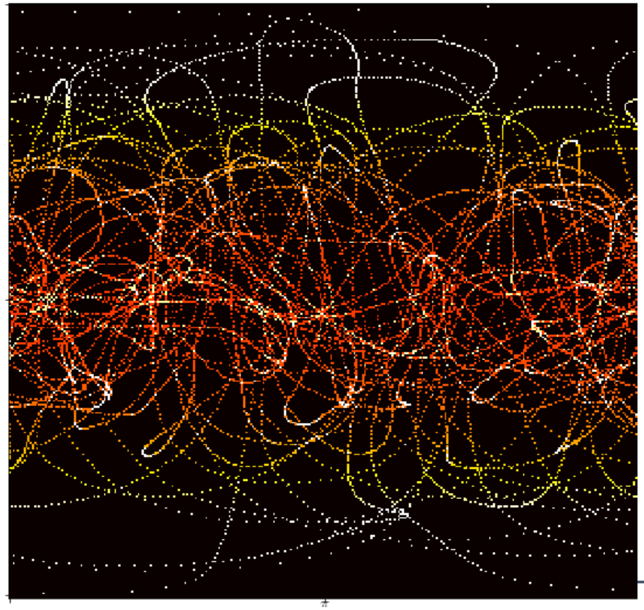
WSS model: Calculating what people care about quickly and accurately enough

Graeme Ackland



CSEC, SUPA, School of Physics and Astronomy, The University of Edinburgh, UK

David Wallace

I can predict R-numbers two weeks ahead of SPI-M consensus

Nobody cares about what you’re doing, Dad.

James Ackland

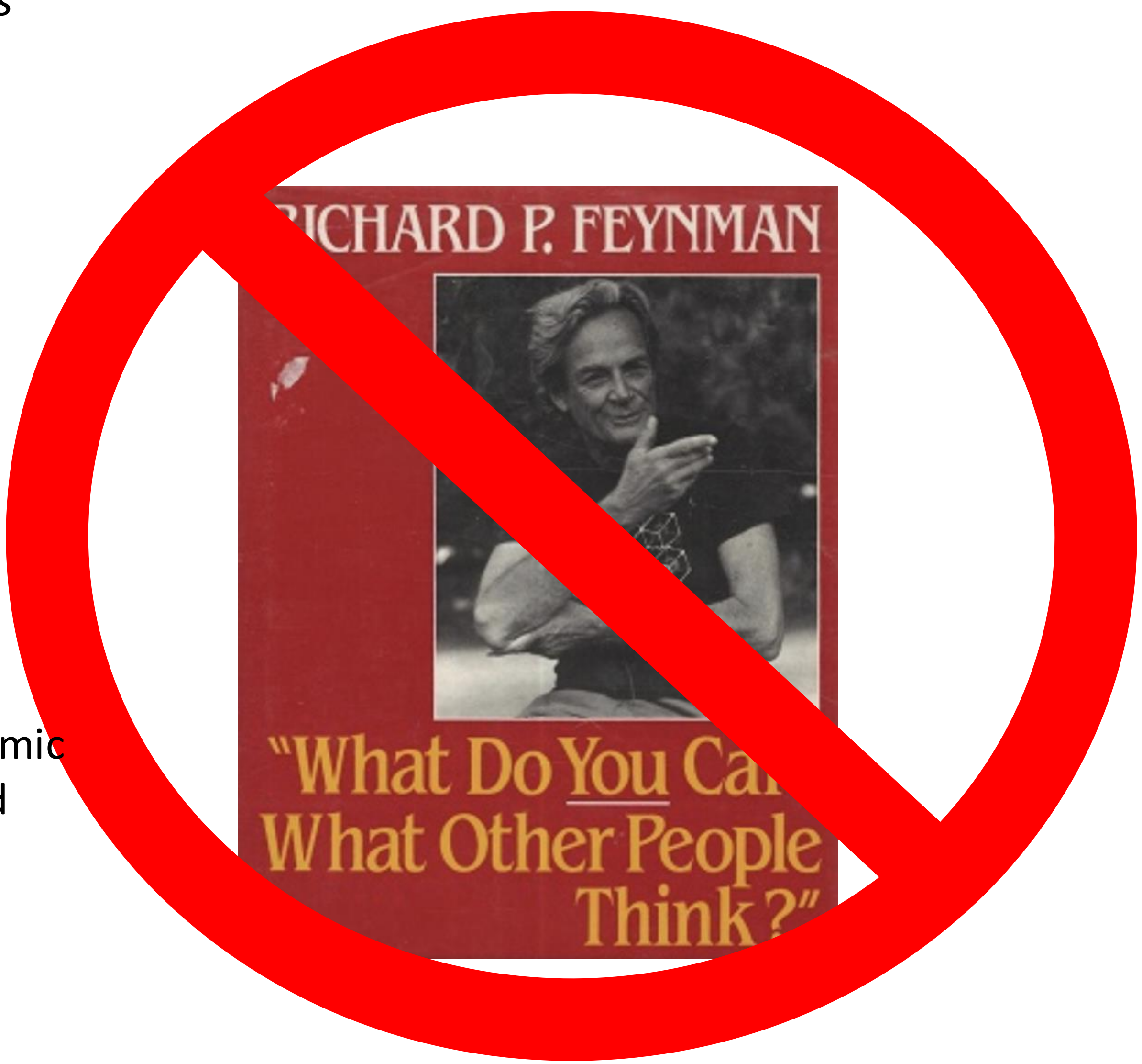
Modelling under pressure.   Why, what and how

- **Why?   To do something *useful right now*.**
- **What? ”The science”**
- **What? R-numbers, medium term predictions**
- **How?   Use real data that actually exists**
- **How?   Model, validate**
- **Philosophy: Build a simple model: enhance it when it breaks**

Why not study theory of high pressure barium tetrahydride?

WSS Calculating Covid specific epidemiological parameters

"An 80% right paper before a policy decision is made it is worth ten 95% right papers afterwards, provided the methodological limitations imposed by doing it fast are made clear."
Chris Whitty, Chief Medical Officer, England



R-numbers	Parameterise by Modelling the entire pandemic
Hospitalisations	Predict by extrapolating current status based
Deaths	on historical trends

Hindcast (for credibility)
Nowcast, Medium term predictions for JBC

WSS Calculating "R" : The number on onward infections per person

Data we want – Infections I(t)

$$\frac{dI(t)}{dt}/I(t) \equiv \frac{d\ln I(t)}{dt} = [(R_t - 1)/\tau]$$

Data we use – Cases C(t).

$$\frac{dC(t)}{dt}/C(t) \equiv \frac{d\ln C(t)}{dt} = [(R_t - 1)/\tau]$$

Relation between Reported Cases and C(t)

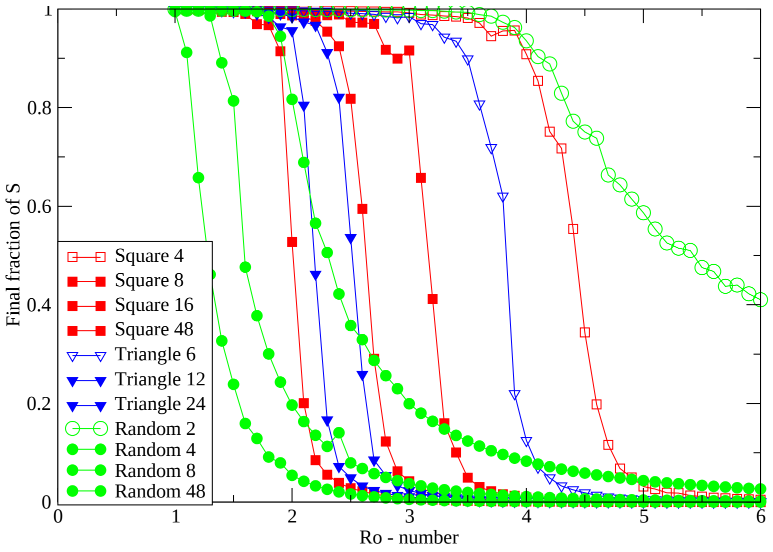
$$\tilde{C}_0(t) = C(t)(1 + a(t)) + \sqrt{C(t)}\eta$$

Where $\tilde{C}_0(t)$ is the reported data, defined only at integer t, $C(t)$ is the underlying trend, $a(t)$ is a systematic reporting error and η represents the stochastic noise in the data. $C(t)$ is a differentiable function, but η is not. To differentiate this function requires methods from stochastic calculus,

- WSS by design focuses on up-to-date Nowcasting
- Three types of data:
- Cases ***drive*** the model
- Historical death, hospital ONS ***parameterizes***
- ("Big" data across the whole pandemic)
- Recent death, hospital ONS ***reparameterizes***
- ("Small" data for recent status)

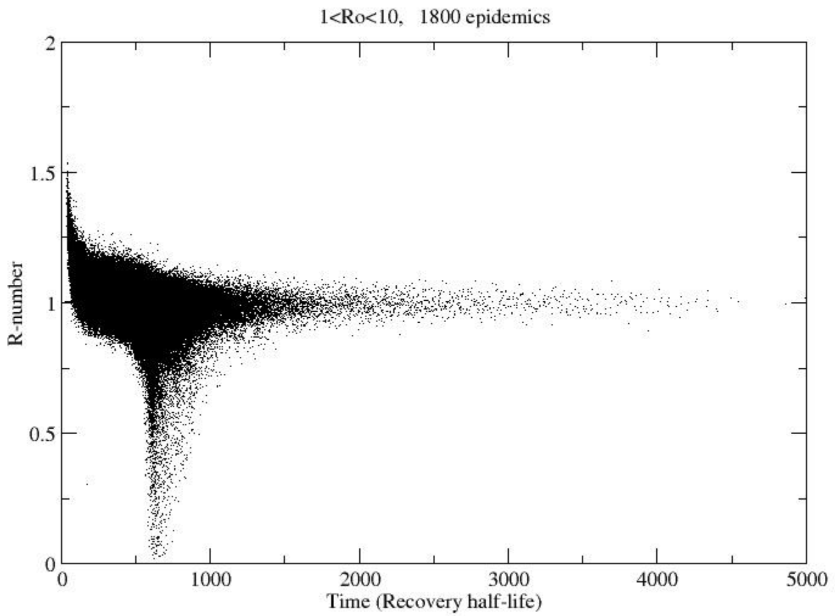
Previous Talk: These predictions match those from SPI-M
Evaluation Phase – sent WSS predictions to Scotgov from June 2021
Contributed to SPI-MO consensus from November 2021

