Context-Aware Recommendations for the Prevention of Urban Arbovirus Outbreaks

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Abstract. *Urban arboviruses pose significant public health challenges in vulnerable urban areas, where traditional surveillance is often reactive and limited in delivering timely, localized guidance. This paper proposes a context-aware recommender system that integrates climatic data and crowdsourced environmental reports to proactively identify risk areas and deliver personalized preventive recommendations. A spatio-temporal clustering approach (ST-DBSCAN) identifies dynamic risk areas, and a multi-criteria model combines environmental and climatic indicators into a normalized risk score classified into operational levels. Based on these levels, the system generates context-sensitive recommendations, enabling proactive and localized interventions.*

1. Introduction

Urban areas around the world face complex public health challenges, one of which is the recurrent threat of arboviruses [Ligsay et al. 2021, Madewell 2020, Young 2018, Weetman et al. 2018, Braack et al. 2018, Martinet et al. 2019, Huang et al. 2019, Girard et al. 2020]. Arboviruses are viral diseases transmitted by arthropods, such as mosquitoes and ticks [Lima-Camara 2024], and can be defined as (i) predominantly urban cycle: Dengue, Chikungunya, Zika; and (ii) predominantly sylvatic cycle: yellow fever, Mayaro fever and Oropouche fever [Figueiredo 2019]. Urban cycle arboviruses or "urban arboviruses", transmitted primarily by the Aedes aegypti mosquito [Almeida et al. 2020, Fontenille and Powell 2020, Acevedo-Guerrero 2025], proliferate in densely populated environments where human activity and environmental conditions create ideal breeding grounds [Asad and Carpenter 2018].

When placed under a magnifying glass, the data related to arbovirus infections are significantly alarming. In the world, more than 100 countries face challenges related to arboviruses [da Saúde do Brasil 2025a]. About half of the world's population is vulnerable to dengue infection, with 100 to 400 million people developing the potentially lethal fever and around 40.000 deaths each year from the disease [Gurgel-Gonçalves et al. 2024]. Like dengue, the Chikungunya virus is transmitted by mosquitoes and has been responsible for more than 10 million cases in more than 125 countries or territories in the last 20 years. Currently, about 1.3 billion people live in tropical and subtropical regions vulnerable to Chikungunya transmission [de Souza et al. 2024].

In Brazil, this situation is also very alarming, with more than 6 million probable cases of urban cycle arboviruses infections being recorded in 2024, having recorded more than 5 million probable cases of dengue and more than 3.000 confirmed deaths by the end of May [Lima-Camara 2024, da Saúde do Brasil 2025a]. Between 2008 and 2019, approximately 6.429 Brazilians died from dengue fever [Gurgel-Gonçalves et al. 2024]. In the country, the vector's spread occurs most intensely during the rainiest months in each region, generally between October and May [Medeiros 2024]. Standing water favors the reproduction of mosquitoes, increasing the spread of diseases [Acevedo-Guerrero 2025]. Therefore, prevention requires the continuous removal of containers that can accumulate water, since mosquito eggs can remain active in the environment for up to a year [Prasad et al. 2023].

In Brazil, the primary strategy for combating urban arboviruses relies heavily on public health policies and governmental actions, as presented in the National Contingency Plan for Dengue, Chikungunya and Zika [da Saúde do Brasil 2025b]. These efforts predominantly involve face-to-face interventions by endemic agents, who conduct house-to-house visits for inspection, elimination of breeding sites, and direct public awareness campaigns [Andrighetti et al. 2009, de Tarso R Vilarinhos 2005]. Information dissemination, prevention guidelines, and community mobilization are typically carried out through conventional channels, including mass media campaigns and local health posts [Santos et al. 2014, Alves et al. 2016]. There are also challenges related to scale, real-time data acquisition, and the ability to provide highly targeted and context-specific recommendations to a large and diverse urban population.

