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Climate-Driven Health Risk Alert Dashboard

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Abstract— Climate change boosts extreme weather, at the same time speeding up disease spread—dengue's hitting harder, messing with public well-being. A fresh tool maps climate-driven health risks in select Indian urban areas, spotlighting dengue and heat stress using visual dashboards. Rather than real-time streams, it works from saved CSVs holding temperature, moisture, and sickness records, giving users click-through access to nearby hazards along with an example layout marking high-risk districts. For now, views are static snapshots, yet forecast threat levels nearly 14 days out; future tweaks may grab updated stats from web APIs and apply learning models to refresh alerts without manual input. This initiative starts building responsive warning setups so authorities can move quickly based on reliable insights nationwide.

Keywords— Climate Change, Health Risk, Dashboard, Dengue, Heat Stress, Early Warning System

I. INTRODUCTION

Global warming is now a major threat to people's health, making bug-borne sicknesses worse while boosting cases tied to extreme heat. Warmer weather, shifting rain patterns, and heavier moisture levels help diseases like dengue thrive across warm zones. Meanwhile, city areas trap more heat, raising dangers during hot spells, especially in crowded parts of India.

India's varied landscapes combined with crowded cities boost risks from these health challenges. International efforts—like *WHO's Climate and Health* reports along with the *Lancet Countdown*—stress tracking climate impacts on health; even so, local systems using solid data remain weak when turning wide-ranging climate facts into clear steps for leaders or medical groups.

This study presents an early version of a health risk map tied to climate conditions in some Indian cities, showing past patterns of dengue and extreme heat. It gives officials a clear way to view threats through simple visuals. While right now it only uses fixed CSV files, future upgrades will add live data feeds via APIs instead. On top of that, smart algorithms may soon help forecast dangers using pattern recognition.

II. LITERATURE REVIEW

The link between shifting weather patterns and people's well-being has drawn attention from fields like disease tracking, climate research, or computer-based analysis. Major studies done by worldwide groups keep showing how global warming boosts not just how often illnesses tied to weather happen, but also their strength and spread across areas. These documents stress that places crowded with residents, weak medical systems, or economies relying heavily on environment-dependent jobs face greater risks.

On a population scale, some reports point out links between weather traits and how often illnesses pop up. Work into dengue plus malaria suggests heat, wetness, or rain shape how well mosquitoes live, feed more often, carry germs longer, or find spots to breed. Scientists using time-based data tend to include past climate details to see later impacts on flare-ups. Findings like these show weather facts may boost tools forecasting spikes - especially where it's hot most of the year.

A modeler might pick different math tricks to guess how diseases spread. Instead of just one way, tools like ARIMA or Random Forest jump in - each works on weekly or monthly numbers. When the data's clean, these guesses tend to hit close. Still, some methods hide their reasoning behind complex layers. Since leaders need clear answers, fuzzy logic can slow things down in actual health decisions.

A different part of the research looks at how vulnerable places are to risks. Experts say you can't really grasp climate's effect on health unless you look at things like who lives there, if people are poor, what homes are like, or whether clinics are nearby -

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so it's about society and systems together. Some blended scores showing weakness have popped up when talking about preparing for disasters or adjusting to shifting weather patterns. Still, only a handful of studies actually plug those fine-grained risk numbers into real-time sickness prediction models.

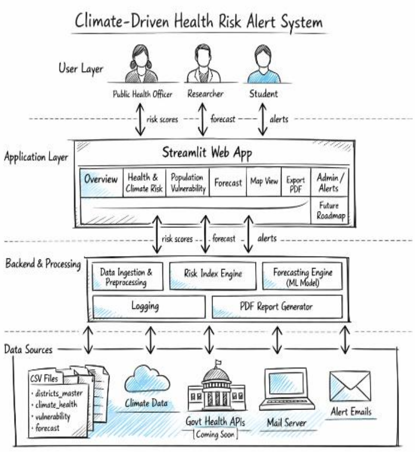
Just like that, studies about health data platforms point out how clear visuals plus clickable features matter. During big disease outbreaks, people built online tools using maps to show where cases pop up. But most of these only track past or current infection numbers - rarely mixing weather patterns, risk zones, along with upcoming projections all in one place.

The current study takes ideas from each of the four research areas, climate–disease relationships, predictive modeling techniques, vulnerability assessment, and visualization/dashboard research.

The main thing here isn't creating a brand-new forecast method, yet linking existing pieces into one flexible, transparent risk model. It builds a combined risk score - breaking it down clearly by each part - and shows results on a live-updating screen that handles streaming data while staying open to later adding smart algorithms.

III. SYSTEM ARCHITECTURE

The structure's built from individual pieces piled up in layers - this way it expands easily, stays under control, or adjusts down the line without headaches



They're split into four key zones:
Data Ingestion Layer
This section pulls data from various places. At the moment, it runs on:
Old or rarely updated CSV files - packed with earlier weather data, health numbers, yet local danger insights.

