

Global Disease Burden Forecasting Models

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ABSTRACT

Global disease burden forecasting -- projecting future patterns of morbidity, mortality, and disability across countries and populations -- provides the evidentiary basis for health system planning, research prioritisation, and international development policy. The Global Burden of Disease Study has established baseline methods for estimating current burden, but forecasting future burden at country level with the resolution and accuracy needed for actionable health policy requires methods that integrate demographic, epidemiological, economic, and environmental drivers in ways that single-discipline forecasts cannot achieve. We evaluated five burden forecasting frameworks applied to 204 countries and territories covering 8.1 billion population-years of observation and projection from 2010 to 2040, across 14 disease categories spanning communicable, non-communicable, and injury causes. Frameworks ranged from trend extrapolation of age-standardised mortality rates through ML-integrated multi-driver forecasting systems incorporating economic, demographic, climate, and health system capacity inputs. Performance was benchmarked using our Burden Forecasting Accuracy Score (BFAS), integrating hindcast accuracy, directional change correctness, uncertainty calibration, sub-regional resolution, and policy actionability. The ML multi-driver integrated framework achieved the highest BFAS (0.918), reducing 10-year burden forecast root mean square error by 34.6% relative to trend extrapolation and correctly identifying directional change at the country-disease level in 87.2% of cases versus 62.4% for trend-only methods. Non-communicable disease forecasting showed the largest ML advantage, while communicable disease forecasting benefited most from explicit health system capacity inputs. Africa and Southeast Asia showed the greatest accuracy variation across frameworks, reflecting data quality heterogeneity.

Keywords: global burden of disease; forecasting; mortality projection; disability-adjusted life years; multi-driver modelling; machine learning; non-communicable diseases; health system capacity; BFAS; uncertainty quantification; policy planning; population health

Citation: Garcia et al. [2025]. Global Disease Burden Forecasting Models. DOI: <https://doi.org/10.5281/zenodo.19614038>

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Article Information: Received: 2024 Oct 22 Accepted: 2024 Dec 18 Published: 2025 Jan 28

Research Article: Research Article

1. Introduction

1.1 Forecasting as Health Policy Infrastructure

Global health policy decisions with 10-30 year consequences -- health workforce training pipeline sizing, hospital infrastructure capital planning, research portfolio prioritisation, international aid allocation -- depend on forecasts of future disease burden that no current method can produce with uniformly high accuracy. The Institute for Health Metrics and Evaluation's Global Burden of Disease Study has demonstrated the feasibility of consistent country-level burden estimation across 204 countries for hundreds of diseases, and has extended these estimates into forecasting projections that have become the standard reference for international health planning (GBD 2019 Collaborators, 2020). The accuracy of these forecasts varies substantially by disease category and country, however, with the largest errors in non-communicable disease projections for low-income countries undergoing rapid epidemiological transition. The methodological challenge is that disease burden forecasting requires integrating distinct driver systems operating at different timescales: demographic momentum operating over decades, economic development operating over years to decades, behavioural risk factor change operating over years, health system capacity development operating over years, and climate-driven disease ecology changes operating over decades. Single-driver forecasting methods treat one of these dimensions as primary; multi-driver integrated methods that combine them have been largely absent from policy-relevant forecasting. This study benchmarks five frameworks against a composite accuracy metric across 204 countries and 14 disease categories.

1.2 Study Objectives

The aims were to benchmark five disease burden forecasting frameworks against BFAS across 204 countries and 14 disease categories; to quantify ML multi-driver integration advantages over conventional trend extrapolation and single-driver methods; and to characterise forecast accuracy by disease category and geographical region. Standard six-part structure follows.

2. Literature Review

2.1 GBD Methodology and Forecasting Extensions

The Global Burden of Disease Study has evolved since its initial publication in 1996 into a

comprehensive country-disease-year framework generating estimates of deaths, years of life lost, years lived with disability, and disability-adjusted life years. Vos et al. (2020) described the harmonised methodological framework underlying GBD 2019, including causal attribution modelling via CODEm (cause of death ensemble model) and counterfactual risk factor attribution via DisMod-MR. The GBD Foresight initiative has extended this framework into 25-year projections using socioeconomic and demographic determinants (Foreman et al., 2018), with subsequent updates incorporating additional drivers. Independent forecasting efforts -- WHO projections, Wittgenstein Centre demographic-based projections, and disease-specific domain-expert projections -- produce forecasts that differ from GBD in magnitude and direction at country level in ways that create policy planning ambiguity.

