ETH zürich (but in Basel)

Forecasting the spatial spread of an Ebola epidemic in real-time: comparing predictions of mathematical models and experts

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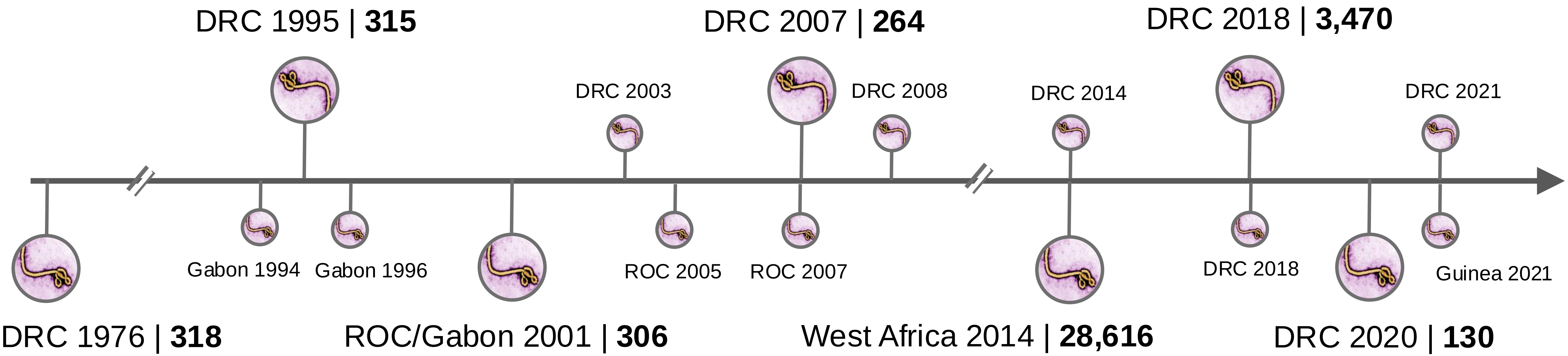
GEOMED | September 2024

Ebola Zaire Virus (EZV)

A brief history…

Place YEAR | **cases**



DRC 1976 | **318**

Gabon 1994

DRC 1995 | **315**

Gabon 1996

ROC/Gabon 2001 | **306**

DRC 2003

ROC 2005

DRC 2007 | **264**

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DRC 2008

DRC 2014

West Africa 2014 | **28,616**

DRC 2018 | **3,470**

DRC 2018

DRC 2020 | **130**

DRC 2021

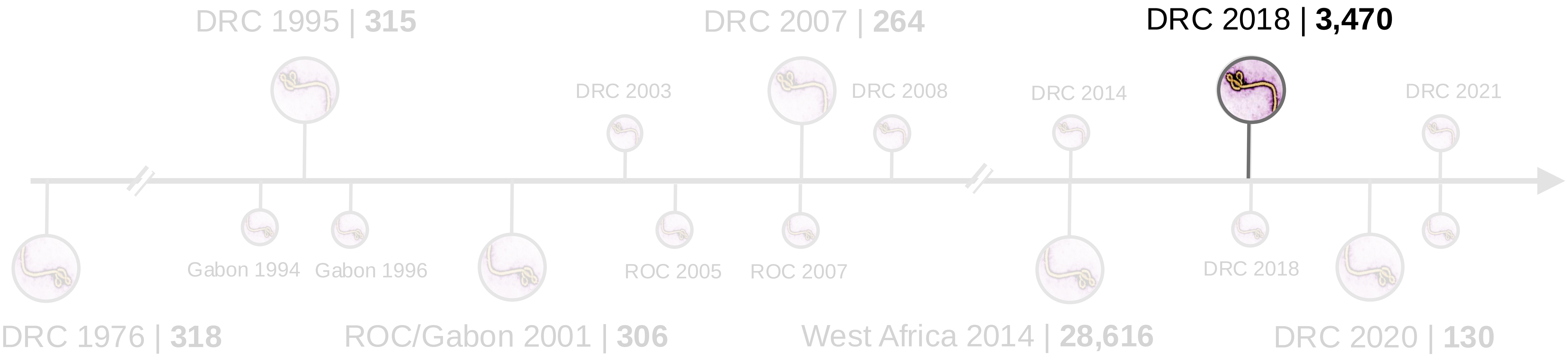
Guinea 2021

Case fatality rate of 25-90%

Transmission by very close contact in the symptomatic phase of → Controllable with active case finding, contact tracing and isolation

Major outbreak in West Africa 2014/15 → Galvanised the global search for an effective vaccine.

