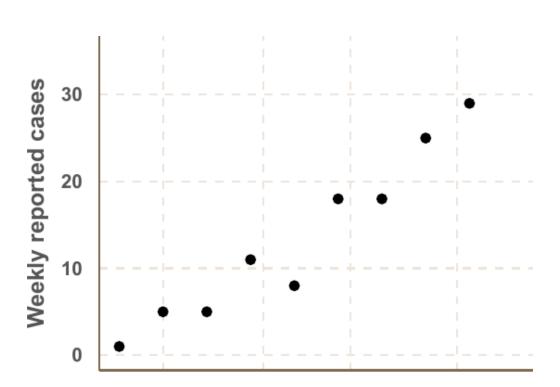
# Real-time modelling and forecasting during infectious disease outbreaks

Sebastian Funk 22 March, 2018 recon gathering, London



centre for the mathematical modelling of infectious diseases

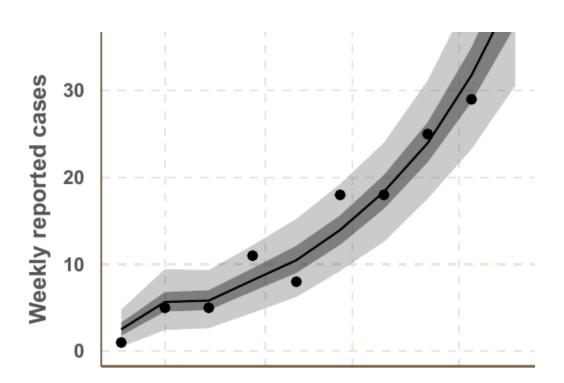


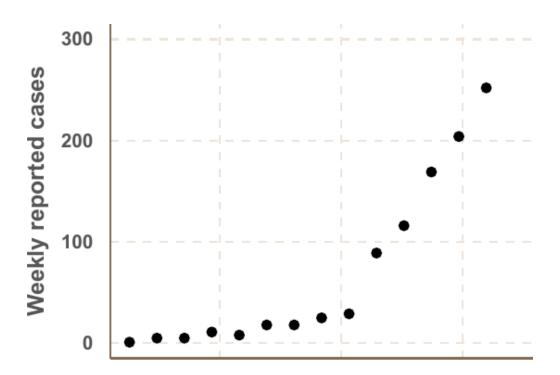
$$S$$
 Infection  $I$  Recovery  $R$ 

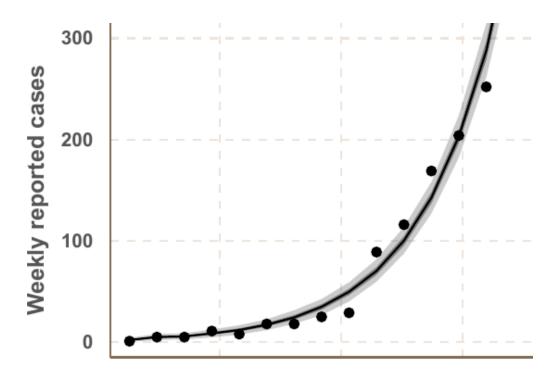
$$\dot{S} = -\beta \frac{S}{N} I$$

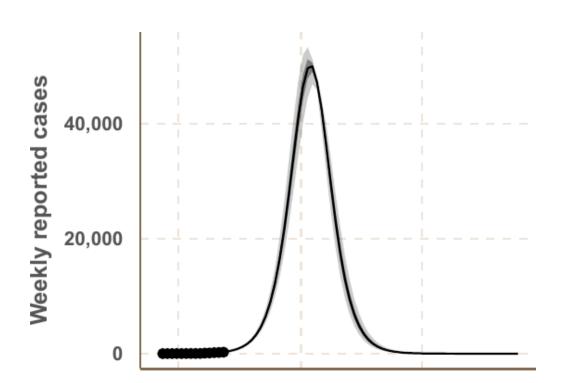
$$\dot{I} = +\beta \frac{S}{N} I - \gamma I$$