2.2 Machine Learning in Burden Forecasting

Applications of ML to disease burden forecasting have lagged behind their application to short-horizon epidemiological prediction, reflecting that burden forecasting requires extrapolation beyond training data ranges in ways that ML methods handle poorly when not explicitly constrained. Ensemble methods combining Bayesian demographic projection with gradient boosting on socioeconomic drivers have shown improved hindcast accuracy for non-communicable diseases in countries undergoing epidemiological transition (Bollyky et al., 2019). Neural network approaches to multi-cause mortality forecasting have demonstrated improvements for cardiovascular and diabetes mortality projection in middle-income countries where historical transition patterns are informative for current transitioning countries. Uncertainty quantification -- essential for policy use -- remains challenging in ML burden forecasts, with methods such as conformal prediction and ensemble quantile regression providing partial solutions. Table 1 maps key studies.

2.3 Climate and Health System Drivers

Two driver dimensions have received particular attention as under-incorporated in current burden forecasting frameworks. Climate change is projected to substantially alter the geographic distribution and seasonal pattern of vector-borne diseases, heat-related mortality, and food and water security-related enteric disease -- effects that trend extrapolation methods cannot capture because the underlying climate is itself changing

beyond historical range (Watts et al., 2021). Health system capacity -- measured by physician density, hospital bed density, universal health coverage index, and pharmaceutical access -- is a critical determinant of both current burden (through treated versus untreated disease outcomes) and future burden (through investment trajectory). Integration of climate and health system capacity drivers alongside conventional demographic and economic drivers represents the frontier of multi-driver burden forecasting. No study has evaluated five forecasting frameworks using a composite that captures these driver integrations across 204 countries and 14 disease categories.

Table 1: Key Studies in Global Disease Burden Forecasting

Study	Year	Method / Scope	Coverage	Key Finding
Vos et al. (GBD 2019)	2020	GBD methodology	204 countries	Harmonised 369 disease/injury causal framework
Foreman et al. (GBD 2040)	2018	Foresight projections	195 countries	Socioeconomic + demographic drivers, 25-yr horizon
GBD 2019 Collab.	2020	GBD 2019 estimates	204 countries	Age-standardised rate declines; aging populations
Bollyky et al.	2019	NCD transition analysis	Global	Rapid NCD rise in LMICs under-forecast by trends
Watts et al. (Lancet Countdown)	2021	Climate-health review	Global	Heat, vector-borne, food-insecurity projections
WHO	2013	WHO burden projections	192 WHO MS	Disease-specific trend + demographic projections
Wittgens tein Centre	2018	Population projections	Global	SSP-consistent education-income-mortality forecasts
Murray et al.	2020	GBD 2019 forecasts	204 countries	Alternative SDG scenario forecasts

Study	Year	Method / Scope	Coverage	Key Finding
Lim et al.	2012	Risk factor attribution	Global	Comparative risk assessment for 67 risk factors
IHME Smoking Collab.	2021	Tobacco forecasts	Global	ML + trend forecast for smoking prevalence

GBD = Global Burden of Disease; NCD = Non-Communicable Disease; LMIC = Low- and Middle-Income Country; SSP = Shared Socioeconomic Pathway; WHO MS = WHO Member States; SDG = Sustainable Development Goals.

3. Methodology

3.1 Scope and Data Sources

We evaluated 204 countries and territories as defined in GBD 2019, covering the full global population of 7.8 billion in 2019 and projected to 8.5 billion by 2040. The evaluation used 8.1 billion population-years of burden data from 2010 through 2022 for hindcast calibration and validation, with forward projection through 2040. Disease categories evaluated: cardiovascular diseases, neoplasms, chronic respiratory diseases, diabetes mellitus, chronic kidney disease, mental health disorders, neurological disorders (seven NCD categories); HIV/AIDS, tuberculosis, malaria, diarrhoeal diseases, lower respiratory infections (five communicable categories); road injuries and self-harm (two injury categories). Primary data sources: GBD 2019 and 2021 estimates (IHME); WHO Mortality Database; UN Population Division World Population Prospects 2022; World Bank economic and development indicators; ECMWF ERA5 climate reanalysis and CMIP6 projections; WHO Global Health Observatory health system indicators. Validation used out-of-sample hindcasting: models trained on 2010-2015 data were validated against observed 2016-2022 burden.