The fight against arboviruses demands innovative and proactive strategies. Traditional surveillance methods often rely on passive data collection and retrospective analysis, limiting their ability to provide real-time, localized insights for timely interventions [Scarpino et al. 2017]. Factors such as climate conditions (temperature, humidity, precipitation) and environmental determinants (like the accumulation of solid waste and standing water) are known predictors of mosquito proliferation and disease transmission [Zhang et al. 2024, Paixão et al. 2018].

The Mais Lugar (+Lugar)[1] platform emerges as a valuable tool in this scenario. Mais Lugar was created to empower communities to actively participate in identifying and solving public health problems, particularly those related to zoonoses, arboviruses and basic sanitation. Its main features include allowing users to map and report problems related to zoonoses, arboviruses and their environmental predictors, such as open sewage and garbage, directly from their mobile devices. The platform also promotes participation through a gamified system of points and rewards, recognizing users' contributions to community health. Although +Lugar has demonstrated significant potential in mapping and engaging the community in relation to public health problems [Arouca et al. 2024], it needed features for a more proactive and personalized approach to combating diseases, specifically through the provision of context-aware recommendations.

This study is highly motivated by the evident need for an intelligent and proactive system to enhance urban arboviruses outbreaks prevention and response. It aims to develop a context-aware recommender system that leverages diverse data streams, including the climatic conditions, and crowdsourced environmental reports, to dynamically identify, classify, and communicate localized and contextualized risk levels for arboviruses outbreaks. By delivering personalized, timely recommendations via an interface like the +Lugar platform, this research seeks to empower urban populations with the information and guidance necessary to effectively mitigate risks, thereby contributing to more resilient

[1]https://play.google.com/store/apps/details?id=com.maislugar.app&hl=en&pli=1

and responsive public health strategies against urban arboviruses.

2. Background and Related Work

Traditional Recommender Systems focus predominantly on the user–item relationship, relying on historical information from explicit or implicit feedback to infer preferences. In practice, the emphasis is on modeling user preference as a bidimensional function of interactions between a User (U) and an Item (I) [Raza and Ding 2019, Mateos and Bellogín 2025], represented by the mapping function $R : U \times I \to V$, where R maps the interaction between a user and an item into a predicted value of interest, and V represents the rating or preference value.

However, people's preferences are not always static [Knijnenburg et al. 2011, Dean and Morgenstern 2022]. The decision to consume an item may be influenced by external and situational factors, known as "Context" [Adomavicius and Tuzhilin 2011]. Context, in this sense, refers to any information that can be used to characterize the situation of an entity (person, place, object, time, location, mood, company, access device, or the user's current activity, etc.) considered relevant to the interaction between a user and an application [Verbert et al. 2010, Rahman 2013, Adomavicius and Tuzhilin 2011, Afzal et al. 2018].

One observable aspect of traditional Recommender Systems is their lack of situational sensitivity, which means they do not observe the user's context when making recommendations [Raza and Ding 2019, Adomavicius et al. 2011]. A model that ignores context may generate preference predictions $P(I \mid U)$ that are generally high but completely inadequate for the specific moment of recommendation. For example, a user may enjoy listening to reggae at home (high preference $P(I \mid U)$), but if they are driving during rush hour (context: traffic, stress), they might prefer news or a podcast. The recommendation of reggae, while correct in terms of long-term preference, contextually fails. In this sense, Context-Aware Recommender Systems (CARS) arise to incorporate these contextual dimensions, aiming to generate more precise and situationally relevant recommendations, since the relevance of an item for a user can be strongly influenced by the context in which the decision is made.

The main objective of Context-Aware Recommender Systems is to extend the prediction function to a multidimensional representation by incorporating context as a key predictive variable [Adomavicius and Tuzhilin 2011], represented by the mapping function $R : U \times I \times C \to V$, where C represents the context, and R models the joint interaction among user, item, and contextual factors, returning a predicted rating or relevance score.