R-numbers from SIR Network simulations tend to 1

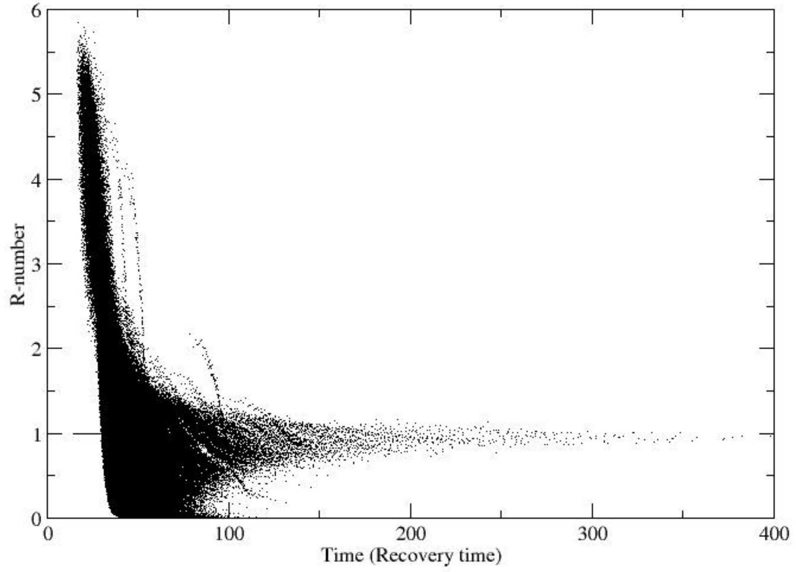


Critical value of R0 > 1

$$\frac{dI(t)}{dt}/I(t) \equiv \frac{d\ln I(t)}{dt} = [(R_t - 1)/\tau]$$

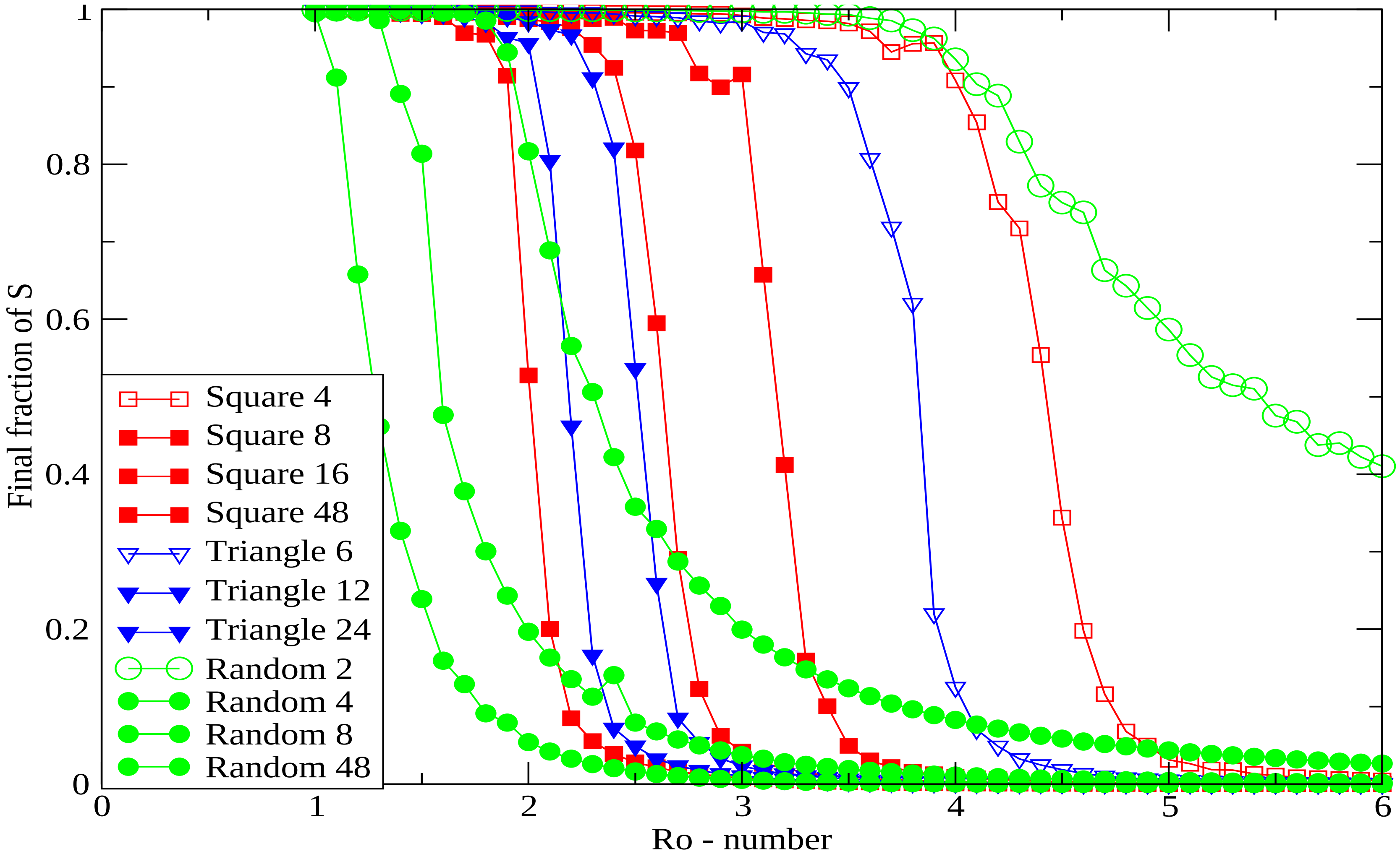


SIR on various 2D/3D lattices
500,000 sites. 1800 “epidemics” 1<R0<10



SIR small world network
500,000 sites. 1800 “epidemics” 1<R0<10

R-numbers from SIR Network simulations tend to 1

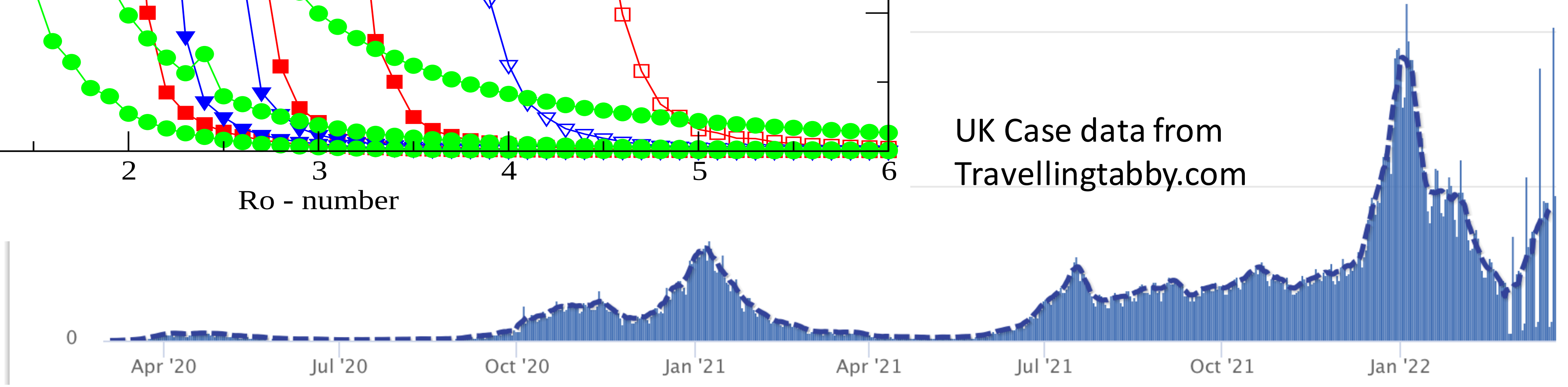


Critical value of R0 > 1

- Initial spread is at R0 – obviously
- Transient period,
- Reaction-diffusion wave R = 1

Is it relevant?
Case data from UK, and elsewhere, suggests transient period about 2 weeks (aka 3 generations).

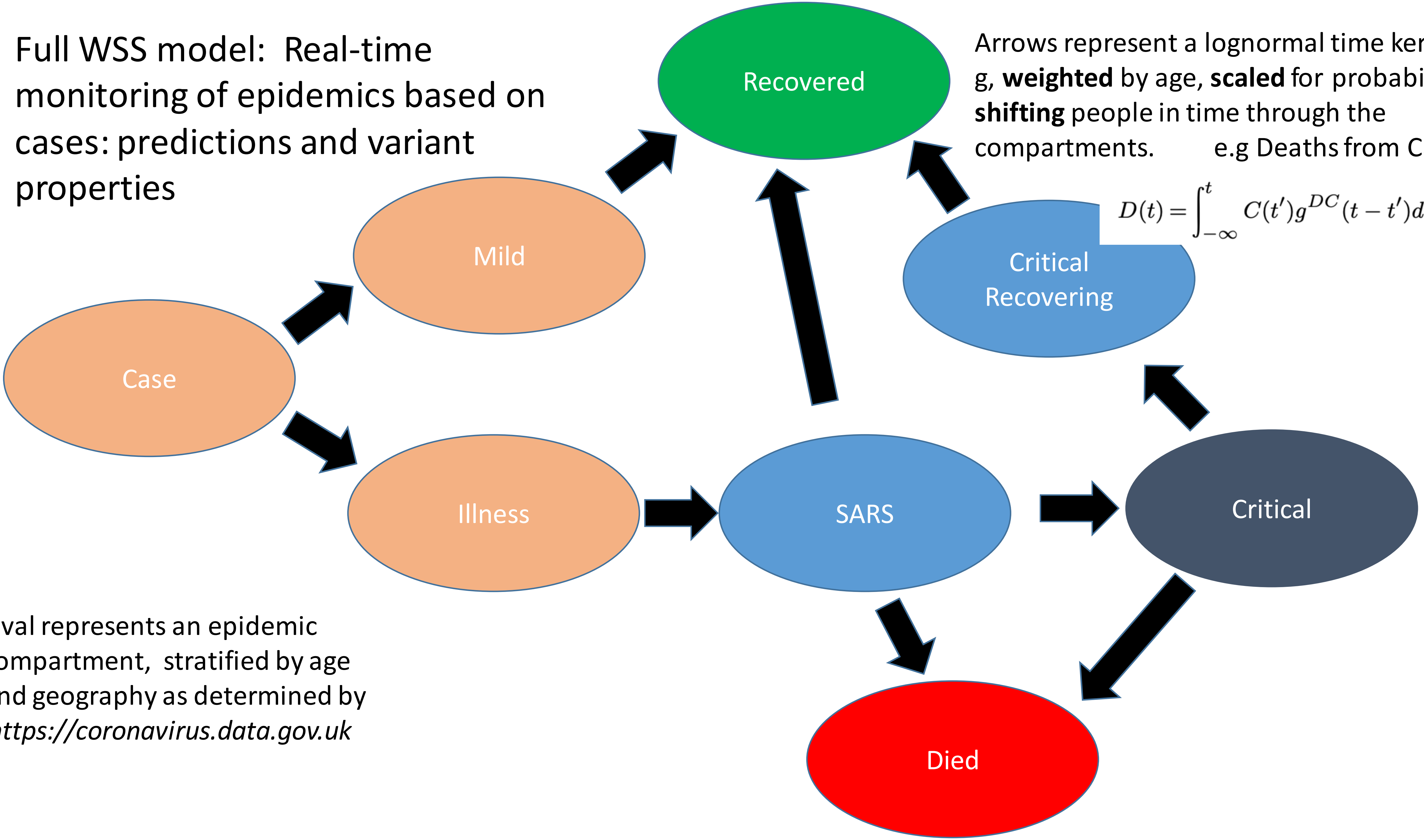
UK Case data from Travellingtabby.com



Full WSS model: Real-time monitoring of epidemics based on cases: predictions and variant properties

Arrows represent a lognormal time kernel, g, **weighted** by age, **scaled** for probability **shifting** people in time through the compartments. e.g Deaths from Cases

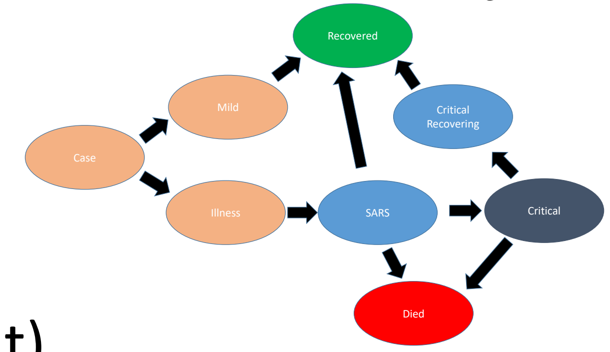
$$D(t) = \int_{-\infty}^{t} C(t')g^{DC}(t-t')dt'$$



