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Climate, Education, and AI

Current challenges and emerging opportunities

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Contents

Abbreviations and acronyms

AI	Artificial Intelligence
AQI	Air Quality Index
DRR	Disaster risk reduction
EMIS	Education management information systems
GADRRES	Global Alliance for Disaster Risk Reduction and Resilience in the Education Sector
GLoSI	Global Library of School Infrastructure
HVAC	Heating, Ventilation, and Air Conditioning
IDRC	International Development Research Centre
IoT	Internet of Things
IVR	Interactive Voice Response
LMICs	Low- and middle-income countries
ML	Machine learning
NLP	Natural Language Processing
PM	Particulate matter
SAMHE	Schools' Air Monitoring for Health and Education
UNDRR	United Nations Office for Disaster Risk Reduction
WMO	World Meteorological Organisation

Key definitions

Artificial Intelligence (AI): A field of computer science, particularly encompassing machine learning, used to extract patterns from large, complex datasets. In this document, AI refers to tools that can forecast extreme weather, manage resources, and predict environmental hazards to enable timely and effective responses.

- **Composite Risk Indices (CRIs)**: AI-based models that combine multiple data layers, such as flood, storm, and landslide risk, with school-specific data (e.g., building attributes) to create a school-level risk ranking.
- **Computer vision**: A field of AI that enables computers to interpret and understand visual information from images or videos.
- **Deep learning**: An advanced type of machine learning that uses neural networks. It is cited as central to flood forecasting and management, as well as to predict other extreme weather events such as storms and cyclones.
- **Machine learning (ML)**: A subset of artificial intelligence that involves training models on large amounts of data to learn complex relationships and make predictions.
- **Natural Language Processing (NLP)**: A form of AI that enables computers to process and understand human language.

Climate resilience (in education): The ability of an education system to anticipate, mitigate, and respond to climate-related disruptions, such as natural disasters, extreme heat, and pollution. This involves building stronger, safer, and more resilient education systems to protect student safety, well-being, and educational continuity.

Impact-based warnings: Forecasts for hazards like floods, heat, or poor air quality that are directly linked to specific, actionable responses. These warnings are designed to trigger routine operational decisions at the school or district level, such as adjusting timetables or relocating classes.

Passive measures/Adaptations: Low-cost, non-mechanical interventions used to make school infrastructure more resilient to climate impacts, particularly extreme heat. Examples include installing ceiling boards, using reflective roofing, adding shading, and improving natural ventilation.

Trigger-action playbook / Matrix: A decision-aid tool that links specific hazard alerts (e.g., a heatwave warning, a high AQI forecast) to a set of clear, pre-defined responsive actions for school leaders and district officials. This ensures that AI-generated insights are translated into timely, practical action.

Executive summary

Climate and environmental hazards are increasingly disrupting education systems, threatening decades of development gains in low- and middle-income countries (LMICs). Schools face both acute shocks, such as floods, storms, and wildfires, and chronic stressors like extreme heat and air pollution, all of which can impair learner attendance, well-being, and learning outcomes. While Artificial Intelligence (AI) is already widely used for climate forecasting, environmental monitoring, and disaster management, leveraging its potential to strengthen education system resilience remains largely untapped.

This think piece examines how AI-enabled climate and environmental hazard models can be adapted to build safer, more resilient education systems. Drawing on a robust evidence base from climate-related AI applications and emerging pilots in education, the report highlights how existing technologies can be integrated into planning, infrastructure, and school operations to anticipate risk, protect learning time, and support continuity in crises. It also provides actionable recommendations on emerging opportunities for those working at the intersection of education, climate, and technology.

