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Intellectual Property Challenges of AI-Based Groundwater Salinity Forecasting in the Indian Sundarbans

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Abstract:
Artificial intelligence (AI)–driven environmental forecasting is rapidly transforming climate-risk assessment in vulnerable deltaic ecosystems. However, the intellectual property (IP) dimensions of such predictive systems remain underexplored. This study examines the intellectual property implications of an AI-governed groundwater salinity forecasting framework developed for the Indian Sundarbans, one of the world's most climate-sensitive mangrove deltas. Using a multi-decadal dataset (1990–2020) from ten monitoring stations across contrasting estuarine regimes, a Neural Autoregressive (NAR) model was implemented to generate seasonal salinity projections up to 2050. The framework integrates algorithmic forecasting, normalized salinity risk indexing (0–1 scale), sectoral heatmap visualization, and climate-risk classification tools for aquifer vulnerability assessment.
Beyond hydrological insights, this research critically evaluates the protectable components of environmental AI systems, including algorithm architecture, predictive workflows, database rights, risk-classification methodologies, and decision-support interfaces. The paper explores whether such integrated forecasting systems qualify for copyright protection, software IP registration, database rights, or patentability under emerging digital-environmental governance frameworks. It also interrogates issues of data sovereignty, algorithmic transparency, public-resource governance, and ethical constraints when predictive tools influence drinking-water planning and climate adaptation strategies.
The findings suggest that while core machine-learning models may not be independently patentable, novel system integration, customized environmental risk indices, and structured decision-support outputs may constitute protectable intellectual assets. The study highlights the tension between proprietary environmental intelligence and public-interest access in climate-vulnerable regions of the Global South. By situating AI-based groundwater forecasting within the broader discourse of intellectual property rights and digital water governance, this paper contributes to the emerging field of environmental algorithm jurisprudence and calls for balanced regulatory frameworks that protect innovation without compromising climate justice and community resilience.
Keywords: Artificial Intelligence (AI); Groundwater Salinity Forecasting; Intellectual Property Rights (IPR); Neural Autoregressive (NAR) Model; Climate Risk Assessment; Digital Water Governance.

Introduction

Climate change is increasingly transforming the physical, ecological, and socio-economic landscapes of coastal regions across the world. Rising sea levels, altered hydrological cycles, increasing frequency of extreme weather events, and changing salinity regimes are creating unprecedented challenges for water security, ecosystem stability, and human livelihoods (Scavia et al., 2002; Roessig, et al., 2004; Weber, 2010; Eissa and Zaki, 2011; Mitra, 2013; Clayton, et al., 2015; Hornsey, et al., 2016; Mishra, et al., 2021; Mitra, et al., 2023). Deltaic ecosystems are particularly vulnerable because of their low elevation, high population density, and close interaction between terrestrial, freshwater, and marine environments. Among the most significant manifestations of climate change in coastal deltas is the progressive salinization of surface and groundwater resources (Ranjan, et al., 2009; Sarma, et al., 2013; Alvarez, et al., 2015; Rahman, et al., 2019). Salinity intrusion affects drinking-water availability, agricultural productivity, public health, and ecosystem functioning, thereby posing a major obstacle to sustainable development and climate adaptation.

The Indian Sundarbans, located within the lower Gangetic delta, represent one of the most climate-sensitive regions of the world. This UNESCO-recognized mangrove ecosystem forms a unique interface between land and sea and provides critical ecological services, including shoreline stabilization, biodiversity conservation, carbon sequestration, fisheries support, and protection from cyclonic storms. At the same time, the region supports millions of inhabitants whose livelihoods depend directly or indirectly on natural resources. Freshwater scarcity has emerged as a growing concern in several islands of the Sundarbans due to increasing salinity intrusion, reduced freshwater inflow, sea-level rise, and anthropogenic pressures. In many locations, groundwater remains the primary source of potable water, making the monitoring and prediction of groundwater salinity a matter of considerable scientific and societal importance.

Traditionally, environmental monitoring has focused on documenting present conditions and identifying historical trends. However, the accelerating pace of climate change demands a transition from reactive management to anticipatory governance. Decision-makers increasingly require reliable forecasts capable of identifying future environmental risks before they manifest as ecological or socio-economic crises. In this context, artificial intelligence (AI) has emerged as a transformative tool in environmental science. Machine-learning algorithms are now widely employed to forecast hydrological variability, groundwater fluctuations, salinity intrusion, biodiversity change, ecosystem degradation, and climate-related hazards. By extracting complex nonlinear relationships from large environmental datasets, AI systems can generate predictive insights that often surpass the capabilities of conventional statistical approaches.

The growing use of AI in environmental forecasting has created a new category of strategic knowledge that extends beyond raw environmental observations. Forecasts generated through advanced computational systems provide actionable information for governments, researchers, industries, insurance agencies, and local communities. Such predictive outputs increasingly influence resource allocation, infrastructure planning, disaster preparedness, climate adaptation strategies, and environmental governance. Consequently, environmental forecasting is no longer merely a scientific exercise; it has become an integral component of decision-making processes that shape societal responses to climate change.

Despite these advances, a critical dimension of AI-driven environmental forecasting remains largely unexplored, preferably the intellectual property status of environmental intelligence generated through artificial intelligence. Existing studies predominantly focus on model performance, prediction accuracy, computational efficiency, and environmental applications. Comparatively little attention has been directed toward questions of ownership, protectability, governance, and accessibility of AI-generated environmental knowledge. This gap is particularly significant because predictive environmental systems increasingly influence public policy, resource management, and climate adaptation planning.

The intellectual-property challenge is especially complex in environmental science because environmental information occupies a unique legal and ethical position. Natural phenomena such as groundwater salinity, rainfall, temperature, biodiversity distribution, or sea-level fluctuations are facts of nature and therefore cannot themselves be owned. However, environmental forecasting systems involve substantially more than natural observations. They require long-term data collection, scientific monitoring, database development, algorithm design, computational modelling, risk classification, visualization frameworks, and decision-support architectures. The transformation of environmental observations into actionable forecasts creates a chain of intellectual contributions that may possess varying degrees of legal protectability.

The present study is situated precisely at this intersection between environmental science, artificial intelligence, and intellectual property law. Unlike many forecasting studies that rely exclusively on publicly available datasets, the groundwater salinity database utilized in this investigation was generated through long-term field monitoring conducted by the authors across representative sectors of the Indian Sundarbans. Seasonal groundwater salinity observations collected from western, central, and eastern sectors over multiple decades constitute a unique scientific resource developed through sustained research effort, field logistics, analytical validation, and data management. The resulting dataset therefore represents not merely a collection of environmental measurements but also a valuable scientific data asset created through extensive intellectual and institutional investment.

This distinction introduces an important conceptual question. If environmental observations generated through long-term scientific monitoring are subsequently used to develop AI-based forecasting systems, what exactly constitutes the protectable intellectual asset? Is protection limited to the forecasting algorithm itself, or can it extend to curated databases, risk-classification methodologies, visualization frameworks, and decision-support systems? More fundamentally, should AI-generated environmental forecasts be viewed as proprietary intellectual products, public-interest resources, or hybrid assets occupying an intermediate position between these categories?