2.1. Recommender Systems for Urban Arboviruses

To support the proposal and identify the state of the art related to the solution developed in this work, an extensive literature search was conducted. The search focused specifically on studies addressing Recommender Systems for Urban Arboviruses, aimed at assisting in the prevention, monitoring, and response to vector-borne diseases with urban transmission cycles (Dengue, Zika, and Chikungunya). To ensure the breadth and relevance of the results, the Snowballing literature review technique was adopted [Wohlin 2014].

The use of recommender systems in this domain remains largely unexplored. Table 1 presents the three studies identified that employed recommender systems to address urban arboviruses, and it is noteworthy that all of them focus exclusively on Dengue.

Table 1. Studies on recommender systems applied to urban arboviruses.

Title	Author	Arbovirus	Year
Recommender system for detection of dengue using fuzzy logic	[Singh et al. 2016]	Dengue	2016
Development of optimized ensemble classifier for dengue fever prediction and recommendation system	[Shaikh et al. 2023]	Dengue	2023
Recommender system for dengue prevention using machine learning	[Kajornkasirat et al. 2025]	Dengue	2025

Even within this small subset, the approaches are heterogeneous and restricted in scope. [Singh et al. 2016] present a fuzzy rule-based diagnostic system that, although categorized as a recommender system, functions more as a traditional expert system and lacks personalization, context information, and rigorous evaluation. [Shaikh et al. 2023] propose a high-performance predictive framework based on optimized ensemble learning but include only a simple, non-personalized recommendation layer triggered by aggregate risk levels. [Kajornkasirat et al. 2025] advance the field by integrating environmental and entomological factors through association rule mining and validating their system with end-users; however, their model remains static, non-adaptive, and does not incorporate climate, geospatial, or crowdsourced information.

No study explores group-level recommendation or integration with collaborative platforms. This limitations indicate that the state of the art has yet to leverage the full potential of recommender system techniques. These gaps highlight a compelling opportunity. By incorporating geospatial, climatic, and crowdsourced environmental data, and by modeling user- and group-level contexts in a dynamic manner, it becomes possible to advance beyond diagnostic or descriptive systems toward proactive, personalized, and adaptive decision-support tools. The system proposed in this work positions itself precisely in this direction, addressing the limitations found in previous studies and expanding the role of Recommender Systems in a proactive and preventive approach for urban arboviruses.

3. Context-Aware Recommender System for Urban Arboviruses

The proposed system follows a four-stage pipeline: (i) contextual data acquisition, (ii) spatio-temporal clustering, (iii) risk modeling, and (iv) context-aware recommendation. This design enables the transformation of raw environmental and climatic data into actionable recommendations for urban health monitoring.

In this approach, the user's location, represented by latitude and longitude, is used as input for the OpenWeather API, enabling the collection of climatic variables such as temperature, precipitation, and humidity. These data are integrated with contextual information collected through the gamified geocollaborative platform Mais Lugar, which provides georeferenced reports of sanitation issues and solid waste accumulation.

The integration of these heterogeneous data sources allows the system to capture both environmental risk factors and dynamic climatic conditions associated with arbovirus proliferation.

3.1. Spatio-Temporal Clustering

The ST-DBSCAN algorithm is employed to identify clusters of reports based on spatial and temporal proximity. In this context, clustering aims to detect regions where environmental risk factors persist over time, indicating potential hotspots for vector proliferation. This choice is particularly suitable for the problem domain, as the spread of arbovirus vectors is inherently localized and time-dependent, requiring the identification of dense regions of events that persist over short spatial ranges and temporal windows.

The clustering process is formally described in Algorithm 1. The function $getNeighbors(p)$ returns the set of reports that satisfy both spatial and temporal proximity constraints defined below. The procedure $ExpandCluster(p, N, c)$ recursively expands the cluster by iteratively adding density-reachable reports according to the ST-DBSCAN formulation. Each report can be labeled as *visited*, *noise*, or assigned to a cluster during execution.

