frontiers | Frontiers in Water

TYPE Editorial
PUBLISHED 06 March 2025
DOI 10.3389/frwa.2025.1579106

Check for updates

OPEN ACCESS

EDITED AND REVIEWED BY
Subimal Ghosh,
Indian Institute of Technology Bombay, India

*CORRESPONDENCE
Poulomi Ganguli
✉ poulomizca@gmail.com

RECEIVED 18 February 2025
ACCEPTED 24 February 2025
PUBLISHED 06 March 2025

CITATION
Ganguli P, Han S, Muñoz DF and Pal S (2025) Editorial: Spatiotemporal modelling and assessment of water-related multi-hazards. *Front. Water* 7:1579106.
doi: 10.3389/frwa.2025.1579106

COPYRIGHT
© 2025 Ganguli, Han, Muñoz and Pal. This is an open-access article distributed under the terms of the Creative Commons Attribution License (CC BY). The use, distribution or reproduction in other forums is permitted, provided the original author(s) and the copyright owner(s) are credited and that the original publication in this journal is cited, in accordance with accepted academic practice. No use, distribution or reproduction is permitted which does not comply with these terms.

Editorial: Spatiotemporal modelling and assessment of water-related multi-hazards

Poulomi Ganguli[1,2]*, Shasha Han[3,4], David F. Muñoz[5] and Sujan Pal[6]

[1]Department of Agricultural and Food Engineering, Indian Institute of Technology Kharagpur, Kharagpur, India, [2]Fulbright – Kalam Visiting Faculty, Department of Civil and Environmental Engineering, Princeton University, Princeton, NJ, United States, [3]School of Geography, Earth and Environmental Sciences, University of Birmingham, Birmingham, United Kingdom, [4]Birmingham Institute for Sustainability and Climate Action, University of Birmingham, Birmingham, United Kingdom, [5]Department of Civil and Environmental Engineering, Virginia Polytechnic Institute and State University, Blacksburg, VA, United States, [6]Argonne National Laboratory (DOE), Environmental Science Division, Lemont, IL, United States

KEYWORDS

extreme weather, compound events, risk, non-stationarity, interdependence

Editorial on the Research Topic
Spatiotemporal modelling and assessment of water-related multi-hazards

Extreme weather and climate events often show synchronicity in space and time (Tonini et al., 2014; Berghuijs et al., 2019; Tuel and Martius, 2021; Gesualdo et al., 2024), challenging disaster management capabilities and recovery times. Moreover, the trail of one event type often acts as a preconditioning driver for subsequent event types that can spread irrespective of geographic borders, overwhelming societal resilience and adaptation efforts (Tang et al., 2023; Fu et al., 2024). The consequences of climate change and the intricate nonlinear relationship between climate and physiographic drivers intensify multi-hazard event chains, which can be a single hazard type with multiple attributes or a combination of different hazard types that often overlap in a short time window (Matthews et al., 2019; Raut et al., 2024). While the majority of hazard management frameworks rely on single hazard types with single attributes, a credible risk assessment of multi-hazard event chains requires an in-depth understanding of the physical controls in the event development and consideration of the spatiotemporal connectedness of process controls (Berghuijs et al., 2019; Gesualdo et al., 2024). One such example could be ignoring the spatial footprint of "preconditioning" elevated water levels in design surge estimation for coastal flood protection and assuming a uniform return period across coastal reaches (Kiesel et al., 2024). Furthermore, the severity (or extremity) of multi-hazard weather and climate events does not necessarily determine their impact; instead, the exposure and vulnerability of assets and livelihoods amplify the overall risk potential.

Following these motivations, seven research articles were published as part of this Research Topic. These can be broadly classified into three categories: three studies dealt with the mapping of coastal compound floods, three introduced and explored the potential of artificial intelligence-based approaches, such as long short-term memory (LSTM) and sequential data assimilation (SDA) techniques as tools to forecast such unprecedented climate hazards with the lead times necessary for operational perspectives, and finally one article dealt with the investigation of the likelihood of wet-dry and dry-wet transitions in the Meuse River basin in the Netherlands, highlighting the preconditioning role of meteorological scenarios in triggering catchment-specific hydrological responses.

