Spatial Modelling of Cyclone-Induced Flood Hazards for Disaster Risk Financing and Parametric Insurance in Sri Lanka

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Abstract—Cyclone-induced compound hazards present a critical challenge for disaster risk financing (DRF) in South Asia, yet spatially-explicit and probabilistically-calibrated hazard models suitable for parametric insurance applications remain largely absent in Sri Lanka. This work-in-progress paper presents an integrated research protocol for developing and evaluating spatially-informed parametric insurance models for cyclone-related hazards. The framework combines GIS-based Fuzzy Analytic Hierarchy Process (FAHP) multi-hazard mapping, coupled with HEC-RAS 1D/2D hydrological-hydraulic simulation, Monte Carlo Probabilistic Cyclone Hazard Analysis (PCHA), and spatial lag and spatial error econometric modeling. This study focuses on five cyclone-affected districts of Sri Lanka, with Kurunegala serving as the primary analytical case study, which collectively displaced more than 95,000 people during Cyclone Ditwa (Nov–Dec 2025). This study will produce Grama Niladhari (GN)-division-level flood inundation maps, probabilistic wind speed and rainfall exceedance surfaces for return-period pricing, empirical basis risk hotspot maps, and Willingness-to-Pay (WTP) estimates. Findings will directly inform parametric trigger design, actuarial premium calibration, and sovereign disaster risk financing strategies for climate-vulnerable developing countries.

Keywords—*parametric insurance; probabilistic cyclone hazard; flood inundation modelling; disaster risk financing; basis risk; Sri Lanka, South Asia*

I. Introduction

Natural disasters, particularly tropical cyclones, floods, and storm surges, are among the most destructive hazards in developing nations, disproportionately affecting low-income communities with limited financial resilience [1]. Cyclone-induced rainfall often generates cascading impacts including wind damage, riverine flooding, and agricultural loss across multiple districts, creating compound risks that single-peril insurance products fail to capture. These events are projected to intensify under future climate scenarios, increasing fiscal pressure on governments with limited contingency reserves [1].

Sri Lanka exemplifies this vulnerability. Seasonal cyclones in the Bay of Bengal frequently impact Northern, Eastern, and North-Western districts. The Nov–Dec 2025 Cyclone Ditwa displaced approximately 171,778 people, with over 56% of displacements concentrated in Kurunegala, Kandy, Badulla, Puttalam, and Trincomalee [2]. Significant agricultural losses, particularly to paddy cultivation, further intensified food-security risks. Despite these recurring impacts, post-disaster recovery in Sri Lanka remains dependent on slow-disbursing emergency budgets rather than pre-arranged Disaster Risk Financing (DRF) mechanisms.

Parametric insurance has emerged as a key DRF instrument due to its ability to provide rapid payouts triggered by predefined geophysical thresholds, eliminating delays associated with traditional loss assessments [3, 4]. This rapid liquidity is particularly critical for agricultural households with limited recovery capacity. Regional initiatives such as Southeast Asia Disaster Risk Insurance Facility (SEADRIF) and World Bank programs have identified Sri Lanka as a potential candidate for sovereign parametric insurance schemes [6, 7].

However, the effectiveness of parametric insurance depends on accurate spatial calibration of triggers. Basis risk the mismatch between index-based payouts and actual losses remains a major challenge [5]. District-level triggers based on sparse monitoring stations often lead to payout inaccuracies, undermining trust and adoption.

https://doi.org/10.54389/TYTE0063

Sri Lanka currently lacks a probabilistically calibrated, high-resolution multi-hazard modelling framework at the Grama Niladhari (GN) division level. Existing hazard assessments rely primarily on historical records rather than probabilistic modelling [8], limiting their applicability for insurance design. This gap has been previously identified as a key constraint in developing robust DRF solutions [7].

This study addresses this gap by proposing an integrated framework combining GIS–FAHP flood susceptibility mapping, HEC-RAS hydraulic modelling, Monte Carlo-based Probabilistic Cyclone Hazard Analysis (PCHA), and spatial econometric analysis across five cyclone-affected districts. The key contributions include: (i) a GN-division-scale probabilistic multi-hazard framework; (ii) spatial basis-risk quantification; and (iii) localized Willingness-to-Pay (WTP) estimates to support sustainable parametric insurance design.

