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Research Article

Integrating Phenology As A Leading Indicator In Climate–Health Surveillance For Early Warning Of Seasonal Pollen And Respiratory Risk

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Abstract

Climate change is altering the timing, duration, and intensity of environmental exposures, yet public health surveillance systems largely rely on calendar-based approaches that fail to capture these dynamics. In this study, we developed a climate-health, surveillance framework that positions phenology, the timing of biological flowering and pollen release events as measurable intermediary linking climate variability to respiratory health risk. Our surveillance framework integrated four primary indicators, including i) phenological exposure, ii) meteorological conditions, iii) air quality, and iv) asthma-related health outcomes into a standardized composite index, using z-score normalization. Analyses were conducted at the ZIP code level to demonstrate indicator development, temporal dynamics, and spatial variation. Phenological signals function as leading indicators of exposure timing, enabling alignment of environmental conditions and health outcomes within biologically defined windows. Application of the framework illustrates how synchronization of exposure, environmental, and health indicators correspond to increased respiratory risk, while misalignment results in lower index values. Time-series outputs demonstrate the ability of the index to capture onset, escalation, and persistence of risk, and spatial summaries highlight heterogeneity in risk patterns across ZIP codes. By translating ecological signals into a unified, interpretable metric, this approach advances climate–health surveillance from a reactive to an anticipatory model. The framework is scalable, interoperable, and adaptable to multiple hazards and settings, providing for a biologically grounded pathway for integrating climate-driven ecological change into public health surveillance and decision-making.

Keywords: Air quality; climate change, pollen, environmental health, asthma.

INTRODUCTION

Climate change is reshaping the timing, duration, and intensity of environmental exposures in ways that challenge existing respiratory health surveillance systems [1-3]. Among aeroallergens, pollen represents a critical and climate-sensitive exposure pathway and risk factor for the development and exacerbation of allergic rhinitis and asthma [4,5]. Changes in temperature, precipitation, and atmospheric carbon dioxide concentrations have been shown to shift pollen seasons earlier, extend their duration, and increase their intensity, contributing to a growing burden of allergic disease and asthma morbidity across the United States [2,6-9].

A growing body of epidemiological evidence has demonstrated strong associations between ambient pollen concentrations and asthma-related emergency department (ED) visits. In 2019, Neumann estimated that tree pollen alone accounted for more than 50,000 asthma-related ED visits annually in the United States, while Katz et al. (2024) reported that pollen exposure may contribute to nearly 19% of asthma-related ED visits among certain age groups during peak seasons in urban settings [10,11]. Together, these findings underscore pollen as a substantial and climate-sensitive driver of acute respiratory morbidity.

Despite advances in pollen monitoring, current surveillance approaches remain limited in their ability to support real-time public health action [12]. Existing systems rely heavily on sparse monitoring networks, calendar-based assumptions, or lagging clinical indicators, and are often fragmented across environmental and health data streams. As a result, they are largely reactive and lack the capacity to detect and respond to rapidly shifting, climate-driven exposure dynamics [12].

Phenology, the timing of recurring biological events such as flowering and pollen release offers a complementary approach for public health surveillance of respiratory aeroallergens and for communicating early exposure warnings. Because