North Kivu, DRC Outbreak



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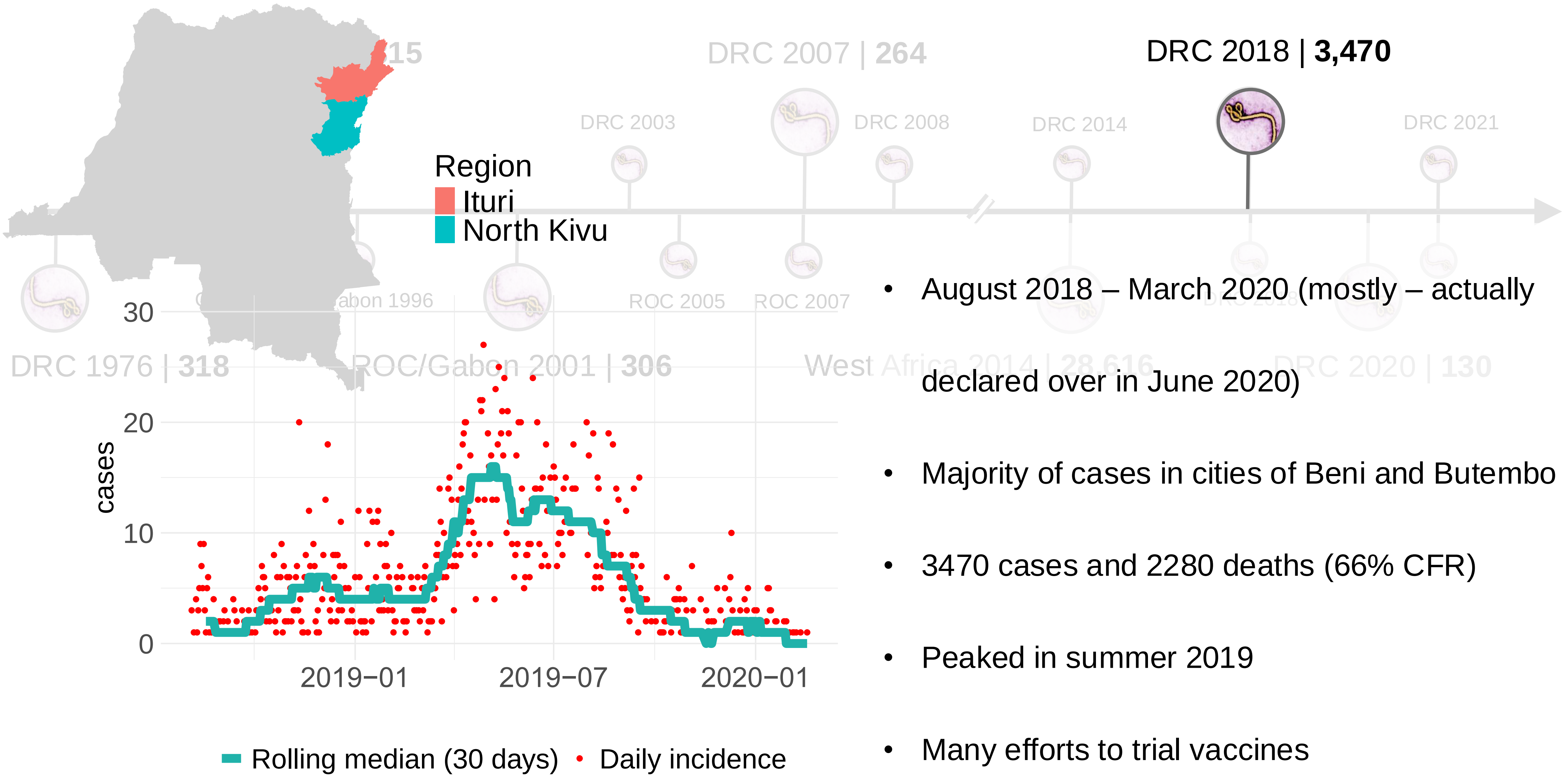

- August 2018 – March 2020 (mostly – actually declared over in June 2020)
- Majority of cases in cities of Beni and Butembo
- 3470 cases and 2280 deaths (66% CFR)
- Peaked in summer 2019
- Many efforts to trial vaccines

Models and their (intended) use in response

Use of models in response

Responding to Ebola outbreaks can be **particularly complex**…

Mobility in the region is **challenging -** difficult for the disease to travel but also hard to respond quickly

Area of **active conflict** -

- **Infectious patients** can **disperse** quickly and some **targetted attacks on Ebola treatment centres** hinders response and puts HCW at risk too.

Limited lines of **communication** can make it **difficult to know whats happening now** let alone what is coming next.

We can **try** to help with **mathematical modelling**…

Improve **situational awareness**

- Estimate Rt
- Nowcasting (accounting for reporting delays)
- Estimate epidemiological parameters:
    - Case ascertainment rate
    - Hospitalisation rate
    - Case fatality rate

Project risk

- Forecast cases/hospitalisations/deaths
- Highlight geographic areas of higher risk of transmission

Do models help?

“*All models are wrong…*

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>
> *so [modellers] belong in prison along with Bill Gates* ”

Many, many twitter users (2020 -2022)

Do models help?

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But this raises an important question in modelling as part of response… **ARE we helping**?

Do models help?

1. We can **evaluate model performace** statistically (although this is rarer than it should be)
    a) Proper scoring rules
    b) Bias

2. We can **compare** broad modelled outcomes with actual outcomes **qualitatively**
    a) Were health care facilities overwelmed?
    b) Did we have enough vaccines?

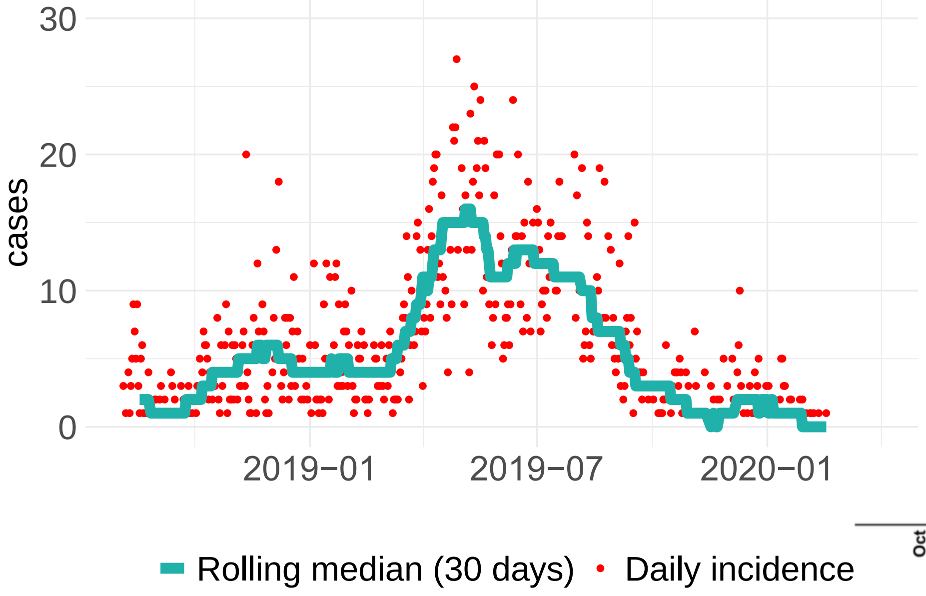
But what did we already know? What would be have done anyway?