Addressing these questions requires a conceptual distinction between three interconnected layers of environmental information. The first layer comprises natural environmental facts. These include observed groundwater salinity values that exist independently of human intervention and generally fall outside conventional intellectual-property protection. The second layer consists of scientific data assets generated through systematic observation, quality control, validation, organization, and long-term monitoring programs. Although the underlying observations remain facts of nature, the structured database and associated data-management systems may embody significant intellectual effort and institutional value. The third layer encompasses AI-generated climate intelligence, including predictive models, risk indices, forecasting outputs, spatial visualizations, and decision-support tools that transform historical observations into actionable knowledge for governance and planning. These three layers differ fundamentally in terms of ownership, protectability, and societal function, yet they remain closely interconnected within modern environmental forecasting systems.

The transition from environmental observations to climate intelligence represents a fundamental shift in the nature of environmental knowledge. Historically, environmental science focused on measuring and describing natural phenomena. Artificial intelligence now enables the transformation of historical observations into predictive assets capable of influencing policy, investment, and adaptation decisions. Consequently, the object of governance is no longer merely environmental data, but climate intelligence itself. Determining who may own, control, disseminate, or restrict such intelligence constitutes one of the emerging legal and ethical challenges of the digital climate era.

The emergence of AI-generated climate intelligence has significant implications for governance in climate-vulnerable regions. Climate intelligence may be defined as predictive environmental knowledge derived through advanced analytical systems that convert historical observations into future-oriented assessments of risk and vulnerability. Such intelligence possesses considerable strategic value because it enables proactive decision-making. Governments may use climate intelligence to allocate resources, design adaptation programs, and prioritize infrastructure investments. Water managers may employ predictive tools to identify vulnerable aquifers. Development agencies may utilize forecasts to support resilience-building initiatives. Communities may depend upon early-warning information to safeguard livelihoods and public health.

However, the growing strategic importance of climate intelligence simultaneously raises concerns regarding ownership, access, transparency, and accountability. Excessive proprietary control over environmental forecasting systems could limit access to information essential for climate adaptation and sustainable development. Conversely, the absence of intellectual-property protection may discourage investment in innovative forecasting technologies and reduce incentives for scientific and technological advancement. Balancing these competing considerations represents one of the defining governance challenges of the emerging digital-environmental era.

These issues are particularly relevant in the Global South, where climate vulnerability frequently coincides with limited technological capacity and institutional resources. In such regions, environmental intelligence often functions as a public good with direct implications for water security, food production, public health, and disaster preparedness. Restricting access to critical forecasting information may inadvertently exacerbate existing inequalities and undermine climate-justice objectives. At the same time, researchers and institutions that invest substantial resources in long-term environmental monitoring and AI-based innovation possess legitimate interests in protecting their intellectual contributions. Developing governance frameworks capable of reconciling these interests therefore represents a pressing policy challenge.

The concept of environmental algorithm governance provides a useful framework for examining these issues. Environmental algorithm governance refers to the legal, institutional, and ethical mechanisms through which AI-generated environmental intelligence is created, owned, regulated, disseminated, and applied within society. It recognizes that predictive algorithms are not merely technical instruments but increasingly function as governance tools influencing environmental decision-making and public policy. Consequently, questions of algorithm ownership and intellectual-property protection cannot be separated from broader considerations of transparency, accountability, equity, and public welfare.

Within this emerging framework, the notion of environmental algorithm jurisprudence assumes particular significance. Environmental algorithm jurisprudence seeks to understand how legal systems should regulate AI-generated environmental intelligence and determine appropriate boundaries between proprietary innovation and public-interest access. It explores whether predictive environmental systems should be treated primarily as commercial technologies, scientific infrastructures, public goods, or hybrid governance mechanisms. Importantly, it extends conventional intellectual-property discourse by incorporating principles of environmental justice, data sovereignty, climate adaptation, and sustainable development.

Against this backdrop, the present study develops an AI-governed groundwater salinity forecasting framework for the Indian Sundarbans using a multi-decadal database generated through long-term field monitoring by the authors. A Neural Autoregressive (NAR) model was employed to project seasonal groundwater salinity trends up to 2050, while a normalized salinity risk index, spatial visualization framework, and vulnerability-classification system were developed to support climate-risk assessment and groundwater governance. Beyond the forecasting exercise itself, the study critically evaluates the intellectual-property dimensions of the integrated system, examining the protectability of databases, predictive workflows, risk-classification methodologies, visualization architectures, and decision-support outputs.

By positioning groundwater salinity forecasting within the broader discourse of climate-intelligence ownership and environmental algorithm governance, this paper argues that AI-generated environmental forecasts should be viewed not merely as scientific outputs but as emerging socio-technical assets with significant legal, ethical, and governance implications. The study ultimately seeks to contribute to the development of balanced regulatory frameworks that encourage innovation while preserving equitable access to environmental knowledge. In doing so, it advances a broader theory of environmental algorithm governance capable of supporting climate adaptation, public-interest decision-making, and community resilience in an increasingly data-driven world.

2. Materials and Methods

2.1 Study Area and Site Selection

The investigation was carried out in the Indian Sundarbans, the world's largest contiguous mangrove ecosystem situated at the apex of the Bay of Bengal. The region represents one of the most climate-sensitive deltaic landscapes globally and is increasingly affected by sea-level rise, salinity intrusion, cyclonic disturbances, and freshwater scarcity.

Ten representative monitoring stations were selected across the western (Stn. 1–5) and central (Stn. 6–10) sectors of the Indian Sundarbans to capture spatial heterogeneity in hydrological conditions, anthropogenic influence, and salinity regimes (Table 1) (Mitra and Zaman, 2016; Mitra, 2020; Mitra et al., 2022; Mitra et al., 2023).

Table 1 Sampling sites at the western (Stn. 1 - 5) and central sectors (Stn. 6 - 10) in the Indian Sundarbans

Sampling site	Longitude & Latitude
Harinbari (Stn. 1)	88°04′22.88″ E; 21°46′53.07″ N
Chemaguri (Stn. 2)	88°08′49.01″ E; 21°39′42.88″ N
Sagar South (Stn. 3)	88°04′00.51″ E; 21°37′49.90″ N
Lothian island (Stn. 4)	88°19′08.47″ E; 21°39′08.04″ N
Prentice island (Stn. 5)	88°17′03.62″ E; 21°42′43.31″ N
Canning (Stn. 6)	88°41′04.43″ E; 22°19′03.20″ N
Sajnekhali (Stn. 7)	88°48′15.78″ E; 22°06′34.19″ N
Chotomollakhali (Stn. 8)	88°54′26.71″ E; 22°10′40.00″ N
Satjelia (Stn. 9)	88°52′49.51″ E; 22°05′17.86″ N
Pakhiralaya (Stn. 10)	88°48′29.00″ E; 22°07′07.23″ N

The western sector, influenced by the Hooghly estuarine system, receives substantial freshwater input but is also subjected to industrial discharges, urban runoff, port-related activities, and other anthropogenic pressures associated with the Kolkata–Haldia industrial corridor. In contrast, the central sector, dominated by the Matla estuarine system, experiences comparatively higher salinity levels and lower freshwater influence, with human activities largely restricted to small-scale tourism, aquaculture operations, and localized fishing activities. This spatial framework enabled the assessment of long-term sectoral differences in groundwater salinity dynamics and provided the basis for developing predictive climate-intelligence models.

2.2 Groundwater Salinity Monitoring and Database Development

Groundwater salinity data were generated through long-term field observations conducted between 1990 and 2020. Water samples were collected from village tube wells located in proximity to the surface-water monitoring stations to ensure representation of groundwater resources utilized by local communities for drinking and domestic purposes.

