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Platform urbanism for resident safety: A real-time predictive microclimate risk monitoring and alert system

Sk Tahsin Hossain [a], Tan Yigitcanlar [a,*], Kien Nguyen [b], Yue Xu [c]

[a] QUT Urban AI Hub, School of Architecture and Built Environment, Queensland University of Technology, 2 George Street, Brisbane, QLD 4000, Australia
[b] School of Electrical Engineering and Robotics, Queensland University of Technology, 2 George Street, Brisbane, QLD 4000, Australia
[c] School of Computer Science, Queensland University of Technology, 2 George Street, Brisbane, QLD 4000, Australia

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A B S T R A C T

Urban microclimates significantly impact public health, liveability, and emergency preparedness, yet traditional weather alert systems often rely on centralised data that fails to capture the spatial variability of conditions within cities. This study presents an innovative platform that integrates ArcGIS GeoEvent Server with AIoT-driven predictive analytics to deliver hyper-localised weather alerts. The platform's adaptable design enables the incorporation of location-specific AI/ML-based predictive models and context-aware notifications, tailored to at-risk populations based on their location, health conditions, and disabilities. Featuring three GeoEvent Services and two ArcGIS Notebook Schedules, the system facilitates real-time data ingestion, processing, predictive modelling, and dissemination. A case study in Brisbane, Australia, demonstrates its capacity to address microclimatic variability, revealing significant differences in thermal stress and precipitation patterns across suburbs. Unlike traditional city-wide alerts, the platform provides targeted notifications prioritising vulnerable groups such as children, elderly, and individuals with chronic conditions or disabilities. This approach enhances urban resilience and offers a scalable framework for applications in health monitoring, emergency response, and public safety.

1. Introduction and background

Urban environments are increasingly vulnerable to the impacts of microclimatic variations, driven by phenomena such as urban heat islands, localised air pollution, and changes in land cover and vegetation patterns (Kamruzzaman et al., 2015; Elliott et al., 2020; Kong et al., 2021; Li et al., 2024a). These factors significantly influence urban weather patterns, resulting in variations of temperatures and rainfall in different parts within a city (Dizdaroglu and Yigitcanlar, 2014; Liu et al., 2024). Such disparities can have profound impacts on residents, especially vulnerable populations such as children, elderly, individuals with chronic illnesses, or those with disabilities (Yigitcanlar, 2010; Kousis et al., 2022; Li et al., 2024b). To mitigate these challenges, existing weather monitoring systems and alert platforms in cities employ various approaches to enhance forecast accuracy and provide timely warnings.

Many of these systems leverage centralised meteorological data, integrating historical climate records with real-time observations from a centralised weather stations to generate city-wide forecasts (Murray, 2021; Oswald et al., 2024). Advancements in artificial

* Corresponding authors.
E-mail addresses: tahsin.hossain@qut.edu.au (S.T. Hossain), tan.yigitcanlar@qut.edu.au (T. Yigitcanlar), k.nguyenthanh@qut.edu.au (K. Nguyen), yue.xu@qut.edu.au (Y. Xu).

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intelligence (AI) have enabled the development of models that can predict weather in microclimate (Yigitcanlar et al., 2023b; Han et al., 2024). Many cities deploy extensive sensor networks across various urban areas to monitor environmental conditions in real time (Maclean et al., 2021; Frustaci et al., 2022; Yigitcanlar et al., 2023a). These networks provide detailed data on environmental conditions, capturing variations in temperature, humidity, air quality and other parameters crucial for understanding urban microclimates. Mobile microclimate stations have emerged as an innovative solution to urban climate monitoring (Tsin et al., 2016; Shi et al., 2021). These stations offer the flexibility to monitor key variables that regulate urban environments across different locations, offering a complementary data source to satellite imagery and fixed weather stations.

Weather monitoring agencies utilise data from centralised and city-wide sensor networks to predict weather conditions and issue alerts, primarily at the city-wide scale (Rashid and Rehmani, 2016; Ostrometzky and Messer, 2024). To effectively communicate these warnings, local governments and city authorities disseminate notifications to residents through text-based alerts (via SMS), official websites, and dedicated mobile applications (Johnson et al., 2022; Ascione et al., 2024). Mobile weather applications also play a crucial role in delivering real-time alerts to users, often sourcing predictions directly from government websites via their Application Programming Interfaces (APIs) (Zabini, 2016; Kaginalkar et al., 2021). While existing weather monitoring systems provide high accuracy in weather forecasts, and alert platforms notify residents before weather events, they exhibit several critical limitations (Yassaghi et al., 2019).

Firstly, weather alerts are usually disseminated uniformly across the city, without considering the specific locations of residents, their ages, health conditions, or disabilities (Acosta-Coll et al., 2018; Casanueva et al., 2019). Vulnerable groups, such as children, elderly, and individuals with health conditions or disabilities, lack access to tailored information that could help them make informed decisions about outdoor activities and necessary preparations (Connon and Hall, 2021).

Secondly, existing systems typically treat the city as a homogenous entity, sending alerts to all residents irrespective of the specific weather conditions in their local area. This one-size-fits-all approach overlooks the microclimatic differences within a city, where weather conditions can vary significantly over short distances (Shaamala et al., 2024). For instance, a slight increase in temperature in cooler parts of a city might have a greater impact on residents there than in consistently warmer areas (Wong et al., 2021).

Finally, local authorities, including municipal governments, lack effective tools to accurately monitor and understand the number of individuals 'at-risk' across various urban locations in real-time or in anticipation of upcoming weather events, hindering effective resource allocation and proactive emergency response planning (Chitwatkulsiri and Miyamoto, 2023).

Fig. 1. Locations of meteorological sensors in Brisbane operated by the Queensland State Government.

To address these challenges, this study proposes a novel platform architecture rooted in platform urbanism and driven by the Artificial-Intelligence-of-Things (AIoT) concept. The platform captures real-time weather data from sensors located in various parts of a city and integrates it with the population's demographic and health information for tailored analysis. By analysing this combined data, the system automatically generates personalised alerts for residents and equips local authorities with insights through a dashboard to monitor and respond to populations at risk. This study uses Brisbane, Australia, as a case study to underscore the significance of such a platform and to demonstrate its effectiveness in addressing localised weather-related challenges.

The integration of demographic and health data of Brisbane into the platform was designed with a strong emphasis on data validity, privacy, and ethical considerations. Demographic and health statistics were sourced from publicly available datasets, primarily from the Australian Bureau of Statistics (ABS), ensuring accuracy and reliability. These datasets undergo rigorous validation processes before publication, ensuring their suitability for research and policy applications (Fair et al., 2019). It is important to note that, this study did not utilise actual personal information, such as individuals' 'real' age, location, or specific health conditions. Instead, we employed aggregated population statistics—such as the total number of residents within different age groups and those with specific health conditions in each suburb. This approach enabled a realistic simulation of the platform's capabilities while adhering to ethical research guidelines.

This study begins by examining the variation in temperature and rainfall across different suburbs in Brisbane, emphasising the shortcomings of centralised weather alert systems that overlook these microclimatic differences. Subsequently, the study introduces the theoretical framework underpinning the platform, grounded in the concepts of platform urbanism and AIoT, followed by the architecture of the platform, implementation and its demonstration.

1.1. *Localised weather variations in the case study area of Brisbane*

Brisbane, the capital of the state of Queensland, is situated on the eastern coast of Australia. Brisbane has a subtropical climate characterised by warm, humid summers and mild, dry winters (Yang et al., 2023). Spanning an area of over 15,800 km^2, Brisbane accommodates a population exceeding 2.5 million, distributed over 190 suburbs across a wide range of urban, and peri-urban regions (Hou et al., 2023). The city's unique topography, encompassing a river system, coastal influences, and varying elevations, contributes to diverse microclimatic conditions across its metropolitan area (Javanroodi et al., 2023).

The Queensland Government maintains a network of over 50 sensors across the state, including devices to monitor air quality, organic matter, hydrogen, metals, meteorological conditions, and smoke (Li et al., 2024d, 2024e; QLD, 2024). Within the Brisbane City, nine meteorological sensors are positioned in various suburbs, as illustrated in Fig. 1. The spatial distribution of these sensors reveals both clustered and isolated patterns. To explore localised temperature and rainfall variations in the vicinity of these sensors, this study utilised the past 10 years' meteorological data (2014–2023) from all stations, except for Deagon. The Deagon sensor, being a recent addition to the network, has only recorded data since 2021. The data was downloaded from the Queensland Governments' Open Data Portal.

The average daytime (6:00 AM to 6:00 PM) and nighttime (6:00 PM to 12:00 AM) temperatures across various seasons—Autumn (March, April, May), Spring (September, October, November), Summer (December, January, February), and Winter (June, July, August)—reveal notable spatial and temporal variations in Brisbane's weather conditions, as depicted in Fig. 2. In Summer, the differences in daytime average temperatures between weather stations are the most pronounced, ranging from 28.7 °C in South Brisbane to 25.8 °C in Wynnum North. Similarly, nighttime temperatures also vary, though less dramatically, between 23.6 °C in South Brisbane and 22.1 °C in Wynnum North. Conversely, during Winter, temperature anomalies between stations are reduced, with differences

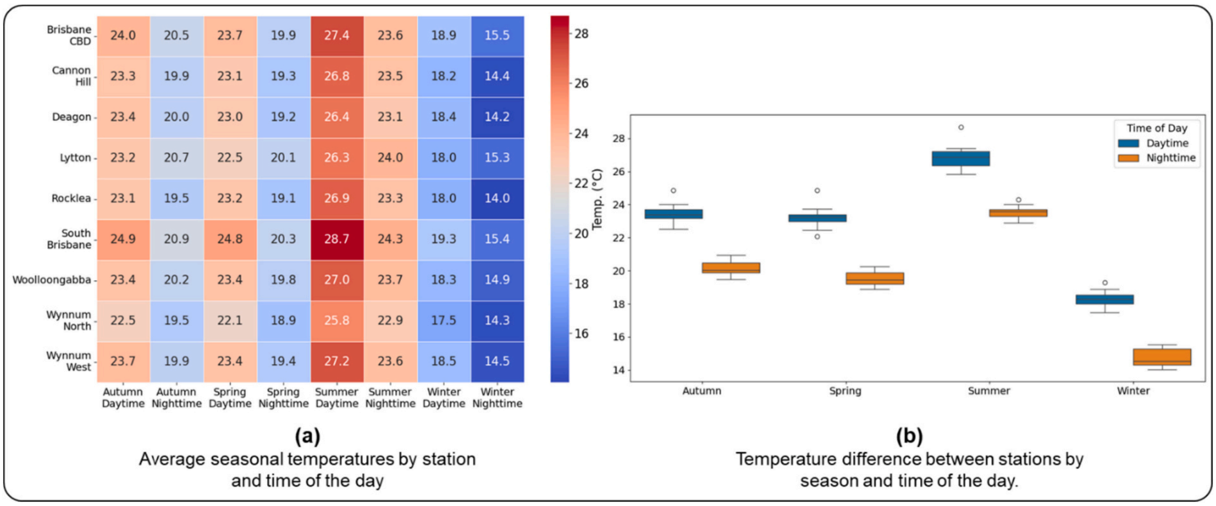

Fig. 2. Seasonal daytime and nighttime temperature and variations across Brisbane based on daily data from 2014 to 2023.

narrowing to around 1 °C. These findings indicates that temperature is not uniformly distributed across the city, even within a relatively compact area, due to microclimatic factors such as heat islands, vegetation cover, land use patterns, and proximity to water bodies (Kong et al., 2021; Li et al., 2024a).

To further highlight the significance of localised temperature variations, an interpolation approach was applied using the Inverse Distance Weighting (IDW) method to spatially represent temperature distributions across Brisbane suburbs (Masoudi, 2021). The focus was on surrounding suburbs of existing stations only due to the uneven distribution of weather sensors, which limits the comprehensive city-wide coverage. Fig. 3 (a-d) illustrates the interpolated average daytime temperatures across all seasons, and Fig. 3 (e-h) presents the interpolated average nighttime temperatures across all seasons in Brisbane. These figures provide insights into how temperatures vary across different parts of the city, emphasising the higher temperatures in core urban areas including the Brisbane City, South Brisbane, and Woolloongabba, that consistently exhibit higher average temperatures across all seasons. On the contrary, suburb located in the outskirts demonstrate comparatively cooler conditions, highlighting localised temperature gradients influenced by factors like urban heat islands, vegetation cover, and proximity to water bodies (Li et al., 2024a; Li et al., 2024b).