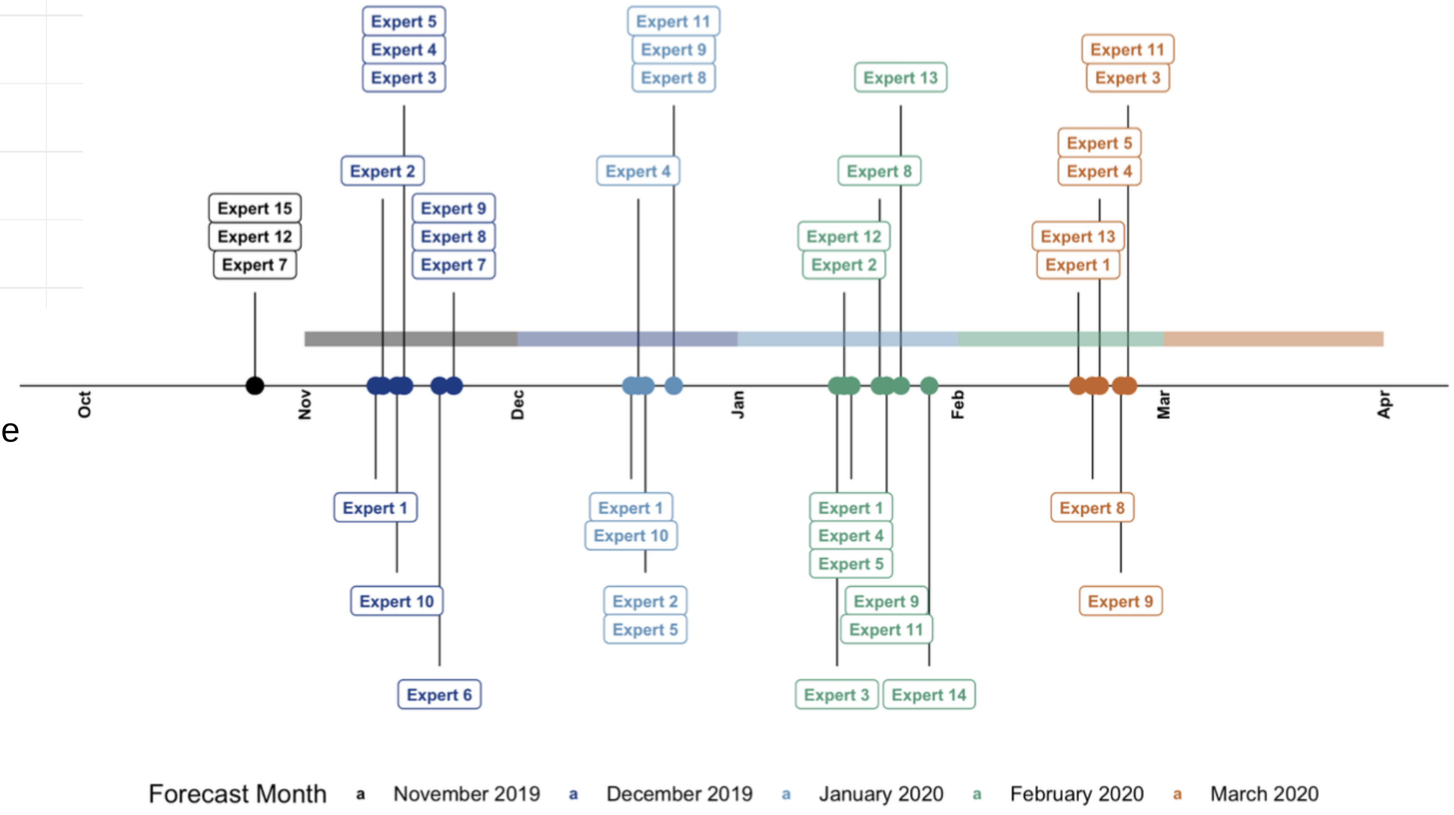
What we **really** want to know is:

Can models can improve on expert state of understanding and practice?

Modelling and expert ellicitation

Interviews timings





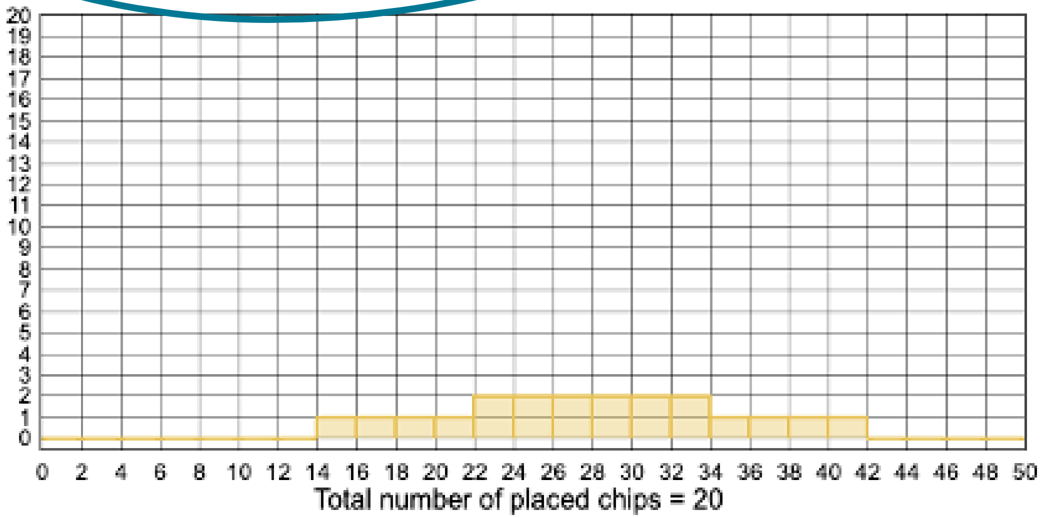
Expert surveys

Experts presented with a map of Health Zones

HZs with cases in the past 2 weeks are all assessed

Each expert distributes 20 ‘coins’ with equal weight into slots between 0 and 50 (in steps of 2)