Sampling was carried out seasonally during the pre-monsoon, monsoon, and post-monsoon periods. A total of 33 observations were obtained from each station during the study period, resulting in a database comprising 330 groundwater salinity records across the ten monitoring stations. Salinity was determined following the standard procedures described by Strickland and Parsons (1972).

The resulting multi-decadal database constituted the foundational environmental dataset for the present investigation. Beyond its application in salinity assessment, the database served as a long-term scientific data asset for the development of AI-based forecasting and climate-risk evaluation frameworks.

2.3 AI-Based Groundwater Salinity Forecasting Framework

To transform historical environmental observations into predictive climate intelligence, a Neural Autoregressive (NAR) modelling framework was employed. The NAR approach was selected because of its ability to capture nonlinear temporal relationships within environmental time-series datasets and generate reliable forecasts under dynamic climatic conditions.

Annual groundwater salinity observations from 1990 to 2020 were used as the training dataset. Model calibration and validation were performed through hindcasting procedures in which historical observations were compared with model-generated outputs to evaluate forecasting performance. Prediction accuracy was assessed using standard statistical performance indicators including the coefficient of determination (R^2), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE).

Following successful validation, recursive multi-step forecasting was implemented to generate annual groundwater salinity projections for the period 2021–2050. Separate NAR models were developed for the western and central sectors of the Indian Sundarbans to account for sector-specific hydrological characteristics and salinity trends (Figs. 1a and 1b).

```python
# Neural Autoregressive (NAR) Model
# Groundwater Salinity Forecast (1990–2050)
# Corrected & Reviewer-Safe Version

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.neural_network import MLPRegressor
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_squared_error, r2_score

# 1. Load annual salinity data
data = pd.read_excel("Groundwater_Salinity.xlsx", sheet_name="Western")
years = data["Year"].values
salinity = data["Salinity"].values.reshape(-1, 1)

# 2. Normalize data
scaler = MinMaxScaler()
salinity_scaled = scaler.fit_transform(salinity)

# 3. Create NAR lagged series
def create_lagged_series(series, lag=3):
    X, y = [], []
    for i in range(lag, len(series)):
        X.append(series[i-lag:i, 0])
        y.append(series[i, 0])
    return np.array(X), np.array(y)

LAG = 3
X, y = create_lagged_series(salinity_scaled, lag=LAG)

# 4. Hindcast validation (2011–2020)
X_train, X_test = X[:-10], X[-10:]
y_train, y_test = y[:-10], y[-10:]

model = MLPRegressor(hidden_layer_sizes=(10,),
                     activation='tanh',
                     solver='adam',
                     max_iter=3000,
                     random_state=42)
```

Fig. 1a Python-Based NAR Model for Groundwater Salinity Prediction for Western Indian Sundarbans

```python
# Neural Autoregressive (NAR) Model
# Groundwater Salinity Forecast (1990–2050)
# Corrected & Reviewer-Safe Version
# Central Sector

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.neural_network import MLPRegressor
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_squared_error, r2_score

# 1. Load annual salinity data
data = pd.read_excel("Groundwater_Salinity.xlsx", sheet_name="Central")
years = data["Year"].values
salinity = data["Salinity"].values.reshape(-1, 1)

# 2. Normalize data
scaler = MinMaxScaler()
salinity_scaled = scaler.fit_transform(salinity)

# 3. Create NAR lagged series
def create_lagged_series(series, lag=3):
    X, y = [], []
    for i in range(lag, len(series)):
        X.append(series[i-lag:i, 0])
        y.append(series[i, 0])
    return np.array(X), np.array(y)

LAG = 3
X, y = create_lagged_series(salinity_scaled, lag=LAG)

# 4. Hindcast validation (2011–2020)
X_train, X_test = X[:-10], X[-10:]
y_train, y_test = y[:-10], y[-10:]

model = MLPRegressor(hidden_layer_sizes=(10,),
                     activation='tanh',
                     solver='adam',
                     max_iter=3000,
                     random_state=42)
```

Fig. 1b Python-Based NAR Model for Groundwater Salinity Prediction for Central Indian Sundarbans

2.4 Climate-Intelligence Generation and Risk Classification

The forecasting outputs generated by the NAR framework were subsequently transformed into climate-intelligence products through a structured risk-assessment procedure. Predicted salinity values were normalized to a 0–1 scale to develop a Groundwater Salinity Risk Index (GSRI), enabling comparison among stations, sectors, and forecast years.

Based on index values, groundwater vulnerability was classified into predefined risk categories representing low, moderate, high, and critical salinity exposure. Spatial heatmaps and decision-support visualizations were generated to facilitate interpretation of future groundwater conditions and to identify areas requiring priority intervention under climate-adaptation planning.

This integrated workflow converted long-term environmental observations into actionable climate intelligence by combining environmental monitoring, artificial intelligence, risk indexing, and decision-support visualization within a single analytical framework.

2.5 Intellectual Property Assessment of the Climate-Intelligence Framework

In addition to environmental forecasting, the study evaluated the intellectual-property dimensions of the integrated climate-intelligence system. Assessment focused on four principal components: (i) the curated groundwater salinity database generated through long-term field monitoring, (ii) the AI-based forecasting workflow, (iii) the salinity-risk classification methodology, and (iv) the visualization and decision-support architecture.

Each component was examined with respect to potential applicability of copyright protection, software-related intellectual-property rights, database protection mechanisms, trade-secret provisions, and patentability criteria. Particular emphasis was placed on distinguishing natural environmental observations from scientific data assets and AI-generated climate intelligence, thereby establishing a framework for evaluating ownership, governance, and public-access considerations associated with environmental forecasting systems.

3.Results

3.1. Long-Term Trends in Western Sector Groundwater Salinity (1990–2020)

The groundwater salinity in the western sector exhibits a consistent rise, though the rate of increment is lower compared to the data of pre-monsoon season. In this season, the groundwater salinity increased from ~0.7 PSU in 1990 to ~2.7 PSU during 2020.

The salinity of the groundwater during the post-monsoon season also exhibits a rising trend with values increasing from ~1.45 PSU in 1990 to ~3.5 PSU in 2020. The year-to-year pattern remains coherent, with marginal dips observed only in isolated years, reinforcing a long-term structural shift rather than a cyclic or temporary change. Collectively, the western sector data show that all three seasons have transitioned to significantly more saline conditions, with the pre-monsoon season emerging as the most vulnerable. Fig. 2 represents the temporal variations of groundwater salinity as the average of five stations (Stn. 1 – Stn. 5) in the western Indian Sundarbans, namely Harinbari, Chemaguri, Sagar South, Lothian island and Prentice island.