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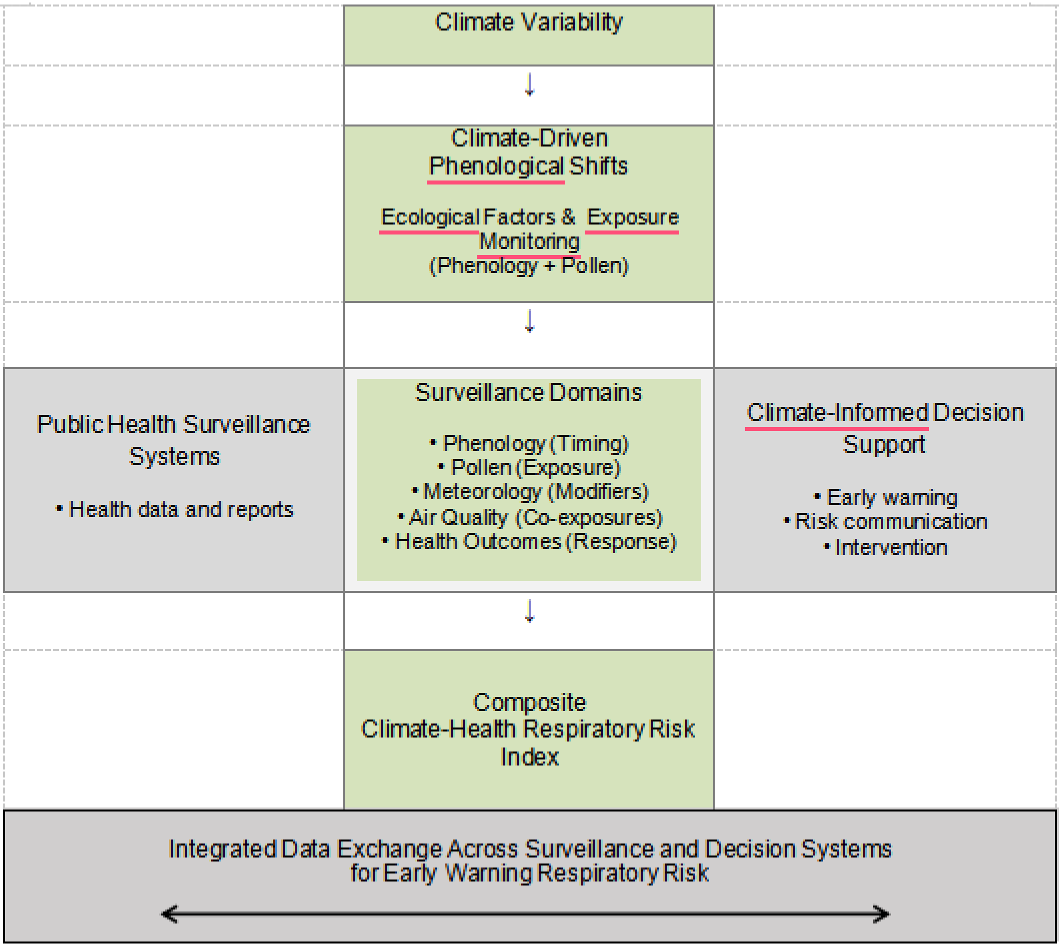
these biological timing indicators respond directly to climatic variability, they provide sensitive, upstream signals of when allergen exposures are likely to occur [13,14,15]. In contrast to traditional monitoring systems, which capture exposure intensity after it has occurred, phenological signals enable anticipatory, place-based risk detection. However, these indicators have not been systematically integrated into operational public health surveillance frameworks.

Citizen science plays a crucial role in providing data to advance climate-health surveillance. Local biological observations, particularly when combined with environmental conditions and health outcome data, offer a scalable opportunity to improve the spatial and temporal resolution of phenology timing and assessing exposure. Incorporating these data streams aligns with emerging transdisciplinary efforts to incorporate natural systems into climate–health research and supports the development of more responsive and predictive surveillance approaches.

The purpose of this study was to develop an operational surveillance framework designed to support real-time monitoring and early warning of climate-sensitive respiratory risk by incorporating biological timing indicators of environmental conditions. The framework integrates indicators of exposure timing (biological signals such as flowering and pollen release), exposure intensity (pollen concentrations and environmental conditions), and population response (health outcomes) within a standardized composite index. This approach is intended to enhance early detection, improve risk communication, and inform timely public health action.

Given the increasing burden of allergenic pollen associated with climate change, this study uses simulated data to demonstrate how multi-source environmental and health data can be standardized and integrated into an operational surveillance system. This illustrative application highlights the feasibility of the framework and its potential utility for strengthening respiratory risk monitoring and early warning in climate-sensitive settings (**Figure 1**).

Figure 1. Conceptual Framework for a Climate-informed Surveillance System Integrating Phenology, Environmental Exposures, and Respiratory Health Outcomes.



Climate variability and change influence phenological shifts, which serve as leading indicators of exposure timing. These signals are integrated with pollen concentrations, meteorological conditions, air quality, and health outcome data to generate a composite Climate–Health Risk Index (C-HRI). The system supports continuous, adaptive surveillance through iterative feedback between environmental monitoring, public health surveillance systems, and climate-informed decision support.