Oval represents an epidemic compartment, stratified by age and geography as determined by *https://coronavirus.data.gov.uk*

- Modelling Modes

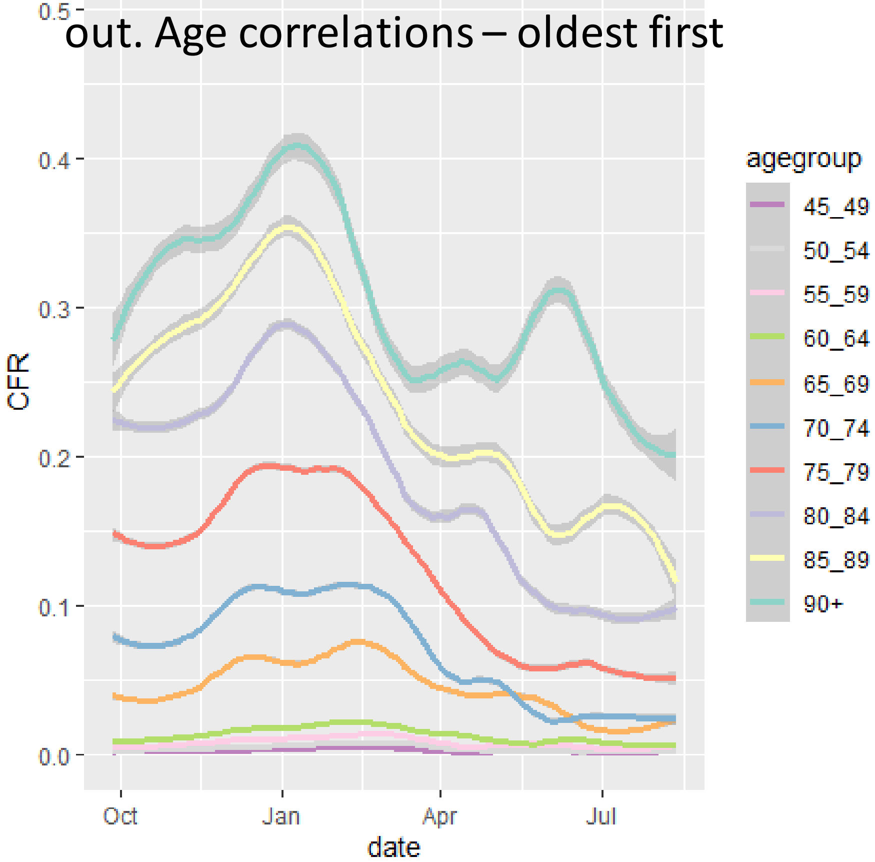
1) Fixed parameters, watch how it breaks: *All models are wrong, some are useful when they're wrong*
2) Optimise parameters: fit whole epidemic
3) Optimise parameters to recent data, Medium Term Predictions



WSS: Type – 1 Results

1) Detect more lethal variants (Kent)
1) Vaccination protection vs severe disease

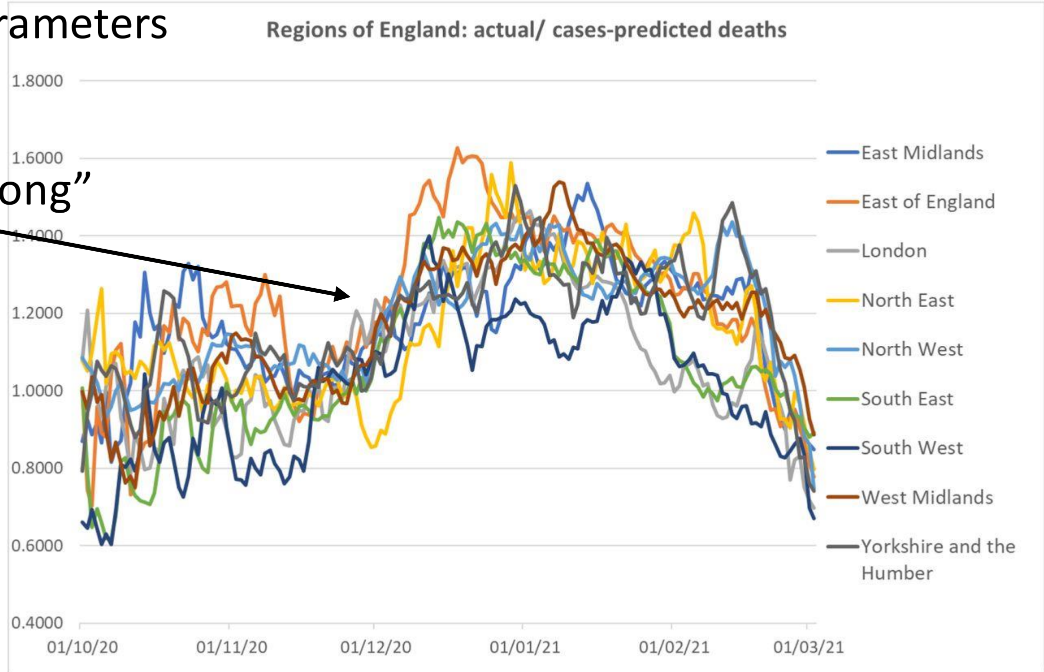
Case fatality ratios fall with vaccine roll out. Age correlations – oldest first



Predicted Deaths with parameters fitted to "wild type"

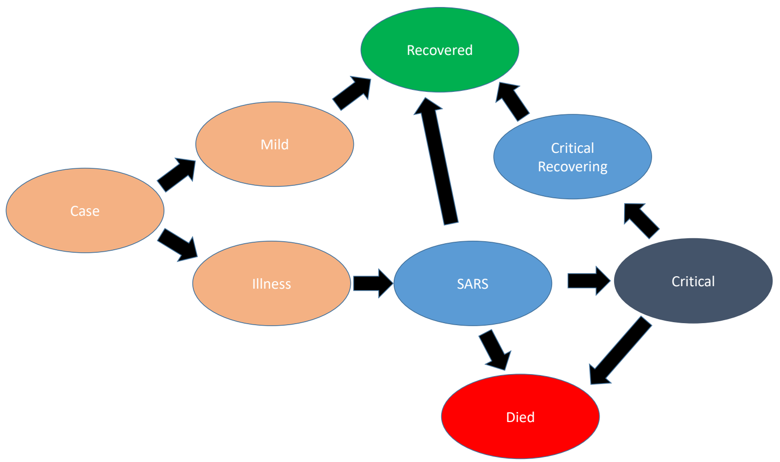
Parameterisation goes "wrong" in SE, then other regions

Prediction = data
Correct parameters



- Modelling Modes

1) Fixed parameters, watch how it breaks
2) **Optimise parameters: variants & vaccines to fit whole epidemic**
3) Optimise parameters to recent data, Medium Term Predictions