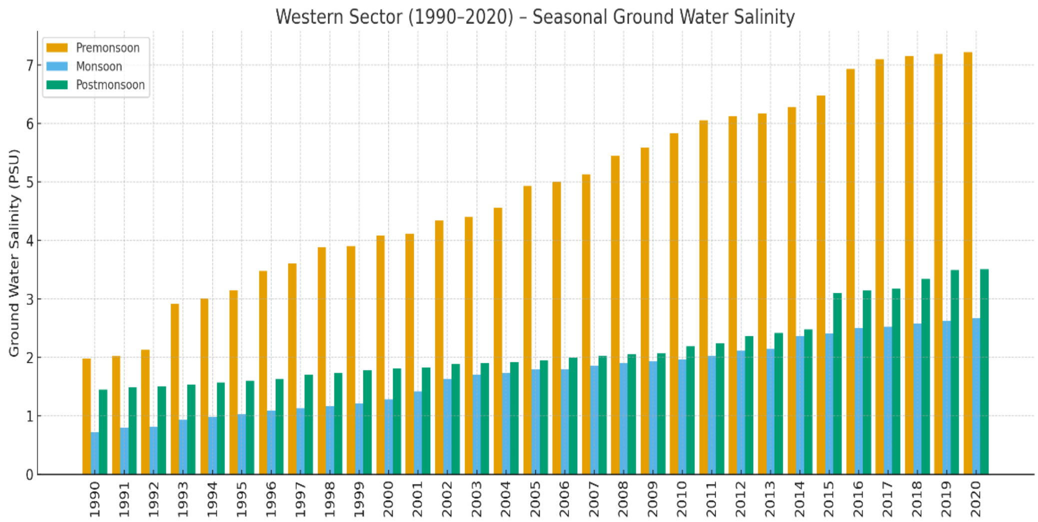

Fig. 2 Long-Term Seasonal Variability of Groundwater Salinity in the western Indian Sundarbans (1990–2020)

3.2. Long-Term Trends in Central Sector Groundwater Salinity (1990–2020)

The central sector shows an even steeper and more alarming increase in groundwater salinity, starting from substantially higher baseline values. Pre-monsoon salinity rose from ~5.0 PSU in 1990 to ~10.25 PSU by 2020, effectively doubling over three decades. Given that the central sector lies closer to the saline-intruded Matla estuary and has weaker freshwater buffering, this rapid increase is consistent with geomorphological and hydrodynamic expectations.

Monsoon salinity in the central sector increased from ~3.7 PSU to ~5.7 PSU between 1990 and 2020. Although the annual rate of increase is lower than in the pre-monsoon, the absolute values remain significantly higher than the western sector. This sustained elevation in monsoon salinity suggests that the monsoon's natural dilution effect is increasingly inadequate to counteract estuarine salinity intrusion, most probably due to sea level rise of the Bay of Bengal and complete cut-off of the freshwater discharge from the upland area due to massive siltation (Chaudhuri and Choudhury, 1994; Hazra, et al. 2002; Mitra, et al. 2009; Banerjee, 2013; Roy et al., 2016; Mitra and Zaman, 2016; Mitra, et al., 2023).

Post-monsoon salinity in the central sector increased from ~4.5 PSU in 1990 to ~6.5 PSU in 2020, again maintaining consistently higher values than the western counterpart. The observed acceleration in post-monsoon salinity after 2012 indicates altered hydrodynamic retention, possibly driven by a series of high-intensity cyclones (Aila in 2009, Phailin in 2013, Bulbul in 2019, Amphan in 2020), embankment breaches, and the consequent mixing of saline water into shallow aquifers (Fig. 3).

Fig. 3 Breaching of Earthen–Brick Embankment in the Indian Sundarbans leads to saline water intrusion

We observed that the central sector demonstrates a high-groundwater salinity regime with rapid progression, with annual salinity levels consistently exceeding those of the western sector across all seasons. This underscores the heightened vulnerability of the central region, where tidal forcing is stronger and freshwater recharge is weaker. The central sector maintains salinity levels that are approximately 2–3 times higher than the western sector during most years. This significant sectoral variation highlights the influence of the hypersaline Matla estuary in the central sector. Fig. 4 highlights the mean values of groundwater salinity of five stations (Stn. 6 – Stn. 10) across three seasons.

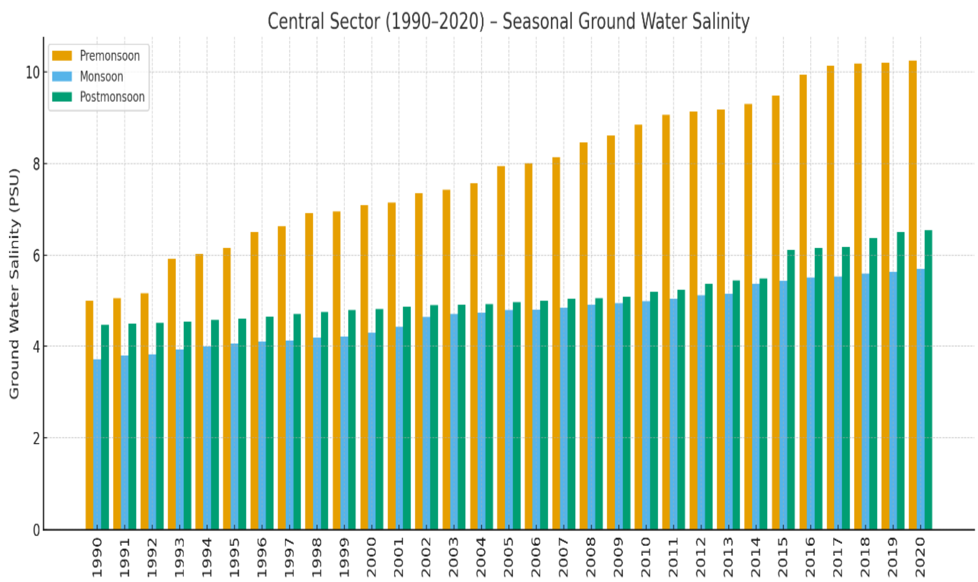

Fig. 4 Mean seasonal variation of groundwater salinity in the central sector of Indian Sundarbans during the study phase of 1990–2020

3.3. Forecasting of Groundwater Salinity (2021–2050) in the Western Sector

The climate-intelligence outputs generated by the NAR framework indicate that groundwater salinity in the western Indian Sundarbans is expected to increase considerably in all three seasons, and this rise is projected to continue steadily up to the year 2050.

3.3.1. Pre-monsoon Forecast

The highest increment of the groundwater salinity is projected for the pre-monsoon season, with salinity increasing from about 7.2 PSU in 2020 to around 17–18 PSU by 2050 as shown in Fig. 5. These levels fall close to the brackish water range, indicating serious deterioration of the groundwater for drinking purpose.

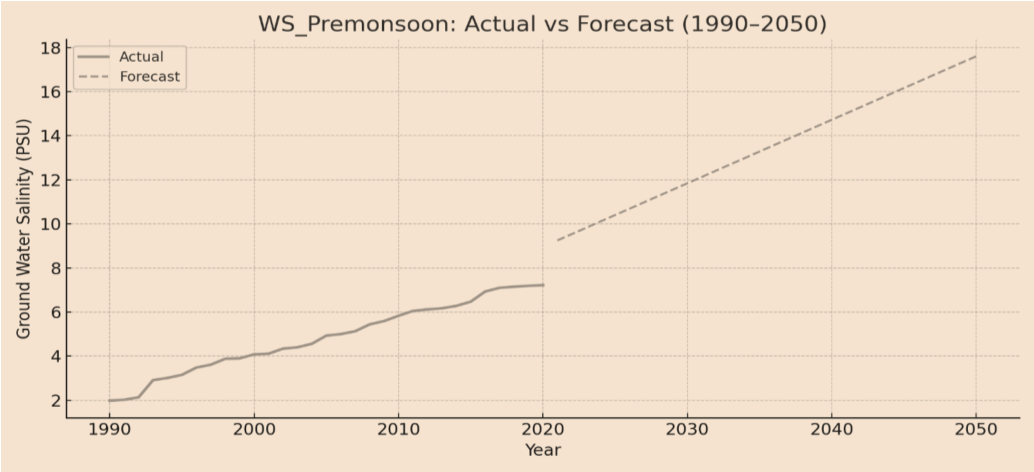

Fig. 5 Western Sector (WS) Pre-monsoon Groundwater Salinity: Actual vs Forecast (1990–2050)

3.3.2. Monsoon Forecast

Monsoon salinity is expected to increase from about 2.7 PSU in 2020 to nearly 4.7 PSU by 2050 (Fig. 6). Even though this remains lower than the other seasons, the rise is significant and shows that heavy rainfall will no longer be enough to restore groundwater salinity back to previous conditions.