Compound flooding (CF) is often driven by a combination of physical processes, such as hurricanes, storm surges, heavy rainfall, and high tides. However, current flood modelling and mitigation strategies typically only focus on individual mechanisms, neglecting the co-occurrence of these sources and their compounded effects (Bevacqua et al., 2020; Radfar et al., 2024). Using statistically grounded methods, such as encapsulating trend analysis with a bivariate probabilistic framework, Lewis et al. showed the existence of non-stationarity (i.e., temporal changes in hydrological and meteorological variables), non-linearity (i.e., complex interactions among flood drivers), and multi-dimensionality (i.e., various factors influencing flood risk) among compound flood drivers, focusing on two coastal areas on the Gulf Coast of the United States. Combined with statistical tests, their study also included a comprehensive review of relevant CF policy documents. The authors found clear evidence of compounding flood drivers and shifts in the first-order statistical moments (i.e., mean shift) of such drivers in a warming climate. However, there remains a significant gap between science and practise, as the majority of current policies fail to adequately address the complex and dynamic nature of CF. This highlights the critical need for an integrated approach that accounts for multi-mechanism and non-stationarity in CF assessments.

To bridge the gap between theory and practise, Wang et al. developed a simple conceptual framework, "c-HAND" (Coastal-Height Above Nearest Drainage) to map compound fluvial and coastal inundation. Subsequently, c-HAND was coupled with a fluvial flood forecasting model to create a workflow for mapping compound fluvial-coastal inundation that can be run in near real-time. The framework's fast wall-clock time and low CPU requirements add value to the near real-time flood inundation mapping of compound coastal—fluvial floods in the low-lying marine fluvial transition regime. The method was validated against results from a state-of-the-art numerical ocean circulation model ADCIRC for massive coastal flooding, resulting from Hurricane Ike (11–13 September 2008) in the Southeast Texas region, along the Gulf of Mexico. One of the practical challenges in CF mitigation is either joint or back-to-back impacts of multiple mutually interdependent climatic and weather stressors within a short time window, leaving little time for recovery, which can propagate through a network of infrastructure systems, causing cascading failures (Najafi et al., 2021). The study by Preisser et al. attempted to prioritise the critical resources (such as hospitals and food) when a storm occurs in near-real time. Based on open-source data and a network-based approach, they proposed a model to solve the "user equilibrium traffic assignment problem" by calculating how an individual's access to critical resources changes during and immediately after the flood event. In a case study for Austin, Texas the authors found that the most vulnerable households are the least resilient to the impacts of flooding and experience the most volatile shifts in redundancy, reliability, and recoverability. The open-source framework developed in the article can benefit emergency planning stakeholders by helping to identify households that require specific resources during and immediately after hazard events.

As a result of climate change consequences, not only are the frequency and magnitude of similar or dissimilar types of hydrological extremes (e.g., floods and droughts) increasing in some regions, but the transitions between these events are also becoming more frequent and abrupt, accelerating economic and societal impacts (Chen and Wang, 2022; Bai et al., 2023; Xi et al., 2023; Banfi et al., 2024; Bowers et al., 2024). Based on observations spanning more than seven decades (1951–2022), Sudha et al. developed a statistical framework to define meteorological extremes—wet (i.e., abundance of water) and dry (i.e., lack of water) events—and investigated the transitions between them using a case study of the Meuse River basin in the Netherlands. Their analysis indicates a statistically significant increase in water deficit due to evapotranspiration in spring and summer, along with an increased length of dry spells due to warming temperatures. They also identified abrupt transitions between wet and dry phases of extremes that challenge water management, with such conditions occurring in 6% of wet-dry transitions and 20% of dry-wet transitions. These findings provide new insights into nonstationary trends of contrasting compound climate stressors in hydrological risk assessment.