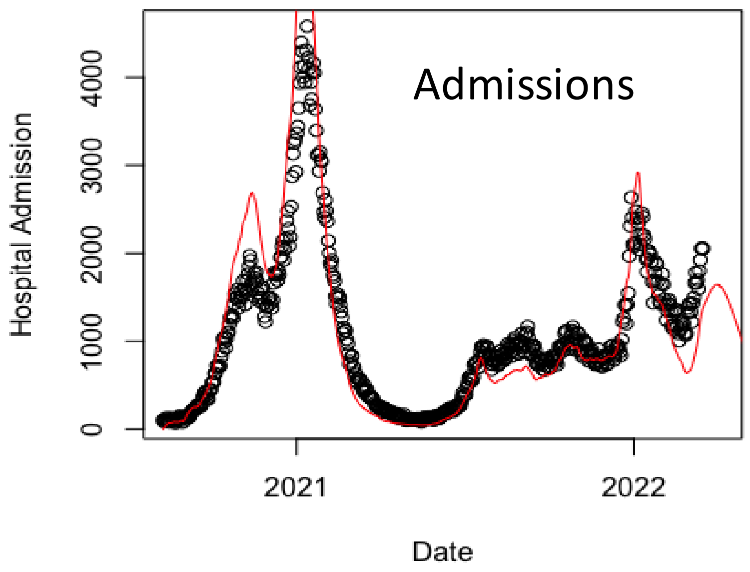


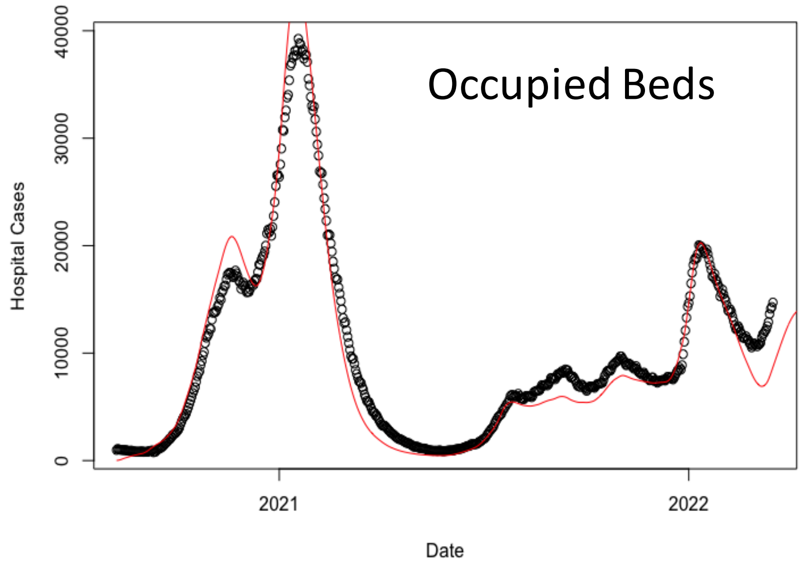
WSS: Type – 2 Hindcast Results

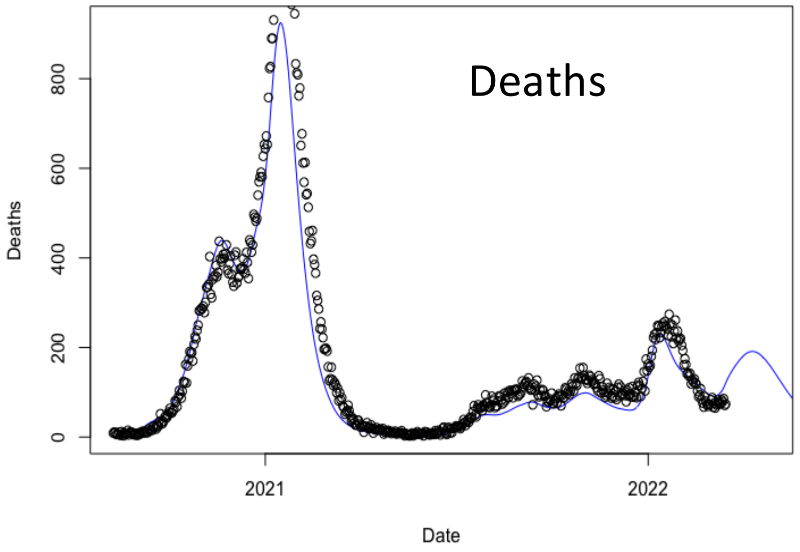
2) Hospital admissions

2) Hospital occupations

2) Deaths

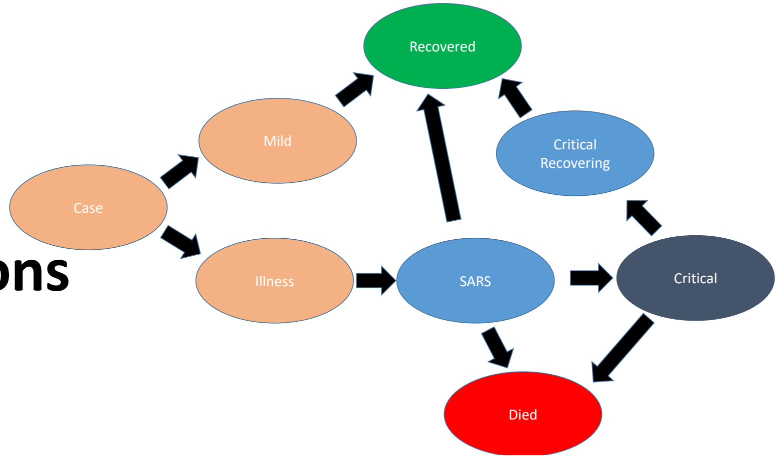






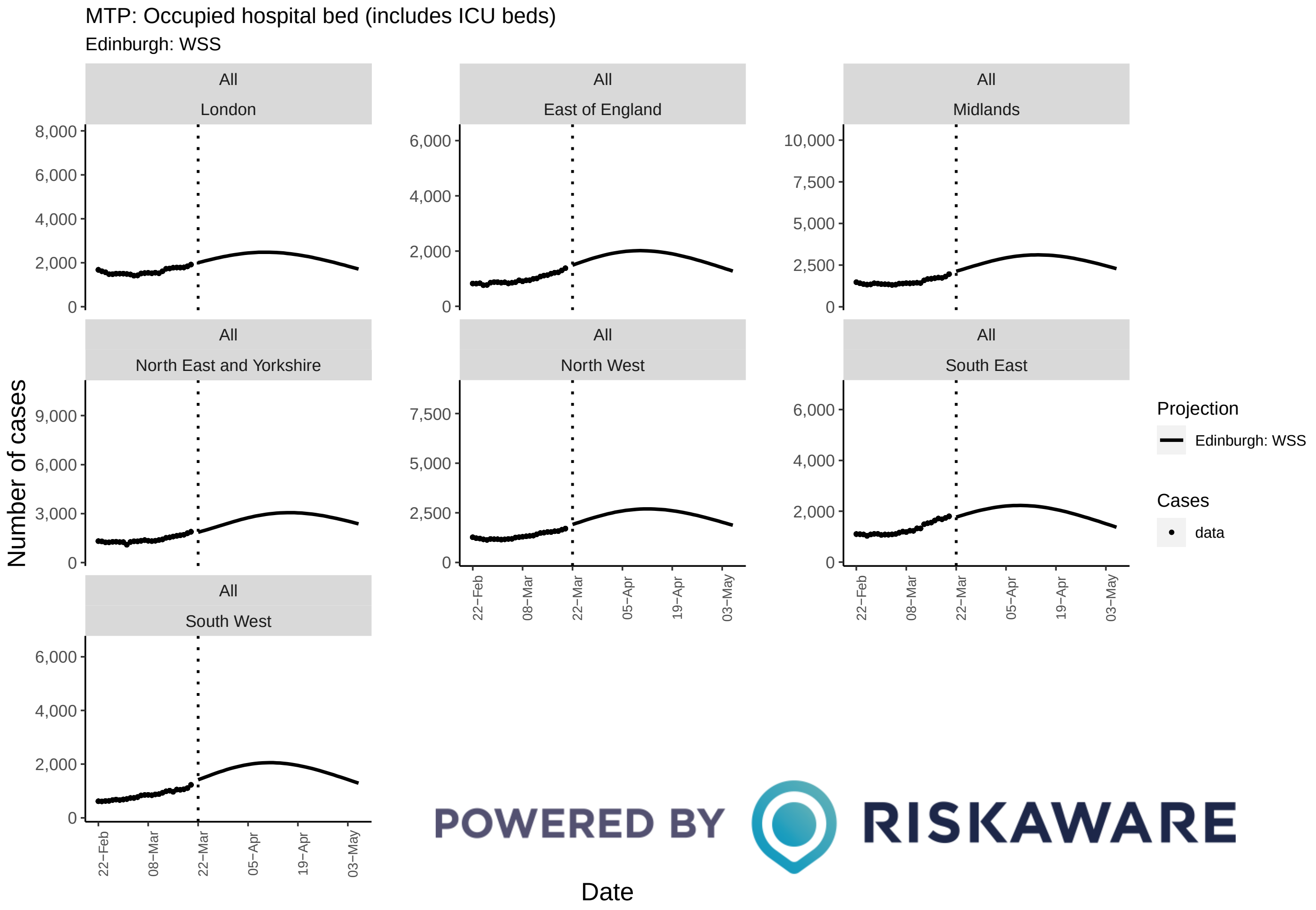
- Modelling Modes

1) Fixed parameters, watch how it breaks.
2) Optimise parameters: variants & vaccines to fit whole epidemic
3) **Optimise parameters to recent data, Medium Term Predictions**



WSS: Type – 3 Predicted Result

2) Hospital admissions
2) Hospital occupations
2) Deaths



WSS Predictions of hospital bed occupations.

Submitted to SPI-M/DSTL CrystalCast yesterday

Grey shading – “error bars” – next project is to formalize how to quantify uncertainty in
Statistics/Data/Model

POWERED BY RISKAWARE

WSS model driven by cases.

WSS Kernels informed by other data

Designed to calculate what is requested by JBC, using available data.

No attempt to model transmission

No attempt at transferability to other epidemics

Hindcast, Nowcast and Predictive capacity

Features added only when nowcast fails to be parameterisable:
Age-weighting, variant & vaccine adjustment

- Is R really R?
The Urban – Rural paradox

To illustrate the effect of mixing on R, we examine a two population SIR model. Consider an urban population 1 which lives mainly in a high R-area ($R_1 = 2$), the rural population 2 which lives mainly in a low R-area ($R_2 = 0.5$). R_1 and R_2 follow the normal definition of R within the SIR model based on contact between individuals. For simplicity, we assume the populations are of equal size. The urban population spends some fraction x of its time in the rural area.

R_1

R_2

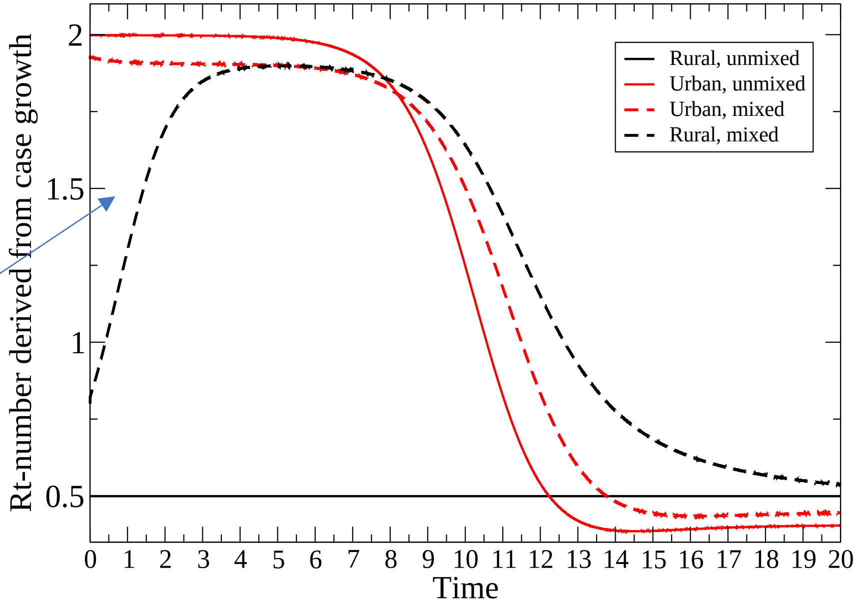
$$\frac{di_1}{dt} = (1-x)(R_1-1)s_1 i_1 + x(R_2-1)s_1 i_2 - i_1$$

$$\frac{di_2}{dt} = x(R_1-1)s_2 i_1 + (1-x)(R_2-1)s_2 i_2 - i_2$$

where the populations s, i, r are fractions of the total, and $\frac{ds_1}{dt}$ and $\frac{dr_1}{dt}$ follow trivially from the terms in $\frac{di_1}{dt}$.

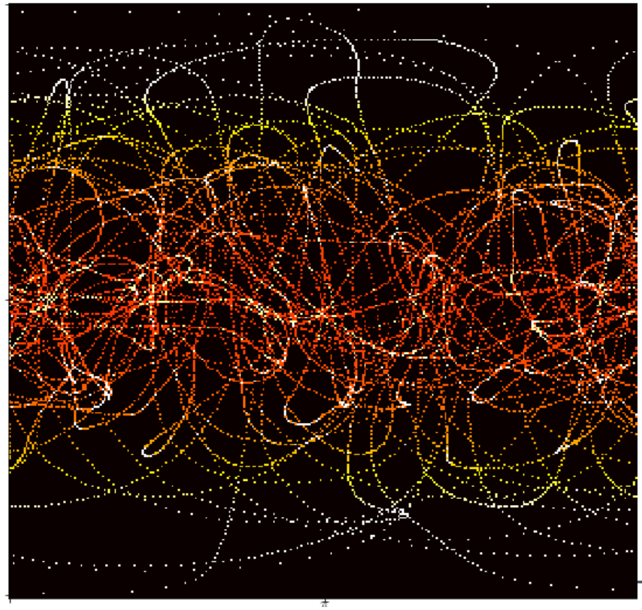
Define Rt by: $$\frac{dI(t)}{dt}/I(t) \equiv \frac{d\ln I(t)}{dt} = [(R_t - 1)/\tau]$$

A small amount of mixing (x) means the R measured in the rural area is actually the R in urban area



Rapid Assistance in Modelling the Pandemic,
And an exploration of the Imperial Individual-based Model

Graeme Ackland



CSEC, SUPA, School of Physics and Astronomy, The University of Edinburgh, UK

RAMP: Rapid Assistance in Modelling the Pandemic

A call for voluntary assistance from qualified modellers to help with EPI-Modelling

1800 responses, many on behalf of large teams

Actions:

Coordinate with SPI-M and SAGE over priorities

Embed volunteers in existing SPI-M Groups

Facilitate effective Rapid Review of preprints

Establish Newton Institute Programme

Convene various Task Teams to initiate new research

March 2020: Royal Society coronavirus response

Embed volunteers in existing groups

Dozens offered on secondment to SPI-M groups

200+ more co-opted into Task Teams after set-up

- Data cleaning / pipelining
- Coding / checking / red-teaming
- Direct research collaboration

Significant minority from commerce/industry:

Banks, retail, nuclear power, logistics, transport....

