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UNDERSTANDING THE SPATIAL PATCHWORK OF PREDICTIVE MODELING OF FIRST WAVE PANDEMIC DECISIONS BY US GOVERNORS

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ABSTRACT. The uneven outcomes of the COVID-19 pandemic in the United States can be characterized by its patchwork patterns. Given a weak national coordinated response, state-level decisions offer an important frame for analysis. This article explores how such analysis invokes fundamental geographic challenges related to the modified areal unit problem, and results in scientific predictive models that behave differently in different states. We examined morbidity with respect to state-level policy decisions, by comparing the fit and significance of different types of predictive modeling using data from the first wave of 2020. Our research reflects upon public health literature, mathematical modeling, and geographic approaches in the wake of the underlying complex pattern of drivers, decisions, and their impact on public health outcomes state by statetime line. Contemplating these findings, we discuss the need to improve integration of fundamental geographic concepts to creatively develop modeling and interpretations across disciplines that offer value for both informing and holding accountable decision makers of the jurisdictions in which we live. *Keywords: Accountability, COVID-19, decision-making, modeling, patchwork.*

While virtually everyone in the United States has felt the direct or indirect effects of the COVID-19 pandemic, the pattern of impacts has unfolded unevenly across the country. Scientists of all disciplines have been working to make better sense of what has essentially come to be seen as an ever-changing patchwork of factors and outcomes. Inspired in part by a metaphor from a May 2020 article in *The Atlantic* entitled "We Live in a Patchwork Pandemic Now" (Yong 2020), our paper reflects upon this phenomenon and a growing public recognition in the early months of the pandemic that while national scale statistics first started to plateau, the underlying patterns of the spread were highly varied and dynamic at the state level, as well as at smaller county and city scales, going up in some places while diminishing in others. It strikes us that COVID-19 represents a compelling case to not only illustrate how modeling efforts, whether explanatory or

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predictive, suffer the unavoidable Modifiable Areal Unit Problem, or MAUP (Gehlke and Biehl 1934; Openshaw 1984), but also to uncover a unique arc of this story, where the real-time unfolding of decisions to respond to the pandemic reveal a spatial struggle (Leitner et al. 2008). Digging deeper, we can see how decision makers like governors, mayors, and state public health officials have issued a patchwork of policies, in absence of a cohesive national approach that forced the weight of the response to a particular intermediate scale, serendipitously opening up a space for our discourse about modeling and its real-time relationship to decisions to be examined and reflected upon. Similarly, public adoption and compliance of protective measures have unfolded unevenly over the nation, as information and trust on this issue reflect a generally fractured society. We furthermore add weight to this argument by assessing how patchwork characteristics can even be seen in the way that scientific predictive models behave in different locations, which is explored in this paper in analytical depth.

Researchers have turned attention and effort to applying their respective knowledge domains and collectively combining known techniques in hopes to innovate and respond with timely insights to inform public policy and influence public behavior during the pandemic. They have formulated and answered questions at many different spatial and temporal scales of analysis. Predictive models and mathematical forecasts have become the currency of academic monitoring and discussion, and ideally, informing the public and elected officials. Most studies are direct—they track infection rates, prevalence dynamics, morbidity or mortality patterns, and even excess deaths to follow the coronavirus across the country. Sometimes studies incorporate decision making into the models, such as the timing or appearance of policies to close activities like schools, restaurants and bars, gyms, or masking. More rarely, however, models may seek to account for both the spatiotemporal nature of decisions and the spatial-temporal behavior of people living in these jurisdictions where the decisions hold sway and are intended to influence their mobility and behavior.

We are interested in powerful machine-learning models, which were widely used as predictive tools for decision makers. In this article, we do not intend to test models. We do not intend to provide an answer about which predictive approach is "best." Instead, we hope to structure a broader, interdisciplinary discussion unraveling the spatial incongruence among these contributing elements. We seek to explore how the human-physical complex system of a pandemic—including behavioral, decision making, and epidemiological data—may be inconsistent and incongruent with each other, and thus point to the centrality of fundamental geographic challenges in the production of knowledge about the pandemic. The importance of this framework is to underscore the need for explicit, well-justified attention to choices of spatio-temporal scale, relevant to the (real-time) decision-making context, to potentially improve transferability of findings (but not necessarily models) from one place to another, as well as to offer a measure of accountability for evidence-based decisions at the scales in which they are made. Ultimately, these insights hold true not only for outbreaks such as COVID-19, but also for understanding and responding to other public health concerns, such as disaster response or future infectious outbreaks.

To reiterate, the purpose of this exploratory discussion paper is not so much to identify a good model or assess a good modeling method, but the main purpose is to reflect upon fundamental geographic principles in the process of the scientific modeling in a real-time complex global pandemic in ways that inform decisionmakers and the public. We raise interdisciplinary awareness of such analytical challenges, and conclude with some recommendations on what we as a scientific community may learn from the first wave experience of COVID-19.

Background and Literature

Actions in the early days and weeks of the COVID-19 pandemic taken to mitigate spread disproportionately affects long-run impacts on public health. Such actions and consequences always entail spatiotemporal components, but linking certain actions to consequences is generally not straightforward in complex human-physical systems, such as a pandemic. The beginning of the COVID-19 pandemic in the United States witnessed a deafening lack of a unified federal response, including mismanagement in controlling the border, lack of workplace standards (Hanage et al. 2020), and not quickly ensuring enough primary protective equipment (PPE) for essential workplaces (Lagu et al. 2020). Additionally, the limited response that did come out of the federal government was slow, and at times confusing (Haffajee and Mello 2020). To make matters worse, the federal government failed to look at evidence-based practices learned from previous outbreaks and disasters to inform the guidelines that did make it to the public (Solinas-Saunders 2020). These sentiments led most Americans to think the United States' national response did a poor job at addressing the pandemic (Pew Research Center 2020). It also forced an interesting natural experiment on the scientific modeling community—to reckon with a set of actors—governors—to monitor and predict a novel coronavirus and the impacts of decisions that were made at this scale in absence of federal powers that typically provide some measure of coordination across states.

To provide context for this study, we first lay out the backdrop of public health dynamics, both in terms of COVID-19 and pandemics more broadly from the public health literature. The varied nature of virus transmission and resulting patterns of cases followed by deaths are in part attributable to the highly contagious character of the novel coronavirus, as well as physiological responses of infected individuals.

Secondly, we lay out a few relevant principles from the perspective of predictive mathematical modeling domains to provide some structure to assess the many attempts to understand moving parts of the pandemic. This also introduces the choice of methodologies explained later that illustrate the challenge of the MAUP.

Finally, we consider fundamental geographic problems within decision making contexts. Clearly the behavior of people—how they move and what precautions they take—matters a great deal, impacting upon the resulting spatial distribution of the disease. These individual decisions are affected both by advice taken directly from public health officials and by the policies put in place by decision makers with jurisdiction to restrict or require mediating activities over the landscape of places where people work and live.

PUBLIC HEALTH CONTEXT

After COVID-19 was declared a national public health emergency by the health and human services secretary on 31 January 2020 (U.S. Department of Health and Human Services 2020), U.S. states began taking their own approaches to address the pandemic within their borders. The response to such widespread outbreaks is by law the joint responsibility of state governors and the federal government. Some states took aggressive immediate measures to limit the spread of COVID-19, for example, declaring a statewide public health emergency or developing a coronavirus task force. Since the turn of the century, the United States has responded to a number of pandemics including Ebola (Gostin et al. 2014; SteelFisher et al. 2015), swine flu (Butler 2009; Coker 2009), and SARS (Park and others 2004; Rothstein 2015). In these responses, researchers were able to assess policy responses to limit disease spread in near real time. Preparation plans are considered a major factor in influenza pandemic preparation, however, these plans must be constantly adjusted and updated based on lessons learned (Leung and Nicoll 2010). Others argue that proper plan execution is more important than the plan itself (Gibbs and Soares 2005). A stark example is found in critiques of responses to Hurricane Katrina. The hurricane itself exposed breakdowns in the chain of support for disaster relief, leaving communities that were already vulnerable in a state of heightened vulnerability (Quinn 2006). Many scholars noted extreme consequences of failing to improve emergency response efforts to disasters after Hurricane Katrina (Schneider 2005; Sobel and Leeson 2006; Holguín-Veras et al. 2007) saying, "unless we take to heart the lessons that Katrina teaches, especially improved systems for communication and coordination, we are likely to repeat the Katrina problems" (Kettl 2006). The same day of the first Ebola-related death in the United States in 2014, the Center for Disease Control announced increased screenings at JFK, Washington-Dulles, Newark, Atlanta, and O'Hare airports (Gostin et al. 2014) in response to the fact that 94 percent of people coming from Sierra Leone, Guinea, and Liberia (Ebola-affected nations) travel through these five airports (Center for Disease Control [CDC] 2014). This exemplifies a federal-level policy that affected state-level prevention efforts taking spatiotemporal realities into explicit account. Similarly, the federal government began an epidemiological surveillance system during the SARS pandemic that stemmed from state and local health departments working to report cases to the CDC (Schrag and others 2004). After declaration of the public health emergency in response to COVID-19, however, the robustness of a federal response seen in previous epidemics was absent. Except for some travel restrictions, minimal federal policies regulated activity to slow the number of new COVID-19 infections within national borders (Haffajee and Mello 2020; Gostin et al. 2020).

