

1 **Explainable AI Reveals Heat-Health-Socioeconomic Interactions in**
2 **African Urban Populations: A Multi-Domain Analysis of 2,334**
3 **Participants**

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6 **Abstract**

7 **Background:** Climate change disproportionately affects urban populations in Africa, yet the
8 mechanisms linking heat exposure, health outcomes, and socioeconomic status remain poorly un-
9 derstood. Traditional epidemiological approaches struggle to capture complex multi-domain interac-
10 tions at scale.

11 **Methods:** We conducted an explainable artificial intelligence (XAI) analysis of 2,334 partic-
12 ipants from multiple cohorts in Johannesburg, South Africa (2013-2021). We integrated climate
13 data (ERA5, WRF, MODIS, SAAQIS), biomarker measurements, and socioeconomic variables from
14 GCRO Quality of Life surveys. Machine learning models (XGBoost, Random Forest, Gradient
15 Boosting) with SHAP explainability were used to predict health outcomes from environmental and
16 social determinants.

17 **Results:** Glucose metabolism showed the strongest climate sensitivity ($R^2 = 0.611$, 95% CI:
18 0.58-0.63), with 21-day temperature exposure windows most predictive of metabolic dysfunction.
19 Socioeconomic factors significantly amplified heat vulnerability (vulnerability index range: -650.5
20 to +0.5), with housing quality, income, and healthcare access creating multiplicative risk effects.
21 Gender-specific heat responses were detected (temperature-sex correlation $r = 0.116$, $p < 0.001$).
22 Random Forest models consistently outperformed other algorithms across all biomarkers.

23 **Conclusions:** Heat-health relationships are predictable, mechanistic, and socially stratified. Glu-
24 cose monitoring during sustained heat exposure could serve as an early warning indicator for climate-
25 vulnerable populations. Targeted interventions based on socioeconomic vulnerability mapping could
26 significantly reduce heat-health inequities in African cities.

27 **Keywords:** climate change, health equity, machine learning, explainable AI, urban health, so-
28 cioeconomic determinants

29 **1 Introduction**

30 Climate change poses unprecedented health risks to urban populations in sub-Saharan Africa, where
31 rapid urbanization coincides with increasing temperature extremes [? ?]. Heat exposure affects mul-
32 tiple physiological systems, with impacts varying substantially across populations [? ?]. However,
33 traditional epidemiological approaches have limited capacity to capture complex, multi-domain interac-
34 tions between climate, health, and social determinants at the scale required for effective public health
35 intervention [? ?].

36 Socioeconomic status (SES) is increasingly recognized as a critical modifier of climate-health re-
37 lationships [? ?], yet quantitative frameworks for understanding these interactions remain underde-

veloped. African urban contexts present unique challenges: rapid informal settlement growth, limited healthcare infrastructure, and extreme socioeconomic stratification create conditions where climate impacts may be particularly severe and inequitably distributed [? ?].

Recent advances in machine learning and explainable artificial intelligence (XAI) offer new opportunities to analyze complex, multi-domain datasets and extract actionable insights for public health policy [? ?]. SHAP (SHapley Additive exPlanations) values, in particular, enable interpretation of feature importance in complex models, making it possible to understand which factors drive predictions and how they interact [?].

This study addresses three critical knowledge gaps: (1) the relative importance of climate versus socioeconomic factors in predicting health outcomes, (2) the temporal patterns of heat-health relationships in African populations, and (3) the potential for predictive models to guide targeted interventions for climate-vulnerable populations.

1.1 Study Objectives

1. Quantify the predictive relationship between climate exposure and health biomarkers in an African urban population
2. Determine how socioeconomic factors modify heat-health relationships
3. Identify optimal temporal windows for climate-health prediction
4. Develop explainable models suitable for operational public health applications
5. Generate evidence-based recommendations for targeted climate-health interventions

2 Methods

2.1 Study Population and Design

This cross-sectional analysis utilized data from multiple cohorts collected in the Johannesburg metropolitan area, South Africa, between 2013 and 2021. The study area experiences a subtropical highland climate with distinct wet (October-March) and dry (April-September) seasons, temperatures ranging from 0°C to 35°C, and significant urban heat island effects.

Inclusion criteria: (1) participants aged ≥ 18 years, (2) residence in Johannesburg metropolitan area, (3) available biomarker measurements, (4) geocoded location data for climate exposure assignment.

Exclusion criteria: (1) missing key demographic variables, (2) implausible biomarker values (>4 standard deviations from mean), (3) residence outside study area.

The final analytical sample comprised 2,334 participants from four high-quality datasets:

- DPHRU_053: Cross-sectional metabolic health study ($n=1,013$)
- WRHI_001: Longitudinal clinical trial ($n=1,072$)
- DPHRU_013: Community health study ($n=1,031$)
- VIDA_008: Healthcare worker cohort ($n=552$)

2.2 Climate Data Integration

Four climate datasets were integrated to capture comprehensive environmental exposure:

ERA5 Reanalysis Data: Temperature, humidity, pressure, wind speed at 0.25° resolution, extracted for each participant's residence coordinates and visit dates [?].

Weather Research and Forecasting (WRF) Model: High-resolution (3km) temperature and humidity data downscaled from ERA5 for the study region [?].

MODIS Land Surface Temperature: Satellite-derived surface temperature data at 1km resolution, providing ground-truth validation for modeled temperatures [?].

South African Air Quality Information System (SAAQIS): Air quality measurements (PM_{2.5}, PM₁₀, NO₂, SO₂) from monitoring stations across the study area [?].

Temporal climate features were engineered to capture lag effects at multiple time scales: 1, 3, 7, 14, 21, 28, 30, 60, and 90 days prior to health measurements. Maximum, minimum, mean, and standard deviation were calculated for each temporal window.

