Project Title

AI-Driven Identification of Compound Climate Hazards in Cities: Extreme Heat and Flooding under Present and Future Scenarios

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Summary

Cities exacerbate climate hazards, particularly extreme heat and flooding. The interaction between cities and climate change magnifies risks to human health and well-being, particularly as high-risk areas often coincide with vulnerable populations lacking adequate resources to adapt. However, current mapping efforts typically focus on single hazards and contain significant gaps in the high-resolution spatial representation of these risks in urban areas worldwide. This project aims to fill these gaps by using AI-based modeling, combined with novel crowdsourced and geospatial datasets, to precisely map multiple climate hazards and vulnerabilities in cities.

By extending the mapping of compound heat and flood hazards to future climate projections, this project will provide crucial insights into spatial dynamics and support the development of equitable adaptation strategies for both present and future scenarios. Additionally, the integration of high-resolution climate maps with vulnerability datasets across urban areas will allow us to quantify the disproportionate impacts on vulnerable communities and highlight climate injustice.

1 Project Outline

1.1 Heat and flooding hazards in cities: now and future

As our cities grow, so does the amount of heat they trap. Changing natural surfaces to built materials directly alters local climates, creating a highly variable distribution of heat in urban areas. The location of the hot and cool spots across the city is then determined by urban form and fabric, such as density and vegetation cover, as well as geographic factors like distance from the coast and elevation. With almost two-thirds of the world's population living in towns and cities, urban heat presents significant health risks and economic burdens, particularly for vulnerable communities who are disproportionately affected by rising temperatures and lack the resources to cope (Hsu et al., 2021; Nazarian et al., 2022).

Urban structures, materials, and infrastructures also directly contribute to urban flooding by exacerbating surface runoff, accelerating river discharge rates, and triggering flash floods. These hazards come with high costs. The Insurance Council of Australia 2021 reported $12.3 billion in claims during 2020-21 from storms and flooding, with 1 in 25 adult Australians making damage claims. The US National Centre for Environmental Education, on the other hand, reported an average cost of $4.6 billion per flooding event. These figures reflect the economic impact in developed countries; the costs and impacts of flooding in vulnerable nations are often underreported or unknown. Beyond health and economic impacts, exposure to flooding is associated with increased long-term mortality risks, including those from mold, structural damage, and personal stress and hardship (Wu et al., 2024).

Both of these hazards are expected to worsen due to climate change and future urban expansion. Global temperatures have risen significantly, with many regions experiencing increased frequency and intensity of heatwaves since the mid-20th century (Meehl and Tebaldi, 2004; Perkins-Kirkpatrick and Lewis, 2020). The higher frequency, intensity, and duration of heat events, compounded by urban heat islands, will have detrimental effects on cities worldwide (Ward et al., 2016). For instance, future healthcare costs related to heat are projected to rise substantially in major cities globally (Tong et al., 2021; Romanello et al., 2021). Similarly, there is clear evidence of increasing short-duration rainfall extremes worldwide (Fowler et al., 2021). In urban areas, this will likely heighten the frequency and severity of flooding, leaving city populations worldwide to contend with multiple, compounding climate hazards now and in the future.

While this research has given us a deeper understanding risks of these climate hazards to public health in urban areas, an essential next step is the development of high-resolution spatial maps that can further quantify climate justice. This approach involves recognizing the simultaneous exposure to multiple hazards, compounded by community vulnerabilities, and considering projected changes due to climate change and future population dynamics. A holistic approach is crucial for addressing the urgent need to mitigate the disproportionate impacts of climate change on marginalized and disadvantaged populations globally.

