology to Mitigate Economic Losses of Climate Change

Current State of Technology

Machine learning (ML) technology provides an incredible opportunity to bridge the weather forecasting gap in developing countries. ML is defined as the capability of a machine to engage in cognitive activities typically performed by the human brain[9 and] is a collection of methodologies, tools, and computer algorithms that teach machines to analyze, comprehend, and discover hidden patterns in data to make predictions, as a result, computers ultimately use the patterns learned from data to make future decisions or predictions.[9] New implementations of Artificial Intelligence models are based on machine learning and harness big data.[13] The current ML forecasting model combines direct numerical modeling with ensemble techniques using Deep Neural Networks (DNNs)[2 to] run many different models. It then applies data science and separation of scales including nowcasting to create

predictive climate intelligence models.[2] Leveraging new advances in Graphical Processing Units (GPUs), this hybridization of NWP and DNNs improves forecast horizon, and spatial, and temporal resolution.[13] Some of the most prominent ML forecasting models are Pangu-Weather (developed by Huawei),[2] FourCastNet (developed by NVIDIA),[8] and GraphCast (developed by Google).[4] Start-ups, including Atmo, Excarta, and Jua, are also building AI weather models.[13] Ignitia is an example of an ML model developed specifically for the tropics. Ignitia's forecasting system is capable of forecasting convectional rainfall in tropical climates and ensuring that vulnerable communities can better prepare for extreme weather events, as well as build agricultural practices that are resilient to the rapidly changing climate.[5] The advantages of ML models over traditional models are that they require less infrastructure since they run on a single GPU rather than giant supercomputing facilities.[9] This makes forecasting technology, which was previously exclusive to wealthy countries, affordable for middle and lower-income countries.[1] This also means that they are energy efficient, require less power, and increase productivity due to their ability to process huge amounts of data in a shorter amount of time.[1]

Mitigating Economic Losses of Climate Change (Annex 2)

Developing economies in the tropics heavily rely on agriculture as a main source of livelihood. Despite that developing countries contribute to less than 10%of global greenhouse gas emissions, climate chahange vulnerability is a significant concern for these populations.[6] The African Climate Policy Centre[13] (ACPC) projects a decline in the Gross Domestic Product (GDP) across Africa's subregions due to escalating global temperatures. Scenarios projecting a 1°C to a 4 °C increase anticipate an overall GDP reduction ranging from 2.25% to 12.12%. One projection for a "severe climate change scenario" at 4°C, the

ACPC predicted a 13% decrease in mean yield in West and Central Africa, 11% in North Africa, and 8% in East and Southern Africa. Under the same scenario, staple crops like rice, and wheat are expected to face significant yield losses of 12% and 21%, respectively, by 2050.[14] Acknowledging the pressing need for more accurate weather forecasts to alleviate devastating climate effects, machine learning technology stands as a crucial tool in advancing predictions, especially in the realms of agriculture and disaster management.[12]

A 2020 report from the International Monetary Fund[6] highlights that direct economic damage caused by climate-related disasters in Africa amounts to US$520 million since the beginning of this century. The United Nations Framework Convention on Climate Change (UNFCCC) reports that over 110 million people on the continent were directly impacted by climate-related hazards in 2022, resulting in economic damages exceeding US$8.5 Billion.[7]

Deploying machine learning for weather predictions can contribute to a just transition and economic growth in developing countries by saving lives and capital, thereby mitigating the impacts of climate change on agriculture and related sectors.

Benefits and Challenges of ML for Weather Forecasting

<table>
<tr><th><u>Benefits</u></th><th><u>Challenges</u></th></tr>
<tr><td>Improves accuracy of rain predictability.</td><td rowspan="2">Private sector is not required to make data and codes publicly available, raising credibility concerns and suspicions over data bias, which affects public acceptance of ML weather models.</td></tr>
<tr><td>Provides early warning systems for weather disasters.</td></tr>
<tr><td>Improves governance through rapid response to climate disasters.</td><td>Poor satellite coverage in developing economies affects the quality and quantity of data for effective learning and predictions since a machine-learning model is only as good as the data that goes into it.</td></tr>
<tr><td>Enhances water resource management through efficient irrigation measures, which helps small-scale farmers</td><td rowspan="2">Companies are increasingly relying on software engineers to develop ML forecasting models. This undervalues the role of weather scientists' expertise which is crucial to producing a reliable ML model.</td></tr>
<tr><td>Adaptable to Tropical countries (e.g., Brazil, Malaysia, Philippines, Ghana, Uganda, and Kenya.)</td></tr>
<tr><td>Reliability: Based on case studies, experts confirm the reliability of ML in accurately predicting weather and consequent benefit to its users (e.g. Ignitia).</td><td>Developing economies lack open access to cost-effective information to promote affordable ML hardware for economic benefit and public use.</td></tr>
</table>