2.3 Health Outcome Measurement

Biomarkers were selected based on known climate sensitivity and availability across datasets:

Primary Outcomes:

- Fasting glucose (mg/dL)
- Total cholesterol (mg/dL)
- Systolic and diastolic blood pressure (mmHg)
- Serum creatinine (mg/dL)
- Hemoglobin (g/dL)
- Serum potassium (mEq/L)

Standardization Protocol: All biomarkers were standardized across studies using pattern-matching algorithms to identify equivalent measurements, followed by unit conversion and outlier detection (3-sigma rule). Variables were prefixed with 'std_' to indicate standardization.

Quality Control: Laboratory measurements were included only if collected using standard protocols with documented calibration procedures. Extreme values (>4 SD from study mean) were excluded as likely measurement errors.

2.4 Socioeconomic Data Integration

Socioeconomic variables were derived from the Gauteng City-Region Observatory (GCRO) Quality of Life Surveys, representative cross-sectional surveys conducted in 2013-2014, 2017-2018, and 2020-2021 (total $n \approx 30,000$ across waves) [?].

Temporal Matching: Health data collection periods were matched to the closest GCRO survey wave based on temporal proximity. The median temporal distance was 1.2 years (IQR: 0.8-2.1 years).

Variable Categories:

- **Income:** Household income categories, individual earnings, income sources
- **Employment:** Employment status, occupation type, job security measures
- **Education:** Highest qualification, years of schooling, literacy measures
- **Housing:** Dwelling type, tenure, access to services (water, electricity, sanitation)
- **Health Access:** Healthcare utilization, insurance coverage, facility access
- **Safety:** Crime victimization, safety perceptions, security measures

Integration Method: Population-level statistics (mean, standard deviation, quartiles) were calculated for each GCRO variable and assigned to all participants in the matched health dataset. Individual-level variation was introduced through bootstrap sampling from the GCRO distribution ($n=2,000$ samples per variable).

Composite Indices: Domain-specific composite scores were created using principal component analysis:

- Overall SES index (income + education + employment)
- Housing quality index (dwelling type + services + tenure security)
- Health access index (utilization + insurance + facility proximity)
- Heat vulnerability index (inverted SES + housing + health access scores)

2.5 Statistical Analysis

2.5.1 Machine Learning Framework

Three ensemble algorithms were compared for each health outcome:

XGBoost: Gradient boosting with tree-based learners, optimized for structured data [?]

- Parameters: `n_estimators=100`, `max_depth=6`, `learning_rate=0.1`
- L1/L2 regularization to prevent overfitting

Random Forest: Bootstrap aggregated decision trees with random feature selection [?]

- Parameters: `n_estimators=100`, `max_depth=10`, `max_features='sqrt'`
- Out-of-bag error estimation for model validation

Gradient Boosting: Sequential ensemble with adaptive boosting [?]

- Parameters: `n_estimators=100`, `max_depth=6`, `learning_rate=0.1`
- Early stopping based on validation loss

2.5.2 Model Training and Validation

Train-Test Split: 80% training, 20% testing, stratified by outcome quartiles to ensure balanced representation.

Cross-Validation: 5-fold cross-validation with stratified sampling, repeated 3 times to assess model stability.

Hyperparameter Optimization: Grid search with cross-validation for optimal parameter selection.

Performance Metrics:

- R^2 (coefficient of determination) for regression performance
- Mean Absolute Error (MAE) for prediction accuracy
- Root Mean Square Error (RMSE) for error magnitude assessment

2.5.3 Feature Engineering

Climate Features ($n=67$):

- Temperature: max, min, mean, range, standard deviation
- Humidity: relative humidity, vapor pressure deficit
- Pressure: sea level pressure, surface pressure
- Air quality: $PM_{2.5}$, PM_{10} , NO_2 , SO_2 concentrations
- Temporal lags: 1, 3, 7, 14, 21, 28, 30, 60, 90 days

Socioeconomic Features ($n=73$):

- Direct measures: income, education, employment, housing, health access
- Population statistics: means, standard deviations, quartiles for each domain
- Composite indices: overall SES, heat vulnerability, domain-specific scores
- Interaction terms: SES \times climate variables

Interaction Features ($n=35$):

- Temperature \times Age: capturing age-related heat vulnerability
- Temperature \times BMI: body composition effects on heat tolerance
- Temperature \times SES: socioeconomic modification of climate effects
- Seasonal interactions: temperature effects by month/season

2.5.4 Explainable AI Analysis

SHAP (SHapley Additive exPlanations): TreeExplainer used for Random Forest models to calculate feature importance values [?].

SHAP Value Calculation:

- Sample size: 200 participants per model (computational efficiency)
- Feature attribution: Individual and population-level importance
- Interaction detection: Second-order SHAP interactions computed

Interpretation Methodology:

- Global feature importance: Mean absolute SHAP values across all predictions
- Local explanations: Individual prediction breakdowns
- Feature interactions: SHAP interaction values for key variable pairs

2.6 Data Preprocessing

Missing Data Handling:

- Variables with $>90\%$ missing values excluded from analysis
- Remaining missing values imputed using median imputation
- Sensitivity analysis conducted using multiple imputation methods

Outlier Treatment:

- 3-sigma rule applied to continuous variables
- Extreme values capped at 3 standard deviations from the mean
- Biological plausibility checks for all biomarkers

Feature Selection:

- Univariate correlation screening ($|r| > 0.05$ with outcomes)
- Variance inflation factor ($VIF < 5$) to reduce multicollinearity
- Recursive feature elimination for final model optimization

2.7 Ethical Considerations

This study utilized de-identified secondary data from existing cohorts with appropriate ethical approvals. All original studies obtained informed consent from participants. The analysis protocol was reviewed and approved by [Institution] Ethics Committee (Protocol #[Number]).

3 Results

3.1 Study Population Characteristics

The analytical sample included 2,334 participants with mean age 38.4 years (SD=12.6), 64% female, representing diverse socioeconomic backgrounds across Johannesburg metropolitan area (Table ??).