METHODS

This was a methodological, proof-of-concept study to demonstrate the feasibility of integrating environmental and health data streams into a composite, early warning surveillance framework. The study period spanned March through May 2024 corresponding to a seasonal window characterized by active pollen release, phenological transitions, and increased asthma-related morbidity in North Carolina. A representative ZIP code (27858) was used to illustrate temporal dynamics of the surveillance indicators, while multiple ZIP codes were included to demonstrate spatial variability in C-HRWI patterns. This framework was developed for surveillance and early warning purposes and was not intended to estimate causal relationships.

Data Sources and Surveillance Domains

Daily observations were organized into four primary domains: (1) phenological and pollen exposure (P_t), (2) meteorological conditions (W_t), (3) air quality (Q_t), and (4) respiratory health outcomes (A_t), as summarized in **Table 1**. The unit of analyses were conducted at the ZIP code level using daily observations from multiple publicly available data sources as described below.

Table 1. Surveillance Domains, Indicators and Operational Definitions for the Climate-Health Respiratory Warning Index (C-HRWI) Framework.

Domain	Indicator	Input Variables	Data Sources	*Metric(s)
Exposure (P_t)	Phenology & Pollen Exposure	Pollen release (PR_t), flowering intensity (FI_t), ambient pollen concentration (grains/m³)	USA-NPN Nature's Notebook; National Allergy Bureau (NAB) or regional pollen monitoring stations	Phenology index (0–1); pollen concentration; combined exposure indicator (P_t)
Meteorological (W_t)	Meteorological, Weather	Temperature, relative humidity, wind speed	NOAA; PRISM Climate Group	Temperature, humidity, and wind speed; averaged meteorological indicator (W_t)
Air Quality (Q_t)	Atmospheric	$PM_{2.5}$, ozone (O_3)	U.S. Environmental Protection Agency (EPA)	$PM_{2.5}$ and O_3 concentrations; averaged air quality indicator (Q_t)
Respiratory- Health (A_t)	Respiratory	Asthma-related ED visits (n)	NC DETECT (North Carolina Disease Event Tracking and Epidemiologic Collection Tool)	Daily ZIP code–level ED visit counts (A_t)

Notes: **Standardized*

Phenological data were obtained from the USA National Phenology Network (USA-NPN) Nature's Notebook platform and included daily observations of phenophase activity aligned with representative ZIP code areas [16]. Variables included pollen release (binary: 0 = absent, 1 = present) and flowering intensity (ordinal scale: none to high), representing the timing and relative magnitude of allergenic activity. Ambient pollen concentration data (grains/m³) were obtained from regional monitoring networks (e.g., National Allergy Bureau), providing direct measures of exposure intensity.

Meteorological variables, including temperature, relative humidity, and wind speed, were obtained from the National Oceanic and Atmospheric Administration (NOAA) and PRISM Climate Group [17]. Air quality data, including particulate matter ($PM_{2.5}$) and ozone (O_3), were obtained from the U.S. Environmental Protection Agency [18]. Health outcome data were derived from the North Carolina Disease Event Tracking and Epidemiologic Collection Tool (NC DETECT), using daily ZIP code–level counts of asthma-related emergency department visits [19].

Within this framework, biological timing indicators provide leading signals of exposure onset, pollen concentrations quantify exposure intensity, meteorological and air quality variables act as environmental modifiers, and health outcome data reflect downstream population response. Together, these domains form an integrated, multi-component surveillance system aligned with the environmental exposure pathway.

Surveillance Indicators

Phenological and Pollen Exposure Indicator (P_t): The exposure domain was represented by a composite indicator integrating biological timing signals and ambient pollen concentrations. Phenological activity was calculated as:

$$P_t^{raw} = \frac{PR_t + \left(\frac{FI_t}{FI_{max}}\right)}{2}$$

where, PR_t represents pollen release (binary: 0/1), FI_t represents flowering intensity, and FI_{max} represents the maximum value of the flowering scale. Phenological activity was smoothed using a 3–7 day moving average to reduce short-term variability and reflect phonologically meaningful trends. The smoothed values were standardized to baseline conditions:

$$P_{phen}^{(z)} = \frac{P_t^{raw} - \mu_P}{\sigma_P}$$

Ambient pollen concentrations were measured in grains/m³ and standardized across the study period as:

$$P_{pollen}^{(z)} = \frac{P_{pollen,t} - \mu_{pollen}}{\sigma_{pollen}}$$

where, $P^{(Z)}_{pollen}$ represents the standardized ambient pollen concentration at time t. Ambient pollen concentration (P_{pollen}) was measured in grains per cubic meter (grains/m³) using data from regional pollen monitoring stations.