1.2 New methods to map urban climate hazards: AI and novel datasets

Mapping flood and heat risk in cities is inherently complex. First, there is a need for methodologies that produce high-resolution and accurate datasets to capture the compounded effects of both hazards, which is currently lacking in the field. Second, this information must be integrated with high-resolution urban characteristics influencing exposure to heat and flooding. While urban datasets are becoming increasingly available and more consistent globally, their systematic integration into the prediction of compound hazard maps remains limited. Third, comprehensive assessments are crucial to needed to factor in anticipated climate change impacts, requiring workflows that compare current risk maps with future projections.

To address these complexities and respond to emerging datasets and methods, the project (Figure 1) will develop an AI-based methodology to map urban climate hazards, focusing on extreme urban heat and flood risks under both present-day and future climate conditions. By leveraging emerging high-resolution urban data as well as global quality-controlled and crowd-sourced climate datasets, machine learning (ML) algorithms will be trained and tested to identify and map areas of high climate hazard risk. Additionally, the project will determine how these spatial patterns will shift and change under multiple future climate scenarios. Initial work will focus on mapping Australian cities as a proof of concept, with the methodology designed for global application. The use of AI-driven analysis and emerging global datasets will ensure scalability across various cities worldwide. The following sections detail the methodology, datasets, and preliminary investigations that ensure the feasibility of this project.

1.2.1 Upscaling temperature observations with convolutional neural networks

High-resolution heat maps are often based on satellite-derived land surface temperatures (LST). However, satellite images capture surface temperatures of roofs and top of the tree canopies, which have limited relevance to human heat exposure and heat stress experienced at street level (Martilli et al., 2020; Naserikia et al., 2023). Air temperature, the most relevant metric for heat exposure, is typically measured by official weather stations, but these are sparse in