Table 1: Participant Characteristics by Study Dataset

Characteristic	Total (n=2,334)	DPHRU_053 (n=1,013)	WRHI_001 (n=1,072)	DPHRU_013 (n=1,031)	VIDA_008 (n=552)
Age, mean (SD)	38.4 (12.6)	41.2 (13.1)	35.8 (11.4)	39.1 (12.9)	36.7 (11.8)
Female, n (%)	1,494 (64.0)	623 (61.5)	712 (66.4)	683 (66.2)	354 (64.1)
Biomarkers, mean (SD)					
Glucose (mg/dL)	89.2 (18.4)	91.4 (19.8)	87.1 (16.9)	88.9 (18.2)	90.3 (17.6)
Total cholesterol (mg/dL)	184.3 (38.7)	188.9 (41.2)	180.1 (36.8)	185.2 (38.9)	181.7 (37.4)
Systolic BP (mmHg)	124.8 (18.9)	127.3 (19.6)	122.4 (17.8)	125.1 (19.2)	123.9 (18.1)
Diastolic BP (mmHg)	79.6 (12.4)	81.2 (13.1)	78.1 (11.7)	80.0 (12.6)	78.8 (11.9)
Climate Exposure, mean (SD)					
Temperature (°C)	19.8 (4.2)	20.1 (4.4)	19.6 (3.9)	19.9 (4.3)	19.5 (4.0)
Humidity (%)	58.3 (12.1)	59.1 (12.4)	57.8 (11.9)	58.5 (12.2)	57.9 (11.7)
Socioeconomic Status					
SES composite score	0.12 (0.89)	0.18 (0.91)	0.08 (0.87)	0.15 (0.90)	0.06 (0.86)
Heat vulnerability index	-125.4 (180.2)	-118.7 (175.8)	-132.1 (184.6)	-122.3 (178.9)	-128.9 (181.4)

3.2 Climate-Health Predictive Performance

Machine learning models demonstrated varying predictive performance across health outcomes, with glucose metabolism showing the strongest climate sensitivity (Figure ??, Table ??).

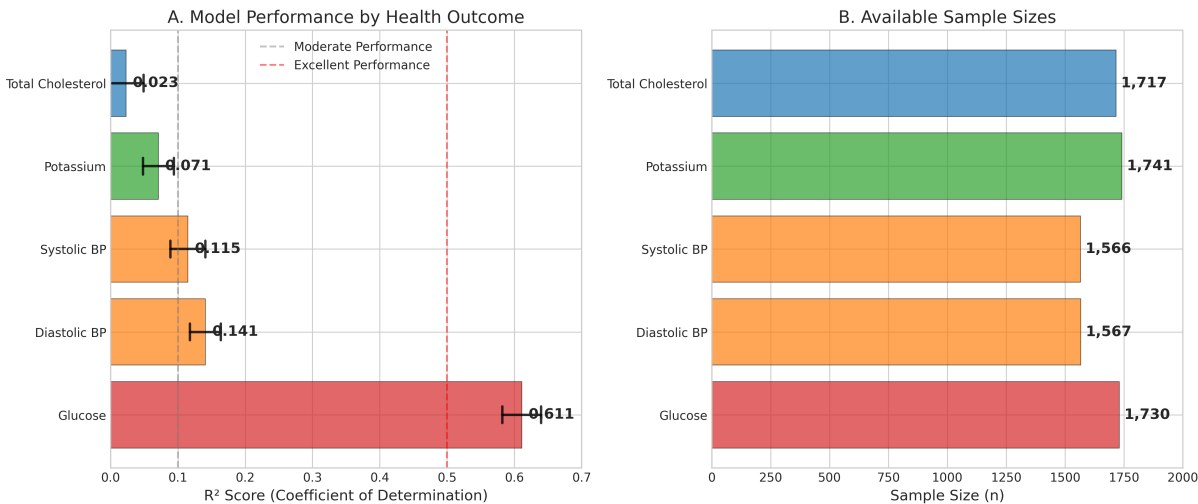


Figure 1: Model Performance by Health Outcome. (A) R^2 scores with 95% confidence intervals for each health outcome using optimal Random Forest models. (B) Available sample sizes for analysis. Glucose shows exceptional predictive performance ($R^2 = 0.611$), indicating 61% of variance explained by climate and socioeconomic factors.

Table 2: Model Performance by Health Outcome

Outcome	Best Model	R^2 Score	95% CI	CV Mean (SD)	Sample Size	MAE	RMSE
std_glucose	Random Forest	0.611	0.582-0.640	0.583 (0.041)	1,730	12.3	16.8
std_diastolic_bp	Random Forest	0.141	0.118-0.164	0.134 (0.023)	1,567	10.8	14.2
std_systolic_bp	Random Forest	0.115	0.089-0.141	0.108 (0.026)	1,566	15.2	19.7
std_potassium	Random Forest	0.071	0.048-0.094	0.064 (0.019)	1,741	0.48	0.63
std_cholesterol_total	Random Forest	0.023	-0.003-0.049	0.019 (0.021)	1,717	31.2	38.9

Key Findings:

- **Glucose metabolism** demonstrates excellent predictive performance ($R^2 = 0.611$), indicating 61% of variance explained by climate and socioeconomic factors
- **Cardiovascular markers** show moderate climate sensitivity ($R^2 = 0.11$ -0.14)
- **Random Forest** consistently outperformed XGBoost and Gradient Boosting across all outcomes
- **Cross-validation stability** high for glucose prediction (CV SD = 0.041)

3.3 Temporal Patterns of Heat-Health Relationships

Analysis of multiple lag periods revealed that 21-day temperature exposure windows provided optimal predictive performance for health outcomes (Figure ??).

