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A Bayesian Spatiotemporal Nowcasting Model for Public Health Decision-Making and Surveillance

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As coronavirus disease 2019 (COVID-19) spread through the United States in 2020, states began to set up alert systems to inform policy decisions and serve as risk communication tools for the general public. Many of these systems included indicators based on an assessment of trends in numbers of reported cases. However, when cases are indexed by date of disease onset, reporting delays complicate the interpretation of trends. Despite a foundation of statistical literature with which to address this problem, these methods have not been widely applied in practice. In this paper, we develop a Bayesian spatiotemporal nowcasting model for assessing trends in county-level COVID-19 cases in Ohio. We compare the performance of our model with the approach used in Ohio and the approach included in decision support materials from the Centers for Disease Control and Prevention. We demonstrate gains in performance while still retaining interpretability using our model. In addition, we are able to fully account for uncertainty in both the time series of cases and the reporting process. While we cannot eliminate all of the uncertainty in public health surveillance and subsequent decision-making, we must use approaches that embrace these challenges and deliver more accurate and honest assessments to policy-makers.

Bayesian hierarchical modeling; coronavirus disease 2019; COVID-19; reporting lag; spatial analysis; surveillance

Abbreviations: CDC, Centers for Disease Control and Prevention; COVID-19, coronavirus disease 2019; OPHAS, Ohio Public Health Alert System.

As coronavirus disease 2019 (COVID-19) spread throughout the United States in early 2020 (1–4), states began to set up risk alert systems to support data-driven decision-making, improve government accountability, and communicate health risks to the public. The goal of such systems when used for risk communication was to provide clear and consistent messaging around the current state of the COVID-19 pandemic and help people adopt protective behaviors while policy-makers implemented appropriate mitigation strategies. Commonly, several key indicators are tied to the reporting of confirmed COVID-19 cases and their date of illness onset (i.e., the date on which an individual first began to have symptoms), which was the index date preferred by the Centers for Disease Control and Prevention (CDC) to improve timeliness of trend interpretation (5). As suggested in decision support materials issued by the CDC (5), the Ohio Public Health Alert System (OPHAS) included indicators based on case rates in the past 2 weeks and whether there was an increasing trend in new cases over the past 3 weeks at the county level (6). However, chronic delays in case investigation and reporting have led to challenges in estimating case-based indicators and communicating health risk in near real-time. When ignored, delays create the false appearance of decreasing trends (5) that can easily be misinterpreted.

Within the context of a fast-moving epidemic, important decisions need to be made in real time despite having incomplete information on the current situation. In Ohio, county-level case-based indicators were important to policy-makers, but assessments of those indicators were particularly challenging, since methods based on rolling averages used by the state health department (6) neglected to account for reporting delays. The CDC suggested gating criteria for reopening based on splines (5) that also neglected delays and were not implemented in Ohio. Ohio also had many rural counties that were sparsely populated with low absolute case counts, which contributed to unstable estimates of rates and trends that were often discounted by policy-makers as statistical "noise." As part of our research team's consulting role with the state of Ohio, we identified these gaps in situational awareness which could lead to delays in the public health response heading into what became the autumn 2020 surge in cases.

With these challenges in mind, we developed a model that could help policy-makers account for reporting delays, provide stable estimates for rural counties, and quantify uncertainty. To do so, we built on literature for "nowcasting" which has emerged from foundational methodology on delayed reporting (7–9). In contrast to forecasting, which focuses on estimating what could happen in the future, nowcasting focuses on estimating what has already happened but has not yet been reported. To enhance model flexibility and interpretability, recent work (10–12) has extended prior work for nowcasting time series (13) and aberration detection (14) within a Bayesian framework. This work has been applied to estimate numbers of COVID-19 deaths in some regions of the United Kingdom (15), to estimate numbers of COVID-19 cases (16, 17), and to incorporate spatial dependence (18, 19). We propose a spatial extension of an autoregressive Bayesian structural time series (20) model to nowcast county-level counts of COVID-19 cases in Ohio while accounting for reporting delay. Additional discussion is provided in the Web Appendix (available at https://doi.org/10.1093/aje/kwac034).

Because our work was done in practice, we had to overcome the methodological challenges mentioned above while working within the constraints and expectations of policy-makers. Questions of interest around rates and trends of cases indexed by onset date were already decided and integrated into multiple levels of statewide decision-making. To have the most impact, we needed to develop a model that could seamlessly integrate into this framework. That is, we needed to be able to address the questions that were already being asked and align our estimated time series with the raw data stream of observed cases used in other areas of state government. To increase our credibility, we needed our efforts to clearly fit within and supplement existing surveillance efforts. While these constraints added additional challenges and did not always align with our best scientific judgment, we aimed to use our model to move the existing system closer to methodological best practice for handling reporting delays.