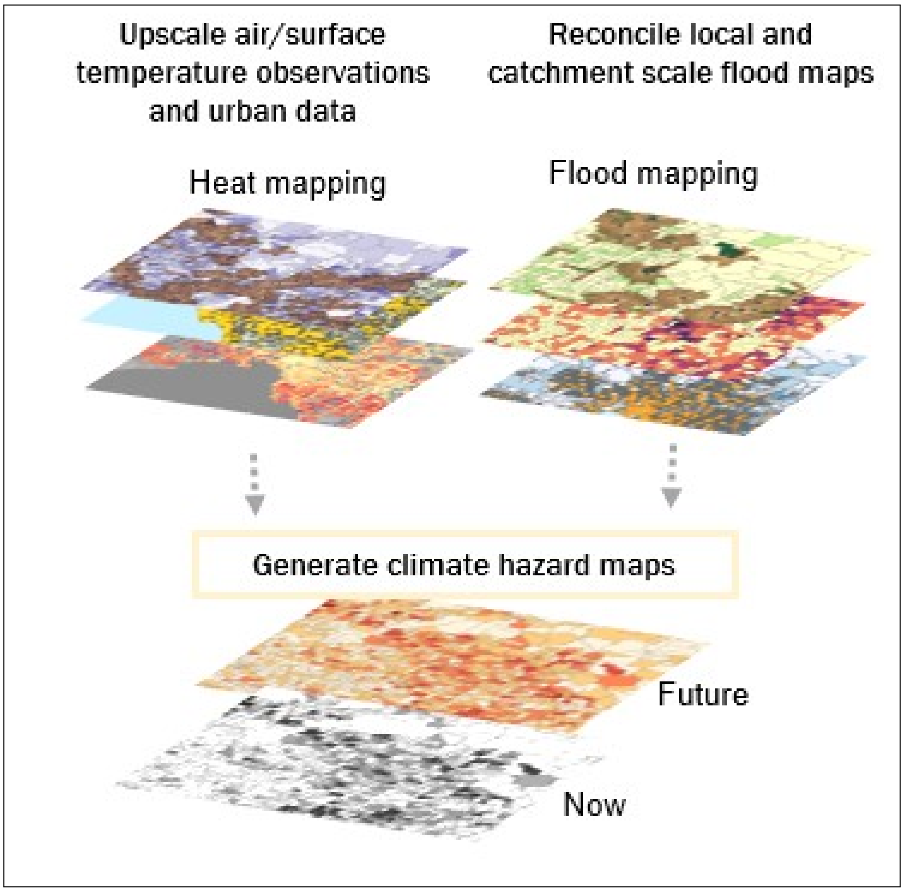

Figure 1: **Climate hazard map creation for present-day and future climates.**

cities and provide only point measurements with limited and inconsistent spatial coverage. To address these gaps, this project will leverage citizen weather observations (Fenner, 2020; Potgieter et al., 2021), which offer broader coverage and more observations in cities, combined with datasets of urban characteristics, and will use ML algorithms to upscale the data to high-resolution heat mappings.

Heat maps will be developed based on the datasets and methodology developed by PI Nazarian (Potgieter et al., 2021; Naserikia et al., 2023; Lipson et al., 2022b; Brousse et al., 2023), leveraging quality-controlled, crowd-sourced citizen weather observations from various global cities. For example, this crowdsourced data includes quality-controlled hourly observations for air temperature, humidity, and wind speed. PI Nice has been collecting crowdsourced observations at hundreds of locations across all the Australian capital cities since 2019. More importantly, the project PIs, through a collaboration with Ruhr University Bochum, have access to their multi-year quality controlled dataset of crowdsourced observations, with coverage of all global cities. The project PIs also have access to and the expertise to utilize additional datasets of urban form and geographic characteristics relevant to heat mapping across global urban areas. These include datasets of urban features and vegetation footprints, heights, and fractions, the World Settlement Footprint 3D (Esch et al., 2022) at 90m, supplemented by worldwide building footprints (Microsoft, 2024a) and global road detections (Microsoft, 2024b). As land cover, especially impervious surfaces, have a large impact on urban heat, we will also use the GISA-10m, Global Impervious Surfaces at 10m resolution dataset (Sun et al., 2022). Finally, these will be combined with influential local geographic characteristics of land use types, topography (elevation), and distance from the coast. Integrating these datasets to assess and inform urban temperature predictions can only be achieved using AI/ML approaches.

Before conducting the heat mapping, it is important to identify which variables most significantly influence heat distribution across cities. To achieve this, we employed Random Forest (Ho, 1995) and Gradient Boosting (Chen and Guestrin, 2016) for feature importance analysis in our pilot investigations (Naserikia et al., 2022). These methods allowed us to extract and rank the most contributing variables, ensuring that the heat maps are built using the most relevant data to enhance accuracy in capturing temperature distribution across heterogeneous urban environments. To further enhance the analysis of spatial patterns and heat mapping, we propose the use of ML techniques that are capable of capturing spatial dependencies, such as Convolutional Neural Networks (CNN). CNNs are highly effective in processing grid-based data, making them well-suited for extracting spatial features from satellite imagery and other urban geospatial datasets such as land cover and urban morphology. By using CNNs, we can capture fine-scale spatial variations in urban heat and flood risks, which allows for more high-resolution identification of heat across urban landscapes. Figure 2 shows an example of the heat maps developed for Sydney on a summer day, using a CNN model and datasets including crowdsourced temperature measurements, LST data (Landsat), and urban land cover/structure variables. This work serves as a proof of concept for the use of AI-driven methods and novel datasets to capture high-resolution maps of air temperature in cities.