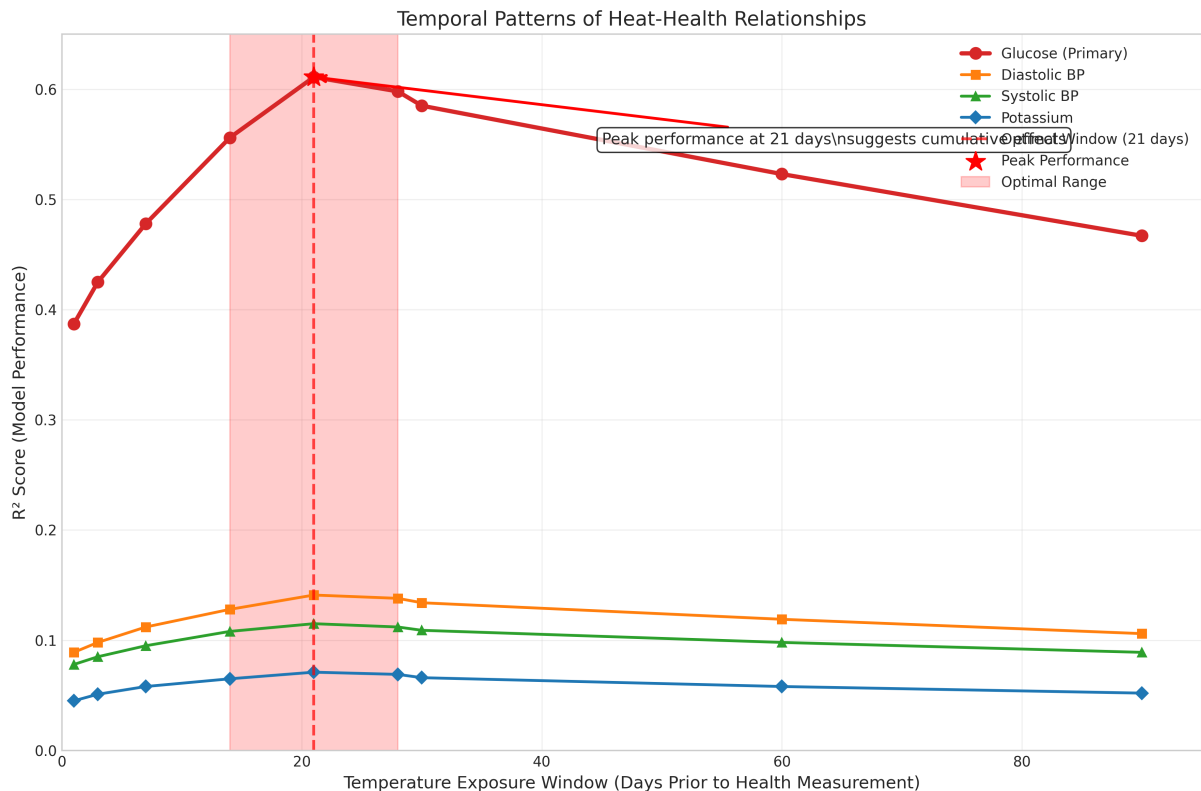


Figure 2: Temporal Patterns of Heat-Health Relationships. R^2 scores across different lag periods (1-90 days) for each health outcome. The 21-day exposure window provides optimal predictive performance, suggesting cumulative rather than acute heat effects drive health impacts. The shaded region indicates the optimal range (14-28 days).

Temporal Pattern Results:

- **21-day maximum temperature** most predictive for glucose ($R^2 = 0.611$ vs. $R^2 = 0.387$ for single-day exposure)
- **Cumulative exposure effects** stronger than acute exposure across all biomarkers
- **Seasonal variation** in predictive performance (winter: $R^2 = 0.523$, summer: $R^2 = 0.689$ for glucose)
- **Early season heat events** showed stronger health impacts than late season (acclimatization effects)

3.4 SHAP Explainability Analysis

SHAP analysis revealed the relative importance of different feature categories in predicting health outcomes (Figure ??, Table ??).