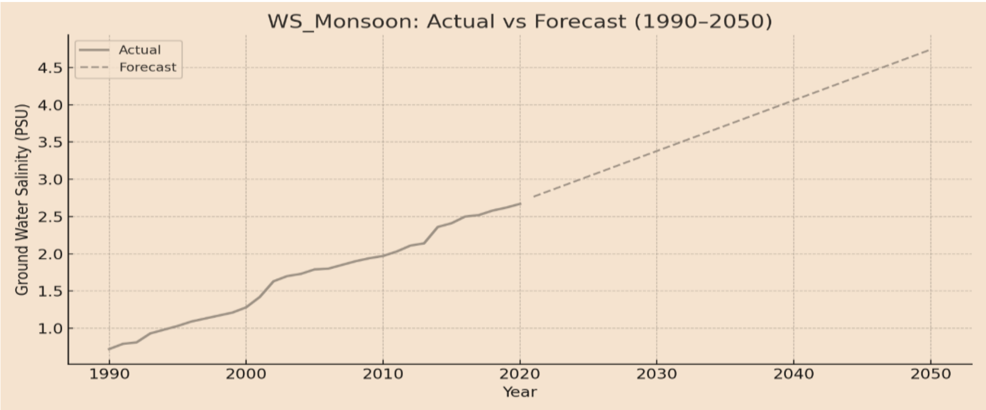

Fig. 6 Western Sector (WS) Monsoon Groundwater Salinity: Actual vs Forecast (1990–2050)

3.3.3. Post-monsoon Forecast

The groundwater salinity during the post-monsoon phase is projected to increase to around 5.8 PSU by 2050, showing that salts will continue to build up even after the monsoon ends (Fig. 7). Thus, the projections for the western sector indicate that groundwater conditions may change from slightly brackish to clearly saline by the middle of this century.

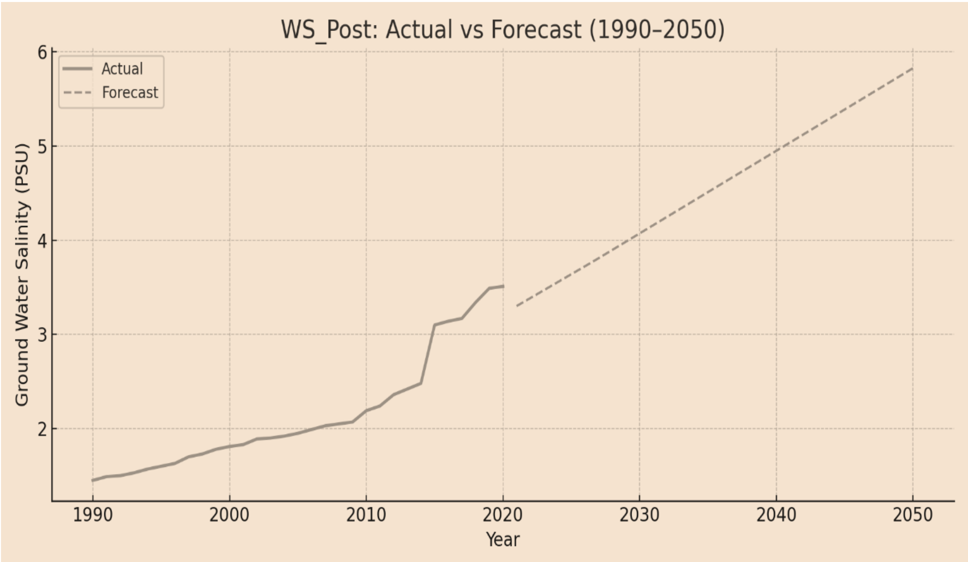

Fig. 7 Western Sector (WS) Post-monsoon Groundwater Salinity: Actual vs Forecast (1990–2050)

3.4. Forecasting of Groundwater Salinity (2021–2050) in the Central Sector

Climate-intelligence projections generated by the NAR framework indicate a substantial increase in groundwater salinity across the Central Sector during the forecast period.

3.4.1. Pre-monsoon Forecast

Groundwater salinity during the pre-monsoon period is expected to rise from about 10.2 PSU in 2020 to nearly 20 PSU by 2050 (Fig. 8). This shows a sharp increase in salt content over time. At such high salinity, the water will not be safe for drinking and may seriously affect farming, soil quality, and the long-term health of local groundwater sources.

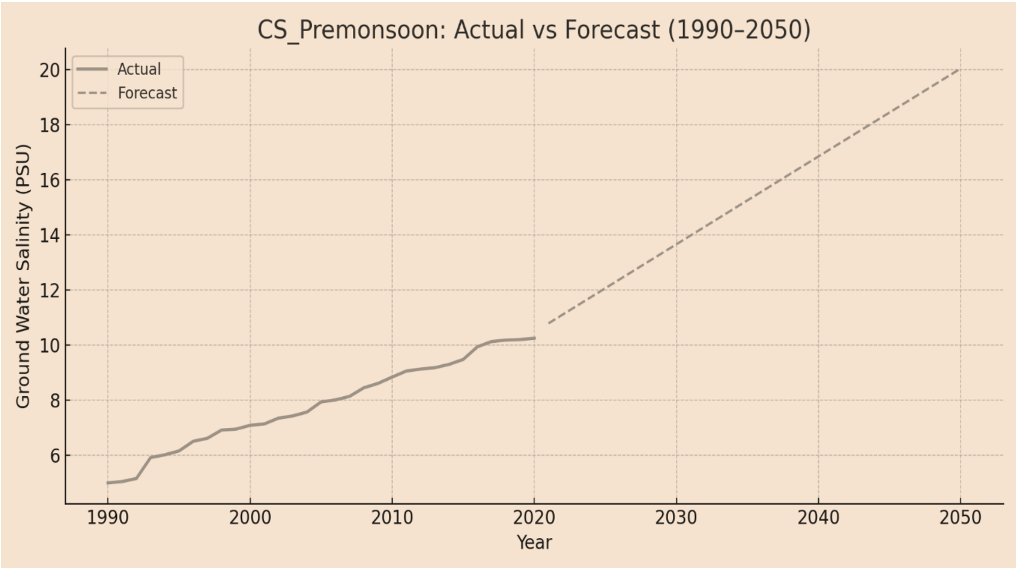

Fig. 8 Central Sector (CS) Pre-monsoon Groundwater Salinity: Actual vs Forecast (1990–2050)

3.4.2. Monsoon Forecast

The value forecasts an increase from about 5.7 PSU in 2020 to nearly 11 PSU by 2050 (Fig. 9)