Another important matrix for understanding microclimatic patterns, particularly temperature variations, is the analysis of warm days, warm nights, cool days, and cool nights. The Bureau of Meteorology (BoM) of the Australian Government defined warm day as a day when maximum temperature exceeds the 90th percentile of baseline values, and a warm night as when minimum temperature surpasses the 90th percentile (Yassaghi et al., 2019; BoM., 2024). Conversely, a cool day and cool night occur when maximum and minimum temperatures fall below the 10th percentile, respectively (BoM., 2024). Figs. 4 and 5 present the percentage of warm and cool days and nights over the past decade across different weather stations. Core urban areas like South Brisbane recorded the highest proportion of warm days (up to 28.7 %) and warm nights, reflecting reduced nocturnal cooling in densely built environments (Li et al., 2024). In contrast, outer suburbs like Wynnum North and Rocklea exhibited higher percentages of cool days and nights (Fig. 5), with Wynnum North experiencing nearly 17.5 % of cool nights annually, highlighting the moderating influence of vegetation and coastal proximity. These temperature variations underscore the potential impacts on health, sleep, and outdoor activities of residents (Kam et al., 2023).

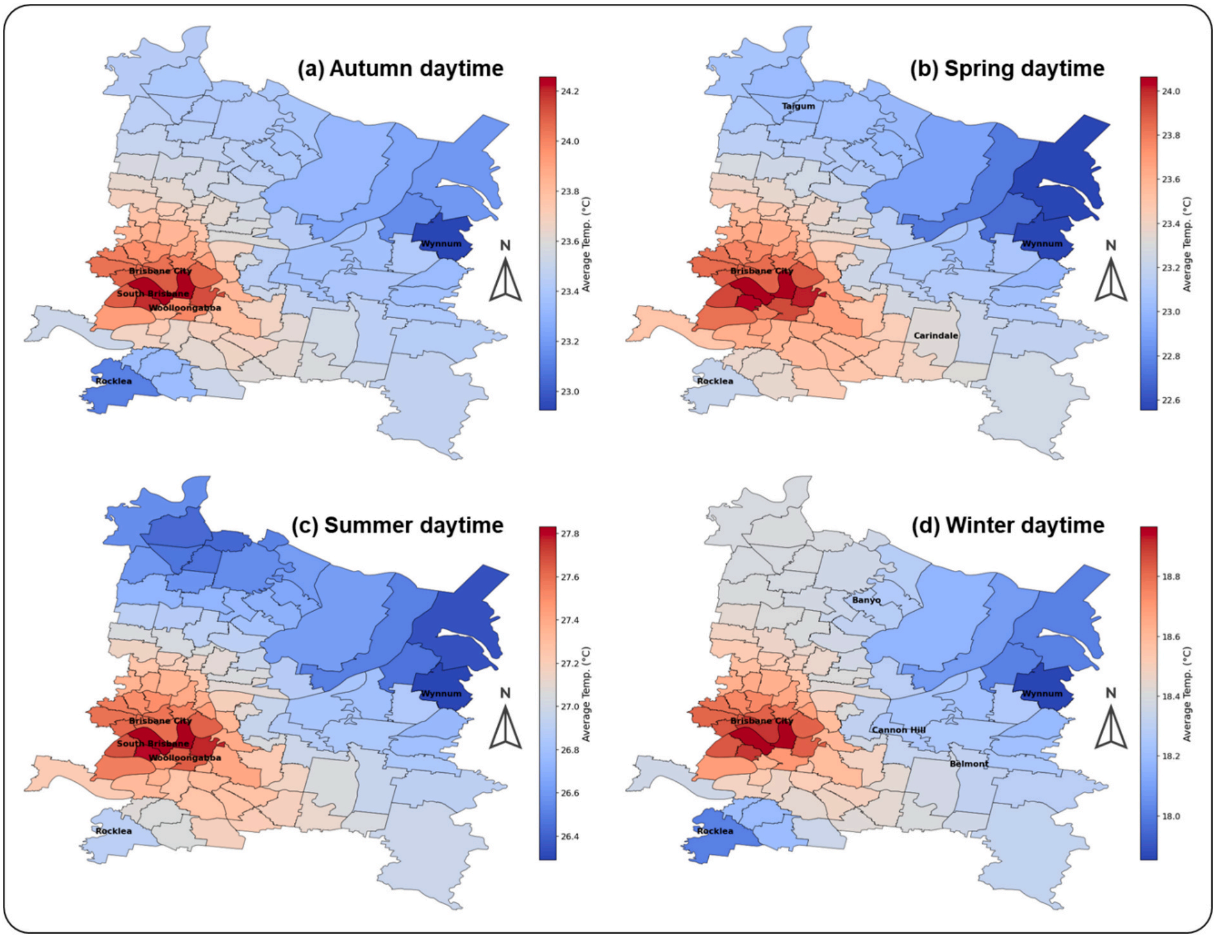

Fig. 3. (a-d): Average daytime temperature across Brisbane suburbs for all seasons based on daily data from 2014 to 2023. (e-h): Average nighttime temperature across Brisbane suburbs for all seasons based on daily data from 2014 to 2023.

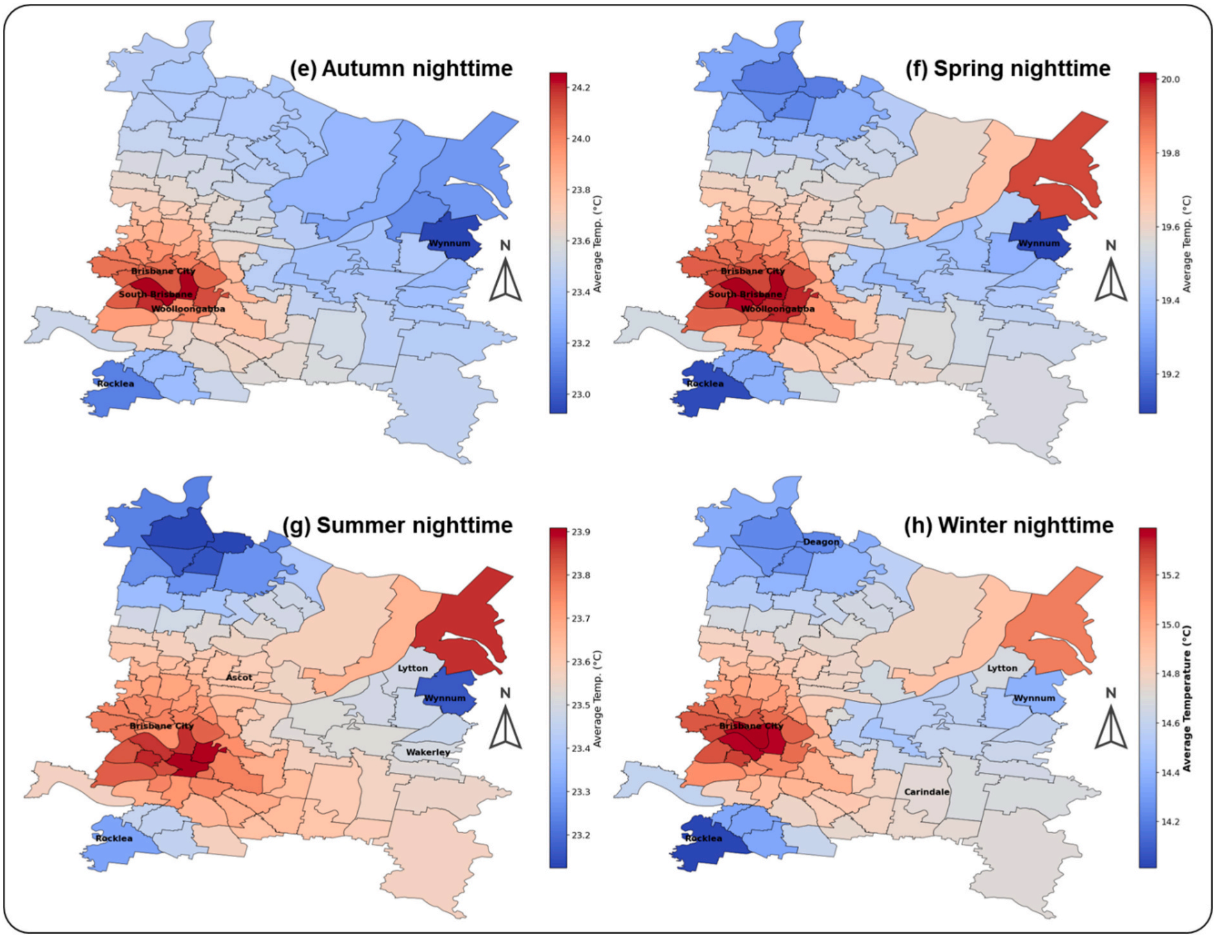

Fig. 3. (*continued*).

Extreme daytime temperatures can increase the risk of heat exhaustion and dehydration, while elevated nighttime temperatures can disrupt sleep patterns, leading to long-term health consequences (Buguet et al., 2023; Chevance et al., 2024). The proposed platform directly addresses these challenges by providing real-time, location-specific weather alerts tailored to the needs of different population groups. By integrating demographic and health data, the platform identifies individuals most susceptible to temperature-related risks and ensures that alerts are sent to those in need, rather than issuing broad, non-targeted warnings. This ensures that individuals in suburbs with historically cooler climates receive timely alerts when temperatures rise beyond their usual range, helping them prepare for unexpected heat stress. Conversely, in consistently warmer areas, alerts can be adjusted to reflect the higher threshold of temperature tolerance among residents while still prioritising the most vulnerable.

The platform equips local authorities with a dashboard that visualises at-risk populations across different suburbs, enabling targeted, localised, and personalised planning, mitigation, and intervention. During prolonged high temperatures or heavy rainfall events, authorities can identify vulnerable areas and implement adaptive strategies such as opening cooling centres, improving drainage systems, distributing tailored weather advisories, or deploying emergency response teams where they are most needed. By providing real-time, location-specific insights, the system facilitates proactive and precise risk management, mitigating climate-related health impacts and ensuring that no vulnerable groups are overlooked.

To measure and classify intensity of precipitation, the BoM defined wet days as those with daily precipitation equal to or exceeding 1 mm, heavy precipitation days as those with daily rainfall equal to or exceeding 10 mm, and very heavy precipitation days as those with daily rainfall equal to or exceeding 30 mm (BoM., 2024). The spatial variability in wet days across Brisbane is evident in Fig. 6, with Wynnum North recording the highest annual count of wet days in 2022, reaching 107 days, while Wynnum West closely follows with 95 wet days. Stations such as Lytton and Cannon Hill also experienced significantly wet years, with 93 wet days in Lytton during 2022.

On the other hand, some stations recorded notably fewer wet days in specific years; for instance, Rocklea only had 24 wet days in 2016. Heavy precipitation days (≥10 mm) are less frequent than wet days, but their occurrence significantly varies by station and year. Wynnum West experienced 42 heavy precipitation days in 2022, marking it as a hotspot for such events, followed by Wynnum North, which recorded 35 heavy precipitation days in 2021. In contrast, Rocklea and Brisbane CBD have relatively fewer heavy precipitation

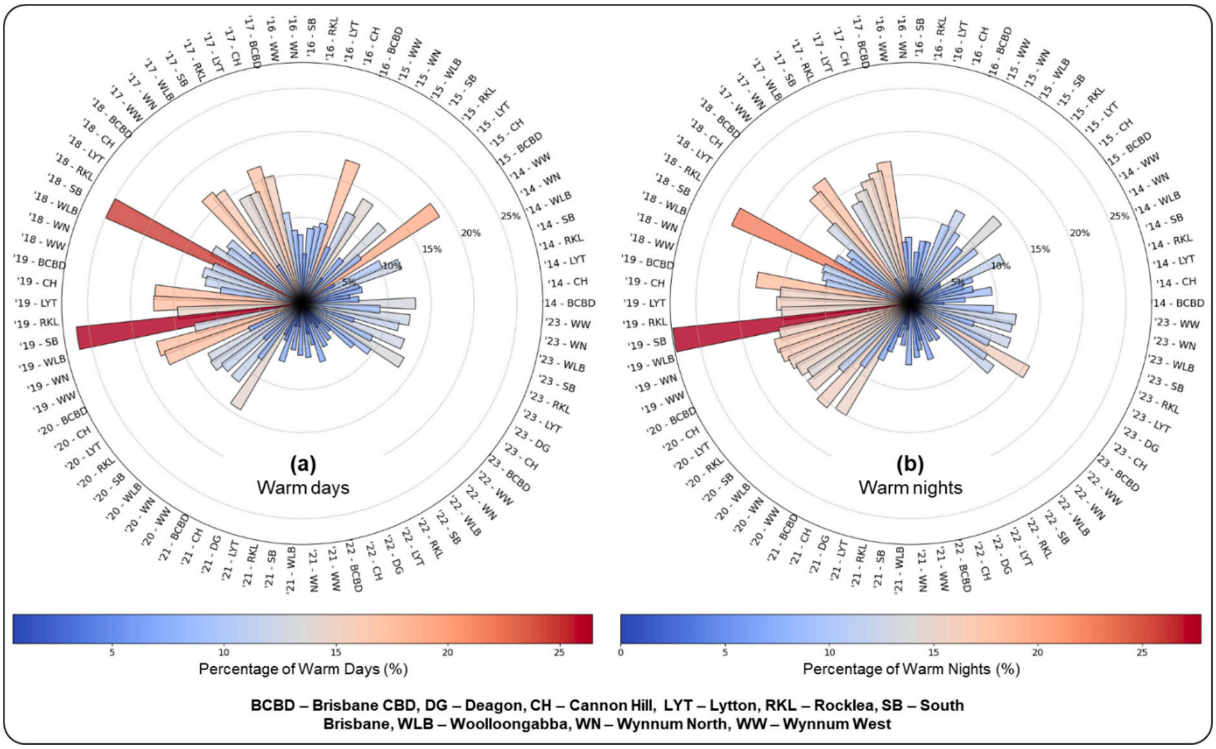

Fig. 4. Percentage of (a) warm days and (b) warm nights recorded across Brisbane weather sensors (2014–2023).

