Artificial intelligence for linking extreme weather forecasting and health impact prediction

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Extreme weather events increasingly threaten human health, yet current weather-health systems often struggle to translate hazard-based forecasts into actionable, impact-oriented guidance. This gap arises primarily from spatiotemporal misalignment between meteorological and health data, reliance on static hazard thresholds, and limited integration of probabilistic risk assessment. Here, we propose a conceptual framework that leverages artificial intelligence (AI) to bridge extreme weather forecasting and health impact prediction. The AI-enabled system aligns heterogeneous data sources, captures nonlinear and lagged exposure-response relationships, and propagates uncertainty throughout the prediction chain. We illustrate the framework using heatwaves, wildfires, and extreme precipitation and outline key priorities for operational implementation, including model interpretability, privacy-preserving architectures, and institutional governance. Integrating interpretable and uncertainty-aware health impact prediction into operational forecasting systems will be essential to enabling anticipatory public health action in a future of intensifying weather extremes.

INTRODUCTION

Extreme weather events are increasing in both frequency and intensity under global warming, posing escalating risks to human health worldwide.[1] Integrating meteorological forecasting with public health preparedness has therefore become a central component of climate risk reduction and an important pillar of national resilience strategies.[2] International initiatives led by the World Meteorological Organization (WMO) and World Health Organization (WHO) have advanced weather-health early-warning capabilities, and many countries have established operational systems linking meteorological information with public health interventions.[3]

Despite these advances, the integration of extreme weather forecasting with public health response remains limited. Most existing systems rely on static hazard thresholds and reactive protocols, making limited use of high-resolution forecasts, probabilistic uncertainty, or dynamically evolving exposure and vulnerability conditions. This misalignment between hazard prediction and health impact assessment constrains the ability to anticipate risks and implement timely and targeted interventions.

Artificial intelligence (AI) offers a transformative opportunity to bridge the gap.[4,5] Existing studies have largely focused either on improving hazard prediction or on refining epidemiological exposure-response relationships, with few efforts to integrate both within operational forecasting systems. Here, we propose a conceptual framework for an end-to-end AI-enabled weather-health prediction system. This framework aligns heterogeneous meteorological and health data, captures nonlinear and lagged exposure-response relationships, propagates uncertainty, and supports decision-relevant risk assessment. By positioning AI as a coordinating layer between meteorological forecasts and public health response, this perspective outlines a roadmap for anticipatory and impact-based health risk management.

CURRENT GAPS IN WEATHER-HEALTH INTEGRATION

Despite increasing awareness of weather-related health risks, operational integration between hazard forecasting and health impact prediction remains limited. The primary barrier is a structural misalignment between meteorological and health data systems. Meteorological forecasts are typically high resolution, probabilistic, and updated in near real time. Health data, by contrast, are often reported retrospectively, aggregated over administrative units, and fragmented across institutions. Although real-time syndromic surveillance data, such as emergency dispatch records, are increasingly available, coverage and quality remain uneven. Differences in variable definitions and data governance further prevent seamless linkage between evolving meteorological hazards and emerging health risks.

Methodological limitations further constrain integration. Most operational health impact models rely on historical exposure-response relationships that assume temporal stationarity and limited interactions among drivers. These assumptions are increasingly untenable under a changing climate, where extreme events are spatially heterogeneous, often compound, and shaped by evolving adaptation measures and health system capacity. Moreover, conventional statistical frameworks are not well suited to accommodate high-dimensional ensemble forecasts and heterogeneous vulnerability factor inputs within operational forecasting environments. As a result, health impact prediction remains largely decoupled from real-time weather forecasting systems.

The third limitation concerns the treatment of uncertainty. Weather forecasts routinely quantify predictive uncertainty through ensemble simulations, yet health impact assessments are often expressed as deterministic risk metrics or simple threshold exceedances. Uncertainties arising from exposure misclassification, population heterogeneity, incomplete health records, and model structural assumptions are seldom propagated into decision-relevant outputs.[6] This mismatch reduces confidence among public health practitioners and limits the practical use of prediction-informed interventions.