II. Background and Related Work

A. Parametric Insurance and Basis Risk

Clarke [4] formalizes the welfare conditions under which index insurance is welfare-improving, demonstrating that basis risk critically determines demand and the feasibility of actuarially fair pricing. Miranda and Farrin [3] provide a comprehensive review of global index insurance applications, concluding that spatial disaggregation of triggers is the central unresolved technical challenge for programs in developing countries. Carter et al. [5] further show that poorly calibrated spatial triggers can negate insurance welfare benefits entirely, motivating fine-grained, empirically grounded basis risk quantification at sub-district scales. Barnett et al. [21] propose a conceptual framework linking basis risk directly to trigger-selection methodology for smallholder agricultural insurance systems, a framework that this study operationalizes at the GN-division scale. Hallegatte et al. [26] further demonstrate that the absence of timely DRF instruments can perpetuate poverty traps following repeated disaster events, highlighting the broader socioeconomic importance of improved parametric insurance design.

B. Flood Hazard Characterization

GIS-based FAHP integrating physiographic and climatic conditioning factors has become a standard first-pass method for flood susceptibility mapping in data-scarce developing contexts, yielding area-under-curve (AUC) validation scores above 0.85 in comparable South Asian watersheds [9, 10]. For inundation depth quantification, 1D/2D hydraulic simulation using HEC-RAS is the international benchmark, generating depth-velocity grids that directly underpin depth-damage functions and parametric trigger design [11, 12]. Sentinel-1 C-band SAR provides independent flood extent validation at 20 m resolution [22], bypassing cloud contamination that restricts optical verification during active cyclone events. Luo et al. [27] demonstrate that coupled GIS-hydraulic frameworks achieve inundation extent accuracy above 88% when validated against post-event SAR imagery in monsoonal river basins comparable to those in Kurunegala District.

C. Probabilistic Cyclone Hazard Analysis

Monte Carlo PCHA using synthetic track ensembles calibrated against International Best Track Archive for Climate Stewardship (IBTrACS) records [13] produces return-period wind and rainfall exceedance surfaces essential for actuarial pricing. Emanuel et al. [14] established the statistical-deterministic PCHA framework; subsequent applications to the Bay of Bengal [15] confirm its transferability to the Sri Lankan domain. The Holland [18] parametric wind model is the standard approach for translating track parameters to surface wind fields and has been validated for Bay of Bengal cyclones by Harper et al. [23]. Importantly, PCHA-derived excessance curves can be directly integrated into catastrophe bond term sheets and sovereign DRF program pricing, linking the scientific output to immediate policy applications [6].

D. Spatial Econometrics of Insurance Demand

Spatial lag (SAR) and spatial error (SEM) model specifications are commonly applied when Willingness-to-Pay (WTP) observations exhibit spatial dependence, a condition often assessed using Moran's I statistic, as demonstrated in prior Sri Lankan agricultural surveys [20]. Anselin [20] and LeSage and Pace [24] provide the theoretical foundations for spatial econometric analysis, while Jensen and Barrett [25] demonstrate their application to index insurance WTP modeling in sub-Saharan Africa, thereby providing a methodological template for this study. Cole et al. [28] further document that insurance literacy and peer effects generate spatially clustered demand patterns, reinforcing the need for spatially explicit demand modelling rather than district-level aggregate approaches.

III. Methodology

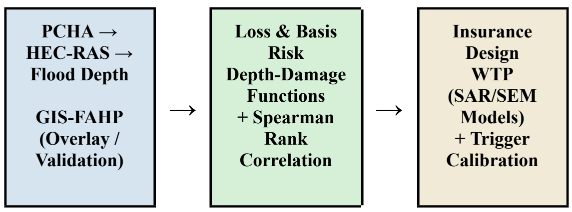

Figure 1: Integrated Research Framework: Three-Stage Pipeline for Hazard, Loss, and Insurance Modeling

A. Study Area

The study covers five districts selected based on Cyclone Ditwa displacement impacts and geographic diversity: Kurunegala (primary case study), Kandy, Badulla, Puttalam, and Trincomalee. Kurunegala encompasses the Deduru Oya and Mee Oya river basins, extensive low-lying paddy cultivation covering tens of thousands of hectares, and a diverse elevation gradient ranging from approximately 5 to 1,500 m above sea level (a.s.l.). This pronounced topographic and hydrological heterogeneity generates substantial intra-district flood-hazard variability, making the district an appropriate analytical testbed for sub-district parametric trigger design. The five districts collectively span coastal, dry-zone, intermediate-zone, and wet-zone climate regimes, providing a representative cross-section of Sri Lanka's cyclone exposure landscape and ensuring that the resulting framework is transferable beyond the primary study district.