Fresh weather details grabbed straight from an outside feed - like OpenWeather - with current temps, humidity levels, or rain intensity shown for each area.
The setup's designed to connect with govt websites - say, storm spotters or disease counters - later on.

Preprocessing & Feature Engineering Layer
Raw data often misses bits, jumbles up formats, or comes at irregular times - this stage fixes that. It deals with messy entries by cleaning timing hiccups while lining up mismatched structures along the way

Type shifts or steady measurements.
Filling holes with guesses or going with simple backups instead.
Just tweak numbers from top to bottom, or bundle info by place with time.
Fresh data pops up when you mix details - say, sickness rates or how vulnerable a group could be.
Analytical & Forecasting Layer
This key section calculates the Composite Risk Index (CRI), yet at the same time gives rough future projections
Tweaks individual pieces - say, temperature force, dampness amounts, storm cycles, sickness numbers, danger triggers, or access to care - in a steady manner.
Blends amount to find CRI by zone.
Keeps up with today's patterns to guess what happens next over 14 days - runs on a simple framework you can replace anytime. Built loose, so sharper systems such as LSTM or Prophet could plug in down the road without changing core parts.

Visualization & Interaction Layer
The frontend runs on Streamlit - a fast way to create live web apps while keeping things snappy. It takes care of main tasks such as:
Show metrics using timeline charts, divided diagrams, or area-specific maps.
People can choose filters based on location, data format - say CSV instead of API - or set alert sensitivity levels.
Saving data as PDFs per district makes it easier to pass along updates or hold onto records. Since these

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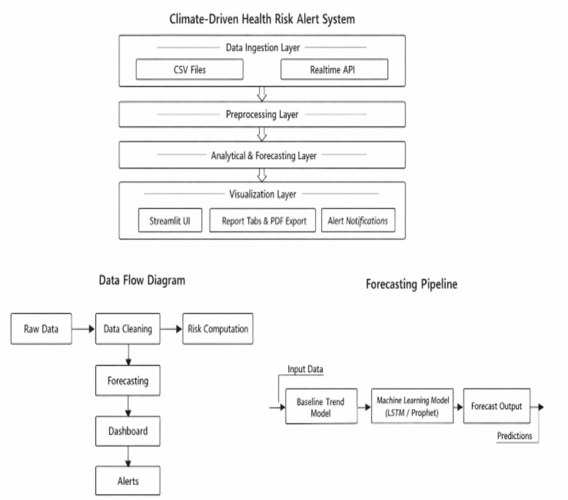
files move quickly, they help folks stay aligned without delay.
Offers an area - Admin or Monitoring - to manage warnings while checking logs.
The split layout holds layers apart, meaning if you switch one piece - say, trading a simple forecast gadget for something smarter - it doesn't wreck the others, kind of mirroring how dependable programs are made.

IV. DATA FLOW MODEL

The data flows through the setup along a straightforward route - from first entry to helpful output - by means of stages you can track without trouble

Input Stage



Old CSV details on regions, climate numbers, illness hints, or soft spots are loaded into RAM.
When switched on, it grabs current weather details from a web feed for each location. Not just using old records, but blending new updates with earlier numbers to create overall snapshots.

Transformation Stage
Each data group is cleaned first, after that sorted using district name as the key label.
Numeric entries shift into proper forms - errors get tweaked, blanks patched in varying ways. Faulty figures change, but missing spots refill uniquely every round.

Mid-level arrangements come together, blending climate trends with sickness numbers and hazards in specific spots on fixed days - using ties such as 'whereas' or 'together with'. These groups pack data by place once timelines match - one piece lands per location, no extra junk.
Computation Stage
The tidy combined info heads into the risk tool - here, the total rating's figured using the number setup explained after this.

Historic risk values, if available, are sorted by date - this lets the forecasting tool work. Instead of stacking them randomly, placing them in time order helps spot trends early. Without this step, predictions could miss key patterns hiding in older records.

The prediction system shows future danger levels for each region over 14 days - updated every day based on what’s happened before, not stuck rules.

Output Stage
The math results along with forecasts go into the screen section to update pieces - digits shown, moving curves, blocks, or shaded areas - by connecting dots across info spots.

A dedicated reporting system grabs those outcomes - after that, it creates PDF summaries so managers can check them.

If a spot’s risk level climbs past the limit, alarms go out via email - down the line, perhaps messages or different methods as well.

This clear step-by-step flow of info shows where figures start, also lets you toss in more steps - say, reviews or model tests - down the line.

