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Research Article

Keywords:

Posted Date: September 1st, 2026

DOI: https://doi.org/10.21203/rs.3.rs-10728416/v1

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Additional Declarations: No competing interests reported.

A Hybrid AI–Ontology Framework for Tropical Cyclone Forecasting, Risk Assessment, and Intelligent Disaster Decision Support

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Abstract

Tropical cyclones pose substantial risks to coastal populations and critical infrastructure, yet conventional forecasting systems primarily emphasize cyclone movement and intensity rather than translating these predictions into location-specific and interpretable risk information. This study addresses this gap through a hybrid artificial intelligence and ontology-based framework designed for context-aware cyclone risk assessment and decision support. The proposed framework combines two data-driven prediction modules with semantic reasoning. A Long Short-Term Memory (LSTM) model processes sequential atmospheric and oceanic variables, including cyclone position, translational velocity, wind speed, central pressure, rainfall, storm-surge characteristics, and sea surface temperature, to generate cyclone trajectory forecasts. An Artificial Neural Network (ANN) is employed to estimate the spatial extent of the cyclone's potential impact. The outputs of these models are subsequently integrated with contextual information describing geographical conditions, population distribution, and infrastructure vulnerability within an ontology-based reasoning environment. Implemented using the Web Ontology Language (OWL) and the Pellet reasoner, the semantic layer applies domain rules to jointly characterize wind, flooding, and storm-surge hazards. The framework consequently derives a normalized severity measure, assigns risk categories, and produces interpretable response recommendations. The framework was evaluated using three Bay of Bengal cyclones—Amphan (2020), Yaas (2021), and Remal (2024). The case studies demonstrate the capability of the integrated system to transform AI-generated cyclone predictions into structured semantic risk information and actionable decision-support outputs. The findings indicate that combining predictive AI with knowledge-based reasoning provides a promising approach for developing transparent and context-aware cyclone risk assessment systems, particularly where decision makers require not only forecasts but also interpretable assessments of potential impacts and appropriate responses.

1 Introduction

TCs are natural disasters that pose significant threats to human life, infrastructure, ecosystems, and economic development in coastal regions around the world [1, 2, 3]. India is highly vulnerable to cyclones due to its long coastline of more than 7,500 km and its position next to the Bay of Bengal and the Arabian Sea, which are two major basins where tropical cyclones form. [4, 5]. Among these, the Bay of Bengal is responsible for the majority of severe cyclonic storms affecting the eastern coast of India due to its favorable oceanic and atmospheric conditions [6, 7]. States such as West Bengal, Odisha, Andhra Pradesh, and Tamil Nadu frequently experience cyclones that result in torrential rainfall, storm surges, and coastal flooding.

The severity of cyclone impacts extends beyond meteorological intensity alone. Although parameters such as maximum sustained wind speed, central pressure, rainfall intensity, and storm surge height are primary indicators of cyclone strength, the actual consequences depend on a combination of dynamic environmental conditions and local socio-economic characteristics [8, 9, 5]. Factors such as cyclone trajectory, distance from the cyclone eye, coastal geography, infrastructure resilience, and population density collec-

tively determine the magnitude of damage and the effectiveness of evacuation strategies [10, 11]. Consequently, disaster management authorities require not only accurate cyclone forecasts but also comprehensive risk assessments that integrate multiple heterogeneous factors to identify vulnerable regions and support timely decision-making.

Cyclone forecasting has improved significantly through advances in numerical weather prediction, satellite remote sensing, and atmospheric simulation models [7, 12, 13]. Complementary approaches based on GIS and vulnerability mapping [11, 14] enable spatial risk analysis through hazard zonation and exposure assessment [10]. However, these systems primarily produce meteorological forecasts or static hazard maps that require expert interpretation and offer limited support for real-time contextual risk assessment or automated decision-making.

Recent AI advances, particularly Long Short-Term Memory (LSTM) networks [15] and deep learning-based sequence models [16, 17, 18], have substantially improved cyclone trajectory and intensity prediction [19]. Nevertheless, most AI-based systems function as black-box algorithms that lack semantic interpretation and explainable decision support [17, 20]. Decision-makers require contextual information such as severity levels, flood risk, infrastructure vulnerability, and recommended response actions rather than raw numerical predictions alone [8], highlighting a persistent gap between data-driven forecasting and knowledge-driven disaster management.

To address this gap, this research proposes a hybrid AI–Ontology framework that integrates predictive machine learning with semantic knowledge representation [21, 22]. The framework consists of three microservice-based modules integrated through RESTful APIs [23]: (i) an LSTM model for multi-step cyclone trajectory prediction, (ii) an ANN model for estimating cyclone impact radius, and (iii) an ontology-based reasoning engine developed using OWL [22, 24] and the Pellet reasoner [25] that infers multi-dimensional risk assessments, severity scores, risk-zone classifications, and actionable response recommendations [26].

The framework was evaluated using three historical Bay of Bengal cyclones: Amphan (2020), Yaas (2021), and Remal (2024). Results demonstrate that the framework successfully transforms AI-generated predictions into interpretable disaster intelligence, enabling automated severity assessment and explainable recommendations for cyclone-prone coastal regions.

2 Literature Survey

With the rapid growth of computational capabilities and the availability of large-scale meteorological datasets, AI-driven models such as Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM) [15], Convolutional Neural Networks (CNN), and hybrid deep learning frameworks have gained considerable attention in cyclone trajectory and intensity prediction. These approaches have demonstrated improved performance in capturing spatiotemporal dependencies and complex environmental interactions.

Recent studies have shown that satellite image-based feature extraction techniques combined with machine learning classifiers can significantly improve TC intensity estimation. Texture descriptors, geometric features, feature fusion, Local Binary Patterns (LBP), and ensemble learning have been successfully employed to estimate cyclone intensity from geostationary satellite imagery with improved accuracy over conventional approaches [27, 28, 29, 30, 31, 32]. Furthermore, machine learning models trained using IMD best-track parameters have demonstrated the feasibility of data-driven cyclone intensity forecasting independent of traditional image-based methods [33, 34, 35].

In parallel, GIS-based systems have been extensively utilized for hazard zonation, infrastructure vulnerability analysis, and evacuation route planning [14]. Table 1 presents a summary of representative global research on TC forecasting and risk assessment.