From the official White House "30 Days to Slow the Spread" report, suggestions on limiting COVID-19 cases were provided, but initial instructions tell residents to "listen to and follow the directions of your state and local authorities"; (The White House 2020). Delegating the bulk of the responsibility to the states to make COVID-19-related decisions precipitated a wide spectrum of state and local level policies, that we suspect further contributed to the patchwork character of the pandemic.

While the literature addresses the spatial variability of factors that lead to disease spread, we find limited scholarly work focused on patchwork policies in public health. Research on the opioid epidemic shows that while the epidemic has been a national emergency since 2017, the epidemic looks different depending on geographic location; (Rigg and Monnat 2015), socioeconomic status (Altekruse et al. 2020), race/ethnicity (Pletcher and others 2008; Alexander et al. 2018), age (Campbell et al. 2010), and gender (Choo et al. 2014; Graziani and Nisticò 2016). Some studies show that prescription-opioid misuse is more common in rural areas compared to urban centers (Keyes et al. 2014). Some studies reveal how federal policies on opioids need to not only be flexible, but also account for variations in state or local realities (Chakravarthy et al. 2011; Nelson et al. 2015). While sensitive to the geography of factors and of outcomes, these studies fall short of analyzing how the spatial variability of policies and choice of spatial unit of analysis relate to accountable decision making.

Journalistic coverage of COVID-19 highlights the need for understanding the ways outbreaks operate as a patchwork over space. *The New York Times* used data from the University of Oxford to visualize varied outcomes, concluding, "the surge is worst now in places where leaders neglected to keep up forceful virus containment efforts or failed to implement basic measures like mask mandates in the first place" (Leatherby and Harris 2020).

Swift responses are essential (Mallinson 2020; Pikoulis and others 2020), but the ability to project future outcomes is also a key component of preparedness. Examples of this include the response to the September 11, 2001, terrorist attacks future implications on mental health and environmental effects (Rosenfield et al. 2002; Reibman et al. 2016); the 2003 outbreak of SARS (Smith 2006; Krumkamp et al. 2009), the 2014–2016 Ebola outbreak (Maffioli 2020), or H1N1 in 2009

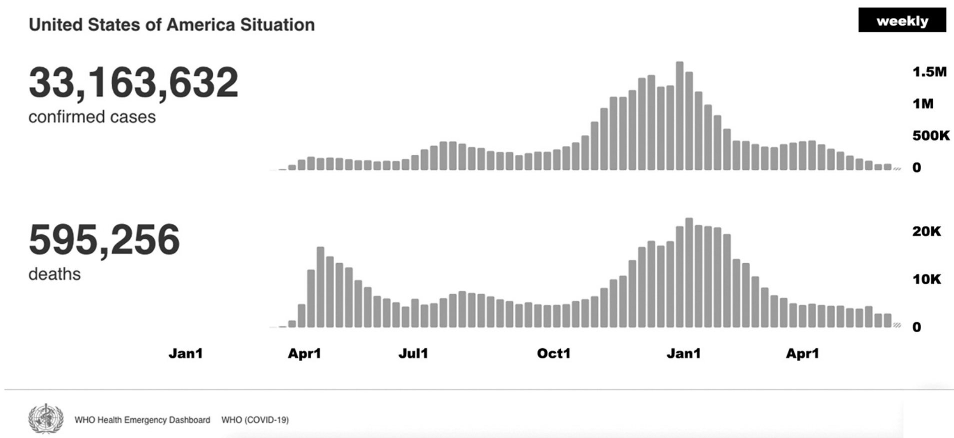

FIG. 1—COVID-19 Cases and Deaths for the entire United States, January 2020 to June 2021; Source: World Health Organization, Dashboard at https://covid19.who.int/region/amro/country/us

(Fineberg 2014), as well as efforts to minimize the impact of annual illnesses like the flu (Thomson et al. 2018). The scientific scramble to respond quickly and with predictive power to the COVID-19 pandemic is exemplified in the sheer number of rapid research grants awarded. The National Institutes of Health issued over 100 grants (National Institutes of Health 2019) and the National Science Foundation awarded roughly 900 grants (National Science Foundation 2019) to address various components of the COVID-19 pandemic.

As the United States might nationally be seen as riding out the "third wave," (see Figure 1), we emphasize that outcomes rely both on the public health decisions and mandates put in place to protect people, as well as their compliance. These vary by place. This national pattern continues to belie state-to-state variance in outcomes and the unfolding of many pandemics. This pattern adeptly illustrates the MAUP. In the following section, we consider how modeling efforts are confounded by this persistent analytical challenge.

MODELING CONTEXT

There has been a tremendous amount of interest in mathematical modeling and forecasting of the COVID-19 pandemic outcomes. Modeling approaches can be grouped into one of two general categories: forecasting models and mechanistic models. Forecasting models are typically statistical in nature and attempt to predict patterns in the data; where predictions "de-noise" the data and learn some latent representation of the phenomenon over time. Such models have been used both in the context of modeling past infectious diseases and in the context of predicting features of the ongoing COVID-19 outbreak. For instance, (Kane et al. 2014) use time-series modeling techniques (Box et al. 2011) to study past (influenza-like) outbreaks. Ceylan (2020) are examples of works that use time-series modeling techniques specifically in the case of COVID-19. Several complementary machine-learning-based sequence models have also been proposed in these scenarios (C. Wang and others 2020; Yang et al. 2020; Wang et al. 2020c).

On the other hand, mechanistic models (such as the SEIR model) attempt to directly understand and exploit the mechanism of the underlying virus under various disease-specific assumptions. There has been a flurry of activity in adapting such models (Wu et al. 2020). Others are hybrids between mechanistic and forecasting models (Reiner et al. 2020). Probability-based COVID future risk estimation approaches like COSRE (Sun and others 2020) provide risk estimation on a county level with strong reliability, supporting day-to-day decisions like risks related to spatial behavior and mobility to inform individual activities.

Regardless of choice among these models, they each require definition of time scale, spatial scale, and a scope of data to frame their application, and are susceptible to the MAUP. This holds implications for understanding past and future accountable decision-making.

DECISION-MAKING CONTEXT

Researchers, applying various models to understand this complex unfolding of the pandemic, will discover patchwork characteristics across spatial units of analysis. By this, we mean that while one would normally expect adherence to such standard geographical phenomena as Tobler's First Law of Geography (1970), patterns of the COVID-19 pandemic do not conform neatly, and how to frame which models is not an obvious exercise—especially in an interdisciplinary setting. In other words, near things might not in fact be more related than distant things when the default jurisdiction of public health decisions is relegated to each governor of every state. As we argue in this paper, given the way that public health outcomes rely on complex systems of spatiotemporal behavior—comprised both of individuals and of the special decision-making behavior of officials that influence individuals—there is underlying patchworkiness, or nonconformity, that can be observed beyond the diversity in state summary statistics of raw health outcomes like prevalence or morbidity. As we will discuss, the modeling performance itself exhibits patchwork results.

The variability and diversity of patterns of the pandemic(s) are revealed when researchers try to create data-driven predictive models of disease statistics in the presence of behavioral measurements such as mobility, mask-wearing, and activity-opening decisions. Our work specifically suggests that these observations beyond the obvious patchworkiness in measurable public health statistics are also reflected significantly in the patchwork patterns of decisions that in turn rely on the monitoring output and performance of predictive models created to explain the pandemic. We interpret this as evidence of the critical importance of the scale incongruence of decision making in responding to spatial phenomenon like the fast-moving coronavirus pandemic.

