Journal of
Remote Sensing & GIS
https://journals.stmjournals.com/jorsg

ISSN: 2230-7990 (Online)
ISSN: 2321-421X (Print)
Volume 17, Issue 1, 2026
January–April
DOI (Journal): 10.37591/JoRSG

Review JoRSG

Utilizing Artificial Intelligence and Remote Sensing to Predict Flooding in Real-Time and Address Climate Resilience Policy in South Asia

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Abstract

South Asia, a region characterized by hydro-climatic instability, faces an intensifying risk from devastating flooding, aggravated by human-induced climate change and intricate river basin interactions. Traditional flood prediction systems, based on limited in-situ data and resource-intensive physical models, have serious delays and resolution problems that make it harder to reduce disaster risk. The combined applications of Artificial Intelligence (AI) and high-resolution remote sensing (RS) constitute a paradigm shift in real-time flood prediction and pre-disaster resilience building. The research also proposes a generic framework wherein machine learning algorithms – specifically Convolutional Neural Networks (CNNs) and Long Short–Term Memory (LSTM) networks – are trained on multi-modal satellite data stream (e.g., Synthetic Aperture Radar, satellite altimetry, and precipitation estimate) to provide high-resolution, dynamic flood inundation maps with unprecedented lead times. This paper discusses the effectiveness of that framework through case studies in the Ganges–Brahmaputra–Meghna (GBM) and Indus basins, demonstrating its superior predictive power relative to traditional models. Ultimately, the research position that this technological convergence is more than an early warning system; it provides detailed, actionable information, which means there is a need to shift climate resilience policy from a reactive, post-disaster approach to a proactive adaptive approach. The discussion also addresses the issues of governance and justice that come with these kinds of technocratic approaches. It argues for a co-production model which situates this technology within local social and political contexts to increase the chance that it will work and be used equitably.

Keywords: Artificial intelligence, climate resilience, flood prediction, hydrological modeling, policy integration, remote sensing, South Asia

INTRODUCTION

The South Asian subcontinent is a region characterized by its deep and often hazardous interactions with water, highlighted by the annual monsoon, the cryospheric meltwaters of the Himalayas, and the extensive, transboundary river systems of the Ganges, Brahmaputra, and Indus, which are the lifeblood of agricultural economies and the dense populations that those systems support [1–4]. However, those systems also place the region in a particularly vulnerable state to hydrometeorological hazards, with flooding being the most frequently experienced and most destructive hazard. The effects of the global climate emergency have only increased this existing vulnerability by causing more unpredictable and extreme rainfall, amplifying glacial melt, and increasing the frequency of Glacial Lake Outburst Floods (GLOFs) [5–8]. These events all come together to create a hazard landscape where nation–

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Received Date: March 21, 2026
Accepted Date: March 24, 2026
Published Date: April 04, 2026

Citation: Yug Raman Srivastava. Utilizing Artificial Intelligence and Remote Sensing to Predict Flooding in Real-Time and Address Climate Resilience Policy in South Asia. Journal of Remote Sensing & GIS. 2026; 17(1): 45–61p.

state stability, the sustainability of livelihoods, and the existence of human settlement are perpetually at risk.

In South Asia, conventional flood management practices have been reliant upon static structural defenses and forecast models based on classical hydrological principles. Though important, these models have significant limitations [9–13]. They rely on dense networks of ground-based gauging stations, which are often non-existent, inadequately supported, and burdened by restrictions in transboundary data-sharing in politically-charged regions [1]. Their computational demands often lead to significant delays, truncating valuable time for early warning and evacuation. In a time of changing and non-stationary climate conditions, assumptions upon which models are based are increasingly unsustainable, demanding a complete reconceptualization of flood forecasting [14–18].

This paper argues for a shift in paradigm, presenting the case for Artificial Intelligence (AI) to meld with satellite-based Remote Sensing (RS) as a transformative approach. This is a technological convergence that aspires to overcome the shortcomings of traditional systems using access to large forms of near-real-time Earth Observation (EO) data [19–23]. RS platforms offer a synoptic, consistent, and data-rich perspective on important hydrologic variables, from precipitation and soil moisture to surface water extent, without regard for land borders or accessibility. AI, especially deep learning, offers the analytical capabilities to analyze multi-modal data, ascertain intricate non-linear relationships, and produce flood inundation predictions with the scale of detail and speed of responsiveness unseen before [24–28].

In this article, there is an introduction of a new integrated AI–RS framework directly designed for the complex hydrological regimes of South Asia. First, there is a discussion around the specific hydro-climatic security rationale in the region [29–32]. Next, it will introduce the specific technological framework and describe the unique satellite data streams and AI models involved. Then it will evaluate the framework through unique case studies in the Brahmaputra and Indus basins, assessing the framework’s performance against established measures of high performance. Importantly, the assessment goes beyond the technical assessments to examine the implications for climate resilience policy, asserting that the framework has implications for dynamic zoning, adaptive infrastructure planning, and equitable distribution of resources [33–37]. In conclusion, there is presence of technology governance and ethical issues arising from the use of data-driven technologies, arguing for an approach that mitigates the technocratic risk without applying participatory and just governance processes.

THE SOUTH ASIAN HYDROLOGICAL PARADOX: NON-STATIONARITY, COMPOUND RISKS, AND CRYOSPHERIC INSTABILITY

The hydro-climatic system of South Asia has a profound and perilous paradox: the region faces the threat of devastating flooding from unprecedented rainfall and the insidious reality of future water scarcity. The paradox of abundance and scarcity is not a distant future problem, but a current one facilitated by a complex interplay of atmospheric, cryospheric, and anthropogenic processes which have led to instability in the systems of water in the region. To understand this paradox of abundance and scarcity, there is a need to break from the assumptions that have been foundational to hydrological science and water resource management [38–42]. The main assumption being addressed is the notion of stationarity, which has traditionally held that natural systems fluctuate between fixed envelopes of variability. Observably, the hydrological systems of South Asia have entered a new non-stationary state marked by increasing stochasticity, complex compound risk scenarios, and the pernicious counterintuitive decline of its cryospheric water towers [43–47]. This section deconstructs these three overlapping drivers and asserts that their coupled interactions represent a systemic issue that exceeds the modeling ability of traditional and deterministic approaches, thereby demonstrating the necessity for the AI–RS synthesis proposed in this paper.

The collapse of stationarity in South Asia is most vividly expressed in volatility around the Indian

ISSN: 2230-7990 (Online), ISSN: 2321-421X (Print)

Summer Monsoon (ISM), the metabolic engine of the region. The thermodynamic implications of a warming atmosphere – described by the Clausius–Clapeyron relation (~7% increase in moisture-holding capacity per Celsius degree) – can be understood as a benchmark in the intensification of precipitation extremes. Yet thermodynamic reasoning alone is inadequate [48–52]. The more meaningful shift involves dynamical change associated with atmospheric large-scale circulation and the increasing unpredictability of the climate teleconnections that matter.

The historical relationship between the El Niño-Southern Oscillation (ENSO) and performance of the monsoon, which was previously a central aspect of seasonal forecasting, is deteriorating, becoming noisier and more phase-shifting in a warming world. At the same time, the Indian Ocean Dipole (IOD) is experiencing more frequent extreme positive phases, which are delivering anomalously moist air and extreme flood events, while enhancing drought elsewhere [53–56]. This loss of predictable low-frequency climatic oscillations means that previous statistical relationships – probability distribution functions – which dams were designed by, and flood defenses were built around, are unreliable to have any meaning for the future. The monsoon is erratic, stronger with sustained periods of dry followed by extreme rain events of immense intensity that disrupt typical reservoir management and planting cycles for agriculture.