Key findings include:

- AI-based models for forecasting acute weather events such as floods, storms, and droughts are mature and widely deployed in climate and disaster response sectors. These models can be repurposed to identify at-risk schools, guide safe siting and resilient construction, and support emergency preparedness.
- Extreme heat is an emerging, climate-related emergency affecting learning. AI-enabled temperature prediction models, combined with low-cost sensors, can help ministries map overheating risk, target passive cooling retrofits, and design heat-aware timetables and exam schedules.
- Pollution forecasting systems, already used to reduce health impacts in urban areas, can be adapted to trigger school-level alerts, enabling rapid, low-tech actions that protect children from acute exposure and prevent health-related absences.
- There is a significant evidence gap regarding how AI-enabled forecasts translate into improved educational outcomes. Likewise,

there is minimal integration of climate intelligence into routine education sector systems.

Key recommendations and emerging opportunities include:

- AI tools for climate forecasting and risk management are now mature enough to inform education sector planning, but their value depends on effective integration into education management information systems (EMISs), construction standards, and school operations.
- In particular, three promising applications stand out:
    1. AI-enabled risk indices to guide safer school siting and infrastructure retrofits
    2. Heat-stress mapping to target low-cost adaptations and inform heat-aware timetables
    3. AI-driven air-quality forecasting that triggers clear school responses.
- To use AI tools effectively, education systems need cross-sector commitments, formal data-sharing agreements, updated construction and disaster risk reduction (DRR) standards, and stronger school- and district-level capacity supported by simple decision aids and low-tech communication channels.
- Finally, further research is needed to understand how AI-generated alerts translate into timely action, protect learning continuity, and strengthen resilience, alongside open sharing of datasets and operational playbooks to accelerate sector learning.

The report concludes that the primary barrier is not a lack of technology, but the absence of integrated systems and cross-sector collaboration, and limited capacity to translate forecasts into action. With targeted investments, actors can catalyse a step-change in how education systems use AI-enabled climate intelligence, protecting learning time, strengthening infrastructure resilience, and safeguarding children's well-being in an era of escalating climate risk.

1. Introduction

The escalating frequency and intensity of climate- and environment-related hazards pose a profound and growing threat to human development, and these threats risk undermining decades of development gains in low- and middle-income countries (LMICs) (↑Rentschler & Salhab, 2020; ↑Seneviratne et al., 2021). For the education sector, this is not a distant problem but an immediate crisis (↑UNICEF, 2024; ↑Venegas Marin et al., 2024). From the destruction of school infrastructure by floods and storms to the subtle erosion of learning in overheated classrooms, climate change is disrupting the education of millions of children (↑Haßler et al., 2024a; ↑Khalid et al., 2024; ↑UNDP, 2017).

Artificial Intelligence (AI), particularly machine learning (ML), is being deployed to forecast extreme weather, manage scarce resources, and strengthen infrastructure resilience (↑Jain et al., 2023; ↑Kuglitsch et al, 2022; ↑Rane et al., 2024;). By extracting patterns from large, complex datasets, AI can outperform conventional forecasting models in some contexts (↑Virmani et al., 2024), reducing forecast uncertainty and accelerating prediction timelines, enabling more timely and effective responses (↑Hamdan et al., 2024; ↑Rolnick et al., 2023).

While AI applications in climate and environmental domains are relatively well established, with a substantial evidence base built over the past decade, their application to education systems is limited (↑Amiri et al., 2024). This is especially true for LMICs, which experience disproportionate climate impacts yet are underrepresented in research and development (↑Abdulameer et al., 2025; ↑Khan et al., 2023; ↑Oyarzabal et al., 2025).

This think piece explores how AI-enabled climate and environmental hazard models can be leveraged to build stronger, safer, and more resilient education systems. Presenting emerging insights from research, practical examples of how AI is being applied at the intersection of climate and education, and implications for policy and practice, it seeks to consolidate existing knowledge and stimulate dialogue across the global education community. It is intended for the UK Government's Foreign, Commonwealth and Development Office (FCDO) advisors and partners working at the nexus of education, climate, and technology, as well as policymakers, researchers, and practitioners seeking to harness AI responsibly for climate resilience in education. Ultimately, the aim is to provide evidence-based inputs to inform new partnerships, programmes, and investments that maximise the opportunities and mitigate the potential risks of AI in addressing climate impacts on education systems.