This paper describes the model that we developed and used during autumn 2020 to help increase the situational awareness of decision-makers within the surveillance structure in Ohio. One focus of the model was to assess whether there had been an increasing trend in case numbers over the last 3 weeks (6), which has not been a primary focus of nowcast models in the past but was particularly important in public health practice in Ohio. We compare our model with the rolling-average–based approach that was used by the state and the spline-based approach provided as part of the CDC's reopening efforts for assessing trends. We also describe the performance of our model for nowcasting case counts, which provided additional situational awareness to policy-makers in a way that the rolling average and spline methods could not.

METHODS

Data

For demonstration, we used data on confirmed COVID-19 cases in the state of Ohio that were publicly available on the state's online dashboard (21). Case data were presented on the dashboard by onset date and county and updated daily. Data were downloaded daily, and newly reported cases were obtained by differencing the current cumulative totals with those from the previous day. In Ohio, case investigation was done by city and county health departments and entered into the state system, and confirmed cases were defined as those in individuals who had a positive result on a laboratory molecular amplification test (1) or another approved test. For each individual case, the system recorded the county of residence and the date of illness onset as determined by case investigators. If the onset date was unknown, the system recorded the earliest date associated with the record (e.g., when the case was first reported to public health officials). Early in the pandemic, policy-makers decided that the onset date would be used for all reporting and analysis at the state level in Ohio. The reporting date was defined as the first date on which a case appeared in the system, and was often several days or possibly weeks after the onset date. Given the public and aggregate nature of the data, we were unable to accurately account for individual-level reassignment of onset date in this analysis; instead, for the purpose of demonstration, we assumed that reassigned cases were originally tabulated with the onset date closest to the date of original reporting and reduced the aggregate count for that onset date by the number reassigned.

To explore the impact of reporting patterns on the calculation and subsequent interpretation of public health alert indicators, we retrospectively considered 4 time points in autumn 2020: August 15, September 15, October 15, and November 15. For each date, we examined cases reported by that date and computed indicators related to the trends in case counts. Since the data were completely reported by June 2021, we could compare the estimates from the indicators with the true trend observed in the onset cases at that point in time. For each approach, we computed sensitivity as the proportion of counties with true increasing trends identified as increasing and specificity as the proportion of counties with true nonincreasing trends identified as nonincreasing.

Rolling average approach

We refer to the current approach for determining whether case rates are increasing used by the Ohio Department of Health as the rolling average approach (6). This approach computes a 7-day rolling average of case counts, indexed by onset date, for each of the last 21 days. The alert indicator for an increasing trend in cases is flagged if there are 5 consecutive days of increasing averages at any point in the 21-day window. This approach crudely accounts for daily reporting variation by averaging across 7 days but makes no attempt to account for reporting lag or any other sources of variation.

Spline approach

A slightly more sophisticated but still simple approach was suggested in decision support materials issued by the CDC for detecting rebounds (5) and will be referred to as the spline approach. This approach is similar to the rolling average approach described above but fits a spline to the time series of rolling averages. For consistency, we used 7-day rolling averages over a 21-day period to align with the temporal window of interest for the alert system. We fitted a cubic spline (5) to each series with 4 knots. By using a spline, we were able to smooth daily and other systematic variation in reporting patterns. In alignment with the CDC (5), we determined whether there was an increasing trend by looking at the fitted values from the spline and determining whether there were any 5-consecutive-day periods where the fit for each day was greater than that for the previous day. Like the rolling average approach, uncertainty and reporting delay are not incorporated into the decision-making process. Splines were estimated using the "mgcv" package in R (R Foundation for Statistical Computing, Vienna, Austria) (22).

Model-based approach

In contrast to the simpler approaches, with the model-based approach we explicitly model both the process for new-onset cases and the reporting delay process. We follow the general setup outlined in previous work (10, 14). In Ohio, COVID-19 cases are reported daily, so we use a daily time scale. To reduce computation time, we take a moving window approach (12) that considers the past 90 days ($T = 90$). From April through September 2020, 94% of cases were reported within 2 weeks of onset and 98% of cases were reported within 30 days. To be conservative, we set a maximum reporting delay time of 30 days following onset ($D = 30$).