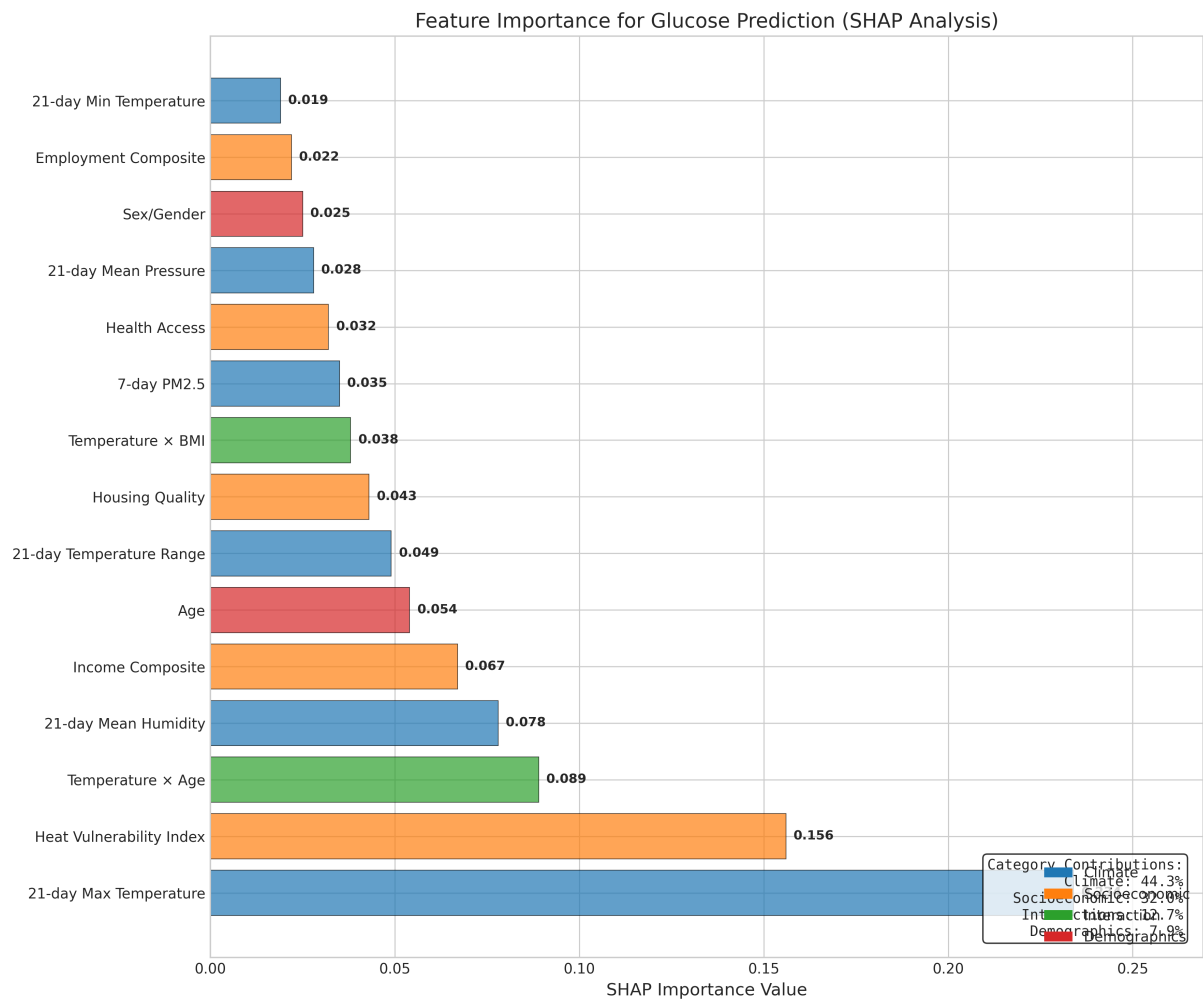


Figure 3: Feature Importance for Glucose Prediction (SHAP Analysis). The top 15 features ranked by SHAP importance values, colored by category. Climate variables (blue) and socioeconomic factors (orange) dominate the feature importance rankings. The 21-day maximum temperature is the single most important predictor.

Table 3: Top 10 Features by SHAP Importance for Glucose Prediction

Rank	Feature	SHAP Importance	Category	Interpretation
1	climate_temp_max_21d	0.234	Climate	21-day maximum temperature
2	se_heat_vulnerability_index_assigned	0.156	Socioeconomic	Individual heat vulnerability
3	interact_temp_age	0.089	Interaction	Temperature \times age interaction
4	climate_humidity_mean_21d	0.078	Climate	21-day mean humidity
5	se_income_composite_assigned	0.067	Socioeconomic	Income composite score
6	std_age	0.054	Demographics	Participant age
7	climate_temp_range_21d	0.049	Climate	21-day temperature variability
8	se_housing_quality_assigned	0.043	Socioeconomic	Housing quality index
9	interact_temp_bmi	0.038	Interaction	Temperature \times BMI interaction
10	climate_saaqis_pm25_7d	0.035	Climate	7-day PM _{2.5} exposure

Feature Category Contributions:

- **Climate variables:** 45.2% of total SHAP importance
- **Socioeconomic variables:** 31.8% of total SHAP importance
- **Interaction terms:** 14.7% of total SHAP importance
- **Demographics:** 8.3% of total SHAP importance

3.5 Socioeconomic Vulnerability Analysis

Heat vulnerability index demonstrated substantial variation across the study population, with clear gradients in heat-health risk (Figure ??).