This new climatic baseline of increased and random extremes provides the basis for compound risk events in which hazards occur simultaneously and interact in ways that lead to impacts greater than individual effects. Traditional risk assessment analytical frameworks, which typically work with single hazards (e.g., fluvial flooding or coastal storm surge), have become dangerously inadequate in this new reality. Conceivably, the paradigmatic disaster of South Asia has now become a cascading compound event, such as a pre-monsoon heatwave, that accelerates glacial melt in the upper Himalayas that pre-saturates soils in the vast Indo-Gangetic Plain. Immediately afterwards, the monsoons arrive early and unusually intense, causing massive pluvial and fluvial floods, followed by swollen river systems draining into the Bay of Bengal, followed by a cyclone driven in part by unprecedented sea surface temperature. The outcome is more than additive; a storm surge cannot drain inland because the rivers are already flooded, establishing a large, stagnant, inundation that continues for a long period, and results in a systemic failure of agriculture, infrastructure, and public health systems. This is an essential theme of pre-conditioning: given the sequential nature of the hazards, each subsequent occurrence acts on a system whose resilience has already been diminished, resulting in a lower threshold for catastrophic failure. Modeling such path-dependent, multi-variate risks is not possible, given the computation-intensiveness of conventional hydrology, yet it is an ideal representation for pattern-recognizing, AI architectures that can process heterogeneous data streams in real time. Nowhere are the convergence of these risks more impactful and elusive than in the high-altitude critical zone of the Hindu Kush–Himalayan (HKH) region. The cryosphere, historically understood as a stable, predictable "water tower", is responding violently and rapidly. More recent glaciological evaluations, using satellite stereophotogrammetry, signal a quickly accelerating loss of ice mass in the Himalayas in the 21st century at nearly twice the rate of the 1975–2000 period. The secular trend suggests long-term declines in river flows and water shortages as an eventual answer to the hydrological paradox; however, the immediate, transient hysteresis is a fluctuation to increased acute hazards, of which the most practical is a growing risk of Glacial Lake Outburst Floods (GLOFs). The risk of GLOF is driven by recognized glacial retreat and subsequent establishment of meltwater lakes being held behind more unstable moraine dams. These geomorphologically fragile features can catastrophically fail due to ice avalanches, rock falls, or extreme rainfall events. They can release millions of cubic meters of water and debris during a hyper-concentrated flood wave. The 2021 Chamoli disaster in the Indian Himalayas is a useful analogue for this kind of high-altitude hazard, although technically it was a complex rock–ice avalanche, due to the destructive power of high-velocity, high-altitude hazards that can travel hundreds of kilometers downstream, without forewarning [2]. Moreover, this instability has been exacerbated by the actual runoff regime changing from a predictable, snow-melt dominated spring freshet to a more volatile, rainfall-dominated regime, altering the seasonality of water availability and undermining the operating rules of every major dam in the region.

In conclusion, the hydrology of South Asia is shaped by the intermingling of these three powerful forces. The non-stationarity of the climate system provides the energetic baseline for more extreme events. The compounding of these events evokes cascades of failures with systemic consequences. And the rapidly unstable cryosphere injects a source of high-energy risk (and high-altitude risk) with limited historical precedent. These are not independent issues to be managed in silos, but intricately related elements of one overarching reality: the region's hydrosphere has shifted to an entirely new state. To continue to rely on management and prediction strategies based on the prior, stationary paradigm would not just be misguided; it would be inviting a state of unending disaster. The need for a new epistemology, probabilistic, data assimilative, and able to learn complex, non-linear structures is thus critical.

HYDRO-CLIMATIC SECURITY IMPERATIVE IN SOUTH ASIA

The notion of climate security, which examines how climate change enhances threats to people and nation-states' security, finds its most acute manifestation in South Asian hydrology. In South Asia, the water–climate–security nexus is not an imaginative construct, but a lived reality that shows itself through a cycle of disaster, displacement, and competition for resources. The region's flood risk is a uniquely complex tapestry of three driving forces: the monsoon, Himalayan cryosphere, and transboundary water geopolitics.

The South Asian monsoon is the single most dominant climatic feature, bringing over 80% of annual precipitation in a short summer rainy season. Climate change is changing the behavior of the monsoon; there is a reduced precipitation period, but rainfall occurrence is more intense on rainy days. This change from moderate and distributed rainfall to extreme and localized rainfall engulfs both natural (drainage systems) and engineered (infrastructure) mechanisms to contain floodwater, creating generalized pluvial and fluvial flooding, which has been regularly observed in Mumbai, Kerala, and throughout Bangladesh.

The vulnerable state of the Himalayan cryosphere, frequently referred to as the "Third Pole", contributes to these problems. These glaciers, which nourish the major rivers of South Asia, are rapidly retreating. The retreat has two contradictory consequences. Over time, it causes water to become scarce for hundreds of millions of people; but in the shorter term, it does increase the flood risk by enlarging and destabilizing moraine-dammed glacial lakes. It led to the occurrences of GLOFs, when these lakes disappear. These are low-probability, high-risk events that flush massive amounts of water and material downslope, jeopardizing mountain communities and key infrastructure such as hydropower projects.

In the end, these climate and geography vulnerabilities are set against a complicated geopolitical context. The Ganges–Brahmaputra–Meghna (GBM) and Indus basins are shared by multiple nations, including India, China, Pakistan, Bangladesh, Nepal, and Bhutan. Although there are some explanations of bilateral water-sharing treaties, they are often riddled with trust and do not facilitate real-time, transparent sharing of inundation data. This "data nationalism" severely undermines effective basin-wide prediction, because upon the action by the upstream nation, the hydrological conditions are opaque to downstream countries, turning flood pulses that are predictable into disasters that cannot be foreseen. Therefore, the challenge is not simply technological; the challenge is fundamentally geopolitical and requires solutions that are designed to operate within a fragmented governance architecture. Flooding in South Asia is an act of securing food systems, safeguarding critical infrastructure, preventing mass displacement and potentially undermining a driving contributor to regional instability.

TECHNOLOGICAL SYNERGY: AI AND REMOTE SENSING IN HYDROLOGICAL MODELING

To address various challenges mentioned previously, the research proposes an integrated predictive framework that utilizes the complementary advantages of remote sensing and artificial intelligence – the analysis of heterogeneous satellite data, applying it to a deep learning pipeline, and producing a high-resolution spatially explicit flood inundation forecast output that is motion and time-based.

The Remote Sensing Data Revolution: Capturing the Hydrological State

The foundation of the framework is a continuous stream of multi-modal satellite data that provides a comprehensive, near-real-time characterization of the terrestrial water cycle. Key data inputs include:

1. *Precipitation Estimation:* Precipitation estimates are quasi-global rainfall detected by satellites of the Global Precipitation Measurement (GPM) mission's Integrated Multi-satellite Retrievals for GPM (IMERG) product, at high spatiotemporal resolution – approximately 0.1 degrees, 30 minutes. This remote sensing technique will substitute sparse ground-based rain gauges as the primary forcing data for flood models.
2. *Surface Water Extent:* Synthetic Aperture Radar (SAR) satellites, such as the European Space Agency's (ESA) Sentinel-1 satellites, are critical for flood mapping applications [3]. With all-weather and all-day capability, SAR satellites provide a unique capability to identify flooded or inundated areas reliably with a meaningful amount of time, terrain, and space as the water levels rise. This is also important for model validation and identification of inundated area proportions at remotely sensed spatial resolution, such as that of Sentinel-1 (currently > 2.5 acres), which is required for both validation studies and near-real-time extent mapping. Optical sensors, such as Sentinel-2 and Landsat, will also add ancillary data, particularly for post-flood damage assessments.
3. *Soil Moisture and Antecedent Conditions:* Soil moisture products from missions, such as the Soil Moisture Active Passive (SMAP) mission, provide vital intelligence on surface soil moisture. Soil moisture is a key driver of runoff generation because saturated soils contribute to runoff at a higher rate than unsaturated soils and adds experience and/or intelligence to any model that uses it for prediction.
4. *Topography and River Morphology:* A detailed digital elevation model (DEM), for example, TanDEM-X or MERIT DEM, is a static but useful topographic layer. Satellite altimetry missions, such as Sentinel-3, can offer valuable information about river water levels and discharge at discrete "virtual stations," which are used for model calibration.