$$\dot{R} = +\gamma I$$

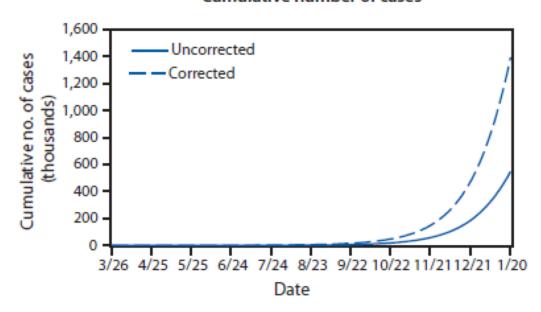








#### **Cumulative number of cases**





home > world > africa

middle east

cities

development europe US

america: = all

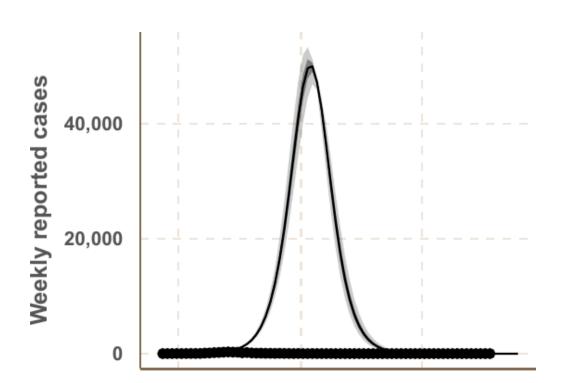
**Ebola** 

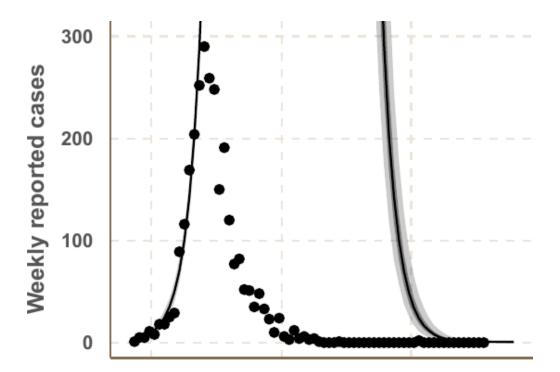
## Up to 1.4m people could be infected with Ebola by January, CDC warns

US doctors warn that without immediate action to quarantine and change burial practices, epidemic will spread

True anima antal duranta ha mucha dita Africa

What really happened



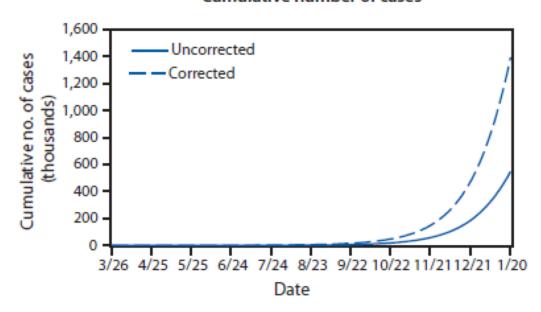




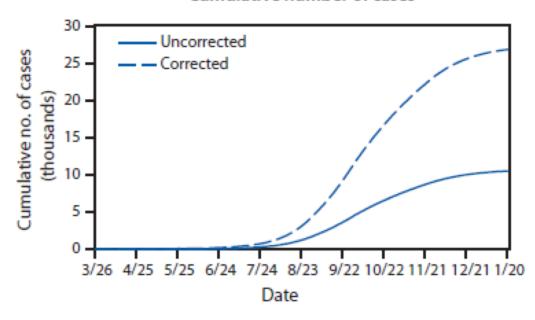
#### Models overestimate Ebola cases

Rate of infection in Liberia seems to plateau, raising questions over the

#### **Cumulative number of cases**







TOWARDS EPIDEMIC PREDICTION: FEDERAL EFFORTS AND OPPORTUNITIES IN OUTBREAK MODELING

PRODUCT OF THE
Pandemic Prediction and Forecasting
Science and Technology Working Group

## "A CDC model [...] was key to increasing the speed and scale of the US and global response.

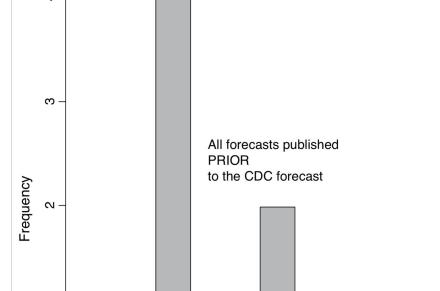
Frieden, 2015

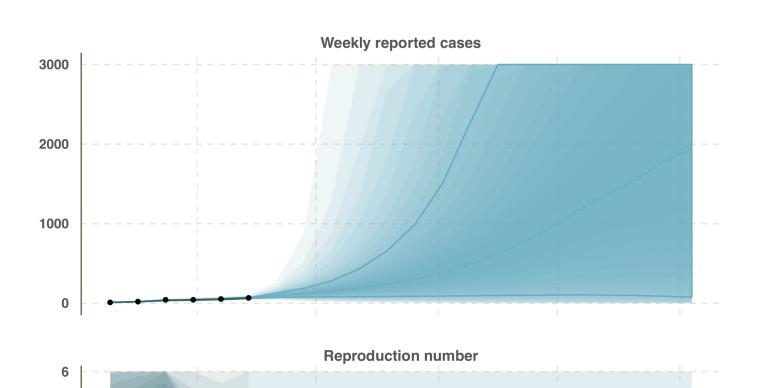
Key findings:

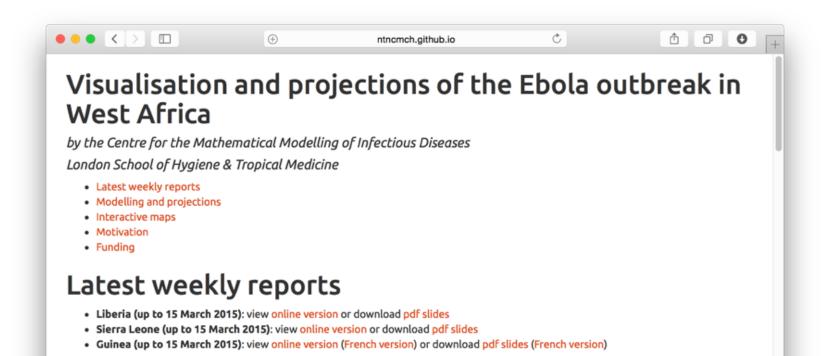
- 1. "cases were increasing exponentially, and the response needed was massive and urgent"
- 2. "the model predicted a severe penalty for delay"
- 3. "the model identified a tipping point at which the epidemic would [..] decline if enough Ebola patients were isolated effectively and decedents buried safely"
- 4. "the model predicted that when the tipping point was reached, transmission would decline rapidly"