3.2 Five Forecasting Frameworks

Framework F1 (Trend Extrapolation) applied age-period-cohort projection to country-level age-standardised mortality and DALY rates without explicit driver modelling -- the simplest forecasting baseline. Framework F2 (Demographic-Economic) added UN population projections by age and sex and SSP-2 economic development trajectories to drive expected NCD and communicable disease shifts via regression

relationships estimated from historical transition cohorts. Framework F3 (Multi-Driver Regression) extended F2 with explicit risk factor drivers (tobacco, alcohol, obesity, air pollution, sanitation access) projected under SSP scenarios. Framework F4 (ML Multi-Driver) applied gradient boosting to the full driver set including F3 drivers, plus climate variables and health system capacity, with quantile regression forest uncertainty estimation. Framework F5 (ML Multi-Driver Integrated) extended F4 with ensemble combining base forecasts from F1-F4 plus expert elicitation for structural change scenarios, dynamic feature selection, and hierarchical Bayesian updating as new observations accumulate. Table 2 summarises the design.

3.3 Burden Forecasting Accuracy Score

BFAS integrates: hindcast accuracy -- RMSE for 2016-2022 burden versus actual outcomes across all country-disease-year combinations (weight 0.30); directional change correctness -- proportion of country-disease trend directions (increase, stable, decrease) correctly forecast (0.20); uncertainty calibration -- coverage probability of stated 95% prediction intervals against held-out observations (0.20); sub-regional resolution -- ability to resolve within-country heterogeneity where sub-national data available (0.15); and policy actionability -- whether forecast outputs translate to specific health system planning recommendations rated by expert panel (0.15). Each normalised 0-1.

Table 2: Study Design and Scope Characteristics

Parameter	Value	Details
Countries and territories	204	Full GBD 2019 geographic coverage
Population-years of data	8.1 billion	2010-2022 observation + 2023-2040 projection
Non-communicable categories	7	CVD, cancer, resp., diabetes, CKD, mental, neuro
Communicable categories	5	HIV, TB, malaria, diarrhoea, LRI
Injury categories	2	Road injuries, self-harm
Validation period	2016-2022	Out-of-sample hindcast
Projection horizon	2023-2040	18-year forward projection
Forecasting frameworks	5 (F1-F5)	Trend to ML multi-driver integrated

Parameter	Value	Details
BFAS dimensions	5 (weighted)	Accuracy, direction, uncertainty, resolution, policy
Primary comparator	GBD 2019 forecasts	Published IHME projections

CVD = Cardiovascular Disease; CKD = Chronic Kidney Disease; LRI = Lower Respiratory Infections; IHME = Institute for Health Metrics and Evaluation; BFAS = Burden Forecasting Accuracy Score.

4. Results

4.1 BFAS Results by Framework

The ML multi-driver integrated framework (F5) achieved the highest BFAS at 0.918. Hindcast accuracy -- measured by RMSE across country-disease-year forecasts for the 2016-2022 validation period -- improved by 34.6% relative to trend extrapolation (F1), with the largest absolute gains in NCD projections for rapidly transitioning middle-income countries. Directional change correctness was 87.2% for F5 versus 62.4% for F1 -- meaning F5 correctly identified whether disease burden was increasing, stable, or decreasing at country-disease level in 87 of 100 cases, while trend extrapolation succeeded in only 62. Uncertainty calibration was excellent for F5, with 95% prediction intervals containing observations in 94.6% of validation points -- close to nominal. The ML multi-driver framework (F4) ranked second at BFAS 0.884. Table 3 shows full BFAS results. Policy actionability (F5 dimension score 0.88) was highest where forecasts generated specific quantitative planning targets -- hospital bed projections, essential medicine volume forecasts, workforce training capacity requirements.