AI IN PREDICTING HEALTH IMPACTS OF EXTREME WEATHER

AI provides a promising pathway to address long-standing gaps in data, methodology, and uncertainty by linking heterogeneous weather and health systems within a unified predictive framework. To tackle misaligned and sparse health data, AI models can map high-resolution meteorological forecasts to health outcomes reported at coarser administrative or clinical scales using convolutional and graph neural networks while simultaneously imputing incomplete or delayed health observations through spatiotemporal context. Semi-supervised learning further alleviates limitations arising from sparse outcome labels by leveraging partially observed data. Beyond these capabilities, AI models enable data-driven downscaling by learning scale-aware representations that translate coarse-resolution climate information into locally relevant signals, improving the representation of extremes and population-specific exposure heterogeneity, thereby strengthening the linkage between evolving hazards and emerging health responses.

Methodological constraints are addressed through flexible modeling of nonlinear, interacting, and lagged exposure-response relationships. Sequence-based architectures, including recurrent neural networks and attention mechanisms, capture cumulative and delayed exposure effects without requiring predefined lag windows. Multi-task and graph-based architectures extend this capability to represent inter-regional dependencies, allowing upstream or neighboring hazards to propagate through environmental and social networks to influence downstream risk. Hybrid physics-informed learning embeds physical constraints, such as energy and mass conservation, enhancing physical consistency, improving extrapolation under non-stationary climate conditions, and enabling the discovery of previously unrecognized environment-health relationships. AI-based predictions can be benchmarked against