The final phenological timing and pollen exposure indicator was defined as:

$$P_t = \frac{P_{phen}^{(z)} + P_{pollen}^{(z)}}{2}$$

where, $P^{(Z)}_{pollen}$ represents the standardized phenological indicator and $P^{(Z)}_{pollen}$ represents the standardized ambient pollen concentration at time t. This formula provides a unitless exposure indicator that integrates the timing of allergenic activity with the magnitude of airborne pollen concentrations, with higher values indicating periods of elevated exposure relative to baseline conditions.

Meteorological Indicator (W_t): Meteorological conditions were treated as modifiers of allergen production, dispersion, and exposure intensity. Daily temperature, relative humidity, and wind speed were averaged and standardized as:

$$W_t = \frac{T_t^{(z)} + H_t^{(z)} + V_t^{(z)}}{3}$$

where, $T_t^{(z)}$ represents the standardized daily temperature at time *t*, $H_t^{(z)}$ represents the standardized daily relative humidity at time t, and $V_t^{(z)}$ represents the standardized daily wind speed at time *t*. This formula produces a unitless meteorological indicator in which higher values reflect conditions more favorable to allergen production, dispersion, or exposure intensity relative to baseline conditions.

Air Quality Indicator (Q_t): Air quality was represented as a distinct domain capturing concurrent respiratory irritant exposure. Standardized concentrations of particulate matter ($PM_{2.5}$) and ozone (O_3) were averaged as:

$$Q_t = \frac{PM_{2.5}^{(z)} + O_3^{(z)}}{2}$$

where, $PM_{2.5}^{(Z)}$ represents the standardized particulate matter concentration at time t, and $O_3^{(Z)}$ represents the standardized ozone concentration at time t. This formula produces a unitless air quality indicator in which higher values reflect greater respiratory (irritant) burden relative to baseline conditions.

Asthma Health Outcome Indicator (A_t): Respiratory health outcome indicator was defined as daily counts of asthma-related emergency department visits aggregated at the ZIP code level and standardized as:

$$A_t^{(z)} = \frac{A_t - \mu_A}{\sigma_A}$$

where, $A_t^{(Z)}$ represents the reported number of asthma-related emergency department (ED) visits at time t, μ_A represents the mean number of asthma-related ED visits over the study period, and σ_A represents the standard deviation of asthma-related ED visits over the study period. This formula produces a unitless health outcome indicator in which higher values indicate elevated asthma-related ED visits to expected baseline levels.

Standardization: To enable comparability across variables measured on different scales, all inputs were standardized using z-score normalization:

$$z_t = \frac{X_t - \mu}{\sigma}$$

where, X_t represents the observed value at time t, and μ and σ represent the mean and standard deviation calculated over the study period. This transformation produces unitless values centered at zero, allowing integration across domains. Z-score standardization was selected to express all indicators as deviations from baseline conditions without imposing assumptions about absolute thresholds.

Composite Climate-Health Respiratory Warning Index (C-HRWI): Following standardization, each of the four domain-specific indicators were combined using equal weighting to construct the composite C-HRWI. Equal weighting was applied to avoid imposing a priori assumptions regarding the relative contribution of each domain and to preserve interpretability within a surveillance context. The C-HRWI is conceptualized as a composite surveillance metric that reflects the alignment of multiple exposure and response indicators. Higher values indicate simultaneous elevation across domains, suggesting increased respiratory risk.:

$$C - HRWI_t = \frac{(P_t + W_t + Q_t + A_t)}{4}$$

where, P_t represents phenology and pollen exposure indicator, W_t represents the meteorological indicator, Q_t represents the air quality indicator, and A_t represents the standardized asthma-related ED visits (or respiratory health) outcome indicator, all measured at time t. Overall, this formula produces a composite, unitless surveillance index reference where higher C-HRWI values indicate simultaneous elevation across multiple asthma-relevant indicators relative to baseline conditions. In general, a higher index value indicates days/times when multiple asthma-relevant indicators are elevated relative to baseline conditions, while lower values reflect typical or below-average conditions.

