An agent-based model of the 2020 international policy diffusion in response to the COVID-19 pandemic with particle filter

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Summary

Global problems, such as pandemics and climate change, require rapid international coordination. One notable example was the imposition of 'lockdown' policies in response to the COVID-19 pandemic in early 2020. Here we build an agent-based model of this rapid policy diffusion, where countries constitute agents and with the mechanism for diffusion being peer mimicry. We utilize data assimilation to constrain the model against observations in 'real-time'. We find that the model is able to predict the policy diffusion relatively well and that the data assimilation improves the fit to the data.

KEYWORDS: Agent-based modelling, data assimilation, similarity metrics, international policy, COVID-19

1 Introduction

Several global challenges hinge on an international coordination of policy. Climate change requires a global fossil fuel phase out (Shukla et al., 2022). Prevention of the next pandemic requires a cohesive bio-security strategy as well as minimum interference with ecosystems (Morse et al., 2012). International security requires negotiation and a willingness to resolve conflict by peaceful means instead of resorting to violence (Bercovitch and Jackson, 2009). Moreover, many of these challenges are immensely time pressing. With respect to climate change, for instance, only few years remain to achieve international climate targets. In the case of a pandemic, a few days of policy inaction can lead to substantial loss of life (e.g. see Spooner et al., 2021).

There has been one recent instance of international policy coordination that was surprisingly rapid, decisive and homogeneous – the implementation of full-scale lockdowns as a response to the COVID-19 pandemic. In March 2020 nearly every country in the world implemented stringent lockdowns, including closures of public venues and schools, mask wearing duties and mandatory home office working. On the first of March 2020 only around 8% of countries had implemented such stringent

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measures, by the end of March 2020 more than 90% had (Ritchie et al., 2020). Figure 3 displays the rapid change in lockdown adoption during March 2020.

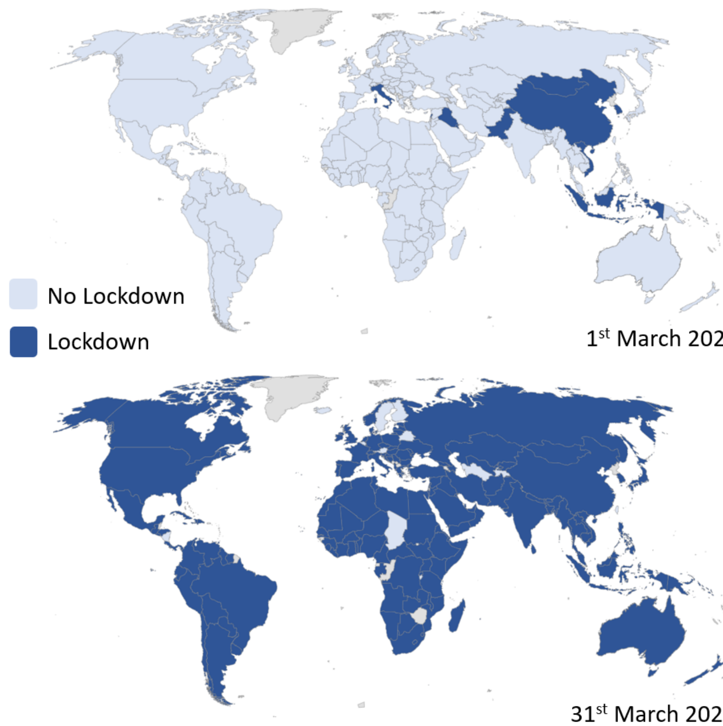

Figure 1: Lockdowns around the world March 2020

The rapid tipping point in March has been debated little from computational and simulation-oriented viewpoints, although there is some quantitative work on the drivers of lockdown policies. To name one notable study, Sebhatu et al. (2020) emphasized the remarkable degree of homogeneity in lockdown adoption by largely heterogeneous countries in a short amount of time. They conclude that the diffusion of lockdown policy resembles peer-adoption processes in which countries mimicked other countries to cope with the threat posed by the pandemic. This insight suggests an agent-based modelling (ABM) approach to further elucidate the diffusion mechanisms and perhaps generalize them.

The aims of our work are to (i) better understand the influence of peer mimicry on national lockdown adoption and (ii) build a model that could be used in the future to predict short-term national policy changes before they occur.

With respect to the second aim, an additional challenge is how to capture the rapidity with which countries adopted lockdown-related policies. Due to this rapidity even small model prediction errors will lead to the simulated tipping point occurring too early, or too late, and subsequently very poor model performance. Hence we employ a novel methodological feature with respect to ABMs to try to align the model with the evolution of the real system; that of data-assimilation (DA). This means we constrain the internal model state with regularly updated real-world observations, thereby improving the accuracy of future model predictions. In our case, these new observations include whether a country has adopted a lockdown or not. The DA approach we choose is a particle filter since it is well-suited for highly non-linear systems and is able to cope with categorical variables; a feature our model relies on. Moreover it has been applied to a few ABMs already, although they were mostly simulating pedestrian dynamics (Wang and Hu, 2015; Malleson et al., 2020; Ternes et al., 2022).