RAMP forums: Crowdsourced Review

Scan and scrutinize emerging literatur

Feed through promising items to RRG

…then onward to SAGE /SPI-M

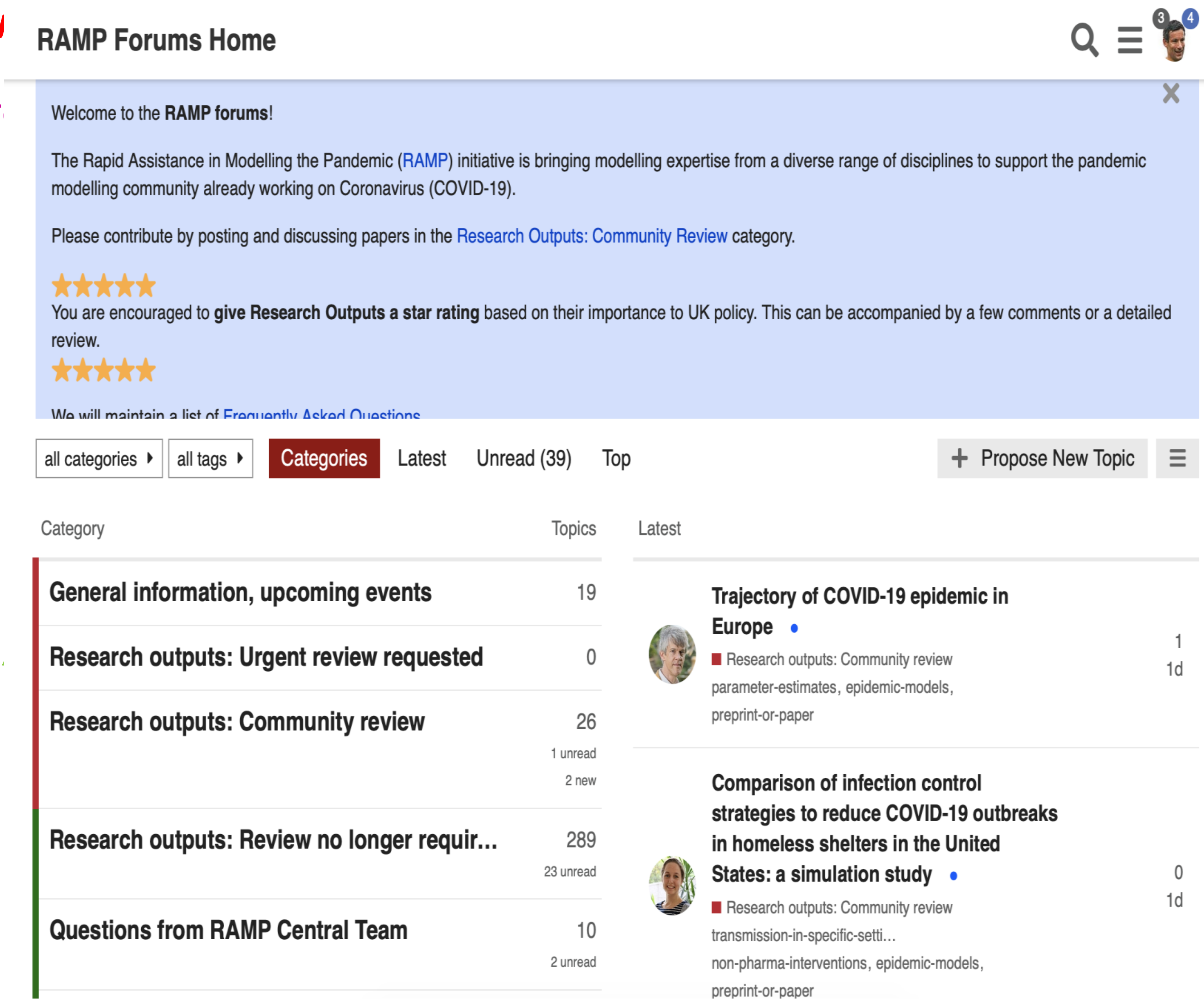
445 Members, most are/were active

300 preprints reviewed

10% sent for expert SAGE/SPI-M

[Moderator team led by Jon Pitchford,

Jamie Wood]



Rapid Review Group [Alain Goriely, Philip Maini]

- Solicit expert review of reports/papers/codes
- Nominated by SPI-M, SAGE, Forums, RAMP, No. 10
- 24/48hr turnaround 1 paper /day April-July
- Send good stuff (with reviews) to SAGE/SPI-M etc.

Newton Institute Programme [David Abraham, Deirdre Hollingsworth]

Infectious Dynamics of Pandemics 5 May – 31 Dec

- Fully online programme (their first) set up in one month (usually 2 years)
- 120+ global participants including many speakers from SPI-M

RAMP Task Teams (large)

New Epidemic Modelling (ca 200 people)

- SCRC consortium: 100 scientists, 21 Universities

  UKAEA, Man Group PLC, BioSS, Invenia Labs

Multi-model platform with shared data pipeline

- PyRoss: DAMTP, Cambridge 25 people

Codebase for compartment models with inference

- + Smaller teams on epi-economics, regional, etc.

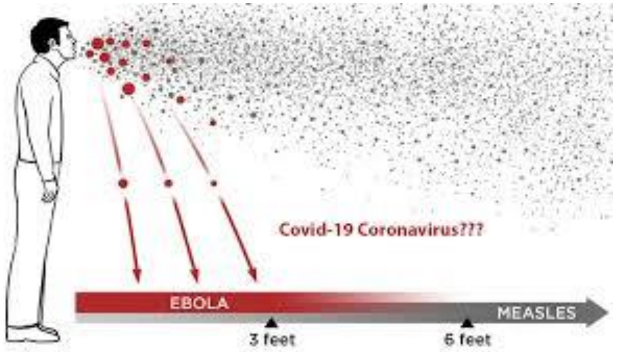
[led by Graeme Ackland]

Urban Analytics (ca 30 people) [Mark Birkin]

- Turing Institute, Leeds, Exeter, Cambridge, UCL, Connected Places Catapult,
- Met Office, Improbable

Adding 'disease state' layer to urban analytics models

Native high-res spatial / behavioural detail



Environmental and Aerosol (ca 200 people) [Paul Linden]

- Cambridge, UCL + multiple other Universities

Fluid mech of respiration/ ventilation/ vocalisation

Dispersal by human movement (CO_2 as virus proxy)

Transportation, Schools case studies

Human Dynamics in Small Spaces (ca 40 people) [Mike Batty]

UCL, U Greenwich, Cambridge BAE, Tesco, Network Rail, Arup, OS, PWC, Sainsbury's, Connected Places Catapult

Extend human dynamics studies down city-scale to supermarket/office/train-station etc

RAMP Task Teams (small)

Within-Host Dynamics [Led by Mark Chapman]

St Andrews, St Georges, Columbia et al

Viral load model, multiscale within-body modelling...

Comorbidities [Led by Ruth Keogh, Karla Diaz-Ordaz]

LSHTM et al,

Risk factor estimation for obesity, diabetes, smoking, etc., stratified by age/gender...

Structured Expert Judgement [Led by Willy Aspinal]

Bristol et al,

Forecasting effects of opening schools...

Steering Committee/forums/RRG remain in place

General Comments

Great offers from (skillful) volunteers
Light-touch guidance from Steering Committee
Autonomous leadership teams essential
(although, hard to assess how useful it all really was)

Genuine gratitude from SPI-M / SAGE and others

Major Obstacle:

- Data access beset by GDPR and secrecy issues.
  [Negotiations > RAMP lifetime]

Open and reproducible pandemic modelling as a national capability

Continuation project

Modelled on the Collaborative Computing Projects in EPSRC, community building initiative around a common set of codes.

Extending a Github/Microsoft initiative to improve open code and data structures, accessible through a single User Interface

Submitted as a UKRI proposal. (With Software Sustainability Institute, github + Deirdre Hollingsworth & Rich FitzJohn)

Reproducing "Report 9". Why?

- Report 9… "The science" "Professor Lockdown".
- Unavailability of code
- I like atomistic modelling and Statistical Mechanics.
- Curious results in tables of report 9.

Back of envelope: 70M people, 1% CFR, 60% Herd immunity = 420k deaths

Report 9, Appendix 1

	Trigger (cumulative ICU cases)	PC	CI	CI_HQ	CI_HQ_SD	CI_SD	CI_HQ_SDOL70	PC_CI_HQ_SDOL70
R0=2.4 Peak beds	100	156	122	85	123	85	61	57
	300	157	122	85	121	78	60	53
	1000	158	122	85	111	65	60	42
	3000	161	122	85	89	45	60	35
R0=2.2 Peak beds	100	125	105	70	120	98	50	83
	300	125	105	70	115	92	50	75
	1000	126	105	70	106	76	49	59
	3000	132	105	70	86	51	49	40
R0=2.4 Total deaths	100	501	421	349	443	406	258	363
	300	499	421	349	440	393	259	360
	1000	498	421	349	432	375	257	356
	3000	498	421	349	415	354	258	347
R0=2.2 Total deaths	100	451	367	308	423	395	238	373
	300	448	367	308	419	384	236	369
	1000	445	367	308	412	366	234	360
	3000	445	367	308	396	340	234	351

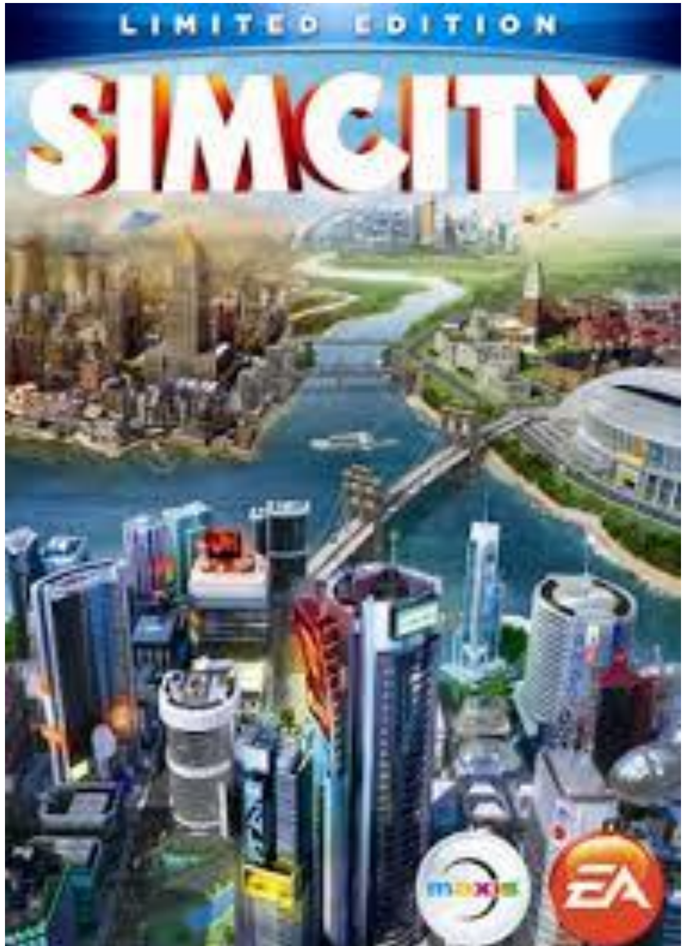
Interventions considered in Report 9

Table 2: Summary of NPI interventions considered.