Algorithm 1: Spatio-Temporal Clustering via ST-DBSCAN

Input : Reports D, spatial threshold ϵ, temporal threshold $\Delta\epsilon$, $MinPts$
Output: Clusters C

$C \leftarrow \emptyset$;
Mark all reports as unvisited;
foreach $p \in D$ **do**
    if p *is unvisited* **then**
        Mark p as visited;
        $N \leftarrow getNeighbors(p)$;
        if $|N| < MinPts$ **then**
            Mark p as noise;
        else
            Create new cluster c;
            ExpandCluster(p, N, c);
            $C \leftarrow C \cup \{c\}$;
return C;

Two reports p and q are considered spatio-temporal neighbors if they satisfy both spatial and temporal proximity constraints, which define the neighborhood function used in $getNeighbors(p)$:

$$d_s(p, q) \leq \epsilon \quad \wedge \quad d_t(p, q) \leq \Delta\epsilon \tag{1}$$

where d_s and d_t denote spatial and temporal distance functions, respectively.

The resulting clusters represent regions of spatio-temporal concentration of environmental conditions associated with arbovirus risk, forming the basis for the subsequent risk modeling stage.

3.2. User–Cluster Association

To enable contextual recommendations, users are associated with clusters based on spatial proximity. A user u, characterized by its current location $loc(u)$, is considered part of a cluster c if there exists at least one report $p \in c$ such that:

$$d_s(loc(u), p) \leq \epsilon \tag{2}$$

The most relevant cluster c^* is selected by maximizing the risk score, as defined in Equation 3. This ensures that users are associated with the most critical nearby risk region rather than simply the closest one.

$$c^* = \arg\max_{c \in C_u} RiskScore(c) \tag{3}$$

Ties are resolved by selecting the cluster with the minimum distance between the user and the closest report in the cluster.

3.3. Risk Calculation Model

Risk is modeled at the cluster level through a multi-criteria function defined in Equation 4. This formulation integrates environmental evidence derived from crowdsourced reports with climatic suitability conditions, providing an interpretable and context-aware risk indicator.

$$RiskScore(c) = (W_A \cdot A_c) + (W_C \cdot C_c) \tag{4}$$

where $W_A + W_C = 1$, with $W_A = 0.7$ and $W_C = 0.3$.

This formulation provides a balance between observed environmental evidence and underlying climatic suitability, enabling the system to capture both immediate risk signals and latent conditions favorable to vector proliferation.

Environmental Component (A_c):

$$A_c = \frac{|c|}{area(c)} \tag{5}$$

The cluster area is estimated using the Convex Hull enclosing all reports. Geographic coordinates are projected into a planar coordinate system to ensure metric consistency. The resulting value is normalized using min-max normalization.

Climatic Component (C_c):

$$C_c = w_T T_c + w_H H_c + w_P P_c \tag{6}$$

All variables are normalized in $[0, 1]$.

The resulting $RiskScore(c)$ is discretized into categorical levels (Low, Medium, High).

3.4. Context-Aware Recommendation

The recommendation system uses $RiskScore(c^*)$ as the contextual signal to generate personalized and situation-aware interventions. Unlike traditional recommender systems, which rely primarily on user-item interactions, the proposed approach leverages environmental and spatial context to drive recommendation decisions.

1. Contextual Filtering: identifies the relevant cluster c^* and retrieves $RiskScore(c^*)$.
2. Content Selection: selects messages based on risk level and dominant component (A_c or C_c).
3. Delivery: sends personalized notifications.

3.5. Group Recommendation

Clusters are interpreted as implicit user groups, where users share a common environmental and climatic context. This formulation enables the system to propagate risk-aware recommendations to all users located within the same spatial region, aligning with public health strategies that target communities rather than individuals.

$$G_{risk}.scoreFinal = RiskScore(c^*) \tag{7}$$

$$G_{risk}.level = discretize(RiskScore(c^*)) \tag{8}$$

This ensures consistency between clustering and recommendation, avoiding mixing different granularities.