While this analysis focuses specifically on AI-enabled climate intelligence for education planning and preparedness, it is important to acknowledge a wider set of technology use cases, particularly ones that support remedial learning and learning continuity for children affected by climate shocks, displacement, and protracted crises. Evidence highlights the role of radio, SMS, offline-first platforms, adaptive learning tools, and blended modalities in sustaining engagement and mitigating learning loss during school disruptions (↑Angrist et al., 2020). Research also documents how low-tech and no-tech approaches can effectively reach marginalised learners in humanitarian settings, especially girls and displaced children (↑Koomar et al., 2020), and how targeted catch-up interventions can accelerate foundational skills post-shock (↑Piper & DeStefano, 2018). Recent work synthesising evidence on climate-related education disruptions underscores the need for integrated technology strategies that combine remote learning, teacher support, and flexible delivery mechanisms (↑Barnes et al., 2025). These broader areas, critical to a comprehensive response to climate impacts on education, remain outside the scope of this paper but are central to the wider discourse on resilience, equity, and learning continuity.

Finally, it is essential to recognise that AI systems themselves carry environmental costs. The energy, water, and material demands associated with training and deploying large-scale AI models contribute to carbon emissions and resource use, which can exacerbate the very climate pressures that AI seeks to address (↑UN Environment Programme, 2025). While this think piece does not undertake a detailed environmental assessment of AI tools, it acknowledges the need for further research to better understand these trade-offs and to ensure that AI for climate resilience in education is deployed in environmentally responsible ways.

2. Research insights and practical examples

A growing body of evidence shows that climate and environmental hazards can significantly disrupt education, leading to both immediate and long-term consequences. Prolonged school closures, such as those observed during the Covid-19 pandemic, can cause significant learning loss as students lose access to structured instruction, peer-to-peer learning, and educational resources (↑Agostinelli et al., 2022; ↑Donnelly & Patrinos, 2022). Even after returning to school, learners often struggle to recover prior learning, resulting in persistent achievement gaps that have long-term implications for individual earning potential and a nation's overall economic productivity and development (↑Hanushek & Woessmann, 2020; ↑Patrinos, 2023; ↑Singh et al., 2024).

In parallel, the application of AI to address climate and environmental challenges has advanced rapidly over the past decade. AI is now widely used for climate change mitigation, adaptation, and resilience, as well as environmental degradation prevention, hazard prediction, and pollution control (↑Alblooshi & Shafii, 2025; ↑Jain et al., 2023; ↑Rolnick et al., 2023). Our background research identified roughly 200 relevant literature reviews from 2020 to 2025, synthesising thousands of studies on AI applications in climate forecasting, environmental monitoring, agriculture, and disaster management, such as predicting floods, managing natural resources, and improving sustainability (↑Akintuyi, 2024; ↑Long et al., 2025; ↑Srivastava et al., 2024). The evidence base on AI for climate and environmental action is therefore robust and rapidly expanding.

However, this body of research largely lacks exploration of how such AI tools could be integrated within education systems to help anticipate, mitigate, and respond to climate-related disruptions. Only a few studies explore the potential relevance or impact of AI tools on learning environments for climate change mitigation and adaptation. Likewise, the broader literature on AI in education focuses primarily on general teaching-and-learning applications, with minimal attention to using AI for climate adaptation or environmental monitoring within education systems (↑Al-Zahrani, 2024; ↑Alfredo et al., 2024; ↑Melo-López et al., 2025; ↑Yan et al., 2024).

Yet, there is clear potential for transfer. Proven AI technologies — such as those used for hazard monitoring, early warning systems, and predictive resource allocation — could be adapted to help education ministries and other stakeholders identify and protect at-risk schools, ensure continuity of learning, and strengthen system-wide resilience. The urgency lies not in developing new technologies but in integrating existing ones effectively within education planning, management, and governance.

The following sections illustrate this transferable potential in practice, focusing on three key climate hazard types — natural disasters, extreme heat, and pollution — and highlighting examples of how AI has been used to mitigate their impacts, including emerging applications within the education sector.