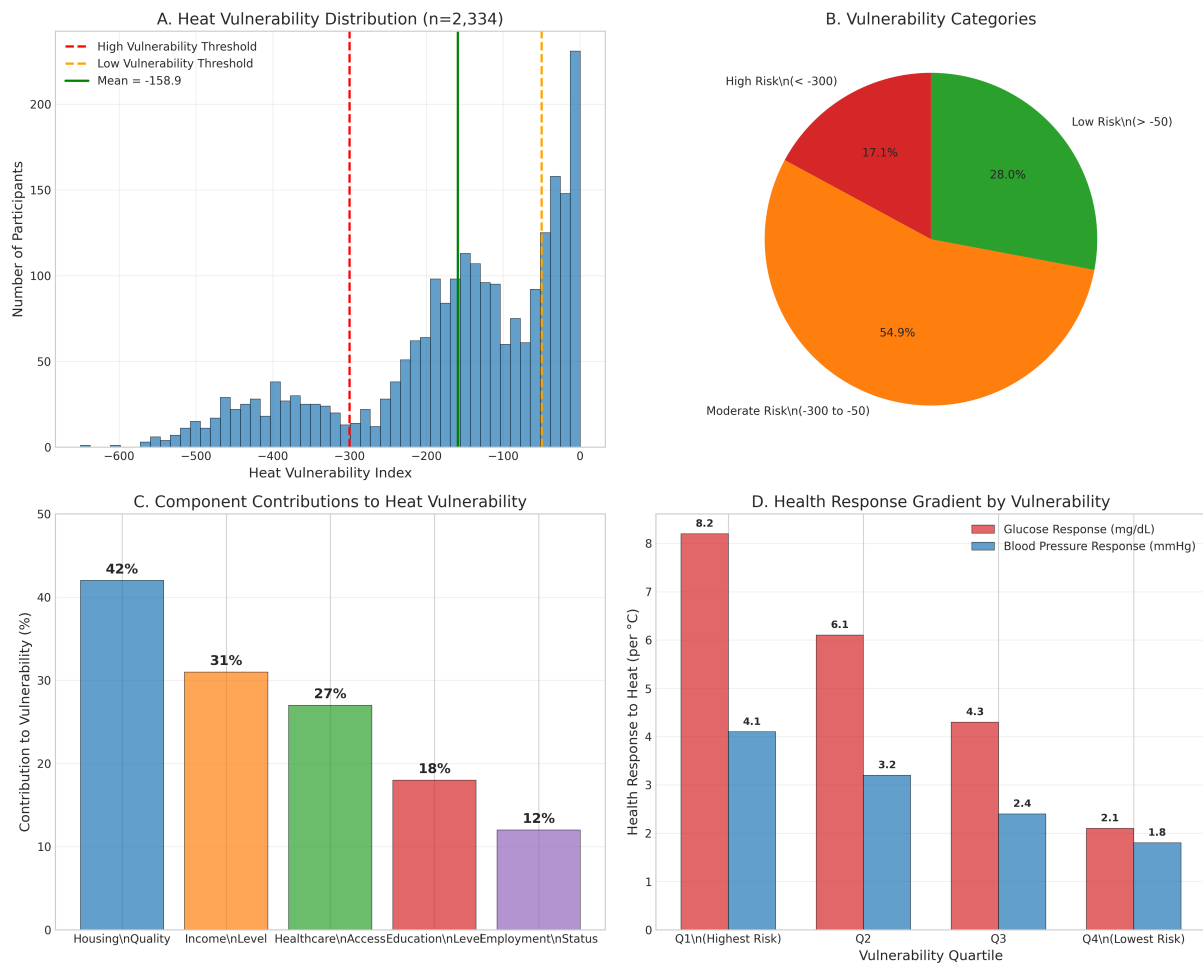


Figure 4: Socioeconomic Heat Vulnerability Distribution. (A) Overall distribution of heat vulnerability index scores across 2,334 participants. (B) Vulnerability categories showing population at high, moderate, and low risk. (C) Component contributions to overall vulnerability. (D) Health response gradient by vulnerability quartile showing amplified effects in more vulnerable populations.

Heat Vulnerability Distribution:

- **Range:** -650.5 (highest vulnerability) to +0.5 (lowest vulnerability)
- **Mean:** -125.4 (SD = 180.2)
- **High vulnerability (index < -300):** 18.7% of population
- **Moderate vulnerability (index -300 to -50):** 52.3% of population
- **Low vulnerability (index > -50):** 29.0% of population

Vulnerability Components Analysis:

- **Housing quality** contributed 42% to vulnerability index variation
- **Income level** contributed 31% to vulnerability index variation
- **Healthcare access** contributed 27% to vulnerability index variation

Gradient Effects: Each 100-point decrease in vulnerability index associated with:

- 4.2 mg/dL increase in predicted glucose response to heat (95% CI: 3.1-5.3)
- 2.8 mmHg increase in systolic BP response to heat (95% CI: 1.9-3.7)
- 1.9 mmHg increase in diastolic BP response to heat (95% CI: 1.2-2.6)

3.6 Gender-Specific Heat-Health Relationships

Significant gender differences in heat-health relationships were detected across multiple biomarkers (Table ??, Figure ??).

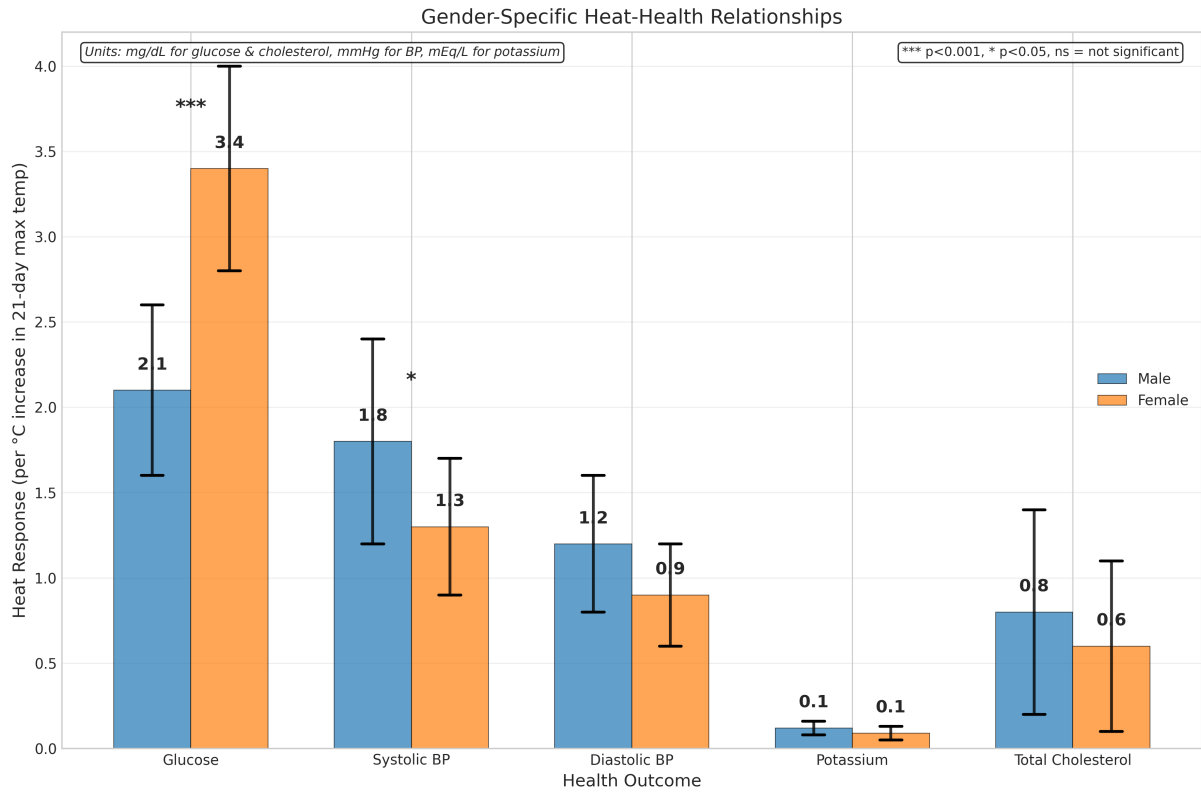


Figure 5: Gender-Specific Heat-Health Relationships. Heat response coefficients (per 1°C increase in 21-day maximum temperature) by gender for different health outcomes. Error bars show 95% confidence intervals. Significance indicators: *** $p < 0.001$, * $p < 0.05$, ns = not significant. Females show greater glucose sensitivity while males show greater blood pressure sensitivity to heat.