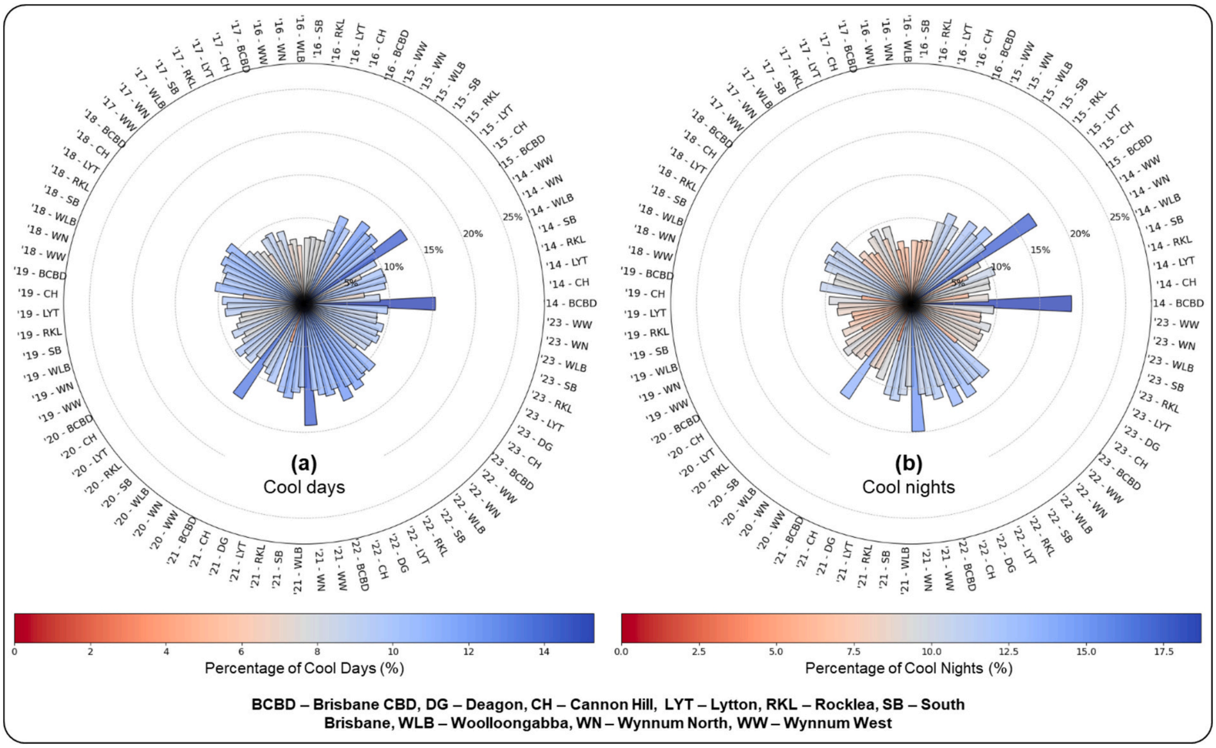

Fig. 5. Percentage of (a) cool days and (b) cool nights recorded across Brisbane weather sensors (2014–2023).

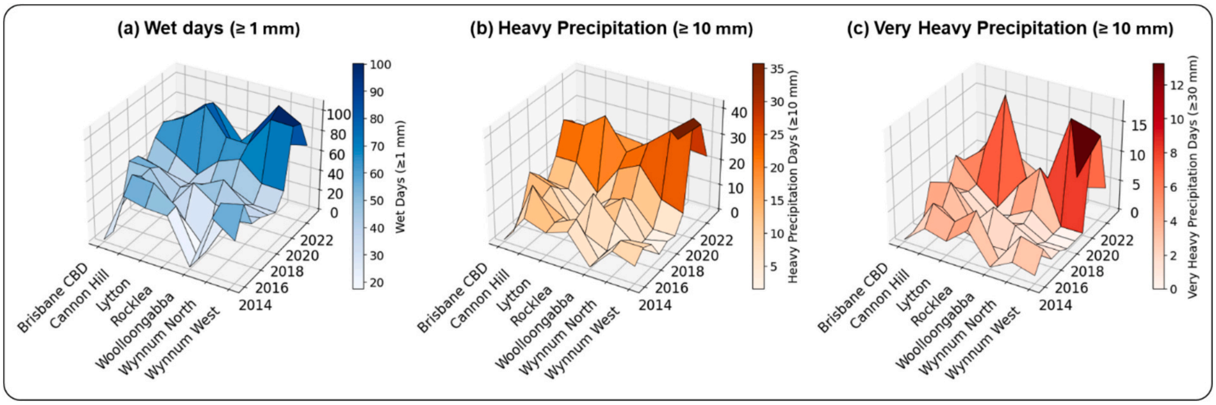

Fig. 6. Yearly counts of wet, heavy, and very heavy precipitation days in Brisbane from 2014 to 2023.

days, with Rocklea experiencing nine days in 2019 and Brisbane CBD seeing just 16 in 2020. Very heavy precipitation days (≥30 mm) are rare but highly impactful. Coastal areas such as Wynnum North recorded a peak of 17 days in 2021, while Wynnum West experienced 16 days in the same year, highlighting these areas as hotspots for extreme rainfall. Conversely, stations like Brisbane CBD had fewer instances, with its maximum being only seven days in 2020.

1.2. Local weather impacts on residents and the need for microclimate-based monitoring systems

The uneven distribution of thermal stress across Brisbane has significant implications for public health, liveability and regular activities (Li et al., 2024b). Areas experiencing more frequent warm days and nights require increased public alerts due to heightened health risks. Nonetheless, individuals in these regions may be more accustomed to such microclimates, potentially exhibiting greater tolerance to incremental increases in thermal stress (Elliott et al., 2020). Conversely, in suburbs with fewer warm days and nights, even slight increases in temperature or a rise in warmer days can significantly disrupt residents' comfort and routines, as they are less acclimated to these changes (Wong et al., 2021).

While the definitions are location-specific, traditional systems often assume uniformity in the application of these metrics, focusing on centralised locations like the Brisbane City (Murray, 2021). However, such an approach disregards microclimatic differences across suburbs, leading to potential inequities in alerts. For example, for Brisbane City and Wynnum, the warm days might be based on a maximum temperature of around 33 °C and 30 °C, respectively, reflecting the city's historical data. Despite experiencing more frequent warm days compared to Brisbane City, Wynnum residents, including 2523 elderly individuals, and 1461 people with respiratory issues, may not receive sufficient alerts under a centralised system. For Rocklea and nearby suburbs, where temperatures are usually cooler, modest increase in temperature or number of warm days or warm nights, could lead to discomfort for about 264 children, and 224 elderly, along with 265 residents with various health conditions such as asthma, heart condition and respiratory issues. Similarly, significant variability in number of wet days, heavy precipitation days, very precipitation days calls localised alert systems, particularly in areas prone to higher rainfall intensities. For example, Wynnum (both north and west) experience high intensity of precipitation whereas suburbs like Rocklea, with fewer heavy precipitation days, may face challenges adapting to sudden increases in heavy rainfall.

Localised weather monitoring and alert systems, thus, should be implemented to provide real-time, community-specific warnings (Clegg et al., 2022). These systems must account for microclimatic conditions and prioritise vulnerable populations by offering proactive notifications (Ascione et al., 2024). By integrating demographic and health data, such systems can enhance urban resilience and public safety (Haraguchi et al., 2022). Recognising these localised disparities in weather impacts and the limitations of traditional weather monitoring and alert systems, this research poses the following question:

- How can a localised weather monitoring and alert platform be designed to account for microclimatic variations and address the needs of vulnerable populations?

To address this, we developed a platform architecture that leverages real-time weather data, demographic profiles, and microclimatic thresholds to provide targeted alerts for each community. The subsequent sections of this paper delve into the shortcoming of traditional weather monitoring and alerts systems, theoretical concept of the platform, discuss the proposed platform's architecture, a demonstration using the Brisbane City's data, platform's usability and scalability, limitations and future research avenues.

2. Theoretical framework: Platform urbanism and AIoT

The rapid growth of urbanisation and the increasing complexity of urban challenges have led to the emergence of platform urbanism as a critical concept for understanding and addressing city-wide issues (D'Amico et al., 2020; Repette et al., 2021). Platform urbanism refers to the increasing reliance on digital platforms to reshape how cities collect, analyse, and respond to data (Rotta et al., 2019; Bibri and Jagatheesaperumal, 2023). The proposed platform in this study provides flexibility to integrate various weather prediction models—whether they are global, regional, or city-specific—making it adaptable addressing the gap between advanced meteorological forecasting and its practical, real-time application in microclimate level. To achieve this adaptability, the platform incorporates the concept of AIoT.

The term AIoT may initially suggest a focus on physical devices such as devices equipped with technologies like NVIDIA Jetson modules or Google's Edge TPU that can perform real-time AI computations at the edge, close to the data source, it extends far beyond physical devices in smart city context (Kuguoglu et al., 2021; Pise et al., 2022). Researchers and practitioners in smart cities conceptualise AIoT mostly as cloud-based platform (Fig. 7) or an entire ecosystem that seamlessly integrates Internet-of-Things (IoT) data with AI-driven analytics and actions (Pise et al., 2022; Forkan et al., 2024). AIoT system captures data thorough various IoT devices such as sensors or cameras (Anthony, 2024). This data is then transmitted to edge/fog layer using connectivity technologies like Wi-Fi, Bluetooth, Zigbee, LoRaWAN, and 5G (Muhammed et al., 2024). The edge/fog layer is a crucial processing tier between data sources and cloud infrastructure, ensuring data quality through preprocessing tasks like filtering and anomaly detection (Song et al., 2021). It supports edge computing capabilities to perform real-time data analytics close to the data source, thereby reducing latency and bandwidth enhancing responsiveness of the smart city applications (Almalki et al., 2023).

After initial processing in the edge/fog layer, data is transmitted to the cloud layer through high-speed communication channels such as 4G, 5G, or equivalent technologies (Toh, 2020). The cloud layer serves as a central hub for comprehensive data management and advanced analytics. In this layer, data undergoes storage, further processing, and AI analysis using advanced machine learning algorithms to extract insights and make predictions. Data undergoes further processing, involving transformations, integration, and enhancement to support advanced analytics (Forkan et al., 2024). AI-driven analysis is then applied, enabling insights, predictions, and decision-making for applications such as resource allocation, environmental monitoring, and public safety (Bibri and Jagatheesaperumal, 2023). Based on these insights, automated actions like alert notifications or system optimisations are triggered (Kuguoglu et al., 2021; Pise et al., 2022). The cloud layer incorporates a feedback loop, where system responses are re-evaluated and fed back to improve AI models, ensuring adaptability and ongoing optimisation in response to changing conditions (Belli et al., 2020).

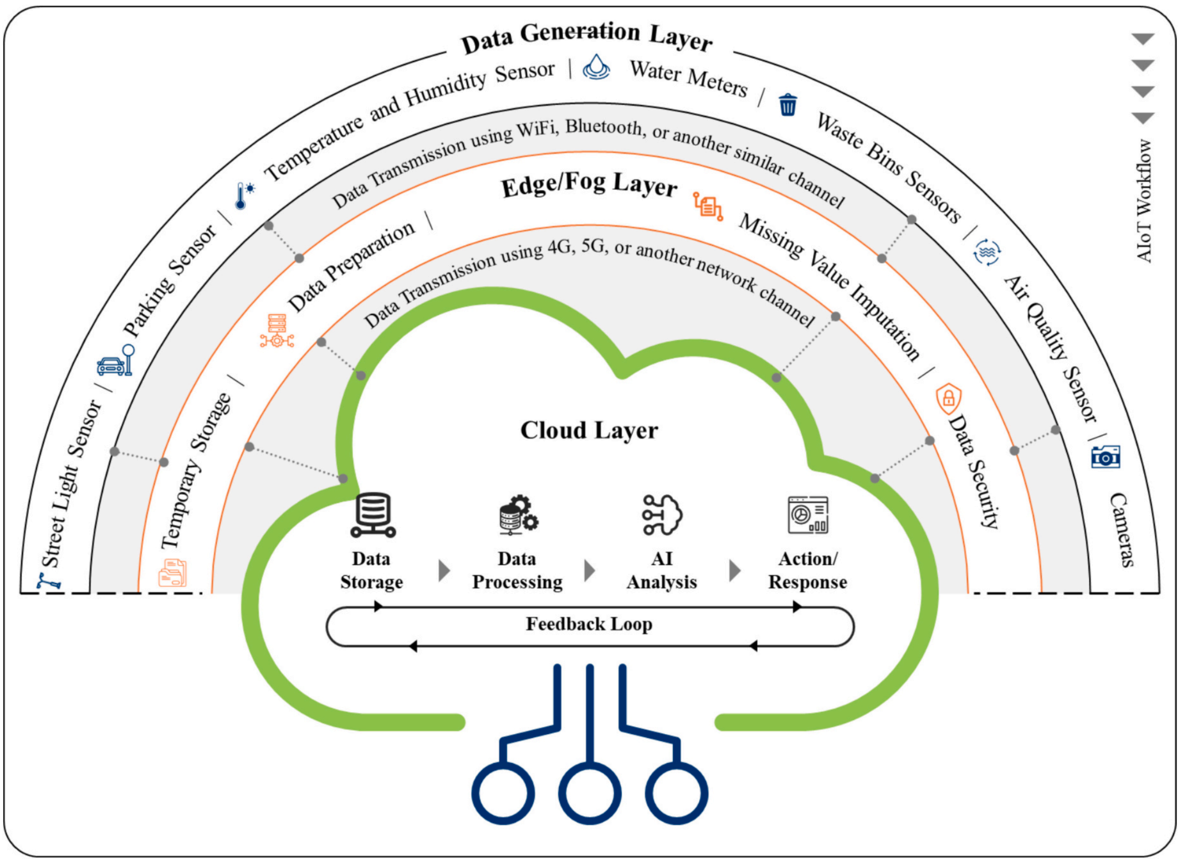

Fig. 7. AIoT-based platform architecture, derived from Bibri et al. (2024), Jagatheesaperumal et al. (2024), and Muhammed et al. (2024).