Outcome model. Let Y_{it} be the count of reported cases in county $i = 1, \ldots, N$ with onset date $t = 1, \ldots, T$. Note that Y_{it} is assumed to be the true total count, which is assumed to be partially observed for time t such that $t + D > T$. We assume

$$Y_{it} \sim \text{Poisson}(\lambda_{it}),$$
$$\log(\lambda_{it}) = O_i + \alpha_{it} + \boldsymbol{X}_t \boldsymbol{\eta}_i,$$

where O_i is an offset of the log population of county i, α_{it} is the latent state of the process, $\boldsymbol{X}_t$ is a design vector indicating the day of the week, and $\boldsymbol{\eta}_i$ is the effect of the day of the week of illness onset. Note that $\boldsymbol{X}_t$ is parameterized using effect coding, so α_{it} reflects the average of the process across days of the week. By using this structure for the model, we are able to remove daily variation from the latent state, α_{it}, through $\boldsymbol{X}_t \boldsymbol{\eta}_i$. After removing the daily variation, we focus on the model for the latent state or structural part of the model. We use a semilocal linear trend model (23). That is, for $t > 1$,

$$\alpha_{it} = \alpha_{i(t-1)} + \delta_{i(t-1)} + \varepsilon_{it}^{\alpha},$$

where $\varepsilon_{it}^{\alpha} \overset{iid}{\sim} N(0, \tau_{\alpha}^2)$ and the initial value at $t = 1$ is $\alpha_{i1} \sim N(0, 100)$. Then, for the model for trend, we let

$$\delta_{i1} = \delta + d_i + \varepsilon_{i1}^{\delta},$$
$$\delta_{it} = \delta + d_i + \rho_{\delta}(\delta_{i(t-1)} - \delta - d_i) + \varepsilon_{it}^{\delta},$$

where δ is a common statewide trend, d_i is a county-specific spatial trend, and ρ_{δ} is an autoregressive term. Let $\varepsilon_{it}^{\delta} \overset{iid}{\sim} N(0, \tau_{\delta}^2)$. A benefit of this parameterization is it allows us to separate changes that are due to white noise ($\varepsilon_{it}^{\alpha}$) from those that are due to more consistent temporal trends (δ_{it}). By using a stationary model for δ, we are able to provide some structure around a longer-term trend while retaining flexibility for local deviations in space and time.

To account for spatial correlation, we assume that the trends in neighboring counties are correlated and specify an intrinsic conditional autoregressive model. That is,

$$d_i \mid d_{-i} \sim N\left(\frac{1}{w_{i+}} \sum_j w_{ij} d_j, \frac{\tau_d^2}{w_{i+}}\right),$$

where d_{-i} is the set of counties excluding county i, w_{ij} is an indicator of whether counties i and j are adjacent, $w_{i+} = \sum_{j \neq i} w_{ij}$, and τ_d^2 is a variance. To ensure a valid process model, we enforce a sum to 0 constraint on the d_i (24). We chose to incorporate spatial dependence in the trend to reflect a belief that cases in a given county are likely to change in a similar fashion as cases in neighboring counties. This decision aligned with existing manual processes in the health department and helped stabilize rural estimates.

We also assume county-specific effects of the day of the week. We assume that while variability exists between counties, the daily patterns are similar across the state. We assume the following hierarchical model:

$$\boldsymbol{\eta}_i \overset{iid}{\sim} N(\boldsymbol{\eta}, \tau_{\eta}^2 \boldsymbol{I}_6),$$

where $\boldsymbol{\eta}$ is a vector of state average day-of-the-week effects, τ_{η}^2 is a variance, and $\boldsymbol{I}_6$ is a 6×6 identity matrix. This allows each county to have its own daily pattern while borrowing strength across all counties in the state as warranted.

Reporting model. Since we know that Y_{it} is observed with a reporting lag, we must specify a model for the delay. Let Z_{itd} be the count of cases observed in county i with onset date t that are observed $d = 0, \ldots, D$ days after t. Note that Z_{itd} corresponds to the number of cases reported d days after onset date t and so is unobserved when $t+d > T$. We assume

$$\boldsymbol{Z}_{it} \mid \boldsymbol{p}_{it}, Y_{it} \sim \text{Multinomial}(\boldsymbol{p}_{it}, Y_{it}),$$
$$\boldsymbol{p}_{it} \sim \text{GD}(\boldsymbol{\alpha}_{it}, \boldsymbol{\beta}_{it}),$$