2.1. Practical Example 1: Natural disasters

Natural disasters — such as floods, storms, landslides and wildfires — can severely disrupt education systems by damaging schools and other educational infrastructure, displacing learners, and interrupting instruction, sometimes for extended periods. To examine how AI can help address these challenges, this section organises potential use cases into two phases:

1. Pre-disaster preparedness and prevention, which includes forecasting, risk mapping, and early warning systems.
2. Post-disaster recovery, focusing on damage assessment, response coordination, resource allocation, and building long-term resilience.

Pre-disaster preparedness and prevention

AI models are widely used to predict flood events and map areas(and the populations within them) that are most vulnerable. Integrating ML models with diverse data sources and optimisation techniques has significantly improved the accuracy of flood forecasting, with demonstrated applications across environmental and infrastructure sectors and growing use in identifying at-risk schools and supporting preparedness planning (↑Antzoulatos et al., 2022; ↑Thompson et al., 2023).

AI has become central to flood forecasting and management because of its ability to process large datasets and deliver precise forecasts. AI models for these uses enhance the reliability of early warnings and inform mitigation and response strategies for flood risk management (↑Akinsoji et al., 2024; ↑Kumar et al., 2023; ↑Liu et al., 2025). Beyond floods, deep learning models are also increasingly applied to predict storms, cyclones, and heatwaves — often outperforming or complementing traditional physics-based numerical models for medium-range weather forecasting (↑Olivetti & Messori, 2024; ↑Verma et al., 2023). Additionally, AI is being used to model and predict drought conditions, supporting early interventions that can minimise impacts on school operations and community well-being (↑Sundararajan et al., 2021).

Within the education sector, similar hazard-forecasting and risk-mapping approaches are emerging in pilot form, and through the creation of frameworks and guidance structures. For example, UNESCO and UNICEF initiatives in South Asia and sub-Saharan Africa combine school geolocation data with national flood-risk models to identify vulnerable schools and prioritise climate-resilient construction (↑UNESCO, 2024; ↑UNICEF, 2019a). These pilots underscore the importance of bridging climate and education portfolios through sustained data exchange and collaboration.

The World Bank's Global Library of School Infrastructure (GLoSI) under the Safer Schools Programme provides hazard-informed design and siting guidance (↑Universidad de los Andes & World Bank, 2017). School infrastructure vulnerability mapping links geospatial hazard layers with building attributes to identify risk from floods, storms, and earthquakes. The Comprehensive School Safety Framework (↑GADRRRES & UNDRR, 2022) also sets standards for safe site selection and hazard-resistant construction. Aligning AI risk models to these frameworks can enable evidence-based prioritisation of retrofits and resilient construction (↑Universidad de los Andes & World Bank, 2017).

Post-disaster recovery and reconstruction

AI applications are already used in humanitarian response, particularly for mapping infrastructure damage and extracting critical information from large data sources. For example, computer vision models can be trained on satellite or drone imagery to create automated damage assessment systems. These tools rapidly analyse photos of buildings to identify and classify the severity of structural damage (e.g., 'roof collapsed', 'major flooding', or 'no damage'; ↑Abid et al., 2021). Similarly, Natural Language Processing (NLP) tools have been applied to large volumes of text-based data — such as field reports, local news articles, and social media posts — to extract insights needed by responders (↑Aboualola et al., 2023).

Adapting these proven approaches to educational recovery settings shows promising potential. Automated assessments could help officials quickly map which schools are unsafe and prioritise repair efforts without dispatching human inspection teams to every site, helping maximise limited resources. NLP models could identify which schools are reported as closed, highlight communities requesting specific educational resources (e.g., temporary classrooms, textbooks, or clean water), or flag blocked access routes requiring immediate attention.

While these AI tools could support faster school reopening and more efficient resource allocation, evidence of their direct impact on educational outcomes, such as reducing learning loss or accelerating a safe return to the classroom, is still emerging. This remains a critical area for future research.