3. Existing weather monitoring and alert systems and limitations

Existing weather and health alert systems have made significant strides in protecting public health during extreme weather events. Country specific system such as BoM in Australia, the National Weather Service (NWS) Alert System in the United States, and the Met Office Weather Warnings in the UK are widely regarded for their ability to disseminate weather alerts at a city or regional level (Casanueva et al., 2019; Neußner, 2021). Global platforms such as AccuWeather and Weather.com provide weather updates and alerts across diverse locations, leveraging sophisticated models and extensive datasets (Atencio et al., 2024). Similarly, state or city specific platforms such as VicEmergency for the State of Victoria in Australia, Emergency WA in the State of Western Australia, NYC Emergency Management Notify NYC in New York, Chicago OEMC Alert System, Singapore's MyENV, Tokyo's Disaster Preparedness Tokyo or London Resilience Alerts offer localised emergency alerts. Despite their utility, most of these tools exhibit notable limitations when addressing localised microclimatic variability and the diverse vulnerabilities of urban populations (Li et al., 2024c). Despite their accuracy for city specific warning or alerts, these systems or platforms often overlook the microclimatic variations that can occur within urban the city (Kousis et al., 2022).

In Brisbane, weather-related alerts are primarily disseminated through the State of Queensland Government's Queensland Alert platform and the Brisbane City Council's alert system. Both systems rely on warnings issued by the BoM, which uses data from a limited number of centralised weather stations to issue alerts for broader regions or cities. While accurate at a macro level, this approach often fails to account for microclimatic variations across suburbs, as discussed in the introduction section (Localised Weather Variations in Brisbane) above. Reliance on a single weather station or generalised dataset for entire city is a common characteristic in weather monitoring and alert system around the world (Hahn et al., 2022).

Another limitation is the lack of personalised alerts. These existing systems fail to account for crucial variables such as a person's specific location, age, health conditions, or disabilities—factors that significantly influence an individual's vulnerability to extreme weather events. For instance, during heavy rainfall, notifications sent to all areas may lack specificity, failing to focus on flood-prone neighbourhoods. In Wynnum North, which experiences more frequent and intense precipitation, residents in low-lying flood-prone areas would benefit from targeted alerts, while similar alerts may be unnecessary for elevated areas like Cannon Hill.

Moreover, many platforms are subscription-based, requiring residents to register to receive alerts. The subscription-based alert system risks excluding vulnerable populations who may lack awareness, access, or resources to subscribe. Marginalised groups—often those most affected by weather extremes—may remain uninformed about imminent risks (Dodd et al., 2024). Furthermore, existing systems typically lack the capability to incorporate microclimate-specific models or demographic data (Barriopedro et al., 2023). For example, warm days and warm nights are defined based on percentile thresholds that vary across suburbs (Barriopedro et al., 2023).

The Brisbane City might define a warm day as a maximum temperature exceeding 33 °C, whereas Wynnum North might set this threshold at 30 °C. Generalised thresholds often fail to accommodate these differences, leaving many residents unprepared for significant weather events. While existing systems provide essential services, they often lack the granularity needed to address the complex interplay between microclimates, individual health status, and location-specific risks. Our research emphasises the need to integrate microclimate data, resident-specific information, and location-based risk assessments for more effective and targeted alerts.

To address these challenges, we developed a platform using ArcGIS GeoEvent, which enables real-time data processing. During the literature review, no evidence was found of GeoEvent being used for a platform specifically designed to generate weather alerts that consider microclimate variability. Nevertheless, several ESRI reports and publications have highlighted the potential of GeoEvent for such applications, indicating its capacity to support microclimate-based alerting systems (Milazzo et al., 2009; McLaughlin, 2017; ESRI, 2021).

The ArcGIS ecosystem was selected for this study due to its widespread use among planners and local government authorities, making it a familiar and trusted platform for urban management. Its comprehensive suite of spatial analysis tools, coupled with the real-time data integration and analytical capabilities of GeoEvent, enables seamless integration of geospatial data from diverse sources. This functionality supports the generation of location-specific insights essential for microclimate monitoring, aligning with the aim of this research. The following section provides an overview of the software and its various elements.

4. ArcGIS GeoEvent

GeoEvent Server, developed by Environmental Systems Research Institute (ESRI), is a server-based application that facilitates real-time geospatial data management, transforming static GIS applications into dynamic decision-support systems (Zhang et al., 2018). Its primary function is to integrate real-time, event-based data streams into the ArcGIS Enterprise ecosystem, allowing for the seamless ingestion, filtering, processing, and analysis of incoming data (McLaughlin, 2017). GeoEvent supports automated notifications when predefined conditions are met, enabling rapid response to critical events (ESRI, 2021). For example, transportation authorities can utilise GeoEvent Server to analyse real-time traffic data and dynamically adjust speed limits based on current road conditions and weather patterns, optimising traffic flow and enhancing road safety.

Similarly, water authorities can leverage ArcGIS GeoEvent Server to enhance environmental monitoring by ingesting real-time sensor data from water stations, tracking critical parameters such as pH levels, dissolved oxygen content, and pollutant concentrations, and automatically alerting relevant authorities when ecological thresholds are exceeded, enabling swift and targeted responses to potential environmental threats. The system's core functionality (Fig. 8) is driven by GeoEvent Services, which facilitate workflows connecting Input Connectors (ICs), Filters, Processors, and Output Connectors (OCs), enabling efficient data transformation and delivery of actionable insights. This architecture allows for the continuous processing of event-driven data, supporting timely alerts and decision-making across diverse operational contexts.

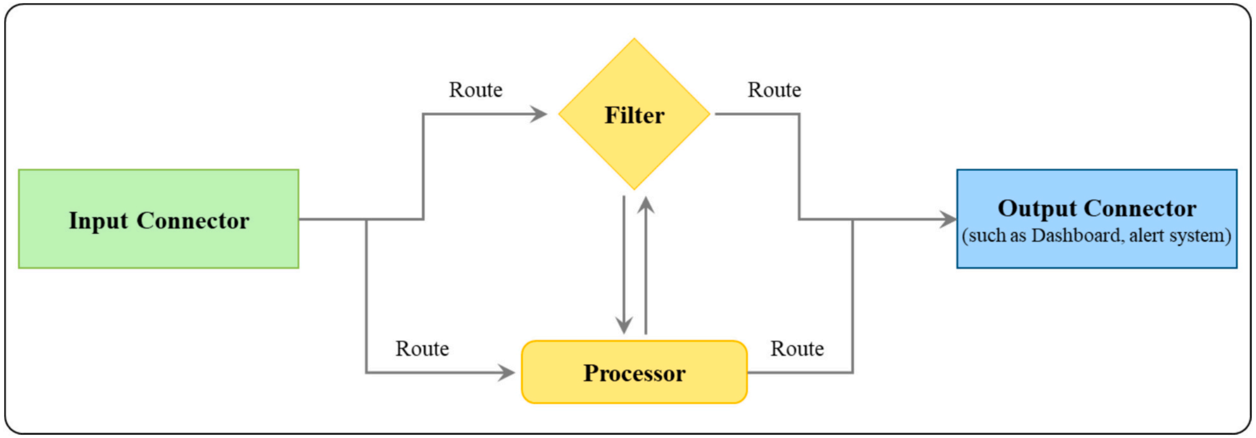

Fig. 8. GeoEvent server elements.

4.1. Real-time data ingestion

GeoEvent revolutionises data ingestion into GIS ecosystem, enable real-time data integration from various sources through ICs (Johnson et al., 2022). This functionality allows organisations to add new data into their daily operations and significantly enhance their situational awareness on the current desired event, enabling faster and more informed decision-making. The ICs within GeoEvent extract data or attribute values from each event, constructing a GeoEvent that can be routed through optional Filters and Processors before reaching an OC. GeoEvent Services require at least one IC, though multiple Connectors can be utilised for complex data sources. GeoEvent offers a wide range of ICs or sources to ingest data as shown in Fig. 9.

4.2. Real-time analytics

The real-time analytics capability of GeoEvent represents a significant advancement in geospatial data processing and analysis (Yao and Wang, 2020). By employing a variety of Filters and Processors, users can define specific criteria for event detection, spatial relationships, and attribute-based conditions. This functionality facilitates the identification of patterns, anomalies, and trends within streaming data, enabling rapid response to evolving situations. Filters are configurable elements used to remove event-data that do not meet specified criteria. These Filters can be based on attributes, spatial conditions, or a combination of both. Filters within GeoEvent include Attribute Filters, Spatial Filters, Property Filters, Tag-based Filters, Regular Expression Filters and Custom Filters.

Processors on the other hand perform specific actions on event data including data aggregation, analysis calculation or transformation. GeoEvent includes following Processors: Add XYZ Values, Bearing Calculator, Buffer Creator, Convex Hull Creator, Difference Creator, Envelope Creator, Event Joiner, Event Volume Controller, Feature to Point, Field Calculator, Field Calculator (Regular Expression), Field Enricher (Feature Service), Field Enricher (File), Field Mapper, Field Reducer, GeoTagger, Incident Detector, Intersector, No Operation, Projector, Range Fan Calculator, Simplifier, Symmetric Difference Creator, Track Gap Detector, and Union Creator. Users can also develop custom Processors using the GoeEvent Server SKD.

4.3. Real-time data visualisation and notification

GeoEvent's ability to visualise assets on a web map, either as discrete features or aggregated data, offers a significant operational advantage by providing a clear understanding of what is happening and where it is occurring in real time (Trilles et al., 2017; Yao and Wang, 2020). Along with visualisation, GeoEvent has the capability to alert and notify key stakeholders about events as they occur or shortly thereafter ensures that critical information is delivered promptly, enabling informed and timely decision-making. The visualisation and notification functionalities within GeoEvent provide a comprehensive spatial context for ongoing events and asset statuses, facilitating enhanced situational awareness and decision-making processes.

The OCs within GeoEvent are used to visualise and notify event data to a designated customer in an appropriate format. A GeoEvent Service must have an Output to operate. GeoEvent Server also includes the following, but not limited to, OCs: Add a Feature, Update a Feature, Send an Email, Write to a CSV File, Write to a GeoJSON File, Write to a JSON File, Send and Instant Message, Write GeoJSON to a Kafka Topic, Write JSON to a Kafka Topic, Publish Text to a UDP or External TCP Socket, Add/Update a Feature to a Spatiotemporal Big Data Store, and Send Features to a Stream Service. GeoEvent also offers creating customised OCs using GeoEvent Manager or the SDK, allowing precise control over data delivery.