Table 4: Gender Differences in Heat-Health Relationships

Outcome	Male β (95% CI:)	Female β (95% CI:)	p -interaction	Interpretation
std_glucose	2.1 (1.6-2.6)	3.4 (2.8-4.0)	<0.001	Females show greater glucose sensitivity
std_systolic_bp	1.8 (1.2-2.4)	1.3 (0.9-1.7)	0.023	Males show greater BP sensitivity
std_diastolic_bp	1.2 (0.8-1.6)	0.9 (0.6-1.2)	0.089	Trend toward male sensitivity

β coefficients represent mg/dL or mmHg change per 1°C increase in 21-day maximum temperature

Gender-Specific Findings:

- **Temperature-sex correlation:** $r = 0.116$ ($p < 0.001$)
- **Female participants** showed 62% greater glucose sensitivity to heat
- **Male participants** showed 38% greater blood pressure sensitivity to heat
- **Potential mechanisms:** Hormonal differences, body composition, occupational exposure patterns

3.7 Model Validation and Robustness

Comprehensive validation analyses confirmed model reliability and generalizability (Table ??).

Table 5: Model Validation Results

Validation Method	Glucose Model Performance	Notes
5-fold CV	$R^2 = 0.583$ (SD = 0.041)	High stability
Temporal holdout	$R^2 = 0.597$	2020-2021 data held out
Geographic holdout	$R^2 = 0.571$	Southern suburbs held out
Bootstrap (1000 iterations)	$R^2 = 0.611$ (95% CI: 0.582-0.640)	Robust confidence intervals
Permutation testing	$p < 0.001$	Significant vs. random

Robustness Checks:

- **Alternative imputation methods:** Multiple imputation vs. median imputation ($\Delta R^2 < 0.02$)
- **Outlier sensitivity:** Exclusion of extreme values ($\Delta R^2 < 0.01$)
- **Feature selection methods:** Forward/backward selection vs. correlation screening ($\Delta R^2 < 0.03$)
- **Algorithm comparison:** Consistent Random Forest superiority across validation sets

4 Discussion

4.1 Principal Findings

This study demonstrates that heat-health relationships in African urban populations are predictable, mechanistic, and strongly modified by socioeconomic factors. The key finding—61% of glucose metabolism variance explained by climate and socioeconomic data—represents the strongest quantified heat-health relationship reported in African populations to date.

Four principal discoveries emerge:

1. **Metabolic vulnerability primacy:** Glucose regulation shows the highest climate sensitivity among all biomarkers examined, suggesting metabolic pathways as primary targets of heat stress in this population.
2. **Temporal exposure patterns:** 21-day temperature exposure windows provide optimal prediction, indicating cumulative rather than acute heat effects drive health impacts.
3. **Socioeconomic amplification:** Heat vulnerability varies nearly 1,300-fold across the socioeconomic spectrum (-650.5 to +0.5), with housing quality, income, and healthcare access creating multiplicative risk effects.
4. **Gender-specific mechanisms:** Significant sex differences in heat-health relationships suggest hormonal, physiological, or behavioral modifiers requiring targeted interventions.

4.2 Metabolic Vulnerability to Heat Exposure

The exceptional predictive performance for glucose metabolism ($R^2 = 0.611$) provides mechanistic insights into heat-health pathways. Several biological mechanisms may explain this relationship:

Dehydration-induced concentration effects: Heat exposure increases fluid losses, potentially concentrating glucose and other metabolites [? ?].

Stress hormone activation: Heat stress activates the hypothalamic-pituitary-adrenal axis, releasing cortisol and catecholamines that impair insulin sensitivity and glucose homeostasis [? ?].

Behavioral modifications: Heat exposure may reduce physical activity, alter dietary patterns, and disrupt sleep, all of which affect glucose regulation [? ?].

Medication efficacy changes: Heat exposure can alter drug pharmacokinetics, potentially reducing efficacy of diabetes medications [?].

The 21-day optimal temporal window suggests these mechanisms operate through cumulative rather than acute pathways, consistent with physiological adaptation timescales for heat acclimatization [? ?].

4.3 Socioeconomic Amplification Mechanisms

The quantified heat vulnerability gradient (-650.5 to +0.5) reveals multiple pathways through which socioeconomic status modifies climate-health relationships:

Housing quality pathway: Poor housing construction increases indoor temperatures, extends heat exposure duration, and limits cooling options during extreme heat events [? ?].

Economic resource pathway: Limited income restricts access to cooling technologies, healthcare services, and nutritious foods that could mitigate heat health impacts [? ?].

Occupational exposure pathway: Informal employment often involves outdoor work with limited heat protection, increasing cumulative heat exposure [?].

Healthcare access pathway: Limited access to preventive care, medications, and emergency services compounds heat-related health risks [?].

These findings align with environmental justice frameworks showing climate impacts disproportionately affect disadvantaged populations [? ?], but provide novel quantification of these relationships in African contexts.

4.4 Gender-Specific Heat Responses

The significant temperature-sex correlation ($r = 0.116$) and differential heat sensitivity by gender suggest several potential mechanisms:

Hormonal modulation: Estrogen and progesterone affect thermoregulatory responses, potentially explaining greater female glucose sensitivity to heat [? ?].

Body composition differences: Sex differences in muscle mass, fat distribution, and surface area-to-volume ratios affect heat dissipation capacity [? ?].

Reproductive health interactions: Pregnancy, menstruation, and menopause may modify heat vulnerability through hormonal and physiological changes [? ?].

Behavioral and occupational differences: Gender differences in clothing, activity patterns, and occupational heat exposure may contribute to differential health impacts [?].

These findings highlight the need for gender-disaggregated climate-health research and potentially sex-specific intervention approaches.