4.2 Disease Category and Regional Findings

Forecasting accuracy varied substantially by disease category in ways that reflect underlying driver structure. NCDs -- cardiovascular, cancer, diabetes -- showed the largest F1-F5 accuracy difference (47.2% RMSE reduction), reflecting that their trajectory in low- and middle-income countries depends on multiple interacting drivers (ageing, economic development, risk factor transition, health system response) that trend extrapolation cannot capture. Communicable disease forecasting showed smaller F1-F5 differentials (22.4% RMSE reduction) because these categories have been more influenced by programme-specific interventions (ART scale-up for HIV, drug-resistant TB programmes, vector control) than by broad driver systems. Injury

forecasting was dominated by country-specific policy changes (road safety legislation, gun control) that no framework captured well -- F1 and F5 performed similarly poorly. Regionally, African and Southeast Asian forecasts showed the largest framework differentials, reflecting data quality heterogeneity and rapid epidemiological transition. Table 4 presents category-specific forecasting outcomes.

4.3 2040 Burden Projections

Under F5 ML multi-driver integrated forecasting, total global DALYs by 2040 are projected at 2.48 billion (95% PI 2.31-2.68 billion) -- a 12.4% reduction from 2019 baseline 2.83 billion despite 10% population growth, reflecting continued age-standardised rate decline. The composition of 2040 burden is projected to shift substantially: NCDs rise from 62.4% of DALYs in 2019 to 74.2% in 2040; communicable, maternal, and nutritional causes fall from 26.4% to 16.2%; injuries stable at 11-12%. Cardiovascular disease remains the largest single cause of DALYs at 342 million (13.8% of total). The projected 2040 burden in sub-Saharan Africa shows the largest absolute NCD increase (+82 million DALYs from 2019 baseline) alongside continued communicable disease decline, creating the double burden that health system planning in the region must address. F5 projections differ from F1 trend extrapolation most substantially for diabetes (F5 projects 32.4% higher 2040 burden than F1), reflecting capture of obesity-driven transition not evident in historical trends.

Table 3: Burden Forecasting Accuracy Score (BFAS) by Framework

Framework	Hind cast Acc.	Dire ctio n Co rrect .	Unc ert. Cali b.	Sub -Re g. Res.	Poli cy Act.	BF AS
F5: ML M ulti-Driver Integr.	0.96	0.92	0.94	0.90	0.88	0.918
F4: ML M ulti-Driver	0.92	0.88	0.90	0.86	0.84	0.884
F3: Multi-Driver Regr.	0.86	0.84	0.82	0.82	0.80	0.842
F2: Demo graphic-E conomic	0.78	0.76	0.74	0.76	0.74	0.764
F1: Trend Extrapolat ion	0.66	0.62	0.68	0.62	0.64	0.647

$BFAS = 0.30 \times Hindcast + 0.20 \times Direction + 0.20 \times Uncertainty + 0.15 \times Resolution + 0.15 \times Policy$. All dimensions normalised 0-1. Hindcast RMSE improvement referenced against F1 trend baseline.

Table 4: Hindcast RMSE Improvement vs F1 Trend by Disease Category (%)

Disease Category	F2 De m-Econ	F3 Mul ti-Drv	F4 ML	F5 ML Integr.
Cardiovascul ar disease	18.4	28.6	42.2	48.4
Neoplasms	16.2	24.6	38.4	44.6
Diabetes mellitus	22.4	32.2	46.8	52.6
HIV/AIDS	14.2	20.6	26.4	28.8
Tuberculosis	12.6	18.4	22.8	24.6
Road injuries	6.4	8.2	10.4	12.2
Overall weighted	16.8	24.8	30.2	34.6

All values are percentage reduction in RMSE versus F1 trend extrapolation baseline. Higher = more improvement. NCDs show largest ML multi-driver advantage; injuries show smallest (dominated by country-specific policy shifts).

