University of Reading

Department of Meteorology

Using machine learning to predict the intensification and propagation of East African storms

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Declaration

I, Sean Kelley, of the Department of Meteorology, University of Reading, confirm that this is my own work and figures, tables, equations, code snippets, artworks, and illustrations in this report are original and have not been taken from any other person's work, except where the works of others have been explicitly acknowledged, quoted, and referenced. I understand that if failing to do so will be considered a case of plagiarism. Plagiarism is a form of academic misconduct and will be penalised accordingly.

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Sean Kelley
August 11, 2025

Abstract

Keywords: a maximum of five keywords/keyphrase separated by commas

Word count: 100

Report code: https://github.com/seangtkelley/uor-msc-dissertation-xai-african-storms

Acknowledgements

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Nomenclature

c	Speed of light in a vacuum
h	Planck constant

Glossary

Mesoscale Convective System A group of thunderstorms organised into a single cloud system that lasts several hours, often resulting in extreme rainfall, flash flooding and hail. ix, 1, 2

Synoptic Scale Meteorological phenomena that occur at a horizontal scale of 200 kilometres and above, often associated with large-scale weather systems. 2

Acronyms

MCS Mesoscale Convective System. 1, 2

Chapter 1

Introduction

Gebrechorkos et al. (2019) Mesoscale Convective System (MCS)

1.1 Research Objectives

This section outlines the primary objectives of the research, which include:

- To investigate the factors contributing to the intensification and propagation of East African storms.
- To develop a machine learning model capable of predicting storm behavior based on historical data.
- To evaluate the performance of the proposed model against existing forecasting methods.

Chapter 2

Background and Literature Review

2.1 Mesoscale Convective Systems (MCSs)

Due to significant size, duration, and impact, Mesoscale Convective Systems (MCSs) constitute a critical component of regional weather forecasting and climatology. Officially, MCSs are defined as complex of thunderstorms which becomes organised on a scale larger than any of the individual thunderstorms (NWS, 2025). Consequently, these storm systems often last for several hours and cover areas of tens of thousands of square kilometres. In addition, they often produce severe weather phenomena, including flooding, strong winds, and hail (Houze, 2014). Unlike many Synoptic Scale systems, MCSs are not usually associated with a well-defined center of circulation and instead are characterized by their multi-scale organization, typically incorporating a variety of convective cells and larger-scale features such as squall lines or mesoscale convective complexes (NWS, 2025; AMS, 2024). These systems are prevalent throughout the world and thus are key to understanding regional climatology. For example, in the United States, MCSs are a primary driver of warm-season precipitation over the Great Plains (Haberlie and Ashley, 2019). The Sahel region of Africa produces some of the strongest MCSs globally due to it being a climatic transition zone with strong seasonal cycles (Zipser et al., 2006).

2.1.1 MCSs in the Horn of Africa

The Horn of Africa is a region with complex topography, diverse climates, and significant seasonal rainfall variability. The Ethiopian Highlands and Rift Valley—plays a key role in modulating convective processes by enhancing moisture convergence and inducing localized wind patterns that favour the formation of MCSs. [SOURCE] Proximity to both the Red Sea and Indian Ocean influences surface humidity and temperature, providing moisture sources and controlling regional monsoon dynamics. Sea surface temperature (SST) anomalies can have teleconnected impacts on rainfall extremes through the modulation of atmospheric circulation[3]. The pattern of land surface temperature and soil moisture, largely dictated by vegetation and recent precipitation, impacts the development and intensification of MCSs. Notably, studies in the Sahel have demonstrated that dry soils downstream of moisture anomalies can intensify convection by triggering enhanced surface sensible heat flux, increasing instability, and strengthening low-to-mid-level wind shear[4][5]. These processes are similarly relevant to the Horn of Africa, especially in transitional climates bridging arid and humid zones.