Opportunity to nominate other HZs they think are at risk (>5% chance of at least 2 cases)



Modelling framework

Static model of spatial risk:

Local transmission   Spatial interaction

$$\lambda_{it} = \sum_{t-(D+L)}^{t-D} \gamma N_{i,t-1} + a \sum_{j} \omega_{ij} N_{j,t-1}$$

$$\omega_{ij} = \frac{P_i P_j}{d_{ij}^k}$$ Gravity model

$$\omega_{ij} = \delta_{ij} P_i P_j$$ Adjacency model

$$N_{i,t} = POIS(\lambda_{i,t})$$

Inputs

N_{it}	Cases	HDX (Sit Reps)
d_{ij}	Distance	Euclidian distance between centroids
δ_{ij}	Adjacency	1 if adjacent 0 if not
P_i	Population	Aggregates from LandScan estimates

Parameters

γ	Internal coeff.	fitted
α	Spatial coeff.	fitted
k	Distance exponent	fitted

Constants

D	Duration of infection	Fixed at 5 days
L	Latent period	Fixed at 7 days

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Fit the model using HMC to previous 60 days of outbreak

↓

Project cases using joint posterior distribution

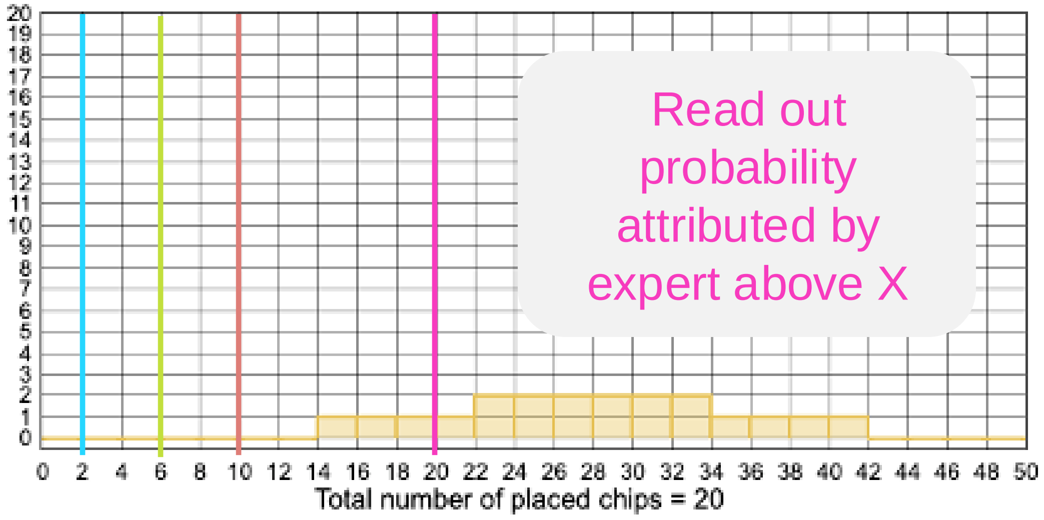
Comparable predtction outputs

What is the probability of the case count in each HZ exceeding X cases in the next calander month?

Thresholds (X)

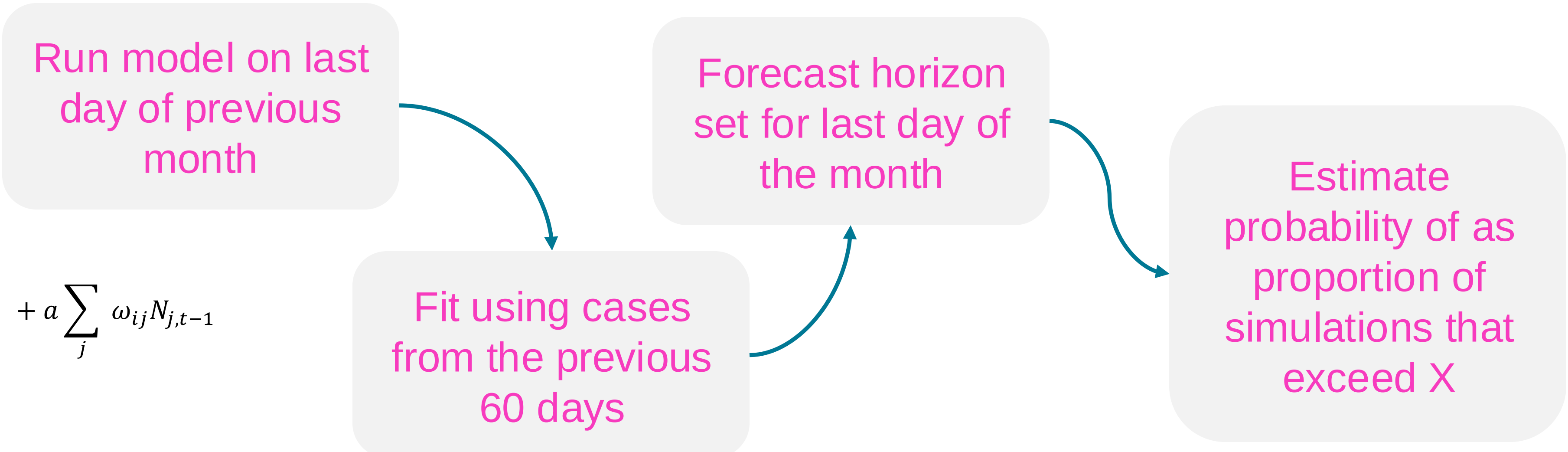
>= 2 cases
>= 6 cases
>= 10 cases
>= 20 cases