where $\boldsymbol{Z}_{it} = (Z_{it0}, \ldots, Z_{itD})0, \boldsymbol{p}_{it}$ is the vector of proportions of the total Y_{it} reported on each of the D days, and GD is the generalized Dirichlet distribution. We use a generalized Dirichlet distribution to properly account for potential overdispersion of the $\boldsymbol{p}_{it}$ (10). This leads to the following conditional distribution:

$$Z_{itd} \mid Z_{it(-d)}, Y_{it} \sim \text{Beta-binomial}\left(\alpha_{itd}, \beta_{itd}, Y_{it} - \sum_{j<d} Z_{itj}\right),$$

where $Z_{it(-d)}$ is the set of counts reported with a delay that is not d days. To model more intuitive quantities, we reparameterize the distribution (10) in terms of the mean ν_{itd} and dispersion φ_d, such that $\alpha_{itd} = \nu_{itd}\varphi_d$ and $\beta_{itd} = (1-\nu_{itd})\varphi_d$. Then, similar to a hazard function, we let $\text{logit}(\nu_{itd}) = \psi_{itd}$ and assume the following autoregressive model:

$$\psi_{i1d} = \beta_d + \boldsymbol{V}_{1d}\boldsymbol{\xi}_i + \varepsilon^{\psi}_{i1d},$$
$$\psi_{itd} = \beta_d + \boldsymbol{V}_{td}\boldsymbol{\xi}_i + \rho_{\psi}(\psi_{i(t-1)d} - \beta_d - \boldsymbol{V}_{(t-1)d}\boldsymbol{\xi}_i) + \varepsilon^{\psi}_{itd},$$

where β_d is the average log odds of remaining cases' being reported by delay d, $\boldsymbol{V}_{td}$ is a design matrix indicating the day of the week, $\boldsymbol{\xi}_i$ is a day-of-the-week effect, ρ_{ψ} is an autoregressive parameter, and ε^{ψ}_{itd} is an error term. We assume $\varepsilon^{\psi}_{itd} \overset{iid}{\sim} N(0, \tau^2_{\psi})$. Note that $\boldsymbol{V}_{td}$ is parameterized using effect coding.

The parameterization of the delay model allows us to accommodate several important features of COVID-19 reporting and should, in general, be customized to reflect the actual reporting process. First, reporting in Ohio is done by county health departments, who may have varying capacity and resources for timely reporting. Thus, the delay model is county-specific. We account for day-of-the-week effects, much like in the outcome model, because in many counties, reporting primarily aligns with the workweek. We also assume autoregressive temporal dependence to capture the potential for administrative backlogs. For example, if a smaller portion of cases is reported today, we may also expect a smaller proportion the next day because of a backlog. We do not incorporate a term to account for spatial dependence in the delay model because we assume that neighboring health departments are independent agencies, and so we would not anticipate spatial structure.

As with the outcome model, we allow for county-specific variability in day-of-the-week reporting effects. We again assume similar patterns across the state and specify the following hierarchical model:

$$\boldsymbol{\xi}_i \overset{iid}{\sim} N(\boldsymbol{\xi}, \tau^2_{\xi}\boldsymbol{I}_6),$$

where $\boldsymbol{\xi}$ is a vector of state average day-of-the-week effects, τ^2_{ξ} is a variance, and $\boldsymbol{I}_6$ is a 6×6 identity matrix.

Prior model and computation. Since we fit our model in the Bayesian paradigm, we must specify prior distributions on all unknown parameters. For each element of $\boldsymbol{\eta}$ and $\boldsymbol{\xi}$, we assign independent normal priors with 0 mean and variance 1. We also assign δ a normal prior with 0 mean and variance 1. We use a variance of 1 for these prior distributions because each parameter reflects a relative daily difference on the log scale, and so these priors reflect a reasonable range for those parameters. We assign β_d independent normal priors with mean 0 and variance 4, which puts adequate probability on reasonable values on the logit scale. We also assign all variance parameters inverse γ priors with shape and scale both set to 0.5. All autoregressive parameters are assigned uniform prior distributions over -1 to 1.

To compare across approaches, we fit the model for each of the 4 dates considered. We treat the last day in the series (i.e., the current date) as missing and forecast the expected case count, which reduces model instability due to the rarity of cases reported on the day of onset ($d = 0$). The model was fitted via a Markov chain Monte Carlo algorithm implemented in R using NIMBLE (25). The algorithm was run for 30,000 iterations, with the first 15,000 discarded as burn-in, and then thinned by keeping every 10th iteration. Computation time was approximately 20 hours.