Risk Classification

The C-HRWI is conceptualized as a surveillance tool in which phenological indicators enhance early exposure onset, while pollen and environmental conditions characterize exposure intensity, and health outcomes reflect population health impact. Because all components are standardized, the index represents relative deviations from baseline rather than absolute risk.

Table 2. C-HRWI Thresholds and Risk Classification.

Table 2. Climate-Health Respiratory Warning Index (C-HRWI) Thresholds and Risk Classification			
C-HRWI Value (z-score)	**Risk Level**	**Interpretation**	**Public Health Relevance**
< 0.0	Near Baseline	Conditions at or below expected baseline levels across exposure, environmental, health indicators	Routine monitoring: no immediate action required
0.1 to < 0.50	Elevated	Early increase in one or more indicators (suggest emerging risk conditions)	Increased awareness; consider targeted communication to climate-sensitive populations
0.51 to 1.0	High	Concurrent elevation across multiple indicators (indicates heightened exposure and potential health impact)	Initiate public health advisories; support clinical providers and community-level interventions
> 1.0	Very High	Strong simultaneous increases across indicators, indicating substantial exposure and elevated likelihood of adverse health outcomes	Implement urgent public health actions; intensify communication and healthcare system preparations

Notes: *C-HRWI values are standardized using z-scores relative to baseline conditions. Thresholds are based on standard deviation units, where values < 0 represent below-baseline conditions, values ≥ +0.5 indicates elevated risk, and ≥ +1.0 indicates very high risk.*

As shown in **Table 2**, risk levels were classified using standard deviation–based thresholds (i.e., z-score ranges corresponding to near baseline, elevated, and high risk), facilitating translation of surveillance outputs into actionable public health guidance.

Data Analysis

Data management, indicator construction, and standardization were conducted using Microsoft Excel. Statistical analyses and descriptive summaries were performed using IBM SPSS Statistics (version 29.0). Time-series visualizations and spatial summaries were generated to evaluate temporal dynamics, indicator synchronization, and geographic variability in C-HRWI values.

Ethical Considerations

This study used de-identified, publicly available data and did not constitute human subjects research and did not require institutional review board approval.

RESULTS

As shown in **Table 3**, daily inputs from April 1 to April 5 illustrate how standardized indicators, phenological activity, meteorological, air quality and asthma-related ED visits, vary over time and combine to produce a single, composite C-HRWI risk value for a representative ZIP code (27858). In this example, the C-HRWI values ranged from −0.21 to 0.74, reflecting transitions from below-baseline to elevated conditions. Lower C-HRWI values occurred when indicators were below baseline, or not temporally aligned (e.g., April 1), whereas higher C-HRWI values emerged when multiple indicators increased concurrently. The combined daily input values for each indicator represents an integrated approach of surveillance, by considering upstream environmental drivers, such as elevated pollen levels and atmospheric conditions and downstream health responses using a single, time-specific risk estimate. Table 3. Integrated Daily Inputs and C-HRWI.

Table 3. Daily Inputs and Climate-Health Respiratory Warning Index (C-HRWI) Calculations for Representative North Carolina ZIP Code (27858).