Experts



Read out probability attributed by expert above X

Models



Run model on last day of previous month

Fit using cases from the previous 60 days

Forecast horizon set for last day of the month

Estimate probability of as proportion of simulations that exceed X

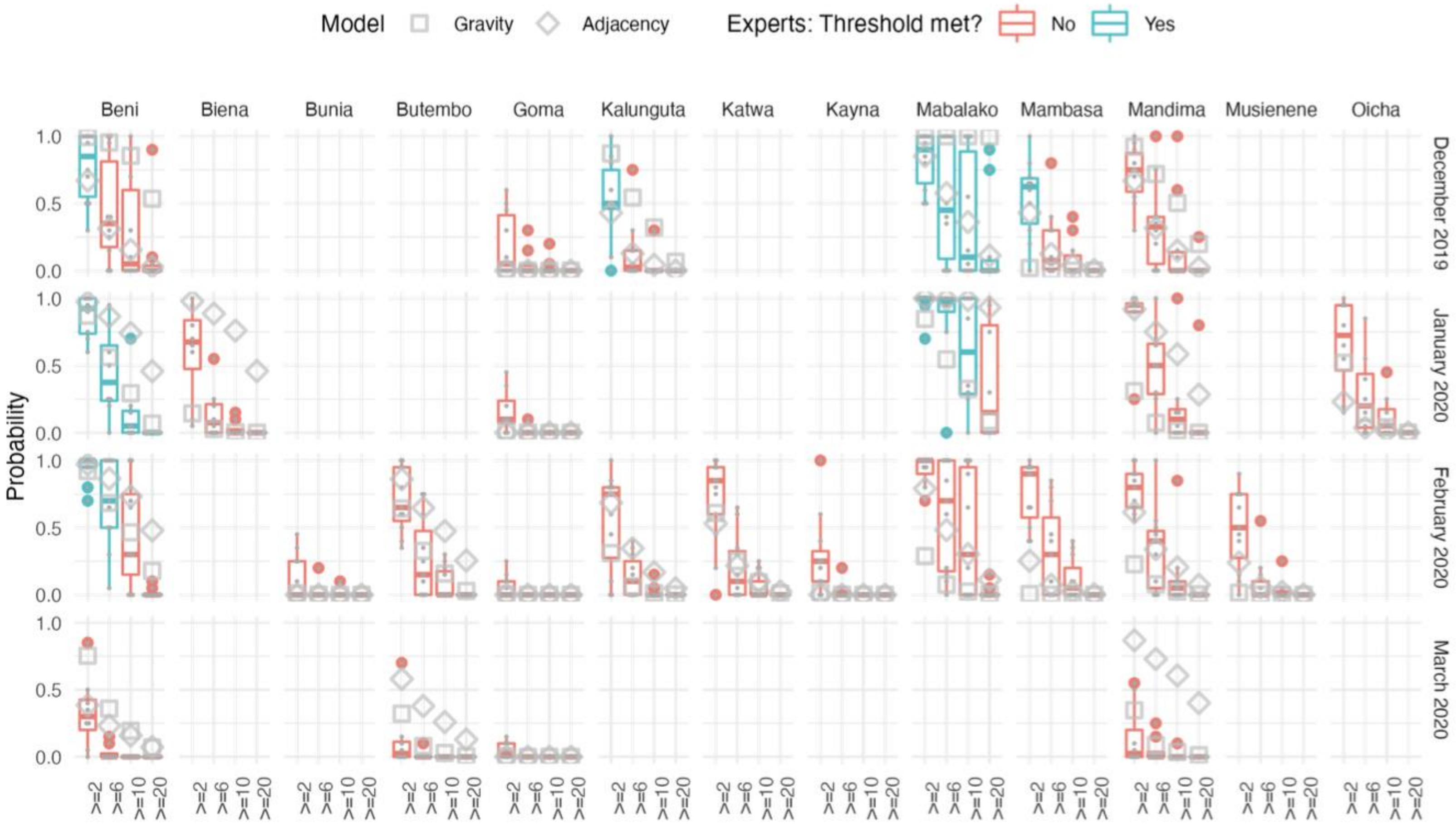
$$\lambda_{it} = \sum_{t-(D+L)}^{t-D} \gamma N_{i,t-1} + a \sum_{j} \omega_{ij} N_{j,t-1}$$

Comparison of model and expert predictions

Characterising model and expert predictions

15 thresholds were met vs. 93 not met

Visually - some experts and models were correlated in their predictions – but difficult make a statement about their relative performance