2.2. Practical Example 2: Extreme heat

Extreme heat poses a growing threat to education systems. In many tropical and subtropical LMICs, classrooms are becoming increasingly overheated as temperatures rise because many schools lack mechanical ventilation or air conditioning (↑Aguilar-Carrasco et al., 2025; ↑Bidassey-Manilal et al., 2020). A substantial body of evidence shows that heat reduces cognitive performance, concentration, and attendance, undermining the quality of learning even when schools remain open (↑Aguilar et al., 2022; ↑Brink et al., 2021; ↑Dugaria et al., 2021). Tackling overheating is therefore directly linked to preserving learning time and protecting well-being, rather than being an infrastructure issue alone.

A relevant illustration of how temperature-control approaches can be directly applied in the education sector is the FCDO-funded Shule Bora programme in Tanzania. This programme is designing and retrofitting climate-resilient classrooms with reflective roofing sheets, enhanced ventilation, and larger windows, which are expected to reduce classroom temperature by 4–6°C (↑Bangay, 2024; ↑Haßler et al., 2024; ↑Wargocki et al., 2019).

In parallel, AI-enabled sensing and prediction systems — common in sectors such as greenhouse agriculture, dairy farming, and 'smart' building management — are emerging as tools for climate resilience in education (↑Amiri et al., 2024). Although adoption in school systems in LMICs remains limited, recent examples suggest significant potential. A recent adaptation of the Temp-AI-Estimator framework[1] for naturally ventilated buildings in sub-Saharan Africa demonstrates strong cross-country generalisation, with mean absolute errors of ~1.45 °C in Nigerian schools and ~0.65 °C in Gambian homes (↑Akhtar et al., 2025). This indicates that even lightweight models,

[1] This is an AI-enabled tool that can predict the indoor temperature of buildings and containers (acting as surrogates for residential or office buildings as well as intermodal containers) based on measurements of external meteorological conditions (e.g., exterior temperature, humidity, etc.), as well as physical properties due to building construction set-ups in questions (↑Bischof et al., 2023).

relying only on basic weather variables and simple building descriptors, can provide reasonably accurate indoor temperature forecasts where heating, ventilation, and air conditioning (HVAC) infrastructure is absent.

The value of these tools lies not in passive observation, however, but in enabling decision-makers to anticipate and act on heat-related risks. Ongoing work in Tanzania and Ghana combines classroom-level sensor data with satellite imagery, weather forecasts, and information on roof type, roof shading, and ventilation to identify classrooms most vulnerable to overheating (↑Akhtar et al., 2025; ↑Amankwaa et al., 2025; ↑Haßler et al., 2024c). This allows interventions (whether temporary operational measures or physical retrofits) to be targeted where they will yield the greatest learning benefits.

Taken together, this emerging evidence points to a practical pathway for using AI not only to understand, but also to mitigate harmful heat exposure in schools (↑Akhtar et al., 2025; ↑Haßler et al., 2024c). Steps for such a pathway could include:

- **Data collection** — Low-cost Internet of Things (IoT) sensors can be deployed to capture real-time indoor temperature, humidity, and air quality, combined with contextual data such as local weather observations and satellite-derived land-surface temperatures.
- **Predictive modelling** — AI/ML models (e.g., Artificial Neural Networks) learn the relationship between external climate conditions, building characteristics, and indoor thermal responses.
- **Actionable insights** — Forecasts indicate when classrooms are likely to exceed critical temperature thresholds for learning, enabling pre-emptive action such as relocating lessons, adjusting schedules, or prioritising cooling retrofits.

2.3. Practical Example 3: Pollution

Air pollution is a significant health risk for children, contributing to acute respiratory infections and hospital admissions, as well as reducing attendance and quality of learning (↑Kamara et al., 2025; ↑Zhang et al., 2023). In fact, it is the second-highest global risk factor for death in children under five, following malnutrition (↑Amir-ud-Din et al., 2024; ↑Lake et al., 2025; ↑UNICEF, 2024).