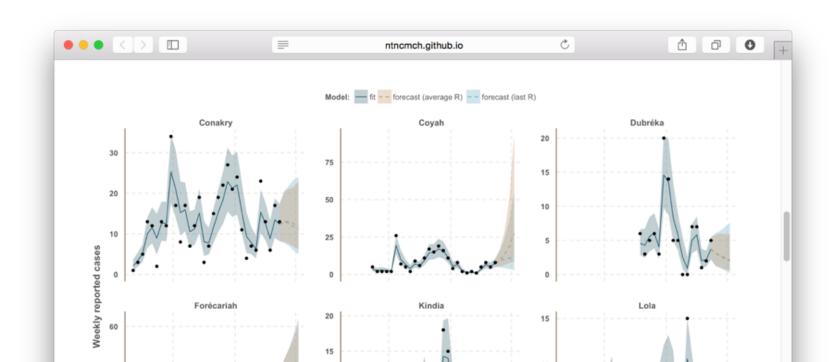


Data from Chretien et al. 2015 10.7554/eLife.09186







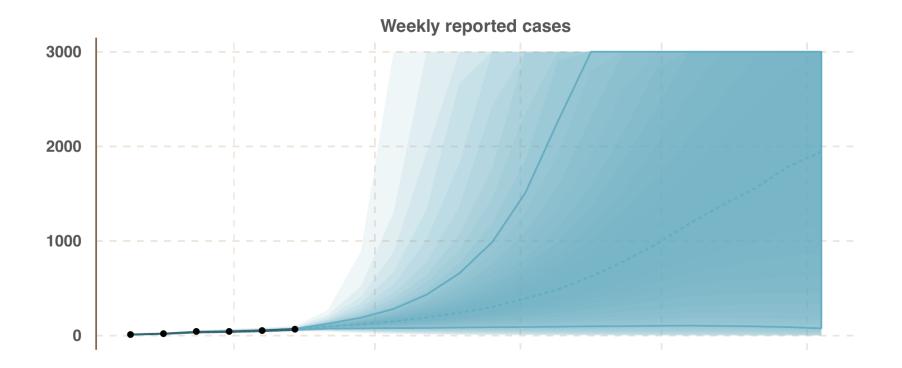


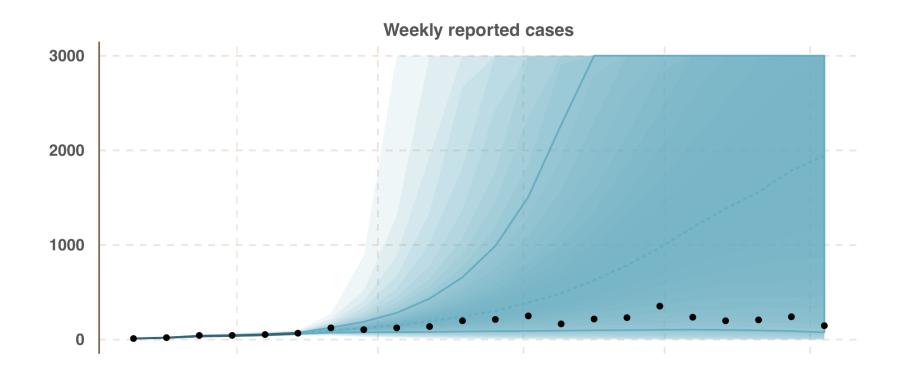
#### Uses of real-time forecasts in outbreaks

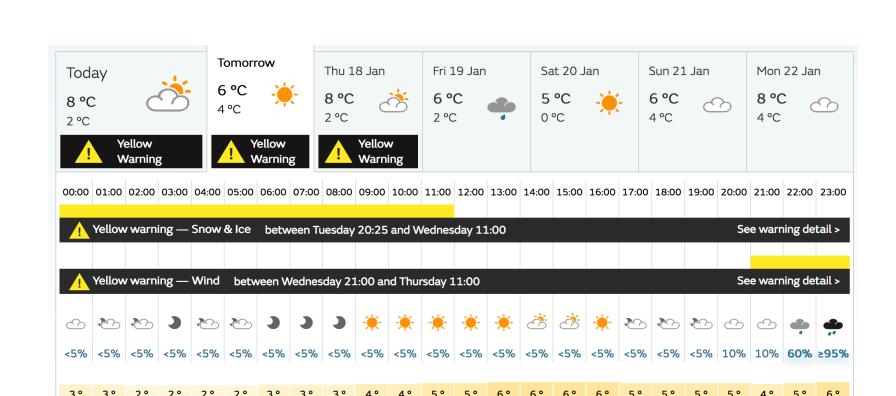
- Plan the scale of a response or intervention
- Allocate resources (e.g., geographically)
- Plan clinical trials

Challenges/opportunities

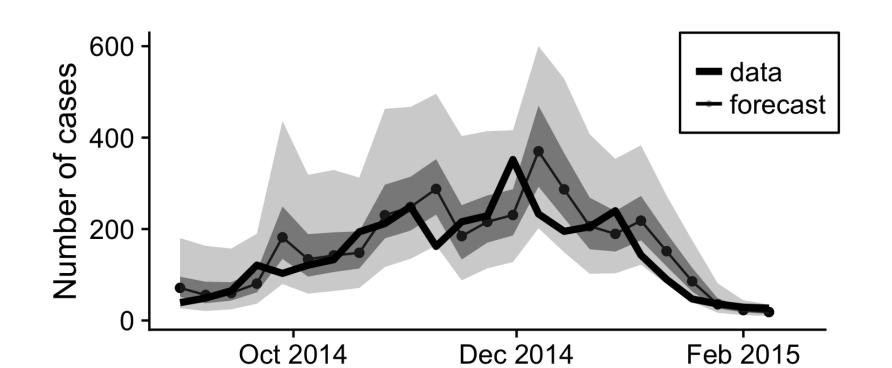
1. Evaluation of probabilistic forecasts