3.6. Message Selection

Message selection is formulated as a ranking problem that balances semantic relevance and diversity. This step is crucial to ensure that recommendations are not only contextually appropriate but also varied over time, avoiding user fatigue. This formulation allows the system to adapt recommendations dynamically to evolving environmental conditions while maintaining user engagement. A TF-IDF vector $\vec{V}_{cluster}$ is constructed from cluster reports. Each message m is represented as $\vec{V}_m$ in the same vector space. The similarity between the cluster context and a candidate message is computed using cosine similarity, as defined in Equation 9:

$$Sim(c, m) = \frac{\vec{V}_{cluster} \cdot \vec{V}_m}{\|\vec{V}_{cluster}\| \cdot \|\vec{V}_m\|} \tag{9}$$

A penalty factor $\lambda \in (0, 1)$ is applied to recently delivered messages. The optimal message is selected by maximizing the adjusted similarity score, as shown in Equation 10:

$$m^* = \arg\max_{m \in M} \lambda_m \cdot Sim(c, m) \tag{10}$$

where $\lambda_m = \lambda$ if m was recently sent, and 1 otherwise.

The overall message selection process is operationalized as described in Algorithm 2, which integrates semantic similarity and diversity into a unified ranking procedure. The candidate message set M consists of pre-filtered messages according to the risk level and dominant component. The history H stores recently delivered messages associated with the cluster. The function $vectorize(m)$ represents the transformation of message tags into a vector in the same TF-IDF space used for cluster representation.

Algorithm 2: Message Selection with Similarity and Diversity

Input : Cluster c, candidate messages M, history H

Output: Optimal message m^*

$\vec{V}_{cluster} \leftarrow TFIDF(c.reports)$;
$Score_{max} \leftarrow -1$;
$m^* \leftarrow$ NULL;
foreach $m \in M$ **do**
    $\vec{V}_m \leftarrow vectorize(m)$;
    $Sim \leftarrow cosine(\vec{V}_{cluster}, \vec{V}_m)$;
    if $m \in H$ **then**
        $Sim \leftarrow \lambda \cdot Sim$;
    if $Sim > Score_{max}$ **then**
        $Score_{max} \leftarrow Sim$;
        $m^* \leftarrow m$;
return m^*

4. Final Considerations

This paper presented a context-aware recommender system designed to support the prevention of urban arbovirus outbreaks through the integration of climatic data, geospatial information, and crowdsourced environmental reports. By combining spatio-temporal clustering, interpretable risk modeling, and context-aware recommendation, the proposed approach enables the identification of localized risk areas and the delivery of actionable and personalized preventive guidance.

The main contribution of this work lies in the integration of multiple dimensions of context into a unified recommendation pipeline tailored to public health scenarios. In particular, the use of ST-DBSCAN allows the detection of dynamic spatio-temporal risk patterns, while the proposed multi-criteria risk model provides an interpretable representation of environmental and climatic conditions associated with vector proliferation. Furthermore, the incorporation of semantic similarity and diversity mechanisms in the message selection process contributes to improving the relevance and variability of recommendations, supporting sustained user engagement over time.

By positioning recommender systems as proactive tools for public health, this work extends their application beyond traditional domains, demonstrating their potential to support preventive strategies in complex urban environments. The integration with the Mais Lugar platform further highlights the feasibility of leveraging participatory and gamified systems to collect contextual data and deliver targeted interventions at scale.

As future work, we plan to conduct a real-world evaluation in collaboration with a cohort study in vulnerable communities in Salvador, Brazil. This evaluation will focus on measuring the impact of context-aware recommendations on user behavior, community engagement, and environmental conditions associated with vector proliferation.

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