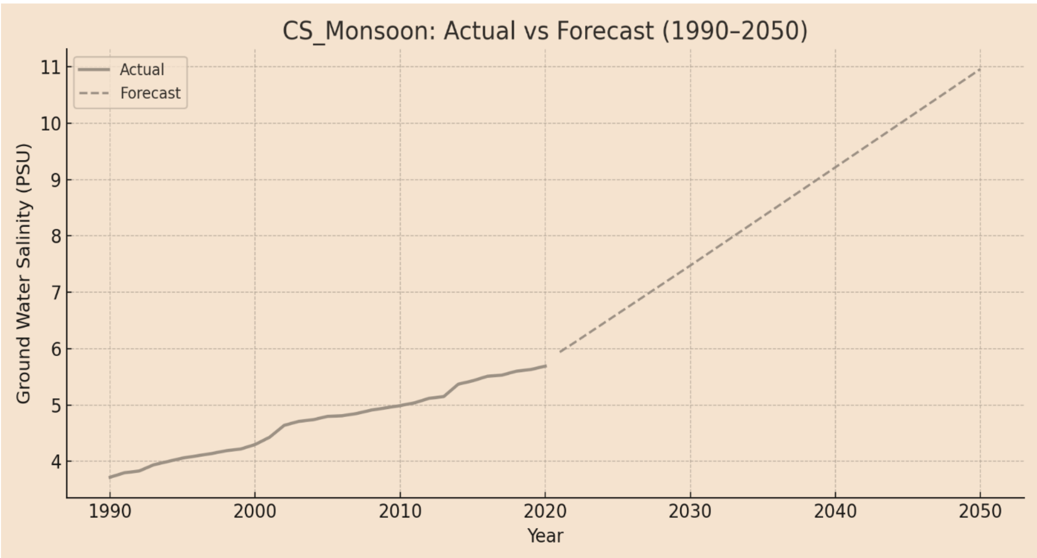

Fig. 9 Central Sector (CS) Monsoon Groundwater Salinity: Actual vs Forecast (1990–2050)

3.4.3. Post-monsoon Forecast

The forecast value touched to approximately 12.7 PSU by 2050 (Fig. 10).

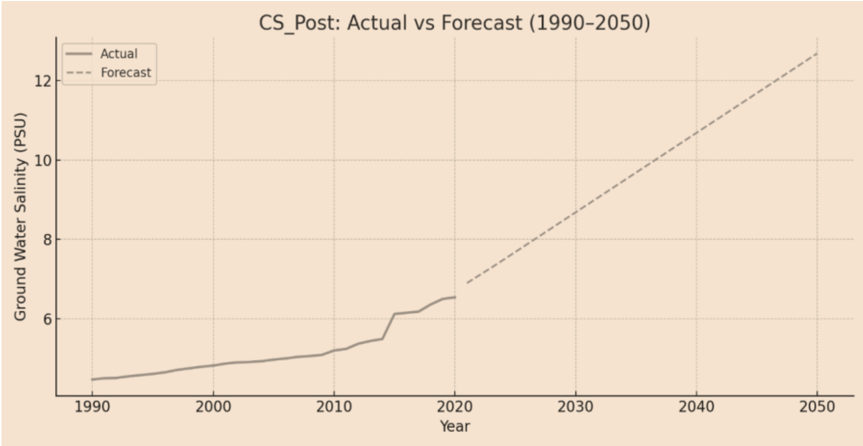

Fig. 10 Central Sector (CS) Post-monsoon Groundwater Salinity: Actual vs Forecast (1990–2050)

3.5. From Environmental Data to Climate Intelligence

The integration of long-term groundwater salinity observations (1990–2020) with the Neural Autoregressive (NAR) forecasting framework transformed historical environmental measurements into predictive climate-intelligence outputs. The forecasting system generated year-wise groundwater salinity projections up to 2050, enabling the identification of future vulnerability trends across the western and central sectors of the Indian Sundarbans. Unlike conventional environmental monitoring, which primarily documents past and present conditions, the AI-based framework produced forward-looking information capable of supporting anticipatory groundwater management and climate-adaptation planning.

The climate-intelligence outputs revealed a progressive increase in groundwater salinity across all seasons and sectors, with the central sector exhibiting consistently higher vulnerability than the western sector. The integration of forecasting, risk assessment, and spatial interpretation converted field-generated environmental observations into actionable decision-support information. These results demonstrate the potential of artificial intelligence to transform long-term environmental datasets into strategic climate intelligence for water-resource governance in climate-sensitive coastal regions.

4. Discussion

The present study reveals a progressive and accelerating increase in groundwater salinity across the Indian Sundarbans over the last three decades and projects a continuation of this trend up to 2050. The observed patterns reflect the combined influence of climate change, declining freshwater inflow, estuarine dynamics, geomorphological alterations, and anthropogenic interventions. Beyond their hydrological significance, however, the results demonstrate how long-term environmental observations can be transformed through artificial intelligence into predictive climate intelligence capable of informing future groundwater governance and climate-adaptation planning.

A central contribution of the present investigation lies in illustrating the transition from environmental observation to climate-intelligence generation. Historically, environmental science has focused on measuring and documenting natural phenomena. Groundwater salinity values collected from the Indian Sundarbans between 1990 and 2020 represent such environmental observations and provide direct evidence of changing hydrographic conditions in one of the world's most climate-sensitive deltas. These observations constitute Natural Environmental Facts that describe the state of coastal aquifers under varying seasonal, hydrological, and climatic conditions. By themselves, such observations are indispensable for scientific understanding but remain primarily descriptive in nature.

The integration of long-term field-generated salinity records with Neural Autoregressive (NAR) modelling transformed these observations into predictive climate intelligence. Through machine-learning-based forecasting, historical measurements were converted into future-oriented assessments of groundwater vulnerability extending up to 2050. The resulting outputs include salinity projections, seasonal vulnerability classifications, and risk-based visualizations capable of supporting anticipatory decision-making. Consequently, the present study demonstrates the progression from Natural Environmental Facts to Scientific Data Assets and ultimately to AI-Generated Climate Intelligence. The structured database developed through long-term monitoring represents a valuable scientific asset, while the forecasting architecture, risk indices, and heatmaps constitute climate-intelligence products capable of influencing policy, investment, and adaptation strategies.

This transition has important implications for environmental governance. Historically, governance frameworks focused on regulating access to environmental resources and environmental information. Increasingly, however, decision-making depends upon predictive intelligence generated through advanced analytical systems. Climate adaptation, water-resource allocation, infrastructure planning, and disaster preparedness are becoming dependent upon future-oriented environmental knowledge. The object of governance is therefore shifting from environmental data alone to climate intelligence itself. Understanding this transformation is essential for evaluating the role of artificial intelligence in environmental management and for assessing the legal, ethical, and policy implications associated with AI-generated environmental forecasts.

The long-term salinity records demonstrate a clear spatio-temporal pattern across the Indian Sundarbans. In both western and central sectors, pre-monsoon salinity remains consistently higher than monsoon and post-monsoon values. This pattern reflects maximum evaporation rates, reduced freshwater recharge, and enhanced saline intrusion during the dry season. Monsoon salinity remains comparatively lower because rainfall provides seasonal dilution of groundwater reserves. Post-monsoon salinity occupies an intermediate position but has increased steadily throughout the study period, indicating incomplete removal of accumulated salts following the monsoon season.

The persistence of increasing salinity across all seasons suggests that natural buffering mechanisms are gradually weakening. Historically, monsoonal rainfall functioned as an effective recharge mechanism capable of restoring groundwater quality following periods of saline stress. The results indicate that this buffering function is becoming progressively less effective. Rising monsoon salinity values demonstrate that rainfall alone is no longer sufficient to counterbalance saline intrusion. Similarly, increasing post-monsoon salinity suggests declining flushing efficiency and prolonged retention of saline water within shallow aquifers. Together, these trends indicate a transition from a seasonally regulated system towards a chronically saline hydrological regime.