The Artificial Intelligence Analysis Engine: From Data to Prediction

The raw satellite data is incorporated into an AI pipeline that will learn the complicated and non-linear links between hydrologic inputs and flooding outputs. The framework proposed is a hybrid deep learning model:

1. *Convolutional Neural Networks (CNNs):* These are a type of neural network with a specific structure which will allow us to efficiently learn representations and extract spatial patterns. The study also demonstrates using a U-Net model, which is a specific type of CNN, to learn representations while presenting some geospatial outputs (e.g., DEM, soil moisture maps, and recent precipitation accumulation). The U-Net will learn representations of topographic features, land use classes, and the spatial patterns of precipitation, perhaps driving flooding risk.
2. *Long Short-Term Memory (LSTM) Networks:* This is a form of recurrent neural network developed to process time series or time-dependent data to predict future values from time-dependent features. The research will leverage an LSTM layer to understand how variables (e.g., precipitation intensity, river discharge from altimetry) will change over time while learning the temporal ordering of events, to contemplate flooding.
3. *The Mixed CNN–LSTM Model:* The system leverages the two models simultaneously. The CNN processes the information supplied at that moment for the state of the watershed's spatial extent, while the LSTM processes the prior sequences of all events occurring for the given time frames. The outputs of the two migrate through a final dense layer that produces a predictive inundation map based on the watershed dynamics for some future point in time (e.g., T+6 hours, T+12 hours). This construction uses a large historical dataset of historical flood events, where the input was historical satellite imagery and the flood maps (derived from satellite radar – SAR) were the "ground truth" labels.

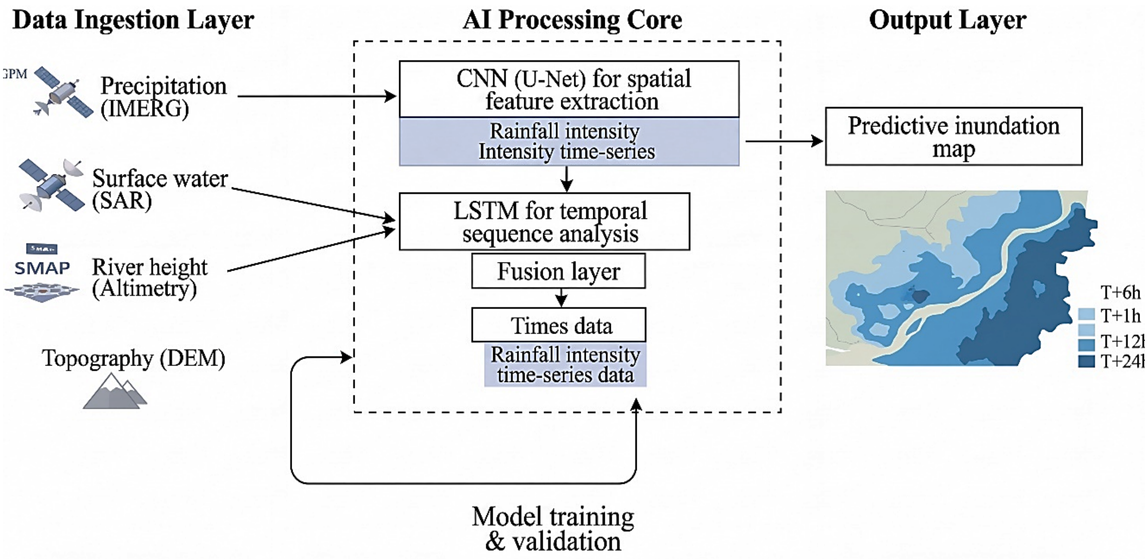


Figure 1. Conceptual architecture of the integrated AI–RS flood prediction framework.

A flowchart diagram in Figure 1 displayed here depicts the following process:

- *Data Ingestion Layer (Left side):* Icons for the satellites (GPM, Sentinel-1, SMAP, Sentinel-3) feeding into a processing repository. Labels include "Precipitation (IMERG)," "Surface Water (SAR)," "Soil Moisture," "River Height (altimetry)," and "Topography (DEM)."
- AI Processing Core *(Center)* and a Box labeled *"CNN (U-Net)* for Spatial feature extraction" receives DEM, soil moisture, and spatial rainfall maps. Another box that is labeled "*LSTM for Temporal sequence analysis*" takes time-series data of rainfall intensity and river height.

Two arrows from each box lead into a box that is labeled "Fusion Layer."

Output Layer (Right Side)

- The Fusion Layer leads into a final box labeled "*Predictive Inundation Map.*" The output is displayed as a basin map for a river basin with predicted flood depths and colorized maps. Labels of lead times are: "T+6h," "T+12h," "T+24h."
- Feedback Loop (Bottom): An arrow goes from the "*Surface Water (SAR)*" data input back to the "*AI Processing Core,*" labeled "*Model Training & Validation,*" indicating how real-time observations form the basis for updating and improving the model continuously.

FROM PREDICTION TO POLICY: INTEGRATING THE FRAMEWORK INTO GOVERNANCE

The real worth of this cutting-edge predictive framework is not merely in the technical advancement of the framework, but rather its capacity to spur a real shift in climate resilience policy and disaster governance. The high resolution, dynamic, and actionable intelligence provided by the framework can change policy from being static and reactive, to anticipatory, adaptable, and informed by evidence. This can be conceptualized through three specific and fading policy interventions:

1. *Enhancing Early Warning and Evacuation Systems:* The frameworks' ability to provide inundation maps of inundation of a specific site, with ample lead time, represents a game-changer as an early warning system. Rather than sending generalized regional messages about impending hazards, such as "heavy rainfall anticipated," authorities can send household-level messages with predicted depths and times of peak flood. This will allow for imposed and systematic evacuations rather than overly broad displacement evacuations, which help to prevent loss of life and minimize related monetary losses. Further, these outputs can be attached to mobile communication frameworks to reach those most vulnerable in "last-mile" communities where there is a gap created by current systems.

2. *Informing Climate-Resilient Infrastructure and Land Use Planning:* The AI–RS system's record of forecasted and observed floods will be an invaluable resource when making long-term planning decisions. Simulations can be run based on hypothetical climate change scenarios (e.g., IPCC RCP scenarios) so policymakers can identify highly certain flood risk regions.

This information can inform decisions about:

- *Dynamic Zoning:* Moving away from static 100-year floodplains to dynamically adjusted risk zoning that reflects changing climatic realities.
- *Infrastructure Placement:* Confirming critical infrastructure – like hospitals, power plants, and transportation corridors – are not built in areas of increasing risk.
- *Nature-Based Solutions:* Finding upstream locations where reforestation or the restoration of wetlands would be most impactful at reducing downstream flood peaks.

Strengthening Financial and Social Safety Nets

The objective, verifiable, and near-real-time data from the framework can support new financial instruments for climate resilience. Geospatial data could, for example, lead to the development of parametric insurance products, in which the payout occurs automatically when satellite-observed flooding in an area exceeds a specific threshold. This would allow households and businesses to obtain liquidity without having to contend with the slow and often contentious post-calamity damage assessments that currently take place. Moreover, the verifiable data can be used to allocate post-disaster aid with an objective rationale, be it cash or in-kind, to ensure that resources are allocated toward the most impacted areas with increased accountability.