2 Methods

2.1 Model

The model is a data-driven agent-based model implemented in Python-MESA. The principal idea of the model is that the diffusion of lockdown policy across countries can be described independently of the actual COVID-case numbers across countries, at least for the period of interest which is March 2020.

The main diffusion mechanism is that countries take note of which other countries already have adopted a lockdown and, if those include countries sufficiently similar to oneself, then they are likely to adopt a lockdown themselves.

Similarity between countries is measured along three dimensions: national income, degree of democracy and geographical location. National income is captured through Gross Domestic Product per capita in Purchasing Power Parity (World Bank, 2022), degree of democracy through the Democracy Index by the Economist Intelligence Unit (Economist Intelligence Unit, 2020) and geographical location simply through latitude and longitude of a country's capital (Techslides.com, 2016).

For measuring similarity, we use an equally-weighted average of each of the the three dimensions. In each case, the quantities pertaining to a dimension are normalised on the unit interval $[0, 1]$. We consider this similarity measure as a distance between two countries. The lower the distance between two countries, the more similar they are. In formal terms, the distance, d_{ij}, between country i and country j is:

$$d_{ij} = \frac{1}{3}\left(\underbrace{\frac{(x_i - x_j)}{(x_{max} - x_{min})}}_{\text{income similarity}} + \underbrace{\frac{(y_i - y_j)}{(y_{max} - y_{min})}}_{\text{political similarity}} + \underbrace{\frac{H(z_i, z_j)}{H_{max}}}_{\text{geo. proximity}} \right) \tag{1}$$

where x_i is the national income of country i, y_i the degree of democracy of country i, z_i is the location (in terms of latitude and longitude) of the capital of country i, and $H(a, b)$ denotes the haversine-formula for the distance between two points, a and b.

2.2 Data assimilation

We implement a particle filter to constrain the evolution of our model to real-world observations as they emerge. A particle filter is essentially a genetic algorithm on the different simulation runs, which are called the particles, filtering out the ones that do not fit incoming data well enough.

A particle filter assigns a weight to each model run based on a specified error metric which compares the model state to the observed system state. The filter can be thus denoted as the following set after Malleson et al. (2020):

$$P_k = \left\{ (x_k^i, w_k^i) : i \in 1, ..., N_p \right\} \tag{2}$$

where N_p is the number of particles, x_k^i is the state vector of the i-th particle at the k-th observation, w_k^i is the corresponding weight associated with particle i at observation k, and the weights are subject to the condition $\sum_{i=1}^{N_p} w_k^i = 1$.

3 Results

3.1 Predicting the policy diffusion curve

We first calibrate our model, then run both the base model and the model plus particle filter 1000 times. We reproduce the empirically observed diffusion curve from March 2020. Figure 2 panel (a) displays the actual diffusion curve (red-dashed line) and an ensemble of model predictions which have been treated by the particle filter (blue shades for specific confidence intervals). The solid black line is the mean of the model ensemble and tracks the data closely. As compared to a model ensemble without particle filter, the filtered ensemble performs better. The dotted purple line displays the ensemble mean without particle filter treatment and the grey dotted curves at the outer edges outline the 95% confidence interval without particle filter. In Figure 2 panel (b) we calculated the mean-squared error (MSE) for the ensemble without particle filter, and for the ensemble treated by the filter. Over time, throughout every day of March, the particle filtered ensemble performs better.

3.2 Predicting the exact transition of countries

While the model is able to predict the aggregate diffusion pattern relatively well, and with the help of the particle filter algorithm even improves the prediction, it remains challenging to tell precisely which countries transition into lockdown at a given date. For example, it is not particularly challenging for the (average of the) model to predict that around 60% of countries are in lockdown at 16^{th} of March but it is difficult to say whether the United Kingdom specifically already has adopted a lockdown or not. Figure 3 compares the predicted map of lockdowns for the 16^{th} March, employing the best particle from an ensemble of 100 particles, with the empirical map. In this specific simulation 116 countries have been correctly (magenta colored countries) estimated and 48 have not. The falsely estimated country either have adopted a lockdown in the model when they should not (yellow), or have not adopted a lockdown in the model if they should have (red). Due to the stochastic nature of the model, other simulations (particles) may perform substantially worse however.