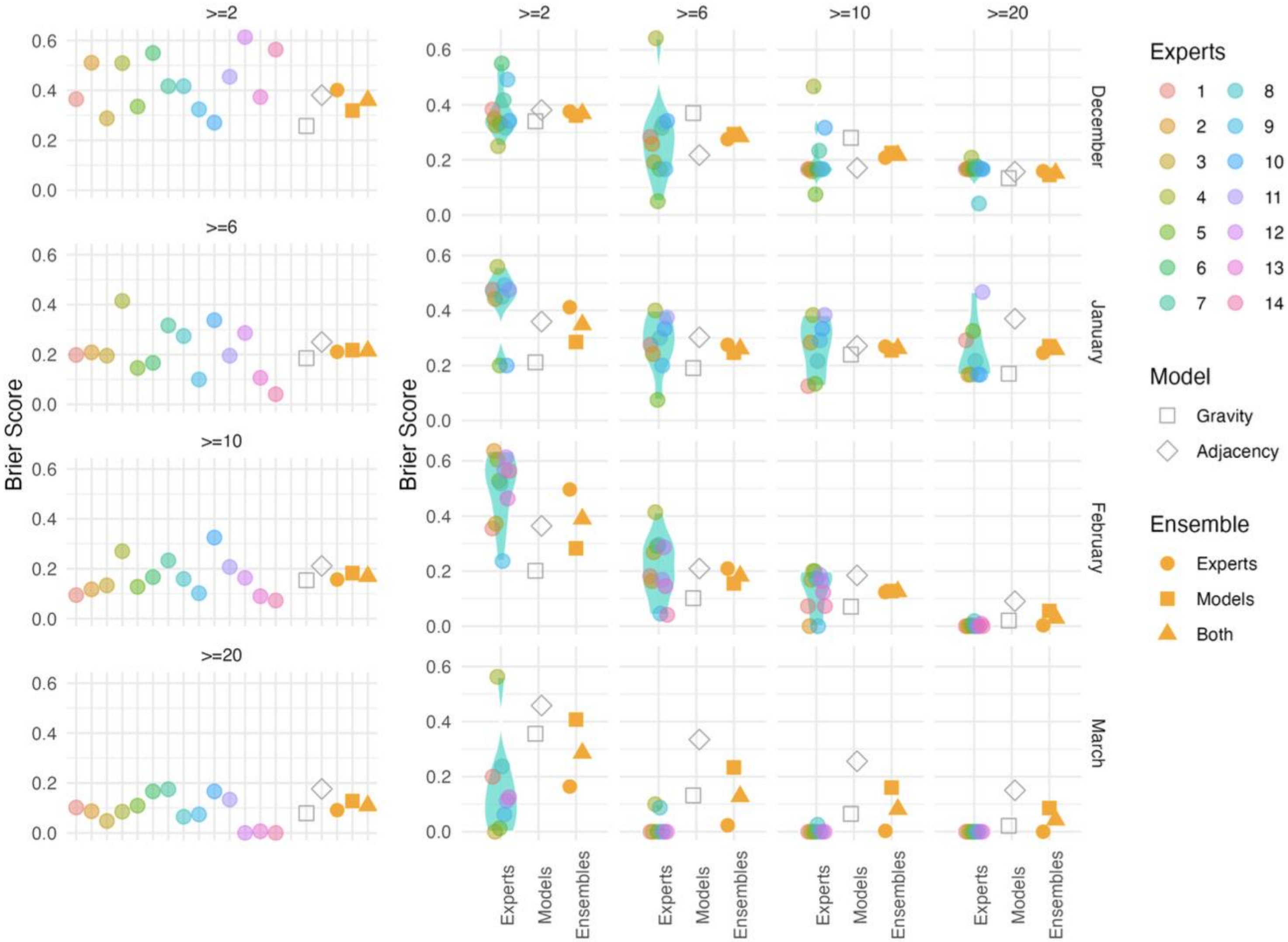


Quantifying prediction accuracy

Brier score:

$$BS = \frac{1}{N}\sum_{i=1}^{N}(p_i - o_i)^2$$

The average **difference between the probability,** $\boldsymbol{p_{i,}}$ attributed to event i **and the outcome,** $\boldsymbol{o_i}$ – 1 (event occurred) or 0 (event not occurred)



Quantifying prediction accuracy

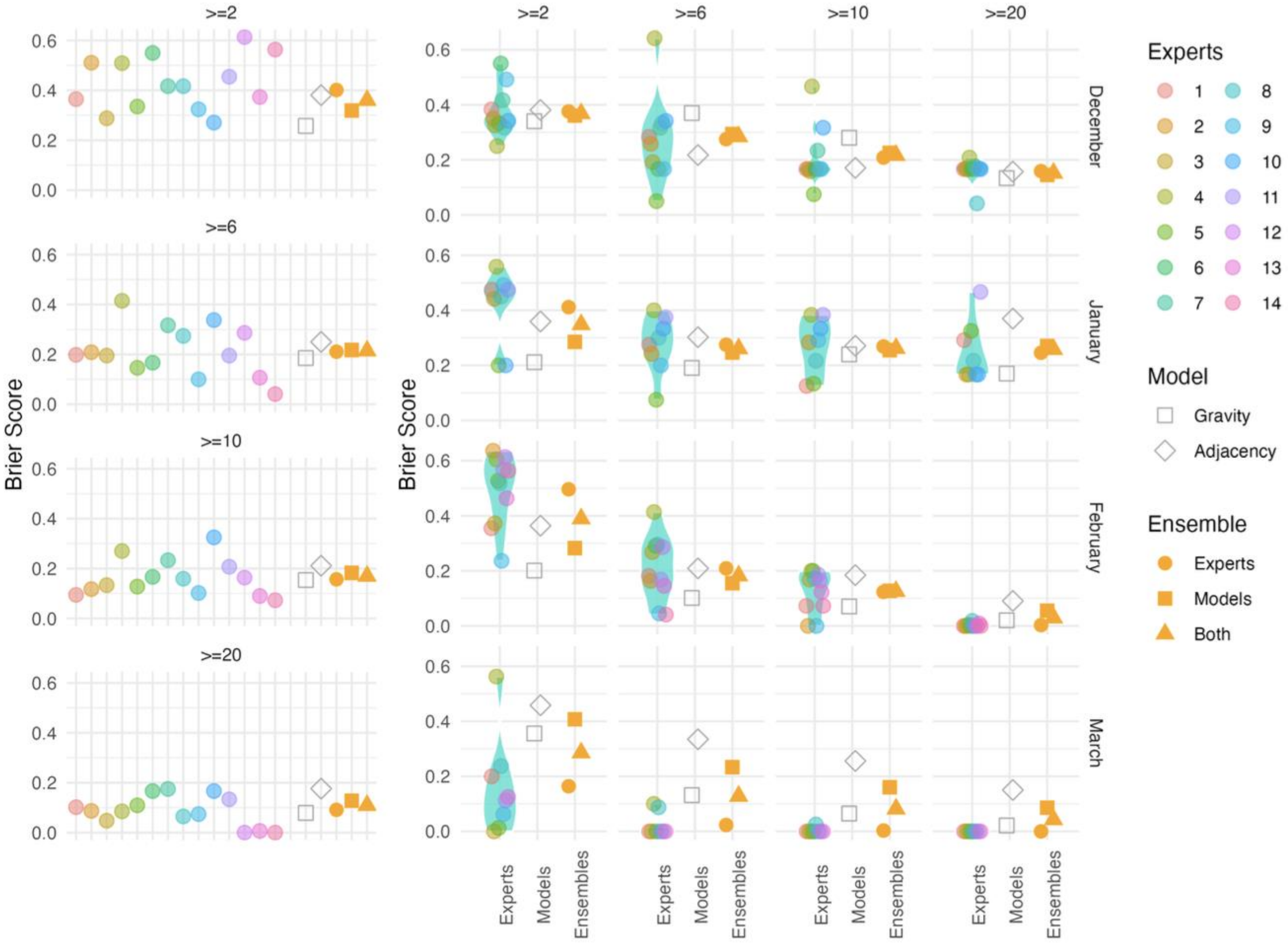
Experts scored between 0 (best) and 0.6 on indevidual forecasts across all thresholds.