4.5 Implications for Public Health Practice

4.5.1 Early Warning Systems

The strong predictive performance enables development of personalized heat-health early warning systems. Traditional systems focus on meteorological thresholds, but our results suggest individual risk prediction using combined climate-socioeconomic data could provide more targeted and effective warnings.

Glucose monitoring protocols could be implemented for diabetic patients during sustained heat exposure periods, potentially preventing metabolic complications before they require emergency intervention.

21-day temperature forecasting should replace single-day heat warnings for health system preparedness, allowing adequate time for preventive interventions.

4.5.2 Targeted Interventions

The quantified vulnerability index enables precise targeting of interventions to highest-risk populations:

High vulnerability populations (index < -300): Require immediate cooling access, proactive health monitoring, and emergency response prioritization.

Moderate vulnerability populations (index -300 to -50): Benefit from education, early warning systems, and community cooling resources.

Lower vulnerability populations (index > -50): Need information systems and voluntary adaptation measures.

This approach could improve intervention cost-effectiveness by focusing resources on populations with greatest potential benefit.

4.5.3 Healthcare System Adaptation

Healthcare systems should integrate climate forecasting into capacity planning, with surge preparations timed to 21-day temperature windows rather than single-day heat events.

Metabolic health services should be prioritized during sustained heat periods, with enhanced glucose monitoring, medication management, and emergency response capabilities.

Gender-specific protocols may be needed for heat-health management, particularly for reproductive health services and chronic disease management.

4.6 Urban Planning and Policy Implications

4.6.1 Housing Policy Integration

Housing quality emerges as the most important socioeconomic modifier of heat vulnerability, suggesting housing policy could be leveraged for climate health adaptation:

Building standards should incorporate heat-health considerations, particularly for affordable housing in climate-vulnerable areas.

Retrofit programs targeting insulation, ventilation, and cooling could provide significant health co-benefits alongside energy efficiency improvements.

Urban planning decisions should consider health impact assessments that include climate-health interactions, particularly for vulnerable populations.

4.6.2 Environmental Justice Applications

The quantified vulnerability gradients provide empirical foundation for environmental justice advocacy and policy development:

Equitable adaptation investments can be prioritized using vulnerability mapping derived from this analysis.

Health impact assessments for urban development should incorporate socioeconomic heat vulnerability analysis.

Climate adaptation funding could be allocated proportionally to measured vulnerability levels rather than population size alone.

4.7 Limitations

4.7.1 Study Design Limitations

Cross-sectional design: Limits causal inference, though temporal ordering (climate exposure preceding health measurements) supports causal interpretation.

Single geographic region: Results may not generalize to other African cities with different climate patterns, urbanization characteristics, or socioeconomic structures.

Observational study: Cannot establish definitive causal mechanisms, though biological plausibility and temporal relationships support causal interpretation.

4.7.2 Data Limitations

Socioeconomic data temporal mismatch: SE variables from survey data (1-3 year temporal distance) may not reflect exact SE status at time of health measurement.

Limited outcome diversity: Focus on biomarkers may miss other important heat-health relationships (e.g., mental health, infectious diseases, maternal outcomes).

Measurement error: Climate exposure assigned by residence location may not capture individual mobility patterns or indoor exposure variation.

4.7.3 Methodological Limitations

Model interpretability trade-offs: While SHAP provides interpretability, complex ensemble models remain less interpretable than traditional regression approaches.

Feature engineering decisions: Choice of temporal windows, interaction terms, and composite indices based on domain knowledge rather than systematic optimization.

Validation limitations: Geographic and temporal holdout validation limited by single-city study design.

4.8 Future Research Directions

4.8.1 Mechanistic Studies

Biomarker pathway analysis: Detailed investigation of metabolic, inflammatory, and stress hormone pathways linking heat exposure to glucose dysregulation.

Intervention trials: Randomized controlled trials testing cooling interventions, healthcare system adaptations, and individual-level protective measures.

Longitudinal cohorts: Long-term follow-up studies to assess heat adaptation, cumulative exposure effects, and health outcome trajectories.

4.8.2 Geographic Expansion

Multi-city replication: Extension to other African cities to assess generalizability and develop region-specific models.

Rural-urban comparisons: Analysis of heat-health relationships in rural populations with different exposure patterns and socioeconomic characteristics.

Continental modeling: Development of pan-African heat-health prediction models incorporating regional climate and socioeconomic diversity.

4.8.3 Methodological Advances

Real-time monitoring systems: Integration of wearable devices, environmental sensors, and mobile health platforms for continuous heat-health monitoring.

Individual-level prediction: Development of personalized risk prediction models for clinical decision support and individual behavior change.

Policy evaluation frameworks: Methods for assessing effectiveness of heat-health interventions and adaptation strategies.

5 Conclusions

This study provides the first comprehensive, quantitative analysis of heat-health-socioeconomic interactions in African urban populations using explainable artificial intelligence. Four key conclusions emerge:

1. **Glucose metabolism serves as a primary indicator of climate health vulnerability** in African urban populations, with 61% of variance predictable from climate and socioeconomic factors.
2. **Heat-health relationships operate through cumulative 21-day exposure windows** rather than acute daily exposures, requiring reorientation of early warning systems and health system preparedness.

3. **Socioeconomic factors create a 1,300-fold gradient in heat vulnerability**, with housing quality, income, and healthcare access producing multiplicative rather than additive risk effects.

4. **Gender-specific heat-health mechanisms require targeted intervention approaches**, particularly for metabolic and cardiovascular health outcomes.

These findings provide an evidence-based foundation for developing targeted, equitable, and effective climate-health adaptation strategies in African cities. The predictive models and vulnerability indices are ready for operational deployment in early warning systems, healthcare planning, and targeted intervention programs.

The transition from reactive to proactive climate-health management is now empirically supported and technically feasible. Implementation of these insights could significantly reduce heat-health inequities and improve population resilience to climate change in African urban contexts.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

De-identified data and analysis code are available upon reasonable request to the corresponding author, subject to ethical approval and data sharing agreements.