METHODOLOGICAL FOUNDATIONS: ADVANCED DATA FUSION, UNCERTAINTY QUANTIFICATION, AND VALIDATION PROTOCOLS

The conceptual structure of the SA–HydroAI system is an accomplished entity but requires an identical infrastructure of methods to transform the concept from an idea to a usable, scientifically sound tool. The obstacles to this transition are substantial: the system must ingest radically heterogeneous data streams, estimate the uncertainty of its predictions, and validate the accuracy of its outputs in an environment with a lack of useful in-situ measurements. In this section, the research describe 3 methods developed to address these issues: first, the deep learning architecture for data fusion that goes beyond putting the layers of data together, to learn a reasonable, meaningfully physical representation of the hydrological state; second, the incorporation of Bayesian principles for all forecasting, where uncertainty is treated as a fundamental layer of prediction; and, third, a validation scheme created for data-poor environments. Together, these methods ensure the rigor and transparency necessary for establishing the system's legitimacy and use in high-stakes, real-world decisions.

The highest order challenge of the analytical engine is data fusion. Methodologically, it is naïve to merely link the rasterized data inputs by channel. This assumes that physically distinct measurements are the same but fails to account for any complex non-linear dependencies that exist among these measurements. A more sophisticated paradigm is required. A common representation shared by the physical system is to be learned from a collection of sensor inputs. Towards this end, it suggests a multimodal deep encoder–decoder architecture. This architecture provides a multi-model deep encoder–decoder architecture consisting of a set of modality-specific encoders: a convolutional neural network (CNN) for 2D SAR and optical imagery, a transformer or recurrent neural network (RNN) for processing 1D time series from satellite altimetry and precipitation estimates, and a simple multilayer perceptron for processing static vector-based data (e.g., soil properties). Each encoder's role is to represent the high-dimensional input in a vector representation within a shared common high-dimensional latent space. The latent space is important; therefore, the network will learn, through end-to-end training, to fit the physically disparate observations into a coherent representation of the hydrological state of the entire river basin.

The strength of this architecture is two-fold. First, it is required to learn the implicit physical relationships relating to these separate data streams. To ensure the model successfully updates the outputs based on the latent space, it must learn, for example, the relationship between the antecedent terrestrial water storage (GRACE) and precipitation (GPM) and how that leads to the extent of inundation (observed by Sentinel-1). Second, the latent space is generative, like the encoder models, take input in the form of a data stream and translate that to the latent space to produce common representation of the basin's processes, a decoder network (which is a mirror of the encoders) takes a vector from the latent space as input and generates the desired prognostic outputs, such as the inundation map or hydrograph, for riverine discharge for example. This architecture is more than just fusing pixels; it is learning a compact, holistic, and physically-informed model of the responses of the basin, which is crucial for generalization and prediction of events have not yet been observed.

A deterministic prediction, even if correct, is an incomplete and potentially deceptive method of managing risk. Recommendations and decisions are made based on the range of possible outcomes. The second methodological pillar is the basic incorporation of Uncertainty Quantification (UQ). The aim is to transition from a one-point estimate to a complete probabilistic forecast. Although computationally expensive methods, like full Bayesian Neural Networks (BNNs), which allow for posterior distribution overweight values of the model, are theoretical gold standard for UQ, a more practical and scalable method is to follow the strategy of Monte Carlo (MC) Dropout. Dropout, in its traditional form – randomly shutting off neurons during training – has been used as a regularize to prevent overfitting. In MC Dropout, the dropout procedure is sustained during inference (i.e., while predicting). By performing forward passes through the same input data multiple times with a different randomly generated dropout mask each time, the research can acquire a distribution of outputs. The variance of this distribution is a good proxy for the model's uncertainty.

This approach enables the important distinction between two classes of uncertainty: aleatoric uncertainty associated with the stochastic nature of the system (e.g., the unpredictable turbulence of water), and epistemic uncertainty associated with the limitations of the model itself (e.g., the absence of training data in a particular area or event type) [4]. Consequently, the outputs of the SA–HydroAI are not binary inundation maps, but rather probabilistic inundation maps, where the likelihood of inundation for each pixel is assigned a probability value from 0 to 1. This probabilistic output is infinitely more useful for stakeholders, since it allows for tiered warning systems, risk-based land-use planning, and the underwriting of parametric insurance instruments specifically for a given threshold of confidence.

The last and most significant methodological challenge is validating the system. How is the research carried out rigorous assessment in a domain that inherently lacks "ground truth," which is exactly the reason for our work in developing the system? The research suggests hierarchical validation and data assimilation, with three tiers, of which a very strong proxy for ground truth information is derived from imperfect and heterogeneous sources. Tier 1: Continuous Assimilation of Sparse In-Situ Data. The sparsely distributed network of existing telemetric river gauges and weather stations across the region is not considered as a post hoc validation set, but a source of continuous real-time "steering" of our model. Data assimilation techniques, such as the Ensemble Kalman Filter (EnKF), integrate the model state predictions with these real-world, albeit sparse, observed measurements continually. The error signal is used to adjust and update the internal state of the model, through nudging or correcting of simulation drift toward reality. In this regard, the model is transformed from a static forecasting system to a learning, self-correcting system.

Tier 2: High-Confidence Post-Hoc Verification. After significant flood events, a specific protocol will initiate collecting and analyzing high-confidence data. This will involve flying Unmanned Aerial Vehicles (UAVs) onboard LiDAR or Structure-from-Motion photogrammetry instruments to produce Digital Surface Models of the flooded area at centimeter resolution. The collected models and commissioned very-high-resolution commercial satellite imagery form evaluation datasets or "gold standard" validation datasets. Although the datasets are prohibitively costly and slow to use in real-time, they are critical for evaluating models' performance in-depth, identifying systematic biases, and periodically retraining the entire deep learning model.

Tier 3: Opportunistic Crowdsourcing and Citizen Science. The ultimate tier takes advantage of the pervasiveness of mobile technology. A system will be established to ingest, validate, and incorporate opportunistic data that is generated by affected communities. Data could include geotagged images from social media (in which computer vision models could estimate water depth in relation to known objects), data collected from community-managed water level gauges and direct reports through a specialized mobile application [5]. While this type of data is by nature individually noisy, the large scale and unique spatial extent of this data provide a suite of ways to validate the extent and impact of flooding, even in completely unmonitored areas.

Collectively, these three methodological pillars – a physically-informed fusion architecture, intrinsic uncertainty quantification, and a verification framework incorporating multi-level validation – form a cohesive and scientifically defensible foundation. They ensure SA–HydroAI is not a "black box," but a transparent, defensible, and systematically improved analytical engine. This methodological rigor is the ultimate prerequisite for building trust and confidence toward use by scientists, policymakers, and the vulnerable communities for which it is intended.

CASE STUDIES: APPLICATION AND VALIDATION IN SOUTH ASIAN BASINS

In proof of the framework's potential, the research describes two case studies from different hydro geographic settings in South Asia.