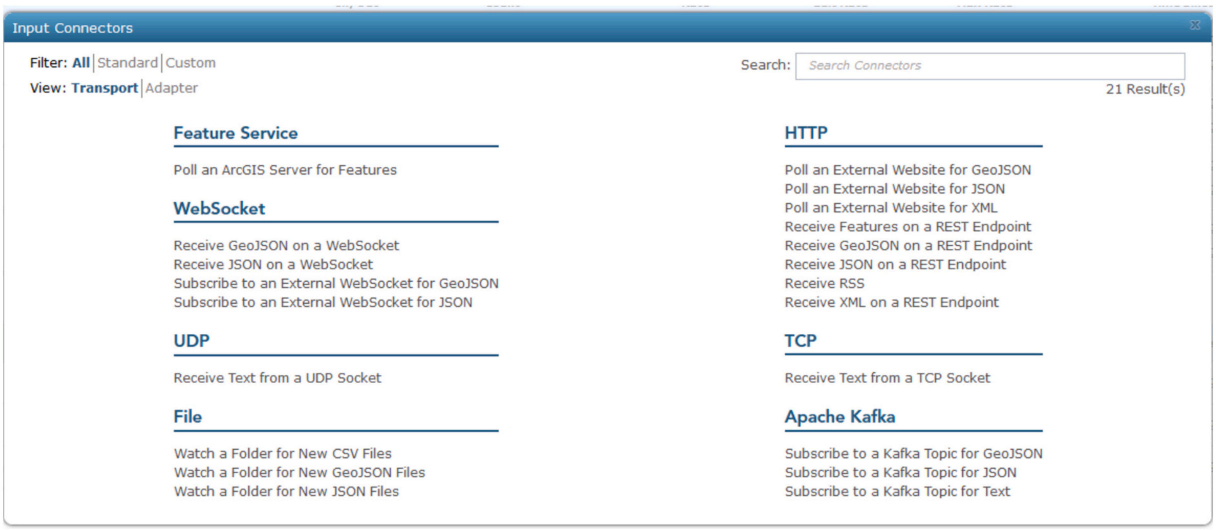

Fig. 9. Available ICs in ArcGIS GeoEvent, screenshot of ICs from the GeoEvent application, November 2024.

5. A novel platform architecture

The platform's architecture is designed to efficiently process and integrate real-time weather data with spatial information. The platform comprises three ICs, three OCs, three GeoEvent Services, and two ArcGIS Notebook Schedules, details of ICs and OCs are presented in Table 1 followed by the platform's conceptual block diagram in Fig. 10 and detailed architecture in Fig. 11.

Fig. 10 illustrates the conceptual block diagram of the platform, highlighting its key components and workflows. The process begins with the ingestion of meteorological data from weather sensors via API into ArcGIS GeoEvent. Filters and Processors ensure data quality by checking for missing values before updating meteorological parameters in the Weather Station Feature Layer. Two ArcGIS Notebooks then activate sequentially. The first Notebook employs an AI/ML-based weather prediction model to forecast weather conditions for the next 12 h. The second Notebook assesses predicted weather data to identify predefined conditions, such as warm days, cool days, wet days, and extreme events, updating the weather station Feature Layer with respective conditions for each suburb.

To identify residents at risk, the platform integrates weather data with the Resident Feature Layer using GeoEvent's Event Joiner Processor. This combined dataset is processed using Filters to detect weather-based risks in each suburb. If a risk is identified, the status of residents in the affected suburb is updated to "At-Risk" within the residents' Feature Layer. This information is displayed in an ArcGIS Dashboard, enabling local government officials to visualise the number and location of at-risk residents. Additionally, Output Connectors trigger notifications via SMS or email to inform residents, ensuring timely, location-specific alerts. The detailed architecture of the platform is depicted in Fig. 11, accompanied by a description of each step and process.

5.1. GeoEvent service 1: Integrating and processing real-time weather data

Service 1 is dedicated to processing real-time sensor data and integrating it with the weather station Feature Layer. IC1 ingests sensor data from a data source using their API and creates a GeoEvent Definition upon the initial ingestion, dynamically updating the definition if the schema changes (e.g., new parameters are added). A GeoEvent Definition serves as the data schema or structure that defines the attributes, field names, and data types for incoming event data. It ensures that data from various sources, such as weather sensors or resident datasets, can be properly interpreted, processed, and merged within the system. IC2 ingests the weather station Feature Layer data hosted in ArcGIS web map, creating a new Definition on the first call. Due to the static nature of the Feature Layer's attribute structure, subsequent calls do not require additional Definition creation.

The sensor data ingested by IC1 passes through a Field Reducer Processor, which filters out extraneous parameters to reduce event data volume and optimise processing speed. The streamlined data is forwarded to a Field Mapper, ensuring compatibility with the Definition of weather station Feature Layer. The Event Joiner Processor then merges the filtered sensor data with the weather station Feature Layer data based on a common field, creating a unified Definition that includes both real-time and static attributes. This combined dataset is then processed through a Choice Processor, which segregates data based on suburbs. The segregated data is then routed through a series of Filters to isolate specific weather parameters such as air temperature, humidity, precipitation, and wind speed. The filtered data is processed by corresponding Field Calculators to compute and assign values to the relevant attributes in the weather station Feature Layer. Finally, the data passes through a second Field Mapper to re-map the Definition to match the structure of the Feature Layer. The updated data is sent to OC1, which updates the weather parameters in the ArcGIS web map in real time.

5.2. ArcGIS notebook schedules: Predictive modelling and weather condition analysis

The platform architecture integrates two Python-based ArcGIS Notebook Schedules designed to enhance predictive capabilities and automate weather-related alert systems. These Notebooks are strategically scheduled to run in every 60 min only after the weather station Feature Layer has been updated by GeoEvent Service 1. Notebook Schedule 1 is designed to execute machine learning-based weather prediction models, which can be flexibly adapted to integrate various AI/Machine Learning (ML) models, depending on the context and requirements. This adaptability is a key feature of the platform, allowing the integration of existing weather prediction models that utilise weather station data alone or combine it with spatial factors such as elevation and land cover. The platform's design within the ArcGIS environment further facilitates spatially driven analyses, a method frequently employed by researchers. By leveraging the platform's capability to work seamlessly with spatial data and scheduling Python scripts, the execution of such models can be fully automated, providing an efficient and scalable solution for predicting weather conditions at a microclimatic level.

The second Notebook builds upon the outputs of the first, using predictive results alongside historical data stored in the ArcGIS Spatiotemporal Big Data Store to analyse and detect predefined weather conditions. These can include but are not limited to detecting

Table 1
Input and OCs required in the proposed platform.

Input Connector (IC)	Output Connector (OC)
IC1 utilises the "Poll an External Website for JSON" feature to capture sensor data via API at 60-min intervals.	**OC1** uses "Update a Feature" to modify the weather station Feature Layer.
IC2 employs "Poll an ArcGIS Server for Features" to ingest weather station point Feature Layer from ArcGIS web map.	**OC2** employs "Update a Feature" to update residents' information Feature Layer.
IC3 uses "Poll an ArcGIS Server for Features" to ingest residents' location as point Feature Layer from ArcGIS web map.	**OC3** utilises "Send a Text Message" and/or "Send an Email" feature for notifications.

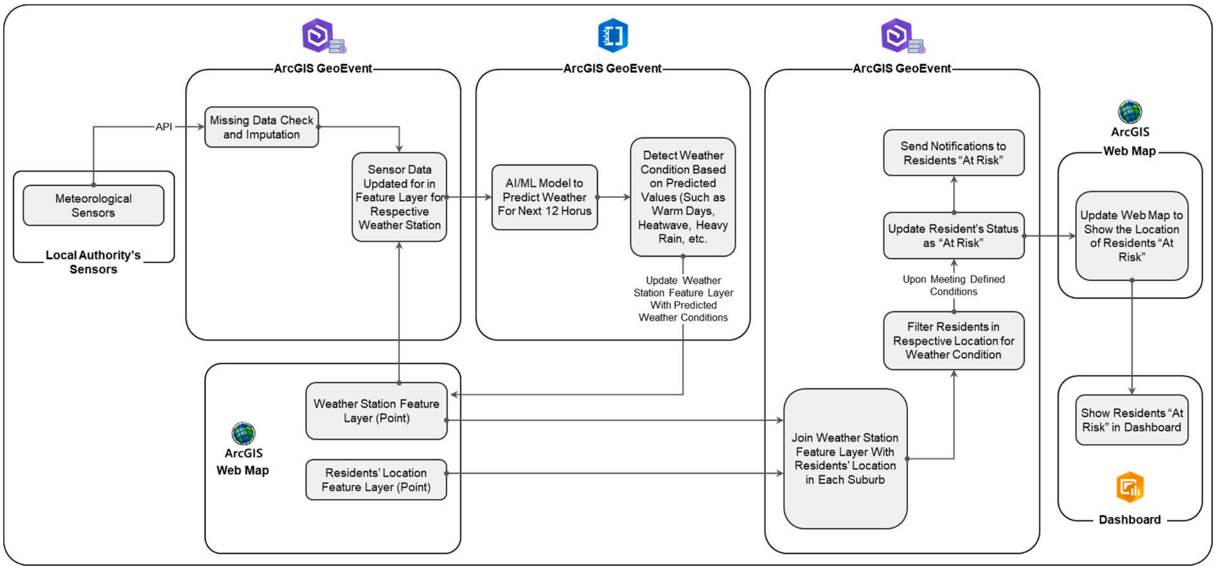

Fig. 10. Conceptual block diagram of the platform.

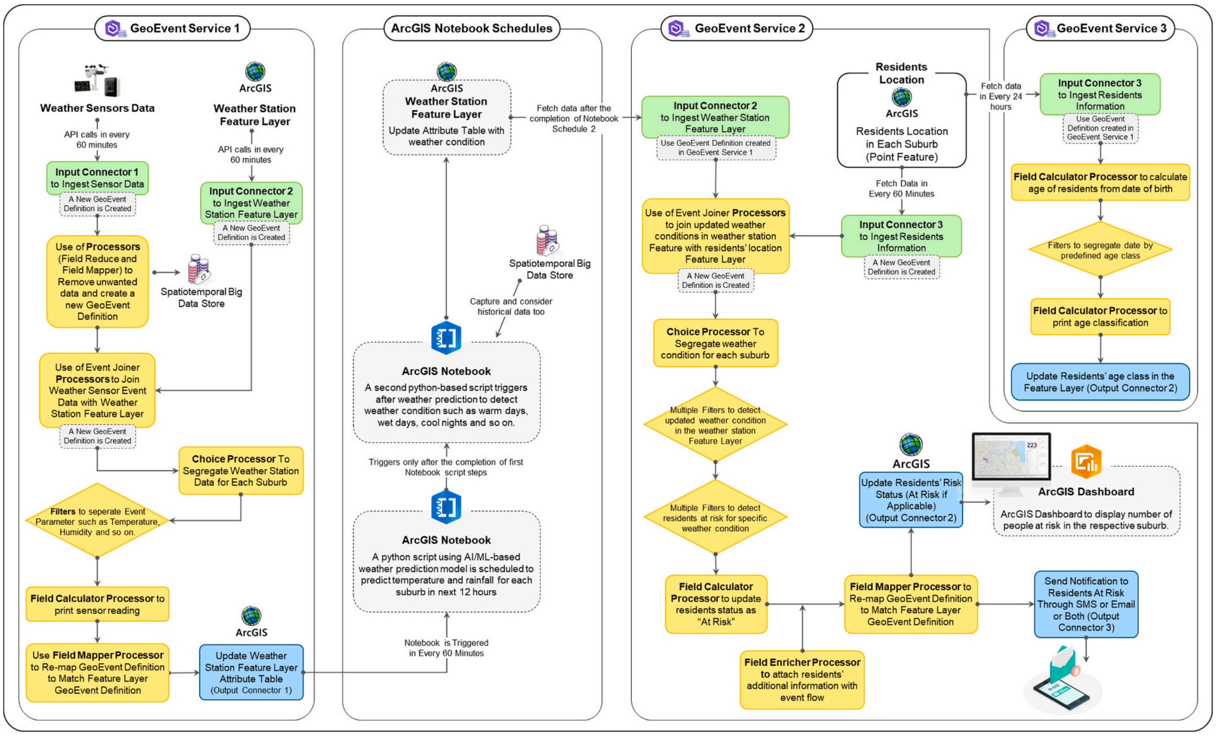

Fig. 11. Architecture of the real-time and predictive risk monitoring and alerts system.

heatwave, heavy precipitation, cool nights, or warm days. The Notebook processes these results to update weather conditions for the next 12 h and systematically records these statuses in the weather station Feature Layer.

5.3. GeoEvent service 2: Dynamic risk detection and resident notification

Service 2 incorporates critical event flows to leverage predictive analytics with residents' risk levels and disseminate risk information through a synchronised dashboard and multi-channel notifications. This service leverages data from two ICs: IC2 and IC3. IC2 utilises the existing Definition from GeoEvent Service 1, maintaining consistency without requiring re-mapping. IC3, upon initial data ingestion, generates a Definition that remains static. An Event Joiner Processor combines these two data streams into a unified Definition, which then cascades through the workflow. First, a Choice Processor segregates data based on suburbs. From here, multiple Filters detect updated weather conditions, as determined by ArcGIS Notebook Schedule 2, for each suburb. Upon identifying a specific weather condition for a suburb, another series of Filters assess the resident data to determine individuals at risk for that condition. A Field Calculator is then employed to label these residents as "At-Risk", updating their status in the event workflow.