This observation builds upon a unique geographical problem first introduced in the *Geographical Review*, that recognizes the special nature of types of spatial decision-making behavior that both incorporate and influence individual decision-making behaviors (Solís et al. 2017). This Decision Accountability Spatial Incongruence Program (DASIP) is a special cause of the MAUP, which draws particular attention to the agency of special actors and sets of actors (elected officials, public administrators, stakeholders, CEOs) who are responsible for jurisdictions that potentially shape or, in the case of nonconforming behaviors such as protesting pandemic remedies, informs outcomes that in turn can affect others in important ways. This paper seeks to underscore the importance of the spatial scale of such decisions (for example, closures and mask mandates), and helps to shed light on how they may be incongruent with the desired outcomes (cases, deaths) in order to open interdisciplinary scholarly discussion and reflection on the unfolding of COVID-19. Furthermore, this framework helps us to ask whether and how decision makers can be held accountable in ways that are more congruent with the data, decisions, or impact.

As noted above, a gap in the public health and epidemic modeling literature so far is thus the explicit inclusion of study elements that focus on the role and scale of decision making as it relates both to this behavior and the outcomes of the pandemic. Furthermore, research that illustrates such problems by interrogating the spatial performance of the models incorporating decisions on COVID-19 is rare, if not nonexistent.

We seek to fill in some parts of this important gap by exploring not only the patchwork character of how decision making about the pandemic has unfolded, but also the patchwork character of model performance to make clear this geographical problem. This reflects upon how the research community has come to understand it, choosing to illustrate this at the state-level as one important key unit of analysis in this case. This is justified given that public health decisions were largely delegated from the federal level to governors (Djulbegovic et al. 2020; Jacobson et al. 2020).

The time period of analysis runs from January through September 2020, largely covering what is seen nationally as the first wave, representing a critical moment in the subsequent ability to manage the pandemic in later stages. By explicitly revealing the patchwork character of some categories of predictive modeling, we open a reflection on our role as a scientific community seeking to support monitoring and response in a context of this pandemic.

METHODOLOGICAL FRAMEWORK

We illustrate how this fundamental spatial challenge played out in the COVID-19 first wave by devising a multifactor, machine-learning model to fit one state, Arizona.[1] We then test the extent of this state-model fit to the other 49 states in terms of how well or poorly it can describe the spatiotemporal pattern found in other states.

To test this idea, we choose several simple representative modeling techniques to perform our analyses. While there has been some recent work; (Kang et al. 2020; Mollalo et al. 2020; Li et al. 2020) in understanding the spatial statistical behavior of COVID-19, these studies typically look at the spatial distribution of raw data/fundamental public health outcomes/corresponding to various metrics of interest related to COVID-19. To the best of our knowledge, ours is the first study that endeavors to do the same using the behavior of models themselves.

The models were built from an increasingly complex scaffolding of data layers in order to illustrate the persistent impact of the MAUP. We began modeling raw outcomes of the pandemic (without decisions[2]), that took changes in daily deaths to predict changes in deaths at a future date. We then added data to reflect decisions about closures, using mobility data as an indicator of the spatial behavior of residents, together with the morbidity data. This was used to understand at what future date changes in public health outcomes would occur, and computed changes in those outcomes themselves. Finally, we added consideration of nonmobile decisions regarding face-mask mandates, as a second policy constraint. For each state, a measure of fit was noted. We operationalize the idea of what we call "patchworkiness" by calculating the spatial autocorrelation of this measure of fit by state. The degree of spatial clustering and its related significance represents what character of patchwork the model can reveal.

DESCRIPTION OF THE DATA USED

The first step to developing a patchwork model relied on depicting a variety and time line of state-level policies. To do this, a time line by state spreadsheet served as the foundation to record and assess the patterns of state level policy decisions. The columns represented dates while rows represented all 50 states, plus the District of Columbia and Puerto Rico. The 52 geographic areas were coded into 6 codes: mask mandate, stay-at-home order, social distance/gathering limitations, antirestriction policies, other, and end of restrictions. "Other" served as a catchall code that included a state's first confirmed case, a declaration of a state public health emergency, when testing began, and several other policy decisions. When a state had a COVID-19 related policy go into effect, that policy would then be noted in the corresponding date column to the day that policy went into effect.

The "mask mandate" code was used whenever a statewide mask mandate went into effect. Not all states implemented mask mandates, and this code was only used for statewide policies and not policies enacted at the county or municipality level. The "stay at home order" code was used whenever governors enacted restrictions of curfews on people's movements within the state. This was also sometimes referred to as shelter-in-place, depending on the state. The "social distance/gathering limitations" code included statewide restrictions on the number of people that could gather at once as well as requirements on keeping a certain amount of distance between people. This also included school closures, cancelation of elective surgeries, and limiting dine-in options at restaurants. "Antirestriction policy" code referred to the instances where governors or state officials prohibited lower-level decision making within the state. For example, on 27 April 2020, Governor Greg Abbot of Texas issued an executive order making local officials unable to enforce a mask mandate or impose any mask related fines. The "other" served as a catchall of pertinent COVID-19 related information, rather than policies. This included relevant information such as the date of the first confirmed COVID-19 case in the state and the date of a state-level declaration of a public health emergency. Finally, the last category, "end of restrictions," chronicled the time line of states reopening. This included the reopening of gyms, restaurants, and other business and the lifting of stay-at-home orders. This spreadsheet[2] consolidated general time lines at state-level policies ranging from 21 January 2020 to 15 August 2020, representing first wave time lines.

To explore the patchwork of models, we choose to use normalized reported deaths as the base data on pandemic outcomes to work with. While there are various options for raw sources of data, we used data available from CDC for morbidity ("CDC COVID Data Tracker" 2020); from the Descartes Lab for mobility (Warren and Skillman 2020); and Blavatnik School of Government for government response, (Hale et al. 2021) in addition to triangulating with our own decisions-by-state tracker described above. The data for our analyses are obtained by first merging the records from CDC and Descartes Lab such that we obtain aligned time series for deaths as well as mobility. For a given day, available information consists of deaths and associated mobility indices for that day for each state in the United States (omitting Puerto Rico and the District of Columbia in the models).

We experimented with different model classes, namely, decision trees, time-series models, and the like, where the input is either a snapshot or contiguous segment of changes in cases, mobility, and deaths, and the output is predicted changes in death at future time. The modeling methodologies of our paper are based on developing statistical forecasters of state-level mortality using past mortality and mobility data.

With our experiments we do not showcase ways of improving existing methods. Instead, we point out how modeling developed at a particular spatial unit performs at other spatial units, to reveal the dependency on geographic principles. The experiments have validated the idea that the variables (model parameters) governing the spread of COVID-19 are different for each state (they depend on the choice of scale and extent).

Our next methodological aim was to quantify and evaluate measures of model variability across geospatial locations. As a first step toward this, we developed a well-tuned forecasting model for one state: Arizona, which in addition to being a convenience choice, has the distinction of being among the top three states of earliest confirmed COVID-19 case, with the longest time lag to a first decision to mediate. We then recorded the performance of this model for other states using an R^2 prediction score. That is, for each state a, we compute a score $s(a)$ that captures the performance of Arizona's forecasting model for state a's data, which is simply the R^2 computed for state a using Arizona's model. We then estimate the spatial variability of $s(a)$ across the states using the standard measure of spatial autocorrelation, Moran's I (Moran 1947, 1948). Moran's I for the scores $s(a)$ is defined as follows:

$$I = \frac{N}{W}\sum\nolimits_a \sum\nolimits_{a'} w_{aa'}(s(a) - \bar{s})(s(a') - \bar{s}) / \sum\nolimits_a (s(a) - \bar{s})^2,$$

where N is the total number of states being considered (50 here, where we omit Puerto Rico and the District of Columbia due to partial data and special status. Thus, $\bar{s}$ is the average score across the states, $w_{aa'}$ is the spatial weight for the pair of states a and a' (using a Euclidean distance-based measure). Comparing the value of I with its expected value (which is $-1/N$ - 1 = - 0.021 here) allows us to estimate the amount of spatial variability of the scores. These measures operationalize and demonstrate our experimental concept of a patchwork pandemic.