B. Data Sources

Table I summarizes the primary geospatial and socioeconomic datasets used in the study. Precipitation is sourced from Global Precipitation Measurement (GPM) using Integrated Multi-satellite Retrievals for GPM (IMERG) Final Run v06 [16], while ERA5 global reanalysis data provide the wind climatology [17]. An ALOS PALSAR Digital Elevation Model (DEM) with 12.5-m spatial resolution supplies topographic inputs to both the FAHP susceptibility analysis and the HEC-RAS hydraulic model. Sentinel-2 multispectral imagery and Sentinel-1 SAR-derived historical flood extents are processed within the Google Earth Engine. Cyclone track parameters are drawn from the IBTrACS v04 archive spanning 1980–2024 [13]. Socioeconomic covariates for the insurance demand model are sourced from the Household Income and Expenditure Survey (HIES 2019) and the 2024 Sri Lanka Population and Housing Census, disaggregated to GN-division level.

TABLE I

Primary Datasets Used in the Study

Dataset	Source	Resolution / Period
Precipitation	GPM IMERG Final Run v06	0.1° spatial / half-hourly temporal
Wind fields	ERA5 Reanalysis (ECMWF)	0.25° spatial / hourly temporal
Cyclone tracks	IBTrACS v04	1980-2024
Elevation (DEM)	ALOS PALSAR DEM	12.5 m spatial resolution
Land cover	Sentinel-2 MSI	10 m spatial resolution
Flood extents	Sentinel-1 SAR	20 m spatial resolution
Socioeconomic	HIES 2019 / Population Census	GN-division level

C. Multi-Criteria Flood Susceptibility Mapping

Flood susceptibility is characterized using a GIS-FAHP integrating seven conditioning factors: elevation, slope, profile curvature, Topographic Wetness Index (TWI), distance to drainage network, soil hydrological group, and land use/land cover [9]. Pairwise factor weights are derived through expert elicitation using a structured questionnaire administered to hydrologists and flood-risk specialists in Sri Lanka, validated using a consistency ratio threshold ($CR < 0.10$). A sensitivity analysis is conducted on the derived weights to assess the influence of factor variability on susceptibility outcomes. Final susceptibility rasters at 12.5 m spatial resolution are classified into five categories (Very Low to Very High) and independently validated against Sentinel-1 SAR-derived inundation extents from four historical events (2011, 2016, 2018, 2025) using Receiver Operating Characteristic (ROC) analysis.

Coupled HEC-RAS 1D/2D hydraulic simulations subsequently generate inundation depth and velocity grids for four return periods (10-, 25-, 50-, and 100-year) across the Deduru Oya and Mee Oya river sub-basins [11]. Boundary conditions are derived from frequency-analyzed discharge records at Kurunegala and Nikaweratiya gauging stations using Log-Pearson Type III distribution fitting. Manning's roughness coefficients are calibrated against observed peak-stage measurements. Model performance is assessed using Nash–Sutcliffe Efficiency ($NSE \geq 0.70$), Root Mean Square Error (RMSE), and Percent Bias (PBIAS within ±10%).

D. Probabilistic Cyclone Hazard Analysis

Monte Carlo-based PCHA generates 10,000 synthetic tropical cyclone tracks across the Bay of Bengal by resampling IBTrACS-derived kernel density distributions of genesis location, translation speed, central pressure deficit, and radius of maximum winds [13, 14]. The Holland parametric wind model [18] translates each synthetic track into 0.01° gridded surface wind fields. IMERG-calibrated statistical rainfall–wind relationships, fitted separately for six bearing sectors relative to the cyclone center, extend the outputs to 24-hour and 72-hour accumulated precipitation grids. Generalized Extreme Value (GEV) exceedance probability curves are fitted at each GN-division centroid to generate return-period hazard surfaces (10–500-year) for wind speed ($m \cdot s^{-1}$) and rainfall (mm). Uncertainty bounds on exceedance estimates are derived via bootstrap resampling of the 10,000-track synthetic ensemble.

E. Loss Modelling and Basis Risk Assessment

Household and agricultural loss functions are developed by overlaying inundation depth and wind speed grids with district-level infrastructure inventories, residential building stock, and paddy exposure layers derived from the 2012 Sri Lanka Population Census and Department of Agriculture crop statistics. Residential depth-damage functions follow UNDRR Sendai Framework guidelines [19] and are adapted for Sri Lankan building typologies (unreinforced masonry, timber frame, and tile-roof structures) based on post-Cyclone Ditwa field damage surveys conducted in Kurunegala District. Agricultural loss curves are parameterized using district-level paddy yield response data and validated against crop insurance payout records from the Agriculture Insurance Board of Sri Lanka.