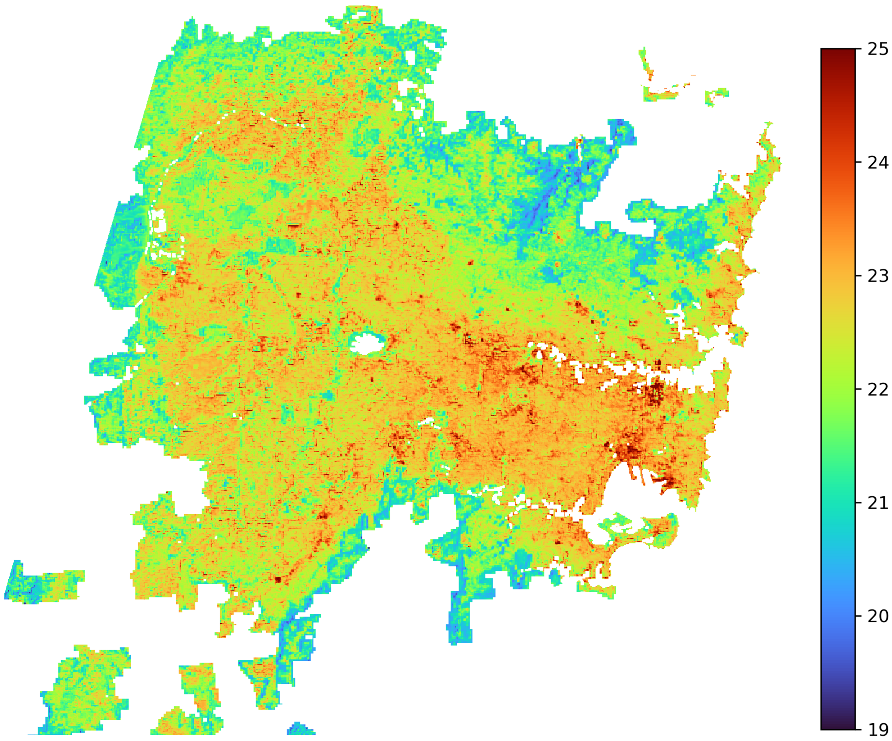

Figure 2: **Heat map of air temperatures in Sydney developed using CNN and datasets of crowdsourced temperature measurements, Landsat imagery, and urban land cover/structure variables for a summer day.**

In the proposed project, the integration, quality control, and accessibility of the urban heat datasets (including Land Surface Temperature and crowdsourced air temperature) will be conducted by a postdoctoral research associate at UNSW, PI Naserikia with prior experience in this area (Naserikia et al., 2023) and enabled by this grant funding, under the direction of PIs Nice and Nazarian.

1.2.2 Reconciling local and catchment scale flood maps

For flooding risks, ML techniques will be employed to reconcile the differing scales between existing local and catchment flood hazard mapping (typically at 5-20 metres resolution based on hydrodynamic modelling) with the coarser resolution extreme rainfall data. The aim here is to develop a model that estimates flood impacts at the spatial scale of the heat impacts. The integration of the rainfall data with the existing flood mapping is required to provide a homogeneous city-wide flood hazard assessment and to translate the high resolution climate model rainfall simulations into flood hazards.

The rainfall data in the form of Intensity, Frequency, Duration (IFD) data, at a resolution of 2.5 kilometres, which was optimised to provide comprehensive information on extreme rainfalls at the national level rather than the scale of any particular catchment or city (Johnson et al., 2016a). PI Johnson's earlier work on spatial disaggregation of climate model simulations suggests that factors representing loss of variance between spatial scales can be used to inform the relationships between the IFD data with the flood mapping (Nahar et al., 2017). Other inputs to the ML modelling will be high-resolution Digital Elevation Models, satellite-derived land cover which controls hydraulic roughness and Mean High Water Spring tide levels which control tailwater levels and hence backwater flood hazard. Random Forest models will be investigated based on their previous good performance in flood susceptibility mapping (Gharakhanlou and Perez, 2023). The flood hazard from the 1% Annual Exceedance Probability event will be assessed, focusing primarily on flood depth but also flood extents and velocities which together create the overall flood hazard.