Despite these advancements, existing studies generally focus on isolated problems such as cyclone intensity estimation, trajectory prediction, flood mapping, infrastructure vulnerability analysis, or evacuation planning independently [16, 11, 14]. Although previous studies have demonstrated promising results in TC intensity estimation using image processing, feature engineering, and machine learning techniques [27, 28, 29, 30, 31, 32], these approaches primarily estimate cyclone intensity and do not incorporate semantic reasoning, contextual infrastructure information, explainable decision support, or automated disaster response generation.

Similarly, machine learning models developed using historical best-track parameters provide accurate cyclone forecasting but lack integration with infrastructure vulnerability assessment and knowledge-based reasoning [33, 34]. Consequently, very limited research has attempted to integrate AI-based cyclone forecasting with ontology-driven semantic reasoning for comprehensive cyclone risk assessment and intelligent disaster management.

Table 1: Representative Global Research on TC Forecasting and Risk Assessment

Author	Methodology	Major Contribution	Limitation
Emanuel [1]	Power Dissipation Index	Established relationship between sea surface temperature and cyclone intensity.	Does not provide infrastructure-level risk assessment.
Peduzzi et al. [11]	GIS + Exposure Modelling	Global cyclone vulnerability mapping.	Static hazard maps without AI prediction.
Hallegatte et al. [10]	Economic damage modelling	Estimated financial risk for coastal cities.	No real-time forecasting capability.
Alemany et al. [16]	RNN	Improved cyclone trajectory prediction.	No semantic reasoning or infrastructure assessment.
Giffard-Roisin et al. [17]	CNN + Satellite imagery	Improved trajectory forecasting accuracy.	Black-box model with limited interpretability.
Chen et al. [36]	Transformer-based Deep Learning	Infrastructure damage assessment.	Applicable only after cyclone landfall.

The proposed framework addresses this research gap by integrating multivariate deep learning-based cyclone trajectory prediction, cyclone impact radius estimation, ontology-driven semantic reasoning, and infrastructure vulnerability analysis into a unified explainable framework. The resulting system provides automated hazard inference, evacuation prioritization, infrastructure risk assessment, and decision support for real-time cyclone disaster management.

Kar et al. developed machine learning frameworks using handcrafted texture features (e.g., Local Binary Pattern, multi-block LBP, and feature fusion) with Random Forest classifiers for tropical cyclone intensity estimation from geostationary satellite imagery [32][31][30]. Their studies demonstrated improved accuracy in predicting cyclone intensity through advanced feature extraction techniques. However, these works were limited to intensity estimation and did not address forecasting cyclone trajectory, infrastructure vulnerability assessment, GIS integration, ontology-based reasoning, explainable decision support, or disaster management applications. Table 2 provides a feature-wise comparison between existing approaches and the proposed framework.

3 Research Gap and Motivation

Existing research on cyclone forecasting and disaster management has made substantial progress in areas such as meteorological prediction, GIS-based vulnerability mapping, storm surge analysis, and AI-driven trajectory forecasting. Global studies have primarily focused on climate impact assessment, economic loss estimation, and large-scale exposure analysis [1, 37, 10], while Indian research has concentrated on cyclone monitoring, operational forecasting, and coastal vulnerability assessment [7, 14, 6]. In recent years, Artificial Intelligence and Computer Vision techniques have further improved cyclone trajectory prediction, satellite image interpretation, and post-disaster damage assessment through deep learning frameworks such as RNNs, CNNs, GANs, and transformer-based architectures [16, 36, 38].

Despite these advancements, several critical limitations remain unresolved. Most existing systems operate in isolation and focus on a single aspect of disaster management, such as trajectory prediction, flood mapping, or infrastructure damage assessment. Very few studies integrate predictive analytics with contextual disaster reasoning and decision-support mechanisms [20]. Additionally, traditional GIS and statistical approaches are predominantly static and lack the capability to process dynamic meteorological inputs in real time [11, 14].

Another major limitation is the absence of semantic interpretation and explainable reasoning within AI-based cyclone management systems. Most deep learning models function as black-box systems [17] and generate predictions without translating them into actionable recommendations such as evacuation prioritization, shelter advisories, or infrastructure risk assessment. Existing frameworks also provide limited integration of heterogeneous parameters including wind speed, storm surge, rainfall intensity, population exposure, infrastructure vulnerability, and geographical constraints within a unified architecture.

Furthermore, current disaster management systems rarely combine real-time cyclone trajectory prediction with ontology-based semantic reasoning for automated risk evaluation. The lack of integrated frameworks capable of generating severity scores,

Table 2: Comparison Between Existing Approaches and Proposed Framework

Feature	Traditional	AI	GIS	Ontology	Existing Hybrid	Proposed
Cyclone Trajectory Prediction	×	✓	×	×	✓	✓
Cyclone Intensity Prediction	✓	✓	×	×	✓	✓
Impact Radius Estimation	×	×	×	×	×	✓
Infrastructure Vulnerability Mapping	×	×	✓	×	Partial	✓
Ontology-based Reasoning	×	×	×	✓	×	✓
Explainable Risk Assessment	×	×	Partial	✓	Partial	✓
Real-time Decision Support	×	Partial	Partial	×	Partial	✓

composite risk metrics, and contextual recommendations significantly reduces operational usability during emergency situations.

To address these limitations, the proposed research introduces a hybrid AI-driven cyclone risk assessment framework that integrates multivariate time-series forecasting with ontology-based semantic inference. The AI Model predicts short-term cyclone trajectories and temporal severity patterns using meteorological and geospatial parameters, while the ontology layer performs contextual risk analysis by incorporating environmental, infrastructural, and population-related factors. Unlike existing approaches, the proposed system generates interpretable outputs including severity scores, wind risk, flood risk, storm surge risk, conceptual risk maps, and actionable recommendations such as evacuation directives and shelter movement advisories.

The proposed framework therefore bridges the gap between predictive analytics and intelligent disaster response by combining real-time forecasting, explainable semantic reasoning, and multi-risk assessment within a scalable and unified decision-support architecture.