Basis risk is quantified at GN-division resolution by computing Spearman rank correlation coefficients between three candidate index triggers (24-hour rainfall, 72-hour rainfall, and peak inundation depth) and simulated plot-level economic losses, following the methodology of Calapini et al. [12]. For each GN division, the trigger that minimizes the Root Mean Square Basis Risk Error (RMSBRE) is identified, and optimal trigger thresholds are estimated using an exhaustive grid search procedure across the empirical distribution. Spatial basis risk maps classify each GN division into low (RMSBRE < 25%), moderate (25-50%), and high (> 50%) misalignment zones, thereby informing whether district-level or sub-district trigger calibration is required.

F. Spatial Econometric Demand Estimation

WTP for a spatially indexed flood-cyclone parametric insurance product is estimated using a stated-preference contingent valuation (CV) survey administered to 1,200 smallholder farm households across the five districts (stratified random sample: 240 households per district; minimum 40 per GN-division stratum). WTP responses are modelled using SAR and SEM specifications [20, 24] with spatial weight matrices constructed from GN-division inverse-distance contiguity. Model selection between SAR and SEM is guided by Moran's I residual diagnostics and likelihood ratio tests. Key covariates include household asset wealth index, flood exposure category derived from the FAHP maps, insurance literacy score, and proximity to the nearest high basis risk GN division, enabling the resulting WTP surface to feed directly into premium segmentation and cross-subsidy analysis. Figure 1 illustrates the overall methodology.

IV. Expected Outcomes and Policy Implications

This study will produce five integrated, policy-ready outputs (Table II), forming the first end-to-end, spatially disaggregated evidence base for parametric insurance in cyclone-prone Sri Lanka. Each output addresses a critical decision-making bottleneck in the DRF value chain, from hazard characterization to sovereign risk transfer.

TABLE II

Expected Outputs and Their Policy Applications

Output	Key Deliverable	Policy Use
Multi-hazard maps	GN-division flood, wind, and rainfall surfaces	DMC hazard profiling
Flood models	HEC-RAS inundation simulations + depth-damage functions	Actuarial loss estimation
PCHA surfaces	Return-period exceedance maps (10–500 yr)	Parametric pricing
Basis risk maps	Trigger-loss divergence by the GN division	Trigger calibration
WTP estimates	Spatial premium surfaces, demand segmentation	Insurance product design

GN-division multi-hazard maps provide the spatial granularity currently absent from Disaster Management Centre (DMC) hazard profiles [8], enabling district-level emergency planning based on probabilistic inundation depths and wind-speed return periods. Calibrated HEC-RAS models with empirical depth-damage functions bridge physical hazard science and actuarial loss quantification, allowing the Agriculture Insurance Board and reinsurers to set credible parametric premiums. PCHA-derived exceedance surfaces (10–500-year return periods) support sovereign catastrophe risk transfer instruments, including catastrophe bonds and multi-year DRF programs. Empirical basis-risk maps identify GN divisions with high trigger–loss divergence, guiding sub-district trigger calibration and composite index design for the SEADRIF.

The spatial WTP surface highlights demand hotspots and subsidy-eligible zones, supporting tiered premiums and targeted government subsidies. Finally, the proposed framework is openly documented, reproducible, and transferable to other cyclone-exposed regions of South Asia, with dissemination through DMC planning cycles, consultations with the Insurance Regulatory Commission of Sri Lanka (IRCSL), and World Bank technical assistance programs [6, 7].

V. Conclusion

This work-in-progress proposes a spatially explicit analytical framework addressing a critical gap in Sri Lanka's DRF architecture. The absence of sub-district probabilistic hazard models and empirically grounded basis-risk assessments has constrained the effective design of parametric insurance instruments for cyclone-exposed communities.

By integrating GIS-based FAHP multi-hazard mapping, HEC-RAS 1D–2D hydraulic simulations, Monte Carlo–based PCHA , and spatial econometric modeling of insurance demand, the study develops a GN-division-scale probabilistically calibrated multi-hazard framework. The framework produces five key outputs: multi-hazard susceptibility maps, calibrated inundation models, PCHA exceedance surfaces, empirical basis-risk maps, and spatial WTP estimates, which collectively address the full DRF value chain. These outputs enable the design of spatially calibrated parametric insurance products that reduce basic risk, enhance household risk protection, and strengthen sovereign disaster resilience.

Future work will extend the framework to additional cyclone-prone districts and evaluate dynamic trigger recalibration under mid-century climate change scenarios.

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