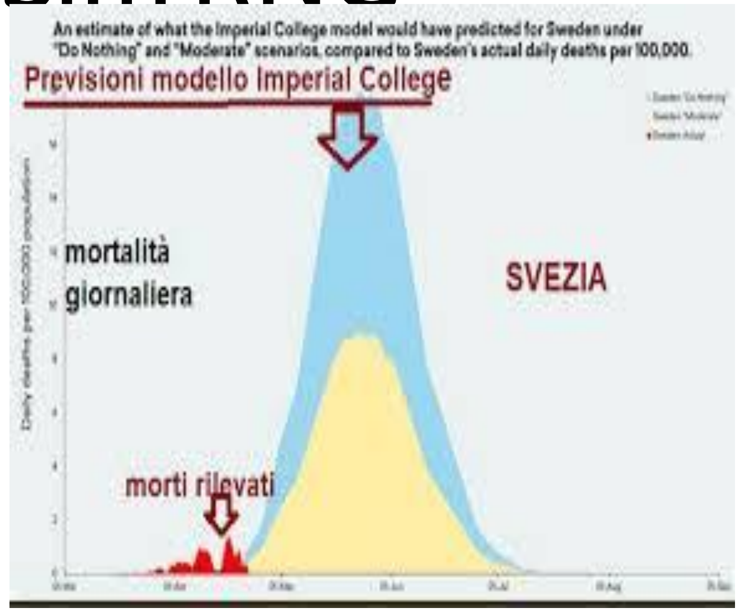
Label	Policy	Description
CI	Case isolation in the home	Symptomatic cases stay at home for 7 days, reducing non-household contacts by 75% for this period. Household contacts remain unchanged. Assume 70% of household comply with the policy.
HQ	Voluntary home quarantine	Following identification of a symptomatic case in the household, all household members remain at home for 14 days. Household contact rates double during this quarantine period, contacts in the community reduce by 75%. Assume 50% of household comply with the policy.
SDO	Social distancing of those over 70 years of age	Reduce contacts by 50% in workplaces, increase household contacts by 25% and reduce other contacts by 75%. Assume 75% compliance with policy.
SD	Social distancing of entire population	All households reduce contact outside household, school or workplace by 75%. School contact rates unchanged, workplace contact rates reduced by 25%. Household contact rates assumed to increase by 25%.
PC	Closure of schools and universities	Closure of all schools, 25% of universities remain open. Household contact rates for student families increase by 50% during closure. Contacts in the community increase by 25% during closure.

CovidSim:
github rewrite of Ferguson's code
Porting and redteaming by UoE

"Like SimCity without the graphics"
Over 900 Input parameters



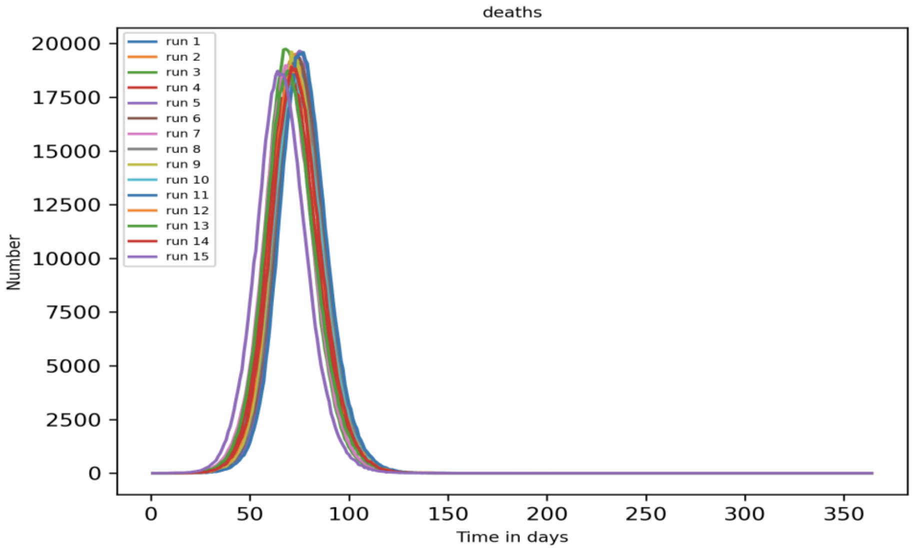
How to misrepresent data – CovidSim RNG

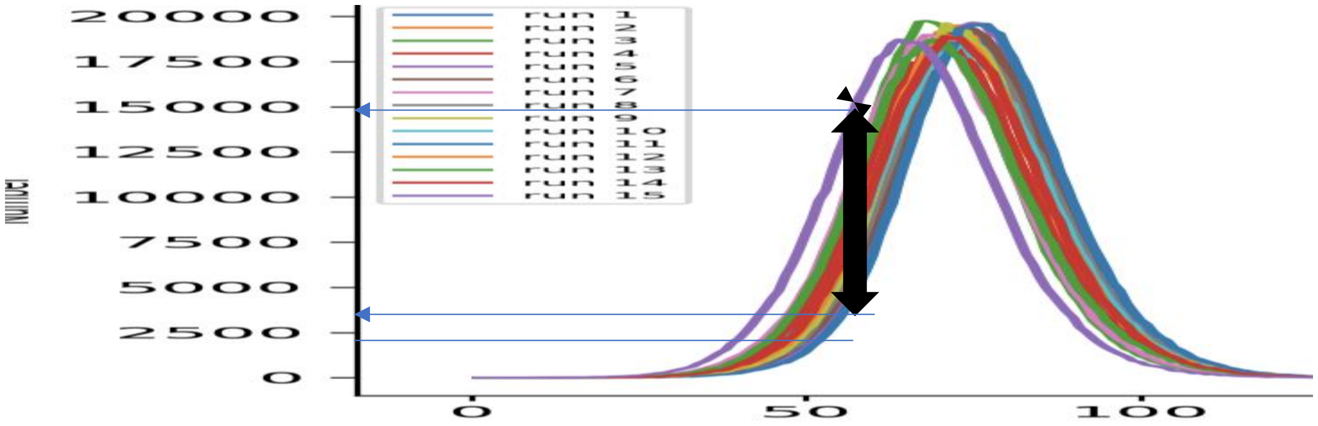


- RAMP – github rewrite then UoE redteaming, Wynne et al.

Found several "issues", including Random number seed initialization. Stochastic effects change the onset, but don't affect the behaviour much.

Unless you want to stretch the truth.





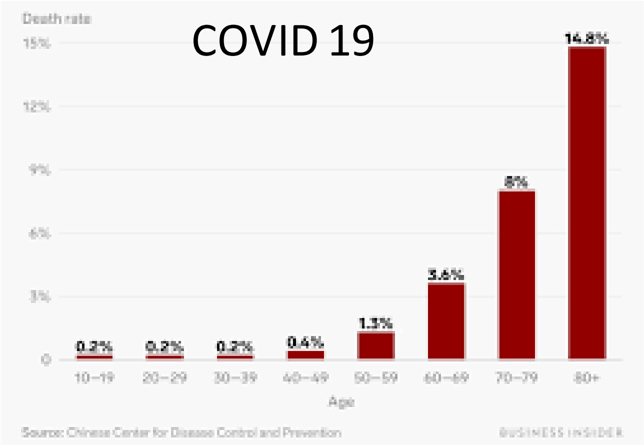
Random number error means CovidSim is wrong by 12000 deaths per day. 400%.