4 Study Area

West Bengal, located off Bay of Bengal has seen an increasingly high incidence of severe cyclones in the recent past [6, 7] [39]. The open coastal area comprising mainly the five densely populated community development blocks of Ramnagar-I, Ramnagar–II, Contai-I, Deshapran and Khejuri-II of Purba Medinipur district in West Bengal India has received little attention and has been considered as the study area. This area is drained by Champa River in the west and Rasulpur River in the east. This area has important economic activities like the fishing harbours of Shankarpur, Jyamrashyampur, Dadanpatrabar, Tajpur, Junput and the beach tourism of Digha-Mandarmani.

4.1 Data Collection and Source Description

The proposed framework utilizes both historical and real-time meteorological datasets for cyclone trajectory prediction and ontology-based risk assessment. The primary historical dataset consists of TC track records collected from IMD Best Track archives and operational cyclone datasets [7, 40] containing Bay of Bengal (BOB) cyclone events from 1982 onwards. The dataset includes sequential meteorological observations such as cyclone latitude, longitude, central pressure, wind speed, pressure drop, cyclone intensity grade, and Dvorak Current Intensity (CI) number based on cyclone intensity estimation methodology [41]. These parameters are recorded at regular temporal intervals and are used for training the AI-based trajectory prediction model.

To ensure domain relevance, only Bay of Bengal cyclone events are selected during preprocessing. Non-numeric entries, incomplete records, and inconsistent temporal observations are removed to maintain data quality. Additional preprocessing steps include temporal interpolation, normalization, and sequence generation for multivariate time-series forecasting.

In addition to historical datasets, the framework is designed to support real-time and semi-real-time data ingestion through Application Programming Interfaces (APIs), meteorological bulletins [42], and manually provided scenario data. Supplementary parameters such as storm surge height, rainfall intensity, sea surface temperature, cyclone direction, and distance from the cyclone eye are incorporated to enhance contextual risk analysis. Official reports and bulletins issued by the India Meteorological Department (IMD) are also considered as auxiliary data sources for obtaining updated cyclone information and validating predicted outcomes.

The collected data serve as the input layer for the AI Model, whose outputs are subsequently integrated into the ontology-based semantic reasoning framework for composite risk evaluation, severity classi-

fication, and disaster response recommendation generation. Figure 1 presents the administrative map of the East Medinipur district.

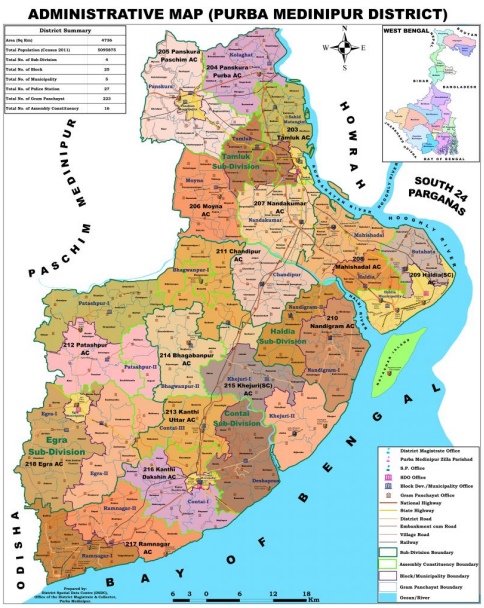


Figure 1: Administrative Map of East Medinipur District [43]

5 Methodology

5.1 Data Sources and Study Area

The framework utilizes cyclone track records from the IBTrACS v04r01 dataset [40] and IMD Best Track archives [7], as described in Section 4.1. The preprocessed multivariate time-series sequences of cyclone position, intensity, and meteorological attributes serve as input to the LSTM-based trajectory prediction model. Supplementary parameters including storm surge height, rainfall intensity, sea surface temperature, and distance from the cyclone eye are incorporated through APIs and official meteorological reports [42] for contextual risk analysis.

These AI-predicted outcomes are then input to an ontology-based semantic model generated in OWL [22] and Owlready2 [24]. Composite risk measures, severity estimates, risk zone categorization, and corresponding disaster response actions can be calculated from the ontology via rule-based inference (using the Pellet reasoner [25]) [20, 26].

5.2 System Workflow

The suggested Integrated Cyclone Decision Support framework adopts a modular approach that integrate AI and semantic reasoning with REST-based services Orchestration in order to facilitate time-effective and understandable cyclones risks evaluation. The suggested process is built around 8 progressive levels starting from data sourcing to the decision support information generation and is Orchestrated via the Gateway API which provides coordination for the various communication channels among the deep learning algorithms and the ontology based reasoning. This approach allows each component to work independently but integrated in a holistic process of combining prediction and reasoning for disaster response and management. All steps are illustrated in Figure 2.

5.2.1 Input Data Acquisition

First, the weather and geographical data that would be useful for the cyclone and its prediction/risk assessment is first compiled. The dynamic data includes variables like cyclones latitude, longitude, wind-speed, direction of movement, time, and month extracted from the IBTrACS database [40]. For semantic analysis, static variables like population, building structure susceptibility, location, and proximity to cyclone center are also collected.

5.2.2 Gateway API Processing

This represents the gateway that the framework uses as an central orchestrator, accepting inputs from end-user, translating them to standardised REST requests and calling sequentially on the LSTM trajectory prediction model, ANN impact radius estimation model, ontology reasoning engine before finally collecting outputs of all called systems into one single response [23].

5.2.3 Cyclone Trajectory Prediction

The confirmed weather parameters are fed into the LSTM-based trajectory prediction model [15]. Based on the learning of the historical observation sequence from cyclones, the model generates a multi-step prediction of the cyclone track for 24 hours which provides the spatial information necessary to perform the next impact assessment.

5.2.4 Cyclone Impact Radius Estimation

The predicted cyclone trajectory and wind speed are supplied to the ANN model [19] to estimate the cy-

clone's impact radius. This prediction defines the geographical extent likely to be affected by the cyclone and serves as a key input for identifying vulnerable regions and exposed populations.

5.2.5 Integration of AI Outputs

The Gateway API combines the predicted trajectory, estimated impact radius, and static environmental information into a unified data structure. This integrated dataset ensures that all meteorological, geographical, and demographic information is available before semantic reasoning is performed.