ANALYSIS

To deal with possible missing data in the time series, we performed basic linear interpolation for removing gaps in data. We then perform a linear de-trending of the data by working with the first derivative of all the available time series. For a given day, which we will denote as t, we will let d_t denote the number of deaths on day t. We will also let ${m_t}^{(1)}$ and ${m_t}^{(2)}$ denote the value of the mobility indices from the Descartes Labs dataset. We further process the data so that the model input variables correspond to changes in cases, deaths, and changes in the various mobility indices. For a given day, denoted by t, the corresponding features are $X_t = [c_t, d_t, {m_t}^{(1)}, {m_t}^{(2)}]$. Then, the model output is given by $Y_t = [d_{t+\Delta}]$, where Δ>0 is the prediction horizon, that is how far in the future our model is asked to predict. In addition to this, we also analyze the results by adding a feature f_t that denotes facial-covering index. Facial covering index is an ordinal value on the 0–4 scale, as defined by (Hale et al. 2021) to represent how strict the facial covering policy is. As a result input tuple $X_t = [c_t, d_t, m_t^{(1)}, m_t^{(2)}, f_t]$ and the model output is given by $Y_t = [d_{t+\Delta}]$.

We deployed four distinct analytical pieces of evidence to characterize the patchwork patterns of the pandemic, relative to the baseline state:

RANDOM FOREST MODEL

In the first model, we used a random forest regressor (Liaw and others 2002) that estimates a function $Y_t = f(X_t)$. A decision-forest based forecaster was fit on Arizona data corresponding to predicting future mortality from data of past mortality and mobility. Decision-forests are considered a standard approach in predictive modeling, thus we started with this choice of modeling method. This devised Arizona model was then tested on other states. To train the model for a given state, we randomly sample 70 percent of the data for training, and reserve 30 percent for testing. We used the implementation from the package sklearn (Pedregosa et al. 2011) with the default number of trees = 100 and max depth of each tree = 2. We first fit an optimal model to the time-series data measured from Arizona. We then used this optimal model for Arizona to attempt a forecast of mortality across all the other 49 states and record the corresponding R^2 score, which is a quantification of the predictive quality of the model. This geospatial spread of R^2 scores is then analyzed using a standard spatial autocorrelation test (Global Moran's I) to compute how spatially variable the scores are.

Auto-regressive model: In the second variation, we developed an analogous approach as above, but this time, we used time series based forecaster that models a window of observations in the past as the basis for predicting a single outcome variable in the future. The technique we used was an auto-regressive moving average (ARMA) model, which fits a linear function $Y_t = f(X_{t:t-\delta}, Y_{t-1:\text{T}-})$, where $X_{t:t-\delta}$ is the time-series data corresponding to the variable X between times $t-\delta$ and t; we chose the hyperparameters to be $\delta = 5, \; = 1$. These choices can be made using an information criterion such as AIC (Bozdogan 1987) as more data becomes accessible from the pandemic. We again choose the best parameters for fitting an ARMA model at Arizona, forecast mortality in other states, record the R^2 score for each state and compute the corresponding Global Moran's I score.

GRANGER CAUSATION MODEL

The models as described above use one state as a base model, Arizona. Data from other states were used to test the model. Ideally to test the patchwork concept, we would like to compare models by estimating them individually per state. This is hard to do since it is nontrivial to compare model-to-model mismatch as compared to model-to-data fit (spatial comparison adds further complexity). In order to bridge the gap between our approach above and this ideal, for each state, we consider another notion of forecasting performance—Granger causality (Ding et al. 2006). In this analysis, we estimate the Granger causation between the mobility index time series $m_t^{(1)}\left(orm_t^{(2)}\right)$ and the mortality time series d_t. Granger causality is computed by measuring the improvement in the predictability of the mortality time series when one includes the mobility time series as part of the time-series fit. For each state, we now optimally tune its own hyperparameter (lag for Granger causality) and choose the respective chi-squared test statistic of highest significance (chosen from the values computed for a series of lags). This value is used again to compute Moran's I of the joint mobility-mortality models.

POLICY MODEL

To depict multiple decision points in one of the models, we incorporated a facial-covering index as a feature in the dataset, permitting us to analyze the impact of policies on our model. We repeated a similar experiment as in the first case where the Arizona model is fit to all other states to obtain an R^2 score. All other aspects of the modeling remain the same as the first random forest model described above barring a change in the input data. The input data on facial coverings is a time series of values on an ordinal scale (0–4), with 4 being the highest degree of enforcement for each state.

Summary of Results

States, given the imperative to implement pandemic policy in the context of a lack of national coordination, began slowly after the first appearances of confirmed COVID-19 cases, to respond, typically by declaring a public health emergency (Figure 2). Only a few states declared a public health emergency prior to their first known case. Typically, weeks later, the first stay-at-home orders began to emerge, generally followed by mask mandates, when they existed. Figure 2 provides an overview of this sequence for all 50 states (plus Puerto Rico and the District of Columbia), although the conflicts between federal and state policy, and state and county or city policy is not depicted. Despite that governors more or less followed a typical order of action, the timing of these decisions varied during the first wave of the pandemic, and showed little relation to political party of the governor.

In terms of modeling public health outcomes relative to behavior and decisions, the results from different experiments are summarized in Table 1. The "Model" column represents the algorithm used; the "Input" and "Output" columns summarize what a particular model outputs were given based on the

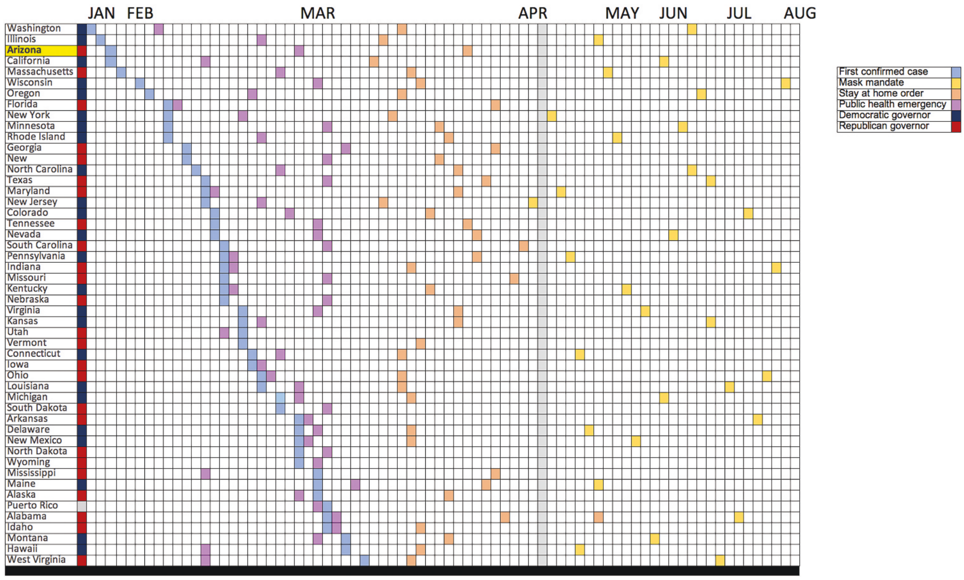

FIG. 2—Visualized time line of decisions by state, January—August 2020.

inputs. For each model we calculated a value representative of each state's quality of fit (to the Arizona model) using the metric specified in the "Measure of model fit" column. These representative values are used as an input to the calculation of spatial autocorrelation whose results are summarized under *p*-value and Moran's I. We found similar results using population normalized deaths. Based on these results, we find that patchworkiness using the random forest regressor with depth 2 was consistent across methods.

When mapped by quality of fit by state, and spatial clustering run, patchwork patterns remained regardless of whether the random forest model, ARMA model, or the Granger model was used to visualize clusters (Figure 3).

This map might be interpreted to depict places with similar differences to the base Arizona model, relatively speaking, and may indicate where the pattern of cases and deaths were similar in similar time ranges, where people behave similarly, or where governors may have even worked together on joint policy. As an experiment in visualizing patchwork patterns resulting from behavior and decisions, the map provides inspiration to consider different levels of conformity and/or fragmentation, despite different significance of spatial mismatch.