To determine whether the numbers of cases were increasing in the most recent 21-day period, we use the posterior distribution of δ_{it}. Since δ_{it} reflects the trend in county i at time t, there is a net increasing trend over the past 21 days if $\sum_{t=T-20}^{T} \delta_{it} > 0$.

True change

One major advantage of a model-based approach is the flexibility to address more complex questions of interest. However, our goal in this paper is to assess the method used to calculate when cases are increasing in a county. To most closely align with the practical question posed, we define a true increase to indicate whether the number of cases in the most recent 7-day period is greater than the number of cases 2 weeks prior. This corresponds to comparing the first week in the most recent 21-day period with the last week in that period.

RESULTS

Spatiotemporal variability in the median reporting delay by county is shown in Web Figure 1. Results from applying each approach to assess whether numbers of cases were increasing are shown in Figure 1. For the model-based approach, we generate a posterior probability of an increasing trend and color counties by their posterior probability. We present the posterior mean estimate of change and the posterior probability continuously in Web Figure 2. In Web Figure 3, we show the posterior mean county-specific estimates of trend, $\delta + d_i$.

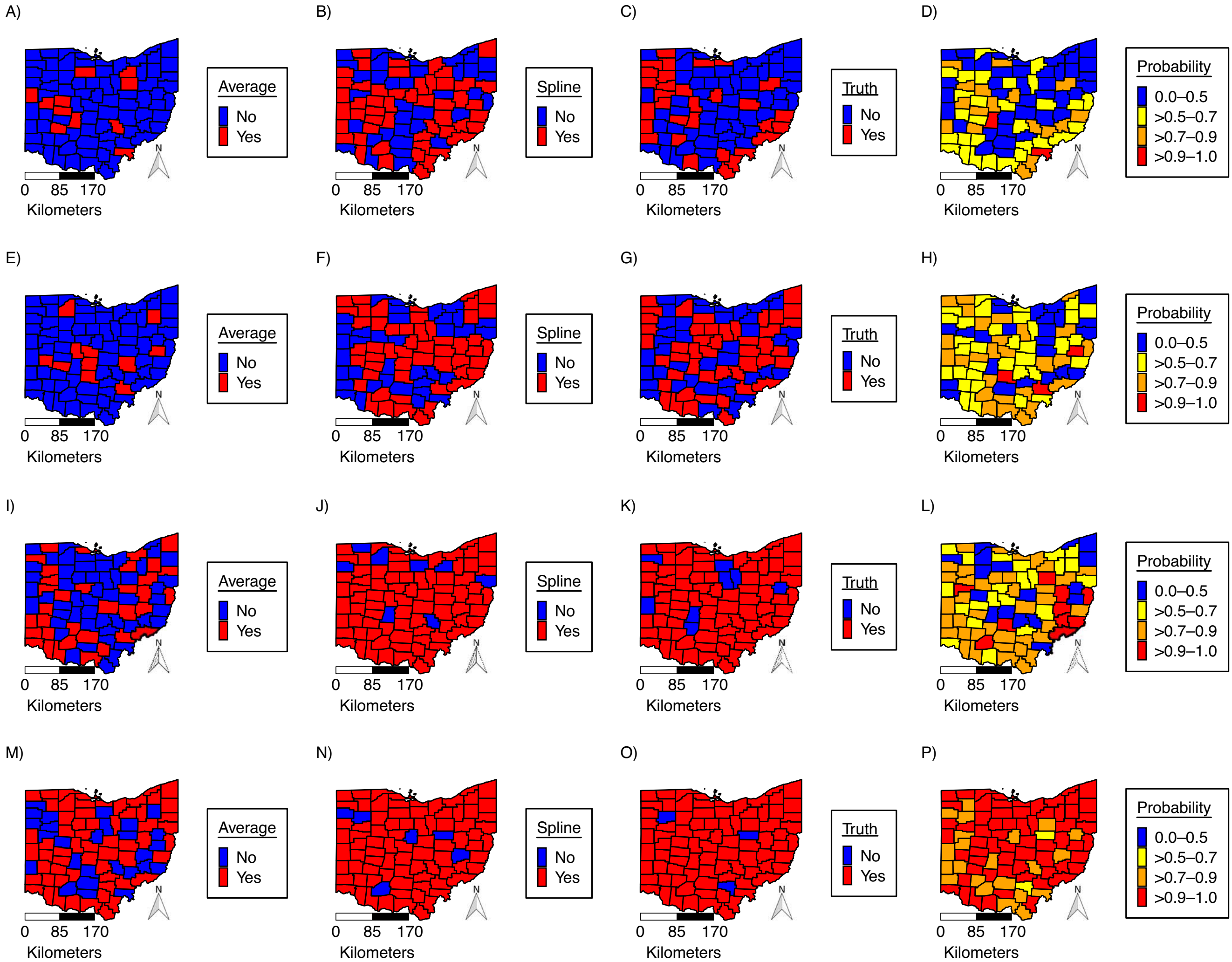

Figure 1. Indicators of trends in coronavirus disease 2019 (COVID-19) cases in Ohio, autumn 2020. The first row of graphs shows the rolling average indicator (A), spline indicator (B), true observed indicator of an increase (C), and proposed model-based posterior probability (D) for August 15, 2020. The second row shows the rolling average indicator (E), spline indicator (F), true observed indicator of an increase (G), and proposed model-based posterior probability (H) for September 15, 2020. The third row shows the rolling average indicator (I), spline indicator (J), true observed indicator of an increase (K), and proposed model-based posterior probability (L) for October 15, 2020. The fourth row shows the rolling average indicator (M), spline indicator (N), true observed indicator of an increase (O), and proposed model-based posterior probability (P) for November 15, 2020.