5.2.6 Ontology-Based Reasoning

The integrated information is processed by the OWL ontology [22] using the Pellet reasoner [25]. The ontology evaluates predefined semantic relationships to infer cyclone severity, infrastructure vulnerability, population exposure, and appropriate disaster response actions based on both AI predictions and domain knowledge.

5.2.7 Semantic Risk Assessment

The ontology-generated inferences are transformed into meaningful risk indicators [20], including severity score, wind risk, flood risk, storm surge risk, and overall risk classification. These explainable outputs assist disaster management authorities in understanding the potential impact of the cyclone.

5.2.8 Decision Support Generation

In the final stage, the outputs of the AI models and ontology are consolidated to generate actionable decision-support information. The system provides the predicted cyclone trajectory, impact radius, risk assessment, and population at risk to facilitate timely warning dissemination [5].

5.3 Methods of Analysis

The proposed framework adopts a hybrid analytical approach that combines Artificial Intelligence (AI) and ontology-based semantic reasoning for cyclone risk assessment. Unlike conventional cyclone management systems that rely solely on meteorological forecasting or static vulnerability analysis, the proposed methodology integrates predictive analytics with knowledge-driven inference to provide both forecasting capability and explainable decision support.

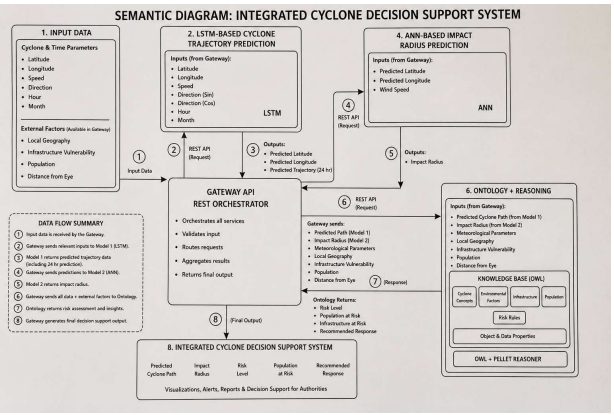


Figure 2: System workflow of the hybrid AI–Ontology framework.

The analytical workflow consists of three major stages: cyclone trajectory prediction, cyclone impact-area estimation, and ontology-based risk assessment.

5.3.1 Cyclone Trajectory Prediction

The first stage focuses on forecasting future cyclone movement using a Long Short-Term Memory (LSTM) network [15]. Cyclone behavior is modeled as a multivariate time-series forecasting problem [15, 44], where historical observations are used to predict future cyclone positions. The model is implemented using the TensorFlow deep learning framework [45].

Let the historical input sequence be represented as:

$$X = \{x_{t-n}, x_{t-n+1}, \ldots, x_t\}$$

where each observation contains meteorological and spatial attributes including latitude, longitude, translational speed, directional information, and temporal features.

The objective of the model is to learn a nonlinear mapping function [19]:

$$f_\theta : X \to Y$$

where:

$$\begin{aligned} Y = \{&(\hat{Lat}_{t+1}, \hat{Lon}_{t+1}), \\ &(\hat{Lat}_{t+2}, \hat{Lon}_{t+2}), \\ &\ldots, (\hat{Lat}_{t+k}, \hat{Lon}_{t+k})\} \end{aligned}$$

and θ denotes the trainable model parameters.

Long Short-Term Memory networks are selected because they effectively capture temporal dependencies [15] and nonlinear relationships within sequential meteorological observations. Unlike traditional

regression approaches, LSTMs maintain memory of previous cyclone states and therefore provide improved trajectory forecasting capability [18, 16].

The model generates future latitude and longitude coordinates that represent the predicted cyclone path over subsequent time intervals.

5.3.2 Cyclone Impact Radius Prediction

Trajectory prediction alone cannot effectively capture the spatial scale of cyclone influence. Cyclone impacts a region rather than a point; thus, the area influenced by cyclone is required for holistic risk analysis. In the second stage, the feed-forward Artificial Neural Network (ANN) [19] is used for cyclone impact radius estimation.

Let the feature vector be represented as:

$$Z = \{Lat, Lon, WS\}$$

where Lat = Cyclone Latitude, Lon = Cyclone Longitude, WS = Wind Speed.

The network learns a nonlinear function [19]:

$$g_\phi : Z \to R$$

where R = Predicted Impact Radius, and ϕ represents the trainable parameters of the impact prediction model.

The target variable is derived from quadrant-based wind field observations surrounding the cyclone center and represents the average radial extent of cyclone influence. The predicted radius provides an estimate of the geographical region likely to experience cyclone-related impacts.

Combining trajectory prediction with impact-radius estimation enables the framework to assess both cyclone movement and spatial coverage simultaneously.

5.3.3 Ontology-Based Risk Assessment

The outputs generated by the AI models are subsequently integrated into an ontology-based semantic reasoning framework developed using the Web Ontology Language (OWL) [22] and Owlready2 [24]. Ontology reasoning is performed using the Pellet reasoner [25].

The ontology formally represents relationships [21] among:

- Environmental Factors
- Geographical Conditions
- Infrastructure Vulnerability
- Population Exposure
- Cyclone Characteristics

Meteorological inputs including wind speed, rainfall intensity, storm surge height, distance from cyclone eye, sea surface temperature, and central pressure are mapped to ontology concepts and properties.

A rule-based inference engine [20, 24] evaluates multiple risk dimensions:

- Wind Risk (R_w)
- Flood Risk (R_f)
- Storm Surge Risk (R_s)
- Infrastructure Risk (R_i)

These inferred risk components are aggregated to generate an overall cyclone severity score [20]:

$$S = w_1 R_w + w_2 R_f + w_3 R_s + w_4 R_i$$

where S = Severity Score, w_i = Risk Weights.

The severity score is normalized and classified into categorical levels such as:

$$Severity \in \{\text{Low}, \text{Moderate}, \text{Severe}\}$$

Based on inferred risk levels and predefined semantic rules, the ontology generates explainable outputs including wind risk classification, flood risk classification, storm surge risk classification, infrastructure risk assessment, severity score, risk zone classification, and recommended response actions.

The ontology therefore transforms numerical AI predictions into human-interpretable disaster-management knowledge.