DISCUSSION

In this study we explored spatial and temporal incongruence among the way that the natural phenomenon of the health pandemic unfolded, the behavior of people via mobility, and the decision makers choices responsible for regulating

TABLE 1—A SUMMARY OF MODELS TESTED, WITH CORRESPONDING INPUTS, OUTPUTS, MEASURES OF FIT, OBTAINED MORAN'S INDEX AS AN INDICATOR OF *PATCHWORKINESS*, AND THE SIGNIFICANCE LEVEL

MODEL	INPUT	OUTPUT	MEASURE MAPPED	MORAN'S I (EXPECTED VALUE: −0.021)	P-VALUE (SIGNIFICANCE LEVEL > 0.05)*
Random Forest	Changes in daily mobility, changes in cases, changes in daily deaths	Changes in deaths at a future date	R^2 value	0.0332	0.0392*
Random Forest	Daily mobility, Population normalized changes in cases, Population normalized changes in daily deaths	Population normalized changes in deaths at a future date	R^2 value	−0.154	0.1513
ARMA	Changes in daily deaths	Changes in deaths at a future date	R^2 value	0.1726	0.01737*
Granger Causality	Changes in daily mobility, changes in daily deaths	Chi-squared statistic for a series of lags	Chi-squared statistic of lag with highest significance	−0.1288	0.2636
Policy Model	Ordinal scale of facial coverings; Changes in daily mobility, changes in daily deaths	Changes in deaths at a future date	R^2 value	0.01	0.51

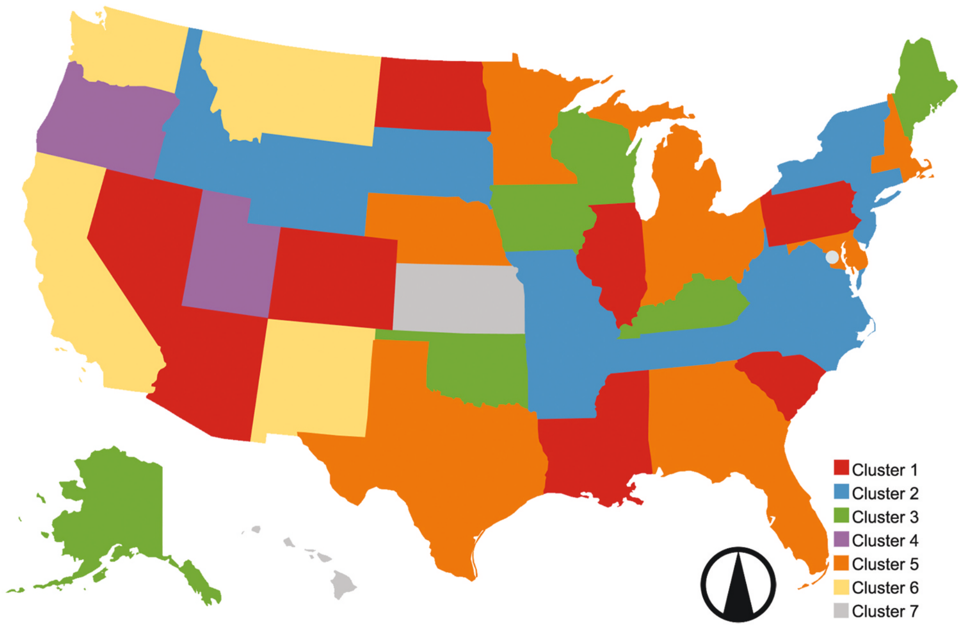

FIG. 3—Cluster Map results of state-wise modeling depicting patchwork relative to the Arizona base model.

and guiding resilience responses to these events, in the serendipitous context of lack of overall national coordinated response. Certainly, the whole story of the pandemic in any place, at whatever scale or spatial unit, cannot be fully told through modeling, and as a representation of the phenomenon, neither can public-facing or even published research fully convey complexities. These partial findings hint at how the resulting patchwork runs deeper than the respective patterns of public health outcomes, but also for our models and understanding of it. We find that designing a base model and comparing it to other states reveals dimensions of match and mismatch. And while the fit varies, significance of all models do not hold universally, modeling persistently shows a patchwork of clusters, beyond just state-by-state decision making. The fact that the patchwork did not conform only to state lines confirms that factors other than governors' decisions still retain an importance for understanding how the pandemic unfolded.

Assessing the model with respect to how well the decision making relates back to behavioral-dependent outcomes affords a framework to ask questions about accountability. The very least of inquiry seeks to understand the spatial and temporal mismatch among the decisions made, outcomes, and accountability for those outcomes, ideas which we began to explore with this work.

We tested the model with respect to how well it does or does not describe these relationships at the state level, not by mapping the patchiness of outputs (cases, deaths) or drivers (mobility), but by graphing the fit.[3] Doing so helps us reflect on our role as scholars in making sense of the fundamental nature of this kind of pandemic: the patchworkiness of the performance of the models underscores the need to not build one model to explain national patterns, but the critical importance of many researchers from many disciplines in many locations building many models that reveal aspects of society, decision making, and behavior in the face of risk, cognizant of fundamental geographic principles like the MAUP. These explanatory or predictive models can often operate in field focused teams or teams with some interdisciplinary approaches. For instance, the team collaborating on this study is vastly interdisciplinary, with expertise coming from the fields of geography, computer science, engineering, artificial intelligence, planning, and public health. This allowed for complex discussions about ways to formulate a model that highlights research practice from multiple disciplines. It precipitated robust debates about the most useful or appropriate spatial and temporal scale to contribute to adding new knowledge, even about the meanings of usefulness or appropriateness.

Limitations of using this set of machine learning modeling approaches to try to uncover relationships reveal potential areas for future research needs. For one, the stand-in data for behavior (and spatial behavior) in terms of mobility is incomplete. The data would not represent the full mobility of the population, nor would it fully be expected to estimate compliance with stay-at-home orders. Compliance with mask mandates is even more uncertain in these data, and such slippage in behavior certainly accounts for some of the spatial incongruence of the models, as well as for the ultimate health outcomes. In other words, some people in some states (or regions) will just comply better.

Furthermore, even the best metrics of social behavior cannot fully account for persistent social vulnerabilities (Wang et al. 2020), which may structure behavior, but we do not portend is conflated with it. Future studies could enable factoring in some of the known vulnerabilities by demographic (age, race, income) or some other empirically derived weighted social vulnerability index, perhaps even at a smaller spatial scale, as the state unit used in this analysis is likely too coarse to overcome this limitation. We believe our illustration of the underlying spatial analytical problem would still be present, no matter how many factors such modeling contains, or how well one model fits to a particular choice of spatial unit (Fotheringham et al. 2017; Li and Fotheringham 2020).

Similarly, findings from more focused studies, or comparative studies like Praharaj et al. (2020) could improve modeling of mobility data to measure the effect of COVID-19 policies on the specific changes observed. While our experiment accommodated a range of data, the models barely accommodated the burgeoning body of knowledge around COVID-19, something that future elaboration of these ideas should do.

The results from this research shows that the Arizona test model fits better in some places and worse in others. Regionally, one might expect the situation with COVID-19 to follow similar patterns (for example, California and Arizona would have more similarities compared to Arizona and Massachusetts). Even when factoring for spatial autocorrelation, the differences in the model still seem to be patchworky. In terms of applicability to public health, this further confirms what public health scholars have already noted: illnesses and diseases can vary based on geographic location, policies, and behavior. We can also see this notion in the example of opioid epidemic noted previously. Moving away from a one size fits all approach to predictive modeling could allow for the capture of these important health behavior, exposure, and healthcare access nuances that drive disease and illness variation.

Finally, the challenge looms about where decisions are made and whether decision makers can accommodate such complexity in their actions. While it was quickly clear that there would be scarce national scale response, and that governors must assume larger than usual responsibility for policy, future research should explore mechanisms to test for the contradictions across variable scaled decisions, decisions that are incongruent with their jurisdictions, and simultaneous decision-making conflicts, since examples of governors who struggled with mayors, and other policy actors abound (Leitner et al. 2008).

It bears repeating that is not our intention in this paper to create a new model or a new class of modeling. We instead seek to illustrate how the patchworkiness in the spatial performance of these different models that seek to explain the pandemic, and in turn serve as real-time, decision-making tools, itself should be a source of reflection in the overall assessment of how it all unfolded and scientists' role in that process.