Experts and models both tended to do better on higher thresholds

No individual expert performed consistently well

Gravity model performed best at X=2 – but was not consistent

Ensembled expert and model forecasts were consistently comparable

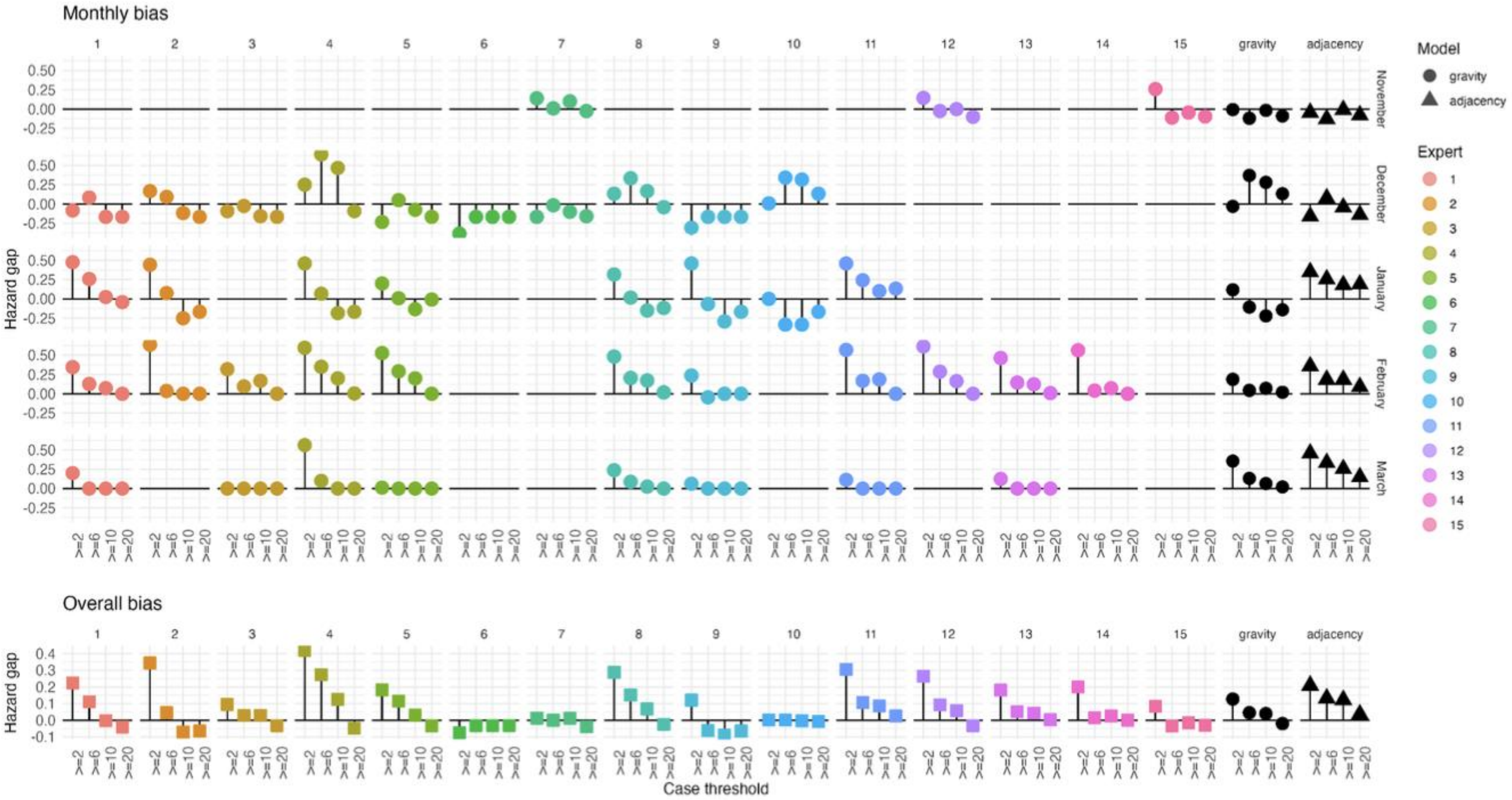


Quantifying predictoin bias

Hazard gap

$$HG = \sum_{\forall HZ} p(c > c_{thresh}) - \sum_{\forall HZ} o(c > c_{thresh})$$