The focus of this phase will be limited to pluvial (i.e. rainfall driven) and fluvial (i.e. river driven) flood hazards as coastal flood hazard from erosion and storm surge is assessed differently from hydrological hazards. One of the key research questions to be answered in this phase is how to resolve temporal scaling questions with the flood mapping. For example the peak flood in small urban catchments can result from very short duration rainfall events. But such events can be embedded in larger flood-producing systems e.g. the so-called Pasha Bulker storm in 2007 led to major flash flooding in Newcastle CBD from thunderstorms that occurred within a wider extra-tropical cyclone system that led to main river flooding of the Hunter River over multiple days (Johnson et al., 2016b). This temporal scale duality will be important to resolve in the mapping because it will need to be considered under future climate scenarios when extracting and bias correcting the precipitation projections. This work has an extensive focus on novel methodologies for flood mapping and will be supported by the RA under the direction of PI Johnson at UNSW.

1.2.3 Urban climate hazards under future climate conditions

To map the shifting and changing temporal and spatial urban heat patterns, future climate projections from the Coupled Model Intercomparison Project Phase 6 (Eyring et al., 2016) (CMIP6) archive, developed within the framework of IPCC's 6th Assessment Report (IPCC, 2021), will be used. This method has been previously used in other future climate scenario work by PI Nice (Nice et al., 2024) and PI Nazarian (upcoming work). A future climate change signal from a number of Shared Socioeconomic Pathways (SSPs) will be superimposed onto present-day time series and generate future heat hazard mapping via a 'morphing' process, shifting (in mean) and stretching (in minimum and maximum) the observed time series, changing both the mean and the variance (Belcher et al., 2005; Pulkkinen and Louis, 2021). Present day urban heat mappings generated in the previous stage of the project will be morphed into projected spatial maps for 2050 and 2080.

It is important to note that for future mapping, the nature of the data changes, as temporal aspects become as important as spatial aspects. Unlike the present-day data used in the first phase, the future climate projections from CMIP6 are derived from simulations that capture both spatial and temporal variability across different climate scenarios. These datasets provide high-resolution insights into future climate conditions, but they also introduce uncertainties related to long-term projections. The spatial maps we expect to generate for 2050 and 2080 will be influenced not only by the urban landscape but also by the temporal trends of climate variability and extremes. Building on what we have learned from the AI trained on the current heat mapping, we will refine our approach to integrate these projections and better anticipate future heat hazard patterns.

To accurately capture these temporal and spatial variations, we propose the use of state-of-the-art ML techniques such as Convolutional Long Short-Term Memory (ConvLSTM) and CNN-Transformer hybrid networks. These models are able to capture both spatial correlations and temporal dependencies. By leveraging large datasets, they can learn patterns and relationships that are often too complex to be captured by traditional methods, particularly in urban environments. Using these data-driven frameworks, we can effectively model the dynamic interactions between excess heat and flooding across Australian cities. PIs Johnson and Nazarian have experience in using Partial CNN models coupled with LSTMs to gap fill remotely sensed data using spatialy and temporally coincident information. This was implemented using U-net-like architecture. Learnings from training such models on multi-spectral data can be translated here to the multi-hazard context of temperature and floods.

Future flood hazard maps will be generated by bias correcting downscaled rainfall simulations from Coordinated Regional Downscaling Experiment (CORDEX) simulations to estimate future IFDs. Earlier work by PI Johnson's team identified the best methods to bias correct dynamically downscaled rainfall projections when estimating IFDs (Li et al., 2017b,a). The future IFDs will be combined with sea level rise projections from CMIP6 and then using ML methods from Phase 1 to map the changes in IFDs into future flood hazards. ML methods are vital for this mapping due to non linearity in the catchment response to flooding. ML methods have been used to emulate high-resolution flood hazard assessments based on low-resolution models under historical climate conditions, but have not yet been used to estimate future flood risk where changes in both rainfall extremes and tailwater conditions will combine to add additional complexity to the problem (Fraehr et al., 2023).

2 Deliverables

Research outputs will target scholarly and public audiences.

