Extreme weather and climate events are shifting in frequency, intensity, and geography as the planet warms, amplifying risks to people, infrastructure, and economies. Credible adaptation therefore requires tools that characterize hazardous phenomena with physical fidelity under data scarcity and translate large-scale environmental conditions into reliable, interpretable estimates of event occurrence across policy-relevant time scales. This thesis advances both aims for cyclone hazards through two complementary lines of work and a supporting causal analysis.

First, it mitigates data scarcity for intense extratropical cyclones by training a progressive growing generative adversarial network on reanalysis and historical tracks to synthesize maps of mean sea-level pressure, 10~m wind speed, and rainfall over the North Atlantic. Evaluation targets diversity (coverage of observed variability) and fidelity (realism of synoptic structure, gradients, and spatial patterns). The generator reproduces the organization of low and high pressure systems and the observed link between pressure gradients and surface winds, yielding credible wind distributions around cyclone centers and realistic rainfall patterns. The main shortfalls occur for the most localized rainfall extremes and for small scale pressure homogeneity in a few regions of high natural variability. Because the system can produce large, physically plausible samples within minutes, the results support generative augmentation for training and testing detection, intensity, and impact models where real events are rare.

Second, the thesis develops an interpretable learning framework for tropical cyclogenesis (XAI-GPI) that estimates annual genesis counts by basin and explains their drivers. Starting from a broad pool of environmental predictors, a wrapper-based selection reduces redundancy and collinearity while retaining the most informative, basin-specific signals. A shallow neural network provides counts aggregated per basins, and SHapley Additive exPlanations quantify each predictor's contribution. Applied across six basins, the index captures interannual variability more faithfully than standard empirical formulations while remaining transparent about mechanism: vertical wind shear, mid-tropospheric humidity, sea-surface temperature, maximum potential intensity, and ENSO emerge having differen roles depending on the basin. Although the framework slightly underestimates extreme years in some basins and performs modestly where data are sparse, it produces compact, region-specific predictor sets that transfer well to projection contexts.

A complementary causal analysis examines the environmental factors that form the Emanuel and Nolan Genesis Potential Index. Three causal inference methods for time series are applied at the pixel and basin scales to infer directed links from environmental conditions to genesis at monthly resolution. Validation with simple neural networks confirms which variables retain predictive value when used alone or in small combinations. A coherent picture emerges: absolute vorticity is the primary driver of genesis variability, with mid-tropospheric humidity and vertical wind shear as secondary contributors; maximum potential intensity adds limited incremental information in this setting. Models trained on data aggregated at the basin level are more stable than models trained for individual grid points, underscoring the benefits of combining information and representing basin scale dynamics for rare events.

Taken together, these contributions show how machine learning can add concrete value to cyclone risk analysis when outputs are physically credible, statistically robust, and explainable. They support adaptation needs by providing richer hazard datasets and clearer links from environment to annual event numbers, and they inform decision processes by delivering transparent diagnostics with quantified uncertainty and basin-aware interpretation suitable for climate services and planning.