In the end, this work showed patchworkiness at a deeper level than that which may be apparent from summary statistics of cases, hospitalizations, or mortality. Instead, we found patchworky behavior in the way predictive models behave in different locations. One way to state this is that we found that when we develop a predictive model, based on past mortality and mobility and policy data, to predict changes in future pandemic related mortality, there is significant model-mismatch of the performance of such a model across geographic locations and at different spatial units. We saw that this finding carries over across a few different variations of whichever underlying predictive modeling paradigm is used, specifically decision forests and auto-regressive models.

Based on these results, we suggest the following recommendations for future research: engaging in interdisciplinary teams, recognition of scale quickly, closer ties to actual decision makers, and reinforcing the contextual nature of geography even in heavy data modeling research. In the context of the COVID-19 pandemic, more geographers working with public health professionals, data scientists, and policy scholars could help amplify and broaden awareness of the fundamental geographic challenges as events such as this pandemic happens in real time. One of the downfalls of the response to the COVID-19 pandemic was the lack of widespread recognition that the performance of predictive models would manifest differently among and within states. Having a quicker recognition of the importance of understanding scale choice in monitoring and predicting behavior of future outbreaks and natural disasters can improve scientists' response to make predictive models that overcome the MAUP. The patchworkiness captured in this study also presents the need for more joint reflection on these challenges between decision makers and data scientists.

Conclusions

A more coordinated, national-level response may mark future interventions for both health-related outbreaks and natural disasters (hurricanes, tornados, and the like), given the prospect of a new federal administration, but the ineffectiveness of a patchwork response in the early weeks and months cannot be underestimated. This exploration reiterates the need to innovate methodologically around decision making as a particular category of spatial behavior, and pandemic patchwork policy making as a specific instance of spatiotemporal, scaled decision making that unfolds differently across jurisdictions, and according to different modeling performances. Our results imply the spatiality of collective, accountable decision-making behaviors as distinct from independent, individual choices. But it also reinforces the connections among policy and compliance/noncompliance, something that this particular pandemic and the complexity of mediating actions brought into stark focus. Future research is needed that involves interdisciplinary teams of scientists engaged reflexively in practice together with decision makers to explore methodological solutions to the modifiable areal unit problem, and to the decision-making accountability spatial incongruence problem. The outcome of geographic contextualization as well as deliberate and justified choice of spatial scale and units would ideally be better support to real-time, evidence-based modeling of the impact of decisions and public accountability for those decisions—as such emergencies as the COVID-19 unfolds.

We conclude with the need for explicit attention toward the integration of researchers who use predictive modeling to proceed at various scales, and work with the multiple scales of decisions and decision makers. While this conclusion on first glance may seem trivial, or superfluous, in reality, the practices of both decision makers and scientists seeking to understand phenomena, especially in a rapid response context, does not always follow this "first mile" best practice. Some of this modeling might also suggest possible clusters of regions where collaboration might be effective—and to help structure federal coordination.

Equally important, reflecting on how these patchwork patterns occur could be applicable for bettering understand of the spread of other infectious diseases—such as HIV, Lyme disease, and chlamydia, or noninfectious diseases—such as diabetes, hypertension, and Alzheimer's, which would have a significant impact to spatial epidemiology and public health research (Hanson et al. 2003; Beale et al. 2008). These ideas might be extended to our understanding of public health impacts of climate change and natural disasters (heat-related illness and death, air-quality impact on comorbidities, flooding, disasters), and how cities and regions have stepped forward in the decision-making arena in the wake of federal/national divestment, denial, or impasse. This exploratory research points to an opportunity to collaboratively work at codeveloping models that better inform local decision makers, where the goal may not be to replicate or reproduce the models, but generalize the knowledge produced to be used locally (Kedron et al. 2019). Our findings may prompt ideas on holding officials accountable to public health outcomes with their decisions—across all of these intersecting complex, mismatched scales, and reinforce the calls for future national-scale coordination with an attention to spatial congruence.

Notes

1 The choice of Arizona is somewhat arbitrary, as any state could serve the purpose to illustrate the patchwork character of model performance. Arizona has the distinction of being among the top three states of earliest confirmed COVID-19 cases, with the longest time lag to a first decision to mediate.

2 While contributing to our process of developing the mathematical models as noted in the following sections, these decision data themselves were ultimately not directly included in the models as presented here. The specific proclamations of gubernatorial decisions are not rapidly time-varying factors, which makes using them in such models ineffective, so the more temporally variable factors accounted for the impact of the decisions on mobility data and mask data, for example.

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References

Alexander, M. J., M. V. Kiang, and M. Barbieri. 2018. Trends in Black and White Opioid Mortality in the United States, 1979–2015. *Epidemiology* 295: 707–715. 10.1097/ede.0000000000000858.

Altekruse, S. F., C. M. Cosgrove, W. C. Altekruse, R. A. Jenkins, and C. Blanco. 2020. Socioeconomic Risk Factors for Fatal Opioid Overdoses in the United States: Findings from the Mortality Disparities in American Communities Study (MDAC). Edited by Becky L. Genberg. *PLOS ONE* 151: e0227966. 10.1371/journal.pone.0227966.

Anastassopoulou, C., L. Russo, A. Tsakris, and C. Siettos. 2020. Data-Based Analysis, Modelling and Forecasting of the COVID-19 Outbreak. Edited by Sreekumar Othumpangat. *PLOS ONE* 153: e0230405. 10.1371/journal.pone.0230405.

Beale, L., J. J. Abellan, S. Hodgson, and L. Jarup. 2008. Methodologic Issues and Approaches to Spatial Epidemiology. *Environmental Health Perspectives* 1168: 1105–1110. 10.1289/ehp.10816.

Box, G. E. P., G. M. Jenkins, and G. C. Reinsel. 2011. *Time Series Analysis: Forecasting and Control*. New York: John Wiley & Sons.

Bozdogan, H. 1987. Model Selection and Akaike's Information Criterion (AIC): The General Theory and Its Analytical Extensions. *Psychometrika* 523: 345–370. 10.1007/BF02294361.

Butler, D. 2009. Swine Flu Goes Global. *Nature* 4587242: 1082–1083. 10.1038/4581082a.

Campbell, C. I., C. Weisner, L. LeResche, G. Thomas Ray, K. Saunders, M. D. Sullivan, and C. J. Banta-Green, et al. 2010. Age and Gender Trends in Long-Term Opioid Analgesic Use for Noncancer Pain. *American Journal of Public Health* 100(12): 2541–2547. 10.2105/AJPH.2009.180646.

Center for Disease Control [CDC]. 2014. Enhanced Ebola Screening to Start at Five U.S. Airports and New Tracking Program for All People Entering United States from Ebola-Affected Countries Washington, D.C. https://www.cdc.gov/media/releases/2014/p1008-ebola-screening.html

_____. 2020. CDC COVID Data Tracker. Washington, D.C. https://covid.cdc.gov/covid-data-tracker/

Center, P. R. 2020. Most Approve of National Response to COVID-19 in 14 Advanced Economies. *Pew Research Center* 23.

Ceylan, Z. 2020. Estimation of COVID-19 Prevalence in Italy, Spain, and France. *Science of the Total Environment* 138817April: 138817. 10.1016/j.scitotenv.2020.138817.

Chakraborty, T., and I. Ghosh. 2020. Real-Time Forecasts and Risk Assessment of Novel Coronavirus (COVID-19) Cases: A Data-Driven Analysis. *Chaos, Solitons, and Fractals* 109850 135: 109850. 10.1016/j.chaos.2020.109850.

Chakravarthy, B., S. Shah, and S. Lotfipour. 2011. Prescription Drug Monitoring Programs and Other Interventions to Combat Prescription Opioid Abuse. *Western Journal of Emergency Medicine* 135: 422–425. 10.5811/westjem.2012.7.12936.

Choo, E. K., C. Douriez, and T. Green. 2014. Gender and Prescription Opioid Misuse in the Emergency Department. Edited by Mark Mycyk. *Academic Emergency Medicine* 2112: 1493–1498. 10.1111/acem.12547.

Coker, R. 2009. Swine Flu. *BMJ* 3383: b1791–91. 10.1136/bmj.b1791.

Ding, M., Y. Chen, and S. L. Bressler. 2006. 17 Granger Causality: Basic Theory and Application to Neuroscience. In *Handbook of Time Series Analysis: Recent Theoretical Developments and Applications*, 437. Wiley Online Library.