V. RELATED WORK

A few studies explored how changing climates influence systems that track health risks and send warnings. The *WHO* recommended global strategies linking weather patterns with sickness data, especially for heat waves or bug-borne illnesses [1]. Likewise, *The Lancet’s environmenta*l publication pushed for mixing climate signals into health records but noted a lack of practical tools for local areas [2]. Articles from *Nature Climate Change* found machine-learning-like approaches might predict dengue outbreaks using rainfall and temperature—yet these models stay in trials, not

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active public platforms [3]. In India, earlier work mostly studied ties between weather figures and disease counts rather than creating live-updating visual displays [4].

A. Comparison with today's systems

The present study brings real-world testing —
A basic version of a tool that displays climate and health details for select Indian cities. Even though live updates or prediction features aren't included yet, it's still a step forward —helping build local alerts based on actual data.

Study	Scope	Limitation	How Ours Differs
WHO Early Warning Systems (2022)	Worldwide systems to warn about hot weather or sickness	No city-level dashboard	Ours is region-specific for India
Nature Climate Change (2023) – ML for Climate Diseases	Predictive models only	Lacks public-facing visualization	We concentrate on visuals to boost understanding
Environmental Research Letters (2020)	Health risk frameworks in developing countries	Theoretical	Ours is a working prototype

VI. METHODOLOGY

A. Data Acquisition

The trial version checks spots with different weather and living setups. That means district-level info makes it easier to see patterns on a map. Temp readings arrive each day or bundled up - humidity mixed in, rainfall too. Disease numbers follow actual or guessed counts for dengue, malaria, or heat-triggered illnesses, showing climate-linked health effects. Hazards include kid populations, elderly residents, low earners, informal housing, alongside distance from clinics.

In real life, get those data sets through government files - health tracking networks - or solid weather archives.

B. Data Preprocessing and Normalization

shaping numbers so they match one scale
Preprocessing turns chaotic info into neat stuff ready for checking. It includes correcting mistakes, tossing out repeats, changing layouts, also patching blank spots
Switching digit inputs into simple forms - such as full numbers or decimal values.
Making sure zone tags line up across different files.
Filling blanks with smart guesses - say, treating empty spots as zero. Rather than tossing out info, plug in sensible stand-ins that fit the situation. Go with median values for numbers, use "unknown" when dealing with groups. Match the fix to each column's kind, skip cookie-cutter tricks.

Rescale numbers so they fall from 0 up to 1 using min–max adjustment or your own set boundaries.
These jobs go via Pandas, wrapped up in neat little functions - so changes are smoother and clutter stays low. Set up like this, fixes need fewer steps and mix-ups vanish quicker.

C. Working out the risk number

In each zone, fresh stats on climate, wellness, and frailty feed into the risk meter. After that, segment ratings pop up - details are spelled out in the number section. From there, the total CRI is built and stored alongside these bits, letting them guide future summaries or splits.

D. Forecasting Procedure

The past CRI figures for each zone, when available, create a sequence. So, a simple predictor uses average trends to sketch a fortnight ahead. Although basic, the output remains steady and easy to grasp - ideal for quick checks or spotting shifts.
The code sets aside a unique area for functions (ml_forecast_placeholder) fitting both input and output demands, but might eventually use LSTM, Prophet, or different approaches within. Thanks to this separation, improving the forecasting engine underneath won't affect how people use it.

E. System Implementation

The setup works with Python, while Streamlit manages the user interface. On the side, Pandas along with NumPy handle number processing and data handling. To show maps visually, it swaps in PyDeck. If a report must be exported, FPDF jumps in to create PDF files. If necessary, notifications are sent by email using a built-in SMTP option when suspicious areas appear. When files load, APIs trigger, or alerts fire - everything's recorded on its own, making problem checks smoother.

F. Dashboard Design

Figure 1. A prototype of climate-driven health risk alert dashboard

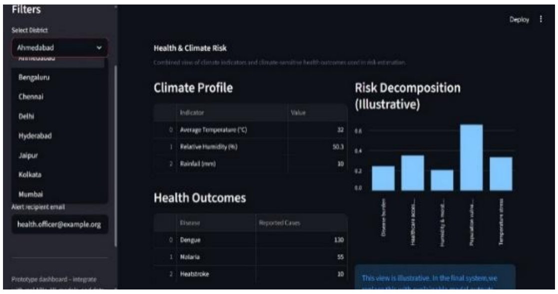

Figure2. The various features of the dashboard: drop-down menu for cities, risk decomposition graph, alert health official email, showcasing climate profile and health outcomes.

VII. RESULTS AND DISCUSSION

The tested setup went through checks using fake plus partly real data from several areas. Main goal? To make sure the risk math worked right - also whether breaking down risks made sense, forecast trends stayed steady, or the dashboard felt easy to use.

The risk index clearly showed which areas faced less or more danger by mixing weather, illness levels, and community weaknesses. Areas with hot air, dampness, heavy rain, yet also high sickness rates ended up with worse CRI numbers. Places that had okay weather but tough living conditions due to poverty still got marked as risky, showing why social issues matter just as much.