Large-scale scale teleconnections also play a major role in governing regional climate patterns and MCS activity. The EAJ, along with the African Easterly Jet (AEJ), is critical in providing the wind shear required for the growth and westward propagation of MCSs. Enhanced meridional temperature gradients, often influenced by soil moisture and orography, strengthen these jets and facilitate system longevity[6][2]. The MJO is a dominant intraseasonal oscillation, modulating rainfall variability in the tropics[7][8][9]. In East Africa, its active phases coincide with increased convection and extreme rainfall events, partly due to anomalous low-level westerlies fostering moisture advection and instability that fuel MCS development. El Niño-Southern Oscillation (ENSO) and the Indian Ocean Dipole (IOD) have also been shown to modulate rainfall patterns in the region, with coupled regional climate models able to reproduce these patterns at various timescales[3][10].

2.2 Data-driven Scientific Discovery Approaches in Meteorology

There is a growing adoption of data-driven techniques in meteorology, particularly for tasks involving the prediction, nowcasting, and understanding of convective systems. Modern nowcasting methods, such as physics-conditional deep generative models (e.g., NowcastNet), unify physical evolution with statistical learning to achieve short-term, high-resolution forecasts of extreme precipitation by leveraging radar data and ensemble neural networks[11]. These methods can accurately capture nonlinear, multi-scale atmospheric processes crucial for predicting MCS behaviour. Physics-guided neural networks permit downscaling of coarse global climate data to regional scales, capturing local meteorological dynamics that drive convection and rainfall. A recent approach uses auto-differentiation within neural nets to infer governing PDEs directly from data, enabling more physically-informed predictions[12]. Automated symbolic learning and sparse regression have enabled discovery of new parameterization schemes for atmospheric models, often improving model accuracy and generalization across regimes. Latent force models supplement explicit physical terms in predictive frameworks, better capturing subgrid convective dynamics relevant to MCSs[12].

2.3 Explainable and Interpretable ML in Meteorology

The emergence of explainable machine learning (ML) methods has enhanced both forecast accuracy and scientific understanding in meteorology. Some techniques and applications include:

- **Feature Attribution Methods**: Techniques such as LIME, SHAP, and Layerwise Relevance Propagation (LRP) have been widely adopted to interpret complex ML models. For example, LIME has helped identify crucial features in random forest models for seasonal precipitation prediction, with explanations aligning closely to known meteorological phenomena like ENSO impacts[13][14].

- **Case Studies in Convective Systems**: - **Tropical Convection and MCSs**: LRP has revealed the importance of large-scale vertical velocity and wind shear in predicting convective area and organization in the tropics, with moisture and thermodynamic factors primarily affecting the convective area, and horizontal wind fields impacting system organization[13]. - **Parameter Estimation**: Bayesian neural networks and interpretable ML models have improved estimation of poorly defined parameters in weather prediction, such as those controlling cloud representation and rainfall post-processing[13][15].

- **Relevant Example—Indian Monsoon Lows**: Hunt and Turner (2023) demonstrated the utility of interpretable gradient-boosted decision-tree ensembles in uncovering new dynamical relationships governing Indian monsoon low-pressure systems[16]. Their results clarified the roles of soil moisture, surface fluxes, and jet–vortex interactions, with implications for the propagation and inland penetration of convective systems. The approach stressed regional surface and dynamical controls similar to those present in the Horn of Africa context.

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These advances motivate the current work: by applying explainable ML approaches to the intensity and propagation of MCSs over the Horn of Africa, researchers can not only improve forecast skill but also illuminate underlying physical processes and inform climate adaptation strategies for a region highly vulnerable to convective extremes.

Sources

Chapter 3

Methodology

Chapter 4

Results

4.1 Summary

Chapter 5

Discussion and Analysis

5.1 Significance of the findings

In this chapter, you should also try to discuss the significance of the results and key findings, in order to enhance the reader's understanding of the investigated problem

5.2 Limitations

Discuss the key limitations and potential implications or improvements of the findings.

5.3 Summary

Chapter 6

Conclusion

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Appendix A

An Appendix Chapter