Modelling and quantifying catastrophic risk requires the interaction of several correlated hazards from natural and anthropogenic stressors. In particular, the coincident and/or lagged occurrence of different hazard categories, responsible for extreme impacts is dictated by the causality or interconnectedness of different stressors, which in turn are influenced by climate change, and urbanisation—leading to changes in land use and land cover (LULC) patterns—and technological advancement. Siddique et al. quantified changes in land use and land cover for an ecologically critical area, a freshwater wetland system, Hakaluki Haor in the Sylhet region of Bangladesh. Leveraging Landsat satellite data in a cloud-based platform (Google Earth Engine Database), coupled with state-of-the-art machine learning models, this study analysed LULC dynamics from 2000 to 2023. While one of the study's striking findings is that, overall more than half of the areas show a reduction in water bodies in the wetland ecosystem, other notable changes include a more than 350% increase in settlements with a substantial decline (>70%) in vegetation cover. Similar shifts in wetland extent have been observed in other locations around the globe. A prominent example is Lake Urmia in northwestern Iran, which has experienced drastic shrinkage due to multiple anthropogenic stressors, such as aggressive water resources development plans, intensive agricultural practises, and competition for water resources in upstream reaches (AghaKouchak et al., 2015). The lake has not managed to recover to its designated ecological threshold, even during normal water years after the persistent 5-year drought of 1998–2002 (AghaKouchak et al., 2015; Alborzi et al., 2018). Although anthropogenic stressors are major drivers, the natural drivers responsible for wetland changes may be shifted in precipitation patterns—more drying in arid environments and increased infiltration in the nival regime due to warmer temperatures that reduce soil ice along with substantial drying of the wetland ecosystem when biotic processes peak (Xu et al., 2024).

In a complex landscape, runoff mechanisms and subsurface flows are dictated by varying geological formations that influence baseflows, soil types, and vegetation, which may be difficult to model given the paucity of data. Merizalde et al. highlighted the importance of feature engineering to improve the performance of deep learning models in ungauged hydrologic systems. The authors combined satellite-derived rainfall products, soil and land cover maps, digital elevation models, and empirical rainfall-runoff methods to feed specialised runoff forecasting models in the Ecuadorian Andes. The results of this research are promising with lead times of up to 11 h, enabling near real-time forecasting and paving the way for more advanced techniques focused on mountainous areas characterised by geographic complexity and data availability constraints. While there are few efforts on the application of statistical learning to runoff forecasting in ungauged catchments (Razavi and Coulibaly, 2013; Pugliese et al., 2018; Prieto et al., 2019; Herath et al., 2021), such approaches have recently started gaining popularity in modelling groundwater flow and contaminant transport (McConnell et al., 2022; Rad et al., 2024). Béraud et al. introduced an innovative data assimilation method that combines Ensemble Smoother with Multiple Data Assimilation, where parameters are updated locally around each observation well through successive assimilations, thus enabling credible calibration of large, complex groundwater models with limited observations. The model is further validated with a synthetic 3D model and a real regional groundwater flow model, showing significant improvements in calibration and prediction in heterogeneous areas, proving the model's ability to predict changes in groundwater flow patterns and contaminant transport.

Finally, a few aspects of this collection are worth highlighting: (1) Water resources modellers and stakeholders need to be aware of the limitations of existing practises, such as assumptions of independence for modelling multi-hazard events in space and time. Proper coordination between scientists and the stakeholder community is required to develop societal resilience to mitigate such hazards. (2) The consequences of climate change have led to shifts in the timing and trend of hydroclimatic extremes, which in turn mediate the frequency of compound hazards (Blöschl et al., 2017; Kemter et al., 2020; Raut and Ganguli, 2024). Through the application of "process-based advanced machine learning" tools, the development and implementation of credible multi-hazard warning systems may be one of the most effective ways to reduce mortality associated with such natural hazards and to protect natural and built environmental systems in multi-hazard risk hotspots in a changing climate (ESCAP, 2023).