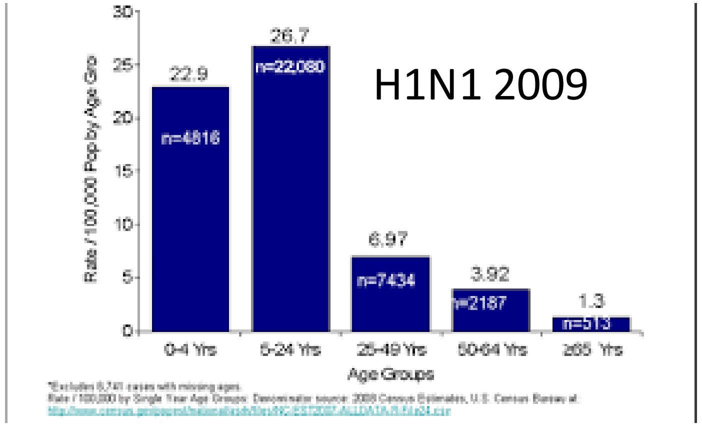
Demographics of COVID-19

Under 65s account for

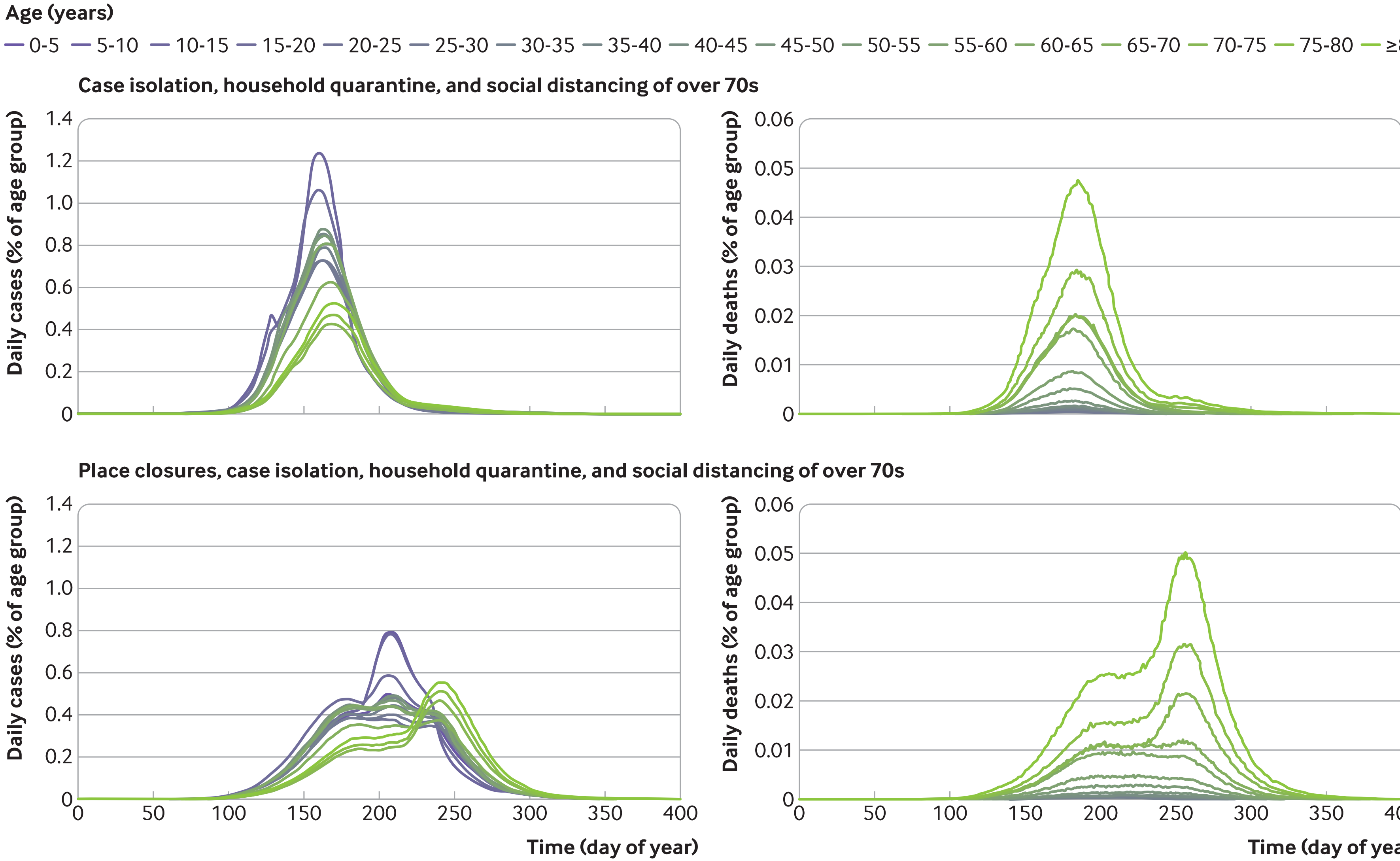
<3% of COVID deaths

>95% of Spanish 'flu deaths

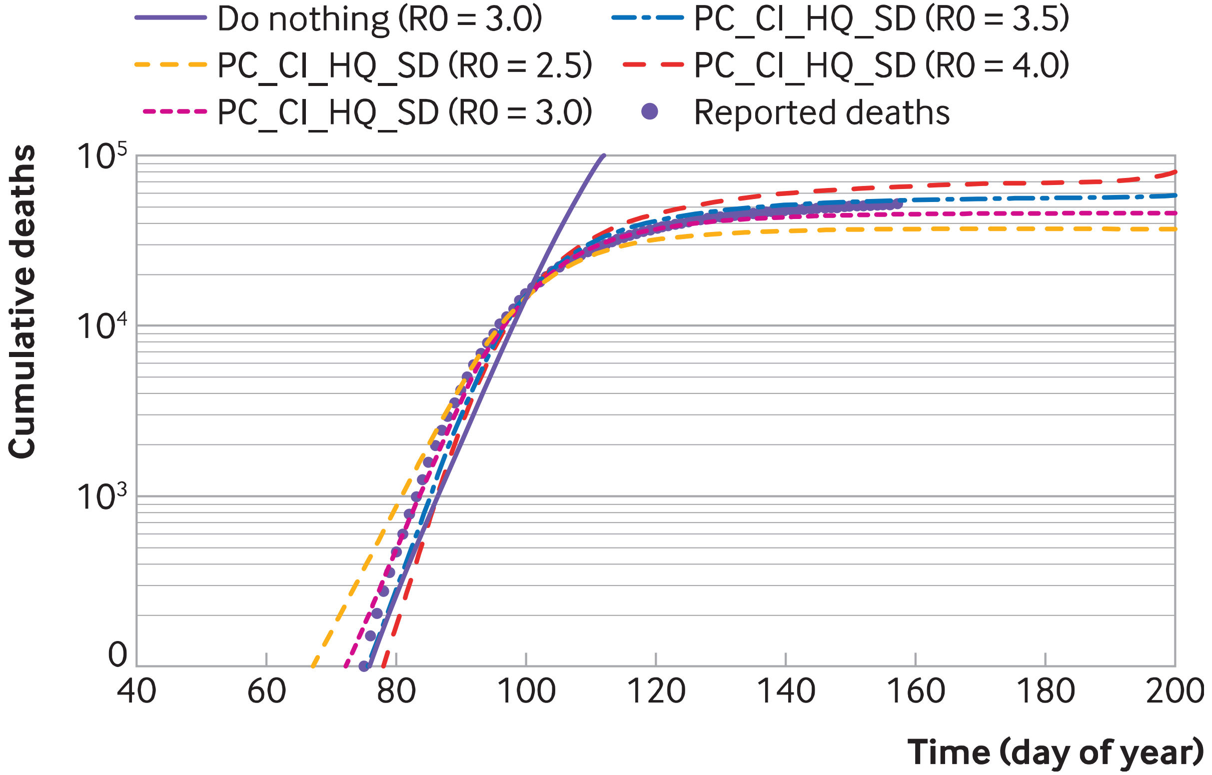




Covidsim predictions: Cases (left) Deaths (right)



- Fit R0 to subsequent data
- Predicted vs actual deaths, best fit is R0=3.5 (original: 2.4)
- Right truncation before second wave. (200 days)

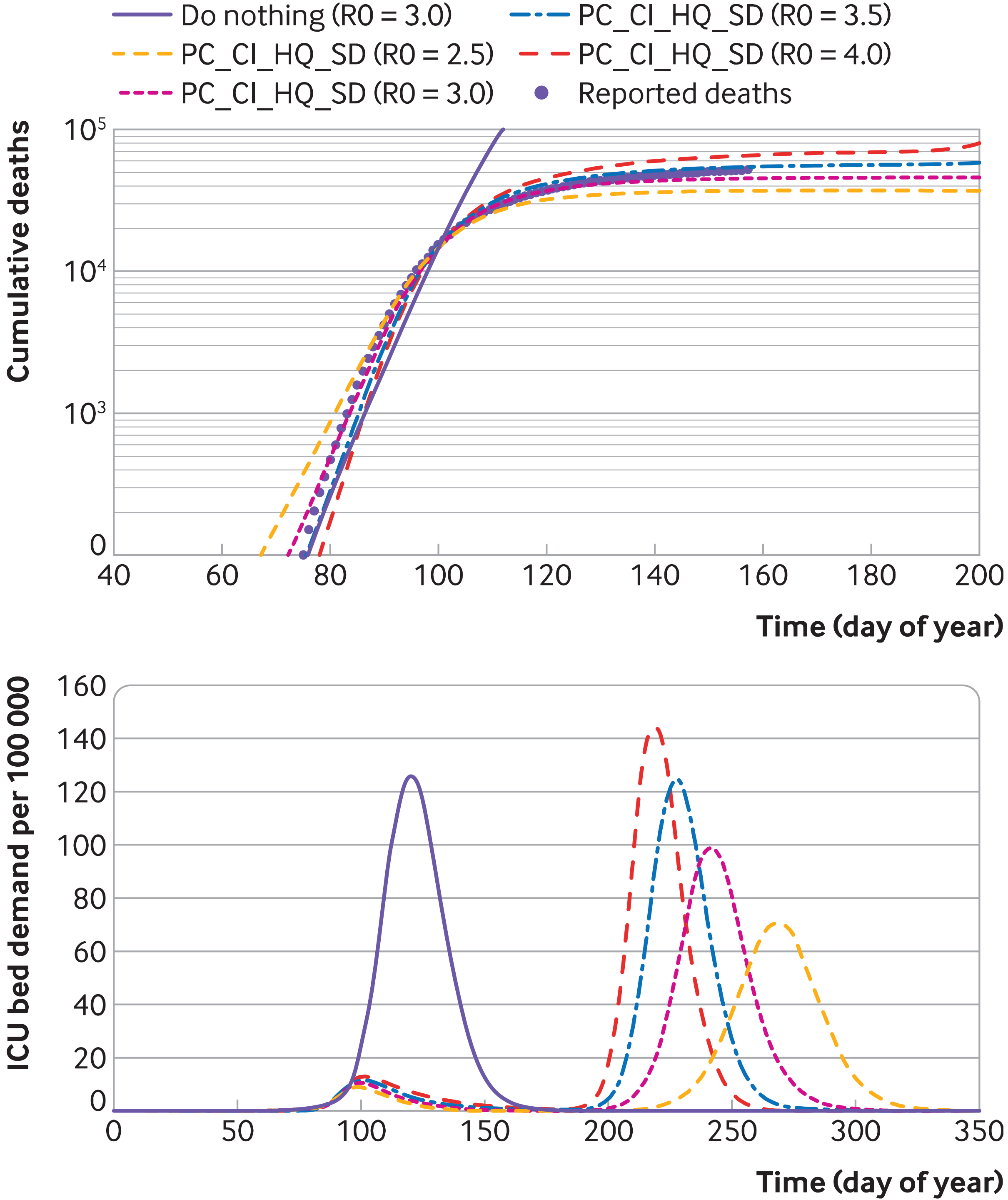


- Fit R0 to subsequent data

- Predicted vs actual deaths, best fit is R0=3.5 (original: 2.4)

- *Right truncation before second wave. (200 days)*

- Unmitigated second wave… Similar magnitude to "do nothing"
- Lower R0 mimics "New Normal"

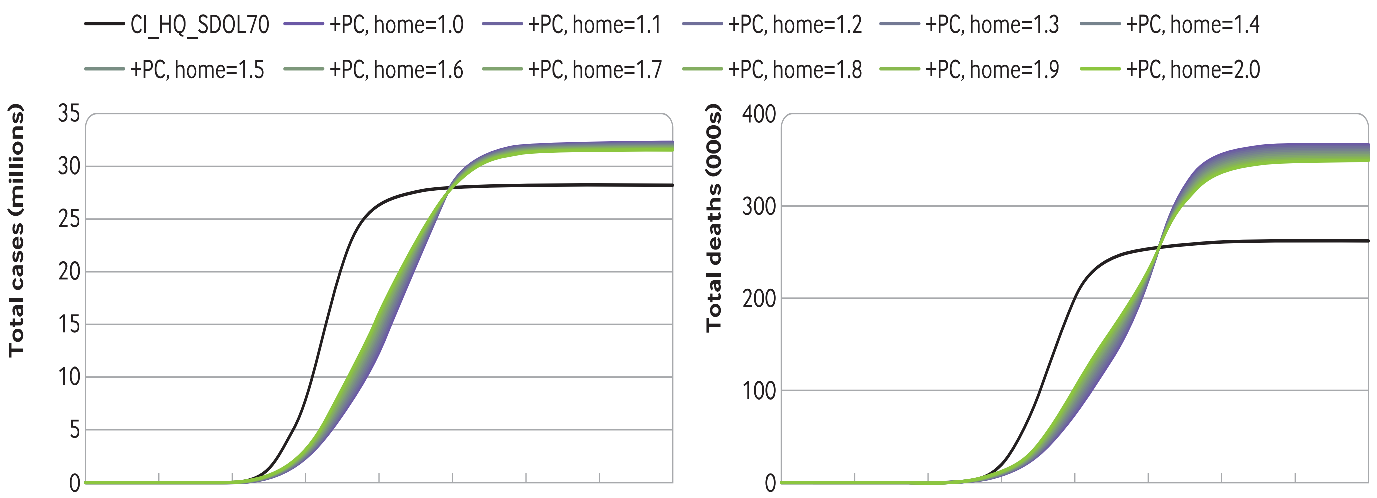


“If the kids are at home they spread it at home more.” - Is not relevant

Case Isolation, Home Quarantine, social distancing enhanced for over 70s

Then close schools and you...