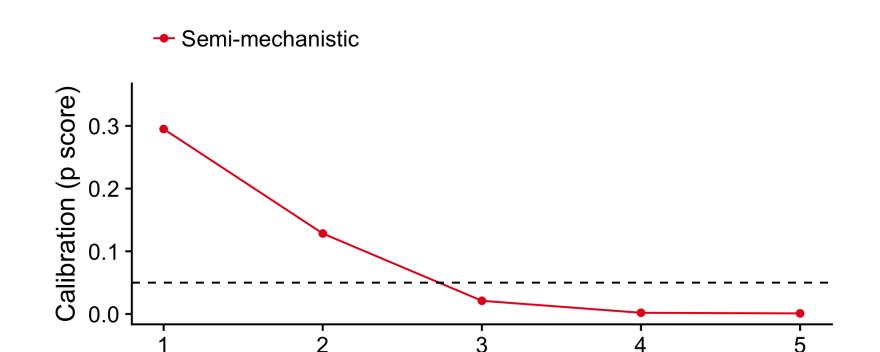




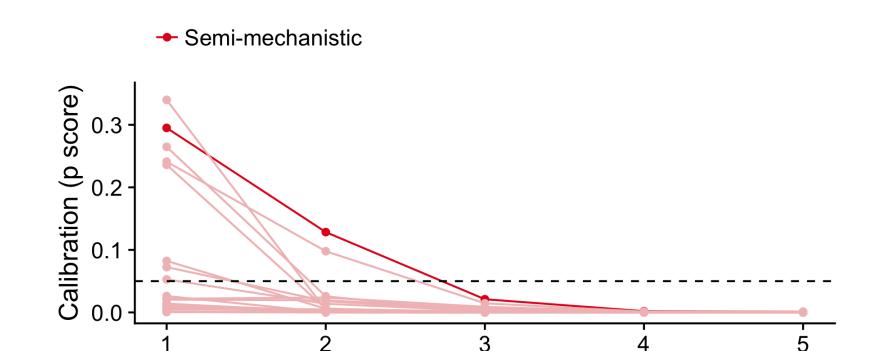
#### 1-week forecasts



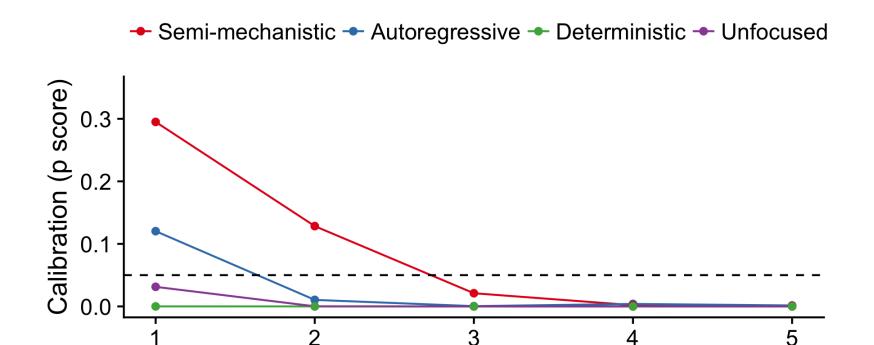
### Calibration: Compatibility of forecasts and observations.



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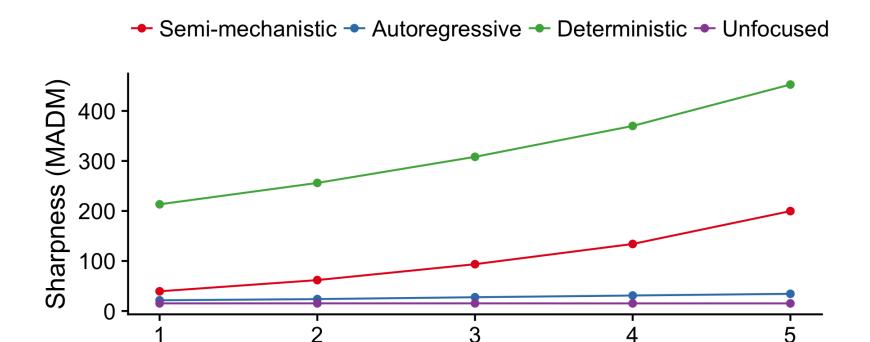


## "Evaluate predictive performance on the basis of maximising the sharpness of the predictive distribution

subject to calibration"

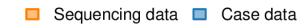
Gneiting et al., J R Stat Soc B (2007)

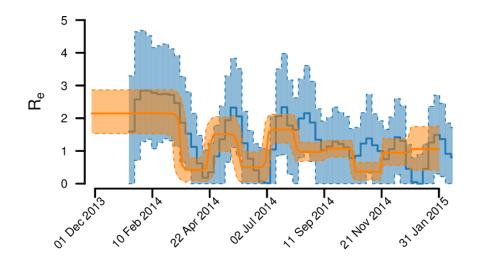
### Sharpness



2. Integration of different data sources

Need to start looking at all available **data streams** (individual/behavioural/spatial/genetic)





3. Forecasting for decision making

#### Acknowledgements

Anton Camacho, Adam Kucharski, Roz Eggo, John Edmunds (LSHTM) Bruce Reeder, Etienne Gignoux, Iza Ciglenecki, Amanda Tiffany (MSF) James Hensman (prowler.io), Lawrence Murray (Uppsala)







#### Summary

- Real-time forecasts can aid decision making
- Meaningful forecasts are probabilistic
- Forecasts must be evaluated to establish reliability and limitations
- Some big challenges remain