Author contributions

PG: Writing – original draft, Writing – review & editing. SH: Writing – original draft, Writing – review & editing. DM: Writing – original draft, Writing – review & editing. SP: Writing – original draft, Writing – review & editing.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

The author(s) declared that they were an editorial board member of Frontiers, at the time of submission. This had no impact on the peer review process and the final decision.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

References

AghaKouchak, A., Norouzi, H., Madani, K., Mirchi, A., Azarderakhsh, M., Nazemi, A., et al. (2015). Aral Sea syndrome desiccates Lake Urmia: call for action. *J. Great Lakes Res.* 41, 307–311. doi: 10.1016/j.jglr.2014.12.007

Alborzi, A., Mirchi, A., Moftakhari, H., Mallakpour, I., Alian, S., Nazemi, A., et al. (2018). Climate-informed environmental inflows to revive a drying lake facing meteorological and anthropogenic droughts. *Environ. Res. Lett.* 13:084010. doi: 10.1088/1748-9326/aad246

Bai, X., Zhao, C., Tang, Y., Zhang, Z., Yang, B., and Wang, Z. (2023). Identification, physical mechanisms and impacts of drought–flood abrupt alternation: a review. *Front. Earth Sci.* 11, 1203603. doi: 10.3389/feart.2023.1203603

Banfi, F., Bevacqua, E., Rivoire, P., Oliveira, S. C., Pinto, J. G., Ramos, A. M., et al. (2024). Temporal clustering of precipitation for detection of potential landslides. *Natural Hazards Earth Syst. Sci.* 24, 2689–2704. doi: 10.5194/nhess-24-2689-2024

Berghuijs, W. R., Allen, S. T., Harrigan, S., and Kirchner, J. W. (2019). Growing spatial scales of synchronous river flooding in Europe. *Geophys. Res. Lett.* 46, 1423–1428. doi: 10.1029/2018GL081883

Bevacqua, E., Vousdoukas, M. I., Zappa, G., Hodges, K., Shepherd, T. G., Maraun, D., et al. (2020). More meteorological events that drive compound coastal flooding are projected under climate change. *Commun. Earth Environ.* 1, 1–11. doi: 10.1038/s43247-020-00044-z

Blöschl, G., Hall, J., Parajka, J., Perdigão, R. A. P., Merz, B., Arheimer, B., et al. (2017). Changing climate shifts timing of European floods. *Science* 357, 588–590. doi: 10.1126/science.aan2506

Bowers, C., Serafin, K. A., and Baker, J. W. (2024). Temporal compounding increases economic impacts of atmospheric rivers in California. *Sci. Adva.* 10:eadi7905. doi: 10.1126/sciadv.adi7905

Chen, H., and Wang, S. (2022). Accelerated transition between dry and wet periods in a warming climate. *Geophys. Res. Letters* 49:e2022GL099766. doi: 10.1029/2022GL099766

ESCAP (2023). "Seizing the moment : targeting transformative disaster risk resilience," in *ESCAP*. Available online at: https://www.unescap.org/kp/2023/seizing-moment-targeting-transformative-disaster-risk-resilience (accessed January 5, 2025).

Fu, Z.-H., Zhou, W., Xie, S.-P., Zhang, R., and Wang, X. (2024). Dynamic pathway linking Pakistan flooding to East Asian heatwaves. *Sci. Adv.* 10:eadk9250. doi: 10.1126/sciadv.adk9250

Gesualdo, G. C., Benso, M. R., Mendiondo, E. M., and Brunner, M. I. (2024). Spatially compounding drought events in Brazil. *Water Resour. Res.* 60:e2023WR036629. doi: 10.1029/2023WR036629

Herath, H. M. V. V., Chadalawada, J., and Babovic, V. (2021). Hydrologically informed machine learning for rainfall–runoff modelling: towards distributed modelling. *Hydrol. Earth Syst. Sci.* 25, 4373–4401. doi: 10.5194/hess-25-4373-2021

Kemter, M., Merz, B., Marwan, N., Vorogushyn, S., and Blöschl, G. (2020). Joint trends in flood magnitudes and spatial extents across Europe. *Geophys. Res. Lett.* 47:e2020GL087464. doi: 10.1029/2020GL087464

Kiesel, J., Wolff, C., and Lorenz, M. (2024). Brief communication: From modelling to reality–flood modelling gaps highlighted by a recent severe storm surge event along the German Baltic Sea coast. *Nat. Hazards Earth Syst. Sci.* 24, 3841–3849. doi: 10.5194/nhess-24-3841-2024