5.3.4 Integrated Decision-Support Framework

The proposed methodology combines the strengths of data-driven prediction and semantic reasoning. While the AI models offer the predictive capabilities for cyclone motion and scale of impact, the ontology layer allows for the interpretation of context and risk inference.

This architecture allows the framework to transcend the capabilities of typical cyclone forecasting systems by yielding actionable and interpretable results, beyond simple meteorological predictions.

5.4 Notation and Variable Definitions

The symbols and variables used throughout the proposed framework are summarized below.

5.4.1 AI Model 1: Cyclone Trajectory Prediction

X = Input feature sequence used for trajectory prediction
x_t = Feature vector at time t
Y = Predicted future trajectory sequence
$\hat{Lat}_{t+i}$ = Predicted latitude at future timestep $t+i$
$\hat{Lon}_{t+i}$ = Predicted longitude at future timestep $t+i$
f_θ = LSTM-based trajectory prediction function
θ = Trainable parameters of the LSTM model

Input Features:
Lat_t = Cyclone latitude at time t
Lon_t = Cyclone longitude at time t
S_t = Cyclone translational speed
D_{sin} = Sine-encoded cyclone direction
D_{cos} = Cosine-encoded cyclone direction
H_t = Observation hour
M_t = Observation month

Output:

$$Y = \{(\hat{Lat}_{t+1}, \hat{Lon}_{t+1}), (\hat{Lat}_{t+2}, \hat{Lon}_{t+2}), \ldots, (\hat{Lat}_{t+k}, \hat{Lon}_{t+k})\}$$

where k denotes the forecasting horizon.

5.4.2 AI Model 2: Cyclone Impact Radius Prediction

Z = Input feature vector for impact-radius prediction
R = Predicted cyclone impact radius
g_ϕ = Impact-radius prediction function
ϕ = Trainable parameters of the ANN model

Input Variables:
Lat = Cyclone latitude
Lon = Cyclone longitude
WS = Cyclone wind speed

Output Variable:
R = Predicted impact radius (km)

The impact radius represents the estimated geographical extent likely to be affected by cyclone-induced hazards.

5.4.3 Ontology-Based Risk Assessment

The ontology receives meteorological, geographical, infrastructural, and socio-economic parameters and performs semantic reasoning to infer cyclone risk.

Environmental Variables:
WS = Wind Speed
RF = Rainfall Intensity
SS = Storm Surge Height
DE = Distance from Cyclone Eye
SST = Sea Surface Temperature
CP = Central Pressure

Socio-Economic Variables:
P = Population Exposure
IV = Infrastructure Vulnerability
LG = Local Geography

5.4.4 Risk Components

The ontology infers multiple risk dimensions:
R_w = Wind Risk
R_f = Flood Risk
R_s = Storm Surge Risk
R_i = Infrastructure Risk

Each risk component is classified into:

$$\{\text{Low},\ \text{Medium},\ \text{High}\}$$

based on ontology rules and inferred relationships.

5.4.5 Severity Assessment

The overall severity score is represented by:
S = Cyclone Severity Score

The severity score is computed as [20]:

$$S = w_1 R_w + w_2 R_f + w_3 R_s + w_4 R_i \tag{1}$$

where w_1, w_2, w_3, w_4 represent weighting coefficients, R_w = Wind Risk, R_f = Flood Risk, R_s = Storm Surge Risk, R_i = Infrastructure Risk.

Severity Classification:

$$Severity \in \{\text{Low},\ \text{Moderate},\ \text{Severe}\}$$

5.4.6 Decision-Support Variables

Z_r = Risk Zone
A = Recommended Action
P_r = Population at Risk

Risk Zone Classification:

$$Z_r \in \{\text{Green},\ \text{Yellow},\ \text{Red}\}$$

Response Advisory:

$$A \in \{\text{Low Alert},\ \text{Moderate Alert},\ \text{High Alert}\}$$

Population at Risk (P_r) represents the estimated number of people potentially affected under the inferred severity level.

5.4.7 Framework Functions

The overall framework can be expressed as:

$$\begin{aligned} Trajectory &= f_\theta(X) \\ ImpactRadius &= g_\phi(Z) \\ RiskAssessment &= O(Trajectory, \\ &\qquad ImpactRadius, \\ &\qquad EnvironmentalFactors, \\ &\qquad SocioEconomicFactors) \end{aligned}$$

where O denotes the ontology-based reasoning function that generates risk classifications, severity scores, and recommended response actions.

6 Result and Discussion

The proposed AI–Ontology framework was evaluated using three historical Bay of Bengal cyclone events. The following subsections present the results obtained from each component of the framework [40].

6.1 Cyclone Trajectory Prediction

The proposed LSTM-based cyclone trajectory prediction model [15] was trained using historical cyclone records from the IBTrACS (International Best Track Archive for Climate Stewardship) dataset [40] for the North Indian Ocean basin. The model utilized sequential observations comprising cyclone latitude, longitude, translational speed, movement direction (encoded using sine and cosine transformations), month, and hour to learn the spatiotemporal evolution of cyclone tracks. A sequence length of 10 consecutive observations was used to predict subsequent cyclone positions. Cyclone-wise data partitioning was adopted to eliminate data leakage, resulting in 32,384 training samples and 7,791 testing samples generated from 1,575 unique cyclone tracks [19]. The model was evaluated using pooled predictions over the 3–24 h forecast horizon, achieving a latitude RMSE of 0.4834°, longitude RMSE of 0.7280°, latitude MAE of 0.3411°, longitude MAE of 0.4951°, and an average geographical position error of 72.49 km. The corresponding R^2 values were 0.9848 for latitude and 0.7424 for longitude, indicating good predictive performance, particularly for short-term cyclone trajectory forecasting. Figure 3 presents the training and validation loss curves, demonstrating stable convergence during model training.

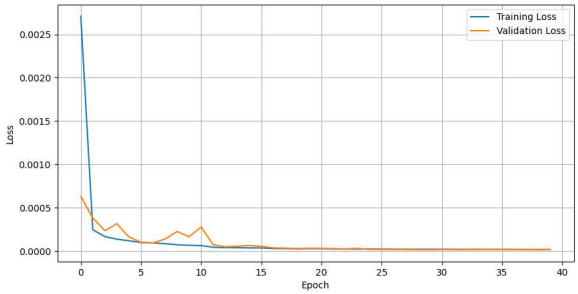


Figure 3: Training and validation loss curves of the LSTM trajectory prediction model.