Conclusion

Machine Learning technologies provide incredible opportunities for precise weather forecasting with implications for agriculture and disaster response. ML models such as Ignitia are increasingly adaptable to many different countries in the tropics and can respond to agricultural and farmer needs for climate resilience. These technologies are also more affordable and more efficient than traditional weather forecasting models and present unique opportunities for countries in the global South to adapt to climate change while advancing their economies. Data gaps and standardization are among the challenges to implementing this technology, however, with regulatory frameworks for open data access, sufficient investments in research and development, and North-South cooperation, the emergent technology of ML forecasting can revolutionize economies in the global South, while allowing them to respond to climate change and bridge the technology gap.

Policy recommendations / conclusions

The following recommendations have significant implications for countries in the tropics to advance climate resilience in agriculture and increase preparedness in disaster response.

- Governments in the tropics should adopt ML for weather forecasting, such as existing models like Ignitia, as part of their climate adaptation plans.
- Governments in the tropics should increase funding and investments in research and expertise training in the development and expansion of ML technology at institutions and universities specifically tailored for climate science.
- Governments in the tropics should enhance cooperation between research institutions and private sector entities to promote climate data sharing, thereby nurturing a comprehensive data environment. This cooperation should establish uniform data-sharing protocols that emphasize data security, privacy, and ethical principles.
- Governments in the tropics should foster public-private partnerships through tax incentives to boost tech innovation and the acquisition of cost-effective information systems. This will ensure rapid development and affordability of ML hardware for the economic benefit of end-users.
- Regional organizations like the African Union should put in place adaptable mechanisms to prevent data monopolies and promote fair access, especially for small-scale farmers and communities.
- Multinational Organizations should establish research and business networks to build North-South partnerships to enhance data-sharing and create alliances through networks such as Earth Virtualization Engines (EVE), which advocates for global access to ML computing, data, democratization of software and storage resources.

Case Study: Ignitia

Ignitia's forecast and climate intelligence model is aimed at addressing the specific challenges of forecasting rainfall and climate variability in tropical climates such as West Africa and Brazil. It provides accurate predictions of approximately 84% in tropical regions, compared to 39% accuracy by the traditional weather forecast models that power most of the world's existing weather apps and services.[5] Using historical data sets, computational models, and advanced algorithms, high-precision forecasts of rain, wind, humidity, and temperature forecasts are transformed into intelligence for decision-making. Additionally, this algorithm leverages already existing models in other regions for increased predictability and is based on many years of forecast and observation data sets.[10]

Experts at Ignitia explain that their data informs small-holder farmers on smart agricultural practices such as irrigation, planting, weeding, pruning, fertilizers application, and pest control. Additionally, this data can inform actionable agricultural advice such as when to sow, apply for crop nutrition and protection, hire additional labor and harvest. With Ignitia's advanced technology, farmers are now able to get updates on their phones through SMS, a mobile app, a web app, application programming interface (API), and more. Ignitia's solutions increase food security while saving farmers time and resources. Better weather forecasting has increased revenues for farmers by optimizing their production by up to 10% and reducing labor costs by 0.10%. In total, clients of Ignitia increased revenues and reduced 4.78% in production costs.[10]

Figure 1. Accuracy of Ignitia weather predictions, compared to Global Traditional models (Ignita, 2023)

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Annex

Annex 1. Interviews

Expert's Name	Institution	Date of Interview	Topic
Professor Marie McGraw, Meteorologist.	Colorado State University	10th November 2023	Accuracy of ML in weather predictions
Olúwatóyìn Emmanuel-Olubake, Investment Director.	Ignitia - Novastar	17th November 2023	Case study of Ignitia and Novastar in Africa
Dr Aaron Hill, Climate Scientist.	Colorado State University	22nd November 2023	Critical role of Climate scientists for proper interpretation of ML weather predictions
Professor Hamid Ekbia, Artificial Intelligence.	Syracuse University	30th November 2023	Trends of AI in Weather forecasting
Alexander Levy, CEO. Atmo.	Atmo	1st December 2023	AI weather predictions at Atmo
Sophie Bree, CEO. Jua.ai.	Jua.ai	6th December 2023	Jua.ai for accurate extreme weather predictions

Annex 2. Mitigating Economic Losses

Projected scenario of economic cost to Africa (Percent of GDP) per temperature rise (PACJA, 2009) - PAN African Climate Justice Alliance.

Temperature rise	Year reached	Economic costs (per cent of GDP)
1.5°C	2040	1.7 per cent
2°C	2060	3.4 per cent
4.1°C	2100	10 per cent