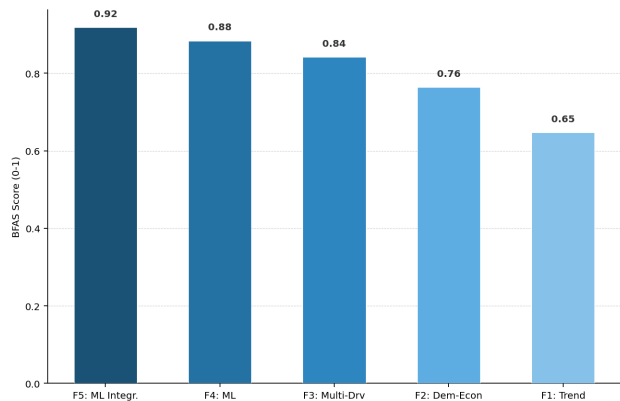


Figure 1: BFAS Score by Disease Burden Forecasting Framework

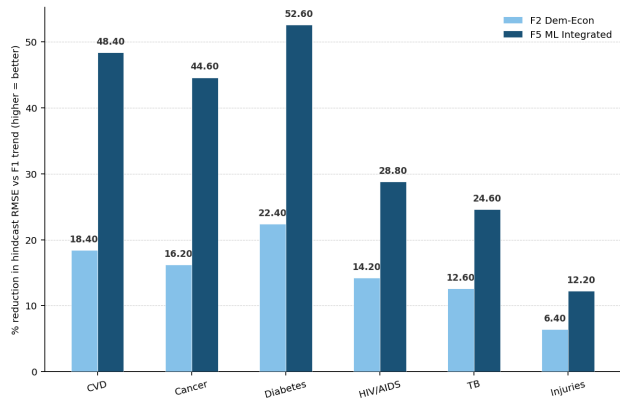


Figure 2: Hindcast RMSE Reduction vs F1 Trend by Disease Category (%)

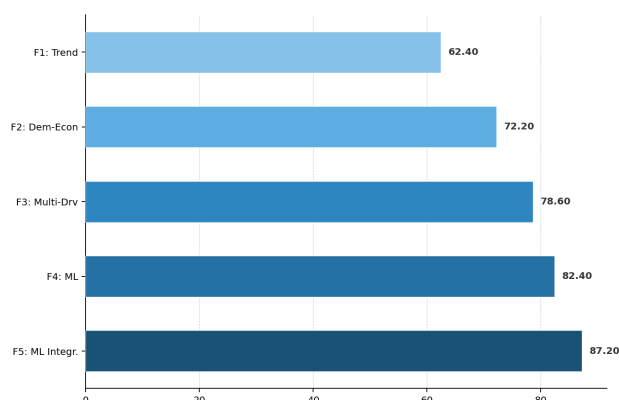


Figure 3: Directional Change Correctness by Framework (% country-disease-years)