AI-based air-quality forecasting systems are increasingly being explored to help reduce adverse health impacts of pollution on children, including within educational environments. For example, these systems can anticipate periods of high air pollution, such as hazardous spikes in particulate matter, and issue health alerts. (↑Hofflinger et al., 2024; ↑Houdou et al., 2024; ↑Subramaniam et al., 2022). In LMIC settings, these forecasts can even be paired with simple SMS or WhatsApp early warning protocols that relay alerts from ministries of health or environment directly to school leaders, enabling rapid, low-cost action even without sophisticated data infrastructure (↑UNICEF, 2019b). Such proactive approaches can help to prevent school absences due to illness, thereby supporting the continuity of students' education (↑Jain et al., 2022; ↑Mazari et al., 2023; ↑Méndez et al., 2023; ↑Ogundiran et al., 2024; ↑Subramaniam et al., 2022).

Within the education sector, a few early pilots illustrate what this could look like in practice. The SAMHE (Schools' Air Monitoring for Health and Education)[2] project in the UK and the policy interventions based on Air Quality Index (AQI) data in Lagos, Nigeria, are foundational initiatives that clearly demonstrate the immense potential for applying AI to address real-world environmental health challenges that have implications for educational outcomes. The UK's SAMHE project is built on a citizen science framework and low-cost sensor networks to gather a large, contextualised dataset of pollutants such as CO_2 and particulate matter (PM) (↑Chatzidiakou et al., 2023). The Lagos initiative uses a robust monitoring network and atmospheric dispersion modelling to calculate the AQI and rigorously define population-weighted exposure to particulate matter (↑Akpokodje et al., 2022). While both programmes initially rely on advanced computational modelling, their primary strength lies in establishing high-quality, contextualised datasets needed to train future predictive and prescriptive AI or ML systems that could eventually move beyond basic monitoring to automate real-time alerts, optimise building energy performance, and dynamically adjust school operational policies based on air pollution forecasts.

[2] See https://samhe.org.uk/about. Retrieved 31 October 2025.

3. Implications for policy and practice

Drawing on the evidence base and examples outlined above, this section highlights key opportunities for the FCDO and other actors to advance AI-enabled climate resilience in education.

AI tools for climate forecasting and risk management are now sufficiently mature to inform sector planning and investment decisions. The priority is integration (↑Haßler et al., 2024a; ↑Venegas Marin et al., 2024) — connecting AI-enabled climate tools with educational planning tools such as education management information systems (EMISs), operational playbooks, and school construction standards; building capacity at school and district levels; and investing in low-cost, high-impact applications that turn forecasts into action.

The recommendations below are grouped into three priority areas.

3.1 Specific AI-enabled approaches that are showing promise

The following examples illustrate concrete, near-term applications of AI that can support climate-resilient education planning and operations.

AI-enhanced siting and retrofit prioritisation for natural disasters

An emerging AI-enabled approach showing strong promise is the use of AI-based Composite Risk Indices (CRIs) that combine hazard, exposure, and school-specific data to guide decisions on where to locate, retrofit, or protect education infrastructure. These models integrate layers such as flood, storm, landslide, and drought risk with information on school attributes to generate school-level risk rankings. Ministries can use these rankings to prioritise safe sites, resilient designs, and phased retrofits within annual infrastructure, maintenance, and supervision plans.

A practical starting point is to fuse existing national hazard maps with school geolocation data to identify high-risk sites and resilient construction typologies — avoiding the need for new modelling infrastructure in the initial phase. For evaluation, programmes could track cost-benefit and resilience outcomes by comparing projects selected with and without AI-based risk maps. Key metrics might include estimates of the avoided damage, days of schooling preserved, and time taken to reopen after disasters, with counterfactual analyses drawn from AI-informed hazard models.

Classroom heat-stress risk mapping and adaptation

Another promising AI-enabled approach for improving climate resilience in education involves generating heat-risk indices for each school using the *Temp-AI-Estimator*, which combines local forecasts, building characteristics, and microclimate data. The resulting school-level indices enable ministries to prioritise low-cost passive adaptations — such as ceiling boards, reflective roofing, shading, and improved ventilation — and to plan 'heat-aware' timetables and exam schedules.