The Field Enricher Processor plays a pivotal role in this workflow by augmenting the GeoEvent with additional resident-specific information stored in an external, secure data repository. For privacy and security reasons, the resident data Feature Layer includes only anonymised identifiers and essential fields such as location and age. The Field Enricher Processor accesses supplementary data, such as contact information, from an encrypted local repository using a shared identifier between the GeoEvent and the external dataset. This approach ensures compliance with data privacy standards and safeguards sensitive information, mitigating risks associated with unauthorised access or cyber threats. The enriched data is then processed through a Field Mapper to re-align the Definition with the structure of the residents' Feature Layer. This refined dataset is forwarded to OC2, which update the ArcGIS web map. An ArcGIS Dashboard is linked to this web map, configured synchronous refreshing at predefined intervals. This setup provides real-time visualisation of residents at-risk. Concurrently, OC3 facilitates the transmission of personalised notifications to affected residents via SMS, email, or both, ensuring timely and direct communication.

5.4. GeoEvent service 3: Updating and managing resident demographic profiles

Service 3 is responsible for dynamically updating residents' age categories within the Feature Layer, ensuring demographic data remains accurate and relevant for risk assessment workflows. This service uses the same Definition created in GeoEvent Service 2 for IC3, which ingests the residents' Feature Layer data in every 24 h. Once the data is ingested, it flows directly into a Field Calculator Processor, where the age of each resident is recalculated based on their date of birth. This recalculated data is routed through a series of Filters that classify residents into predefined age categories such as children, adults and elderly. Each category is assigned through dedicated Field Calculators, which label the respective residents accordingly. The updated data from the Field Calculator is then sent directly to OC2, which updates the ArcGIS web map.

6. Case study: Demonstrating the platform's architecture and practical application in Brisbane

To demonstrate the platform's architecture in a real-world scenario, weather station data from Brisbane CBD and Wynnum North were utilised, along with demographic data from these two suburbs. The selection criteria focused on suburbs with existing weather stations to ensure access to accurate, localised data. Brisbane CBD and Wynnum North were chosen due to their contrasting geographic and microclimatic contexts (Fig. 1)—Brisbane CBD representing the urban core and Wynnum North situated in a coastal area. This contrast offers a compelling case for evaluating the platform's capabilities in diverse climatic conditions. Table 2 presents the demographic and health profiles of these two suburbs based on data from the ABS.

The platform's architecture, demonstrated in the Brisbane context, is presented across multiple segments. It follows the conceptual framework illustrated in Fig. 11, with detailed breakdowns provided in Fig. 13, Fig. 16, and Fig. 19 for greater clarity The demonstration platform's architecture adheres to the same structure outlined in the "Proposed Platform Architecture" section, maintaining a consistent number and functionality of Connectors, Processors, Filters, GeoEvent Services, and Notebook Schedules. Fig. 12 provides a detailed snapshot of the ArcGIS GeoEvent Manager interface, illustrating the configuration and operation of the platform's ICs, OCs, and GeoEvent Services, along with their respective data flow rates.

6.1. GeoEvent service 1

Fig. 13 illustrates the architecture and workflow of GeoEvent Service 1, which integrates real-time weather data into the platform. Two ICs were set up for this Service following the configuration in Fig. 14. IC1 ingests meteorological data from the Queensland Government Open Data Portal via their Air Quality Monitoring Data API (https://airquality.des.qld.gov.au/v1). The API provides a comprehensive dataset that includes meteorological parameters as well as air quality metrics, such as particulate matter and other pollutants. The data fetch frequency is configured to 3600 s, corresponding to an interval of 60 min. The Default Spatial Reference 4326 represents the WGS 84 (World Geodetic System 1984), a widely used geographic coordinate system based on latitude and longitude. The ingested data undergoes processing through a Field Reducer, which selectively retains essential meteorological parameters (temperature, humidity, rainfall, wind speed, wind direction, and barometric pressure) while discarding extraneous

Table 2
Demographic and health profiles of suburbs with weather sensors.

Suburb	Population				Health Record				Disability
	Total	Children	Adults	Elderly	Asthma	Diabetes	Heart	Lung	
Brisbane CBD	12,579	604	10,937	1038	234	226	788	917	216
Wynnum (North)	14,034	2441	9070	2523	516	657	1483	1461	769

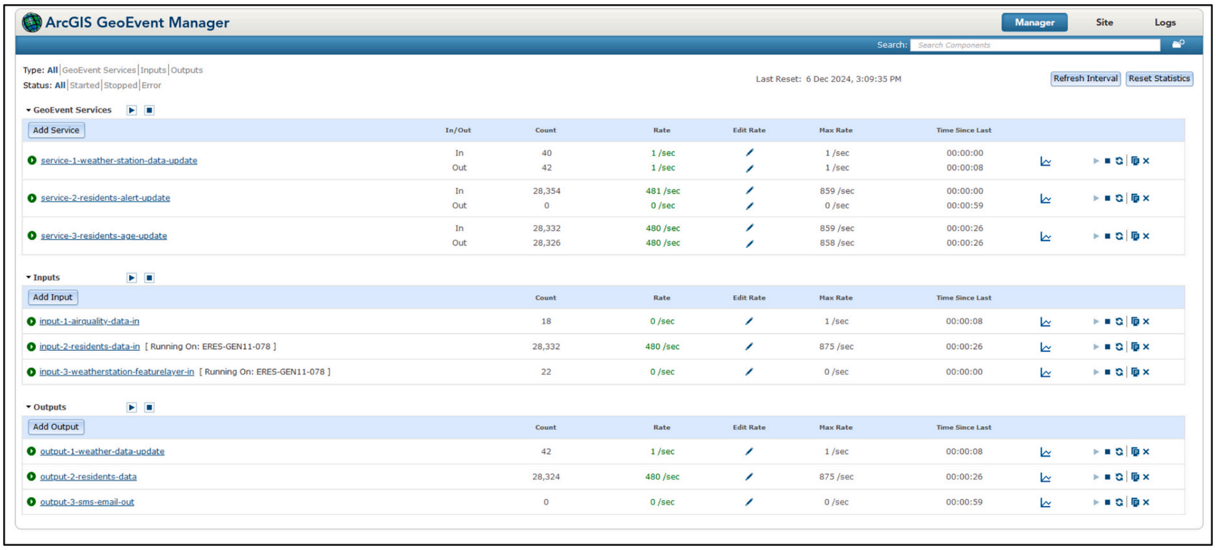

Fig. 12. ArcGIS GeoEvent manager displaying ICs, OCs, and GeoEvent services with Brisbane event data flow.

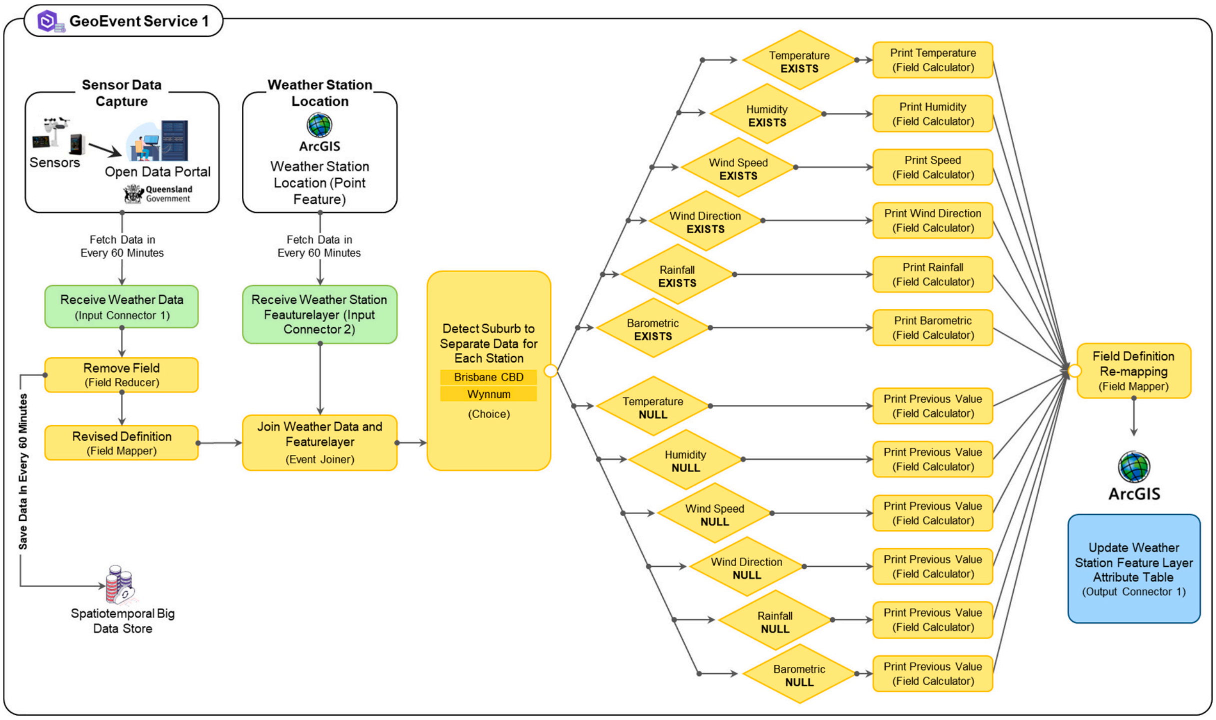

Fig. 13. GeoEvent Service 1 architecture.

information. From the Field Reducer Processor, the data flows to a Field Mapper Processor. Initially, the ingested data adheres to a default Definition that includes a broader set of parameters. The Field Mapper reconfigures the data to a refined Definition (as shown in Fig. 15), ensuring compatibility with downstream processing stages.

Concurrently, IC2 retrieves weather station Feature Layer, hosted in the ArcGIS Online web map. An Event Joiner Processor then merges this spatial data with the sensor data, combining two distinct Definitions using the common field "suburb", as illustrated in Fig. 15. The Event Joiner Processor is set with a cache size of 1000 and the "Clear After Join" option, ensuring efficient memory management by maintaining a limited number of records in the cache, thereby optimising performance. Following the Event Joiner, the data enters a Choice Processor, which filters information based on the associated suburbs. While this demonstration involves only two suburbs, the Choice Processor is particularly advantageous for larger datasets, such as Brisbane's 190+ suburbs, as it consolidates

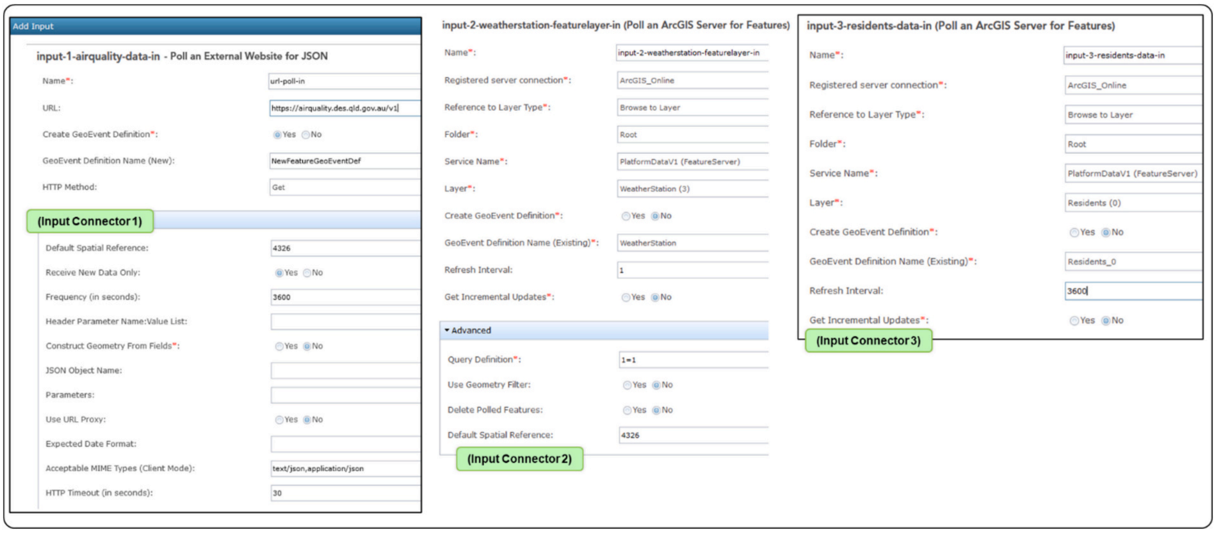

Fig. 14. Configuration of IC1, IC2 and IC3 utilised for demonstration within the ArcGIS GeoEvent environment.