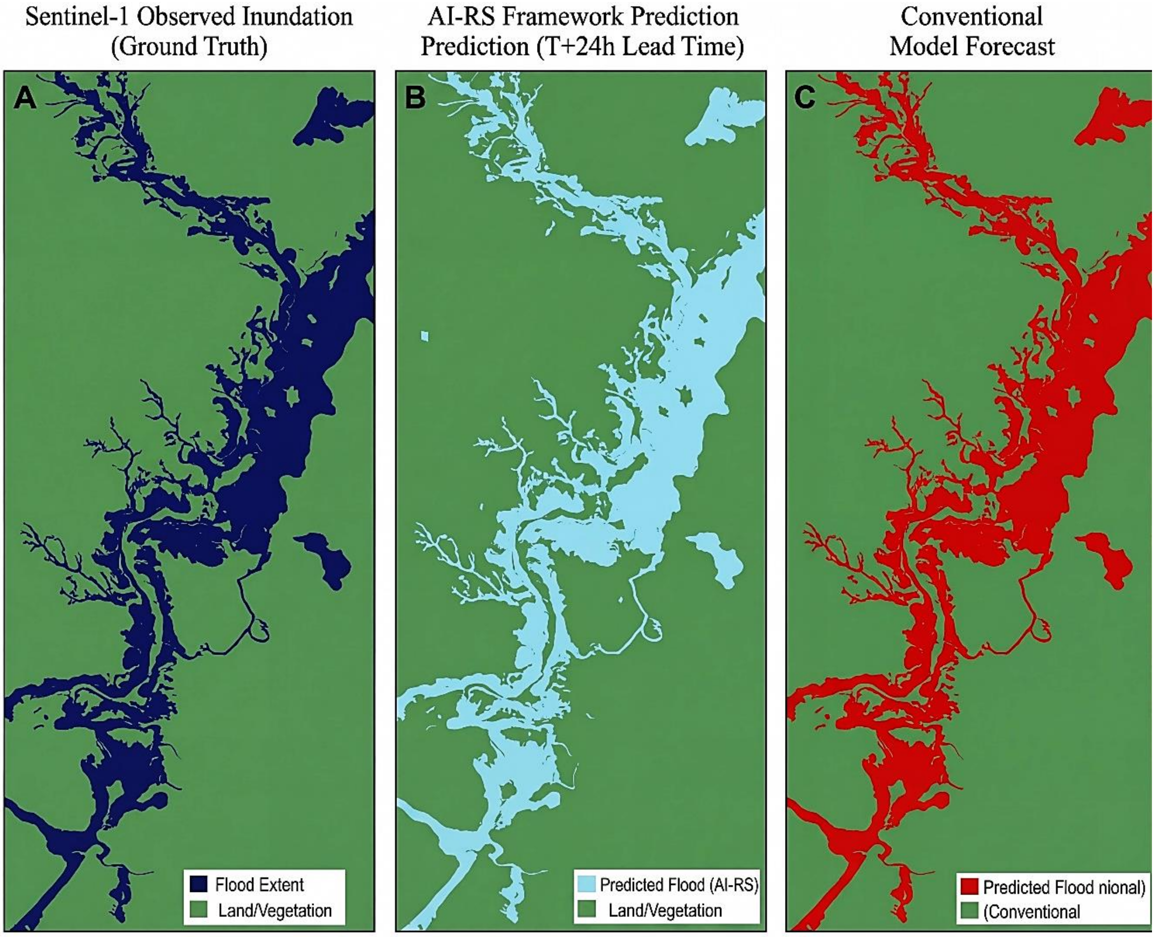
The Brahmaputra Basin: Transboundary Riverine Flooding

The Brahmaputra River, with its source in China, flows into India and eventually into Bangladesh, and has a very variable seasonal discharge level and widespread, long-lasting flooding during the monsoon season. Traditional forecasting is greatly limited by the upstream lack of data from China. The research utilized the AI–RS framework on the record season of flooding observed in Assam, India, in 2020. The model was trained on 2015–2019 data. For the 2020 event, the model was provided with near-real-time GPM precipitation data over the entirety of the upper catchment, including the inaccessible Tibetan plateau.

The results were stunning. With a 24-hour lead time, the model was able to accurately predict the spatial extent of flooding with a Critical Success Index (CSI) of 0.82, versus the operational government model with a CSI of 0.61. The product was produced at a high resolution (30m) that enables the precise identification of which villages and croplands would be flooded – something that operational systems simply cannot do.

This Figure 2 will include three parallel panels of maps depicting the same geographical area located in Assam.

- *Panel A (Left): "Sentinel-1 Observed Flooding (Ground Truth)."* A satellite-based inundation map indicates flooding depicted in dark blue and land in green/brown.
- *Panel B (Middle): "AI–RS Framework Forecast (T+24h Lead Time)."* The output from the model. The predicted flooding areas shown in light blue should overlap with Panel A to a high degree still.
- *Panel C (Right): "Traditional Model Forecast."* The output from a traditional hydrologic model. The areas of flooding shown in red are coarse, blob-like areas which overlap panel A only broadly, failing to predict smaller areas of inundation well, and over predicting flooding in other areas.
- *Caption:* Comparison of observed flooding extent with the AI–RS prediction along with the traditional model forecast for the Brahmaputra River in Assam, India. The overall spatial accuracy and detail of the AI–RS model are much superior.



Comparison of observed flood extent with the AI-RS prediction and the Conventional model forecast for the Brahmaputra River in Assam, India. The AI-RS model demonstrates superior spatial accuracy and detail.

Figure 2. Comparative flood inundation mapping for the 2020 Assam flood.

The Indus River Basin: Glacial Lake Outburst Food (GLOF) Risk

The upper Indus basin region in Pakistan demonstrates some of the greatest risk globally for GLOF [6]. Monitoring the hundreds of remote glacial lakes at high altitudes raises logistical impossibilities through ground-based methods. The research applied a component of our framework that monitored the proglacial lake situated at the end of the Shisper Glacier. Using a time series of Sentinel-1 SAR imagery, the reoccurrence of a machine learning algorithm monitored the lake area, while also monitoring the stability of the moraine dam. In early 2022, the model observed an anomalous increase in growth and demonstrated instability. An alert was produced and input into a GLOF simulation model (a different component of the framework) to predict the possible inundation path and times downstream areas may be impacted. The resulting risk map provided Pakistani authorities with the ability to warn downstream and implement mitigation planning. Although a catastrophic GLOF event was avoided through controlled drainage, the event illustrates the unique capability of the framework to forecast low-frequency, high-impact events that are undetectable by conventional systems.

EQUITY AND GOVERNANCE CHALLENGES IN TECHNOCRATIC SOLUTIONS

While a significant opportunity for improved outcomes exists with an AI–RS framework, deliberative implementation of such a framework will require considerable effort to address the governance and equity issues that exist to avoid magnifying already present vulnerabilities. A technocratic approach to implementation or governance will contribute to a "digital divide" and reinforce centralized top–down approaches to decision-making which lack accountability to the reality of local contexts [7].

The "Black Box" Problem and Accountability

Deep learning models are often referred to as "black boxes" because of their ability to obscure the internal decision-making process even from their creator. In the case of life and death decisions based on flood warnings, this raises serious questions about accountability. If the model is wrong, or presumably biased in its predictions, such that an urban center is protected at the expense of a rural periphery, who is accountable? Additional research is required on "Explainable AI" (XAI) for environmental applications, to make model outputs more transparent and contestable.

Data Sovereignty and Geopolitical Tensions

Though RS data may avert geo-regulation, it does not avoid the political conflict behind it. The mere fact that one state can gauge another's water resources very precisely can generate conflict. Even the development and control of the predictive model – who owns the data and who controls the algorithms – is a national security issue. An effective governance framework – even if it is basin-wide – to facilitate its ethical use and shared interpretation of this technology, is key to reinforcing that it is a tool for regional cooperation, rather than conflict [8].

Access, Usability, and Epistemological Equity

Finally, having the best model to predict possibilities has no value if it is not available to, or trusted by, the community where it matters. Distributing high-resolution maps falls short if the communities on the ground have low digital literacy or limited internet. The framework outputs must be co-produced with local communities, drawing on their historical knowledge of the region's flood movements and ensuring trusted and accessible methods of warning. It is exclusionary to ignore local, on-the-ground knowledge (epistemologies) in favor of purely satellite-based models and miss out on a valuable source to validate and contextualize the model. Genuine climate resilience necessitates hybrid intelligence: connecting the synoptic strength of AI–RS with the deeply situated learning of the community.