1/ Flatten the curve
2/ Reduce ICU demand
3/ Increase long term deaths



“If the kids are at home they spread it at home more.” - Is not relevant

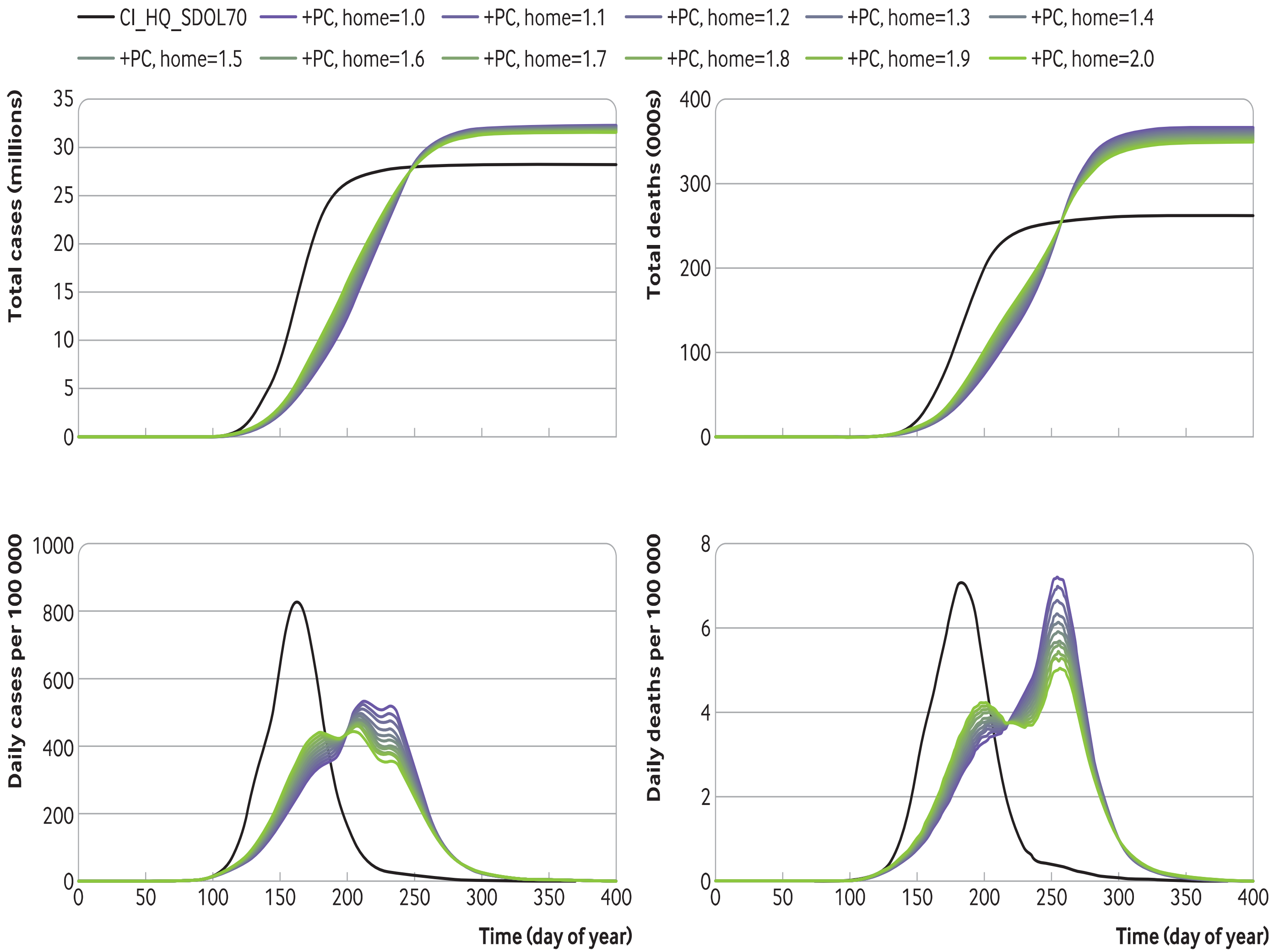
Case Isolation, Home Quarantine, social distancing enhanced for over 70s

Then close schools and you...

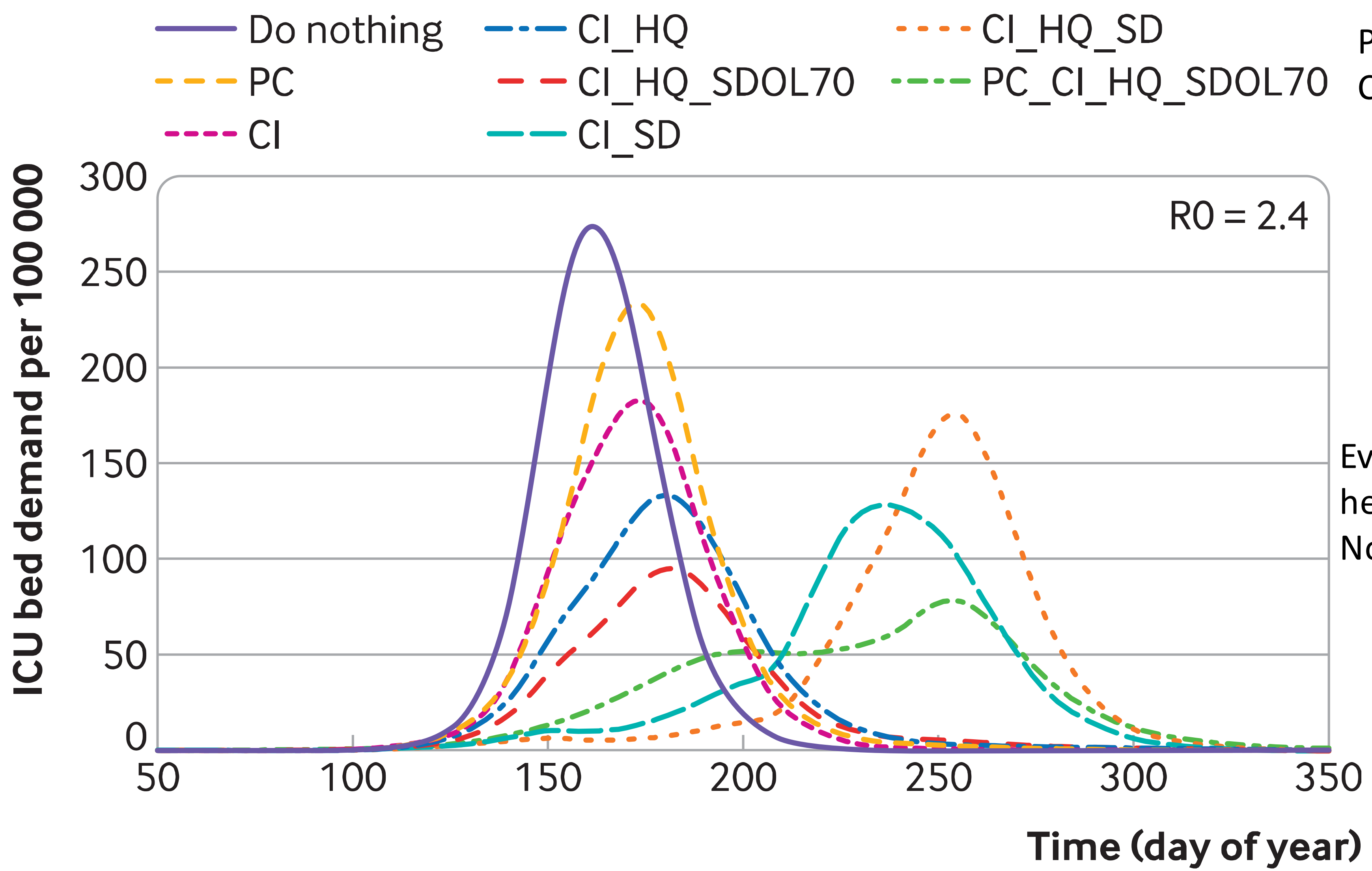
1/ Flatten the curve
2/ Reduce ICU demand
3/ Increase long term deaths

WHY?

Investigate various enhancements of contact at home (lots of overlapping curves), no significant effect on long-term outcomes.



Actual interventions are those predicted to be most effective at "Saving the NHS"



PC School/Uni Closure
CI Case Isolation

Every intervention helps with the slope,
Not the total numbers.

Personal View – weaknesses of the model

- No vaccine, just right truncation

- Too many parameters (flu-based) to disentangle sensitivity

- No special consideration of care-home / nosocomial transmission

What about Herd Immunity?

- CovidSim epidemic ends with Herd Immunity and 200-500k deaths

- Well mixed result Rt=1; => 1-1/R0,   with R0=3.5 about 70%.

  Can't talk about herd immunity, but OK to talk about Rt=1

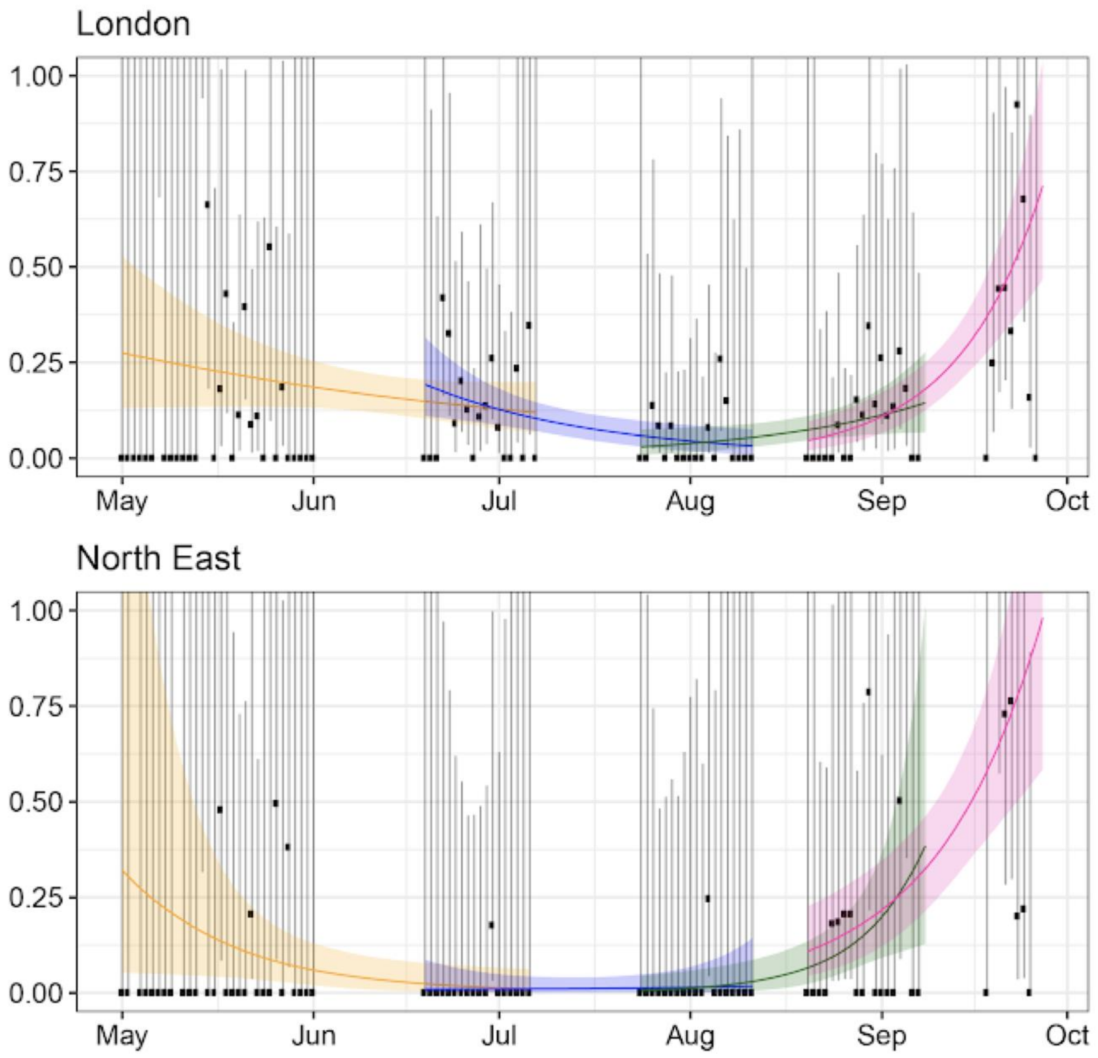
- Herd Immunity is not explicit in an IBM …

  but can define as cases when Rt=1.

- Predicts about 15 million cases… or 25%
- "Overshoot"   Many deaths occur *after* Herd Immunity achieved. distinguishing factor between scenarios for final mortality.

React study – prevalence model

- React, from Imperial college, is the largest randomised study of incidence.
- Black points are actual data…



Summary slide…

SAGE knew in March already that …

COVID is not flu.

The chosen strategy was optimal for reducing ICU peak

School closures risk extra deaths

Reopening before herd immunity would give second wave