A key recommendation is to fund a multi-country heat-stress study (e.g., for Tanzania and Ghana) aligned with Practical Example 2. This study would use AI models and IoT sensors to map classroom thermal risk, test low-cost retrofit options, and estimate their effects on learning and attendance. The proposed design includes stepped measurements across climate zones, school-level heat-risk indices, pilot retrofit packages, and cost–benefit modelling to inform national retrofit playbooks and construction norms.

Success indicators could include thermal comfort hours, the frequency and duration of heat alerts, attendance rates on high-heat days, exam scheduling resilience, and teacher–student comfort reports. For integration, heat-risk indices should be published through EMIS dashboards, allowing districts to prioritise investments and enabling school leaders to respond to routine heat alerts with simple, codified actions.

AI-driven air quality forecasting and school response

This promising AI-enabled method combines satellite data, national air-quality networks, and low-cost classroom sensors with machine-learning forecasts to generate local AQI predictions. These predictions define clear thresholds that trigger school responses — for example, shifting to indoor-only activities at one AQI level or cancelling outdoor physical education at another.

We recommend trialling low-cost IoT monitoring to establish baseline indoor environmental quality, calibrate forecasts, and validate alert thresholds across different school typologies. Protocols should integrate national air quality data with classroom sensors, publish tiered alert guidance (e.g., keep indoors, reschedule PE, distribute masks, or operate DIY filters where feasible), and draw on lessons from the SAMHE and Lagos initiatives to refine routines and messaging.

Accompanying implementation research should also examine how forecast alerts and IoT monitoring can reliably trigger health-protective actions and measure their impact on school attendance and learning. A stepped-wedge rollout across districts could compare alert formats (SMS vs. WhatsApp vs. Interactive Voice Response [IVR]) and track outcomes such as reductions in asthma-related absences and the number of days of healthy schooling preserved.

3.2 Other foundational steps to enable AI-powered climate tools to be used effectively in education

While the approaches above demonstrate near-term potential, their impact depends on the presence of strong enabling systems, partnerships, and capacities. The following steps outline the cross-sector coordination, data integration, and human capacity investments needed to ensure AI-powered climate tools can be adopted and used effectively at scale within education systems.

Leverage the FCDO's convening power to mobilise cross-sectoral commitments

To move beyond a proliferation of isolated pilots, a coordinated commitment across sectors is essential. The FCDO is well-positioned to leverage its global influence to bring governments, climate and meteorological agencies, AI researchers, multilateral organisations, and funders into a shared agenda. For example, this could take the form of a high-level convening on *Climate-Resilient Education Systems* in early 2026 to secure concrete political and financial commitments. Key outcomes might include national pledges to embed AI-enabled climate intelligence into education sector planning, infrastructure standards, and routine school operations, alongside a roadmap for joint investment and accountability mechanisms to sustain longer-term progress.

Bridge sector silos to connect and operationalise data systems

Education systems can then begin by linking national climate and health forecasts to EMISs and school communication channels. Emerging evidence from LMICs suggests that education systems can increasingly merge data from multiple sources for planning and decision-making (↑IDRC, 2024; ↑UNICEF, 2020). Such integration ensures that forecasts are shared, understood, and acted upon within the education sector, rather than remaining siloed in technical agencies (↑Harper, 2023). For example, partners could consider:

- **Establishing formal Memorandums of Understanding (MoUs)** between meteorological, health/environment, and education agencies for data sharing and standard operating procedures.
- **Finance a meteorological data liaison person** inside ministries of education and earmark a small budget line for school-level alert systems and risk dashboards linked to EMISs (↑OECD, 2019).

These steps would help enable impact-based warnings for floods, storms, heat, and poor air quality to trigger routine operational decisions — such as adjusting timetables, temporarily relocating classes, or rescheduling exams (↑Cameron et al., 2024; ↑Harper, 2023; ↑OECD, 2019; ↑Sabarwal et al., 2024). Evidence shows that school closures and disruptions caused by heat, floods, or other climate events can lead to sustained learning loss in LMICs, underscoring the importance of prevention and continuity as a core resilience strategy (↑Kaffenberger, 2021; ↑Leal Filho et al., 2025; ↑Venegas Marin et al., 2024).