Using Figure 1 to visually compare the results, we see that the spline and the probabilities from the model much more closely resemble the truth than the rolling average indicator, which was actually used in practice by OPHAS. We computed sensitivity and specificity for each date and overall across all 4 dates (Table 1). In general, the sensitivity of the rolling average was poor, except in November, when the state was already in the midst of a major surge in cases. Overall sensitivity and specificity were similar for the spline and the model using a cutoff probability of 0.5. We see that as the probability gets closer to 1, the overall specificity increases to 0.85 with a cutoff of 0.7 and to 1.00 with a cutoff of 0.9.

While the sensitivity and specificity are similar between the spline and the proposed model, we can gain additional insight by examining Web Figures 4 and 5, which show time-series estimates for 3 urban counties and 3 rural counties. It becomes clear that the spline and rolling average are based on incompletely reported data, as they always decrease over approximately the last week of each series regardless of the true trend. This implies that when the criteria are met for flagging an increase, it will generally reflect increasing trends that occurred 2–3 weeks in the past. In contrast, by accounting for reporting delays, the case counts estimated from the model much more closely align with the true series over the entire time period, thus providing a more

Table 1. Estimated Sensitivity and Specificity of Methods for Detecting Increasing Trends in COVID-19 Cases (the Rolling Average Indicator, the Spline Indicator, and the Model-Based Indicator With 3 Different Posterior Probability Cutpoints) at 4 Time Points, Ohio, Autumn 2020

Date and Measure	Method				
	Rolling Average Indicator	Spline Indicator	Model-Based Indicator		
			PPC: >0.9	PPC: >0.7	PPC: >0.5
August 15					
Sensitivity	0.10	0.84	0.06	0.48	0.84
Specificity	0.86	0.56	1.00	0.93	0.61
September 15					
Sensitivity	0.20	0.72	0.07	0.43	0.83
Specificity	0.95	0.55	1.00	0.76	0.38
October 15					
Sensitivity	0.41	0.93	0.13	0.59	0.83
Specificity	0.75	0.25	1.00	0.75	0.38
November 15					
Sensitivity	0.71	0.95	0.75	1.00	1.00
Specificity	0.67	0.67	1.00	0.67	0.00
Overall					
Sensitivity	0.43	0.88	0.33	0.69	0.89
Specificity	0.88	0.54	1.00	0.85	0.49

Abbreviations: COVID-19, coronavirus disease 2019; PPC, posterior probability cutpoint.

accurate look at current conditions and, in turn, reducing uncertainty in the level of health risk communicated to the public and improving the confidence of decision-makers who use OPHAS in Ohio (e.g., school superintendents). This is also clear as we see considerable reductions in prediction error for the case counts for the model relative to the spline, as shown in Web Figure 6.