The risk breakdown visuals worked well to show main risk sources. In certain areas, things like heat and dampness pushed up the CRI more, but in different zones, weak systems or poor clinic access stood out instead. This kind of detail helps shape better local actions - say, one place could use bug control along with weather prep steps, meanwhile another spot might need stronger clinics or aid programs.

The forecasting part made clean 14-day risk lines - no wild swings - so it's easier for people to grasp. Even though the model right now is kept basic, what it shows works fine for explaining near-term risk trends. These predictions could act as a starting point, letting later studies stack smarter machine learning methods beside them.

The Streamlit dashboard felt easy to use, guiding users smoothly from one section to another through well-labeled tabs while letting them pick districts using simple dropdowns that responded fast. Switching views brought instant visuals, making trends clear right away. Users can grab PDF summaries anytime, which works great when prepping for reviews or sharing updates offline. A dedicated Admin area shows problem zones at a glance alongside recent system logs, helping teams keep track of what needs attention.

Still, findings show that even with basic models, a well-built linked setup can offer clear, useful info for handling climate health risks. Key drawbacks involve missing data plus depending on fake or fixed datasets for some parts - these issues get tackled later in planned research steps.

VIII. CONCLUSION

This study introduced a tool that warns about health risks linked to climate - mixing weather data, illness records, who's most at risk, and how close people are to medical care. It builds an overall risk score, breaks it down so it's easier to understand, then gives near-future predictions to help officials act ahead of time.

From one angle, this work shows that basic yet organized setups can team up with today's visual aids to link data science and public health more smoothly. Its block-like design means newer prediction methods or live feeds could plug in later - no need to overhaul the front end or main system.
Even though this version's just a test model, it still shows how useful climate-smart health tracking could be in India. Using solid proof, fine-tuning, plus linking up with government data flows, the system might grow to cover states or the whole country - while also working for different illnesses or weather threats.

IX. FUTURE WORK

A few solid ideas for what comes next stand out:

Figure3. Showcasing a graph of the risk forecast of the next 14 days.

A. Integration of Advanced Machine Learning Models.

The forecasting part could get better with tools like LSTM, GRU, or Temporal Convolutional Networks - or even mix models that use weather data along with other factors. Looking at results through measures like RMSE, MAE, or MAPE might show which model works best depending on location and illness.

B. Real-Time Multi-Source Data Integration.

Later updates could pull live weather data, linking up with public health networks - using feeds from meteorology sources or government disease trackers. To keep things running smoothly, auto processes would handle data transfer, reshaping info while scanning for errors.

C. Advanced Alerting and Decision Support

Figure4. Risk map of India highlighting the cities with different colours depending on their risk factor.

Besides email warnings, texts or phone alerts - alongside links to official crisis networks - boost how well things work. Shifting trigger points, shaped by past data or risk exposure, offer smarter alert timing.

D. Expanded Vulnerability Modeling

More social and economic details - like how much schooling people have, whether they can get safe water and toilets, or how hot cities feel - might be added to make risk maps more detailed. Grouping similar areas by location might show regions where dangers overlap.

E. User-Centered Design and Field Validation

Getting health workers involved early helps shape tools people actually use. Testing in a few areas - while listening
to users and checking results - shows what works on the ground.

F. Policy and Governance Integration

Finding ways to match the system with local efforts on climate shifts, cutting disaster risks, or boosting healthcare should matter most. Also, the analysis setup could shift over time - giving regular updates and visual tools that fit various government layers.

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Why use it?

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This study is different because it links hot weather, damp air, or downpours to sudden jumps in dengue infections.

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Githeko A. K. worked with Lindsay S. W., teaming up with Confalonieri U. E., while also including Patz J. A. (2000). Changing weather trends that impact diseases carried by bugs – results from local studies. Appeared in a WHO publication, issue 9 of volume 78, spanning pages 1136 through 1147.
Why use it?
Firm clues tie weather patterns to illness - useful when checking your risk setup. Try it out.

[3] Noticing illness dangers sooner if the climate changes
World Health Organization. 2015. Climate linked to health per country – India. Released through WHO Press.
Why use it?
WHO claims quick alerts matter - shows your system works.

[4] Machines that predict illness patterns
Adiga, A., together with colleagues (2019), explored using machine learning to predict infections via a thorough review. The study showed up in the Journal of Biomedical Informatics, issue 95, from page 103 to 183.
Why use it?
Fuels your prediction apps - unlocks chances for future smart tech upgrades.

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Huang, C., working alongside Barnett, A. G., Wang, X. - as well as Tong, S. (2012) - checked heat's impact on life length in Brisbane, Australia. The research showed up in Nature Climate Change; it was in volume 2, issue 4, running pages 265 through 270.

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