Public outputs: A dedicated project website will collect and host the data and articles and reports to make all of these project outputs publicly and freely available. Publication of scientific summaries and opinion pieces in venues such as the Conversation will help provide access to the project insights to a lay audience.

Code generated in the project will be made available through a publicly available repository (such as Github) but permanently archived in a digital object identifier (DOI) referenced Zenodo repository.

Datasets will be consist of GIS layers or NetCDF spatial and temporal maps for present day climate hazards and for future SSP scenarios in 2050 and 2080.

Scholarly outputs: As a multi-disciplinary project, the outputs will be published in a range of top ranked peer-reviewed journals across urban climates, and modelling (e.g. Science of the Total Environment, Urban Climate, Geoscientific Model Development), hydrology (e.g. Journal of Hydrology), and data publishing (e.g. Earth Systems Science Data, Scientific Data). Topics covered will include methodologies for urban heat mapping (present-day and future predictions) and methodologies for mapping flooding risks. Finally, datasets generated by this project will be published as open datasets.

3 Timeline

The timeline (Figure 3) provided by the project funders indicates that notifications of the results will be delivered in December 2024, with project funding beginning in February 2025 and ending in February 2026. We will begin recruitment of the research associate immediately on the award notification. A preferred candidate has already been identified, as of the grant writing, so the commencement of the project can take place on time in February 2025.

TASKS	Feb 2025-Feb 2026)					
	Feb/Mar	Apr/May	Jun/Jul	Aug/Sep	Oct/Nov	Dec/Jan
Heat present-day hazard mapping						
Flood present-day hazard mapping						
Future climate projections						
Mapping future climate hazards						
Journal publication and finalizing dataset						

Figure 3: **Project timeline.**

The project has four major components to deliver. They are present-day heat mappings, present-day flood mappings, projections of future climate shifts in heat and rainfall, and future heat and flood mappings. PI Naserikia will produce the present-day heat mappings in the first four months. Concurrently, PI Nice and Nazarian will produce the future climate shifts in heat while PI Johnson will generate the same for rainfall. The second four months, the present day flood hazard mappings will be produced. In month eight, the future trends will be applied to the present-day heat and flood mappings to generate future maps. Finally, in the last two months, the data description journal article will be written and submitted and final datasets and code be deposited into the Zenodo repository.

4 Team

The investigator team assembled for this project is exceptionally qualified to execute the proposed research requiring interdisciplinary datasets and methodologies. Our collective expertise spans climate science, flood hazards, and most crucially the use of novel data sources and machine learning.

This project will be supported by five team members, with PI Naserikia as the postdoctoral research associate (1 year 1.0 FTE) focusing on generating heat datasets and flood hazard mapping under the supervision of the other three PIs. A fifth member, a level 6.2 research assistant (250 hours over 10 weeks) will be responsible for data preparation of data to be upscaled.

Heat mapping will be led by PIs Nazarian and Nice, established urban climate scientists with extensive experience in urban heat assessments and urban climate informatics, including machine learning, data analysis, and innovative data sources like quality-controlled weather stations with active collaborations and co-publications, including contributions to the Western Sydney Region of Councils Cool Suburbs rating and assessment tool for building heat resilience in urban development.

PI Nazarian, one of the four experts who established the field of urban climate informatics (UCI), has notable ML contributions in a review of ML in UCI (Middel et al., 2022) and land cover analysis (Naserikia et al., 2022). PI Nice has published research utilising ML in air pollution prediction (Wijnands et al., 2022), sky detection in urban imagery (Nice et al., 2020b), and neural network clustering of urban design typologies (Nice et al., 2020a). PIs Nazarian and Nice will supervise the research associate, focused on urban heat data integration and quality control. PI Naserikia has done a proof-of-concept for present-day heat mapping over one city which will directly contribute to the success of the project.