The contrasting behavior of the western and central sectors provides important insights into the role of estuarine forcing in groundwater salinization. The western sector has historically benefited from freshwater influence associated with the Hooghly estuary. The continued connection between the Hooghly River and the freshwater discharge originating from the Gangotri glacier has traditionally maintained a relatively low-salinity environment compared with other regions of the Sundarbans (Mitra, et al. 2011; Zaman et al. 2013; Mitra and Zaman 2016; Trivedi et al. 2016; Dhar et al. 2021; Mitra et al. 2021; Mitra and Zaman 2021; Mitra et al. 2022). Nevertheless, the observed increase in groundwater salinity across all seasons indicates that this freshwater buffering capacity is weakening.

Several factors contribute to this deterioration. Freshwater abstraction upstream, channel modification, sedimentation, and altered river hydrology have reduced freshwater discharge reaching the lower estuarine system. Reduced river flow weakens the hydraulic barrier that traditionally limited saline intrusion into groundwater reserves. At the same time, sea-level rise increases hydrostatic pressure along the coast, facilitating landward movement of saline water. The combined effect is a gradual shift in the salinity balance of coastal aquifers.

The situation is considerably more severe in the central sector. Groundwater salinity values in this region were already higher than those of the western sector during the early 1990s and have continued to increase at a substantially faster rate. The central sector is strongly influenced by the Matla estuary, a hypersaline tidal system characterized by limited freshwater input and strong tidal forcing. Unlike the Hooghly estuary, the Matla River lacks substantial upstream freshwater support and remains highly susceptible to marine influence. Consequently, saline water penetrates farther inland and exerts greater influence on both surface-water and groundwater systems.

Geomorphological conditions further enhance vulnerability in the central sector. The Matla estuary contains wide tidal channels directly connected to the Bay of Bengal. Freshwater inflow remains limited, while tidal exchange is intense. Historical records suggest that progressive siltation of distributary channels has reduced freshwater connectivity since at least the fifteenth century (Chaudhuri and Choudhury 1994). Reduced freshwater discharge, combined with strong tidal forcing, creates conditions highly favorable for saline intrusion. These characteristics explain why salinity values in the central sector consistently exceed those observed in the western region.

Cyclonic disturbances constitute an additional driver of groundwater salinization throughout the Sundarbans. Major cyclonic events such as Aila (2009), Phailin (2013), Bulbul (2019), and Amphan (2020) caused extensive breaching of embankments and direct intrusion of saline water into agricultural lands, freshwater ponds, and shallow aquifers. The effects of such events extend far beyond the immediate period of inundation. Salts deposited during cyclonic flooding may persist within soils and groundwater systems for years, thereby contributing to long-term salinity accumulation. Repeated cyclone impacts therefore accelerate the transition towards a more saline groundwater regime and reduce the effectiveness of natural recovery processes.

The forecasting results indicate that these trends are likely to continue throughout the coming decades. The NAR model projects substantial increases in groundwater salinity across both sectors and all seasons. Pre-monsoon salinity in the western sector is projected to approach 17–18 PSU by 2050, while values in the central sector may reach approximately 20 PSU. Similar increases are projected for monsoon and post-monsoon conditions. These forecasts suggest that seasonal distinctions, although still evident, will become progressively less important as salinity increases throughout the year. Such projections indicate that groundwater resources in large parts of the Sundarbans may transition from slightly brackish conditions to persistent saline conditions within a few decades.

The climate-intelligence outputs generated by the forecasting framework provide important decision-support information. Heatmap-based vulnerability assessments reveal that the central sector, particularly during the pre-monsoon season, represents the most critical risk zone. The normalized Salinity Risk Index further highlights spatial and temporal patterns of vulnerability. These visualizations transform complex environmental datasets into accessible information capable of supporting policy formulation and adaptation planning. Such outputs demonstrate how AI-generated climate intelligence can bridge the gap between environmental monitoring and practical governance.

The implications of rising groundwater salinity extend beyond hydrology. Freshwater scarcity directly affects drinking-water availability, agricultural productivity, public health, and ecosystem resilience. Saline groundwater reduces crop yields, accelerates soil degradation, and increases the vulnerability of rural communities. The projected salinity increases therefore represent a multidimensional challenge with ecological, economic, and social consequences. Adaptation strategies must consequently address not only hydrological conditions but also broader issues of livelihood security and community resilience.

Several adaptation measures emerge from the present analysis. Community-scale freshwater harvesting systems can reduce dependence on saline groundwater reserves. Rainwater harvesting ponds, recharge pits, and managed aquifer recharge systems may enhance freshwater availability during dry seasons. Conservation and restoration of mangrove ecosystems can strengthen natural coastal defenses and reduce saline ingress. Innovative approaches such as geo-jute-based permeable embankments combined with halophytic vegetation, including Suaeda maritima and Salicornia brachiata, may enhance aquifer recharge while reducing substrate salinity. In highly vulnerable regions, desalination technologies and real-time monitoring systems based on Internet of Things (IoT) sensors may provide additional support for water-resource management.

An important dimension of the present study concerns the ownership and governance of AI-generated climate intelligence. The groundwater salinity observations analysed here were generated through long-term field monitoring conducted by the research team. Although the observed salinity values themselves represent naturally occurring environmental phenomena and therefore remain Natural Environmental Facts, the structured database developed through decades of monitoring constitutes a Scientific Data Asset. Furthermore, the forecasting workflow, vulnerability classifications, salinity-risk indices, and visualization products represent AI-Generated Climate Intelligence created through analytical and technological innovation.

This distinction raises important questions regarding ownership, accessibility, transparency, and public-interest use. Climate-adaptation planning increasingly depends upon predictive environmental information. Restricting access to such intelligence could limit the ability of governments and communities to respond effectively to climate-related threats. At the same time, the development of sophisticated forecasting systems requires substantial investments in scientific monitoring, data management, algorithm development, and computational infrastructure. The resulting climate-intelligence products therefore embody significant intellectual and technological effort.

The challenge lies in balancing innovation with accessibility. Equally important is the issue of algorithmic transparency. As AI-generated forecasts become integrated into environmental decision-making, stakeholders must be able to evaluate the reliability, reproducibility, and limitations of predictive systems. Transparent model architecture, validation procedures, and uncertainty reporting are therefore essential components of responsible climate-intelligence governance. Without adequate transparency, confidence in AI-assisted environmental planning may be compromised, particularly when forecasting outputs influence critical decisions concerning drinking-water security and public-resource allocation.

Excessive proprietary control over environmental forecasting systems may conflict with broader societal objectives related to climate resilience and environmental justice. Conversely, complete absence of intellectual-property recognition may reduce incentives for developing innovative climate-intelligence platforms. A balanced governance framework is therefore required, one that recognizes scientific innovation while ensuring equitable access to information essential for public welfare. Such an approach is particularly important in climate-vulnerable regions of the Global South, where predictive environmental intelligence increasingly functions as a critical public resource.

The present study therefore contributes not only to understanding groundwater salinity dynamics in the Indian Sundarbans but also to the broader discourse on environmental algorithm governance. By demonstrating how long-term environmental observations can be transformed into climate intelligence through artificial intelligence, the study highlights the growing importance of predictive knowledge in environmental management. Future governance frameworks will need to address not only environmental resources but also the ownership, dissemination, and ethical use of climate intelligence itself. As climate change intensifies and artificial intelligence becomes increasingly embedded within environmental decision-making, the governance of climate intelligence may emerge as one of the defining challenges of twenty-first-century environmental policy.