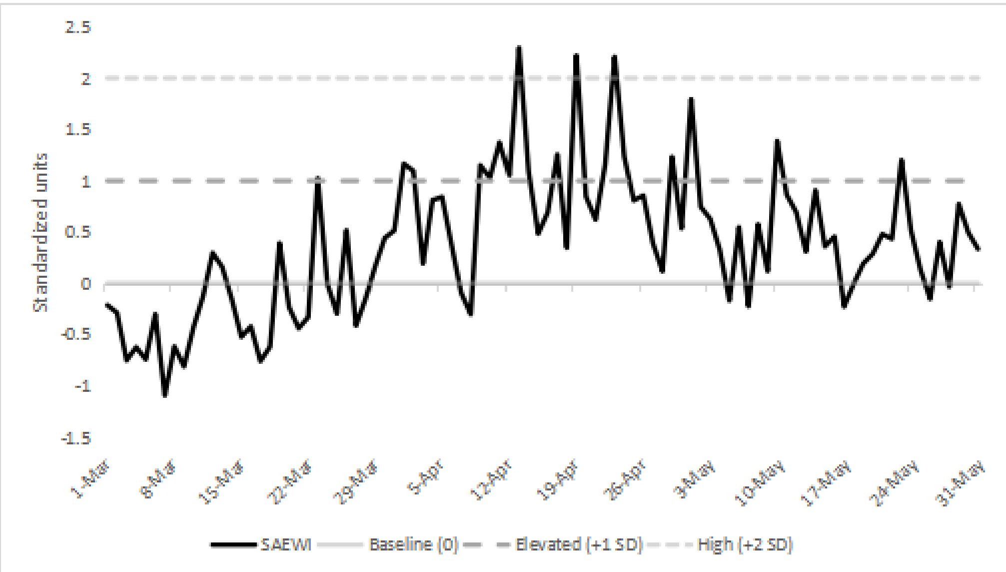
				Indicator			
Date	**ZIP Code**	**Phenology/ Pollen (P_t)**	**Meteorological (W_t)**	**Air Quality (Q_t)**	**Asthma-ED Visits (A_t)**	**C-HRWI**	**Risk Category**
2024-04-01	27858	-0.35	-0.28	-0.12	-0.10	-0.21	Baseline
2024-04-02	27858	0.10	0.05	0.02	0.15	0.08	Baseline
2024-04-03	27858	0.55	0.42	0.28	0.60	0.46	Elevated
2024-04-04	27858	0.80	0.70	0.60	0.85	0.74	High
2024-04-05	27858	0.25	0.55	0.25	0.30	0.34	Elevated

Notes: *Values are standardized (z-scores) relative to baseline conditions and represent deviations from expected levels. The phenology–pollen indicator (P_t) integrates (observational) biological timing (phenology) with exposure intensity (ambient pollen counts). The meteorological (W_t) and air quality (Q_t) indicators represent environmental modifiers of exposure, while the respiratory health outcome indicator (A_t) reflects number of daily asthma-related emergency department visits. Risk categories are defined using standard deviation thresholds relative to baseline conditions: values below 0 indicate below-baseline conditions, 0 to +0.5 SD represent baseline to moderate conditions, ≥ +0.5 SD indicate elevated risk, and ≥ +1.0 SD indicate high-risk conditions.*

Temporal Patterns

Building on these daily inputs, Figure 2 presents a time-series trajectory of C-HRWI for the same ZIP code (27858), illustrating how "day-to-day" variation accumulates into broader temporal patterns. Specifically, C-HRWI values began below baseline in early March and increased progressively into April as phenological activity (e.g., flowering and pollen release) and environmental conditions intensified. This upward trend reflects increasing temporal alignment between exposure and respiratory health response. Peak conditions in mid-April (C-HRWI > 2.0) corresponded to concurrent increases across all indicators, followed by a gradual decline into late April and early May, with intermittent elevations persisting. These temporal patterns demonstrate the ability of C-HRWI to capture the onset, escalation, and persistence of exposure-related risk, while standardized thresholds facilitates classification into actionable risk categories for timely public health decision making.

Figure 2. Climate-Health Respiratory Warning Index (C-HRWI) Time Series with Respiratory Risk Thresholds.



Notes: Daily C-HRWI values for ZIP code 27858 demonstrating integration of phenological, meteorological, and health outcome signals. Horizontal thresholds indicate risk categories (e.g., low, moderate, elevated, high).

Table 4.Spatial Patterns and Distribution of Elevated Respiratory Risk Across N.C. ZIP Codes

Table 4. Spatial Patterns in C-HRWI and Distribution of Elevated Respiratory Risk Across ZIP Codes.