PI Johnson, internationally recognised for her leading research in rainfall extremes, flood hazards, and humanitarian engineering, is best known for designing methods to remove biases, enabling impact-relevant climate change assessments directly relevant to this project and a CI in the ARC Training Centre for Data Analytics for Resources and Environments as the water domain lead working with industry partners on integrating data science methods into their operations. She will lead the reconciliation of scales in existing flood hazard mapping and develop new methodologies to project these mappings into the future and will supervise the research associate at UNSW to assist with this research.

A 1.0 FTE 1-year post-doctoral researcher (PI Naserikia) at UNSW will perform the assessment of the present and future climate hazards mapping for this project under the direction of the project PIs. PI Naserikia has experience developing global dataset of land surface temperature using high resolution satellite imagery. She also has experience applying various AI models for spatial analysis in urban areas including mapping heat for multiple projects with different scales, work she published (as lead author) in two high impact journals (Naserikia et al., 2022, 2023).

5 Pathway to Impact

Climate hazards threaten people and livelihoods. Cities, where most people live, are especially vulnerable and exacerbate two hazards: urban heat and flooding. Heat is a silent killer, harming more Australians than any other natural disaster (Nazarian et al., 2022), while flooding accounts for the majority of disaster claims and costs the Australian economy $5 billion annually (Department of Veteran’s Affairs, 2022). Both hazards are closely linked to how urban areas are developed and grow (Nazarian et al., 2022; Feng et al., 2021), and they disproportionately impact the most vulnerable communities in Australian cities (Australian Government Bureau of Meteorology, 2022). Despite the severity of these impacts, there remains a significant gap accurately mapping urban climate hazards, especially the combined heat and flood risks (**multi-hazard assessment**) across urban areas.

Accurately mapping heat and flooding hazards remains a challenge, primarily due to the limitations of existing datasets and inadequate spatial coverage for informing high-resolution mappings. In the case of heat, spatial maps often come from satellite-sensed land surface temperatures (LST) which are of limited relevance to heat exposure of people (Martilli et al., 2020; Naserikia et al., 2023). Similarly, fine-grained data representing flood hazards are consistently lacking across cities, as flood mapping is typically prepared on a catchment scale. This leads to variability in resolution and coverage due to misalignment with local government boundaries. In addition estimating high-resolution flood hazards for large river systems, for example, the Hawkesbury-Nepean River in New South Wales in Australia, poses substantial computational challenges.

This project aims to leverage innovative urban climate informatics methods, including ground-level citizen weather observations (Fenner, 2020; Potgieter et al., 2021) upscaled by machine learning (ML) algorithms to overcome the identified gaps in high-resolution heat mappings and reconciling previously incompatible flood mappings, to capture and develop spatial data on urban climate justice. Through advanced deep learning models such as CNNs and ConvLSTM, we aim to enhance prediction accuracy, optimize the model's ability to generalize across different regions and climate scenarios, and ultimately improve urban hazard identification and response strategies.

Increasingly governments are looking to alleviate climate change impacts by using better predictive models that allow first responders to prioritise efforts during disasters and planners and urban managers to identify areas that are at higher risk, and to take steps to mitigate that risk to reduce the impact of natural hazards. For example, improving flood mapping can increase awareness among residents that their neighbourhoods are flood prone. Water sensitive urban design interventions such as swales, detention basins and permeable paving seek to reduce stormwater runoff. In rarer cases managed retreat by moving at-risk populations away from highly flood prone areas, such as the town of Grantham in the Lockyer Valley, Queensland have also occurred. So too has buy-back of houses in highly flood-prone areas such as Lismore, NSW. But governments still struggle to identify the co-location of populations experiencing socio-economic marginality and disadvantage and climate change related extreme events. A particularly vexing question is how to predict future risk based on future populations, a task taken up by this project.