Representative trajectory predictions are presented in Table 3, where the predicted cyclone positions closely follow the observed tracks with moderate spatial deviations. The evaluation indicates that the proposed LSTM effectively captures the temporal dynamics of cyclone movement and provides reliable short-term trajectory forecasts for the North Indian Ocean. Compared with earlier ANN-based approaches, the proposed model achieves lower trajectory errors, while exhibiting performance comparable to recent deep learning-based forecasting methods over a 24-hour prediction horizon. These results demonstrate that the predicted trajectories provide sufficiently accurate spatial information for the subsequent ANN-based impact radius estimation and ontology-driven cyclone risk assessment modules within the proposed hybrid decision-support framework.

Table 3: Representative Trajectory Prediction Samples from the Testing Dataset

SID	Act. Lat	Act. Lon	Pred. Lat	Pred. Lon	Err. (km)
1878301N	16.30	83.30	16.22	83.32	8.95
1878301N	16.50	83.20	16.46	83.18	5.35
1878301N	16.70	83.10	16.67	83.03	8.29
1878301N	16.90	82.90	16.88	82.92	2.85
1878301N	17.10	82.80	17.10	82.81	0.76

6.2 Cyclone Impact Radius Estimation

The predicted cyclone trajectories generated by the LSTM model were subsequently provided to the

ANN-based impact radius prediction model [19]. The model was evaluated using three historical Bay of Bengal cyclones—Amphan (2020), Yaas (2021), and Remal (2024)—comprising a total of 69 observations [40]. Overall, the model achieved a pooled R^2 of 0.9365, RMSE of 16.21 km, and MAE of 12.24 km, indicating a high degree of agreement between the predicted and observed impact radii. In terms of individual case studies, the model performed well in the Cyclone Amphan case, yielding R2=0. 9698, RMSE=9. 71 km and MAE=7. 64 km over 38 observations.

Similarly, the model predicted impact radius of Cyclone Yaas and Cyclone Remal with R2 of 0. 8883 and 0. 8722 respectively and the model generated RMSE 21. 28 km and 22.58 km, suggesting the robust predicting performance for cyclones with varying intensities. Figure 4 shows the actual versus the predicted impact radius over the period for Cyclone Amphan. It appears that the prediction closely mimics the real pattern during the lifetime of the cyclone including expanding impact radius up to peak intensity and the contraction when cyclone is weakening. Minor variation can be found around the impact radius of the peak period, yet the predicted impact radius can be considered in good agreement with observed impact radius [19].

Then, the impact radius is used to inform the ontology based reasoner for the assessment of the exposed populations, the infrastructure damage as well as to provide an understandable output of recommendations for disaster response [26].

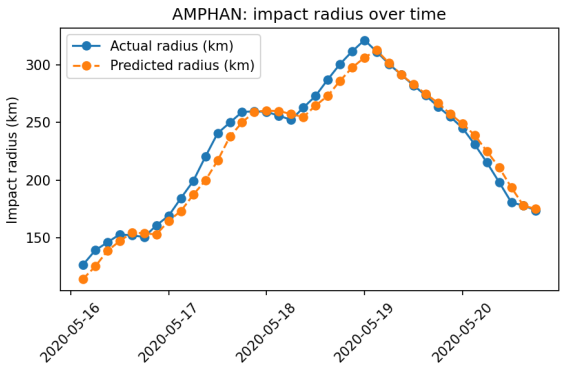


Figure 4: Variation of actual and predicted impact radius of Cyclone Amphan(2020) with respect to time.

6.3 Ontology-Based Risk Assessment

The ontology based reasoning framework managed to turn the results from the AI prediction models into meaningful risk assessments. Regarding Cyclone Amphan (2020), the ontology produces a severity score of 0.90 and classifies the event as Severe along with a Red Risk Zone. This outcome corresponds to the actual historical event for Amphan where it was classified as an Extremely Severe Cyclonic Storm (ESCS) (according to the IMD definition) with wind speed up to 185 km/h, resulting in a high-impact emergency response.

Similarly, Cyclone Yaas (2021) had a severity score of 0.70, resulting in a Severe classification and a Red Risk Zone. Despite a lower severity score than Amphan, the ontology successfully identified it as a high-impact cyclone. The historical cyclone was classified as a Very Severe Cyclonic Storm (VSCS) with major flooding along the coasts.

Cyclone Remal (2024) received a severity score of 0.50 from the ontology, resulting in a Moderate classification and a Yellow Risk Zone. This signifies a comparatively less intense cyclone than Amphan and Yaas, although still warranting caution. The ontology thus displayed a good degree of consistency with actual cyclone events and correctly distinguished severe from moderate events.

The generated semantic outcomes severity level, wind risk, flood risk, infrastructure risk, risk zone and recommended action provides interpretability to the system and effectively supports the decision making process over pure numerical prediction values obtained from AI models. The ontology thus effectively fills the gap between AI prediction outcomes and real-time disaster management decisions. Figure 5 illustrates the overall architecture of the ontology-based reasoning framework including meteorology input, AI prediction output and ontology based semantic reasoning for producing output of risk assessment and recommendations for cyclone event. A comparison between historical information of cyclones Amphan (2020), Yaas (2021), and Remal (2024) and their respective ontology-based risk assessments has been presented in Table 4.

The ontology generated severity level, risk zone, and recommended action correlates well with the historical action that were taken in the cyclones mentioned [40, 5].