The Indian Sundarbans serves in this study as a real-time experimental bed, and provides more than a regional case study of groundwater salinization. They offer a real-world example of how long-term environmental observations can be transformed into predictive climate intelligence through artificial intelligence. As climate risks intensify worldwide, similar forecasting systems will increasingly shape adaptation strategies, infrastructure investments, and resource-governance decisions. The future challenge will not be limited to generating accurate forecasts but will also involve determining how climate intelligence is owned, shared, regulated, and utilized for the collective benefit of society. In this context, the governance of climate intelligence may emerge as one of the defining environmental-policy challenges of the twenty-first century.

References

1. Alvarez, M.D.P., Carol, E., Dapeña, C. (2015). The role of evapotranspiration in the groundwater hydrochemistry of an arid coastal wetland (Península Valdés, Argentina). Science of the Total Environment, 506-507, 299-307.
2. Banerjee, K. (2013). Decadal Change in the Surface Water Salinity Profile of Indian Sundarbans: A Potential Indicator of Climate Change. Journal of Marine Science: Research & Development, S11. DOI: 10.4172/2155-9910.S11-002.
3. Chaudhuri, A. B., & Choudhury, A. (1994). Mangroves of the Sundarbans (Vol. 1: India). IUCN; IUCN Southeast Asia Regional Office.
4. Clayton, S., Devine-Wright, P., Stern, P. et al. (2015). Psychological research and global climate change. Nature Clim Change 5, 640–646. https://doi.org/10.1038/nclimate2622.

5. Dhar I, Sengupta G, Biswas S, Sinha M, Mitra A. (2021) Salinity: A Major environmental factor in sustainability of the Blue Carbon. Journal of Mechanics of Continua and Mathematical Sciences, 16 (11), 34-42. https://doi.org/10.26782/jmcms.2021.11.00004.
6. Eissa, A.E., Zaki, M.M. (2011). The impact of global climatic changes on the aquatic environment. Procedia Environmental Science, 4, 251–259.
7. Hazra S, Ghosh T, DasGupta R, Sen G. (2002). Sea Level and associated changes in the Sundarbans. Science and Culture, 68 (9-12), 309-321.
8. Hornsey, M. J., Harris, E. A., Bain, P. G., & Fielding, K. S. (2016). Meta-analyses of the determinants and outcomes of belief in climate change. Nature Climate Change, 6(6), 622–626. https://doi.org/10.1038/nclimate2943.
9. Mishra, B.K., Kumar, P., Saraswat, C., Chakraborty, S., Gautam, A. (2021) Water Security in a Changing Environment: Concept, Challenges and Solutions. Water, 13, 490. https://doi.org/10.3390/w13040490.
10. Mitra A, Banerjee K, Sengupta K. (2011) Impact of AILA, a tropical cyclone on salinity, pH and dissolved oxygen of an aquatic sub-system of Indian Sundarbans. National Academy of Science Letters, India, 81 (Part II), 198 - 205.
11. Mitra A, Gangopadhyay A, Dube A, Andre CKS, Banerjee K. (2009) Observed changes in water mass properties in the Indian Sundarbans (Northwestern Bay of Bengal) during 1980 - 2007. Current Science, 97 (10), 1445-1452.
12. Mitra A, Zaman S, Pramanick P. (2022) Blue Economy in Indian Sundarbans: Exploring Livelihood Opportunities. Springer ISBN 978-3-031-07908-5 (e-Book), XIV: pp. 403 DOI: https://doi.org/10.1007/978-3-031-07908-5.
13. Mitra A, Zaman S, Pramanick P. (2023) Climate Resilient Innovative Livelihoods in Indian Sundarban Delta. Springer, Hardcover ISBN 978-3-031-42632-2, eBook ISBN 978-3-031-42633-9, XII, pp. 297. DOI: https://doi.org/10.1007/978-3-031-42633-9.
14. Mitra A, Zaman S. (2016) Basics of Marine and Estuarine Ecology; Publisher Springer India, ISBN 978-81-322-2707-6, pp. 481.
15. Mitra A, Zaman S. (2021) Estuarine Acidification: Exploring the Situation of Mangrove Dominated Indian Sundarban Estuaries. Springer, Chem, e-Book ISBN 978-3-030-84792-0, XII, pp. 402, DOI: https://doi.org/10.1007/978-3-030-84792-0.
16. Mitra A. (2013) Sensitivity of Mangrove Ecosystem to Changing Climate. Published by Springer New Delhi Heidelberg New York Dordrecht London, ISBN-10: 8132215087; ISBN-13: 978-8132215080. ISBN 978-81-322-1509-7 (eBook).
17. Mitra A. (2020) Mangrove Forests in India: Exploring Ecosystem Services. Springer eBook ISBN 978-3-030-20595-9 XV: pp. 361. DOI: https://doi.org/10.1007/978-3-030-20595-9
18. Mitra S, Chanda A, Das S, Ghosh T, Hazra S. (2021) Salinity Dynamics in the Hooghly-Matla Estuarine System and Its Impact on the Mangrove Plants of Indian Sundarbans. In: Sundarbans Mangrove Systems, published by CRC Press, pp. 24. DOI: 10.1201/9781003083573-15.
19. Rahman MM et al. (2019) Salinization in large river deltas: drivers, impacts and socio-hydrological feedbacks. Water Security, 6, 100024.
20. Ranjan P, Kazama S, Sawamoto M, Sana A. (2009) Global scale evaluation of coastal fresh groundwater resources. Ocean & Coastal Management, 52 (3-4), 197-206.
21. Roessig, J.M., Woodley, C.M., Cech, J.J., Hansen, L.J. (2004). Effects of global climate change on marine and estuarine fishes and fisheries. Reviews in Fish Biology and Fisheries, 14, 251–275.
22. Roy, S., Kumar, V., Manna, R.K., Suresh, V.R. (2016). Sundarbans mangrove deltaic system – An overview of its biodiversity with special reference to fish diversity. Journal of Applied and Natural Science, 8 (2), 1090 - 1099.
23. Sarma, B., Sarma, A.K., Singh, V.P. (2013). Optimal ecological management practices (EMPs) for minimizing the impact of climate change and watershed degradation due to urbanization. Water Resource Management, 27(11), 4069-4082.
24. Scavia D. et al. (2002). Climate change impacts on US coastal and marine ecosystems. Estuaries, 25, 149–164.
25. Strickland JDH, Parsons TR. (1972). A Practical Hand Book of Seawater Analysis. Fisheries Research Board of Canada Bulletin, 157, 2nd Edition, pp. 310.
26. Trivedi, S., Zaman, S., Ray Chaudhuri, T., Pramanick, P., Fazli, P., Amin, G., Mitra, A. (2016). Inter-annual variation of salinity in Indian Sundarbans. Indian Journal of Geo-Marine Science, 45 (3), 410 - 415.
27. Weber, E.U. (2010) What shapes perceptions of climate change? WIREs Climate Change, 1: 332-342. DOI: https://doi.org/10.1002/wcc.41.
28. Zaman, S., Bhattacharyya, S.B., Pramanick, P., Raha, A.K., Chakraborty, S., Mitra, A. (2013). Rising water salinity: A threat to mangroves of Indian Sundarbans. In: Water Insecurity: A Social Dilemma (Edited by Md. Anwarul Abedin, Umma Habiba and Rajib Shaw) published by Emerald Group Publishing Limited (ISBN: 9781781908822).