The model-based approach also provides a rich set of additional results that can produce useful insights. Typically, the main goal of these models is to nowcast case counts without formally assessing trends. In Figure 2, we show nowcast estimates with their 90% credible intervals and the true counts in gray for an urban county and a rural county. In Table 2, we show coverage of 90% and 50% credible intervals on each date and overall across all dates. Coverage is approximately at the nominal levels. We also note that when case rates were more stable in August and September, coverage tended to be above nominal levels. However, coverage was nominal in October and November when cases were growing at near-exponential rates, and it was a far more volatile period of the pandemic in Ohio. Thus, our model performs as expected for nowcasting cases. In Figure 2, we also show time-series plots of the latent state, which removes the day-of-the-week effects, and the trend. The trend can also be viewed as the derivative of the latent state curve, so when it is greater than 0, it indicates increasing case counts. In Web Figures 7 and 8, we further explore the performance of the model-based approach by county population size.

DISCUSSION

We found that our proposed model for nowcasting addressed a number of the shortcomings of simpler models advocated by our state and federal governments. When assessments are linked to onset date, case reporting is subject to reporting lag or delay. We illustrated that the simple rolling average approach used in OPHAS does not perform well, as it fails to account for lag and other variation in reporting. Although our model with a cutoff of 0.5 performed similarly to the spline approach outlined by the CDC in terms of sensitivity and specificity, it provided additional benefits in other ways. We illustrated several advantages of the proposed model, including posterior probabilities to continuously summarize evidence for an increasing trend, the ability to nowcast case counts, and the quantification of uncertainty. These added benefits are important for public health practice, as continuous estimates convey additional meaning to policy-makers that can improve decision-making and allocation of limited resources (26, 27). This results in a better trade-off between sensitivity and specificity and can allow for prioritization of areas where the evidence of an increase is strongest. This was particularly important within a political climate that was averse to the perception of overreaction. In addition, through use of a single model to both nowcast cases and infer trends, it ensures a coherent message across case-based indicators of interest to policy-makers, which is important for credibility.