The **difference** between **expected number** of events and the **actual number** observed. ,

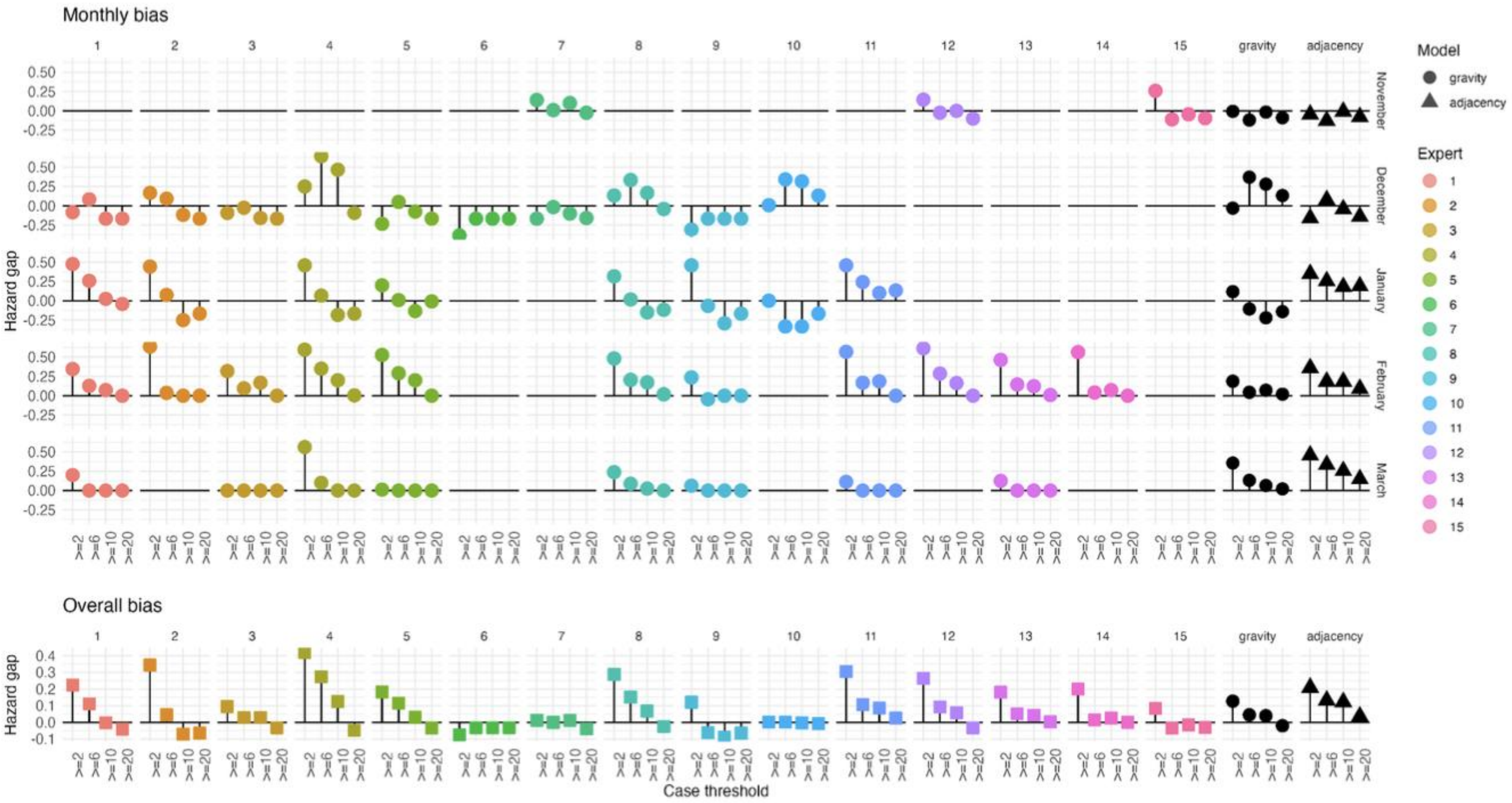


Quantifying predictoin bias

Experts forecasted higher risk of the lowest threshold (>=2 cases) … but lower risk of exceeding the highest threshold (>=20 cases)

When calculated across all months, this bias was present in 12 of the 15 experts.

The models showed some bias, but not as pronounced.



Summary

1. We evaluated forecasts made my experts and two mathematical models of spatially explicit Ebola risk
2. We found that forecasts made by experts and models performed comparably overall when experts were ensembled
3. Experts tended to be slightly more biased towards predicting that a small number of cases would persist
4. There was no single expert that performed as well as the model or ensemble of experts
5. Models continue to provide a convenient way to summarise collected knowledge in an impartial way – we advocate the use of expert predictions in modelling to improve insights.

Thanks!

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Sebastian Funk

Sir W. John Edmunds

LONDON SCHOOL *of* HYGIENE &TROPICAL MEDICINE

cmmid

centre *for* mathematical modelling *of* infectious diseases

wellcome

NIHR | National Institute for Health and Care Research

Expert panel: Xavier de Radiguès, Neale Batra, Nabil Tabbal, Mathias Mossoko, Chris Jarvis, Thibaut Jombart, Denis Ardiet, Michel Van Herp, Silimane Ngoma, Olivier le Polain, Esther van Kleef, Noé Guinko, and Amy Gimma + 2 who wished not to be named

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