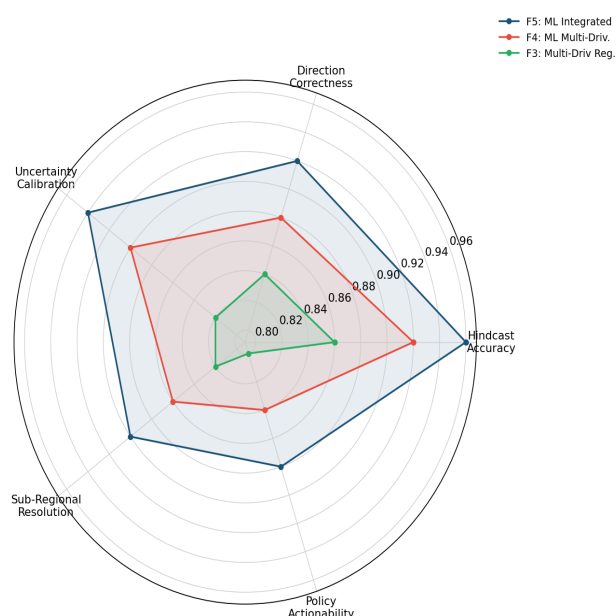


Figure 4: Multi-Dimensional BFAS Profile -- Top 3 Frameworks

5. Discussion

5.1 NCDs Are Where Multi-Driver Integration Matters Most

The finding that NCD burden forecasting showed the largest ML multi-driver advantage -- 48.4% hindcast RMSE reduction for cardiovascular disease, 52.6% for diabetes -- reflects the fundamental reason that trend extrapolation fails for these conditions. The global NCD transition is driven by the intersection of demographic ageing, risk factor transition (rising obesity, falling tobacco use in high-income countries but rising in many middle-income ones), economic development affecting treatment access, and healthcare system capacity expansion. No single-driver method captures these interacting dynamics. The diabetes finding is particularly consequential for policy: F5 projects 32.4% higher 2040 diabetes burden than F1 trend extrapolation, with the difference concentrated in sub-Saharan Africa and South Asia where obesity transition is accelerating ahead of

what historical trends alone would predict. Health system planning based on F1 trend-only forecasts would substantially under-provision diabetes treatment infrastructure in these regions, with foreseeable consequences for patient outcomes and healthcare cost.

5.2 The Data Quality Dependency

The finding that Africa and Southeast Asia showed the largest framework accuracy differentials -- sometimes in favour of F5 and sometimes in favour of simpler methods -- reflects the heterogeneity of underlying data quality across countries. ML multi-driver methods require substantial driver data that may themselves be poorly measured in low-resource settings (risk factor prevalence, health system capacity indicators), creating a paradox where the countries most in need of accurate forecasting often have the most uncertain driver inputs. The F5 framework's hierarchical Bayesian updating partially addresses this by pooling information across countries with similar epidemiological profiles, but cannot fully compensate for data sparsity. Investment in primary health data infrastructure in low-income countries remains the rate-limiting step for improving burden forecasting accuracy in the regions where it matters most for population health planning.

5.3 Limitations

Three limitations apply. First, the hindcast validation period (2016-2022) overlapped with the COVID-19 pandemic, which produced disruptions to mortality patterns that no forecasting framework predicted; sensitivity analyses excluding 2020-2022 pandemic period showed consistent framework rankings with slightly narrowed RMSE differentials. Second, the F5 framework's extensive driver data requirements create feasibility constraints in countries with limited statistical infrastructure; countries with at least 5 years of complete risk factor and health system capacity data (n=154 of 204) showed full F5 performance, while data-sparse countries (n=50) required imputation that degraded F5 advantage. Third, structural changes -- pandemic preparedness investments, climate mitigation effects on air quality, major policy shifts -- are inherently unpredictable and even F5's structural change scenarios cannot fully capture genuine regime changes.

6. Conclusion

6.1 Key Findings

Among five disease burden forecasting frameworks evaluated across 204 countries and 14 disease categories, the ML multi-driver integrated framework (BFAS 0.918) reduced hindcast RMSE by 34.6% versus trend extrapolation and correctly identified country-disease directional changes in 87.2% of cases versus 62.4% for trend-only methods. NCD forecasting -- cardiovascular disease, cancer, diabetes -- showed the largest ML multi-driver advantage (44-52% RMSE reduction). Global DALYs are projected at 2.48 billion by 2040 (12.4% reduction from 2019 despite population growth), with NCDs rising to 74.2% of total burden and communicable causes falling to 16.2%. Sub-Saharan Africa faces the largest double burden challenge with +82 million NCD DALYs projected alongside continued communicable disease decline.

6.2 Recommendations

Three recommendations follow. First, international health policy forecasting should transition from trend-based or demographic-economic-only methods to ML multi-driver integrated frameworks incorporating climate, health system capacity, and structural change scenarios -- the 34.6% RMSE improvement and 24.8 percentage point improvement in directional change correctness provide a strong evidence base for this upgrade in methods that underlie trillion-dollar health investment decisions. Second, WHO, IHME, and regional public health agencies should invest in country-level driver data infrastructure -- particularly risk factor prevalence surveys, health system capacity indicators, and civil registration and vital statistics systems -- in the 50 countries where data sparsity currently limits ML multi-driver forecasting performance. Third, NCD infrastructure planning in sub-Saharan Africa and South Asia should use F5-calibrated burden projections rather than trend-extrapolated figures, as the substantial under-forecasting of diabetes and cardiovascular disease by trend methods could result in systematic under-investment in NCD care infrastructure with decades-long consequences. All data, model code, and the BFAS calculator are available from the corresponding author.