Table 4 presents a consolidated comparison of the historical cyclone characteristics and the corresponding ontology-based risk assessment outputs for Amphan (2020), Yaas (2021), and Remal (2024). The ontology-generated severity levels, risk zones, and recommended actions demonstrate strong agreement with the actual historical responses observed during these cyclone events [40, 5]. This validates the capability of the proposed ontology-driven reasoning engine to produce reliable and contextually appro-

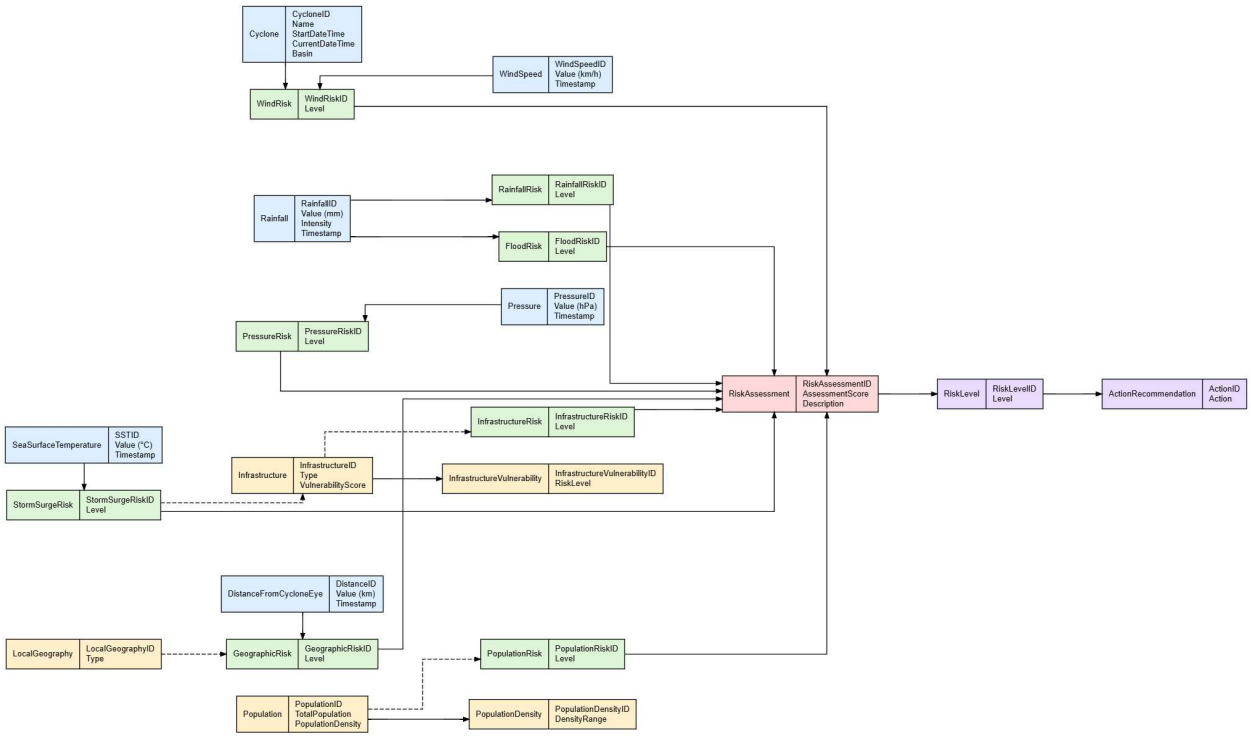


Figure 5: Overview of entire Ontology Architecture.

priate disaster management recommendations across cyclone events of varying intensity.

6.4 End-to-End Execution of the Proposed Framework: Cyclone Amphan (2020)

To validate the complete pipeline, the framework was executed end-to-end using Cyclone Amphan (2020) as a case study [40]. Table 5 summarizes the eight sequential stages of the workflow, detailing the input consumed, output produced, and the subsequent processing step at each stage. The execution concluded with a severity score of 0.80 (Severe), a Red risk zone, and an estimated 640,000 people at risk [5].

6.5 Analytical Results - Case Study

Table 6 provides a comparative overview of the predicted and risk-assessed key outcomes of the framework, for the 3 cases considered (cyclones Amphan-2020, Yaas-2021, Remal-2024). More detailed case-wise discussion follows.

6.5.1 Case Study 1: Cyclone Amphan (2020)

Of the three simulated cyclone events analysed, Cyclone Amphan [40] presented the worst impact level with a severity score of 0.80 and an estimated impact radius of 214.56 km, generated by the LSTM over a 24-hour forecast horizon. The event was classified by the ontology as Severe with a Red risk zone, with approximately 640,000 individuals estimated to be at risk.

This serves as proof of concept of the models capacity to accurately forecast a significant cyclone impact and issue rapid decision-support information.

6.5.2 Case Study 2: Cyclone Yaas (2021)

When Cyclone Yaas was evaluated, it resulted in a predicted impact radius of 197. 04 km and severity score of 0. 55; suggesting it as a Moderate cyclone event. The ontology had predicted it as a Yellow risk zone with High risk for wind, flood, and infrastructure.

The estimated population at risk was 200,000, indicating a high-impact event requiring priority response attention relative to Remal.

6.5.3 Case Study 3: Cyclone Remal (2024)

Cyclone Remal [40]: For the proposed framework, the computed impact radius for Cyclone Remal was 189. 60 km and severity score 0. 45 leading to a final assessment of Low severity. The ontology output the

Table 4: Comparison of Historical Cyclone Characteristics and Ontology-Based Risk Assessment

Cyclone	Historical IMD Classification	Historical Response	Ontology Severity	Ontology Risk Zone	Ontology Recommendation	Overall Agreement
Amphan (2020)	Extremely Severe Cyclonic Storm (185 km/h)	Large-scale emergency response	Severe (0.90)	Red	High Alert	High
Yaas (2021)	Very Severe Cyclonic Storm (145 km/h)	Coastal disaster preparedness	Severe (0.70)	Red	High Alert	High
Remal (2024)	Very Severe Cyclonic Storm (120 km/h)	Localized flood management	Moderate (0.50)	Yellow	Moderate Alert	Moderate

High risk of Wind but Medium flood and infrastructure risks leading to a Green risk zone.

The affected population estimate was about 42,000 and the advised precaution was stay indoors. It seems that despite Remals hazardously windy conditions, the combined semantics gave a lesser risk assessment in comparison with Amphan and Yaas.

6.6 Comparison with Existing Approaches

The present work attempts to overcome a few deficiencies in the existing systems for management of tropical cyclones. Vulnerability mapping approaches [11, 14] identify susceptible regions but lack predictive capabilities. Recent AI models have improved trajectory accuracy [16, 17] but function as black-box systems. Ontology-based systems offer explainable reasoning [21, 20] but lack forecasting integration.