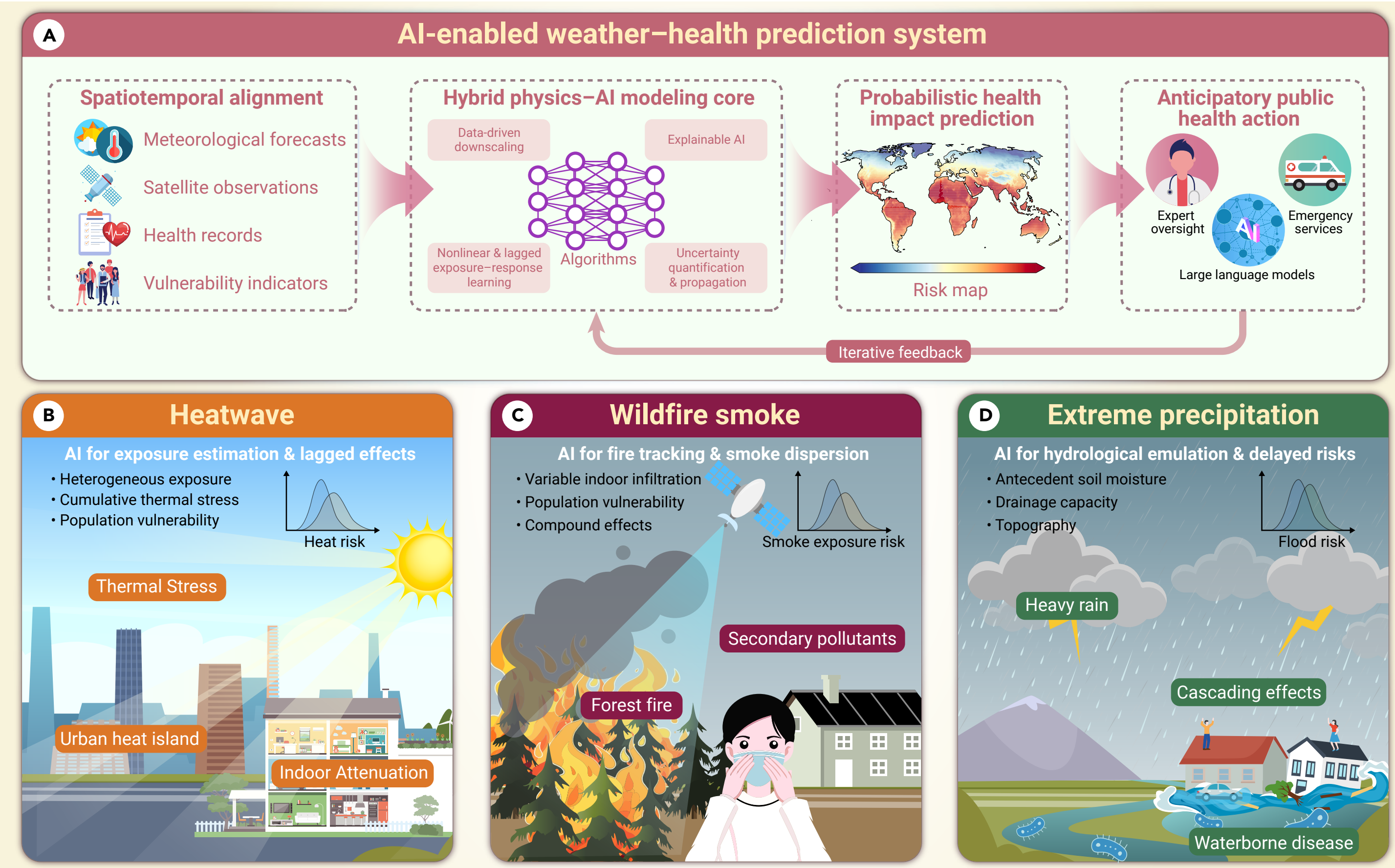

Figure. AI-enabled weather-health prediction framework Schematic diagram of (A) AI-enabled weather-health prediction system and three illustrative scenarios: (B) heatwave, (C) wildfire smoke, and (D) extreme precipitation.

established epidemiological methods, such as distributed lag nonlinear models, while explainable AI techniques, including Shapley additive explanations (SHAP), quantify the contribution of meteorological drivers and lag structures to predicted health risks, supporting interpretable risk communication. Integration with causal inference frameworks, including counterfactual analysis and representation learning, further reduces confounding from socio-demographic factors and strengthens the credibility of inferred exposure-response relationships.

AI also enables explicit propagation of uncertainty from meteorological hazards to health impacts. Ensemble weather forecasts serve as probabilistic inputs, transmitting forecast uncertainty into health risk estimates. Model uncertainty can be quantified through Bayesian neural networks, Monte Carlo dropout, and ensemble learning, while data-related uncertainty arising from sparse or delayed health records can be addressed via hierarchical modeling and likelihood-based treatment of observation error. Distinguishing aleatoric from epistemic uncertainty separates irreducible variability from uncertainty due to limited data or model structure, and attribution analyses identify dominant contributors to predictive variance. Operational validation using proper scoring rules, alongside rolling hindcasts and calibration procedures, ensures the reliability of probabilistic health forecasts in real-world decision contexts.

These components converge within an integrated AI-based weather-health prediction system that links hazards to health impacts in an operational framework (Figure 1A). Numerical weather prediction ensembles, satellite and ground-based observations, mobility indicators, and routinely collected health records are harmonized through spatiotemporal alignment modules that address resolution mismatches and reporting delays. Sensitive health data can remain locally stored and be incorporated via federated-learning-based distributed training, enabling cross-institutional modeling without raw data exchange. A hybrid modeling core combines bias-corrected forecasts with learned exposure and vulnerability representations, in which indoor attenuation and behavioral adaptation are treated as dynamic modifiers, to generate probabilistic health impact estimates at decision-relevant spatial and temporal scales. Uncertainty is propagated across forecast, exposure, and health components, yielding calibrated risk distributions rather than deterministic thresholds. Large language models can support translation of probabilistic outputs into structured risk summaries and policy-relevant narratives, while final interpretation and intervention decisions remain under expert oversight. Continuous incorporation of observed health outcomes through iterative feedback loops enables model recalibration and adaptation to evolving climate conditions and baseline risks.

ILLUSTRATIVE SCENARIOS

Heatwaves threaten human health through sustained thermal stress, often intensified by high humidity, elevated nighttime temperatures, and urban heat island effects.[7] Predicting health impacts is complicated by heterogeneous indoor and outdoor exposure, cumulative thermal stress over consecutive days, and population vulnerability shaped by age, pre-existing health conditions, housing quality, and access to cooling (Figure 1B).[8] The AI-enabled system addresses these challenges by estimating indoor exposure from outdoor meteorological forecasts combined with building characteristics and energy use proxies, integrating ensemble temperature and humidity forecasts with spatially resolved population data to capture cumulative and lagged exposures, and modeling subgroup-specific vulnerability through stratified and hierarchical representations. Together, these capabilities enable probabilistic predictions of heat-related health outcomes that evolve with exposure conditions and population vulnerability, moving beyond static temperature threshold approaches.