ZIP Code	Mean C-HRWI	Elevated Days (≥ +0.5 SD) (%)	High-Risk Days (≥ +1.0 SD) (%)	Dominant Indicator Contribution	Interpretation
27858	0.22	35%	12%	Balanced (P_t, W_t, A_t)	Frequent multi-factor alignment; recurrent risk
28532	0.20	32%	10%	Exposure + Meteorology	Environment-driven elevated risk
28590	0.18	28%	8%	Balanced across indicators	Moderate, stable system interaction
28562	0.15	25%	7%	Health Outcome (A_t)	Health-driven risk pattern
27837	0.10	12%	3%	Low across indicators	Low alignment; lower overall risk

Notes: *Mean C-HRWI values represent the average standardized deviation from baseline conditions across the study period. Elevated days (≥ +0.5 SD) indicate above-average conditions requiring monitoring or preparation, while high-risk days (≥ +1.0 SD) represent substantially elevated conditions warranting public health action. These thresholds define C-HRWI risk categories as follows: below 0 = below baseline, 0 to +0.5 SD = baseline to moderate conditions, ≥ +0.5 SD = elevated risk, and ≥ +1.0 SD = high risk. The proportion of elevated and high-risk days reflects the frequency of temporal synchronization across phenological, environmental, and health indicators. "Dominant indicator contribution" identifies the primary driver of elevated C-HRWI within each ZIP code.*

Spatial Patterns

Extending from temporal dynamics within a single ZIP code to comparisons across multiple locations, **Table 4** summarizes how daily C-HRWI patterns translate into spatial variation. The spatial metrics, mean C-HRWI , percent elevated days, and percent high-risk days, are derived by aggregating daily C-HRWI values and their temporal classifications (as shown in **Table 3 and Figure 2**). Thus, **Table 4** represents the cumulative expression of repeated daily risk signals and their temporal alignment across ZIP codes.

Spatial variation in C-HRWI across North Carolina ZIP codes reflects differences not only in overall risk magnitude, defined as the average level of combined environmental and health-related respiratory risk over time, but also in how frequently and consistently elevated-risk conditions occur and what drives those patterns. For example, ZIP code 27858 exhibits higher mean C-HRWI values and a greater proportion of elevated-risk days, indicating frequent temporal synchronization between phenological activity, environmental conditions, and asthma-related health outcomes. In contrast, ZIP code 28562 shows elevated risk patterns driven primarily by respiratory health outcome signals, suggesting a stronger influence of the underlying population dynamics, such as higher social vulnerability, low access to care, etc.., rather than environmental exposure alone.

Overall, **Tables 3** and **4** and **Figure 2** work together to show how C-HRWI operates across time and place. Daily values (**Table 3**) show how environmental conditions and health outcomes combine to produce a single risk estimate, the time series (**Figure 2**) shows how that risk changes over time, and the spatial summary (**Table 4**) shows how those patterns differ across ZIP codes. Together, they show where risk occurs, how often and how severe it is, and what is driving it. ZIP codes with more elevated-risk days reflect repeated alignment of environmental conditions and health responses, indicating ongoing climate-related respiratory risk, while lower C-HRWI areas suggest a weaker or less consistent relationship between exposures and health outcomes.

DISCUSSION

The C-HRWI framework demonstrates how integrating phenological, meteorological, air quality, and health outcome data can enhance public health surveillance by shifting from reactive to upstream, proactive risk detection. Unlike traditional approaches that rely on calendar-based assumptions or lagging clinical indicators, C-HRWI captures dynamic, climate-driven exposure patterns by incorporating upstream ecological signals alongside environmental modifiers and downstream health outcomes. The resulting time series provides a single, interpretable metric that identifies periods of elevated respiratory risk, facilitating earlier detection of emerging hazards. Standardized thresholds further translate complex data into actionable categories that support risk communication, clinical preparedness, and targeted intervention strategies. Because C-HRWI can be applied at fine spatial scales (e.g., ZIP code or county level), it enables identification of localized risk patterns and supports efforts to address geographic disparities in climate-sensitive health outcomes

One of the key advancements of this framework is the explicit integration of phenological observations with pollen monitoring station data. While phenology provides an early indicator of when allergenic exposures are likely to occur, pollen measurements quantify the magnitude of those exposures. Together, these data streams bridge a critical gap between ecological processes and human exposure, improving both the temporal precision and interpretability of surveillance outputs. This dual-signal approach strengthens confidence in early warning indicators and enhances their applicability for public health decision-making.