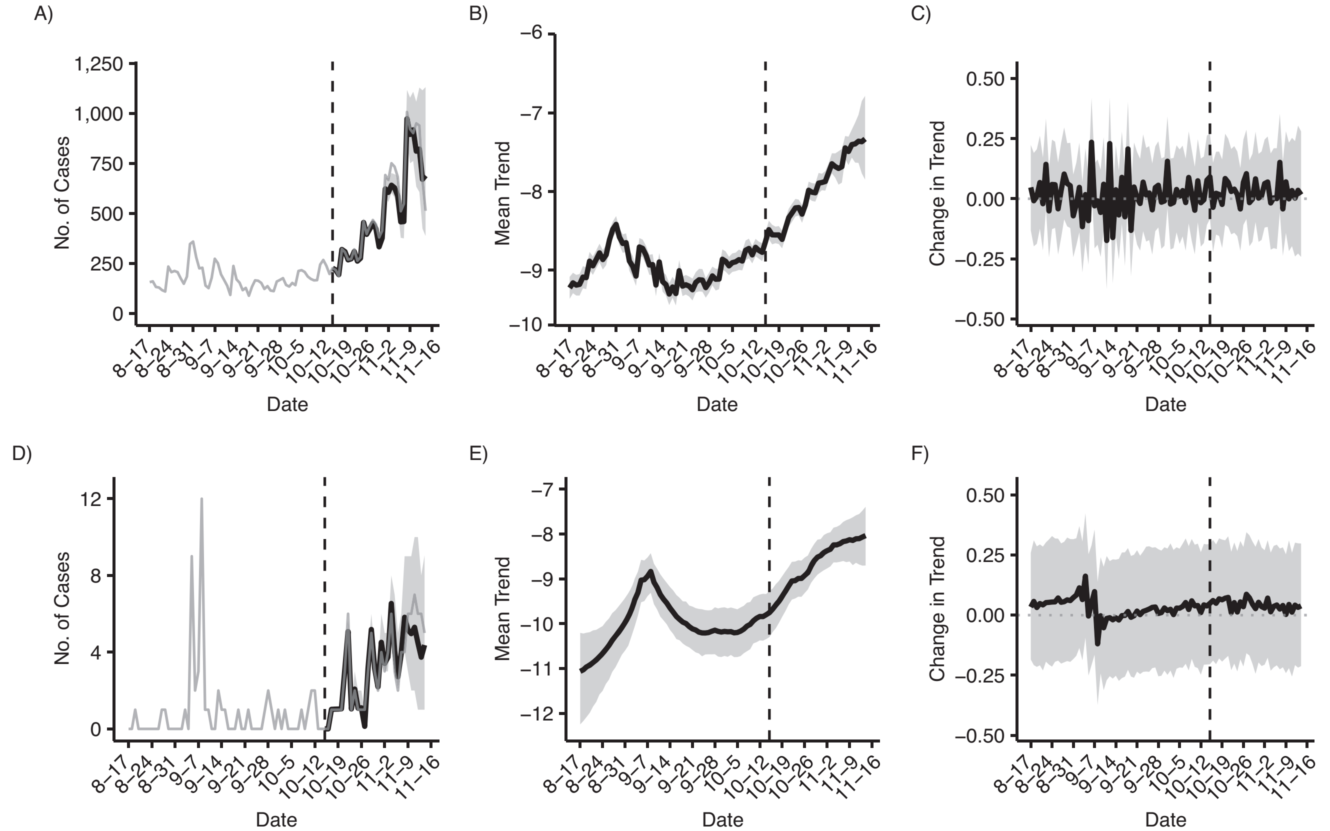

Figure 2. Nowcast projections of coronavirus disease 2019 (COVID-19) case trends and time-series model components for an urban county (Franklin County) and a rural county (Harrison County) in Ohio, November 15, 2020. The left-hand graphs (panels A (Franklin County) and D (Harrison County)) show the posterior mean number of cases (black line), the 90% credible interval (gray shading), and the true number of cases (gray line). The middle graphs (panels B (Franklin County) and E (Harrison County)) show the posterior mean value (black line) and 90% credible interval (gray shading) of the latent state (α_{it}), which is the mean process on the log scale with daily variation removed. The right-hand graphs (panels C (Franklin County) and F (Harrison County)) show the posterior mean value (black line) and 90% credible interval (gray shading) for the daily change in trend (δ_{it}), with a horizontal dotted reference line at 0. The vertical dashed line indicates the divide between complete and incomplete reporting periods for all panels.

The additional epidemiologic information gained from use of the proposed model is a clear advantage over the simpler approaches.

In practice, our proposed model added value to the existing surveillance infrastructure. One notable impact was the ability to more confidently identify changes in trends in sparsely populated rural counties. By smoothing some of the noise due to small counts, we were able to identify and draw attention to rural counties that ended up being some of the first locations to experience the autumn 2020 surge. These trends were difficult to manually identify because of the noise of small counts and heterogeneity in reporting delays, and, as illustrated with its poor sensitivity, the rolling average approach that was in use largely missed these communities. The largest impact of our model was during the fall surge, when increasing case trends were obvious throughout the state. However, the nowcast estimates and credible intervals proved to be invaluable tools for helping policy-makers understand the current situation. As cases surged, nowcast estimates helped to communicate how many cases were likely to have already occurred, improving real-time situational awareness for making public health policy decisions.

While common in epidemic forecasting, probabilistic thinking and uncertainty should play an increased role in our interpretation of data from the present and recent past for public health decision-making. Uncertainty, due to both the volatility of exponential growth and known features of the reporting process (i.e., daily variation, reporting delay, etc.), is not adequately captured through point estimates alone and is often ignored. Instead, it is critical to incorporate features of the reporting process into models and to generate estimates with credible intervals to quantify uncertainty. These intervals help policy-makers to understand a plausible range of case counts on a given day, which can lead to more proactive policies, as it enables the use of all available data rather than relying on completely reported data that were, in the case of COVID-19, already at least a week old. In

Table 2. Credible Interval Coverage of Model-Based Nowcast Projections for Estimating the Number of COVID-19 Cases in the Most Recent 7-Day Period at 4 Time Points, Ohio, Autumn 2020

Date	90% CrI	50% CrI
August 15	0.95	0.70
September 15	0.94	0.65
October 15	0.88	0.50
November 15	0.88	0.52
Overall	0.92	0.59

Abbreviations: COVID-19, coronavirus disease 2019; CrI, credible interval.

general, Bayesian models, like the one proposed, provide a framework for incorporating more of our knowledge about the case-reporting process and enabling us to better inform decision-making under the uncertainty imposed by a dynamic, novel pandemic.

In conclusion, we have illustrated shortcomings in using simpler approaches for public health decision-making. We have also illustrated how more sophisticated statistical models can account for the real-world complexities associated with surveillance data. Despite the added complexity, the output from these models can be summarized in a relatively simple and concise form that still appropriately reflects uncertainty. While we cannot eliminate all of the uncertainty in public health surveillance and decision-making, we must use approaches that embrace these challenges and deliver more accurate and honest assessments to policy-makers.

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Data and software code are available on GitHub (28).

A preprint of this article is available in *arXiv* (29).

The content of this article is solely the responsibility of the authors and does not necessarily represent the official views of the Ohio Department of Health.

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