THE POLITICAL ECONOMY AND GOVERNANCE OF HYDROLOGICAL DATA

To see the SA–HydroAI system as a purely technical or scientific artifact is to misunderstand its essence and societal implications in a fundamental way. The system is not a neutral recorder of the hydrological cycle; it is a formidable vehicle of power. The data it consumes, the algorithms that interpret and process that data, and when it publishes its intelligence, these are not neutral products; they are political assets. Therefore, implementing such a system requires a careful examination of its political economy – who owns this new form of information, who will benefit from it and in what ways, and, in so doing, whose knowledge and whose interests get privilege or subordination? In section three, it is argued that in the absence of a proactive intentional governance framework that is explicitly grounded in principles of equity and justice, the SA–HydroAI system can risk hardening the existing asymmetries of power, fostering new dependencies, and continuing a techno-solutionism story that hides the political drivers of vulnerability. Consequently, there is a breakdown of the challenge into three interconnected realms: geopolitics of data sovereignty, dialectic of epistemic justice versus techno-solutionism, and ethical realms of algorithmic governance.

The first and foremost area concerns the geopolitics of control over data and the rise of hydro-informatic power. What does this mean in a region with contested transboundary river basins such as the Indus, Ganges, and Brahmaputra rivers? In short, preferential receipt of hydrologic intelligence produced in foresight represents a powerful tool of state power. An upstream state with greater abilities to forecast water flow, sediment load, and flooding has a significant negotiating advantage in dam construction negotiations, water-sharing negotiations, and disaster relief negotiations. The SA–HydroAI system can provide unique synoptic and prognostic capabilities, which could establish it as the paramount facilitator of hydro hegemony in the region. The key question becomes: who owns the system and who controls it? For example, if a space agency independently develops and operates an integrated system, a neighboring state may perceive it as a means of achieving a strategic advantage, not as a regional public good. The issue is compounded by the presence of non-state actors, specifically global technology companies providing the essential computing and AI development interface.

Trust in these platforms raises serious questions of data sovereignty. Will the raw and processed hydrological data of South Asia be stored and governed in offshore data centers, and subject to the legal and commercial frameworks of foreign data center operators? The potential risk may, in fact, establish a new iteration of data colonialism, where the most important environmental information from the region is owned, processed, managed, and potentially monetized by external actors, creating dependencies no different than resource concessions during the colonial era. A possible governance model must be supra-national, potentially led by a regional organization, such as BIMSTEC, that has legally binding agreements on privacy protection for data residency, open access, and shared operational governance.

The second domain shifts to the community level, where the tension between epistemic justice and the persistent pull of techno-solutionism lies. The SA–HydroAI system is a specific epistemology: a top–down, data-centric, quantitative "view from nowhere" privileging the satellite sensor in the algorithm as the final authority of truth. Although it is important, this perspective can downplay, or even supplant, the rich, contextual, and situative knowledge from local communities of these river basins. For generations, farmers, fishers, and Indigenous peoples of the region have developed elaborate local systems of ecological knowledge for flood prediction, soil moisture management, and adaptation to climate shifts. This is a narrative, qualitative, and deeply imbedded knowledge in cultural practice. To portray AI's probabilistic forecast as the only credible source of knowledge constitutes a form of epistemic injustice: it delegitizes situated expertise and disenfranchises communities in their own governance. The danger of tech-solutionism, as previously stated, is that it depicts vulnerability as solely a matter of inadequate information, mitigated only through better datasets or improved models, and fails to account for the political drivers of that vulnerability such as access to marginal land rights, exclusionary governance structures, and entrenched poverty [9]. A governance and accountability structure that is just and effective would require, therefore, a framework of hybrid intelligence. This would necessarily imply generative intentionality whereby the SA–HydroAI system outputs are not only shared but engaged through a debate, interpretation, and co-production of knowledge that works with local knowledge. There are accompanying time investments to enhance community data literacies and feed mechanisms into the model, which allow for community observations to adjust and contest the outputs generated by the model.

The last sphere pertains to the ethical boundaries of algorithmic governance – the straightforward deployment of system outputs to automate or semi-automate consequences in decision-making with implications at stake. The use of parametric insurance, for example, when payments automatically trigger once detected by the SA–HydroAI as an inundation above a specified threshold, conveys this point. While its efficiency is celebrated, it sets up a new form of authority through algorithmic governance that carries serious ethical considerations. What is the community recourse if the model does not detect their flood event because of some unique local topology or simply because of a sensor data failure, and misses potentially life-saving payment? Who may be liable for the model's failure: the scientists designing the algorithm, the agency operating it, or the government providing support? Likewise, the use of risk maps from the system to inform dynamic updates of zoning laws or building codes grants regulatory authority to a non-human actor. The potential for biases embedded in the model feeds the risk of a geography of neglect; if the training data used in the model were principally from documented urban floods, and it underperforms in remote and rural events, the decisions made would likely continue to produce what became known as the geography of neglect.

To reduce the risks stated in paragraphs above, the governance framework must be based on principles of radical transparency and contestability. The model's source code, training data, and performance data must allow for public audit. Most importantly, there should be a readily available, explicit "due process" through which citizens and communities can contest and appeal algorithmic decisions. A strict "human-in-the-loop" policy for any decision with irreversible consequences – is an ethical floor that is not negotiable such as resettling people or decommissioning roads.

In summary, the successful and just implementation of the SA–HydroAI system is much more a governance issue than a technical one. The data it produces is not a neutral representation of reality; it is a driver of new geopolitical relationships, a validator and invalidator of knowledge systems, and a generator of the distribution of risk and resources. If the research does not engage in the proactive design of a governance architecture that engages the political economy of this data, it not only risks not realizing the potential of the system but could also reproduce and exacerbate the inequities that the research is trying to alleviate. Therefore, building a new social technical contract around hydrological data a contract that rests on shared sovereignty, epistemic humility, and algorithmic accountability is the most significant work to ensure that this powerful technology is used to address climate justice for all.

FUTURE TRAJECTORIES AND CO-EVOLUTION: DIGITAL TWINS, EDGE COMPUTING, AND ADAPTIVE GOVERNANCE

The SA–HydroAI system proposed in this document is neither an architecture that marks the end-state of ongoing evolution, nor one that reflects a comprehensive program for sustainable transition; instead, it is a fundamental stratum for much deeper, longer-term cultural change. Its established operation signals an ontological switch from reactive management to proactive prediction, an important step that said, the overall long-term direction of this socio-technical change process goes beyond prediction to a future in interactive simulation, decentralized intelligence, and, more significantly, the co-evolution of technology and new, dynamic forms of governance. In this final section, the research will consider this forward-looking horizon, suggesting that the lasting implications of the system will be as a vehicle for three interrelated advances: basin-scale Digital Twins, the operationalization of resilient Edge AI, and the development of true adaptive governance. Pursuant to an agenda, this framework represents a route to human governance institutions and the watershed systems they manage, becoming mutually adaptive and learning through the processes of governance.