A central contribution of this work is the operationalization of phenology as a measurable intermediate linking climate variability to population health [13]. While prior climate–health frameworks have described general pathways between environmental change and health outcomes, few have explicitly incorporated the timing of exposure as a quantifiable and actionable component [11]. (By positioning phenological indicators as sentinel signals within a surveillance system, this framework improves temporal precision in identifying when populations are most at risk. The integration of phenological, meteorological, and health data into a composite early warning index further demonstrates how these signals can be translated into operational surveillance outputs.

Importantly, this approach advances public health surveillance from a reactive model, where interventions are triggered after increases in respiratory morbidity, to an anticipatory model that leverages leading environmental indicators. In the case of respiratory health, phenological signals such as flowering and pollen release precede increases in aeroallergen exposure and subsequent asthma morbidity [15]. When combined with meteorological conditions that influence exposure intensity and dispersion, these signals provide a basis for earlier risk detection and more timely intervention. This anticipatory capacity has direct implications for risk communication, clinical preparedness, and resource allocation during periods of heightened environmental exposure.

The framework also supports integration across traditionally siloed data systems [15, 20- 22]. Environmental monitoring, ecological observation, and health surveillance are often conducted independently, limiting the ability to identify cross-domain relationships. By standardizing and integrating these data streams within a unified analytical structure, C-HRWI facilitates a more comprehensive understanding of climate-sensitive health risks and strengthens the capacity for coordinated public health response. By aligning upstream ecological signals with downstream health outcomes in near real time, the framework supports earlier detection of risk and more timely intervention. Additionally, because all indicators are standardized and structured within a consistent framework, C-HRWI is inherently scalable and interoperable, making it well-suited for integration into digital health platforms, environmental monitoring systems, and emerging AI-driven analytics pipelines. This positions C-HRWI as a foundational component of next-generation, climate-informed public health surveillance infrastructure.

Relevance for Rural and Resource-Limited Settings

Our framework has particular relevance for rural and resource-limited regions, where formal environmental monitoring infrastructure may be sparse. In these settings, phenological observations collected through citizen science networks, agricultural systems, and local ecological knowledge represent an underutilized source of environmental intelligence. Farmers, land managers, and extension personnel routinely observe seasonal biological transitions that are directly linked to environmental conditions and exposure risk. Integrating these observations into structured surveillance systems can expand spatial coverage and improve the timeliness of environmental monitoring. In rural regions, climate-sensitive exposures often intersect with social and health vulnerabilities [9]; phenology-informed surveillance offers a scalable and cost-effective strategy for strengthening early warning capacity. By leveraging locally generated data within a standardized framework, this approach enhances geographic coverage and contextual relevance, supporting more targeted and responsive public health interventions.

Limitations

Several limitations should be considered. First, this study presents a conceptual and illustrative framework rather than an empirical evaluation; the respiratory use case demonstrates feasibility but does not assess causal relationships or predictive performance. Second, integrating heterogeneous data streams introduces challenges related to data quality, spatial coverage, and temporal resolution, including variability in phenological observations and constraints in health surveillance data. Third, the use of standardized metrics (e.g., z-scores) assumes sufficient historical data to establish stable baselines, which may be limited in some settings. Fourth, although the framework acknowledges population vulnerability, it does not explicitly model differential exposure or susceptibility across subpopulations. Additionally, environmental and exposure-related factors influencing pollen dynamics, such as distance from source, wind characteristics, terrain, urban form, and atmospheric composition introduce complexity and variability that are not fully captured within the current index structure. Variability in pollen thresholds associated with symptom onset, differences across allergen types, and heterogeneity in study designs further complicate interpretation. Finally, the weighting structure of the composite index is conceptually derived and not empirically optimized; future work should include validation, calibration, and sensitivity analyses to refine model performance across diverse settings .

CONCLUSION

Integrating phenology into public health surveillance systems enhances early detection of climate-sensitive exposures, improves temporal alignment between environmental and health data, and supports the development of actionable early warning indicators. This framework illustrates a shift from reactive to anticipatory public health practice, with phenological signals serving as critical inputs for climate-informed decision-making.

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Author Contributions

G.K. designed, supervised and analyzed the study. G.K., G.H. and J.V. designed the figures, tables, and graphs. G.H. and J.V. contributed to review and editing.

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Data Availability

The data used for this project are publicly available.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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