6 Dataset Plan

Climate science has a long history of making datasets publicly available. This project will not be an exception to this common practice. In fact, this project would not be possible without the datasets made public by other researchers. We intend to make the data available following the model of Lipson et al. (2022a). A data description paper will be published describing and publicising the dataset. The paper will reference the Zenodo repository containing the data. The data will be released under a Creative Commons Attribution licence (CC-BY-4.0). Both the publication and the Zenodo repository will document the structure of the datasets and provide sufficient metadata to enable other researchers to fully utilise the datasets. Additionally, the code used to generate and process the datasets will also be deposited in the Zenodo archive to allow reuse as well as independent replication of the data generation.

This plan addresses the FAIR Data Principles in the following ways. The data will findable, as the publication and Zenodo data set will be assigned a DOI number. The metadata and structural descriptions of the datasets in the publication and in the repository will fully describe the datasets. The dataset will be globally accessible through the DOI number and dataset will be stored permanently on Zenodo.

The data will be shared in commonly used formats, NetCDF and GIS raster and vector files to make them broadly usable and utilise extensive internal metadata to make the datasets self-descriptive, in addition to the documentation provided in the publications and repository metadata.

Finally, an overriding principle of this project will be to ensure the datasets are widely used. The datasets will be created and documented in the manner commonly used in shared climate science datasets, but will also enable non-scientists (government agencies, consultants, NGOs) to utilse the information they contain. Finally, the Creative Commons license will allow unrestricted use of the data generated by this project.

7 Equity Considerations

This project advances equity-related considerations in a number of ways.

1. The first is the composition of the research team. The four PIs are all early to mid-career researchers. Three of the four PIs are female. And the project is being led by PI Nazarian, a person of color. PI Nazarian has also been active over her career in mentoring early-career female academics, with notable success (two securing USyd Horizon Fellowship and one Assistant Professor at the Pratt Institute), as well as acting as UNSW Gender Equity Champion with substantial input on policies at her university. PI Naserikia (the preferred candidate for the research associate position) is also female and an early career academic.

2. The second consideration is the nature of the research itself. The four PIs have been engaged in research around climate justice and how climate hazards have a disproportional impact on the most disadvantaged members of society. The climate hazard mappings produced by this project are a critical step in identifying these inequitable risks and enabling mitigation and responses to reduce the injustices carried by these groups.

8 Ethical Considerations

Ethical considerations for the project include:

1. Considerations about the environmental sustainability of the research. For the proposed project, this includes project travel and scope 3 emissions from data centres and outsourced computational cost of the project to the Australian National Computing Infrastructure (NCI). Both UNSW and the University of Melbourne have reached net zero emissions for their scope 1 and scope 2 emissions. NCI uses 100% renewable energy so has zero carbon emissions. Data centres are major water users and Gadi at NCI is water and evaporatively cooled which reduces its energy need but increases the water footprint of the infrastructure. Given the project team has already existing ongoing strong collaborative links, no face to face travel specific to the project has been budgeted and project team meetings will be facilitated through the use of virtual project team meetings using Zoom or similar.

2. Mapping flood hazards has ethical implications for communities through its impacts on insurance coverage and property prices. Communities have the right to be informed of

the true flood hazard that they are exposed to. However the implications of this knowledge are potential increases in insurance premiums and in some cases inability to obtain insurance coverage at all. In addition, if properties are known to be flood affected then their resale value is reduced. The flood mapping to be undertaken as part of this project is not new but is instead bringing together existing information on flood hazard and its coincidence with heat hazards. Therefore it is considered that the additional ethical implications are minor over existing government funded flood mapping.

3. Finally as discussed above in terms of the equity implications of the project, the rationale for this work are issues of injustice facing already vulnerable communities due to their uneven exposure to climate hazards and the intersectionality of this exposure with other forms of inequality or disadvantage including for example poverty and migrant populations. Therefore there is a strong ethical impetus to complete this project to better understand the extent of the current and future climate injustice facing the case study populations. And more broadly to develop tractable methodologies to identify such injustice globally.

Publications by PIs, titles in **bold**.

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