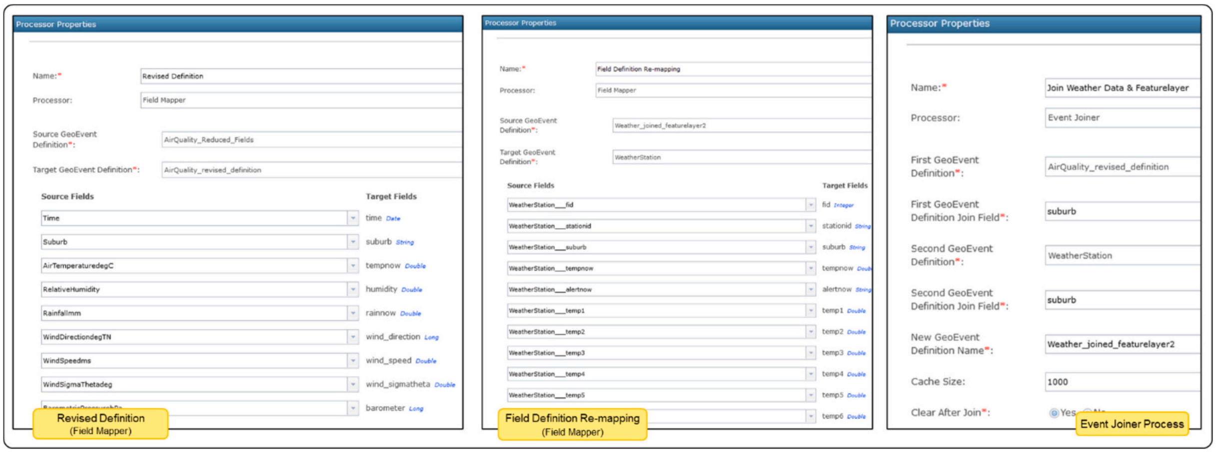

Fig. 15. Configuration of field mappers and event joiner processors used in GeoEvet Service 1.

decision-making and reduces the complexity of workflows. Separate data goes through six Filters and verify the existence of valid weather station data for each suburb Post-filtering, the data undergoes through Field Calculators to update with existing values or in case of missing values, previously predicted data for the current hour is printed (discussed further under Notebook Schedule 1). From Field Calculators, data goes to a Field Mapper Processor to align with the target Definition before updating the weather station Feature Layer in ArcGIS web map.

6.2. Notebook schedules 1 and 2

ArcGIS Notebooks are scheduled to execute every 60 min as integral components of the platform. The first script implements a machine learning-based weather prediction model, drawing inspiration from studies by Ren et al. (2021) and Scher and Messori (2018). For this demonstration, we employed a Random Forest Regression model, which has shown promising results in short-term weather forecasting (Massaoudi et al., 2021; He et al., 2022). While more sophisticated or geographically tailored weather prediction models could enhance accuracy, the focus of this research was to showcase the platform's capability to integrate AI and ML methodologies seamlessly, rather than developing new predictive models. As highlighted in the introduction, considerable academic research has already been dedicated to the development of complex weather prediction models (Massaoudi et al., 2021; He et al., 2022; Li et al., 2024).

Our research aims to bridge the gap by creating a platform capable of integrating such models into actionable workflows. It is worth noting that the development of more sophisticated, location-specific models presents an avenue for future research, as discussed in our future research directions section. The prediction model utilises weather data from the weather station Feature Layer, updated by

GeoEvent Service 1, to forecast the next 12 h of weather conditions on an hourly basis. These predictions are then used to update the respective fields in the attribute table for each station.

The second ArcGIS Notebook script is triggered subsequently, leveraging historical data stored within the ArcGIS Spatiotemporal Big Data Store. This script analyses various weather conditions, including warm days, warm nights, cool days, cool nights, wet days, heavy precipitation, and very heavy precipitation, adhering to the definitions established by the Queensland Government (as outlined in the introduction). For this demonstration, the focus was limited to the conditions listed above. However, the platform is inherently flexible, allowing for the inclusion of additional conditions to meet the specific needs of different regions or cities. This adaptability reinforces the platform's potential as a scalable tool for localised weather monitoring and alert systems.

6.3. GeoEvent service 2

GeoEvent Service 2 is a critical component of the architecture, designed to detect weather conditions and identify residents at risk in specific locations. As illustrated in Fig. 16, two critical datasets underpin this service: the Weather Station Feature Layer, updated by ArcGIS Notebook Schedule 2 to provide real-time weather condition data, and the Resident Feature Layer, which contains spatial and demographic information. Both datasets are ingested at 60-min intervals through ICs. Since these datasets have distinct schemas, an Event Joiner Processor merges their definitions into a unified schema referred to as the Secondary GeoEvent Definition, ensuring seamless integration of spatial and non-spatial attributes for analysis.

The combined dataset is then routed through a Choice Processor, which segregates data based on suburb names. For each suburb, the data undergoes a series of Filters designed to detect specific weather conditions. Initially, three primary Filters identify daytime periods, nighttime periods, and precipitation alerts. Data from the daytime Filter is further analysed to detect warm days and cool days, while the nighttime filter output is examined for warm nights and cool nights. Additionally, the precipitation alert Filter detects precipitation conditions such as wet days, heavy precipitation, and very heavy precipitation through three distinct Filters.

When any of the specified conditions are detected for a particular suburb, the subsequent set of Filters, each linked to the corresponding seven condition-detection Filters, updates the status of residents in that suburb based on the risk matrix illustrated in Table 3. This matrix, developed for demonstration purposes and informed by methodologies from Sharma and Bhaskaran (2024) and Chesnais et al. (2019), assigns risk levels to residents based on the detected conditions. While the matrix is tailored to this demonstration, it can be adapted to meet the needs of specific regions.

The Field Enricher (File) Processor accesses securely stored .txt or .csv files containing sensitive personal information. It links this data to the Resident Feature Layer using a common ID, ensuring personal information remains separate from the main Feature Layer to uphold data security, as outlined in the platform's architecture. Two OCs (OC2 and OC3) are configured with GeoEvent Service 2. The OC2 is configured to print risk status of the residents and update the Feature Layer in the web map. This web map within ArcGIS Online is connected to a dashboard that shows the number of people at risks and their location as illustrated in Fig. 17. OC3 is configured as shown in Fig. 18 to send messages and/or emails to residents "at risk". The function ${FIELD-NAME} is used here to dynamically calls for respective information of residents from the csv file through read by the Field Enricher Processor.

6.4. GeoEvent service 3

Service 3, as illustrated in Fig. 19, is designed to calculate and update residents' age data. Recognising the sensitivity of personal data, we adhered to strict ethical guidelines and did not access or attempt to use exact resident locations or personal details. Instead, for demonstration purposes, we utilised publicly available demographic data from the ABS 2021 census. This dataset provided an overview of the population figures, age distributions, and the prevalence of various health conditions and disabilities within Brisbane suburbs. Dummy point feature data were then randomly generated within the boundaries of the respective suburbs in ArcGIS web map to simulate a resident database. This approach ensured that the platform's functionalities could be tested without compromising privacy.

IC3 ingests the residents' Feature Layer every 24 h at a rate of 448 events per second. The data is processed through a Field Calculator to compute and update residents' ages in the attribute table. Three Filters then categorise residents into Children (0–14 years), Adults (15–64 years), and Elderly (65+ years), with each group assigned its respective classification via dedicated Field Calculators. OC2 updates the residents' age categories in the Feature Layer every 24 h. While the demonstration did not incorporate real-time location updates due to the unavailability of precise locational data, this capability remains a key future enhancement. Local governments could utilise housing authority data through an API to periodically update residents' residential addresses, ensuring accurate and current information. Additionally, GeoEvent's GeoTag feature could enable real-time tracking of vulnerable populations, providing critical support during extreme weather events or emergencies.

6.5. Customised notifications: Potential technical and social challenges

In the case study, the platform demonstrated its ability to personalise notifications by integrating real-time weather data with demographic and health profiles to identify and prioritise at-risk populations. For example, during warm nights in Wynnum North, notifications were prioritised for elderly residents and individuals with respiratory conditions, given that prolonged nighttime heat can exacerbate cardiovascular and respiratory issues. Similarly, during heavy rainfall events, alerts were directed to residents in flood-prone areas, particularly those with mobility impairments, to provide timely warnings and support proactive decision-making. The ability to dynamically adjust notification priorities based on weather severity and demographic vulnerability demonstrates the

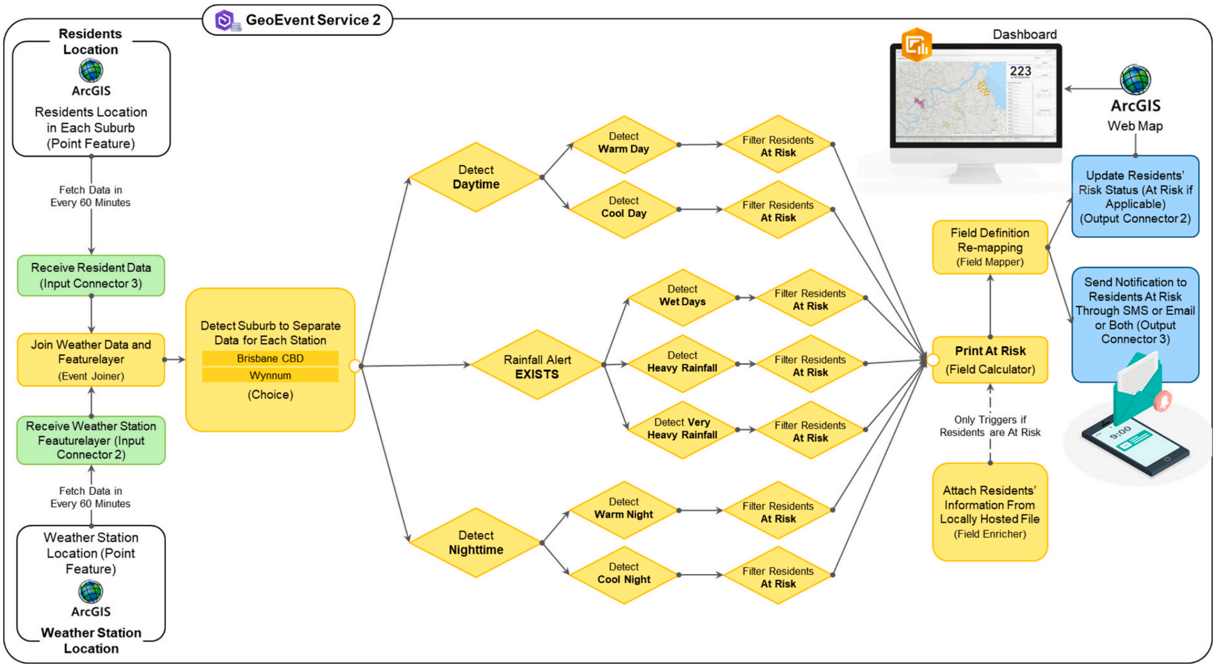

Fig. 16. GeoEvent Service 2 architecture.

Table 3
Risk matrix for weather stressor and vulnerable groups considered for demonstration purpose only.

	Warm Days	Warm Nights	Cool Days	Cool Nights	Wet Days	Heavy Precipitation	Very Heavy Precipitation
Children	Risk	Risk	Risk	Risk	Risk	Risk	Risk
Adults	–	–	–	–	–	–	–
Elderly	Risk	Risk	Risk	Risk	Risk	Risk	Risk
Asthma Patients	Risk	Risk	Risk	Risk	–	–	–
Diabetic Patients	Risk	Risk	–	–	–	–	–
Heart Diseases	Risk	Risk	–	–	–	–	–
Lung Diseases	Risk	Risk	Risk	Risk	–	–	–
Disability	Risk	–	–	–	Risk	Risk	Risk

platform's potential for context-sensitive risk communication.

Since this was a demonstration project, no technical challenges were encountered. However, in real-world deployment, potential technical issues could include incomplete or outdated demographic datasets, requiring continuous updates and validation to maintain accuracy. Additionally, integrating real-time sensor data with predictive models across diverse urban environments could present calibration challenges, particularly when adapting the platform to cities with different data infrastructures or weather monitoring capabilities. Addressing these challenges would require interoperability between datasets, automated validation processes, and adaptive calibration techniques.

Beyond technical considerations, social acceptance and public engagement are crucial factors influencing the effectiveness of personalised alerts. Challenges such as alert fatigue—where frequent notifications may lead residents to ignore warnings—would need to be addressed through careful optimisation of notification thresholds and customisation options. To mitigate this, future iterations of the platform could incorporate user preference settings and feedback mechanisms, allowing residents to customise alert thresholds while ensuring high-risk individuals remain adequately informed. By addressing these considerations, the platform has the potential to enhance urban resilience through personalised weather risk communication tailored to diverse urban contexts.