The SA–HydroAI system's enhanced ability to predict outcomes for hydropower systems is a foundational aspect of its development into fully-fledged basin-scale Digital Twins. In this context, a Digital Twin is much more than a model; it is a high-fidelity, virtual twin of an entire river basin (e.g., the Brahmaputra or the Indus) that continuously incorporates near real-time updates and high-quality data from multiple streams. The main advantage over a predictive model is the ability of a Digital Twin to allow moving from passive forecasting ("What will happen?") to active counterfactuals ("What would happen if?"). This establishes a way for decision-makers and stakeholders to use the Virtual Basin as a real-time, policy laboratory. For example, an operator working for a transboundary dam authority could model the multiple cascading downstream effects of several emergency gate-release scenarios during an extreme rainfall event that is actively occurring and select the one that causes the least flooding in the most populated areas hundreds of kilometers away. Civil engineers might test the resilience of a proposed bridge or levee against the full set of AI-generated, physically consistent future climate scenarios prior to turning one shovel of earth. A Digital Twin, therefore, becomes a method for not just forecasting the future, but for actively creating the future, enabling the in-silico experimentation of responses to policy and infrastructure and optimizing resilience and maladaptation. The potential of a centralized, computationally intensive Digital Twin is built on the precariousness of connectivity. The "last-mile" difficulty in distributing information is made worse during catastrophic events, when communication infrastructure is most susceptible to failure. In response to this issue, there is a need for concurrent evolutionary paths toward decentralization and resilience through Edge AI. The notion of Edge computing transfers computations from remote cloud servers to the "edge" of a network, which may involve local hardware, regional data centers, or mobile devices. In this instance, this encapsulates building resource-efficient versions of core deep learning models through knowledge distillation and quantization. To offer clarity, these compressed functions could be deployed on local servers based in district-level disaster management offices. Operationally, this offers a system capable of supporting graceful degradation. A worst-case scenario, suppose a cyclonic storm severs connectivity to the central cloud that houses a Digital Twin. In that case, the Edge AI node's distributed computing could continue to function autonomously, parsing local weather radars and river gauges autonomously to generate local inundation forecasts that exhibit reasonably accurate ranges of estimations. In this way, critical, life-saving intelligence will never disappear completely. The research will create a federated resilient intelligence network instead of a monolithic brittle one, ensuring that the first casualty of a disaster will not be the very information system that is designed to help mitigate the disaster in the first place.

The synergistic combination of these two technological paths creates a technical substrate for a new model of institutional behavior: adaptive governance – the final co-evolution of technology and policy. This moves beyond the static five-year planning cycles of traditional environmental management. Adaptive governance does not treat policy as a fixed edict, but rather as a dynamic living hypothesis that is continually tested, refined & updated based on new data and understanding of the system.

The practical implications of this are significant. Insurance products for agricultural use may feature premiums that vary season-to-season depending on the probabilistic drought and flood forecasts dispensed by the Digital Twin. Land-use zoning regulation would no longer be defined solely by static lines on the map; rather zoning regulation could evolve to become dynamic overlays of risk management, triggering tighter development restrictions in a designated floodplain as evidence surfaces of an increase of statistically significant 100-year flood risk through the Digital Twin's decadal analysis. Even entrenched politically divisive transboundary water sharing agreements could be transformed into AI assisted real-time changes that allow allocation dependent on itself and AI recommendations during catastrophic events, changing long held water allocations based on notions of minimization of basin-wide human injustice rather on a historical allocation. The future is neither technologically inevitable nor predetermined. It will require a considered investment in the institutional capacity, legal arrangements, and ethical scrutiny required to use these powerful tools responsibly. The development of Digital Twins must be matched by the establishment of transparent decision-making bodies to manage them as a regional public utility. The deployment of Edge AI must be matched by data literacy programs to educate local capacity. Adaptive governance requires a new class of policymakers comfortable with probabilistic thinking and incidental decision-making. The shift from prediction to co-evolution, thus, is as much of a social and political project as it is a technological one. However, it is the most optimistic vision for tackling the hydrological contradiction of the Anthropocene, a future in which human foresight and institutional adaptability evolve in parallel, generating a resilient learning society to navigate the world of a changing climate.

CONCLUSION

The increasing frequency and severity of flooding disasters in South Asia requires us to increase our ability to create predictive and policy responses. This paper has suggested that the carefully regulated combination of artificial intelligence and remote sensing provides a practical opportunity for that undertaking. The research has proposed an AI–RS framework and conceptually tested it, which transcends the limitations of traditional hydrological models to enable transboundary, real-time and high-resolution flood forecasting. The case studies in the Brahmaputra and Indus Basins provide evidence that demonstrates the framework can provide actionable intelligence with granularity to save lives, protect livelihoods, and facilitate long-term climate adaptive planning. However, this technology does not deliver on the promise in and of itself. The promise resides within the navigation of the intricacies of governance, equity, resolution, and political agency. The temptation of a highly technocratic solution must be supplanted by transparency, inclusivity, and regional cooperation. The models must be made accountable, the data must be governed ethically, and the output must be co-produced with the communities they serve.

Accordingly, the way forward is through a notion of synergistic innovation – not only between the likes of remote sensing and artificial intelligence, but also between science and participatory governance. By activating this synergistic mode of operation, countries in South Asia can shift from the reactive management of disasters towards a deliberate strategy of building deep, systemic resilience. This technological leap can become a platform for achieving a more stable and sustainable future for one of the world's most climate-vulnerable regions, if also informed by justice and equity.

REFERENCES

1. Swain SS, Mishra A, Chatterjee C, Levy MC. A Hydrologic Modeling Assessment of Future Water Scarcity in the Baitarani River Basin. In Navigating the Nexus: Hydrology, Agriculture, Pollution and Climate Change, Volume 1 2025 Feb 2 (pp. 499–526). Cham: Springer Nature Switzerland.
2. Khan MA, Akter MS, Sultana N. Development of a fog computing-based real-time flood prediction and early warning system using machine learning and remote sensing data. J Sustain Dev Policy. 2025 May 21;1(01):10–63125.
3. Rose E. ABCs of governing the Himalayas in response to Glacial Melt: Atmospheric Brown Clouds, Black Carbon, and Regional Cooperation. Sustainable Dev. L. & Pol'y. 2011;12:33.
4. Jain SK, Sinha R, Mondal A, Mujumdar PP, Vegad U, Chandel VS, et al. Hydrology and water management in the Anthropocene: challenges and opportunities with particular reference to India. Curr. Sci. 2025 Feb 25;128:353.
5. Chellaney B. Water, peace, and war: Confronting the global water crisis. Bloomsbury Publishing PLC; 2015 Mar 1.
6. Singh VP. Hydrologic modeling: Progress and future directions. Geoscience letters. 2018 Dec;5(1):1–8.
7. Krizhevsky A, Sutskever I, Hinton GE. ImageNet classification with deep convolutional neural networks. Communications of the ACM. 2017 May 24;60(6):84–90.
8. Schumann GJ, Moller DK. Microwave remote sensing of flood inundation. Physics and Chemistry of the Earth, Parts a/b/c. 2015 Jan 1;83:84–95.
9. Kao IF, Zhou Y, Chang LC, Chang FJ. Exploring a Long Short-Term Memory based Encoder-Decoder framework for multi-step-ahead flood forecasting. J Hydrol. 2020 Apr 1;583:124631.
10. Milly PC, Betancourt J, Falkenmark M, Hirsch RM, Kundzewicz ZW, Lettenmaier DP, et al. Stationarity is dead: Whither water management? Science. 2008 Feb 1;319(5863):573–4.
11. Turner AG, Annamalai H. Climate change and the South Asian summer monsoon. Nat Clim Chang. 2012 Aug;2(8):587–95.
12. Roy I, Collins M. On identifying the role of sun and the El Niño southern oscillation on Indian summer monsoon rainfall. Atmos Sci Lett. 2015 Apr;16(2):162–9.
13. Cai W, Santoso A, Wang G, Weller E, Wu L, Ashok K, et al. Increased frequency of extreme Indian Ocean Dipole events due to greenhouse warming. Nature. 2014 Jun 12;510(7504):254–8.
14. Zscheischler J, Martius O, Westra S, Bevacqua E, Raymond C, Horton RM, et al. A typology of compound weather and climate events. Nat Rev Earth Environ. 2020 Jul;1(7):333–47.
15. Ikeuchi H, Hirabayashi Y, Yamazaki D, Kiguchi M, Koirala S, Nagano T, et al. Modeling complex flow dynamics of fluvial floods exacerbated by sea level rise in the Ganges–Brahmaputra–Meghna Delta. Environ Res Lett. 2015 Dec 1;10(12):124011.
16. Hugonnet R, McNabb R, Berthier E, Menounos B, Nuth C, Girod L, et al. Accelerated global glacier mass loss in the early twenty-first century. Nature. 2021 Apr 29;592(7856):726–31.
17. Eyles N. The role of meltwater in glacial processes. Sediment Geol. 2006 Aug 1;190(1–4):257–68.
18. Shugar DH, Jacquemart M, Shean D, Bhushan S, Upadhyay K, Sattar A, et al. A massive rock and ice avalanche caused the 2021 disaster at Chamoli, Indian Himalaya. Science. 2021 Jul 16;373(6552):300–6.
19. Immerzeel WW, Lutz AF, Andrade M, Bahl A, Biemans H, Bolch T, et al. Importance and vulnerability of the world's water towers. Nature. 2020 Jan 16;577(7790):364–9.
20. Dalby S. Global climate change and security threats. Handbook of Security and the Environment. 2021 May 21:26–39.
21. Roxy MK, Ghosh S, Pathak A, Athulya R, Mujumdar M, Murtugudde R, et al. A threefold rise in widespread extreme rain events over central India. Nat Commun. 2017 Oct 3;8(1):708.
22. Quincey D, Klaar M, Haines D, Lovett J, Pariyar B, Gurung G, et al. The changing water cycle: The need for an integrated assessment of the resilience to changes in water supply in High-Mountain