Matthews, T., Wilby, R. L., and Murphy, C. (2019). An emerging tropical cyclone–deadly heat compound hazard. *Nat. Clim. Chang.* 9, 602–606. doi: 10.1038/s41558-019-0525-6

McConnell, L., Karimi Askarani, K., Cognac, K. E., Mack, E. E., Bartlett, C., Ronayne, M. J., et al. (2022). Forecasting groundwater contaminant plume development using statistical and machine learning methods. *Groundw. Monit. Remediat.* 42, 34–43. doi: 10.1111/gwmr.12523

Najafi, M. R., Zhang, Y., and Martyn, N. (2021). A flood risk assessment framework for interdependent infrastructure systems in coastal environments. *Sustain. Cities Soc.* 64:102516. doi: 10.1016/j.scs.2020.102516

Prieto, C., Le Vine, N., Kavetski, D., García, E., and Medina, R. (2019). Flow prediction in ungauged catchments using probabilistic random forests regionalization and new statistical adequacy tests. *Water Resour. Res.* 55, 4364–4392. doi: 10.1029/2018WR023254

Pugliese, A., Persiano, S., Bagli, S., Mazzoli, P., Parajka, J., Arheimer, B., et al. (2018). A geostatistical data-assimilation technique for enhancing macro-scale rainfall–runoff simulations. *Hydrol. Earth Syst. Sci.* 22, 4633–4648. doi: 10.5194/hess-22-4633-2018

Rad, M., Abtahi, A., Berndtsson, R., McKnight, U. S., and Aminifar, A. (2024). Interpretable machine learning for predicting the fate and transport of pentachlorophenol in groundwater. *Environm. Pollut.* 345:123449. doi: 10.1016/j.envpol.2024.123449

Radfar, S., Moftakhari, H., and Moradkhani, H. (2024). Rapid intensification of tropical cyclones in the Gulf of Mexico is more likely during marine heatwaves. *Commun. Earth Environ.* 5, 1–13. doi: 10.1038/s43247-024-01578-2

Raut, A., and Ganguli, P. (2024). Observed trends in timing and severity of streamflow droughts across global tropics. *Environ. Res. Lett.* 19:034006. doi: 10.1088/1748-9326/ad25a1

Raut, A., Ganguli, P., Kumar, R., Das, B. S., Reddy, N. N., and Wöhling, T. (2024). Streamflow drought onset and severity explained by non-linear responses between climate-catchment and land surface processes. *Hydrol. Process.* 38:e15245. doi: 10.1002/hyp.15245

Razavi, T., and Coulibaly, P. (2013). Streamflow prediction in ungauged basins: review of regionalization methods. *J. Hydrol. Eng.* 18, 958–975. doi: 10.1061/(ASCE)HE.1943-5584.0000690

Tang, S., Qiao, S., Wang, B., Liu, F., Feng, T., Yang, J., et al. (2023). Linkages of unprecedented 2022 Yangtze River Valley heatwaves to Pakistan flood and triple-dip La Niña. *NPJ Clim. Atmos Sci.* 6, 1–8. doi: 10.1038/s41612-023-00386-3

Tonini, M., Pedrazzini, A., Penna, I., and Jaboyedoff, M. (2014). Spatial pattern of landslides in Swiss Rhone Valley. *Nat Hazards* 73, 97–110. doi: 10.1007/s11069-012-0522-9

Tuel, A., and Martius, O. (2021). A global perspective on the sub-seasonal clustering of precipitation extremes. *Weather Clim. Extremes* 33:100348. doi: 10.1016/j.wace.2021.100348

Xi, D., Lin, N., and Gori, A. (2023). Increasing sequential tropical cyclone hazards along the US East and Gulf coasts. *Nat. Clim. Chang.* 13, 258–265. doi: 10.1038/s41558-023-01595-7

Xu, D., Bisht, G., Tan, Z., Sinha, E., Di Vittorio, A. V., Zhou, T., et al. (2024). Climate change will reduce North American inland wetland areas and disrupt their seasonal regimes. *Nat. Commun.* 15:2438. doi: 10.1038/s41467-024-45286-z