Wildfires primarily endanger health through smoke exposure, the composition and dispersion of which evolve with fire behavior, atmospheric transport, and chemical transformations.[9] Health impact prediction is challenged by rapidly fluctuating exposure, variable indoor infiltration, heterogeneous population vulnerability, and the compound nature of wildfire events, which often co-occur with heatwaves and elevated air pollution levels (Figure 1C). The AI-enabled system integrates satellite fire detections, meteorological forecasts, and fuel and atmospheric indicators to track fire growth and smoke plume evolution, capture cross-hazard interactions, and refine estimates of indoor and outdoor smoke concentrations using data-driven dispersion modeling. Combined with spatially resolved population and vulnerability data, probabilistic smoke exposure maps enable dynamic forecasts of respiratory and cardiovascular risks across space and time.

Extreme precipitation triggers cascading impacts across multiple timescales, from flash floods following short-duration intense rainfall to riverine flooding and infrastructure disruption during prolonged precipitation events (Figure 1D). Associated health consequences range from immediate injuries to displacement and waterborne disease,[10] with risks shaped by antecedent soil moisture, drainage capacity, and topography. The AI-enabled system improves precipitation forecasts through ensemble bias correction and downscaling, emulates hydrological and hydraulic responses, and integrates land surface characteristics, drainage networks, and population exposure to estimate where and when flooding may occur. These components support dynamic risk assessments that capture both immediate and delayed health impacts following extreme precipitation events.

CHALLENGES AND PRIORITIES

Despite rapid methodological advances, operationalizing the AI-enabled weather-health system remains challenging. Health and exposure data are often delayed or inconsistently aggregated, hindering alignment with meteorological predictors and potentially biasing risk estimates, particularly for hazards with complex exposure pathways. Model generalizability is another concern, as relationships learned in one region may not transfer across populations with different baseline health conditions or adaptive capacities. Even with adequate data, models may underrepresent vulnerable groups because optimization objectives favor overall accuracy. Deployment further raises challenges related to interpretability, data privacy, and institutional accountability. Addressing these issues requires coordinated advances in data infrastructure, ethical governance, and interdisciplinary collaboration to ensure robust and equitable real-world applications.

In the short term, priorities should focus on operational pilot projects that link hazard forecasts to health outcomes in high-risk settings. Urban heatwave pilots, for example, could integrate ensemble temperature and humidity forecasts with urban morphology and population vulnerability to generate probabilistic estimates of heat-related emergency demand, which can be validated against observed health records. Similar pilot programs for wildfire and extreme precipitation should be embedded in real-time decision-making contexts, with explicit uncertainty communication and intervention thresholds co-developed with public health authorities. Establishing benchmark datasets spanning hazards, exposures, and health outcomes will be critical for reproducible cross-regional evaluation and for demonstrating improvements in prediction accuracy and decision-making efficiency relative to existing threshold-based warning systems.

Over the medium to long term, AI-enabled weather-health systems should evolve from single-hazard pilots to integrated multi-hazard risk assessment frameworks capable of capturing concurrent exposures and cascading impacts. Continuous incorporation of health observations, intervention outcomes, and emerging climate risks would enable dynamic updating of exposure-response relationships and population vulnerability. National weather-health AI committees could coordinate meteorological and health agencies, establish data-sharing protocols and validation standards, define accountability frameworks, and oversee responsible model deployment. Modular and scalable system architectures, combined with distributed learning approaches, can facilitate deployment in low- and middle-income countries using publicly available weather forecasts and routinely collected health data, thereby extending early-warning benefits to high-exposure but resource-limited regions.

CONCLUSION

The growing health burden of extreme weather reveals a persistent gap between meteorological forecasting and public health response. This perspective proposes that AI can help bridge this gap by aligning heterogeneous meteorological and health data, capturing complex exposure-response relationships, and quantifying uncertainty in health impact prediction. Across hazards such as heatwaves, wildfires, and extreme precipitation, AI-enabled systems could shift risk assessment from static hazard thresholds toward probabilistic, impact-based, and decision-relevant guidance. Integrating AI-enabled weather-health prediction into public health systems enables a transition from reactive response to anticipatory risk management as weather extremes intensify.

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AUTHOR CONTRIBUTIONS

G.H. and H.T. led the study, conceptualized the research, and drafted the manuscript. D.C., C.H., S.W., Y.W., M.G., M.Y., L.Q., and Y.Z. reviewed and revised the manuscript. All authors contributed to and approved the final version of the manuscript.

DECLARATION OF INTERESTS

The authors declare that they have no competing interests.

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