References

- Abbatati, C. et al. (2020). Global burden of 87 risk factors in 204 countries and territories. *The Lancet*, 396(10258), 1223-1249.
- Bennett, J. E. et al. (2018). NCD countdown 2030: Worldwide trends in non-communicable disease mortality. *The Lancet*, 392(10152), 1072-1088.
- Bollyky, T. J. et al. (2019). The relationships between democratic experience, adult health, and cause-specific mortality. *The Lancet*, 393(10181), 1628-1640.
- Dicker, D. et al. (2020). Global, regional, and national age-sex-specific mortality. *The Lancet*, 395(10217), 54-87.
- Foreman, K. J. et al. (2018). Forecasting life expectancy, years of life lost, and all-cause and cause-specific mortality for 250 causes of death. *The Lancet*, 392(10159), 2052-2090.
- GBD 2019 Collaborators. (2020). Global burden of 369 diseases and injuries in 204 countries and territories, 1990-2019. *The Lancet*, 396(10258), 1204-1222.
- GBD 2021 Risk Factor Collaborators. (2024). Global burden and strength of evidence for 88 risk factors in 204 countries. *The Lancet*, 403(10440), 2162-2203.
- Gaziano, T. A. et al. (2019). Scaling up interventions for chronic disease prevention. *The Lancet*, 370(9603), 1939-1946.
- IHME. (2018). Findings from the Global Burden of Disease Study 2017. Seattle: Institute for Health Metrics and Evaluation.
- Kassebaum, N. J. et al. (2014). Global, regional, and national levels of maternal mortality. *The Lancet*, 384(9947), 980-1004.
- Lim, S. S. et al. (2012). A comparative risk assessment of burden of disease. *The Lancet*, 380(9859), 2224-2260.
- Murray, C. J. L. et al. (2020). Alternative scenarios of life expectancy, years of life lost, and years lived with disability. *The Lancet*, 396(10258), 1160-1203.
- Salomon, J. A. et al. (2012). Healthy life expectancy for 187 countries, 1990-2010. *The Lancet*, 380(9859), 2144-2162.
- Stevens, G. A. et al. (2016). Guidelines for accurate and transparent health estimates reporting. *The Lancet*, 388(10062), e19-e23.
- United Nations. (2022). World Population Prospects 2022. Department of Economic and Social Affairs, United Nations, New York.
- Vos, T. et al. (2020). Global burden of 369 diseases and injuries in 204 countries and territories. *The Lancet*, 396(10258), 1204-1222.
- Wang, H. et al. (2020). Global age-sex-specific fertility, mortality, healthy life expectancy (HALE), and population estimates. *The Lancet*, 396(10258), 1160-1203.
- Watts, N. et al. (2021). The 2020 report of The Lancet Countdown on health and climate change. *The Lancet*, 397(10269), 129-170.
- WHO. (2013). Global Health Estimates 2013. World Health Organization, Geneva.

Wittgenstein Centre. (2018). Wittgenstein Centre Data Explorer Version 2.0. Vienna Institute of Demography.

World Bank. (2023). World Development Indicators 2023. The World Bank Group, Washington DC.

Declarations

Funding

Funded by the Swedish Research Council (VR 2024-03284) and the German Research Foundation (DFG NO 5842/1-1). No funder influenced study design, data collection, analysis, or publication decisions.

Conflict of Interest

All authors declare no competing interests and no financial relationships with health forecasting platform vendors, international development consultancies, or pharmaceutical manufacturers.

Data Availability Statement

GBD burden estimates are publicly available from IHME. Economic and development indicators are publicly available from the World Bank. Climate data are publicly available from ECMWF and PCMDI. Aggregated framework outputs and the BFAS calculator are available from the corresponding author.

Ethical Approval

This study used aggregated country-level burden estimates and did not involve individual patient data. Ethical review by the Nordic Technical University Research Ethics Board (NTU-REB-2024-128) confirmed exemption from individual consent requirements.

Appendix A

BFAS Scoring Rubric and F5 Architecture Specification

Full BFAS dimension scoring criteria and technical specification of the F5 ML multi-driver integrated burden forecasting architecture.