6.6. *Privacy and cybersecurity*

The proposed platform incorporates various forms of sensitive data, including residents' demographic details, health conditions, and location-based information. As such, privacy and cybersecurity considerations are crucial to its design, development, and deployment. Ensuring the confidentiality, integrity, and security of this information is essential for maintaining public trust and ensuring compliance with legal and regulatory standards, such as Australia's Privacy Act 1988 (Yuvaraj, 2018). Organisations should ensure informed consent when collecting data and maintain transparency regarding its usage. Robust security measures, including

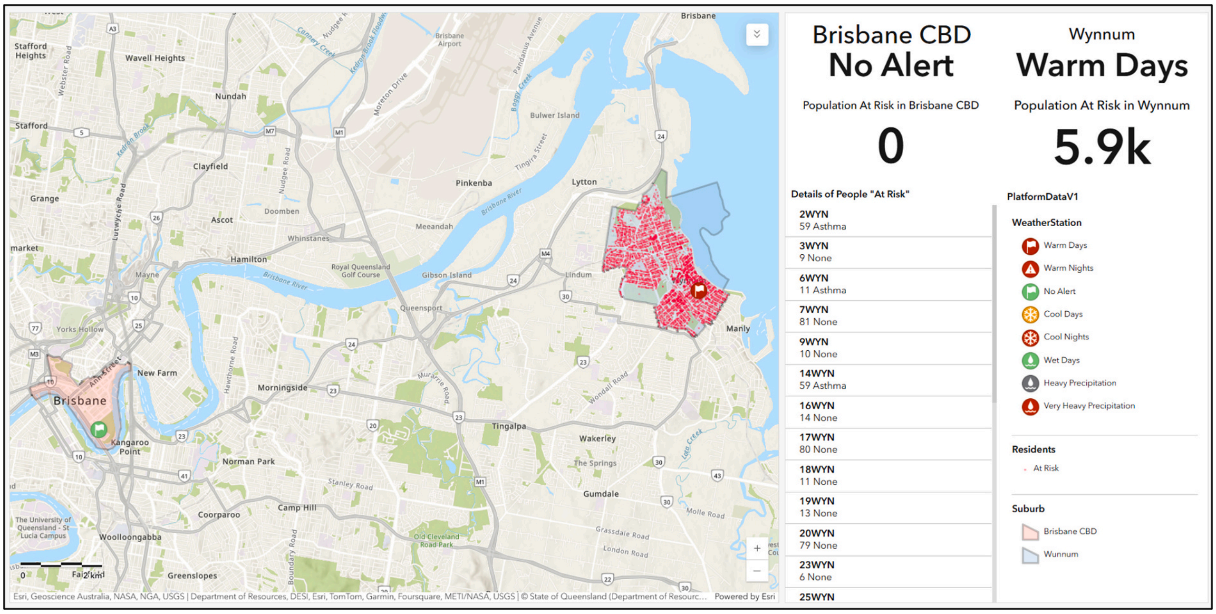

Fig. 17. Dashboard displaying residents 'at-risk' to authorised officers.

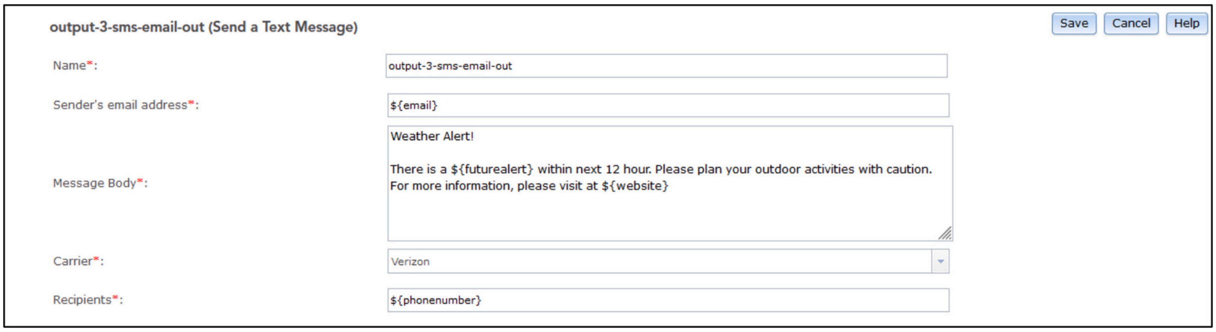

Fig. 18. OC3 to send alert to residents.

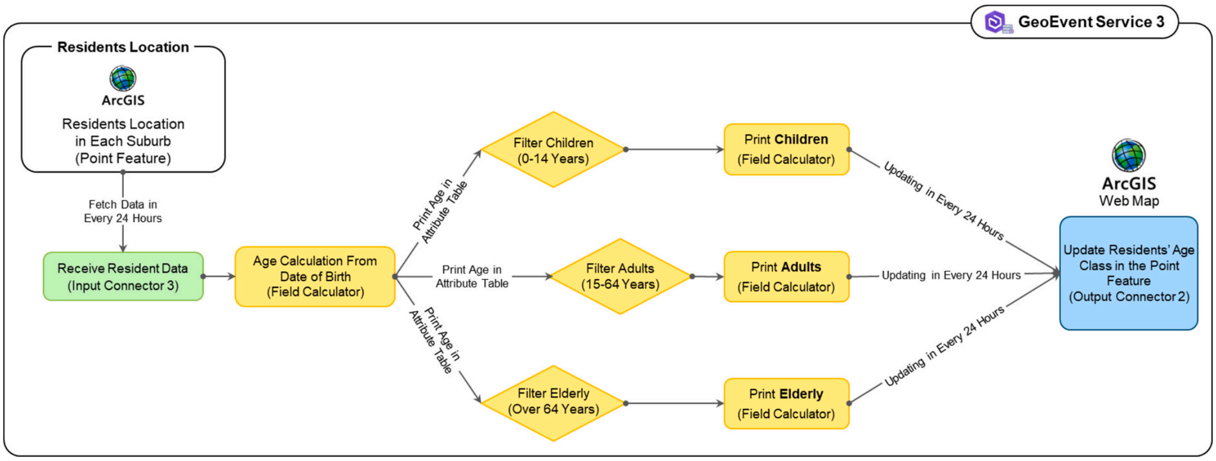

Fig. 19. GeoEvent Service 3 architecture.

access controls and encryption protocols, are critical for safeguarding sensitive information from unauthorised access.

Adhering to a privacy-by-design approach, the platform incorporates measures to protect the confidentiality, integrity, and security of sensitive data throughout its operations. One of the key features supporting privacy is the Field Enricher (File) Processor, which isolates personally identifiable information (PII) from the primary Resident Feature Layer. Instead of storing sensitive details like phone numbers and email addresses in the Feature Layer, this information is securely stored in encrypted .txt or .csv files within an access-controlled environment. These files are linked to the Resident Feature Layer via a shared unique identifier, allowing the platform to access essential personal information only when an "at-risk" alert is triggered.

To further enhance security, it is recommended to implement role-based access control for local government officials, ensuring that access to the dashboard and the platform's backend configuration is restricted to authorised personnel only. Additionally, regular security audits and assessments are advised to identify and mitigate potential vulnerabilities within the GeoEvent Services, web maps, and dashboards. These measures can collectively strengthen the platform's overall security, promoting data privacy, integrity, and confidentiality in alignment with data protection laws and ethical standards.

6.7. Platform prospects, limitations and integration into local government system

Although this study demonstrated the platform's capabilities in Brisbane CBD and Wynnum North, its modular architecture and customisable components enable flexible adaptation to diverse urban contexts beyond Brisbane. Its flexibility stems from three key design features: API-driven interoperability, adaptability of AI-based weather prediction model, and configurable demographic integration. By modifying API configurations, cities can integrate local weather monitoring networks and tailor the platform to their specific meteorological data sources.

A key feature of the platform is its ability to integrate diverse AI and machine learning-based weather prediction models, allowing for region-specific forecasting through Python scripts or spatial analytical models. This capability addresses the critical need identified in AI weather prediction systems for location-sensitive modelling, particularly when adapting to cities with distinct topographic features or unique microclimate dynamics. Beyond meteorological data integration, the platform's modular architecture allows for the seamless incorporation of city-specific demographic and health datasets within ArcGIS. This capability enables local governments and researchers to input customised population distributions, health vulnerabilities, and risk thresholds, ensuring that risk assessments reflect the specific socio-environmental dynamics of a given region. Such adaptability is particularly crucial for cities with varied population densities, infrastructure profiles, and environmental risk factors, where the effects of extreme weather events can differ significantly. Future research can involve testing the platform in cities with diverse topographies, climatic conditions, and population densities to more comprehensively evaluate its generalisability and effectiveness across varied urban settings.

The platform's modular design allows for dynamic adjustments to suit varying climatic conditions, geographic regions, and user-specific requirements. Customisation options include region-specific definitions for weather thresholds and conditions, ensuring that alerts are contextually relevant. Its architecture supports the inclusion of additional Connectors and Processors to incorporate new data streams, such as real-time energy consumption or social media feeds for disaster response, thereby extending its utility beyond weather monitoring to a broader spectrum of urban resilience applications (McLaughlin, 2017; Yao and Wang, 2020).

While the platform offers a robust solution for localised weather monitoring and alerting, its reliance on API-based sensor data introduces several challenges. API disruptions, such as server outages, connectivity issues, or high-frequency request limitations, can result in data gaps that compromise the platform's ability to deliver timely and accurate weather insights. Additionally, delays in API-configured data updates reduce the platform's capacity to respond to rapidly changing weather conditions, limiting real-time alerting efficiency. Addressing these limitations requires future iterations of the platform to incorporate strategies for handling missing or delayed data, such as interpolative modelling or the integration of alternative data sources to ensure continuous system functionality.

Local governments aiming to deploy this platform require an ArcGIS Enterprise subscription, which many local government authorities already maintain for urban planning and management purposes. This subscription provides access to ArcGIS GeoEvent and Portal for ArcGIS, enabling the creation of web maps and dashboards to support real-time data visualisation and monitoring. Alternatively, web maps and dashboards can be developed in ArcGIS Online and integrated with GeoEvent by configuring the ArcGIS Online server as a registered server within the GeoEvent environment. Another option for local governments is ArcGIS Velocity, a fully cloud-based solution that offers similar functionality but does not require manual installation or local server configuration. Unlike GeoEvent, which necessitates manual installation and the establishment of connections between ArcGIS platforms, Velocity operates as a complete Software as a Service (SaaS) solution. However, Velocity requires a separate subscription, which may result in additional costs for local governments. Given these considerations, GeoEvent was selected for this research, as it is included within the ArcGIS Enterprise subscription and is already widely utilised by local governments, particularly in Australia. The use of GeoEvent avoids the need for additional subscription costs while still supporting the platform's functional requirements for real-time data integration, processing, and visualisation.

7. Conclusions and research directions

This research presents a novel platform for real-time weather monitoring and personalised alert generation that addresses the need for localised weather monitoring and risk-based alert systems. Leveraging platform urbanism and AIoT concepts, the platform enables dynamic data integration to detect weather conditions and issue targeted alerts for residents considering their location, age, health conditions, and disabilities. The proposed platform offers distinct advantages over existing weather monitoring and alert systems in terms of cost-effectiveness, scalability, and ease of implementation.

The platform's scalable architecture allows for the integration of multiple environmental hazard assessments, positioning it as a cost-effective and adaptable solution for climate risk management. By integrating additional data streams and analytical models, the system can evolve into a comprehensive multi-hazard monitoring platform capable of addressing threats such as floods, bushfires, heatwaves, and air pollution events. Consolidating hazard assessments within a single interface simplifies operations for local governments, eliminating the need to manage separate systems for heatwave, flood, and air quality monitoring. Additionally, as the platform is built within the widely adopted ArcGIS ecosystem, local governments and urban planners can deploy it without requiring entirely new infrastructure, minimising implementation costs. The use of automated data ingestion, processing, and notification dissemination reduces manual intervention, ensuring operational efficiency.

We identified several future research areas to enhance its capabilities and impact. One promising direction involves the development of more accurate microclimate-based weather prediction models tailored to integrate seamlessly into the platform. Along with the station data, these models can incorporate other microclimate variables such as elevation, land cover, proximity to water bodies, and urban heat island effects. Future research directions include enhancing cybersecurity and data security, particularly as the platform manages sensitive resident information. While current measures involve data anonymisation and encrypted storage, addressing potential vulnerabilities in data transmission and system integration remains a critical focus. Advancements in encryption protocols, secure data transmission methods, and access control systems are key areas for exploration.

Another direction involves refining the platform's risk classification system from a binary “at-risk” model to a more nuanced approach with high, moderate, and low-risk categories, requiring interdisciplinary collaboration between climatologists, public health experts, and data scientists. Expanding the platform to incorporate a broader range of risk events, such as floods, bushfires, and air quality issues, presents an opportunity to streamline emergency response and strengthen community resilience. Additionally, exploring the integration of citizen science and crowdsourced data through mobile applications could enhance data granularity, supporting more accurate risk analysis and prediction.

Additionally, the strategic placement of weather sensors in urban areas requires further research, particularly in cities (like in our case study context of Brisbane) where weather station distribution is uneven. With nine weather stations in Brisbane, some clustered together, an estimated 34–44 % of the city lacks coverage, assuming a 3–5 km radius per station. Addressing these gaps could enhance the capture of microclimatic variations across diverse urban environments. Prospective research could explore methods to optimise sensor placement for comprehensive city-wide coverage, thereby improving data accuracy and inclusivity. Advancing these areas would contribute to a more robust platform for urban weather monitoring and risk management, ultimately supporting urban resilience and public safety.

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CRediT authorship contribution statement

Sk Tahsin Hossain: Writing – original draft. **Tan Yigitcanlar:** Writing – review & editing, Supervision, Conceptualization. **Kien Nguyen:** Writing – review & editing. **Yue Xu:** Writing – review & editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests (Tan Yigitcanlar reports financial support was provided by Australian Research Council. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.)

Data availability

Data will be made available on request.

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