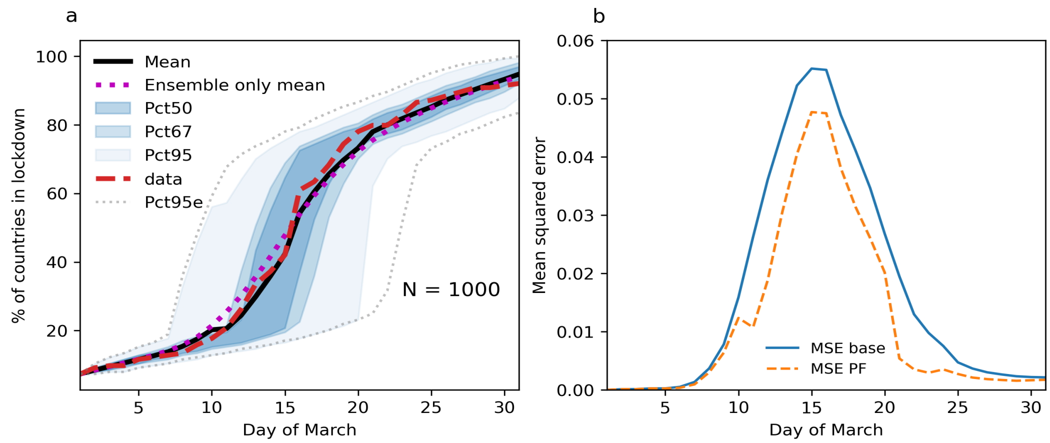

Figure 2: Particle filter compared to base model ensemble

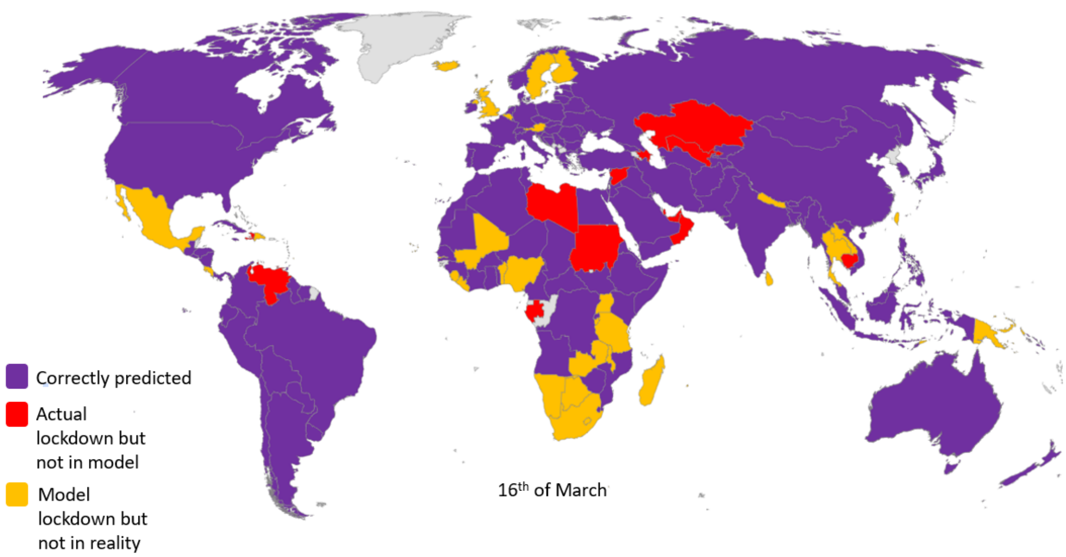

Figure 3: Lockdown prediction per country in specific simulation

4 Conclusion

In this paper we have demonstrated that a simple agent-based model based on peer mimicry suffices to capture the international diffusion of lockdown policies during the COVID-19 pandemic. Moreover we have shown that computational political science can be aided by data assimilation methods such as a particle filter to produce more accurate system descriptions and forecasts.

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Dr Oswald is a Postdoctoral Researcher in agent-based modelling and data-assimilation at the School of Geography, University of Leeds. He has a PhD in Ecological Economics and a M.Sc. in International Sustainable Development. His research covers inequality, climate change, complex systems and computational social science. Recently, he has taken interest in the merger of data science and complexity science and applications to global-scale challenges such as climate change, pandemics and inequality.

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Dr Malleson is a Professor of Spatial Science at the Centre for Spatial Analysis and Policy at the School of Geography, University of Leeds, UK. He has a PhD in Geography and undergraduate degrees in Computer Science (BSc) and Multidiciplinary Informatics (MSc). Most of his research focuses on the development of spatial computer models that help to understand and explain social phenomena. He has a particular interest in simulations of crime patterns, and in models that can be used to describe the flows of people around cities. More recently, he has become in interested in how 'big data', agent-based modelling, and smart cities initiatives can be used to better understand the daily dynamics of cities and reduce the impacts of phenomena such as pollution or crime.

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