To quantitatively position the proposed trajectory prediction model, Table 7 compares its performance against existing cyclone trajectory forecasting methods at a 24-hour forecast horizon.

The proposed framework achieves a mean track error of 72.49 km at 24 hours, comparable to ConvLSTM-based approaches [48]. While standalone LSTM models [47, 49] achieve lower positional errors, they are limited to trajectory forecasting and do not provide impact-radius estimation, semantic risk assessment, or decision-support capabilities. The proposed framework uniquely integrates trajectory prediction with ontology-based reasoning to generate explainable, actionable disaster intelligence.

As a result, the framework supports both forecasting and risk assessment rather than treating them as independent tasks.

7 Conclusion and Future Work

This research is highly relevant and impactful in supporting the effective disaster preparedness and risk-aware decision-making. AI-driven forecasting combined with the ontology-based semantic reasoning capability can help in augmenting the situational awareness, increasing consistency of risk assessment, decrease reliance on manual processing and providing explainable recommendations to disaster management authorities. Additionally, its flexible and modular architecture ensures future extensibility with incorporation of new data and advanced forecasting techniques. Conclusively, combining the power of predictive analysis with semantic interpretation in an integrated architectural setup presents a strong prospect for an intelligent and explainable cyclone disaster management system. The work has put forward a hybrid AIOntology framework for cyclone risk assessment and decision support comprising LSTM-based cyclone track prediction, ANN-based cyclone impact area estimation, and ontology-based semantic reasoning in a single architecture. A significant nov-

Table 5: End-to-End Workflow Execution for Cyclone Amphan (2020)

Stage	**Input**	**Output**	**Next Step**
1. Data Acquisition	IBTrACS records, geography, demographics	Validated meteorological & static parameters	Gateway API
2. Gateway API	Validated inputs via REST [23]	Preprocessed data routed to AI models	LSTM Model
3. Trajectory Prediction	Sequential observations [15]	24-h forecast: 19.16°N→13.26°N	ANN Model
4. Impact Radius	Predicted trajectory + wind speed (185 km/h) [19]	Impact radius: 214.56 km	AI Integration
5. AI Integration	Trajectory, radius, static parameters	Unified dataset for reasoning	Ontology
6. Ontology Reasoning	Unified dataset + OWL axioms [22, 25]	Severity, vulnerability, exposure inferences	Risk Assessment
7. Risk Assessment	Inferred knowledge [20]	Score: 0.80, Red zone, High wind/flood risk	Decision Support
8. Decision Support	All AI + ontology outputs	Severity: Severe, Red zone, 640K at risk	—

Table 6: Comparative Results of Three Cyclone Case Studies

Parameter	**Amphan (2020)**	**Yaas (2021)**	**Remal (2024)**
Forecast Horizon (h)	24	24	24
Wind Speed (km/h)	185	145	120
IMD Cyclone Scale	Extremely Severe Cyclonic Storm	Very Severe Cyclonic Storm	Very Severe Cyclonic Storm
Predicted Impact Radius (km)	214.56	197.04	189.60
Severity Score	0.90	0.70	0.50
Severity Label	Severe	Severe	Medium
Wind Risk	High	High	High
Flood Risk	High	High	Medium
Storm Surge Risk	High	Medium	Medium
Risk Zone	Red	Red	Yellow
Infrastructure Risk	High	High	Medium
Response Advisory	High Alert	High Alert	Moderate Alert

Table 7: Comparison of Cyclone Trajectory Prediction Performance with Existing Approaches

Reference	**Method**	**Horizon**	**Lat RMSE (°)**	**Lon RMSE (°)**	**Lat MAE (°)**	**Lon MAE (°)**	**Track Err. (km)**
Ali et al. (2007) [46]	ANN	24 h	1.01	1.16	—	—	137.50
Kumar et al. (2021) [47]	LSTM	24 h	—	—	0.24	0.37	51.70
ConvLSTM (2022) [48]	ConvLSTM	24 h	—	—	0.303	0.393	71.27
Comparative DL (2025) [49]	LSTM	24 h	0.29	0.45	0.18	0.33	—
Proposed	**LSTM+ANN+Ont.**	**24 h**	**0.4834**	**0.7280**	**0.3411**	**0.4951**	**72.49**

elty is the combined usage of predictive analytics and explainable reasoning: while the AI models offer predictive intelligence of cyclone motion and its potential spatial extent, the ontology layer translates the predictions into intelligible risk levels, classifications of severity, and decision recommendations. Based on the test on three real cyclones in the Bay of Bengal Amphan (2020), Yaas (2021) and Remal (2024), the proposed framework provides relevant disaster intelligence for emergency response planning. The framework is still at its nascent stage and has several scope for further development: the current system is mainly based on historical datasets and hard-coded rules for the ontology.

Incorporating real-time data from weather APIs, satellites, and operational forecasting models could enhance real-time risk monitoring. The ontology could be further enriched by additional environmental, infrastructure, and social factors, along with mechanisms to update the dynamic knowledge base with real-time observations. A promising avenue for future research would be the integration of higher-resolution geospatial datasets to improve the accuracy of population exposure and infrastructure vulnerability assessments. In summary, the proposed framework demonstrates that combining AI-based forecasting with ontology-based semantic reasoning provides an effective approach for developing intelligent, interpretable, and scalable cyclone management systems capable of supporting disaster preparedness and resilience in cyclone-prone regions.

Acknowledgement

The authors would like to express their sincere gratitude to the Government of West Bengal (Gov. of WB) for providing administrative maps, demographic data, and infrastructure details of the study area in Purba Medinipur district. We are also grateful to the India Meteorological Department (IMD) for the meteorological images, bulletins, and best-track datasets. Additionally, we acknowledge the International Best Track Archive for Climate Stewardship (IBTrACS) and other open-source portals for providing the cyclone trajectory and meteorological datasets used to train and validate our predictive models.

Code and Data Availability

The code and processed dataset used in this study are publicly available at the following GitHub repository:
`https://github.com/Subhash-ch/IBTrACS-v04r01-IMD-Dataset`

Funding

No funding was received for this study.

Ethics and Consent to Participate declarations

Not applicable.

Consent to Publish

Not applicable, as no human participants were involved.

Competing interests

The authors declare no competing interests

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