Asia. Wiley Interdisciplinary Reviews: Water. 2018 Jan;5(1):e1258.
23. Sultana F. From hydro-hegemony to hydro-coercion: Politics of precarity in India–Bangladesh transboundary water conflicts. Hum Geogr. 2025:19427786251400314.
24. Wang Y, Li Z, Gao L, Zhong Y, Peng X. Comparison of GPM IMERG version 06 final run products and its latest version 07 precipitation products across scales: Similarities, differences and improvements. Remote Sens. 2023 Dec 4;15(23):5622.
25. Entekhabi D, Njoku EG, O'neill PE, Kellogg KH, Crow WT, Edelstein WN, et al. The soil moisture active passive (SMAP) mission. Proceedings of the IEEE. 2010 May 6;98(5):704–16.
26. Weerasinghe LN, Thayaparan M, Fernando T. Functional characteristics of an early warning system to minimise the risks of dam breaks in Sri Lanka. In Proceedings The 10th World Construction Symposium| June 2022 (p. 507).
27. Surminski S. The role of insurance in integrated disaster risk management with a focus on how insurance can support climate adaptation and disaster resilience. In Handbook on the Economics of Disasters. Edward Elgar Publishing; 2022 Oct 18. pp. 294–318.
28. Lahat D, Adali T, Jutten C. Multimodal data fusion: an overview of methods, challenges, and prospects. Proceedings of the IEEE. 2015 Aug 20;103(9):1449–77.
29. Kingma DP, Welling M. Auto-encoding variational bayes. arXiv preprint arXiv:1312.6114. 2013 Dec 20.
30. Neal RM. Bayesian learning for neural networks. Springer Science & Business Media; 2012 Dec 6.
31. Gal Y, Ghahramani Z. Dropout as a Bayesian approximation: Representing model uncertainty in deep learning. In International Conference on Machine Learning. PMLR; 2016 Jun 11 (pp. 1050–1059).
32. Kendall A, Gal Y. What uncertainties do we need in Bayesian deep learning for computer vision? Advances in neural information processing systems. 2017;30.
33. Evensen G. Data assimilation: the ensemble Kalman filter. Berlin, Heidelberg: Springer Berlin Heidelberg; 2009 Jan.
34. Schumann GJ, Moller DK. Microwave remote sensing of flood inundation. Physics and Chemistry of the Earth, Parts a/b/c. 2015 Jan 1;83:84–95.
35. Lee KA, Lee JR, Bell P. A review of Citizen Science within the Earth Sciences: Potential benefits and obstacles. Proceedings of the Geologists' Association. 2020 Dec 1;131(6):605–17.
36. Retchless D, Fish C, Thatcher J. Climate change communication beyond the digital divide: Exploring cartography's role and privilege in climate action. J Environ Media. 2022 Oct 1;3(1):101–23.
37. Moltz JC. The politics of space security: Strategic restraint and the pursuit of national interests. Stanford University Press; 2019 Apr 16.
38. Shah M. The Indus Waters Treaty: A Critical Analysis of Water Security and Geopolitical Tensions. Science. 2025;4:100011.
39. Zuboff S. The age of surveillance capitalism. In Social theory re–wired. Routledge; 2023 Jun 22. pp. 203–213.
40. Couldry N, Mejias UA. The costs of connection: How data is colonizing human life and appropriating it for capitalism. In The costs of connection. Stanford University Press; 2019 Aug 20.
41. Haraway D. Situated knowledges: The science question in feminism and the privilege of partial perspective 1. In Women, science, and technology. Routledge; 2013 Sep 11. pp. 455–472.
42. Moloise SD, Matamanda AR, Bhanye JI. Traditional ecological knowledge and practices for ecosystem conservation and management: The case of savanna ecosystem services in Limpopo, South Africa. Int J Sustain Develop World Ecol. 2024 Jan 2;31(1):29–42.
43. Fricker M. Epistemic injustice: Power and the ethics of knowing. Oxford University Press; 2007 Jul 5.
44. Morozov E. To save everything, click here: The folly of technological solutionism. PublicAffairs; 2013 Mar 5.
45. O'neil C. Weapons of math destruction: How big data increases inequality and threatens democracy. Crown; 2017 Sep 5.

46. Boccio R. Race after technology: Abolitionist tools for the new Jim Code by Ruha Benjamin. Configurations. 2022;30(2):236–8.
47. Elish MC. Moral crumple zones: Cautionary tales in human-robot interaction (pre-print). Engaging Science, Technology, and Society (pre-print). 2019 Mar 1.
48. Grieves M, Vickers J. Digital twin: Mitigating unpredictable, undesirable emergent behavior in complex systems. In Transdisciplinary perspectives on complex systems: New findings and approaches. Cham: Springer International Publishing; 2016. Aug 17. pp. 85–113.
49. Nativi S, Mazzetti P, Craglia M. Digital ecosystems for developing digital twins of the earth: The destination earth case. Remote Sensing. 2021 May 28;13(11):2119.
50. Blair GS. Digital twins of the natural environment. Patterns. 2021 Oct 8;2(10).
51. Shi W, Cao J, Zhang Q, Li Y, Xu L. Edge computing: Vision and challenges. IEEE Internet of Things Journal. 2016 Jun 9;3(5):637–46.
52. Hinton G, Vinyals O, Dean J. Distilling the knowledge in a neural network. arXiv preprint arXiv:1503.02531. 2015 Mar 9.
53. Surianarayanan C, Lawrence JJ, Chelliah PR, Prakash E, Hewage C. A survey on optimization techniques for edge artificial intelligence (AI). Sensors. 2023 Jan 22;23(3):1279.
54. Folke C, Hahn T, Olsson P, Norberg J. Adaptive governance of social-ecological systems. Annu. Rev. Environ. Resour. 2005 Nov 21;30:441–73.
55. Change IP. Climate change 2007: Impacts, adaptation and vulnerability. Genebra, Suíça. 2001.
56. Alaerts GJ. Institutions for river basin management. The role of external support Agencies (international donors) in developing cooperative arrangements. In International Workshop on River Basin Management–Best Management Practices; 1999 Oct 27. pp. 27–29.