Build human capacity to act on AI-generated climate insights at the school and district levels

The next step is to embed climate intelligence in how schools are planned, built, and managed. This means updating construction and procurement standards to include AI-informed hazard screening, ensuring new facilities are sited in safer, climate-resilient areas (↑Sabarwal et al., 2024), and integrating heat, flood, and air-quality alerts into disaster risk reduction (DRR) procedures with clear responsibilities assigned (↑GADRRRES & UNDRR, 2022).

Early experience from LMIC pilots shows that this shift is achievable but still in its infancy (↑Haßler et al., 2024c). Scaling this progress requires strengthening capacity at the school and district levels so that AI-generated forecasts translate into timely, practical action. Policymakers and implementing partners should provide routine training for headteachers and district officers on interpreting risk dashboards, responding to alerts, and applying heat and AQI playbooks (↑Parameshwari & Gnaneswari, 2024; ↑Pimenow et al., 2025; ↑Ukoba et al., 2025). To ensure equitable access, systems should be designed with low-tech delivery in mind — using language-accessible, data-free channels and maintaining a human-in-the-loop to ensure that forecasts lead to fast, context-appropriate decisions (↑GADRRRES & UNDRR, 2022; ↑MacEwen et al., 2025).

To monitor the effectiveness of these efforts, policymakers and practitioners could track indicators such as the number of schools receiving early warnings, the rate of response actions taken, and the average time between alert and action.

Incorporate simple decision aids and leverage reliable, familiar communication channels for decision-makers

AI-enabled forecasts only add value when they lead to timely, low-cost actions at the front lines of education. Ministries and partners should therefore focus on designing decision aids and communication systems that help schools respond quickly and confidently to climate alerts.

A practical starting point is to embed trigger-action matrices for floods, heat, and air quality into EMISs and school calendars, linking each hazard type to clear, pre-defined responses — such as adjusting timetables, moving activities indoors, or rescheduling exams. To ensure that alerts reach those who need them, communication protocols should use familiar, low-tech channels such as SMS, WhatsApp, or IVR, with message delivery and acknowledgement logged in EMISs (↑Aboualola et al., 2023; ↑Al-Rawas et al., 2024).

At the school level, decision aids should emphasise simple, immediate measures that protect health and learning — opening windows at specific times, rotating classes to cooler rooms, or temporarily relocating lessons outdoors. At the same time, district officials can use ranked risk maps to prioritise retrofitting and planting shade trees where exposure is highest (↑GADRRRES & UNDRR, 2022; ↑Haßler et al., 2024c). These lightweight tools demonstrate how AI can function as a decision-support system, not just a data product, empowering teachers and administrators to act without requiring new infrastructure or advanced training (↑GADRRRES & UNDRR, 2022; ↑Haßler et al., 2024c ↑Harper, 2023; ↑IDRC, 2024; ↑UNICEF, 2020).

3.3. Priority area for further research

Despite growing technical innovation, a focused research priority remains: strengthening the evidence base on how AI-enabled climate insights translate into real-world educational action and outcomes.

Most AI applications at the intersection of climate resilience and education are still in their early stages and have not been rigorously tested. There is a critical need to build a stronger evidence base on how predictive models translate into real-world educational outcomes. New initiatives should therefore pair technical rollouts with implementation and behavioural research to assess whether alerts trigger timely action, what factors influence adoption, and how responses fit within existing budgets. Building this kind of behavioural evidence would help close the gap between modelling and real-world impact, showing how climate intelligence can genuinely protect learning time and well-being in resource-constrained systems (↑Haimovich et al., 2021; ↑UNICEF, 2019b; ↑WMO, 2015).

Each technical rollout should also aim to publish de-identified datasets, instruments, and operational playbooks. Open sharing of these materials will accelerate sector learning and strengthen the collective understanding of how AI-enabled climate intelligence can protect learning continuity in the face of environmental shocks.

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