Djulbegovic, B., D. J. Weiss, and I. Hozo. 2020. Evaluation of the U.S. Governors' Decision When to Issue Stay-At-Home Orders. *Journal of Evaluation in Clinical Practice* 265: 1347–1351. 10.1111/jep.13458.

Fineberg, H. V. 2014. Pandemic Preparedness and Response — Lessons from the H1N1 Influenza of 2009. *New England Journal of Medicine* 370(14): 1335–1342. 10.1056/nejmra1208802.

Fotheringham, A. S., W. Yang, and W. Kang. 2017. Multiscale Geographically Weighted Regression (MGWR). *Annals of the American Association of Geographers* 1076: 1247–1265. 10.1080/24694452.2017.1352480.

Gehlke, C. E., and K. Biehl. 1934. Certain Effects of Grouping upon the Size of the Correlation Coefficient in Census Tract Material. *Journal of the American Statistical Association* 29185: 169. 10.2307/2277827.

Gibbs, W. W., and C. Soares. 2005. Preparing for a Pandemic. *Scientific American* 2935: 44–54. 10.1038/scientificamerican1105-44.

Gostin, L. O., J. G. Hodge, and S. Burris. 2014. Is the United States Prepared for Ebola? *JAMA* 31223: 2497. 10.1001/jama.2014.15041.

Gostin, L. O., J. G. Hodge, and L. F. Wiley. 2020. Presidential Powers and Response to COVID-19. *JAMA* 32316: 1547–1548. 10.1001/jama.2020.4335.

Graziani, M., and R. Nisticò. 2016. Gender Difference in Prescription Opioid Abuse: A Focus on Oxycodone and Hydrocodone. *Pharmacological Research* 108: 31–38. 10.1016/j.phrs.2016.04.012. June.
Haffajee, R. L., and M. M. Mello. 2020. Thinking Globally, Acting Locally—The U.S. Response to Covid-19. *New England Journal of Medicine* 382: 22. 10.1056/nejmp2006740.
Hale, T., N. Angrist, R. Goldszmidt, B. Kira, A. Petherick, T. Phillips, and S. Webster. others. 2021. A Global Panel Database of Pandemic Policies (Oxford COVID-19 Government Response Tracker). *Nature Human Behaviour* 1–10. 10.1038/s41562-021-01079-8. March.
Hanage, W. P., C. Testa, J. T. Chen, L. Davis, E. Pechter, M. Santillana, and N. Krieger. 2020. COVID-19: U.S. Federal Accountability for Entry, Spread, and Inequities. *Harvard Center for Population and Development Studies* 20(2). [https://cdn1.sph.harvard.edu/wp-content/uploads/sites/1266/2020/10/20_covid-19_federal-response_FINAL_for-HCPDS_1001_HCPDS-working-paper_volume-20_number-2_FINAL.pdf.
Hanson, K., M. K. Ranson, V. Oliveira-Cruz, and A. Mills. 2003. Expanding Access to Priority Health Interventions: A Framework for Understanding the Constraints to Scaling-up. *Journal of International Development* 151: 1–14. 10.1002/jid.963.
Holguín-Veras, J., N. Pérez, S. Ukkusuri, T. Wachtendorf, and B. Brown. 2007. Emergency Logistics Issues Affecting the Response to Katrina. *Transportation Research Record: Journal of the Transportation Research Board* 20221: 76–82. 10.3141/2022-09.
Jacobson, P. D., D. Chrysler, and J. Bresler. 2020. Executive Decision Making for COVID-19: Public Health Science through a Political Lens. Assessing Legal Responses to COVID-19, August, 7.
Kane, M. J., N. Price, M. Scotch, and P. Rabinowitz. 2014. Comparison of ARIMA and Random Forest Time Series Models for Prediction of Avian Influenza H5N1 Outbreaks. *BMC Bioinformatics* 15: 1. 10.1186/1471-2105-15-276.
Kang, D., H. Choi, J.-H. Kim, and J. Choi. 2020. Spatial Epidemic Dynamics of the COVID-19 Outbreak in China. *International Journal of Infectious Diseases,* 94: 96–102. 10.1016/j.ijid.2020.03.076.
Kedron, P., A. E. Frazier, A. B. Trgovac, T. Nelson, and A. S. Fotheringham. 2019. Reproducibility and Replicability in Geographical Analysis. *Geographical Analysis* 531: 135–147. 10.1111/gean.12221.
Kettl, D. F. 2006. Is the Worst yet to Come? *The ANNALS of the American Academy of Political and Social Science* 6041: 273–287. 10.1177/0002716205285981.
Keyes, K. M., M. Cerdá, J. E. Brady, J. R. Havens, and S. Galea. 2014. Understanding the Rural–Urban Differences in Nonmedical Prescription Opioid Use and Abuse in the United States. *American Journal of Public Health* 1042: e52–59. 10.2105/ajph.2013.301709.
Krumkamp, R., H.-P. Duerr, R. Reintjes, A. Ahmad, A. Kassen, and M. Eichner. 2009. Impact of Public Health Interventions in Controlling the Spread of SARS: Modelling of Intervention Scenarios. *International Journal of Hygiene and Environmental Health* 2121: 67–75. 10.1016/j.ijheh.2008.01.004.
Lagu, T., A. W. Artenstein, and R. M. Werner. 2020. Fool Me Twice: The Role for Hospitals and Health Systems in Fixing the Broken PPE Supply Chain. *Journal of Hospital Medicine* 159: 570–571. 10.12788/jhm.3489.
Leatherby, L., and R. Harris. 2020. States that Imposed Few Restrictions Now Have the Worst Outbreaks. *The New York Times,* November 18.
Leitner, H., E. Sheppard, and K. M. Sziarto. 2008. The Spatialities of Contentious Politics. *Transactions of the Institute of British Geographers* 332: 157–172. 10.1111/j.1475-5661.2008.00293.x.
Leung, G. M., and A. Nicoll. 2010. Reflections on Pandemic (H1N1) 2009 and the International Response. *PLoS Medicine* 710: e1000346. 10.1371/journal.pmed.1000346.
Li, H., H. Li, Z. Ding, Z. Hu, F. Chen, K. Wang, Z. Peng, and H. Shen. 2020. Spatial Statistical Analysis of Coronavirus Disease 2019 (Covid-19) in China. *Geospatial Health* 15: 1. 10.4081/gh.2020.867.
Li, Z., and A. S. Fotheringham. 2020. Computational Improvements to Multi-Scale Geographically Weighted Regression. *International Journal of Geographical Information Science* 347: 1378–1397. 10.1080/13658816.2020.1720692.

Liaw, A., and M. Wiener, et al. 2002. Classification and Regression by RandomForest. *R News* 23: 18–22.

Maffioli, E. M. 2020. How Is the World Responding to the Novel Coronavirus Disease (COVID-19) Compared with the 2014 West African Ebola Epidemic? the Importance of China as a Player in the Global Economy. *The American Journal of Tropical Medicine and Hygiene* 1025: 924–925. 10.4269/ajtmh.20-0135.

Mallinson, D. J. 2020. Cooperation and Conflict in State and Local Innovation during COVID-19. *The American Review of Public Administration* 50(6–7): 543–550. 10.1177/0275074020941699.

Mollalo, A., B. Vahedi, and K. M. Rivera. 2020. GIS-Based Spatial Modeling of COVID-19 Incidence Rate in the Continental United States. *Science of the Total Environment* 728138884: 138884. 10.1016/j.scitotenv.2020.138884.

Moran, P. A. P. 1947. Random Associations on a Lattice. *Mathematical Proceedings of the Cambridge Philosophical Society* 433: 321–328. 10.1017/s0305004100023550.

______. 1948. The Interpretation of Statistical Maps. *Journal of the Royal Statistical Society: Series B (Methodological)* 10(2): 243–251. 10.1111/j.2517-6161.1948.tb00012.x.

National Academies of Sciences, Engineering, and Medicine. 2019. *Reproducibility and Replicability in Science*. Washington, D.C.: The National Academies Press. 10.17226/25303.

Nelson, L. S., D. N. Juurlink, and J. Perrone. 2015. Addressing the Opioid Epidemic. *JAMA* 31414: 1453. 10.1001/jama.2015.12397.

Openshaw, S. 1984. The Modifiable Areal Unit Problem. *Geo Abstracts* Norwich, U.K.: University of East Anglia

Orenstein, W. A., B. G. Gellin, T. Buck, L. A. Jackson, P. S. LaRussa, J. O. Mason, and M. McCormick, and others. 2013. Strategies to Achieve the Healthy People 2020 Annual Influenza Vaccine Coverage Goal for Health-Care Personnel: Recommendations from the National Vaccine Advisory Committee. *Public Health Reports* 1281: 7–25. 10.1177/003335491312800103.

Park, B. J., A. J. Peck, M. J. Kuehnert, C. Newbern, C. Smelser, J. A. Comer, D. Jernigan, and L. C. McDonald. 2004. Lack of SARS Transmission among Healthcare Workers, United States. *Emerging Infectious Diseases* 10(2): 217–224. 10.3201/eid1002.030793.

Pedregosa, F., G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, and M. Blondel, et al. 2011. Scikit-Learn: Machine Learning in Python. *The Journal of Machine Learning Research* 12 JMLR. org: 2825–2830.

Pikoulis, E., K. Puchner, E. Riza, E. Kakalou, E. Pavlopoulos, C. Tsiamis, V. Tokakis, G. Boustras, A. Terzidis, and V. Karamagioli. 2020. In the Midst of the Perfect Storm: Swift Public Health Actions Needed in order to Increase Societal Safety during the COVID-19 Pandemic. *Safety Science* 129104810: 104810. 10.1016/j.ssci.2020.104810.

Pletcher, M. J., S. G. Kertesz, M. A. Kohn, and R. Gonzales. 2008. Trends in Opioid Prescribing by Race/Ethnicity for Patients Seeking Care in US Emergency Departments. *JAMA* 299: 1. 10.1001/jama.2007.64.

Praharaj, S., D. King, C. Pettit, and E. A. Wentz. 2020. Using Aggregated Mobility Data to Measure the Effect of COVID-19 Policies on Mobility Changes in Sydney, London, Phoenix, and Pune. *Findings*, 20 October. 10.32866/001c.17590

Quinn, S. C. 2006. Hurricane Katrina: A Social and Public Health Disaster. *American Journal of Public Health* 962: 204–4. 10.2105/ajph.2005.080119.

Reibman, J., N. Levy-Carrick, T. Miles, K. Flynn, C. Hughes, M. Crane, and R. G. Lucchini. 2016. Destruction of the World Trade Center Towers. Lessons Learned from an Environmental Health Disaster. *Annals of the American Thoracic Society* 135: 577–583. 10.1513/AnnalsATS.201509-572PS.

Reiner, R. C., R. M. Barber, J. K. Collins, P. Zheng, C. Adolph, J. Albright, and C. M. Antony, et al. 2020. Modeling COVID-19 Scenarios for the United States. *Nature Medicine* October: 1–12. 10.1038/s41591-020-1132-9.

Rigg, K. K., and S. M. Monnat. 2015. Urban Vs. Rural Differences in Prescription Opioid Misuse among Adults in the United States: Informing Region Specific Drug Policies and Interventions. *International Journal of Drug Policy* 265: 484–491. 10.1016/j.drugpo.2014.10.001.

Rosenfield, A., S. S. Morse, and K. Yanda. 2002. September 11: The Response and Role of Public Health. *American Journal of Public Health* 921: 10–11. 10.2105/ajph.92.1.10.

Rothstein, M. A. 2015. From SARS to Ebola: Legal and Ethical Considerations for Modern Quarantine. *Indiana Health Law Review* 121: 227–280. 10.18060/18963.

Schneider, S. K. 2005. Administrative Breakdowns in the Governmental Response to Hurricane Katrina. *Public Administration Review* 655: 515–516. 10.1111/j.1540-6210.2005.00478.x.

Smith, R. D. 2006. Responding to Global Infectious Disease Outbreaks: Lessons from SARS on the Role of Risk Perception, Communication and Management. *Social Science & Medicine* 6312: 3113–3123. 10.1016/j.socscimed.2006.08.004.

Sobel, R. S., and P. T. Leeson. 2006. Government's Response to Hurricane Katrina: A Public Choice Analysis. *Public Choice* 1271–2: 55–73. 10.1007/s11127-006-7730-3.

Solís, P., J. Vanos, and R. Forbis. 2017. The Decision-making/Accountability Spatial Incongruence Problem for Research Linking Science and Policy. *The Geographical Review* 1074: 680–704. 10.1111/gere.12240.

SteelFisher, G. K., R. J. Blendon, and N. Lasala-Blanco. 2015. Ebola in the United States—Public Reactions and Implications. *New England Journal of Medicine* 3739: 789–791. 10.1056/nejmp1506290.

The White House, 2020. The President's Coronavirus Guidelines for America. Washington, D.C. 780 https://www.whitehouse.gov/wp-content/uploads/2020/03/03.16.20_coronavirus-guidance_8.5x11_315PM.pdf

Thomson, A., G. Vallée-Tourangeau, and L. S. Suggs. 2018. Strategies to Increase Vaccine Acceptance and Uptake: From Behavioral Insights to Context-Specific, Culturally-Appropriate, Evidence-Based Communications and Interventions. *Vaccine* 3644: 6457–6458. 10.1016/j.vaccine.2018.08.031.

Tobler, W. R. 1970. A Computer Movie Simulating Urban Growth in the Detroit Region. *Economic Geography* 46: June 234. 10.2307/143141.

U.S. Department of Health and Human Services. 2020. Determination that a Public Health Emergency Exists. *Public Health Emergency*. January 31. Washington, D.C. https://www.phe.gov/emergency/news/healthactions/phe/Pages/2019-nCoV.aspx

Wang, C., Z. Li, M. Mathews, S. Praharaj, B. Karna, and P. Solís. 2020a. The Spatial Association of Social Vulnerability with COVID-19 Prevalence in the Contiguous United States. *International Journal of Environmental Health Research* 10.1080/09603123.2020.1847258. 1–8.

Wang, C., L. Liu, X. Hao, H. Guo, Q. Wang, J. Huang, and N. He, et al. 2020b. Evolving Epidemiology and Impact of Non-Pharmaceutical Interventions on the Outbreak of Coronavirus Disease 2019 in Wuhan, China. *MedRxiv*. Cold Spring Harbor, N.Y.: Cold Spring Harbor Laboratory Press.

Wang, P., X. Zheng, J. Li, and B. Zhu. 2020c. Prediction of Epidemic Trends in COVID-19 with Logistic Model and Machine Learning Technics. *Chaos, Solitons, and Fractals* 139:110058. Elsevier. 10.1016/j.chaos.2020.110058.

Warren, M. S., and S. W. Skillman. 2020. Mobility Changes in Response to COVID-19. ArXiv Preprint ArXiv:2003.14228.

Wils, F. 1996. Scaling Up, Mainstreaming, and Accountability: The Challenge to NGOs. In *Beyond the Magic Bullet: NGO Performance and Accountability in the Post-Cold War World*, edited by M. Edwards and D. Hulme, 67–79. West Hartford, Conn.: Kumarian Press.

Wu, J. T., K. Leung, and G. M. Leung. 2020. Nowcasting and Forecasting the Potential Domestic and International Spread of the 2019—NCoV Outbreak Originating in Wuhan, China: A Modelling Study. *The Lancet* 395: 10225. 10.1016/s0140-6736(20)30260-9.

Yang, Z., Z. Zeng, K. Wang, -S.-S. Wong, W. Liang, M. Zanin, and P. Liu, et al. 2020. Modified SEIR and AI Prediction of the Epidemics Trend of COVID-19 in China under Public Health Interventions. *Journal of Thoracic Disease* 123: 165–174. 10.21037/jtd.2020.02.64.

Yong, E. 2020. We All Live in a Patchwork Pandemic Now. *The Atlantic*. 20 May. https://www.theatlantic.com/health/archive/2020/05/patchwork-pandemic-states-reopening-inequalities/611866/20May

Zhang, S., M. Y. Diao, W. Yu, L. Pei, Z. Lin, and D. Chen. 2020. Estimation of the Reproductive Number of Novel Coronavirus (COVID-19) and the Probable Outbreak Size on the Diamond Princess Cruise Ship: A Data-Driven Analysis. *International Journal of Infectious Diseases* 93: 201–204. 10.1016/j.ijid.2020.02.033.